APPLY NEURAL NETWORK FOR IMPROVING PRODUCTION PLANNING AT SAMARANG PETROL MINE

QUOC TRUNG PHAM

School of Industrial Management, HCMC University of Technology
268 Ly Thuong Kiet, District 10, Ho Chi Minh City, Vietnam
E-mail(s): pqtrung@hcmut.edu.vn

THI KIM DUNG PHAN

Schlumberger Information Solution, Schlumberger Malaysia Services, Malaysia
E-mail: kimdungphan@gmail.com

Abstract

Purpose –ANN is considered a good solution for building non-linear relationship between input and output parameters, which is suitable for solving production back allocation, which is the most important step for production planning of petroleum mine. The purpose of this paper is to suggest a solution for solving production back allocation problem at Samarang petrol mine based on ANN approach.
Design/methodology/approach –In this study, well operational parameters' surveillance was conducted and artificial neural network (ANN) was used to build relationships between operation parameters and production rates. Experimental method is used for testing and evaluating the possibility of using ANN for supporting production planning at Samarang mine.
Findings – Consequently, the proposed ANN solution can increase the accuracy of predicted values and could be used for supporting production planning at Samarang mine. Because ANN uses well test data for training and predicting (without adding new devices), it could be a feasible and cheap solution.
Practical implications – The ANN models helped operation engineers to understand well production performance and make decision to improve production plan in timely manner. This solution could be generalized for the whole mine or to similar petroleum mines in practice.
Originality/value –This paper aims to propose a solution based on ANN for solving production back allocation problem of petroleum industry. The solution is tested at Samarang mine.
Keywords – Artificial Neural Network, Production Plan, Production Back Allocation, Petroleum Industry, Well Test, Samarang mine, Malaysia
Paper type – Case study

1 Introduction

Today, petroleum industry plays an important role in many countries. However, with the advance of the mining technology, planning and management activities become more and more complicated (Suslick, 2004). It is necessary for petrol engineers to understand about mining situation and to forecast potential mining problems.
In order to know current situation of mining wells, production flow should be measured. However, currently, there is no measurement tool on each mining well because of high installation cost. Instead, engineers have to calculate and to estimate production flow of each well based on sample data. The popular method for this task is production back allocation. More accurate of this estimation will lead to more effective of mining management.

Currently, the most difficulty of production back allocation process at Samarang mine is ensuring the accuracy of well test samples (Wong et al., 2012b). It depends on various factors, such as: the number of wells, the testing schedule, the complex of mining operation… Therefore, sampling data should be managed well for supporting data analysis. Moreover, because the frequency of testing schedule is usually once a month, there is a need for estimating current mining flow by week or day for keeping operation activities continuously.

One of the most popular techniques for estimating the relationship between input parameters of petrol mining and production flow is artificial neural network (ANN). Neural network model is considered a powerful tool in clustering and forecasting problems. Besides, neural network model is proved to be suitable for those problems with low quality sampling data, and its calculating results could be self-improved during utilizing process (Ali, 1994). Therefore, in this paper, ANN is chosen for solving production back allocation problem of Samarang petrol mine.

From above reasons, this research tries to apply neural network model for improving production planning at Samarang Petrol Mine in Malaysia. This research aims at (1) Applying neural network for production back allocation problem at Samarang petrol mine, (2) Collecting operation data for training and testing neural network model, (3) Designing mining parameters for neural network model, and (4) Conducting a project for production back allocation and evaluating the method.

The structure of this paper is organized as follows: (2) Research method; (3) Literature review; (4) Problems of production planning at Samarang petrol mine; (5) Approach for solving problems of Samarang; (6) Experimentation and Results; and finally (7) Evaluation and Conclusion.

2 Research Method

2.1 Research approach

According to Suslick et al. (2004), the decision making process in the petroleum industry becomes more complex because of the necessity of (1) more accurate prediction of field performance, and (2) integration with production strategy. Therefore, approach for production planning of petroleum mine requires a suitable model for production back allocation, which could provide more accurate prediction data and could satisfy current constraints of the petrol mine.

Currently, there are several methods for modeling and solving similar problems from Artificial Intelligence science, such as: Bayesian network, Evolutionary computation, Fuzzy logic, Artificial neuron network (ANN)… In the petroleum industry, ANN has been used in the exploitation and exploration phase to reduce risks and operation costs. However, the application of ANN in production back allocation problem is limited. Besides, estimating the exploitation rate of each wells at a petrol mine is very complex because of several reasons: (1) frequently changing input parameters, (2) lack of mathematical model for calculating the production flow correctly, (3) high error rate because of estimation method of measured data (simple mean).

Compared with other methods, ANN is considered a powerful tool in solving complicated problems, especially, it could be used for simulating non-linear relationships between multiple input and output parameters. Moreover, with learning capability, ANN can accept high error rate of input data and can be self-improved during utilization process (Ali, 1994). Therefore, the approach for solving production back allocation problem at Samarang petrol mine is using ANN for increasing the accuracy of predicting data with the use of current well test data.

2.2 Methodology

- This research uses back-propagation neural network for forecasting production rates based on sample data of Samarang petrol mine, which is managed by Petronas Carigali Sdn Bhd Company (PCSB), Malaysia. The research data focuses on SMDP-B rig of Samarang mine, which is collected from Sep 2013 to Mar 2014. Data sources include: operation data (mining report, well test report, database), and other related data, reports from operation engineers. Well test data: 20,419 samples (2,000-4,500 samples/ well), Direct data from database: 180 samples.
- Document analysis: analyze operation documents of Samarang mine; literature review about ANN and its application in petrol mining industry.
- Experiment method: Design neural network using Qwiknet software ; Adjust the operation parameters ; Apply proposed neural network model for production back allocation at Samarang mine ; Based on evaluating results, suggest procedures, guidelines for real application of this solution for the whole mine.

