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FORECASTING WATER DEMAND USING BACK PROPAGATION NETWORKS IN THE OPERATION OF RESERVOIRS IN THE CITARUM CASCADE, WEST JAVA, INDONESIA

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ABSTRACT

This study investigates the use of Neural Networks (NN) as a potential means of more accurately forecasting water demand in the Citarum River basin cascade. Neural Networks have the ability to recognise nonlinear patterns when sufficiently trained with historical data. The study constructs a NN model of the cascade, based on Back Propagation Networks (BPN). Data representing physical characteristics and meteorological conditions in the Citarum River basin from 1989 through 1995 were used to train the BPN. Nonlinear activation functions (sigmoid, tangent, and gaussian functions) and hidden layers in the BPN were chosen for the study.

1. INTRODUCTION

The Citarum River basin in West Java as shown in Figure 1, Indonesia, has a cascade of three reservoirs: Saguling Reservoir, Cirata Reservoir, and Juanda Reservoir, linked in series from upstream to downstream. Cirata and Saguling Reservoirs function primarily for hydroelectric power production, while Juanda Reservoir is multifunctional, with functions including flood control, irrigation, recreation, and fishing. Management of the three reservoirs focuses on control of water discharge at each of the three reservoirs to meet the various demands placed on the system as a whole. Successful operation depends on accurate forecasting of water demand, which changes from month to month depending on changing needs for water for various functions, especially for power generation and irrigation. Changes in the forecasted water demand require appropriate changes in the operational plan. Accurate forecasting of water demand is, therefore, critical to the successful management of the system. Present forecasting methods do not allow optimal reservoir management, and the need for better forecasting led to this research.

Operation of the reservoirs is established on hydrologic models[1]. The hydrologic models are based on the behaviour of surface water hydrology. Surface water hydrology deals principally with river modeling and basin modeling. River modeling involves equations that approximate river flow. Basin modeling is based on equations that approximate rainfall-runoff relationships. A hydrologic model requires a great deal of detailed data (e.g., a topographical map, river networks and characteristics, soil characteristics, rainfall, and runoff data). Often, these data are not available, which causes great difficulty in model calibration. Given the reported successes in applications of Artificial Neural Networks (ANN) in pattern recognition and simulation of unknown relationships, it would appear that a suitably designed artificial neural network might be able to complete the hydrologic models or to provide an alternative methodology. Users of ANN have recently found many applications in civil engineering such as detecting damage in structures, simulating structural behaviour, determining truck attributes, estimating construction costs, predicting river flow, forecasting floods, and estimating rainfall and surface water supply[2].

In the hydrological context, as in many other fields, ANN is increasingly used as black-box, simplified models[3]. For hydrological applications, the advantage of (ANN) models is their capability to reproduce unknown relationships existing between a set of input variables descriptive of the system and a set of output variables[4].

The objective of this research is to use ANN methodology to forecast the total demand on a series of reservoirs in the Citarum River basin area in West Java Province, Indonesia. Linear programming, non-linear programming, dynamic programming and multiple regression have previously been used for this operation and have not given satisfactory results[5]. Total demand is an input parameter in the operation. The lack of data available for this input parameter is the prime reason for using an ANN methodology in order to estimate the water demand.

