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A New Approach to Reservoir Characterization Using Deep Learning Neural Networks

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Abstract

Reservoir description and characterization is one of the main/critical engineering components which require a good understanding to ensure the optimum reservoir development that leads to the highest recovery. Reservoir modeling uses all available information which includes at a minimum logs data, and fluid and rock properties. In this study, a deep learning neural network was developed to estimate the petrophysical characteristics required building a full field earth model for a large reservoir. This was accomplished through a learning process whereby the model was presented with diverse and large volumes of log data measured in the field.

The study demonstrates the capability of the deep learning neural network model when tested against the newly drilled wells in the field. The model proved to generate synthetic logs almost identical to those recorded in the new wells. In a future paper, we will demonstrate how the reservoir model constructed using generated data led to significant improvement in the full field reservoir as contrasted to the existing earth model developed using Kriging technology.

Introduction

Deep learning neural networks are an emerging technology getting significant attention in image recognition, language translation and signal/voice processing. In contrast to the classic neural networks, deep learning requires large volumes of data, in terms of both features and samples, for proper training. Using an innovative approach consisting of batches of wells, the deep learning network was trained to learn the characteristics of the nine productive formations of the subject field. The model captured the correlation between the well logs, the geographic well locations, and reservoir facies. Once successfully trained, the system was applied to estimate reservoir properties at any point in the formation, and to generate synthetic logs for future drilling locations. Additional capability includes generation of synthetic logs for wells with incomplete suite, as well as filling missing or corrupted data segments across the logs. The deep learning structure was implemented in parallel and distributed processing; hence, it leads to an exponential computation processing speed, making it the ideal tool to be used on big data.

The Kern River field located in San Joaquin Valley, California, is characterized as a heavy oil reservoir consisting of nine productive formations. Discovered in 1899, the field was initially produced in primary depletion until the entire reservoir energy was exhausted. Starting with early 1960's, steam injection was introduced as an enhanced oil recovery technology, commencing a new development direction and a bright life for the reservoir. Today, the field continues to sustain a strong production with the introduction of horizontal well drilling and intelligent steam management.

Since its discovery, the field witnessed a rapid development and over its 117 year life, more than 20,000 wells were drilled to produce the nine productive formations. Despite the large number and age, most of the wells in the field have a good suite of logs including SP, GR, SRES, MRES, DRES, NPHI, CALIPER, etc. The data is collected and stored in large databases that are easily accessible to different tools for reservoir surveillance and modeling. The good organization and structure of historical well data in databases, together with the availability of such large volume of information, enabled the use of deep learning neural networks technologies in the current study.

The methodology presented works in the alluvial deposit seen in the Kern River Field and more research should be done to investigate if it can be used in general in other geologies where laterally formations vary in characteristics or where pinch outs cause disappearance of certain features or where faulting affect the continuity

The article is structured in four sections as follows: the first section covers the literature review, section two provides an overview of deep learning neural networks technology, the methodology is covered in section three, and the results and conclusions are presented in section four.

Literature Review

Given the theme of this study, a comprehensive review of the entire reservoir characterization domain was not conducted; rather the authors focused only on the application of artificial intelligence and machine learning technologies within the domain.

A large number of publications discussed the use of artificial intelligence technologies for reservoir characterization. Comprehensive research completed for both rock and fluid properties estimation were presented by Mohaghegh [1-2], Wong [3], Ertekin [4], and Kohli [5].

Largely the literature review revealed a few types of models being developed. For example, in the work presented by Mohaghegh and Wong, both log data and core data was used to train the model. Thus the neural network mapped a set of log values to a physical core measurement such as permeability, porosity or saturation. A second type of model was demonstrated by Mohaghegh [1] where multiple suites of logs were used in the process of training. In their approach, the model was train based on a suite of conventional logs (Resisitivities, NPHI, DPHI, etc) to generate the suite of expensive logs (MRI's logs). While very successful, the model did not expand to more than 20+ wells due to data loading and training limitations. The other models found in the literature used clustering techniques and support vector machine Nazari [6] and Anifowose [7] to estimate rock properties. The latter seemed to be less accurate and again bounded by the data availability and processing capabilities.

All the examples discussed above used relatively simple models such as back propagation, radial basis functions, or recurrent neural networks and support vector machine to estimate the reservoir characteristics. Moreover, the models were developed and trained using only relatively small volumes of data due to the limitation in both loading and processing of the available tools.

Objective

The endless demand of gathering more and more data to improve reservoir characterization does not come cheap. Running comprehensive suite of logs to measure formation properties for every new drill becomes unfeasible and unsustainable for mature reservoirs with hundreds or thousands of wells. Given the importance of data and the continuous demand for information, the objective of this work was the use of technologies that can create accurate data by virtual means, such as deep learning neural networks.

The current study differentiates itself from all the previous work completed so far, and briefly presented in the literature review, for two main reasons: first, we are attempting to generate virtual logs anywhere in the reservoir without any information available at that location (logs, cores, etc.), and second, by using a large volume of data from the nearby wells.

