Approximation of Evaporation using Support Vector Regression Model

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Abstract - Evaporation, which is one of the most important component of hydrological cycle, is under the effect of many dynamic factors. Due to its complex structure, it is a difficult parameter to predict. In this study, estimation of evaporation was performed using support vector machines. Different input combinations of metrological data including maximum (Max. Temp), minimum (Min. Temp) air temperature, relative humidity (RH), wind speed (WS) and sunshine hours (SH) were used to estimate evaporation (Evap). Support vector Regression models with different kernel functions were tried and their performance was evaluated using statistical tests Root Mean Square Error (RMSE), Mean Absolute Error (MAE) , Mean Square Error (MSE) and the coefficient of determination (R^2). According to performance criterion, the most successful model for evaporation estimation was determined as Model ε-SVR M-1 with R^2(0.85) with radial basis kernel function.

Keywords: Evaporation approximation, Support Vector Regression model, Kernel Function

I. INTRODUCTION

Evaporation, as a major component of the hydrologic cycle, it plays an important role in water resources development and management. Water scarcity is a major issue of the semi –arid region. The loss of water from open bodies in form of evaporation is inevitable. Therefore, the determination of Evaporation (E) in reservoir is necessary. Different methods for prediction of evaporation are used since 1976,(Stewart and Rouse, 1976). Later Bruin 1978, Anderson and Jobson, 1982; Abtew, 2001; Murthy and Gawande, 2006). Deswal and Pal (2008). They have successfully exercised Artificial Neural Network (ANN) for the resolution of evaporation in reservoirs. ANN is a black box approach having some limitations, low generalization capability, arriving at local minima, overtraining problem and absence of probabilistic output (Kecman, 2001). As a result, alternative methods are needed, which can predict evaporation more accurately.

In this study Support Vector Machine (SVM) is used for predicting evaporation in the reservoir. SVMs have been used for pattern recognition problems. Lately, nonlinear regression estimation is been solved by introducing ε-insensitive loss function (Mukherjee et al., 1997; Vapnik et al., 1997; Samui, 2008). The SVM applies the structural risk minimisation principle (SRMP), which has been recorded to be superior to the more traditional Empirical Risk Minimization Principle (ERMP) which is employed by several other modelling techniques (Osuna et al., 1997; Gunn, 1998). SRMP diminishes an upper bound of the generalisation error whereas, ERMP minimizes the training error. In this way, it produces the better generalisation than traditional techniques.

The objective of this study was to investigate usability of support vector regression (SVR) methods for estimating evaporation using meteorological data such as maximum and minimum temperature (◦C), wind speed (km/hr), relative humidity (%), and sunshine hours (hrs).

Support Vector Machine

Support vector machine (SVM), a supervised learning model which is based on statistical learning theory is introduced by Vapnik (1995).Support vector regression (SVR) is generally used to describe regression with SVM. It performs classification by establishing an N-dimensional hyper plane that optimally separates the data into two categories. SVM models are closely related to neural networks. A detailed principles and algorithms of SVM can be found in Müller et al. (1997). The basic idea is to map the data x into a high dimensional feature space via a nonlinear mapping π and to do linear regression in this space (Boser et al. 1992; Vapnik 1995).

The regression estimation with SVR is to estimate a function according to a given data set {(xi,yi)}i n, where xi denotes the input vector; yi denotes the output value and n is the total number of data sets.

In SVM, the regression function is estimated by the following function:

$$f(x) = \omega \cdot \varphi(x) + b$$

where ω is the weight vector, and b is a bias. $\varphi(x)$ denotes a nonlinear transfer function that maps the input vectors into a high-dimensional feature space in which theoretically a simple linear regression can cope with the complex nonlinear regression of the input space. The coefficients ω and b can be estimated by minimizing the following regularized risk function:

$$R_{reg}(f) = C\frac{1}{n}\sum_{i=1}^{N} L_{\varepsilon}(f(x_i), y_i) + \frac{1}{2}\|\omega\|^2$$

$$L(f(x), y) = \begin{cases} |f(x) - y| - \epsilon & \text{for} |f(x) - y| \geq \epsilon \\ 0 & \text{otherwise} \end{cases}$$

where C is a positive constant named penalty parameter, Lε(f(xi),yi) is called ε-insensitive loss Support-Vector-Machine-Based Models function that measures the empirical risk of the training data; (1/2)||ω||2 is the regularization term; ε is the tube size of SVM.

