TIME SERIES FORECASTING OF THE VOLUME OF WATER IN SIRIKIT DAM USING ARTIFICIAL NEURAL NETWORK

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TIME SERIES FORECASTING OF THE VOLUME OF WATER IN SIRIKIT DAM USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT

This research has been done to study the way to forecast the water volume in a dam using a neural network method as well as comparing the effectiveness of the neural network method with an adaptive neuro-fuzzy inference system method and holt-winters' exponential smoothing method. The Sirikit Dam was used as a sample in this research. The daily volume of water in The Sirikit Dam was gathered from January 1, 2006 until August 25, 2010. All forecasting outcomes from the three methods was compared by Mean Squared Error or MSE. The method that was given the lower MSE was considered as the more effective forecasting method.

The research found that the neural networks method accomplished the most accurate results. The forecasting outcomes, for April 1, 2010 to April 15, 2010 and August 11, 2010 to August 25, 2010, using the neural networks method given the MSE value at 9.572 and 55.0692 while the adaptive neuro-fuzzy inference system method given the MSE values at 51.1379 and 62.9031 and holt-winters' exponential smoothing method given the MSE values at 15.3664 and 102.4066 respectively.

KEY WORDS: TIME SERIES FORECASTING / NEURAL NETWORK /
ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM /
HOLT-WINTERS' EXPONENTIAL SMOOTHING METHOD

55 pages

การพยากรณ์อนุกรมเวลาปริมาตรน้ำในเขื่อนสิริกิต์โดยใช้โครงข่ายใยประสาทเทียม

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วท.ม. (เทคโนโลยีการจัดการระบบสารสนเทศ)

คณะกรรมการที่ปรึกษาวิทยานิพนธ์: ทรงพล องค์วัฒนกุล, Ph.D. ปัญญา ไข่มุก, M.D., บันลือ เอมะรุจิ, Ph.D.

บทคัดย่อ

งานวิจัยนี้ได้ศึกษาวิธีการพยากรณ์ปริมาตรน้ำในเขื่อนสิริกิต์โดยใช้โครงข่ายประสาทเทียม รวมทั้งศึกษาเปรียบเทียบประสิทธิภาพของการพยากรณ์โดยใช้โครงข่ายประสาทเทียม กับการพยากรณ์โดยใช้นิวโรฟัซซี่แบบปรับตัวได้ และ การพยากรณ์โดยใช้วิธีปรับให้เรียบแบบโฮลท์และวินเทอร์ส โดยข้อมูลที่ใช้ในในการพยากรณ์ คือ ข้อมูลปริมาตรน้ำรายวันของเขื่อนสิริกิต์ ซึ่งรวบรวมตั้งแต่วันที่ 1 มกราคม 2549 ถึงวันที่ 25 สิงหาคม 2553 โดยใช้ค่าความคลาดเคลื่อนกำลังสองเฉลี่ยในการวัดประสิทธิภาพของการพยากรณ์ หากวิธีใดที่มีค่าความคลาดเคลื่อนกำลังสองเฉลี่ยต่ำกว่าแสดงว่ามีประสิทธิภาพในการพยากรณ์ที่ดีกว่า

ผลการวิจัยพบว่าการพยากรณ์โดยใช้โครงข่ายประสาทเทียมให้ผลที่มีความแม่นยำมากกว่านิวโรฟัซซี่แบบปรับตัวได้ และวิธีปรับให้เรียบแบบโฮลท์และวินเทอร์ส โดยผลจากการพยากรณ์ข้อมูลล่วงหน้าวันที่ 1 เมษายน 2553 ถึงวันที่ 15 เมษายน 2553 และวันที่ 11 สิงหาคม 2553 ถึงวันที่ 25 สิงหาคม 2553 การพยากรณ์โดยใช้โครงข่ายประสาทเทียมมีค่าความคลาดเคลื่อนกำลังสองเฉลี่ยเท่ากับ 9.572 และ 55.0692 ในส่วนของการพยากรณ์โดยใช้นิวโรฟัซซี่แบบปรับตัวได้มีค่าความคลาดเคลื่อนกำลังสองเฉลี่ยเท่ากับ 51.1379 และ 62.9031 และการพยากรณ์โดยใช้วิธีปรับให้เรียบแบบโฮลท์และวินเทอร์สมีค่าความคลาดเคลื่อนกำลังสองเฉลี่ยเท่ากับ 15.3664 และ 102.4066

55 หน้า

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CHAPTER I
INTRODUCTION

1.1 Background and Statement of Problem

Thailand is an agricultural country; and for farming, farmers not only rely on rainwater, but they also rely on water supplies from dams especially in the state of water scarcity. Thus, dams are considered an important element for Thai agriculture as well as for Thai society. Besides farming, dams are essential for the country in many other ways such as power generation, flood mitigation, fisheries, water transport, etc.

Currently many dams in Thailand have experienced some water scarcity problem during dry season and dams' flood capacity problems in rainy season due to many reasons such as climate variability, increase in population, etc. More importantly, these problems have also happened to Sirikit Dam, which is considered the largest earth dam in Thailand situated in Uttaradit province. This dam was built for multi purposes such as irrigation, power generation (generating maximum of 500,000 kilowatts), etc. The quantity of water in Sirikit dam has been decreasing annually. Until 2010, the dam experienced the lowest water volume in the past 10 years which has caused a huge impact to Thai society.

Consequently, the concept of time series forecasting techniques was introduced for quantitative prediction of water in Sirikit Dam and the data was gathered in chronological order in the past to forecast the future. Such prediction is necessary to the dam's management team in order to plan and specify policies to deal with possible problems and reduce possible impacts.

This research aimed to apply artificial neural network for predicting the quantities of water in Sirikit Dam. Moreover, it was also prepared to compare the effectiveness of 3 different forecasting methods: neural networks, adaptive neuro-fuzzy inference system and holt-winters' exponential smoothing method. The daily volume of water in Sirikit Dam was collected since January 1, 2006 to August 25, 2010 (1,698 days) and made 15 days forward forecast dividing into 2 periods: April 1-

15, 2010 and August 11-25, 2010. The result was expected that the neural networks would be the most appropriate forecasting method and given more accurate results than an adaptive neuro-fuzzy inference system and a holt-winters' exponential smoothing method.

1.2 Objective of This Work

1.2.1 To study the principles and component of the neural network.

1.2.2 To study the principles and component of the adaptive neuro-fuzzy inference system.

1.2.3 To test the neural network model that is optimal for the forecast volume of water in the Sirikit Dam.

1.2.4 To compare the efficiency of each forecasting method.

1.3 Scope of Work

1.3.1 The data used in this research would be the daily volume of water in Sirikit dam since January 1, 2006 to August 25, 2010 (1,698 day) and made 15 day forward forecast by dividing the forecasting period into 2 periods: April 1-15, 2010 using training data set since January 1, 2006 to March 31, 2010; and August 11 -25, 2010 using training data set since January 1, 2006 to August 10, 2010.

1.3.2 The forecasting models will be compared by applying the daily volume of water of the Sirikit Dam into the neural network, the adaptive neuro-fuzzy inference system model and the holt-winters' exponential smoothing method.

1.3.3 Neural network model in this research is multi-layer feed-forward neural network with back propagation algorithm.

1.3.4 Holt-winters' exponential smoothing method in this research is holt–winters' additive seasonal exponential smoothing method and holt–winters' multiplicative seasonal exponential smoothing method.

1.3.5 The statistics used in the comparison models in this study is the mean square error (MSE).

1.4 Expected Results

1.4.1 The neural network is more effective for predicting water quantities of Sirikit Dam than the adaptive neuro-fuzzy inference system and the holt-winters' exponential smoothing method.

1.4.2 The forecasting results from this research can be used to create some strategic planning and policy for the dam's management.

CHAPTER II
LITERATURE REVIEW

2.1 Sirikit Dam [1,2]

Sirikit Dam is Thailand's largest earth dam, began to be constructed in 1967 and was completed in 1974. Their Majesties the King and The Queen accompanied by Her Royal Highness Princess Sirindhorn Mahachakkri officiated the opening ceremony of Sirikit Dam and the hydroelectric plant on March 4, 1977

Sirikit Dam located at Phasom Village, Tambon Tha Pla. It is an earth dam, the ridge of which is clay; its is 113.60 meters tall and 810 meters long; the maximum capacity is about 10,500 million cubic meters, capable of generating electricity to supply to several provinces.

Sirikit Dam is beneficial to society in many ways:

- Irrigation: water from the dam has been released to many cultivated areas, both sides along Nan River and in the area of Toong Chaophya, during both rainy season and dry season.

- Flood Relief: the dam can hold a big amount of water before flowing over the lower areas. It relieves the event of flooding both sides along Nan River, "Toong Chaophya" area and Bangkok.

- Power Generation: Sirikit Dam can produce electricity power up to 500,000 kilowatts, which can be used in many provinces around the area.

- Fisheries: Sirikit Dam is considered a huge source for inland fisheries which can help the local people to generate their income.

- Water Transportation: It facilitates the water transportation in the area above the dam to Nan province which can be used throughout the year.

- Tourism: Sirikit Dam offers very beautiful landscapes; particularly in winter, the serenity atmosphere above the dam among decorative plants and flowers, which would bloom beautifully to challenge the wintry wind moving by during the season, was amazing.

2.2 Time Series

2.2.1 Time Series Forecasting

Time series is a sequence of observations over time, such as the hourly, daily or weekly, etc.

Time Series Forecasting takes an existing series of data $x_{t-n}, \ldots, x_{t-2}, x_{t-1}, x_t$ and forecasts the $x_{t+1}, x_{t+2}, \cdots$ data values. The goal is to observe or model the existing data series to enable future unknown data values to be forecasted accurately. Examples of data series include financial data series (stocks, indices, rates, etc.), physically observed data series (sunspots, weather, etc.), and mathematical data series (Fibonacci sequence, integrals of differential equations, etc.). The phrase "time series" generically refers to any data series, whether or not the data are dependent on a certain time increment. [3] Figure 2.1 show a time series example: The monthly accidental deaths data, 1973-1978.

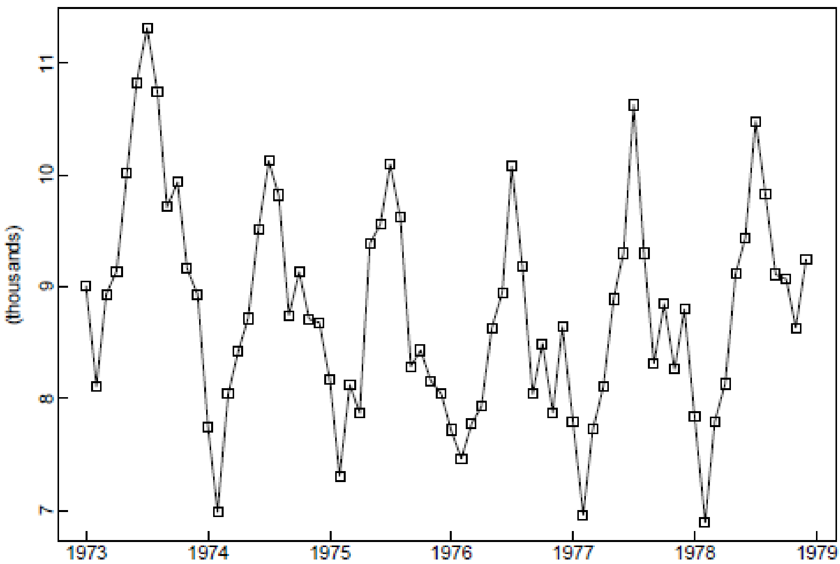


Figure 2.1 Time series example. [4]

- Trend: the upward or downward movement that characterizes a time series over a period of time. Trend reflects the long-run growth or decline in the time series.

- Cycle: recurring up and sown movements around trend level. It usually has duration of more than 1-year.

- Seasonal: periodic patterns in a time series that complete themselves within a calendar year and are then repeated on a yearly basis.

- Irregular: fluctuations random movement in a time series.

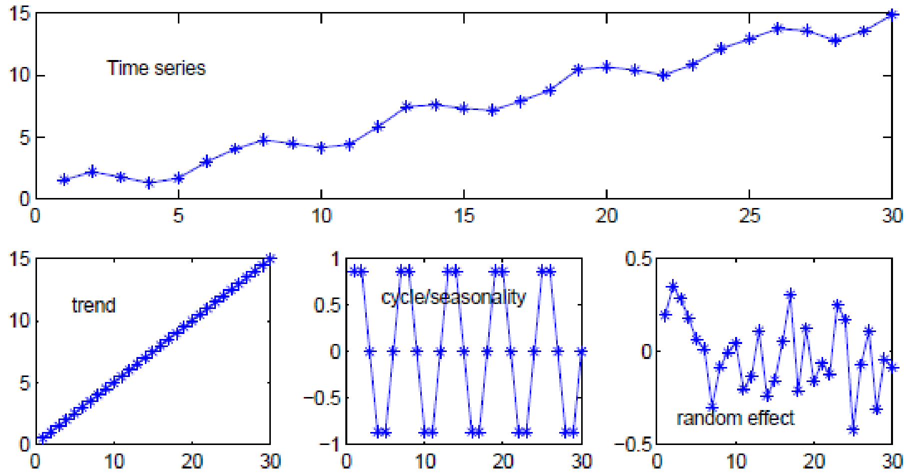


Figure 2.2 Components of a time series.

