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Optimum parameterization in grillage design under a worst point load

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Abstract : *The optimum grillage design belongs to nonlinear constrained optimization problem. The determination of beam scantlings for the grillage structure is a very crucial matter out of whole structural design process. The performance of optimization methods, based on penalty functions, is highly problem-dependent and many methods require additional tuning of some variables. This additional tuning is the influences of penalty coefficient, which depend strongly on the degree of constraint violation. Moreover, Binary-coded Genetic Algorithm (BGA) meets certain difficulties when dealing with continuous and/or discrete search spaces with large dimensions. With the above reasons, Real-coded Micro-Genetic Algorithm (RμGA) is proposed to find the optimum beam scantlings of the grillage structure without handling any of penalty functions. RμGA can help in avoiding the premature convergence and search for global solution-spaces, because of its wide spread applicability, global perspective and inherent parallelism. Direct stiffness method is used as a numerical tool for the grillage analysis. In optimization study to find minimum weight, sensitivity study is carried out with varying beam configurations. From the simulation results, it has been concluded that the proposed RμGA is an effective optimization tool for solving continuous and/or discrete nonlinear real-world optimization problems.*

Key words : *Real-coded micro-genetic algorithm, Grillage, Optimum beam scantling, Direct stiffness method*

1. Introduction

Grillage is one of the common types of structures in marine and land-based structural system. Grillage system that increases the stiffness of plate used by two rectangular stiffeners is a part of deck, side shell and bottom of ships. The worst loading point of those structures is dependent on the loads, which are vertical, in-plane or combination of those directions as well as boundary conditions. The worst deflection point is produced when the point load is examined at central intersection. But the worst loading point would not necessarily be at the central point. To find the worst loading point, a traveling point load is applied to along the vertical and horizontal beams around mid-spans. Direct stiffness method is used as a numerical tool for the grillage analysis.

In general, it has known that an effective way to solve the nonlinear constrained optimization problems is to transform it into a sequence of unconstrained minimization. Several methods, which are based on penalty functions, have been proposed for handling nonlinear/linear constraints by genetic algorithm for numerical optimization problems. The performance of these methods is highly problem-dependent and many methods require additional tuning of some variables. This additional tuning is the influences of penalty coefficient, which depend strongly on the degree of constraint violation (Koziel and Michalewicz, 1999). Moreover, each traditional optimization method is specialized to solve a particular type of problems. When faced with a different type of problem, the same method may not work as well.

The Binary-coded Genetic Algorithm (BGA) meets certain difficulties when dealing with continuous and/or discrete search spaces with large dimensions. One difficulty is the Hamming cliffs associated with certain strings from which a transition to a neighboring solution requires the alteration of many bits. The other difficulty is the inability to achieve a great numerical precision in the optimal solution (Herrera et al., 1998).

With the aforementioned reasons, Real-coded Micro-Genetic Algorithm (RμGA) is proposed to find the optimum beam configuration of grillage structure without handling any of penalty functions. Micro-Genetic Algorithm (μGA) explores in a small population with some genetic operators to find the global optimum solution-spaces (Kim et al., 2006).

The proposed approach has the robustness of parallel exploration and asymptotic convergence with real value parameters. Therefore, RμGA can help in avoiding the premature convergence and search for better global solution, because of its wide spread applicability, global perspective and inherent parallelism.

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The weight function is mainly determined from the scantling design variables and the arranging geometric variables of a structure. To find the optimum weight of grillage structure under a given point load, sensitivity studies are carried out over the variation of scantlings of beam section by using RμGA.

From the simulation results of this paper, it is shown that the RμGA implementation overcomes the poor convergence properties and finds the global optimum solution than results obtained from other metaheuristic methods. Therefore, it has been concluded that the proposed RμGA is an effective optimization tool for solving continuous and/or discrete nonlinear real-world optimization problems within a suitable computational time frame.

