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Empirical Mode Decomposition for River Flow Forecasting

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ABSTRACT

Background: This paper investigates the ability and capability of Empirical Mode Decomposition (EMD) with Least Square Support Vector Machine (LSSVM) model as a forecasting tool to improve the accuracy of river flow forecasting. **Objective:** EMD is used to decompose the monthly river flow data into several Intrinsic Mode Function (IMFs) components and residue. After the decomposition, LSSVM will employ on these components and aggregated to produce the final forecasting values for each input. To assess the effectiveness of this model, monthly river flow recorded data from Selangor River in Malaysia has utilized as the case study. The performance of the EMD-LSSVM model is compared with Single LSSVM model using various statistics measures which is MAE, RMSE, R and CE. **Results:** The results showed that EMD-LSSVM was able to provide a better representation and good forecasting results compared to Single LSSVM model. **Conclusion:** Preliminary results indicated that EMD-LSSVM serves as a useful tool and provide a promising new method for river flow forecasting.

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INTRODUCTION

Having accurate information on river flow is a key factor for the planning and management of water resources. The flow is critical to many activities such as designing flood protection works for urban areas and agricultural land and assessing how much water may be drawn from a river for water supply or irrigation. With the development of software technology, there have been numerous approaches affiliated to the technique used including artificial neural network (ANN). An ANNs is the most widely and comprehensive statistical methods used for time series forecasting including modeling a complex hydrology system and has been successfully employed in modeling a wide range of hydrology process. There were some researchers employed ANN for a stream flow forecasting, and some of them used to compare ANNs with the other traditional statistical technique for stream flow prediction. The majority of the studies showed that ANNs are able to outperform other traditional statistical techniques (Wu *et al*. 2008).

Aside from ANN, Suykens and Vandewalle (1999) have proposed another method for forecasting purpose namely Least Square Support Vector Machine (LSSVM). LSSVM is a modification form of SVM model with an additional advantages that its requires solving a set of only linear equations, rather that quadratic programming which is much easier and computationally more simple. LSSVM method uses equality constraints instead of inequality constraints and adopts the least squares linear system as its loss function, making it computationally attractive and also has an excellent convergence and high precision. LSSVM has been successfully applied in diverse fields (Afshin *et al*., 2007; Gestel *et al*., 2001). In the water resource field, the LSSVM method has received very little attention and only a few applications of LSSVM to modeling of environmental and ecological systems such as water quality prediction (Yunrong & Liangzhong, 2009) have been performed.

However, river flow data are full with non-linearity and non-stationary. These issues cannot simply ignore as it will lead to worse forecasting. Several researcher believe of the idea of divide and conquer principle are important in constructing a river flow forecasting (Lin *et al*., 2012, Yu *et al*., 2008). An EMD offers solutions to non-linearity and non-stationary issues as EMD is a time frequency resolution approach offers a new way by which the non-linearity and non-stationary behavior of time series can be decomposed into series of valuable independent time resolutions (Tang *et al*., 2012). It also reveals the hidden patterns and trend of time series

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applications (At *et al*., 2012). Yu and Chen (2012) also proposed a hybrid model of EMD-BP for short-term passenger flow forecasting. Guo *et al*. (2012) decomposed wind-speed series using EMD and FFNN was used as a forecasting tool. Other than that, Chen *et al*. (2012) proposed an combination of EMD and ANN for tourism-demand forecasting. Lin *et al*. (2012) proposed a combination between EMD based LSSVR for foreign exchange rate forecasting.

In this paper, the main purpose of this study is to further develop a forecasting technique of EMD and LSSVM and used it, to present a river flow forecasting in order to improve the accuracy of river flow forecasting. The application of EMD-LSSVM is expected to increase the accuracy and capability of river flow forecasting as the EMD will decomposed river flow data into several signals in terms of overcoming the non-linearity and non-stationary limitations to the linear model. The proposed approach is compared with the Single LSSVM model and it is shown that the proposed model can yield more accurate results.

