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# The Successive Zooming Genetic Algorithm and Its Applications

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## 1. Introduction

Optimization techniques range widely from the early gradient techniques <sup>1</sup> to the latest random techniques <sup>16, 18, 19</sup> including ant colony optimization <sup>13, 17</sup>. Gradient techniques are very powerful when applied to smooth well-behaved objective functions, and especially, when applied to a monotonic function with a single optimum. They encounter certain difficulties in problems with multi optima and in those having a sharp gradient, such as a problem with constraint or jump. The solution may converge to a local optimum, or not converge to any optimum but diverge near a jump.

To remedy these difficulties, several different techniques based on random searching have been developed: full random methods, simulated annealing methods, and genetic algorithms. The full random methods like the Monte Carlo method are perfectly global but exhibit very slow convergence. The simulated annealing methods are modified versions of the hill-climbing technique; they have enhanced global search ability but they too have slow convergence rates.

Genetic algorithms <sup>2-5</sup> have good global search ability with relatively fast convergence rate. The global search ability is relevant to the crossover and mutations of chromosomes of the reproduced pool. Fast convergence is relevant to the selection that takes into account the fitness by the roulette or tournament operation. Micro-GA <sup>3</sup> does not need to adopt mutation, for it introduces completely new individuals in the mating pool that have no relation to the evolved similar individuals. The pool size is smaller than that used by the simple GA, which needs a big pool to generate a variety of individuals.

Versatile genetic algorithms have some difficulty in identifying the optimal solution that is correct up to several significant digits. They can quickly approach to the vicinity of the global optimum, but thereafter, march too slowly to it in many cases. To enhance the convergence rate, hybrid methods have been developed. A typical one obtains a rough optimum using the GA first, and then approaches the exact optimum by using a gradient method. Other one finds the rough optimum using the GA first, and then searches for the exact optimum by using the GA again in a local domain selected based on certain logic <sup>7</sup>.

The SZGA (Successive Zooming Genetic Algorithm) <sup>6, 8-12</sup> zooms the search domain for a specified number of steps to obtain the optimal solution. The tentative optimum solutions

are corrected up to several significant digits according to the number of zooms and the zooming rate. The SZGA can predict the possibility that the solution found is the exact optimum solution. The zooming factor, number of sub-iteration populations, number of zooms, and dimensions of a given problem affect the possibility and accuracy of the solution. In this chapter, we examine these parameters and propose a method for selecting the optimal values of parameters in SZGA.

## 2. The Successive Zooming Genetic Algorithm

This section briefly introduces the successive zooming genetic algorithm<sup>6</sup> and provides the basis for the selection of the parameters used. The algorithm has been applied successively to many optimization problems. The successive zooming genetic algorithm involves the successive reduction of the search space around the candidate optimum point. Although this method can also be applied to a general Genetic Algorithm (GA), in the current study it is applied to the Micro-Genetic Algorithm (MGA). The working procedure of the SZGA is as follows. First, the initial solution population is generated and the MGA is applied. Thereafter, for every 100 generations, the elitist point with the best fitness is identified. Next, the search domain is reduced to  $(X_{OPT}-\alpha^k/2, X_{OPT}+\alpha^k/2)$ , and then the optimization procedure is continued on the reduced domain (Fig. 1). This reduction of the search domain increases the resolution of the solution, and the procedure is repeated until a satisfactory solution is identified.

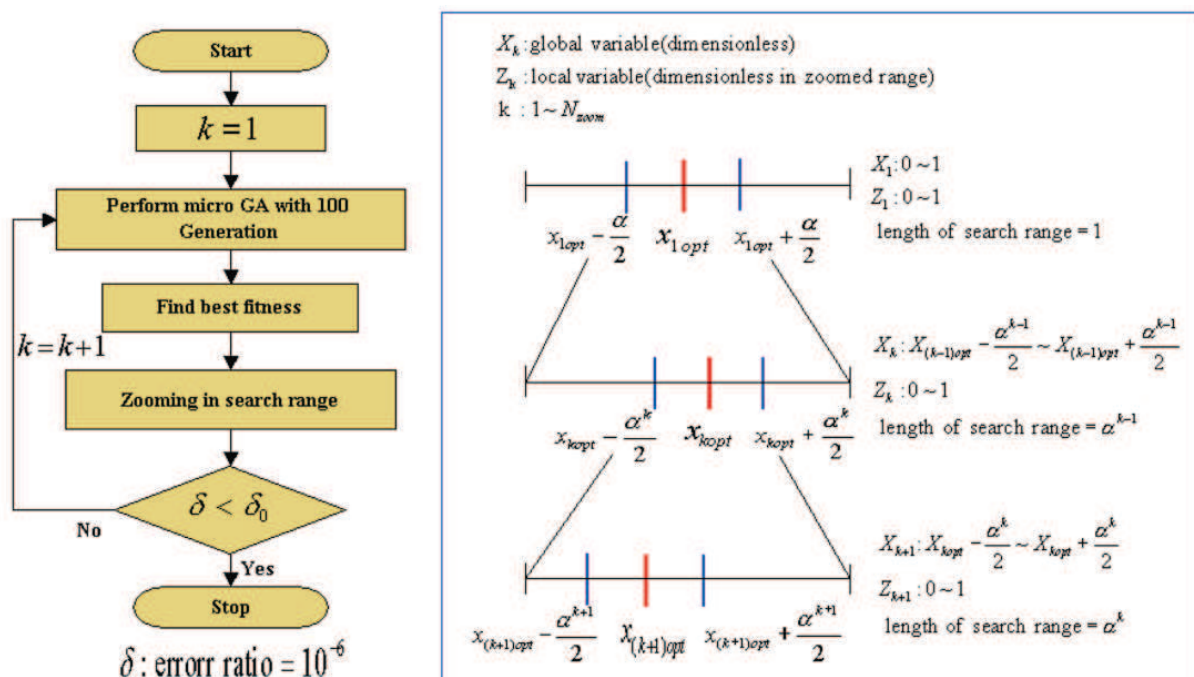


Fig. 1. Flowchart of SZGA and schematics of successive zooming algorithm

The SZGA can assess the reliability of the obtained optimal solution by the reliability equation expressed with three parameters and the dimension of the solution  $N_{VAR}$ .

