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EVALUATION OF NEURO-SIMULATION TECHNIQUES AS PROXIES TO RESERVOIR SIMULATOR

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Abstract

Proxy models are becoming more widely used as they can simplify highly complex processes with reasonable accuracy. Process such as production history matching, well placement, risk analysis, for example, generally involve large number of reservoir simulations and large computational effort. To minimize this problem some techniques such as Spline, Neural Networks, Kriging and Experimental Design, have been presented in the literature to be used as proxies to reservoir simulator. Due to the importance of the decisions related to the development and management of petroleum fields, the development of proxies with high accuracy can be a decisive aspect in a project. The successful applications of Neural Networks in several research fields suggest the investigation of appropriated architectures to be used as proxies to reservoir simulator. In this article novel proxies to reservoir simulator, based in Neuro-Simulation Techniques, are presented. These proxies present a high accuracy to reservoir simulator. Five different architectures of Neural Networks were studied and applied in two case studies related to history matching. The results obtained showed the large potential of application of the techniques introduced.

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1. Introduction

In the last years is growing the development of researches related to generation of proxies to reservoir simulators. Neural network based proxies, for example, is being very used in several process involving reservoir simulation (Singh, 2005; Reis, 2006; Zangl, 2006, Al-Thuwaini, 2006). The common methodologies generally used for the elaboration of the proxies are: thin plane spline; kriging; experimental design and artificial neural networks. There are two principal criteria for evaluation of proxies (1) The proxies must exactly reproduce the data which they used in the their elaboration; (2) The correlation between the data produced by the proxies and the real data it is satisfactory if the value is between 0.7 and 0.8. In this article are presented the results of researches related to application of several different types of Artificial Neural Networks as proxies to reservoir simulators. It is showed that determined types of Artificial Neural Networks are able to yield proxies of high accuracy. Two case studies related to History Matching are examined, a synthetic case and a real case. These cases were used only as data source for the proxies generation. The proxies were not effectively applied in the history matching process.

2. Methodology

The methodology developed in this research presents the following main steps:
(1) To create knowledge base with reservoir simulations;
(2) To train, to test and validate Artificial Neural Networks with the reservoir simulations of the knowledge base;
(3) To apply the proxy in the simulation parameters;
(4) To compare the results of the proxy with results of the reservoir simulator.
In this methodology, reservoir simulations compose a knowledge base. The simulations of this knowledge base are used in the training, test and validation of the Artificial Neural Networks. When the Neural Networks are trained, tested and validated these networks constitute proxies. These proxies are applied in parameters of reservoir simulations which were not used to create the proxies and the results are compared with the results of the reservoir simulator. Along with the work are showed comparisons between results obtained from proxies and from the reservoir simulator in two case studies related to History Matching. In order to generate the proxies, several Artificial Neural Networks were used:

(1) Radial Basis Network (RBN) - The RBN is a known Neural Network, often applied to approximate functions, Orr [1995]. The basic architecture of the RBN which we implemented consists in a network with three layers: (1) The first layer is an input layer; (2) The second layer is an hidden radial basis layer, with transfer function e-n2, where n is the distance between the input vector and weights of the links, multiplied by a bias; (3) The third layer is an output layer with a linear function. Two types of this basic architecture were implemented:
Type 1: With a fixed number of neurons in the hidden radial basis layer. This number is equal to the number of samples in the training set;
Type 2: With the neurons in the hidden radial basis layer added at each interaction until the minimal sum-squared error.

(2) Adaptive Neuro Fuzzy Inference System (ANFIS) - This fuzzy inference system was applied for the data modeling. From a set of Input/Output data related to a multiple input simple output system a fuzzy inference system was produced. The parameters of this system were estimated with base in Neuro-adaptive learning techniques. These techniques operate as in the conventional learning of the Neural Networks, but they use a combination of the least squared estimation and back-propagation algorithms, Jang [1993].

