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MULTIPLE TIME-SCALES NONLINEAR PREDICTION OF RIVER FLOW USING CHAOS APPROACH

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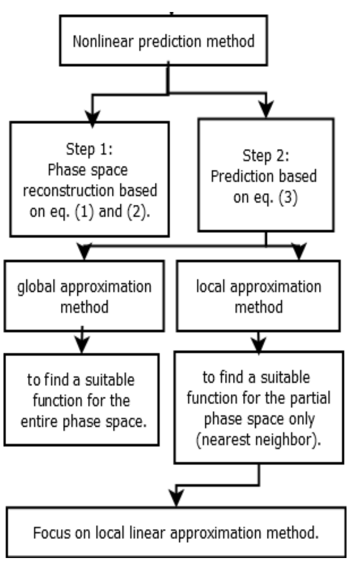
Graphical abstract



Nonlinear prediction method

Abstract

River flow prediction is important in determining the amount of water in certain areas to ensure sufficient water resources to meet the demand. Hence, an analysis and prediction of multiple time-scales data for daily, weekly and 10-day averaged time series were performed using chaos approach. An analysis was conducted at the Tanjung Tualang station, Malaysia. This method involved the reconstruction of a single variable in a multi-dimensional phase space. River flow prediction was performed using local linear approximation. The prediction result is close to agreement with a high correlation coefficient for each time scale. The analysis suggests that the presence of low dimensional chaos as an optimal embedding dimension exists when the inverse method is adopted. In addition, a comparison of the prediction performance of chaos approach, autoregressive integrated moving average (ARIMA), artificial neural network (ANN), support vector machine (SVM) and least squares support vector machines (LSSVM) were performed. The comparative analysis shows that all methods provide comparable predictions. However, chaos approach provides a simpler means of analysis since it only use a scalar time series (river flow data). Therefore, the relevant authorities may use this prediction result for the creation of a water management system for local benefit.

Keywords: Chaos approach, multiple time-scales, nonlinear prediction, river flow

Peramalan aliran sungai adalah penting bagi menentukan jumlah air bagi sesuatu kawasan. Ini adalah untuk memastikan permintaan sumber air dapat dipenuhi. Maka, analisis dan peramalan bagi aliran sungai pelbagai skala masa iaitu harian, mingguan dan purata 10-hari dilaksanakan menggunakan pendekatan kalut. Analisis ini dijalankan di stesen Tanjung Tualang, Malaysia. Pendekatan ini adalah melibatkan pembinaan semula ruang fasa bagi satu pembolehubah (satu dimensi) kepada beberapa dimensi ruang fasa. Peramalan aliran sungai adalah melibatkan kaedah peramalan setempat. Hasil peramalan adalah baik dengan nilai pekali korelasi yang tinggi bagi setiap skala masa yang dikaji. Kehadiran telatah kalut pada data siri masa yang dikaji dapat dibuktikan dengan pendekatan songsang. Tambahan lagi, perbandingan hasil peramalan dengan menggunakan pendekatan kalut, purata bergerak bersepadu autoregresi (ARIMA), rangkaian neural buatan (ANN) dan sokongan vektor mesin kuasa dua terkecil (LSSVM) dilaksanakan. Analisis perbandingan memberikan hasil peramalan yang setanding. Namun, peramalan dengan menggunakan pendekatan kalut lebih mudah iaitu hanya melibatkan satu pembolehubah (aliran sungai). Maka, pihak yang bertanggungjawab dapat menggunakan hasil kajian ini bagi sistem pengurusan air untuk memenuhi permintaan pengguna.

Kata kunci: pendekatan kalut, pelbagai skala masa, peramalan tak linear, aliran sungai

1.0 INTRODUCTION

Efficient management of water resources is essential to catalyze the development of the country. Water management is closely related to river flow prediction. Accurate prediction can help in the allocation of water for different sectors, such as agriculture, tourism and manufacturing. Therefore, an accurate prediction method for predicting the river flow is necessary to provide information concerning water resource management. In addition, the better allocation of water resources due to the increase in daily demand in the future arising from population growth and rapid economic development is important. This scenario can be seen clearly in the Kinta District, Perak, Malaysia. The rapid development in this area has had an impact on water management. Kinta Dam is capable of supplying 639,000 m^3 of water each day and will be able to meet the demand for water consumption by the year 2020 [1]. Thus, water resource management is important to ensure that the water supply of Kinta Dam can be allocated productively to the user.

