Optimization of ICDs' Port Sizes in Smart Wells Using Particle Swarm Optimization (PSO) Algorithm through Neural Network Modeling

Morteza Hassanabadi*[1], Seyyed Mahdia Motahhari [2] and Mahdi Nadri Pari [2]
[1]Amirkabir University of Technology Tehran Polytechnic, Tehran, Iran
[2] Research Institute Of Petroleum Industry, Tehran, Iran
(Received 3 April 2012, Accepted 20 November 2012)

Abstract

Oil production optimization is one of the main targets of reservoir management. Smart well technology gives the ability of real time oil production optimization. Although this technology has many advantages; optimum adjustment or sizing of corresponding valves is still an issue to be solved. In this research, optimum port sizing of inflow control devices (ICDs) which are passive control valves is focused on by designing a neural network to simulate reservoir behavior and applying Particle Swarm Optimization algorithm to find optimum port size for ICDs. Indeed; this work eliminates the need for lots of expensive and time consuming iterations through reservoir simulator. The objective of the work is to maximize the oil production.

Keywords: Inflow control device (ICD), Smart well, Artificial neural network (ANN), Particle swarm optimization (PSO), Optimization

Introduction

Heterogeneity of hydrocarbon reservoir leads to various behavior in oil production within different time periods. In this respect smart well technology has been developed in recent years which consists of a set of down-hole sensors to measure temperature, pressure, and flow rate and in higher level inflow control valves (ICVs) and inflow control devices (ICDs) to control oil production with respect to reservoir characteristics. Meanwhile; the difference between ICDs and ICVs is that ICDs have constant port size and cannot be remotely adjusted but ICVs are active valves with various port sizes and can be adjusted remotely. The advantages of smart well technology with respect to conventional completion are oil production increase, water production decrease, better recovery factor, and production cost reduction [7,16-17,22].The first smart well technology was implemented in North Sea in August 1997. So far, more than 300 smart well systems have been implemented worldwide. Consequently; optimization of the system setting has become an important issue. In 2002 Gao.C; optimization of intelligent control valves' (ICVs) setting was performed via conjugate gradient method. This method was acknowledged in almost researches up to 2011 to optimize adjustment of ICVs, [1-2, 18, 20-21, 23]. In 2006, neural network (NN) method was employed for optimization of smart wells Moreno.J.C, (2006). In 2008, Multi-Step Quasi-Newton (SSMQN) Method was used as an algorithm to optimum ICVs adjustment [14]. In 2009, genetic algorithm was implemented for ICVs' setting optimization Ghreeb.Z.M, Al *(2009)*.

As stated; ICDs are passive control valves with fixed port sizes which need optimum port sizing before installing in downhole. In this paper we try to find optimum port sizes of ICDs for ahorizontal well by integrating Artificial Neural Network (ANN) with Particle Swarm Optimization Algorithm. Indeed; by solving non-linear partial differential equations through reservoir simulator; the results can be input into the optimization algorithm for identifying optimum port sizes of ICDs within predetermined period of production time. It is noted that solving these equations through reservoir simulator is costly and time consuming. Therefore, it is necessary to find

* Corresponding author: Tel: +98-311-52786435 Fax: +98-21-44739731 Email: m_hassanabadi@aut.ac.ir

a procedure with minimum error and constraint-respected to simulate reservoir behavior while eliminating the need for reservoir simulator. This applied method in this paper gives ability of high speed (time reduction) generation of estimation function (Meta model) with low error with respect to objective function through integration of ANN, Experimental Design and PSO. Comparison of productions from smart well and conventional well both modeled in this work shows good justification for future decisions.

2. Problem description and mathematical model

A mathematical model is developed for a horizontal well with N numbers of ICDs.
The following notations are used to define the mathematical model:

Name	Description	Units
$i \in I$	ICD	
t	Time period	
Parameters		
W_c	Maximum Water cut	Percentage
q_o	Maximum producible oil	bbl/day
ρ_o	Oil density	lb/ft^3
ρ_w	Water density	lb/ft^3
μ_o	Oil viscosity	Cp
μ_w	Water viscosity	Cp
S_o	Oil saturation	Percentage
S_w	Water saturation	Percentage
k_{ro}	Oil relative permeability	
k_{rw}	Water relative permeability	
k	Absolute permeability	Md
g	Gravity	m/s^2
e_z	Vectors point in the direction of gravity	
f	Coefficient friction	
D	Pipe Diameter	M
L	Length of pipe between control valves	m
q_{o_i}	Oil rate	ft^3/s
q_{w_i}	Water rate	bbl/day
C_u	Unit conversion factor, 2.159×10^{-4}	field units
C_v	Valve flow coefficient	dimensionless
V_c	Fluid Velocity	ft/s
A_c	Cross Section	ft^2
p	Pressure	psi
ϕ	Porosity	fraction
ΔP_t	Total pressure drop	psi
ΔP_c	Frictional pressure losses	psi
ΔP_t	Pressure losses due to the ICD	psi
Variables		
q_t	Total flow rate of fluid in time period t	bbl/day
N_p	Cumulative Oil	Bbl
W_p	Cumulative Water	Bbl
W_{c_i}	Water flow rate out of control of valvei	Percentage

