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A Reservoir Release Optimization-Simulation Model Using Particle Swarm Optimization (PSO) Algorithm

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Abstract: In a reservoir operation model, it is very important to check the efficiency by means of some performances measuring indexes. Risk analysis of this kind of optimization-simulation model may consist - reliability, vulnerability and resiliency of the model. These basic performance measuring indices are analyzed in this study. A Particle Swarm Optimization (PSO) algorithm is used to minimize the water deficit of a reservoir system. Also another well-established optimization technique, Genetic Algorithm (GA) has used to compare the results. Inflow patterns are categorized into three different situations (high, medium and low) to construct optimum release curves for every month. The release curves, constructed for a particular month indicates the amount of water release for a known storage condition. After constructing the release policy, simulation has done with historical inflow data. The simulation results showed that the PSO provide better results in terms of reliability analysis of the model. Also, it can handle the critical situation of low inflow more efficiently than GA optimization technique.

Key words: Reservoir release optimization, risk analysis, PSO, GA, high

INTRODUCTION

Reservoir system operation is a nonlinear and complex problem that deals with natural uncertainties and water demands. A release policy is essential to operate a reservoir system in optimum manners. Here the release policy is refered as a quantitive measurements for the consecutive time periods that the reservoir authority may follow to get desired benefits from the whole system. The policy also should ensure exact supply and safety to the commodity. It also encorporates the reservoirs operational and physical constraints. Conventionally the optimization prfoblems for the operation policy of a reservoir system is done by using Dynamic Programming (DP) (Yakowitz, 1982), Linear Programming (LP) (Crawley and Dandy, 1993) and most popular Stochastic Dynamic Programming (SDP) (Braga *et al*., 1991).

After uncovering the basic idea of GA by Holland (1975) and efficiency improvement of GA application by Goldberg (1989), many researchers used the algorithm to solve different kind of optimization problem. GA becomes very popular as it solves nonlinear problems very easily. In optimizing releases many studies prove the efficiency of GA by solving both single and multi-objective problems (Oliveira and Loucks, 1997; Chang and Chen, 1998; Ahmed and Sarma, 2005). GA has some drawbacks and complexities too. Encoding and decoding of decision variables is one of the main problems of GA. The basic idea of GA mimicked the biological behavior of chromosomes of living beings. The algorithm consists of three main operators – selection, crossover and mutation. The complexities arise with handling all operators and sensitive parameters of GA leads researcher to use PSO, another population based swarm intelligence. Kennedy and Eberhart (1995) firstly proposed the algorithm after observing the intelligence of natural bird flocks in searching foods. Unlikely GA in PSO algorithm, the whole population of decision variables reached optimum states rather than a single string. Less parameter handling, relatively simple algorithm and better searching capabilities are the main features of PSO over GA. Many studies also proof the efficiency of PSO in different fields (Kumar and Reddy, 2007; Khajehzadeh *et al*., 2011).

In this study a reservoir release policy has developed by using both PSO and GA. The policy developed in this study consists release curves for every month. With the release curves a simulation has done. For the case study Klang gate dam of Malaysia has chosen. The 22 year of historical inflow data have used for simulation purposes. From the simulation results reliability, vulnerability and resiliency of the models has measured. In following sections of the paper the application methods of GA and PSO has given briefly, after that problem formulation and risk analysis associated with using release curves has described sequentially.

GA in reservoir operation policy: In a typical reservoir operation problem, usually releases are considered as the decision variables. The population of GA is simply generated by randomly created decision variables. Each and every value of the variables represents a gene in the algorithm and different combination of these genes construct different chromosomes or strings. So, the population size of the algorithm actually refers the number of strings of any iteration. As GA starts with a population of variables so the set of monthly release policy in this case was feeded to the algorithm as chromosomes. All the initial value of the variables are created by maintaining the boundary condition of the release amount of reservoir. Here a set of tewelve consecutive monthly release amount is created and considered as a string or chromosomes of GA. The next phase of the algorithm is selection process. The selection process for standard GA can be easily found in the study by Goldberg and Deb (1991). Here the strings were shorted according to its objective function values. As the problem is minimization of water deficit, the sorting has done as a manner of lower to greater fitness values. Thus the algorithm selected only those release policy those provides lower fitness values. Afetr selecting the chromosomes the crossover operators start working. In this process two chromosome interchange their variables and creats two new chromosome (release options). The new chromosomes were again tested through the objective function for fitness. Mutation also done by randomly selecting a variable within the chromosome chain. Then the chromosome were developed to achieve higher values in terms of fitness. The crossover and mutation techniques were taken from the study by Haupt and Haupt (2004). The whole process continues to iterate till its reach the given number as generation. Normally the algorithm reach to a optimal solution after certain iteration.