Generally structure for a time series

- Additive

$$X(t) = T(t) + C(t) + S(t) + R(t) \qquad t = \ldots -1,0,1,2,\ldots \qquad (2.1)$$

- Multiplicative

$$X(t) = T(t) + C(t) + S(t) + R(t) \qquad t = \ldots -1,0,1,2,\ldots \qquad (2.2)$$

T(t) is the trend component

C(t) is the cycle component

S(t) is the seasonal component

R(t) is the irregular or random component

2.2.2 Forecasting Method

A major objective of time series analysis is forecasting of future values of the series. Forecasting methods have been utilized which are classified into two basic types:

- Qualitative forecasting methods: use the opinions of experts to predict future events subjectively.

- Quantitative forecasting methods: Based the historical data, use statistic methods such as moving average, regression analysis, decomposition methods, holt-winter’s exponential smoothing method, and the Box-Jenkins methodology to predict future values of a variable.

2.2.3 Holt-Winter’s Exponential Smoothing Method

Holt-winter’s exponential smoothing method can data series that include, trend, random, and seasonal elements. Holt-winter’s exponential smoothing method uses three smoothing constants, α (alpha), β (beta), and γ (gamma) that are used to arrive at the current estimates of level, trend, and seasonality.

- Holt–winters’ additive seasonal exponential smoothing method

$$\begin{aligned} L_t &= \alpha(Y_t - S_{t-7}) + (1-\alpha)(L_{t-1} + b_{t-1}) \\ b_t &= \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1} \\ S_t &= \gamma(Y_t - L_t) + (1-\gamma)S_{t-s} \\ F_{t+m} &= L_t + b_t m + S_{t-m+s} \end{aligned} \tag{2.3}$$

- Holt–winters’ multiplicative seasonal exponential smoothing method

$$\begin{aligned} L_t &= \alpha(Y_t / S_{t-7}) + (1-\alpha)(L_{t-1} + b_{t-1}) \\ b_t &= \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1} \\ S_t &= \gamma(Y_t / L_t) + (1-\gamma)S_{t-s} \\ F_{t+m} &= (L_t + b_t m)S_{t-m+s} \end{aligned} \tag{2.4}$$

2.3 Neural Network

2.3.1 Biological Neurons

A neuron consists of a Soma (cell body), Axons (sends signals), and Dendrites (receives signals). A neuron has a roughly spherical cell body called soma. The signals generated in soma are transmitted to other neurons through an extension on the cell body called axon. Another kind of extensions around the cell body like bushy tree is the dendrites, which are responsible from receiving the incoming signals generated by other neurons. [5] A Figure 2.3 shows schematic of biological neuron.

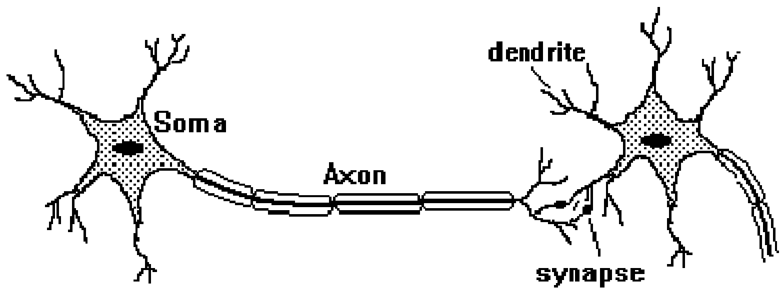


Figure 2.3 Biological neuron. [5]

2.3.2 Artificial Neural Networks

Artificial neural network (ANN) is a system based on the operation of biological neuron system. The processing ability of the network is stored in the inter-unit connection strengths, or weights, obtained by a process of learning from a set of training patterns. The learning process is by repeatedly applying numerical data and the learning algorithms integrated in a conventional. Neural network will automatically adjust the weights and thresholds of the processing elements. Once adjusted with minimal difference between neural network output and targeted output, the network is said to be trained. The functional dependencies between input and output need not be specified due to the neural network ability to evolve during the training process. In this research, multi layer feed forward with back-propagation method is used for weight adjustment. Figure 2.4 basic principles of neural networks.

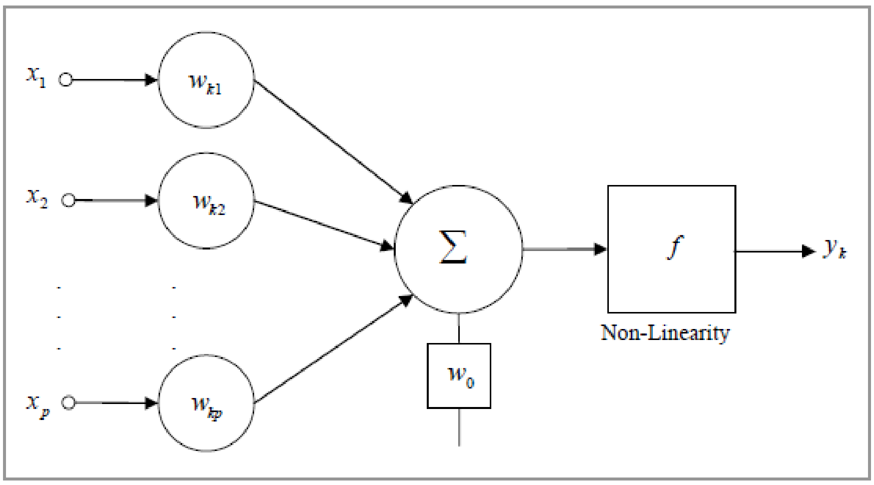


Figure 2.4 Basic principles of neural networks. [6]

2.3.3 Activation Function

In neural computing three different types of activation functions are being used almost exclusively

- Threshold Function

$$\varphi(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases} \tag{2.5}$$

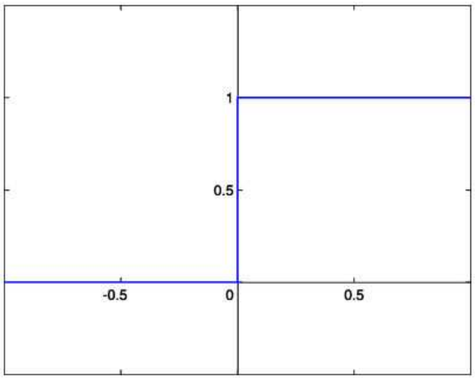


Figure 2.5 Threshold function. [7]

- Piecewise-Linear Function

$$(x) = \begin{cases} 1, & x \geq +\frac{1}{2} \\ v, & -\frac{1}{2} < x < \frac{1}{2} \\ 0, & x \leq -\frac{1}{2} \end{cases} \tag{2.6}$$

- Sigmoid Function

$$\varphi(v) = \frac{1}{1+e^{-a(x)}} \tag{2.7}$$

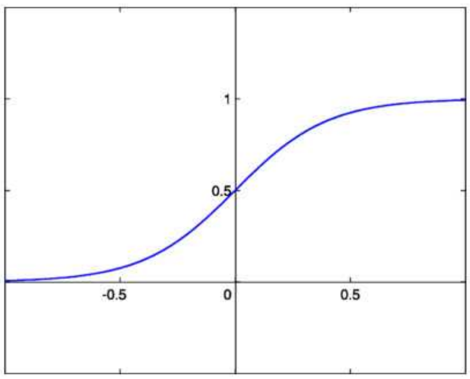


Figure 2.6 Sigmoid function. [7]

2.3.4 Back-Propagation Neural Network

The back-propagation is most commonly method of teaching artificial neural networks that uses back-propagation algorithm. It is a supervised learning method and most useful for feed-forward networks.

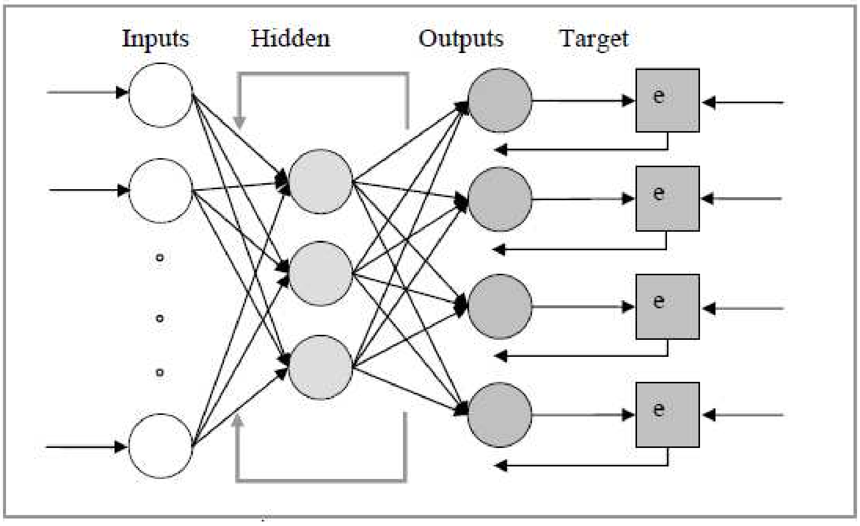


Figure 2.7 Multilayer feed-forward back-propagation neural networks. [6]

Back-propagation training cycle consists of two distinct phases: a forward pass and a backward pass. [8]

In the forward pass the synaptic weights remain unaltered and the function signals of the network are computed on a neuron-by-neuron basis. Thus the forward phase of computation begins at the first hidden layer by presenting it with the input vector, and terminates at the output layer by computing the error signal for each neuron of this layer. One of the set of p training input patterns is applied to the input layer. The activations of units in the hidden layer are calculated by taking their net input and passing it through a transfer function.

- Net input to hidden layer unit j

$$net_j = \sum_{i=1}^{n} w_{ji} x_i \tag{2.8}$$

- Output (activation) of hidden layer unit j

$$oh_j = \int(net_j) \tag{2.9}$$

The activations of the hidden layer units calculated are then used in updating the activation of the output units (or unit in the case of XOR), the activation of the output units is calculated by taking their net input (the sum of the activations of the hidden layer units they are connected to multiplied by their respective connection weights) and passing it through the same transfer function.

- Net input to output unit k

$$net_k = \sum_{j=1}^{L} w_{kj}\, oh_j \tag{2.10}$$

- Output of output unit k

$$oo_j = \int(net_k) \tag{2.11}$$

In the backward pass the synaptic weights are all adjusted in accordance with the error-correction rule. Specifically, the actual response of the network is subtracted from a desired (target) response to produce an error signal. This error signal is then propagated backward through the network, against direction of synaptic connections-hence the name “error back-propagation”. The synaptic weights are adjusted so as to make the actual response of the network move closer the desired response.

The difference between the actual activation each output unit and the desired target activation (d_k) for that unit is found, and this difference is used to generate an error signal for each output unit. A quantity called delta is then calculated for all of the output units.

Error signal for each output unit is difference between its actual output oo_k and its desired output

$$(d_k - oo_k) \tag{2.12}$$

Delta term for each output unit is equal to its error signal multiplied by the output of that unit multiplied by (1 - its output).

$$\delta o_k = (d_k - oo_k)\, oo_k (1 - oo_k) \tag{2.13}$$

The error signals for the hidden layer units are then calculated by taking the sum of the deltas of the output units a particular hidden unit connects to multiple by the weight that connects the hidden and output unit. The deltas for each of the hidden layer units are then calculated.

- Error signal for each hidden unit j

$$\sum_{k=1}^{W} \delta o_k w_{kj} \quad (2.14)$$

Delta term for each hidden unit j is equal to its error signal multiplied by its output, multiplied by (1 - its output).

$$\delta h_j = (oh_j)(1 - oh_j)\sum_{k=1}^{W} \delta o_k w_{kj} \quad (2.15)$$

The weight error derivatives for each weight between the hidden and output units are calculated by taking the delta of each output unit and multiplying it by the activation of the hidden unit it connects to. These weight error derivatives are then used to change the weights between the hidden and output layers.

$$wed_{jk} = \delta o_k (oh_j) \quad (2.16)$$

The weight error derivatives for each weight between the input unit i and hidden unit j are calculated by taking the delta of each hidden unit and multiplying it by the activation of the input unit it connects to. These weight error derivatives are then used to change the weights between the input and hidden layers.

$$wed_{ij} = \delta h_j (x_i) \quad (2.17)$$

To change the actual weights themselves, a learning rate parameter n is used, which controls the amount the weights are updated during each back-propagation cycle. The weights at a time (t + 1) between the hidden and output layers are set using the weights at a time and the weight error derivatives between the hidden and output layers using the following equation.

$$w_{jk}(t+1) = w_{jk}(t) + \eta(wed_{jk}) \quad (2.18)$$

In a similar way the weights are changed between the input and hidden units

$$w_{ij}(t+1) = w_{ij}(t) + \eta(wed_{ij}) \quad (2.19)$$

Using this method, each unit in the network receives an error signal that describes its relative contribution to the total error between the actual output and the target output. Based on the error signal received, the weights connecting the units in different layers are updated. These two passes are repeated many times for different input patterns and their targets, until the error between the actual output of the network and its target output is acceptably small for all of the members of the set of training inputs.

2.4 Fuzzy Logic

Fuzzy logic is one of the recent developing methods in control that are gaining more popularity. The idea behind fuzzy logic is to write rules that will operate the controller in a heuristic manner, mainly in an (If A Then B) format. The arguments A and B are not exact numbers or equations, but they are descriptive words or phrases like small, pretty cold, and very high. [9]

Normally, any fuzzy inference system consists of three main stages: fuzzification, knowledge base and defuzzification stages.

