Multiobjective Planning of Surface Water Resources by Multiobjective Genetic Algorithm with Constrained Differential Dynamic Programming

Chao-Chung Yang[1]; Liang-Cheng Chang[2]; Chao-Hsien Yeh[3]; and Chang-Shian Chen[4]

Abstract: Owing to the conflict encountered between the two objectives of fixed cost in reservoir installation and operating cost in time-varying water deficit, multiobjective planning of surface water resources is a difficult job. Instead of combining these two objectives into just one objective using the weighting factor approach, this investigation proposes a novel method by integrating a multiobjective genetic algorithm (MOGA) with constrained differential dynamic programming (CDDP). A MOGA is employed to generate the various combinations of reservoir capacity and estimate the noninferior solution set. However, applying this algorithm to solve the dynamics of the operating cost, the number of variables increasing with time will dramatically increase the use of computational resources. Consequently, the CDDP is herein adopted to distribute optimal releases among reservoirs to satisfy water demand as much as possible. Next, the effectiveness of the proposed methodology is verified by solving a multiobjective planning problem of surface water in southern Taiwan. This real application demonstrates that MOGA can be linked with CDDP to resolve a complex water resources problem. Additionally, the ability of MOGA on addressing multiple objectives simultaneously without converting to a weighted objective function provides the opportunity for significant advancement in multiobjective optimization. Finally, this investigation also proposes three suitable strategies of reservoir construction to decision makers with budget concerns through the analysis of all noninferior solutions.

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Introduction

Many planning problems in water resources involve fixed charges attributed to the construction of new facilities or the expansion of existing facilities. Reservoirs, the most important hydraulic facilities in a water resource system, can significantly impact regional water conservation because of their ability to consistently distribute water. They fulfill the demands of specified locations in a region where precipitation is unevenly distributed temporally and spatially. However, due to financial and environmental constraints, only a limited number of reservoirs can be built in a river basin. Therefore, an appropriate policy is necessary to consider the fixed costs and operating costs during the reservoir planning stage.

Past studies discuss several different methods used in water resources management and planning. To assess state-of-the-art optimization of reservoir system management and operation, Labadie (2004) reviewed various optimization methods, including multiobjective optimization models and application of heuristic programming methods using evolutionary and genetic algorithms. Also designed to solve the multireservoir problem, the "network flow programming," was introduced by Khaliquzzaman and Chander (1997) for optimizing reservoir capacities through defining the best zones for the reservoirs with unit cost in the objective function. However, the study did not separate the "cost" of reservoir operation as an objective like this paper has done. Watkins and McKinney (1998) used two decomposition algorithms to a conjunctive system of surface and groundwater with the cost function containing both discrete and nonlinear terms. With a discrete investment cost and a continuous operating cost in its objective function, their work failed to minimize a nonlinear programming formulation of these two terms because the reservoir capacity is preset rather than being a decision variable. Utilizing a penalty function, Hirad and Ramamurthy (2000) proposed a method of converting two objectives, minimum cost and minimum water deficit, into a single objective function to determine the optimal multireservoir system design for water supply. Nonetheless, this methodology did not simultaneously consider the fixed costs for reservoirs installation and the time-varying operating costs of water deficit.

Dynamic programming is capable of handling the many prob-

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lems encountered during the decision-making process. Dynamic optimal control algorithms encounter difficulties in resolving a problem with an objective function that includes fixed costs due to the requirement of a separable objective function for each stage. Consequently, the multiobjective genetic algorithm, (MOGA), is attractive because it does not stipulate the differentiability of the objective function. Further, the MOGA-based solution technique has two merits over conventional multiobjective programming approaches. First, it can generate both convex and concave points on the trade-off curve. Second, it can create large portions of the trade-off curve in a single iteration.

MOGA has been successfully employed in water resources for various purposes. For example, Cieniawski et al. (1995) presented an optimization method of MOGA to solve a multiobjective groundwater monitoring problem with the objectives of maximizing reliability and minimizing contaminated zones when first detected. In order to overcome the rising complexity when both location and sizing of detention dams are involved in a multiobjective framework, Yeh and Labadie (1997) utilized MOGA for the planning of a watershed-level detention dams system. Burn and Yulianti (2001) explored the capabilities of genetic algorithms for finding solutions to waste-load allocation problems with the objectives of focusing on the cost of treatment as well as the effect of water quality improvement. In order to design a water distribution network with the objectives of minimizing pipe network costs and maximizing reliability, Prasad and Park (2004) presented a MOGA approach to produce a set of Pareto-optimal solutions. Kim and Heo (2004) focused on the application of MOGA to the multireservoir system optimization. You et al. (2004) adopted MOGA to solve the conflict between power generation and water supply.

Even with various applications of MOGA in solving multiobjective optimization problems, using this approach to overcome time-varying policies of operating cost will nonetheless significantly increase the use of computational resources. Therefore, the constrained differential dynamic programming (CDDP) method is used in order to calculate the operating cost, which is then supplied to MOGA for further processing.

Methodology

The basic planning problem of a water resources system that considers fixed costs and operating costs can be described as follows and is denoted as Problem A in this study (Problem A: Original form):
Objective

$$\operatorname*{Min}_{\vec{a},\tilde{u}}\{Z_1(\vec{a}),Z_2(\tilde{u}(\vec{a}))\} \tag{1}$$

$$Z_1(\vec{a})=F(\vec{a}) \tag{2}$$

$$Z_2(\tilde{u}(\vec{a}))=\sum_{t=1}^{n}\{g_t(\tilde{u})|\vec{a}\} \tag{3}$$

Subject to

$$\vec{s}_{t+1}=T(\vec{s}_t,\vec{u}_t),\quad t=1,\ldots,n \tag{4}$$

$$f(\vec{s}_t,\vec{u}_t,\vec{a})\leqslant 0,\quad t=1,\ldots,n \tag{5}$$

$$\vec{a}^{\min}\leqslant\vec{a}\leqslant\vec{a}^{\max} \tag{6}$$

$$0\leqslant\vec{s}_t\leqslant\vec{a},\quad t=1,\ldots,n \tag{7}$$

$$0\leqslant\vec{u}_t\leqslant\vec{U}_t^{\max},\quad t=1,\ldots,n \tag{8}$$

The original problem has two objectives, Z_1 and Z_2, called fixed cost, and operating cost respectively, and are to be minimized. The fixed cost Z_1 represents the design capacity cost, denoted as vector $\vec{a}$ to represent the reservoirs to be created and it is defined by a function $F(\vec{a})$. The operating cost Z_2=cost of operating decisions identified by vector $\tilde{u}$ for each period, and defined by function $g(\tilde{u})$. The vector $\tilde{u}$ represents the feasible decisions, such as reservoir outflow and spill, required to satisfy the physical and policy constraints imposed on operational procedures. This investigation assumes that the fixed cost rises linearly with reservoir size, and that the shortage index (SI) surrogates the operating costs. Proposed by the U.S. Army Corps of Engineers (HEC 1966, 1975), the SI is often adopted to reflect the water deficit in Taiwan (Hsu 1995) and is utilized as a surrogate index for the objective function of operating cost in this study. Calculated by the following equation, this index specifies the sum of the indicated values for all periods

