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Multilayer Neural Network with Multi-Valued Neurons in time series forecasting of oil production

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ABSTRACT

In this paper, we discuss the long-term time series forecasting using a Multilayer Neural Network with Multi-Valued Neurons (MLMVN). This is a complex-valued neural network with a derivative-free backpropagation learning algorithm. We evaluate the proposed approach using a real-world data set describing the dynamic behavior of an oilfield asset located in the coastal swamps of the Gulf of Mexico. We show that MLMVN can be efficiently applied to univariate and multivariate one-step- and multi-step ahead prediction of reservoir dynamics. This paper is not only intended for proposing to use a complex-valued neural network for forecasting, but to deeper study some important aspects of the application of ANN models to time series forecasting that could be of the particular interest for pattern recognition community.

1. Introduction

An oilfield is described by a set of time series (TS) of fluids from petroleum wells (oil, gas, and water), which are characterized by different starting points and mutual influence. Production performance is both controlled by the reservoir properties and is affected by operational constraints and surrounding wells performance. Since the rock and fluid properties of the reservoirs are highly nonlinear and heterogeneous in nature, production TS comprise high-frequency multipolynomial components and represent a long memory process and are often discontinuous (or piecewise continuous).

Several important tasks of petroleum reservoir engineering are concerned with the forecasting of oil production from the reservoir. Usually, production prediction problem is considered within several different settings [14]: i) prediction of existing wells based on that well's previous production data, ii) spatial prediction of a new infill drilling well based on the reservoir's model, iii) backward prediction, known as "backcasting", for some brown fields with no record of the measured wells' production, iv) prediction of the well's behavior under a certain recovery technology, especially in the case of cyclic steam injection, to mention few. Many prediction models (both traditional ones and those using machine learning techniques) are good for predicting the next sample in a time series. Unfortunately, all the real-world tasks mentioned above need a longer forecasts with the horizon of prediction $s > 1$ (or in most cases $s > 12$). Thus multi-step prediction model is in fact very important. This model and some new ways for multi-step prediction using a complex-valued neural network are studied in the paper.

Traditional methods of production prediction in petroleum engineering include decline curve analysis (DCA), black oil model history matching, exploration analogies and exploration trend extrapolations. The main disadvantage of such tools is that they are based on subjective data interpretation: to pick the proper slope, to tune the parameters of the numerical simulation model in such a way that they keep the reasonable values, to interpret reservoir geology [30].

The underlying idea of TS forecasting is that patterns associated with past values in a data series can be used to project future values [7]. In real-life dynamic systems the task for a TS forecasting can be stated as follows: given measurements of one component of the state vector, reconstruct the (possibly) chaotic dynamics of the phase space and thereby predict the evolution of the measured variable [10]. Machine learning based prediction models showed to be especially good for TS governed by nonlinear dynamics, like that of oil and gas production. Most of them use artificial neural networks (ANN) with different topologies developed both in univariate and multivariate settings. Multilayer perceptron (MLP) and recurrent neural networks (RNN), such as NARX, Elman and Jordan RNN, can be applied for multi-step-ahead

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TS forecasting. In [15,22] a forecasting model based on the use of MLP was suggested to predict existing and infill oil well performance using only production data. Chakra et al. described higher order neural networks (HONN) applied to forecast water, oil and gas production [9]. On relatively short-term (6–18 months) forecasting intervals and rather small data sets (up to 10 TS) most of these models outperformed DCA results with mean absolute percentage error (MAPE) about 14–16% [22], but forecasting on longer time intervals is still a challenge.

Recently, we reported on the application of pattern recognition (the associative model) and recurrent neural networks (NARX) techniques to oil production prediction [20,26,28]. Both models showed very competitive behavior on short prediction horizons (up to one year) but, in the current state of the development of forecasting algorithm, had some difficulties on longer intervals. In this paper, we extend the ideas first reported in [4], and analyze the problem of long-term forecasting using a Multilayer Neural Network with Multi-Valued Neurons (MLMVN) introduced in [1] and further developed in [2,3]. This network with complex-valued weights, being more flexible and functional than for example MLP, has shown promising results in the long term time series prediction in different areas [3,13]. Thus it is natural to employ it in the long term prediction of oil production. The paper studies an oilfield behavior reflected in the oil well's monthly production TS analyzing both the architecture and the parameters (time lag, memory size, etc.) which better describe and are able to predict its dynamics on long time intervals. We illustrate the representation of TS patterns with MLMVN, several aspects of the prediction problem as the prediction horizon increases (for up to 5–15 years) and compare the univariate and multivariate forecasting with real data from an oilfield located in the coastal swamps of the Gulf of Mexico.