Methodology:

This section discuss about EMD, LSSVM and EMD-LSSVM models used for river flow forecasting. The choice of these models in this study was due to the fact that these methods have been widely and successfully used in time series forecasting.

Empirical Mode Decomposition:

The basic idea of EMD is to decompose time series into a sum of oscillatory functions which is called intrinsic mode functions (IMF). Each IMF must satisfy two conditions (Appiah, and Adetunde, 2011) which are:

1. In the whole data set, the number of extrema (maximum and minimum) and the number of zero-crossings must either equal or differ at most by one;
2. At any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero.

The IMFs can be extracted from the time series data set through an iterative decomposition process as described as the following steps:

Step 1: Identify all the local extrema of time series $x(t)$;

Step 2: Connect all the local maxima by a cubic spline line as the upper envelope $x_u(t)$, repeat the procedure for the local minima to produce the lower envelope $x_1(t)$ of the $x(t)$;

Step 3: Calculate the mean of the upper and lower envelops and the first mean time series $m_1(t)$, that is:

$$m_1(t) = [x_u(t) + x_1(t)]/2 \quad (1)$$

Step 4: Evaluate the difference between the original time series $x(t)$ and the mean time series and get the first IMF , that is:

$$h_1(t) = x(t) - m_1(t) \quad (2)$$

Step 5: Obtain the first IMF, and repeat the above steps is necessary to find the second IMF and several other IMFS, until the data reach the final time series $r(t)$ as a residue component becomes constant, a monotonic function, which is suggested for stopping the decomposition procedure.

Step 6: Then the original time series $x(t)$ can be expressed as the sum of these IMFs and a residue,

$$x(t) = \sum_{i=1}^{n} h_i(t) + r(t) \quad (3)$$

where n is the number of IMF components and $r(t)$ is the final residue.

Least Squares Support Vector Machine:

The LSSVM, as a modification of SVM was introduced by Suykens *et al*. (2005). The LSSVM provides a computational advantage over the standard SVM by converting a quadratic optimization problem into a system of linear equations. This new version of SVM simplifies and converge the problem quickly. The LSSVM predictor is trained using a set of time series historic values as inputs and a single output as the target value. The LSSVM has been developed to find the optimally non-linear regression function:

$$y(x) = w^T \phi(x) + b \quad (4)$$

When LSSVM is used for function estimation, the optimization problem is formulated by minimizing the regular function (Suykens *et al.*, 2005) as:

$$\min R(w,e) = \frac{1}{2}w^T w + \frac{\gamma}{2}\sum_{i=1}^{n} e_i^2 \tag{5}$$

subject to the equality constraints

$$y(x) = w^T \phi(x_i) + b + e_i, \quad i = 1, 2, \ldots, n.$$

To solve this optimization problem, Lagrange function is constructed as:

$$L(w,b,e,\alpha) = \frac{1}{2}w^T w + \frac{\gamma}{2}\sum_{i=1}^{n} e_i^2 - \sum_{i=1}^{n}\alpha_i\{w^T\phi(x_i) + b + e_i - y_i\} \tag{6}$$

where α_i is Lagrange multipliers. The solution of (6) can be obtained by partially differentiating with respect to w, b, e_i and α_i accordingly:

$$\frac{\partial L}{\partial w} = 0 \rightarrow w = \sum_{i=1}^{n}\alpha_i\phi(x_i),$$

$$\frac{\partial L}{\partial b} = 0 \rightarrow \sum_{i=1}^{n}\alpha_i = 0,$$

$$\frac{\partial L}{\partial e_i} = 0 \rightarrow \alpha_i = \gamma e_i,$$

$$\frac{\partial L}{\partial \alpha_i} = 0 \rightarrow w^T\phi(x_i) + b + e_i - y_i = 0, \qquad .$$