2.3 Research Process

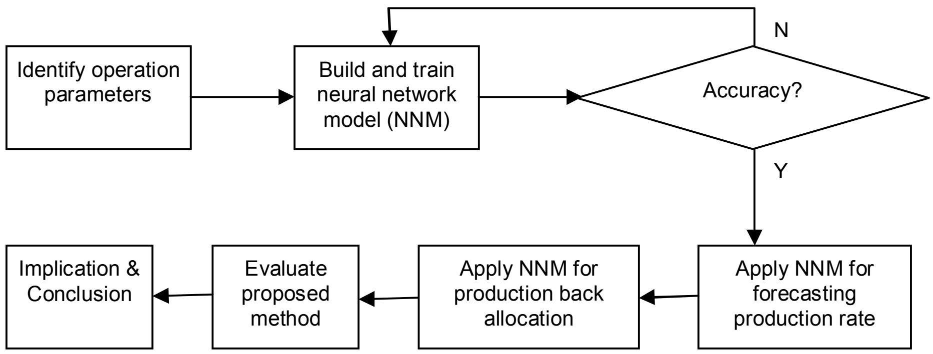


Figure 1. The research process

- Identify operation parameters: interviews, discussion with experienced engineers in mining operation for choosing key impact factors on production flow.
- Build and train neural network model: Based on operation parameters and collected data, set up the non-linear relationship between input parameters and production rate. Collected data is used for training NNM various times, with maximum training cycle is 10,000, and using Root Mean Squared error (RMSE) for evaluating learning result of NNM.
- Apply NNM for forecasting production rate: Based on above NNM, creating a

forecast report about production flow for each well.

- Apply NNM for production back allocation: Based on forecast report, using NNM for production back allocation for selected wells by day.
- Evaluate proposed solution: Compare the effectiveness of production back allocation using NNM and old method. Realize advantages and disadvantages of NNM solution & recommend for practical application of NNM at Samarang mine.

3 Literature Review

3.1 Artificial Neural Network

Artificial neural networks (ANNs) are a family of statistical learning models inspired by biological neural networks and are used to estimate functions that can depend on a large number of inputs and are generally unknown (Patterson, 1996). Artificial neural networks are generally presented as systems of interconnected "neurons" which exchange messages between each other. The connections have numeric weights that can be tuned based on experience, making neural nets adaptive to inputs and capable of learning. There is no single formal definition of what an artificial neural network is. However, a class of statistical models may be called "neural" if it possesses the following characteristics:

- contains sets of adaptive weights, i.e. numerical parameters that are tuned by a learning algorithm, and
- Capability of approximating non-linear functions of their inputs.

An ANN is typically defined by three types of parameters:

- The interconnection pattern between the different layers of neurons
- The learning process for updating the weights of the interconnections
- The activation function that converts a neuron's weighted input to its output activation.

Networks with directed acyclic graph (1-way direction) are commonly called feed-forward ones. Networks with cycles (2-way direction) are commonly called recurrent ones. What has attracted the most interest in neural networks is the possibility of learning. The cost function is an important concept in learning, as it is a measure of how far away a particular solution is from an optimal solution to the problem to be solved. Learning algorithms search through the solution space to find a function that has the smallest possible cost.

There are three major learning paradigms, each corresponding to a particular abstract learning task. These are: supervised learning, unsupervised learning, and re-enforcement learning.

Perhaps the greatest advantage of ANNs is their ability to be used as an arbitrary function approximation mechanism that 'learns' from observed data. However, using them is not so straightforward, and a relatively good understanding of the underlying theory is essential.

- Choice of model: This will depend on the data representation and the application. Overly complex models tend to lead to problems with learning.

- Learning algorithm: There are numerous tradeoffs between learning algorithms. Almost any algorithm will work well with the correct hyper-parameters for training on a particular fixed data set. However, selecting and tuning an algorithm for training on unseen data requires a significant amount of experimentation.
- Robustness: If the model, cost function and learning algorithm are selected appropriately the resulting ANN can be extremely robust.

With the correct implementation, ANNs can be used naturally in online learning and large data set applications. Their simple implementation and the existence of mostly local dependencies exhibited in the structure allows for fast, parallel implementations in hardware.

3.2 Petrol mining industry and related concepts

Oil/gas mine (Schlumberger, 2014): is an area of mining wells for producing raw oil and natural gas from reservoir. The reservoirs may locate in land or off-shores. Operation activities will be more difficult and complicated for overseas oil/gas mine.
Oil/gas well (Schlumberger, 2014): is cylindrical structure with a small width (from a few centimeters to a few decimeters) and a great depth (from a few tens of meters to several thousand meters, depending on the depth of the reservoir). Normally, engineers would drill a hole with a larger width to install the pipeline to the location of the reservoir. These pipelines must be reinforced well to operate safely for decades.
Collection network and mining processing system (Wang, 2002): The oil and gas products from these wells will be put into a single collection network of petroleum products. Configuration of the collection network can be very simple (straight) or complex (loop) depending on exploitation conditions. After going through the collection system, petroleum products will continue to go into mining processing system (processing plant). Here, depending on the purpose, engineers can carry out several activities, such as: water purification, filtering substances which are harmful to health/ environment, or have bad effect on the quality of product, compressing gas into liquefied petroleum gas (LPG), compressing product flow for the purpose of transportation, or storing, etc...
Well test operation: In petroleum industry, well test is a sequence of data collection of wells operating parameters aimed at a deeper understanding of the characteristics of exploited petroleum products (Aminzadeh et al., 2006). Depending on the current phase of the oilfield lifecycle, the purpose of well test will vary. During the exploration phase, parameters (flow rate, pressure, etc...) should be collected for building models to assess the oil/gas quantity and to estimate commercial reserves of oil reservoir. During the development phase, well test will help to develop models to support the strategic planning and to determine optimal locations for drilling additional wells. During the exploitation phase, well test will help engineers know the flow rate of each well in the system.

