行政院國家科學委員會專題研究計畫 成果報告

應用最先進的多目標與多群集遺傳演算法於水庫操作
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計 畫 主 持 人：陳莉

計畫參與人員：碩士班研究生-兼任助理人員：陳星翰
碩士班研究生-兼任助理人員：陳大元
碩士班研究生-兼任助理人員：彭暐鈞
博士班研究生-兼任助理人員：王泰盛

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行政院國家科學委員會補助專題研究計畫 ■ 成 果 報 告 □期中進度報告

應用最先進的多目標與多群集遺傳演算法於水庫操作

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共同主持人：
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中文摘要

使用最佳化與模擬模式，發展一個有效率且強健的長期水庫操作方法，是水資源相關問題的一個重要議題。近年來，遺傳演算法證明是非常有效的最佳化方法，根據先前的研究，實數編碼遺傳演算法(RGA)比二進位編碼遺傳演算法有較多的優勢，因此，本研究採用 RGA 獲得 10 天（台灣傳統水庫操作的時期）水庫系統的操作規線。對於水庫規線編碼，RGA 結合有效的和可彈性組合的方式，將其應用於台灣一個重要的水庫，考慮到 2021 年水庫供水目標。評估每條規線是使用複雜的模擬模式，以決定給定之流量序列之表現指標，重複執行疊代與估算之參數的過程，直到沒有獲得更進一步的改善而停止。做許多次的實驗是為了決定適合的 RGA 運算元，包括宏觀進化（ME）的選擇與 blend-α交換。宏觀進化（ME）可用於防止傳統 GA 在傳統的選擇機制上之過早收斂的問題。調整交換參數 α 的目的是為了決定探勘或開發不同次群集的程度。藉由 RGA 以尋找合適之規線，可以使缺水最小化並保持水庫之高水位，結果也顯示，所提出之 RGA，由一些修正運算元構成之模式，可顯著改善系統的表現，且對於執行其它高度非線性系統亦非常有效率。

關鍵字：長時期水庫操作，實數編碼遺傳演算，規線，宏觀進化選擇，blend-α交換。

ABSTRACT

Developing an efficient and robust method for long-term reservoir operation, using an optimization and simulation model, is a critical issue related to water resources. Recently, genetic algorithms have been demonstrated to be highly effective optimization methods. According to previous studies, a real-coded genetic algorithm (RGA) has many advantages over a binary coded genetic algorithm. Accordingly, this work applies an RGA to obtain the ten-day (the traditional period of reservoir operation in Taiwan) operating rule curves for the proposed reservoir system. The RGA is combined with an effective and flexible scheme for coding the reservoir rule curves, and applied to an important reservoir in Taiwan, considering a water reservoir development scenario to the year 2021. Each rule curve is evaluated using a complex simulation model to determine a performance index for a given flow series. The process of generating and evaluating decision parameters is repeated until no further improvement in performance is obtained. Many experiments were performed to determine the suitable RGA components, including macro-evolutionary (ME) selection and blend-α crossover. Macro-evolution (ME) can be applied to prevent the premature problem of the conventional selection scheme of genetic algorithm. The purpose of adjusting α of crossover scheme is to determine the exploratory or exploitative degree of various subpopulations. The appropriate rule curve searched by a RGA can minimize the water deficit and maintain the high water level of the reservoir. The results also show that the most promising RGA for this problem consists of these revised operators significantly improves the performance of a system; it is also very efficient for optimizing other highly nonlinear systems.

Key Words: long-term reservoir operation, real-coded genetic algorithm, rule curves, macro-evolutionary selection, blend-α crossover.