After elimination of e_i and w as the solution is given by the following set of linear equations:

$$\begin{bmatrix} 0 & \mathbf{1}^T \\ \mathbf{1} & \phi(x_i)^T\phi(x_j) + \gamma^{-1}I \end{bmatrix}\begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix} \tag{7}$$

where $y = [y_1, \ldots, y_n]$, and $\mathbf{1} = [1; \ldots; 1]$, $\alpha = [\alpha_1, \ldots, \alpha_n]$. This finally leads to the following LSSVM model for function estimation:

$$y(\mathbf{x}) = \sum_{i=1}^{n}\alpha_i K(\mathbf{x}_i, \mathbf{x}) + b \tag{8}$$

where α_i and b are the solution to the linear system. For LSSVM, there are many kernel functions, and the examples of the kernel function are as follows:

Linear: $K(x_i, x_j) = x_i^T x_j$

Polynomial: $K(x_i, x_j) = (\gamma x_i^T x_j + r)^d, \quad \gamma > 0$

Radial basis function (RBF): $K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2), \quad \gamma > 0$

where γ, r and d are kernel parameters. The most popular kernel function used in LSSVM is the Radial Basis Function (RBF) because of RBF has superior efficiency compare to other kernels.

Proposed EMD-LSSVM Model:

River flows forecasting is used to predict future values based on past values and other variables. However, the river flows datasets are full with non-linearity and non-stationary. For this reason, the proposed model is employed according to the principal of decomposition and ensemble (He *et al.*,2010; Wang *et al.*,2011; Lin *et al.*,2012). The proposed model of EMD-LSSVM is believe that able overcome the non-linearity and non-stationary problems. The procedures of the proposed model consist of four main steps:

(1) Monthly river flows data time series $x(t)$ were decomposed into n IMF components and one residue component, $r(t)$ EMD technique.
(2) After the decomposition process, each obtained IMFs and residue components is analysed and determine the input models.
(3) After the input models determined, the data is further input to the LSSVM forecasting technique model and consequently, the corresponding forecasted values for all of the input models for all IMFs and residue components are acquired from the forecasting tool.
(4) The forecasted value of each of the input models for all IMFs and residue components in the previous stage will be reconstructed as a sum of all components and will be used as final results accordingly compared with single model LSSVM using several performance measurements. The idea of EMD-LSSVM is presented in Figure 1.

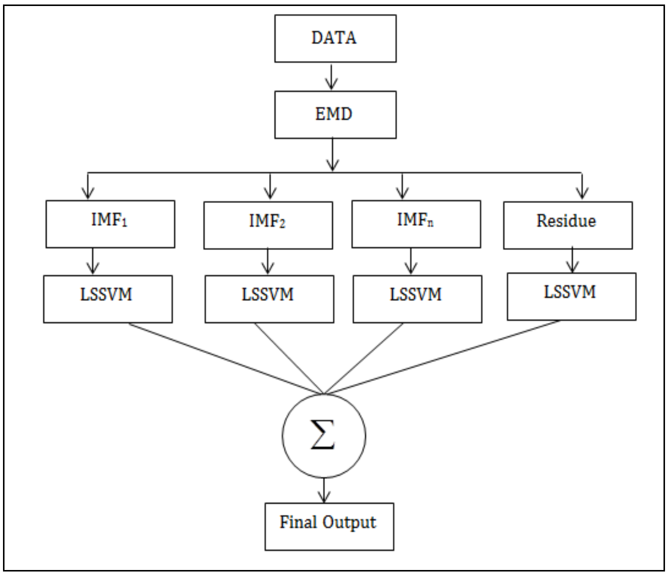

Fig. 1: The proposed model of EMD-LSSVM Model.

Study Area and Data:

In this research, we examined the data obtained from the monthly river flow of the Selangor River located in Selangor, Penisular Malaysia. Selangor River is the third largest river basin catchments area in Selangor, Malaysia. The length of the Selangor River about 110 km from the Main Range mountains bordering the State of Pahang, near the Fraser Hill's resort and flows through the town of Kuala Kubu Baru and Daerah Hulu Selangor, next to the Batang Berjuntai and Kuala Selangor in Kuala Selangor District before entering the mouth of the Malacca Straits. Selangor River basin 70 km in length and catchment area exceeding 2.200 square kilometres and it's also contributes of 60% of water supply for domestic and industrial use of the State of Selangor and the Klang Valley in general. The observation data for Selangor River was recorded from January 1960 to December 2006.