3.3 Related researches

Recently, there are a few researches in optimizing or improving the quality of production back allocation in petroleum industry. Some of them could be summarized as follows:

- Hamad et al. (2004) utilized the correlation map between the devices in the network to quantify the exploitation capability of wells. However, this method does not directly propose specific model or calculation for production back allocation problem. Besides, depending on the users of this map, the reallocated results could be varied.
- McCracken et al. (2006) proposed using the pressure gauges installed at the bottom of the well and using a simple oil reservoir model to estimate exploitation flow when there is a change in the pressure at the bottom of the well. This method requires the installation of additional instrument at the bottom of the well. This is quite a risky and costly activity because it may interrupt the normal operation of the well after installing the gauge. The used model is a simplified form of oil reservoir model to examine the activity of a single well. Therefore, it cannot be used in case there are multiple wells in the network.
- Kappos et al. (2011) used exploitation wells network model to calculate and re-allocate production rate. The authors simulated exploitation wells network using software and adjusted the parameters of the model to fit the final approximated result with the actual measurement data. This method fails when simulation program does not converge due to many reasons. Besides, the final result is not accurate because they used parameters from other areas for their model. Moreover, this method requires frequent updating of model parameters, which will increase the cost and reduce the quality of final results because it takes a lot of time and effort for updating model.

Based on above analysis, recent studies about production back allocation problem of petroleum industry are still limited in approach and solution. Therefore, more researches should be conducted and new approaches should be used for solving this problem of petroleum industry. Actually, Samarang was established long ago (1975), so, installing advanced equipments to serve the mining study is an expensive solution. In the context of Petronas Company, there is a need for another solution for calculating production rate and re-allocating production without adding any new devices. Therefore, this paper proposes a solution based on ANN for solving problems of mining operation of Petronas Company at Samarang mine.

4 Problems of Production Planning at Samarang Petrol Mine

4.1 Introduction of Samarang mine

Located off the northern shore of Sabah, Malaysia, Samarang (Maslennikova, 2013) is an oil field which was exploited by Shell Company since 1975. In 1995, Samarang returned for Petronas Carigali Sdn Bhd Company (PCSB) to manage and operate. From this time, PCSB also converted Samarang mining areas become central station to develop two neighbor mines for reducing investment costs.

However, in 2003, the rapid reduction of production rates of Samarang mine and the exhaustion of reserves could lead to a decision to close the mine. Since 2004, PCSB began hiring experts from many different disciplines to jointly assess the possibility of developing the mine. Based on investments in technology and people, operation capability was significantly improved and the mining areas were maintained for exploiting.

In 2004, Petronas began to build a database to manage exploited data and an information system - PIMS (Production Integration Management System, developed by Schlumberger) - was put in used (Wong et al., 2012a). This system was developed based on Oracle platform, and data was inputted by hand through faxed report sent from rig. Therefore, the data accuracy is low and number of errors in production back allocation is high.

In 2012, Petronas replaced PIMS by a project to develop Samarang IO (Integrated Operation), which is provided by Schlumberger (Wong et al., 2012a). The goal of the project is to improve the exploitation of the mine by installing additional equipment measuring production flow, pressure in the extraction system, and applying automatic exploiting operation... In parallel, Schlumberger will transfer the knowledge and operation experience to Petronas engineers for improving operation skills.

4.2 Problems of production planning at Samarang

The study area is SMDP-B wells cluster of Samarang mines, which has 6 wells operating with the help of gas lift system. The wells are connected together at the well head and put on the surface gathering system and transported to storage vessels. At SMDP-B rig, there is a gauge for measuring total exploiting flow of 6 wells.

In 2009, Samarang began installing 3 gauges for measuring total exploiting flow at 3 clusters A, B and C. This allows for the reallocation of production more precisely than before (total flow of Samarang managed by Shell). However, production back allocation is made for each month based on measuring data from wells test.

In general, current problems in managing of the production rate of Samarang mine are summarized as follows:

- Because there are a lot of rigs and there is no place for engineers to stay on rigs, engineers have to sail to the rig to get data for each day. Therefore, the data is not updated regularly and must depend on the weather to be able to sail to the rig.
- There are 70 active wells to be tested, but engineers can only test 2-3 wells/ day. Thus, the test data can only be updated for each well by month. However, if the test data do not meet the minimum standard, the measured value will not be accepted and it must be tested again until satisfying the criteria. Therefore, qualified data may not be updated frequently (within 1 month), in some cases, it could be delayed until 2 or 3 months for updating.
- Many wells are operated without meters because of their old age and old equipments installed. It is very expensive for installing 3-phase meters at the top of these wells.
- There is a lack of management experience of complicated platforms like Samarang mine. Besides, there is a lack of an information system for sharing information throughout the company.

5 Approach for Solving Problems of Samarang

5.1 Solution for production back allocation problem at Samarang

From above analysis, the most important problem of Samarang mine is increasing the precision of production forecast for supporting production back allocation of exploiting operations. The constraints of the problem include: (1) use the current well test data, which is not updated frequently, (2) do not add any other measurement devices, and (3) create a model for calculating production rates, which can accept low quality data (high error rate).

In general, from literature review and above analysis, the approach for solving problems of Samarang mine is applying ANN for calculating production rates at each well for supporting production back allocation problem.

5.2 Proposed Neural Network Architecture

Because each well has different activities and different status, different neuron network models (NNMs) must be used for each well. The architecture of each NNM includes 3 layers: input layer, hidden layer and output layer.