Particle swarm optimization in reservoir operation policy: The PSO algorithm searches the optimum solutions of any problem by creating an initial population with randomly generated decision variables, like GA. Two important factors in the algorithm control the whole population in finding optimal solutions “velocity update” and “position update”. The candidate solutions (decision variables) of any particle calculate and remember its own fitness. The position of any particle accelerated towards the global best position by using Eq. 1 and 2. In any search step t, the i’th particle use to update its candidate solution’s current position x^t_{ij} by using local best p^t_{ij} and global best p^t_{gj} position achieved yet:

$$v_{ij}^{t+1} = \chi[wv_{ij}^t + \phi_1 r_1^t (p_{ij}^t - x_{ij}^t) + \phi_2 r_2^t (p_{gj}^t - x_{ij}^t)] \quad (1)$$

$$x_{ij}^{t+1} = v_{ij}^{t+1} + x_{ij}^t \quad (2)$$

Here, for the next iteration (t+1) the velocity updates as v_{ij}^{t+1} by using Eq. 1 where, χ = constriction co-efficient; ϕ_1 and ϕ_2 = acceleration co-efficient; w = inertial weight and r_1 and r_2 = random numbers in [0, 1]. The steps followed in this study in view of applying the PSO algorithm in searching optimum release are given:

- Define the objective function and penalties of constraint violation
- Initialization of the PSO parameters
- Generate an initial population with random values within the allowable water release ranges
- Calculate the fitness of the particles
- Store the local best and global best among the population
- Generate random initial velocity with the same dimension as population in step 3
- Update the particles to create new population by using equation-1 and 2
- Crop to upper and lower range to maintain the allowable water release bounds
- Back to the step 4, if the iteration criteria not fulfilled.

MATERIALS AND METHODS

Model formulation for Klang Gate Dam (KGD): The study was aimed to solve a real life problem ad so the KGD was choosen to develop a release policy. KGD is the major supplier of water for domestic use of Taman Melawati, Malaysia. The important particulars and the characteristics of the dam is lited below in Table 1.

The Klang gates dam mostly supply water and provide safety from flood to the community. The objective function for this dam is choosen to minimize the water deficit. The total inflow to the dam is categorized as three sector. High, medium and low to cover the overall scenario (Table 2).

The water deficit equation is given in Eq. 3 which is set to be minimized as much as possible with maintaining release and storage constraints:

Table 1: KGD dam characteristics

Parameters	Values
Height of the dam	37 m
Total capacity	6194 Miliion Gallon (MG)
Dead storage (S_{min})	1648.67 MG
Maximum capacity (S_{max})	6194 MG
Release constraint	868<R<1379.50 MG

Table 2: Monthly inflow to the KGD and water demands[a] of the community

	Inflow (MG)			
Months	High	Medium	Low	Demand
Jan.	1506.89	760.85	123.12	1298.64
Feb.	1901.08	1024.49	259.34	1083.09
Mar.	2831.70	1646.31	923.24	1152.45
Apr.	2919.74	1959.92	764.88	1173.00
May	2974.20	1786.87	938.31	1198.73
Jun.	2825.69	1355.22	447.97	1271.73
Jul.	2717.32	1618.95	645.61	1258.14
Aug.	2948.26	1644.53	816.78	1206.41
Sep.	3368.12	1859.86	631.15	1160.05
Oct.	3545.83	2316.13	654.35	1204.14
Nov.	3838.47	2342.89	1021.79	1213.09
Dec.	2699.30	1455.7	340.69	1290.59