The aim is to maximize the cumulative oil production while minimizing cumulative water production by means of optimum port sizing of ICDs. In mathematical term we have the following model:

$$Z = MAX \quad (N_p - W_p) \tag{1}$$

$$N_p = \sum_{i=1}^{N} q_{t_i} \left(1 - w_{c_i}\right) \tag{2}$$

$$W_p = \sum_{i=1}^{N} q_{t_i} w_{c_i} \tag{3}$$

Equation (1) shows objective function in terms of difference between cumulative produced oil and water that defined as (2) and (3) respectively. Here q_{t_i} is total flow rate and w_{c_i} shows water percentage from i[th]ICD.

$$q_{t_i} = q_{o_i} + q_{w_i} \tag{4}$$

$$W_c = \frac{\sum_{i=1}^{N} q_{w_i}}{\sum_{i=1}^{N} q_{t_i}} \tag{5}$$

Equation (4) shows relationship between oil rate q_{o_i} and water rate q_{w_i} with total flow rate q_{t_i}. Equation (5) cites water cut w_c in terms of water rate q_{w_i} and total flow rate q_{t_i}.

$$\sum_{i=1}^{N} q_{o_i} <= q_o \tag{6}$$

$$W_c <= W_{c_0} \tag{7}$$

The constraints (6) and (7) bound the total produced oil and water to constants q_o and W_{c_0} respectively.

$$\nabla.\left[\left(\rho_o \kappa k_{ro} / \mu_o\right)\left(\nabla p_o - \rho_o g \nabla e_z\right)\right] = \phi \frac{\partial\left(\rho_o S_o\right)}{\partial t} \tag{8}$$

$$\nabla.\left[\left(\rho_w \kappa k_{rw} / \mu_w\right)\left(\nabla p_w - \rho_w g \nabla e_z\right)\right] = \phi \frac{\partial\left(\rho_w S_w\right)}{\partial t} \tag{9}$$

$$S_w + S_o = 1 \tag{10}$$

$$q_o = f(s_o) \tag{11}$$

$$q_w = f(s_w) \tag{12}$$

Oil and water flow through porous media of reservoir is modeled with partial differential equations (8) and (9). The level of saturation for oil and water can be obtained by solving these equations for any reservoir grid in different time period. Oil and water flow rates are function of oil and water saturation in the reservoir as shown in equations (10), (11) and (12). These equations are governing when no ICDs are implemented. When the production is restricted by ICDs in addition to above equations other equations must be taken into account. By employing ICDs, the flow rate from the reservoir to the well changes. This causes additional pressure drop as shown in equation (13). Thus total pressure variation is equal to pressure drop due to fluid friction with wellbore and that of cross section of ICDs' ports. Equation (14) shows pressure drop due to fluid flow through ICDs.

$$\Delta P_t = \Delta P_c + \Delta P_f \tag{13}$$

$$\Delta P_c = C_u \rho \frac{V_C{}^2}{2C_v} \tag{14}$$

This equation shows that variation of pressure drop (ΔP_c) due to fluid flow through ICDs and depends only upon fluid velocity (V_C).

$$V_C = \frac{q_t}{A_c} \tag{15}$$

Equation (15) shows the relationship between fluid flow rates with cross section of ICDs' ports. The cross section (A_C)of ICDs' ports has inverse relation with fluid velocity (V_C) and direct relation with flow rate. Cross section (A_C)can be calculated with equation (16) Conejeros. Rand Lenoach.B *(2004)*, Meun. P (2008).

$$0 \le A_C = \frac{A_{choke}}{A_{Total}} \le 1 \tag{16}$$

In equation (16), A_{total} is cross section of maximum ICDs' ports size available in the market (manufacturer can make it- here is 0.022 ft^2) and A_{choke} is the required cross section of ICDs which should be acquired through reservoir simulator and optimization algorithm.

Suppose T is production duration and a horizontal well is equipped with N numbers of ICDs. There are infinite situations and combinations for port sizes of ICDs. Hence; in this study we reduce the numbers of combinations through Experimental Design methods to train Neural Network. By then; the optimum port sizes are obtained via Particle Swarm Optimization (PSO).

3. Solution procedure

In this section we elaborate the role of Neural Network as a replace for reservoir simulator, Particle Swarm Optimization Algorithm, and Central Composite Design of kind of Response Surface method to select the samples. Figure 1 shows the solution procedure.

3.1. Structure of artificial neural network

Neural Network simulates human's brain in the form of an Artificial System. It consists of many processors [Artificial Neurons) designed regularly (there is a complete graph between each two layers] Harrison. S.J and Marshall. R.F *(1991)*.
Neural Network consists of variables such as numbers of layers in one network, activation function for each layer, numbers of neurons in each layer, and connection between neurons. The most important element of neural network is Processing Element. Neurons are organized in the form of layers. ANN consists of three layers as input layer, middle (hidden) layer, and output layer [11].

3.1.1. Selection of training samples

Training samples set includes input data and corresponding output. The selection of appropriate set is important and should be included by many input data. In fact; the quality of output depends on selected training samples in the stage of training.

