An Effective Fuzzy Feature Selection and Prediction Method for Modeling Tidal Current: A Case of Persian Gulf

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***Abstract*— This paper develops a new two-stage approach for accurate modeling and prediction of tidal current. The proposed method makes use of a novel fuzzy feature selection to extract the most preferable features from the tidal current speed and direction data set. The selected features are further used to train a support vector regression for accurate prediction. The setting parameters of the proposed model are trained by a new optimization algorithm based on the harmony search algorithm to get to the most optimal training targets. The proposed optimization algorithm makes use of the crossover and mutation operators from genetic algorithm to escape from the local optima and find the global solutions. Experimental tidal data from Persian Gulf, Iran, are used to assess the accuracy and performance of the proposed model. The results show the appropriate performance and high precision of the proposed model in comparison with other famous methods.**

***Index Terms*— Fuzzy feature selection, harmony search (HS) algorithm, support vector regression (SVR), tidal current.**

Nomenclature

σ	Spread factor of the membership function.
x,y	Input/output samples points.
μ_{ij}	Membership function connecting x_i to y_j
N_p	Number of features.
m_i	Mean value of data set y_i.
Γ_1	Height of the fuzzy membership function.
Γ_2	Fuzzy membership function Roughness.
$\Gamma_i^{\max}$ / $\Gamma_i^{\min}$	Maximum and minimum values of Γi.
ω_i	Weighting for the i^{th} criterion.
Nc	Number of targets, here 2.
Ψ	Mother wavelet.
$\phi_{j0,k}$	Scaling function of the coarse scale.
$c_{j0,k}/\omega_{j0,k}$	Scaling functions of detail coefficients.
Ω	Problem search space.
N	Number of tidal current samples.
Θ_ε	ε-insensitive loss function.
C	Constant for trade-off between two terms.
W/b	Weighting/biasing factor of SVR function.
$\theta(x_t,x)$	Kernel function.
ξ	Training error.
Π^* & Π	Lagrangian multipliers.
HMCR	HM considering rate in HS
PAR	Pitch adjusting rate in HS.
bw(g)	Distance bandwidth in HS.
$bw_{\max}$/$bw_{\min}$	Max/Minvalue of the bandwidth.
NI	Number of improvisations.
$PAR_{\max}$/$PAR_{\min}$	Max/Min value of *PAR* parameter.
g	Iteration number.
$\beta_1,\ldots,\ \beta_6$	Random values in the range of [0,1].
I_{rand}	Random integer.
X_{best}	Best solution found to data.
HMCR	HM considering rate in HS algorithm.
PAR	Pitch adjusting rate in HS algorithm.
rand()	Random value generator.

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I. Introduction

GLOBAL warming and high price of fossil fuels have attracted the attention of researchers toward the renewable energy sources as sustainable power productions. Some of the most popular and well-known renewable energy sources can be named as wind, solar, tidal, biomass, and biogas. Nevertheless, the unreliable and intermittent characteristics of renewable energy sources are big barriers in front of transferring and wide usage of these energy sources in the power grids [1]. Among different types of renewable energy sources, high load factors resulting from the fluid properties and the high predictable feature make tidal currents mainly attractive for power generation. In order to harness this big source of energy, many attempts have been made by the researchers and engineers in the last years [2]. Fig. 1 shows a concept for harnessing the tidal energy in the sea.