$$R_{SZGA} = [1 - (1 - (\alpha / 2)^{N_{VAR}} \times \beta_{AVG})^{N_{SP}}]^{N_{ZOOM} - 1} \quad (1)$$

where,

$\alpha$ : zooming factor,  $\beta$ : improvement factor  
 $N_{VAR}$ : dimension of the solution,  $N_{ZOOM}$ : number of zooms  
 $N_{SUB}$ : number of sub-iterations,  $N_{POP}$ : number of populations  
 $N_{SP}$ : total number of individuals during the sub-iterations ( $N_{SP}=N_{SUB} \times N_{POP}$ )

Three parameters control the performance of the SZGA: the zooming factor  $\alpha$ , number of zooming operations  $N_{ZOOM}$ , and sub-iteration population number  $N_{SP}$ . According to previous research, the optimal parameters for SZGA, such as the zooming factor, number of zooming operations, and sub-iteration population number, are closely related to the number of variables used in the optimization problem.

## 2.1 Selection of parameters in the SZGA

The zooming factor  $\alpha$ , number of sub-iteration population  $N_{SP}$ , and number of zooms  $N_{ZOOM}$  of SZGA greatly affect the possibility of finding an optimal solution and the accuracy of the found solution. These parameters have been selected empirically or by the trial and error method. The values assigned to these parameters determine the reliability and accuracy of the solution. Improper values of parameters might result in the loss of the global optimum, or may necessitate a further search because of the low accuracy of the optimum solution found based on these improper values. We shall optimize the SZGA itself by investigating the relation among these parameters and by finding the optimal values of these parameters. A standard way of selecting the values of these parameters in SZGA, considering the dimension of the solution, will be provided. .

The SZGA is optimized using the zooming factor  $\alpha$ , number of sub-iteration population  $N_{SP}$ , and the number of zooms  $N_{ZOOM}$ , for the target reliability of 99.9999% and target accuracy of  $10^{-6}$ . The objective of the current optimization is to minimize the computation load while meeting the target reliability and target accuracy. Instead of using empirical values for the parameters, we suggest a standard way of finding the optimal values of these parameters for the objective function, by using any optimization technique, to find the optimal values of these parameters which optimize the SZGA itself. Thus, before trying to solve any given optimization problem using SZGA, we shall optimize the SZGA itself first to find the optimal values of its parameters, and then solve the original optimization problem to find the optimal solution by using these parameters.

After analyzing the relation among the parameters, we shall formulate the problem for the optimization of SZGA itself. The solution vector is comprised of the zooming factor  $\alpha$ , the number of sub-iteration population  $N_{SP}$ , and the number of zooms  $N_{ZOOM}$ . The objective function is composed of the difference of the actual reliability to the target reliability, difference of the actual accuracy to the target accuracy, difference of the actual  $N_{SP}$  to the proposed  $N_{SP}$ , and the number of total population generated as well.

$$F(\alpha, N_{SP}, N_{ZOOM}) = \Delta R_{SZGA} + \Delta A + \Delta N_{SP} + (N_{SP} \times N_{ZOOM}) \quad (2)$$

where,

$\Delta R_{SZGA}$  : difference to the target reliability

$\Delta A$  : difference to the target accuracy

$\Delta N_{SP}$  : difference to the proposed  $N_{SP}$

The problem for optimization of SZGA itself can be formulated by using this objective function as follows:

$$\text{Minimize } F(X) \quad (3)$$

where,

$$X = \{\alpha, N_{SP}, N_{ZOOM}\}^T$$

$$0 < \alpha < 1$$

$$N_{SP} \sim 100$$

$$N_{ZOOM} > 1$$

The difference of the actual reliability to the target reliability is the difference between  $R_{SZGA}$  and 99.9999%, where reliability  $R_{SZGA}$  is rewritten with an average improvement factor as

$$R_{SZGA} = [1 - (1 - (\alpha / 2)^{N_{VAR}} \times \beta_{AVG})^{N_{SP}}]^{N_{ZOOM} - 1} \quad (4)$$

Here, we can see the average improvement factor  $\beta_{AVG}$ , which is to be regressed later on. The difference of realized accuracy to the target accuracy is the difference between accuracy  $A$  and  $10^{-6}$ , where accuracy  $A$  is actually the upper limit and may be written as,

$$A = \alpha^{N_{ZOOM} - 1} \quad (5)$$

The difference of the actual  $N_{SP}$  to the proposed  $N_{SP}$  is difference between  $N_{SP}$  and 100<sup>7</sup>. In organizing the optimization algorithm, each element in the objective function is given different weights according to its importance. Thus, the target reliability and target accuracy are met first, and then the number of total population generated is minimized. Although any optimization technique could have been used to solve eq.(3), one can adopt the SZGA in optimizing the SZGA itself to obtain a solution fast and accurately.

The parameters in SZGA have been optimized by using the objective function and improvement factor averaged after regression for a test function<sup>9</sup>. The target reliability is 99.9999% and target accuracy of solution is  $10^{-6}$ . The proposed number of sub-iteration population  $N_{SP}$  is 100. Table 1 shows the optimized values for the SZGA parameters for four cases of different number of design variables.