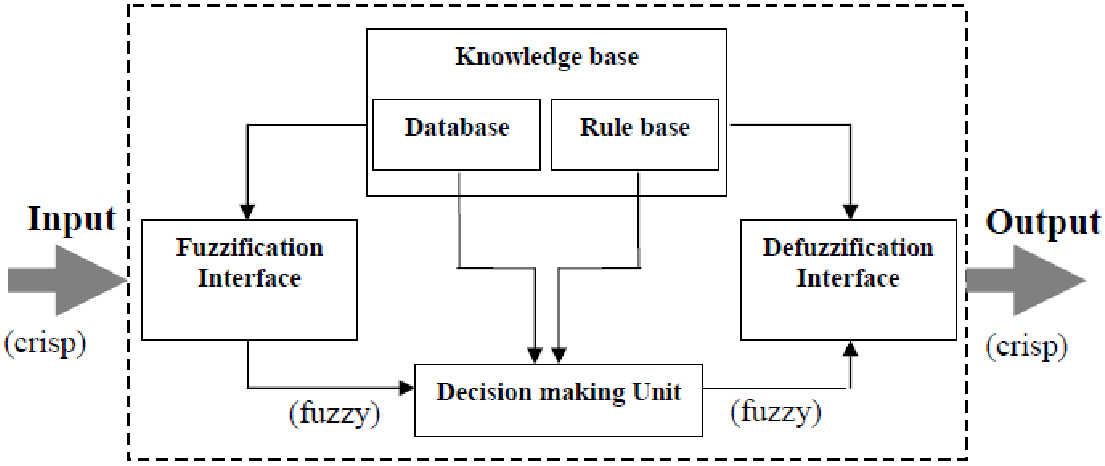


Figure 2.8 Fuzzy inference system. [10]

2.4.1 Membership Function

The membership function is a graphical representation of the magnitude of participation of each input. It associates a weighting with each of the inputs that are processed, define functional overlap between inputs, and ultimately determines an output response. The rules use the input membership values as weighting factors to determine their influence on the fuzzy output sets of the final output conclusion. Once the functions are inferred, scaled, and combined, they are defuzzified into a crisp output which drives the system. [11]

- Pi Membership Function

A pi membership function is specified by four parameters given by:

$$A = f\,(x;\, a,\, b,\, c,\, d)$$

The function is described as:

$$A = \begin{cases} 0, & x \le a \\ 2\left(\dfrac{x-a}{b-a}\right)^2, & a \le x \le \dfrac{a+b}{2} \\ 1-2\left(\dfrac{x-b}{b-a}\right)^2, & \dfrac{a+b}{2} \le x \le b \\ 1, & b \le x \le c \\ 1-2\left(\dfrac{x-c}{d-c}\right)^2, & c \le x \le \dfrac{c+d}{2} \\ 2\left(\dfrac{x-d}{d-c}\right)^2, & \dfrac{c+d}{2} \le x \le d \\ 0, & x \ge d \end{cases} \qquad (2.20)$$

It has four parameters a, b, c and d that determine the shape of the Pi. Figure 2.9 Shows the function of pi (x; 1,4,5,10)

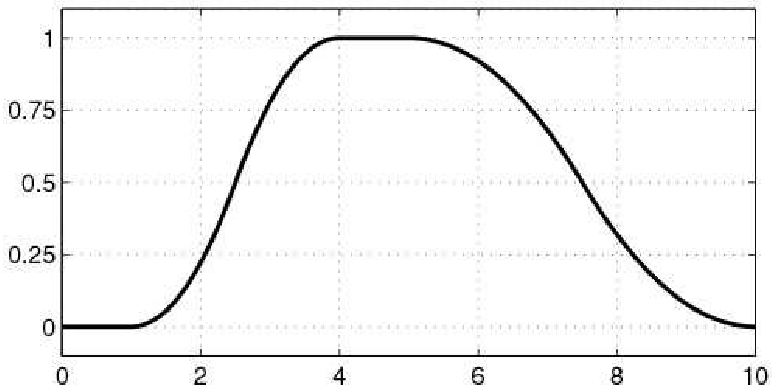


Figure 2.9 Pi membership function. [12]

- Trapezoidal Membership Function

Trapezoidal membership function is specified by four parameters given by

$$A = f\,(x;\, a,\, b,\, c,\, d)$$

The function is described as:

$$A = \begin{cases} 0, & x \le a \\ \dfrac{x-a}{b-a}, & a \le x \le b \\ 1, & b \le x \le c \\ \dfrac{d-x}{d-c}, & c \le x \le d \\ 0, & d \le x \end{cases} \tag{2.21}$$

or, more compactly, by

$$A = \max\left(\min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-b}\right), 0\right) \tag{2.22}$$

Figure 2.10 shows the trapezoidal function of trapezoid (x; 1,5,7,8)

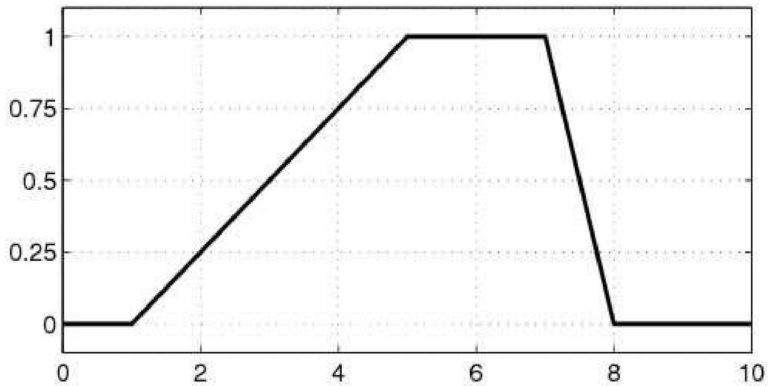


Figure 2.10 Trapezoidal membership function. [13]

- Triangular membership function

Trapezoidal membership function is specified by four parameters given by

$$A = f\,(x;\, a, b, c)$$

The function is described as:

$$A = \begin{cases} 0, & x \le a \\ \dfrac{x-a}{b-a}, & a \le x \le b \\ \dfrac{c-x}{c-b}, & b \le x \le c \\ 0, & c \le x \end{cases} \tag{2.23}$$

or, more compactly, by

$$A = \max\left(\min\left(\frac{x-a}{b-a},\ \frac{c-x}{c-b} \right), 0 \right) \tag{2.24}$$

It has three parameters a, b and c that determine the shape of the triangle. Figure 2.11 shows the triangular function of triangle (x; 3,6,8)

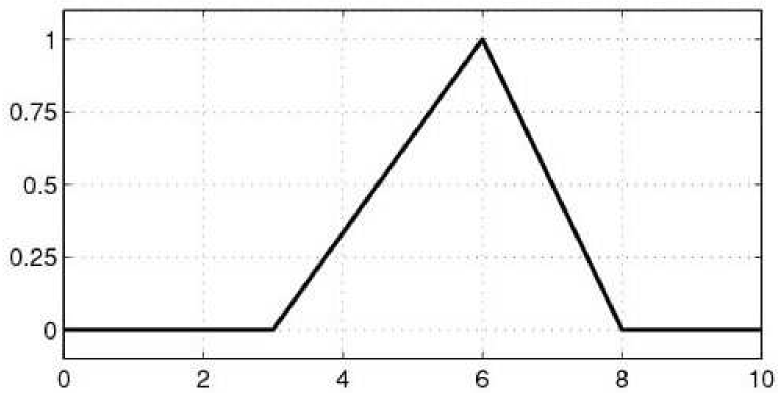


Figure 2.11 Triangular membership function. [14]

2.4.2 Adaptive Neuro-Fuzzy Inference System

ANFIS is about taking an initial fuzzy inference (FIS) system and tuning it with a back propagation algorithm based on the collection of input-output data. The basic structure of a fuzzy inference system consists of three conceptual components: A rule base, which contains a selection of fuzzy rules; a database, which defines the membership functions used in the fuzzy rules; and a reasoning mechanism, which performs the inference procedure upon the rules and the given facts to derive a reasonable output or conclusion. [15]

The basic model of the ANFIS is the Sugeno fuzzy model. In the model, assuming and are two input fuzzy sets and is the output fuzzy set, and the fuzzy if-then rules is formatted as: [16]

$$\text{If } x = P \text{ and } y = Q \text{ then } z = f(x, y) \tag{2.25}$$

Consider two first-order rules of Sugeno fuzzy model, the if-then rules can be:

$$\text{Rule } A\text{: If } x = P_a \text{ and } y = Q_a\text{, then } f_a = m_a x + n_a y + c_a\text{,} \tag{2.26}$$

$$\text{Rule } B\text{: If } x = P_b \text{ and } y = Q_b\text{, then } f_b = m_b x + n_b y + c_b \tag{2.27}$$

Where P_a, Q_a, P_b and Q_b are fuzzy set values and m_a, n_a, c_a, m_b, n_b and c_b are constants. In figured presentation, Fig. 2.13 shows the Sugeno model and the corresponding ANFIS structure with a five-layer artificial neural network.

Denote that the output of the i th node of layer l are $O_{l,i}$. In Layer 1 of the ANFIS,

$$O_{1,i} = \mu_{M_i}(x),\ i = 1, 2, \tag{2.28}$$

Where μ_{M_i} and $\mu_{N_{i-2}}$ are fuzzy membership functions that can be any membership type such as triangular or generalized bell function.

For nodes in Layer 2, the outputs w_i are the product of the outputs of layer 1 and are used as the weights of Layer 3:

$$O_{2,i} = w_i = \mu_{M_i}(x)\mu_{N_i}(y),\ i = 1,2 \tag{2.29}$$

In Layer 3, the output of every node is normalized by a calculation as the following:

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2},\ i = 1, 2. \tag{2.30}$$

Next, Layer 4 is the defuzzy layer which adapts node values with equation:

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i(m_i x + n_i y + c_i),\ \text{for } i = 1, 2 \tag{2.31}$$

where m_i, n_i, and c_i are consequent parameters of the nodes.

Finally, the fifth layer is to compute the output of all the input signals using the equation:

$$O_{5,1} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i},\ \text{for } i = 1, 2 \tag{2.32}$$

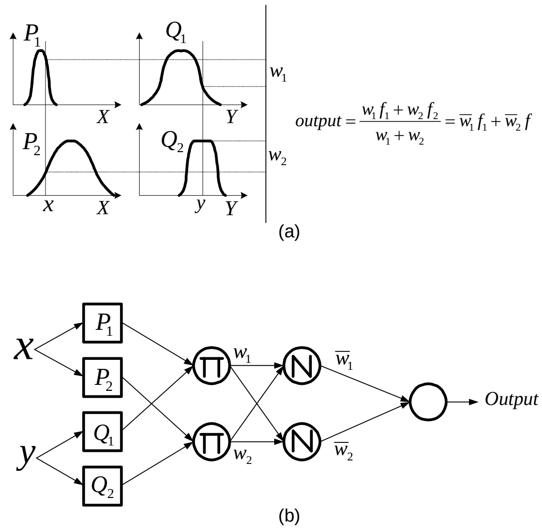


Figure 2.12 (a) The sugeno fuzzy mode; (b) The ANFIS structure.

2.5 MATLAB Software

MATLAB is a high-performance language for technical computing. It integrates computation, visualization, and programming in easy-to-use environment where problems and solution are expressed in familiar mathematical notation.

MATLAB is an interactive system whose basic data element is an array that does not require dimensioning, MATLAB Toolboxes are add-ons that extend MATLAB with specialized functions and easy-to-use graphical user interfaces. Toolboxes are accessible directly from MATLAB interactive programming environment. MATLAB employs the same language for both interactive computing and structured programming.

The Neural Network Toolbox extends the MATLAB with tools for designing, implementing, visualizing, and simulating neural networks. Neural networks are used for applications where formal analysis would be difficult or impossible, such as pattern recognition and nonlinear system identification and control. The toolbox supports feedforward networks, radial basis networks, dynamic networks, self-organizing maps, and other proven network paradigms. [17]

The Fuzzy Logic Toolbox extends the MATLAB technical computing environment with tools for the design of systems based on fuzzy logic. Graphical user interfaces (GUIs) for fuzzy inference system design. Functions are provided for many common fuzzy logic methods, including fuzzy clustering and adaptive neuro-fuzzy learning. [18]

2.6 Related Researches

Coulibaly.P, Anctil.F, Bobee.B, Daily Reservoir Inflow Forecasting using Artificial Neural Networks with Stopped Training Approach. In this study, an early stopped training approach (STA) is introduced to train multi-layer feed-forward neural networks (FNN) for real-time reservoir inflow forecasting. The proposed method takes advantage of both Levenberg–Marquardt Backpropagation (LMBP) and cross-validation technique to avoid underfitting or overfitting on FNN training and enhances generalization performance. The methodology is assessed using multivariate hydrological time series from Chute-du-Diable hydrosystem in northern Quebec (Canada). The performance of the model is compared to benchmarks from a statistical model and an operational conceptual model. Since the ultimate goal concerns the real-time forecast accuracy, overall the results show that the proposed method is effective for improving prediction accuracy. Moreover it offers an alternative when dynamic adaptive forecasting is desired. [19]

Porntip Visetsripong, Naphtha's Price Forecasting using Neuro-Fuzzy System. This research has objectives, compare the forecasting efficiency of ANFIS model with Exponential Smoothing Method. The data used in this study is Daily-Naphtha's Price starting from January 2000 to June 2007, 1950 data. It was found that the Neuro-Fuzzy System is more accurate than the Exponential Smoothing Method when forecast in the range of 4-6 days. Both forecasting deviation measurements is statistical different with the level of confidence at 95%. [20]

Prapaphan Pan-o, A Stock Price Prediction Model By The Neural Network Approach. This research proposes a stock price prediction based on the back-propagation neural network approach. The predicted results of the traditional learning methodology and those derived from using the approach will be compared. The model performance is measured with various setting of network parameters and topologies. The average of experimental results derived from using the TSCFD for predicting the next value point only by using 20-2-1 network can reach 75%, 90% and 80% accuracy by the Tolerance 1%, Tolerance 5% and POCFD, respectively. [21]

Boonlong Rodrangboon, The Application of Adaptive Neuro-Fuzzy Inference System for the Water Level Forecasting. In this study ANFIS model was used to forecast water levers in two different watersheds including 1) Yom watershed with small and steep basin and 2) ChoaPhraya watershed with large and flat basin. Water levels in there watersheds were forecasted in advances, for 1,2, and 3 days. In addition, ANFIS was tested in the case of incomplete data of the ChaoPhraya watershed. In the same day, the data from nearly stations were filled-up and used for predicting the missing data of water levels. The results of water level computed by ANFIS were compared with the results from an artificial neuron networks (ANN). It was found that the ANFIS has a capability for forecasting water levels in both areas even though these basins have different characteristics in nature. When ANFIS was compared with ANN, it was found that the results of water level prediction were quite the same. However, the results of highest and lowest water levels computed by ANFIS were found agree well with the observed ones and were better than those computed by ANN. [22]

CHAPTER III
MATERIALS AND METHODS

3.1 Research Methodology and Procedure

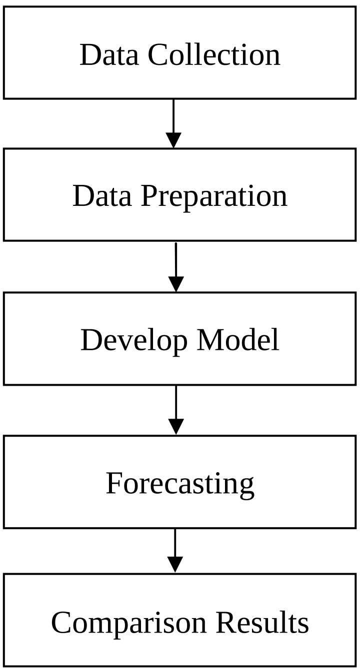


Figure 3.1 Flow diagram of the research methodology.