$$\mathrm{SI}=\frac{100}{N}\sum_{i=1}^{N}\left(\frac{\mathrm{Sh}_i}{\mathrm{DT}_i}\right)^2 \tag{9}$$

where N=number of periods and Sh_i and DT_i=shortage and the target demand at time period i.

Constraint (4) is the transition equation of a surface water system during time interval $[t,t+1]$, and the reservoir level at end of the stage S_{t+1} depends on the initial level state of reservoir S_t and the decision vector $\tilde{u}$. As Constraint (5) represents the mass balance or inequality of a surface system, the system limitations of state variables and decision variables are articulated by constraints (6)–(8).

An appropriate solution to a multiobjective problem is often difficult to obtain from the original form as expressed in Problem A. Therefore, merging multiple objective functions into a scalar function by weighting factors is usually employed for Problem A such that it can be solved by single objective optimization methods, i.e., dynamic programming or nonlinear programming for our problem. Because dynamic programming needs a separable objective function for each stage t, it faces difficulties in overcoming this problem for the objective function containing the fixed costs formulated by vector $\vec{a}$ which is independent of time, and it turns the weighted function into a nonseparable problem with time t (Hsiao and Chang 2002). Although nonlinear programming can estimate the noninferior solutions for both separable and nonseparable problems, the computation time becomes huge (increases geometrically proportional to time step) as the operating time increases. Further, the weighting factor method can only be applied to the problem with a concave feasible solution set where the objective function has orthogonal characteristics (Hsiao and Chang 2002).

Rather than combining these two competing objectives with a weighting factor, this investigation presents a methodology employing MOGA embedded with CDDP for Problem A through a two-stage formulation. To accomplish this, the original form is first modified into Problem B, comprised of a main form and a minor form. The main form is formulated to estimate noninferior solutions, while the minor form searches for optimal system operation Z_2^* for all time stages under specific capacity decision $\vec{a}$ provided by the main form. The mathematical expression is elu-

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cidated as follows (main form of Problem B)
Objective

$$\underset{\vec{a}}{\text{Min}}\{Z_1(\vec{a}), Z_2^*(\vec{a})\} \tag{10}$$

$$Z_1(\vec{a}) = F(\vec{a})$$

Subject to

$$\vec{a}^{\min} \leq \vec{a} \leq \vec{a}^{\max}$$

(minor form of Problem B)
Objective

$$Z_2^*(\vec{a}) = \underset{\tilde{u}}{\text{Min}} \sum_{t=1}^{n} \{g_t(\vec{u}) | \vec{a}\} \tag{11}$$

Subject to

$$\vec{s}_{t+1} = T(\vec{s}_t, \vec{u}_t), \quad t = 1, \ldots, n$$

$$f(\vec{s}_t, \vec{u}_t, \vec{a}) \leq 0, \quad t = 1, \ldots, n$$

$$0 \leq \vec{s}_t \leq \vec{a}, \quad t = 1, \ldots, n$$

$$0 \leq \vec{u}_t \leq \vec{U}_t^{\max}, \quad t = 1, \ldots, n$$

Although still a multiobjective problem, the main form of Problem B becomes a type of problem without time-variant decision variables and constraints, such that MOGA is performed to generate a set of noninferior solutions for the various combinations of reservoir capacities. Under the given vector $\vec{a}$ from MOGA, the minor form of Problem B for the single objective $Z_2(\vec{a})$ is expected to define the best system operation $\tilde{u}^*$ and its optimal value Z_2^*. As $\vec{a}$ is a constant rather than a decision variable in the minor form of Problem B, the difficulty of a nonseparable problem for dynamic programming vanishes.

In the past, Murray and Yakowitz (1981) presented a CDDP algorithm and applied it to a multireservoir control problem. They formulated the problem as a discrete optimal control problem with a linear transition function and linear constraints on the state and control variables. Their algorithm adapted the quadratic programming method into the DDP framework. As an extension of the same algorithm, Yakowitz (1986) presented a stage-wise Kuhn–Tucker condition to ensure the convergence of the algorithm with the assumption of linear constraints. Chang et al. (1992) and Hsiao and Chang (2002) had successfully solved the problem of groundwater remediation by CDDP. From the abovementioned studies, they mention that the CDDP outperforms conventional DP and mathematical programming algorithms in computational efficiency. They also point out the state and control vectors of the problem need not be discrete, implying that CDDP overcomes the "curse of dimensionality," a serious limitation of conventional DP. CDDP can reduce a significant "working" dimensionality of the algorithm over that of mathematical programming algorithms (Hsiao and Chang 2002). Based on those advantages, we adopt the CDDP instead of DP. The CDDP used herein is a modified procedure suggested by Murray and Yakowitz (1981). Within each iteration, quadratic programming is applied at each stage of the backward and forward sweep. The iterations are repeated until the solution converges. The more detailed discussion of the CDDP algorithm and application is provided in Murray and Yakowitz (1981), Chang et al. (1992), and Hsiao and Chang (2002).

As CDDP module is embedded in the structure of MOGA as a subroutine, CDDP is employed to distribute the release among reservoirs in every time step. Therefore, MOGA not only estimates noninferior solutions but also provides the input variables to CDDP (the capacity design combination of reservoirs.) The comparison between the original multiobjective problem and its modified problem is illustrated in Fig. 1.