[a]Puncak Niaga (M) Sdn. Bhd., Malaysia

$$\text{Min } f(x) = \sum_{t=1}^{12} (D_t - x_t)^2 \quad (3)$$

In Eq. 3, x_t denotes release and D_t stands for demand in a time period t = 1, 2, ……, 12. The storage condition (S) for a month, related to a certain release calculated by using water mass balance (Eq. 4):

$$S_{t+1} = S_t + \text{Inflow}_t - x_t - \text{Losses}_t \quad (4)$$

The penalty function approach is very effective, simple and hugely advised (Wardlaw and Sharif, 1999) in reservoir release policy to handle the constraints of the objective function. The approach is start with adding a extra parameter with the objective function to control the violation of the constraints by the variables. Basically it's a huge value created and named as penalty once the constraint is not satisfied. This big numerical value is added with the objective function value (in case of minimizing objective function value) and thus eliminated through the process. In this study the release options was eliminated once it leads to violate the storage constraints (Eq. 4). For this purpose two penalty terms are introduced to Eq. 3. The penalty terms are:

$$\text{Penalty 1} = \begin{cases} 0 \quad \text{if } S_t > S_{min} \\ C_1(S_{min} - S_t)^2 \text{ if } S_t < S_{min} \end{cases}$$

and:

$$\text{Penalty 2} = \begin{cases} 0 \quad \text{if } S_t > S_{max} \\ C_2(S_t - S_{max})^2 \text{ if } S_t < S_{min} \end{cases}$$

Here, C_1 and C_2 are the penalty co-efficients usually given a large numerical value to be added with the objective function. The value of these coefficients is totally problem dependent. To construct the release curves for every month, we run the model with two input parameters inflows and initial storage. For each run of the optimization model, we got a chain of sequential monthly (Jan-Dec) optimum releases. From this sequential monthly release release curves for every month has developed.

Risk analysis of reservoir release policy: In developing a reservoir release policy, the most three common indices for measuring the level of the performances are reliability, resilience and vulnerability (Hashimoto *et al*., 1982). We considered all these measures and also add some extra observations (such as model performance in critical low/high flow) to analyze the risk associated with adopting the release curves proposed in this study.

Reliability: Reliability is the most important indices in checking the model performance in terms of achieving the main goal of a reservoir system. Wurbs (1996) provides the concept of volumetric (R_v) and periodical (R_p) reliability as Eq. 5 and 6:

$$R_v = (v / V) \times 100\% \quad (5)$$

$$R_p = (n/N) \times 100\% \quad (6)$$

In Eq. 5, v is the volume of water supplied or releases and V is the volume of total targeted demand, so the ratio of this two, gives the idea of water shortage. In Eq. 6, n is the number of time period (here months) in which the model can satisfied the demand and N is the total time period of the observation. In this study, we considered water deficit values rather than only water shortages. So, the squared deficit provides a magnitude of model failure covering both conditions water shortage and excess releases. Also for periodical reliability measures we provided the results from the simulation in three different manners exact period (releases meeting demand), oversupply or surplus period (releases more than demand) and shortage period (releases less than demand).

Resiliency: By resiliency of any model, we can measure the capability of the model to recover the failure (here in terms of meeting demands). Resilience is the probability for a shortage period to meet the demand for the next period release. Loucks and Beek (2005) took the ratio of no. of satisfied releases that follows an unsatisfied value and the total no. of unsatisfactory occurred as resilience of a model. According to this formula we simply took the ratio of maximum period of consecutive satisfied period occurred by a model output to the total number of water shortage period. So, mathematically it can be expressed as:

$$\text{Resilience} = \frac{\text{No. of period a satisfactory value follows an shortage}}{\text{No. of total shortage period}} \quad (7)$$

There is another simple way to define resiliency. The maximum no. of consecutive failure can be taken to measure the ability of a model to get back in track after one failure. But in this way the lower no. of consecutive failure is better in analyse of the resiliency for a model.

