A Novel Decomposition-Based Localized Short-Term Tidal Current Speed and Direction Prediction Model

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Abstract—To integrate tidal energy into the existing grid, it is important to accurately predict the amount of tidal energy available in the short-term horizon. In this regard, the short-term prediction of tidal current becomes crucial. The tidal energy depends not only on the tidal current speed (TCS), but also on the tidal current direction (TCD). The non-stationarity and non-linearity of the TCS and TCD time series lower the predictability of them. Using decomposition approaches, these non-linear and non-stationary time series can be decomposed into several components which are more predictable. On the other hand, in order to predict any volatility of a non-linear time series, localized approaches perform better compared to training the prediction model in a global fashion. In this regard, this paper proposes a novel prediction model based on ensemble empirical mode decomposition (EEMD) and localized least squares support vector machine (LSSVM) to increase the prediction accuracy of TCS and TCD. The proposed model is compared with the auto-regressive integrated moving average (ARIMA) model and the LSSVM- based model. The actual data recorded from the Shark River Entrance (Florida, U.S.) is used to verify the applicability of the proposed prediction model.

Index Terms— **Tidal current speed (TCS); tidal current direction (TCD); short-term prediction; ensemble empirical mode decomposition (EEMD); least squares support vector machine (LSSVM).**

I. Introduction

With the growing concerns about the climate change, renewable energy sources (RESs) are considered as a viable option to replace conventional environment-polluting fossil-fuel-based power plants. In this regard, various alternative sources of energy have been found and successfully deployed all over the world. Among the newly developed ways of harnessing renewable energy sources, tidal power generation has recently grabbed much attention. According to the International Energy Agency (IEA), tidal energy harvesting is expected to increase to 60 TWh by 2035 [1].

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As the penetration of tidal power generation units will be increased in the near future, the inherent stochasticity and variability of the tidal power can create serious issues in the power system operation [2]. In such case, an accurate short-term and medium-term prediction of tidal power becomes highly important. Accurate short-term prediction of tidal power provides a reliable and controllable power that can leave out the need for energy storage systems and thus reduce the total cost of power generation [2].

To predict tidal power, first the tidal speed and tidal direction can be predicted, and then the tidal current speed is converted to tidal power using the characteristics curves [3] of the turbines. It is also important to consider the TCD, as it determines the effective component of the speed that faces the turbine and produces the output power.

Similar to other time-series prediction applications, in short-term prediction of TCD and TCS, prediction engine is the main building block. Recently, there has been an increasing trend of using neural networks (NNs) [4, 5] and support vector machine (SVM) [2, 6] in TCS and TCD. In [4], the performance of different short-term TCD prediction models, including multi-layer perceptron neural network (MLPNN), focused time delay neural network (FTDNN), adaptive neuro-fuzzy inference system (ANFIS), and auto-regressive moving average (ARMA), have been compared with each other. It has been concluded that the FTDNN-based model has a higher accuracy in comparison to other prediction engine. In [5], a prediction model based on hybridizing MLPNN and least square method is proposed. NNs may face overfitting issues in the training process which reduce their effectiveness for predicting the future values. Besides, during the training process, NNs may be trapped in a local minimum. On the contrary, in SVM, the chance of being trapped in a local minimum is lower [3, 6]. For this reasons, two prediction models based on SVM have recently been proposed in [2, 6] for tidal current speed and direction forecast. Comparison of the prediction accuracies of the SVM-based model and the NN-based model confirms the superiority of SVM in TCS and TCD prediction [2]. SVM training involves quadratic programming which requires a high computational burden [7]. In this regard, an SVM variant, known as least-square support vector machine (LSSVM) has been proposed in [8]. In this powerful machine learning tool, the training process is done by solving linear equations instead of quadratic programming. Hence, the computational cost of LSSVM is considerably lower than SVM, while LSSVM has all the advantages of SVM [8]. LSSVM has been successfully used as the prediction engine in several applications [9]. In spite of distinguished features of LSSVM, so far, it has not been applied in TCS and TCD [2]. To predict the volatility of a non-linear time series localized approaches has better performance then training the prediction model in a global fashion [10]. However, to the best of the authors' knowledge this important fact has not been considered in TCS and TCD prediction.