We found a similar tendency to Table 1 for test functions of various numbers of design variables. We also found that the recommended number of sub-iteration population  $N_{SP}$  would no longer be acceptable to assure reliability and accuracy for the cases whose number of design variables is over 1. A much greater number of sub-iteration population is needed to obtain an optimal solution with the proper reliability (99.9999%) and accuracy ( $10^{-6}$ ).

To confirm our optimized result, we fixed two parameters in the feasible domain that satisfy the target reliability and target accuracy, and checked the change in the objective function as a function of the remaining parameter. Examples of the change in the objective function for the case of four design variables showed the validity of the obtained optimal values of the

parameters. Although these values may not be valid for all the other cases, they can be used as a good reference for new problems. Some other ways of choosing the values of these parameters will be given later on.

No. of Variables	2	4	8	16
Zooming Factor $\alpha$	.02573	.1303	.4216	.5176
N <sub>zoom</sub>	5	8	17	22
N <sub>sp</sub>	1,000	2,000	9,510	1,479,230
No. of Function Evaluation	5,000	16,000	161,670	32,543,060

Table 1. Result of optimized parameters in SZGA for different number of design variables

2.2 Programming for successive zooming and pre-zoning algorithms

Programming the SZGA is simple, as explained below. This zooming philosophy may not be confined only in GA, but can be applied to most other global search algorithms. Let  $Y(I)$  be the global variables ranging  $YMIN(I) \sim YMAX(I)$ , where  $I$  is the design variable number.  $Z(I)$  consists of local normalized variables ranging 0~1. Thus, the relation between them is as follows in FORTRAN;

```
DO 10 I=1,NVAR ! NVAR=NO. of VARIABLES
10 Y(I)=YMIN(I)+(YMAX(I)-YMIN(I))*Z(I)
```

The relation between local variable  $Z(I)$  and local variable  $X(I)$  (0~1) in the zoomed region is as follows;

```
DO 12 I=1,NVAR
12 Z(I)=ZOPT(I,JWIN)+ALP** (JWIN-1)*(X(I)-0.5)
```

Where,  $ZOPT(I,JWIN)$  is the elitist in the zoom step (JWIN-1), and ALP is the zooming factor. Note that  $ZOPT(I,JWIN-1)$  is more logical. However, the argument is increased by one to meet old versions of FORTRAN, which require a positive integer as a dimension argument. Based on the elitist in step (JWIN-1), we are seeking variables in step JWIN. Please note that  $ZOPT(I,1)=0$ .

A pre-zoning algorithm adjusts the gussed initial zone to a very reasonable zone after one set of generation.

```
DO 14 I=1,NVAR
YMIN(I)=YINP(I)-BTA*ABS(YINP(I))
14 YMAX(I)=YINP(I)+BTA*ABS(YINP(I))
```

Where,  $YINP(I)$ is the elitist obtained after one set of generation. Thus, we eliminate the assumed initial boundary, and establish a new reasonable boundary. The coefficient BTA may be properly selected, say 0.5.



### 2.3 Hybrid genetic algorithm

Genetic algorithms are stochastic global search methods based on the mechanism of natural selection and natural reproduction. GAs have been applied to structural optimization problems because they can solve optimization problems that involve mixing continuous, discontinuous, and non-convex regions etc. The SGA (simple GA) has been improved to MGA by using some techniques like tournament selection as well as the elitist strategy. Yet, GAs have some difficulty in fast searching the exact optimum point at a later stage. The DPE (Dynamic Parameter Encoding) GA<sup>4</sup> uses a digital zooming technique, which does not change a digit of a higher rank further after a certain stage. The SZGA (Successive Zooming GA) zooms the searching area successively, and thus the convergence rate is greatly increased. A new hybrid GA technique, which guarantees to find the optimum point, has been proposed<sup>7,14</sup>.

The hybrid GA first identifies a quasi optimal point using an MGA, which has better searching ability than the simple genetic algorithm. To solve the convergence problem at the later stage, we employed hybrid algorithms that combine the global GA with local search algorithms (DFP<sup>1</sup> or MGA). The hybrid algorithm using the DFP (Davidon Fletcher Powell) method incorporates the advantages of both a genetic algorithm and the gradient search technique. The other hybrid algorithm of global GA and local GA at the zoomed area is called LGA (Locally zoomed GA), checks the concavity condition near the quasi minimum point. The enhancement of the above hybrid algorithms is verified by application of these algorithms to the gate optimization problem.

In this hybrid algorithm of minimization problem, an MGA is performed generation-by-generation until there is no further change of the objective function, and then the approximate optimum solution is found at  $Z_{MCA}$ . The gradients of the objective function as a function of the design variables are checked, if the concavity condition<sup>1</sup> is satisfied at the boundary of a small zoomed area (Fig. 2). If the condition is not satisfied, the small zoomed area is increased by  $\delta$ . After several iterations, concavity conditions are finally achieved at the boundary of the final zoomed area ( $\kappa\delta \times \kappa\delta$ ) centered at  $Z_{MCA}$ . With the elitist solution from the global GA (approximate optimum solution,  $Z_{MCA}$ ) and the concavity condition, the optimum point is found within the final zoomed area  $[Z(i) : (Z_{MCA}(i) - \kappa\delta) \sim (Z_{MCA}(i) + \kappa\delta)]$ . From this point, a local GA is performed for the small finally zoomed area, which probably contains the optimum point. Usually, this area is much smaller than the original are, so the convergence rate increases considerably (note that the first approximate solution prematurely converged to an inexact but near optimum point).

Water gates need to be installed in dams to regulate the flow-rate and to ensure the containing function of dams. Among these gates, the radial gate is widely used to regulate the flow-rate of huge dams because of its accuracy, easy opening and closing, endurance etc. Moreover, 3-arm type radial gate has better performance than 2-arm type, in connection with the section size of girders and the vibration characteristics during discharging operation. Table 2 compares the optimized results for a 3-arm type radial gate, which considers the reactions to the minimized main weight of the structure including vertical girders with or without arms. The hybrid algorithm (MGA+DFP, MGA+LGA) obtained the exact optimal solution of 0.690488E+10 after far fewer generations of 4100 than the 9000 by MGA, which result in a close but not the exact solution of 0.690497E+10.