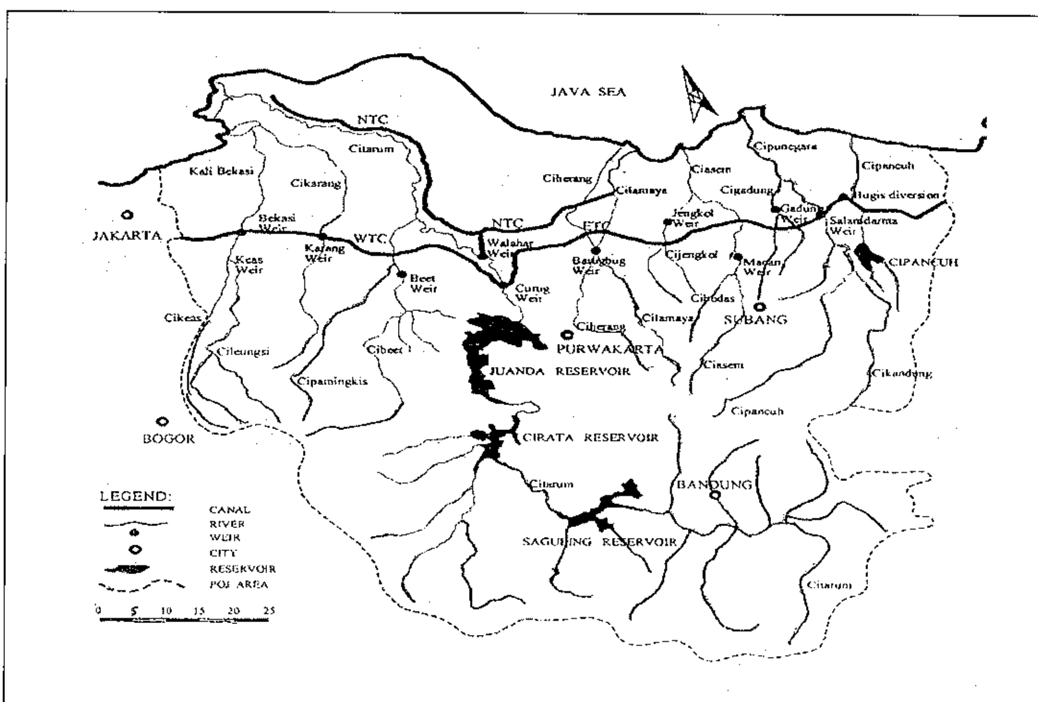

Figure 1: Citarum-reservoirs system.

Source: Nedeco, Indec & Accos. Lmt., PT Virama Karya, and PT Gamma Epsilon. *Jatiluhur Water Resources Management Project Preparation Study (JWRMP)-Feasibility Study Main Report Draft.* Republic of Indonesia: Ministry of Public Works Directorate General of Water Resources Development, March 1998.

2. RESERVOIRS PROBLEM

The three reservoirs are operated simultaneously in a series using non-linear programming as a methodology for their model operation. The operation uses water demand prediction and water supply forecast. The water supply forecast is placed in the operation as an input parameter. However, water demand always changes from month to month. This requires the operation authority to update the water supply forecast every month, which causes inefficiency in the operation of the reservoir.

Changes in the input parameters can keep the methodology from working, as the operation authority would like it to. Data unavailability in the field for estimating water demand forces the operation to use inaccurate input data. The largest portion of the water supply (80%) is consumed by irrigation demand. Therefore, it is very important to create a model which can effectively forecast water demand and supply. The data needed in order to estimate water demand is mostly unavailable. Therefore, in forecasting the water supply for irrigation demand, Perusahaan Umum Otorita Jatiluhur (POJ), as the operation authority, depends on the demand reports from the kabupaten (counties) which contain the irrigation area under POJ authority. However, these are not always accurate. Actual water demands are always different from reported water demands. The irrigation waters cover 243,000 ha of rice fields and are supplied free of charge by the POJ. Since irrigation water is free of charge, water stored in the Juanda Reservoir has little commercial value. The water that does have commercial value, because it is used for electricity, drinking and industry, mostly pays for operational costs and only creates a small net revenue. Due to the conditions above, some consequences of the problem are as follows:

(i) Water supply needs must be modified every month in order to produce an accurate water demand estimate;
(ii) Although the existing operation's objective is to support the water supply plan, the actual water demand always varies from the plan;
(iii) Optimum electricity production cannot be obtained, since water demand always changes; and
(iv) Monthly changes create inefficiency in the operation process.

This research is intended to provide an alternative methodology for forecasting the water demand.

3. NEURAL NETWORKS

Neural Networks, a new information processing technique, are computer simulations of living nervous systems. The concept of neural networks comes from the biological neural nets in the human brain, which consists of around 10^{11} electrically active cells called neurons[3].