(3) Fuzzy System with Subtractive Clustering (FSSC) - Given a set of Input/Output data of a multiple input simple output system, a cluster analysis was realized by using the technique of subtractive clustering Chiu [1994]. The centers of the clusters were used to define the rules of a fuzzy inference system. That is, a fuzzy inference system was structured with base in rules extracted by using subtractive clustering of a set of Input/Output data.

(4) Generalized Regression Neural Network (GRNN) - This Neural Network has been used in many applications to approximate functions. We implement the following architecture of this Neural Network: A network with three layers: (1) The first layer is an input layer; (2) The second layer is an hidden radial basis layer with the number neurons equal to the number of samples in the training set; (3) The third layer an output layer. The output layer of this network has a linear function, but the input of this linear function is the output of the second layer multiplied by weights submitted to a normalization function Shoiad et.al. [2004].

3. Case Study – History Matching

3.1. Case1

In this case, a synthetic reservoir derived from SPE 10 was used. The characteristics of the reservoir for this case are described in Maschio et al. [2005] and in Maschio and Schiozer [2004]. The reference model was used to generate a synthetic history and the coarse model is to be adjusted constrained to the history generated through the fine grid. The matching parameters used were the horizontal permeability of the six layers, with 27 multipliers between 0.3

and 2.5. The objective function (difference between simulated and observed data) was composed by the water rate of the 4 producer wells.

3.2. Case 2

Case 2 is derived from a real reservoir. The main characteristics of the case is also describe in Maschio et al. [2005] and Maschio and Schiozer [2004]. The objective function was composed by field pressure, field water rate and field oil rate. The matching parameters (all of them in the field domain) was porosity and net to gross, both with 9 multipliers ranging between 0.7 and 1.3, horizontal permeability with 9 multipliers between 0.4 and vertical permeability with 9 multipliers between 0.3 and 2.5.

4. Comparisons of the proxies with the reservoir simulator

In this section are showed graphical representations of the comparisons between the proxies and the reservoir simulator. As mentioned above, the two cases studies are related to History Matching. So that objective functions (FO) were obtained from reservoir simulations to adjust parameters of the reservoir model. The associations between parameters and the values of the objective function to train, to test and validate the proxies are used. When the proxies were trained, tested and validated are compared the results of the objective functions obtained from proxies with the results of the objective functions obtained from reservoir simulator. Figures 1, 2, 3 and 4 are related to Case 1. Figures 5, 6, 7 and 8 are related to Case 2. In these Figures the blue curves represent the responses of the reservoir simulator and the green curves represent the responses of the proxies. Note that the proxies present high accuracy.

