Aceh Int. J. Sci. Technol., 2 (2): 44-50
August 2013
DOI: 10.13170/AIJST.0202.01

Aceh International Journal of Science and Technology

ISSN: 2088-9860
Journal homepage: http://jurnal.unsyiah.ac.id/aijst

Determination of the Cascade Reservoir Operation for Optimal Firm-Energy Using Genetic Algorithms

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Received : September 26, 2012
Accepted : April 12, 2013

Abstract - Indonesia today face a new paradigm in water management where aim to apply integrated water resources management has become unavoidable task in purpose of achieving greater level of effectiveness and efficiency. On of most interesting case study is the case of Citarum river, one of the most potential river for water supply in West Java, Indonesia. Alongside the river, Saguling, Cirata and Djuanda Reservoirs had been constructed in series/cascade. Saguling and Cirata reservoirs are particularly operated for hydroelectric power and Djuanda is multipurpose reservoir mainly operated for irrigation and contribute domestic water supply for Jakarta (capital city of Indonesia). Basically all reservoirs are relying on same resources, therefore this condition has considered addressing management and operational problem. Therefore, an approach toward new management and operation system are urgently required in order to achieve the effective and efficient output and to avoid conflicts of water used. This study aims to obtain energy production from Citarum Cascade Reservoir System using Genetic Algorithms optimization with the objective function to maximize firm-energy. Firm-energy is the minimum energy requirements must be available in a certain time period. Then, the result obtained by using the energy produced by GA is compared to the conventional searching technique of Non-Linier Programming (NLP). The GA derived operating curves reveal the higher energy and firm-energy than NLP model.

Keywords: Genetic Algorithms, Citarum Cascade Reservoir, Firm-Energy, Electrical Energy

Introduction

Citarum Cascade Reservoir is a complex reservoir, besides structurally different, the three reservoirs also have a different contradicted management system (Saguling and Cirata hydropower plant as a single purpose reservoir, and Djuanda as a multipurpose reservoir). To obtain the optimal reservoir operation, it would require complex algorithms for Citarum Cascade Reservoir.

There are many optimation techniques being used to operate the cascade reservoir, they are Linier Programming, Non Linier Programming, Stocastic, and Dynamic Deterministic Programming. Hadihardaja and Matnali (2002) carried out a study to optimize cascade reservoir operation using Chance-Constrained Linear Programming and then Hadihardaja *et al.* (2004) investigated an optimal trade-off between water demand and electrical energy in Saguling-Cirata-Jatiluhur (Djuanda) in Indonesia (Cascade Reservoir) using Non-Linier Programming. Azmeri *et al.* (2006) investigated an optimal operation of single reservoir to increase potential of it's energy. In order to obtain the appropriate solution for the operation of Citarum Cascade Reservoir, the Genetic Algorithm (GA) is utilized for the purpose. GA optimation model is particularly potential to be applied for the problems considering multireservoir system, in which its objective function is complex and simplified by the other optimation techniques (Azmeri *et al.*, 2007). Furthermore, GA may overcome the difficult problems to obtain optimum global solution (Gen and Cheng, 2000).

Genetic Algorithm (GA) is a search algorithm based upon the mechanics of natural selection, derived from the theory of natural evolution (Koza, 1992). GAs simulates mechanisms of population genetics and natural rules of survival in pursuit of the ideas of adaptation. Indeed this has led to a vocabulary borrowed from natural genetics. GA is a robust method for seaching the optimum solution to a complex problem, although it may not necessarily lead to the best possible solution. GA generally represents a solution using string (also refered to as chromosomes) of variables that represent the problem .

Wardlaw and Sharif(1999) from Golberg (1989) identifies the following as the significant differences between GAs and more traditional/convensional optimization methods:

- GAs work with a coding of the parameters set, not with the parameters themselves.
- GAs search from a population of points, not a single point.
- GAs use objective function information, not derivativies or other auxiliary knowledge.
- GAs use probabilistic transition rules, not deterministic rules.