1. 前言

The operation of a reservoir system is a complex decision-making process, involving many variables and objectives, as well as considerable risk and uncertainty (Oliveira and Loucks, 1997). Fixed rules governing the operation of a reservoir system are commonly presented in the form of graphs or tables (Wurbs, 1996). An optimal operating procedure is need for the purposes of planning of a complex water resources system. Finding the optimal operating rules of a reservoir system for planning purposes has been a major area of study. The management of most reservoirs in Taiwan uses operating rule curves. These curves primarily guide the release of the reservoir system according to the current storage level and the time of year. Existing policies may need to be modified if demand changes, sediment effects occur, or new facilities such as water treatment plants are installed.

The need for an efficient optimization method to re-evaluate the system is obvious since the many currently used operating rule curves have been developed from experience and/or from trial-and-error simulation. Traditional optimization techniques including linear programming (LP) and dynamic programming (DP) have been used to solve the reservoir operation problems. Yeh (1985) presents a comprehensive in-depth state-of-the-art review of reservoir-operation models, with a strong emphasis on optimization techniques. Generalized computer codes are available for solving LP problems, but the strict linear form of LP does limit its applicability (Wurbs 1993). Nonlinear properties of a problem can be readily reflected in a DP formulation. However, the usefulness of DP for multireservoir systems is limited by the huge demand that it can induce on computational resources. The choice of methods depends on the characteristics of the reservoir system being considered, on the availability of data, and on the objectives and constraints specified. Most of these models, however, are valid only for simplified reservoir systems. Genetic Algorithms (GAs) have received much attention for their potential use as optimization techniques for complex systems.

2. 研究目的

GAs may be set up in many ways, but as yet there is little guidance in the literature on the type of formulation most appropriate for reservoir operations. This paper is intended to address that gap through consideration of the application of real-coded genetic algorithm (RGA) to a complex actual reservoir, including hydropower simulation, water supply according to the rule curves of the reservoir. The object has been present GAs could deal easily with nonlinear problems and are shown to be very robust optimization tools.

3. 文獻探討

In the reservoir operation system fields, GAs have been demonstrated as powerful optimization approaches but there are few references in the literature. In one study, Esat and Hall (1994) applied a GA to the four-reservoir problem. They concluded GAs have potential in water resources optimization and that significant savings could be achieved in both memory and execution times. Olivera and Loucks (1997) used GAs to develop operating policies for multi-reservoir systems, and concluded that GAs are practical and robust methods, which could lead to effective operating policies. Chang and Chen (1988) applied real-coded GA for rule-based flood control reservoir management. The results show that the real-coded GA perform better in terms of efficiency and precision than the binary-coded GA. Wardlaw and Sharif (1999) demonstrated that using GAs can provide a robust and acceptable solutions for a four reservoir deterministic problem. Further, they could acquire the known global optimum. Sharif and Wardlaw (2000) presented multi-reservoir systems optimization using GAs. They compared with discrete differential dynamic programming (DDDP) that GA results are very close to the optimum, and the technique appears to be robust.

The need for solving optimization problems arises in almost every field. As a consequence, many analytic and numerical optimization techniques have been developed. However there exist a great number of functions, such as discontinuous, non-differentiable, non-convex, or multi-modal functions, which are beyond analytical methods and present profound difficulties for numerical techniques. Moreover, traditional optimization techniques depend highly on a deterministic relationship between the model's parameters and its performance. To date, these techniques have been unable to optimize the performance of complex systems. Consequently, new and more robust optimization techniques capable of handling such problems are needed.

Recently, there has been an increasing interest in solving optimization problems. The genetic algorithm (GA) is one of the most promising techniques in that domain and has received a great deal of attention regarding optimizing complex systems. The GA is essentially a Darwinian natural selection process, which combines an artificial survival of the fittest with natural genetic operators (Holland, 1975). Through the genetic evolution method, an optimal solution can be found and represented by the final winner of the genetic evolution.

The GA is an iterative procedure, which maintains a population of individuals that are candidate solutions to specific domain. During each generation, the individuals in the current population are rated for their effective evaluations, and a new population of candidate solutions is formed using specific genetic operators such as reproduction, crossover, and mutation (Grefenstette, 1986). Then, Goldberg (1989) and Davis (1991) reviewed many important applications of GAs.