A neuron is a nerve cell with all of its processes. There are three parts of a typical nerve cell in a simple neuron. Dendrites carry signals in (input). The cell body contains the nucleus (black-box). The axon which carries signals away (output).

The summation of the inputs creates a function. This function is called the summation function or activation function. The output from the summation function does not give a final output. Instead, this output will be transformed to reach a final output. The summation function can be formed as follows:

$$y_j = \sum x_i w_i \tag{1}$$

A function, which will transform the summation function into a final output, is called the transfer function or threshold[1]. The transfer function can be linear or non-linear; however, it is generally non-linear. Basically, the output from the summation function may or may not trigger the neuron to give an output. The final output depends on how the output from the summation function is transformed by the transfer function. Therefore, a transfer function represents a relationship between the summation function and the final output. There are many transformation functions and the selection of a transformation function impacts the efficiency of the network. Many types of activation function are in use; however, the sigmoid, hyperbolic tangent, and gaussian functions used in the research.

The ANN model which was used has the ability to compare results with the expected output. The comparison provides difference values which can be used for error correction in the ANN model. The ANN is then run again using the error correction value. This simulation is run until the differences between the expected result and the ANN output reach a minimum error. When the ANN reaches the minimum error, the ANN model is ready to be implemented.

The network paradigm for this research, the Back Propagation Network (BPN) as shown in Figure 2, is an error-correction process which takes place after the forward-propagation step is completed; the calculation begins at the output layer and progresses backward through the hidden layer to the input layer[6].

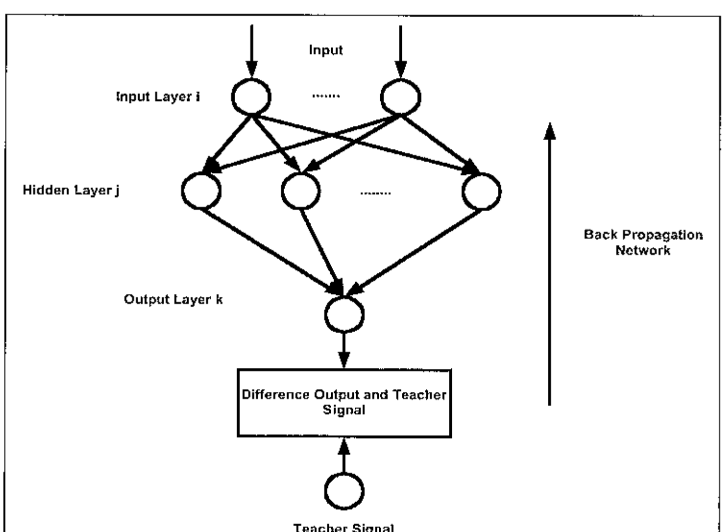

Figure 2: Structure of back propagation networks.

The functions used in processing elements in BPN are the non-linear functions, which are fitted with the characteristics of input and output data. BPN is also fitted with a supervised learning system in ANN. This study required a supervised learning system, in order to have sufficiently accurate results with ANN.

Some successful studies and research on forecasting in the water resources area have been conducted. In 1992, French *et al.* developed a three-layer feedforward neural network to forecast rainfall intensity in space and time and compared the results with two other methods of short-term forecasting[7]. Karunanithi *et al.* in 1994 used neural networks for flow predictions[8]. At the same time, Zhu *et al.* used neural networks to predict runoff[9]. Zhang *et al* used neural networks to forecast daily water demands[10]. Deo *et al.* in 1997 used neural networks to forecast the real time of ocean wave heights[11]. In 1999, Liong *et al.* conducted river stage forecasting in Bangladesh, also using a neural networks approach[12]. Most of the research above were using Back Propagation Networks with sigmoid function.

4. DATA ORGANISATION

The data collection was conducted in West Java Province, Indonesia in the institutions which are involved in the operation of the Citarum cascade, and the local university, The Institute of Technology of Bandung (ITB), which has been conducting research in the area for years. The institutions are the Jatiluhur Authority Project (POJ), The Institution of Research in Water Resources of Public Works Department, South Australia Waters Corporation, Institution of Meteorology and Geophysics of West Java Province (BMG), and the Institution of Cooperation of Water Resources Development of West Java Province.

