

# Development of an Adaptive Surrogate Model for Production Optimization

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## Abstract

Recently production optimization has gained increasing interest in the petroleum industry. The most computationally expensive part of the production optimization process is the evaluation of the objective function performed by a numerical reservoir simulator. Employing surrogate models (a.k.a. proxy models) as a substitute for the reservoir simulator is proposed for alleviating this high computational cost.

In this study, a novel approach for constructing adaptive surrogate models with application in production optimization problem is proposed. A dynamic Artificial Neural Networks (ANNs) is employed as the approximation function while the training is performed using an adaptive sampling algorithm. Multi-ANNs are initially trained using a small data set generated by a space filling sequential design. Then, the state-of-the-art adaptive sampling algorithm recursively adds training points to enhance prediction accuracy of the surrogate model using minimum number of expensive objective function evaluations. Jackknifing and Cross Validation (CV) methods are used during the recursive training and network assessment stages. The developed methodology is employed to optimize production on the bench marking PUNQ-S3 reservoir model. The Genetic Algorithm (GA) is used as the optimization algorithm in this study. Computational results confirm that the developed adaptive surrogate model outperforms the conventional one-shot approach achieving greater prediction accuracy while substantially reduces the computational cost. Performance of the production optimization process is investigated when the objective function evaluations are performed using the actual reservoir model and/or the surrogate model. The results show that the proposed surrogate modeling approach by providing a fast approximation of the actual reservoir simulation model with a good accuracy enhances the whole optimization process.

**Keywords:** Reservoir Simulation, Surrogate Modeling, Production Optimization, Artificial Neural Network, Adaptive Sampling

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## 1. Introduction

Recent advances in computer science have greatly affected scientific fields. Nowadays, detailed numerical simulation with higher accuracy has been frequently used as a powerful tool for engineering design and optimization. Numerical simulation of petroleum reservoirs, as the most accurate available tool to predict the fluid flow behavior in the reservoir, is frequently used in all levels of field development in the oil and gas industry. In order to perform an optimization task, hundreds or thousands reservoir simulation runs are required. A single run of the simulated reservoir model, which is made of thousands or even millions of grid blocks, takes several hours. Moreover, the large number of control parameters exacerbates this reservoir simulation-based optimum design problem. Surrogate model (also known as Meta model or proxy model) is an approximation function that mimics the original system's behavior, but can be evaluated much faster (Crombecq et al., 2011). Developed surrogate model partly or completely substitute the full reservoir model to reduce the computation time associated with running full reservoir model as the objective function. In the petroleum engineering literature, various works have been done in the field of surrogate modeling (Badru and Kabir, 2003; Haghghat Sefat et al., 2012; Mohaghegh, 2011; Ozdogan et al., 2005). (Centilmen et al., 1999) trained an ANN to be used in well placement optimization problem. They selected several key wells scenarios and evaluated them using a numerical reservoir simulator. The simulation results were used to train an ANN. Finally, the ANN was used as a fast predictive tool for optimizing locations of the new wells in the reservoir. (Guyaguler et al., 2000) proposed a hybrid optimization technique using GA employing surrogate model developed by ordinary Kriging algorithm as the approximation function. They used this approach to optimize the location of new injection wells and their corresponding rate in a water flooding project in the Gulf of Mexico Pompano field. (Queipo et al., 2002) constructed a surrogate model employing ANN as the approximation function while using DACE (Design and Analysis of Computer Experiment) methodology for the experimental design. The developed surrogate model is used to optimize the operational parameters of a Steam Assisted Gravity Drainage (SAGD) process. (Zerpa et al., 2005) employed multiple surrogate models coupled with a global optimization algorithm to estimate optimal design variables of Alkaline-Surfactant-Polymer (ASP) flooding process.

Most of these studies have used one-shot approach to develop the surrogate model. In one-shot approach the surrogate model is constructed during one stage and will be used for all future optimization without further updates. However, one-shot approach has a main problem as generally the number of training points needed to achieve an acceptable accuracy is not known in advance while we are interested to train the surrogate model with as few as possible number of points. Adaptive sampling approach by sequentially selecting the training points addresses this problem.

In this study, an adaptive surrogate model is developed for the application in production optimization problem. The large number of control variables and response parameters is addressed by

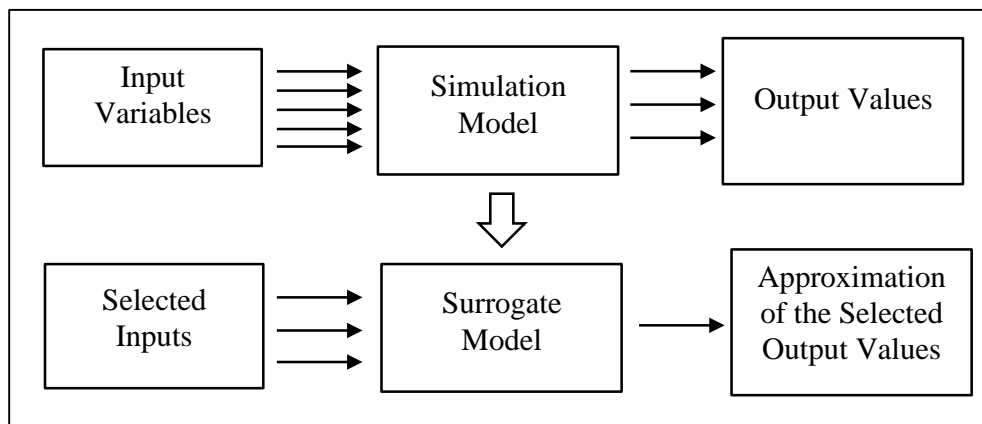
- 1- Using a dynamic ANN as the approximation function.
- 2- A modified problem definition while the network receives consecutive well control parameters and sequentially predicts the points of the cumulative production curves of interest.
- 3- Developing individual surrogate model for predicting each output parameter (e.g. one surrogate model for predicting oil and another one for predicting water).

The outline of this manuscript is as follows. In section 2, different stages of the surrogate modeling process are explained. Section 3 presents details of the developed framework. Section 4 shows the numerical results on the PUNQ-S3 case study. Optimization is performed using GA while the developed surrogate model and/or the actual reservoir model evaluates the objective function. Section 5 presents the general conclusions.

## 2. Constructing the surrogate model

Surrogate models, according to their approximation strategy, can be divided into two main categories, (1) model driven or physics based approach (Cardoso and Durlofsky, 2010; Rousset et al., 2014; Wilson and Durlofsky, 2013); (2) data driven or black box approach (Jones et al., 1998; Keane and Nair, 2005; Kleijnen, 2007). Model driven approaches, known as Reduced Order Models (ROM), approximate the original equations with lower order equations and finally reduce the computational cost. To apply these approaches access to the reservoir simulator source codes is required which is generally impossible when using a commercial reservoir simulator. In contrast, data driven approaches by considering the reservoir simulator as a black-box, generate the surrogate model using only input data and output responses. The data driven approach is the focus of this study.

A surrogate model replaces the true functional relationship  $f$  by a mathematical expression  $\hat{f}$  that is much cheaper to evaluate. The schematic diagram comparing the surrogate model with the actual reservoir model is shown in Figure 1.



**Figure 1: Schematic diagram of the data driven surrogate modeling approach.**

Four major steps of the surrogate model construction are as follows:

1. Statement of the problem,
2. Selecting the approximation function,
3. Design of experiments,
4. Surrogate quality assessment.

These steps are explained in the following subsections.

