The Use Support Vector Machine and Back Propagation Neural Network for Prediction of Daily Tidal Levels along the Jeddah Coast, Saudi Arabia

E. A. Mlybari, M. S. Elbisy, A. H. Alshahri, O. M. Albarakati

***Abstract*—**Sea level rise threatens to increase the impact of future storms and hurricanes on coastal communities. Accurate sea level change prediction and supplement is an important task in determining constructions and human activities in coastal and oceanic areas. In this study, support vector machines (SVM) is proposed to predict daily tidal levels along the Jeddah Coast, Saudi Arabia. The optimal parameter values of kernel function are determined using a genetic algorithm. The SVM results are compared with the field data and with back propagation (BP). Among the models, the SVM is superior to BPNN and has better generalization performance.

***Keywords*—**Tides, Prediction, Support Vector Machines, Genetic Algorithm, Back-Propagation Neural Network, Risk, Hazards.

I. Introduction

DUE to the dynamic interaction of biophysical factors from both the Earth's land surface and ocean, and the high human population present, coastal areas are often at risk to natural and human-induced hazards. One such hazard, which is focused on in this study, is sea level rise. Sea level rise will affect and threaten coastal communities and infrastructure through more frequent flooding and gradual inundation, as well as increased cliff, bluff, dune and shoreline erosion. This will affect transportation facilities; electric utility systems and power plants; wastewater treatment plants, outfalls and storm water systems; ports and harbors; and large wetland areas and coastal development, including homes and businesses.

Numerous models for sea level change forecasting have been carried out in the past. To describe the characteristics of the tide-level variations in an open sea, Darwin [1] proposed a classic equilibrium tidal theory. However, Darwin's model was incapable of accurately estimating the tidal level for the complicated bottom topography, especially in near shore areas. Doodson [2] employed the least-squares method to determine harmonic constants. This harmonic analysis has been used widely for tidal forecasting in the past. The accuracy of harmonic models depends entirely on accurately observed data over a long-term tidal record, which is used to determine the parameters of the tidal constituents. This is the major shortcoming of the harmonic models. Kalman [3] applied the Kalman filtering method to calculate the harmonic parameters instead of the least squares method, which did not require so much tidal data. Mizumura [4] also proposed that the harmonic parameters using the Kalman filtering method could be easily determined from only a small number of historical tidal records. Yen et al. [5] applied the Kalman filtering method to determine harmonic parameters with a limited amount of tidal measured data. However, the model is only applicable for short-term prediction, rather than long-term predication.

Based on limited field data, the neural network method can predict hourly, daily, weekly or monthly tidal levels more accurately than the harmonic analysis method. Vaziri [6] compared the ability of an artificial neural network (ANN) with multiplicative autoregressive integrated moving average modeling. Deo and Chaudhari [7] used ANN which was trained using three algorithms, namely error back-propagation, cascade correlation and conjugate gradient for predicting tides. Tsai and Lee [8] applied the back-propagation neural network for the real-time prediction of a tidal level using the field data of diurnal and semi-diurnal tides.

Lee and Jeng [9] extended the diurnal and semi-diurnal tides to mixed tides, which are more likely to occur in the field. However, their model is only applicable for instant prediction, and not for long-term prediction. Lee et al. [10] and Lee [11] applied a neural network to predict different types of tides and found that the technique can be effective. However, their methods depend on harmonic parameters and cannot predict non-astronomical tidal levels.

Steidley et al. [12] used an ANN to improve predictions of water levels where the performance of the tide charts is particularly poor. Rajasekaran et al. [13] developed functional and sequential learning neural networks to predict tidal levels with a typhoon surge effect. Rajasekaran et al. [13] used a promising support vector regression (SVR) technique for storm surge predictions.

This investigation aims to measure the accuracy of a SVM approach and uses different kernel functions to predict daily tidal levels. To this end, a GA is used to determine the optimal values of the parameters for the different kernel functions of the SVMs. The results are compared with those obtained from the BPNN model.