Deep Learning Overview

Deep learning neural network is a machine learning algorithm that can learn complicated functions. It composes multiple levels of non-linear transformations that can approximate any complex function. Each level can be seen as separate quantity which can transform its input to its output deploying non-linear functions. The non-linearity in layers is distributed throughout the network where parameters of non-linear transformations are optimized using historic data. To achieve this, large quantity of data describing the process must be available. The learning process of deep learning algorithm extracts useful information from raw data in a sequential way. Deep learning methods aim at extracting features in hierarchical orders where higher-level features are formed by the composition of lower level features. Deriving features in hierarchical order allows the deep learning model to learn complex correlations from data. The mapping between inputs and outputs is critical in complicated systems; even experts often are unable to explicitly specify information in raw data. The ability to automatically learn features will become increasingly important as the amount of data and range of applications to machine learning methods continues to grow.

One of the differences between current machine learning algorithms and deep learning networks consists in depth of architecture where the number of levels of non-linear transformations is significantly higher. Each layer within the series between input and output data identifies important features and further processes them in a series of stages. Through this capability, the deep learning nets are taking away the time consuming, difficult, and sometimes impossible feature selection task from the expert. The deep learning network process is described in Figure 1. Deep neural networks naturally are exposed to raw data; next they pre-process the data, extract and select critical features for complex mapping problems, and use them for prediction or classification (Fig. 1).

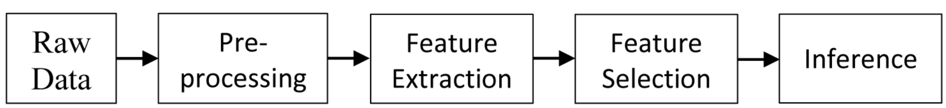


Figure 1—Deep neural network process

Due of limited access to computational power and large data sets during the 80's and 90's, all experimental results were typically obtained from few non-linear hidden layers in classic neural networks. However, after 2006, when the computational power, data storage, and learning algorithms barriers were solved [9], deep learning neural networks have been applied successfully in many applications including classification [10-12], regression [13], image processing [14], natural language processing [15-16], text mining [17], and robotics [18] and petroleum industry [19-20]. The technology enjoyed significant growth and can be found in many commercial applications of corporations like Facebook, Google, Microsoft, etc.

Feed forward network

Deep learning consists of neurons which are processing units of operation of a neural network. Fig. 2 shows the model of a neuron which forms the basis of designing an artificial neural network. Three basic elements of a neural model are 1) connection link which is characterized by a weight (an input signal to a neuron is multiply to the connection weight); 2) a linear combiner of all input signals weighted by connection links to a neuron; and 3) activation functions which determines a neuron output by constraining the summation to finite values [13]. In addition, a neuron may have a bias which shifts the net input of activation function depending on its range.

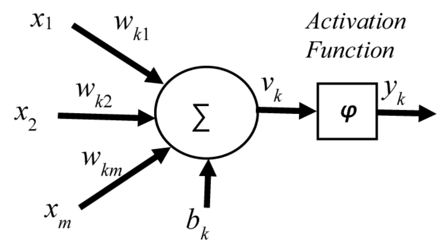


Figure 2—A neuron model

The mathematical model that describe a neuron is

$$v_k = b_k + \sum_{i=1}^{m} w_{ki} x_i \tag{1}$$

and

$$y_k = \varphi(v_k) \tag{2}$$

where x_i are input signals, w_{ki} are weights of neuron k, b_k is the bias, φ is the activation function, and y_k is the output of the neuron k. A common activation function is a sigmoid function; however, other activation functions like piece-wise linear, threshold, tangent hyperbolic, or linear may be used for variety of applications.

The architecture of a deep neural network is constructed by organizing neurons in form of layers where output of one layer is the input of the next layer. Fig. 3 shows the structure of a deep neural network (multi-layer feedforward network) with input, output, and hidden layers.

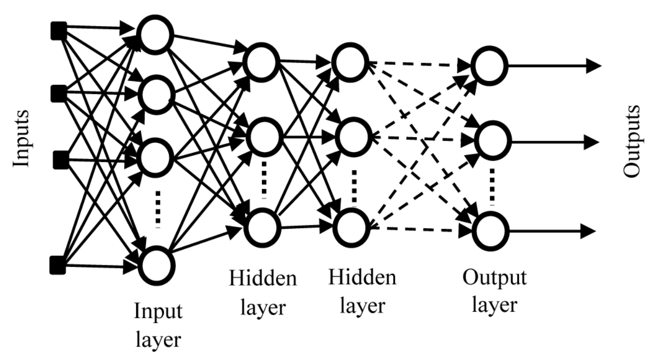


Figure 3—Deep neural network architecture

One significant property of deep neural network is the ability of the model to learn from big data and improve its performance through learning. Increasing the performance is an iterative process in which parameters of the network adjust according to historical data. Activities associated with learning process are 1) calculate output from input in feed forward network; 2) find the error between calculated and actual output; 3) propagate back the error to adjust parameters of the network (weights and biases). These steps are performed sequentially for many iterations for all input/output pairs until an equilibrium point which is defined by an objective function achieves (Fig. 4). This is a very computational intensive task where complexity of the network depends on the number of neurons in each layer, number of layers, and size of data.

