Wavelet Kernel Least Squares Twin Support Vector Regression for Wind Speed Prediction

Barenya Bikash Hazarika

NIT Arunachal Pradesh: National Institute of Technology Arunachal Pradesh

Deepak Gupta (✉ deepak@nitap.ac.in)

NIT Arunachal Pradesh: National Institute of Technology Arunachal Pradesh <https://orcid.org/0000-0002-6375-8615>

Narayanan Natarajan

Dr Mahalingam College of Engineering and Technology

Research Article

Keywords: Wind speed prediction, wavelet, kernel, twin support vector regression, primal least squares

Posted Date: August 17th, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-522218/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Version of Record: A version of this preprint was published at Environmental Science and Pollution Research on January 24th, 2022. See the published version at <https://doi.org/10.1007/s11356-022-18655-8>.

Wavelet kernel least squares twin support vector regression for wind speed prediction

Barenya Bikash Hazarika¹, Deepak Gupta², Narayanan Natarajan³

^{1,2}Department of Computer Science and Engineering, National Institute of Technology
Arunachal Pradesh, Yupia, Papum Pare – 791112, Arunachal Pradesh, India.

³Department of Civil Engineering, Dr. Mahalingam College of Engineering and Technology,
Pollachi – 642003, Tamil Nadu, India.

Abstract: Wind energy is a potent yet freely available renewable energy. It is essential to estimate the wind speed (WS) precisely to make a precise estimation of wind power at wind power generating stations. Generally, the WS data is non-stationary. Wavelets have the potential to deal with the non-stationary in datasets. On the other hand, the prediction ability of primal least square support vector regression (PLSTSVR) has never been tested to best of our knowledge for WS prediction. Hence, in this work, wavelet kernel-based LSTSVR models are proposed for WS prediction. They are Morlet wavelet kernel LSTSVR and Mexican Hat wavelet kernel LSTSVR. Hourly WS data are collected from four different stations namely Chennai, Madurai, Salem and Tirunelveli in Tamil Nadu, India. The performance of the proposed models is evaluated using root mean square, mean absolute, symmetric mean absolute percentage, mean absolute scaled error and R^2 . The results of the proposed models are compared with twin support vector regression (TSVR), PLSTSVR and large-margin distribution machine-based regression (LDMR). Based on the results of the performance indicators, the performance of the proposed models is better when compared to other models.

Keywords: Wind speed prediction; wavelet; kernel; twin support vector regression; primal least squares

¹barenya1431@gmail.com

² Corresponding author: deepak@nitap.ac.in

³itsrajan2002@yahoo.co.in

1. Introduction

Renewable energy sources are progressively made use of because of the amazingly booming contamination degrees in the air, water, and soil. Wind energy has ended up being the prime focus for energy developers as a result of the accessibility of megawatt size wind equipment, environmental friendliness, low cost of maintenance, ease of availability, etc. Moreover, wind resource is a tidy, limitless and free resource. This resource has offered mankind for numerous centuries in driving the wind turbines and pumping water (Bakhsh et al. 1985). To utilize this resource efficiently, prediction of WS plays a critical role. This is necessary for site planning, performance analysis, and deciding the optimal size of the wind turbine. Rehman and Halawani (1994) predicted wind speed using the autoregressive moving average method. Recently, machine learning (ML) models such as Artificial Neural Network (ANN), Support Vector Machine (SVM), Gaussian Process Regression (GPR), Fuzzy Logic (FL), and Extreme Learning Machine (ELM) has been extensively used for this purpose. Selection of the most appropriate ML technique is very important for obtaining accurate results. Apart from these ML techniques, researchers are nowadays focused on the development of hybrid ML tools to achieve accurate WS forecasting. Furthermore, hybrid ML has the advantage of both algorithms.

Salcedo-Sanz et al. (2011) tried to estimate the short wind speed using an evolutionary SVR model. Wang et al. (2015) forecasted the WS using support vector regression (SVR) optimized by the cuckoo search optimization algorithm. Wang et al. (2016) utilized the SVM whose parameter search was optimized using a novel Steepest descent Cuckoo search algorithm for the dataset which was pre-processed using the empirical mode decomposition. Khosravi et al. (2018) forecasted the WS and wind direction with the help of multi-layer feed-forward ANN, SVM with radial basis function (RBF) and adaptive neuro-fuzzy inference system (ANFIS) optimized using a swarm optimization (SO) called particleSO algorithm. Mi et al. (2019) developed a new WS multi-step forecasting framework based on the singular spectrum analysis, empirical mode decomposition and convolution SVM. Wu and Lin (2019) forecasted the WS based on LS-SVM optimized using the bat optimization algorithm. They applied variation mode decomposition to disintegrate the original WS series into separate sub-series with different frequencies. Fu et al. (2019) coupled SVM with improved chicken SO algorithm for the prediction of WS and the results were compared with SVM-CSO. Xiang et al. (2019) forecasted WS based on the hybrid of improved empirical wavelet transform and LS-SVM. Li et al. (2020)

performed wind power prediction based on SVM with improved dragonfly algorithm. Kumar and Deeba (2020) used a long short-term memory network model and variants of the SVMs for forecasting the WS in the neighbourhood of windmills.

In addition to the above discussed hybrid SVM models, wavelet transform has been used in combination with SVM for the forecasting the WS of a location. There are two types of studies where the wavelet transform (WT) has been adopted. In some of the earlier studies, wavelet has been adopted for the processing of the WS data by considering the same as a signal, while in some other cases a wavelet-based kernel has been used in the SVM model. Some of the studies which fall under the former category have been performed by Liu et al. (2014), Sangita and Deshmukh (2011), Sun et al. (2013), Sivanagaraja et al. (2014), and Prasetyowati et al. (2019). While most of them have considered the only SVM for the former case, Dhiman et al. (2019) have adopted not only SVM but also its variants. They analyzed the efficiency of a hybrid model consisting of WT and several variants of SVR like ϵ -SVR, Least squares SVR, Twin SVR (TSVR) and ϵ -TSVR for the prediction of WS at a farm in Spain. Only a few studies about the latter case have been performed for WS prediction. Zeng et al. (2012) performed wind power prediction using a novel wavelet SVM that changes between the RBF kernel and a Mexican hat kernel. They established that the wavelet SVM outperforms the radial basis function kernel and Mexican hat kernels. He and Xu (2019) predicted the WS of Ningxia using a combination of a wavelet as well as polynomial kernel function and concluded that the combined kernel has better accuracy compared to the single kernel function. Few very recent prominent works are portrayed in Table 1.