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II. Tidal Levels Prediction Methods

A. Support Vector Machine

In regressive SVM, the basic idea is to map a low-dimensional input space x onto a higher dimensional feature space F via a nonlinear mapping φ. Then, the following estimation function is used to make linear regressions in that feature space:

$$f(x) = w.\varphi(x) + b \tag{1}$$

where $\varphi(x)$ represents the high-dimensional feature space that has been nonlinearly mapped from the input space, w is the weight vector, and b is the bias term. The coefficients w and b are estimated by minimizing the following regularized risk function:

$$R(C) = \frac{1}{2}\|w\|^2 + C\frac{1}{l}\sum_{i=1}^{l} L_\varepsilon\left(y_i, f(x_i)\right) \tag{2}$$

$$L\varepsilon\left(y_i, f(x_i)\right) = \begin{cases} |y_i - f(x_i)| - \varepsilon & |y_i - f(x_i)| \geq \varepsilon \\ 0 & |y_i - f(x_i)| < \varepsilon \end{cases} \tag{3}$$

where ε is a precision parameter representing the radius of the tube located around the regression function, $L\varepsilon\left(y_i, f(x_i)\right)$ is the ε-insensitive loss function, and C is a regularization constant that determines the trade-off between the training error and the generalization performance. The term $\frac{1}{2}\|w\|^2$ measures the flatness of the function $L\varepsilon\left(y_i, f(x_i)\right)$.

Introducing the slack variables ξ and ξ^* into (2), the overall optimization is formulated as follows:

Minimize

$$\varphi(w, \xi, \xi^*) = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l}\left(\xi + \xi^*\right) \tag{4}$$

subject to

$$\begin{cases} y_i - w.\varphi(x) - b \leq \varepsilon + \xi_i & \xi_i \geq 0 \\ w.\varphi(x) + b - y_i \leq \varepsilon + \xi_i^* & \xi_i^* \geq 0 \end{cases}$$

This constrained optimization problem is solved using the following Lagrangian form:

Maximize

$$H(\alpha, \alpha^*) = -\frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l}\left(\alpha_i - \alpha_i^*\right)\left(\alpha_j - \alpha_j^*\right)K\left(x_i, x_j\right) + \sum_i^l y_i\left(\alpha_i - \alpha_i^*\right) - \varepsilon\sum_i^l\left(\alpha_i + \alpha_i^*\right) \tag{5}$$

subject to

$$\sum_i^l\left(\alpha_i - \alpha_i^*\right) = 0 \qquad 0 \leq \alpha_i, \alpha_i^* \leq C$$

where α_i and α_i^* are Lagrangian multipliers.

Finally, the support vector machine regression function can be written as follows:

$$f(x) = \sum_i^l y_i\left(\alpha_i - \alpha_i^*\right)K\left(x_i, x\right) + b \tag{6}$$

where $K(x_i, x) = \varphi(x_i)\varphi(x)$ is called the kernel function. Using the kernels, all necessary computation can be undertaken directly in the input space without calculating the explicit map $\varphi(x)$. In this paper, three SVM kernel functions are employed and are defined as follows:

- the radial basis function (RBF) $K(x_i, x) = e^{(-\|x_i - x\|^2/2\delta^2)}$,
- the sigmoid function $K(x_i, x) = \tanh(k(x_i x) + \nu)$, and
- the linear function $K(x_i, x) = x_i x$

where δ^2 is the kernel parameter of the radial basis function kernel, k is the scaling parameter of the input data, and ν is a shifting parameter that controls the mapping threshold.

B. Determination of SVM Model Parameters

The selection of the SVM model parameters (cost constant C, and the radius of the insensitive tube ε) and the kernel function parameters (δ^2, k, and ν) is important to the accuracy of the forecasting. However, structural methods for efficiently confirming the selection of parameters are lacking. Therefore, a GA is used in the proposed SVM model to optimize parameter selection. GAs are based on the principle of survival of the fittest member in a population, which retains genetic information by passing it from generation to generation. The execution of a GA is described in the following. Fig. 1 represents the framework of the proposed SVM model. Fig. 2 represents the process of optimizing the SVM parameters with a genetic algorithm.