The simplicity application of GA is expected to reduce the reservoir operator's unwillingness (the decision maker) to utilize this optimation model in conducting their duties.

The main purpose of this research is to apply a GA to the operation of Citarum Cascade Reservoir system. The specific objectives of the research are as follows:

1. to apply a GA to optimize the operating curves for reservoir system in study area, the objective function is the maximization of the total firm-energy;
2. to evaluate a GA performance against Non Linier Programming (NLP).

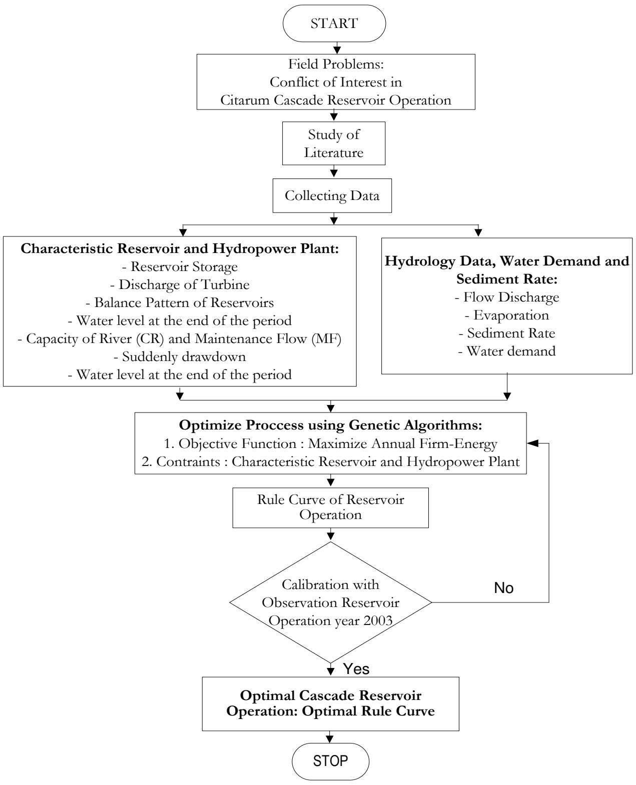

Figure 1. Flow chart of research model concept

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Materials and Methods

The quantitative experimental method was used in this study to searching optimum value from the cascade reservoir operation system by studying several constraints in achieving the optimum goal. From the modeling, it is expected that the optimum recommended advantages of water reservoir operation system will result. The complete concept of this model is figured in the form of flowchart in Figure 1.

The cascade reservoir system can be decomposed into several systems of single reservoir (Wurbs, 1996). By using the principle of water balance the following equations can be written:

$$V_{t+1}^{Sag} = V_t^{Sag} + \Delta V_t^{Sag} = V_t^{Sag} + In_t^{Sag} - O_t^{Sag} - Ev_t^{Sag}$$

$$V_{t+1}^{Cir} = V_t^{Cir} + \Delta V_t^{Cir} = V_t^{Cir} + (InLok_t^{Cir} + O_t^{Sag}) - O_t^{Cir} - Ev_t^{Cir} \quad (1)$$

$$V_{t+1}^{Dju} = V_t^{Dju} + \Delta V_t^{Dju}$$

$$= V_t^{Dju} + (InLok_t^{Dju} + O_t^{Dju}) - O_t^{Dju} - Ev_t^{Dju}$$

where: $InTot_t^i$ = the total inflow and $InLok_t^i$ = the local inflow of the reservoir.

Firm-energy is the minimum energy requirements must be available in a certain time period. In this paper, certain time is one year reservoir operation. Firm-energy has *reliability* or exceeds probability 90% is based on Cumulative Distribution Function (CDF) for Norm Distribution Standard from 12 values of monthly energy during one year reservoir operation. Firm-energy can be written:

$$x_{10\%} = \mu - \sigma \cdot \Phi^{-1}\ 90\% \quad (2)$$

where $\Phi^{-1}\ 90\%$ is invers of: $\Phi\ 90\% = Pr\ Z \leq 90\% = \int_{-\infty}^{90\%} \frac{1}{\sqrt{2\pi}} \exp\left[-\frac{1}{2}z^2\right] dz \quad (3)$

z can be written:

$$z = \frac{x_{10\%} - \mu}{\sigma} \quad (4)$$

where μ is mean of the monthly energy, and σ is deviation standard of the monthly energy .

