

Modeling of Energy Production of Sengguruh Hydropower Plant Using Neuro Fuzzy Network

Daniel Rohi and Hanny H. Tumbelaka

Electrical Engineering Department, Petra Christian University, Surabaya, Indonesia
rohi@petra.ac.id

Abstract—The hydroelectric power plant needs to be operated carefully to obtain optimal results, as it is highly dependent on water availability. Factors to take into account are the water discharge and the duration of time for the operation. Decomposition analysis method is the method chosen to manage the operation of hydropower. This paper discusses the hydropower operation model using artificial intelligence with Neuro Fuzzy Takagi-Sugeno (NFTS) network technique. The Hydropower plant selected for modeling is Sengguruh Hydroelectric Power Plant with a capacity of 29 MW. This model was developed using three factors as inputs. They are the discharge of water, turbine water discharge and duration of operation time. The output is electric energy production. The data used is the operating data for one year, from January to December. The model testing shows satisfactory results as it reveals the real conditions and the errors occurred on the network was below 6.7%.

Index Terms—Artificial Intelligence; Hydropower Plant; Neuro-fuzzy; Renewable Energy.

I. INTRODUCTION

Hydropower is the most dominant renewable energy generation in the world today. Hydropower contributes 16% of the total energy mix in the world. Worldwide hydroelectric growth increased significantly by 715 GW in 2004 to 1,018 GW in 2013 and 1,055 GW in 2014 or an increase of 32.22% over 10 years or an average growth of 3.22% /year.[1].

The development of electric energy in Indonesia faces several challenges, namely the disparity between the provider and the needs, the limitation of fossil energy, the dependence on fossil energy and environmental issues, and the demand for CO₂ emission reduction from the power generation sector [2][3].

Based on the development plan of electricity by the National Electricity Company Indonesia (2011-2020), electricity demand in Indonesia is growing by an average of 8.46%/ year. The power plant is the dominant fossil energy by 81%, consisting of coal by 64%. The capacity of power plants that exist today reaches a total of 34 928 MW [4].

The national electricity demand is 8.5%, while the growth of power plant development is 6.5% / year. Power plants are predicted to reach around 115 GW in 2025 and 430 GW by 2050. Electricity needs per capita, by 2013 764 kWh per capita increased threefold to 1,987 kWh per capita. In 2050 it is predicted to reach 6,112 kWh per capita [4].

Sengguruh Hydroelectric Power Plant is located at Sengguruh Dam, at Sengguruh village, Malang Regency, East Java Province. The dam began to operate in 1998. Sengguruh Dam is located at the upper reaches of the Brantas River. The total area of the Brantas River basin is 1659 km². The types of dams are concrete composites and rocks with

soil core. The dam body volume is 650,000 m³. The yearly electricity production target is 98.5 million kWh/year. This dam was built to keep the sediment from entering the Sutami dam.

The Hydroelectric Sengguruh is designed to bear the peak load for 5 hours every day. The main water discharge is 32.5 m³/sec. The effective waterfall height is 22.78 m and the type of turbine used is Kaplan turbine, with vertical shell type Kaplan reaction, and 15.1 MW energy output with 176.5 rpm rotation. The Turbines are operating at a maximum water height of 24.5m and a minimum water height of 18.5m. The generators used are two Synchronous AC Generators, 11KV, 16200 KVA / unit. The total installed capacity is 2x 14.5MW. The Technical characteristics of the dams and hydroelectric Sengguruh —is shown in Figure 1.

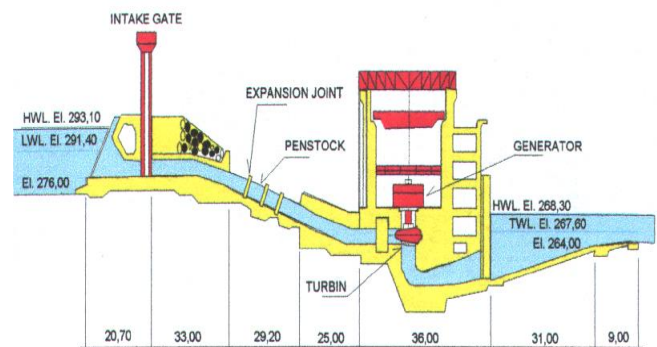


Figure 1: Profile of Sengguruh Hydroelectric Power Plant

The operation of the Sengguruh Hydroelectric Power Plant is facing a serious problem because the dam condition has been reduced up to 50% of the capacity. It is due to the amount of sediment coming in, exceeding the planned capacity [5]. The high sedimentation rate reaches 1,713,454,968 m³/year, this condition greatly affects the power production capability of the Sengguruh power plant. [6][7]

