A Review on Prediction of Abnormal Geo-Pressure via Seismic Travel Time and Wire Line Log Correlation Modeling Using Neural Network

Haravinthan A., Ayob M. R., Salleh S., and Japper-Jaafar A.

***Abstract*—Various basins in the world comprises of areas with abnormal pore-fluid pressures (higher or lower than normal hydrostatic pressure). Undesirably, predicting pore pressure parameters (depth, extension, magnitude, etc.) in such areas are challenging tasks. The compression seismic travel time converted into sonic logs (DT) is often used as a predictor because it responds to changes in porosity or compaction produced by abnormal pore-fluid pressures. The objective of the paper is to propose a model using an artificial neural network (ANN) to synthetically create wire line logs (sonic logs (DT), Density logs and Resistivity Logs (RIED) by identifying the mathematical dependency between Seismic Travel time and wire line logs of neighboring wells. A neighboring well will be used as a training well to enable the system to learn the relationship among the predictors. Once the system has trained and learnt the relationship, the model will be used to predict the next well's pore pressure position and magnitude, using only seismic travel time logs.**

***Index Terms*—Abnormal Pore Pressure, artificial neural network (Ann), density log, resistivity log (Reid), seismic travel time, sonic log (DT).**

I. Introduction

Encompassing reliable information to build a drilling plan before drilling a well is one of the most common industrial problems faced. Oil and gas companies have regarded the seismic survey as a rather essential exploration tool in the last ten years [1]. Outlays in seismic acquisition, processing and interpretation have conveyed important information about reservoir structures. Also, these have been of great aid for drillers to carry out drilling plans more competently and cost effectively. At present, countless companies are in a lookout for more means in achieving additional gains from their seismic data by expanding their search. Boosting the value of assets at every phase of the field is one of the core advantages of the seismic data [2]. High-resolution surface seismic data facilitates to perk up a prospectus geological model, extend the understanding of a petroleum system, optimizing preliminary well location selection, and providing information for risk analysis. Developed mechanical models that are established through seismic data and pressure models aid in the appraisal-stage drilling and eventually, help to predict the location of subsurface hazards such as high formation pore pressure.

The pressure detection techniques often lie on the basis that several overpressure rocks are often associated with under compacted shale [3]. With greater under compaction comes a higher porosity, which eventually leads to greater fluid pressure. Besides the normal compaction trend, under compaction and decomposition are two other reasons for high formation porosity. The latter is vital for the evaluation of abnormal pressures.

Abnormal pore-fluid pressure and abnormal pressure regimes have always been recognized as important factors in the evolution of hydrocarbon provinces. The ability to predict their presence, location, magnitude and distribution has been limited by three critical factors, namely our limited knowledge of those regimes and their physics, lack of robust technologies for predicting pressures in the subsurface and lack of human capacity to process a lot of preconditions, geological data, mathematical constraints and recalling the neighboring well information to predict the abnormal pressure.

The proposed optimization technique for this problem is by using a bio-inspired computing technique such as artificial neural network, hereafter referred to as ANN, to increase the density of the controlled data and more effectively map changes in pore pressure. This paper stretches to other sections by explaining more on previous works done within this subject area in Literature Review and also by going into more detail on solution framework in Methodology and finally a wrap up in Conclusion.

II. Literature Review

Over-pressure formation is a significant geological crisis in various regions of the world. Hence, knowledge of over pressure zones is essential in drilling of boreholes, well casing designs, learning of hydrocarbons migrations and others. Seismic prospecting is the most efficient technique to estimate a rock's condition before the drilling process. Abnormal intense state of rocks, abnormal porosity, and density are among the common characterizations of the over-pressured zones. These features are the physical requirements for over-pressure prediction from seismic data.

The earliest researches on over-pressure predictions were originated and initiated in the Gulf of Mexico [1]. Initial data were obtained through the study and researches which were carried out for one-dimensional (1D) cases and interval transit time (return size of velocity). Pennebaker

Manuscript received October 13, 2011; revised October 31, 2011.This work was supported in part by Talisman Energy Malaysia.

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accomplished the first achievements in 1968 which then, instigated other researches to foresee over-pressure in diversified regions (see [2] and [3]). The finest outcome in under-compacted shale-dolomite contexts were obtained by a method which was proposed by Eaton by finding the normal compaction line using regression method [4]. On the other hand, a geological fragment that encloses an equal amount of shale and sand facilitates as a method for normal compacted shale-curves to work well [5]. However, for both categories of geological fragments that contains plenty of shales or sand, the method of equivalent depth illustrates satisfactory results [6]. In addition, the usage of a compression curve method is convenient for carbonate sections [7].

