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A Robust Methodology for Prediction of DT Wireline Log

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Abstract

DT log is one of the most frequently used wireline logs to determine compression wave velocity. This log is commonly used to gain insight into the elastic and petrophysical parameters of reservoir rocks. Acquisition of DT log is, however, a very expensive and time consuming task. Thus prediction of this log by any means can be a great help by decreasing the amount of money that needs to be allocated for acquisition. Support vector machine (SVM) is one of the best artificial intelligence techniques proven to be a reliable method in the prediction of various real world problems. The aim of this paper is to use SVM to predict the DT log data of a well located in the southern oilfields of Iran. By comparing the results of SVM with those obtained by a Back Propagation Neural Network (BPNN) we were able to verify the accuracy of SVM in the prediction of P-wave velocity. Hence, this method is recommended as a cost effective tool in the prediction of P- wave velocity.

Keywords: *Prediction, DT Wireline Log, Back Propagation Neural Network, Support Vector Machine, Southern Oil Field.*

1. Introduction

The prediction of rock mechanical parameters is necessary for reservoir development, management and prospect evaluation when very sparse or no borehole-based rock mechanical data are available. The most direct way of determining the rock mechanical data is through laboratory tests of cores or through the analysis of plug samples. A core-based test for the whole reservoir interval in each well is very expensive and requires an extensive amount of coring to be sampled and analyzed. Thus, a simple yet effective method is required to predict rock mechanical characterization [1]. Conventional well logs data can be indirectly used to predict these properties but logging acquisition can be very expensive and time consuming. According to recent studies, correlations have been proposed relating acoustic velocities and reservoir rock properties [2]. DT log is the most well-known log, after dipole shear sonic imager (DSI) log, used to determine reservoir rock properties. This log contains information about P-wave slowness (i.e. inverse of velocity) and thus will be a great aid in the identification of the quality and weak portions of reservoirs. Although this log is often acquired through logging process, it imposes additional cost on the project. Thus, if this log could be predicted using other conventional logs, the associated cost incurred by the acquisition of this log will be decreased. In recent years, artificial intelligence (AI) techniques have been proven to be successful methods for understanding the complex relationships of real world problems.

Artificial Neural networks (ANNs) are AI techniques often used to solve nonlinear problems. There are several neural network architectures such as radial basis function (RBF), back propagation neural network (BPNN), counter propagation and learning vector quantization (LVQ) networks [5, 6] which are successfully employed to solve regression or classification problems. ANNs can be trained very easily as long as a large amount of data is available. In most cases, these methods require normalization processes to provide relevant outputs. Error-back propagation (EBP) algorithm, [7, 8] which is the most popular learning algorithm in ANNs discussion used to reduce errors and increase the generalization ability of the networks, is not able to handle complex problems [9, 10]. More recently, support vector machine (SVM) technique [11] was introduced and successfully used for many applications as it does not suffer from the shortcomings of ANN methods. This is an easy to train method with good generalization and estimation ability in finding the best global models. SVM was introduced in the early of 1990s by Vapnik to solve nonlinear related problems [12]. It was found that SVM has a high power of extension which allows it to deal with noise and a lack of data [13-16]. The aim of this paper is to use SVM for the prediction of DT wireline log for a well located in the southern oilfields of Iran. The results provided by SVM are compared with those given by a BPNN to highlight the ability of each network in the prediction process.

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2. Study Area

The oilfield used for this study is located in Khuzestan Province, in the petroliferous area of the Dezful Embayment. The middle and upper Cretaceous sediments of the Dezful Embayment are one of the richest petroleum systems in the Middle East, with the presence of the Gurpi, Khazdumi and Gadvan source rocks as well as Lurestan, Asmari, Khuzestan and Khami/ Bangestan reservoirs. This oilfield is near the western portion of Basrah. The structures of the Basrah area consist of gentle anticlines showing a north-south general trend. These structures continue south to Kuwait and show the same orientation. Well log datasets used for this study and obtained from well No. 10 including, calibrated compressional sonic logs, density log and neutron porosity log were considered in order to study the quantitative relationships between the acoustic and litho-petrophysical properties of the reservoir's layers. Figure 1 shows the geographical location of the oilfield in southern Iran.