The integrated model proposed in this study has two critical features: First, the search for the noninferior solution set is achieved by MOGA at the main form, and second, CDDP calculates the releases of the system associated with the combination of designed reservoirs scale at the minor form. Although the CDDP used herein is a procedure suggested by Murray and Yakowitz (1981), the operation procedures of MOGA are modified from the study of the Pareto-optimal ranking method (Goldberg 1989) and elitist conservation (Yeh and Labadie 1997). Although this paper does not focus on the performance of various multiobjective genetic algorithms, it designs a test case to justify the utility of the proposed methodology as shown in the Appendix. With several trial runs of the MOGA for the test case, the parameters are identified as those shown in Table 1.

The flow chart of our integrated model is shown in Fig. 2, and the detail operational procedures are described step by step as follows.

1. Select the potential scale of reservoirs. MOGA requires encoding schemes that transform the decision varable vectors into a structure (chromosome) that enables genetic operations: Reproduction, crossover, and mutation. These genetic operations generate new sets of chromosomes (decision variables) with, on average, enhanced performance. This step mainly focuses on encoding the decision variable as a chromosome, randomly generating an initial population of given size, 100 in this case. A chromosome represents a possible reservoir capacity design, and its length is determined by the number of bits required to represent a decision variable and the number of decision variables. In this investigation, each decision variable denotes the possible capacity of a reservoir such that each chromosome denotes a combination of the capacities of all reservoirs.
2. Define the system network and prepare hydrologic data.
3. Distribute the releases among reservoirs using CDDP in a system network under the target of optimal distribution between supply and demand. After the chromosomes (reservoir capacity) of the initial population have been determined as in Step 1, the release of the system in every period is calculated by the CDDP corresponding to each chromosome. This procedure is repeated for all chromosomes in each generation. The CDDP is embedded in the MOGA to calculate the release of the system under the target of optimal distribution between supply and demand. Finally, the release of the system for each chromosome is returned to the MOGA to measure the operating cost.
4. Evaluate the fixed cost using the fixed cost-coefficient and reservoir capacity, and the operating cost using the shortage index. In this study, however, the SI surrogates the operating costs.
5. Search for the noninferior solution set. The values of the fixed cost (Z_1) and operating cost (Z_2) can be identified for every chromosome of one generation through Step 3 and 4, and MOGA finds the noninferior solution set based on these values at Step 5. A chromosome $a1$ is defined as inferior to chromosome $a2$ if the following condition holds.

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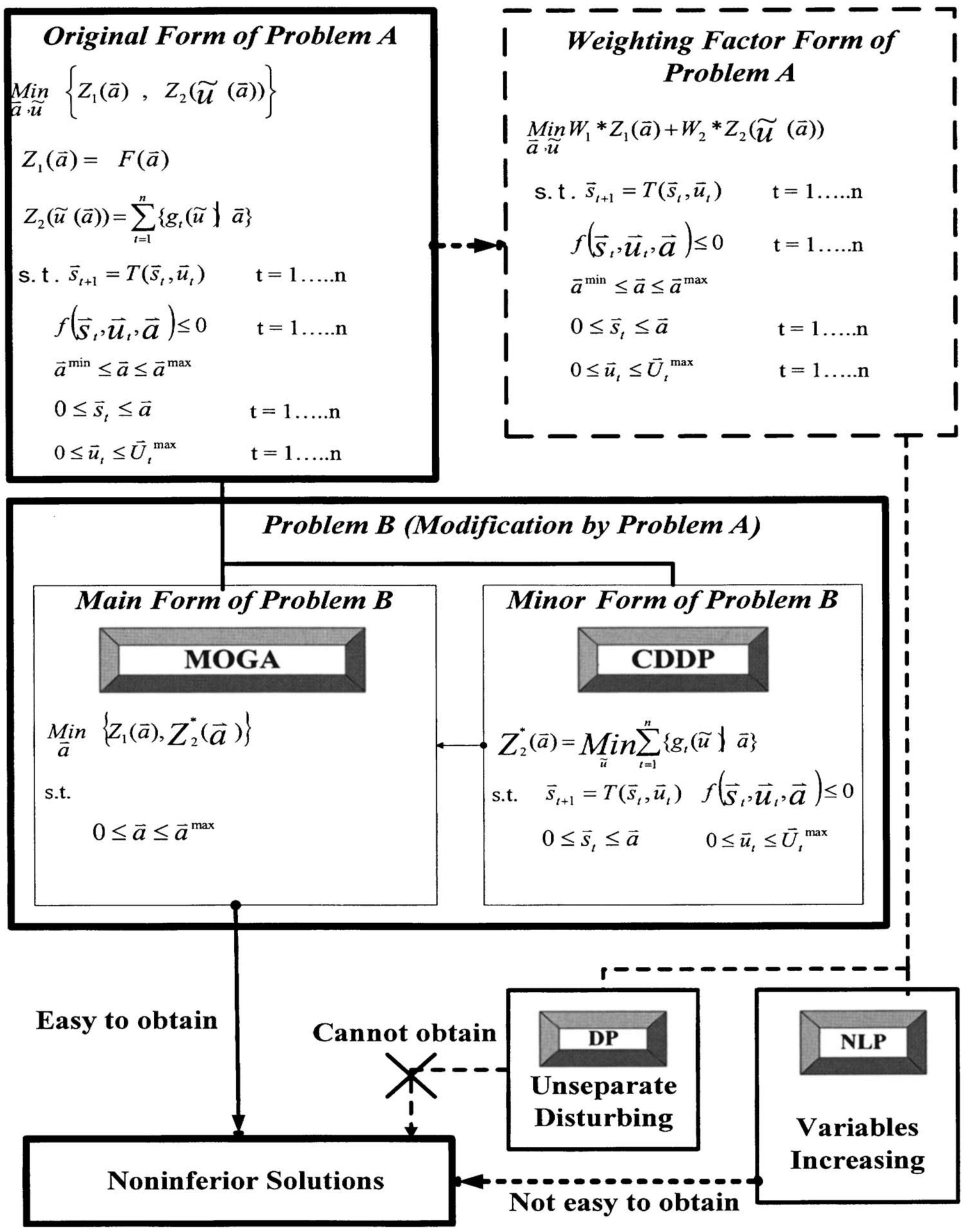

Fig. 1. Original multiobjective problem and its modified problem

$$Z1(a1) \geqslant Z1(a2), \quad Z2(a1) \geqslant Z2(a2)$$

If $a1$ is neither inferior nor superior to $a2$, then $a1$ and $a2$ are noninferior with respect to each other, or $a1 \approx a2$. The noninferior solution set is composed of chromosomes that are nondominated by any other chromosome in one generation. Additionally, all noninferior solutions from every generation are accumulatively recorded and updated in the indicated file to serve as stopping criteria for the MOGA.