### 2.1. Statement of the problem

At this step, inputs and outputs of the surrogate model and the corresponding variation limits are defined. The production optimization problem can be formulated as:

$$\max J(\mathbf{u}), \mathbf{u} \in R^k \text{ Subject to: } c(\mathbf{u}) \leq 0, \quad (1)$$

where  $J(\mathbf{u})$  is the objective function (e.g. Net Present Value (NPV) or cumulative oil produced),  $\mathbf{u}$  is the vector of control variables (e.g. well Bottom Hole Pressures (BHPs) and/or well rates) and  $c$  represents the nonlinear constraints. In this study a simplified formulation of the NPV is used as the objective function defined as (Asadollahi et al., 2014):

$$J(\mathbf{u}) = \sum_{t=1}^{nt} \Delta t \frac{Q_o^t r_o - Q_w^t r_w - Q_i^t r_i}{\left(1 + \frac{b}{100}\right)^{p^t}}, \quad (2)$$

where  $nt$  is the total number of control steps,  $\Delta t$  is the difference between two control steps in days,  $Q_o^t$ ,  $Q_w^t$  and  $Q_i^t$  are the total field oil production rate, water production rate and water injection rate all in STB/day over the  $t^{\text{th}}$  control step,  $r_o$ ,  $r_w$  and  $r_i$  are the oil price, cost of water removal and cost of water injection, respectively all in USD/STB,  $b$  is the discount rate in percent per year, and  $p^t$  is the elapsed time in years.

The aim is to evaluate the objective function using the surrogate model instead of the reservoir simulator. As a result, surrogate model's inputs are the control variables and its outputs are different components of the objective function. Moreover, our developed surrogate model instead of predicting a single point predicts the cumulative oil and water production curves versus time. Later on, these values are used to calculate the objective function (i.e. NPV).

### 2.2. Selecting the approximation function

Different approximation functions have been employed for constructing the surrogate model (Forrester et al., July 2008. ; Jurecka, 2007; Keane and Nair, 2005). Among them, the most popular methods are Kriging ((Giunta et al., 1998); Jones, 2001; Sacks et al., 1989), Radial Basis Function (RBF) (Gutmann, 2001; Regis and Shoemaker, 2005), Polynomial Regression (Myers et al., 2009) and Artificial Neural Network (ANN) (Samarasinghe, 2006). Efficiently handling high-dimensional and highly nonlinear problems and the capability to predict time series, make

ANN a suitable approximation function for our application. Development of ANN is inspired by the function of human brains (Samarasinghe, 2006). An ANN is composed of one input layer, one output layer, and one or more hidden layer. Each of these layers contains several nodes which represent the neurons in human brain. The neurons of each layer are connected to the neurons of other layers by connections with defined weights. Mathematically, data flow within an ANN with one hidden layer for an input matrix  $\mathbf{Z}$  can be expressed as following (Samarasinghe, 2006):

$$\hat{y}_i(\mathbf{Z};\theta) = \sum_{j=1}^H \omega_{ij} s\left(\sum_{k=1}^L \mu_{jk} z_k + \zeta_j\right) + \eta_i, \quad (1 \leq i \leq M), \quad (3)$$

where  $\hat{y}_i$  is the network output,  $\theta = (\omega_{ij}, \dots, \omega_{MH}, \eta_1, \dots, \eta_M, \mu_{11}, \dots, \mu_{HL}, \zeta_1, \dots, \zeta_H)$  represents weights,  $M$  is the number of outputs,  $H$  is the number of hidden neurons,  $L$  is the number of input variables and  $s(t) = (1 + e^{-t}) / (1 - e^{-t})$  is the transfer function. The weights are adjustable parameters of the network which are tuned through a process called training. During the training process, the weights of the network are iteratively adjusted to minimize the network prediction error on the training data set. In this study Levenberg-Marquardt back propagation method, which appears to be the fastest method for training moderate-sized feed forward neural networks, is employed to train the ANN (Hagan et al., 1996). In order to avoid over-fitting and improve the network generalization, Bayesian regularization is used (For more details about the training process see (Foresee and Hagan M.T, 1997)). Only one hidden layer with a nonlinear transfer function can precisely approximate any function with finite discontinuities in a feed-forward neural network trained using back propagation method which is supported by the universal approximation theorem (Kroese and Smagt, 1996). Therefore, one layer ANN with a tangent sigmoid transfer function is employed in this study. A large number of hidden layer's neurons are considered in this study (three times of input layer's neurons) in order to ensure a good network generalization is obtained when using Bayesian regularization.

The total number of control variables in a production optimization problem is equal to  $np \times nt$  where  $np$  is the total number of wells to be controlled and  $nt$  is the total number of control steps. A modified formulation is proposed in order to reduce the large number of input variables in a surrogate model applied to production optimization problems. It is assumed that cumulative production at control step  $t$ ,  $y(t)$ , depends on the well control parameters at that control step,  $U(t) = [u_1(t), \dots, u_{np}(t)]$ , difference in well control parameters with respect to the previous control step,  $\Delta U(t) = U(t) - U(t-1) = [u_1(t) - u_1(t-1), \dots, u_{np}(t) - u_{np}(t-1)]$ , and cumulative productions at two preceding control steps,  $y(t-1)$  and  $y(t-2)$ . Therefore, the inputs of ANN are  $U(t)$ ,  $\Delta U(t)$ ,  $y(t-1)$  and  $y(t-2)$ , its output is  $y(t)$  at control step  $t$  and  $t=1, \dots, nt$ . The structure of the resulting ANN with a feedback loop is shown in Figure 2.

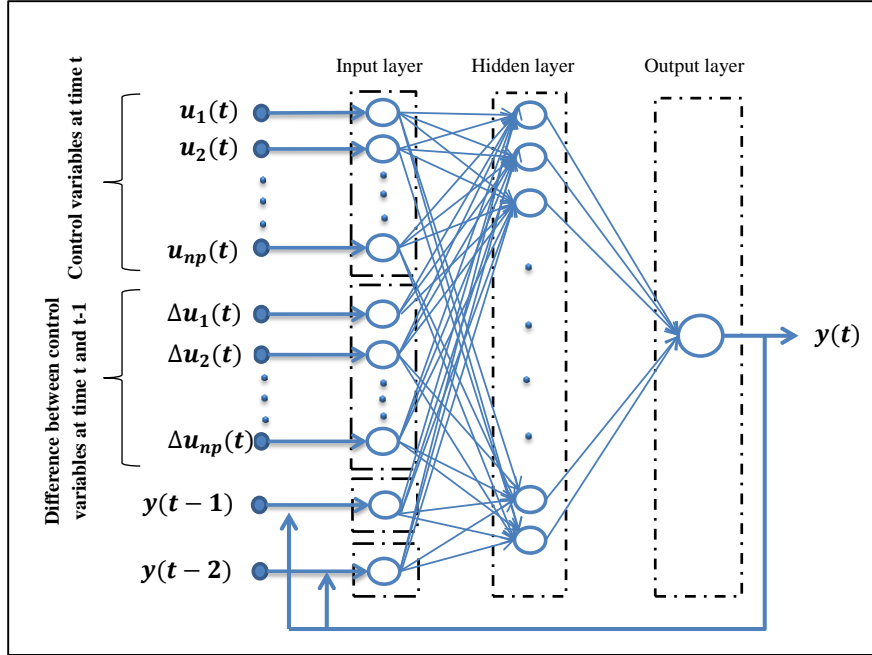


Figure 2: Structure of the developed dynamic ANN.