Support Vector Machine

Support Vector Machine (SVM) which is used for regression analysis is called support vector regression (SVR). The aim of SVR is to find a function for the approximation of the output according to the available dataset [17, 18]. To estimate a function, a small fraction of training samples called support vectors (SVs) are taken into account. In addition, a specific loss function called ε-insensitive is used to create a sparseness property for the SVR algorithm. The basis of the theory was developed based on a regression algorithm as well as the inner product of two vectors in Hilbert Space (i.e. a space in which the inner product of two vectors has a real value). To control the risk minimization, simultaneous control of the complexity and error of the model are taken into consideration. This is the basic idea used to improve the generalization ability of SVR [19, 20]. However, to get a better generalization in non-linear cases, the data points are mapped into a space called feature space (i.e., Hilbert or inner product space) through utilization of a function known as a kernel function [21, 22]. Selecting a suitable kernel makes it possible to separate the data in the feature space while the original input space is still non-linear. Thus, while data for n-parity is not separated by a hyper plane in the input space, it can be separated in the feature space by a proper kernel [23, 24, 25]. According to the definition of kernel, the nonlinear regression estimation problem of SVR can be proposed and utilized for solving any regression analysis [19].

Back-Propagation Neural Network

The goal of ANN is to develop a mathematical model that can imitate the capabilities of neural structures in purposing an intelligent information processing system. Back propagation neural network (BPNN) has been an active research topic in recent years because of its efficiency in modeling nonlinear dynamic systems [17, 18]. Numerous applications can be found in various papers indicating the abilities of this typical neural network [19, 20]. BPNN is usually recognised for its prediction capabilities and ability to generalise well on a wide variety of problems. For example, Liang and Gupta studied the stability of dynamic back propagation training algorithm using the Lyapunov Method [21]. This network is a supervised type of network which means that it should be trained with both input and target output data. During the training, the network tries to match the outputs with the desired target values. Learning starts with the assignment of random weights. The output is then calculated and the error is estimated. This error is used to update the weights until the stopping criterion is reached. In this case, the stopping criteria will be the average error of epoch.

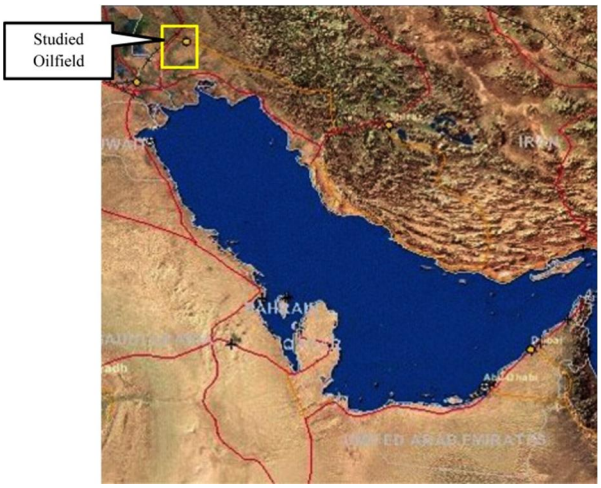

Fig.1. Geographical location of the studied oilfield

Dataset

As mentioned before, the aim of this work is to predict the DT wireline log of a well located in the southern oilfields of Iran. The available database used for this study includes sonic log (DT), Neutron Porosity logs (NPHI), Formation Density logs (RHOB), Standard Resolution Caliper logs (CAL), Gamma Ray log (GR) and Formation Resistivity log (RT) (See Figure 2). To identify the most relevant logs to be used as the input for training the networks, principle component analysis was used. Principle component analysis (PCA) is a conventional dimensionality reduction technique used to transform data and reveal the most relevant features of any type of system [22, 23]. PCA is a technique for extracting a smaller set of variables with less redundancy from high-dimensional data sets to retain as much of the information as possible [24, 25].