Finally, a nonlinear regression function is obtained using the following expression.

$$f(x) = \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) k(x_i, x) + b$$

where 'αi' and 'αi *'are the introduced Lagrange multipliers.

With the utilization of the Karush- Kuhn-Tucker (KKT) conditions, only a limited number of coefficients will not be zero among αi and αi *. The related data points could be revealed to the support vectors. k(xi,x) refers to kernel function describes the inner product in the D-dimension feature space.

$$k(x_i, x) = \sum_{i=1}^{D} \varphi_j(x_i)\varphi_i(x)$$

It can be shown that any symmetric kernel function k satisfying Mercer's condition corresponds to a dot product in some feature space (Boser et al. 1992).

The selection of the kernel function to be used and of model parameters plays a vital role to determine the SVR performance. However, there is no any determinant criterion with respect to selection of either kernel function or model parameters (Lin 2006).

The three factors which have potent in SVR performance are ε error term, C configuration factor, and type of kernel function, thereby the parameter of the kernel function (Ekici 2007). The kernel functions commonly used in SVR applications are given in the Table:1.

Table:1 Common Kernel Functions

Kernel types	**Kernel functions**
Linear	$k(x_i, x) = x_i^T x_j$
Polynomial	$k(x_i, x) = (\gamma x_i^T x_j + r)^d$
Radial Basis Function (RBF)	$k(x_i, x) = \exp(-\gamma\|x_i\|^2), \lambda > 0$
Sigmoid (S-shaped).	$k(x_i, x) = \tanh(\gamma x_i^T x_j + r)$

The SVR applications can be carried out in two different models such as ε-SVR and υ-SVR. In this study, ε-SVR model and υ-SVR model along with the four kernel functions are studied.

The program known as DTREG Software has been used to estimate evaporation by the SVR method.

II. MATERIAL AND METHOD

1. Study area

The area selected for the present study is the Nath Sagar Project also called as Jayakwadi Project located (19°29’8.7” N latitude and 75°22'12”E longitude) in Marathwada region of Maharashtra, India. It is one of the largest multipurpose irrigation project of Maharashtra State. The water is mainly used for irrigation in the drought prone regions of Maharashtra state. The water also serves the purpose of drinking and industrial use. Jayakwadi is noted among the largest earthen dams in Asia.

