Research Journal of Applied Sciences, Engineering and Technology 6(10): 1895-1901, 2013
ISSN: 2040-7459; e-ISSN: 2040-7467

Submitted: November 24, 2012 Accepted: January 11, 2013 Published: July 20, 2013

Competence-Oriented Decision Model for Optimizing the Operation of a Cascading Hydroelectric Power Reservoir

Tilahun Derib Asfaw, Khamaruzaman Wan Yusof and Ahmad Mustafa Hashim
Department of Civil Engineering, Universiti Teknologi PETRONAS (UTP), 31750, Tronoh, Malaysia

Abstract: The operation of the four Perak cascading reservoirs namely, Temenggor, Bersia, Kenering and Chenderoh analyzed using the newly developed genetic algorithm model. The reservoirs are located in the state of Perak of Peninsular Malaysia that used for hydroelectric power generation and flood mitigation. The hydroelectric potential of the cascading scheme is 578 MW. However, the actual annual average generation was 228 MW, which is about 39% of the potential. The research aimed to improve the annual average hydroelectric power generation. The result of the fitness value used to select the optimal option from the test of eight model runs options. After repeated runs of the optimal option, the best model parameters are found. Therefore, optimality achieved at population size of 150, crossover probability of 0.75 and generation number of 60. The operation of GA model produced an additional of 12.17 MW per day. The additional power is found with the same total annual volume of release and similar natural inflow pattern. The additional hydroelectric power can worth over 22 million Ringgit Malaysia per year. In addition, it plays a significant role on the growing energy needs of the country.

Keywords: Cascading reservoirs, fitness value, genetic algorithm, hydroelectric power

INTRODUCTION

The real-world reservoir operation is very complex (Mousavi *et al*., 2004; Liu *et al*., 2011) and the application of operation rule in the case of cascade reservoirs that recapture the inflow is the most complex (Lund, 2000). Normally, the planning and the management of water in a reservoir systems ends with the optimization of the reservoir operation (Schumann, 1995). Therefore, different models and algorithms were developed to determine the reservoirs operation rules (Homayoun-Far *et al*., 2010) and the operation methods were presented as a form of a rule-curve. A rule-curve is a guideline for the long-term reservoir operation (Hormwichian *et al*., 2009). Hedging rule (Shiau, 2009; Tu *et al*., 2008), dynamic programming neural-network simplex model to developed the refill operation (Liu *et al*., 2006), an integrated rough set approach (Barbagallo *et al*., 2006) were some of the techniques that developed to operate the reservoir.

Genetic Algorithm (GA) is among the modern optimization technique applied in water resource planning and management. Cheng *et al*. (2008) mentioned that GA model has been widely applicable in water resource system optimization. The model also used to optimize a reservoir operation. For example, Mathur and Nikam (2009) used GA to optimize reservoir operation and the result showed that the model could perform efficiently if it applies in the real world

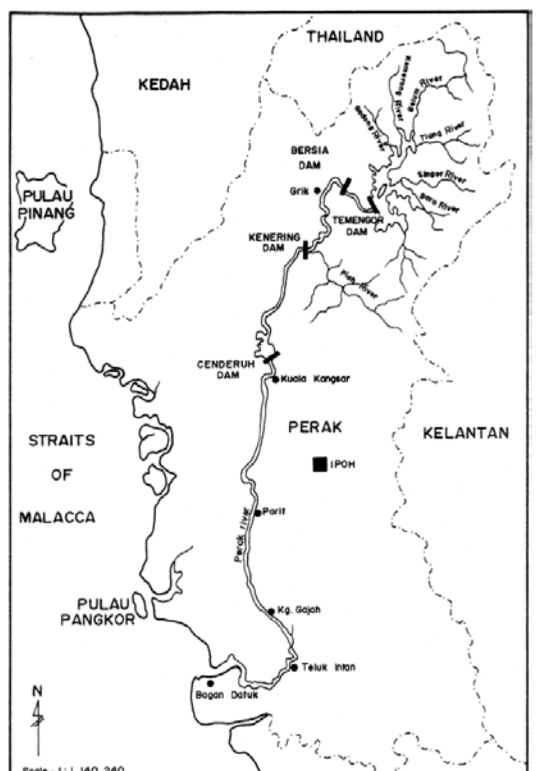

Fig. 1: Map of Perak River Basin, Malaysia (Bu and Seng, 1997)