1. Initial Population

The free parameters are encoded in binary format and represented by a chromosome. Each bit of the chromosome represents whether the corresponding feature is selected or not. An initial population of chromosomes is randomly generated.

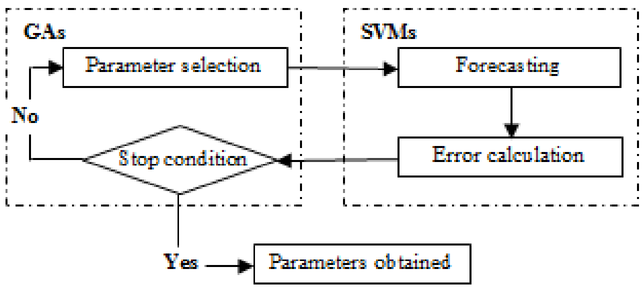


Fig. 1 Framework of proposed SVM model

2. Fitness Function

A training subset is used to calculate the fitness of each chromosome. In this study, a negative mean absolute percentage error (-*MAPE*) is used as the fitness function.

3. Genetic Operators

Selection, crossover, and mutation are the operators used to ensure reproduction in GAs. The purpose of selection is to emphasize the fittest individuals in the population in the hope that their offspring will in turn be even more fit. In this study, the fitness proportionate (i.e. a roulette wheel) selection method is used to select chromosomes for reproduction. The single-point crossover technique is used to randomly exchange genes between two chromosomes. Mutation is a mechanism that ensures the algorithm does not become stuck in local minima. It switches the binary code from 0 to 1 or vice versa. The rate of mutation is set to 0.01. The offspring replace the old population and form a new population in the next generation. The evolutionary process continues until stop conditions are satisfied.

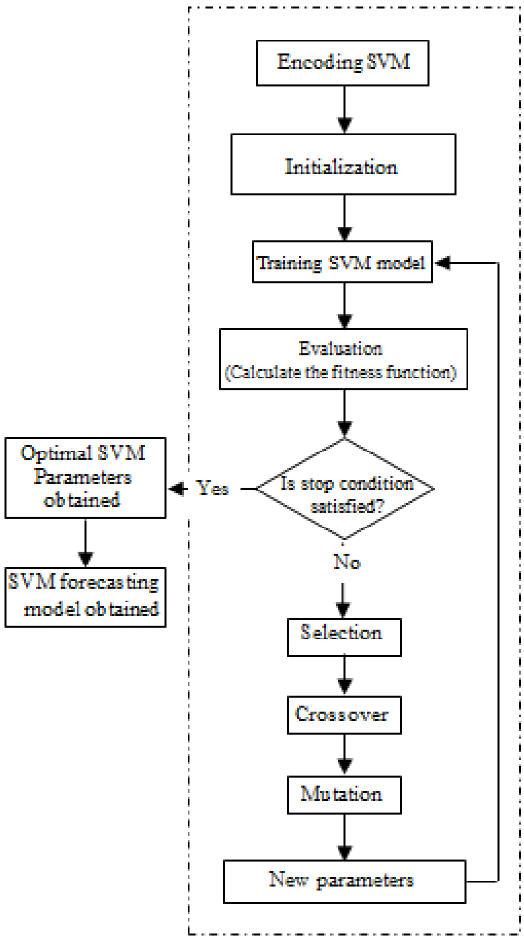


Fig. 2 Framework of genetic algorithms

C. Determination of SVM Model Parameters

A NN is a novel non-algorithmic approach that models the brain as a continuous-time nonlinear dynamic system in connectionist architectures and uses a mathematical model or computational model for information processing. The back-propagation neural network (BPNN) developed by Rumelhart et al. [14] is the most representative learning model for the NN. It is widely applied in a variety of scientific areas, especially in applications of forecasting.

As a feed forward architecture, BPNN models contain an input layer, an output layer and at least one hidden layer, which are all fully interconnected. Although BPNN models embody feed forward architectures, where information is passed in one direction, the models actually implement multi-directional operations.