Adequate water supply can stimulate and sustain economic growth. Water demand is expected to increase the domestic, industrial, commercial and institutional demand for users in the Kinta and Kampar region. Table 1 shows that the demand for water resources will increase to 471,000 m^3 per day by 2050 compared to 277,200 m^3 per day in 2010 [2]. Hence, river flow prediction for the short-term and long-term is important to optimize the distribution of water supply for the area.

River flow prediction can optimize water distribution. However, as the dynamics of river flow is nonlinear [3], some conventional methods have been used to predict the flow of rivers in Malaysia, such as gene-expression programming [4], fuzzy logic [5], hydrodynamic modeling, autoregressive integrated moving average (ARIMA) [6, 7], artificial neural networks (ANN) [7, 8], support vector machine (SVM) [7, 9] and support vector machines smallest power (LSSVM) [7]. Nevertheless, there are several methods that have yet to be explored for the purpose of river flow prediction applications in Malaysia, such as chaos approach, Bayesian and Wavelet methods. Bayesian and Wavelet methods depend on the number of the dominant variables the same as the conventional methods. In this respect, a transitional approach of only a single variable is applied to predict the flow of the rivers in Malaysia using the chaos approach. River flow prediction using multiple time-scales is employed to predict the flow behavior of the river.

A study was conducted in the Kinta District for monthly river flow prediction using autoregressive integrated moving average (ARIMA), artificial neural network (ANN), support vector machine (SVM) and least squares support vector machines (LSSVM) [7]. However, all of these methods involve several variables to achieve the objectives of prediction. Referring to the above, the second focus of this study was to examine the comparative prediction performance involving chaos approach, ARIMA, ANN, SVM and LSSVM.

Accurate information on river flow is an important factor in planning and managing water resources. However, the irregular pattern in the river flow data showed that river flow is a complex system. The system is complex, as influenced by catchment characteristics (size, slope, shape), the characteristics of the storm (and the increase in rainfall), geographic characteristics (topology, terrain, soil type) and climatic characteristics (temperature, humidity, wind) [7, 10, 11]. Hence, a few decades ago, stochastic hydrology approach of multiple time series was more widely used in the study of river flow [12].

Developments in this study on river flow prediction can be seen in river flow modeling using single time series even though this river flow is associated with several variables. Hydrological studies that use a single variable begin by using the chaos approach that can deal with complex phenomena through low dimensional systems. A number of studies have been carried out by applying the principles of the chaos approach in hydrologic time series data to reveal the chaotic behavior in hydrological systems [13 - 15]. The study focused on the future value of the time series data, which is significant with the objective of prediction. The results showed that river flow and other hydrological processes give a reasonably good prediction in respect of the observed data [16 - 18]. Apart from being able to provide accurate prediction results, the chaos approach can reveal the number of variables that influence river flow in a certain area. Thus, the dynamic behavior of the river flow prediction can help to provide information for the efficient management of hydraulic structures.

Table 1 Water demand in Kinta and Kampar region [2]

Water demand (m^3 per day)	2010	2015	2020	2030	2040	2050
Domestic	188,800	205,700	223,500	234,500	258,900	269,500
Industrial	51,900	56,600	61,300	81,600	112,000	147,600
Commercial	27,400	30,000	32,800	36,100	38,800	40,400
Institutional	9,100	9,900	10,900	12,000	12,900	13,500
Total demand	277,200	302,200	328,500	364,200	422,600	471,000

Table 2 Population growth in Kinta and Kampar region [2]

Year	2010	2015	2020	2030	2040	2050
Population	807,000	843,000	880,000	928,000	966,000	987,000

Table 3 Statistics of river flow series at Tanjung Tualang station from 1981 to 1990