Table 1: List of a few recent contributions for wind speed prediction.

Sl No.	Reference	Model/Models proposed	Country/Countries	Term
1	Mi et al. (2019)	Singular spectrum analysis, empirical mode decomposition and convolution neural network-SVM	China	Short-term
2	Zhang et al. (2019)	LSTM and Gaussian process regression (GPR)	China	Short-term
3	Tian et al. (2019)	Improved PSO optimized error minimized extreme learning machine (EM-ELM)	China	Short-term
4	Jamil and Zeeshan (2019)	ANN based chaotic approach	India	Short-term and Long-term
5	Qolipour et al. (2019)	Grey-ELM	Iran	Long-term
6	Jha and Bilalovikj (2019)	ANN	North Macedonia	Very short-term
7	Harboola and Coors (2019)	1 dimensional-CNN	Germany and Netherlands	Short-term
8	Jamil and Zeeshan (2020)	ANN and chaotic approach	India	Short-term and Long-term

9	Vinothkumar and Deeba (2020)	LSTM and SVM	India	Short-term
10	Zhang et al. (2020)	GA-ANN	China	Short- term
11	Tian (2020)	Local mean decomposition and Improved FA optimized least squares SVM	China	Short- term
12	Blanchard and Samanta (2020)	ANN	USA	Short- term
14	Biswas and Sinha (2020)	Singular spectrum analysis, SVM and variational mode decomposition	India	Short-term
15	Liu et al. (2020)	Jaya-SVM	China	Short-term
16	Ruiz-Aguilar et al. (2021)	EMD-ANN	Spain	Short-term and Long-term
17	Xiao et al. (2021)	Self adaptive kernel ELM	China	Short-term
18	Wanag and Yang (2021)	Optimized Elman Neural Network	China	Very short- term

79

80 In this study, the main contributions are:

- 81 1. Motivated by the contribution of Zhang et al. (2004) and Ding et al. (2014), two novel
82 wavelet-based models, namely, Morlet wavelet kernel LSTSVR(MKLSTSVR) and
83 Mexican Hat LSTSVR (MHKLSTSVR) models are proposed for WS prediction.
- 84 2. Inspired by the PLSTSVR model, the optimization problem of the proposed MKLSTSVR
85 and MHKLSTSVR are solved in primal, which always shows better performance
86 compared to solving them in duals (Gupta 2017).
- 87 3. To expand the kernel selection range of the PLSTSVR model and to improve its
88 generalization ability, the wavelet kernels are embedded in the PLSTSVR model.

89 The models have been applied to WS data of four locations in the state of Tamil Nadu,
90 India and the performance of these models has been compared with other ML models such as
91 TSVR, primal least squares twin support vector regression (PLSTSVR) and large-margin
92 distribution machine-based regression (LDMR). The rest of this paper is organized as follows:
93 Section 2 briefly describe the related works. Section 3 describes the wavelet analysis briefly.
94 Section 3 proposes the two novel models. Dataset description and area of study is presented in
95 Section 4. Experimental and numerical analyses are presented in Section 5 while Section 6 shows
96 the conclusion.

97 2. Related works

98 Consider m is the total number of samples. The total training samples can be represented
99 as $\{x_i\}_{i=1}^m \in R^n$. $x_i \in R$ and $y_i \in R^N$ indicates the input training points and original output

respectively. Also, let us consider $A \in R^{m \times n}$ are the training datapoints. Here the i^{th} row vector can be represented as x_i^t . $y = (y_1, \dots, y_m)$ denotes the observed datapoints.

2.1 The TSVR model

TSVR (Peng, 2010) seeks for two non-parallel functions termed as ε – insensitive down-bound $f_1(x) = K(x^t, D^t)w_1 + b_1$ and up-bound function $f_2(x) = K(x^t, D^t)w_2 + b_2$, respectively. The primal problems of TSVR are expressed as:

$$\min \frac{1}{2} \|y - \varepsilon_1 e - (K(G, G^t)w_1 + b_1 e)\|^2 + C_1 e^t \psi_1, \quad (1)$$

$$s.t., y - (K(G, G^t)w_1 + b_1 e) \geq \varepsilon_1 e - \psi_1, \psi_1 \geq 0$$

and

$$\min \frac{1}{2} \|y - \varepsilon_2 e - (K(G, G^t)w_2 + b_2 e)\|^2 + C_2 e^t \psi_2, \quad (2)$$

$$s.t., y - (K(G, G^t)w_2 + b_2 e) \geq \varepsilon_2 e - \psi_2, \psi_2 \geq 0.$$

where regularization parameters are $C_1, C_2 > 0$, and input parameters are $\varepsilon_1, \varepsilon_2 > 0$; the slack variables are indicated by ψ_1 and ψ_2 .

By introducing the Lagrangian multipliers $\gamma_1, \gamma_2 > 0$ and apply the K.K.T. sufficient conditions on (2), the duals of (1) and (2) are expressed as:

$$\max -\frac{1}{2} \gamma_1^t M_1 (M_1^t M_1)^{-1} M_1^t \gamma_1 + R^t M_1 (M_1^t M_1)^{-1} M_1^t \gamma_1 - R^t \gamma_1, \quad (3)$$

$$s.t., 0 \leq \gamma_1 \leq C_1 e$$

and

$$\max -\frac{1}{2} \gamma_2^t M_1 (M_1^t M_1)^{-1} M_1^t \gamma_2 + Q^t M_1 (M_1^t M_1)^{-1} M_1^t \gamma_2 - Q^t \gamma_2, \quad (4)$$

$$s.t., 0 \leq \gamma_2 \leq C_2 e,$$

where, $R = (Y - \varepsilon_1 e)$, $Q = (y + \varepsilon_2 e)$ and $M_1 = [K(G, G^t) \ e]$. The unknowns w_1, w_2, b_1, b_2 can be determined as:

$$\begin{bmatrix} w_1 \\ b_1 \end{bmatrix} = (M_1^t M_1 + \partial I)^{-1} M_1^t (R - \gamma_1)$$

and

$$\begin{bmatrix} w_2 \\ b_2 \end{bmatrix} = (M_1^t M_1 + \partial I)^{-1} M_1^t (Q + \gamma_2),$$

where $\partial > 0$ and I is an identity matrix.