Back propagation utilizes supervised learning, which requires a desired output to be declared during the training phase. During the training phase, root mean square error (RMSE) is calculated between the desired output and the actual output. The RMSE is then propagated backwards to the input layer and the connection weights between the layers are readjusted (Fig. 1). After the weights have been adjusted and the hidden layer neurons have generated an output result, the error value is re-determined.

Before the training phase begins the total number of input neurons, the number of hidden layer neurons and the total number of iteration (propagations) must be declared. When the training phase initializes, the connection weights between the input and hidden layers are assigned random values by means of an activation function. The goal of any training algorithm is to minimize the global (mean sum squared) error *E*, defined below:

$$E = \frac{1}{2}\sum (O_n - P_n)^2 \tag{7}$$

where O_n is the observations, and P_n is the predictions for any n output node. The summation has to be carried out over all output nodes for every training pattern. A pair of input and output values constitutes a training pattern.

D. Model Assessment

The performance of all SVM and NN models was assessed based on calculating mean error *ME*, mean absolute percentage error *MAPE*, and root mean square error *RMSE*. The correlation coefficient *R*, of linear regression line between the predicted values of either the SVM or the NN model and the desired output was also used as a measure of performance. The four statistical parameters used to compare the performance of various SVM and NN configurations are:

$$ME = \frac{1}{N}\sum_{i=1}^{N} |P_i - O_i| \tag{8}$$

$$MAPE = \left[\frac{1}{N}\sum_{i=1}^{N}\left|\frac{(P_i - O_i)}{P_i}\right|\right] \times 100 \tag{9}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i - O_i)^2} \tag{10}$$

$$R = \frac{\sum_{i=1}^{N}\left(P_i - \bar{P}\right)\left(O_i - \bar{O}\right)}{\sqrt{\sum_{i=1}^{N}\left(P_i - \bar{P}\right)^2 \sum_{i=1}^{N}\left(O_i - \bar{O}\right)^2}} \quad (11)$$

where O_i is the observed value, P_i is the predicted value, N is the total number of data points in validation, $\bar{O}$ is the mean value of observations, and $\bar{P}$ is the mean value of predictions.

III. Study Area and Data

The sea level change data refer to hourly observed sea level changes during the years 2003 and 2004. The data were obtained from the Saudi Aramco Company (Hydrographic Unit, Surveying Services Div., Protect Support and Controls Department) by a pressure type recorder (OSK LP2) during the year 2003 and 2004 at a depth of 3m at Jeddah (see Fig. 3). The data return was greater than 95% with gaps filled by linear interpolation. The sea level station (Jeddah station (21° 25' 52" N and 39° 09' 17" E) is situated at the entrance of the Obhur creek, a finger of the Red Sea extending inland. The creek serves as an ideal location for sea level gauge instillation as it is protected from direct effects of wind and waves. The accuracy of the device is ± 0.5cm. Timing error on the records was minimal (of the order of a few minutes per 45 days chart length).

Fig. 3 Location of study area

IV. Results and Discussion

A. Back-Propagation Neural Network

In this study, standard three-layer BPNN is used as a benchmark. The inputs to be used in constructing the model are the previous daily tidal level observations. Evaluating the model with a different number of previous daily sea level change values led to a conclusion that the best result could be achieved when using only three previous tidal level values. Adding more of the previous data to the inputs did not change the result.To determine the optimum sizes of BPNN based on the determined input numbers, the networks with one hidden layer were used for training and testing by changing neuron sizes in a hidden layer in order to test the stability of the network. Deo et al. [7] and El-Bisy [15] implied that any nonlinear mathematical dependency structure can be approximated using one hidden layer. Model results for different BPNN architectures are presented in Fig. 4 which shows the performance of the BPNN with various numbers of neurons in one hidden layer. Overall, it could easily be observed from that BPNN that having architecture 3-5-1 (three neurons in input and five neurons in first hidden layers, and one neuron in output layer) produced the best result in this study.