Corresponding Author: Tilahun Derib Asfaw, Department of Civil Engineering, Universiti Teknologi PETRONAS (UTP), 31750, Tronoh, Malaysia

Table 1: Reservoirs and power plants specifications

Item description	Unit	Reservoir			
		Res-1	Res-2	Res-3	Res-4
Installed power capacity	MW	348	72	120	38
Storage capacity at maximum operating level	10^6 m^3	6050	70	345	95.4
Full supply level	m asl*	248.41	141.43	111.31	60.42
Normal drawdown level	m asl*	239.30	139.90	108.50	59.13
Range of operating levels	m	9.11	1.53	2.81	1.29
Warning level	m asl*	246.00	141.00	111.00	60.00
Rated head	m	101.00	26.50	34.70	18.29
Tailrace level	m asl*	142.07	115.52	75.87	41.41
Operation hour per day	hr	24	24	24	24

*: above sea level (asl)

operation of a reservoir. The research of Azamathulla *et al*. (2008) compared GA and linear programming in the operation of irrigation reservoir and it found that the performance of GA model was superior to the linear programming. In addition, Asfaw and Saiedi (2011) compared GA and excel optimization solver on the operation of a hydroelectric power reservoir, it showed that the result found from the GA model advanced in two ways: greater electricity generation and convenience in operation.

This research conducted on the operation of four cascading reservoirs that found along the Perak River of Peninsular Malaysia. As shown in Fig. 1, the river comprises Temenggor (Res-1), Bersia (Res-2), Kenering (Res-3) and Chenderoh (Res-4) reservoirs that found in cascade from upstream to downstream, respectively. In addition, Table 1 presented the details of the reservoirs. The largest storage capacity reservoir, Res-1 locates at most upstream side and then follows the smallest storage capacity, Res-2. The reservoirs are used for hydroelectric power generation and flood mitigation. The research aimed to maximize the annual hydroelectric power generation of the cascading scheme using the genetic algorithm. Therefore, analysis was made taking the hydroelectric power generation as the fundamental purpose and the flood mitigation as one of the constraint of the operation.

DETERMINATION OF INFLOW RATE

Depending on the relative position of the reservoir in the cascading system, inflow rate has two features. For the most upstream reservoir, the rate of inflow relies on the catchment characteristics and the hydro-meteorological situations. However, in the case of the downstream reservoirs the major inflow takes place from the release of the preceding reservoir. The aggregate of the release from preceding reservoir and the direct (natural) inflow constitutes the total inflow to the reservoir. Direct (natural) inflow occurs from the catchment area that found between the reservoirs of interest to its immediate preceding ones.

Twenty years (1991-2010) data used to determine the rate of inflow to the most upstream reservoir. Figure 2 showed the average weekly long-term Historical

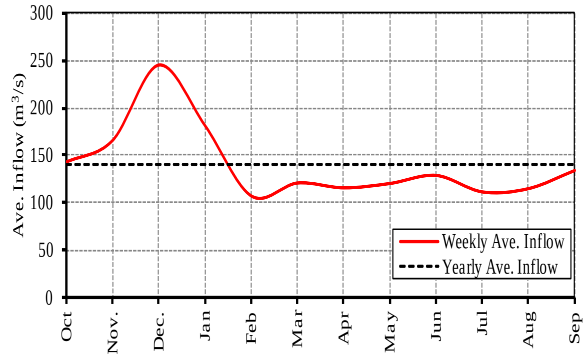

Fig. 2: Inflow hydrograph of the most upstream reservoir, Res-1

Average (HA) inflow to the most upstream reservoir, Res-1. Furthermore, water balance equation used to equate the total inflow to the downstream reservoirs. The difference between total inflow and the release from preceding reservoir equal to direct (natural) inflow to the reservoir. The relationship expressed as:

$$Q_{it} = I_{it} - R_{(i-1)t} \tag{1}$$

where, I_{it} is the total inflow rate, Q_{it} is the direct (natural) inflow rate to the reservoir i during the week t; whereas, $R_{(i-1)t}$ is the rate of release from the preceding reservoir during the week t. In all cases, the release from preceding reservoir joins to the next down reservoir within few hours. The maximum lag time occurs between Res-3 and Res-4, that is 7 h.

COMPUTATION OF STATE TRANSFORMATION EQUATION

The state transformation equation developed with the assumption of all reservoirs initially at the warning level. The equation constitutes with the predicted values of inflow, areal rainfall and open water evaporation rates too. A weekly time horizon used to evaluate the variation of the storage volume. It was from the first week of February, the period where reservoirs have been reaching at warning level, to the last week of January of following year. The average weekly storage volume computed sequentially starting from week *1* (beginning of February). Hence, the state transformation equation of the cascading scheme expresses as:

$$S_{t+1} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \times \left[S_t + Q_t + (F-E)_t A_t\right] + \begin{bmatrix} -1 & 0 & 0 & 0 \\ 1 & -1 & 0 & 0 \\ 0 & 1 & -1 & 0 \\ 0 & 0 & 1 & -1 \end{bmatrix} \times R_t \tag{2}$$

where,
S_t = The storage volume
Q_t = The natural inflow
F = The areal rainfall over the reservoir
E = Open water evaporation
A_t = The average water surface area
R_t = The turbine release during the week *t*

OPTIMIZATION USING THE GENETIC ALGORITHM MODEL

The head of water and the rate of turbine release are the two major influential variables for the generation of a hydroelectric power. The weekly hydroelectric power generation from a reservoir is computed using:

$$P_{it} = \gamma \eta_i R_{it} h_{it(net)} = \gamma\left(a_i\left(\beta_i S_{it} + \lambda_i\right) + b_i\right) R_{it}\left(\beta_i S_{it} + \lambda_i - h_{i(tail)}\right) \tag{3}$$

Although the annual hydroelectric power generation from the entire cascading system determined using the relationship of:

$$P = \sum_{i=1}^{4}\sum_{t=1}^{52} P_{it} = \gamma \sum_{i=1}^{4}\sum_{t=1}^{52}\left(a_i\left(\beta_i S_{it} + \lambda_i\right) + b_i\right) R_{it}\left(\beta_i S_{it} + \lambda_i - h_{i(tail)}\right) \tag{4}$$

In Eq. (3) and (4), P_{it} is the hydroelectric power generation, R_{it} is the rate of the turbine release and $h_{it(net)}$ is the effective head of water for reservoir *i* during the week *t*; η_i is the overall efficiency for reservoir *i*, γ is unit weight of water, β_i and λ_i are the stage-storage relationship constants; whereas, a_i and b_i are the efficiency-stage relationship constants of the reservoir *i*.