3.1.2. Validation of estimation function (Meta model) designed by ANN

Factors in estimation function designed by ANN are analyzed through regression curves passed over training data, validation data and test data. The numbers of training data, test data and validation data are 80%, 15% and 5% of total data respectively. If Coefficient Of Correlation in regression curve (R^2) is near to one it indicates that estimation function has high accuracy.
Another method to investigate accuracy of estimation function is Mean Square Error (MSE)with equation 17 Graudenz. S and Bornholdt. D *(1992)*.

$$MSE = \frac{\sum_{i=1}^{n} (O_i - T_i)^2}{n} \quad (17)$$

In this equation (17) O_i is desired (target) output and T_i is ANN outputs for training data, i and n are the numbers of training samples set. Here; the best result is for that ANN with the least MSE Moselhi.T, Fazio.O and Hegazy.P *(1994)*.

3.2. How to select training samples for ANN through Experimental Design method

Experimental Design is a set of tests to realize effective factors on a process and their effectiveness. The applications of this method can be found in identification of effective factors on a process, identification of optimum conditions, process correction in terms of results obtained from feasible conditions, identification of resistant conditions and reduction of variations in process response [5].

To fit quadratic model in RSM there are three applied methods as Central Composite Design (CCD), Box-Behnken Design (BBD) and Doehlert Design. Among these; CCD is the best. By using CCD; better training samples for ANN can be selected. Moreover we could select to training samples by simulator for ANN.

Suppose the manufacturers have ICDs with port sizes of between zero and 0.022 ft^2. This range shows availability of ICDs in the market and all studies should be based on that. There are infinite cases in mentioned range. CCD helps us to reduce the numbers of cases to arbitrarily five as shown in Table 1. In fact; we transform continuous range of ICDs' port size to discrete range but covering continuous one to obtain training samples. Hence; according to the mathematical model for N numbers of ICDs; CCD transforms mentioned range to 5^N different port sizes as training samples for ANN.

Table1:ICDs' Port Size (ft^2) Number

ICDs' Port Size Number	Port Size (ft^2)
1	0
2	0.3*0.022
3	0.5*0.022
4	0.8*0.022
5	1*0.022

3.3. Particle Swarm Optimization Algorithm

Particle Swarm Optimization Algorithm was adopted from group flying of birds. This algorithm is a group intelligence method for solving global optimization (gbest) problem. PSO includes particles looking for their optimum positions (pbest) in authorized space. This process is based on experiences of particles themselves or of other particles to achieve global optimization. These particles are correcting their knowledge over authorized space within considered time. The particles in PSO are recognized in terms of their position and velocity. Searching process dispatches any particle toward optimum positions [12].

The particle identifies their next position with equations 18 and 19.

$$V_{t+1}= W_t . V_t + c_1 . rand\,()\,(pbest-present_t) + c_2 . rand\,()\,(gbest-present_t) \quad (18)$$

$$present_{t+1} = present_t + V_{t+1} \quad (19)$$

In equation 18; c_1 and c_2 are learning parameters. $rand()$ is a function for random generation of number within [0, 1]. $present_t$ and V_t indicate current position and velocity of particles respectively. W_t is a control parameter to adjust next velocity with respect to current velocity and creates equilibrium between local and global search in the algorithm [6].

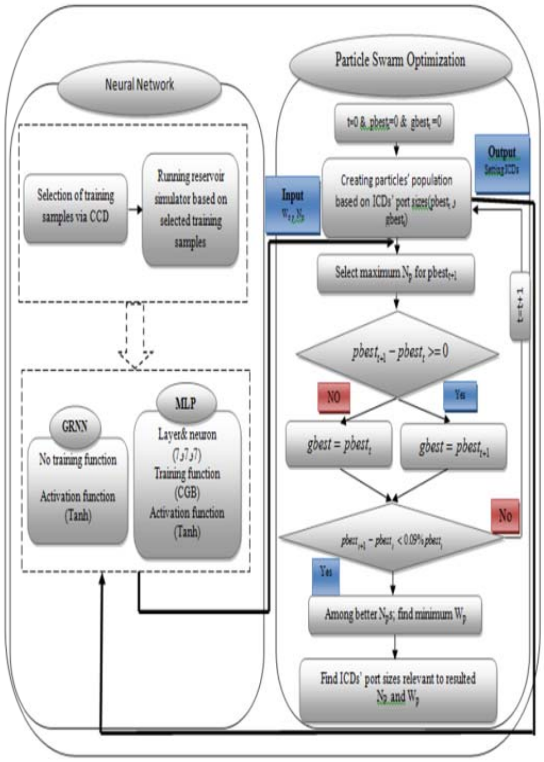


Figure 1: Solution Procedure

4. Implementation of solution procedure- case study

In this section we apply aforementioned procedure on a smart horizontal well drilled in an oil reservoir. The reservoir specifications are mentioned in the following section.

4.1. Reservoir characteristics

In this study we have a heterogeneous symmetric anticline sandstone reservoir with high permeability and porosity channel. The reservoir dimensions are 4×4 km^2 and thickness of 50 m. The reservoir does not have gas cap and it has a strong aquifer. The reservoir characteristics are presented in Table 2 and 3. Figure 2 shows three-dimensional view of smart horizontal well equipped with ICDs.