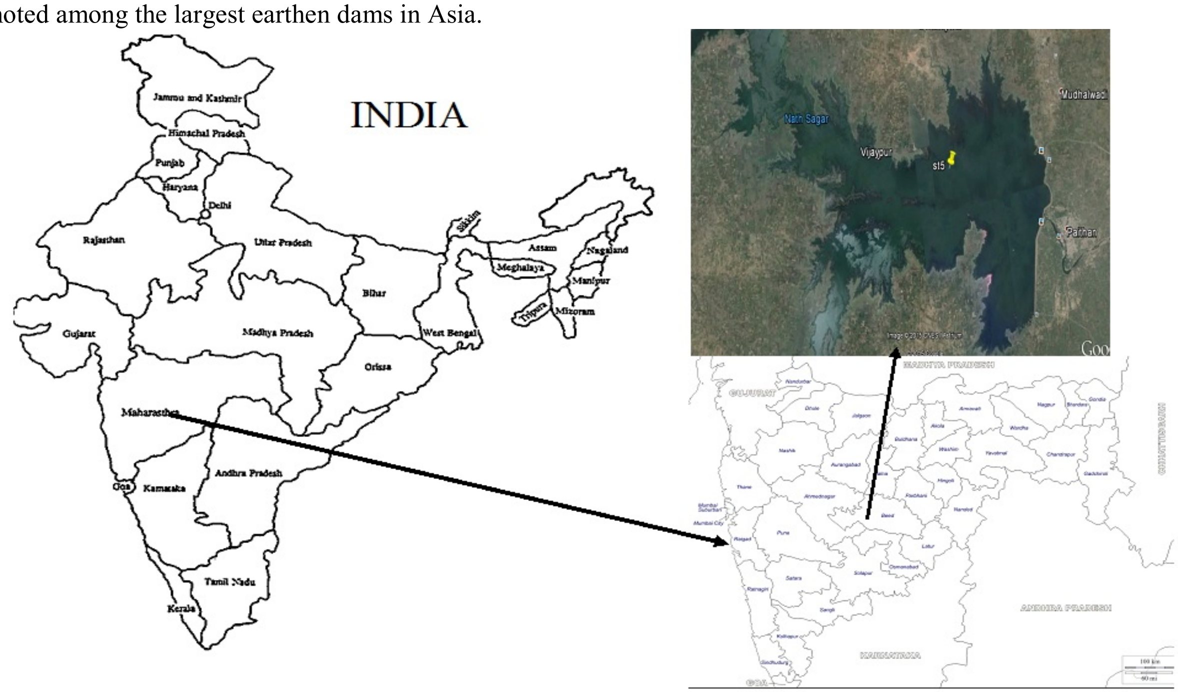

Figure 2. The Location of NathSagar Reservoir

Its height is roughly about 41.30 m and length of 9,998 m (10 km approx) with a total storage capacity of 2,909 MCM (million cubic meters) and effective live storage capacity is 2,171 MCM. The total catchment basin of dam is 21,750 km^2. The Nath Sagar reservoir formed by Jayakwadi Dam is fed by the Godavari and Pravara rivers, the reservoir is about 55 km long and 27 km wide. The total submergence area produced by the reservoir is approx 36,000 hectares.

2. Data Collection

The metrological data of the Nath Sagar reservoir is obtained from the Indian Metrological Department, Pune. The metrological data includes maximum (Max. Temp) and minimum (Min. Temp) air temperature, relative humidity(RH), wind speed(WS), sunshine hours(SH) and evaporation (Evap).Daily data sets for a period of 2000-2013 were available. The data of 2000to 20010 i.e. data of 7 years was considered for the selection of the model and 4 years for validation. This data set was divided into training and testing data sets 70% training and 30% testing. The best model satisfying this data was further used to predict the data for the remaining years. The meteorological data used in this study were divided as input and output parameters to determine the effects of meteorological factors on evaporation. The in Input data were maximum and minimum air temperature (T), relative humidity (RH), wind speed (WS), and sunshine hours (SH); output data was evaporation (Evap). The monthly statistical parameters of the climatic data are given in Table 2;

Table 2. Descriptive statistics of the Nath Sagar Reservoir

Sr no.	Variables*	Units	Minimum Observed	Maximum Observed	Mean	Standard Deviation	Correlation coefficient with evaporation
1	Maximum Air Temperature	°C	19.20	43.30	32.67	4.17	0.76
2	Minimum Air Temperature	°C	5.40	30.80	18.88	4.94	0.37
3	Wind Speed	Km/hr	1.00	23.50	6.94	4.13	0.27
4	Sunshine Hours	Hours	0.19	11.80	7.55	2.73	0.43
5	Relative Humidity	%	13.50	98.50	56.36	19.33	-0.50
6	Evaporation	mm/day	0.20	20.40	4.18	2.13	1.00

Statistical analysis of the meteorological parameters given in Table 1 indicated that all have positive correlation coefficient with evaporation except relative humidity. The highest correlation coefficient is 0.76 of maximum air temperature followed by relative humidity of (-0.5), sunshine hours with (0.43) and (0.37) with minimum air temperature. The lowest correlation coefficient is with wind speed of (0.27).

III. METHODOLOGY

1. Selection of inputs

The selection of input data was done on the bases of the gravity of metrological parameter on evaporation. The input layer includes the input variables: temperature, relative humidity, sunshine hours and wind speed. Four SVM models are proposed ε-SVR M1, ε-SVR M2, ε-SVR M3 and M ε-SVR 4 having five, four, three and two input variables respectively. The preference of variables in the model, is done on the basis of correlation coefficient. The highest correlation value, positive or negative enters first in the model Table: 3 and the variable with the lowest correlation value leaves first.

Table:3 SVM Input Structure

Sr. No.	Model	Max. Temp	Relative Humidity	Sunshine Hours	Min. Temp.	Wind speed
1	ε-SVR M-1	I	I	I	I	I
2	ε-SVR M-2	I	I	I	I	-
3	ε-SVR M-3	I	I	I	-	-
4	ε-SVR M-4	I	I		-	-

2. *Selection of model classification or regression:-*

For classification models with a absolute target variable, you can select either C-SVC or ν-SVC models. For regression models with a uninterrupted target variable, you can select either ε-SVR or ν-SVR models. For many applications, the results generated by the various models are quite similar. There is no way to predict in advance which method will perform better for a specific problem, so it is best to undertake each one.