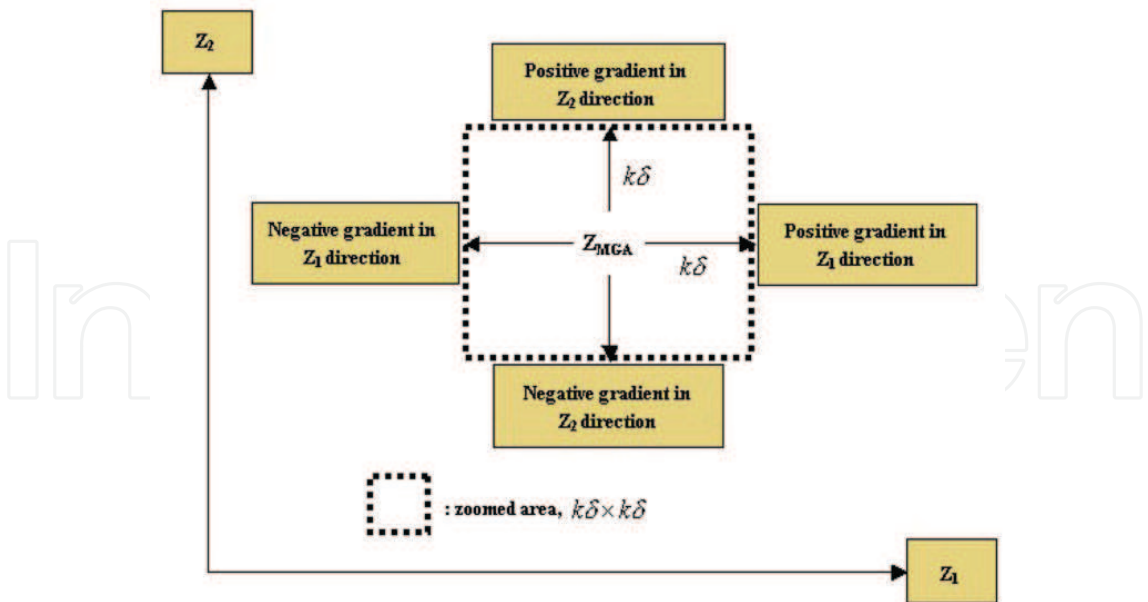


Fig. 2. Confirmed zoomed region after checking the concavity condition

3-arm type	Micro GA	MGA+DFP	MGA+LGA
Convergence Generation	9000	4000+α	4100
Objection Function	0.690497E+10	0.690488E+10	0.690488E+10

Table 2. Comparison of results: MGA, MGA+DFP, MGA+LGA

3. Example of the SZGA

The value of the zooming factor  $\alpha$ , an optimal parameter was obtained in reference [8], and was found to show good match with the empirical one. Using this zooming factor in SZGA, the displacement of a truss structure was derived by minimizing the total potential energy of the system. The capacity of the servomotor, which operates the wicket gate mounted in a Kaplan type turbine of the electric power generator, was optimized using SZGA with the value of zooming factor <sup>8</sup>.

This is just one parameter among the full optimal parameters discussed in sec.2.1 <sup>9</sup>. Therefore, the analysis done with this factor <sup>8</sup> is a simplified analysis. As commented in section 2.1, the values of the parameters of a well-behaved test model suggested in the Table 1 can be used for an optimization, or the values of the parameters obtained in another way as discussed in the next section can be used.

Several additional examples of SZGA optimization are presented in the following sections to provide more insight on SZGA and to find another way of choosing the values of the SZGA parameters. The first example finds the Moony-Rivlin coefficients of a rubber material to compare with those from the least square method. The second example is a damage detection problem in which the difference between the measured natural frequencies and those of the assumed damage in the structure is minimized. The third example finds the



optimal link specification (lengths and initial angular positions of members) to control the double link system with one motor in an automotive diesel engine. The fourth and last example finds an optimal specification (parametric sizes at specified positions) of a ceramic jar that satisfies the required holding capacity.

### 3.1 Determination of Mooney-Rivlin coefficients

The rubber is a very important mechanical material in everyday life, used widely in mechanical engineering and automotive engineering. Rubber has low production cost and many advantages such as its characteristic softness, processability, and hyper-elasticity. The development of the rubber parts including most process of the shape design, product process, test evaluation, ingredient blending for the required property has used the empirical methods. CAE based on advances in computer-aided structural analysis software is applied to many products. FEM method is applied on various models of rubber parts to evaluate the non-linearity property and the theoretical hyper-elastic behavior of rubber, and to develop analysis codes for large, non-linear deformation.

The structure of rubber-like materials are difficult to analyze because of their material non-linearity and geometric non-linearity as well as their incompressibility. Furthermore, unlike other linear materials, rubber materials have hyper-elasticity, which is expressed by the strain energy function. The representative strain energy functions in the finite element analysis of rubber are the extension ratio invariant function (Mooney-Rivlin model) and the principal extension ratio function (Ogden model). This case uses the Mooney-Rivlin model to investigate the behavior of a rubber material.

The value of the zooming factor changes according to the number of variables and the population number of a generation. If the population number is large, more exact solution can be obtained than the approach with smaller one. For a large population number, which is inevitable in the case of many design variables, longer computation time is needed. In this case, because six design variables are used to solve the six material properties, nine hundred population units per one generation are used. At this time, whenever zooming is needed, the function is calculated 90,000 times, where, 900 is the population number per one generation and 100 is generation number per one zooming because zooming is implemented after 100 generations. So the point number searched per one variable is 6 units ( $=90,000^{1/6}$ ). To search the optimum point, the zooming factor must be not less than  $1/6$ . Therefore, the zooming factor of 0.2 is used.