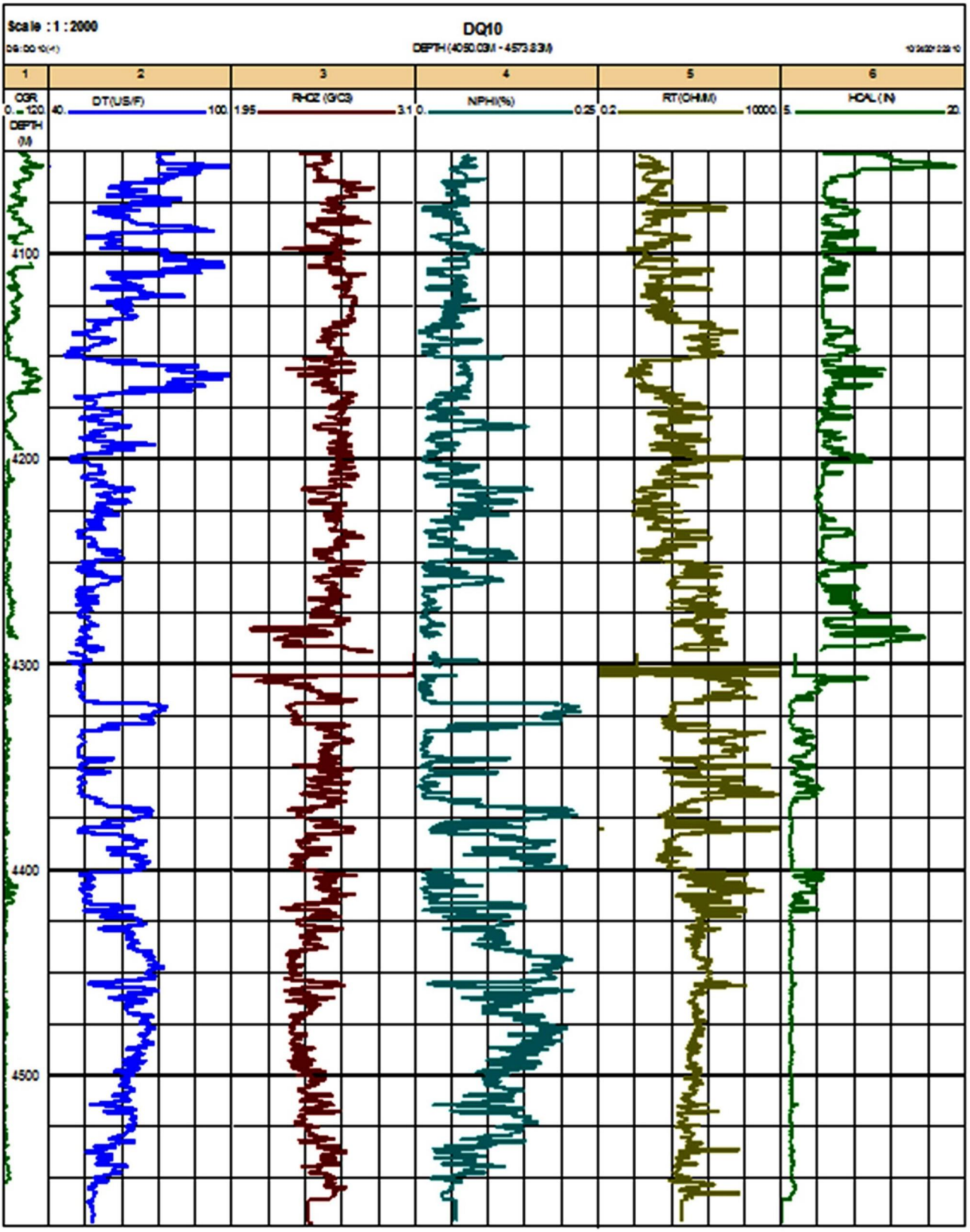

Fig.2. Conventional well logs used for the purpose of this study.

Determination of linear combinations of variables featuring, extraction, dimensionality reduction, visualization of multidimensional data and identification of underlying variables are among the most important abilities of PCA [26, 27, 28]. The principle components, which are the projection of the data onto the eigenvectors (principle axes), can capture most of the structure in the data [29, 30].

After applying PCA analysis, correlation and component were obtained. Tables 1 and 2 respectively give the correlation matrix and component matrix used to assess the possible relationship between DT log and other available logs. Figure 3 shows the component plot visually depicting the relationship of various well logs in 3D space.

Table 1. Component matrix of the well logs data.