The objective function: $F = Maximize \sum_{i=1}^{m} Firm\,Energy_t = Maximize \sum_{i=1}^{m} \mu - \sigma.(\Phi^{-1}(90\%)) \quad (5)$

Which subject to the following:

a. Maximum and minimum discharge of turbine*:*

$$O_{\min}^{Sag} \le O_t^{Sag} \le O_{\max}^{Sag},\ O_{\min}^{Cir} \le O_t^{Cir} \le O_{\max}^{Cir},\ O_{\min}^{Dju} \le O_t^{Dju} \le O_{\max}^{Dju} \qquad (6)$$

b. Capacity of River (CR) and Maintenance Flow (MF):

$$MF^{Sag} \le O_t^{Sag} \le CR^{Sag},\ MF^{Cir} \le O_t^{Cir} \le CR^{Cir},\ MF_{\min}^{Dju} \le O_t^{Dju} \le CR_{\max}^{Dju} \qquad (7)$$

c. *Upper Rule Curve (URC) and Lower Rule Curve (LRC):*

$$V_{\min}^{Sag} \le V_t^{Sag} \le V_{\max}^{Sag},\quad V_{\min}^{Cir} \le V_t^{Cir} \le V_{\max}^{Cir},\quad V_{\min}^{Dju} \le V_t^{Dju} \le V_{\max}^{Dju} \qquad (8)$$

d. Water level at the end of the period:

$$H_{end}^{Sag} \ge H_{initial}^{Sag},\quad H_{end}^{Cir} \ge H_{initial}^{Cir},\quad H_{end}^{Dju} \ge H_{initial}^{Dju} \qquad (9)$$

e. The percentage of effective patching volume of dividing from Citarum cascade:

$$Kes_{i+1}^{Sag} = \frac{V_{eff\ i+1}^{\ Sag}}{V_{eff\ i+1}^{\ Sag} + V_{eff\ i+1}^{\ Cir} + V_{eff\ i+1}^{\ Dju}} = Kes_{pola}^{Sag},\ Kes_{i+1}^{Cir} = \frac{V_{eff\ i+1}^{\ Cir}}{V_{eff\ i+1}^{\ Sag} + V_{eff\ i+1}^{\ Cir} + V_{eff\ i+1}^{\ Dju}} = Kes_{pola}^{Cir};$$

$$Kes_{i+1}^{Dju} = \frac{V_{eff\ i+1}^{\ Dju}}{V_{eff\ i+1}^{\ Sag} + V_{eff\ i+1}^{\ Cir} + V_{eff\ i+1}^{\ Dju}} = Kes_{pola}^{Dju} \qquad (10)$$

f. Water demand: $$O_t^{Dju} \ge O_{\min t}^{\ Dju} \qquad (11)$$

g. Suddenly drawdown: $$\Delta h / \Delta t \ge -10 cm/day \text{ (for all of reservoirs)} \qquad (12)$$

where: m = the number of reservoir; Kes_{t+1}^{Sag}, Kes_{t+1}^{Cir}, Kes_{t+1}^{Dju} = the percentage of effective storage from the three reservoir in the end of the *t* or in the beginning of the *t+1* ; H_{end}^{Sag}, H_{end}^{Cir}, H_{end}^{Dju} = the water level minimum value at the end of the period water demand in Djuanda lower course in the *t* month. $\Delta h/\Delta t$ = deviation of water level between the number of hours.