Table 2:Characteristics of the reservoir model

Type of repository	The sand channel
Total grade for(X)N_X	83
Total grade for (Y) N_Y	73
Total grade for (Z) N_Z	20
Total number of grades	121180
Grid size in order (X) /ft	100
Grid size in order (Y) /ft	100
Grid size in order (Z) /ft	8

Table 3:The properties of the reservoir under study

Reservoir temperature(0F)	170	Formation volume factor(Rbbl/stb)	1.112
Oil Viscosity(cp)	3.8	Gas oil ratio(mcf/STB)	0.172
Average matrix porosity (%)	12	Base Depth(ftss)	-11808
The average percentage of oil saturation (%)	64	Medium pressure deep in the tank base(psi)	5000
Rock compressibility(1/psi)	5×10^{-6}	Oil density (lb/ft^3)	53
The average permeability on the horizon(md)	17	Contact the depth of water - oil(ftss)	-11808
Average permeability in the vertical(md)	3.5	API	35

The most important characteristics of this reservoir are its porosity and permeability. The permeability is illustrated in the three directions x, y and z in the reservoir in Figures (3-a), (3-b) and (3-c) respectively. Also, porosity distribution can be observed in Figure 4.

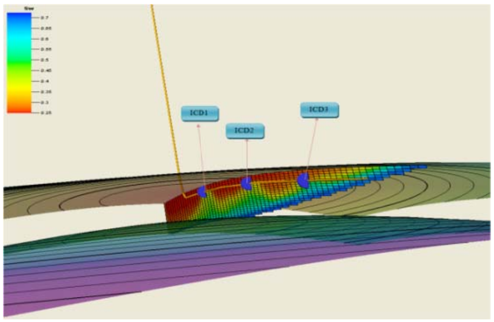
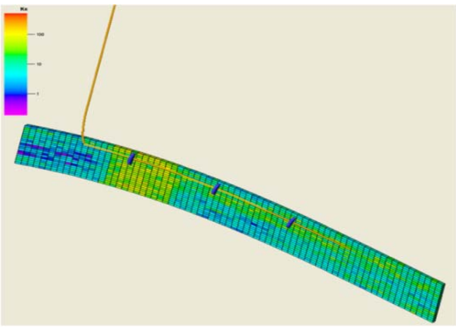
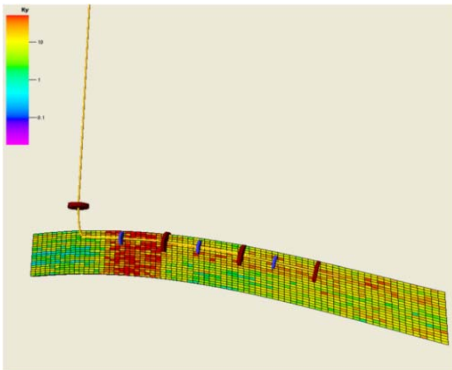


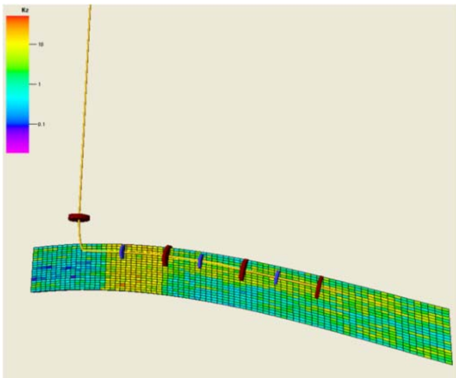
Figure 2: Three-dimensional views of the reservoir model



Figures (3-a): Cross-section on the axis X of the permeability distribution in the reservoir



Figures (3-b): Cross-section on the axis Y of the permeability distribution in the reservoir



Figures (3-c): Cross-section on the axis Z of the permeability distribution in the reservoir

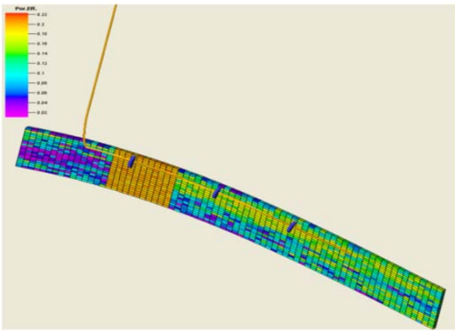


Figure 4: Cross-section of the porosity distribution in the reservoir

The horizontal well has 1400m horizontal section equipped with three ICDs with 400m distance from each other. The first ICD is located in heel part, the second in middle part and the third in toe part of horizontal section. ICDs are fixed port size valves.

In this study, the production time horizon is set to 10 years. To implement mathematical model the maximum acceptable water cut is equal to 60 % and total summation of oil produced from ICDs utmost equal to 3000 bbl/day. These constraints are based on limitations of surface production equipments to handle water production and analysis over authorized daily oil production which is done by experts.