3.1.1 Data Collection

The data used in this research is daily volume of water of Sirikit Dam since January 1, 2006 to August 25, 2010 (1,698 day), These data derived from the database for water management (System Manage Water), Electricity Generating Authority of Thailand.

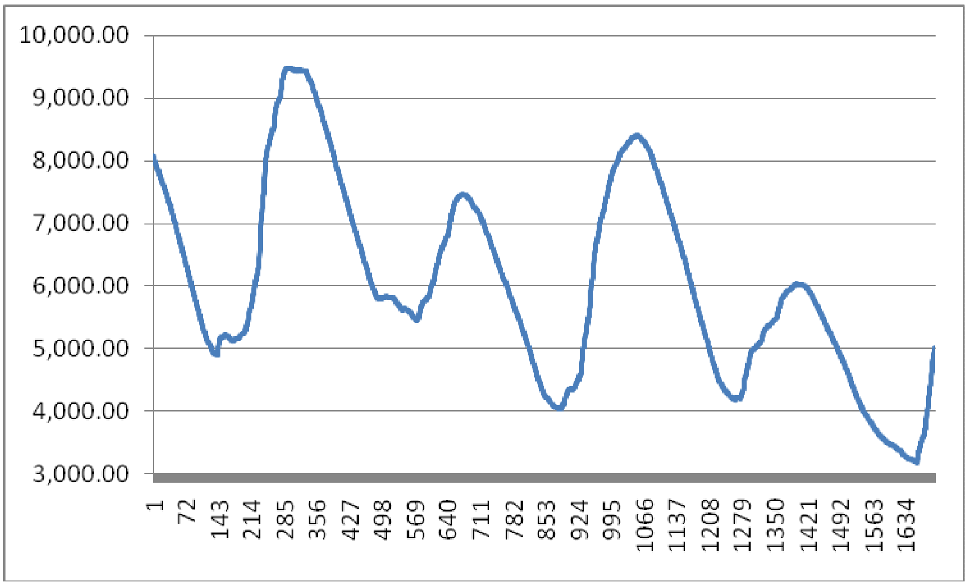


Figure 3.2 Volume of water in Sirikit Dam since January 1, 2006 to August 25, 2010.

3.1.2 Data Preparation

The data collected were divided into 2 prediction sets. First, for forecasting the water volume during April 1-15, 2010, the training data gathered between January 1, 2006 - March 31, 2010 would be used. Second, for forecasting the water volume during August 11-25, 2010, the training data gathered between January 1, 2006 - August 10, 2010 would be applied. Moreover, due to the fact that the input data, the quantities of water in Sirikit Dam, were univariate time series data, they would be organized using a sliding window technique for the neural networks method and adaptive neuro-fuzzy inference system. In contrast, the sliding window technique was not necessary for the holt-winters' exponential smoothing method.

The data would be transformed by "Min-Max Normalization" as the original values had to be changed to some real values between 0-1 before inputting the derived results into neutral network and adaptive neuro-fuzzy inference system. We normalized the input, X_i, using the following function as follow:

$$X_i' = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}} \tag{3.1}$$

where X_{min} is the minimum value and X_{max} is the maximum value from the training data sets However, there is no need to transform any data for the holt-winters' exponential smoothing method.

3.1.3 Develop Model

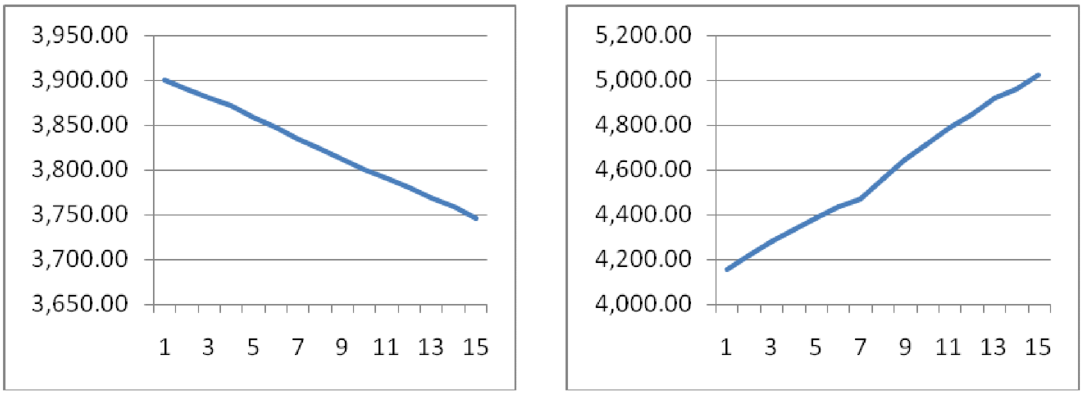
Multi-layer feed forward neural network was applied for the neural network model with back propagation for supervised learning consisting of a fully connected three-layer network (one input layer, one hidden layer and one output layer). The data input format was sliding window, which comprised of 20, 30 and 40 window sizes (number of input nodes). The number of hidden node in the hidden layer was set into 20 formats, which were 20, 40, 60, 80 and 100 nodes. The training function was set as trainlm (levenberg-marquardt backpropagation). The learning function was set as learngdm (gradient descent with momentum weight and bias learning function). In addition, the transfer function was tansig (hyperbolic tangent sigmoid transfer function) in hidden layer and purelin (linear transfer function) in the output layer. The value of initial weights was randomized. Learning epochs had to be set to the total of 300 epochs with the goal set at 0.00001.

The adaptive neuro-fuzzy inference system model comprised of 3 Membership Function formats, which were, trapmf (trapezoidal membership function), trimf (Triangular membership function) and pimf (Pi membership function). For teaching, sugeno method would be utilized. Grid partition would be applied for data management. The learning epochs would be set from 50, 100, 200 and 300 epochs.

3.1.4 Forecasting

All the three forecasting method would be predicted 15 days in advance by dividing the forecasting periods into 2 periods: April 1-15, 2010 and August 11-25, 2010. For the April 1-15, 2010 period, the training data gathered since January 1, 2006 to March 31, 2010 would be used. However, for the August 11 -25, 2010 period, the training data gathered since January 1, 2006 to August 10, 2010 would be applied.

For the neural networks model and the adaptive neuro-fuzzy inference system, simulation models derived from the training set would be utilized in the forecasting process in order to find the simulation model that gave the lowest MSE.



(a) (b)

Figure 3.3 Volume of water in Sirikit Dam
(a) April 1 – 15, 2010 (b) August 11 – 25, 2010.

The forecast result of neural networks and adaptive neuro-fuzzy inference system must denormalization before evaluate MSE values using the following function as follow:

$$X_i = X_i'(X_{\max} - X_{\min}) + X_{\min} \tag{3.2}$$

The holt–winters' exponential smoothing method in this study, selected holt–winters' additive seasonal smoothing method and holt–winters' multiplicative seasonal smoothing method which were suitable for the forecasting data, were composed trend component and seasonal component. Forecast using Program Crystal Ball 7 for parameter smoothing, the appropriate data set of training were analyzed by vertical cut-off point (α), slope (β) and the seasonal index (γ) from the mean absolute error data set of training the lowest.

For all three forecasting methods, the output values derived from the forecasting process would be reused as input values for further forecasting until the end of the procedure. Figure 3.4 shows the method of reusing the output as the next input for the neural network methods.

3.1.5 Comparison Result

In this process, the forecast effectively gained from neural network model will be compared with adaptive neuro-fuzzy inference system model and holt-winters' exponential smoothing method using mean square error (MSE)

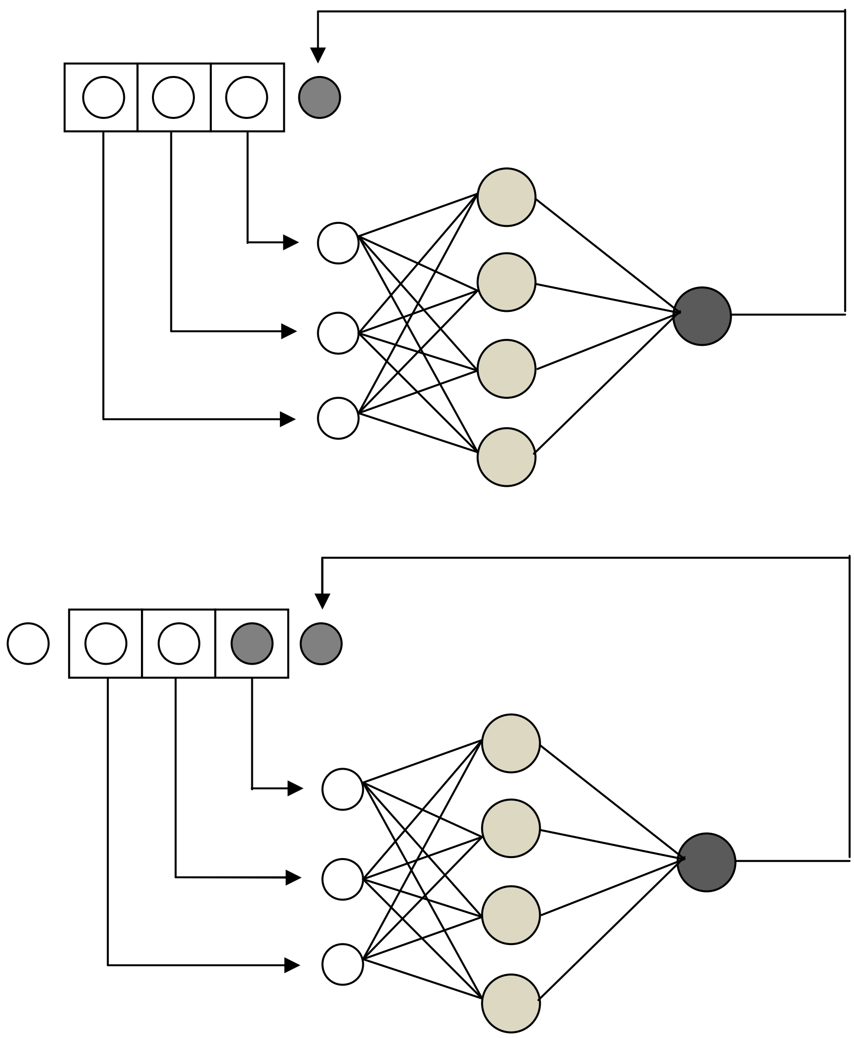


Figure 3.4 The method of taking an output from forecasting method to use as an input for further forecasting process in the neural network method. [23]

3.2 Statistic for Research Evaluation

3.2.1 Mean Square Error

The average squared predicted error between actual and predicted values for the forecasts made over a series of forecast patterns.

$$MSE = \frac{\sum_{t=1}^{n}\left(Y_t - \hat{Y}_t\right)^2}{n} \tag{3.3}$$

3.3 Research Tools

3.3.1 Hardware

Laptop:

- CPU:	Intel Core 2 Duo T6500 2.1GHz
- RAM:	DDR 2048 MB
- Hard Disk:	320 GB
- Display:	14.1 WXGA
- Peripherals:	Keyboard, Mouse, Printer, Diskette and CD-ROM Drive

3.3.2 Software

- Operating System:	Microsoft Windows XP
- Programming Language:	Matlab R2008b, Crystal Ball 7
- Documentation:	Microsoft Word 2007

CHAPTER IV
RESULTS

4.1 Forecasting Results

4.1.1 Neural Network

To forecast by the neural network model, number of window size and number of hidden node will be changed as set continuously, starting with the lowest value of both window size and hidden node and add up to more and more values. The table 4.1 and 4.2 are the MSE values from forecasting by the neural network model. From the table 4.1, MSE values from forecasting since April 1-15, 2010 the lowest MSE, which is 9.5720, given from 40 hidden node and 20 window size. From the table 4.2, MSE values from forecasting since August 11-25, 2010 the lowest MSE, which is 55.0692, given from 60 hidden node and 30 window size.