Interval velocity is the fundamental seismic parameter which is applied in over-pressure prediction. The interval velocity was utilized by researchers such as Pennebaker, Reynolds, Aud [1], [2],[3] and authors in the past (such as in [5], [6] and[8]). As mentioned by early researchers, interval velocities are crucial to generate the special requirements (see [3], [6], [9] and [10]). A thorough study of the seismic velocity is the root in which the prediction of over-pressure should be carried out.

In 1978, researches were carried out in Po river valley (Adriatic basin) by Italian experts from AGIP and the use of derivative of interval velocities have been presented from an array of interval velocity to a normal ratio [10]. In 1982, a similar method was used in Nigeria and also in northwest Russia (Murmansk, 1990) [11]. Over-pressure can be predicted through perspective direction, which is utilized in the dynamic parameters of seismic signal [4]. However, these researches have not been circulated extensively and the rationale is related to the ambiguous elucidation of dynamic parameters such as porosity, pore pressure, fracture gradient. Initially, Pennebaker and Reynolds prediction models were created for 1D cases [1], [2] but from the end of 70's two-dimensional (2D) models have been applied for over-pressure prediction (see [5], [6], [8], [9], [10], and [11]). Nonetheless, 1D model is still being used [5] although the creations of three-dimensional (3D) models have now grown rapidly since the 90s (see [9], [12]). Drilling engineers find the outcome of over-pressure prognosis vital and hence, the usage by them is becoming significant. This results in the increase of value in any prognosis if the researches are completed within the specific recommendations for realization of drilling which are optimum mud density, value of fracture pressure, casing design, and others. The accuracy of calculated over-pressure values, mud density, position of abnormal pressure and others that are covered by initial researchers (Pennebaker, Reynolds, other) had reached a fraction of 25 - 30 % and sometimes 50% of total error percentage of the prediction. However, researches of the past years have shown an improvement, which proportionately reaches up to 8 – 12 % in reduction of the uncertainties involved in this subject area [6], [13]. The usage of computers and the progress of software for over-pressure prediction from seismic data are highly valued. The development of computer technology has benefited in the wide usage of computer engineering, which helped in extending over-pressure prognosis (see [6], [9], [14], and [15]). Despite that development, there isn't any integral commercial software which are capable to efficiently work with data on various geological divisions, especially with use of a wide set of seismic parameters.

TABLE I: METHODS USED FOR PREDICTING PRESSURE AT DIFFERENT PHASES OF DRILLING PROCESS FOR A SINGLE WELL

Before Drilling	While Drilling	Post Drilling
• Shallow Seismic Survey • Deep Seismic Survey • Comparison with Nearby Well	• Drilling rate, Gas in Mud • D-Exponent • Dc-Exponent • MWD & LWD • Shale Density(cuttings)	Wireline • Resistivity log • Density log • Sonic log • Gamma Ray

The accuracy of prediction & detection of pressure increases higher from before drilling to post drilling. Wire line logs are one of the most accurate devices used in operation to detect the pressure point and magnitude (Table 1).

A. Velocity Analysis for Pre-Drill Geo pressure Prediction

The reflection seismic method is the common geophysical surface technique for prediction of geo pressures. Customarily, the direction of this method is based on estimating changes in interval velocities with depth, which are extracted via the Dix approximation, from stacking velocity analysis performed on CMP seismic data during data processing. In this context, the compression velocity (P wave velocity) is called the rock velocity. Seismic velocities are strongly affected by compaction, which in turn is also affected by changes in pore pressure. Under this assumption, seismic velocities can be used to predict variations in pore pressure regimes in undrilled locations. The rock velocity is also affected by several associated properties, which are not independent of each other including density, porosity, pore fluid type, fluid saturation, litho logy, and clay content. As a result, special attention deserves the fact that not every velocity anomaly can be caused by pore pressure variations. In this stage, the geological knowledge of the area and the sensitivity of sonic velocity, electrical resistivity and density to pore pressure variations must guide the seismic velocity analysis to avoid ambiguities in the interpretation.

The core of this process is then the use of detailed seismic velocity analysis. While stacking velocities are helpful in providing a stacked seismic section useful to identify the structural framework and some stratigraphic features, new alternatives in robust velocity analysis allow estimating small variations in pore pressure regimes. It includes inversion of prestack gathers (travel time and amplitude), variations in amplitude versus offset (AVO) attributes, and ray trace modeling (seismic tomography), whereas other related approaches include the estimation of seismic attenuation (Qbased pore pressure) for this purpose.