### 2.3. Design of experiments

The quality of the training data significantly impacts the accuracy of the resulting surrogate model. Hence, a suitable Design Of Experiment (DOE) approach by selecting optimum number and location of the training data points can significantly enhance the surrogate modeling process (Alam et al., 2004). A space filling design is suggested for deterministic numerical experiments (a.k.a. computer experiments) in those the same inputs always yield the same responses (Booker, 1998; Sacks et al., 1989). In space filling design, sample points are distributed as evenly as possible over the entire design space to ensure covering a wide range of the design space.

Moreover, the training data points are generated using a sequential approach in this study. In sequential approach, first the surrogate model is constructed using a number of initial training points. Then, the surrogate model accuracy is improved by adding more data points to the initial training set in a stage-wise manner. While the number of training points required to achieve an acceptable level of accuracy is not known in advance, it is desired to train the surrogate model with minimum number of points. The sequential approach stops the sampling process as soon as sufficient information is achieved.

The main goal during the sequential adaptation of the surrogate model is to select new points in areas where the response of the surrogate model is not accurate. Among the introduced approximation functions, only Kriging can provide an estimation of the prediction error in not previously observed areas. Jin et al., (2002) proposed using Cross-Validation (CV) to provide an estimation of the prediction error for RBFs. In this study the CV and jackknifing approach proposed by Kleijnen and Van Beers, (2004) is employed to perform sequential adaptation of the

surrogate model. Initially,  $C$  candidate points are preselected by a space filling DOE method. Then, the variance of the surrogate model prediction at each candidate point is estimated using CV and jackknifing as explained following.

### 2.3.1. Cross-Validation

Cross-Validation (CV) (Meckesheimer et al., 2002; Refaeilzadeh et al., 2009) is a statistical method of evaluating and comparing machine-learning algorithms. The basic form of CV is  $N$ -fold CV. In  $N$ -fold CV the data set,  $S\{X, Y\}$ , consisting of  $n$  pairs of input-output data ( $X, Y$ ), is divided into  $N$  equal and independent subsets or folds,

$$S\{X, Y\} = S^1\{X^1, Y^1\}, S^2\{X^2, Y^2\}, \dots, S^N\{X^N, Y^N\}. \quad (4)$$

The surrogate model is constructed  $N$  times, each time leaving out one of the subsets from the training data sets. The prediction of these  $N$  surrogate models is calculated for each of the  $C$  candidate points.

### 2.3.2. Jackknifing

Jackknife estimate for each candidate point,  $j$ , is calculated as,

$$\tilde{y}_{j;i} = N \times \hat{y}_j^{(-0)} - (N-1) \times \hat{y}_j^{(-i)}, \quad j = 1, 2, \dots, C, i = 1, 2, \dots, N \quad (5)$$

where,  $\hat{y}_j^{(-0)}$  is prediction of the surrogate model trained with all data points,  $\hat{y}_j^{(-i)}$  is prediction of the surrogate model trained with all data points except those in the  $i^{th}$  fold which is held-out when using  $N$ -fold cross validation. The prediction variance is calculated as,

$$\tilde{s}_j^2 = \frac{1}{N(N-1)} \sum_{i=1}^N (\tilde{y}_{j;i} - \bar{\tilde{y}}_j)^2, \quad (6)$$

where,

$$\bar{\tilde{y}}_j = \frac{1}{N} \sum_{i=1}^N \tilde{y}_{j;i}. \quad (7)$$

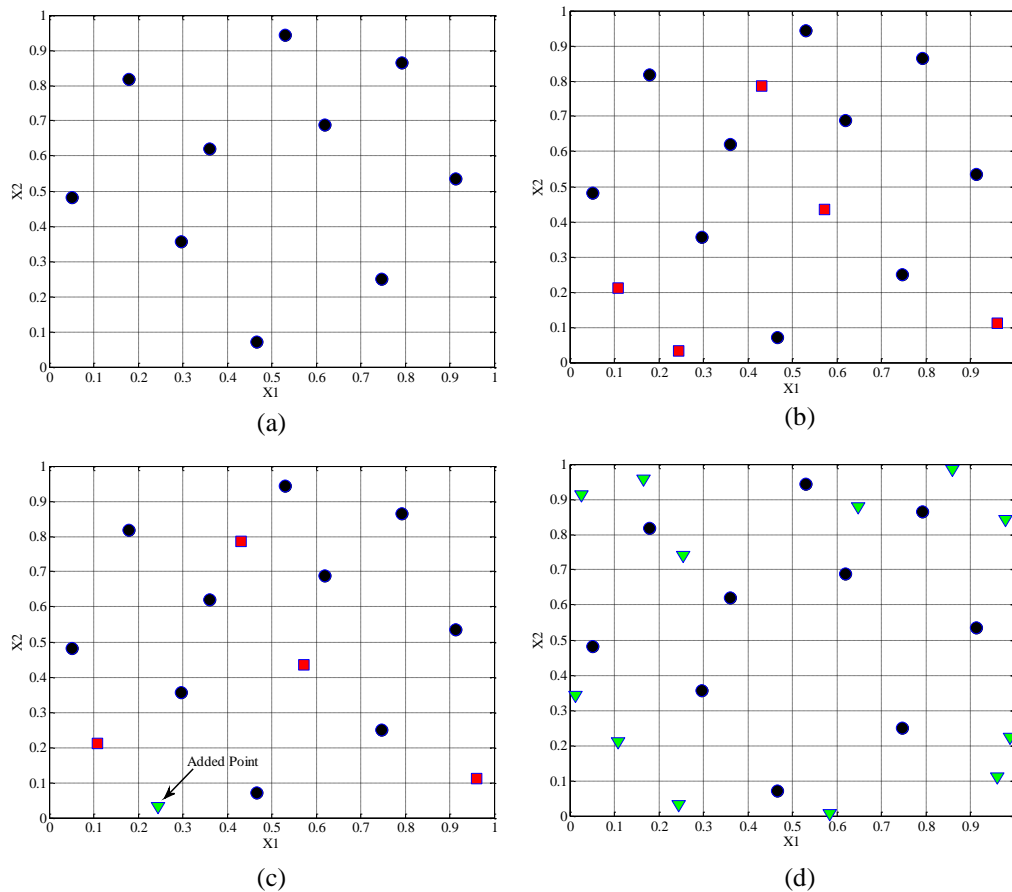
Here, larger variance indicates higher prediction error hence, the point among the  $C$  candidates with maximum variance is selected as the new training point. Reservoir simulation is performed for the selected point which is then added to the existing training points.

Figure 3 presents an example of the proposed sequential training approach using a function with two variables.

1. Initial training points are generated (circles in Figure 3-a).

2. Candidate points are created (squares in Figure 3-b). It must be noted that the values of the candidate points are calculated by the surrogate model constructed using the available training points.
3. The point with the largest prediction variance is selected (the triangle in Figure 3-c).
4. The actual reservoir simulation is performed for the new points and added to the training data set.
5. The process is repeated until the desired prediction accuracy is achieved.

Figure 3-d shows final configuration of data points after the sequential training.