The whole dataset are split up into two parts of 90% and 10% for training and testing respectively. The first dataset consist of 504 monthly records from January 1960 to December 2001 is used for training, while the remaining 60 recorded from January 2002 to December 2006 is used for testing phase. Training data is used exclusively for model development and testing data is used to measure the performance of the model on untrained data. The testing set is also used to evaluate the forecasting ability of the model and to compare the proposed model with others. Figure 2 shown the data plotting for January 1960 until December 2006 for Selangor River in Selangor. This graph shows the time series has a pattern of behaviour is going up and down, and seasonal variation with the highest monthly flow usually occurs between October to December each years.

Performance Criteria:

There are different types of performance evaluation that have been documented in the literature (Luchetta & Manetti, 2003; Goswami *et al*., 2005). The performance evaluation for each model should have at least a measure of absolute error, such as Mean Absolute Error (MAE) or Root Mean Square Error (RMSE) (Legates & McCabe, 1999). Wang *et al*. (2006) stated that RMSE is a good performance evaluation measurement because it is very sensitive to even small errors, in which case it is better to compare the small differences in the model's performance.

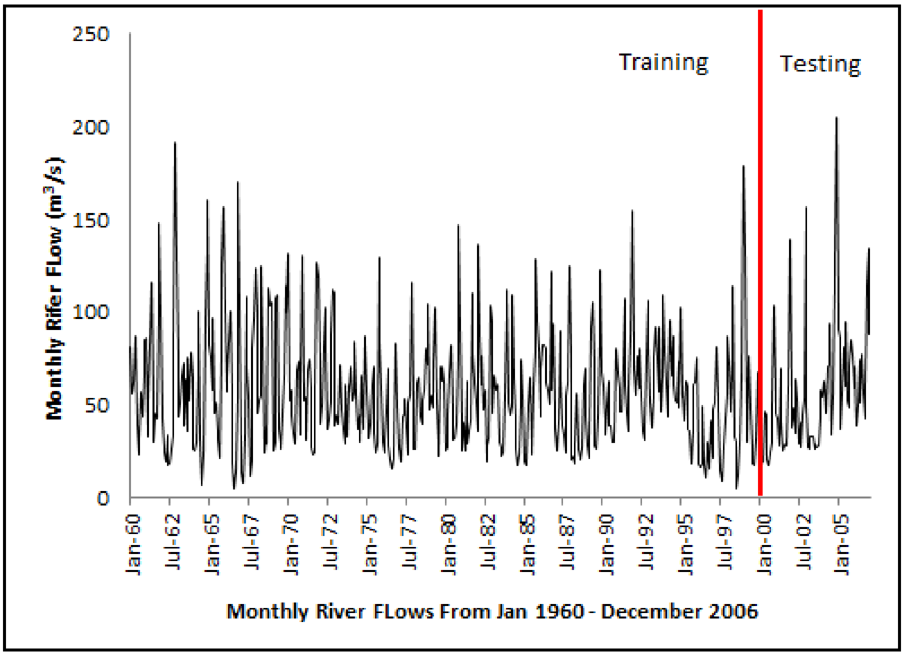

Fig. 2: Monthly Stream flow for Selangor River From January 1960 – December 2006.

The criterions to judge for the best model are relatively small of MAE and RMSE in the modeling and forecasting. Other than that, the Correlation Coefficient (R) was also used as a performance measurement. R was also used to test the ability of the model to capture the complex nature of the process that was being modelled. It is a measure of how well the future outcomes are likely to be predicted by the model, where the predicted flows correlate with the observed flows. The R value is used to evaluate the linear correlation between the observed and the predicted flow. Clearly, an R value close to 1, indicates a satisfactory result, while a low value or close to 0 to implies an inadequate result.

Other than using MAE, RMSE and R, other researchers believe that CE known as Nash–Sutcliffe Coefficient Efficiency is one of the best performance measurements that can be used to assess the predictive power of hydrological models. Essentially, the closer the CE is to one, the more accurate the model.