Statistics	Daily	Weekly	10-day
Number of data	3650	521	365
Average	81.26	81.23	81.31
Max	367.47	342.45	330.14
Min	4.02	5.26	5.85
Standard deviation	53.57	50.35	49.37
Skew	1.49	1.42	1.37
Kurtosis	3.32	3.33	3.15

2.0 METHOD

Summary of the methodology implement in this research is based on chaos theory (refer to Figure 1). Chaos theory in time series analysis and prediction can be explain teorem Takens. Refer to teorem Takens [19], the dynamic of real system can be demonstrated using mathematical equation (phase space reconstruction). Hence, the nonlinear prediction method based on phase space reconstruction is employed in this study to predict the future values of river flow data with multiple time-scales and to reveal the chaotic behavior of the river flow by using the inverse approach. This method is implemented by using the observed data in the form of one-dimensional and reconstructed into the *m*-dimensional phase space to reflect the actual dynamics of the system [20, 21]. Then, the second step is prediction.

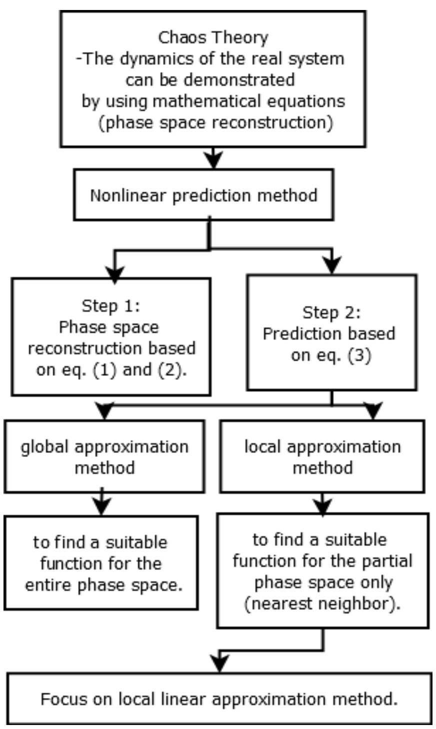


Figure 1 Flow chart of methodology.

The first step is phase space reconstruction. The scalar time series $x(t)$ of the river flow data in one-dimensional time series:

$$\{x_i\} = \{x_1, x_2, x_3, \ldots\ldots, x_N\} \tag{1}$$

where N is the total number of points in the time series. From this signal, we can construct an *m*-dimensional signal:

$$\mathbf{Y}_i = \left\{x_i, x_{i+\tau}, x_{i+2\tau}, \ldots, x_{i+(m-1)\tau}\right\} \tag{2}$$

where τ is an appropriate time delay and m is the chosen embedding dimension.

Two parameters have to be determined, the time delay, τ, and the embedding dimension, m. In this study, τ is a predetermined value while the value of m varies. The most optimal value of τ can provide a separation of neighboring trajectories in any dimension embedded in the phase space. If the value of τ is too small, the coordinates of the phase space cannot describe the dynamics of the system. Meanwhile, information on the trajectories in the phase space will diverge if the value is too large [22, 23]. Previous studies on the river flow prediction showed that when a condition of time delay $\tau = 1$ is used in the phase space reconstruction, the result indicates a good prediction [17, 18, 24]. Thus, in this study, the time delay $\tau = 1$ is used. Meanwhile, the optimal value of the *m*-dimensional embedding phase space can describe the attractor topology. In this study, the *m*-dimensional is varied (m = 2, 3, 4, ..., 10) to find the best set of dimensions that can provide good prediction results.

A correct phase space reconstruction in a dimension m allows one to interpret the underlying dynamics in the form of *m*-dimensional f_T, that is:

$$\mathbf{Y}_{i+T} = f_T(\mathbf{Y}_i) \tag{3}$$

where $\mathbf{Y}_i$ and $\mathbf{Y}_{i+T}$ are vectors in *m*-dimension that describe the state of the system at time i (current state) and $i + T$ (future state). There are two types of f_T approximation: (1) global method is to find the f_T using entire phase space and (2) local method is to find the f_T using the partial phase space only. In this study, we only use local approximation method that focus on local linear approximation method.