Some research work has investigated the amount of energy which can be extracted from the tidal power in a specific site

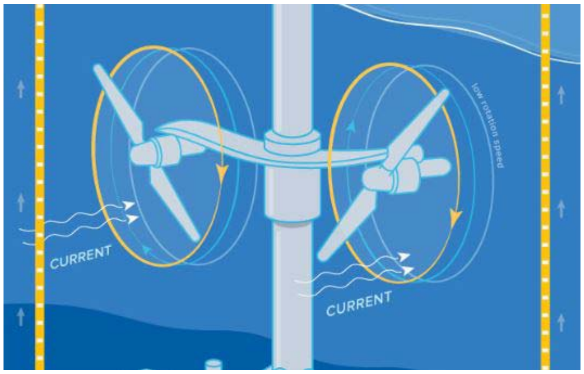

Fig. 1. Tidal current deployment in the sea [2].

with specific geometry characteristics including simple uniform channel [3], a channel with a varying cross section linking two large water bodies [4], a channel connecting a bay to a large basin [5], or sites where the flow is less restricted such as the accelerated flow around headlands [6]. There are some works assessing the effect of sea level rise on the tidal energy distribution using numerical models [7], [8]. Recently, a few researchers have started focusing on the prediction of tidal current and direction for accurate modeling and harnessing of the tidal energy. In [9], a hybrid model based on autoregressive integrated moving average and support vector regression (SVR) is proposed to model the linear and nonlinear components of the tidal current for prediction. In [10], a probabilistic method based on neural network (NN) is developed to generate optimal prediction intervals around the actual tidal sample records. In [11] and [12], different NN models are proposed to model the tidal current and power. In [13], the tide-generating forces are considered to predict the tidal current based on NN.

Each of the above works has caused good progress in the tidal current energy and power harness. Nevertheless, none of them have addressed the significance of feature selection on the prediction quality and precision. In the statistics and machine learning, feature selection is the process of selecting a subset of relevant features to construct the most appropriate model. Some of the well-known feature selection methods are mutual information [14], sequential search algorithms [15], genetic algorithms (GAs), and particle swarm optimization (PSO)—support vector machine [16]. The main drawback with these methods is the high computational burden with the increase of the number of input features and model complexity. Therefore, this paper proposes a new feature selection approach based on fuzzy set theory and clustering to extract the most preferable features in the input set. The best features are further feed to a prediction model based on SVR to find the most accurate results. In order to adjust the SVR parameters, harmony search (HS) algorithm is proposed. HS algorithm is a heuristic optimization algorithm which mimics the interactive collaboration among the musicians for getting to the most harmony. A new modification method is proposed for HS to improve its search ability by escaping from the local optima. The feasibility and performance of the proposed feature selection and prediction models are examined using the practical tidal data from Persian Gulf, Iran.

II. Fuzzy Feature Selection

Feature selection is the process of mitigating the number of features by getting rid of the inappropriate, noisy, and redundant features such that the remained features would result in a more accurate prediction, classification or modeling. Also, a proper feature selection will increase the training process and avoid high complexity and thus computational burden. Considering the importance of this technique, this section proposes a new feature selection based on fuzzy theory. In order to explain the mathematical formulation, a data set with the input and output features (x_{ij}, y_i) are assumed. In this notation, x_{ih} shows the data of jth pattern in ith input. Considering N_p number of training patterns, one can plot N_p number of curves for (x_{ij}, y_i) $\forall j \in N_p$, each showing the dependence of output y_i on the input feature x_{ij}. Considering the above 2-D plot, a fuzzy membership function $\mu_{\ i,j}$ can be defined as follows:

$$\mu_{ij} = e^{\left(-\left(\frac{x_{ij}-x_i}{\sigma}\right)^2\right)};\ j \in N_p \tag{1}$$

where σ is the spread factor of the membership function which is considered about 20% of the input interval. It should be noted that other fuzzy membership functions such as trapezoidal and triangular can also be used. Here, a fuzzy Mamdani rule is generated which states "If x_i is $\mu_{\ i,j}$ then y is y_j." Considering N_p as the number of features, N_p numbers of membership functions are generated. For each input feature x_i, the centroid defuzzification is employed to produce an output variable d_i as follows:

$$d_i(x_i) = \frac{\sum_{j=1}^{N_p} \mu_{ij}(x_i).y_j}{\sum_{j=1}^{N_p} \mu_{ij}(x_i)}. \tag{2}$$