Table 1: Performance Criterion Used in the Case Studies

Criterion	Label	Formula
Mean Absolute Error	MAE	$\text{MAE} = \frac{1}{n}\sum_{t=1}^{n}\lvert y_t - \hat{o}_t\rvert$
Root Mean Square Error	RMSE	$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{o}_t)^2}$
Correlation Coefficient	R	$R = \frac{\frac{1}{n}\sum_{t=1}^{n}(y_t - \bar{y})(\hat{o}_t - \bar{\hat{o}})}{\sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - \bar{y})^2}\sqrt{\frac{1}{n}\sum_{t=1}^{n}(o_t - \bar{\hat{o}})^2}}$
Coefficient of Efficiency	CE	$\text{CE} = 1 - \frac{\sum_{t=1}^{n}(y_t - \hat{o})^2}{\sum_{t=1}^{n}(y_t - \bar{y})^2}$

$\therefore\ y_t, \bar{y}, \hat{o}_t$ and $\bar{\hat{o}}$ denotes the observed series, the mean of the observed series, the predicted series, and the mean of the predicted series, respectively.

Forecasting Results:

The forecasting results of the proposed model EMD-LSSVM are compared to the non-EMD forecasting models known as single LSSVM model. For the proposed model of EMD-LSSVM, an EMD was first applied to the datasets of monthly river flow data Selangor river. The basic concept of the proposed model is that the data will decomposed into several IMFs and one residue. Based on Figures 3, it indicates that the monthly rivers flow data were decompose into n number of IMFs and one residue respectively. These decomposition results are believe will enhance the models forecasting accuracy. After the decomposition, the independent IMFs and residual components are used in LSSVM model constructions. An LSSVM can do a better forecast for each group of the IMFs.

In this study, RBF was used as the kernel function for LSSVM model. An RBF kernel employed some diverse kernel functions for their modelling and demonstrated that the RBF kernel has superior efficiency than other kernel. In order to better evaluate the performance of the proposed approach, we considered a grid search of (γ, σ^2) within γ the range 10 to 1000, and σ^2 in the range 0.01 to 1.0. For each hyper parameter pair (γ, σ^2) in the search space,10-fold cross validation on the training set was performed to predict the prediction error. The motive of choosing LSSVM is because it involves the equality constraints. Hence, the solution is obtained by solving a system of linear equations. Efficient and scalable algorithms, such as those based on conjugate gradient can be applied to solve LSSVM. At the reconstruction step, all forecasted values from the individual EMD-LSSVM models were combined in order to compare them with other models.