Local linear approximation method involves finding the nearest neighbor in the current phase space $\mathbf{Y}_i$. The Euclidean distance between the current vector $\mathbf{Y}_i$ and the vector before $\mathbf{Y}_w$ (w=1, 2, ..., i-1) is calculated. The minimum distance is taken to form the vector of the nearest neighbors $\mathbf{Y}_M$.

Assuming k nearest neighbors is $\mathbf{Y}_p$, then the vector of the nearest neighbor image $\mathbf{Y}_p$ is $\mathbf{Y}_{p+1}$ for the same dimension. The values of $\mathbf{Y}_p$ and $\mathbf{Y}_{p+1}$ are used to solve equation (4):

$$\mathbf{Y}_{p+1} = A\mathbf{Y}_p + B \tag{4}$$

Constant values of A and B are calculated by applying the least squares method. The predictive value of $\mathbf{Y}_{i+1}$ can be calculated using equation (5):

$$\mathbf{Y}_{i+1} = A\mathbf{Y}_i + B \tag{5}$$

Evaluation of the prediction performance is done using the correlation coefficient (CC) and root mean square error (RMSE). A diagram of the time series and scatter diagrams are used to choose good prediction results in multiple time-scales.

3.0 DATA

River flow prediction was carried out to provide information about the flow of the river in the future and prove the presence of chaotic behavior. River flow information is essential to the relevant authorities that are responsible for managing the water resources. Kinta District, Malaysia was chosen as the study area, as this area has been identified as a developing area. In addition, the area is expected to experience a population increase along with the increasing use of water, as shown in Table 2 [2].

The Kinta River catchment area comprises the entire 2540km^2 covering the Kinta River in the eastern state of Perak, which is located at latitude 04' 19' 20' and longitude 101' 04' 30'. Kinta River is an important water source in the state because this river is the main source of drinking water and irrigation. The topology of the catchment area consists of forest cover in the hills to the north and south. Land use in the Kinta Valley consists of urban development; former unproductive mines; and agriculture; namely, rubber, oil palm and fruit trees [26]. Three streams contribute to the Kinta River flow system – the Pari River at 245km^2, the Raia River at 250km^2 and the Kampar River at 430km^2.

Tables 1 and 2 show the increasing water demand and population in the Kinta and Kampar region. Thus, analysis of the flow of the Kinta River in this area is suitable for providing the information about the flow of the river. The Kinta River is measured at several gauging stations situated along the river. Thus, the river flow station in Tanjung Tualang (station number: 4310401) is used for analysis. River flow data from the station Department of Irrigation and Drainage Malaysia are available from 1973. However, this study only involves daily, weekly and 10-day averaged time series data from 1981 to 1990. The data involved in this analysis have 0.006% missing data. The missing data are replaced with the results from the computation of the linear interpolation method. Table 3 presents some of the important statistics of the time series and Figure 2 shows the variation of data involved.