3. Selection of Kernel function:-

SVM models are built around a kernel function that transforms the input data into an n-dimensional space where a hyperplane are often constructed to partition the data. DTREG furnishes four kernel functions, Linear, Polynomial, Radial Basis Function (RBF) and Sigmoid (S-shaped). There is no way to predict which kernel function will suit best for an application, but the RBF function has been found to do best job in the majority of cases. An SVM model employing a radial basis function kernel has the architecture of an RBF network. However, the tactic for determining the number of nodes and their centers is different from standard RBF networks with the centers of the RBF notes on the support vectors.

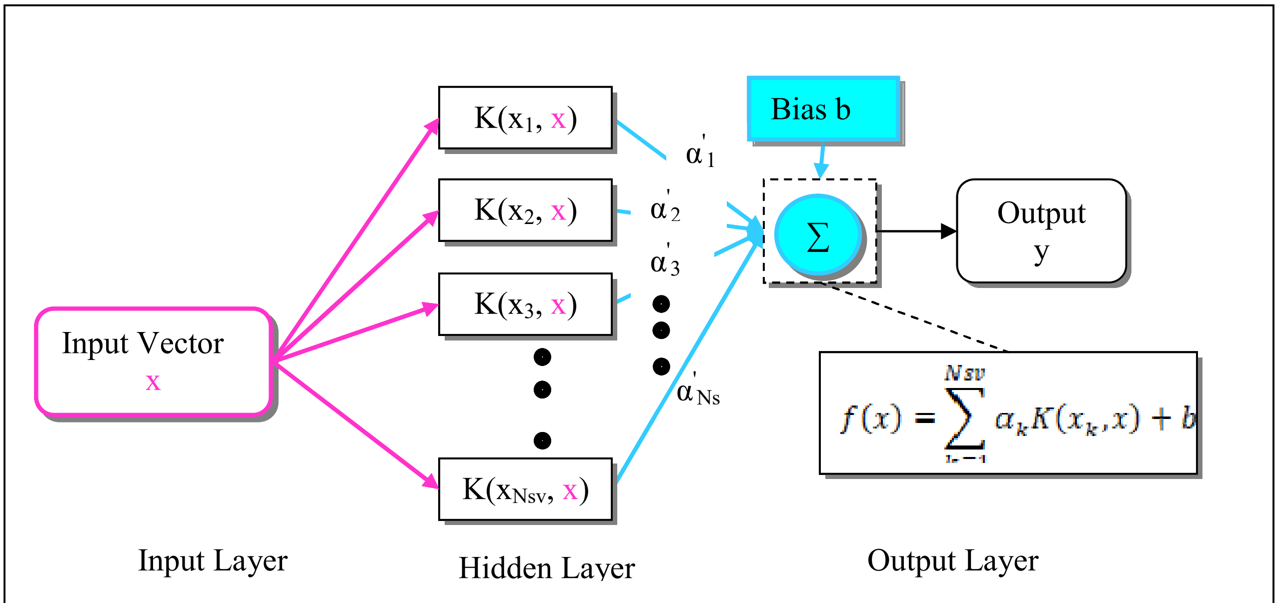

Figure:2. Archetecture of Support Vector Model

4. *Selection Of Optimum Model*

For SVM model, the design values of C, ε and γ have to be determined for best performance of the SVM Model. Researches use trial and error approach for determination of best performance of SVM models (Sivapragasam and Nitin Muttil, 2004; Khan and Coulibaly, 2006; Pal, 2006; Goh and Goh, 2007; Pal and Deswal, 2008; Samui and Sitharam, 2008; Das et al., 2009). The trial and error approach has been done based on the following guidelines: A large C assigns higher penalties to errors so that the regression is trained to minimize error with lower generalisation, whereas a small C assigns fewer penalties to errors; this allows the minimisation of margin with errors, thus, higher generalisation ability. If C approaches to infinitely large, SVM would not allow the occurrence of any error and result in a complex model, whereas when C approaches to zero, the result would tolerate a large amount of errors and the model would be less complex. With regards to the selection of ε, if ε is too large, too few support vectors are selected, which leads to a decrease of the final prediction performance (Thissen et al., 2004). If ε is too small, many support vectors are selected which leads to the risk of over fitting. A large γ indicates a stronger smoothing of Gaussian kernel. So, the trial and error approach has not been done blindly. The adopted trail and approach has robust scientific justification. The developed SVM have been already validated for testing dataset. The performance of the testing dataset is very good for SVM model.