2.2 The PLSTSVR model

In order to diminish the computational complexity of the TSVR model, Huang et al. (2013) suggested a novel LSTVSR solved in primal termed as least PLSTSVR. The formulation of PLSTSVR can be expressed as:

$$\min \frac{1}{2} \| R - (K(G, G^t) w_1 + b_1 e) \|^2 + \frac{1}{2} C_1 \psi_1^t \psi_1, \quad (5)$$

$$s.t., y - (K(G, G^t) w_1 + b_1 e) = \varepsilon_1 e - \psi_1$$

and

$$\min \frac{1}{2} \| Q - (K(G, G^t) w_2 + b_2 e) \|^2 + \frac{1}{2} C_2 \psi_2^t \psi_2, \quad (6)$$

$$s.t., (K(G, G^t) w_2 + b_2 e) - y = \varepsilon_2 e - \psi_2,$$

where $R = (Y - \varepsilon_1 e)$ and $Q = (y + \varepsilon_2 e)$.

Now, by putting the values of (5) and (6) the slack vectors in the objective functions, and further compute the gradient with respect to w_i and b_i for $i=1,2$, and equate to zero; we get,

$$\begin{bmatrix} w_1 \\ b_1 \end{bmatrix} = (M_1^t M_1 + \partial I)^{-1} M_1^t R \quad (7)$$

and

$$\begin{bmatrix} w_2 \\ b_2 \end{bmatrix} = (M_1^t M_1 + \partial I)^{-1} M_1^t Q, \quad (8)$$

where $M_1 = [K(G, G') \quad e]$ is the augmented matrix; $\partial > 0$ is a small positive integer and I is an identity matrix.

The final regressor of PLSTSVR for any new instance $x \in R^n$ can be calculated as:

$$f(x) = \frac{1}{2} (K(x', G)(w_1 + w_2) + (b_1 + b_2)).$$

2.3 The LDMR model

Recently, Rastogi et al.(2020) introduced a margin distribution-based LDMR which was on the spirit of the LDM model (Zhang and Zhou 2014). LDMR simultaneously minimizes the ε – insensitive loss function and the quadratic loss function. Hence, LDMR shows improved regression performance for noisy data and it considers the minimization of scattering which is inside the ε – tube. The primal problem of LDMR can be expressed as

$$\min \frac{l_2}{2} \|y - (Gw + eb)\|^2 + \frac{1}{2} C e^t (\psi_1 + \psi_2) + \frac{l_1}{2} \|w\|^2, \quad (9)$$

$$s.t., y - (Gw + eb) \leq e\varepsilon + \psi_1, \psi_1 \geq 0,$$

$$(Gw + eb) - y \leq e\varepsilon + \psi_2, \psi_2 \geq 0,$$

where the input parameters are $\varepsilon, l_1, l_2, C > 0$; $\|w\|^2 = u_2^t I_0 u_2$ where $I_0 = \begin{bmatrix} I & 0 \\ & \cdot \\ & \cdot \\ 0 & \dots 0 \end{bmatrix}$; $I^{m \times m}$ is an identity matrix.

The dual problem of (9) may be obtained after adding the Lagrangian multiplier and applying the KKT condition as:

$$\min \frac{1}{2} (\gamma_1 - \gamma_2)^t M_1 (l_1 I_0 + l_2 M_1^t M_1)^{-1} M_1^t (\gamma_1 - \beta_2) + y^t M_1 (l_1 I_0 + l_2 M_1^t M_1)^{-1} M_1^t (\gamma_1 - \gamma_2), \quad (10)$$

$$- y^t (\gamma_1 - \gamma_2) + \varepsilon e^t (\gamma_1 + \gamma_2),$$

$$s.t., 0 \leq \gamma_1 \leq Ce, 0 \leq \gamma_2 \leq Ce,$$

where $M_1 = [K(G, G') \quad e]$.

After determining the solution from (10) for β_1 and β_2 , the unknowns w and b can be obtained as (Hazarika et al. 2020a):

$$\begin{bmatrix} w \\ b \end{bmatrix} = (l_1 I_0 + l_2 M_1^t M_1)^{-1} M_1^t (\gamma_1 - \gamma_2 + y).$$

The LDMR regressor $f(\cdot)$ can be obtained for any new sample $x \in R^n$ as:

$$f(x) = [K(x^t, G^t) \quad 1] \begin{bmatrix} w \\ b \end{bmatrix}.$$

3. Proposed Models

The wavelet transform (WT) is an enhanced version of the conventional Fourier transform (FT) that was introduced by Jean Morlet in 1982 (Morlet et al. 1982a; Morlet et al. 1982b). Recently, the WT analysis has gained a lot of interest among the researchers as it overcomes the two key disadvantages of FT (Sifuzzaman et al. 2009; Hazarika et al. 2020a, Hazarika et al. 2020b):

- 1) FT is suitable only for stationary signals whereas WT is suitable for both stationary as well as non-stationary datasets.
- 2) In FT the time information is lost while transforming the time domain to the frequency domain whereas, in WT, the time information is not lost.

Wavelet analysis was initially suggested to enhance seismic signal analysis by switching from short-term analysis of Fourier to improved algorithms to identify and analyze abrupt signal changes (Daubechies 1990; Daubechies 1992; Mallat 1999). The wavelet has the multi-resolution and localization capacity in both, time-domain (TD) and frequency domain (FD). Wavelet transform's TD properties can be elaborated through the wavelet functions which are translated from a wavelet base function (Holland 1992).