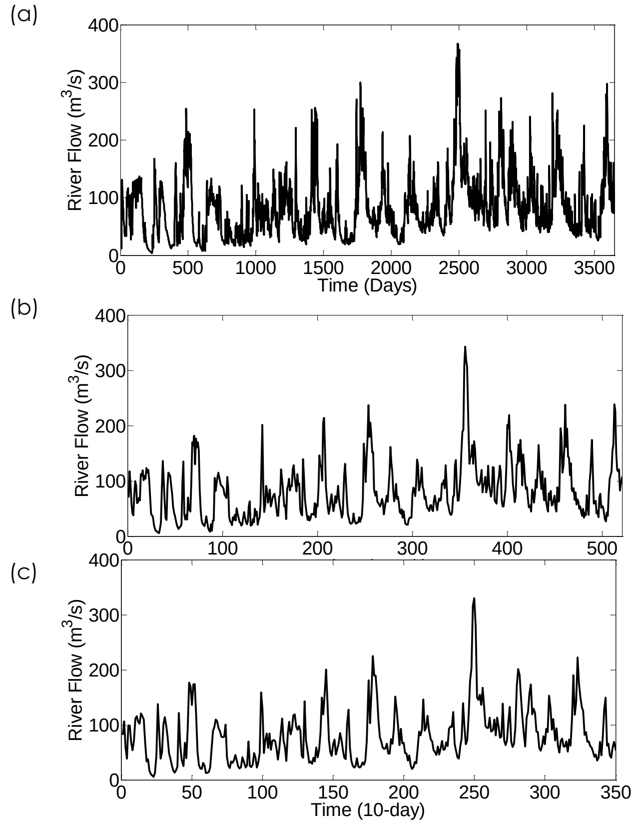


Figure 2 Time series plots of observed data at Tanjung Tualang station from 1981 to 1990

4.0 RESULTS AND DISCUSSION

The discussion of the findings is divided into two parts. The first part is the prediction value of the future river flow in multiple time-scales and to determine the chaotic behavior of the river flow. There are three different time-scales involved in the analysis – daily, weekly and 10-day averaged time series data. The purpose of the prediction of multiple time-scales is to evaluate the prediction accuracy based on the chaos approach. The prediction accuracy assessment results can provide information concerning implementing a better system in the management of water resources. The second part of the river flow analysis is to compare the prediction performance of monthly river flow involving data from October 1976 to July 2006. This comparative study proves that river flow is deterministic and can be predicted.

4.1 Multiple Time-scales Nonlinear Prediction

The phase space diagram is based on the phase space equation (2). The purpose of the phase diagram is to describe the dynamics of the system through the trajectories of attractor that is generated from the time series data. Figure 3 shows the phase diagram of two-dimensional (m = 2) with time delay τ = 1. In referring to the figure, the attractor seems clear on the daily data, while the attractor for the weekly and 10-day averaged data shows a large space (less clear) in the phase space. Thus, the attractor becomes less clear when reducing the resolution from high resolution (daily data) to low resolution (weekly and 10-day). The less clear trajectories are due to the repeated river flow and the presence of extreme values [27]. Therefore, the dynamics of the system can be explained by using chaos approach without involving stochastic approach.

Nonlinear prediction based on local linear approximation method is used for the purpose of prediction. The whole data set for 10 years (January1981 to December1990) is involved. The river flow data for 9 years (1981 to 1989) were used for the reconstruction of the phase space for prediction of the river flow for the subsequent one year. The phase space is built by using different embedding dimensions from 2 to 10. The performance results in terms of the correlation coefficient (CC) and root mean squared error (RMSE) are presented in Table 4. In referring to the table, the best prediction possible is when the dimension is m = 3 (m_{opt}) for daily data, the average weekly and the 10-day average, while for the monthly average data it is when m = 6 (m_{opt}). Prediction of daily data, the average weekly and the 10-day average is more accurate than prediction using monthly data. The smallest RMSE value can be shown on the m_{opt}. Thus, the presence of the optimal value embedding dimension indicates the presence of low-dimensional chaotic behavior on river flow dynamics [28].