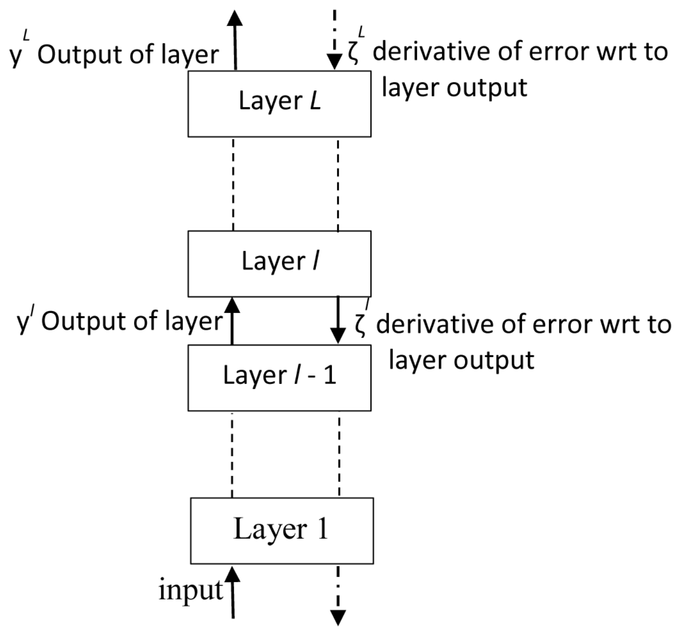


Figure 4—Backpropagation learning process

Methodology

With more than 20,000 wells drilled, Kern River field presents an attractive testbed for deep learning technology. Most of the wells in the field have a good suite of logs including SP, GR, SRES, MRES, DRES, NPHI, RHOB, etc. and are easily available in structured databases.

In this study we used a batch of 473 wells with more than 7814590 data points. To validate our methodology, we used 425 wells for training and 48 wells for testing. Only training wells which have 7025250 data points are used for learning. Fig. 5 shows random training and testing wells' location where positions of wells are normalized. We also divided training data set into training and validation to avoid overfitting deep neural network [14]. A data set is defined by

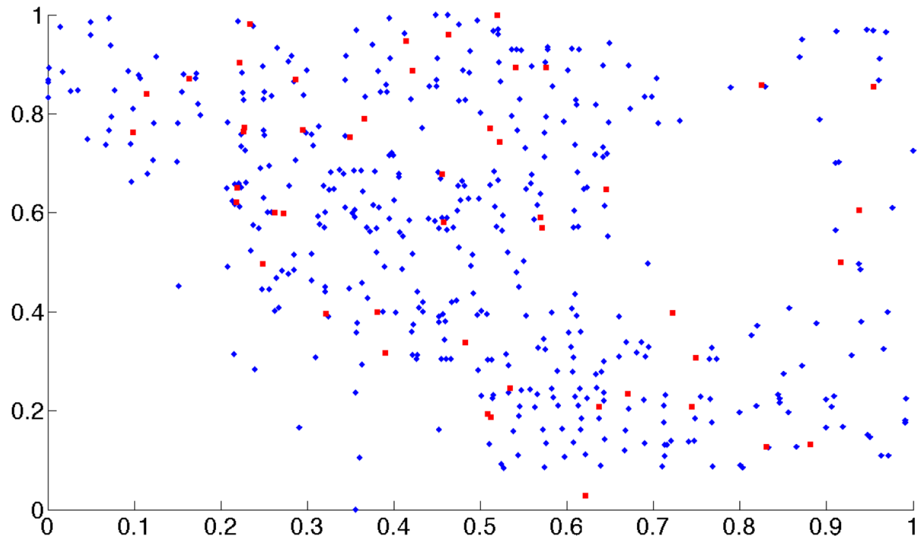


Figure 5—Location of wells: Blue circles indicate training and red circles indicate testing wells

$$S_{Data} = \left\{ \{S_{Training}, S_{Validation}\}, S_{Testing} \right\} \tag{3}$$

Training subset of the data set is

$$S_{Training} = \left\{ \mathrm{x}_i \middle| \mathrm{x}_i = \{x_{i1}, x_{i2}, ..., x_{im}\}, i = 1, ..., N \right\} \tag{4}$$

where N is number of data points in training set and m number of features in the data set. Defining validation and testing set is also similar to (4).

Due to physical device measurement errors, recorded raw log data presented some values that were considered outliers when compared to normal expected ranges. To remove these extreme observations, we plotted histograms of every feature and limited the range of variables into histogram bins which cover 90 percent of data. As an example, more that 95% of DRES data points are in the range of [0, 150], so we limit the range of DRES to [0, 150]. Then we normalized each data log within [0, 1] range to ensure all the values of all features are in alignment. Normalized values allow clear comparison of corresponding features in deep neural network.

We observed that each well log has a different depth of measurement. In order to train a deep neural network with a data set, the size of input data sets as well as the size of output data sets must be the same for all training pairs. Therefore, we scaled well's length to the average well length which has 1650 data points covering the entire interval of interest.