For each input x_i, the fuzzy curve d_i shows the dependence level of output y_i on input x_i. If the shape of fuzzy curve d_i is smooth lacking big distance between the maximum and minimum heights, then the input variable $x_i$has little influence on the output variable y and thus is assumed as an unimportant feature in the model. On the other hand, a rough and irregular fuzzy curve with big distance between the maximum and minimum heights is considered as an effective feature in the modeling process. Therefore, the importance of each feature is determined based on: 1) the height and 2) roughness. The difference (height) between the maximum and minimum points of d_i can be easily measured

$$\Gamma_1(i) = \max(y_{ik} - y_{ij})\ \ \forall\, k,\quad j \in N_p,\quad i \in N. \tag{3}$$

For roughness, another fuzzy criterion is required which is defined as follows:

$$\Gamma_2(i) = \sqrt{\frac{1}{N_p}\sum_{j=1}^{Np}(y_{ij} - m_i)^2}\quad \forall i \in N. \tag{4}$$

Therefore, the significance of each variable x_i is determined by the corresponding values of $\Gamma_1(i)$ and $\Gamma_2(i)$.Due to the difference range values of the above two criteria, the idea

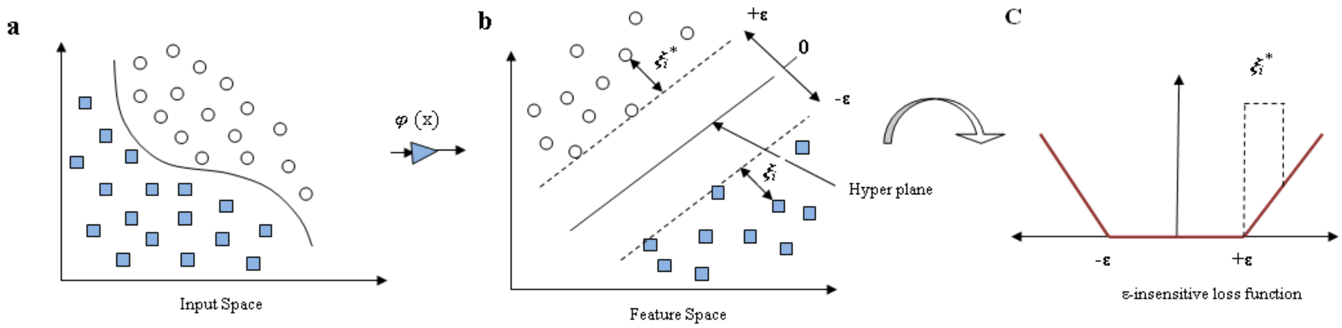

Fig. 2. Conceptual illustration of the SVR for (a) input space, (b) feature selection, and (c) ε-insensitive loss function.

of minimum—maximum fuzzy can be used here to convert the above multi-objective optimization problem into a single-objective optimization problem. Therefore, for each criterion, a fuzzy membership function can be defined as follows:

$$\mu_{\Gamma_i}(X) = \begin{cases} 0; & \Gamma_i(X) \quad \geq \Gamma_i^{\max} \\ \dfrac{\Gamma_i^{\max} - \Gamma_i(X)}{\Gamma_i^{\max} - \Gamma_i^{\min}} \Gamma_i^{\min} \leq; & \Gamma_i(X) \leq \Gamma_i^{\max} \\ 1; & \Gamma_i(X) \leq \Gamma_i^{\min}. \end{cases} \tag{5}$$

Here $\Gamma_i^{\max}$and $\Gamma_i^{\min}$ are determined among the N number of input variables. Finally, the most appropriate features are sorted by the use of the following equation:

$$N_\mu(j) = \frac{\sum_{i=1}^{N} \omega_i \times \mu_{\Gamma_i}(X_j)}{\sum_{j=1}^{Nc} \sum_{i=1}^{N} \omega_i \times \mu_{\Gamma_i}(X_j)}. \tag{6}$$