Component Matrix			
	1	2	3
RHOB	.852	-.258	-.245
NPHI	.248	-.256	.746
CAL	.701	.382	
DT	.638	.439	-.400
GR	.572	.346	-.301
RT	.673	.337	.241

Table 2. Correlation matrix of the well logs data.

Correlation Matrix						
	RHOZ	GR	DT	RT	NPHI	CAL
RHOZ	1.000					
GR	-.340	1.000				
DT	.612	.695	1.000			
RT	.007	.153	.521	1.000		
NPHI	-.719	-.047	.206	-.214	1.000	
CAL	.350	-.009	.682	.311	-.566	1.000

Shown in Table 1, DT has a close relationship with all of the well logs except NPHI log. This inference can be proven by the component matrix given in Table 2. According to the PCA theory, all of the variables located in the same column with a correlation coefficient up to 0.5 are assumed to be in close relationship with each other. Looking at Table 2, since DT, NPHI, RHOZ, GR and RT logs are located in component 3 and have a correlation up to 0.5, they can be considered to have suitable relationships with each other. Figure 4 visually proves the relationships given in Table 1 and Table 2.

Shown in Figure 3, those well logs located on the same side of the plot have a close relationship with each other. This is verification which shows the reliability of the results presented in Table 2.

After selecting the relevant input well logs, 70% of the data (data from depth of 4080m up to 4412m) was randomly used for training and the remainder (data from depth of4412mup to 4554m) was considered for testing using Automated Bayesian Regularization methods. This type of regularization can significantly reduce a large amount of error called over-fitting. The very popular MATLAB Neural Network Toolbox [31] is not able to handle arbitrarily connected BPNN and SVM methods. Therefore, two codes were developed using MATLAB software to run these two networks. Normalization of data helps artificial networks to better understand the relationship between input and output data as well as increasing the accuracy of prediction so high efficiency will be achieved during the testing phase. The normalization process for the raw inputs has a great effect on making the data suitable for the training process. Without this normalization, training the networks would have been very slow. It can be used to scale the data in the same range of values for each input feature in order to minimize bias within the networks from one feature to another. Data normalization can also speed up training time by starting the training process for each feature within the same scale. It is especially useful for modeling application where the inputs are generally on widely different scales [28, 29, 30]. There are many different type of normalization typically used to scale data including, Z-Score Normalization, Min-Max normalization, Sigmoid normalization, Statistical column normalization, etc. In view of the requirements of the network's algorithm, available data from the input and output variables were normalized [32, 33]. Therefore, the data were normalized using Eq. (10) for being in the range of -1 and 1 [35].

$$\left[X = 2\frac{X_i - X_{\min}}{X_{\max} - X_{\min}} - 1 \right] \qquad (10)$$

Where X is the normalized value, X_i is the actual value and X_{max} and X_{min} are the maximum and minimum value of data respectively. When the min-max normalization is applied, each feature will lie within the new range of values and will remain the same. Min-max normalization has the advantage of exactly preserving all relationships in the data []. Leaving out one cross-validation of the whole training set was also used to adjust the associated parameters of each network [36].

Support Vector Machine Implementation

According to the information mentioned in the SVM section, the efficiency of SVM depends on the selection of a suitable kernel. Thus, because of the performance and robustness of Gaussian Radial Basis function [37, 38, 42, 33], it was considered for the purpose of this study. The formulation of this kernel is as follows:

$$k(x_i, x_j) = e^{-\left\|x_i - x_j\right\|^2 / 2\sigma^2} \qquad (11)$$

Where σ is a constant parameter used to control the amplitude of the Gaussian function as well as the generalization ability of SVM in the prediction process.

This parameter needs to be optimizes to have a suitable SVM. Thus, the trade-off parameters C, ε of ε -insensitive loss function, the kernel type K and its corresponding σ parameters need to be determined. C is a regularization parameter that controls the trade-off between maximizing the margin and minimizing the training error. If C is too small, insufficient stress will be placed on fitting the training data. If C is too large, the algorithm will over fit the training data.