5. *Model Evaluation*

Models performance of each model was studied by judging its statistical performance. Statistical tests were used in this study follow the suggestion by Willmott and Jacovides and Kontoyiannis . The statistical parameters used to test the statistical importance of the evaporation estimate, obtained using a given model are:

Root Mean Square Error (RMSE), Mean Absolute Error (MAE) , Mean Square Error (MSE) and the coefficient of determination (R^2).The following equations were used for the computation of the parameters.

$$\mathbf{R^2 = \frac{E_0 - E}{E_0}}$$

$$\mathbf{E_0 = \sum_{1=1}^{n}\left(E_{1,obs} - E_{mean}\right)^2}$$

$$\mathbf{E = \sum_{1=1}^{n}\left(E_{1,obs} - E_{1,pred}\right)^2}$$

$$\mathbf{RMSE = \left[\frac{1}{n}\sum_{1=1}^{n}\left(E_{1,pred} - E_{1,obs}\right)^2\right]^{1/2}}$$

$$\mathbf{MAE = \frac{1}{n}\sum_{1=1}^{n} | E_{1,obs} - E_{1,pred} |}$$

$$\mathbf{MSE = \frac{1}{n}\sum_{1=1}^{n}\left(E_{1,obs} - E_{1,pred}\right)^2}$$

where, Ei,obs is observed evaporation, mm/day, Ei,pred is predicted evaporation, mm/day and n is number of data pairs.

IV. RESULTS AND DISCUSSION

The data set were applied to the support vector regression models to estimate the amount of evaporation from the Nath Sagar reservoir has been divided into two sub-sets; a training dataset to build the model, and a testing dataset to estimate the model performance. In this study data sets of 2000-2006 are considered as the training dataset and 2007-2010 are considered as the testing dataset. Researchers have used different data division between testing and training datasets and it generally varies with problems. There is no thumb rule for data division between training and testing. In this study, adopted data division between training and testing is 70% (i.e. 70% of the available data was used for training) has been given best result. The training and testing datasets have been chosen randomly form the original dataset. By using the inputs maximum (Max. Temp) and minimum(Min. Temp) air temperature, relative humidity(RH), wind speed(WS), sunshine hours(SH) and evaporation(Evap) different combinations of meteorological parameters were used to find the most successful SVR model for the estimation of evaporation amount.

In order to eliminate dimension difference, all the metrological parameters were scaled to [0, 1] before input in the SVM model. The formula is defined as following

$$X = \frac{X_i - X_{min}}{X_{max} - X_{min}}$$

Where X=standardized metrological data of $X_{i;}$ $X_{max=}$ Maximum metrological data; $X_{min=}$minimum metrological data

After estimation of the output values the values are transformed back to original scale by.

$$X_i = X_{min} + X(X_{max} - X_{min})$$

The SVR applications can be performed in two different models such as ε-SVR and υ-SVR. The inputs were fed to both the models with all kernel functions, Linear, Polynomial, Radial Basis Function (RBF) and Sigmoid (S-shaped) Table:4 to decide the best kernel function. In this study, ε-SVR model with Radial Basis Function (RBF) and Sigmoid (S-shaped) is preferred.

Table:4. Comparison between Linear, Polynomial, Radial Basis Function (RBF) and Sigmoid (S-shaped) Kernal function

Kernel Function		**Linear**	**Polynomial**	**RBF**	**Sigmoid**
Training	RMSE	0.905	0.931	0.905	0.94
	MAE	0.777	0.813	0.777	0.808
	MSE	0.820	0.868	0.819	0.883
	R^2	0.72370	0.728	**0.742**	**0.7430**
Testing	RMSE	0.963	0.965	0.963	0.9428
	MAE	0.822	0.834	0.822	0.8198
	MSE	0.9275	0.9315	0.927	0.8892
	R^2	0.7099	0.708	**0.7199**	**0.7219**

The different input combinations on the basis of correlation coefficients were used for the evaporation estimation Table. These models decided the model, the first model ε-SVR M-1 with five inputs Maximum Temperature, Relative Humidity, Sunshine Hours, Minimum Temperature and Wind Speed. The second model ε-SVR M-2with four inputs Maximum Temperature, Relative Humidity, Sunshine Hours and Minimum Temperature. The third model ε-SVR M-3with three inputs Maximum Temperature, Relative Humidity and Sunshine Hours. And the Fourth model with two inputs Maximum Temperature and Relative Humidity.