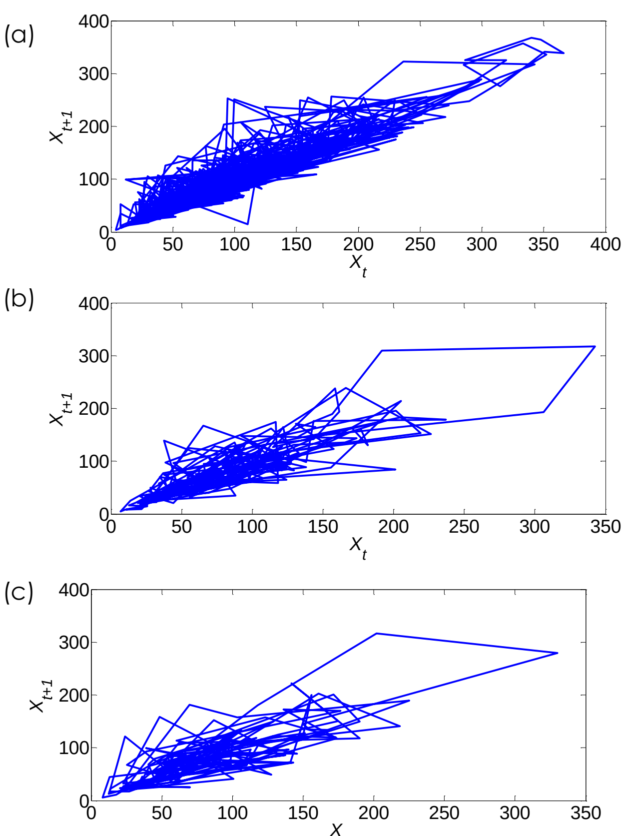


Figure 3 Phase space diagram for (a) daily data, (b) weekly data and (c) 10-days data

4.2 Comparison of Different Techniques Of Prediction Performance

This comparative analysis involves chaos approach, autoregressive integrated moving average (ARIMA), artificial neural network (ANN), support vector machine (SVM) and least squares support vector machines (LSSVM). ARIMA, ANN, SVM and LSSVM are the listed model for prediction time series and need to be compared with the prediction result based on chaos approach. Basically, ARIMA model involves three iterative steps: identification, estimation and diagnostic checking. The autocorrelation (ACF) and partial autocorrelation function (PACF) are used to determine whether or not the series is stationary in order to identify the appropriate ARIMA model in the identification step. After that, the parameters of the model are estimated. Final step of this model building is diagnostic checking for model adequacy, which basically checks whether the model's assumptions about the error. If the model is inadequate, a new tentative model should be identified followed by the steps of parameter estimation and model verification. The process is repeated several times until finally a satisfactory. Meanwhile, ANN has the capability to execute complex mapping between input and output and could form a network that approximates nonlinear functions. A single hidden layer feed forward network is the most widely used model form for time series modeling and forecasting. This model usually consists of three layers: the first layer is the input layer where the data are introduced to the network followed by the hidden layer where data are processed and the final or output layer is where the results of the given input are produced [7].

The basic idea of a SVM for regression is to introduce a kernel function, map the input data into a high-dimensional feature space by a nonlinear mapping and then perform linear regression in the feature space. The LSSVM, as a modification of a SVM. The LSSVM provides a computational advantage over the standard SVM by converting a quadratic optimization problem into a system of linear equations.

The prediction performance for ARIMA, ANN, SVM and LSSVM are taken from previous studies involving the Tanjung Tualang station [7]. The performance, which involves a correlation coefficient (CC) and root mean square error (RMSE) for the four methods, is shown in Table 5. The purpose of comparative of the prediction result using these methods is to compare the prediction performance and to prove that the river flow is deterministic and predictable without involving stochastic approach. Therefore, the analysis was performed on the same data and stations to achieve the second objective.

The local linear approximation method described in the methodology is used to predict the future value of river flow. Analysis was conducted using the inverse approach to determine the number of variables that affect the river flow dynamics and reveal the chaotic behavior. Monthly river flow data for 24 years (287 months, 80% of the data) are used for the reconstruction of the phase space to predict the next72 months. The phase space is builtusingdifferentembeddingdimensionsfrom2to 10. Revenue prediction involving the correlation coefficient (CC) and root mean square error (RMSE) are shown in Table 6.

In referring to Table 5 and Table 6, a comparison of performance evaluation has been done using five methods – chaos approach, ARIMA, ANN, SVM and LSSVM. The correlation (CC) shows that the best prediction results for the chaos approach is when embedding is m = 6 (m_{opt}) with 0.586. The smallest RMSE value is 19.467 with m = 6 (m_{opt}). While the range of the correlation coefficient of ARIMA, ANN, SVM and LSSVM is between 0.525 and 0.652, and the RMSE values range from 16.496 to 21.783. A comparative analysis shows that all the methods used for prediction provide comparable predictions. Thus, the river flow in Tanjung Tualang is deterministic and predictable when using chaos approach. Based on the inverse approach, the optimal embedding dimension is m = 3 (m_{opt}), which suggests the possible presence of low dimensional chaos in the river flow dynamics.