The wavelet functions can be derived from the mother wavelet (MW). Let $\lambda(z)$ be the MW function (Hazarika and Gupta 2020). The wavelet function $\lambda(z)$ can be obtained by the temporal translation t and with dilation δ as:

$$f_t(\delta, t) = \frac{1}{\sqrt{\delta}} \int_{-\infty}^{\infty} t(z) \lambda\left(\frac{z-t}{\delta}\right) \delta z \quad \delta > 0. \quad (11)$$

Equation (11) can be represented in the time domain as:

$$f_t(\delta, t) = \frac{1}{\sqrt{\delta}} \int_{-\infty}^{\infty} t(\omega) \lambda(a\omega) e^{i\omega \delta z} \delta z \quad \delta > 0. \quad (12)$$

From (11) and (12) one can observe that the local characteristics of a signal can be reflected through the wavelet transform. Hence the wavelet transforms as an analytical technique has shown great potential (Zhang et al. 2004; Zhou and Ye, 2006; Ding et al. 2016).

3.1 Translation-invariant kernel

The kernel of translation-invariant (TI) is acceptable if and only if the FT is always positive.

Lemma1: Let $\lambda(z)$ be an MW, and let δ and t denote the dilation and translation. If $z, z' \in R^N$, then the dot-product wavelet kernel may be expressed as:

$$K(z, z') = \prod_{i=1}^N h\left(\frac{z_i - t_i}{\delta}\right) h\left(\frac{z'_i - t'_i}{\delta}\right). \quad (13)$$

The TI kernel of (13) may be expressed as

$$K(z, z') = \prod_{i=1}^N h\left(\frac{z_i - z'_i}{\delta}\right). \quad (14)$$

In (14) N represents the total quantity of the sample (Ding et al. 2014).

To generate the TI kernel function, this work uses two wavelet kernel function. They are:

a. Morlet wavelet kernel: $\left(\lambda(z) = \cos(1.75z) \exp\left(-\frac{z^2}{2}\right) \right)$ and

b. Mexican Hat wavelet kernel: $\left(\lambda(z) = (1 - z^2) \exp\left(-\frac{z^2}{2}\right) \right)$.

3.2 Proposed MKLSTSVR

MKLSTSVR indicates the PLSTSVR embedded with the Morlet wavelet kernel instead of using the traditional kernels. To be an acceptable kernel the Morlet kernel should satisfy the TI kernel theorem as shown in equation (14).

Lemma 2: The Morlet wavelet kernel function (MK) satisfies the TI kernel theorem as:

$$K(z, z') = \prod_{i=1}^N \left(\cos\left(1.75 \times \frac{z_i - z'_i}{\delta}\right) \exp\left(-\frac{\|z_i - z'_i\|^2}{2\delta^2}\right) \right),$$

which is an admissible kernel (Zhang et al. 2004). Hence, it is a kernel by which the wavelet kernel trick can be used to construct MKLSTSVR. The basic goal of MKLSTSVR is to search for the optimum wavelet coefficients in feature space spanned by multidimensional wavelet basis (MWB). Thus it obtains the optimal prediction function. Thereby the prediction function for MKLSTSVR can be obtained as:

$$f(z) = \frac{1}{2} \prod_{i=1}^N \left(\cos \left(1.75 \times \frac{z_i - z'_i}{\delta} \right) \exp \left(- \frac{\|z_i - z'_i\|^2}{2\delta^2} \right) \right) (w_1 + w_2) + \frac{1}{2} (b_1 + b_2).$$

3.3 Proposed MHKLSTSVR

MHKLSTSVR indicates the PLSTSVR combined with the Mexican Hat wavelet kernel rather than the traditional kernels. To be an admissible kernel function, the Mexican Hat kernel should also satisfy the TI kernel theorem as shown in equation (14).

Lemma 3: The Mexican hat wavelet kernel function (MHK) follows the TI kernel theorem as:

$$K(z, z') = \prod_{i=1}^N \left(1 - \left(\frac{z_i - z'_i}{\delta} \right)^2 \right) \exp \left(- \frac{1}{2} \left(\frac{z_i - z'_i}{\delta} \right)^2 \right),$$

which also can be considered as an admissible kernel (Zhang et al. 2004). Therefore, the Mexican Hat wavelet kernel trick can be used to construct MHKLSTSVR. Similar to MKLSTSVR, the basic goal of MHKLSTSVR is to find the optimum wavelet coefficients in feature space spanned by MWB. Thereby it obtains the optimum predictor. Thereby the predictor for MHKLSTSVR can be obtained as:

$$f(z) = \frac{1}{2} \prod_{i=1}^N \left(1 - \left(\frac{z_i - z'_i}{\delta} \right)^2 \right) \exp \left(- \frac{1}{2} \left(\frac{z_i - z'_i}{\delta} \right)^2 \right) (w_1 + w_2) + \frac{1}{2} (b_1 + b_2).$$

4. Dataset Description

The state of Tamil Nadu is situated in the southern part of India. Tamil Nadu is bordered by the Eastern Ghats in the north, Anaimalai hills and Kerala in the west, Bay of Bengal in the east, Gulf of Mannar and Palk Strait in the southeast, and the Indian Ocean in the south. The climate of Tamil Nadu ranges from sub-humid to semi-arid. The sites selected for this study has been provided in Figure 1. The geographical information such as latitude (LAT), longitude (LON) and altitude (ALT) of the chosen sites are provided in Table 2. Hourly averageWS data recorded at a height of 50m above ground level was collected from MERRA -2 analysis database

(NASA) for the period of Jan 1980 to May 2018. However, in our experiments, we have considered the data from Jan 2014 to May 2018.

Figure 1. Map of Tamil Nadu showing the chosen four sites (marked with boxes)

Table 2. Geographical locations of the cities in Tamil Nadu, India

S.No	Station	LAT (°N)	LON (°E)	ALT (m)
1	Chennai	13.08	80.27	13
2	Madurai	9.92	78.11	137
3	Salem	11.66	78.14	286
4	Tirunelveli	8.71	77.75	41

The statistics of the WS data of the above four stations has been provided in Table 3 below.

Table 3. Statistics of the wind speed data

S.No	Station	Mean wind speed (m/s)	Median (m/s)	Maximum wind speed (m/s)	Standard deviation (m/s)
1	Chennai	6.228	6.38	18.1	2.381
2	Madurai	4.522	4.5	13.86	1.916
3	Salem	4.619	4.5	14.43	2.049
4	Tirunelveli	5.468	5.41	22.64	2.377

The maximum wind speed of 22.64 m/s is noticed in Tirunelveli and the lowest wind speed of 13.86 m/s is noticed in Madurai. The observation is similar for the mean WS too. Figure 2 shows the hourly wind speed data from January 2014 to May 2018.