Decomposition methods are widely used to attain a more accurate prediction model for non-stationary and non-linear time series. In the context of time series prediction, different decomposition methods such as wavelet decomposition [11] and empirical mode decomposition (EMD) [12] have been utilized. In [11], it is shown that for nonlinear and nonstationary time-series, EMD variants are better than the wavelet decomposition variants. Among decomposition approaches, a variant of EMD, known as ensemble EMD (EEMD), is the only EMD variant which has been mathematically proved to have almost the same computational burden as other decomposition approaches such as wavelet decomposition [13]. In this regard, for the first time in the tidal current prediction, this paper applies EEMD to the tidal current time series in order to increase the prediction accuracy.

The main objective of this paper is to propose a novel decomposition based LSSVM method to forecast the short-term tidal current and tidal direction. In the proposed EEMD-LSSVM prediction model, the EEMD addresses the issue related to non-linearity and non-stationarity of TCS and TCD time series. Moreover, by using a localized learning strategy in training LSSVM, the TCS and TCD are predicted with a considerably high accuracy.

The remainder of the paper is organized as follows. Section II presents a brief introduction to EEMD. In Section III, LSSVM is described. The proposed model is presented in Section IV. Section V explains the application of the proposed model on the test data. Finally, Section VI concludes the paper.

II. A Brief Discussion on EEMD

As EEMD is one of the main building blocks of the proposed prediction model, it is briefly described in this section. More details about EEMD can be found in [13].

Given a time series $\{X(nT)\}$, where n is the sample number and T is the sampling time, the steps of EEMD are as follows:

Step 1. Add l (number of ensembles) different white noise to the original time series to obtain l amalgamation of original time series and white noise. Obtained amalgamated time series (ensembles) can be shown as $\{X^i(nT)\}$, where i=1,…,l.

Step 2. For every $\{X^i(nT)\}$, identify all the local extrema.

Step 3. For every $\{X^i(nT)\}$, use cubic spline line to connect all the local maxima to generate the upper envelope, $\{X^i{}_{up}(nT)\}$. Similarly, the lower envelope, $\{X^i{}_{low}(nT)\}$, can be found.

Step 4. For every $\{X^i(nT)\}$, compute the mean envelope, $\{M^i(nT)\}$, as follows:

$$M^i(nT) = \frac{X^i{}_{up}(nT) + X^i{}_{low}(nT)}{2} \tag{1}$$

Step 5. Extract $\{M^i(nT)\}$ from $\{X^i(nT)\}$ as follows:

$$Z^i(nT) = X^i(nT) - M^i(nT) \tag{2}$$

Step 6. If $M^i(nT) \le \varepsilon$, $Z^i(nT)$ is one of the components corresponding to the ith ensemble which is called intrinsic mode function (IMF). It is noteworthy to mention that ε is the acceptable error in finding EMD components and should be selected based on the trade-off between computation time and accuracy. If $Z^i(nT)$ is an IMF, then set $C^i_j(nT) = Z^i(nT)$, where j represents the number of components. Note that for the first IMF components, j is one. Then, replace $X^i(nT)$ with the residual $R^i(nT) = X^i(nT) - C^i_j(nT)$. If $Z^i(nT)$ is not IMF, then replace $X^i(nT)$ with $Z^i(nT)$ and repeat Steps 2-5 until $M^i(nT) \le \varepsilon$.

Step 7. Repeat Steps 2-6 until all the IMFs are found.

Step 8. Calculate the jth IMF of EEMD, that is $C_j(nT)$, by averaging the respective components $C^i_j(nT)$ of all amalgamated time series.

Finally, the original time series can be reconstructed by its IMF as follows:

$$X(nT) = \sum_{j=1}^{m} C_j(nT) \tag{3}$$

where m is the number of IMF components.

III. A Brief Discussion on LSSVM

As LSSVM is another building block of the proposed prediction model, here a brief description of the LSSVM is provided. Further details can be found in [8].