An efficient optimization algorithm is depends on its searching ability for global optimum solution and its accuracy (Kuo *et al*., 2004). GA is an efficient tool for large-scale nonlinear optimization problems (Gallagher and Sambridge, 1994) and powerful in searching optimal strategy for multi-use reservoir operation (Chang *et al*., 2010). This research used the GA optimization technique to optimize the hydroelectric power generation of the Perak cascading scheme. The fitness function was to minimize the difference between the total potential (P_{pot}) and sum of actual generation capacities of the entire cascading schemes and it is expressed as:

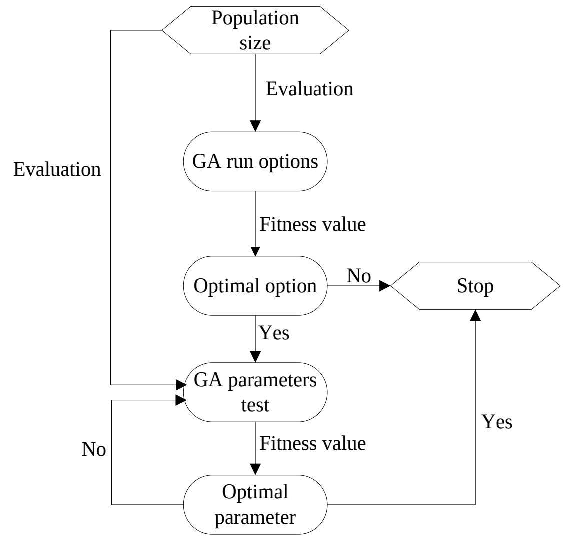

Fig. 3: GA run flowchart

$$\min\left(P_{pot} - cP\right) \tag{5}$$

In Eq. (5), the constant of multiplier, *c* deals with the unit conversion factors and division by 52 in order to determine the annual average value on weekly basis.

The constraints are related to the state transformation equation of the reservoir, the threshold value for flood release, the maximum and the minimum headrace level and the rate of release, the relationship between the cumulative turbine releases and inflow volume. Hence, the constraints are expressed as:

$$k_{1i}\left(h_{i(t+1)}^2 - h_{it}^2\right) + k_{2i}\left(h_{i(t+1)} - h_{tj}\right) - k_{3i}\left(I_{it} - R_{it}\right) - F_{it} + E_{it} = 0 \tag{6}$$

$$R_{it\ \min} \le R_{it} \le R_{it\ \max} \tag{7}$$

$$h_{it\ \min} \le h_{it} \le h_{it\ \max} \tag{8}$$

$$\sum_{t=1}^{52} R_{it} \le \sum_{t=1}^{52} I_{it} \tag{9}$$

where,
R_{it} = The rate of turbine release
h_{ij} = The headrace level
F_{it} = The areal rainfall
E_{it} = The rate of open water evaporation of the reservoir *i* for the week of *t*, k_{1i} and k_{2i} are the constants that depend on the stage-storage relationship and k_{3i} is the unit conversion factor. Analysis started from the most upstream reservoir that is from Res-1.

The developed GA model had 208 equality and 104 inequality constraint equations. Only eight GA run options analyzed since the other provided infeasible

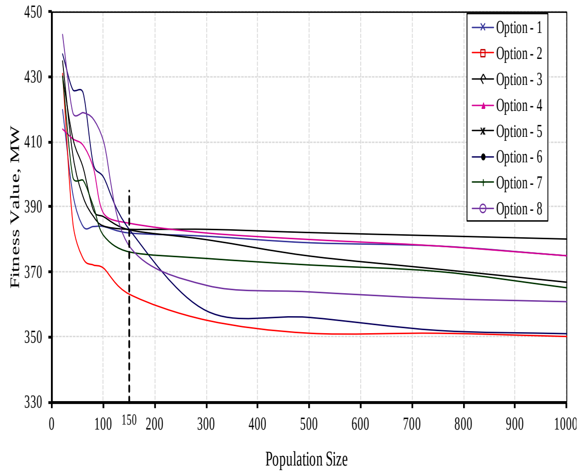

Fig. 4: GA runs options for the decision of population size

solution. Initially, all runs options were tested using generation number of 50 and crossover probability of 0.8. As shown in Fig. 3, the fitness value was the major criteria of determine the optimal values of population size, crossover probability and generation number. The best GA run option has found after the repeated runs. The optimal value decided when the fitness value has no more improvement after the repeated runs. The stopping criterion of the iterations was the generation number.