Table 4.1 MSE values from forecasting since April 1-15, 2010 by neural network.

Number of Hidden Node	**Number of Window Size**		
	20	**30**	**40**
20	332.5525	13.5616	13.9865
40	**9.5720**	113.0243	13.3008
60	72.2147	22.0666	44.2237
80	131.3644	327.2833	291.7244
100	52.6469	84.8087	10.2771

Table 4.2 MSE values from forecasting since August 11-25, 2010 by neural network.

Number of Hidden Node	**Number of Window Size**		
	20	**30**	**40**
20	72.1898	216.1351	166.9185
40	136.8449	185.0704	178.1221
60	432.2579	**55.0692**	190.0587
80	208.4817	86.2017	322.2532
100	152.8810	548.3595	166.9185

Table 4.3 The results of forecasting since April 1-15, 2010 by neural network.

	Water Volume (million cubic meters)	
Day	**Real values**	**Forecasting values**
1	3,899.98	3,899.66
2	3,890.46	3,888.89
3	3,879.38	3,879.15
4	3,871.48	3,869.83
5	3,858.86	3,860.13
6	3,846.28	3,849.88
7	3,833.73	3,839.37
8	3,822.77	3,828.90
9	3,811.84	3,818.61
10	3,799.39	3,808.73
11	3,790.07	3,799.22
12	3,779.22	3,789.66
13	3,768.39	3,779.95
14	3,757.60	3,770.34
15	3,745.29	3,760.98

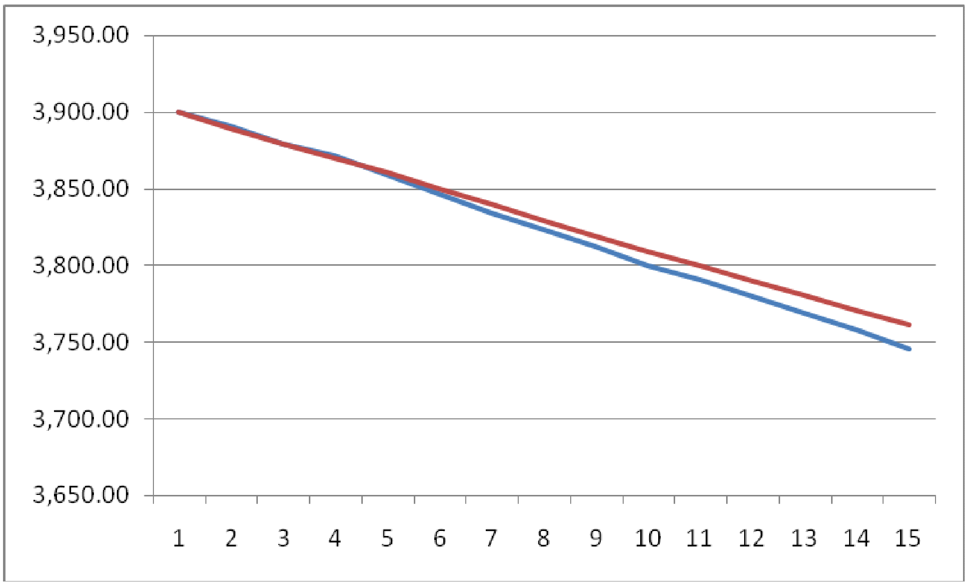


Figure 4.1 The graph comparing between forecasting values and real values since April 1-15, 2010 using neural network

Table 4.4 The results of forecasting since August 11-25, 2010 by neural network.

	Water Volume (million cubic meters)	
Day	**Real values**	**Forecasting values**
1	4,153.96	4,136.91
2	4,221.03	4,200.84
3	4,283.75	4,266.96
4	4,329.92	4,332.29
5	4,286.83	4,395.66
6	4,433.77	4,455.87
7	4,472.26	4,514.27
8	4,560.57	4,575.58
9	4,644.60	4,639.86
10	4,716.89	4,702.57
11	4,791.71	4,764.84
12	4,858.76	4,830.24
13	4,919.26	4,897.41
14	4,962.22	4,966.30
15	5,022.36	5,035.70

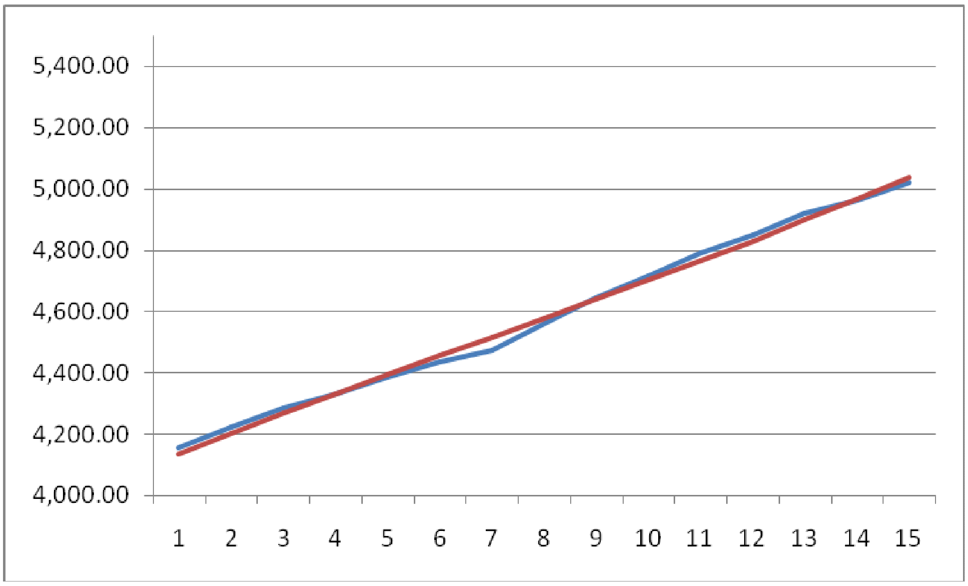


Figure 4.2 The graph comparing between forecasting values and real values since August 11-25, 2010 using neural network

4.1.2 Adaptive Neuro-Fuzzy Inference System

To forecast by the adaptive neuro-fuzzy inference system (ANFIS), the number of learning epochs and the type of membership function will be changed as set prior. The table 4.3 and 4.4 are the MSE values from forecasting by the adaptive neuro-fuzzy inference system model. From the table 4.3, MSE values from forecasting since April 1-15, 2010 the lowest MSE, which is 51.1379, given from 200 learning epochs and membership function type as triangular. From the table 4.2, MSE values from forecasting since August 11-25, 2010 the lowest MSE, which is 62.9031, given from 100 learning epochs and membership function type as pi.

Table 4.5 MSE values from forecasting since April 1-15, 2010 by ANFIS.

Epochs	**Type of Membership Function**		
	Pi	**Triangular**	**Trapezoidal**
50	193.4611	91.1441	270.5819
100	165.2915	121.2384	270.1971
200	150.4891	**51.1379**	563.0587
300	150.7420	80.0718	271.2823
400	150.7556	80.4150	269.9599
500	150.7556	80.3119	269.8235

Table 4.6 MSE values from forecasting since August 11-25, 2010 by ANFIS.

Epochs	**Type of Membership Function**		
	Pi	**Triangular**	**Trapezoidal**
50	64.3116	125.8031	382.0156
100	**62.9031**	158.2509	367.2816
200	68.7167	158.2509	368.2722
300	77.8473	158.2509	368.3790
400	78.0621	158.2509	368.3861
500	78.5914	158.2509	368.3867

Table 4.7 The results of forecasting since April 1-15, 2010 by ANFIS.

	Water Volume (million cubic meters)	
Day	**Real values**	**Forecasting values**
1	3,899.98	3,899.85
2	3,890.46	3,887.22
3	3,879.38	3,875.50
4	3,871.48	3,865.73
5	3,858.86	3,857.98
6	3,846.28	3,851.75
7	3,833.73	3,845.22
8	3,822.77	3,837.09
9	3,811.84	3,826.84
10	3,799.39	3,815.61
11	3,790.07	3,805.44
12	3,779.22	3,798.06
13	3,768.39	3,793.86
14	3,757.60	3,791.34
15	3,745.29	3,787.94

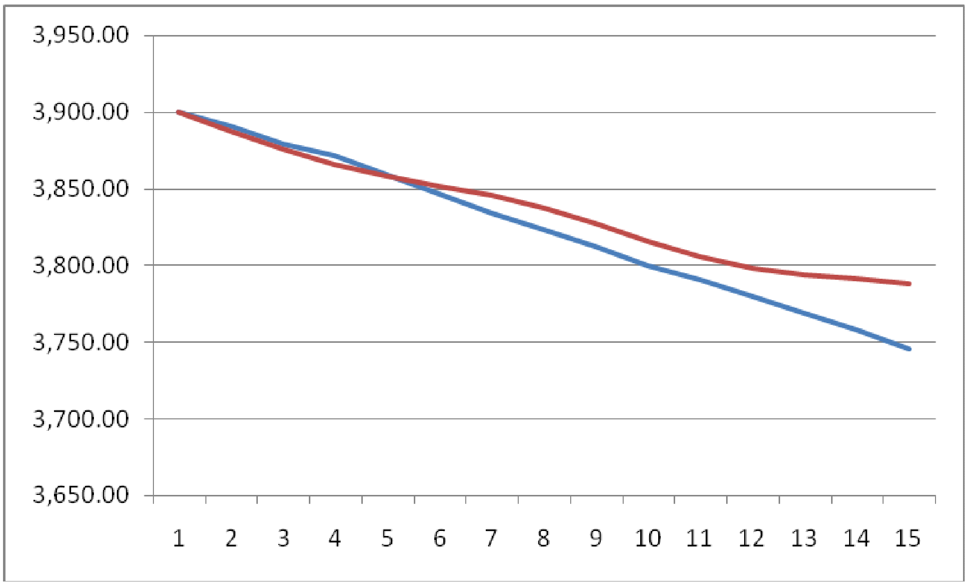


Figure 4.3 The graph comparing between forecasting values and real values since April 1-15, 2010 using ANFIS.

Table 4.8 The results of forecasting since August 11-25, 2010 by ANFIS.

	Water Volume (million cubic meters)	
Day	**Real values**	**Forecasting values**
1	4,153.96	4,141.73
2	4,221.03	4,209.82
3	4,283.75	4,273.82
4	4,329.92	4,333.95
5	4,286.83	4,395.60
6	4,433.77	4,456.67
7	4,472.26	4,517.47
8	4,560.57	4,578.31
9	4,644.60	4,639.62
10	4,716.89	4,701.07
11	4,791.71	4,763.03
12	4,858.76	4,825.38
13	4,919.26	4,887.49
14	4,962.22	4,949.35
15	5,022.36	5,011.32

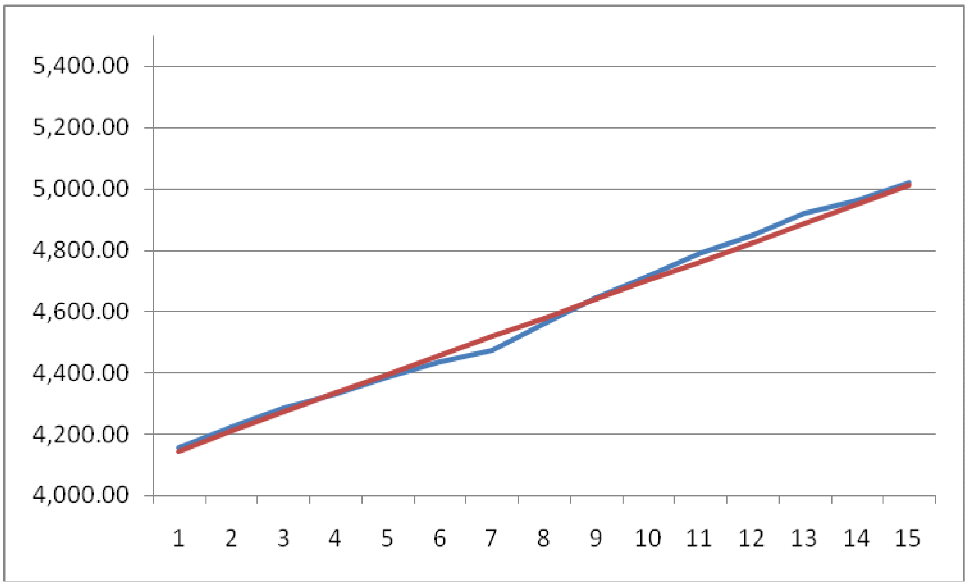


Figure 4.4 The graph comparing between forecasting values and real values since August 11-25, 2010 using ANFIS.

4.1.3 Holt-winters' Exponential Smoothing Method

The Holt–winters' exponential smoothing method that is suitable for forecasting is the holt–winters' multiplicative seasonal exponential smoothing method (multiplicative HWS) due to the lower deviation in the forms of MSE value when comparing to the holt–winters' additive seasonal exponential smoothing method. Equation 4.1 to show alpha, beta and gamma values from forecasting since April 1-15, 2010, the MSE, which is 15.3664, alpha is 0.853, Beta is 0.214 and Gamma is 0.999. Equation 4.2 to show values from forecasting since August 11-25, 2010 the MSE, which is 102.4066, alpha is 0.854, Beta is 0.219 and Gamma is 0.999.

$$\begin{aligned} L_t &= 0.853(Y_t / S_{t-7}) + 0.147(L_{t-1} + b_{t-1}) \\ b_t &= 0.214(L_t - L_{t-1}) + 0.786 b_{t-1} \\ S_t &= 0.999(Y_t / L_t) + 0.001 S_{t-7} \\ F_{t+m} &= (L_t + b_t m) S_{t-m+7} \end{aligned} \tag{4.1}$$

$$\begin{aligned} L_t &= 0.854(Y_t / S_{t-7}) + 0.146(L_{t-1} + b_{t-1}) \\ b_t &= 0.219(L_t - L_{t-1}) + 0.781 b_{t-1} \\ S_t &= 0.999(Y_t / L_t) + 0.001 S_{t-7} \\ F_{t+m} &= (L_t + b_t m) S_{t-m+7} \end{aligned} \tag{4.2}$$

Table 4.9 The results of forecasting since 1-15 April 2010 by multiplicative HWS.