Vulnerability: In the study by Loucks and Beek (2005) measures of vulnerability of a model has given as Eq. 8. Vulnerability expresses the magnitude of the shortage of any reservoir system operation model:

$$\text{Vulnerability} = \frac{\text{Sum of positive values of (demand-release)}}{\text{No. of unsatisfactory period}} \quad (8)$$

In this study we followed Eq. 8 to calculate the vulnerability and also the maximum shortage has recorded to explain vulnerability of the model. Another useful measure can be helpful to proof model efficiency in system performance and risk analysis. We have computed the mean inflow for every year and point out the critical inflow situation (lowest average inflow) of a particular year. For that critical period we compute the water deficit and observed the performance of each model.

RESULTS AND DISCUSSION

Figure 1 is representing a release policy for Jan to Dec and constructed for a definite inflow pattern. So once the inflow data is recorded the curve can provide optimal release policy for a certain period of time. It can be easily observed from Fig. 1 that the releases for high inflow can supply ample amount of water to meet the demand and it is struggling to meet the demand during low inflow period. Also most of the time the release curve are trying to maintain the demand amount regardless the inflow is recorded as high or low which a good optimizaition model should maintain. The curve is created also for different level/ storage condition of the dam. Here it also success to provide a logical optimum solution as it is suggesting less release for low storage level and high release for high storage level.

Figure 2 presents the fitness values of 1000 iteration for GA and PSO optimization process (obtained single run of the model considering medium inflow and medium initial storage). For both cases same problem formulation has used. According to Fig. 2, PSO optimization model seems to achieve optimum state more quickly (before 400 iterations) comparatively GA procedures (>700 iterations).

Total 22 year (Jan, 1887 to Dec, 2008) of actual inflow data was feeded in the system to simulate the release policy from the developed release curves. Figure 3 and 4 is the simulation results (only 14 years is presented for better graphical presentation and understanding). The