6. Identify a final set of noninferior solutions through the procedures of fitness calculation, elite, reproduction, crossover and mutation of MOGA until reaching converge condition.
   - Evaluate the fitness for each chromosome. The solutions of the noninferior solutions set determined through Step 5 are assigned as Rank 1. The fitness of all feasible solutions is estimated by

$$f_i = d_{\max} - d_{i_{\min}} \tag{12}$$

where $d_{\max}$ denotes the maximum distance between all feasible solutions and all noninferior solutions in Rank 1, i.e.,

Table 1. Key Parameters of MOGA

Parameter	Value
Population size	100
Chromosome length	18 loci
Elitist set size	30
Crossover rate	0.7
Mutation rate	0.03
Stopping criterion	The change ratio of the number of noninferior solutions sets over ten consecutive generations is smaller than 5%

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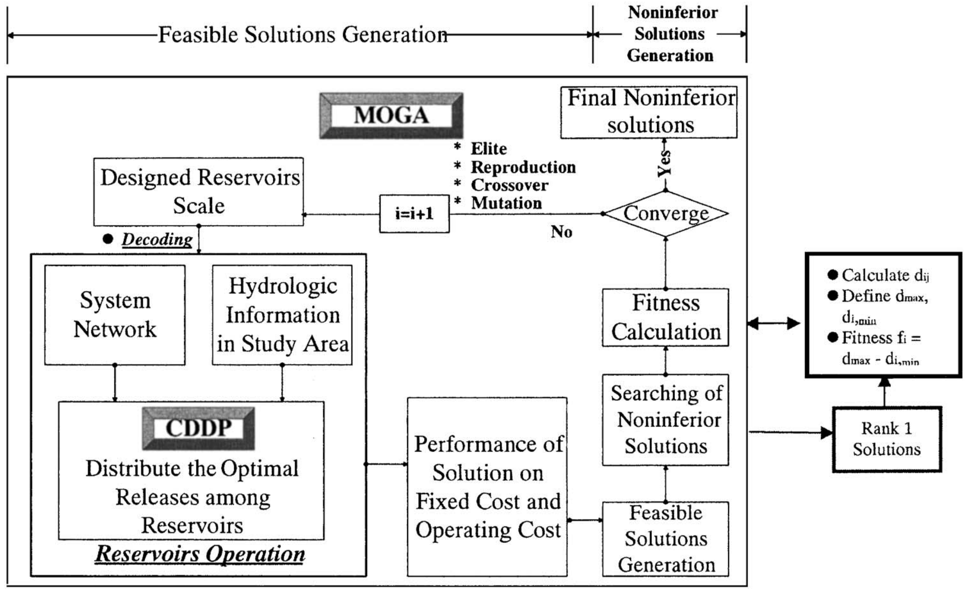

Fig. 2. Flow chart of our proposed model, integration of the MOGA and CDDP, for the multiobjective planning of surface water

$d_{max}=\max\{d_{ij(i=1-pop,j=1-N)}\}$; $d_{i_{min}}$ represents the minimal distance between the feasible solution i and the noninferior solution j in Rank 1, $d_{imin}=\min\{d_{ij(j=1-N)}\}$; d_{ij}=distance between the feasible solution i and any noninferior solution j in Rank 1; f_i=fitness of feasible solution i; pop represents the total number of feasible solutions; and N=total number of noninferior solutions in Rank 1. Fig. 3 clearly demonstrates that the distance between any feasible solution of chromosomes and the members of Rank 1 is closer with respect to bigger fitness value compared to the other chromosomes.

- Store the elite solutions. This study proposed a new way to store the elite solutions to ensure that the set of noninferior solutions can proceed with the crossover step to avoid any component among this set from disappearing in the reproduction process. This procedure also performs the function of diversity maintaining mechanism which is one of the key ingredients of a MOGA. If the number of solutions with Rank 1 is lower than the size of the elite set, then all of these solutions are included in this set. The rest of the elite set comprises feasible solutions with better fitness. Otherwise, a portion of solutions with Rank 1 is chosen to compose the elite set. The number of the elite set in this study is 30, and thus the number of reproductions is 70.

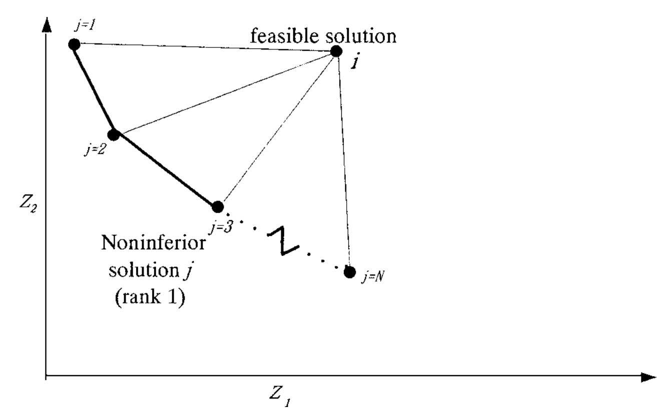

Fig. 3. Definition of fitness (Z_1 and Z_2 are objectives in minimal problem)

- Reproduce the best strings. This investigation undertakes reproduction by tournament selection. The selection mechanism plays an important role in driving the search toward superior individuals and maintaining high genotypic diversity in the population. MOGA selects parents from a population of strings based on the fitness. In each tournament selection, a group of five individuals are randomly selected from the population, and the fittest individual(s) is selected for reproduction. The procedure is repeated until the number of chromosomes required for crossover is met.
- Crossover. Crossover involves randomly coupling the newly reproduced strings and exchanging information within a pair of strings. Crossover occurs with a constant probability of p_{cross} for each pair of strings. In this work, p_{cross} was set to 0.7 with a uniform crossover operator.
- Mutation. Mutation restores lost or unexplored genetic material to the population to prevent the GA from converging prematurely to a local optimum. A mutation probability p_{mutat}, $p_{mutat}=0.03$ in this study, is specified, and mutation is applied randomly to individual genes. If a random number generated from a uniform distribution function is smaller than the mutation probability, then mutation is conducted by changing the binary value of the gene in the offspring strings produced by the crossover operation.
- Termination mechanism. A new population for the next generation is created after the mutation operation, and the noninferior solutions set is extracted as from in Steps [3–5]. The stopping criterion in this study is based on the variation rate, which is defined as the change ratio in the noninferior solutions sets. The procedure finishes if the user-defined stopping criterion is met or the maximum allowed number of generations is reached; otherwise, Step 6 proceeds for another cycle (another generation).