2. Real-coded ga versus binary-coded ga

Genetic Algorithm (GA) had a great measure of success in search and optimization problems. The reason for a great part of its success is an ability to exploit the information accumulated about an initially unknown search space in order to bias subsequent searches into useful subspaces.

The binary representation meets certain difficulties when dealing with continuous and/or discrete search spaces with large dimensions. One difficulty is the Hamming cliffs associated with certain strings from which a transition to a neighboring solution requires the alteration of many bits. The other difficulty is the inability to achieve a great numerical precision in the optimal solution (Herrera et al., 1998). Hamming cliff is produced when the binary coding of two adjacent values differs in each one of their bits (for example, the string 01111 and 10000 represent the values 31 and 32, respectively), and the values of each one of their positions are different. The Hamming cliff may produce problems under some conditions, such as the convergence towards no global optimums. This problem may be solved by using the Gray code (Caruana and Schaffer, 1988), but doing so introduces higher order nonlinearities with respect to recombination, which causes the degree of implicit parallelism to be reduced (Goldberg, 1989).

It would seem particularly natural to represent the genes directly as real numbers for optimization problems of parameters with variables in continuous domains. A chromosome is a vector of floating point numbers whose size is kept the same as the length of the vector, which is the solution to the problem. Each gene represents a variable of the problem. The values of the genes are forced to remain in the interval established by the variables which they represent, so the genetic operators must observe this requirement.

The use of real parameters makes it possible to use large domains (even unknown domains) for the variables, which is difficult to achieve in binary implementations where increasing the domain would mean sacrificing precision, assuming a fixed length for the chromosomes. Another advantage when using real parameters is their capacity to exploit the graduality of the functions with continuous variables, where the concept of graduality refers to the fact that slight changes in the variables correspond to slight changes in the function. A highlighted advantage of the RGA is the capacity for the local tuning of the solutions. For example, Legendre-Gauss mutation allows the tuning to be produced in a more suitable and faster way than in the BGA, where the tuning is difficult because of the Hamming cliff effect.

Using real coding the representation of the solutions is very close to the natural formation of many problems, e.g., there are no differences between the genotype (coding) and the phenotype (search space). Therefore, the coding and decoding processes that are needed in the BGA are avoided, thus increasing the computational speed. Radcliffe (1992) suggested that a distinction between genotype and phenotype is not necessary for evolution. Thus, it is not justified that the definition of the genetic operators should be made upon the representation chosen. Clearly, since with the use of real coding the genotype and phenotype are similar, the expressiveness level reached is very high. Most real-world problems may not be handled using binary representations and an operator set consisting only of binary crossover and binary mutation (Davis, 1989). The reason is that nearly every real-world domain has associated domain knowledge that is of use when one is considering a transformation of a solution in the domain. Davis (1989) believes that the real-world knowledge should be incorporated into the GA, by adding it to the decoding process or expanding the operator set. Real coding allows the domain knowledge to be easily integrated into the RGA for the case of problems with non-trivial restrictions.

According to the above reasons, Real-coded Micro-Genetic Algorithm (RμGA) is proposed to solve the real-world optimization problems with nonlinear constrained functions without handling any of penalty terms. RμGA, based on an idea of Michalewicz (1994), explores in a small population with multiple genetic operators to find the global optimum solution-spaces.

3. Real-coded micro-genetic algorithm

Many optimization methods have been developed by using point-to-point as well as multi-point approaches. While a point-to-point approach begins with one candidate solution and updates the solution iteratively in the hope of reaching the optimum solution, a multi-point approach deals with a number of solutions in each iteration. The point-to-point approach is beneficial only when the starting point belongs to the region of attraction of the global optimum. This implies that any deterministic method could be attracted by a local optimum instead. Starting with a number of candidate solutions, the multi-point approach updates one or more solutions in a synergetic manner in the hope of steering the population towards the optimum.