This model uses the well test data. The input layer includes the operating parameters of well. The output layer includes production rates of oil, gas, and water. The hidden layer includes learning weights of NNM. The parameters used in the model will be standardized in the range of 0 to 1 for sensitivity analysis. Partial results of wells test in history will be used to verify the accuracy of NNM. After increasing the accuracy of NNM to an acceptable level, it will be used to calculate the production flow of each well and to re-allocate the production rate from the measured data.

6 Experimentation and Results

6.1 Selecting input parameters for NNM

Expert interviews are used to select variables affecting the production flow of wells.

- Step 1: Identify the factors that affect the flow of exploitation of Samarang mine. These parameters include: (1) Bottom of the well, (2) Head of the well, (3) Equipments in the well, (4) Surface operating parameters, and (5) Errors and limits of operating parameters
- Step 2: Conduct a survey by direct interviews with engineers with expertise in the field of mining operation to select the variables useful for training. Participating in the study were 5 operating engineers and 5 managers. The questionnaire is described in Appendix 1. The result showed that there are 10 most important variables (total score > 25) effecting on production flow of Samarang mine. This result is summarized in the following figure.
- Step 3: Compare these 10 variables with storing data in the dataset, there are 2 parameters not recorded in the daily operation of the wells. They must be removed (Production Header Pressure, Production Header Temperature).

Finally, a list of remaining 8 input variables with 3 output variables (liquid, oil, and gas flow) is created and used to build neural networks at Samarang mine.

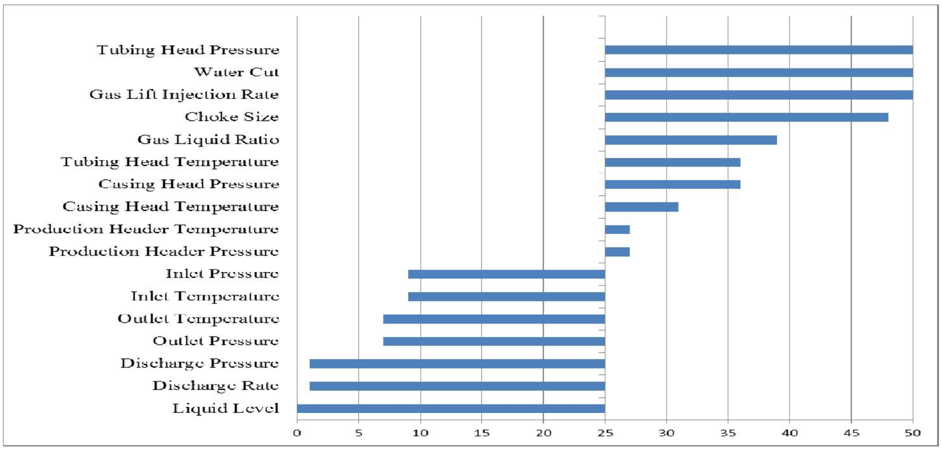


Figure 2. Level of impact of input parameters

6.2 Pre-processing of data

Pre-processing of data before being put into the model is conducted as follows:

- Step 1: Clean up data by some tasks, such as: removing abnormal data, adding missing values, smoothing noisy data, removing outliers, and eliminating inconsistencies... For the research data, if production rate = 0 (at a time point) and other operating parameters are unchanged, then the production rate of present time = the one of previous time.
- Step 2: Remove duplicate data and standardize measurement unit of datasets.
- Step 3: Normalize the input and output data: turn the value in the dataset into a number from 0.0 to 1.0 by min-max method.

6.3 Dataset, training parameters and transfer function

Firstly, the above dataset is divided randomly into 2 parts. The 1st part (70%) is used for training NNM, and the 2nd part (30%) is used for examination.
Then, the selection of appropriate parameters for NNMs is based on the opinions of experts in artificial intelligence and partly from experimental data.
Theoretically, there are 2 most popular transfer functions, which are sigmoid and tangent-hyperbolic function. They are proved to be effective for forecasting problems; therefore, they are selected for NNM of Samarang mine.
Sigmoid function (logistic) is as follows:

$$f(x) = \frac{1}{1+e^{-x}} \tag{1}$$

Tangent–hyperbolic function is as follows:

$$f(x) = \tanh(x) = \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}} \tag{2}$$

6.4 Evaluation criteria, hidden layer and weight updating method

There are a lot of error functions for evaluating whether NNM is good or not. In this research, RMS (Root Mean Squared) error is used for evaluate NNMs. Here, NNM is good if RMS < 0.05. The formula for calculating RMS is as follows:

$$E = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(P_j - T_j)^2} \tag{3}$$

In which: Pj = forecasting value for jth sample
Tj = real value of jth sample
n = sample size

This study used an available tool (Qwiknet) to support the development of NNM to determine the number of hidden layers and method of updating weights accordingly. To find the optimal hidden layers and weights updating method for well, different NNMs are designed with the maximum training period is 10,000. Each NNM will be tested with at least two hidden layers; the number of hidden layers will be increased gradually until the change of the error function is almost negligible.

Based on test results, the suitable number of hidden layers is identified to be 13 or higher, the suitable transfer function for hidden layer is Tanh function, for output layer is Logistic function (sigmoid), and suitable learning method is Online Back Propagation method. Therefore, this configuration of NNMs will be used for identifying the most suitable NNM for each well.

6.5 Identify suitable NNM for each well

After selecting 2-3 NNMs from above models, these NNMs are training to find the best one by adjusting the speed of learning. According to Rumelhart (1986), the best learning coefficient is from 0.05 to 0.5. Training process will periodically stop to assess error (RMS) on testing samples. When the error on testing sample increases, the match has started and the training process will stop.