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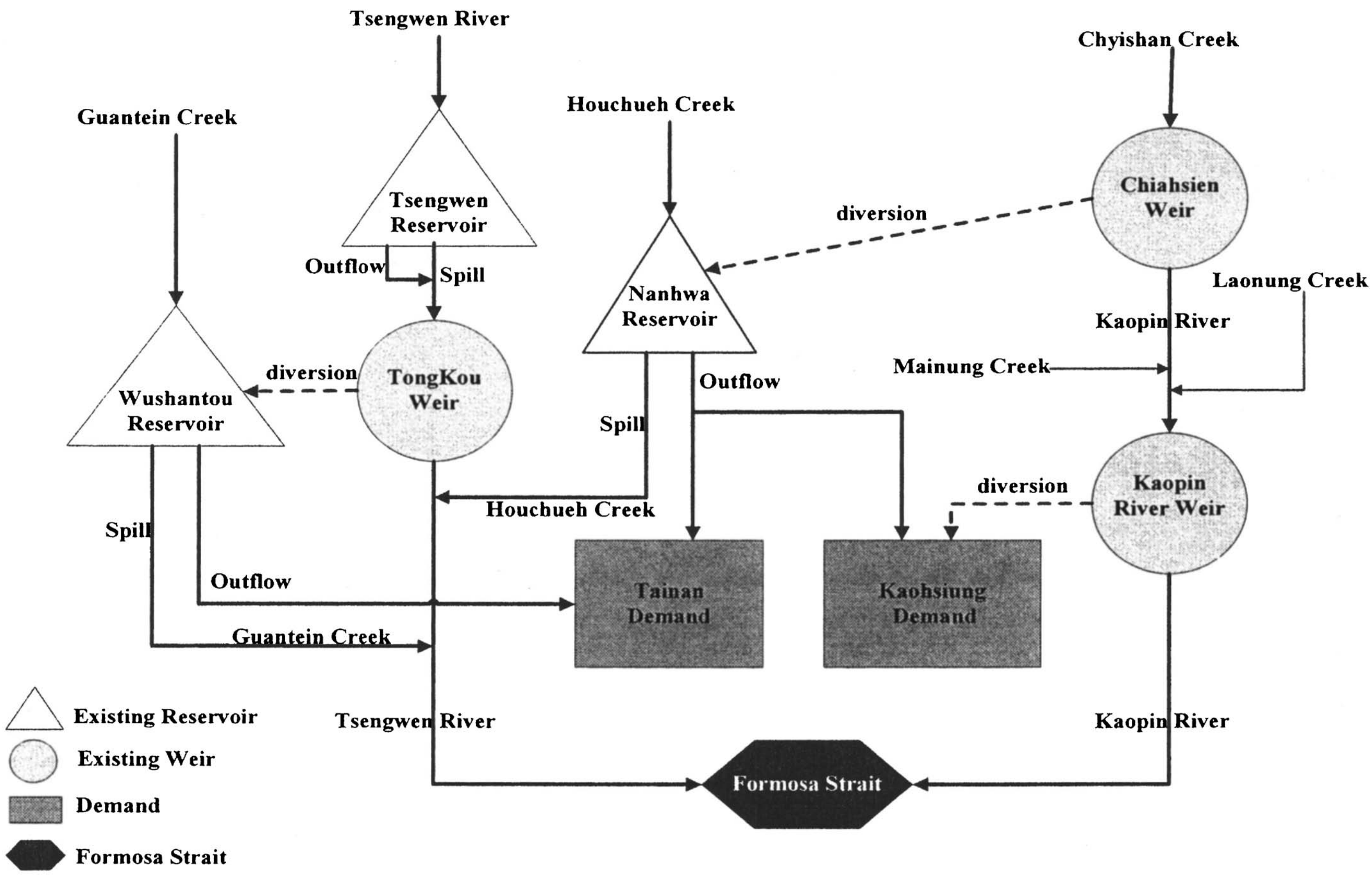

Fig. 4. Water system diagram for southern Taiwan

Application

Description of Study Area

Located in southern Taiwan, the study area includes two major watersheds, the Tsengwen River and the Kaopin River, and two metropolitan areas, Tainan and Kaohsiung. Although Tainan is supplied by the Wushantou Reservoir with an effective storage capacity of 81.45×10^6 m^3 and the Nanhwa Reservoir with an effective storage capacity of 149.46×10^6 m^3, the water supply for the Kaohsiung area is completed by the Nanhwa Reservoir and the Kaopin River Weir. To raise the inflow for the two above-mentioned reservoirs, two diversions from weirs have been made: One from the Tongkou Weir to Wushantou reservoir, the other from the Chiahsien Weir to the Nanhwa Reservoir. Additionally, the Tongkou Weir receives water from the Tsengwen Reservoir which has an effective storage capacity of 581.23×10^6 m^3. The water system diagram in southern Taiwan is shown in Fig. 4.

Problem Definition

To define how the fixed cost and operating cost affect one another, the proposed methodology is demonstrated to find appropriate facilities' capacities and their operation procedures in order to meet future demands by 2011. The range of the storage capacities for the three above-mentioned reservoirs (Nanhwa, Wushantou, and Tsengwen) is set between half and double of their original capacities. The objective function and system dynamics in the main form of this problem are formulated in the following equations (application problem; main form):
Objective

$$\operatorname*{Min}_{\vec{Y}}\{Z_1(\vec{Y}),Z_2^*(\vec{Y})\} \tag{13}$$

$$Z_1(\vec{Y}) = \sum_{i=1}^{m} c \times Y_i \tag{14}$$

Subject to

$$Y_i^{\min} \leqslant Y_i \leqslant Y_i^{\max} \tag{15}$$

where Y1, Y2, and Y3 denote the installation capacities of the Wushantou Reservoir, the Tsengwen Reservoir, and the Nanhwa Reservoir, respectively; the assumption of a linear function and the coefficient for the unit construction cost of reservoirs (C=2.62. N.T. dollars/ton) are cited from Wu (1997), and m (m=3)=total number of reservoirs.