One of the most interesting strength of a deep neural network is the ability to handle many input features and performs feature selection and feature extraction on raw data. In order to increase the number of features in our data set, we included the information of nearest neighbor wells to predict a specific well feature. Thus, we constructed a new data set to predict well logs based on the nearby wells. The new constructed data set will have sufficient features and it is suitable to predict logs everywhere in the field. The number of nearby wells could be based on the distribution of wells in a field. Then for each specific well, p nearest wells are selected and direction and distance to them are calculated. Fig. 6 shows how the new data set is constructed based on nearby wells. The new constructed data set is

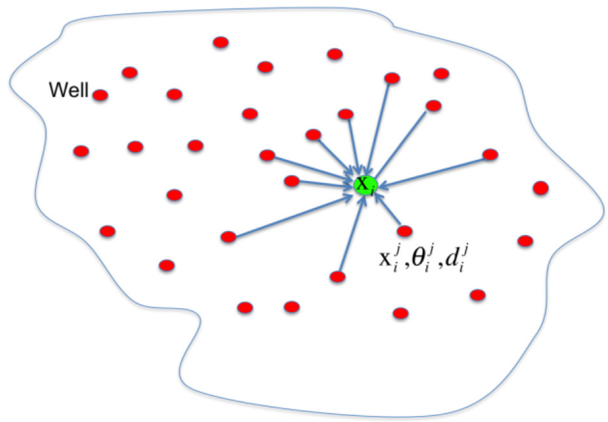


Figure 6—Nearby wells used to construct a new data set for deep neural network

$$D = \{x_i^1, \theta_i^1, d_i^1, x_i^2, \theta_i^2, d_i^2, \ldots, x_i^p, \theta_i^p, d_i^p \,|\, x_i\} \tag{5}$$

where, $x_i^j, j = 1, \ldots, p$ are p nearby wells that are being used as an inputs of deep learning and x_i is the specific well feature that is used as an output of deep learning.

Once the data set was completed, the training process was commenced. Fig. 7 shows the flow chart of the entire process from data collection to training and validation.

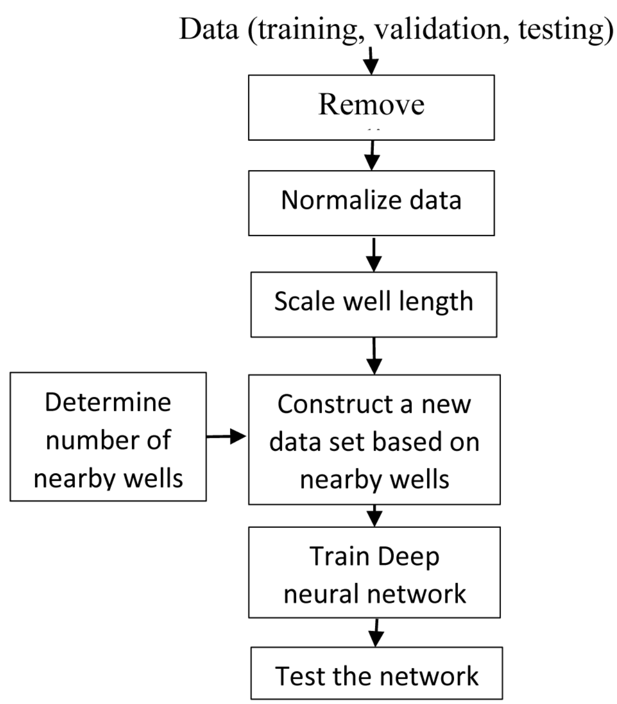


Figure 7—Flow chart of the process

Results

A suite of different deep learning models were constructed based on the characteristic of features, such as DRES, MREs, DRES, NPHI, etc. A dataset was generated for each network, and a deep neural network with 80 input neurons and 3 outputs (DRES, MRES, SRES of target well) was designed. The model used 8 features for each well: direction to target well, angle to target well, x-y location, depth, DRES, MRES, SRES of closest nearby wells. Hidden layers of the network have 150, 100, 3 neurons, respectively. Fig. 8 illustrates error during the network training process. In the case of the training set, the error is continuing decreases; however, the validation error reaches a minimum after which it reverses to an increasing trend. Generally, the network is selected when the minimum validation error is reached to prevent over fitting. The trained deep learning networks were employed for three purposes. First, the networks were used to generate missing log data or sections from a well (Fig. 9). The figure shows how the network models enables to fill the missing part of a well log when it is trained on all data. It can also be used for validation of logs. The second application was for validation of measurements errors. Fig. 10 illustrates that part of the actual long has measurement errors because it is out of range of the DRES log. Deep neural network can be used to correct it.