According to several previous works, real-coded genetic algorighm (RGA) has several advantages over binary coded GAs (Wright, 1991; Eshelman and Schaffer, 1992). The reproduction operator may be implemented in algorithmic form in a number of ways, such as Roulette Selection (Goldberg 1989), Tournament Selection (Goldberg and Deb 1991, Chen 2003a) and Macro-Evolutionary (ME) Selection (Marin and Sole 1999). There are three famous methods for implementing the crossover scheme: Linear Crossover (Wright, 1991), Flat Crossover (Radcliffe, 1990) and BLX-0.5 Crossover (Eshelman and Schaffer, 1992).

4. 研究方法

The area of study is Fei-Tsui reservoir, which was completed over 16 years, and the proposed water treatment plant Kan-Yuan, which will be installed in the year, 2021. The purpose of this paper is to demonstrate application of the RGA approach in the optimization of the rule curves of this reservoir.

4.1 System Description

The Fei-Tsui reservoir, which was completed in 1985 and has an efficient storage capacity of $359*10^6$ m^3, is one of the major storage reservoirs in northern Taiwan. The hydropower plant at Fei-Tsui has a generating capacity of 70 MW. This reservoir is a multi-purpose reservoir for flood control, hydroelectric power generation and water supply. The primary water use in the basin is potable for water demand to the city of Taipei. A system schematic water supply network is shown in Fig. 1. There are four inflow points, one reservoir (with power plant), three water treatment plants, one diversion and four merger points to connect the flow net of this system.

4.2 Simulation Method

The purpose of the simulation model in this paper is to recreate the ten-day (the traditional reservoir operation period in Taiwan) operations of the Fei-Tsui Reservoir by following its rule curve. The operating rule defines the release within each year period as a function of existing storage level and overall release target amounts. The rule curve of Fei-Tsui reservoir consists of three curves is shown in Fig. 2. The ten-day operations are described as following four operating rules (see Fig.2).

(1) When the water level is above the upper limit, hydropower generation should be maximized to keep the water level at the upper limit.

(2) When water level is between the upper and lower limit, all operations, including public water and hydropower generation are under normal operating condition, but hydropower should be generated at most six hours per day.

(3) When the water level is between lower and critical limits, public water can be supplied as usual, but hydropower generation is halted.

(4) When the water level is below critical limits, public water supply must be reduced.

4.3 Parameters Coding

Applying RGA to water resources problems, chromosomes may be generated that fail to meet system constraints. Therefore, each generated chromosome must be checked against such system constraints. Binary strings are the common encoding schemes, but real strings are more efficient. Owing to the range of a parameter is a real number, it does not have to encode as a bit string. There are three curves the upper limit, lower limit and critical limit. Each curve is composed of six decision variables, which are coded in a real string. The lower limit defines the hydropower generation; and the critical limit determines whether cuts back the water for public use or not. In order to maintain the function of flood control, the upper limit curve will not be changed, so the total number of decision variables is twelve, i.e. six for lower limit and six for critical limit curve. The details of these variables are described in Table 1 and Fig. 2. By doing this, each chromosome is a real-valued vector $\bar{x} = (x_1, x_2, ...x_{12}) \in R^{12}$ (which is the decision variables of a rule curve).

Constraints of decision variable:

$MAXlevel > X_1 > X_2$

$1 \leqq X_3 < X_4 < X_5 < X_6 < 36$

$X_7 > X_8 >$ MINlevel

$1 \leqq X_9 < X_{10} < X_{11} < X_{12} \leqq 36$

MAXlevel $> X_1 > X_7$

$165 > X_2 > X_8 >$ MINlevel

where MAXlevel = 170 (meter)

MINlevel = 117.5 (meter)

The coding of parameters may vary according to the nature of the problem itself. An appropriate number of parameters, 12, that could describe the whole decision space are presented in this paper.