	Water Volume (million cubic meters)	
Day	**Real values**	**Forecasting values**
1	3,899.98	3,896.04
2	3,890.46	3,884.07
3	3,879.38	3,873.20
4	3,871.48	3,862.60
5	3,858.86	3,853.94
6	3,846.28	3,841.52
7	3,833.73	3,826.83
8	3,822.77	3,811.82
9	3,811.84	3,799.85
10	3,799.39	3,788.96
11	3,790.07	3,778.32
12	3,779.22	3,769.58
13	3,768.39	3,757.17
14	3,757.60	3,742.55
15	3,745.29	3,727.60

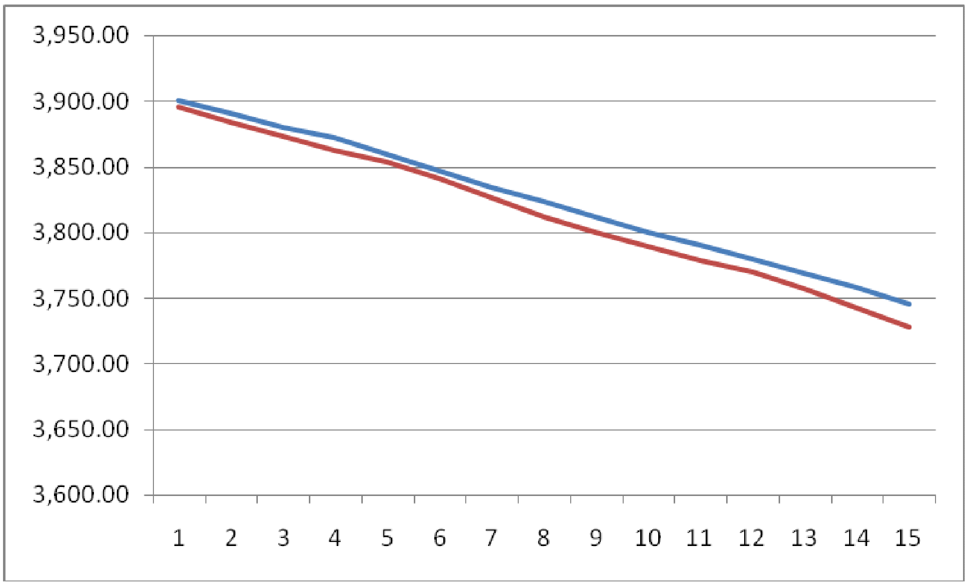


Figure 4.5 The graph comparing between forecasting values and real values since April 1-15, 2010 using multiplicative HWS.

Table 4.10 The results forecasting since August 11-25, 2010 by multiplicative HWS.

	Water Volume (million cubic meters)	
Day	**Real values**	**Forecasting values**
1	4,153.96	4,130.31
2	4,221.03	4,177.47
3	4,283.75	4,233.92
4	4,329.92	4,295.46
5	4,286.83	4,348.36
6	4,433.77	4,405.07
7	4,472.26	4,467.98
8	4,560.57	4,521.96
9	4,644.60	4,568.30
10	4,716.89	4,624.80
11	4,791.71	4,686.87
12	4,858.76	4,739.49
13	4,919.26	4,796.27
14	4,962.22	4,859.80
15	5,022.36	4,913.61

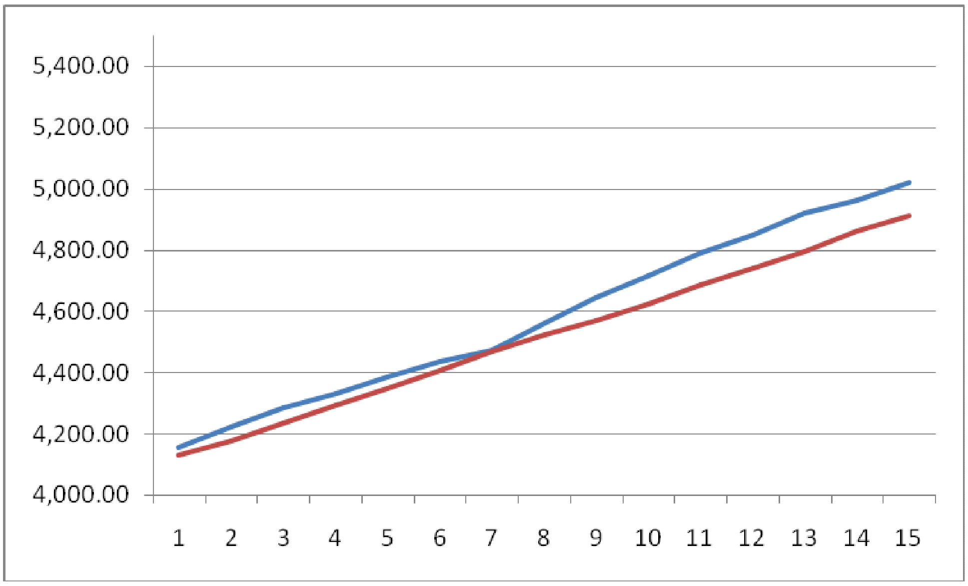


Figure 4.6 The graph comparing between forecasting values and real values since August 11-25, 2010 using multiplicative HWS.

4.2 Comparison of the Forecasting Results

The part compare the forecasting performance with MSE values the neural network model**,** adaptive neuro-fuzzy inference system model and Holt–winters' exponential smoothing method.

Table 4.11 MSE from forecasting since April 1-15, 2010 by NN, ANFIS and HWS.

Neural Network			Adaptive Neuro-fuzzy			Holt-winter's	
window size			Type of membership function			Type of Holt-winter's	
20	30	40	Pi	Triangular	Trapezoidal	Additive	Multiplicative
9.5720	13.5616	10.2771	150.4891	51.1379	269.8235	34.5145	15.3664

Table 4.12 MSE from forecasting since August 11-25, 2010 by NN, ANFIS and HWS

Neural Network			Adaptive Neuro-fuzzy			Holt-winter's	
window size			Type of membership function			Type of Holt-winter's	
20	30	40	Pi	Triangular	Trapezoidal	Additive	Multiplicative
72.1898	**55.0692**	166.9185	62.9031	125.8031	367.2816	1249.5145	102.4066

From table 4.11 compare MSE values from forecasting since April 1-15, 2010 and table 4.12 compare MSE values from forecasting since August 11-25, 2010. The neural network gave the lowest MSE values comparing to the adaptive neuro-fuzzy inference system and holt-winter's exponential smoothing method. That means the neural network model is able to produce more accuracy outcome than the adaptive neuro-fuzzy inference system model and holt-winter's exponential smoothing method. The MSE values that neural network from forecasting since April 1-15, 2010 produce the lowest MSE, which is 9.5720, given from 40 hidden node and 20 window size and the MSE values from forecasting since August 11-25, 2010 produce the lowest MSE, which is 55.0692, given from 60 hidden node and 30 window size. In term of the adaptive neuro-fuzzy inference system that given the lowest MSE at 51.1379 from forecasting since April 1-15, 2010, the number of learning epochs has to be 200, membership function type as triangular and MSE values from forecasting August 11-25, 2010 the lowest MSE, which is 62.9031, the number of learning epochs has to be 100, membership function type as pi. Lastly the lowest MSE of the holt–winters' exponential smoothing method from forecasting since April 1-15, 2010 equals to 15.3664 and MSE value from forecasting since August 11-25, 2010 equals to 102.4066**.**

CHAPTER V
DISCUSSION

5.1 Discussion

This research has been done to forecast the volume of water in Sirikit Dam using three forecasting methods: the neural networks, adaptive neuro-fuzzy inference system and holt-winters' exponential smoothing method. From this study, the forecasting results by the neural network model were more accurate in forecasting the water volume in Sirikit Dam than the results derived from the adaptive neuro-fuzzy inference system and the holt-winters' exponential smoothing method. The neural network gave the lowest MSE values comparing to the other two methods. For the first period prediction, April 1-15, 2010, the forecasting results gave the MSE value at 9.5720 by the neural network, MSE at 15.3664 by the holt–winters' multiplicative seasonal exponential smoothing method and MSE at 51.1379 by the adaptive neuro-fuzzy inference system. For the second period, August 11-25, 2010, the neural network gave the MSE value at 55.0692, the holt–winters' multiplicative seasonal exponential smoothing method gave the MSE value at 102.4066 and the adaptive neuro-fuzzy inference system gave the MSE value at 62.9031.

By testing the effectiveness of the three forecasting methods showed that the MSE derived from the first period, April 1-15, 2010, was lower than the MSE derived from the second period, August 11-25, 2010. This was because the second period was during rainy season; and the variance of the water volume in rainy season is normally higher than the water volume during summer. During rainy season, rainwater was the major factor that controlled the water volume in the dam. Moreover, in this research, only a single type of input data were utilized which were the quantities of water in Sirikit Dam. Thus, the forecasting outcome from August 11-25, 2010 was less accurate than the outcome from April 1-15, 2010.

Forecasting by the adaptive neuro-fuzzy inference system involved some overtraining problem which derived from too many learning epochs. When the simulation model, derived from the training set, was used to forecast, the result showed that the simulation model with higher learning epochs given higher MSE than the simulation model that lower learning epochs were set.

During August 11-25, 2010, forecasting by the holt–winters' multiplicative seasonal exponential smoothing method gave much lower MSE value than the value forecasting by the holt–winters' additive seasonal exponential smoothing method. This was due to that the holt–winters' multiplicative seasonal exponential smoothing method was more suitable for the data set with a trend and seasonality that increase over time.

5.2 Limitations

1. The data used in this forecasting study were univariate time series, which were the quantities of water in Sirikit Dam.

2. There are no definite theories of format setting for the neural network method such as number of window size, number of hidden layer and number of hidden node. Thus, in this research, all the values in the neural network model were tested and set artificially.

CHAPTER VI
CONCLUSION AND RECOMMENDATION

6.1 Conclusion

This research presents the development of the neural network model to forecast the quantities of water in Sirikit Dam and comparing the efficiency of the forecasting models between neural networks model, adaptive neuro-fuzzy inference system model and holt-winters' exponential smoothing method. This study employed data gathered from daily volume of water in Sirikit Dam since January 1, 2006 to August 25, 2010, which derived from the database for water management (System Manage Water), Electricity Generating Authority of Thailand. In order to test the effectiveness of each forecasting method, the prediction process would be done 15 days in advance dividing into two periods: April 1-15, 2010 and August 11-25, 2010. For first April period, the training data gathered since January 1, 2006 to March 31, 2010 would be used. However, for the second August period, the training data gathered since January 1, 2006 to August 10, 2010 would be applied. The statistics used in the comparison models in this study was the mean square error (MSE).

The neural network model used multi-layer feed forward neural network with back propagation for supervised learning consisting of a fully connected three-layer network (one input layer, one hidden layer and one output layer). To forecast the quantities of water in Sirikit Dam, the study examined the most appropriate form of neural network by finding the number of hidden node and number of window size, with 300 learning epochs and goal at 0.00001 being set. For the first forecasting period, April 1-15, 2010, the result showed that the most suitable hidden node value was 40 nodes and the window size value was 20, which both given MSE value at 9.5720. However, for the second forecasting period, August 11-25, 2010, the result showed that the most suitable hidden node value was 60 nodes and the window size value was 30, which both given MSE value at 55.0692.

However, the adaptive neuro-fuzzy inference system model seeks the most appropriate form for the forecasting by changing types of membership function and number of learning epochs, with the goal at 0.00001 being set. For forecasting period April 1-15, 2010, the outcome expressed that the lowest MSE was at 51.1379 when the number of learning epochs was 200 and the membership function type was Triangular. Yet, for forecasting period August 11-25, 2010, the outcome expressed that the lowest MSE was at 62.9031 when the number of learning epochs was 100 and the membership function type was Pi.

Lastly, in this study, the holt-winters' exponential smoothing method, selected holt–winters' additive seasonal smoothing method and holt–winters' multiplicative seasonal smoothing method could be concluded that the holt-winters' multiplicative seasonal smoothing method was more suitable for forecasting for both periods: April 1-15, 2010 and August 11-25, 2010. The method gave MSE values at 15.3664 and 102.4066 respectively.

The results appeared that, among the three forecasting systems, the neural network gave the lowest MSE value comparing to others. Therefore, the research can be summarized that for the water quantity forecasting, the neural network gave more accurate results in both periods comparing to the adaptive neuro-fuzzy inference system model and the holt-winters' exponential smoothing method.

6.2 Recommendation

1. The input data for this study were univariate time series which were water quantities. For future development, the factors that influenced the water quantities, such as air temperature, rainfall intensity, etc, should be considered as input neurons of neural network.

2. In order to choose the appropriate forecasting method, components of time series need to be considered such as trend, seasonal, cycle and irregular.

3. The neural network model could give more accurate outcome by changing the values of parameter in the simulation model.

4. In order to fix the overtraining problems, the data should be divided into 2 parts: training set and testing set.

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APPENDIX

Volume of water in Sirikit Dam Data Year 2006.