**Figure 3: Illustration of adaptive sampling; a) initial points b) initial points and candidate points c) selected point d) final points.**

#### 2.4. Surrogate model quality assessment

Quality of the constructed surrogate model must be assessed using a set of test points other than those used for the training stage. Our aim is to use a method which performs the quality assessment stage using available training data sets rather than requiring computationally demanding new data sets. The  $N$ -fold cross-validation (Meckesheimer et al., 2002) is used as the



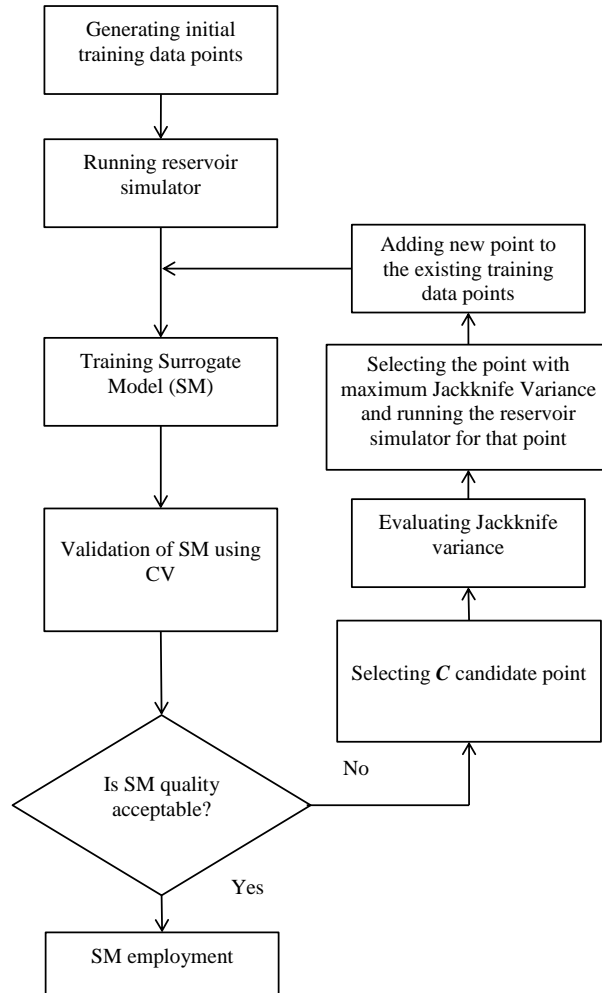
assessment method in this study. The Relative Error (RE) of each data point in omitted subsets is used as the quality measure calculated as follows:

$$\text{RE}_i = \frac{|\hat{y}_i - y_i|}{y_i}, \quad (8)$$

where,  $\hat{y}_i$  is the surrogate model prediction and  $y_i$  is the simulation model output for data point  $i$ , respectively. The maximum error is compared with a predetermined value. Data points are added sequentially to the existing training data set to enhance the prediction accuracy of the surrogate model if the maximum error is higher than the predetermined value.

### **3. Developed algorithm for adaptive surrogate modeling**

The developed algorithm for surrogate model construction is summarized in Figure 4.



**Figure 4: Flow diagram of the developed algorithm for Surrogate Model (SM) construction.**

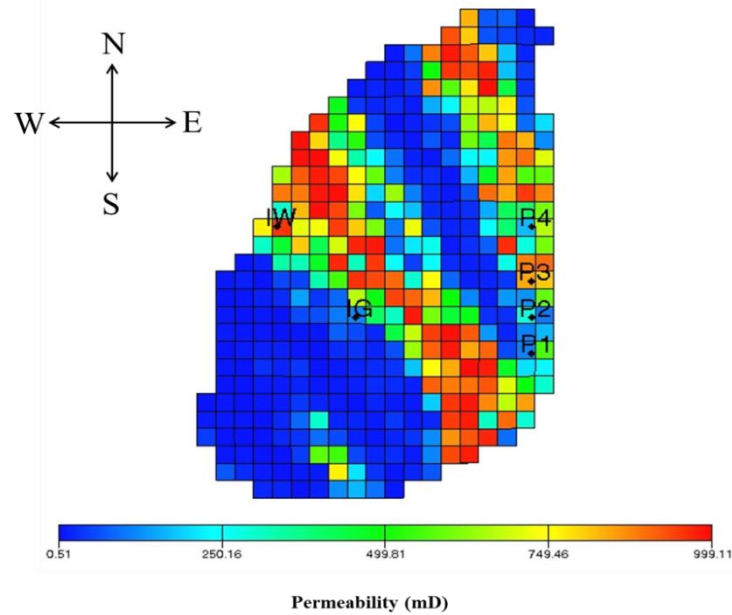
First, a set of initial training points are generated using the *mc-interosite* method and the corresponding outputs are calculated using the reservoir simulator. This data set is employed for initial training of the ANN which are constructing the surrogate model. The surrogate model quality is then assessed using CV method. It must be noted that large number of folds in CV slows down the validation process while small number of folds reduces the validation accuracy. The number of folds in CV,  $N$ , is considered to be 5 for this study which is observed to provide a good assessment in a reasonable computational time. The sequential training process starts when the surrogate model prediction quality is not acceptable. During the sequential training first,  $C$  candidate points are generated using *mc-interosite* method. Then, Jackknife variance is evaluated for each of these candidate points. The point with the maximum jackknife variance is selected as a new training point. The reservoir simulator calculates the corresponding outputs for the new point and the data set is added to the existing training sets which are then used for retraining the ANN. The employed *mc-interosite* method is associated with a relatively slow

optimization process which is proportional to the value of  $C$ . It was observed for this study  $C = 5$  provides a balance between accuracy and the computational cost. Moreover, 4 points which are not selected at each recursive training iteration are saved in a data-bank which is then added to the candidate points in the next iteration. The recursive training continues until the stopping criteria are satisfied. In this study the stopping criteria are maximum CV relative error is smaller than 0.1 or maximum number of simulation runs is equal to 250. More complex correlations between inputs and outputs are expected when the number of control variables increases. The developed adaptive surrogate modeling approach captures this complexity by larger number of training data points. It is worth noting that, the developed surrogate modeling approach can be modified to select more than 1 data point at each recursive training stage (maximum Jackknife variance is still the selection criterion). This is particularly important in order to take advantage of the available parallel computing environment while we expect to speed-up the whole training process.

## **4. Results and Discussion**

### **4.1. Case study: PUNQ-S3 reservoir model**

The developed algorithm is applied to optimize the production in a publicly available, synthetic reservoir simulation model based on a real, North Sea field known as PUNQ-S3 (Floris et al., 2001). The model is three-phase, three-dimensional consists of  $19 \times 28 \times 5$  grid blocks, of which 1761 are active. This field is bounded to the east and south by a fault, and is connected to a strong aquifer from the north and west. A small gas cap is located at the center of the dome shaped structure. Four production wells are located in the east of the reservoir. The produced gas is injected into the gas cap and water injector keeps the reservoir pressure constant. The injectors are operated under a constant BHP of 300 bar (4351 psi). Figure 5 shows the permeability field of the top layer and wells location.



**Figure 5: Permeability field of the top layer and wells location.**

The production wells are operated at a constant rate of 630 STB/day. Early water breakthrough is observed in some of the production wells due to the reservoir heterogeneity. The aim is to prevent early water breakthrough and increase total oil recovery by an optimal control of production wells (by manipulating BHPs). In this study an initial period of uncontrolled production for 8 years which is followed by production control for 10 years is considered. The control frequency is 180 days (i.e. 20 control steps) resulting a total of 80 control variables. The BHP is assumed to remain constant during each control interval. Surrogate model's inputs are consecutive well control variables (i.e. BHPs of 4 producers at each of the 20 control steps) and its outputs are 20 points of the cumulative production curve (The surrogate model structure is shown in Figure 2). Two surrogate models are developed while one predicts cumulative oil production curve and another one predicts cumulative water production curve.

#### **4.2. Surrogate Model prediction quality assessment**

In this study, the prediction quality of the developed surrogate model is assessed using 20 test data to illustrate the performance of the developed approach. The test data are generated in a space-filling manner using Latin Hypercube Sampling (LHS) method (for more information about LHS see McKay et al., (1979)). The relative error is calculated for all control steps of each test data. Two tests are performed where the developed adaptive surrogate modeling approach is (1) compared to the conventional one-shot approach and (2) assessed regarding the prediction quality performance in the presence of abrupt changes.