The main contributions of the paper are the following: 1) it was shown that MLMVN, a complex-valued neural network, can successfully be applied to long-term time series forecasting of oil production, showing competitive results; 2) for the first time MLMVN was applied to multivariate time series prediction; 3) we provide a deep comparative observation of the use of different types of artificial neural networks in time series forecasting in petroleum engineering including conventional recurrent neural networks (Elman architecture) and dynamic networks with a feedback (NARX); and 4) experimental results clearly show that MLMVN outperforms these types of ANNs in long-term forecasting of oil production time series.

The rest of the paper is organized as follows. In the next section, the foundations of the MLMVN and their use for time series forecasting are briefly observed for the reader's convenience. Univariate and multivariate, one-step- and multi-step ahead MLMVN models are defined in Section 3. Section 4 presents experimental settings and results, which are discussed and compared with the state-of-the-art in Section 5. In Section 6, the main findings of the paper are summarized.

2. The MLMVN neural network foundations

MLMVN consists of Multi-Valued Neurons (MVN) with complex-valued weights, and this is its main distinction from a classical feedforward neural network. Complex-valued neural networks are as natural as the real-valued ones. Using complex-valued inputs/outputs, weights and activation functions, it is possible to increase the functionality of a single neuron and a neural network, to improve their performance, and to reduce the training time [3,5,15].

MVN was initially introduced as a discrete MVN in [1]. A continuous MVN was then introduced in [6]. In this paper, we

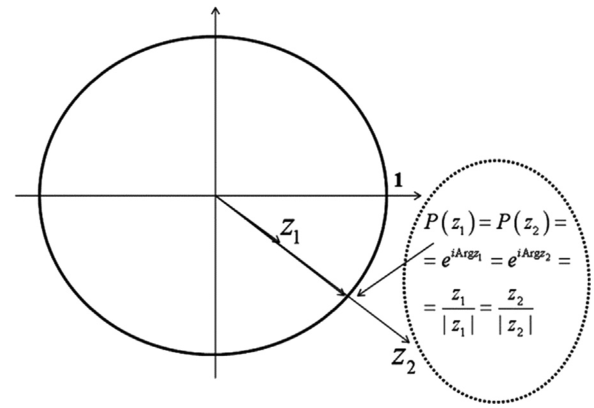

Fig. 1. Geometrical interpretation of the continuous MVN activation function (2).

will employ a continuous MVN. It implements a mapping between n inputs and a single output. While MVN's inputs and output are complex numbers located on the unit circle, its weights are arbitrary complex numbers. An input/output mapping of a continuous MVN is described by a function of n variables $f(x_1,...,x_n)$, $f:O^n \to O$, where O is a set of points located on the unit circle. Such a function can be represented using $n+1$ complex-valued weights as follows [3]:

$$f(x_1,...,x_n)=P(w_0+w_1x_1+...+w_nx_n), \tag{1}$$

where $x_1,...,x_n$ $(x_j \in E_k, j=1,...,n)$ are neuron inputs and $w_0, w_1, ..., w_n$ are the weights. P is the activation function (Fig. 1), which is:

$$P(z)=e^{i\mathrm{Arg}(z)}=z/|z| \tag{2}$$

where $z=w_0+w_1x_1+...+w_nx_n$ is the weighted sum, Arg z is the main value of the argument of the complex number z. Thus a continuous MVN output is a projection of its complex-valued weighted sum onto the unit circle.

The MVN learning is based on the error-correction learning rule [3]:

$$W_{r+1}=W_r+\frac{C_r}{(n+1)|z_r|}(D-Y)\overline{X}, \tag{3}$$

where $\overline{X}$ is the vector of neuron inputs complex-conjugated, n is the number of neuron inputs, D is the desired output of the neuron, $Y=P(z)$is the actual output of the neuron, r is the number of the learning step, W_r is the current weighting vector, W_{r+1} is the following weighting vector, C_r is a learning rate (it is complex-valued in general, but in all simulations, which we have done in this work, we used $C_r=1$), and $|z_r|$ is the absolute value of the weighted sum obtained on the rth learning step. A factor $1/|z_r|$ should be used when correcting the weights of the hidden neurons in a neural network, which for the exact errors are not known. But it should not be used for output neurons in the network, which for the exact errors are known. The error-correction learning rule is illustrated in Fig. 2.

The use of MVN as a basic neuron in a MLMVN was suggested in [1,6]. MLMVN is a feedforward neural network (like MLP), but its significant distinctions and advantages are determined by using MVN as its basic neuron. The most important advantages of MLMVN are its higher functionality, better generalization capability and simplicity of learning when compared to MLP. MLMVN learning is derivative-free. Its backpropagation learning algorithm [1–3], which is based on the error-correction learning rule, is constructed in the following way. Let w_i^{js} be the weight corresponding to the ith input of the $j$sth neuron (jth neuron of the sth layer), Y_{js} be the actual output of the jth neuron from the sth layer ($j=1,\ldots,m$), and N_s be the number of the neurons in the sth layer. It means that the neurons from the $s+1$st layer have exactly N_j