Real-coded Genetic Algorithm (RGA) is one of the optimization methods with multi-point approaches. A solution is directly represented as a vector of real-parameter decision variables. Starting with a population of such solutions (usually randomly created), a set of genetic operators (such as crossover and mutation) is performed to create a new population in an iterative manner. Although most RGA differs from each other mainly in terms of their crossover and mutation operators, they mostly follow one of a few algorithmic models.

As has already been pointed out, RμGA explores in a small population with multiple genetic operators to find the global optimum solution-spaces. The major difference between the Micro-Genetic Algorithm (μGA) and Simple-Genetic Algorithms (SGA) is how to make a reproductive plan for better searching technique due to the population choice. Therefore, multiple genetic operators are proposed for the reproductive plan.

RμGA offers the advantage that the continuous parameters can gradually adapt to the fitness landscape over the entire search space whereas parameter values in binary implementations are limited to a certain interval and resolution. RμGA blurs the distinction among genotype and phenotype, since in many problems the real number vector already embodies a solution in a natural way. The proposed algorithm has the robustness of parallel exploration and asymptotic convergence with real value parameters. Moreover, RμGA is a steady-state, elite-preserving, and computationally fast algorithm for creating offspring near parents than anywhere in the search-space. The main skeleton of the proposed RμGA is illustrated in Fig. 1.

RμGA finds the global optimum solution by maintaining two types of population as follows: search population and steering population (Kim et al., 2006). Initial populations, consisting of five to seven chromosomes, are generated in a random fashion to serve as the starting feasible solution-spaces. The populations, satisfying the engineering design constraints, serve as a reservoir of information about the environment and as a basis for generating new trials.

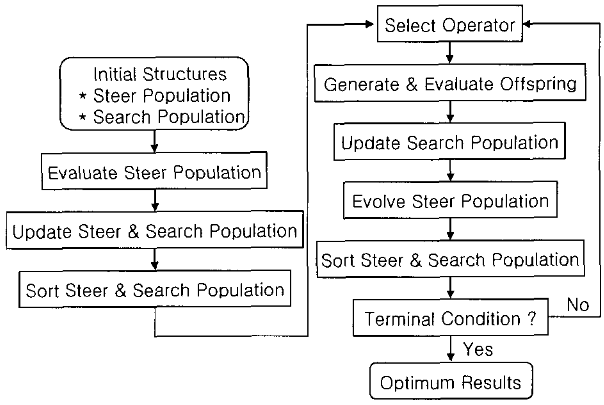

Fig. 1 Skeleton of the proposed RμGA

The search population, which satisfies linear constraints of the problem, is a population for searching the solution-spaces in each generation. A development of the search population influences evaluations of individuals in the steering population, satisfying all constraints.

At each generation step, a feasible search-space is searched by making steering points from the search points. Some steering points are moved into the population of search points, where they undergo transformation by specialized operators. That is, the fitter chromosome is selected to produce offspring, which inherit the best characteristics of the parents, for the next generation schedule. RμGA terminates the optimization procedure when a pre-specified number of generations is elapsed. Then, the result is hopefully a population that is substantially fitter than the original.

In the reproductive plan of RμGA, the main challenge is how to use a pair of decision variable vectors to create a new pair of offspring vectors or how to perturb a decision variable vector to a mutated vector in a meaningful manner. Therefore, multiple operators are adopted for exploration of new solution-spaces, and more detailed descriptions for these operators are mentioned in Kim *et al.* (2005).

4. Grillage structural analysis

Grillage is common types of structures in marine and land-based structural system. Grillage system that increases the stiffness of plate used by two rectangular stiffeners is a part of deck, side shell and bottom of ships. The worst loading point of those structures is dependent on the loads, which are vertical, in-plane or combination of those directions as well as boundary conditions.

The worst deflection point is produced when the point load is examined at central intersection. But the worst loading point would not necessarily be at the central point. To find the worst loading point, a traveling point load is applied to along the vertical and horizontal beams around mid-spans.