#### 4.2.1. Comparison of the developed adaptive surrogate modeling approach with the conventional one-shot approach

The same numbers of training points are used to develop the surrogate models using two different approaches. In adaptive approach, surrogate model is initially constructed using 100 training data points. Then, new points are added sequentially until a total of 200 data points are generated (equivalent to 200 simulation runs). In one-shot approach, 200 training data points are generated in one stage in a space-filling manner. Figure 6 shows a graphical distribution of relative errors calculated for the 20 test data at all control steps using a box plot. Two ends of whiskers show minimum and maximum values while bottom and top of the boxes show first and third quartile, respectively. Table 1 summarizes min, max, mean and the standard deviation (std) of the relative prediction error for all 400 tests while employing the developed adaptive approach and the one-shot approach. The developed adaptive approach outperforms the conventional one-shot approach by providing lower mean and variance of the relative prediction error for both oil and water production (Figure 6 and Table 1) which is used for the rest of this study.

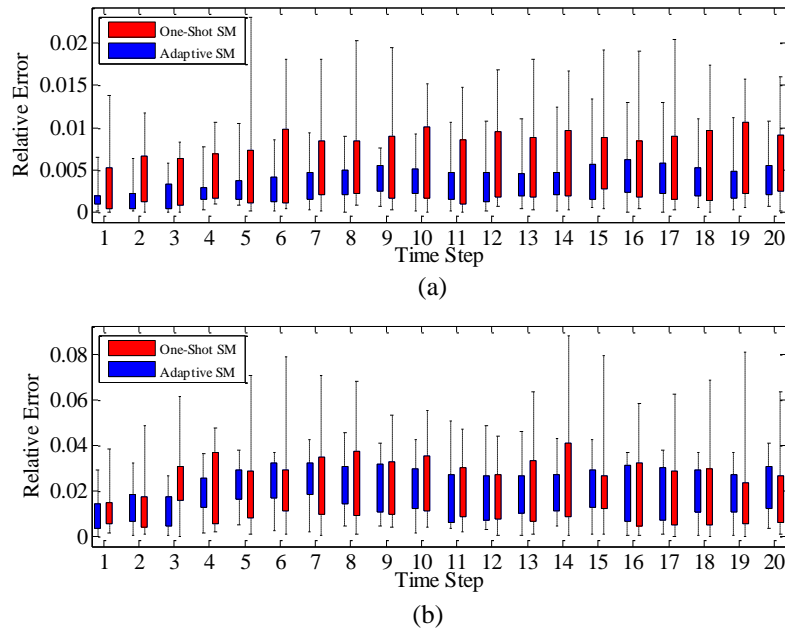


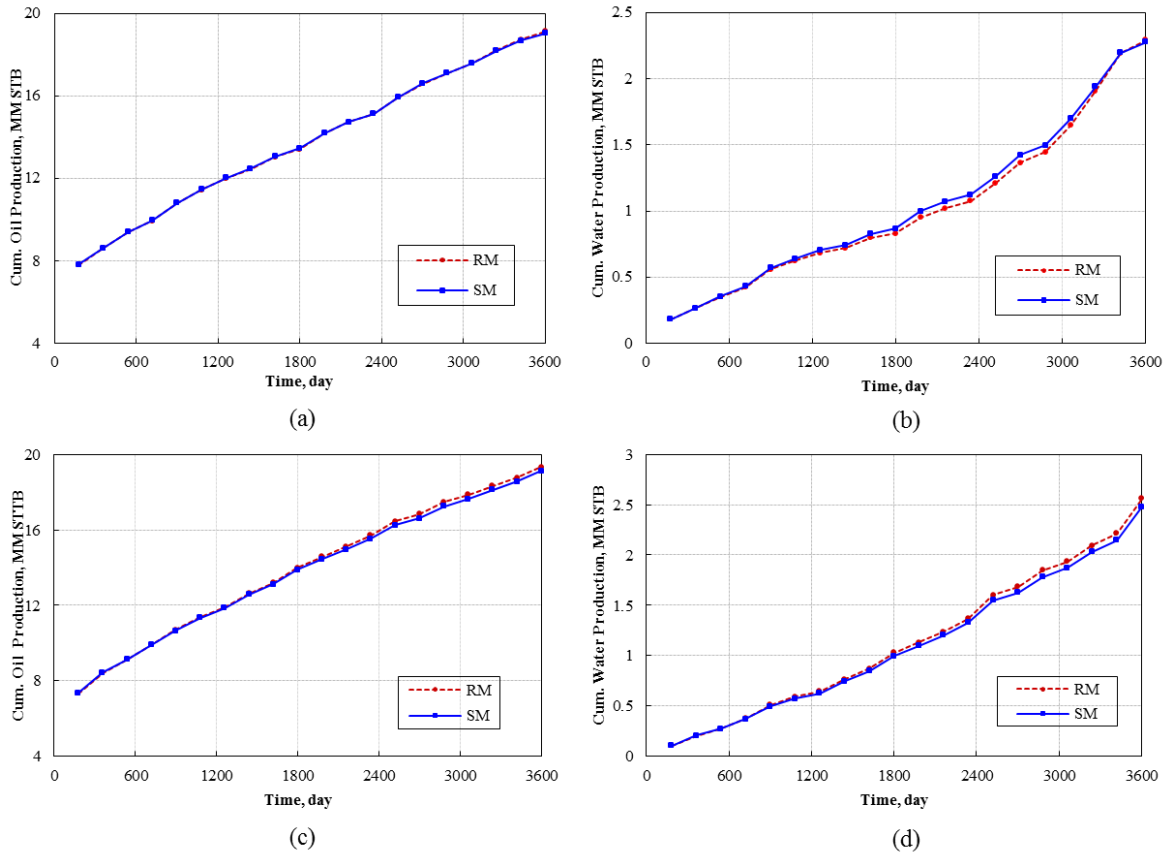
Figure 6: Box plot of relative error for SM constructed with adaptive approach and one-shot approach  
a) Oil production b) Water production.

Table 1: Quantitative comparison of adaptive surrogate modeling approach and conventional one-shot approach

Training approach	oil				water			
	min	max	mean	std	min	max	mean	std
adaptive	0	0.0134	0.0034	0.0026	0	0.0507	0.0189	0.0113
one-shot	0	0.0230	0.0055	0.0048	0	0.0881	0.0210	0.0176

#### 4.2.2. Prediction quality assessment of the developed adaptive surrogate model

The cumulative oil and water production curves calculated using Surrogate Model (SM) and Reservoir Model (RM) for 2 test data with maximum relative prediction errors (among 20 test data) are compared in Figure 7.