In LSSVM, the relationship between the input vector (X) and the output y is as follows:

$$y = w.\varphi(X) + b \tag{4}$$

where w and b are the weight vector and bias, respectively. In (4), φ is the feature vector and depends on kernel function. Here, due to the advantages of the Gaussian kernel function in prediction, we use this kernel function [14].

To find w and b, the following constrained optimization should be solved.

$$\begin{aligned} &Min \quad \mathrm{C}=\frac{1}{2}\left\|w^2\right\| + \sigma\sum_{k=1}^{K}\varepsilon_k^2 \\ &s.t. \quad \left|y_k - \langle w, x_k\rangle - b\right| \le \varepsilon_k \quad k = 1,2,...,K \end{aligned} \tag{5}$$

where σ and ε are user defined parameters which make a trade-off between the empirical risk and the model flatness. These parameters have been chosen by trial and error. Evolutionary optimization techniques can also be used to obtain the optimal values for those parameters. However, optimization of these parameters demands further research.

Based on K training input vectors and their corresponding output, the optimization problem formulated in (5) can be simply solved by the method of Lagrange multipliers.

IV. Proposed Prediction Model

Let assume that we are at time LT and we have L data point to predict the value of TCS and TCD at time $(L+1)T$. As the starting point of the prediction process, historical data should be decomposed into different components using EEMD described in Section II. Then, for every component, the Hankel matrix can be obtained as follows:|

$$\boldsymbol{X}_j = \begin{bmatrix} C_j(T) & C_j(2T) & \dots & C_j(dT) \\ C_j(2T) & C_j(3T) & \dots & C_j((d+1)T) \\ \vdots & \vdots & \ddots & \\ C_j((L-d+1)T) & \dots & \dots & C_j(LT) \end{bmatrix} \tag{6}$$

where d is the length of input vector for the LSSVM. Each row of the matrix, except the last row, is a candidate input vector for training the LSSVM to predict the value of jth component of time series at $(L+1)T$. The last row is the input vector for predicting the value of jth component of time series at $(L+1)T$ and it is known as test vector (X_j^{Test}).

The corresponding output for every input candidate can be shown as:

$$\boldsymbol{Y} = \left[C_j((d+1)T) \quad C_j((d+2)T) \quad \dots \quad C_j((L)T) \right]^T \tag{7}$$

To make the training process localized, using K-nearest neighbors (KNN) algorithm is used to find K training row vectors, which are the nearest to test vector (X_j^{Test}), are chosen from the rows of $\boldsymbol{X}_j$ in (6). Hereafter, we represent the K chosen training vectors and their corresponding output vectors for jth component by $\boldsymbol{X}_j^{Train}$ (K by d matrix) and $\boldsymbol{Y}_j^{Train}$ (K by 1 matrix), respectively.

In order to make the learning process efficient, the localized learning is based on the centered version of $\boldsymbol{X}_j^{Train}$, X_j^{Test} and $\boldsymbol{Y}_j^{Train}$. For this reason, the mean of each column in $\boldsymbol{X}_j^{Train}$ is deducted from the training input vector and test vector as follows:

$$\begin{aligned} \tilde{\boldsymbol{X}}_j^{Train} &= \boldsymbol{X}_j^{Train} - \mathbf{1}\bar{\boldsymbol{X}}_j^{Train} \\ \tilde{X}_j^{Test} &= \tilde{X}_j^{Test} - \bar{\boldsymbol{X}}_j^{Train} \end{aligned} \tag{8}$$

where, $\bar{\boldsymbol{X}}_j^{Train}$ is a 1 by d and $\mathbf{1}$ is a K by 1 matrix of ones. Similarly, the mean of output matrix $\boldsymbol{Y}_j^{Train}$ is subtracted from each element of $\boldsymbol{Y}_j^{Train}$ as follows:

$$\tilde{\boldsymbol{Y}}_j^{Train} = \boldsymbol{Y}_j^{Train} - \mathbf{1}\bar{\boldsymbol{Y}}_j^{Train} \tag{9}$$

where $\bar{\boldsymbol{Y}}_j^{Train}$ is the mean of the output matrix.