Hence, to implement SVM, the appropriate values of parameters C (trade-off parameter), and σ need to be determined. To obtain the value of these parameters, cross-validation was used. Cross-validation techniques can be used to adjust the parameters involved in SVM structure as they make no biased assumptions about the data and noise distribution. The Leave-One-Out method(LOO) is a cross validation method comprised of removing one portion from the training set and constructing the decision function based on the remaining training data [39, 43]. The root mean square error (RMSE) was used to evaluate the quality of the model built through training and testing steps. To obtain the optimal value of σ, the SVM with different σs was trained, the σ varying from 0.05 to 0.22, every 0.01. Finally, the optimal σ was found as 0.13. In order to find an optimal ε , the RMSE of different εS were calculated. Eventually, the optimal value of ε was found to be 0.09. According to data [40, 41, 42, 44] it was found that a large value should be set for C (e.g., C = 2100). Figure 5 presents the performance of SVM in the prediction of DT logs using conventional well logs.

As shown in Figure 5, SVM showed a high level of accuracy during the testing phase as it provided a good estimation of the DT log data.

Prediction of DT Logs Using BPNN

To check the accuracy of SVM in the prediction of DT log, the results obtained from SVM were compared with those of a BPNN. To optimize the best network topology (e.g. number of hidden layers and corresponding neurons), trial and error procedure was utilized. The structure of the BPNN used for the purpose of this paper includes one input layer consisting 5 neurons, two hidden layers of the 8-8 neurons and an output layer containing only one neuron. Multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear and linear relationships between the input and output vectors. Figure 6 shows the optimum BPNN structure used for this paper.

The prediction performance of the model built by BPNN for DT log was done by calculating the mean square error (RMSE) and correlation coefficient (R). The results obtained by neural network were run using an m.file written using MATLAB commercial software. Figure7 shows the performance of BPNN in the prediction process of DT log.

A comparison of Figure 7 with Figure 5, clearly shows that the SVM is a better predictor in terms of accuracy compared to BPNN. Although BPNN gives a good estimation of DT, the results are not as good as those of the SVM. This proves the application and strength of SVM in the prediction of DT log. In the next section, a detailed comparison is made between the results presented by these two networks.

3. Discussion

In this paper, the efficiency of SVM in the prediction of DT log was demonstrated using a real case study. Two MATLAB codes (i.e. m.files) were developed and utilized to compare the performance of SVM with that of BPNN. It was found that SVM had a much better performance and a higher rate of accuracy compared to BPNN in the prediction process. Figure 8 shows the scatter plots representing the correlation coefficient between the measured and predicted DT in the testing phase.

The plots shown in Figure 8 indicate that an acceptable agreement (i.e. R=0.98) was obtained through the utilization of SVM method. All of these expressions show the ability of SVM as a suitable algorithm for the prediction of DT logs.

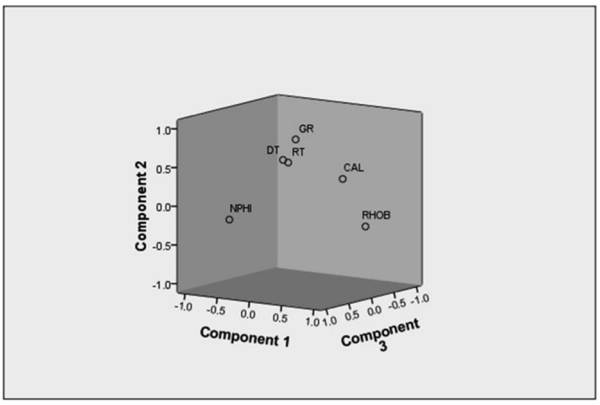

Fig.3. Component plot of the well log data.

4. Conclusions

In this paper, we showed the application of SVM in the prediction of DT log of a well located in the oilfields of southern Iran. Support vector machine (SVM) is a novel machine learning methodology based on statistical learning theory. It has considerable features including, the reliance on a kernel and the fact that the optimization problem results in a uniquely global optimum, high generalization performance and prevention of convergence to a local optimal solution. Although both methods used proved to be reliable in

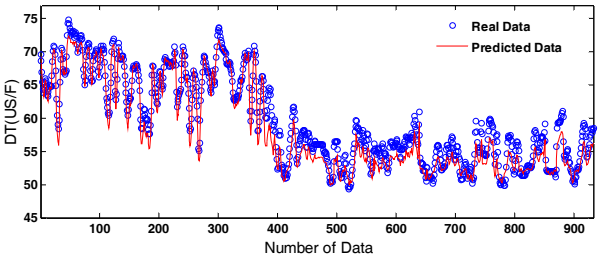

Fig.5. Performance of SVM in prediction of DT logs using testing step.