Accuracy percentage is the number of sample (with training RMS < 0.05) divided by total number of sample. NNMs' training will stop when the accuracy percentage is highest and unchanged. Models of 6 wells are different in the number of hidden nodes and training loops. The training results are summarized in following table.

Table 1. Training results of NNM for each well

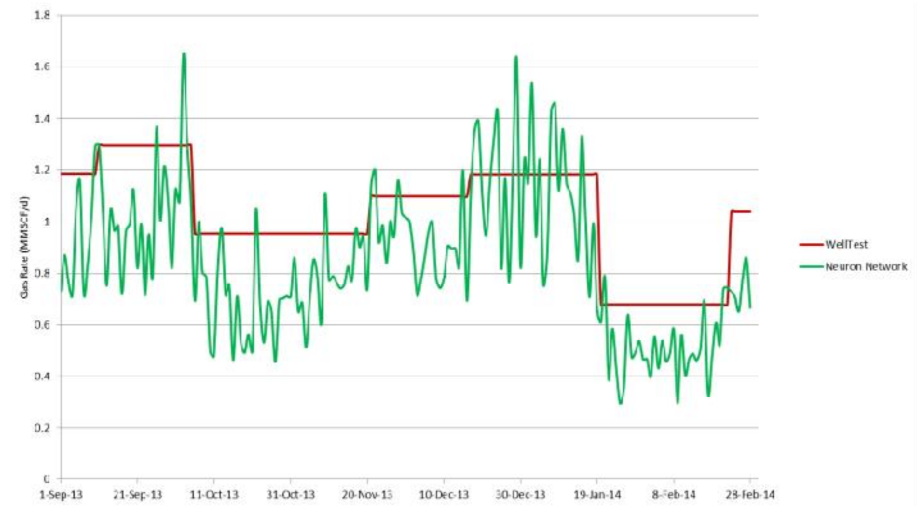
Well's code	# of hidden layers	# of iterations	RMS		Accuracy Percentage	
			Training	Testing	Training	Testing
B042S	14	1335	0.046	0.053	82%	82%
B053S	15	2446	0.031	0.040	93%	92%
B063L	13	4807	0.052	0.052	73%	73%
B063S	9	5000	0.052	0.055	80%	74%
B063S	18	3692	0.029	0.032	95%	93%
B068S	13	2510	0.029	0.039	92%	88%

The result of training the NNM for B042S well showed that, for gas flow, predictability of NNM is low, but for oil flow and water flow, forecasting value of NNM is quite accurate in comparison with the real value.

7 Evaluation & Discussion

7.1 Production flow forecasting and evaluation

After building the suitable NNM, it will be used to calculate daily production rate of each well based on daily operating parameters. The forecast results of B042S well using NNM (green line) and old method (red line) are summarized below.



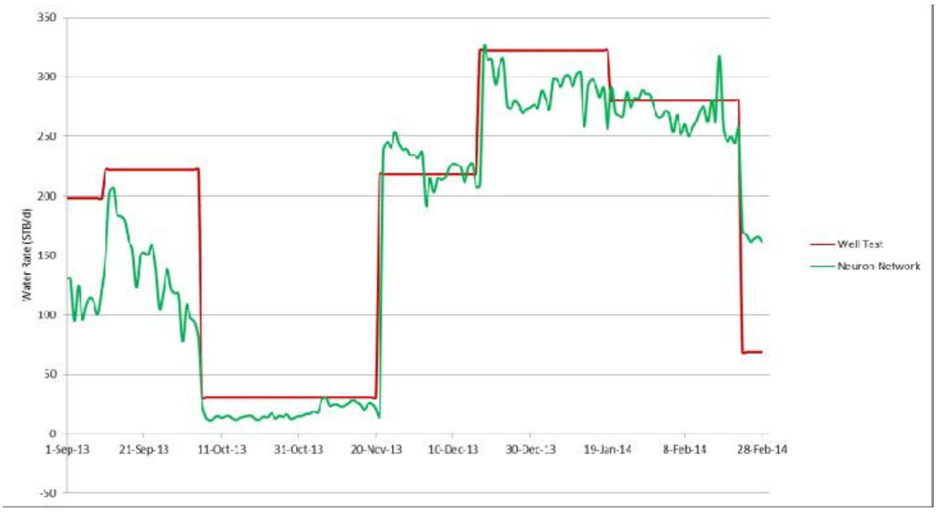


Figure 3. Forecast results of B042S: NNM vs. old method (gas, oil, water)

Because well test is performed once a month for each well, and the daily production flow is assumed to be unchanged between two testing points of time. Above results showed that at the testing point (the step change of the red line), NNM provides predicted values relatively close to the measured values. This demonstrates the ability for simulation and prediction of NNM is relatively good. Due to the operation of wells changes every day, the assumption of unchanged production flow of the old method is not suitable. While NNM provides specific forecasting results by day based on daily operational parameters of the well should be more detailed and reliable.
The comparison between the predicted values of new (NNM) and old (well test) method for other wells showed the similar results. Therefore, NNM could be a good solution to improve the accuracy of production planning at Samarang mine.