(a) Chennai Station

(b) Madurai Station

(c) Salem Station

(d) Tirunelveli Station

Figure 2. Hourly wind speed data measured during January 2014 to May 2018

5. Experimental setup and numerical analysis

To illustrate the prediction capability of the proposed MKLSTSVR and MHKLSTSVR models their performances on a few WS data are compared with TSVR, PLSTSVR and LDMMR. The performances of these implemented models are evaluated using RMSE (Root Mean Squared Error), MAE (Mean Absolute Error), SMAPE (Symmetric Mean Absolute Percentage Error), MASE (Mean Absolute Scaled Error) and R^2 (Coefficient of correlation). The definitions of these evaluators can be expressed as:

$$\text{RMSE} = \sqrt{\frac{\sum_{k=1}^N (o - p)^2}{N}},$$

$$\text{MAE} = \frac{\sum_{k=1}^N |o - p|}{N},$$

$$\text{SMAPE} = \frac{\sum_{k=1}^N |o - p|}{N(p + o)},$$

$$\text{MASE} = \text{mean}|z|; \text{ where } z = \frac{f}{\frac{\sum_{k=2}^N |o_i - o_{i-1}|}{N-1}}, \text{ } f \text{ is the forecast error in the given period.}$$

Here, o and p indicates the observed and the predicted WS values respectively.

All the experiments are conducted on Window 8 installed laptop computer with 4 GB RAM. The QPPs of TSVR and LDMR models are solved using the external MOSEK optimization toolbox. The Gaussian kernel is used for the TSVR, PLSTSVR and LDMR models. The Gaussian kernel may be represented as:

$$K(d_m, d_n) = \exp\left(-\mu \|d_m - d_n\|^2\right), \text{ for } m, n = 1, \dots, m,$$

where d_m, d_n indicates the input data samples. The Gaussian kernel parameter $\mu > 0$ is selected from the range $\{2^{-5}, \dots, 2^5\}$ for TSVR, PLSTSVR and LDMR models. The value of the ε parameter is set from $\varepsilon = \{0.05, 0.1, 0.5, 1, 1.5, 2\}$ for all models including the proposed MKLSTSVR and MHKLSTSVR. The model parameters $C_1 = C_2$ are considered from $\{10^{-5}, 10^{-3}, \dots, 10^5\}$ for all models. The Gaussian kernel parameter λ is taken from the set $\{2^{-5}, 2^{-3}, \dots, 2^5\}$ for TSVR, PLSTSVR and LDMR models. The λ values are chosen from $\{10^{-5}, 10^{-3}, \dots, 10^5\}$ for LDMR. For the proposed MKLSTSVR and MHKLSTSVR models, the wavelet kernel parameter d is fixed to 1.

Two different lag periods are used namely 1-3 and 1-5. Table 4 and Table 5 portray the results based on the various performance evaluators used in this study for the various cities considered for 1-3 and 1-5 respectively. From Table 4, the following conclusions can be derived:

- a) The proposed MKLSTSVR and MHKLSTSVR show the best performance based on RMSE in 0 and 2 cases out of 4 respectively.
- b) In the case of MAE, the proposed MKLSTSVR and MHKLSTSVR obtains best results in 1 case each.
- c) The proposed MKLSTSVR and MHKLSTSVR report the best results based on SMAPE in 2 and 1 cases respectively.
- d) The proposed MKLSTSVR and MHKLSTSVR indicate the best performance based on MASE in 1 and 1 case out of 4 respectively.
- e) The proposed MKLSTSVR and MHKLSTSVR show the best performance based on R^2 in 0 and 2 cases out of 4 respectively.

Table 4. Comparison of TSVR, PLSTSVR, LDMR, MKLSTSVR and MHKLSTSVR based on the performance evaluators, optimum parameters and the computational times for 1-3 lag time period. (Best results are bolded)

Dataset (train, test)	Performance Evaluators	TSVR (C, μ, ε) time (sec)	PLSTSVR (C, μ, ε) time (sec)	LDMR ($C_1, \mu, C_2, \varepsilon$) time (sec)	MKLSTSVR (C, ε) time (sec)	MHKLSTSVR (C, ε) time (sec)
Chennai	RMSE	0.040317	0.032152	0.031793	0.031951	0.031890
	MAE	0.030705	0.023787	0.023889	0.023762	0.024037
	SMAPE	0.110742	0.090936	0.091312	0.091740	0.095099
	MASE	0.943912	0.731252	0.734401	0.730474	0.738916
	R ²	0.91958	0.94218	0.9434	0.942841	0.942999
	Parameters	(10 ⁻³ ,8,1.5)	(10 ⁻⁵ ,4,1)	(10 ⁻¹ , 8, 0.001, 0.05)	(10 ⁻⁵ ,0.5)	(10 ⁻⁵ ,1.5)
	Time	9.77998	1.18909	1.09127	0.992544	0.861059
Madurai	RMSE	0.065534	0.05581	0.053725	0.054514	0.055597
	MAE	0.049161	0.041094	0.040596	0.040875	0.041337
	SMAPE	0.183424	0.154061	0.152974	0.153802	0.156680
	MASE	0.959875	0.802353	0.79264	0.798084	0.807099
	R ²	0.79137	0.84623	0.85563	0.851104	0.845275
	Parameters	(10 ⁻¹ ,8,0.05)	(10 ⁻⁵ ,8,1)	(10 ⁻³ , 8, 0.001, 1)	(10 ⁻⁵ ,2)	(10 ⁻⁵ ,2)
	Time	5.44994	1.52731	1.15297	0.96967	0.887909
Salem	RMSE	0.066159	0.056481	0.058038	0.055535	0.055013
	MAE	0.053527	0.041053	0.041513	0.040799	0.040412
	SMAPE	0.196464	0.154028	0.156257	0.153872	0.155207
	MASE	1.04695	0.802962	0.811969	0.798012	0.790428
	R ²	0.82664	0.84468	0.83438	0.848699	0.85122
	Parameters	(10 ⁻¹ ,2,0.05)	(10 ⁻⁵ ,2,1.5)	(10 ⁻³ , 8, 0.001, 0.1)	(10 ⁻⁵ ,2)	(10 ⁻⁵ ,2)
	Time	9.36352	1.64833	1.15626	1.01518	0.879462
Tirunelveli	RMSE	0.037187	0.029061	0.029063	0.029685	0.290056
	MAE	0.027843	0.0215	0.021501	0.021537	0.021516
	SMAPE	0.131682	0.112339	0.11234	0.112068	0.111240
	MASE	1.05238	0.812639	0.812653	0.814044	0.813238
	R ²	0.90645	0.93187	0.93186	0.928904	0.932099
	Parameters	(10 ⁻¹ ,2,2)	(10 ⁻⁵ ,2,2)	(10 ⁰ , 2, 0.00001, 0.5)	(10 ⁻⁵ ,0.1)	(10 ⁻⁵ ,2)
	Time	9.31972	1.22065	1.11234	0.927693	0.893671