With the shortage index (Hsu 1995), the minor form of the problem discussed in this application is formulated as (application problem; minor form).

Table 2. Data Sources for Parameters

Data/parameter	Source
Demand	According to predictions made by Water Resources Planning Commission (1986).
Reservoir or weir	Chang, and Yang (2002).
Shortage index	Hsu (1995).
Inflow	Taiwan Water Resources Agency (http://www.wra.gov.tw/)
Cost coefficient	Wu (1997).

Objective

$$Z_2^*(\vec{Y}) = \underset{UO,WD}{\mathrm{Min}} \frac{100}{n} \sum_{t=1}^{n} \left\{ \sum_{j=1}^{s} \left[\frac{\mathrm{UO}_{j,t} + \mathrm{WD}_{j,t} - D_{j,t}}{D_{j,t}} \right]^2 \right\} \quad \text{for known } \vec{Y} \tag{16}$$

Subject to:

Transition equation of reservoir

$$S_{i,t+1} = S_{i,t} + \mathrm{RI}_{i,t} + \mathrm{WD}_{i,t} - \mathrm{UO}_{i,t} - \mathrm{US}_{i,t}, \quad i = 1, \ldots, m, \quad t = 1, \ldots, n \tag{17}$$

Mass balance of weir

$$\mathrm{WI}_{k,t} + \mathrm{RS}_{k,t} + \mathrm{RO}_{k,t} = \mathrm{WQ}_{k,t} + \mathrm{WD}_{k,t}, \quad k = 1, \ldots, g, \quad t = 1, \ldots, n \tag{18}$$

Water level

$$0 \leqslant S_{i,t} \leqslant Y_i \tag{19}$$

Capacity constraints

the upper limits of capacities for reservoirs and pipelines (20)

$$\text{supply capacity:} \quad \mathrm{UC}_{j,t} + \mathrm{WD}_{j,t} \leqslant D_{j,t} \tag{21}$$

nonnegativity: all variables are larger than or equal to zero, where, $D_{j,t}$=demand in the supply area j at time t; S_{t+1} and S_t denote the storage of the reservoir at time $t+1$ and t, respectively; UO_t, US_t, and RI_t represent the amounts of outflow, spill, and inflow of reservoir at time t; WO_t, WD_t, and WI_t=amounts of outflow, diversion, and inflow of weir at time t; g=total number of weirs (g=3), and s=total number of demands (s=2).

On the other hand, reservoirs are fully utilized due to the extreme temporal-varied distribution of precipitation as well as site/capacity constraint in Taiwan. Even if the largest reservoir in Taiwan, the Tsengwen Reservoir, were expanded to twice its present capacity, it would be almost full once (0.85 times) per year. For those reservoirs discussed in this paper, the average ratios of annual inflow for the last ten years to reservoir capacity are 2.6, 1.7, and 4.3 for the Wushantou, Tsengwen, and Nanhwa Reservoirs, respectively. Therefore, final level constraint becomes a minor concern in this study.

Some key values or parameters in this paper's optimization problem are cited from several papers and websites related to Taiwan's reservoir system operations (Water Resources Planning Commission 1986; Chang and Yang 2002; Hsu 1995; Wu 1997). The sources of data or parameters for illustration are listed in Table 2.

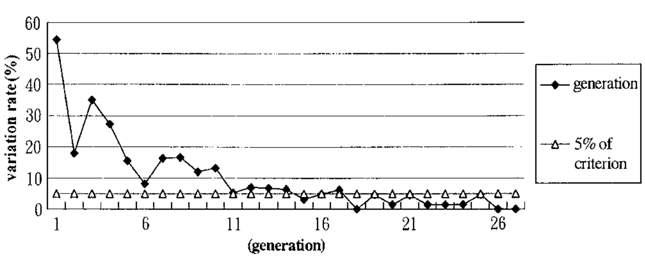

Fig. 5. Variation rates by generation

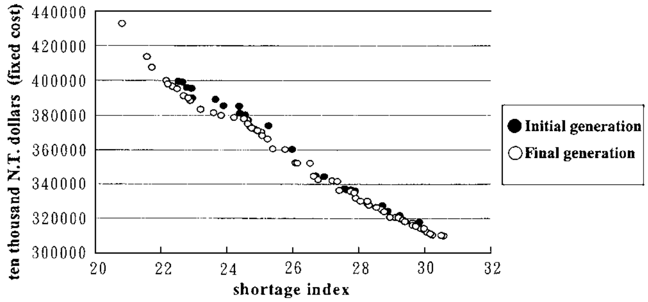

Fig. 6. Initial and final noninferior solutions set

Results

An integrated model is applied to the problem defined by Eqs. (13)–(21). The model estimates the noninferior solutions consisting of fixed cost and operating cost for the area of interest. The decision variables must be encoded as a chromosome before the MOGA is applied. For each decision variable, reservoir capacity is represented by six binary bits. As three decision variables (reservoirs) are involved, a chromosome consists of a total of 18 loci. In the problem considered here, there are 100 chromosomes in each population, and the initial population is randomly generated. As indicated in Fig. 2, the CDDP is used repeatedly within each generation to simulate the operation of the system according to the reservoir's scale via the chromosomes. The stopping criterion for MOGA is that the variation rate of noninferior solutions over ten consecutive generations should be under 5%. The computations are implemented for 93.28 h on a PC Pentium III733 running Microsoft Windows 98. Fig. 5 shows that the variation rate decreases from the initial value to convergence, and that the final noninferior solution appears in generation number 27.

Fig. 6 indicates the results with the initial and final noninferior solutions set, plotting the fixed cost against the shortage index. The trend of the results for the final noninferior solutions set are significant compared with the initial set. Solutions of the final noninferior solutions set with fixed costs range from 4,327,149,000 N.T. dollars to 3,098,960,000 N.T. dollars with the shortage index from 20.81 to 30.57. We choose one noninferior solution to conduct a more detailed analysis.

Figs. 7–9 display the operating results of the three reservoirs from one noninferior solution (fixed cost=4,327,149,000 N.T. dollars, SI=20.8), demonstrating that the water storage for every reservoir in the wet season (June–November) is larger than that in the dry season (December–May). This implies that the water storage of the reservoirs has seasonal variations.