Table:5 Input Combinations for different models

Sr. No	**SVR models**	**No. Of Inputs**	**Input Combinations**
1	ε-SVR M-1	5	Max. Temp , RH, SH, Min. Temp., WS
2	ε-SVR M-2	4	Max. Temp , RH, SH, Min. Temp
3	ε-SVR M-3	3	Max. Temp , RH, SH
4	ε-SVR M-4	2	Max. Temp , RH

Different combinations of C, $^{\varepsilon}$and γ have been tried to get the best results. The evaluation criteria of the most successful ε-SVR (C, $^{\varepsilon}$and γ) models obtained from these experiments are listed in Table:6 for training and testing data.

Table:6 Results obtained from the ε-SVR model for different input combinations

	Model Name	I/P	Kernel Function	Model Parameters			R2	RMSE	MAE	MSE
				C	ε	γ				
Training	ε-SVR M-1	Max. Temp , RH, SH, Min. Temp, WS	RBF	482.29	0.001	0.003	0.722	0.831	0.786	0.689
			sigmoid	1477.1	0.001	0.012	0.721	0.798	0.791	0.630
	ε-SVR M-2	Max. Temp , RH, SH, Min. Temp.,	RBF	0.3051	0.001	0.68	0.6827	0.7653	0.862	0.585
			sigmoid	427.72	0.001	0.036	0.6499	0.772	0.894	0.595
	ε-SVR M-3	Max. Temp , RH, SH,	RBF	0.669	0.001	0.408	0.699	0.7327	0.855	0.536
			sigmoid	0.861	0.001	0.407	0.662	0.7296	0.8683	0.532
	ε-SVR M-4	Max. Temp , RH,	RBF	1.105	0.001	0.407	0.684	0.6964	0.862	0.484
			sigmoid	499	0.0011	0.077	0.646	0.699	0.8587	0.488
Testing	ε-SVR M-1	Max.Temp , RH, SH, Min.Temp , WS	RBF	482.29	0.001	0.003	0.850	0.594	0.909	0.350
			sigmoid	1477.1	0.001	0.012	0.894	0.511	0.900	0.261
	ε-SVR M-2	Max. Temp, RH, SH, Min. Temp.,	RBF	0.3051	0.001	0.68	0.845	0.572	0.744	0.327
			sigmoid	427.72	0.001	0.036	0.798	0.7338	0.838	0.538
	ε-SVR M-3	Max. Temp , RH, SH,	RBF	0.669	0.001	0.408	0.866	0.594	0.785	0.35
			sigmoid	0.861	0.001	0.407	0.8072	0.6826	0.755	0.465
	ε-SVR M-4	Max. Temp , RH,	RBF	1.105	0.001	0.407	0.8232	0.818	0.762	0.669
			sigmoid	499	0.001	0.077	0.823	0.661	0.7923	0.436

According to the results obtained from ε-SVR models for different input combinations; the most successful model for both kernel functions was determined as ε-SVR M-1 and ε-SVR M-3 model. The models ε-SVR M-1 and ε-SVR M-3 gave a comparative higher value of R^2 in radial basis function of 0.72 and 0.699 respectively for training data set and a value of 0.85and 0.866 for testing data sets. Model ε-SVR M-1 when used with sigmoid kernel function gave a R^2 value of 0.721in training and a value of 0.894 in testing. Model ε-SVR M-3 gave aR^2 value of 0.662 in training and 0.807 in testing when used with sigmoid kernel function. The models ε-SVR M-2 and ε-SVR M-4 gave better results for radial basis functions for testing data sets rather than training datasets. Comparing the results of all models for RBF and Sigmoid function for training and testing model ε-SVR M-1 performed well for both the functions for R^2.

Literature observes that the models obtained by using radial basis kernel function were more successful. It is observed that the models set up with radial basis function resulted more successfully evaluated in terms of both training and testing data. Model ε-SVR M-1 with R^2(0.85),RMSE(0.594), MAE(0.90), and MSE(0.35) was more successful than other models. Although the results for testing data belonging to sigmoid function seemed to be less successful than radial basis, generally it's possible to say that Radial basis kernel function was more successful for ε-SVR M-1 model.

V. CONCLUSIONS

The accurate estimation of evaporation is one of the most important issues in the management of water resources. This work investigated the applicability of SVM for evaporation in Nath Sagar Reservoir using available metrological data.

Four models were developed using different combinations of metrological data including Maximum Temperature, Relative Humidity, Sunshine Hours, Minimum Temperature and Wind Speed for estimation of evaporation. The developed SVM models were tested validated on the basis of Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Square Error (MSE) and the coefficient of determination (R^2). The result demonstrates the applicability of Support Vector Regression model for estimating evaporation with available metrological data.

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