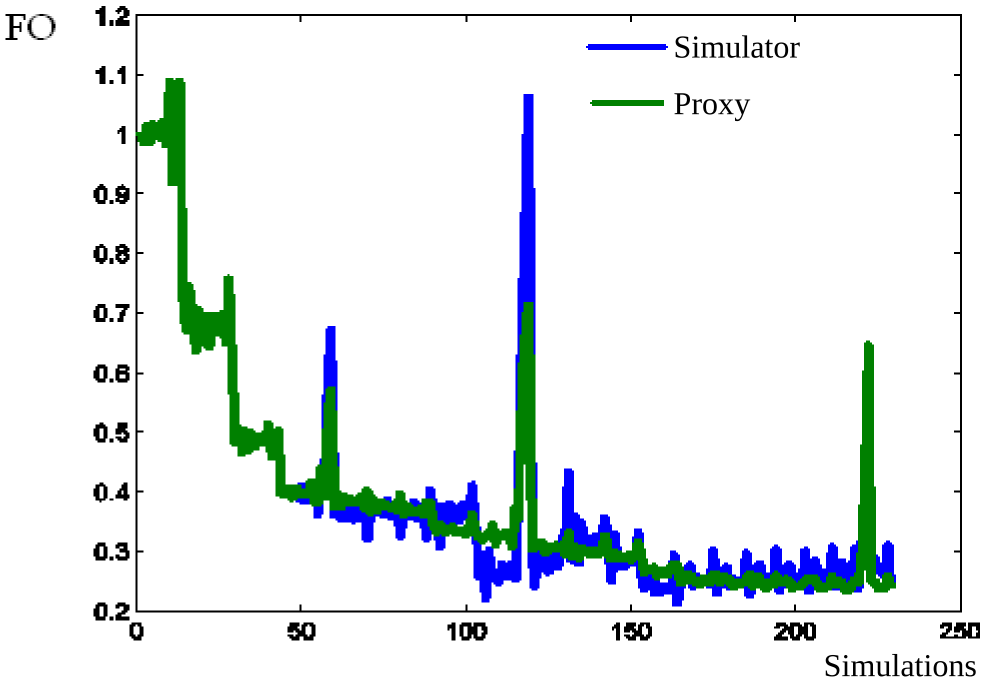

Figure 1 - Adaptive Neuro Fuzzy Inference System (ANFIS), Case 1

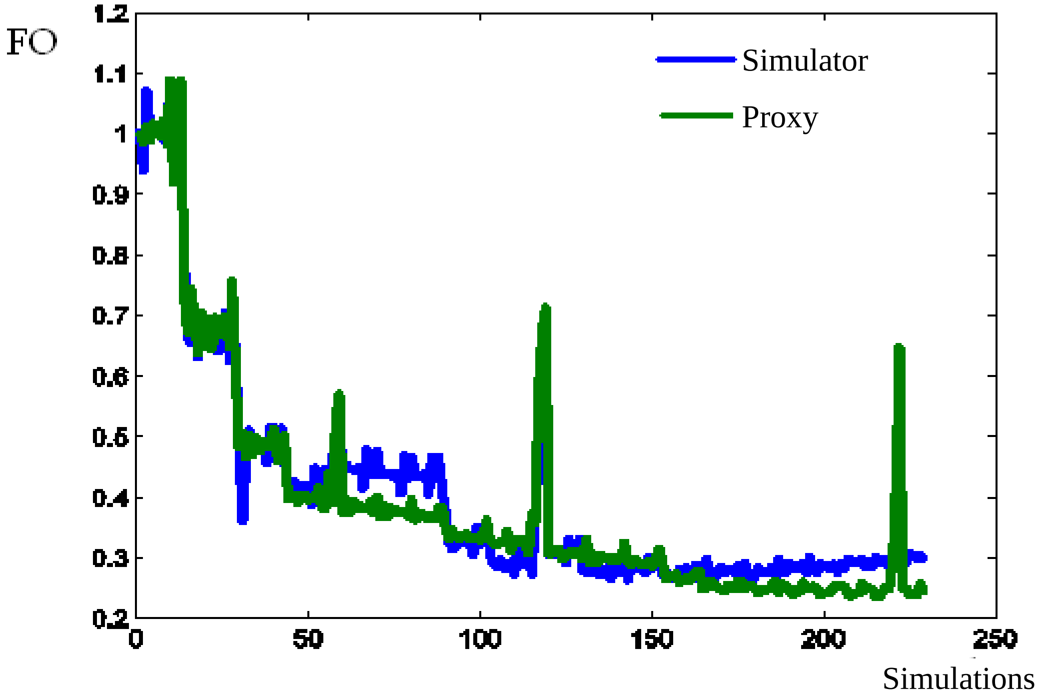

Figure 2 - Radial Basis Network (RBN) - Type 1, Case 1

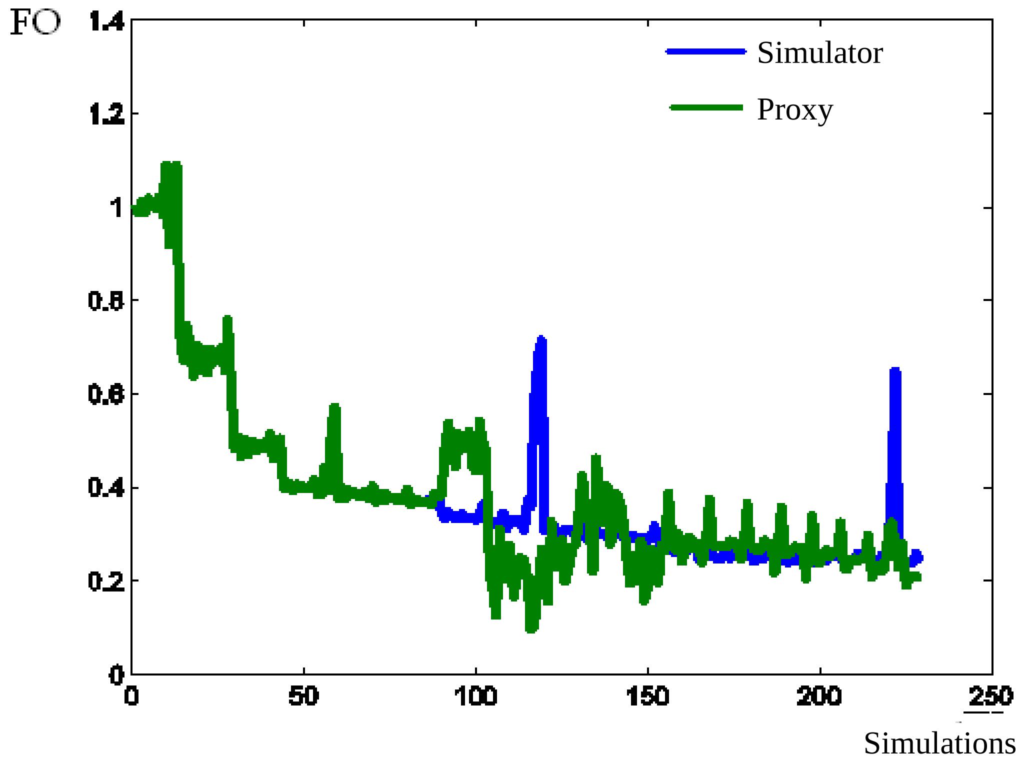

Figure 3. Radial Basis Network (RBN) - Type 2, Case 1

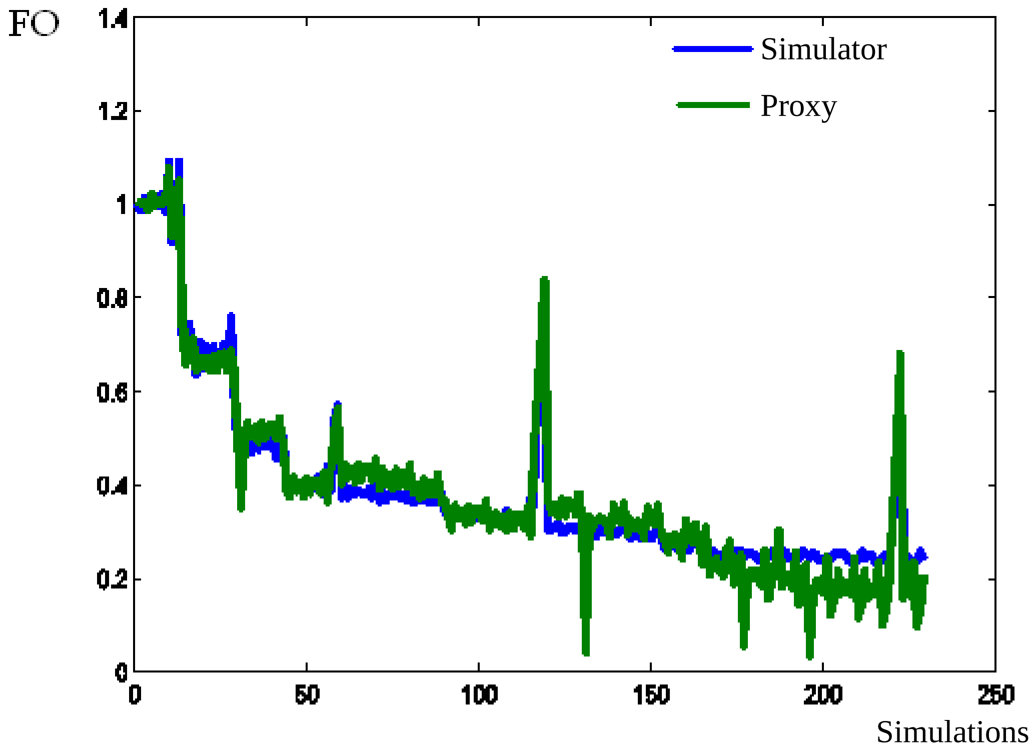

Figure 4 - Fuzzy System with Subtractive Clustering (FSSC), Case 1