Population Size (PS) is a critical parameter in GA, if it is too small the solution is poor or if it is too large it spends unnecessary computational resources (Lobo and Goldberg, 2004). Hence, the research used PS of 20 as the initial value. Consequently, the impact of PS was studied by randomly increase the value up to 1000. Likewise, the generation number examined between 20 and 200. Similarly, the test of the crossover probability analyzed between 0.60 and 0.95 with consideration of the fitness value.

RESULTS AND DISCUSSION

Optimal parameters of GA*:* among the eight GA run options, comparatively the result found from option 2 was optimal. The optimal run option used fitness scaling of rank, selection of uniform, crossover option of scattered and mutation option of constraint dependent. Based on the variation of the fitness function as shown in Fig. 4, the impact of the PS categorized into three groups: up to PS of 150, between PS of 150 and 300 and over PS of 300. The improvement of fitness value up to the PS of 150 was large, while between the PS of 150 and 300 an apparent change observed for only three options (Options 2, 6 and 8). Over PS of 300, the change of the fitness value was insignificant. Hence, the choice of optimal PS relied on between 150 and 300. Likewise, for the operation of reservoir using GA McMahon and Farmer (2009) obtained the optimal PS value in the range 64 to 300. However, this study adopted PS of 150 as an optimal value with consideration of the computational runtime.

As shown in Fig. 5a, the actual hydroelectric power generation continuously improving up to the generation number of 60, while after the PS of 100 the value was decreasing. The minimum fitness value attained at the generation number of 60. Therefore, optimal generation number was 60. Similarly, the test result of CRP as shown in Fig. 5b indicated that the optimal value achieved at 0.75.

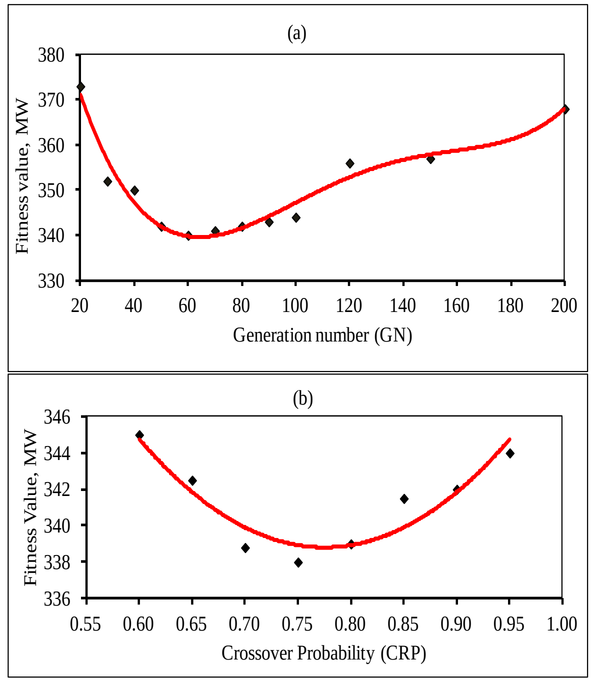

Fig. 5: Test results of (a) generation number; (b) crossover probability

The model achievement: the model decision on the energy-storage, the weekly rate of turbine release pattern and the hydroelectric power generation presented comparatively to the long-term Historical Average (HA) values. As shown in Fig. 6a, the weekly energy-storage at *Res-1* using the GA provides higher than the HA. Hence, decision of GA maintained a higher head of water in each week of the year. In the other three downstream reservoirs, the maximum variation of headrace level was found 1.35, 1.15 and 1.07 m, respectively in the case of GA operation, while 0.23, 0.96 and 0.52 m of the HA at Res-2, Res-3 and Res-4, respectively. It showed that the annual variation of the energy-storage using the operation of HA had smaller variation than the GA.