4.4 Objective Function

The main consideration of objective function of the optimization model is to minimizing the deficit of water supply for different purposes. As a consequence, the shortage index (SI) proposed by the U.S. Army Corps of Engineer could reflect the severity of the water shortage. This SI for the ten-day periods is defined as follows:

$$SI = \frac{100}{N} \sum_{t=1}^{N} \left(\frac{\text{Water deficit in the period } t}{\text{Designed water supply for the period } t} \right)^2$$

where t is the operating time step of Fei-Tsui in ten-day.

N is the total number of time steps, N = 41 *36 = 1476 in this study.

4.5 Experiments of RGA

The entire procedure of this study includes two parts: the simulation model and the optimization model. Combining these two parts to search the best set of rule curves is a very important task. The optimization model using RGA could generate a set of rule curves, i.e. 12 decision variables. Whereas the simulation model programming could use these decision variables to calculate their fitness function values. The repetition of these two steps is necessary to produce the required number of generations.

Two experimental procedures for choosing the proper selection and crossover schemes were: three selection schemes: ME, roulette and tournament, and three crossover schemes: linear, flat and BLX-0.5.

5. 結果與討論

The experimental results show that the RGA converges quickly and reaches an optimal solution, where the objective value is close to the theoretical minimum point. Several experiments were discussed that when the ME selection and BLX-0.5 crossover could obtain the best results.

Although the results of ME selection were not good at the beginning, it was shown that its results became better than the other two selection schemes finally (See Fig. 3). In standard GA, the selection operator like roulette selection chooses individuals with a probability proportional to their relative fitness, but this can lead to "premature convergence". In ME, large extinctions can generate coherent population responses that are very different from the slow Darwinian dynamics of a classical GA. Further, the population of candidate solutions/species might be understood in terms of an ecological system with connections among different species, instead of just a number of independent entities with a given assigned fitness value. The biological model of macroevolution simulates the dynamics of species extinction and diversification for large time scales. These dynamics are based the relation between species and the links that are constructed between each species at each generation to determine whether the species could be alive or not.

The BLX-0.5 crossover could make the best performance than all the other cases (See Fig. 4). Crossover is a technique that takes two parent chromosomes and produces two child chromosomes. Crossover operator of the real-coded GA is mimicking the k-point crossover of binary-coded GA, which considers offspring some perturbations from the values of their parents. A weakness with this crossover approach is any offspring may be much worse than either parent. There are three methods, linear, flat or blend crossover, for solving this problem. Blend crossover (BLX-α) uniformly picks values that lie between two points that contain the two parents, but may extend equally on either side determined by a user specified GA-parameter α. The function of adjusting α is to achieve the exploratory or exploitative degree of different subpopulations. Only when α =0.5 is a balanced relationship reached between convergence (exploitation) and divergence (exploration), the probability that a gene will lie in the exploitation interval is then equal to the probability that it will lie in an exploration interval (Chen 2003b).

Fig.5 indicates that the optimal lower limit is above that of the original rule curve and the critical limit is below that of the original rule curve. Table 2 presents the optimal values of the variables. The results reveal that the shortage index of optimal solution equals zero and the average water level of reservoir are higher than those obtained following the original rule curve. Table 3 displays these comparisons including average water level of reservoir and the number of deficit water. These results demonstrate that the higher lower limit could increase the hydropower efficiency about 1.8% and the lower critical limit could decrease the deficit of water release, shortage index, to zero. Therefore, the optimal parameters of rule curve generated from RGA are reasonable and efficient.

The RGA has the specific advantages in the context of reservoir systems optimization. First, discretization of decision space and initial trial state trajectories are not required. Second, decomposition complex reservoir systems into successive approximation-based approaches are not to be needed. Third, discontinuous and complex objective functions are acceptable. The last is that complex simulation models can be coupled to evaluate the fitness function of the reservoir system.