III. Support Vector Regression

This section explains the prediction model. Support vector machine is a class of prediction models which is fundamentally constructed based on two main features: 1) minimizing the training error and 2) avoiding high complexity in the prediction model. The first concept aims to learn the training set optimally. The second concept is for avoiding the overfitting issues in the face of highly nonlinear and complex data. SVR characteristics are its kernels, absence of local minima, sparseness of the solution, and controllability provided by changing the margin. Theoretically, it is proven that SVR can model any nonlinear relationship with a linear function in the high-dimensional space. Be on this concept, nonlinear relationship between the input and output data set $\{(x_i, y_i)\}^N$ can be modeled by the linear function f is a linear relationship in a higher dimensional space $\varphi(.) : \Re^n \to \Re^{n_h}$. This linear function, known as SVR function, is formulated as follows:

$$f(x) = W^T \varphi(x) + b \tag{7}$$

wherein the coefficient W and b are determined through the following optimization framework:

$$\text{Min } R_{\text{SVR}} = \frac{1}{N} \sum_{t=1}^{N} \Theta_\varepsilon(y_t, W^T \varphi(x_t) + b) \tag{8}$$

$$\Theta_\varepsilon(y, f(x)) = \begin{cases} |f(x) - y| - \varepsilon; & |f(x) - y| \geq \varepsilon \\ 0; & |f(x) - y| < \varepsilon. \end{cases} \tag{9}$$

In (4), optimizing the model structure results in an optimum hyper plane which does not let over-fitting issues happen. This combinatorial concept can be reflected in a new form as shown in the following:

$$\text{Min}_{W,b,\xi*,\xi} R_\varepsilon(W, \xi*, \xi) = \frac{1}{2} W^T W + C \sum_{t=1}^{N} (\xi_i * + \xi_i). \tag{10}$$

In (10), the first term avoids large weighting factors and flattens the regression function. The second term penalizes a large training error using the ε-insensitive loss function. This concept is depicted in Fig. 2.

In Fig. 2, ξ_t verifies the training error underneath $-\!-\varepsilon$ and ξ_t^* verifies the training error above $+\varepsilon$. Be on this concept, the SVR optimization problem may be reformulated as follows:

$$\begin{aligned} y_t - W^T \varphi(x_t) - b &\leq \varepsilon + \xi_t^*; \quad t = 1, \ldots, N \\ -y_t + W^T \varphi(x_t) + b &\leq \varepsilon + \xi_t; \quad t = 1, \ldots, N \\ \xi_t^* &\geq 0; \quad t = 1, \ldots, N \\ \xi_t &\geq 0; \quad t = 1, \ldots, N. \end{aligned} \tag{11}$$

Equation (11) can be solved easily by the quadratic optimization to determine W

$$W = \sum_{t=1}^{N} \left(\Pi_t^* - \Pi_t\right) \varphi(x_t). \tag{12}$$

Therefore, (8) and (9) can be shown as follows:

$$\begin{aligned} f(x) &= \sum_{i=1}^{N} \left(\Pi_t^* - \Pi_t\right) \theta(x_t, x) + b \\ \theta(x_t, x) &= \varphi(x_t) \circ \varphi(x_t). \end{aligned} \tag{13}$$

Here (x_t, x) is the kernel function which defines the distribution of similarities of point x around the given point x_t.

IV. Modified Harmony Search Algorithm

This section explains the HS algorithm and a new modification method for determining the optimal setting parameters of SVR including the kernel function (σ) and optimal hyper plane parameters (C and ε). HS algorithm was first introduced in 2001 by Xiang *et al.* [17] to mimic the harmony among the musicians for producing a powerful optimization algorithm. Initially, a random set of solutions are generated which are stored in the harmony memory (HM). Each note in HM is played by a musician to get to the highest harmony based on three main concepts: 1) memory consideration; 2) pitch adjustment; and 3) random research. By combining these three methods, two main improvisation stages are produced.