The H_{eff_t} (average effective head in the *t* month) is calculated using the following equation:

$$H_{eff\ t} = \tfrac{1}{2} \times \left[\ H_t - TW_t\ +\ H_{t+1} - TW_{t+1}\ \right] \qquad (13)$$

where: H_t = the reservoir water elevation in the beginning of the *t* month, TW_t = tailwater (tailrace) elevation in the beginning of the *t* month*,* H_{t+1} = reservoir water elevation in the beginning of the t+1 month or the end of the *t* month, and TW_{t+1} = tailwater/tailrace elevation in the beginning of the t+1 month or at the end of the *t* month.

Population Initialization and Ranking Method

Real-value coding is now proving more effective in many problems than binary coding (Wardlaw and Sharif, 1999 from Oliveira and Loucks, 1997). Coding components of possible solutions into a chromosome is the first part of a GA formulation. Each chromosome is a potential solution and is comprised of a series of substrings or genes, representing components or variables that either form or can be used to evaluate the objective function of the problem. The first step in this model is random determination of the Saguling reservoir outflow as many as population size. This population initialization uses the real-value (*floating point*). Maximum and minimum discharge of turbine each reservoir is: Saguling: a = 74 MCM and b = 594 MCM; Cirata: a = 98 MCM and b = 1453 MCM; and Djuanda: a = 54 MCM and b = 851 MCM. Where: a = lower outflow; and b = upper outflow.

For an excellent selection function, the second generation may be produced by selecting the best individual from the parents and derivative individual. The chosen chromosome to be the next generation is performed by using the Rangking method.

Application to Citarum Cascade Reservoir Problem

A reservoir operation optimation model has to observe the studied system. Hence it is a great need to understand the reservoir characters. Citarum has great potential for the water resource to be developed. Presently there are 3 (three) reservoirs being connected to each other in cascade, they are Saguling, Cirata and Ir. H. Djuanda (Jatiluhur) Reservoir. The global illustration of location of each reservoir in the Citarum Cascade Reservoir system is illustrated in Figure 2.

DOI: 10.13170/AIJST.0202.01

The water resource development in Citarum DAS is not only useful for providing the need of irrigation requirement but also for the sake of generating electrical power (power generation), the need of municipal water supply, and water requirement for industry.

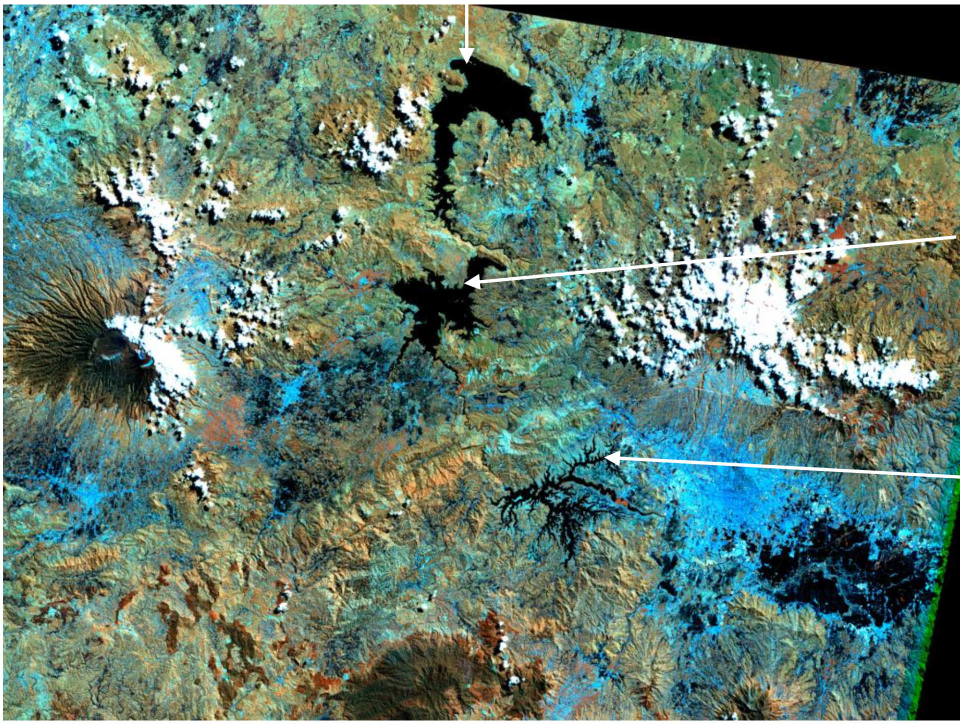

Figure 2. Citarum cascade reservoir (Djuanda's Authority Concern, 1990)