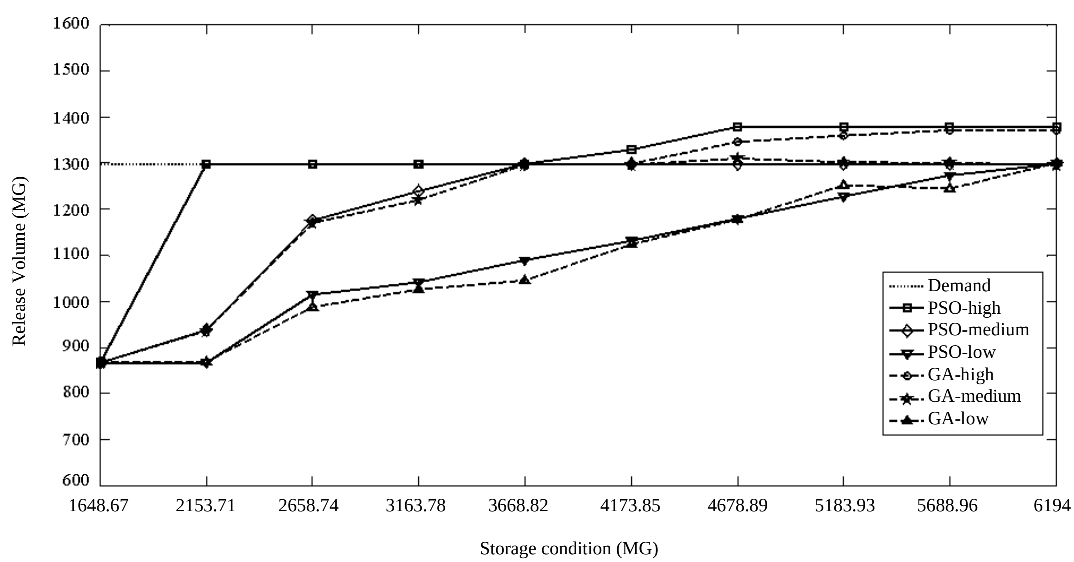

Fig. 1: Release curves of January month for three inflow category

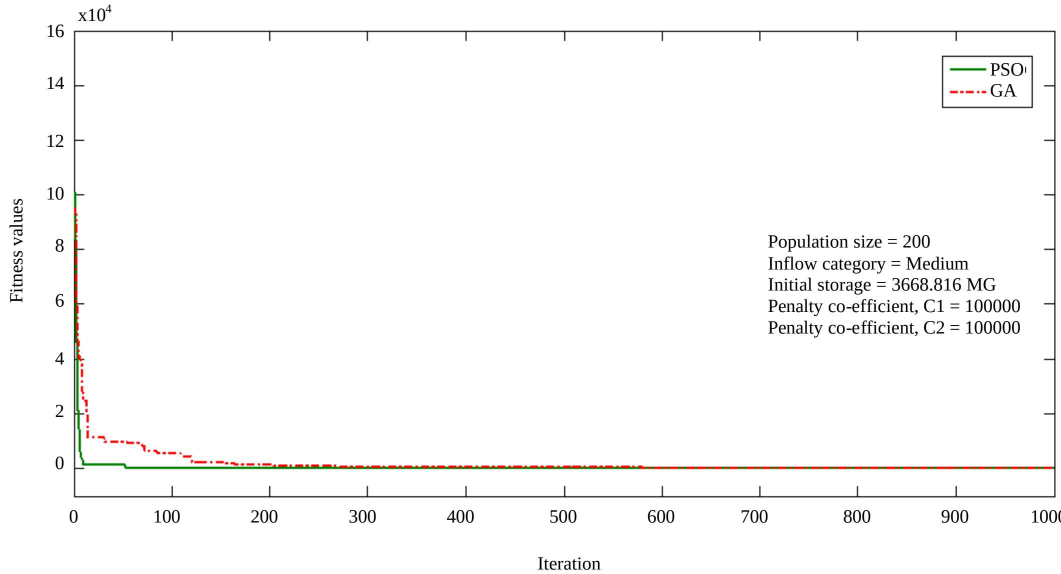

Fig. 2: Fitness values of 1000 iteration of GA and PSO optimization process

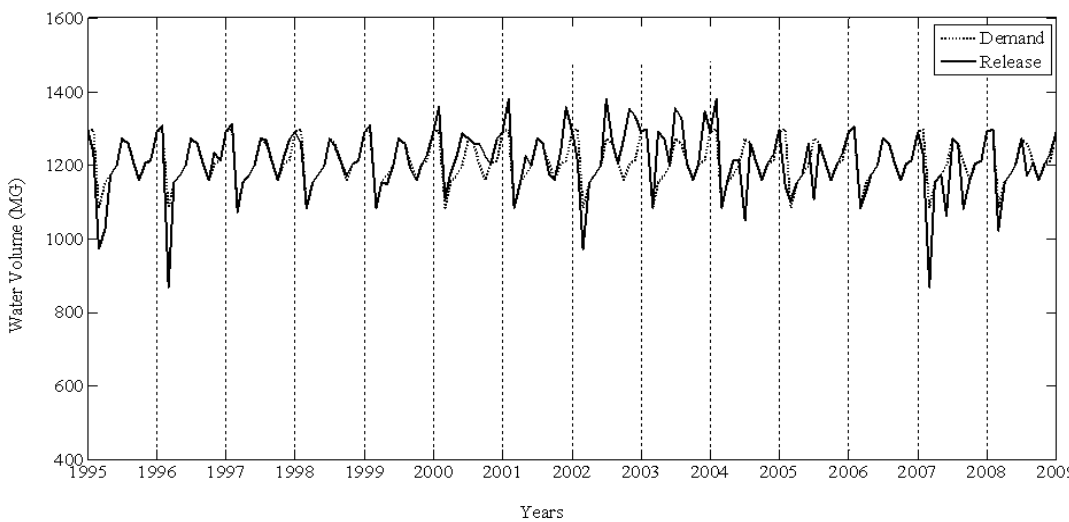

Fig. 3: Simulation results obtained from PSO release curve

simulated release amount from those historical value is showing that the PSO release policy is better in achieving water release more closer to the demand than the GA release curves.

The periodical reliability of both models on the basis of their simulation results has presented in Table 2. Here, we can see that around 60% of total time period PSO release policy has been able to release the exact amount of demand where GA release policy showed 55.7% among the total 264 month of simulation period. The excess release from demand also cause wastage of water and is not preferable for any hydrological optimization models. In case of PSO model release curves provides excess release for 32 times (12.12%) which is less than GA release policy. The volumetric reliability, resiliency, vulnerability and other performance checking measures are given in Table 3.