Hydroelectric energy production is influenced by two factors namely the availability of water and the capacity of the dam. The availability of water depends on rainfall whereas the capacity of the dam depends on the effective volume of the dam. The effective volume of the dam is shrinking due to the increasing amount of sediment buried in the dam. As a result, if the rainfall is high, the water contained in the dam is low, because the water will quickly overflow through the spillway of the dam.

In addition, the production of electrical energy from hydropower is also determined by the effective height and operation time. The effective height depends on the water

elevation at the dam. The Operation time–depends on the availability of water and hydropower equipment maintenance conditions, if the maintenance takes a long time, then the hydropower operation time becomes shorter.

The Factors affecting the production of electrical energy in Sengguruh Hydroelectric Power Plant can be studied by developing modeling. The modeling developed, will make it easier to control or manage those factors so as to obtain optimal electrical energy production conditions.

The data needs for modeling is the data directly related to the operation process. Those data are collected from daily recorded data on a regular basis

II. NEURO-FUZZY SYSTEM FOR MODELING OF PLTA SENGURUH

A neuro-fuzzy network with an improved training algorithm for Multi Input Single Output (MISO) case was developed by Palit and Popovic [8] and Pasila et.al [9-14]. They can be used for forecasting or modelling in time series, modelling material composite for artificial muscle and controlling discrete manipulator.

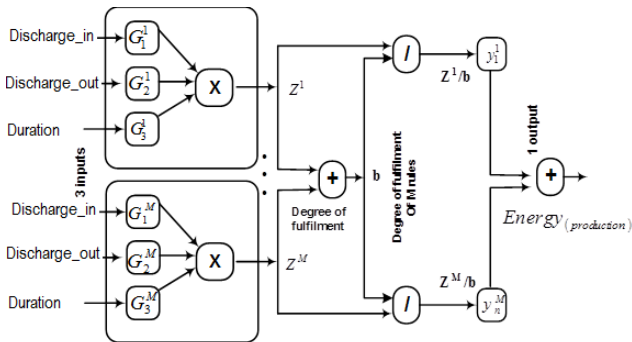


Figure 2: Sengguruh Hydropower Plant MIMO Model Using Feedforward Neuro-Fuzzy (NF) Network, Type Takagi-Sugeno with Training Method: Levenberg-Marquardt Algorithm (LMA)

The proposed model of NF network as shown in Figure 2 is based on Gaussian. It uses Takagi Sugeno rules, product inference, and weighted average defuzzification. The first nodes compute the degree of membership of the input values (debit input, debit output and duration) in the antecedent sets. The product nodes (x) denote the antecedent conjunction operator and the output of this node is the corresponding to the degree of fulfillment of the rule. The division (/), together with summation nodes (+), join to make the normalized degree of fulfillment (z^l/b) of the corresponding rules, which after multiplication with the corresponding TS rule consequent (y_j^l), is used as input to the last summation part (+) at the defuzzified output value, which, being crisp, is directly compatible with the next output data (energy production).

Neuro-fuzzy representation of the FS is based on the inference TS-type which has been explained clearly by Palit [8]. There are two important steps in this representation: calculating the degree of fulfillment and normalized degree of fulfillment. The FS considered here for constructing neuro-fuzzy structures is based on TS-type fuzzy model with Gaussian membership functions. It uses product inference rules and a weighted average defuzzifier.

The corresponding rule from the above FS can be written as:

$$R_l = \text{If } x_1 \text{ is } G_1^l \text{ and } x_2 \text{ is } G_2^l \text{ and } \dots x_m \text{ is } G_m^l \text{ then } y_j^l = W_{0j}^l + W_{1j}^l x_1 + \dots + W_{mj}^l x_m \quad (1)$$

where, “and” are the m system inputs and “n” system outputs, “and” are the Gaussian membership functions of the form (1) with the corresponding mean and variance parameters and respectively “and with” as the output consequent of the rule.