Results and Discussion

The increase of the optimum fitness values within a generation with respect to the progress of generations is presented in Figure 3. It can be observed from Figure 3 that the GA run begin with poor initial solutions but converge quickly to the true solution. By the end of 700 generations, a number of good solution have been found. Once the GA locates good solutions, some fine-tuning may be required to improve the solution. At the end of the run, a large number of feasible and near optimal solutions have been obtained.

Various impact from the generation numbers which show the result similar to NLP are type Pc=0.25Pm=0.05Ps=30Gen=700. The type produces total energy of 4,672.78 GWh and the total firm-energy of 3,344.78 GWh.

Sensitivity to crossover probability

Sensitivity to crossover probability was carried out using a population size of 30 and a mutation probability of 0.05. Crossover probabilities from 0.25 to 0.95 were considered through runs with a fixed length of 300 generations. Sensitivity of the GA performance to crossover probability is presented in Figure 4. Fitness is expressed as the proportion of the maximum fitness produced by teh GA run with the best crossover probability.

The best values were achieved for the crossover probability 0.95. It can be observed from Figure 4 that the performance of GA might not be good if too low values of crossover probabilities are used. The reasonable solutions were produced when the value of crossover probability had risen. With the impact from the gene crossover probability variation (Pc), it can be shown that the result similar to NLP is the type Pc=0.75Pm=0.05Ps=30Gen=300. This type produces total energy of 4,662.89 GWh and the total firm-energy of 3,339.47 GWh.

Sensitivity to mutation probability

The impact of mutation probability on the performance of GA has also been analised using a crossover probability of 0.25. Sensitivity of the GA performance to crossover probability is presented in Figure 5. Again, the fitness has been expressed as the proportion of the maximum fitness achieved by the GA run with he best mutation probability. The analized impact of gene alteration probability is varied between 0.05-0.20. The impact from the mutation probability variation (Pm) showing the result be similar to NLP be the type

DOI: 10.13170/AIJST.0202.01

Pc=0.75Pm=0.20Ps=30Gen=300. This type produces total energy of 4,663.90 GWh and the total firm-energy of 3,347.16 GWh.

Population sizes

Consideration has been given to the influence of population size on the performance of GA. The best parameters obtained from sensitivity test were used. The GA was run with different population sizes ranging from 10 to 50. The sensitivity of achieved maximum fitness to population size is shown in Figure 6. It was found that the acceptable results are produced with a population of 40. The choice of the proper population size depends upon the judgment and experience of the user.