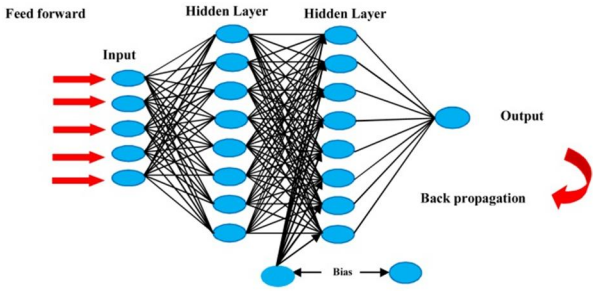

Fig.6. Block diagram of the optimum BPNN Structure.

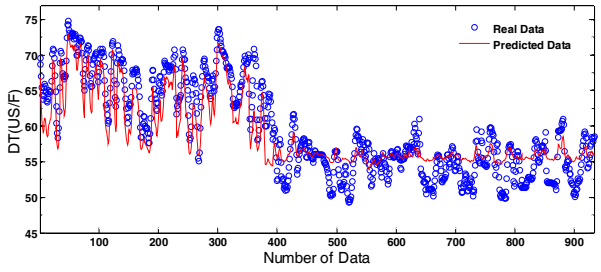

Fig.7. Performance of BPNN in the prediction of DT logs in testing data.

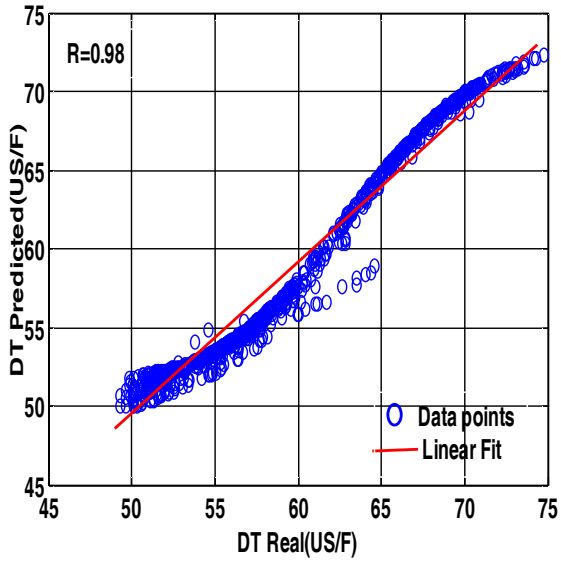

Fig.8. Relationship between measured and predicted data of DT log (SVM left and BPNN right).

the prediction of DT log, it was found that the SVM made the running time considerably faster and showed a higher rate of accuracy. In Addition, the SVM technique resulted in a better prediction relative to that of the BPNN model (Figure 8). As a result, SVM method is recommended to be used for these types of predictions where cost and running time are a real issue.

Appendix
Support Vector Machine Algorithms

SVM, when used for regression analysis, is called support vector regression (SVR). SVR aims to find a function such as f(x) as an approximation of the value y(x) with minimum error based on the available data, i.e.

$$(x_1, y_1), \ldots, (x_m, y_m) \subseteq (X \subseteq R^n \times Y \subseteq R) \quad (1)$$

In this algorithm, a specific loss function called ε-insensitive loss was developed to create a sparseness property for SVR. This function is described as follows:

$$|y - f(x)|_\varepsilon = \begin{cases} 0 & \text{if } |y - f(x) \le \varepsilon| \\ |y - f(x)| - \varepsilon & \text{Otherwise} \end{cases} \quad (2)$$

Where f(x) is the estimated value of the y and the corresponding errors being less than ε-boundary (ε-tube) are not penalized (Figure 9).

Development of this algorithm was started using linear function estimation. It is clear that every linear function of input vector x has the following representation: [17]

$f(x) = \langle w.x \rangle + b$ Where

$$w, x \in X \subseteq R^n, b \in R \quad (3)$$

Note that angle brackets ($\langle . \rangle$) indicate the inner product of two vectors in Hilbert space (i.e. a space in which the inner product of two vectors has a real value). In ε-SVR, ε controls the complexity of the approximating functions where small values tend to penalize a large portion of the training data leading to tight approximating. Therefore, the proper choice of the ε value is critical for the generalization of regression models.