Kim *et al.* (2004) examined the experimental tests to confirm the numerical analysis results of the grillage models obtained from the direct stiffness method. In this article, the direct stiffness method is also used to calculate the maximum bending stress of the grillage structure under elastic analysis. To find the maximum stress in the beam section, only the bending stress is considered because the others as shear stress and torsional stress can be negligible. The numerical results agree to the experimental tests as well. The main process of direct stiffness method is illustrated in Fig. 2.

In order to analysis and design of the grillages, the following hypotheses are assumed to the members of structure.

(1) Elastic and small deflection behaviour.
(2) At each intersection, members are rigidly connected with the same level.
(3) Beam is a uniform cross-section along its length in each direction.
(4) Boundaries are simply-supported.
(5) Equal spacing between each intersections.
(6) The Rules and Regulations of Lloyd's Register of shipping are adopted for the linear/nonlinear constraints (Lloyd's Register of shipping, 2003)

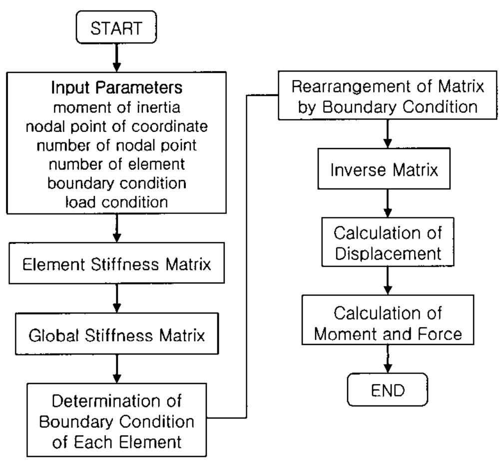

Fig. 2 Main process of direct stiffness method

5. Grillages design for weight minimization

The weight function is mainly determined from the scantling design variables and the arranging geometric variables of a structure. The weight of grillages may be determined by designing to an arbitrary limiting value of the maximum bending stress, which, in general, may arise either in the longitudinal or transverse beams. It is assumed that the material of both beams is identical.

To find the optimum weight of grillages under a given worst point load, the RμGA is examined by optimizing the weight function for the parameterization in beam configuration of grillages. It means that the parameterization study in optimum beam configuration which was carried out over the variation of scantlings of beam section for a given section modulus likely to occur in structures. Fig. 3 shows the flowchart to find the optimum beam scantlings of grillages while considering the direct stiffness method to calculate a maximum bending moment.

5.1 Objective Function and Design Variables

In minimum weight design by using RμGA, the fitness evaluation involves defining an objective function against which each chromosome is evaluated for suitability for the environments under consideration. The objective function for minimum weight grillages design can be:

$$F = (H_w \cdot T_w + 2B_f \cdot T_f) \cdot \rho \cdot (LT \cdot m + LL \cdot n) \quad (1)$$

where,

H_w : Height of web, T_w : Thickness of web,
B_f : Width of flange, T_f : Thickness of flange,
ρ : Density ($7{,}850 kg/m^3$),
LL : Longitudinal length, LT : Transverse length,
m : Total number of transverse members,
n : Total number of longitudinal members