4.2. Implementation of ANN on the mathematical model

As previously mentioned; for N numbers of ICDs there are 5^N situations for fixed port sizes to be investigated. In this study; the horizontal well is equipped with three ICDs resulting to 125 situations for fixed port sizes (Note: By accepting one of these situations we cannot update port size unless we pull the completion out of the hole).

In this paper; two neural networks are employed to solve the mathematical model named as Multilayer Perceptron (MLP) of kind of feed forward trained by back propagation algorithm (Conjugate Gradient with Powell/Beale Restarts (CGB)) and Generalized Regression Neural Network (GRNN) includes a radial basis layer and particular linear layer. Figure 5 illustrates back propagation algorithm for error in a MLP.

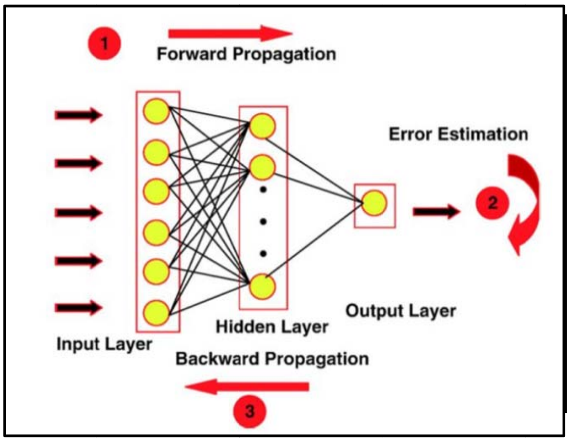


Figure 5: MLP with Back Propagation Algorithm with a hidden layer

Two independent validation methods are used to investigate validity of our work. They are Mean Square Method and Regression on responses of cumulative oil and water production.

To find an appropriate neural network from MLP and GRNN; various neural networks with different training algorithms are investigated. Investigated neural networks in this study are Radial basis function (RBF), Fletcher-Powell Conjugate Gradient (CGF), Polak- Ribiére Conjugate Gradient (CGP), Scaled Conjugate Gradient (SCG) and CGB with different hidden layer. In all investigated neural networks the transform function is Tangent Hyperbolic which is used for selection of network type and training algorithms.

In parallel with above investigation; effect of changes in number of hidden layers and neurons on MSE for each neural network is evaluated. Based on this evaluation the best one is CGB. Table 4 shows how to find the best number of hidden layers and neurons for CGB.

Table 4: Effect of various numbers of hidden layers and neurons on CGB

Number of ANN	No. of Hidden Layers and Neurons	Validation with MSE
1	10	3.56×10^{2}
2	12	7.79×10^{1}
3	(5,5)	2.73×10^{0}
4	(7,5)	1.17×10^{-1}
5	(7,7)	2.47×10^{-3}
6	(10,5)	2.98×10^{-2}
7	(5,10,5)	3.5×10^{-2}
8	(10,10,5)	1.33×10^{-3}
9	**(7,7,7)**	$\mathbf{4\times10^{-4}}$
10	(5,10,10,5)	2.2×10^{0}

As Table 4 and Figures 6 and 7 show due to less MSE for cumulative oil and water production the best numbers of hidden layers and neurons are three layers with seven neurons for each. It is noted that GRNN in comparison with MLP has less MSE (10^{-6}) and high accuracy in regression. Table 5 and Figures 8 and 9 show the result of GRNN.

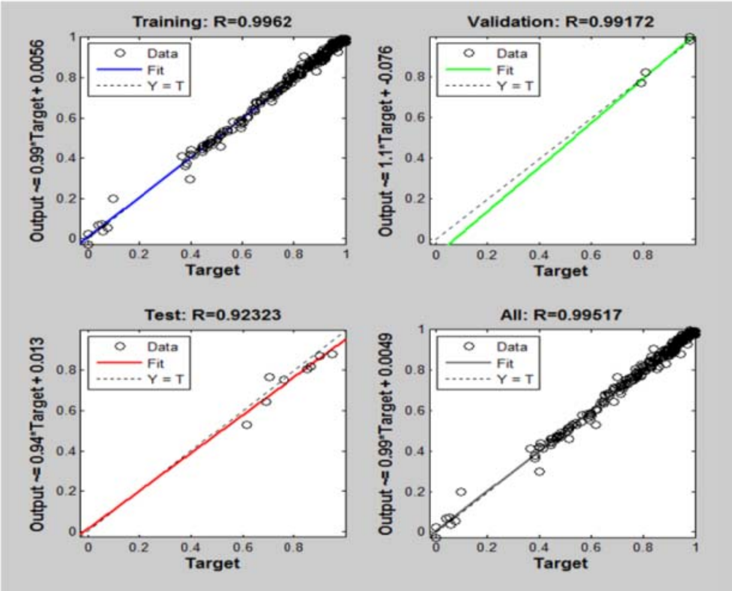


Figure 6: Regression on responses of cumulative oil and water production for validation of meta model obtained by ANN_{MLP}