When the noninferior solutions from the multiobjective problem are identified, the decision maker's preference has to be provided for choosing the compromise solution from noninferior

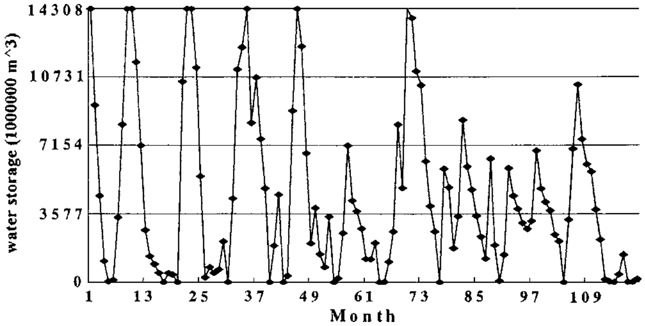

Fig. 7. Water storage in the Wushantou Reservoir (fixed cost=4,327,149,000 N.T. dollars, SI=20.8)

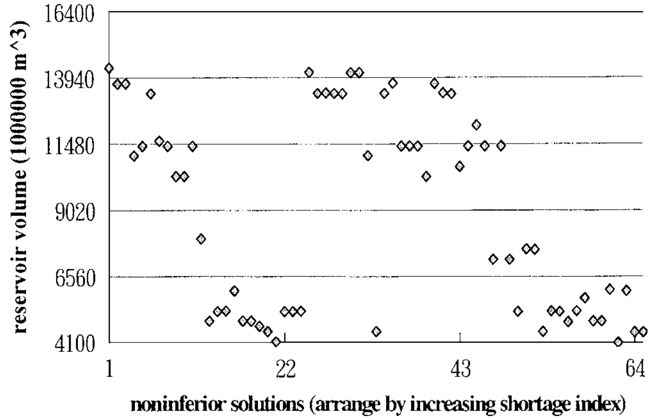

Fig. 10. Noninferior solutions of the Wushantou Reservoir

solutions. This investigation attempts to find an appropriate compromise solution from all alternatives if the decision maker has no strong preference. Figs. 10–12 show the volumes of all noninferior solutions for these three reservoirs, individually arranged in order according to shortage index performance. The *y* axis indicates reservoir volume, whereas the *x* axis indicates the noninferior solutions which are numbered in order according to increasing shortage index. Obviously, the most congregated volume for the Nanhwa Reservoir is 202×10^6 m^3 in Fig. 12. On the other hand, the majority of Tainan's water resources originate in the Tsengwen and Wushantou Reservoirs which together have a large volume and operate in series. Therefore, the appropriate volumes for the Tsengwen and Wushantou Reservoirs should be relative to each other. In Fig. 11, most noninferior solutions are located in and close proximity to the volumes $1{,}175\times10^6$ m^3 and 940×10^6 m^3. When the volume of the Tsengwen reservoir remains at 940×10^6 m^3, closely corresponding to the noninferior solutions between the 32nd and 65th, the related volume change of the Wushantou Reservoir in Fig. 10 is from 141×10^6 m^3 falling to 41×10^6 m^3, and the shortage index is from 27 rising to 30.5. Although capacity extension facilitates the improvement in the shortage index, the shortage index is still larger than 27. Conversely, when the volume of the Tsengwen Reservoir increases to $1{,}175\times10^6$ m^3, closely corresponding to the 1st–21st noninferior solutions, the related volume change of the Wushantou Reservoir in Fig. 10 is from 141×10^6 m^3 falling to 41×10^6 m^3 and the shortage index rises from 20.8 to 25. The result is the shortage index is always less than 27. Also, the volume capacity of the

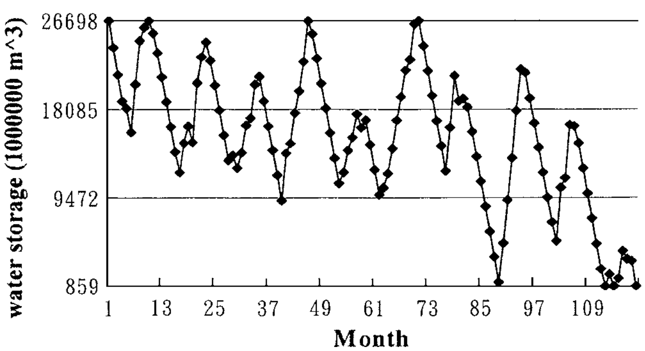

Fig. 8. Water storage in the Nanhwa Reservoir (fixed cost=4,327,149,000 N.T. dollars, SI=20.8)

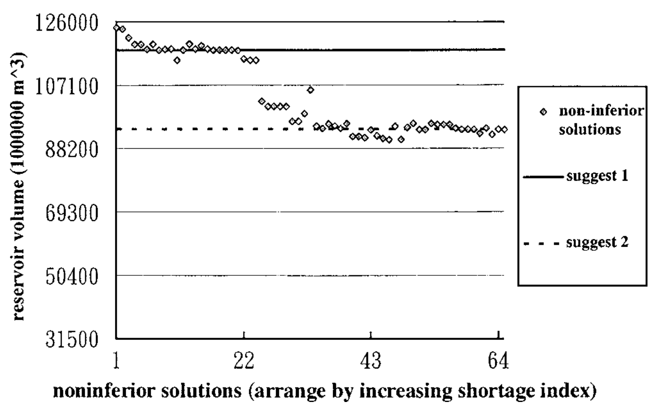

Fig. 11. Noninferior solutions of the Tsengwen Reservoir

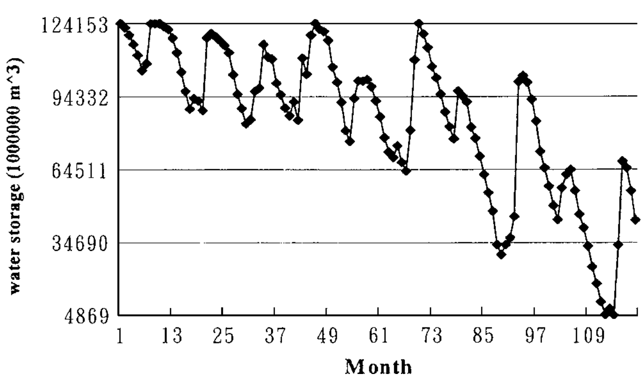

Fig. 9. Water storage in the Tsengwen Reservoir (fixed cost=4,327,149,000 N.T. dollars, SI=20.8)