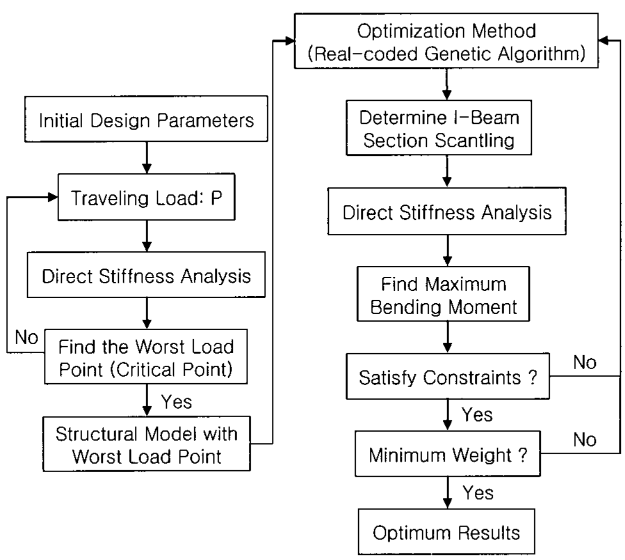

Fig. 3 Flowchart for analysis and design of grillage structure

5.2 Linear/Nonlinear Constraints

In weight minimized grillages design, the most important procedure has been to convert the required maximum bending moment values into suitable cross-sectional dimensions of the beams under the given constraints. The cross-sectional area due to the number of infinite combinations of the dimension of the web and flange is a large component of the total grillages weight. Therefore, decisions have to be made regarding the geometric parameters of the beam element to get an optimal cross-section shape considering the following constraints. In nonlinear constraint, a safety factor for design condition is set at 1.5 and yield stress is 240 MPa for mild steel.

(1) All domains for design variables are float greater than zero

$$H_w,\ T_w,\ B_f,\ T_f\ > 0.0$$

(2) Linear constraints for web and flange buckling

$$\frac{H_w}{T_w} \le 50.0,\quad \frac{T_f}{T_w} \le 1.5,\quad \frac{B_f}{T_f} \le 18.0$$

(3) Nonlinear constraint for design condition

$$\frac{M_{max}}{\sigma_a} \le Z_I$$

where,

$$\sigma_a = \frac{\sigma_y}{sf} = \frac{240.0}{1.5} = 160.0 \text{ MPa}$$

(σ_a: Allowable Stress, σ_y: Yield Stress, sf: Safety Factor)

$$Z_I = \frac{B_f(2T_f+H_w)^3 - H_w^3(B_f-T_w)}{6(2T_f+H_w)}$$

6. Computational results

In example grillages chosen for the application of analysis and design, the beams are a constant cross-section as an I-section. Fig. 4 shows the geometric topologies for analysis and design of grillage structure. Table 1 shows the mechanical properties and design data for the example grillages.

Structural analyses are carried out for 4 types of grillage models when the load is traveling along the beam span as shown in Fig. 5~8. For the convenience of analysis the load span is divided into 10 points with equal intervals. In these figures, the total stress only considers bending stress and stresses for the mid-span beam are shown. The stress distributions are compared with each of models as shown in Fig. 9. Maximum bending stress occurs at the near mid-point between intersections on the grillage.

Optimum designs that can be able to obtain more efficiently as a result of the minimum structural weight. R μGA had been examined by optimizing the design variables as sensitivity study in beam configuration of grillages under a given worst point load during 100,000 independent trial iterations. The total weights and maximum bending stresses of any m by n grids calculated by R μGA are shown in Table 2, and the 2 by 2 grids can be selected as an optimum grillage structure with minimum weight grids. Table 3 shows the optimum beam scantling by using R μ GA and direct stiffness method.

In order to compare the effectiveness of the proposed R μ GA approach, four more global optimization methods shown in Table 4 were tested and compared on grillage structure. All methods are developed with binary representation by Kim *et al.* (2003). Table 5 shows the performance comparisons of the total weights of the grillage structure with any m by n grids.