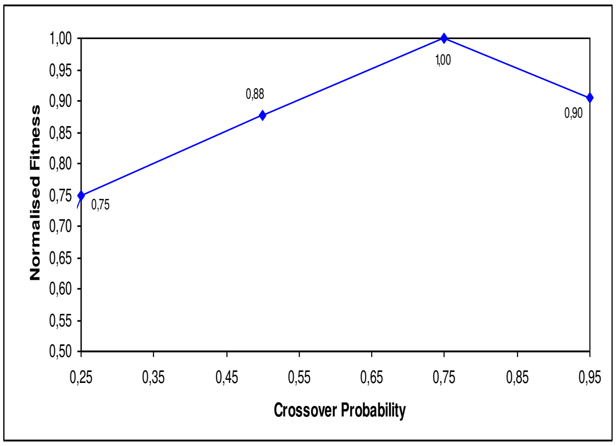

Figure 4. Crossover sensitivity using genetic algorithms

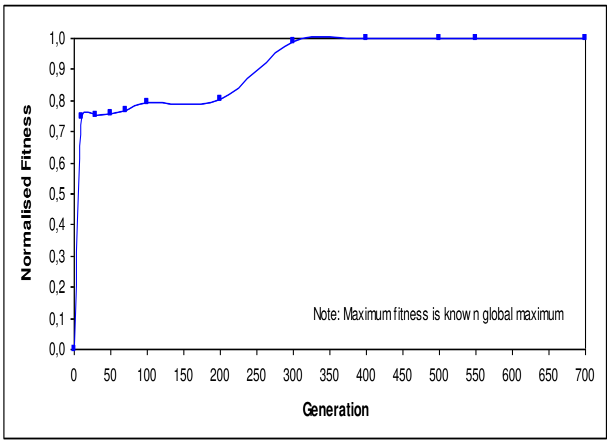

Figure 3. The optimal total fitness values varying with generations using genetic algorithms

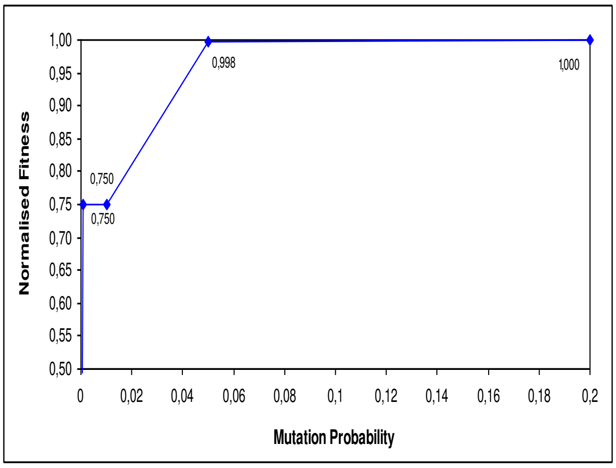

Figure 5. Mutation sensitivity using genetic algorithms

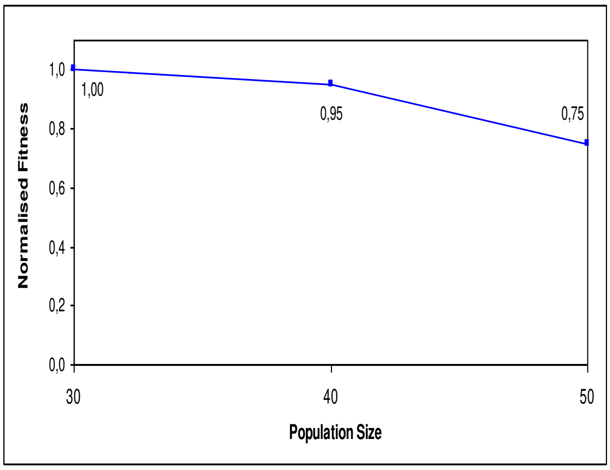

Figure 6. Population size sensitivity using genetic algorithms

After conducting several variations of population number, it turned out that the results similar to NLP are the type Pc=0.75Pm=0.20Ps=30Gen=300. This type produces total energy of 4,663.90 GWh and the total firm-energy of 3,347.16 GWh.

In Genetic Algorithms model, the objective function in the modelling is to maximize the firm-energy, that is maximizing the total of produced minimum energy in a year of operation period. Total firm-energy produced from the varied type of optimation shows that the model with the type Pc=0.75Pm=0.20Ps=30 Gen=300 provides the greatest firm-energy. This type produces 4,663.90 GWh total energy and the total firm-energy produced is 3,347.16 GWh. Table 1 shows the monthly energy and firm-energy production, the production itself is generated by the Citarum Cascade Reservoir System. Production of annual total energy of the three reservoirs by NLP model 4,663.90 GWH and the total firm-energy produced is 3,347.16 GWH. Production of monthly total firm-energy by GA model 278.92 GWH, and by NLP model 276.77 GWH.

Water level of Saguling, Cirata, and Djuanda Reservoir water level is plotted in Figure 8, 9 and 10. Generally, the water level pattern produced from GA model follows the water level pattern of the NLP model. Upper Rule Curve (URC) and Lower Rule Curve (LRC) of Saguling are 642.50 meters and 625.00 meters. URC and LRC of Cirata are 219.50 meters and 206.00 meters. URC and LRC of Djuanda are 106.50 meters and 87.50 meters.