A. Memory Consideration and Random Research

In this phase, each musician plays a note based on his/her memories (using HM) and some random search to improve its harmony. Therefore, a constant parameter called HM considering rate is defined first. Then, the following equation is used to construct the first improved notes [16]:

$$x_{\text{kh}}^{\text{new}} = \begin{cases} x_{\text{kh}}^{\text{HM}}; & \text{rand} < \text{HMCR} \\ x_{\text{kh}}^{\text{rand}}; & \text{otherwise.} \end{cases} \tag{14}$$

B. Pitch Adjustment and Random Research

Any new note produced by the last step is double checked to see whether it requires a pitch adjustment or not. Pitch adjustment process is done by defining pitch adjusting rate (PAR) parameter as follows [16]:

$$x_{\text{kh}}^{\text{new}} = \begin{cases} x_{\text{kh}}^{\text{HM}} \pm \text{rand} \times bw; & \text{rand} < \text{PAR} \\ x_{\text{kh}}^{\text{rand}}; & \text{otherwise.} \end{cases} \tag{15}$$

$$bw(g) = bw_{\max} \times e^{\rho g}$$

$$\rho = Ln\left(\frac{bw_{\min}}{bw_{\max}}\right) \times NI^{-1}. \tag{16}$$

Also, it is shown in the literature that PAR can be updated to improve the improvisation stage as follows:

$$\text{PAR}(g) = \text{PAR}_{\min} + \frac{g}{\text{NI}} \times (\text{PAR}_{\max} - \text{PAR}_{\min}). \tag{17}$$

While HS algorithm is a powerful tool for optimizing the nonlinear constrained problem, this paper proposes a new modification method to improve its search ability. In each iteration and after the improvisations stages, three dissimilar notes X_a, X_b, and X_c are chosen in HM such that $a \neq b \neq c$. Then the mutation operator borrows from the GA to create a mutated solution as follows:

$$X_{\text{mut}} = X_a + \beta_1 \times (X_b - X_c). \tag{18}$$

Considering X_{mut}, X_i,and X_{best}, crossover operator is employed to produce three random solutions as follows:

$$x_h^{\text{new1}} = \begin{cases} x_{\text{mut},h}; & \beta_1 \le \beta_2 \\ x_{\text{best},h}; & \text{otherwise} \end{cases} \tag{19}$$

$$x_h^{\text{new2}} = \begin{cases} x_{\text{mut},h}; & \beta_2 \le \beta_3 \\ x_{\text{kh}}; & \text{otherwise} \end{cases} \tag{20}$$

$$X^{\text{new3}} = \beta_4 \times X_{\text{best}} + \beta_5 \times (X_{\text{best}} - \text{HM}(I_{\text{rand}})). \tag{21}$$

In order to improve the convergence characteristics of HS, a second formulation is developed which will force the HM to move toward the best solution in the population as follows:

$$X^{\text{new4}} = X_i + \beta_6 \times (X_{\text{best}} - X_i). \tag{22}$$

TABLE I
INPUT AND OUTPUT VARIABLES OF MLP—ANN

Feature selection method	MAPE	CPU Time (Sec.)
PCA	2.5530	47.0
PSO-SVR	2.7117	323.8
Tabu search-SVR	2.4312	317.2
GA-SVR	2.8940	311.6
Fuzzy feature selection-SVR	2.2471	5.146

V. PREDICTION QUALITY AND CRITERIA

In order to compare the prediction accuracy of different methods, some criteria are required to determine the prediction quality. Given the discreteness of the input features, this paper makes use of the mean absolute percentage error (MAPE) to assess the predictive quality of the proposed model. Nevertheless, other prediction criteria might also be interesting for different experts in the area which a set of the most popular ones are provided below as follows.