A major limitation of the mentioned techniques is the seismic data quality itself. In this stage, seismic data conditioning, involving prestack time migration, increased trace editing as well as multiple attenuation and amplitude balancing, has to be employed so that the seismic data is suitable for detailed velocity analysis. Velocity calibration with check-shot curves is also a critical step in the process. Once the velocity analysis is performed, a velocity smoothing is needed to avoid non-desired spikes and high frequency effects on the data.

B. Geo pressure Evaluation from Seismic Data

Seismic data is an indispensable tool for geo pressure detection, moreover in the area where is has been common for the overpressure to be detected in a wide spread of most hazardous environment. Of all the geophysical method, the reflection seismic method is the only technique used to predict pore pressure. The seismic method detects the changes of interval velocity with depth from velocity analysis of seismic data. These changes are related to litho logy, pore fluid type, rock fracturing and pressure changes within a stratigraphic area. When the factors affecting the velocity are understood for a given area, a successful pressure prediction can be made.

C. ANN Background

A division of computational systems, which imitates the biological neural networks of the mammalian brain, is also known as artificial neural networks (ANN). The human brain contains about 100 billion neurons (neural cells) that are interconnected in a complicated manner via synapses (a junction between axons and dendrites) which eventually builds a network in the human brain. Living neural networks are in fact, the abridged models of the ANN. ANN are also an important study and development instrument that permits effortless conversion of log data into any preferred output parameter.

The ANN that imitates the human brain's problem-solving methods can be utilized to gain knowledge from precedent experiences and applied to solve new problems and occurrences. As an outcome, the ANN uses training skills to construct a system of neurons and weight links that permits them to formulate new decisions, classifications, and predictions.

To be able to mimic the human's brain neural system, it is necessary for an ANN to comprise a set of nodes (artificial neurons) where the nodes perform simple computations, a set of interconnections or synapses linking pair of nodes, and a set of labels known as weights, associated with each interconnection and identifying some property of interconnection. These weights correspond to the synaptic efficiency of the biological neurons [16].

The neurons in the network perform two simple tasks. The first is to build a weighted summation of the input data. Specifically, a signal x_j at the input of the synapse, j connected to neuron, k is multiplied by the synaptic weight, w_{kj}. A summing junction, P, acts as an adder for summing the input signals, weighted by the respective synapses of the neuron.

The second task is to apply a function to this summation to yield an output than can serve as an input to other neurons or that can go to the output layer. An activation function limits the amplitude of a neuron such that it squashes the permissible amplitude range of the output signal to some finite value. The neuronal model also includes an externally applied bias (threshold) b_k that increases or decreases the net input of the activation function, depending on whether it is positive or negative, respectively.

We may describe the ANN by the following pair of equations:

$$u_k = \sum_{j=1}^{n} W_{kj}\, x_j \tag{1}$$

And

$$y_k = \emptyset(u_k + b_k) \tag{2}$$

where x_1; x_2;…;x_n are the input signals;w_{k1}; w_{k2}; …; w_{kn} are the synaptic weights of neuron *k;* U_k is the linear combiner output due to the input signals; b_k the bias; ∅ is the activation function; and y_k is the output signal neuron. The weights, w_{kn}, associated with each connection indicate the extent to which the conveyed signal is amplified or diminished. The activation function ∅ is often a sigmoid (S-shaped) function, but other functions have been used (Heaviside or threshold or piece-wise linear). Given a network whose weights are initially random and assuming that we know the task needed to be accomplished by the network, a learning algorithm is required in order to determine the values of the weights that will achieve the desired task.

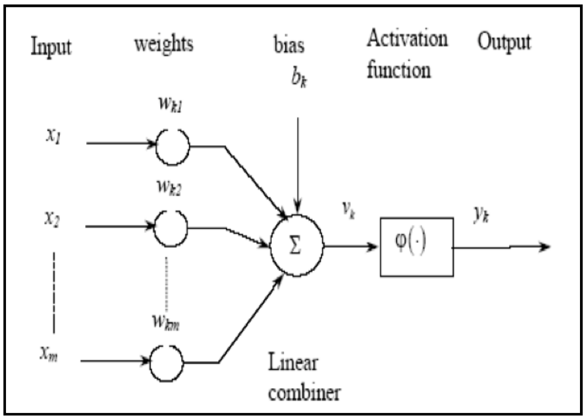

Fig. 1. Model of a Neuron

III. Methodology

A. Level 1. Supervised Training of the Neural Network by using Training Wells

The training process is initiated by the ANN by haphazardly conveying the preliminary link weights between the layers of the neurons. Subsequently, an input signal is conferred to the first layer of processing elements, while an equivalent output is retorted to the last layer of the processing elements. Then, the connections between the input layer, hidden layers, and output layers are regulated via an objective purpose such as the mean-squared error or the global error [24]. For example, the global error $E(n)$ is computed as the sum of the squared differences between the computed output y_k and the desired output d_k (i.e., the local errors). For iteration n, the global error $E(n)$ is thus:

$$E(n) = \frac{1}{2}\sum_{k=1}^{n} [\![d_k(n) - y_k(n)]\!]^2 \tag{3}$$

In back propagation (BP) networks, the weight adjustment for every connection is computed in a gradient descent method in weight space, whereby the local gradient $\partial E / \partial w_{jk}$

is calculated and a correction to the previous weight is made through multiplication of $\partial E/\partial w_{jk}$ with a learning rate *n* and momentum α according to the formula [17].

$$w_{jk}(t) = -n\frac{\partial E}{\partial w_{jk}} + \alpha \cdot \Delta w_{jk}(t-1) \quad (4)$$

where, *t* is the time step and Δw is the weight change from one cycle to another.

The learning rate *n* is a small number ($0.1 \le n \le 1.0$) [17] that control the amount of the error that will be added, negatively, to the interconnection weights for the next cycle.

If the learning rate is large, then large changes are allowed in weight calculations. Conversely, if the learning rate is small, only small changes are allowed, which can increase the learning time.

Momentum α is a term that dampens the amount of weight change Δw by adding in a portion of the weight change from the previous cycle. The addition of momentum is credited with smoothing out wild changes of weights, and also with helping the network to converge faster when error is successively changing in the correct direction. Typical values for momentum fall between 0 and 1.0

The local error on every connection is used to calculate corrected activity levels in the processing elements of the previous layer, which in turn are used to calculate new local errors. Thus, the error gets propagated backward through the entire network and new connection weights are obtained with every step.

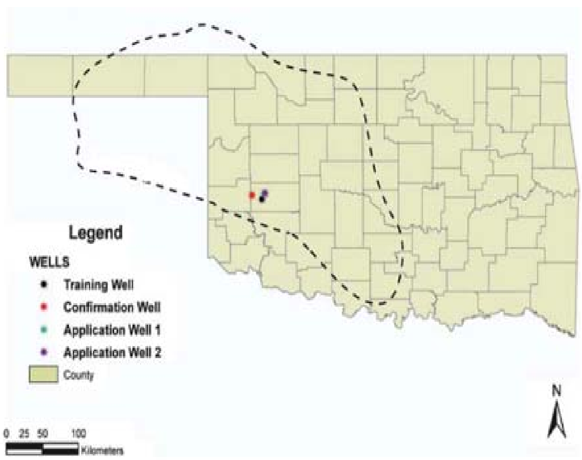

Fig. 2. Geological wells of testing

B. Level 2. Confirmation and Validation of the Model

The back-predicted input curves reflect how well the input data are being used in the prediction of the target value in the training well and can be used to verify the model in confirmation and application wells. For these steps to be performed with high confidence, the user must ensure that all rock types, expected to be found in confirmation and application wells, are represented in the training well. If all rock types cannot be represented in a single training well, more than one well can be used to train the neural network. A careful interpretation of the available data (well logs, cores, drilling reports, etc.) is necessary. Confirmation and validation of the model was performed by applying the modeled solution obtained in the training well to additional sets of data that contain the same inputs. During this step, the solution from the training well can be validated through back-prediction of the predictor data and the fit between the predicted sonic and the recorded sonic in the confirmation well.

C. Level 3. Application of the Model to the Predicting Well

Finally, the confirmed model is used to predict sonic, density and resistivity in application wells containing only the input curves of seismic travel time and cross-matching with previously trained well's seismic travel time logs to simulate a predicted sonic, density and resistivity.