The maximum generation number must be decided after the zooming factor is chosen. If the zooming factor is large, the exact solution can be solved as increasing zooming step. Generation numbers have to be decided by the user because they affect the amount of calculation like the population numbers do. For example, when zooming factor of 0.3 is chosen and Maxgen (maximum allowed generation number) is decided as 1000 ( $N_{\text{ZOOM}} = 10$ ), the accuracy of the final searching range becomes  $Z_{\text{RANGE}} = \alpha^{(N_{\text{ZOOM}}-1)} = 0.3^{(10-1)} = 1.97\text{E-}05$ , and if Maxgen is decided by 1500 ( $N_{\text{ZOOM}} = 15$ ) the final searching range becomes  $Z_{\text{RANGE}} = \alpha^{(N_{\text{ZOOM}}-1)} = 0.3^{(15-1)} = 4.78\text{E-}08$ , where  $Z_{\text{RANGE}}$  is the value related with the resolution of solution and is the searching range after N steps of zooming. The smaller this value is, the more exact the solution becomes. In this case, Maxgen=900 is adopted. SZGA minimized the total error better than the other two methods.

Errors to be minimized	Haines & Wilson	Least Square	SZGA
Simple extension	0.757932	0.709209	0.921277
Pure shear	0.702015	0.620089	0.370579
Equi-biaxial	13.2580	0.242475	0.139983
Total error	14.7180	1.57177	1.43184

Table 3. Comparisons of errors among the different methods for obtaining Mooney-Rivlin 6 coefficients

3.2 Damage detection of structures

Structures can sometimes experience failures far earlier than expected, due to fabrication errors, material imperfections, fatigue, or design mistakes, of which fatigue failure is perhaps the most common . Therefore, to protect a structure from any catastrophic failure, regular inspections that include knocking, visual searches, and other nondestructive testing are conducted. However, these methods are all localized and depend strongly on the skill and experience of the inspector. Consequently, smart and global ways of searching for damages have recently been investigated by using rational algorithms, powerful computers, and FEM.

The objective function of the difference between the measured data and the computed data is minimized according to an assumed structural damage to find the locations and intensities of possible damages in a structure. The measured data can be the displacement of certain points or the natural frequencies of the structure, while the computed data are obtained by FEM using an assumed structural damage, whose severity is graded between 0 and 1. For example, Chou et al. used static displacements at a few locations in a discrete structure composed of truss members, and adopted a kind of mixed string scheme as an implicit redundant representation. Meanwhile, Rao adopted a residual force method, where the fitness is the inverse of an objective function, which is the vector sum of the residual forces, and Koh adopted a stacked mode shape correlation that could locate multiple damages without incorporating sensitivity information <sup>11</sup>.

Yet, a typical structure can be sub-divided into many finite elements and has many degrees of freedom. Thus, FEM for a static analysis, as well as for a frequency analysis, takes a long time. For a GA, the analysis time is related to the number of functions used for evaluating fitness. This number can become uncontrollable when monitoring a full structure, and as a result, the RAM or memory space required becomes too large and the access rate too slow when handling so much data.

Accordingly, the proposed SZGA is very effective in this case, as it does not require so many chromosomes, even as few as 4, thereby overcoming the slow-down of the convergence rate of the conventional GA, which need many chromosomes in determining the extent of a damage. Furthermore, the issue of many degrees of freedom can also be solved by sub-dividing the monitoring problem into smaller sub-problems because the number of damages will likely be between 1~4, as long as the structure was designed properly. Moreover, the fact that cracks usually initiate at the outer and tensile stressed locations of a

structure is also an advantage. As a result, the number of sub-problems becomes manageable, and the required time is much reasonable.

Several tests were performed first to determine the effectiveness of the SZGA for structure monitoring, where regional zooming is not necessary. Next, the procedure used to sub-divide the monitoring problem is presented, along with a comparison of the amount of computation required between a full-scale monitoring analysis and a sub--divide monitoring analysis according to the number of probable damage sites. The optimization problem for various cases of structural damage detection was solved by using three or six variables, zooming factor of 0.2 or 0.3, and total number of function evaluations of 100,000 or 150,000, which is  $N_{ZOOM} \times$  sub-iteration population number. The sub-iteration population number means the total population number in a sub-generation of one zooming.