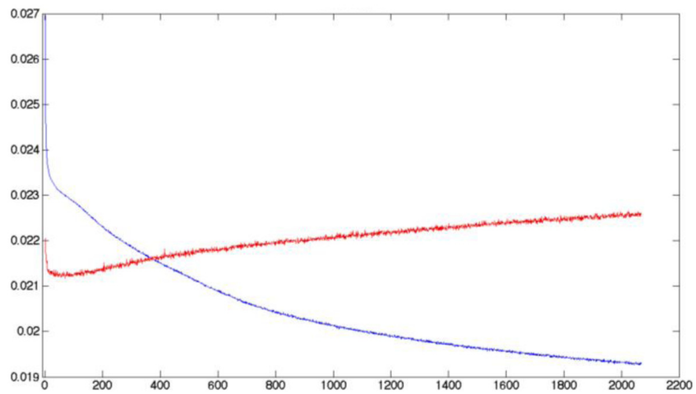


Figure 8—Training error vs. validation error: training error (blue curve) always decreases but validation error (red curve) after some epoch increases which shows that the network is over fitting.

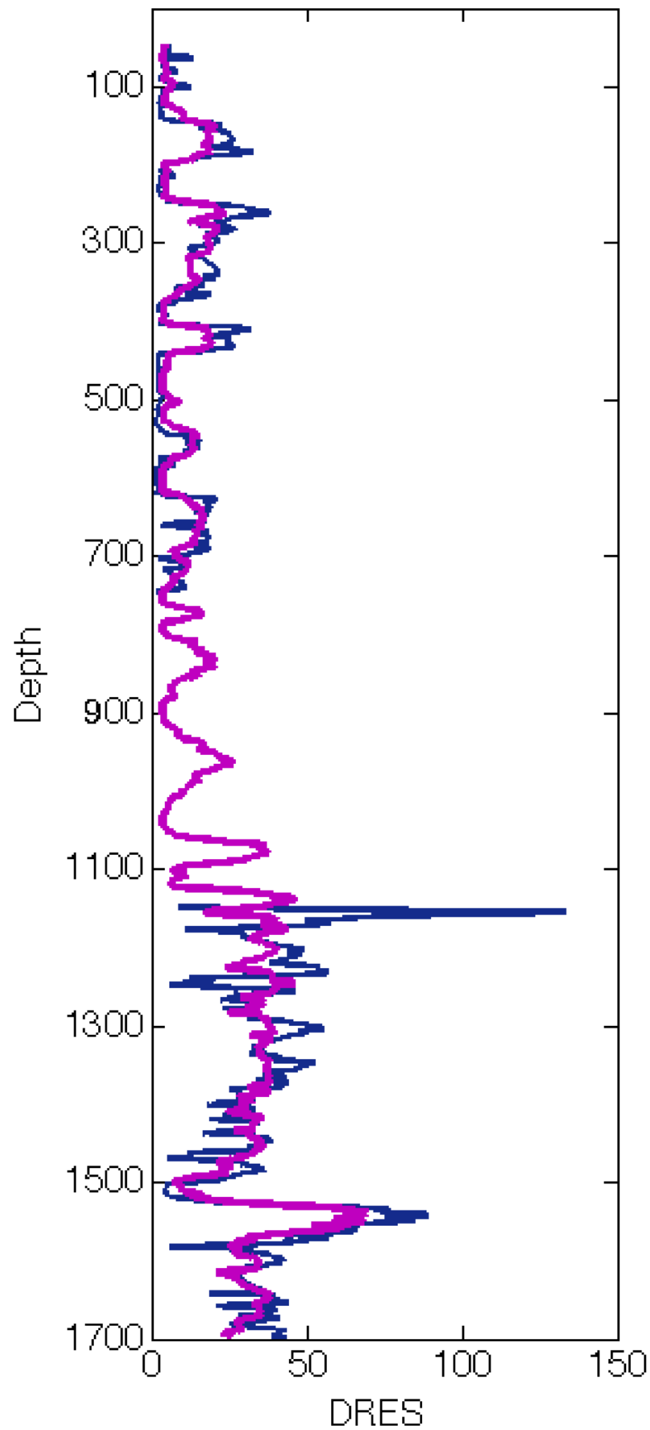


Figure 9—Generating missing logs for a well log using Deep Neural Network

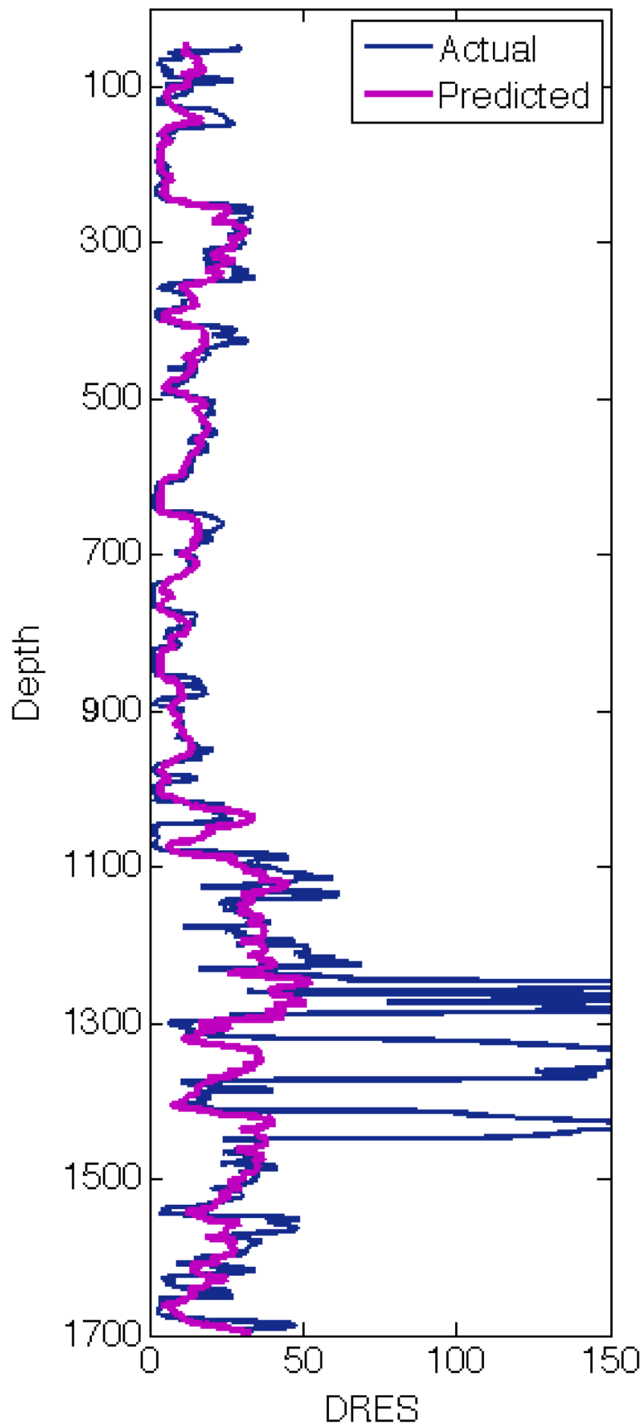
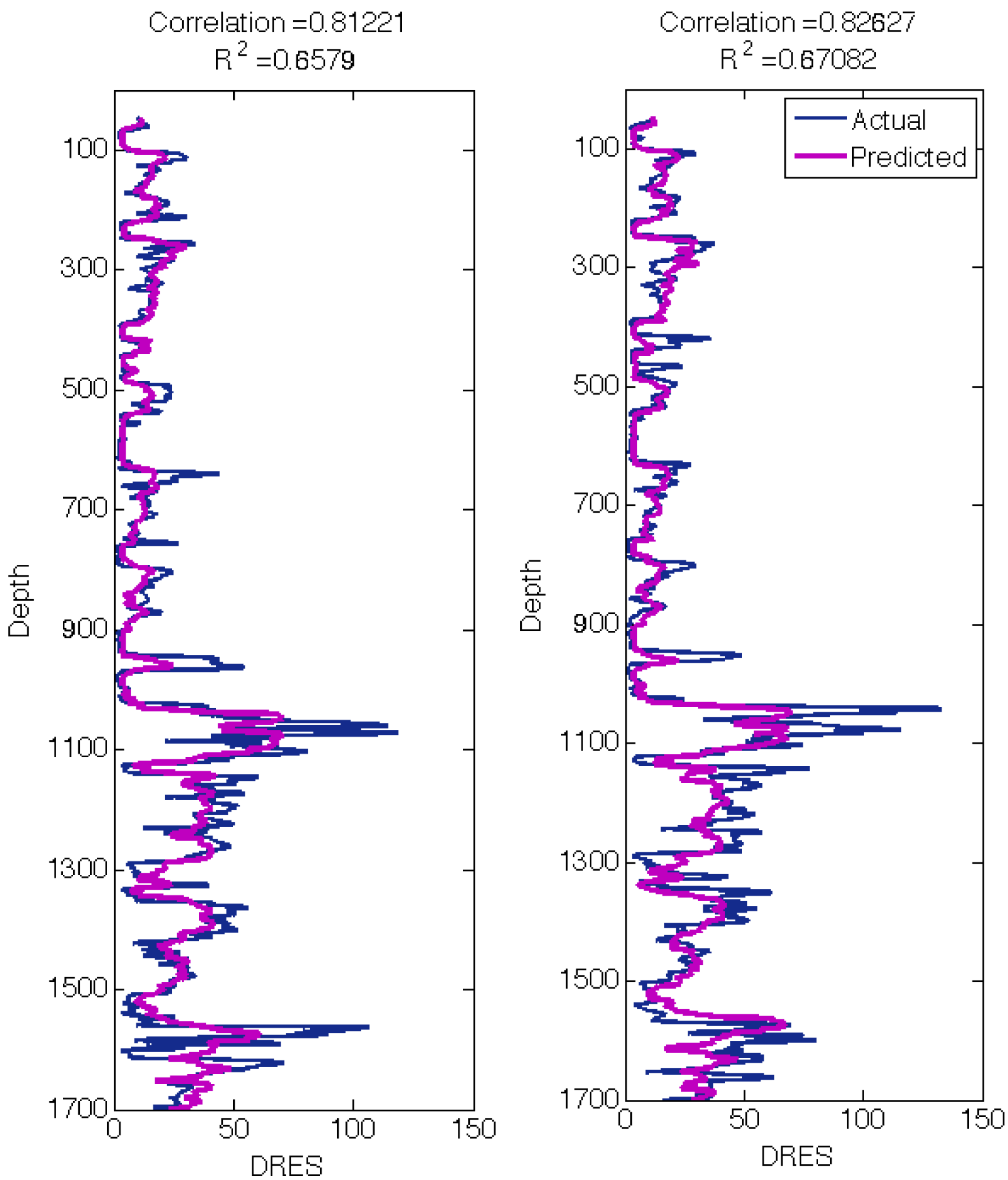