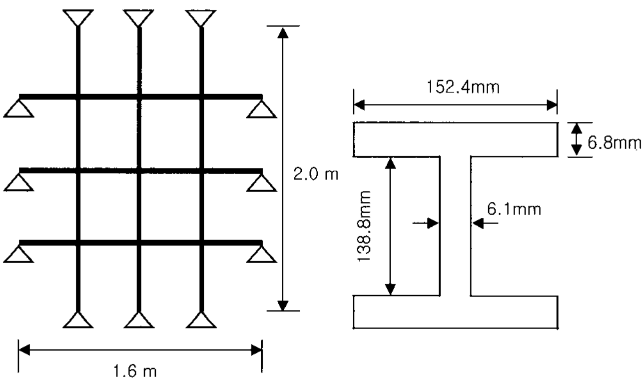

Fig. 4 Geometric topologies of grillage structure

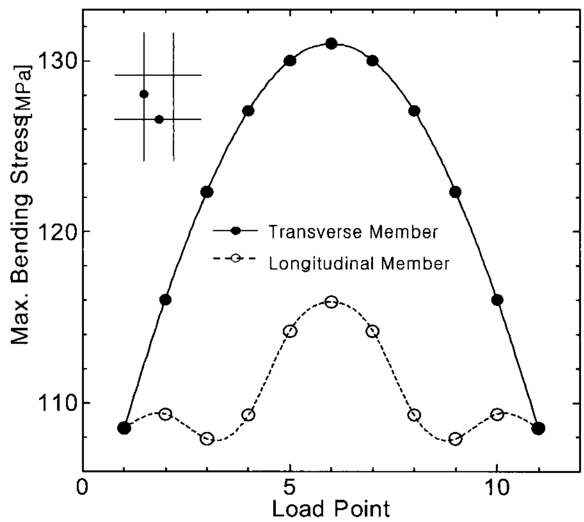

Fig. 5 Maximum bending stress (2×2 Grids)

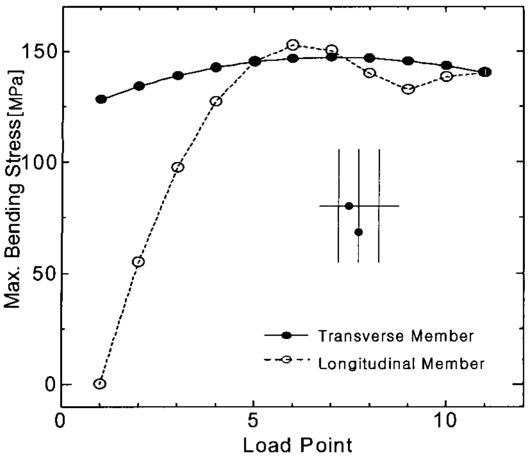

Fig. 6 Maximum bending stress (3×1 Grids)

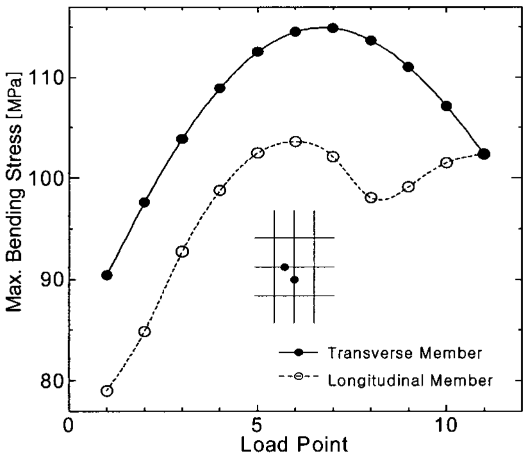

Fig. 7 Maximum bending stress (3×3 Grids)

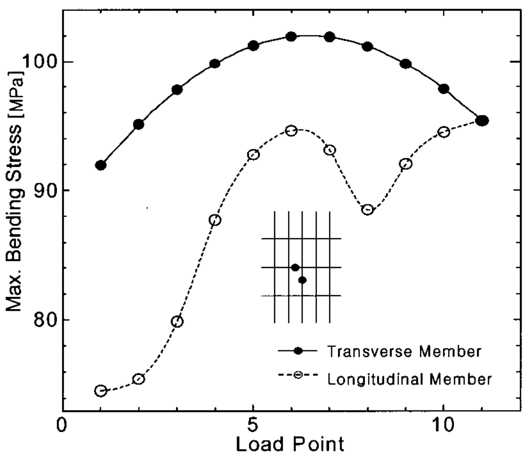

Fig. 8 Maximum bending stress (5×3 Grids)