348

349 Further, the size of the window is increased from l-3 to l-5 to enhance the performance.

350 In Table 5, the results are tabulated using a lag window of 5. From Table 5, the following
351 conclusions can be derived:

352 a) The proposed MKLSTSVR and MHKLSTSVR reveal the best results based on RMSE in
353 2 cases each out of 4 respectively.

354 b) The proposed MKLSTSVR and MHKLSTSVR report the best performance based on
355 MAE in 2 cases each.

- c) Based on SMAPE, the proposed MKLSTSVR and MHLSTSVR show the best performance in 3 and 1 case out of 4 respectively.
- d) The best results are noticeable in 2 and 2 cases out of 4 cases for the proposed MKLSTSVR and MHLSTSVR respectively, based on MASE.
- e) For R^2 , the proposed MKLSTSVR and MHLSTSVR portray the best results in 1 and 3 cases out of 4 respectively.

Table 5: Comparison of TSVR, PLSTSVR, LDMR, MKLSTSVR and MHLSTSVR based on the performance evaluators, optimum parameters and the computational times for 1-5 lag time period. (Best results are bolded)

Datasets	Performance Measures	TSVR (C, μ, ε) time (sec)	PLSTSVR (C, μ, ε) time (sec)	LDMR ($C_1, \mu, C_2, \varepsilon$) time (sec)	MKLSTSVR (C, ε) time (sec)	MHLSTSVR (C, ε) time (sec)
Chennai	RMSE	0.033796	0.032002	0.032002	0.302911	0.031758
	MAE	0.025916	0.024031	0.024031	0.023576	0.023781
	SMAPE	0.101085	0.096189	0.096194	0.091211	0.094595
	MASE	0.7968	0.738843	0.73885	0.724851	0.731174
	R^2	0.93735	0.94259	0.94259	0.943063	0.943473
	Parameters	($10^0, 0.125, 2$)	($10^{-5}, 0.03125, 1.5$)	($10^3, 0.03125, 0.00001, 1$)	($10^{-5}, 2$)	($10^{-5}, 2$)
	Time	4.36071	0.96549	0.96191	0.90619	0.89235
Madurai	RMSE	0.060527	0.055502	0.055412	0.054339	0.054904
	MAE	0.047553	0.041597	0.041871	0.041230	0.041442
	SMAPE	0.180651	0.157376	0.160724	0.156715	0.158961
	MASE	0.928585	0.812287	0.817626	0.808513	0.809240
	R^2	0.82487	0.84747	0.84682	0.852824	0.849298
	Parameters	($10^{-1}, 2, 0.05$)	($10^{-5}, 2, 2$)	($10^{-1}, 0.5, 0.00001, 0.05$)	($10^{-5}, 1$)	($10^{-5}, 0.05$)
	Time	5.66962	1.38711	1.20347	1.02159	0.89073
Salem	RMSE	0.063572	0.05765	0.05618	0.061270	0.053512
	MAE	0.050841	0.040804	0.04118	0.041425	0.039551
	SMAPE	0.188865	0.154535	0.156842	0.144427	0.155378
	MASE	0.994576	0.798223	0.805592	0.810834	0.773722
	R^2	0.836	0.84186	0.84954	0.824340	0.860144
	Parameters	($10^{-1}, 2, 0.05$)	($10^{-5}, 2, 2$)	($10^{-1}, 8, 0.001, 0.05$)	($10^{-5}, 0.05$)	($10^{-5}, 1$)
	Time	6.48069	1.61223	1.34246	1.01786	0.03955
Tirunelveli	RMSE	0.033316	0.029369	0.029087	0.032374	0.028655
	MAE	0.026206	0.02196	0.02177	0.021404	0.021260
	SMAPE	0.139118	0.117655	0.116576	0.110642	0.110273
	MASE	0.986401	0.826578	0.81941	0.809213	0.803793
	R^2	0.92185	0.9317	0.93306	0.915509	0.933839
	Parameters	($10^{-3}, 0.125, 1$)	($10^{-5}, 0.03125, 0.5$)	($10^{-1}, 0.5, 0.00001, 0.1$)	($10^{-5}, 0.5$)	($10^{-5}, 2$)
	Time	5.92681	1.43613	1.12457	0.99901	0.88512

Overall, it is noticeable that the increase in the time lag period shows improved performance for the proposed MKLSTSVR and MHKLSTSVR. Figures 3-6 show the comparison between the actual and predicted WS values of TSVR, PLSTSVR, LDMR and the proposed MKLSTSVR and MHKLSTSVR for 1-5. Although all the plots seem to be similar, the overall performances of the proposed models are better compared to TSVR, PLSTSVR and LDMR models based on the evaluators.

Figure 3. Comparison of observed and predicted WS values for Chennai using a lag window of 5.

Figure 4. Comparison of observed and predicted WS values for Madurai using a lag window of 5.

It can also be observed from Table 4 and Table 5 shows that the proposed MKLSTSVR and MHKLSTSVR take less time for computation compared to other models. Thus, it will be interesting to see how the proposed MKLSTSVR and MHKLSTSVR behave in short term WS prediction at different sites.

Figure 5. Comparison of observed and predicted WS values for Salem using a lag window of 5.

Figure 6. Comparison of observed and predicted WS values for Tirunelveli using a lag window of 5.