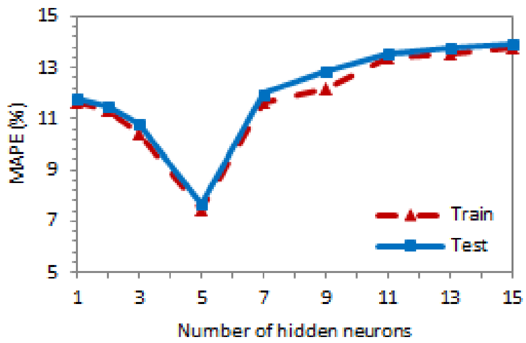


Fig. 4 Performance of the BPNN with various numbers of neurons in one hidden layer

The applied network parameters for the learning rate, the momentum and the input noise were found as 0.70, 0.86 and 0.01, respectively. For trained data, it was observed that a maximum error of 15.11%, a minimum error of -15.2% and the mean absolute percentage error of 9.47% were obtained. Also for tested data, a maximum error of 15.4%, a minimum error of -16.1% and the mean absolute percentage error of 9.63% were obtained. The correlation coefficients of 0.93 and 0.91 were obtained for the training and testing data. The prediction errors of the BPNN model are shown in Fig. 5.

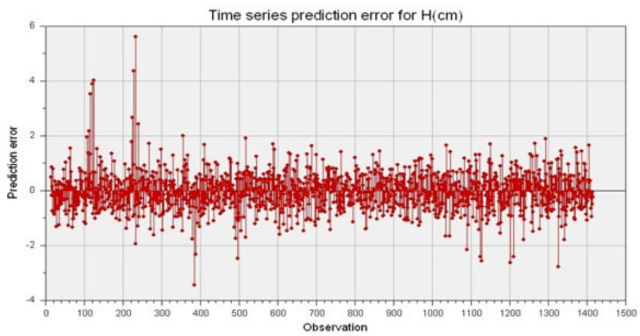


Fig. 5 Prediction error of tidal level by BPNN model

B. Support Vector Machine

When applying SVM, the first thing that needs to be considered is what kernel function is to be used. As the dynamics of tide time series are strongly nonlinear, it is intuitively believed that using nonlinear kernel functions could achieve better performance than the linear kernel. In this work, the RBF is used as a kernel function of the SVM, because it tends to give good performance under general smoothness assumptions. Consequently, they are especially useful if additional knowledge of the data is available [16]. This is also demonstrated in the experiment by comparing the results obtained using the RBF with the results obtained using polynomial kernel and sigmoid kernel. The performance of SVM constructed by polynomial basis function or sigmoid function is not more efficient than that by radial basis function. The polynomial kernel gives inferior results and takes longer in the training of SVM. The second thing that needs to be considered is what values of the three free parameters of radial basis kernel function (δ^2, C andε) are to be used. It is necessary to investigate impacts of selecting these parameters on the resultant generalization errors. Here, the three free parameters of radial basis kernel function (δ^2, C andε) are user-determined parameters; the election of the parameters plays an important role in the performance of SVM. The genetic algorithm employed in this study to search for the optimal values of the SVM parameters (C, ε and δ^2).

The adjusted parameters with minimum validation error are selected as the most appropriate parameters. Then, the optimal parameters are utilized to train the SVM model. The optimal parameters for different SVM models are shown in Table I.

TABLE I
THE OPTIMAL PARAMETERS FOR SVM MODEL

Kernel function	Kernel parameters		
	C	ε	δ^2
Radial basis	67.831	0.0014	43.321

The water level changes forecasting as above based on BPNN was repeated by using the SVM. The free parameters of radial basis kernel function used in the SVM model are C = 67.831, δ^2 = 43.321 and ε = 0.0014.These values produced the best possible results according to the testing set. For trained data, a maximum error of 10.5%, a minimum error of -11.03% and the mean absolute error of 6.37% were obtained. Also for tested data, a maximum error of 10.2%, a minimum error of -12.2% and the mean absolute percentage error of 6.53% were obtained. The correlation coefficients of 0.969 and 0.966 were obtained for the training and testing data. From the experimental results, the predictions values were fairly close to the corresponding actual measurements values. All ups and downs in the observed time series were modeled well in the predicated series. The prediction errors of SVM model are shown in Fig. 6.