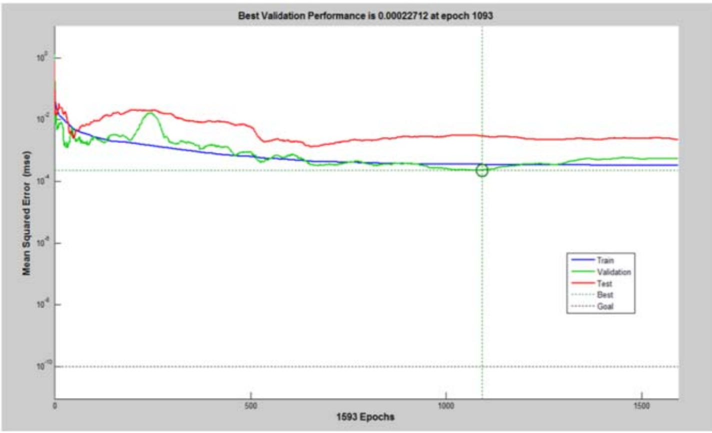


Figure 7: Best fitness (MSE) versus generation

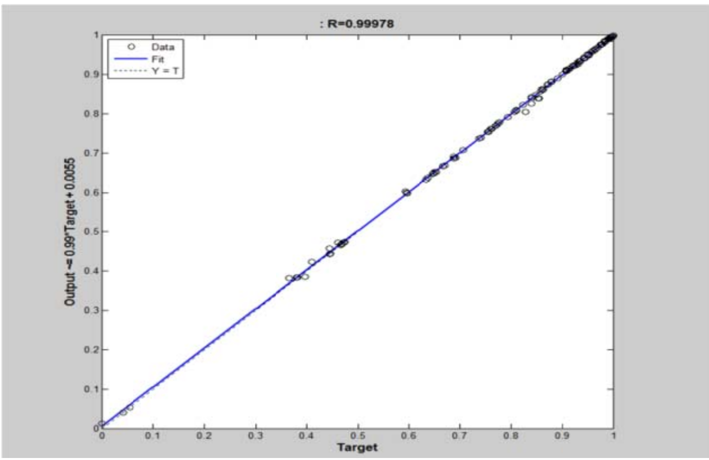


Figure 8: Regression on training responses of cumulative oil and water production for validation of meta model obtained by ANN_{GRNN}

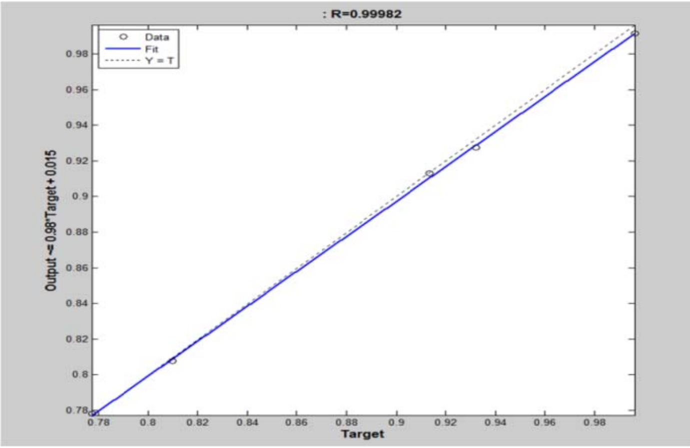


Figure 9: Regression on test responses of cumulative oil and water production for validation of meta model obtained by ANN_{GRNN}

Table 5: Comparison of two designed neural networks

Neural Network	Mean Square Error (MSE)	Coefficient Of Correlation (R^2)	Recovery Factor (RF)	Optimum Port Size	Cumulative Oil Production (MMbbl)	Error in comparison with results of reservoir simulator
MLP	4×10^{-4}	0.995	%9.5	(0.2و0.2و1)	6.15	%3
GRNN	10^{-6}	0.9998	%9.5	(1و0.54و1)	6.027	%1

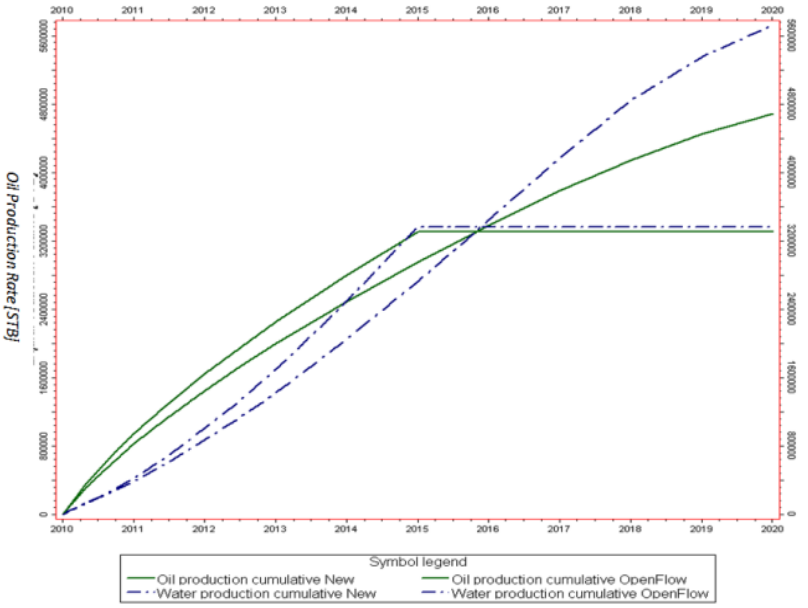


Figure 10: Comparison of cumulative oil production and water levels using theIntelligentcontrol (New) and conventional (Open Flow)