6. Conclusion

The wavelets are powerful enough to deal with the non-stationary datasets. Moreover, the PLSTSVR model shows excellent prediction performance. Hence in this work, the wavelet kernels are embedded in the PLSTSVR models and two novel wavelets kernel-based PLSTSVR models namely, MKLSTSVR and MHKLSTSVR are proposed for WS prediction in four different wind-stations in India. The results show that the proposed models to be superior when compared to the related models: i.e., TSVR, PLSTSVR and LDMR. Among the proposed MKLSTSVR and MHKLSTSVR models, the latter shows a closer relationship with the original data. Moreover, the proposed models are computationally efficient as they take less time for computation compared to the other reported models. Overall, one can conclude that both MKLSTSVR and MHKLSTSVR are efficient models and applicable for short term WS prediction. These models can also be applied in the field of engineering like a prediction of river suspended sediment load, rainfall forecasting, runoff prediction, etc.

Availability of data and materials: The datasets that has been used in this study are available from co-author on reasonable request.

Authors Contribution: Role of Barenya Bikash Hazarika- Conceptualization, methodology, writing original draft and visualization. Role of Deepak Gupta- Investigation, validation, writing review and editing. Role of Narayanan Natarajan- Writing original draft and formal analysis.

Funding: Not applicable

Declarations

Ethics approval: Not applicable

Consent to participate: Not applicable

Consent to publish: Not applicable.

Competing interests: Authors have no competing interests.

References

- Bakhsh, H., Srinivasan, R., & Bahel, V. (1985). Correlation between hourly diffuse and global radiation for Dhahran, Saudi Arabia. *Solar & Wind Technology*, 2(1), 59-61.
- Blanchard, T., & Samanta, B. (2020). Wind speed forecasting using neural networks. *Wind Engineering*, 44(1), 33-48.
- Daubechies, I. (1990a). The wavelet transform, time-frequency localization and signal analysis. *IEEE transactions on information theory*, 36(5), 961-1005.
- Daubechies, I. (1992b). *Ten lectures on wavelets*. Society for industrial and applied mathematics.
- Dhiman, H. S., Anand, P., & Deb, D. (2019). Wavelet transform and variants of svr with application in wind forecasting. In *Innovations in Infrastructure* (pp. 501-511). Springer, Singapore.
- Ding, S., Wu, F., & Shi, Z. (2014). Wavelet twin support vector machine. *Neural Computing and Applications*, 25(6), 1241-1247.
- Ding, S., Zhang, J., Xu, X., & Zhang, Y. (2016). A wavelet extreme learning machine. *Neural Computing and Applications*, 27(4), 1033-1040.
- Fu, C., Li, G. Q., Lin, K. P., & Zhang, H. J. (2019). Short-term wind power prediction based on improved chicken algorithm optimization support vector machine. *Sustainability*, 11(2), 512.
- Gupta, D. (2017). Training primal K-nearest neighbor based weighted twin support vector regression via unconstrained convex minimization. *Applied Intelligence*, 47(3), 962-991.
- Harbola, S., & Coors, V. (2019). One dimensional convolutional neural network architectures for wind prediction. *Energy Conversion and Management*, 195, 70-75.
- Hazarika, B. B., & Gupta, D. (2020). Modelling and forecasting of COVID-19 spread using wavelet-coupled random vector functional link networks. *Applied Soft Computing*, 96, 106626.
- Hazarika, B. B., Gupta, D., & Berlin, M. (2020a). A coiflet LDMR and coiflet OB-ELM for river suspended sediment load prediction. *International Journal of Environmental Science and Technology*, 1-18.
- Hazarika, B. B., Gupta, D., & Berlin, M. (2020b). Modeling suspended sediment load in a river using extreme learning machine and twin support vector regression with wavelet conjunction. *Environmental Earth Sciences*, 79, 234.
- He, J., & Xu, J. (2019). Ultra-short-term wind speed forecasting based on support vector machine with combined kernel function and similar data. *EURASIP Journal on Wireless Communications and Networking*, 2019(1), 248.
- Holland, J. H. (1992). *Adaptation in natural and artificial systems: an introductory analysis with applications to biology, control, and artificial intelligence*. MIT press.
- Huang, H. J., Ding, S. F., & Shi, Z. Z. (2013). Primal least squares twin support vector regression. *Journal of Zhejiang University SCIENCE C*, 14(9), 722-732.
- Jamil, M., & Zeeshan, M. (2019). A comparative analysis of ANN and chaotic approach-based wind speed prediction in India. *Neural Computing and Applications*, 31(10), 6807-6819.
- Jamil, M., & Zeeshan, M. (2019). A comparative analysis of ANN and chaotic approach-based wind speed prediction in India. *Neural Computing and Applications*, 31(10), 6807-6819.
- Jha, S. K., & Bilalovikj, J. (2019). Short-term wind speed prediction at Bogdanci power plant in FYROM using an artificial neural network. *International Journal of Sustainable Energy*, 38(6), 526-541.
- Khosravi, A., Koury, R. N. N., Machado, L., & Pabon, J. J. G. (2018). Prediction of wind speed and wind direction using artificial neural network, support vector regression and adaptive neuro-fuzzy inference system. *Sustainable Energy Technologies and Assessments*, 25, 146-160.
- Li, L. L., Zhao, X., Tseng, M. L., & Tan, R. R. (2020). Short-term wind power forecasting based on support vector machine with improved dragonfly algorithm. *Journal of Cleaner Production*, 242, 118447.
- Liu, D., Niu, D., Wang, H., & Fan, L. (2014). Short-term wind speed forecasting using wavelet transform and support vector machines optimized by genetic algorithm. *Renewable Energy*, 62, 592-597.
- Liu, M., Cao, Z., Zhang, J., Wang, L., Huang, C., & Luo, X. (2020). Short-term wind speed forecasting based on the Jaya-SVM model. *International Journal of Electrical Power & Energy Systems*, 121, 106056.
- Liu, Y., Shi, J., Yang, Y., & Lee, W. J. (2012). Short-term wind-power prediction based on wavelet transform-support vector machine and statistic-characteristics analysis. *IEEE Transactions on Industry Applications*, 48(4), 1136-1141.
- Mallat, S. (1999). *A wavelet tour of signal processing*. Elsevier.
- Mi, X., Liu, H., & Li, Y. (2019). Wind speed prediction model using singular spectrum analysis, empirical mode decomposition and convolutional support vector machine. *Energy Conversion and Management*, 180, 196-205.
- Morlet, J., Arens, G., Fourgeau, E., & Giard, D. (1982a). Wave propagation and sampling theory—Part II: Sampling theory and complex waves. *Geophysics*, 47(2), 222-236.
- Morlet, J., Arens, G., Fourgeau, E., & Glard, D. (1982b). Wave propagation and sampling theory—Part I: Complex signal and scattering in multilayered media. *Geophysics*, 47(2), 203-221.
- Natarajan, Y. J., & Nachimuthu, D. S. (2019). New SVM kernel soft computing models for wind speed prediction in renewable energy applications. *Soft Computing*, 1-18.
- Peng, X. (2010). TSVR: an efficient twin support vector machine for regression. *Neural Networks*, 23(3), 365-372.