Afterward, using $\tilde{\boldsymbol{X}}_j^{Train}$ and $\tilde{\boldsymbol{Y}}_j^{Train}$, the LSSVM can be trained. Then, the prediction value for time $(L+1)T$ can be calculated as follows:

$$\begin{aligned} \tilde{y}_j^{Test}\left((L+1)T\right) &= w.\varphi(\tilde{X}_j^{Test}) + b \\ \hat{y}_j^{Test}\left((L+1)T\right) &= \tilde{y}_j\left((L+1)T\right) N_j^{Test} + \bar{\boldsymbol{Y}}_j^{Train} \end{aligned} \tag{10}$$

The prediction value for all EEMD components can be obtained. Then, using (3), the final prediction value can be obtained as follows:

$$X\left((L+1)T\right) = \sum_{j=1}^{m} \tilde{y}_j\left((L+1)T\right) \tag{11}$$

V. Case Study and Results

A. Data

The data sets from the Shark River Entrance (Florida, U.S.) recorded by the National Oceanic and Atmospheric Administration (NOAA) [15] are used as a case study. The data sets include the 6-min instantaneous readings from October 1 to October 25, 1999. 6-min ahead prediction is undertaken by using the data collected 18 days prior to the prediction moment. The prediction in carried out for the last 7 days of available historical data.

B. Performance Evaluation

For comparing the proposed prediction model with other methods, certain indices are used. These indices include the mean percentage absolute error (MAPE) [6], the normalized mean absolute error (NMAE) [9], the normalized root-mean-squared error deviation (NRMSD) [16], and absolute error (AE). MAPE can show the relative error of the prediction model. Since MAPE can produce erroneous results when the data points are close to zero, NMAE is also calculated. NRMSD, which is more sensitive to large errors compared to small errors, is also calculated to evaluate large prediction errors. AE can be used for analyzing the prediction error distribution of the prediction model. The indices can be calculated as follows:

$$\begin{aligned} \text{MAPE} &= \frac{1}{N} \cdot \sum_{i=1}^{N} \frac{|x_i - \hat{x}_i|}{x_i} \\ \text{NMAE} &= \frac{1}{(x_{\max} - x_{\min}) \cdot N} \cdot \sum_{i=1}^{N} |x_i - \hat{x}_i| \\ \text{NRMSD} &= \frac{1}{x_{\max} - x_{\min}} \cdot \sqrt{\frac{1}{N} \cdot \sum_{i=1}^{N} (x_i - \hat{x}_i)^2} \\ AE_i &= |x_i - \hat{x}_i| \end{aligned} \tag{12}$$

where x_i and $\hat{x}_i$ are the actual and predicted values at sample i, respectively. N is the number of points in the test dataset.

C. Benchmark Models

In order to validate and compare the effectiveness of the proposed prediction model, two benchmark models have been considered. These include ARIMA-based and LSSVM-based models. The reason for using ARIMA is that it has been recently used in tidal current speed and direction prediction [6]. LSSVM is chosen as the second benchmark because it is used as one of the building blocks of our proposed tidal prediction model and a comparison with this benchmark can help assess the efficacy of using EEMD.

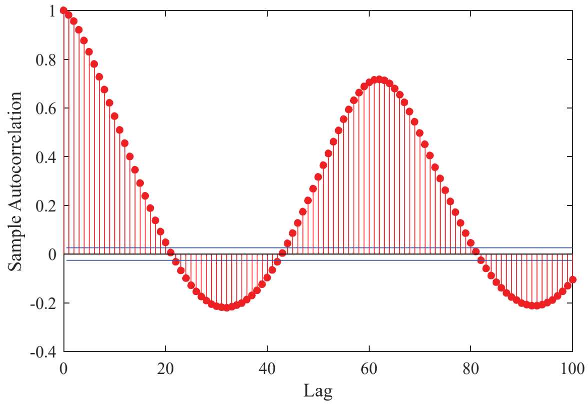

Figure 1. Autocorrelation for TCS.