Table 3: Periodical reliability analysis for PSO and GA release policy

	Time			
Optimization techniques	More than demand	Meet the demand	Less than demand	Total no. of simulation period
PSO	32	157	75	264
GA	38	147	79	264

Figure 5 presents the monthly average inflow for the historical period of 1987-2008. The lowest inflow

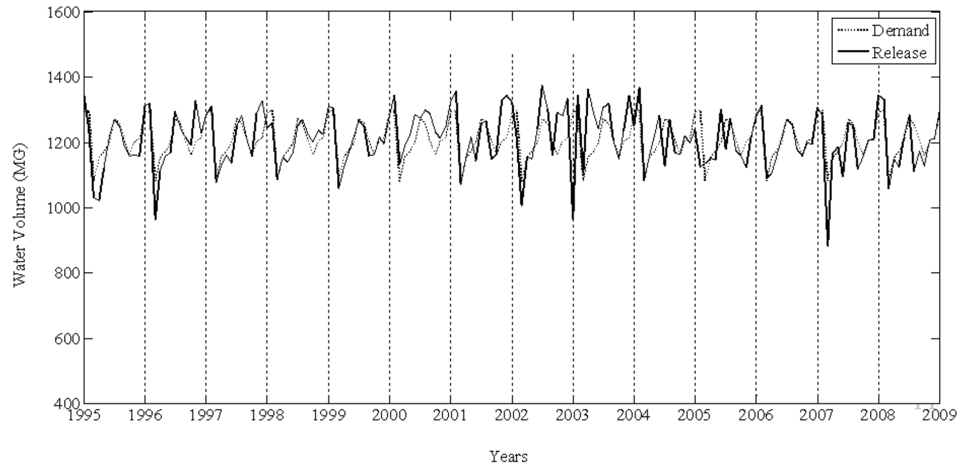

Fig. 4: Simulation results obtained from GA release curve

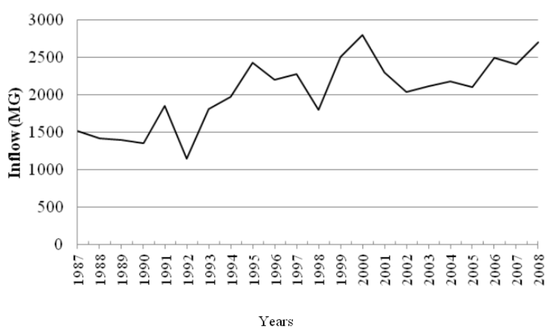

Fig. 5: Average monthly historical inflows for KGD

Table 4: Risk analysis and performance measuring indices of PSO and GA release policy

Measures	PSO	GA
Wastage due to excess release (% of total period)	12.12	14.4
Meeting demand (% of total time period)	59.5	55.68
Volumetric reliability (Eq. 5)	96%	96%
Resiliency (Eq. 7)	0.2	0.15
Vulnerability (Eq. 8) (MG)	203.2	199.2
Max consecutive failure (months)	10	11
Worst shortage ever (% of demand)	53	51
Water deficit in lowest inflow period (MG)	2465.78	2498.92

occurred in the year of 1992. So, we observed the model performance during that time period. In Table 4 the water deficit (here shortage of water) occurred by using both PSO and GA release curve has given from the simulation results.

Though in measuring vulnerability GA release policy showed slightly better performances in all other cases PSO outperforms. In meeting demand for greater time period, less wastages due to oversupply, ability to recover a failure and in handling critical situation of low flow, PSO release policy performs better than GA.

CONCLUSION

In this study a reservoir release policy is developed by using PSO and GA. By adopting both optimization procedures we developed monthly release curves showing the optimal release for a certain inflow and storage condition. Simulation has done by using actual historical inflow data. Risk analysis has done from the simulation results of each operation policy, in terms of reliability, vulnerability and resiliency. PSO release policy seems more reliable in meeting water demand. Simplicity in problem formulation and ability to handling critical low inflow situation also suggest the proposed reservoir release model.

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