Day	January	February	March	April	May	June
1	8,082.45	7,418.80	6,689.36	5,825.00	5,105.75	5,186.08
2	8,056.16	7,391.25	6,660.92	5,800.48	5,090.53	5,191.85
3	8,039.46	7,370.61	6,632.54	5,778.05	5,077.23	5,195.70
4	8,013.23	7,350.00	6,604.22	5,749.57	5,062.06	5,203.39
5	7,987.05	7,327.13	6,582.47	5,719.14	5,045.03	5,207.24
6	7,965.66	7,302.01	6,556.42	5,688.79	5,028.02	5,209.17
7	7,944.30	7,281.49	6,530.42	5,658.53	5,009.17	5,213.02
8	7,925.33	7,254.17	6,506.63	5,634.38	4,992.24	5,220.73
9	7,901.64	7,229.17	6,476.41	5,614.30	4,977.22	5,213.02
10	7,882.72	7,201.94	6,450.56	5,572.24	4,958.48	5,207.24
11	7,863.82	7,174.76	6,426.91	5,542.31	4,947.25	5,199.54
12	7,844.94	7,152.14	6,388.30	5,516.44	4,936.04	5,193.77
13	7,826.08	7,129.56	6,356.21	5,492.61	4,921.12	5,184.16
14	7,797.83	7,093.50	6,326.34	5,466.86	4,915.53	5,176.48
15	7,776.68	7,066.51	6,296.53	5,445.13	4,911.81	5,166.89
16	7,750.86	7,039.57	6,266.79	5,419.50	4,915.53	5,159.23
17	7,727.42	7,012.68	6,237.11	5,395.90	4,913.67	5,149.65
18	7,706.35	6,990.30	6,213.85	5,368.45	4,911.81	5,149.65
19	7,682.97	6,956.80	6,192.74	5,341.06	4,902.51	5,142.00
20	7,664.30	6,927.83	6,161.14	5,315.71	4,896.93	5,140.09
21	7,645.64	6,903.36	6,135.91	5,286.53	4,898.79	5,121.00
22	7,624.68	6,881.16	6,108.64	5,265.19	4,913.67	5,121.00
23	7,606.06	6,850.12	6,079.35	5,249.70	5,024.25	5,121.00
24	7,587.47	6,821.36	6,052.21	5,220.73	5,096.23	5,122.90
25	7,564.26	6,799.27	6,027.21	5,195.70	5,130.54	5,128.63
26	7,543.40	6,772.82	6,004.33	5,176.48	5,157.31	5,136.27
27	7,522.57	6,746.41	5,979.43	5,153.48	5,164.97	5,143.91
28	7,499.45	6,715.66	5,935.99	5,138.18	5,168.81	5,147.74
29	7,478.68		5,902.99	5,124.81	5,168.81	5,147.74
30	7,457.93		5,876.25	5,113.37	5,170.73	5,149.65
31	7,439.50		5,845.47		5,174.56	

Volume of water in Sirikit Dam Data Year 2006 (continue).

Day	July	August	September	October	November	December
1	5,151.57	5,658.53	7,847.30	8,977.37	9,455.80	9,383.78
2	5,157.31	5,690.81	7,944.30	8,987.43	9,453.22	9,368.38
3	5,159.23	5,719.14	8,010.85	9,010.07	9,445.50	9,347.86
4	5,163.06	5,767.87	8,072.89	9,027.69	9,442.92	9,324.81
5	5,164.97	5,808.65	8,111.17	9,050.38	9,440.34	9,306.91
6	5,168.81	5,845.47	8,144.74	9,105.96	9,442.92	9,296.68
7	5,176.48	5,876.25	8,195.21	9,164.25	9,440.34	9,283.91
8	5,189.93	5,900.93	8,228.94	9,212.53	9,440.34	9,271.14
9	5,201.47	5,960.79	8,257.90	9,283.91	9,442.92	9,260.93
10	5,209.17	6,016.80	8,296.60	9,332.49	9,442.92	9,253.28
11	5,216.88	6,054.29	8,328.09	9,368.38	9,437.77	9,237.99
12	5,226.52	6,079.35	8,376.66	9,388.91	9,442.92	9,220.16
13	5,230.38	6,102.36	8,413.17	9,406.90	9,442.92	9,197.27
14	5,236.17	6,163.24	8,418.05	9,424.90	9,442.92	9,171.86
15	5,241.97	6,201.18	8,432.68	9,442.92	9,442.92	9,149.02
16	5,245.84	6,241.35	8,459.53	9,450.65	9,440.34	9,131.28
17	5,247.77	6,268.91	8,481.53	9,460.96	9,440.34	9,105.96
18	5,251.64	6,300.78	8,498.66	9,463.53	9,442.92	9,080.68
19	5,263.25	6,358.35	8,515.80	9,466.11	9,442.92	9,063.00
20	5,290.42	6,448.41	8,559.97	9,468.69	9,442.92	9,035.25
21	5,309.86	6,586.82	8,626.41	9,463.53	9,440.34	9,007.55
22	5,327.40	6,766.21	8,705.48	9,463.53	9,440.34	8,982.40
23	5,356.70	6,954.57	8,769.97	9,468.69	9,437.77	8,962.30
24	5,374.32	7,084.50	8,817.24	9,466.11	9,432.62	8,939.72
25	5,401.80	7,165.71	8,847.16	9,466.11	9,440.34	8,919.67
26	5,423.44	7,265.54	8,877.13	9,463.53	9,437.77	8,899.64
27	5,476.76	7,354.57	8,899.64	9,463.53	9,432.62	8,879.63
28	5,528.37	7,434.90	8,922.17	9,466.11	9,430.05	8,862.14
29	5,570.25	7,492.53	8,942.23	9,466.11	9,427.47	8,829.71
30	5,602.26	7,592.12	8,962.30	9,463.53	9,396.62	8,809.77
31	5,634.38	7,706.35		9,458.38		8,794.84

Volume of water in Sirikit Dam Data Year 2007.

Day	January	February	March	April	May	June
1	8,779.91	7,960.91	7,258.72	6,491.51	5,841.37	5,818.86
2	8,760.04	7,932.44	7,224.62	6,463.48	5,825.00	5,818.86
3	8,730.26	7,908.75	7,199.67	6,437.66	5,810.69	5,814.78
4	8,698.05	7,885.09	7,174.76	6,411.88	5,798.44	5,812.73
5	8,665.90	7,861.46	7,149.88	6,384.02	5,804.56	5,816.82
6	8,641.21	7,835.51	7,120.54	6,362.62	5,808.65	5,814.78
7	8,621.48	7,811.95	7,093.50	6,343.40	5,816.82	5,808.65
8	8,596.85	7,786.08	7,068.76	6,324.20	5,812.73	5,800.48
9	8,572.25	7,748.51	7,044.06	6,302.91	5,810.69	5,790.28
10	8,547.69	7,727.42	7,026.12	6,277.40	5,806.61	5,782.13
11	8,518.25	7,706.35	6,992.54	6,251.94	5,798.44	5,767.87
12	8,491.31	7,682.97	6,970.19	6,224.42	5,798.44	5,751.61
13	8,471.75	7,652.63	6,950.11	6,190.63	5,802.52	5,739.42
14	8,454.64	7,629.33	6,923.38	6,169.56	5,802.52	5,727.25
15	8,427.80	7,603.74	6,896.70	6,148.52	5,808.65	5,713.06
16	8,400.99	7,573.54	6,872.28	6,127.52	5,812.73	5,700.92
17	8,374.23	7,552.67	6,852.33	6,102.36	5,816.82	5,690.81
18	8,349.93	7,531.83	6,832.41	6,079.35	5,820.91	5,682.73
19	8,325.67	7,506.39	6,808.10	6,056.38	5,820.91	5,684.75
20	8,303.86	7,480.98	6,781.63	6,035.53	5,822.95	5,684.75
21	8,277.24	7,457.93	6,759.61	6,016.80	5,825.00	5,676.68
22	8,253.07	7,428.00	6,737.62	5,998.10	5,827.04	5,662.56
23	8,228.94	7,400.43	6,715.66	5,979.43	5,827.04	5,648.46
24	8,192.81	7,382.07	6,693.74	5,960.79	5,827.04	5,632.37
25	8,163.95	7,363.73	6,674.04	5,938.05	5,822.95	5,614.30
26	8,135.14	7,336.27	6,650.00	5,919.48	5,820.91	5,604.27
27	8,108.78	7,313.42	6,621.64	5,900.93	5,818.86	5,618.31
28	8,082.45	7,286.05	6,593.34	5,886.53	5,814.78	5,632.37
29	8,051.39		6,556.42	5,868.03	5,812.73	5,650.47
30	8,022.76		6,530.42	5,853.67	5,816.82	5,654.50
31	7,991.81		6,523.93		5,818.86	

Volume of water in Sirikit Dam Data Year 2007 (continue).

Day	July	August	September	October	November	December
1	5,652.49	5,514.45	6,058.46	6,794.86	7,451.02	7,242.80
2	5,644.43	5,554.27	6,075.17	6,803.69	7,453.32	7,233.71
3	5,636.39	5,610.28	6,091.89	6,814.73	7,455.62	7,224.62
4	5,628.35	5,638.40	6,108.64	6,830.20	7,457.93	7,215.54
5	5,618.31	5,666.59	6,152.72	6,870.06	7,457.93	7,206.47
6	5,610.28	5,674.66	6,226.53	6,927.83	7,455.62	7,197.40
7	5,610.28	5,682.73	6,268.91	6,974.66	7,455.62	7,188.34
8	5,606.27	5,698.90	6,302.91	7,014.92	7,453.32	7,177.02
9	5,600.26	5,719.14	6,326.34	7,048.54	7,446.41	7,167.97
10	5,596.25	5,737.39	6,343.40	7,098.00	7,441.81	7,154.40
11	5,588.24	5,749.57	6,366.90	7,134.07	7,441.81	7,138.59
12	5,580.24	5,757.70	6,401.16	7,163.44	7,437.20	7,120.54
13	5,568.25	5,761.77	6,439.81	7,197.40	7,430.30	7,100.25
14	5,562.26	5,763.80	6,467.79	7,226.89	7,423.40	7,082.25
15	5,556.27	5,765.84	6,491.51	7,258.72	7,416.51	7,071.01
16	5,544.30	5,763.80	6,515.28	7,283.77	7,409.61	7,041.81
17	5,536.33	5,780.09	6,545.58	7,311.14	7,405.02	7,028.36
18	5,522.40	5,798.44	6,560.76	7,333.98	7,402.72	7,014.92
19	5,508.49	5,812.73	6,580.30	7,352.29	7,393.54	6,999.25
20	5,498.56	5,816.82	6,608.57	7,370.61	7,377.48	6,979.13
21	5,492.61	5,814.78	6,630.36	7,377.48	7,361.44	6,959.04
22	5,482.70	5,822.95	6,643.45	7,384.36	7,343.13	6,934.51
23	5,474.78	5,841.37	6,654.37	7,393.54	7,324.84	6,916.71
24	5,468.84	5,865.98	6,665.29	7,405.02	7,315.70	6,901.14
25	5,460.93	5,905.05	6,676.23	7,411.91	7,297.45	6,881.16
26	5,455.00	5,942.18	6,684.98	7,421.10	7,290.60	6,863.41
27	5,451.05	5,969.07	6,702.51	7,428.00	7,281.49	6,843.48
28	5,447.10	5,985.65	6,735.42	7,434.90	7,272.38	6,823.57
29	5,455.00	6,002.26	6,766.21	7,439.50	7,260.99	6,805.90
30	5,458.95	6,018.88	6,781.63	7,444.11	7,249.62	6,786.04
31	5,498.56	6,043.87		7,446.41		6,768.41

Volume of water in Sirikit Dam Data Year 2008.

Day	January	February	March	April	May	June
1	6,748.61	6,110.74	5,548.29	4,889.50	4,241.29	4,031.96
2	6,731.03	6,096.08	5,530.36	4,859.85	4,231.15	4,033.59
3	6,711.28	6,083.53	5,514.45	4,839.53	4,226.09	4,033.59
4	6,691.55	6,068.90	5,494.60	4,813.75	4,224.40	4,036.85
5	6,674.04	6,054.29	5,474.78	4,789.88	4,222.71	4,049.92
6	6,654.37	6,033.45	5,456.98	4,767.91	4,209.23	4,064.67
7	6,630.36	6,016.80	5,437.24	4,742.36	4,192.43	4,081.09
8	6,606.40	6,000.18	5,417.53	4,715.07	4,184.04	4,107.48
9	6,582.47	5,981.51	5,393.94	4,689.70	4,174.00	4,112.44
10	6,558.59	5,964.93	5,370.40	4,662.61	4,165.64	4,112.44
11	6,536.92	5,944.25	5,350.83	4,639.21	4,152.29	4,115.75
12	6,519.60	5,925.66	5,331.30	4,617.68	4,147.30	4,117.41
13	6,504.47	5,900.93	5,304.02	4,594.42	4,138.98	4,120.72
14	6,487.19	5,880.36	5,280.71	4,567.68	4,130.67	4,189.07
15	6,465.63	5,857.77	5,259.38	4,544.59	4,122.38	4,234.53
16	6,444.11	5,841.37	5,240.04	4,523.34	4,109.13	4,256.54
17	6,422.62	5,820.91	5,216.88	4,503.92	4,099.22	4,276.93
18	6,399.02	5,800.48	5,195.70	4,481.04	4,090.97	4,287.15
19	6,375.46	5,778.05	5,172.65	4,458.24	4,079.45	4,297.39
20	6,356.21	5,755.67	5,151.57	4,439.01	4,079.45	4,314.49
21	6,334.86	5,733.33	5,128.63	4,412.87	4,077.80	4,331.64
22	6,313.55	5,711.04	5,109.56	4,398.97	4,072.87	4,348.84
23	6,296.53	5,694.86	5,098.14	4,383.37	4,064.67	4,354.00
24	6,273.15	5,668.61	5,065.85	4,360.90	4,059.75	4,357.45
25	6,251.94	5,648.46	5,045.03	4,341.95	4,061.39	4,364.35
26	6,232.88	5,630.36	5,024.25	4,321.35	4,056.47	4,360.90
27	6,213.85	5,608.28	5,001.64	4,300.81	4,054.83	4,355.73
28	6,182.20	5,588.24	4,979.09	4,276.93	4,049.92	4,347.12
29	6,163.24	5,568.25	4,954.73	4,261.63	4,046.65	4,343.67
30	6,142.21		4,939.78	4,248.07	4,038.49	4,355.73
31	6,125.42		4,921.12		4,031.96	

Volume of water in Sirikit Dam Data Year 2008 (continue).