Table 1. The monthly energy and firm-energy production of Citarum Cascade Reservoir using genetic algorithms (GA) and non-linier programming (NLP)

Month	Energy Production (GWH)		Firm-Energy Production (GWH)	
	GA	NLP	GA	NLP
January	378.31	442.96	278.92	276.77
February	402.33	373.24	278.92	276.77
March	408.33	436.74	278.92	276.77
April	448.15	445.46	278.92	276.77
May	431.71	397.46	278.92	276.77
June	393.94	377.90	278.92	276.77
July	351.14	345.94	278.92	276.77
August	322.36	321.80	278.92	276.77
September	295.62	291.34	278.92	276.77
October	347.71	348.16	278.92	276.77
November	440.57	439.82	278.92	276.77
December	443.25	389.99	278.92	276.77

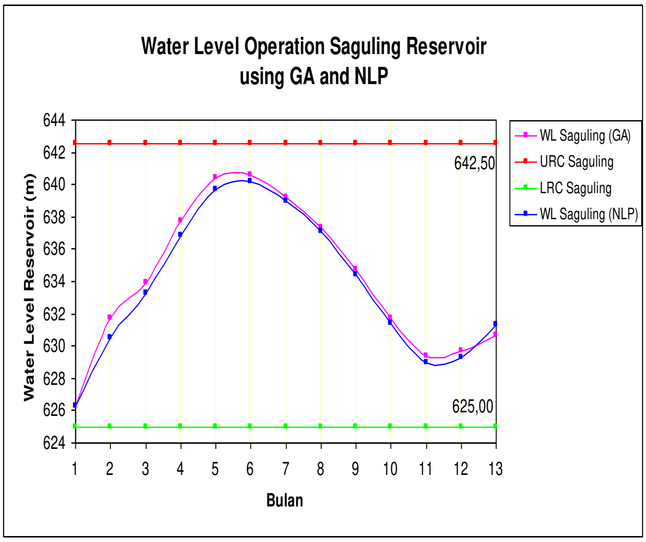

Figure 8. Water level operation Saguling Resevoir using genetic algorithms and non-linier programming

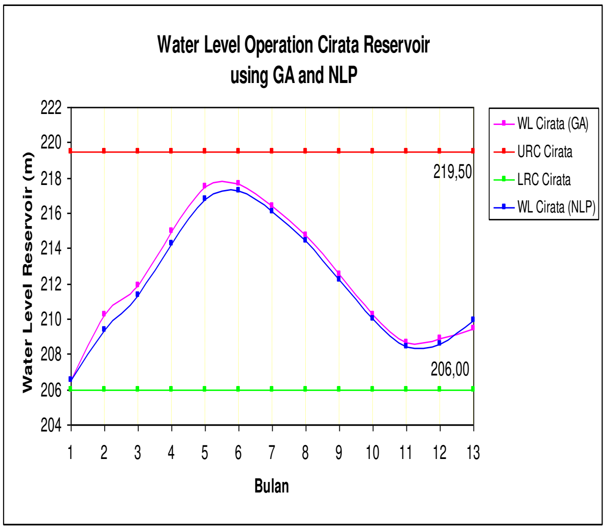

Figure 9. Water Level Operation Cirata Resevoir using Genetic Algorithms and Non-Linier Programming

Based on the stochastic mechanism stating that the genetic algorithm does not always provides appropriate solution unless there is continuation of iteration process, the optimum solution will be obtained. The main parameter values of genetic algorithm that may allow the searching process are the number of population, the degree of crossover probability, and the degree of muatation probability. The accuracy in choosing the GA parameters could provide optimum solution. Generally, the water level pattern produced by GA model may follow water level pattern of the NLP model. It has been demostrated that GA model provide robust and acceptable solution to Citarum Cascade Reservoir Operation System, and can reproduce the known global optimum. Several possible formulations have been considered, along with their sensitivity to various parameters. A crossover probability of 0.75 and mutation probability of 0.15 are appropriate for Citarum Cascade Reservoir problem. For Citarum Cascade Reservoir problem, a solution very close to the known global optimum can be achieved within 700 generations with a population of 30.