Since the research was a comparative study between an existing methodology and the artificial neural networks methodology, the data collection range was the same as that of the existing methodology when research was conducted for it.

Data collection requires the same range of data in each input. In order to have all data in the same range, the range is the data hydrology from 1989 to 1995. The training input data that were used are as follows:

(i) Local inflows in Saguling Reservoir (m^3/Second)
(ii) Evaporation in Saguling Reservoir (mm)
(iii) Water level in Saguling Reservoir (m)
(iv) Local inflows in Cirata Reservoir (m^3/Second)
(v) Evaporation in Cirata Reservoir (mm)
(vi) Water level in Cirata Reservoir (m)
(vii) Local inflows in Juanda Reservoir (m^3/Second)
(viii) Evaporation in Juanda Reservoir (mm)
(ix) Water level in Juanda Reservoir (m)
(x) Average rainfall in West Tarum Canal (mm)
(xi) Average rainfall in North Tarum Canal (mm)
(xii) Average rainfall in East Tarum Canal (mm).

The Actual Total Demands on the Juanda Reservoir (m^3/Second) was used as desired output. Data in the Planned Total Demands on the Juanda Reservoir (m^3/Second) was used for a comparative study

The data for this research is from years 1989 through 1995. The Juanda, Saguling, and Cirata Reservoirs started their series operation in 1989. The data on the Tarum Canal areas were available from 1920 through the present time, but the data conditions from 1996 through 1998 were missing and unavailable. Collecting the missing Tarum Canal data was not feasible. The consideration of collecting data was to have all input data in the same range of years. Therefore, the chosen range was taken in order to have all data available; otherwise, the data could not be used to complete this research.

Normalisation was performed in order to have the data transformed to the neural networks range. Two transformation types were made in the research; first is the range 0 to +1, and second, the range -1 to +1.

5. NETWORK TRAINING

Neural networks are used in pattern recognitions and forecasting applications. To do so, the neural networks studies the behaviour of an application from past data. The study of past behaviour of a system is called the training process and must take place before a neural network is capable of simulating the systems' behaviour under a different set of conditions.

Training in the Back Propagation Networks is a gradient descent system that tries to minimise the mean square error of the system[13]. The ability of neural networks to converge depends on the success of its training. To have successful training, historical data availability is crucial. The more data available, the better the neural networks' results. In the experiments reported here, 80% of the available data (68 patterns) was used for training and 20% (16 patterns) for testing.

In the training phase, over-training of the model may occur[14]. In this research, the error on the training set kept on decreasing during training, while the error on the test set started increasing at a certain point. To avoid over training in the neural networks training phase, training was stopped when the minimal test set error was achieved.

6. FORECAST PERFORMANCE EVALUATION

The neural networks performed using different non-linear functions. Campolo *et al.* used *R* squared and Mean Square Error *(MSE)* to estimate neural network forecasting ability results in river flood forecasting[15]. Liong *et al.* also obtained *R* squared and *MSE* to analyse neural networks' abilities in forecasting river stage in Bangladesh[12]. Statistical analysis using R squared, and *MSE* was carried out to examine the result of the neural networks. For comparison to the neural networks results, the *R* squared and *MSE* of the total plan water demand (as current method result) was calculated against the actual output (actual water demand). *R* squared is the coefficient of multiple determination. It is a statistical indicator usually applied to multiple regression analysis. It compares the accuracy of the model to the accuracy of a trivial benchmark model, wherein the prediction is just the mean of all of the samples. A perfect fit would result in an R squared value of 1, a very good fit near 1, and very poor fit less than 0. The coefficient of multiple determination R squared is defined as follows:

$$R^2 = \frac{\sum (y_a - \bar{y}_a)^2 \sum (y_a - y_p)^2}{\sum (y_a - \bar{y}_a)^2} \tag{2}$$

where y_a is the actual value, y_p the predicted value, and $\bar{y}_a$ the mean of the y values.