Determining trends in seismic transit time on sonic, density and resistivity is a conventional method of predicting abnormal pressure in shale [18-20]. This is because the velocity of a compressional wave in sedimentary rock is dependent on the effective rock stress, an increase in transit time is interpreted as indicating a lower effective rock stress hence over pressure

IV. Conclusion

In conclusion, the most successful methods used to estimate pore pressure is the wireline log analysis which could only be conducted while or post drilling stage. Nevertheless, in prior drilling conditions, the only information that can be congregated are Seismic Travel Time logs which should be used and optimized to foresee pore pressure results more effectively. Several methods of pore fluid pressure inference, such as those using resistivity, density, or sonic logs, shows that it is essential to generate logs for improved interpretation, because sonic logs are considered to be precise and sensitive to modification in the rock stress regime (e.g., overpressure), thus we propose to employ ANN to simulate synthetic wireline logs (sonic, density and resistivity) curves based on mathematical relationships attained from Seismic Travel Time curves. There are three efficient steps that the ANN entails, administrated training of the neural network, verification of the model validity by blind testing the solution in other wells that include the predictor curves used in developing the model from the training well and applying the model to well enclosed only with Seismic Travel Time log to attain the synthetic sonic, density and resistivity logs.

It has been considered that the evaluation of geopressure from seismic data must combine a good understanding of both rock properties and normal compaction trends, a robust velocity analysis applied to the conditioned seismic data, a suitable relationship between velocity and effective pressure, and a proper final geopressure calibration. A methodology to use robust seismic velocity analysis to evaluate geopressure in the interwell space has been then constructed following several steps. All available wells are posted including any measurement of pressures along with the identification of key geological horizons and the conditioning of the seismic data.

Acknowledgment

Thanking Talisman Malaysia for their support and contribution for this project.

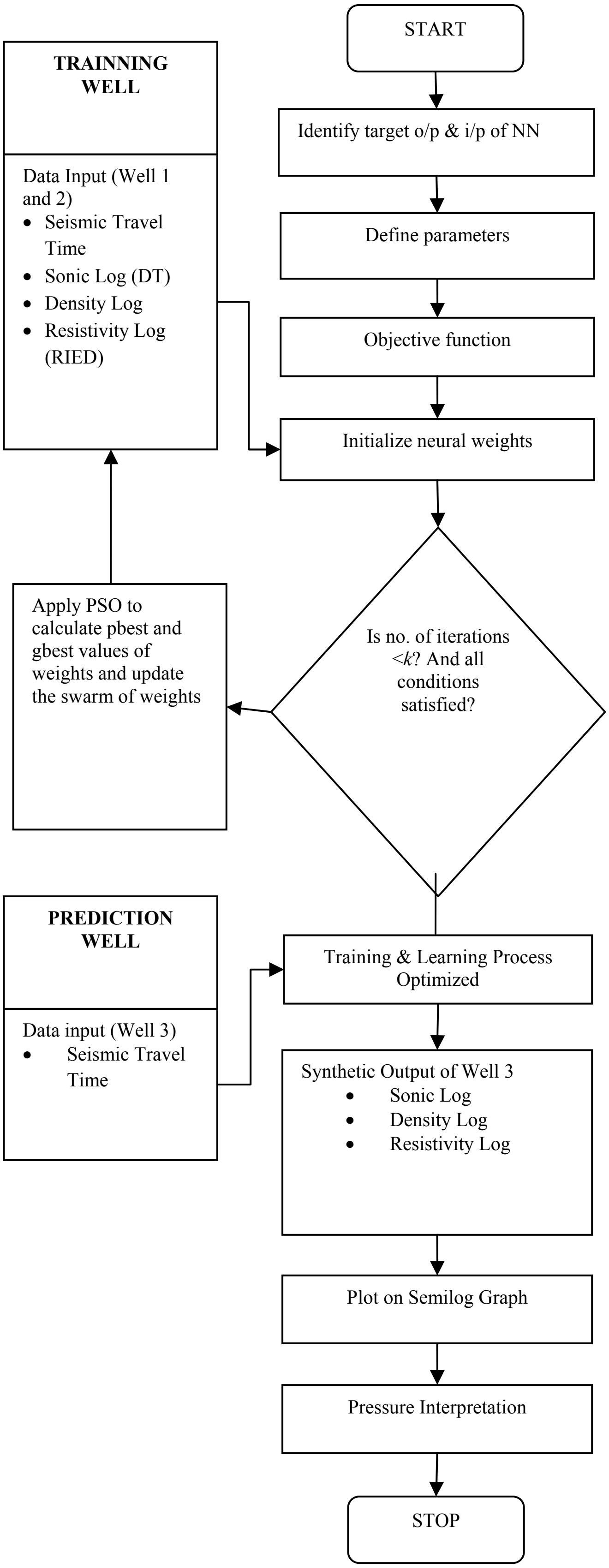

Fig. 3. Flow Chart of Hybrid Solution.

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