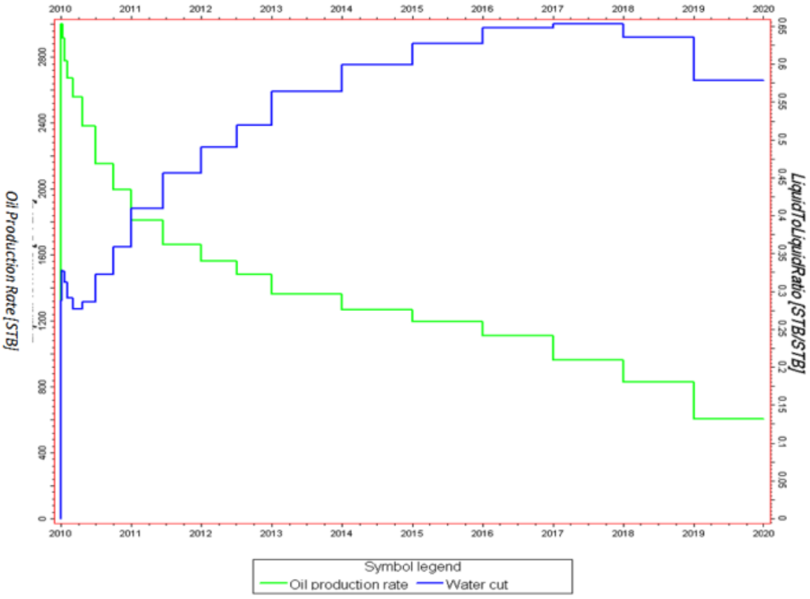


Figure 11: The rates of oil production and water cut using intelligent control (ANN)

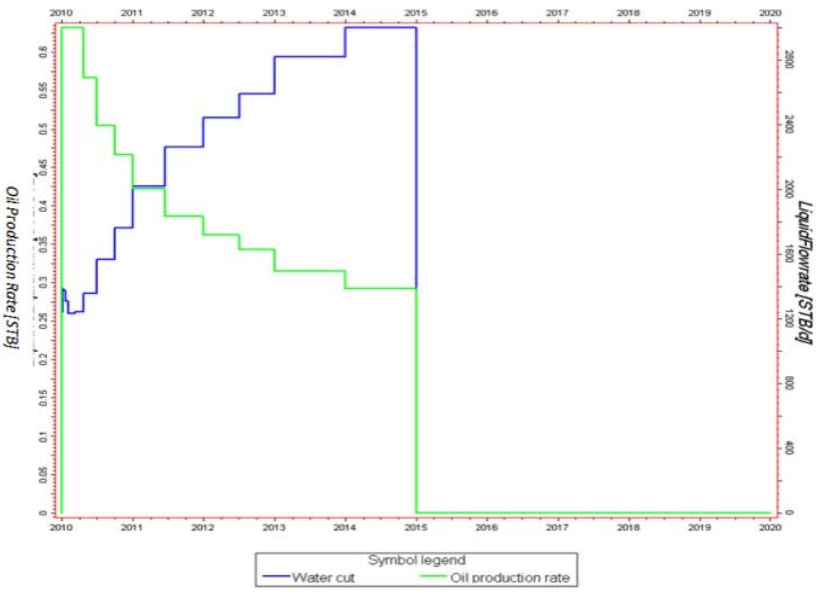


Figure 12: The rates of oil production and water cut without control (conventional)

In this work; ANN‘s inputs are port sizes set and outputs are cumulative oil and water production calculated from reservoir simulator.

High accuracy in above curves indicates good training and convergence of test data to training data.

4.3. Particle Swarm Optimization Algorithm (PSO)

After validation of estimation function obtained by ANN; PSO is implemented to find the best port sizes for the ICDs within 10 years of production.

Indeed; we apply PSO on the Meta model with priority of maximization of cumulative oil production to find the optimum port sizes set. By then; we put N_p in interval of $\pm 0.09\%$ of N_p means [N_p-0.0009* N_p, N_p+0.0009* N_p] to find optimum port sizesset based on cumulative water production minimization. Figure 1 shows the solution procedure.

In this study; the optimum port sizes for three ICDs obtained from MLP-CGB are vector of $(ICD1, ICD2, ICD3) = (0.2, 0.2, 1)$. The results for N_P and W_p for 10 year production period are 6.15 and 7 MMbbl respectively. Also we put these optimum port sizes in the reservoir simulator. The error between above results and those of reservoir simulator is only three percent.

Similarly; the optimum port sizes for three ICDs obtained from GRNN are vector of $(ICD1, ICD2, ICD3) = (1, 0.54, 1)$. The results for N_P and W_p for 10 year production period are 6.027 and 7.05 MMbbl respectively. Also we put these optimum port sizes in the reservoir simulator. The error between above results and those of reservoir simulator is only one percent.