The Mean Square Error is the mean over all patterns of the square of the actual value minus the predicted value. Good forecasting neural networks results had *MSE* smaller than the Total Plan Water Demand. Bad forecasting neural networks results have *MSE* larger than or equal to the Total Plan Water Demand. The *MSE* is defined as follows:

$$MSE = \frac{1}{N}\sum_{i=1}^{N} (y_{ai} - y_{pi})^2 \tag{3}$$

where N is total number of patterns, y_{ai} the target desired value for the ith pattern, y_{pi} the predicted output value for the *ith* pattern. Actual values form past years were used as a target or desired values for neural network during training.

The Mann-Whitney test was used to determine whether the actual demand (expected output) and neural networks results or the current method forecasting water demand plan was significantly different at a selected probability level. Accurate forecasting of neural networks results did not have significant difference to the expected output. The Mann-Whitney test sample probability significant level is 5% (α =0.05). In order to have the representable forecasting results, the probability level of neural networks results needs to be above test sample probability significance (α). The result of the Mann-Whitney test was marked as *W*.

The neural networks training results and the neural networks testing results are compared to the values in Table 1 to determine the good forecasting results. The neural networks

Table 1: Total plan water demand measurements.

No.	**Description**	**R squared**	**Mean squared error**	**Mean absolute error**	**Min. absolute error**	**Max. absolute error**	**[W] α>0.05?**
1	Total Plan Water Demand, the whole pattern	0.3860	811.534	4.767	18.460	21.118	(7410) 0.321
2	Total Plan Water Demand, the testing pattern	0.6446	640.238	11.844	20.750	0.940	(285) 0.4397

training results were matched against the first description of Table 1. The neural networks results were matched against the second description of Table 1. The good result of neural networks had to pass both descriptions in the Table 1.

7. CONCLUSION

The result of neural networks experiments in this study proves that neural networks give better forecasting results than the current method. The input values in the neural networks were collected based on the river basin characteristics as alternative data. The good result of neural networks experiments demonstrated the ability of neural networks to perform well with limited data and alternative data.

There were three non-linear functions (sigmoid, tangent and gaussian functions) used in these experiments. Table 2 and 3 display the best result of each function in the neural networks results and testing results. The [W] values in Table 2 and 3 are the Mann-Whitney two sample t test results at significance level 5%. The requirement to accept the neural network models were achieved as shown in [W], *MSE* and *R* square values of the Table 2 and 3.

Table 2: Best function neural network result.

No.	**BPN NN Types**	**R squared**	**Mean squared error**	**Mean absolute error**	**Min. absolute error**	**Max. absolute error**	**[W]** α>0.05?
1	Ward Net with Sigmoid Function	0.909	121.687	7.751	0	34.868	(7096) 0.9962
2	Ward Net with 3 slabs and using tangent function	0.8566	191.786	10.638	0.411	43.709	(7133) 0.9129
3	Standard with Gaussian Function and 2 hidden layers	0.9226	103.473	6.596	0.063	33.782	(7300) 0.5227

Table 3: Best function neural network testing result.

No.	**BPN NN Types**	**R squared**	**Mean squared error**	**Mean absolute error**	**Min. absolute error**	**Max. absolute error**	**[W]** α>0.05?
1	Ward Net with Sigmoid Function	0.7636	425.859	17.665	1.006	34.868	(266) 0.9546
2	Ward Net with 3 slabs and using tangent function	0.7061	529.471	19.102	1.944	43.709	(264) 1.0000
3	Standard with Gaussian Function and 2 hidden layers	0.8126	337.623	15.14	1.076	33.782	(264) 1.0000

Table 2 and 3 show, the Mann-Whitney statistic tests gave no significance difference to the actual water demand. In accordance with Table 2 and 3, a standard Back Propagation Network using the gaussian function and 2 hidden layers gave the highest *R* squared value and the smallest *MSE* value in the neural networks result and testing result, followed by the sigmoid function and the tangent function. As a result, the H_3 hypothesis was rejected. The gaussian function outperformed the sigmoid function.