Day	July	August	September	October	November	December
1	4,357.45	5,417.53	7,104.76	7,937.18	8,311.13	8,306.28
2	4,359.18	5,460.93	7,131.82	7,953.79	8,315.97	8,296.60
3	4,367.81	5,492.61	7,161.18	7,965.66	8,330.52	8,289.33
4	4,390.30	5,528.37	7,179.28	7,979.92	8,340.22	8,277.24
5	4,405.91	5,576.24	7,197.40	7,991.81	8,352.36	8,260.32
6	4,421.57	5,630.36	7,231.44	8,006.09	8,362.08	8,250.66
7	4,435.51	5,688.79	7,279.21	8,025.15	8,366.94	8,241.00
8	4,445.99	5,782.13	7,313.42	8,044.23	8,371.80	8,228.94
9	4,458.24	5,905.05	7,340.85	8,060.94	8,371.80	8,219.30
10	4,482.80	6,006.41	7,363.73	8,084.84	8,369.37	8,207.25
11	4,491.59	6,079.35	7,398.13	8,101.59	8,386.39	8,197.62
12	4,502.16	6,138.01	7,423.40	8,120.76	8,386.39	8,185.59
13	4,510.98	6,232.88	7,448.71	8,137.54	8,388.82	8,168.76
14	4,521.58	6,343.40	7,492.53	8,149.54	8,388.82	8,154.34
15	4,558.79	6,426.91	7,527.20	8,156.74	8,393.69	8,135.14
16	4,573.02	6,482.88	7,568.90	8,163.95	8,396.12	8,115.96
17	4,585.50	6,528.26	7,592.12	8,173.56	8,398.56	8,094.41
18	4,606.93	6,562.93	7,633.99	8,180.78	8,398.56	8,080.06
19	4,671.63	6,621.64	7,666.63	8,187.99	8,393.69	8,058.55
20	4,760.60	6,674.04	7,699.33	8,190.40	8,391.26	8,037.07
21	4,839.53	6,715.66	7,725.08	8,200.03	8,383.96	8,013.23
22	4,924.85	6,753.01	7,755.55	8,212.07	8,381.52	7,991.81
23	4,986.60	6,788.24	7,788.43	8,228.94	8,374.23	7,965.66
24	5,037.46	6,814.73	7,811.95	8,241.00	8,369.37	7,941.92
25	5,088.63	6,845.69	7,826.08	8,253.07	8,357.22	7,918.22
26	5,149.65	6,896.70	7,842.58	8,269.99	8,349.93	7,892.18
27	5,189.93	6,943.43	7,859.10	8,274.82	8,340.22	7,880.36
28	5,222.66	6,988.07	7,870.91	8,282.08	8,330.52	7,866.18
29	5,251.64	7,030.60	7,894.55	8,286.91	8,323.24	7,835.51
30	5,307.92	7,059.77	7,920.59	8,294.17	8,313.55	7,814.31
31	5,356.70	7,082.25		8,301.44		7,793.13

Volume of water in Sirikit Dam Data Year 2009.

Day	January	February	March	April	May	June
1	7,771.98	7,071.01	6,392.59	5,550.28	4,778.89	4,293.98
2	7,753.20	7,048.54	6,366.90	5,526.38	4,753.30	4,283.75
3	7,732.10	7,023.88	6,337.00	5,500.55	4,727.79	4,270.13
4	7,713.37	6,999.25	6,309.29	5,474.78	4,704.19	4,256.54
5	7,689.98	6,974.66	6,281.65	5,447.10	4,680.66	4,248.07
6	7,668.96	6,956.80	6,249.82	5,417.53	4,659.00	4,244.68
7	7,647.97	6,936.74	6,224.42	5,391.98	4,639.21	4,242.99
8	7,627.00	6,901.14	6,199.07	5,362.57	4,617.68	4,236.22
9	7,606.06	6,878.94	6,175.87	5,335.21	4,592.64	4,226.09
10	7,582.83	6,852.33	6,146.42	5,311.81	4,571.24	4,219.34
11	7,564.26	6,830.20	6,119.13	5,286.53	4,553.46	4,210.92
12	7,541.09	6,805.90	6,081.44	5,261.32	4,528.65	4,207.55
13	7,515.63	6,781.63	6,056.38	5,238.10	4,503.92	4,202.51
14	7,492.53	6,757.41	6,027.21	5,218.80	4,486.32	4,197.46
15	7,469.45	6,737.62	6,000.18	5,195.70	4,472.26	4,190.75
16	7,441.81	6,717.86	5,973.22	5,168.81	4,458.24	4,189.07
17	7,416.51	6,695.93	5,946.32	5,142.00	4,442.50	4,185.72
18	7,398.13	6,676.23	5,919.48	5,115.28	4,430.28	4,202.51
19	7,375.19	6,654.37	5,892.70	5,090.53	4,421.57	4,210.92
20	7,352.29	6,612.93	5,863.93	5,063.96	4,411.13	4,212.60
21	7,324.84	6,586.82	5,835.23	5,035.58	4,400.70	4,215.97
22	7,299.73	6,562.93	5,808.65	5,007.29	4,388.56	4,214.28
23	7,274.65	6,539.08	5,780.09	4,979.09	4,372.99	4,210.92
24	7,249.62	6,513.11	5,749.57	4,956.60	4,366.08	4,210.92
25	7,233.71	6,487.19	5,723.19	4,932.31	4,352.28	4,214.28
26	7,211.01	6,465.63	5,696.88	4,906.23	4,336.80	4,210.92
27	7,192.87	6,439.81	5,674.66	4,882.08	4,321.35	4,207.55
28	7,163.44	6,416.17	5,652.49	4,854.31	4,311.07	4,204.19
29	7,140.85		5,626.34	4,830.31	4,304.23	4,202.51
30	7,118.28		5,600.26	4,804.56	4,300.81	4,209.23
31	7,093.50		5,574.24		4,295.68	

Volume of water in Sirikit Dam Data Year 2009 (continue).

Day	July	August	September	October	November	December
1	4,232.84	5,014.82	5,376.28	5,835.23	6,023.04	5,849.57
2	4,254.85	5,022.36	5,391.98	5,843.42	6,018.88	5,837.28
3	4,275.23	5,037.46	5,399.83	5,851.62	6,016.80	5,820.91
4	4,297.39	5,046.92	5,407.70	5,868.03	6,014.73	5,806.61
5	4,319.63	5,054.49	5,411.63	5,878.30	6,014.73	5,792.32
6	4,369.53	5,058.27	5,417.53	5,884.47	6,014.73	5,780.09
7	4,439.01	5,060.17	5,427.38	5,890.64	6,014.73	5,765.84
8	4,502.16	5,073.44	5,437.24	5,909.17	6,014.73	5,749.57
9	4,533.96	5,084.83	5,447.10	5,913.29	6,014.73	5,735.36
10	4,553.46	5,094.33	5,451.05	5,917.41	6,014.73	5,719.14
11	4,569.46	5,100.04	5,458.95	5,921.54	6,012.65	5,704.97
12	4,581.93	5,111.46	5,462.91	5,927.73	6,010.57	5,684.75
13	4,596.21	5,121.00	5,470.82	5,933.92	6,008.49	5,672.64
14	4,650.00	5,132.45	5,476.76	5,940.12	6,004.33	5,660.54
15	4,707.82	5,151.57	5,480.72	5,946.32	6,002.26	5,644.43
16	4,742.36	5,188.01	5,478.74	5,952.52	5,998.10	5,630.36
17	4,762.43	5,228.45	5,514.45	5,956.66	5,993.95	5,614.30
18	4,784.38	5,251.64	5,562.26	5,958.72	5,989.80	5,600.26
19	4,837.69	5,263.25	5,592.25	5,969.07	5,981.51	5,582.24
20	4,882.08	5,284.59	5,622.32	5,971.15	5,971.15	5,566.25
21	4,913.67	5,290.42	5,644.43	5,979.43	5,960.79	5,548.29
22	4,934.18	5,309.86	5,670.62	5,989.80	5,950.45	5,536.33
23	4,947.25	5,321.55	5,702.94	6,000.18	5,940.12	5,518.43
24	4,960.35	5,329.35	5,723.19	6,008.49	5,931.86	5,504.52
25	4,965.97	5,341.06	5,735.36	6,016.80	5,921.54	5,488.65
26	4,971.59	5,346.92	5,759.74	6,023.04	5,911.23	5,474.78
27	4,979.09	5,358.66	5,782.13	6,025.12	5,898.87	5,460.93
28	4,984.72	5,360.61	5,802.52	6,027.21	5,888.58	5,445.13
29	4,986.60	5,362.57	5,818.86	6,029.29	5,878.30	5,427.38
30	4,994.12	5,362.57	5,825.00	6,027.21	5,863.93	5,407.70
31	5,007.29	5,366.49		6,023.04		5,390.01

Volume of water in Sirikit Dam Data Year 2010.

Day	January	February	March	April	May	June
1	5,374.32	4,896.93	4,378.18	3,899.98	3,584.01	3,417.80
2	5,360.61	4,880.22	4,357.45	3,890.46	3,578.10	3,412.16
3	5,344.97	4,863.55	4,336.80	3,879.38	3,572.20	3,405.12
4	5,327.40	4,846.92	4,317.92	3,871.48	3,566.31	3,405.12
5	5,309.86	4,830.31	4,299.10	3,858.86	3,560.43	3,398.09
6	5,294.30	4,813.75	4,282.04	3,846.28	3,553.10	3,391.08
7	5,284.59	4,799.05	4,265.03	3,833.73	3,545.77	3,385.48
8	5,267.13	4,782.55	4,249.76	3,822.77	3,538.46	3,381.29
9	5,255.51	4,766.08	4,234.53	3,811.84	3,531.17	3,374.31
10	5,243.90	4,747.83	4,215.97	3,799.39	3,523.89	3,371.52
11	5,230.38	4,729.61	4,195.79	3,790.07	3,520.98	3,365.95
12	5,216.88	4,709.63	4,177.35	3,779.22	3,513.72	3,356.24
13	5,199.54	4,693.32	4,160.63	3,768.39	3,506.47	3,347.93
14	5,184.16	4,675.24	4,137.32	3,757.60	3,499.24	3,338.26
15	5,166.89	4,659.00	4,127.35	3,745.29	3,493.46	3,328.63
16	5,145.83	4,641.01	4,112.44	3,733.01	3,490.58	3,321.76
17	5,130.54	4,624.85	4,097.57	3,722.30	3,483.38	3,312.18
18	5,115.28	4,603.36	4,082.74	3,713.14	3,479.06	3,305.35
19	5,100.04	4,583.71	4,067.95	3,702.48	3,479.06	3,297.18
20	5,086.73	4,560.57	4,053.20	3,691.84	3,474.76	3,287.67
21	5,071.54	4,537.50	4,040.12	3,681.24	3,469.02	3,278.19
22	5,058.27	4,519.81	4,028.70	3,667.63	3,460.43	3,268.74
23	5,043.13	4,498.64	4,014.06	3,655.58	3,459.00	3,267.39
24	5,031.80	4,477.53	3,997.84	3,645.06	3,456.15	3,262.00
25	5,012.94	4,456.49	3,980.05	3,636.07	3,453.29	3,260.66
26	4,996.00	4,435.51	3,965.54	3,625.60	3,450.44	3,255.29
27	4,979.09	4,411.13	3,954.29	3,618.14	3,446.16	3,251.27
28	4,962.22	4,393.76	3,943.06	3,609.21	3,441.90	3,243.24
29	4,945.38		3,931.86	3,597.33	3,436.21	3,236.56
30	4,924.85		3,922.27	3,586.96	3,430.54	3,232.57
31	4,909.95		3,911.12		3,424.87	

Volume of water in Sirikit Dam Data Year 2010 (continue).

Day	July	August	September	October	November	December
1	3,227.25	3,603.27				
2	3,227.25	3,616.65				
3	3,229.90	3,640.57				
4	3,229.90	3,696.40				
5	3,228.57	3,728.42				
6	3,224.59	3,777.67				
7	3,219.28	3,868.32				
8	3,217.96	3,954.29				
9	3,213.99	4,009.19				
10	3,213.99	4,076.16				
11	3,211.34	4,153.96				
12	3,207.38	4,221.03				
13	3,203.42	4,283.75				
14	3,198.16	4,329.92				
15	3,195.53	4,386.83				
16	3,187.65	4,433.77				
17	3,181.11	4,472.26				
18	3,181.11	4,560.57				
19	3,252.61	4,644.60				
20	3,319.02	4,716.89				
21	3,349.31	4,791.71				
22	3,359.01	4,848.76				
23	3,382.68	4,919.26				
24	3,417.80	4,962.22				
25	3,441.90	5,022.36				
26	3,471.89					
27	3,507.92					
28	3,529.71					
29	3,554.56					
30	3,573.68					
31	3,585.49					

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