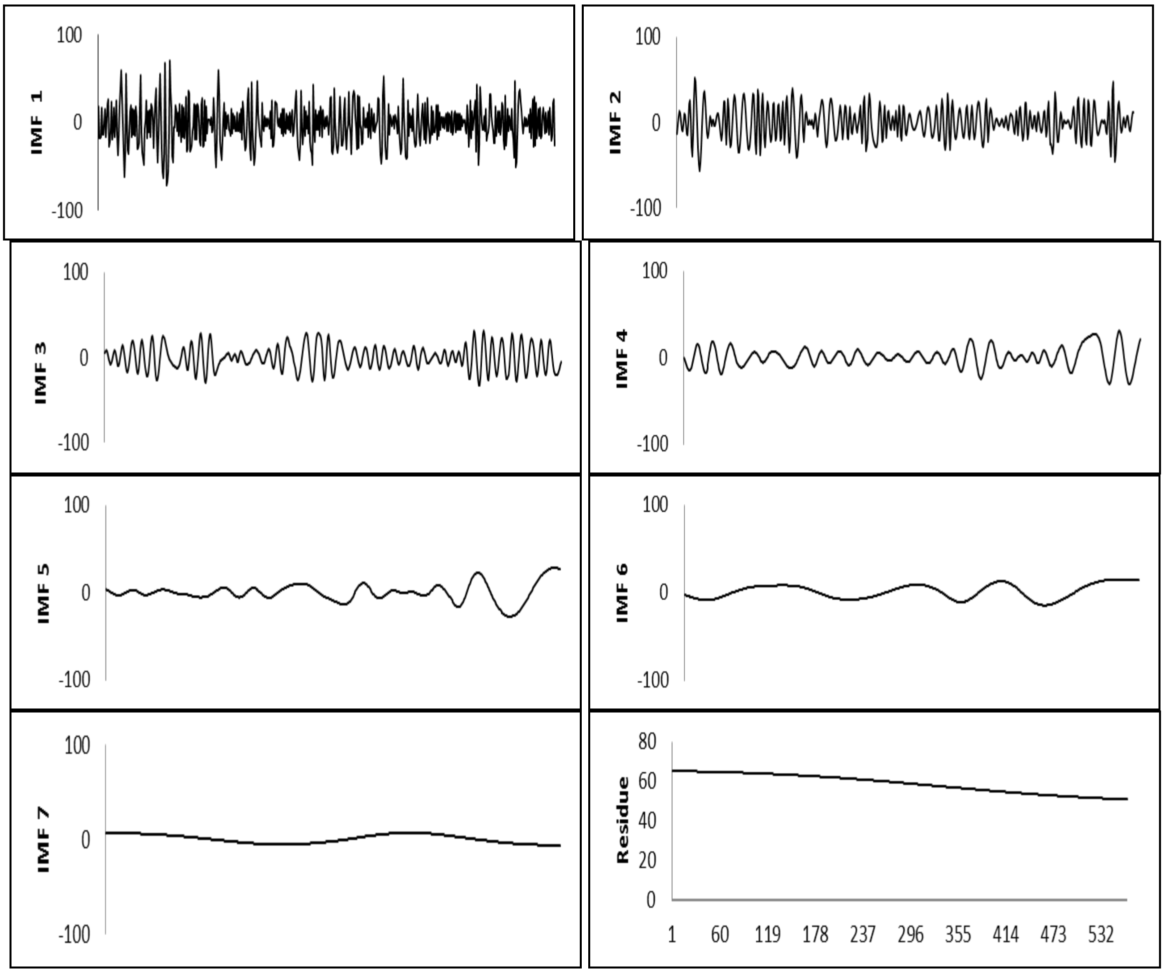

Fig. 3: The extracted IMFs and Residue Components.

Comparison of Forecasting Results:

In this section, the predictive capabilities of the proposed EMD-LSSVM model are compared with single LSSVM for the Selangor monthly river flow. Furthermore, the MAE, RMSE, R and CE are used to evaluate the performance of the both models. The statistical results of the different models are summarized in Table 2. From

Table 2, it can be noted that the EMD-LSSVM model has the best performance with the lowest MAE and RMSE, and the largest R and CE for both of training and testing phase for Selangor River.

In the training phase for Selangor River, the proposed EMD-LSSVM model improved over single LSSVM model with about a 31.76% and 35.35% reduction in MAE and RMSE values respectively, 30.07% and 105.96% improvements for the *R* and *CE* values respectively. As for testing phase, EMD-LSSVM improved over single LSSVM model with about a 176.34% and 45.56% in R and CE values respectively, 32.48% and 37.17% reductions in MAE and RMSE values respectively.

Table 2: Selangor River Comparative performance of LSSVM and EMD-LSSVM.