6. 建議

This study proposed a real-coded genetic algorithm (RGA) combined with the simulation model and demonstrated that it can be used efficiently to optimize of the operating rule curves of a major reservoir system in Taiwan. These operating rule curves define long-term target storage levels and target release. They can be used to help system operators to make decisions. In particular, means of determining the decision parameters that could represent a set of rule curves were considered. The results show that the release could optimize the objective function for a specified inflow and initial storage level.

7. 計畫成果自評

In this study, solutions very close to the optimum were achieved within 200 generations with a population of 100. A real-value representation, incorporating ME selection and BLX-0.5 crossover, is concluded to produce the best results. The new rule curve, optimized by RGA, can maintain a higher water level of the reservoir and a lower water deficit than could the original rule curve.

The method is not limited by the type of the objective function. In contrast to various conventional optimization algorithms, the objective function need not be differentiable or continuous. Since the GA uses a simulation model to evaluate each generated rule curve, no restrictions apply to the definition of the operating policy. Besides, a significant advantage of the GA approach is that no initial trial release policy must be imposed. The algorithm used herein of parallel structures, which may help to reduce the number of computations and evaluations.

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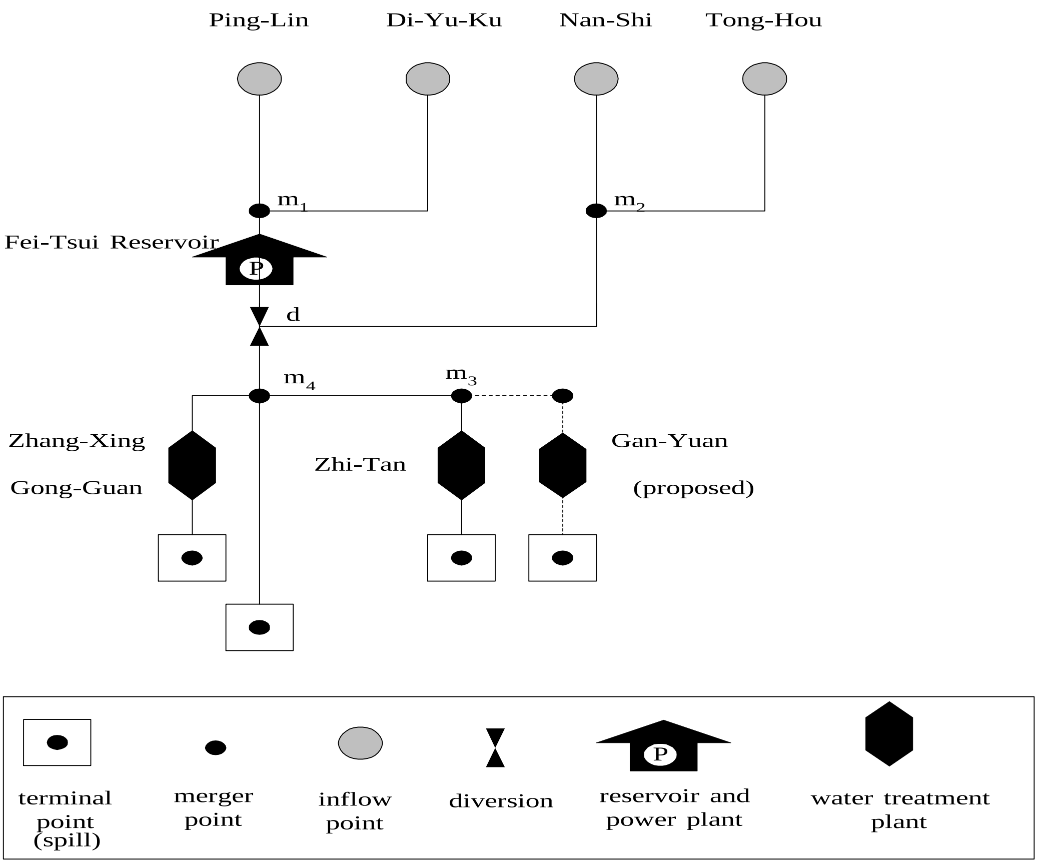