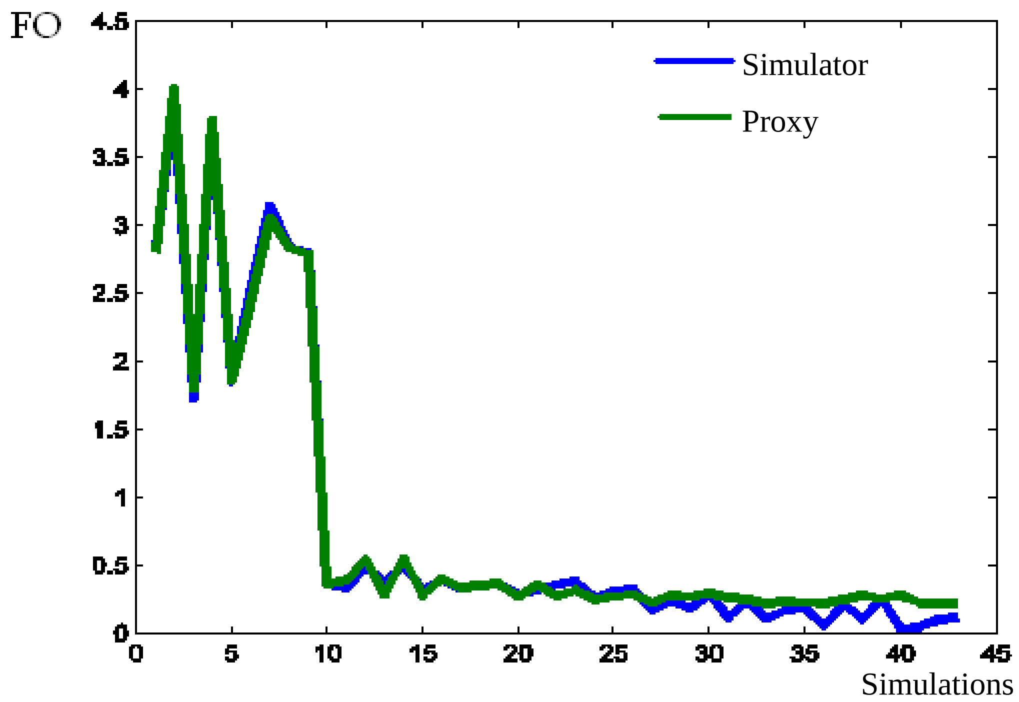

Figure 5. Fuzzy System with Subtractive Clustering (FSSC) - Case 2

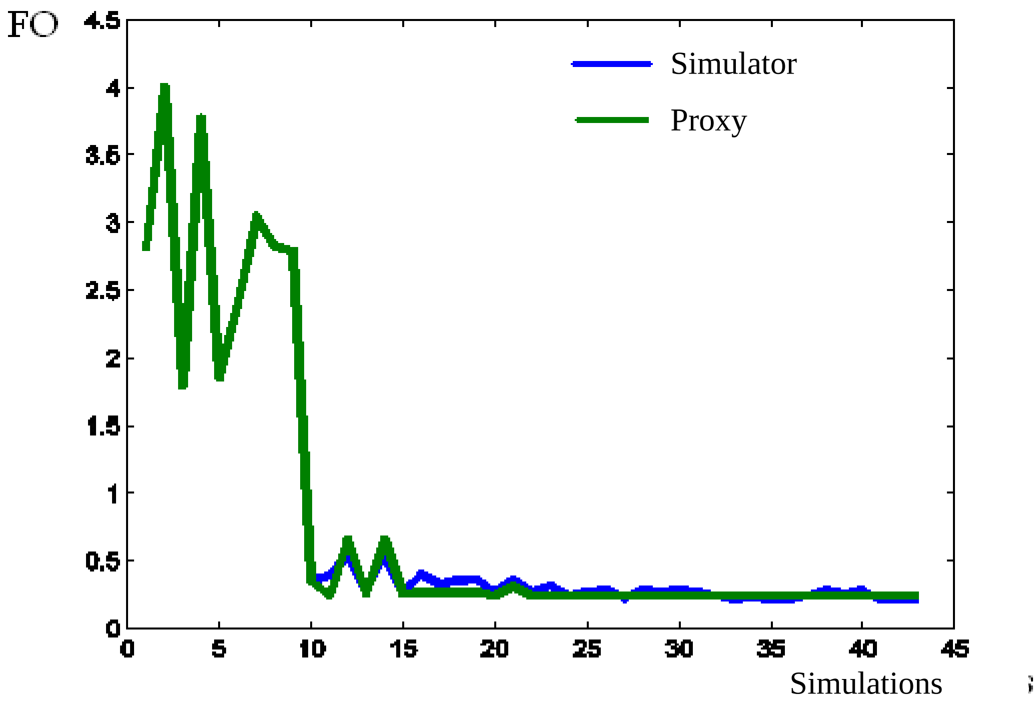

Figure 6. Radial Basis Network (RBN) - Type 2, Case 2

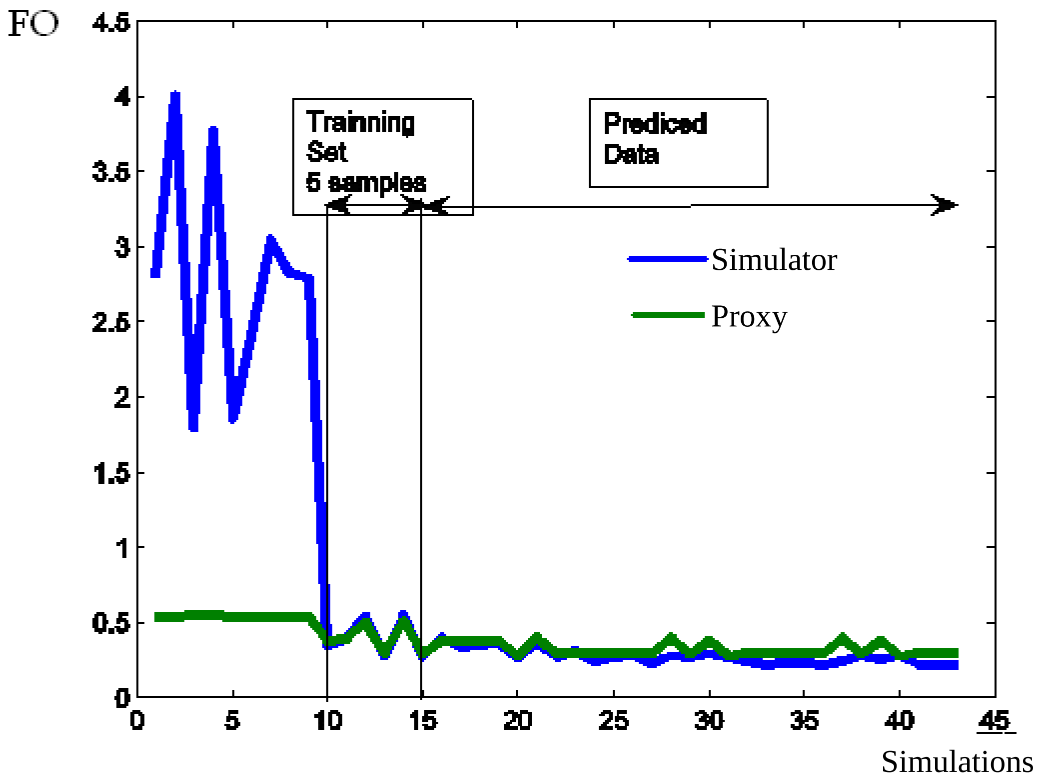

Figure 7. Generalized Regression Neural Network (GRNN), Case 2

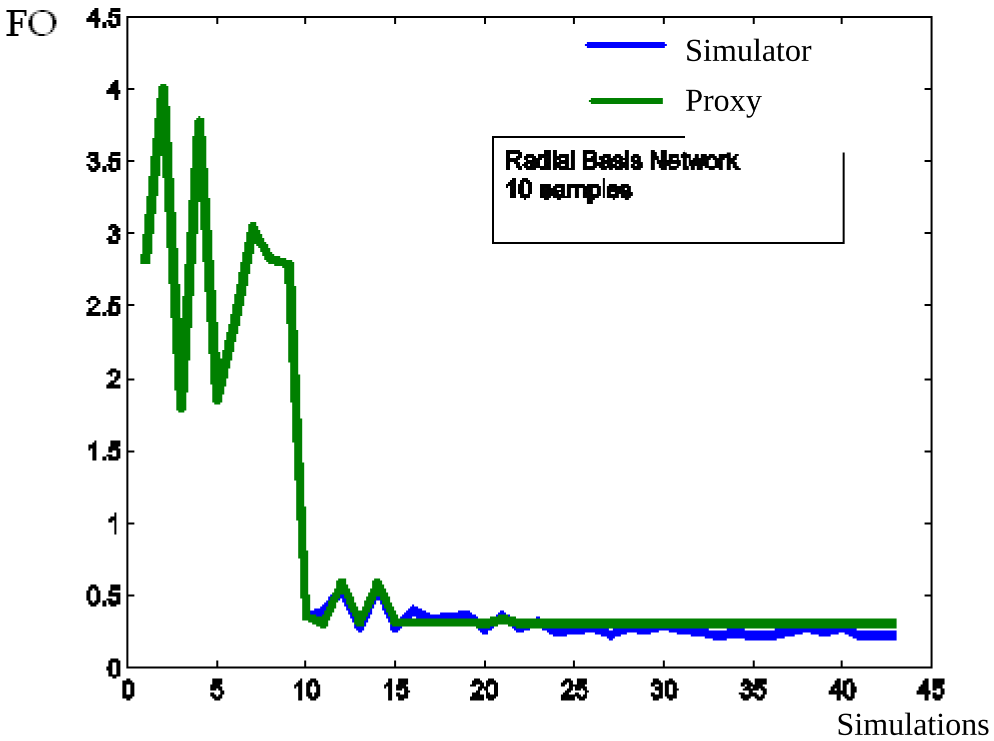

Figure 8. Radial Basis Network (RBN) - Type 1, Case 2

The number of reservoir simulations used for the elaboration of the proxies in all the cases was inferior to 50 % of the available simulations. This meant a considerable reduction of simulations. The proxies elaborated can be applied in studies that require a very large number of reservoir simulations, for example optimization studies. In these studies the proxies can work directly with optimization methods, for example genetic algorithm, with considerable reduction of the reservoir simulations.

5. Conclusion

In this article are showed that proxies to reservoir simulators with high accuracy can be obtained from Artificial Neural Networks. Different neural networks were examined in two case studies of history matching: a synthetic case and a real case. The proxies showed good agreement to the solution obtained from simulator, which permits to conclude that for cases tested, it could be used in the optimization process. The use of neural networks is an promise area in the processes involving reservoir simulations.

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