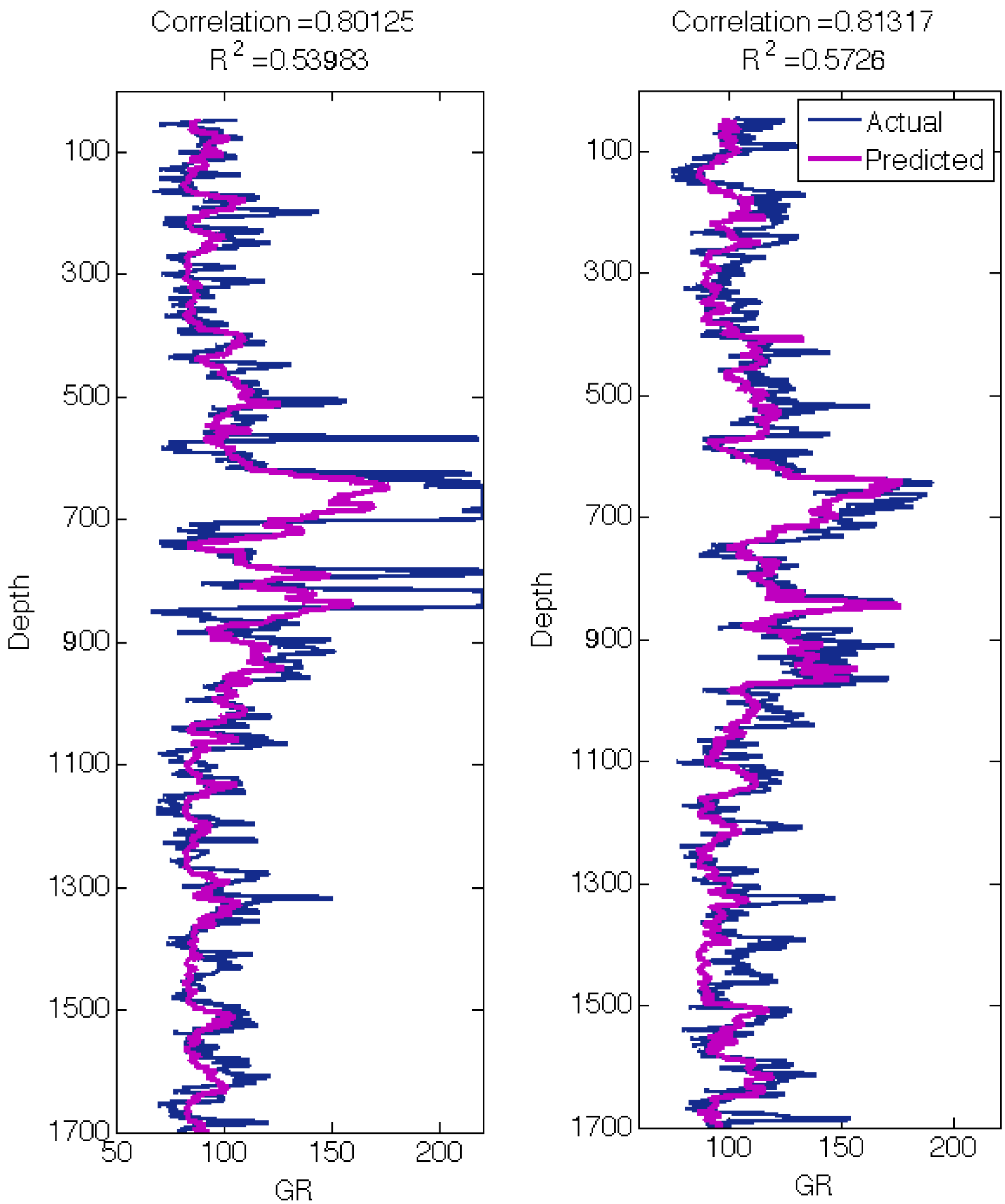
Figure 10—Validation of DRES log (out of range values between depth 1200-1400) using Deep Neural Network

The last and probably the most impactful application of this technology was the generation of virtual logs at any location in the reservoir. The accuracy of these logs where tested against new wells drilled in the field at the time the system was developed and trained. In the interest of space, we are demonstrating the capability of the network for two new wells and three types of logs, DRES, GR and respectively NPHI. Fig. 11 shows the DRES log of the two wells. The trend validation for the actual and predicted logs is given by the correlation coefficient which show values higher that 80% for the two wells. Correlation and R-square statistical measures are used to determine the closeness of predicted values to actual ones. The performance of the deep learning network constructed to predict GR information of wells is shown in Fig. 12. The trend validation for the actual and predicted GR log of two wells shows values of correlation coefficient higher than 80%, similar to the DRES logs. Lastly, the performance of the neural network model constructed for the NPHI for the wells is shown in Figure 13. The correlation coefficient measured between the actual and predicted log shows values higher than 70%. On can observe that while the correlation coefficient is a little lower than DRES, the trends and meaning of the logs does not impede any interpretation. Furthermore, by interrogating the two logs, one can observe that the neural network seemed to have missed capturing the lower value for NPHI (mostly in the shale formation); however, the prediction of NPHI in the productive formation appear to be reasonably accurate.