7.2 Product back allocation and evaluation

After building neural networks, they will be used to calculate the allocation of production flows for Samarang mine. Then, the estimated results of the NNM will be compared with the old method for evaluation. The old method (well test) for production back allocation at Samarang mine could be summarized as follows:

- Step 1: Calculate the total daily volume by adding up all the existing values of wells test corresponding to three phases: oil, gas and water
$$\sum_{i=1}^{N} Q_{i\_WellTest} \quad (4)$$
- Step 2: Calculate the extraction coefficient (Field Factor) by comparison with the total output value measured by the day.
$$Field\ Factor\ (FF_{WellTest}) = \frac{Q_{SMDP-B}}{\sum_{i=1}^{N} Q_{i\_WellTest}} \quad (5)$$
Q_{SMDP-B}: total mining production for SMPD-B of the day
$Q_{i\_WellTest}$: last test value at that time of well i
- Step 3: The final flow after reallocation of output Qi of each well will be:
$$Q_i = Q_{i\_WellTest} \times FF_{WellTest} \quad (6)$$

Currently, the production back allocation is conducted by month, which is not accurate. In this section, proposed production back allocation method will be conducted by day based on NNM forecasting values.
Similar to the old method (well test), the new method based on NNM uses the following formula for calculating production rate:

$$Field\ Factor\ (FF_{NN}) = \frac{Q_{SMDP-B}}{\sum_{i=1}^{N} Q_{i\_NN}} \tag{7}$$

In which: Q_{SMDP-B}: total production rate for SMPD-B rig per day.

Q_{i_NN}: forecasting value of production flow for the ith well by its NNM

The final production rate Qi after production back allocating for each well will be:

$$Q_i = Q_{i\_NN} \times FF_{NN} \tag{8}$$

Using forecasting values from NNM, production back allocation results for B042S well are summarized in following figures. The blue line is the estimated values of old method and the red line is the calculated results of neural network method. According to this result, NNM provided better results than well test method (more precise & near real value). The result is similar for other wells at Samarang mine.

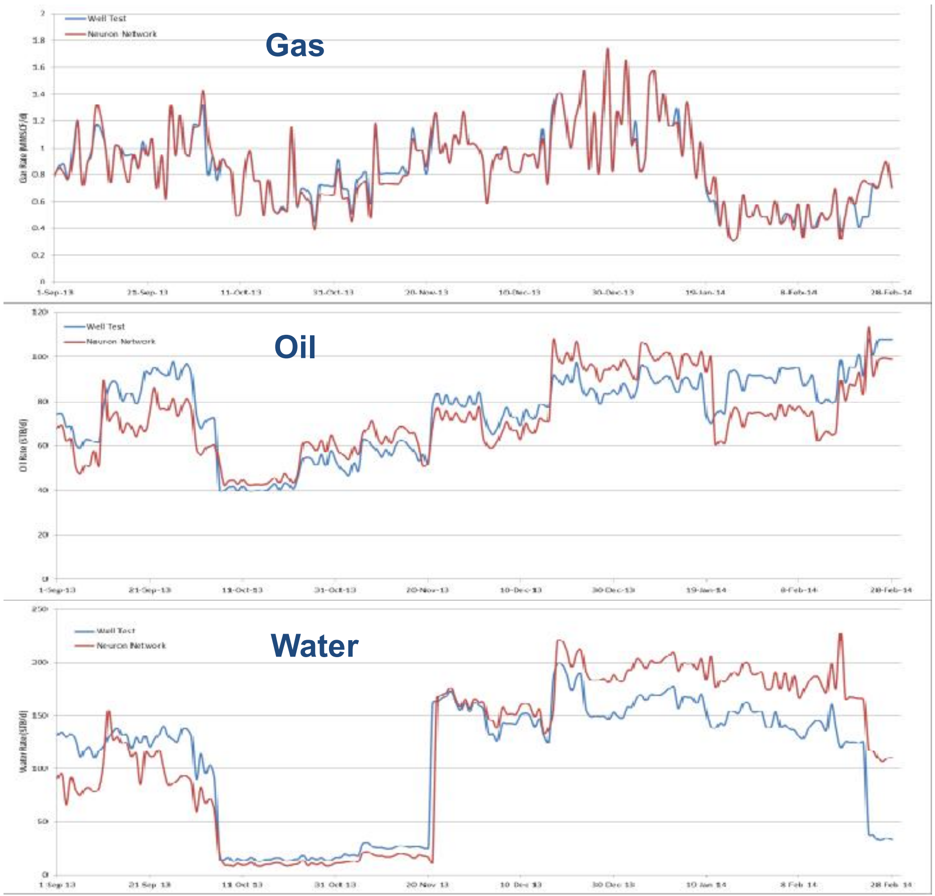


Figure 4. Production back allocation for B042S well: NNM vs. old method

The result of production back allocation based on NNM showed that forecast values relatively close to the real values. This proved the ability to predict quite accurate by using neural network method.
Typically, total estimated production rate of each well will deviate from the measured value of the total production in the clock, so engineers must modify the estimated value of each well (production reallocation). Adjustment must base on exploitation coefficient, which is the difference between total measured production flow and estimated value of each well. According to the formula, if exploitation coefficient is close to 1, the estimated value Qi is reliable. This means that the initial estimated value of that day is pretty accurate, and it could be used.
Below table showed the exploitation coefficients of the 3 phases (gas, oil and water) for SMDP-B wells network from Sep. 01st, 2013 to Feb. 28th, 2014.

Table 2. Exploitation coefficients of gas, oil, water: NNM vs. Well test

	Exploitation coefficient by well test method			Exploitation coefficient by neuron network method		
	Gas	Oil	Water	Gas	Oil	Water
Minimum	0.681	1.017	1.009	0.791	0.939	1.213
Maximum	2.221	1.732	2.462	1.259	1.438	1.696

According to above table, exploitation coefficients of well test method are varied and far from the desired value (1), ranged from 0.68 to 2.46. Meanwhile, exploitation coefficients calculated by NNMs are relatively stable (from 0.79 to 1.69) and closer to the desired value (1). This means that the production flow calculated by the NNMs will be more accurate, reliable, and can be used directly in the process of estimating production rate at any given time.
In summary, production back allocation tasks currently have to correct high error rate between measured values and estimated values. Using NNMs, the estimated values by the NNMs are quite close to the measured values, so that, the correction task is almost negligible. This showed practical benefits of NNMs in solving production back allocation problem and improving production plan at Samarang mine.
However, in order to increase the accuracy of forecast report, petrol engineers at Samarang mine should increase the size of dataset for training NNMs. This may require more time and effort for application of this solution in practice.
Moreover, the evaluation results could be improved if proposed solution (ANN) was compared with other approaches, such as: support machine vector, nonlinear autoregressive models… (Not just with the old method).
Besides, previous researches (McCormarck, 2004; Yazdi et al., 2010) showed that a combination of ANN other methods, e.g. Fuzzy logic, could help increasing the accuracy of predicted values and reducing the uncertainty. In order to apply ANN at Samarang mine in practice and generalize the result for similar petroleum mines, a combination of ANN and other methods should be considered.