Figure 7 and Table 2 showed the weekly release pattern and its statistical analysis, respectively. The maximum release made by the operation of HA was greater than the corresponding GA, while the standard

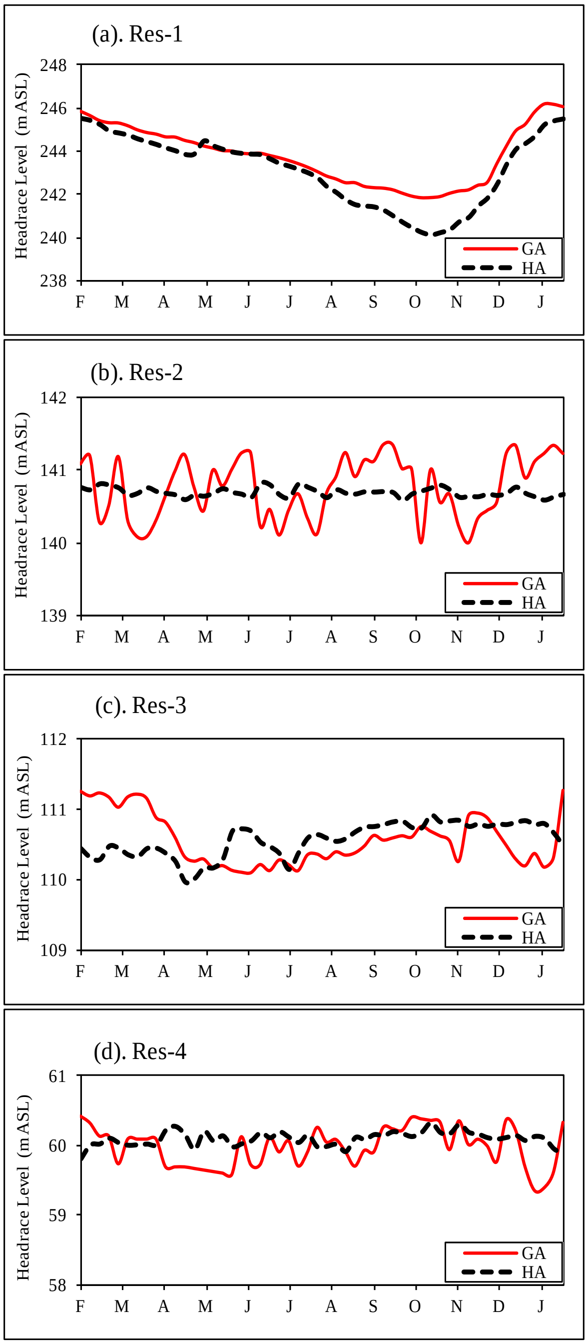

Fig. 6: Average weekly headrace variation of the reservoirs

deviation of the weekly releases made by the GA was less than the HA. Only the release data of Res-3 positively skewed. It indicated that over 50 percent of the total operational period, the rate of the release was above the annual average. Furthermore, the GA release data at Res-2 had positively skewed and negative kurtosis. However, both values were close to zero (it means the data follow the normal distribution).

As shown in, the HA power generation was 228.07 MW (39.46% of the potential); while, the operation of GA improved in to 240.24 MW (41.56% of the potential). Additional of 12.17 MW per day power found with the same annual volume of releases and inflow patterns. The economic benefit of the additional power evaluated with the consideration of the current energy price of Malaysia. The Tenaga Nasional Berhad (TNB), the major electricity utility of the country, classified the electricity tariff rate based on the type of customers and quantities of power utilized per the billing month. Accordingly, analysis was made taking the domestic customers that utilizes less than 200 kWh per the billing month. On this condition, the tariff rate per kWh is 0.218 Ringgit Malaysia. It is the least tariff rate of the utility. Taking transmission efficiency of 95%, the total benefit of the additional power became more than 22 million Ringgit Malaysia.