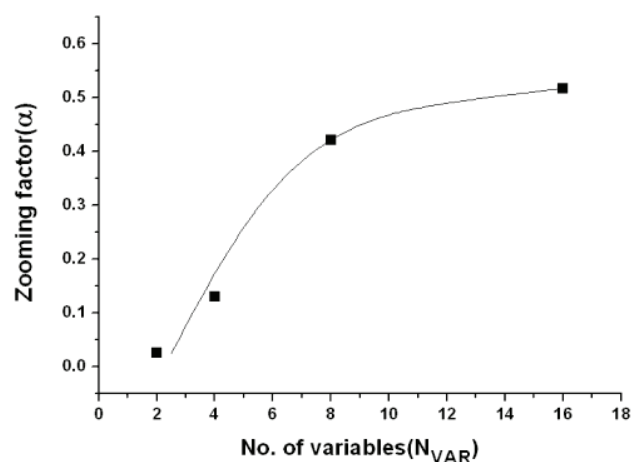


Fig. 3. Zooming factor with respect to the number of variables

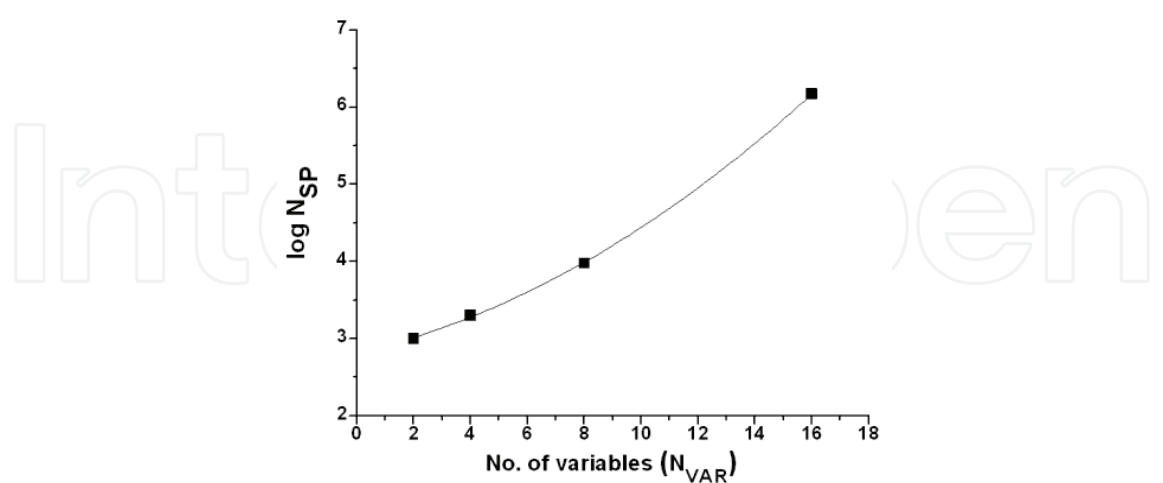


Fig. 4. Number of sub-iteration population with respect to the number of variables

Fig. 3, Fig. 4 and Fig. 5 are the fitting curves of ' $N_{VAR} - \alpha$ ', ' $N_{VAR} - N_{SP}$ ' and ' $N_{VAR}$  - Number of function calculation' relationship data, respectively, based on Table 1. These figures are prepared for the data point not shown in Table 1 for interpolation purpose.

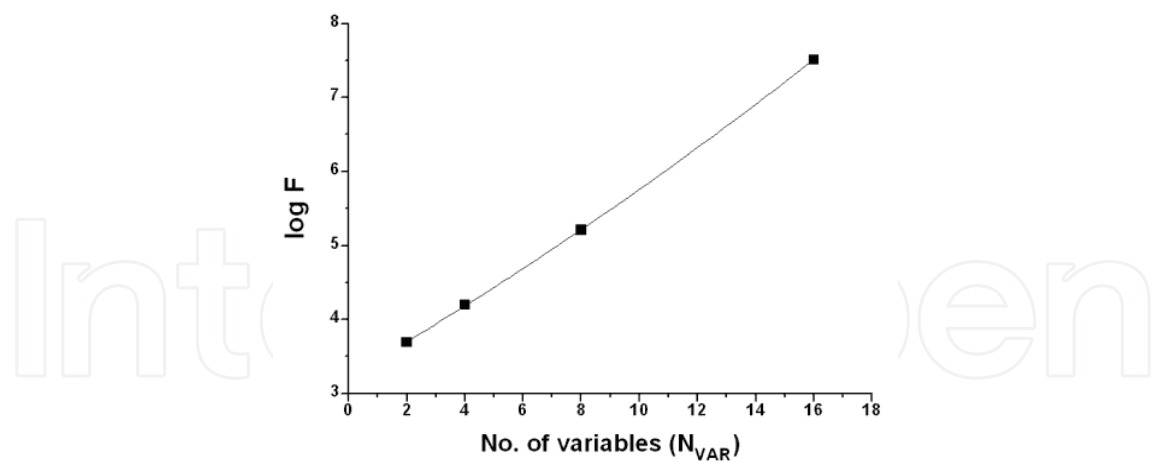


Fig. 5. Number of function calculations with respect to the number of variables

The SZGA can pinpoint an optimal solution by searching a successively zoomed domain. Yet, in addition to its fine-tuning capability, the SZGA only requires several chromosomes for each zoomed domain, which is a very useful characteristic for structural damage detection of a large structure that has a great number of solution variables. In the present study, just four or six digits of chromosomes were used. The accuracy of optimal solution is guaranteed by the successively zoomed infinitesimal range.

Most structures have few cracks, which may exist at different locations. Therefore, a combinational search method is suggested to search for separate cracks by choosing probable damage site as  ${}_nC_k$ .  $n$  denotes the number of total elements and  $k$  denotes the number of possible crack sites (1~4). Thus, up to four cracks ( $k$ ) were considered in a continuum structure modelled with  $n$  ( $=20$ ) elements, and the number of function calculations between the combinational search and the full scale search was compared.

$${}_nC_k = \frac{n!}{k!(n-k)!}$$

(6)

No. of cracks	${}_nC_k$	No. of function calculation		Ratio (Combinational/Full)
		Combinational search	Full scale search	
1	20	$0.580671 \times 10^5$	$0.578096 \times 10^9$	$0.100445 \times 10^{-3}$
2	190	$0.950000 \times 10^6$	$0.578096 \times 10^9$	$0.164332 \times 10^{-2}$
3	1140	$0.990843 \times 10^7$	$0.578096 \times 10^9$	$0.171398 \times 10^{-1}$
4	4845	$0.740788 \times 10^8$	$0.578096 \times 10^9$	0.128143

Table 4. Result of combinational searching method to reduce amount of calculation in SZGA

When monitoring the entire structure, the number of function calculations became about six hundred million based on the relation between the number of variables and the number of

function calculations. However, when the combinational searching method was used, the number of function calculations was reduced by about  $10^{-1}\sim 10^{-4}$  times when compared to the full-scale monitoring case, as shown in Table 4. Table 5 shows the good detection of the damage using the combination method and SZGA.