Table 4 Prediction performance of local linear approximation method for Tanjung Tualang station with different m-embedding dimension from 1981 to 1990

m	Daily		Weekly		10-day		Monthly	
	CC	**RMSE**	**CC**	**RMSE**	**CC**	**RMSE**	**CC**	**RMSE**
2	0.9194	12.488	0.7980	19.468	0.8027	17.289	0.3920	24.913
3	0.9257	10.747	0.8369	19.944	0.8133	18.195	0.4813	33.018
4	0.9204	11.891	0.8098	18.125	0.7853	21.057	0.4699	20.401
5	0.9241	12.915	0.8065	20.596	0.8031	26.232	0.5062	37.995
6	0.9225	14.943	0.8276	24.389	0.7731	29.535	0.5596	35.262
7	0.9217	14.333	0.8095	24.799	0.7587	29.306	0.3444	39.597
8	0.9199	16.485	0.8105	29.377	0.7489	31.318	0.3250	37.331
9	0.9175	16.879	0.8309	29.879	0.8113	34.329	0.4293	45.446
10	0.9221	18.594	0.8086	31.622	0.7527	33.060	0.1795	74.559

Table 5 The performance results of ARIMA, ANN, SVM and LSSVM methods at Tanjung Tualang station from July 1976 until December 2006 [7]

Method	**ARIMA**	**ANN**	**SVM**	**LSSVM**
CC	0.525	0.610	0.565	0.652
RMSE	21.783	17.058	16.715	16.496

Table 6 Monthly river flow prediction using local linear approximation method at Tanjung Tualang station with different m-embedding dimension from July 1976 until December 2006

m	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
CC	0.563	0.454	0.440	0.480	0.586	0.450	0.458	0.473	0.32
RMSE	22.932	22.114	22.779	21.863	19.467	22.242	23.897	22.174	23.479

4.0 CONCLUSION

This study involves the analysis and prediction of river flow at a station in Tanjung Tualang, Perak, Malaysia. The station was selected based on the expected high water demand until 2050, which involves domestic demand, industrial, commercial and institutional, in the Kinta and Kampar region. In addition, the expected increase in the population in this area is significantly related to the water demand. Thus, it is essential to conduct analysis and prediction of river flow using the nonlinear prediction method based on chaos approach in this area.

Chaos approach involves two parts. The first part is the reconstruction of the phase space involving variations of the embedding dimension from 2 to 10 dimensions. Meanwhile, the second part is the prediction using the local linear approximation method. Analysis and prediction of river flow for this study is divided into two parts. The first part involves the analysis and prediction of the river flow, which involves multiple time-scales – daily, weekly and 10-day averaged data from 1981 to 1990. A reasonably good prediction was achieved with CC > 0.8 for daily, weekly, 10-day averaged data while CC > 0.5 for the monthly averaged data. The smallest value of RMSE can be shown by m_{opt}. The presence of low dimensional chaotic behavior of the river flow can be proven with the optimal embedding dimension, m = 3 (m_{opt}) for daily data, weekly and 10-day averaged and m = 6 (m_{opt}) for monthly averaged data.

Analysis and prediction in the second part involve comparing the prediction performance of chaos approach, ARIMA, ANN, SVM and LSSVM. The monthly river flow data from July 1976 to December 2006 are used. A comparative analysis shows that all the methods provide comparable predictions. We suggest that multivariate analysis based on chaos approach for future research in order to improve the accuracy of prediction. Thus, the flow of the river in Tanjung Tualang is deterministic and predictable using chaos approach. In addition, at least six variables affect the river flow dynamics in Tanjung Tualang. The variables that may affect the river flow prediction include the watershed size, slope and shape retention, increased rainfall and the rain, topology, terrain, soil type, temperature, humidity and wind. Thus, chaos approach, which only involves a time series (river flow data), is recommended for analysis and river flow prediction to provide information to the authorities for the optimal management of water resources.

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