8 Conclusion

In petroleum industry, creating an accurate production plan based on well test data is very necessary. However, a lack of frequently updated data and the complexity of operation parameters of petroleum industry make it difficult for production planning activities, especially for production back allocation problem.

Currently, Samarang mine (Malaysia) has some problems in production planning, such as: (1) Lack of well test data (there is only one sample a month), (2) Production flow is assumed not changed between 2 testing points of time, which reduces the accuracy of calculation, and (3) Difficulty in adding new measurement devices.

Although the application of ANN in several industries is not new, it is rarely used for petroleum industry, because of special constraints of each mining area. From literature review, ANN is considered a powerful tool in simulating non-linear relationships between multiple input and output parameters. With learning capability, ANN can accept high error rate of input data and can be self-improved during utilization process (Ali, 1994). Therefore, the approach for solving above problems at Samarang mine is applying ANN for improving predicting data of each well and supporting production back allocation activities.

Experimental method is used for testing and evaluating the possibility of using ANN for supporting production planning at Samarang mine. Firstly, a NNM has been built based on operating data of SMDP-B rig of Samarang mine. The collected data for training NNM include: exploiting reports of selected mining area, well test data, and operating data of 6 wells in this area. Secondly, based on interviews and available data, 8 most important input parameters are selected. Then, through training processes, non-linear relationships between input parameters and output production flow have been established. As a result, 6 NNMs for 6 wells at SMDP-B rig have been created. Using these NNMs for production back allocation of Samarang mine provided stable exploitation coefficients and better plan than using old method.

These results confirmed that ANN can help to increase the accuracy of predicting data with the use of current well test data (no need to add any new measurement devices), and it could be used for solving production back allocation problem at Samarang mine. In general, this solution could be generalized and applied broadly to all mining areas with similar conditions.

However, there are still some limitations of this paper, such as:

- It needs more data for training ANNs for a more accurate forecasting result.
- There is a need to integrate neural network models in the whole operating system for reallocating production automatically and reducing effort of engineers.
- There is a need for applying other methods, such as: support machine vector, nonlinear autoregressive models… for better evaluation of ANN solution.

Therefore, some directions for future research could be as follows:

- Using NNMs for the whole mine for improving forecasting data and planning results for a better operation performance.
- Building an information system integrating NNMs and other source of data for improving the accuracy of NNMs and creating production plans automatically.
- Comparing and combining with other methods, such as: genetic algorithm, fuzzy logic, dynamic programming… for optimizing the production plan.

Acknowledgements.

Many thanks to employees and managers of Samarang mine, who provided data for

analysis or participated in several interviews of this research for discussing possibility of applying neural network in improving production plan at Samarang mine.

References.

[1]. Ali, J.K. (1994). Neural Networks: A new tool for the petroleum industry?, *Proceedings of European Petroleum Computer Conference*, Aberdeen, United Kingdom.

[2]. Aminzadeh, F., & Groot. P.D. (2006). *Neural networks and other soft computing techniques with applications in the oil industry*, EAGE Publications.

[3]. Bean, M. & Jutten, C. (2000). Neural networks in geophysical applications. Geophysics, *SEG Society of Exploration Geophysicists Annual Meeting*, 65(4), 1032-1047.

[4]. Guo, Y., Hansen, R.O. & Harthill, N. (1992). Artificial Intelligence Neural Networks in Geophysics, *SEG Society of Exploration Geophysicists Annual Meeting*, 1-5.

[5]. Hamad, M., Shuharman, S. & Al-Mutairi, A. (2004). Back Allocation System with Network Visualization, *11th Abu Dhabi International Petroleum Exhibition and Conference,* Abu Dhaibi, 99-103.

[6]. Holland, J., Oberwinker, C., Huber, M. & Zangl, G. (2004). Utilizing the value of continuously measured data, *SPE Annual Technical Conference and Exhibition*, 1-6.

[7]. Kappos, L., Economides, M.J., & Buscaglia, R. (2011). A Holistic Approach to Back Allocation of Well Production, *SPE Reservoir Characterisation and Simulation Conference and Exhibition*, 9-11.

[8]. Kohli, A. & Arora, P. (2013). Application of Artificial Neural Networks for Well Logs, *IPTC International Petroleum Technology Conference*, pp. 1-8.

[9]. Maslennikova, Y. (2013). Permeability Prediction Using Hibrid Neural Network Modelling, *SPE Annual Technical Conference and Exhibition*, 1-6.

[10]. McCormarck, M.D. (2004). Geophysical Applications of Artificial Neural Networks and Fuzzy Logic, *Modern Approaches in Geophysics*, 21, 1-12.

[11]. McCracken, M., & Chorneyko, D. (2006). Rate Allocation Using Permanent Downhole Pressures, *SPE Annual Technical Conference and Exhibition*, 103-222.

[12]. Oviraes, G., Pemex, P.O., Escalona, C., Vargas, C., Baarda, M. & Vernus, J.C. (2010). Production Management Solution "Back Allocation and Advance Well Monitoring" – Litoral de Tabasco Asset, *SPE Intelligent Energy Conference and Exhibition*, 1-16.