Element No.	19	20	25	26	31	32
Actual soundness factor	1	1	0.5	1	1	1
Damage detection result	1.0	1.0	0.499999	1.0	1.0	1.0

Table 5. Result of structural damage detection using the combination method and SZGA

3.3 Link system design using weighting factors

This section presents a procedure involving the use of a genetic algorithm for the optimal designs of single four-bar link systems and a double four-bar link system used in diesel engines. Studies concerning the optimal design of the double link system comprised of both an open single link system and a closed single link system which are rare, and moreover the application of the SZGA in this field is hard to find, where the shape of objective function have a broad, flat distribution <sup>12</sup>.

During the optimal design of single four-bar link systems, one can find that for the case of equal IO angles, the initial and final configurations show certain symmetry. In the case of open single link systems, the radii of the IO links are the same and there is planar symmetry. In the case of closed single systems, the radii of the IO links are the same and there is point symmetry.

To control the Swirl Control Valve in small High Speed Direct Injection engines, there are two types of actuating systems. The first uses a single DC motor controlled by Pulse Width Modulation, while the second uses two DC motors. However, this study uses the first type of actuator for the simultaneous control of two Swirl Control Valves using a double link system. When two intake valves in a diesel engine are controlled by a single motor, they usually exhibit quite different angular responses when the design variables for the control link system are not properly selected. Therefore, in order to ensure balanced performance in diesel engines with two intake valves, an optimization problem needs to be formulated and solved to find the best set of design variables for the double four-bar link system, which in turn can be used to minimize the different responses to a single input.

Two weighting factors are introduced into the objective function to maintain balance between the multi-objective functions. The proper ratios of weighting factors between objective functions are chosen graphically. The optimal solutions provided by the SZGA and developed FORTRAN Link programs can be confirmed by monitoring the fitness. The reduction in the objective functions is listed in the tables. The responses of the output links that follow the simultaneously acting input links are verified by experiment and the Recurdyn 3-D kinematic analysis package. The experimental and analysis results show good correspondence.

The proposed optimal design process was successfully applied to a recently launched luxury Sports Utility Vehicle model. Table 6 shows the original response and that of the optimized model. The optimal model exhibits almost the exact left and right outputs, and the difference between the left and right responses of 0.603 is thought to be a least value for the given positions of the link centers and the double control system adopting a single input motor.

Model	Input ( degree )	Output( degree )		
		Left	Right	Max. Difference
Original	0-90	0-89.144	0-91.958	2.044
Optimal	0-90	0-89.999	0-89.999	0.603

Table 6. Comparison of original and optimal models

3.4 Proper band width for equality constraints

In a problem having an equality constraint, it is not so simple for GA to satisfy the constraint while maintaining efficiency. Optimal solution lies on the line of equality constraint. It is very important to generate individuals on or near the equality line. However, the desirable narrow area including the equality line is very small compared with the whole area. The number of individual generated in this narrow area is much less than those in the outer area of the desirable narrow area including the equality line. Therefore, the convergence rate of GA or SZGA is significantly slow for the problems with equality constraints. The bandwidth method is proposed to overcome this kind of slow convergence rate.

For the minimization problems, we added a basic penalty function to meet the equality constraint, which will be explained soon. For this problem with the basic constraint, we can not expect a rapid convergence rate as mentioned above. Therefore, we added an additional penalty function to the region, located out of the desirable narrow area including the equality line, to make an infeasible area of a very highly increased objective function. The bandwidth denotes the half width of the narrow region with the basic penalty only.

There are three methods to handle the equality constraints using GA. One is to give both sides the penalty functions along the equality condition. The other is to give one side the monotonic function and other side the even (jump) penalty function along the equality constraint. However, the one side with the monotonic penalty should be feasible. And, the final one is to apply one side with no penalty function and the other side with the even (jump) penalty function along the equality constraint, and the one side of no penalty function should be feasible.

The penalty methods provided in Fig. 6 only with original penalty, is the basic technique for handling the equality constraint <sup>15</sup>. With this kind of basic technique only, however, the convergence rate would be too slow to reach the optimal point. Many generated individuals are wasted because they mostly too far from the equality constraint line. Therefore we need an additional penalty function to increase the effectiveness of GA. That is an additional



penalty to the objective function if the condition is located in outer region of a certain bandwidth centered with the equality constraint.

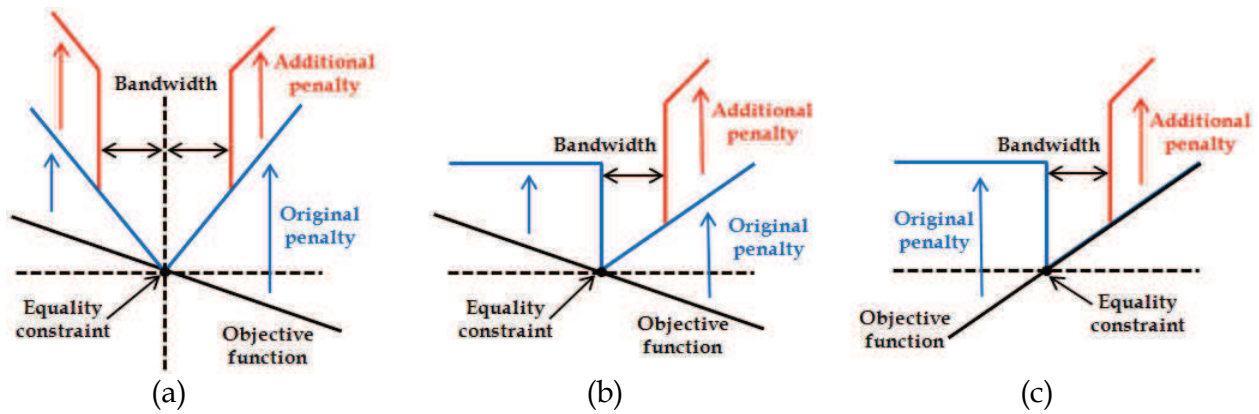


Fig. 6. Three methods to handle the equality constraint in GA.