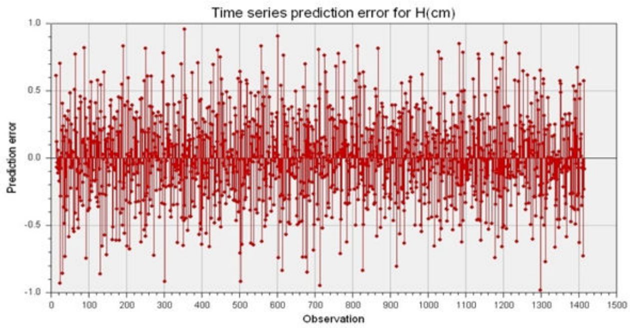


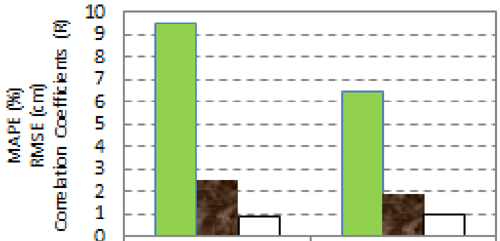
Fig. 6 Prediction error of tidal level by SVM model

The results comparing SVM and BPNN are given in Table II. The SVM model, however, can significantly reduce the overall forecasting errors. In terms of RMSE, the percentage improvements of the SVM model over the BPNN model for daily forecasting were 24.51%. The results showed that SVM performance is superior to BPNN in forecasting daily tidal levels. The statistical results showed that SVM models performed well and were able to accurately estimate the sea level changes (see Fig. 7). According to the indices (*RMSE*, *ME*, *MAPE* and *R*), the SVM model with RBF produced the best performance and was able to accurately estimate the sea level changes.

TABLE II
EVALUATING PERFORMANCE OF MODELS

Method	BPNN (3-5-1) model			SVM model		
	Training set	Test set	Whole set	Training set	Test set	Whole set
MAPE (%)	9.47	9.63	9.51	6.37	6.53	6.43
RMSE (cm)	2.41	2.60	2.53	1.79	1.97	1.91
R	0.93	0.91	0.92	0.969	0.966	0.97

In general, the SVM with RBF forecasting results have better accuracy than that of the BPNN model. This is because its structure risk minimization (SRM) principle is implemented to minimize the upper bound of the generalization error rather than the training error, which is applied in NN [13]. SVM has fewer free parameters to optimize and can be determined easily [17], [18]. Moreover, the SVM model can eliminate over-fitting training and local minima [19]. Finally, SVMs are trained much more rapidly [13].



	BPNN model	SVM model
MAPE (%)	9.51	6.43
RMSE (cm)	2.53	1.91
Correlation coefficient (R)	0.92	0.97

Fig. 7 Comparison of RMSE, MAPE, and correlation coefficient (*R*) for the SVM and BPNN models

V. Conclusions

Sea level rise is a risk with impact to cause shoreline retreat through coastal erosion and dune migration, coastal inundation and flooding through enhanced tidal reaches and an increase in the frequency of storm surges. Rising sea levels can also cause groundwater and fresh coastal surface water contamination (with associated impacts on agriculture and aquaculture due to the decrease in soil and water quality), the loss of cultural and archaeological resources, and the possible destruction of important coastal habitats such as wetlands, mangroves, estuaries etc.

The support vector machine approach was implemented in this study to predict sea level changes. The best accuracy for predicting tidal levels was achieved by using only three previous sea level change values. Genetic algorithm is used in the proposed SVM model to optimize SVM parameter selection. Results of SVM are also compared with those of back propagation neural networks. In conclusion, the SVM model with RBF kernel has the highest level of accuracy and better generalization performance than BPNN. The SVM with RBF provides a promising alternative tool to the neural network for tidal level forecasting.

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