Adding the hidden layer in a neural network can give better convergence of neural networks results. Table 2 and 3 show that adding a hidden layer in the standard Back Propagation network using the gaussian function gave a good prediction result. Nevertheless, increasing the number of hidden layers cannot always give better performance of a neural network. The standard Back Propagation Network using the tangent function with input range (0, +1) could not converge to the expected output by adding a hidden layer. Table 4 and 5 show that the *R* squared and *MSE* of the standard Back Propagation Network using the tangent function were decreased as a result of increasing hidden layers from one to two.

Table 4: Result of standard BPN using tangent function.

No.	BPN NN Types	R squared	Mean squared error	Mean absolute error	Min. absolute error	Max. absolute error
1	Standard with Tangent Function	0.8099	254.287	11.509	0.2	56.057
2	Standard with Tangent Function and 2 hidden layers	0.5525	598.551	18.085	0.06	88.827

Table 5. Testing result of standard BPN using tangent function.

No.	BPN NN Types	R squared	Mean squared error	Mean absolute error	Min. absolute error	Max. absolute error
1	Standard with Tangent Function	0.6461	637.537	19.45	3.273	56.057
2	Standard with Tangent Function and 2 hidden layers	0.4606	971.753	25.596	4.712	66.167

Previous results in the water resources field recommend the sigmoid function in Back Propagation Networks as the most widely used, but the results in this research do not confirm this. The good architecture of neural networks can be formed by trial and error. Adding hidden layers and neurons, changing activation functions, or even new neural networks methods are not guaranteed to give successful results. The best function and architecture of neural networks based on the experiments conducted was the neural networks results have the lowest value of *MSE* and the highest value of *R* square.

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Appendix I - Comparison Values Between Actual Water Demand, BPN (Gaussian Function and 2 Hidden Layers), and Total Plan Water Demand

Abbreviations:
Actual (1) = Actual Water Demand.
Network (1) = Standard BPN using Gaussian Function and 2 Hidden Layers.
PlanTotWtrDm = Total Plan Water Demand.
Act-Net (1) = Error Value between BPN (Gaussian Function and 2 Hidden Layers) to Actual Water Demand.
Act-Plan = Error Value between Total Plan Water Demand to Actual Water Demand.

Statistics Measurements

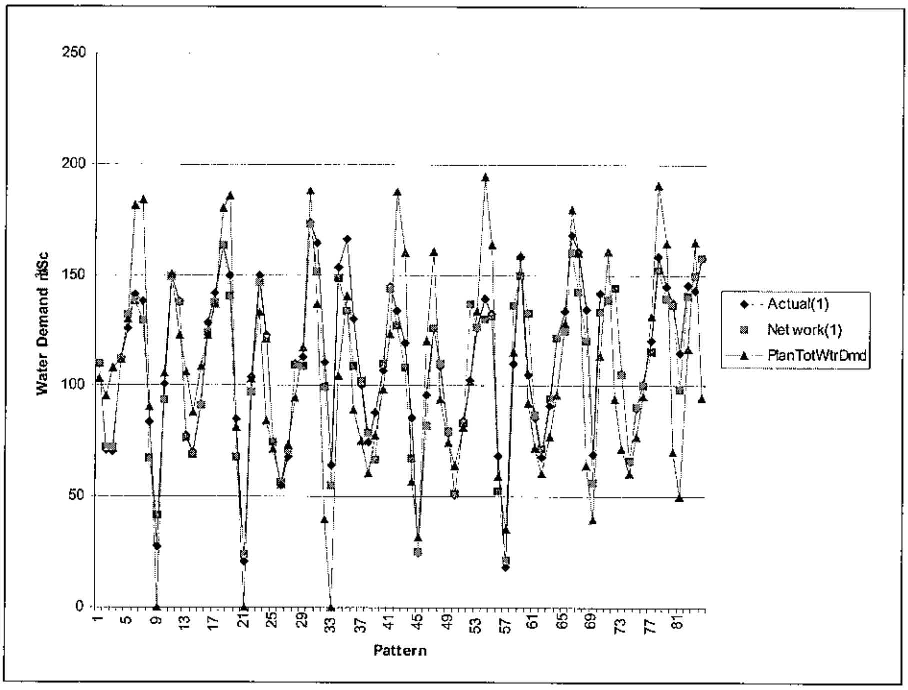
Table Statistics Measurements Neural Network Result and Total Plan Water Demand.