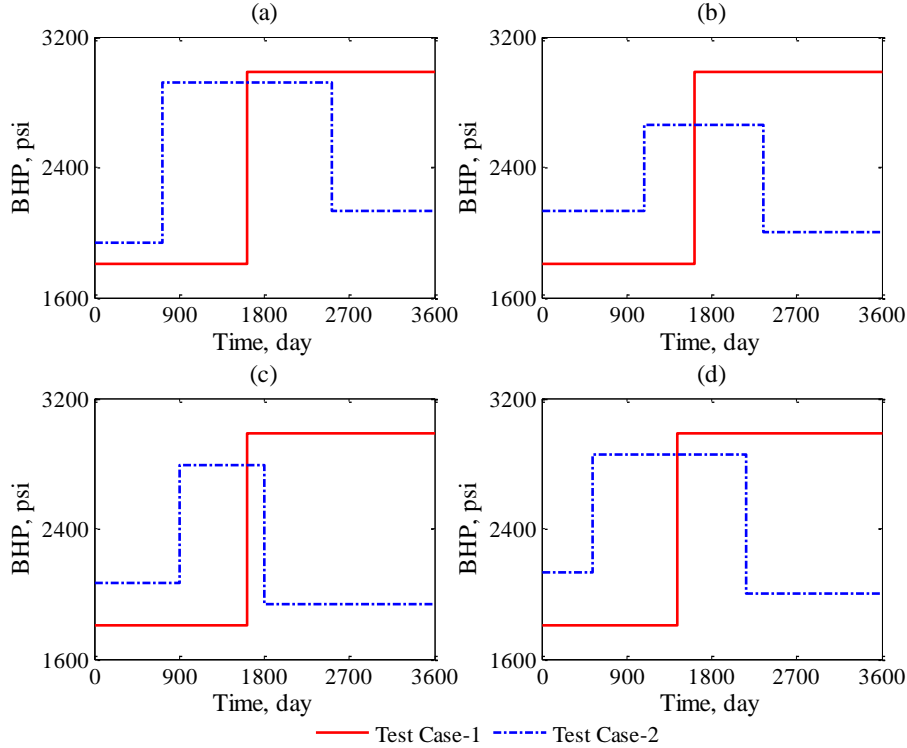


**Figure 7: Comparison of SM prediction and actual RM; a) Cumulative Oil production- test data #1, b) Cumulative Water production- test data #1, c) Cumulative Oil production- test data #2, d) Cumulative Water production- test data # 2**

As shown in Figure 7 and also **Error! Reference source not found.**, the surrogate model predicts oil production more accurately compared to the water production. This is mainly due to the nonlinear characteristics of water production comparing to oil production after water breakthrough. Moreover, we observed that the prediction quality of the surrogate model decreases at later control steps. This is due to accumulation of error from previous control steps when feed-back loop is used in the ANN.

One of the essential features of the surrogate model, developed for production optimization problem, is its robustness in prediction under abrupt changes of the control variables. To test this capability, 2 test cases are developed with sharp changes in the well BHPs as shown in Figure 8.

Test case-1 represents a step increase in BHP of all production wells (red line in Figure 8). Test case-2 represents a pulse change which is a random increase followed by a random decrease with different values (dashed blue line in Figure 8).



**Figure 8: BHP versus production time for two test cases with abrupt change in the control; a) well p1, b) well p2, c) well p3, d) well p4.**

For both test cases, the cumulative oil and water production curves are calculated using actual reservoir simulator and the developed surrogate model. **Error! Reference source not found.** compares minimum, maximum, mean and standard deviation of relative prediction error for two test cases when considering all control steps. We observed that for both cases the surrogate model is capable of providing a good prediction of oil and water production (**Error! Reference source not found.** and Figure 9). However, the step change is a relatively easier case for the surrogate model to predict (smaller error in **Error! Reference source not found.**, Case-1and Figure 9-a and Figure 9-b).

**Table 2: Minimum, maximum, mean and standard deviation of relative prediction error of the developed SM for two cases with abrupt changes in the control variables**

Test Cases	oil				water			
	min	max	mean	std	min	max	mean	std
Case-1	0.0004	0.0094	0.0038	0.0025	0.0008	0.0133	0.0076	0.0046
Case-2	0.0001	0.0081	0.0041	0.0029	0.0015	0.0517	0.0220	0.0175

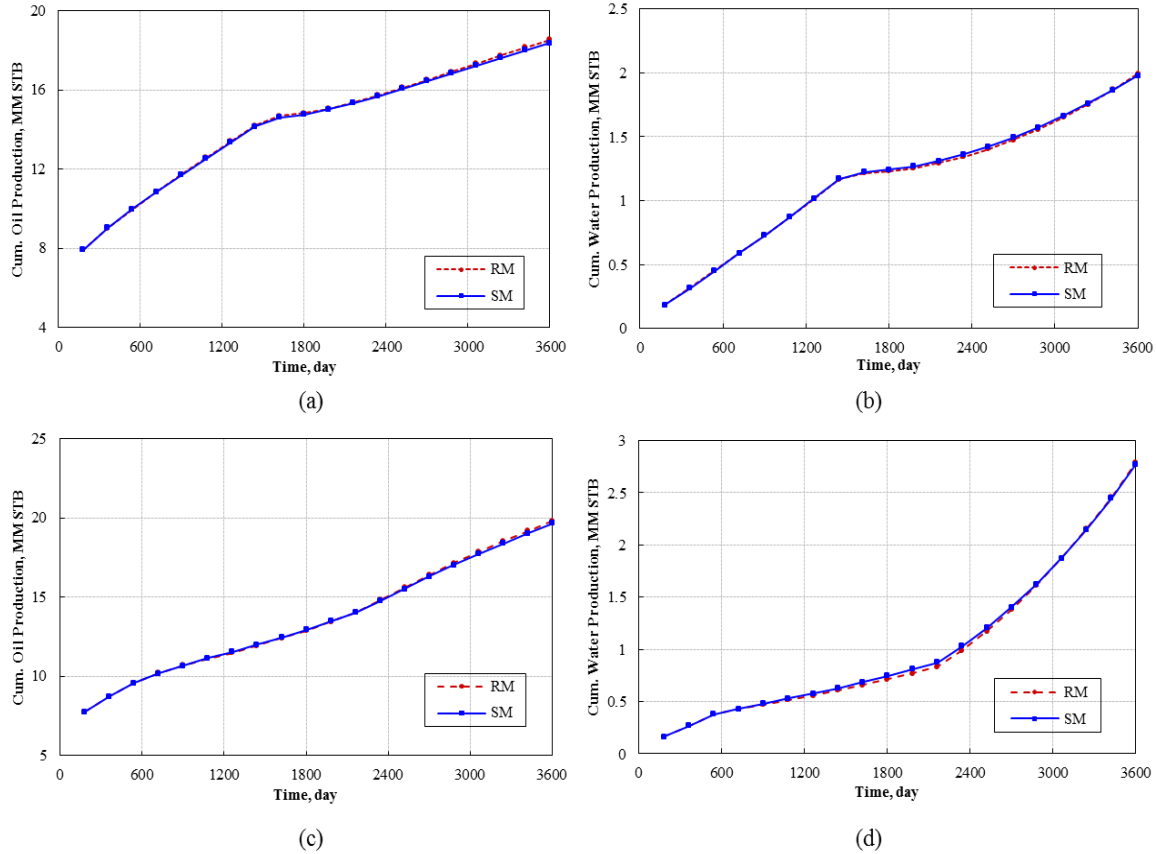


Figure 9: SM and RM prediction for two cases with abrupt changes in control variable; a) Cumulative oil production for test case-1, b) Cumulative water production for test case-1, c) Cumulative oil production for test case-2, d) Cumulative water production for test case-2.

### 4.3. Optimization results

The constructed surrogate model is employed to perform the production optimization process. Genetic Algorithm (GA) (Haupt and Haupt, 2004) is used as the optimizer. NPV is the objective function which is calculated using the economical parameters shown in Table 2. The control parameters are BHP of the producers varying in the range of 1740-3050 psi (120-210 bar). The best tuning parameters of GA is obtained by try and error (Table 3).

Table 2: Economical parameters.