To find f(x), one should minimize the regulated risk functional (R_{reg}) (instead of just the empirical risk functional used in traditional learning algorithms such as ANN) defined as follows [19]:

$$R_{reg}[f] = \frac{1}{2}\|w\|^2 + C.R^{\varepsilon}_{emp}[f] \qquad \text{where } R^{\varepsilon}_{emp}[f] = \frac{1}{m}\sum_{i=1}^{m}|y_i - f(x_i)|_\varepsilon \quad (4)$$

The R_{emp} is the empirical error over training data. The parameter C is the regularization coefficient indicating the complexity of function f and penalizes the error by setting the trade-off between training error and model complexity. It was proven that minimizing the Eq. (5) is equivalent to the following convex quadratic optimization problem [20].

$$L(w,\xi,\xi') = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}(\xi_i + \xi_i') \quad (5)$$

$$Subject\ to \begin{cases} y_i - w^T x - b \le \xi_i + \varepsilon \\ w^T x + b - y_i \le \xi_i' + \varepsilon \\ \xi_i, \xi_i', x_i \ge 0 \end{cases}$$

Where ξ_i and ξ_i' are slack variables introduced to satisfy constraints on the function. The first term of Eq. (6) is the Vapnik– Chervonenkis (VC) confidence interval, whereas the second term is the empirical risk. Both terms limit the upper bound of the generalization error rather than limiting the training error. This means that SVR strikes a balance between the empirical error and VC-confidence interval leading to an improvement of the generalization performance of the models [21]. According to Eq. (6), any error smaller than ε does not require a nonzero ξ_i or ξ_i', and does not enter the objective function [22].

By introducing Lagrange multipliers (α and α') and allowing for C >0, ε >0, the equation of an optimum hyper plane is achieved by maximization of the following relations:

$$L(\alpha,\alpha') = \frac{1}{2}\sum_{i=1}^{N}\sum_{i=1}^{N}(\alpha_i - \alpha_i')x_i'.x_i(\alpha_i - \alpha_i') +$$

$$\sum_{i=1}^{N}((\alpha_i - \alpha_i')y_i - (\alpha_i + \alpha_i')\varepsilon) \quad (6)$$

$$Subject to 0 \le (\alpha_i - \alpha_i') \le C \quad (7)$$

Where x_i only appears inside an inner product. To get a potentially better representation of the data in a non-linear case, the data points can be mapped into an alternative space, generally called feature space, through the replacement below:

$$x_i.x_j \rightarrow \varphi(x_i).\varphi(x_j) \quad (8)$$

The functional form of the mapping $\varphi(x_i)$ does not need to be known since it is implicitly defined by the choice of a suitable kernel function: $k(x_i, x_j) = \varphi(x_i).\varphi(x_j)$ or inner product in Hilbert space. With a suitable choice of kernel the data can become separable in feature space while the original input space is still non-linear [23, 24]. Then, the nonlinear regression estimate takes the following form:

$$y_i = \sum_{i=1}^{N}\sum_{j=1}^{N}(\alpha_i - \alpha_i')\varphi(x_i)^T\varphi(x_j) + b = \sum_{i=1}^{N}\sum_{j=1}^{N}(\alpha_i - \alpha_i')K(x_i,x_j) + b$$

(9)

Where b is computed using the fact that constrains of equation (6) becomes ξ_i= 0 if 0<α_i<C, and ξ_i' = 0 if 0 < α_i' < C [25].

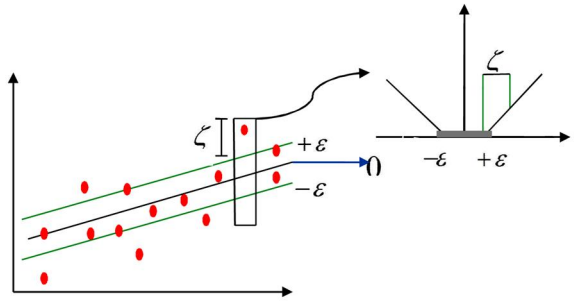

Fig.9. ε-Insensitive loss function [18]

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