Moreover, FS is represented as a three-layer MIMO feedforward network as shown in Figure. 1 Due to the implementation of the Takagi-Sugeno-type FS, this figure represents a Takagi-Sugeno-type of MIMO neuro-fuzzy network, instead of the connection weights and the biases in training algorithm. We introduce the mean and the variance parameters of Gaussian functions, along with parameters from the rules consequences, as the equivalent adjustable parameters of TS-type network. If all parameters for NF network are properly selected, then the FS can correctly approximate any nonlinear system based on given related data between four inputs and four outputs.

$$F_j = \sum_{i=1}^M y_j^i \cdot H^i \quad (2)$$

$$H^i = \left(z^i / \sum_{l=1}^M Z^l \right), \quad Z^i = \prod_{i=1}^m \exp \left(- \left(\frac{x_i - c_i^l}{\sigma_i^l} \right)^2 \right) \quad (3)$$

$$y_j^l = W_{0j}^l + W_{1j}^l x_1 + W_{2j}^l x_2 + \dots + W_{mj}^l x_m \quad (4)$$

Prior to their use, NFTS and NFLUT models require the tuning of the parameters c_j^n , σ_j^n , w_{0i}^n , w_{ji}^n (for $j = 1, 2, 3$; $i = 1$);). Here, the number of parameters depends on n (membership functions), j (input) and i (output). If n, j and i are set to the values of 7, 3 and 1 respectively then we have a total of 70 parameters. The optimized values of these parameters are found by an optimized learning procedure. The learning procedure employs all data (100%) of the input-output XIO correspondences from the known dataset.

III. RESULTS AND DISCUSSION

The model of the Sengguruh Hydroelectric Power Plant was built using historical data for one year. The data was taken from the daily data for one year or 365 days. The data was from 1 January 2012 up to 31 December 2012. They were recorded and reported data used as the operational report of HEPP Sengguruh. This modeling used the data of 2012.

The Data of water discharge entering the dam is recorded every day. The data changes depending on the rainfall conditions that occur around the dam. The water discharge conditions change following the changing season. Indonesia is located — at the tropics. So it has only two seasons, rainy and dry seasons. Dry season occurs in April to September and the rainy season occurs during October up to March.

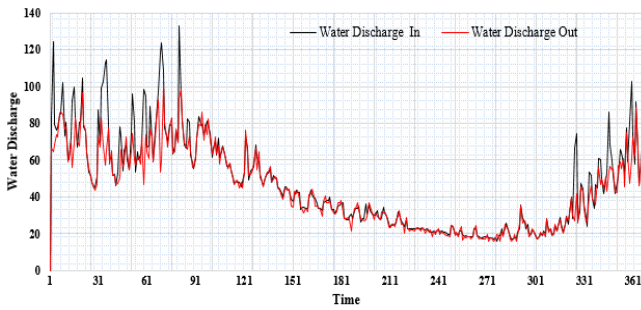


Figure 3: Comparison between Incoming Water Discharge and Outflow Water Discharge of Sengguruh Hydroelectric Power Plant

The pattern of water discharge data coming into the dam and discharge of water coming out of the dam or that is used to drive the hydro turbine is shown in Figure 3.

The average water discharge coming in 2012 was 46.96 m³/sec. The highest discharge was 132.71 m³/sec and the lowest was 16.18 m³/sec. The highest occurred in March and the lowest in July 2012. The average water discharge coming out in 2012 was 43.92 m³/sec. The highest discharge was 100.17 m³/sec and the lowest was 15.93 m³/sec. The highest occurred in March 2012 and the lowest in July 2012.

The data shows that the discharge of water used for turbine was smaller compared to the incoming water discharge. This condition is to keep the water in the dam in a stable elevation, to obtain maximum effective height.

The hours of operation from Sengguruh Hydroelectric Power Plant follow the conditions of water availability. Figure 4 shows that there is a similar pattern between the discharge water to drive the turbine with the operating-time. As the amount of water discharge increases, the operating time is also seen to be increasing.