To make a fair comparison, optimal parameters for ARIMA model are chosen. As it can be observed from autocorrelation function, shown in Figures 1 and 2, the time series for both speed and direction are non-stationary. Hence, the time series of TCS and TCD are differenced. Using ACF and PACF, it is observed that both time series become stationary after the first differencing. Then, Akaike's information criterion (AIC) is used to find the most appropriate order for ARIMA.

D. Numerical Results and Analysis

The simulation was performed on a PC with Intel Core i7 CPU, 3.4 GHz, 16 GB memory and running Windows 7. The proposed method was implemented on MATLAB 2015b.

Table I depicts the performance indices evaluated for TCS prediction, using three prediction models. As can be seen, using LSSVM can slightly increase the accuracy of the prediction.Whereas, the proposed EEMD-LSVVM markedly increases the prediction accuracy. Figure 3 pictorially shows the accuracy of the proposed model in predicting TCS. It is clear that even during sudden increase or decrease of tidal current speed, the predicted values are very close to the actual values. Figure 4 shows a detailed view of all prediction models. The prediction results obtained from ARIMA-based and LSSVM-based models show deviation from the actual TCS. Whereas, the proposed model can accurately track the changes in actual speed. For the purpose of further comparing the stability and reliability of the prediction, the distribution of

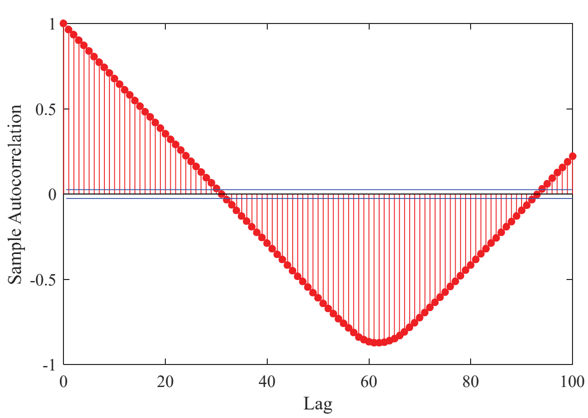

Figure 2. Autocorrelation for TCD.

TABLE I
PERFORMANCE EVALUATION OF DIFFERENT PREDICTION MODEL FOR TCS

Method	MAPE (%)	NMAE (%)	NRMSD (%)
ARIMA	10.62	2.64	3.42
LSSVM	9.27	2.52	3.23
Proposed Model	**5.03**	**1.05**	**1.41**

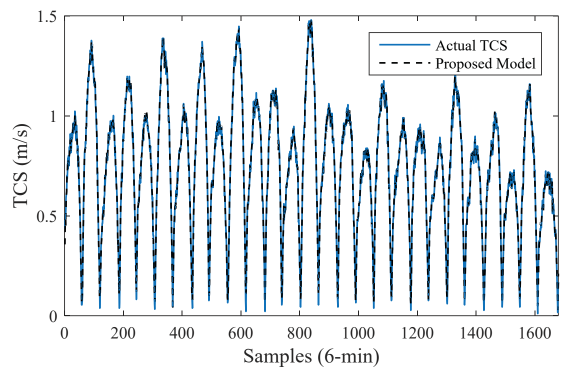

Figure 3. TCS prediction based on the proposed model.

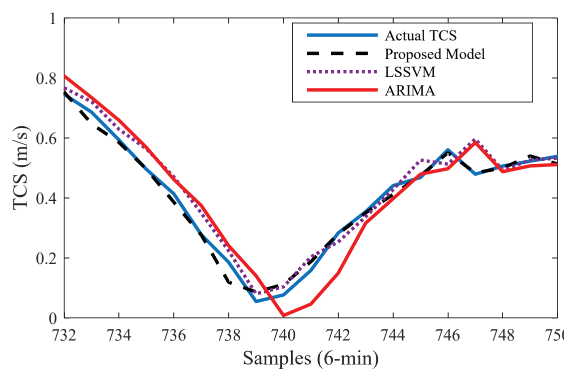

Figure 4. Comparison of different predcition models for TCS.