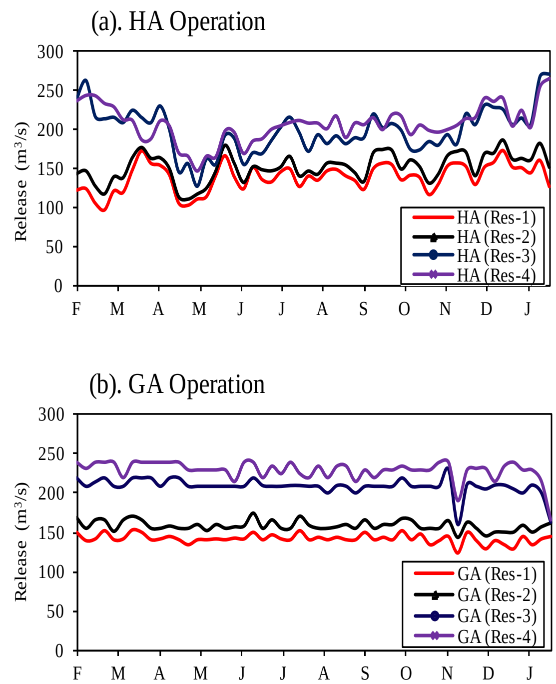

Fig. 7: Release decisions of the HA and the GA operations

CONCLUSION

The sensitivity of the three most important GA parameters namely, PS, CRP and generation number were analyzed. The test results showed Table 3, optimality reached at PS of 150, CRP of 0.75 and generation number of 60. Similarly, Jothiprakash and Shanthi (2006) used GA for the optimization of a reservoir operation and optimality attained at PS of 150 and CRP of 0.76.

The comparison of the GA and HA showed that the weekly turbine release decision using the GA model had been smaller range and standard deviation than the HA. In addition, the entire period of the GA model operation at Res-1 provided higher headrace level than

Table 2: Statistics of the release decisions of HA and GA

		HA				GA			
Item	Unit	Res-1	Res-2	Res-3	Res-4	Res-1	Res-2	Res-3	Res-4
Maximum Release	m^3/s	173	187	271	265	153	175	230	240
Minimum Release	m^3/s	98	111	127	148	125	143	160	165
Range	m^3/s	75	76	144	117	28	32	70	75
Standard Deviation	m^3/s	17.78	18.15	29.24	23.45	0.78	0.93	11.06	13.30
Skewness		-0.38	-0.37	0.20	-0.02	-0.48	0.30	-2.84	-2.82
Kurtosis		-0.35	-0.28	0.55	0.44	1.20	-0.04	11.69	10.99

Table 3: Comparison of model results

Item description	Unit	Res-1	Res-2	Res-3	Res-4	Total
a. Average HA generated	MW	109.57	31.39	56.90	30.21	228.07
b. Power generated using GA model	MW	112.27	32.17	60.29	35.51	240.24
c. Improve in power generated [b-a]	MW	2.70	0.78	3.39	5.30	12.17
d. Percent of improvement [c/a]	%	2.46	2.48	5.96	13.77	5.34

the HA. This had two advantages for hydroelectric power generation: higher head and energy-storage because *Res-1* is the largest storage and generation capacity in the scheme. Moreover, GA model improved the total cascading hydroelectric power generation by 5.34% (equivalent to 12.17 MW per day). The economic benefit of the additional power was over 22 million Ringgit Malaysia per year. Additionally, it plays a significant role in the growing energy demand of the country.

ACKNOWLEDGMENT

The authors would like to express sincere appreciation to Tenaga Nasional Berhad (TNB) and the Department of Irrigation and Drainage of Malaysia for providing relevant data and their kind cooperation for this research. Our acknowledgement also goes to Universiti Teknologi PETRONAS (UTP) for providing the facility and funding to conduct this research.

REFERENCES

Asfaw, T.D. and S. Saiedi, 2011. Optimal short-term cascade reservoirs operation using genetic algorithms. Asian J. Appl. Sci., 4(3): 297-305.