No.	BPN NN Types	R squared	Mean squared error	Mean absolute error	Min. absolute error	Max. absolute error	[W] $\alpha = 0.05$?
1	Total Plan Water Demand	0.3860	811.534	4.767	18.460	21.118	(7410) 0.321
2	Standard with Gaussian Function and 2 hidden layers	0.9226	103.473	6.596	0.063	33.782	(7300) 0.5227

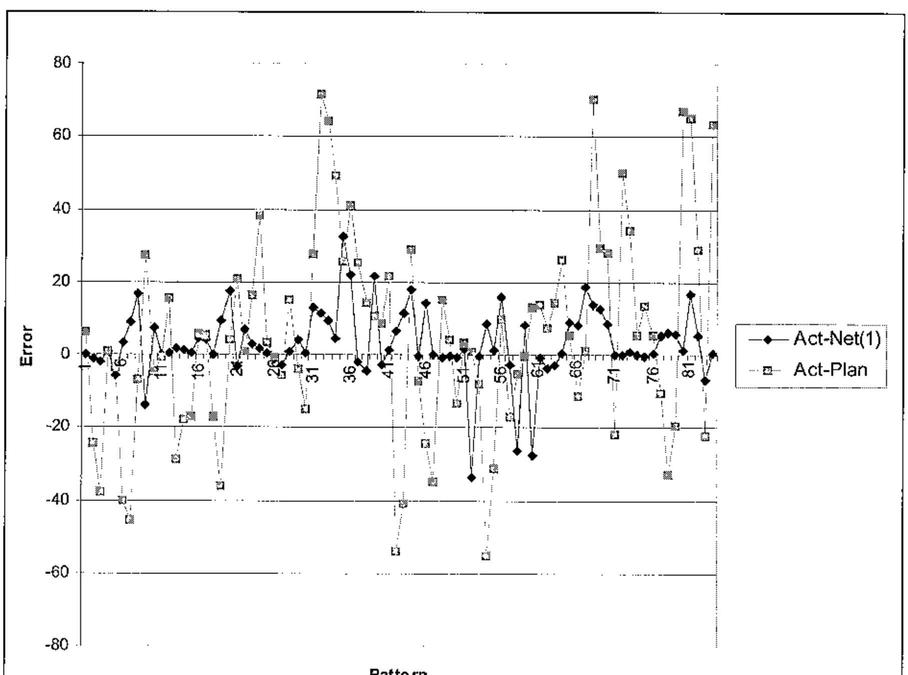
Table Statistics Measurements Neural Network Testing Results and Total Plan Water Demand.

No.	BPN NN Types	R squared	Mean squared error	Mean absolute error	Min. absolute error	Max. absolute error	[W] $\alpha = 0.05$?
1	Total Plan Water Demand, the testing pattern	0.6446	640.238	11.844	20.750	0.940	(285) 0.4397
2	Standard with Gaussian Function and 2 hidden layers, testing pattern	0.8126	337.623	15.14	1.076	33.782	(264) 1.0000