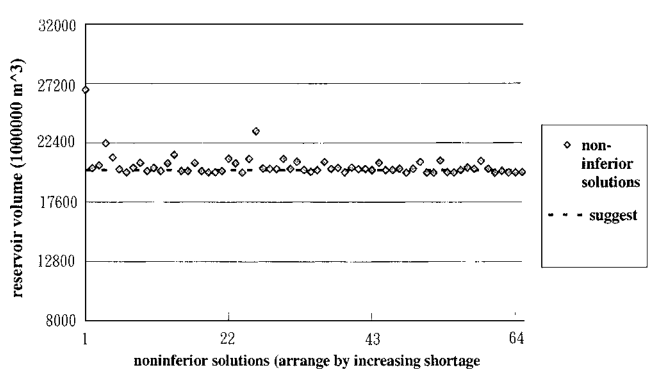

Fig. 12. Noninferior solutions of the Nanhwa Reservoir

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Wushantou Reservoir becomes insignificant as long as the the Tsengwen Reservoir maintains a large volume capacity. This indicates that the reservoir extension upstream is better than that downstream for series operation in terms of unit cost investment.

From the previous discussion, this study recommended three strategies for governmental authorities depending on the budget condition as follows:

1. The appropriate scales for Tsengwen, Wushantou, and Nanhwa are 940×10^6, 41×10^6, and 202×10^6 m^3, respectively, in the event of a constrained budget.
2. The appropriate scales for Tsengwen, Wushantou, and Nanhwa are 1175×10^6, 141×10^6, and 202×10^6 m^3, respectively, if there are no serious budget constraints.
3. Two construction options based on Strategy 1 can be selected if the initial budget is modest. One is the expansion of Wushantou to 141×10^6 m^3, and the other is the expansion of Tsengwen to $1{,}175 \times 10^6$ m^3.

Conclusions

This investigation reveals MOGA's ability to be linked with CDDP to resolve a complex water resources problem. Additionally, the power of MOGA to address multiple objectives simultaneously without resorting to a weighted objective function provides the opportunity for significant advancement in multiobjective optimization. Further, the use of MOGA not only shows its capability in generating the noninferior solutions set, but also proposes three suitable strategies of reservoir construction to decision-makers with budget concerns through the analysis of all noninferior solutions.

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Appendix. Multiobjective Problem for Test

With fundamental understanding of MOGA, we developed our algorithm consisting of various essential components in 1998. This algorithm, although 8 years old, is still suitable for solving multiobjective problems despite the appearance of newly developed MOGAs, such as *NSGAII*. So the following test case has been designed to justify the utility of the proposed methodology.

- Multiobjectives problem
  Objective

$$\min Z_1 = 2{,}500 - x_1^2 \tag{22}$$

$$\min Z_2 = 50x_1x_2 - x_2 \tag{23}$$

Subject to

$$1 \leqslant x_1 \leqslant 50 \tag{24}$$

$$1 \leqslant x_2 \leqslant 10 \tag{25}$$

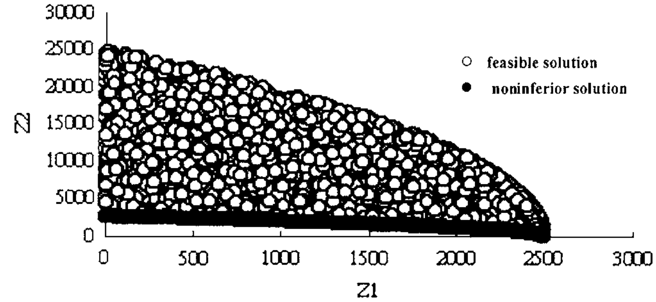

Fig. 13. All real feasible solutions and noninferior solutions set in test case

$$x_1, x_2 \in R$$

Fig. 13 displays all real feasible solutions and noninferior solutions sets to this test case. The population in each generation has 100 chromosomes, and the initial population is randomly generated. The distribution of problem solutions for these 100 chromosomes is shown in Fig. 14. In Fig. 14, although all solutions in the first generation located within the domain of feasible solutions are clearly observed, only three solutions are noninferior. The stopping criterion for MOGA is that the variation rate of noninferior solutions over ten consecutive generations should be under 5%. Based on the stopping criterion, the final noninferior solutions set appears in generation number 30, and its distribution of problem solutions for 100 chromosomes is presented in Fig. 15. Compared with Figs. 13–15, it demonstrates the most noninferior solutions exist in generation number 30 and the trend of the noninferior solutions set is significant.

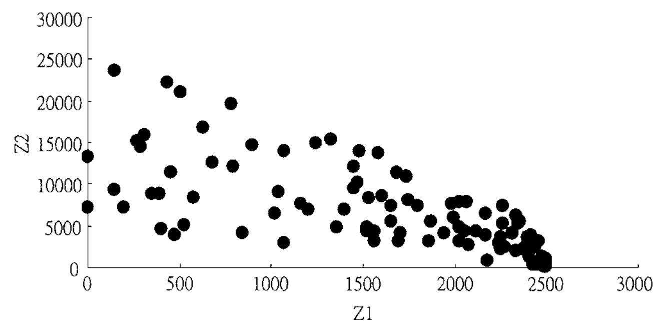

Fig. 14. Distribution of problem solutions to 100 chromosomes in first generation

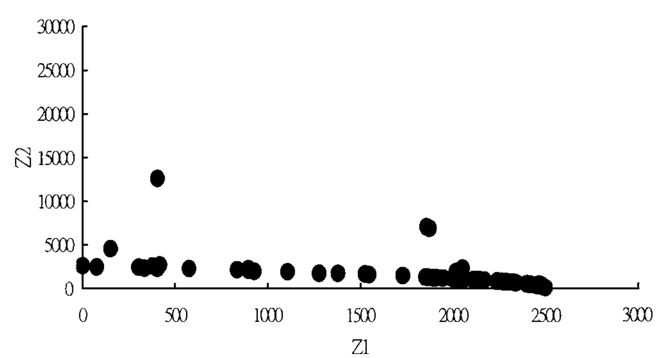

Fig. 15. Distribution of problem solutions to 100 chromosomes in generation number 30

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