Reported errors in Table 5 show that the estimation function could simulate reservoir behavior perfectly. In continuation; we compare above cumulative oil production with one obtained from running reservoir simulator for horizontal well equipped with conventional completion as shown in Figure 10. It shows 55% increase in N_P by employing ICDs.

4.4. Comparison of performance of conventional completion with intelligent completion

Figures 11 and 12 show that oil production from intelligent completion survives within 10 years of study but in the case of conventional completion it dies after 5 years of production. Indeed; lack of control over liquid production causes water production exceeds its limit and consequently shuts the well in.

In this study; recovery factor from conventional and intelligent wells are 6 % and 9.5 % respectively.

5. Conclusions

In this paper we presented a novel approach for smart well optimization. We elaborated the role of Neural Network as a replace for reservoir simulator, Particle Swarm Optimization Algorithm, and Central Composite Design of kind of Response Surface method to select the samples. The conclusions of this study are as follow:

- Considerable increase in oil production from intelligent well with respect to conventional well
- Increasing the production period for intelligent well with respect to conventional well
- Considerable increase in recovery factor for intelligent well with respect to conventional well.

Acknowledgment

The authors wish to express sincere thanks and appreciation to Research Institute of Petroleum Industry (RIPI) for its help and support particularly Mr, Hendi – Head of Exploration and Production Center- and Mr, Jahanbakhsh- Head of Reservoir Studies Division. Also thank Dr. Ghatee from Amir Kabir University of Technology for its guidance in designing neural network in MATLAB.

References:

1- Alhuthali, A.H., Gupta, A.D., Yeten, B. and Fontanilla, J.P. (2009). Field applications of waterflood optimization via optimal rate control with smart well. SPE, Woodlands conference.

2- Alhuthali, A.H., Gupta, A.D., Yeten, B. and Fontanilla, J.P. (2008). Optimal rate under geologic uncertainty. SPE, Oklahoma conference.

3- Al-Ghreeb, Z.M. (2009). Monitoring and control of smart wells. Thesis for MSc.

4- Aitokhuehi, I. and Durlofsky, L.J. (2005). "Optimization the performance of smart well in complex reservoirs using continuously updated geologcal models."*Pet. Sci. Eng.*, pp. 254-264.

5- Beielstein, T.B., Chiarandini, M., Paquete, L. and Preuss, M. (2010). Experimental Methods for the analysis of optimization algorithms.Springer, Berlin.

6- Eberhart, J. and Kennedy, R. (1995). Particle Swarm Optimization. IEEE, Conference on Neural Networks.

7- Gao, c., Ranjeswaran, T., Curtin, U. and Nakagawa, E. (2007). A literature review on smart-well technology. SPE, Oklahoma, March-April.

8- Graudenz, S. and Bornholdt, D. (1992). General asymmetric neural networks and structure design by genetic algorithms. NeuralNetw, Vol.5. pp. 327-334.

10- Harrison, S.J. and Marshall, R.F. (1991). Optimozation and training of feedforward neural network by Gas. IEEE Conference on Artificial Neural Network. 39-43.

11- Kamali, M.R., Madadi F, A. and Fakhari, A. (2011). Application of intelligent methods in Petroleum Engineering and Geosciences. Research Institute of Petroleum Industry (RIPI).

12- Kennedy,C. (2002). The particle swarm Explosion, stability and convergence in a multideimentional complex space. IEEE, Vol. on Evolutionary Computation, 2002.

13- Moreno, J.C. (2006). Optimization workflow for designing complex wells. SPE, Vienna Conference.

14- Meun, P., Tondel, P., Godhavn, J.M. and Aamo, O.M. (2008). Optimization of smart well production through nonlinear model predictive control. SPE, Amsterdam conference.

15- Moselhi, T., Fazio, O. and Hegazy, P. (1994). "Developing practical neural network applications using back-propagation." *Microcomput.Civ.*, Vol. 9. pp. 145-159.

16- Naus, M.M.J.J., Dolle, N. and Jansen, J. (2005). "Optimization of commingled production using infinitely variable Inflow Control Valves." SPE, Houston conference.

17- Oberwinker, C., Stundener, M. and Team, D. (2004). From real time data to production optimization. SPE conference, March.

18- Shuai, Y., White, C.D., Zhang, H. and Sun, T.(2011). using multiscale regularization to obtain realistic optimal control strategies. SPE, Woodlands Conference.

19- Sobieski, G. and Venter, J. (2002). Particle Swarm Optimization. Structural Dynamics, and Materials Conference, Denver.

20- Taware, S., Sharme, M., Alhuthali, A.H. and Gupta, A.D. (2010). Optimization water flood management under geological uncertainty using accelerated production strategy. SPE, Florence conference.

21- Van Essen, G.M. (2009). Optimization of smart wells in the St.Joseph Field, SPE, Jakarta conference.

22- Yeten, B., Brouwer, D.R., Durlofsky, L.J. and Aziz, K. (2004). "Decision analysis under uncertainty for smart well deployment."*J. pet. Sci.Eng.*, pp. 183-199.

23- Yeten, B., Durlofsky, L.J. and Khalid, A. (2002). Optimization of smart well control. SPE, Alberta, November conference