Using the type (c) equality constraint and additional bandwidth penalty, the design of a ceramic jar was optimized for three values of zooming factors and various bandwidths of equality constraint, as shown in Fig. 7 and Table 7. The result showed a proper range of bandwidth for the equality constraint. In Table 7, the optimal solutions were found for the jar, satisfying the equality constraint of 2 liter volume.

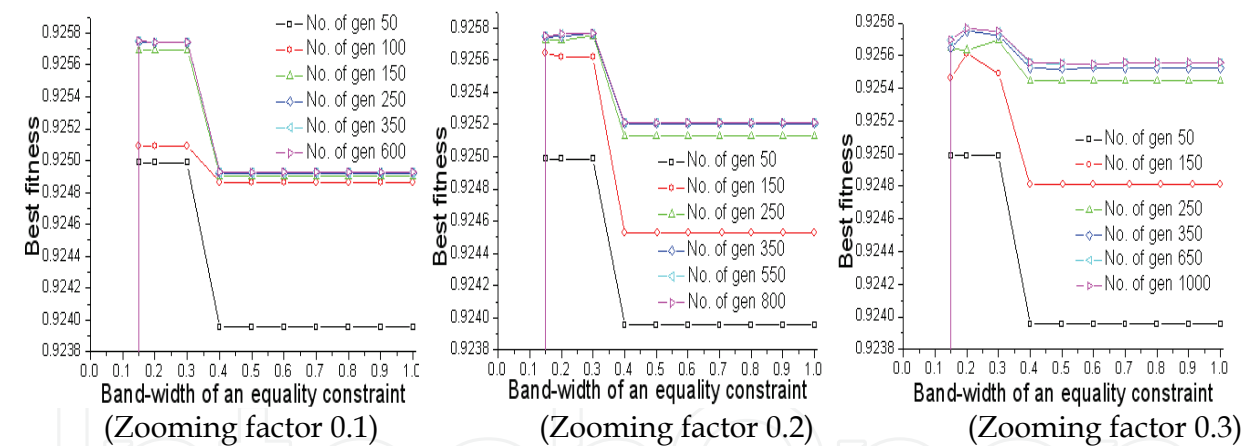


Fig. 7. Best fitness for band-width of an equality constraint and numbers of generation.

Zooming factors	Proper band-width	Weight (kg)	Volume (liter)	$Z_1$	$Z_2$
0.1	0.15~0.3	0.0802	2.000	0.4790	1.000
0.2	0.15~0.3	0.0802	2.000	0.4790	1.000
0.3	0.15~0.3	0.0802	2.000	0.4790	1.000

Table 7. Proper bandwidths and the optimal solutions for three zooming factors

This optimization problem does not converge below 0.15 of the band-width of an equality constraint, because the objective function is rather complicated and the band-width is relatively too narrow to give the most candidated optimal individual out of feasible region.

When the band-width is bigger than about 0.3, the best fitness dropped rapidly. In other words, if we open the full range as the feasible solution range, the optimal ridge would be too narrow to be chosen by GA. In conclusion, a too narrow bandwidth may lead to a divergence and a too wide bandwidth may result in inefficiency.

#### 4. Further studies and concluding remarks

The SZGA explained in the foregoing sections may be applied to more fields of interest, such as, the optimal design of ceramic pieces considering important factors like beauty, usage, stability, strength, lid, and exact volume. Prediction of a long-term performance of a rubber seal installed in an automotive engine is another possible application.

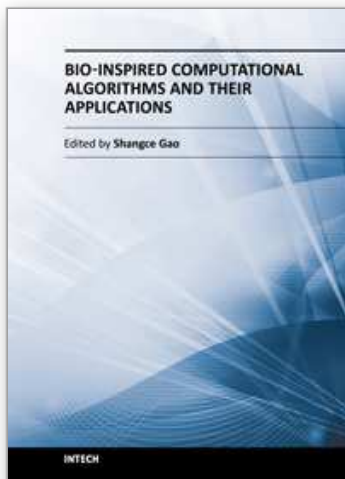
The most dominant characteristics of SZGA are its accuracy up to the required significant digits, and its rapid convergence rate even in the later stage. However, users have to properly select the parameters, namely, the zooming factor, number of zooms, and number of sub-domain population. A useful reference can be found in Table 1, Fig. 3, Fig. 4, and Fig. 5. The number of zooms can be determined by eq.(5) for a given upper limit of accuracy. The number of sub-domain population has been recommended as a fixed number until now, however, it may be varied as a function of the zooming step.

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## **Bio-Inspired Computational Algorithms and Their Applications**

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Bio-inspired computational algorithms are always hot research topics in artificial intelligence communities. Biology is a bewildering source of inspiration for the design of intelligent artifacts that are capable of efficient and autonomous operation in unknown and changing environments. It is difficult to resist the fascination of creating artifacts that display elements of lifelike intelligence, thus needing techniques for control, optimization, prediction, security, design, and so on. Bio-Inspired Computational Algorithms and Their Applications is a compendium that addresses this need. It integrates contrasting techniques of genetic algorithms, artificial immune systems, particle swarm optimization, and hybrid models to solve many real-world problems. The works presented in this book give insights into the creation of innovative improvements over algorithm performance, potential applications on various practical tasks, and combination of different techniques. The book provides a reference to researchers, practitioners, and students in both artificial intelligence and engineering communities, forming a foundation for the development of the field.

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