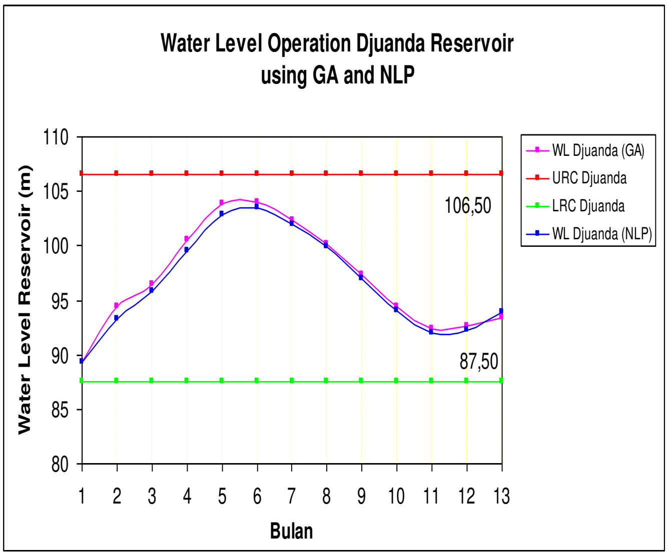

Figure 10. Water Level Operation Djuanda Resevoir using Genetic Algorithms and Non-Linier Programming

The water level of the three reservoirs in GA and NLP model can be seen at the final period of operation, that is in December (the 12th month) which is higher than that of the water level initial. This is caused by the fixed constraints for the three reservoirs stating that the water level for the 13th month should be higher or equal to the initial operation period. So that at the 12th month, the model starts to prepare water level to get into the constraints.

Conclutions

Result of GA model give higher total energy and total firm-energy than NLP model. From the water level graphic illustration for the three reservoirs, it shows that GA model tends to maintain water level, so it automatically will produce higher effective head to produce higher energy. On the other hand, there is other variable that has its impact to the energy, which is the outflow.

References

Azmeri, Hadihardaja, I.K., and Suryadi Y. (2006). Expansion of the electrical energy of single-reservoir using genetic algorithm (GA), Case Study: Cimeta Reservoir, Bandung Regency, West Java. Pertemuan Ilmiah Tahunan Himpunan Ahli Teknik Hidraulik Indonesia ke-23 (PIT HATHI XXIII), Manado.

Azmeri, Hadihardaja, I.K., Tuah, H. and Legowo, S. (2007). Cascade reservoir modeling using genetic algorithm (case study: Saguling, Cirata and Djuanda Reservoir in West java, Indonesia). Proceeding of International Conference on Soft Computing, Intelligent System and Information Technology: 87 – 90.

Gen, M. and Cheng, R. (2000). Genetic algorithms and Engineering Design. John Wiley and Sons Inc. A Wiley Interscience Publication, New York USA.

Hadihardaja, I.K.. and Matnali, R. (2002). Cascade resevoir operation using chance-constrained linear programming. Jurnal dan Pengembangan Keairan Volume, 9(2): 28-37.

Hadihardaja, I.K., Vannya, E., Soekarno, I. (2004). Simulation of impact increase of water demad toward electrical energy in Cascade Resevoir modelling. Jurnal Teknik Sipil Volume, 11(1): 47-54.

Koza, J.R. (1992). Genetic programming on the programming of computers by means of natural selection. The MIT Press Cambidge, Masssachusset.

Wardlaw, R. and Sharif, M. (1999). Evaluation of genetic algorfithms for optimal reservoir system operation. Journal Water Resources Planning and Management, 125(1): 25-33.

Wurbs, A.R. (1996). Modelling and analysis of reservoir system operations. Prentice Hall PTR, Upper Saddle River NJ.