Figure 1. The System Description of Fei-Tsui Reservoir in Taiwan

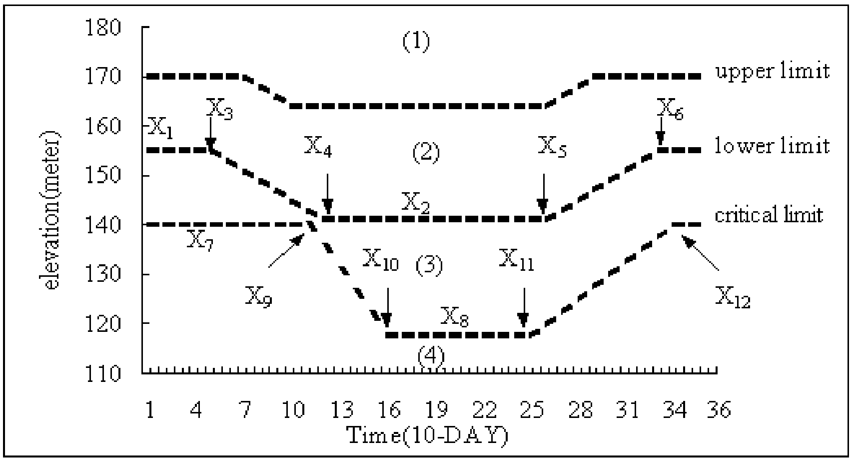

Figure 2. The Definition of All Decision Variables on the Original Rule Curves of Fei-Tsui Reservoir (see Table 1)

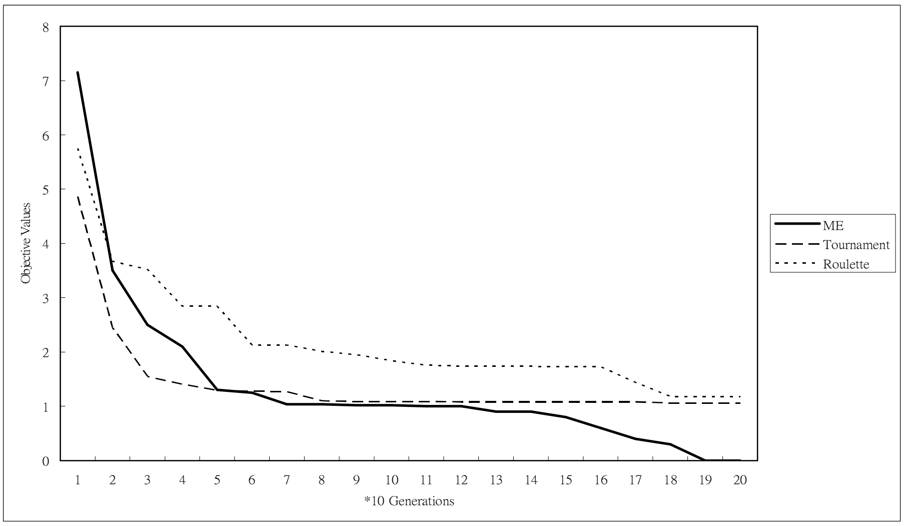

Figure 3. A Comparison of the On-line Performances for Different Selection Methods