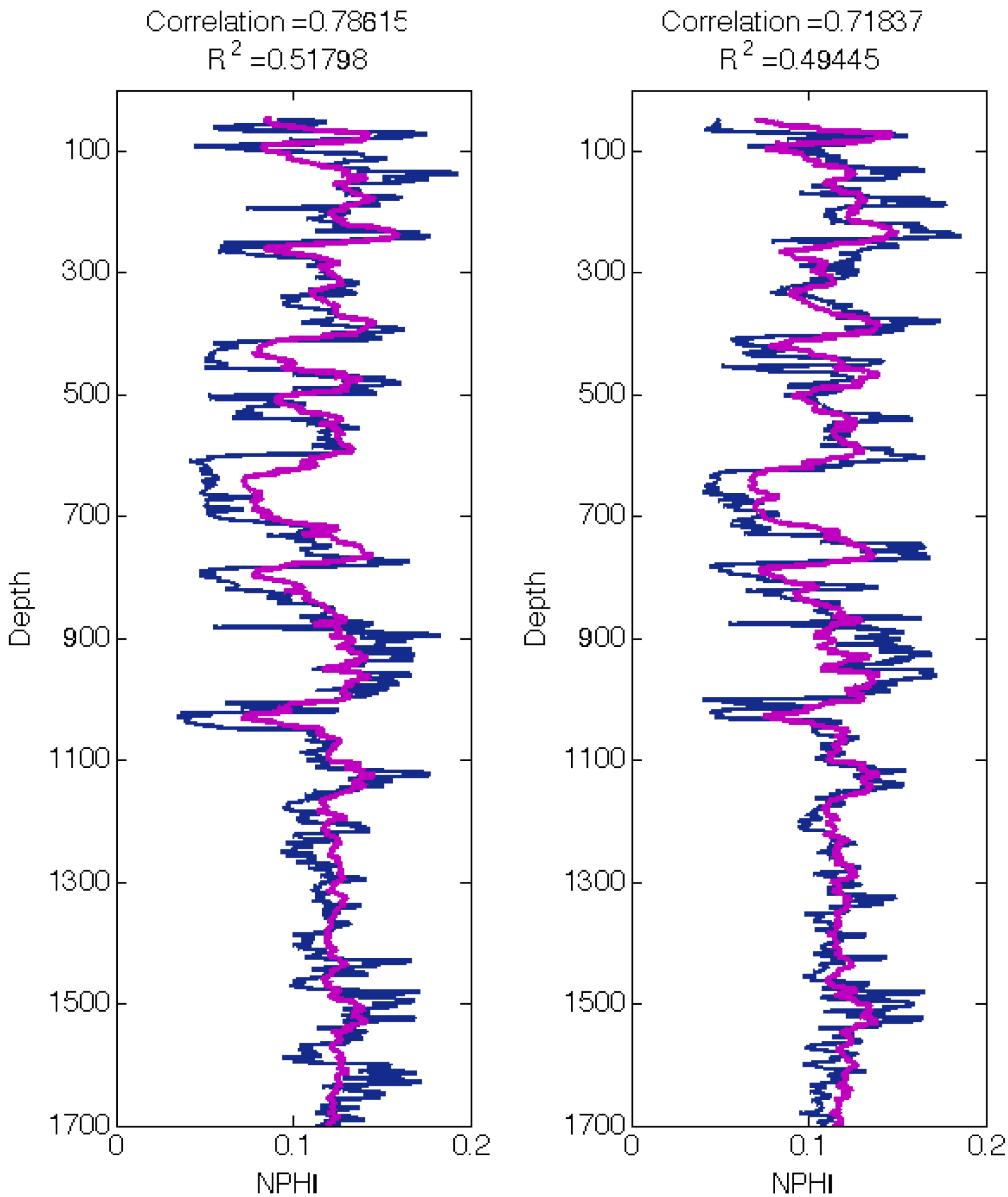
(A) (B)

Figure 11—Actual vs. predicted DRES logs for new wells



(A) (B)

Figure 12—Actual vs. predicted GR logs for new wells



(A) (B)

Figure 13—Actual vs. predicted NPHI logs for new wells

Conclusions

For the reservoir consisting of alluvial fans constituting the geology in the Kern River field, the application of deep learning neural network proved to be a powerful technology for improved reservoir characterization when large volumes of data are available. The methodology, as presented, is simple, practical and can be used for any reservoir with a good number of wells and suite of logs. We have formed the problem to predict well logs using nearby wells information and applied successfully deep learning neural network on the new data set to forecast synthetic well logs in any location in the field.

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