AE is studied and the results are shown in Figure 5. From this figure, it can be concluded that the absolute error of the proposed model prediction for 75 percent of times is less than 0.02 m/s. While, the other prediction models can cause large absolute errors.

As previously mentioned, the tidal current direction is important to calculate the effective tidal speed that incidents on the turbine and produces the output power. Figure 6 shows that the proposed model is able to effectively predict the tidal current direction. Table II indicates that the proposed method outperforms the other two methods for predicting tidal current direction. Figure 7 shows the result in a more detailed fashion, including all the prediction models. When the tidal current direction remains almost constant, all of the three models perform reasonably well. However, when the direction of tide changes suddenly, the ARIMA model predicts this change

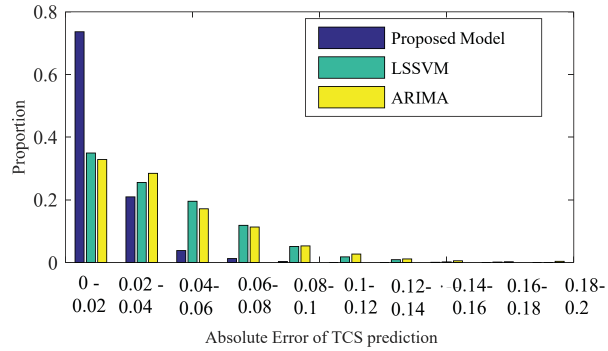

Figure 5.Distribution of AEs TCS prediction.

after a certain delay. The proposed model predicts the change in direction with better accuracy as compared to the other two.

The last but not least, the average computation time required for predicting with ARIMA, LSSVM, and the proposed model are 0.0594 s, 0.5532 s, and 1.2362 s, respectively. The computation time of the proposed prediction model is higher than benchmark models, but his computational time is acceptable for the prediction horizon of 6-min.

TABLE II
PERFORMANCE EVALUATION OF DIFFERENT PREDICTION MODEL FOR TCD

Method	MAPE (%)	NMAE (%)	NRMSD (%)
ARIMA	4.19	1.39	5.94
LSSVM	2.97	0.98	5.52
Proposed Model	**1.73**	**0.73**	**2.74**

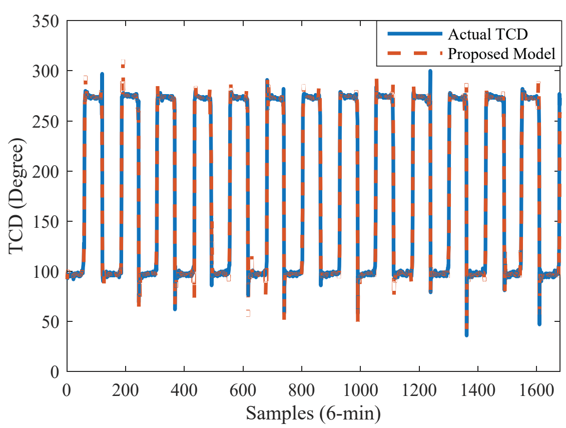

Figure 6. Comparison of different models for TCD.

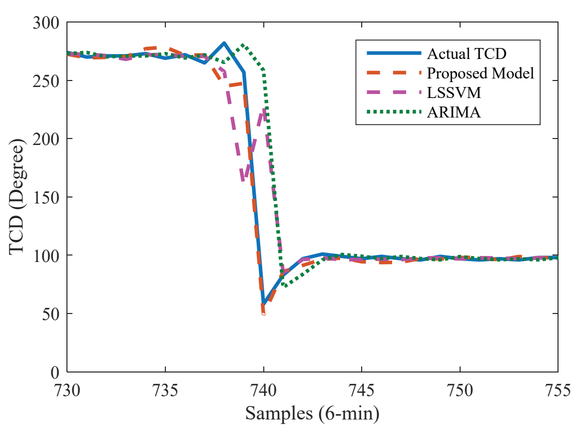

Figure 7. Comparison of different predcition models for TCD.