The duration of operating time of the Sengguruh Hydroelectric Power Plant in 2012 was 22.26 hours on average. The highest duration time was 46.67 hours and the lowest was 9.55 hours. The highest duration of operating time occurred during the rainy season and the lowest occurred during the dry season.

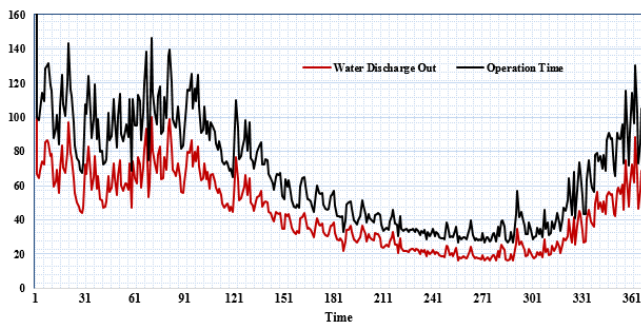


Figure 4: Comparison between Water Discharge Outflow and Operation Time of Sengguruh Hydroelectric Power Plant

Energy production is the output of hydropower operations. The average production of Hydroelectric Energy Sengguruh is 222,783 kWh per year, with the maximum of 513,800 kWh and the minimum of 75,100 kWh. The Energy production has a correlation with the water discharge and operating time.

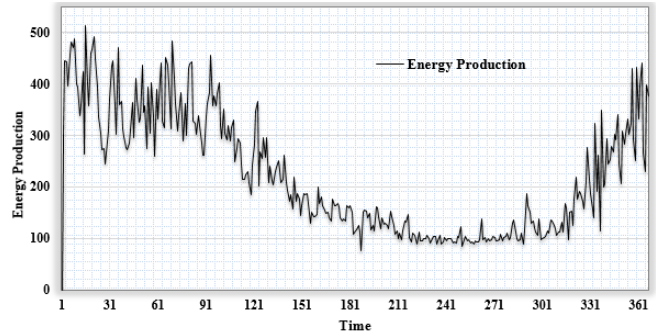


Figure 5: Total Annual Energy Production of Sengguruh Hydroelectric Power Plant

Maximum production occurs at the time of maximum water discharge and maximum hours of operation. This condition occurs during the rainy season. While the production is decreasing following the decrease of water discharge entering the dam. The pattern of production of electrical energy is shown in Figure 5.

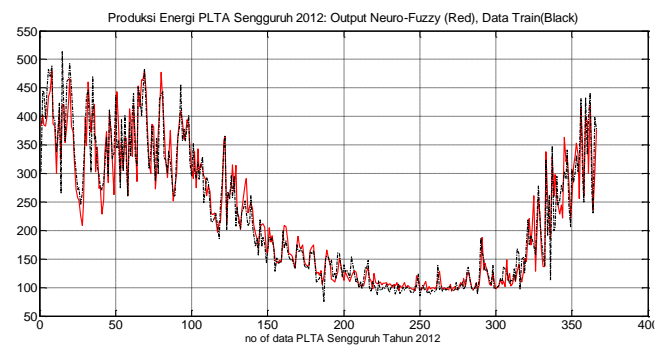


Figure 6: PLTA Sengguruh Plant Result Using Feedforward Neuro-Fuzzy (NF) Network

Figure 6 shows the comparison of the results obtained by NFTS network. In this regards, the results achieved by the NF method is taken as the baseline. The performance of NFTS network is quite satisfactory. The error generated in the network is 6.7 %, which is quite low and acceptable.

IV. CONCLUSION

This paper presents the implementation of Artificial Intelligence (AI) tool based —on the model of PLTA Sengguruh energy production in Indonesia. The model of AI is using Neuro-Fuzzy with three Inputs and one Output. It proves that the model can perform well and the results obtained in term of errors is very promising. The AI model using feedforward Neuro-Fuzzy (NF) Network proved to be effective to model Sengguruh Hydroelectric Power Plant with satisfactory results. The level of accuracy reached 92.3%. The Modeling has been tested to determine the operation pattern of the reservoir, so that the electrical energy produced reaches the optimum condition. This modeling is tested by considering the discharge of water entering the dam, the water discharge to move the turbine and the correct amount of operation time based on the condition. Further research should be conducted for developmental action. More data is needed to generate a more accurate level of accuracy.

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