	Input	Training					Testing			
		MAE	RMSE	R	CE		MAE	RMSE	R	CE
	Input 2	19.8325	25.8352	0.5804	0.3370		21.0176	29.3920	0.5287	0.2773
	Input 4	17.8379	24.7913	0.6374	0.3919		22.1629	29.7939	0.4968	0.2574
LSSVM	Input 6	19.6361	25.9302	0.5807	0.3358		20.4746	29.5992	0.5157	0.2670
	Input 8	19.4290	25.7017	0.5935	0.3478		20.2821	29.5487	0.5229	0.2695
	Input 10	18.6484	25.0947	0.6191	0.3805		19.9669	29.1916	0.5380	0.2871
	Input 12	**17.6232**	**23.6165**	**0.6746**	**0.4526**		**19.0753**	**28.1986**	**0.5884**	**0.3348**
	Input 2	12.7626	16.4598	0.8552	0.9209		13.0922	18.6639	0.8450	0.9170
	Input 4	12.9710	16.3261	0.8582	0.9222		13.7885	18.2454	0.8462	0.9206
EMD-LSSVM	Input 6	12.3833	15.6515	0.8708	0.9285		15.0632	18.3421	0.8451	0.9198
	Input 8	**12.0196**	**15.2676**	**0.8775**	**0.9322**		**12.8785**	**17.7161**	**0.8565**	**0.9252**
	Input 10	12.1346	18.0294	0.8311	0.9056		13.4873	17.8095	0.8560	0.9244
	Input 12	12.2246	19.6128	0.8030	0.8882		14.2090	18.4008	0.8506	0.9193

Figure 4 show the comparison the observed and predicted flows data for the last sixty months for the testing phase on the Selangor River between EMD-LSSVM and Single LSSVM. From Figure 4, EMD-LSSVM gave the most close approximation to the actual observation data compared to Single LSSVM model.

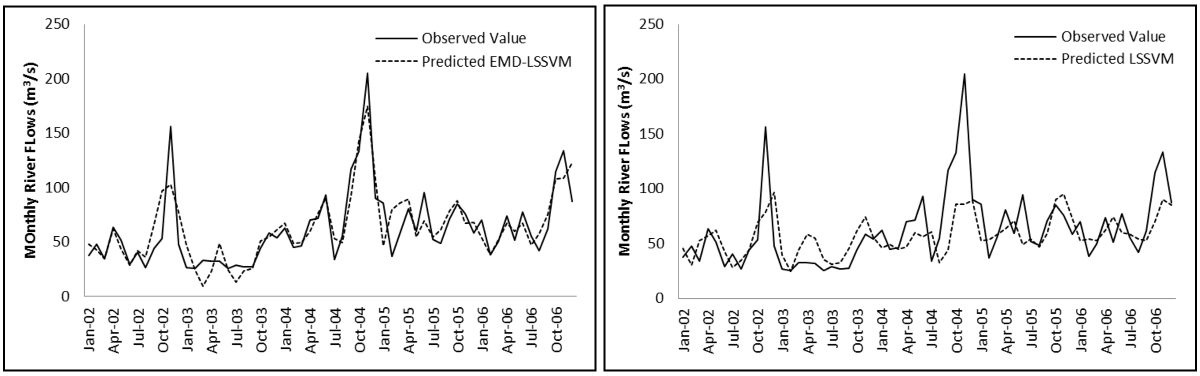

Fig. 4: Predicted and Observed River Flow during Testing Period by EMD-LSSVM and Single LSSVM models For Selangor River

Conclusions:

There has been increasing attention given to finding an effective model to address the problem of river flow forecasting in terms of non-linearity and non-stationary characteristics. In this paper, an EMD-LSSVM model is proposed for river flow forecasting. In this study, Selangor River was used as a case study to demonstrate the capability and ability of EMD-LSSVM in river flow forecasting. An EMD was used to decompose the dataset into several IMFs and a residue. After the decomposition, LSSVM was then used as a forecasting tool.

Through empirical comparison between the proposed EMD-LSSVM and Single LSSVM model, it is proven that EMD-LSSVM model outperforms a single LSSVM based on several performance criteria. The result demonstrates that the performance of river flow forecasting can be significantly enhanced by using the proposed EMD-LSSVM model. Hence, it can be concluded that the proposed EMD-LSSVR model may be an alternative and an effective tool for river flow forecasting. Furthermore, throughout comparison applied in monthly river flow data, it can be concluded that the reduction of the numbers of input variables resulted in the shortening the LSSVM training and testing periods. In this study, only river flow data were considered in analysis, so in the future research can further test the idea of the proposed model by employed the rainfall-runoff data, weather forecast, economic and so on to prove its capability and usability.

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