1) Relative percentage error

$$\text{E}_t\% = \frac{|\widetilde{y}_t - y_t|}{y_t} \times 100, \quad t = 1, 2, \ldots, N. \tag{23}$$

2) MAPE

$$\text{MAPE}\% = \frac{1}{N}\sum_{t=1}^{N} \text{E}_t. \tag{24}$$

3) Maximum absolute relative percentage error (MARPE)

$$\text{MARPE} = \max(\text{E}_t\%), \quad t = 1, 2, \ldots, N. \tag{25}$$

4) Root-mean-square error (RMSE)

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} \text{E}_t^2}. \tag{26}$$

VI. EMPIRICAL RESULTS

In this section, the performance of the proposed method is examined using the experimental tidal data in Persian Gulf, Iran, 2014. Tidal current direction and speed are recorded in the 10-min time intervals. The size of HM in modified harmony search (MHS) algorithm is supposed to be 25 and the maximum number of 150 iterations is assumed as the termination criterion. In fact, it was seen that the proposed algorithm has converged before 150 iterations and there is not any progress after that. For better comparison, the simulation results of PSO and GA are provided. For PSO, the initial number of particles is 30 and the algorithm optimization is terminated after 1000 iterations. Also, the velocity and weighting factor are assumed as 1.5 and 0.6, respectively. For GA, the size of the population is 600 and the crossover and mutation probabilities are assumed 0.9 and 0.07, respectively. In the first part of the simulations, the performance of the proposed feature selection method is assessed. In order to have a fair comparison; SVR model with the same setting parameter is considered as the prediction tool and different feature selections are compared together. Table I shows the prediction results using different feature selection

TABLE II
COMPARATIVE PREDICTION OF TIDAL CURRENT DIRECTION

Method	MAPE(%)	RMSE	MARPE
ARMA	3.947	3.125	3.927
ANN	2.913	2.833	3.939
SVR	2.847	2.764	3.748
GA-SVR	2.814	3.732	3.637
PSO-SVR	2.712	2.566	3.654
MHS-SVR	2.048	**1.884**	**2.212**

TABLE III
COMPARATIVE PREDICTION OF TIDAL CURRENT SPEED

Method	MAPE(%)	RMSE	MARPE
ARMA	3.735	2.997	3.648
ANN	2.721	2.762	3.621
SVR	2.622	2.600	3.483
GA-SVR	2.593	3.518	3.358
PSO-SVR	2.534	2.442	3.302
MHS-SVR	2.135	**1.873**	**2.203**

methods including principal component analysis, PSO—SVR, Tabu Search—SVR, GA—SVR, and the proposed fuzzy feature selection. Here, the MAPE and computational time (sec) are shown in Table I. According to Table I, the proposed fuzzy feature selection requires much less computational time to determine the optimal features for the SVR model. This event roots in the non-iterative characteristics of the proposed feature selection while the other methods require several iterations to get to converge. From the prediction accuracy, the lower MAPE value shows the superior performance of the proposed feature selection. It is worth noting that the initial possible number of features is 40 which is reduced to seven effective features after feature selection by the proposed model. In fact, the proposed fuzzy feature selection sorts the input features in a descending order. Then, the decision maker can decide to choose a specific number of most significant features based on his/her experience. Nevertheless, the value of N_μ in (6) can always be used as an appropriate criterion for approximating the number of input variables. It is worth noting that the optimal values of the SVR parameters after optimization by MHS are $C = 672$, $\varepsilon = 0.23$, and $\sigma = 0.806$.

Until now, the appropriate performance of the proposed fuzzy feature selection is demonstrated. In the second part of the simulations, the prediction ability of the proposed hybrid MHS—SVR is investigated. After determining the optimal features by the proposed fuzzy feature selection method, they are feed to the MHS—SVR model to predict the tidal data. The prediction results for both tidal current direction and speed are shown in Tables II and III, respectively. In order to have fair comparison, different methods are used to predict the tidal data. In Table II, the proposed method could get to 2.04, 1.884, and 2.212 for MAPE, RMSE, and MARPE criteria, respectively, which are the lowest values for all targets. The lower values of RMSE by the proposed method shows the higher stability of the prediction model in comparison with the other methods in Table II. Similar conclusion can be made from the results in Table III. The superiority and accuracy of the proposed method is deduced from these results, clearly.