Table 1 Mechanical properties and loading condition

Variables	Values	Comments
LL	1.6 *m*	Longitudinal length
LT	2.0 *m*	Transverse length
E	200 *GPa*	Young's modulus
G	80 *GPa*	Shear modulus
P	100 k*N*	Applied load

Table 2 Total weights and maximum bending stresses

Grids	Maximum Bending Stress (MPa)	Total Weight (kg)	Weight Ratio
2×2	1.310×10^2	105.385	1
3×1	1.527×10^2	123.175	1.169
3×3	1.149×10^2	144.799	1.374
5×3	1.019×10^2	183.239	1.739

Table 3 Optimum beam scantling (unit: *mm*)

Grids	H_w	T_w	B_f	T_f
2×2	214.808	4.296	92.062	5.115
3×1	226.035	4.521	96.876	5.382
3×3	205.584	4.112	88.113	4.895
5×3	197.556	3.951	84.674	4.704

Table 4 Global optimization methods for performance comparison

Method	Full Name
RμGA	Real-coded Micro-Genetic Algorithm
SGA	Simple-Genetic Algorithm
μGA	Micro-Genetic Algorithm
SA	Simulated Annealing
μGSA	Micro-Genetic Simulated Annealing

Table 5 Performance comparisons in total weight

Grids	Methods	Total Weight (*kg*)	Ratio
2×2	RμGA	105.385	1
	SGA	111.831	1.061
	μGA	115.310	1.094
	SA	107.109	1.016
	μGSA	120.849	1.147
3×1	RμGA	123.175	1
	SGA	137.691	1.118
	μGA	134.741	1.094
	SA	123.623	1.004
	μGSA	126.198	1.025
3×3	RμGA	144.799	1
	SGA	151.218	1.044
	μGA	155.878	1.077
	SA	153.165	1.058
	μGSA	148.404	1.025
5×3	RμGA	183.239	1
	SGA	183.643	1.002
	μGA	192.905	1.053
	SA	198.202	1.082
	μGSA	220.626	1.204

7. Concluding remarks

A new approach, referred to as Real-coded Micro-Genetic Algorithm or RμGA, to solve continuous nonlinear optimization problems is proposed and developed with the help of multiple genetic operators introduced in this article. RμGA approach is an abstraction of natural genetics and theoretical physics and is aimed to search global optimum solution space in global optimization problems. Therefore, RμGA can help in avoiding the premature convergence and search for better global solution, because of its wide spread applicability, global perspective and inherent parallelism.

The 2 by 2 grids can be selected as an optimum grillage structure with minimum weight as shown in Table 2. From the simulation results of Table 5, it was shown that the RμGA approach converged to global optimum solution with a marvellous explorability than the other optimization methods in application of grillages structure. Therefore, it is concluded that the proposed RμGA is both efficient and effective in identifying a global optimum solution.

Consequently, the Real-coded Micro-Genetic Algorithm can be suggested as useful tool for solving continuous and/or discrete nonlinear global optimization problems in any types of engineering structures.

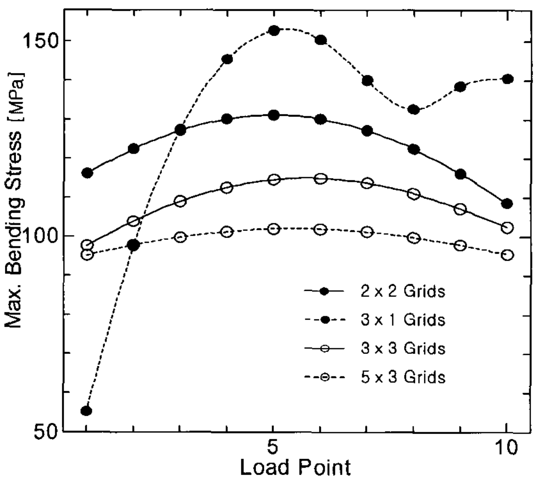

Fig. 9 Comparing maximum bending stress distribution

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