Parameter	Value
Oil price, $r_o$	80 USD/STB
Cost of water operation, $r_w$	10 USD/STB
Cost of water injection, $r_i$	10 USD/STB
Discount rate, $b$	10 percent per year



**Table 3: Optimization parameters.**

Parameter	Value
Population size	50
Maximum generations	50
Crossover fraction	0.6
Mutation rate	0.2
Selection function	Roulette wheel

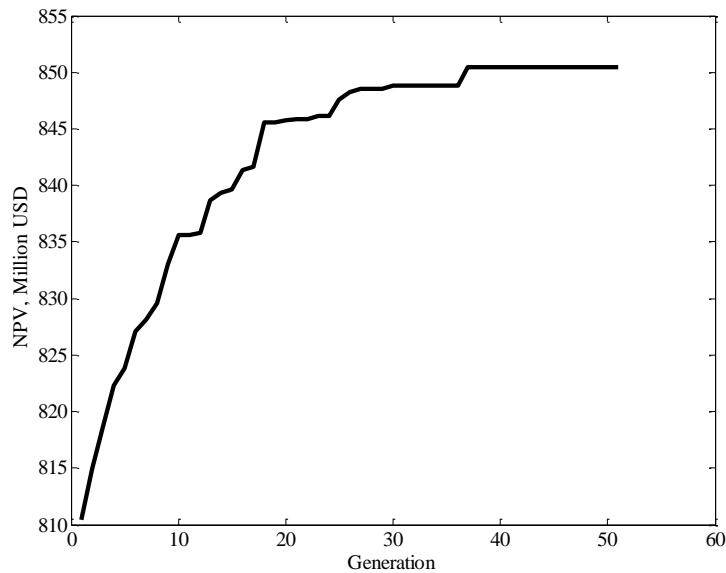
Three different cases are considered:

- Case-1: Optimization is performed using only actual reservoir model.
- Case-2: Optimization is performed using only the surrogate model.
- Case-3: Optimization is performed using combination of the actual reservoir model and the surrogate model.

In order to eliminate the random sampling effect of GA, 10 independent runs are performed and the average results are presented.

#### 4.3.1. Case-1

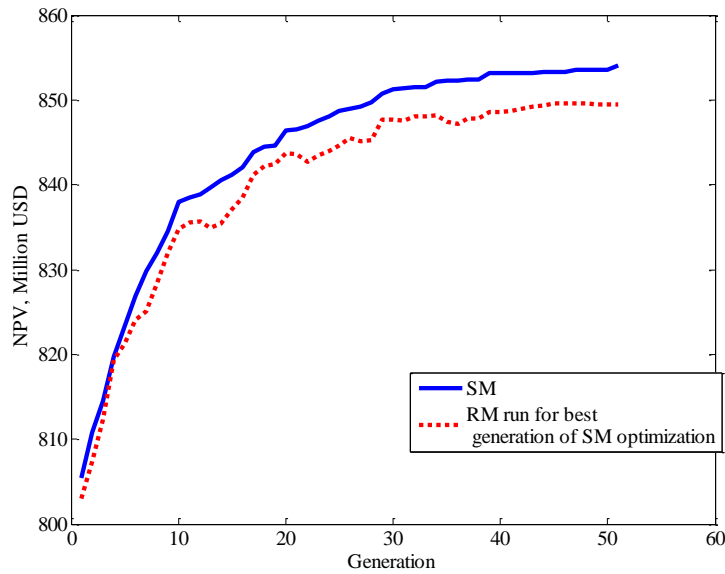
This case presents the ideal optimization approach when objective function is calculated using the actual reservoir model. The optimization is performed for 50 generations resulting 2500 runs of the actual reservoir simulator. Figure 10 shows the maximum NPV obtained at each generation.



**Figure 10: NPV versus generation number for RM optimization; case-1.**

### 4.3.2. Case-2

In this case, first surrogate model is constructed using the developed approach. After achieving the defined accuracy of the surrogate model, the actual reservoir model goes offline and the optimization is performed using only the surrogate model. Figure 11 shows NPV of the best control scenario obtained at each generation calculated using surrogate model (SM, solid blue line) and actual reservoir model (RM, dashed red line). Please note that the best control scenario obtained at each generation is calculated using the actual reservoir model in order to illustrate the prediction accuracy of the surrogate model.



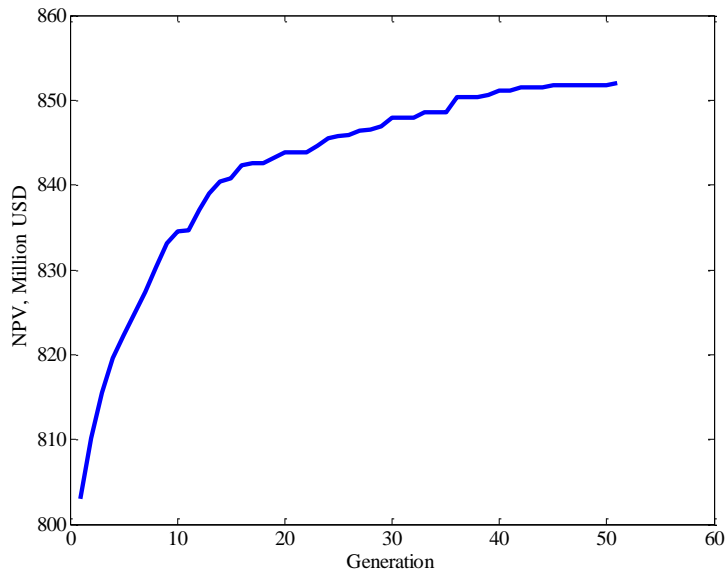
**Figure 11: NPV versus generation number for SM optimization; case-2.**

A general trend of increasing the surrogate model prediction error is observed which is mainly due to the fact that the prediction performance of the surrogate model is poor in the recently observed area of the search space discovered by the optimization algorithm (Figure 11). In this case, the surrogate model is constructed using 200 training data points hence provides a rough approximation of the search space leading to a near optimum solution.

### 4.3.3. Case-3

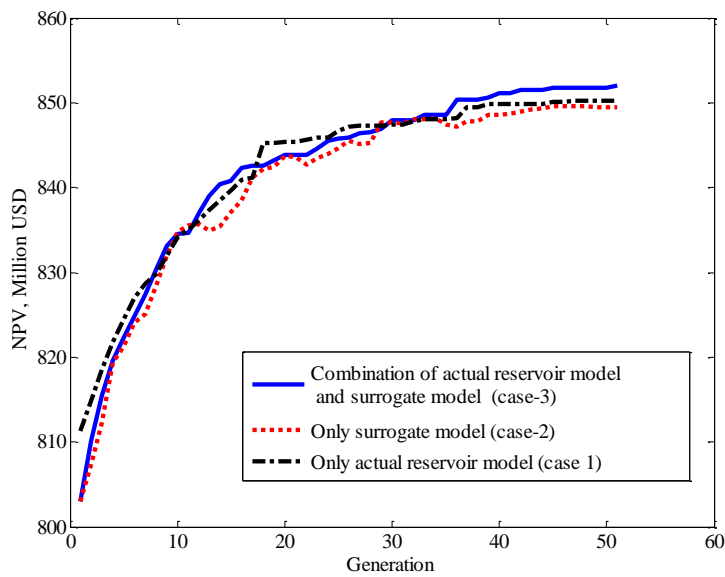
This case addresses the main problem of Case-2 which was low accuracy of the surrogate model in calculating the objective value in recently discovered area of the search space. Initially, the developed surrogate model is employed to calculate the objective value for all individuals at each generation. Then, the actual reservoir model calculates the objective value for the best individual obtained (i.e. maximum NPV). This new point is added to the existing training points and the surrogate model is retrained. The updated surrogate model is used for the next generation. Figure 12 shows NPV for the best control scenario obtained at each generation. It should be noted that this value is calculated using actual reservoir model. In this case, 250 reservoir simulation runs

are performed which includes 200 runs for generating the initial surrogate model and 50 runs (one at each generation) to update the surrogate model.