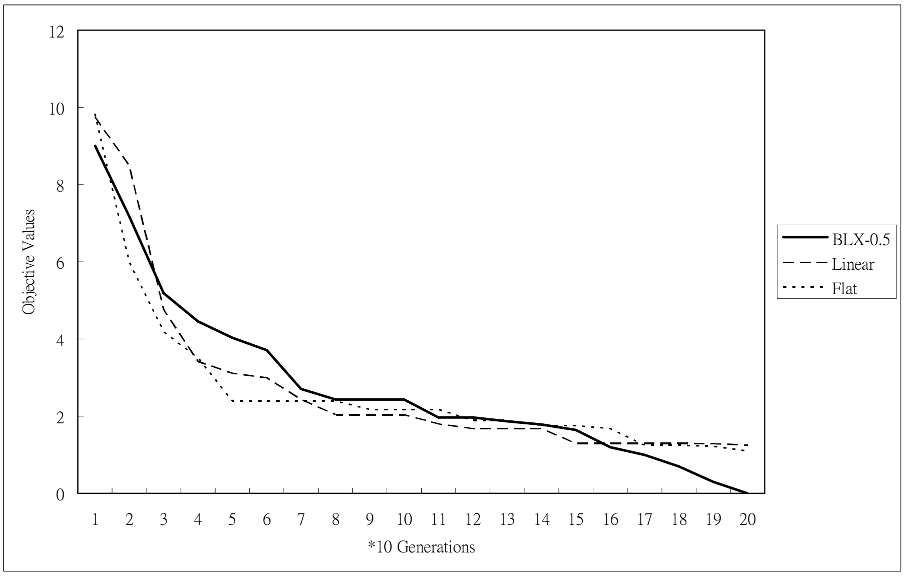

Figure 4. A Comparison of the On-line Performances for Different Crossover Schemes

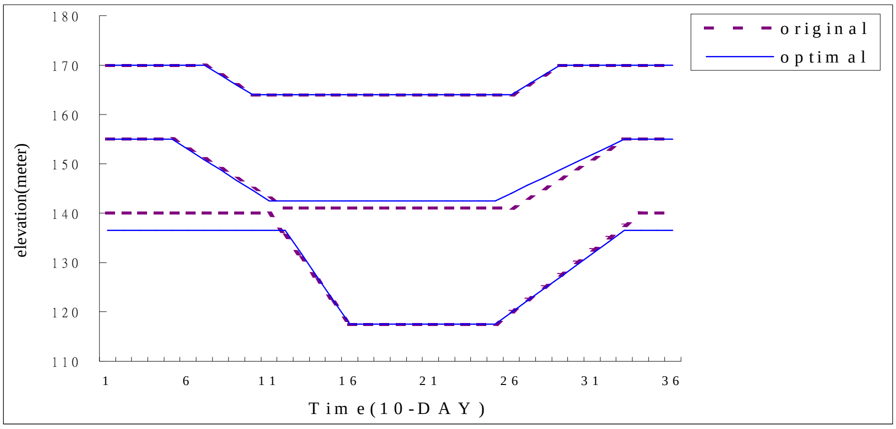

Figure 5. The Comparison of Two Rule Curves

Table 1. The Definitions of Decision Variables on the Rule Curves of Fei-Tsui Reservoir

Variable	Represents	Example of Fig. 3. (original value)
X1	Elevation of upper horizontal segment on the lower limit	155
X2	Elevation of lower horizontal segment on the lower limit	141
X3	Starting time of first inclined line on the lower limit	5
X4	Ending time of first inclined line on the lower limit	12
X5	Starting time of second inclined line on the lower limit	26
X6	Ending time of second inclined line on the lower limit	33
X7	Elevation of upper horizontal segment on the critical limit	140
X8	Elevation of lower horizontal segment on the critical limit	117.5
X9	Starting time of first inclined line on the critical limit	11
X10	Ending time of first inclined line on the critical limit	16
X11	Starting time of second inclined line on the critical limit	25
X12	Ending time of second inclined line on the critical limit	34

Table 2. The Optimal Value of Decision Variables through RGA

Variables	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
Value	155	142.5	5	11	25	33	136.5	117.5	12	16	25	33

Table 3. The Comparison Results of Rule Curves

Rule Curve	Average water level of reservoir (meter)	The frequency of water shortage (10-day)
Original (Table 1.)	142.8	55
Optimal (Table 2.)	144.1	0