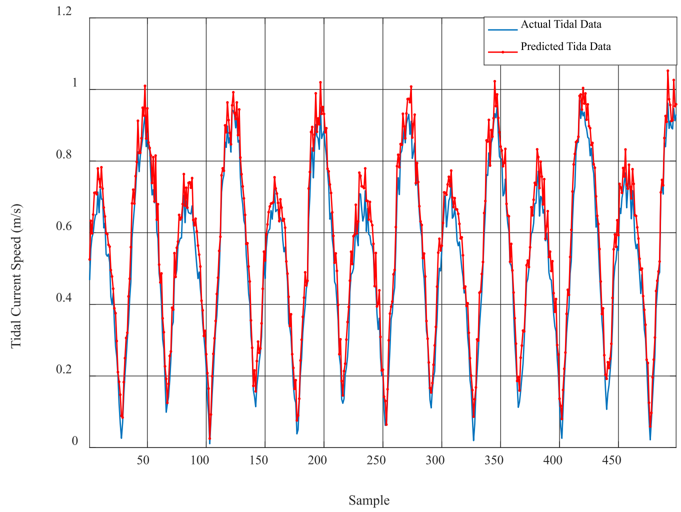

Fig. 3. Tidal current speed prediction results.

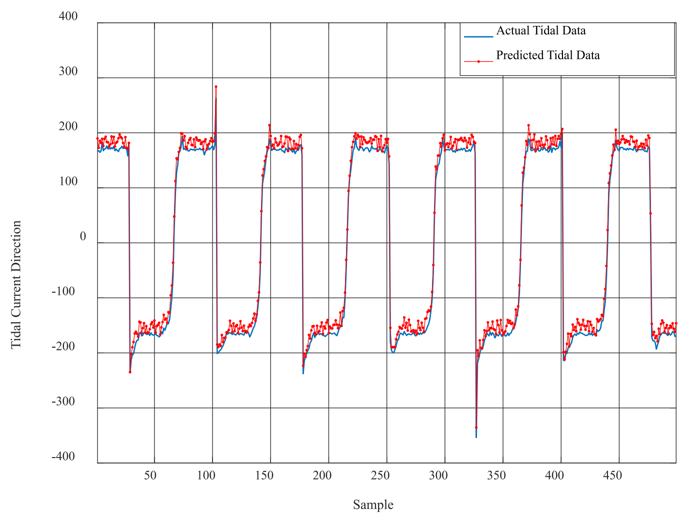

Fig. 4. Tidal current direction prediction results.

Figs. 3 and 4 show the actual data along with the predicted tidal current speed and direction results, respectively. According to Figs. 3 and 4, the prediction results are appropriate in most of the sample points. The main challenging points of prediction have been the peak samples in both tidal current speed and direction data set. Nevertheless, the prediction method could show acceptable tracking capability even in these high volatile points. Similarly, the proposed method could track the sharp points of the tidal data samples with high accuracy which shows the sufficient modeling mechanism of the proposed model. These results show that accurate prediction models can be useful tools for exploiting the tidal power and energy as effective and reliable renewable energy sources in the power grids.

VII. CONCLUSION

This paper proposes a sufficient and practical method based on fuzzy feature selection and support vector machine to develop a reliable prediction model. Also, a new optimization algorithm based on modified HS is proposed to adjust the SVR setting parameters during the training process. The experimental tidal data gathered from Persian Gulf, Iran, are used to examine the performance of the method. The proposed fuzzy feature selection method requires less computational effort when getting higher prediction results. Also, the prediction model based on MHS and SVR shows superior modeling ability in comparison with other well-known methods such as autoregressive moving average, artificial neural network, PSO-SVR, GA-SVR, and original SVR.

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