**Figure 12: Optimizing NPV function using SM coupled with RM; case-3.**

Figure 13 compares NPV of the best control scenario obtained at each generation (calculated using actual reservoir model) for 3 different cases considered while Table 4 compares the best objective value obtained and the required simulation runs.



**Figure 13: Comparison of NPV obtained from three cases.**

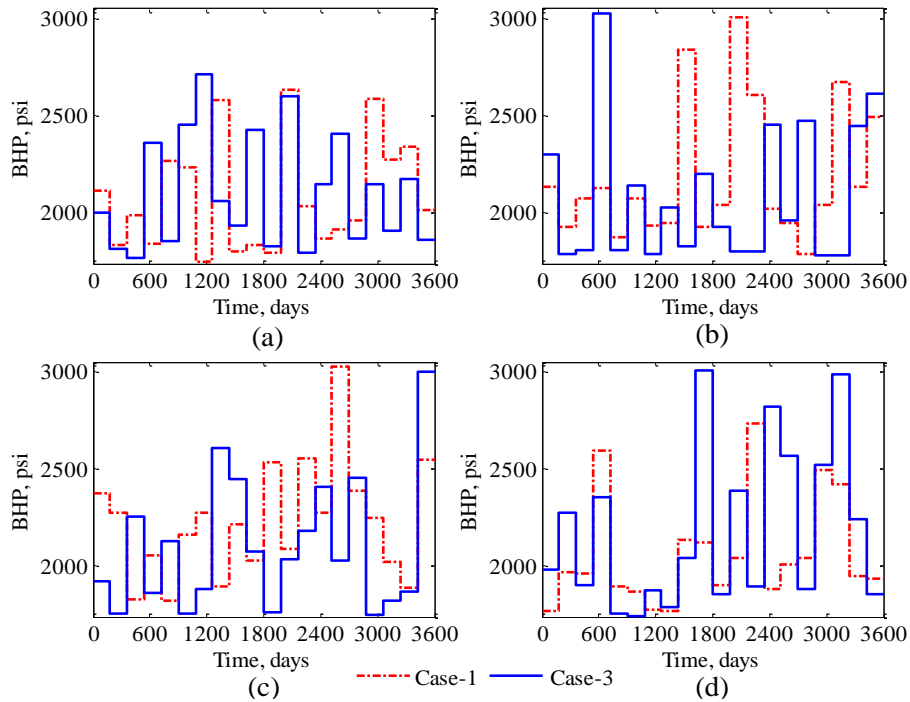
**Table 4: Optimization results.**

Cases	NPV (million USD )	Number of Simulation Run
Case-1	850	2500
Case-2	849	200
Case-3	852	250

The computation time associated with Case-1 prohibitively increases with large full-field reservoir models. Surrogate modeling assisted optimization alleviates this problem and increases the practicality of performing full-field optimization.

As shown in Figure 13 and Table 4, the best result is obtained by Case-3. This is due to the fact that in contrast to Case-2 the surrogate model is updated at each generation in Case-3. The greater added value in Case-3 in comparison to Case-1 can be due to the smooth estimation of the objective function provided by the surrogate model in Case-3. Hence, the optimization algorithm can provide a faster convergence to a superior solution in the smooth search space of Case-3.

Figure 14 shows BHP values of the 4 production wells in the best control scenario obtained using Case-1 (optimization is performed using only actual reservoir model) and Case-3 (optimization is performed using combination of the surrogate model and the actual reservoir model). We observed that although the objective function values are showing a small difference (~0.24 %), the obtained control scenarios are considerably different. This behavior has been previously observed (e.g. Do and Reynolds, (2013)) and illustrates that two cases are discovering different areas of the search space which is characterized by several local optima with objective values close to each other and close to the global optimum .



**Figure 14: The optimum control scenarios for production wells obtained using Case-1 and Case-3; a) well p1, b) well p2, c) well p3, d) well p4.**

## 5. Conclusions

In this paper, an efficient methodology for constructing adaptive surrogate models with the application in production optimization has been developed. A modified formulation is developed which reduces the large number of input variables by receiving the well control parameters at consecutive control steps while generating the resulting cumulative production curves. An ANN equipped with a feedback loop is shown to perform efficiently as approximation function for the new configuration. A space-filling initial design followed by Jackknifing and Cross-Validation is employed to perform the adaptive training of the surrogate model. The developed surrogate model successfully applied to optimize production on the PUNQ-S3 reservoir model. Following conclusions were warranted:

- The developed adaptive surrogate modeling approach outperformed the conventional one-shot approach. This is due to the fact that in the developed approach adequate number of training data points are iteratively selected from the undiscovered area which enhances the accuracy of the surrogate model.
- The developed surrogate model was capable of mimicking the reservoir simulator responses with an acceptable accuracy. It provides good a prediction of the oil and water production under abrupt changes of the control variables which is particularly important for production optimization applications.

- The best performance is achieved when the optimization is performed using combination of the actual reservoir model and the developed surrogate model (Case-3). The developed surrogate model provides a global presentation of the search space which is refined during the optimization process in the promising area (where optimum solution is located).
- The developed adaptive surrogate modeling assisted optimization approach not only provides an accurate and significantly faster substitute for the reservoir simulator-based optimization but also enhances the optimization performance by smoothing the search space.

## Nomenclature

### *Acronyms*

ANN	Artificial Neural Network
ASP	Alkaline-Surfactant-Polymer
BHP	Bottom Hole Pressure
CV	Cross-Validation
DACE	Design and Analysis of Computer Experiment
DOE	Design Of Experiment
GA	Genetic Algorithm
NPV	Net Present Value
RBF	Radial Basis Function
RE	Relative Error
RM	Reservoir Model
ROM	Reduced Order Models
SAGD	Steam Assisted Gravity Drainage
SM	Surrogate Model

### *Symbols*

$b$	discount rate, percent per years
$c$	nonlinear constraint
$C$	number of candidate points
$f$	true function
$\hat{f}$	approximation function
$H$	number of hidden neurons
$J$	objective function
$k$	number of input variables
$L$	number of inputs of ANN
$M$	number of outputs of ANN

$N$	number of fold in N-fold cross-validation
$np$	number of wells
$nt$	total number of control steps
$p^t$	elapsed time, year
$Q_i^t$	total field water injection rate of $t^{\text{th}}$ control step, STB/day
$Q_o^t$	total field oil production rate of $t^{\text{th}}$ control step, STB/day
$Q_w^t$	total field water production rate of $t^{\text{th}}$ control step, STB/day
$R$	design space of variables
$r_i$	cost of water injection, USD/STB
$r_o$	oil price, USD/STB
$r_w$	cost of water removal, USD/STB
$s(t)$	transfer function
$S$	training data set
$\tilde{s}$	jackknife variance
$t$	control step
$\mathbf{u}$	vector of control variables
$X$	input data
$y$	simulation output
$Y$	Output data
$\hat{y}$	surrogate model prediction
$\tilde{y}$	Jackknife estimate
$\bar{\tilde{y}}$	Average of jackknife estimate
$\mathbf{Z}$	input matrix of ANN

*Greek symbols*

$\theta(\omega, \eta, \mu, \zeta)$	weights of ANN
$\Delta t$	difference between two control steps, day

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