Azamathulla, H.M., F.C. Wu, A.A. Ghani, S.M. Narulkar, N.A. Zakaria and C.K. Chang, 2008. Comparison between genetic algorithm and linear programming approach for real time operation. J. Hydro-Environ. Res., 2: 172-181.

Barbagallo, S., S. Consoli, N. Pappalardo, S. Greco and S.M. Zimbone, 2006. Discovering reservoir operating rules by a rough set approach. Water Res. Manag., 20: 19-36.

Chang, L.C., F.J. Chang, K.W. Wang and S.Y. Dai, 2010. Constrained genetic algorithms for optimizing multi-use reservoir operation. J. Hydrol., 390: 66-74.

Cheng, C.T., W.C. Wang, D.M. Xu and K.W. Chau, 2008. Optimizing hydropower reservoir operation using hybrid genetic algorithm and chaos. Water Res. Manag., 22: 895-909.

Gallagher, K. and M. Sambridge, 1994. Genetic algorithms: A powerful tool for large-scale nonlinear optimization problems. Comput. Geosci., 20(7-8): 1229-1236.

Homayoun-Far, M., A. Ganji, D. Khalili and J. Harris, 2010. Two solution methods for dynamic game in reservoir operation. Adv. Water Res., 33: 752-761.

Hormwichian, R., A. Kangrang and A. Lamom, 2009. A conditional genetic algorithm model for searching optimal reservoir rule curves. J. Appl. Sci., 9(19): 3575-3580.

Jothiprakash, V. and G. Shanthi, 2006. Single reservoir operating policies using genetic algorithm. Water Res. Manag., 20: 917-929.

Kuo, H.C., J.R. Chang and K.S. Shyu, 2004. A hybrid algorithm of evolution and simplex methods applied to global optimization. J. Marine Sci. Technol., 12(4): 280-289.

Liu, P., S. Guo, L. Xiong, W. Li and H. Zhang, 2006. Deriving reservoir refill operating rules by using the proposed DPNS model. Water Res. Manag., 20: 337-357.

Liu, X., S. Guo, P. Liu, L. Chen and X. Li, 2011. Deriving optimal refill rules for multi-purpose reservoir operation. Water Res. Manag., 25: 431-448.

Lobo, F.G. and D.E. Goldberg, 2004. The parameter-less genetic algorithm in practice. Inform. Sci., 167: 217-232.

Lund, J.R., 2000. Derived power production and energy drawdown rules for reservoirs. J. Water Res. Plann. Manag., 126(2): 108-111.

Mathur, Y.P. and S.J. Nikam, 2009. Optimal reservoir operation policies using genetic algorithm. Int. J. Eng. Technol., 1(2): 184-187

McMahon, G.F. and M.C. Farmer, 2009. Rule-based storage accounting for multipurpose reservoir systems. J. Water Res. Plann. Manag., 135(4): 286-297.

Mousavi, S.J., M. Karamouz and M.B. Menhadj, 2004. Fuzzy-state stochastic programming for reservoir operation. J. Water Res. Plann. Manag., 30(6): 460-470.

Schumann, A.H., 1995. Flexibility and Adjustability of Reservoir Operation as an Aid for Sustainable Water Management. In: Simonovic, S.P., Z.W. Kundzewicz, D . Rosbjerg and K. Takeuchi (Eds.), Modelling and Management of Sustainable Basin-Scale Water Resource Systems. IAHS Publ. No. 231, pp: 291-297.

Shiau, J.T., 2009. Optimization of reservoir hedging rules using multiobjective genetic algorithm. J. Water Res. Plann. Manag., 135(5): 355-363.

Tu, M.Y., N.S. Hsu, F.T.C. Tsai and W.W.G. Yeh, 2008. Optimization of hedging rules for reservoir operations. J. Water Res. Plann. Manag., 134(1): 3-13.