- Prasetyowati, A., Sudiana, D., & Sudibyo, H. (2019, October). Prediction of Wind Power Model Using Hybrid Method Based on WD-SVM Algorithm: Case Study Pandansimo Wind Farm. In *Journal of Physics: Conference Series* (Vol. 1338, No. 1, p. 012048). IOP Publishing.
- Qolipour, M., Mostafaeipour, A., Saidi-Mehrabad, M., & Arabnia, H. R. (2019). Prediction of wind speed using a new grey-extreme learning machine hybrid algorithm: A case study. *Energy & Environment*, 30(1), 44-62.
- Rastogi, R., Anand, P., & Chandra, S. (2020). Large-margin distribution machine-based regression. *Neural Computing and Applications*, 32(8), 3633-3648.
- Rehman, S., & Halawani, T. O. (1994). Statistical characteristics of wind in Saudi Arabia. *Renewable Energy*, 4(8), 949-956.
- Ruiz-Aguilar, J. J., Turias, I., González-Enrique, J., Urda, D., & Elizondo, D. (2021). A permutation entropy-based EMD-ANN forecasting ensemble approach for wind speed prediction. *Neural Computing and Applications*, 33(7), 2369-2391.
- Salcedo-Sanz, S., Ortiz-García, E. G., Pérez-Bellido, Á. M., Portilla-Figueras, A., & Prieto, L. (2011). Short term wind speed prediction based on evolutionary support vector regression algorithms. *Expert Systems with Applications*, 38(4), 4052-4057.
- SangitaB, P., & Deshmukh, S. R. (2011, December). Use of Support Vector Machine, decision tree and Naive Bayesian techniques for wind speed classification. In *2011 International Conference on Power and Energy Systems* (pp. 1-8). IEEE.
- Sifuzzaman, M., Islam, M. R., & Ali, M. Z. (2009). Application of Wavelet Transform and its Advantages Compared to Fourier Transform. *Journal of Physical Sciences*, 13, 121-134.
- Sivanagaraja, T., Tatinati, A. K., & Veluvolu, K. C. A Hybrid Method based on Discrete Wavelets and Least Squares Support Vector Machines for Short-Term Wind Speed Forecasting.
- Sun, Y., Li, L. L., Huang, X. S., & Duan, C. Y. (2013). Short-term wind speed forecasting based on optimized support vector machine. In *Applied Mechanics and Materials* (Vol. 300, pp. 189-194). Trans Tech Publications Ltd.
- Tian, Z. (2020). Short-term wind speed prediction based on LMD and improved FA optimized combined kernel function LSSVM. *Engineering Applications of Artificial Intelligence*, 91, 103573.
- Tian, Z., Ren, Y., & Wang, G. (2019). Short-term wind speed prediction based on improved PSO algorithm optimized EM-ELM. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, 41(1), 26-46.
- Vinothkumar, T., & Deeba, K. (2020). Hybrid wind speed prediction model based on recurrent long short-term memory neural network and support vector machine models. *Soft Computing*, 24(7), 5345-5355.
- Wang, C., Wu, J., Wang, J., & Hu, Z. (2016). Short-term wind speed forecasting using the data processing approach and the support vector machine model optimized by the improved cuckoo search parameter estimation algorithm. *Mathematical Problems in Engineering*, 2016.
- Wang, J., & Yang, Z. (2021). Ultra-short-term wind speed forecasting using an optimized artificial intelligence algorithm. *Renewable Energy*, 171, 1418-1435.
- Wang, J., Zhou, Q., Jiang, H., & Hou, R. (2015). Short-term wind speed forecasting using support vector regression optimized by cuckoo optimization algorithm. *Mathematical Problems in Engineering*, 2015.
- Wu, Q., & Lin, H. (2019). Short-term wind speed forecasting based on hybrid variational mode decomposition and least squares support vector machine optimized by bat algorithm model. *Sustainability*, 11(3), 652.
- Xiang, L., Deng, Z., & Hu, A. (2019). Forecasting short-term wind speed based on IEWT-LSSVM model optimized by bird swarm algorithm. *IEEE Access*, 7, 59333-59345.
- Xiao, L., Shao, W., Jin, F., & Wu, Z. (2021). A self-adaptive kernel extreme learning machine for short-term wind speed forecasting. *Applied Soft Computing*, 99, 106917.
- Zeng, J., & Qiao, W. (2012). Short-term wind power prediction using a wavelet support vector machine. *IEEE transactions on sustainable energy*, 3(2), 255-264.
- Zhang, L., Zhou, W., & Jiao, L. (2004). Wavelet support vector machine. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, 34(1), 34-39.
- Zhang, T., & Zhou, Z. H. (2014, August). Large margin distribution machine. In *Proceedings of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining* (pp. 313-322).
- Zhang, Y., Pan, G., Chen, B., Han, J., Zhao, Y., & Zhang, C. (2020). Short-term wind speed prediction model based on GA-ANN improved by VMD. *Renewable Energy*, 156, 1373-1388.
- Zhang, Z., Ye, L., Qin, H., Liu, Y., Wang, C., Yu, X., ... & Li, J. (2019). Wind speed prediction method using shared weight long short-term memory network and Gaussian process regression. *Applied energy*, 247, 270-284.
- Zhou, X. Y., & Ye, Y. Z. (2006). Application of wavelet analysis to fault diagnosis. *Control Engineering of China*, 13(1), 70-73.