Neural Networks Result Graphs

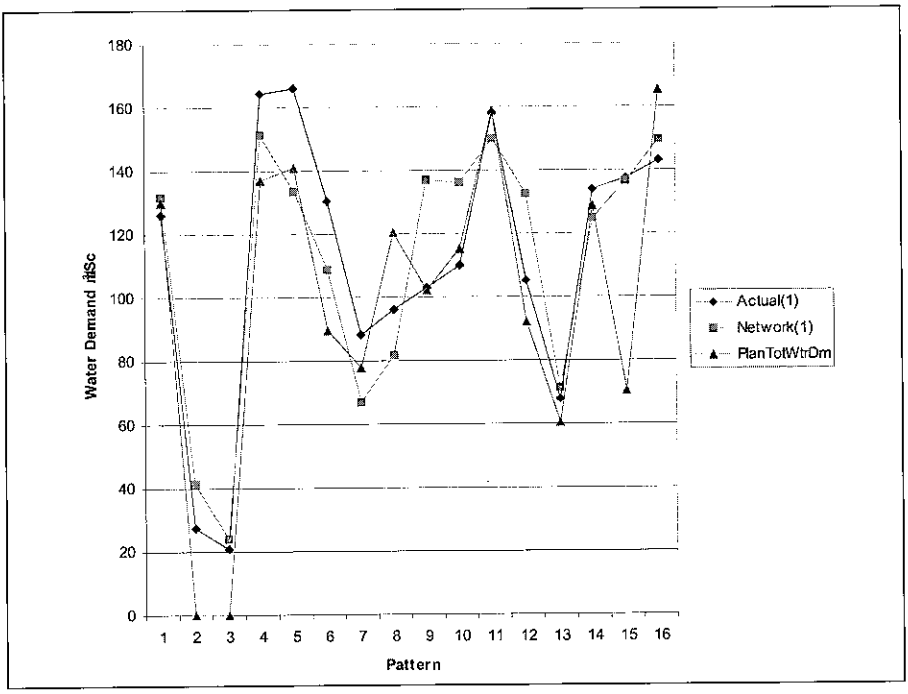


Comparison Results Between Actual Demand, BPN Gaussian Function with 2 Hidden Layers, and Total Plan Water Demand.

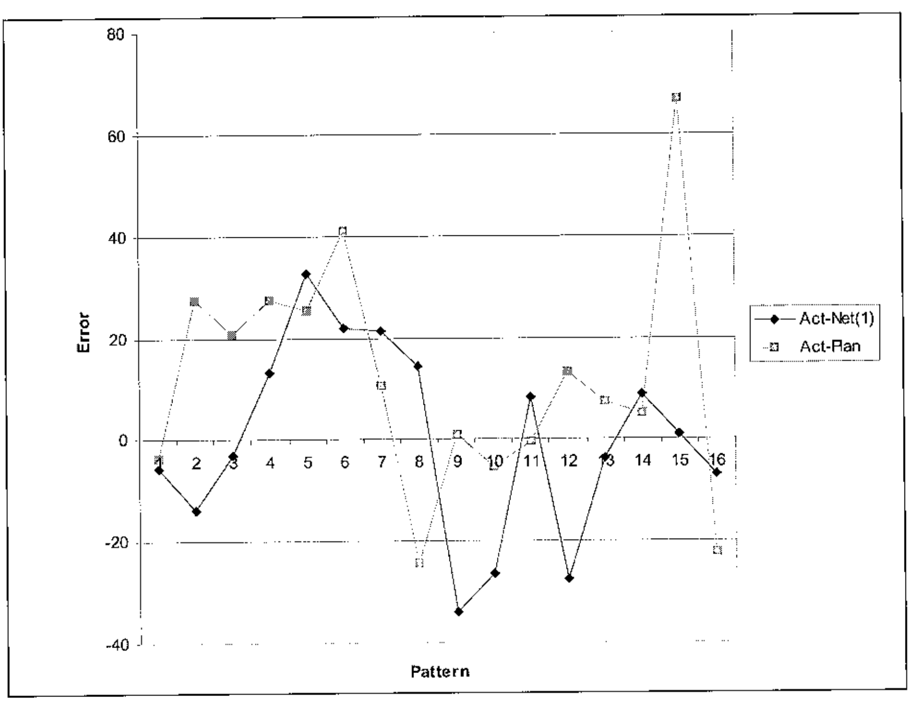


Error Comparison Between Neural Networks Result (Standard BPN with Gaussian Function and 2 Hidden Layers) and Total Plan Water Demand.

Neural Networks Testing Result Graphs



Comparison Testing Results Between Actual Water Demand, BPN using Gaussian Function and 2 Hidden Layers, and Total Plan Water Demand.



Error Comparison of Testing Result between BPN using Gaussian Function (2 Hidden Layers) and Total Plan Water Demand.