VI. CONCLUSION

In this paper, a novel prediction model for TCS and TCD is presented. The proposed model makes use of the advantages of EEMD in decomposing TCS and TCD time series to increase the accuracy of the prediction. Meanwhile, a localized training process is applied to more efficiently train the LSSVM. It has been shown that the proposed model outperforms ARIMA-based and LSSVM-based models. The proposed model can be used to obtain the tidal power and, in this way, it can be utilized in various power system studies ranging from unit commitment and economic dispatch to power system planning.

REFERENCES

[1] International Energy Agency, World Energy Outlook 2010.

[2] A. Kavousi-Fard, "Modeling uncertainty in tidal current forecast using prediction interval-based SVR", *IEEE Trans. Sustain Energy*, vol. PP, no. 99, pp. 1-1, 2016.

[3] M. Liu, W. Li, C. Wang, R. Billinton, and J. Yu, "Reliability evaluation of a tidal power generation system considering tidal current speeds," *IEEE Trans. Power Syst.,* vol. 31, no. 4, pp. 3179-3188, Sept. 2015.

[4] M. J. Jahromi, A. I. Maswood, and K. J. Tseng, "Comparison of different techniques for short-term prediction of tidal current speeds," in *2010 IEEE Power and Energy Society General Meeting*, 25-29 Jul. 2010.

[5] H. H. H. Aly and M. E. El-Hawary, "A proposed ANN and FLSM hybrid model for tidal current magnitude and direction forecasting," *IEEE J. Ocean. Eng.*, vol. 39, no. 1, pp. 26-31, Jan. 2014.

[6] A. Kavousi-Fard, "A hybrid accurate model for tidal current prediction," *IEEE Trans. Geosci. Remote Sens.*, vol. PP, no. 99, pp. 1-7, 2016.

[7] W. Haifeng and H. Dejin, "Comparison of SVM and LS-SVM for regression," in *2005 International Conf. on Neural Networks and Brain*, pp. 279-283, 2005.

[8] J. A. Suykens and J. Vandewalle, "Least squares support vector machine classifiers," *Neural processing letters,* vol. 9, pp. 293-300, 1999.

[9] J. L. Wu, T. Y. Ji, M. S. Li, P. Z. Wu, and Q. H. Wu, "Multistep wind power forecast using mean trend detector and mathematical morphology-based local predictor," *IEEE Trans. Sustain. Energy,* vol. 6, no. 4, pp. 1216-1223, May 2015.

[10] H. Yang, K. Huang, I. King, and M. R. Lyu, "Localized support vector regression for time series prediction," *Neurocomputing*, vol. 72, no.10, pp. 2659-2669, 2009.

[11] H. Liu, H. Q. Tian, and Y. F. Li, "Comparison of new hybrid FEEMD-MLP, FEEMD-ANFIS, wavelet packet-MLP and wavelet packet-ANFIS for wind speed predictions," *Energy Conversion and Management*, vol. 89, pp. 1-11, Jan. 2015.

[12] Y. Ren, P. N. Suganthan, and N. Srikanth, "A comparative study of empirical mode decomposition-based short-term wind speed forecasting methods," *IEEE Trans. Sustain Energy,* vol. 6, no. 1, pp. 236-244, Jan. 2015.

[13] Y. H. Wang, C. H. Yeh, H. W. V. Young, K. Hu, and M. T. Lo, "On the computation complexity of the empirical mode decomposition," *Physica A*, no. 400, pp. 159-167, 2014.

[14] Zhou, Junyi, Jing Shi, and Gong Li. "Fine tuning support vector machines for short-term wind speed forecasting," Energy Convers. Manage., vol. 52, no. 4, pp. 1990-1998, 2011.

[15] NOAA. *Tidal Current Data* [online]. Available: http://www.noaa.gov/.

[16] F. J. Los. "Eco-hydrodynamic modeling of primary production in coastal waters and lakes using BLOOM," Vol. 1. IOS Press, 2009.