[13]. Patterson, D. (1996).*Artificial Neural Networks – Theory and Applications*.Prentice–Hall.

[14]. Rumelhart, D.E, Hinton, G.E., & Williams, R.J. (1986). Learning representations by back-propagating errors, *Nature*, 3(2), 533-536.

[15]. Schlumberger (2014), Oilfield Glossary, Retrieved from: www.glossary.oilfield.slb.com

[16]. Suslick, S.B. & Schiozer, D.J. (2004). Risk Analysis Applied to Petroleum Exploration and Production: an Overview, *Journal of Petroleum Science and Engineering*, 44 (2), 1-9

[17]. Tee, T.L., Sung, Y.P., Huang, C.J., Tsai, C.P., & Wen, C.C. (2013). The Sea-Level predictions around Taiwan in 2030 using Artificial Neural Network, *ISOPE International Offshore and Polar Engineer*, 820-823.

[18]. Verma, A.K. (2012). Porosity and Permeability Estimation using Neural Network approach from Well Log Data, *SPE Annual Technical Conference and Exhibition*, 1-6.

[19]. Wang, P. (2002), Optimization of Production Operations in Petroleum Fields, *SPE Annual Technical Conference and Exhibition*, 1-8.

[20]. Wong, L.H., Gonzalez, N.J.R., Hermann, R., Spears, C., Nitura, J.B., & Traboulay, I. (2012a). *Samarang IO Conceptual Study Solution Architecture Report*, Schlumberger.

[21]. Wong, L.H., Gonzalez, N.J.R., Hermann, R., Spears, C., Nitura, J.B., & Traboulay, I. (2012b). *Samarang IO Conceptual Study Information Gathering Findings Report*,

Schlumberger.
[22]. Yazdi, H.S., Pourreza, R., & Yazdi, M.S. (2010). Constraint learning using adaptive neural-fuzzy inference system, *International Journal of Intelligent Computing and Cybernetics*, 3 (2), 257 - 278

Appendix. Important parameters of production back allocation

PROVISION OF INTEGRATED OPERATION (IO) SOLUTION IMPLEMENTATION & SERVICES FOR INTEGRATED FIELD AND EOR SURVEILLANCE, MONITORING AND OPTIMIZATION FOR SAMARANG REDEVELOPMENT PROJECT

SAMARANG PROJECT

WELL TEST INPUT DATA FOR PRODUCTION BACK ALLOCATION CALCULATION

Please kindly rank below Operating parameters per their degree of influence to Production Back Allocation Calculation (from 1 to 5). If the proposed parameter(s) is not in your understanding of its influence, kindly select "0" (unknown). Also let us known, if the parameter is measurable in actual Operation.

	0 Unknown	1 Least	2 Less	3 Adequate	4 More	5 Most	Measurable? Yes	No
Well Head								
Casing Head Pressure	☐	☐	☐	☐	☐	☐	☐	☐
Casing Head Temperature	☐	☐	☐	☐	☐	☐	☐	☐
Choke Size	☐	☐	☐	☐	☐	☐	☐	☐
Gas Lift Injection Rate	☐	☐	☐	☐	☐	☐	☐	☐
Production Header Pressure	☐	☐	☐	☐	☐	☐	☐	☐
Production Header Temperature	☐	☐	☐	☐	☐	☐	☐	☐
Tubing Head Pressure	☐	☐	☐	☐	☐	☐	☐	☐
Tubing Head Temperature	☐	☐	☐	☐	☐	☐	☐	☐
Test Separator								
Gas Liquid Ratio	☐	☐	☐	☐	☐	☐	☐	☐
Inlet Pressure	☐	☐	☐	☐	☐	☐	☐	☐
Inlet Temperature	☐	☐	☐	☐	☐	☐	☐	☐
Liquid Level	☐	☐	☐	☐	☐	☐	☐	☐
Outlet Pressure	☐	☐	☐	☐	☐	☐	☐	☐
Outlet Temperature	☐	☐	☐	☐	☐	☐	☐	☐
Water Cut	☐	☐	☐	☐	☐	☐	☐	☐
Gas Lift Compressor								
Discharge Pressure	☐	☐	☐	☐	☐	☐	☐	☐
Discharge Rate	☐	☐	☐	☐	☐	☐	☐	☐
Discharge Temperature	☐	☐	☐	☐	☐	☐	☐	☐

Additional comments:

____

____

About the authors

QUOC TRUNG PHAM, is Vice Dean of School of Industrial Management, Ho Chi Minh City (HCMC) University of Technology, Vietnam. He has been working in Department of Management Information System since 2005. From 2001 till now, he was a visiting lecturer at several universities of Vietnam, such as: HCMC University of Foreign Language and Information Technology, HCMC National University, Lotus University, HCMC University of Economics... He has published and spoken on several topics, such as: ICT, MIS, management science, and knowledge management. He received his B.S. and M.S. in Information Technology from HCMC University of Natural Science, and his PhD. in Economics from Kyoto University, Japan. His main interested topics include Information Retrieval, ICT management, MIS, e-Commerce, Management Science, DSS, Knowledge Management System, etc. For more information, please send e-mail to: pqtrung@hcmut.edu.vn

THI KIM DUNG PHAN, currently is a manager at MIS department, Schlumberger Information Solution, Schlumberger Malaysia Service. She had worked as an MIS engineer at Schlumberger Vietnam, team leader of Web application at Elink Telecom Inc., IT engineer at VSL, Vietnam. She received her B.S. in Computer Science from HCMC University of Foreign Languages & Information Technology, and her MS. in MIS from HCMC University of Technology. For more information, please send e-mail to: kimdungphan@gmail.com