공학석사학위논문

Particle Swarm Optimization via Global-Local Scheme for Structural Design of Aerospace System

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2015년 2월

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지도교수 김 승 조

이 논문을 공학석사 학위논문으로 제출함

2014년 12월

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강희진의 공학석사 학위논문을 인준함

2014년 12월

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ABSTRACT

To ensure the structure to be safely maintained in flight phase, it is important to design and optimize the structures including aerospace system such as flight wing, launch vehicle and satellite. The structures of aerospace system are usually configured with stiffener and panel. Since panel is surrounded by stiffener, it can be seen that local characteristics in a particular analysis such as buckling analysis. Because load path does not change significantly, panel is suitable to perform the local buckling analysis because the buckling mode is present in the local area surrounded by the stiffener. This buckling analysis is time consuming work in the structural design optimization. To perform the structural design optimization effectively, it is essential that separate the optimization problem into the global optimization problem and the local optimization problem.

In this study, the global-local structural optimization problem was configured for the effective optimization of the structures including aerospace system structures. Particle swarm optimization algorithm which is useful for structural design optimization was used. To apply the global-local scheme into particle swarm optimization algorithm, optimization module was developed. This module is called the global-local PSO module. This module was constructed with three interface dialog. One is for setting optimization problem. And other one is for setup optimization environmental parameter. Third interface dialog is to start

optimization and monitoring. All of these functions were realized in DIAMOND/IPSAP which is being developed by Aerospace Structures Laboratory in Seoul National University.
To evaluate a performance of the particle swarm optimization algorithm using the global-local PSO module, Stiffened shell box and launch vehicle models were designed and were optimized by the global-local PSO algorithm. In case of stiffened shell box, local static buckling analysis was performed. Critical buckling load was used for constraint of the local optimization. Last example was the optimization of the launch vehicle.
The significance of this study was that it was possible to faster optimization by using the global-local PSO algorithm which is appropriate approach for the structures which are able to separate into the global and local area. Also, using the computer aided engineering including the high performance solver named IPSAP and the optimization module with in-house pre/post tools, the time and effort for finding the optimal design variables which are used in the aerospace system structures including flight wing box, launch vehicle, etc are decreased efficiently.

Keywords : Structural design optimization, Particle swarm optimization, Localization, Launch vehicle, Stiffened shell
Student number : 2013-20639

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1. Introduction

In this chapter, background of this study was suggested and recent research which are related with this area are summarized. Research which study on structural optimization and application with improving the particle swarm optimization algorithm are especially referred. At the same time, research concept and scope were determined based on this prior investigation and the particle swarm optimization algorithm via global–local scheme for the aerospace system structures was suggested.

1.1. Background

Aircraft and space launch vehicle is almost impossible to repair during the operating environment. So, it is important that the structural reliability and robustness. Especially, launch vehicle has a extreme load during launching sequence and flight phase. For structural safety, there are methods which are that change materials and include stiffeners. When additional structure is added on the launch vehicle, a structural ratio will be increase. So, the optimization is necessary for decreasing a cost of development and a structural ratio.

Computer aided engineering has being used for the structural design because of it's convenience and availability. As the computer resources development, a large structure problem could be solved using FEM in short time. Under the environment for fast iterative calculation, the structural optimization problem could be used with FEM for detail structural responses. In the other hand, the complex and large structure which including many design variables needs proper optimization algorithm. Traditional optimization algorithms which are a quasi-newton method, gradient descent and conjugate gradient, are a gradient-based method. These are given true solution for the problem which has continuous, linear and convex design space. But the structure optimization problem has nonlinear, nonconvex design space usually. Heuristic search technique ia one of the method for solving a large structural optimization problem which has nonlinear, nonconvex design space. Unlike gradient-based methods in a convex design space, heuristic techniques are not guaranteed to find the true global optimal solution in a single objective problem, but should find many good solutions. Genetic algorithm, simulated annealing and particle swarm optimization are heuristic search technique[1].

Particle swarm optimization (PSO) algorithm was developed by Kennedy and Eberhart in 1995 [2]. This algorithm is inspired by the behavior of the swarm of birds. For the complex and large function alike evolutionary computation, PSO is able to find the global optimization value.

1.2. Research Status

Improving PSO algorithm and optimization for the structural design were proceeded by several researchers, and their studies are summarized in Table 1. J. Kennedy et al (2002) evaluated the performance of PSO as topology of the particle swarm. A. Ratnaweera et al (2004) improved the performance of PSO as changing the acceleration coefficient over time. Moon et al (2007) performed the virtual optimal design of satellite adapter using PSO in parallel computing environment. Y. Toyoda et al (2007) improved the PSO with a neighborhood search algorithm. Park et al (2009) performed the evaluation of benchmark function and the optimal design of the satellite using genetic algorithm and PSO. A low cost PSO using metamodels and inexac pre-evaluation was suggested by C. Praveen et al (2009). Yoon et al (2012) developed an asynchronous PSO and improved the fast convergence. They performed the optimal design of satellite adapter-ring using asynchronous PSO. A. Kaveh et al (2014) developed a democratic PSO for truss layout and size optimization.

Table 1. Recent optimization analysis studies related to particle swarm optimization.

		Scope	Method	Purpose
2002	J. Kennedy et al [3]	Benchmark Functions	Particle Swarm Optimization	PSO Performance Improvement
2004	A. Ratnaweera et al [4]	Benchmark Functions	Particle Swarm Optimization	PSO Performance Improvement
2007	Moon et al [5]	Satellite	Particle Swarm Optimization	Structural Optimal Design
2007	Y. Toyoda et al [6]	Benchmark Functions	Particle Swarm Optimization	PSO Performance Improvement
2009	Park et al [7]	Benchmark Functions Satellite	Genetic Algorithm Particle Swarm Optimization	Structural Optimal Design
2009	C. Praveen et al [8]	Flight Wing	Particle Swarm Optimization	Structural Optimal Design
2013	Yoon et al [9]	Satellite	Particle Swarm Optimization	PSO Performance Improvement
2014	A. Kaveh et al [10]	Truss Structure	Particle Swarm Optimization	Structural Optimal Design

1.3. Concept and Scope

In this study, the PSO algorithm using global-local scheme which named global-local PSO algorithm was suggested and structural optimizations of stiffened shell box, launch vehicle using global-local PSO algorithm were performed. Analysis results which are linear static analysis, failure analysis, static buckling analysis were used for objective function and constraints. Examples which were stiffened shell box and launch vehicle were performed and were compared with results using other optimization algorithms. Computational environment of structural design optimization was constructed for development of global-local PSO algorithm. This study based on a virtual analysis and structural optimization can help an initial design of structures under various load conditions.

1.4. Overview

As previously mentioned, optimization process will be performed for stiffened shell box and launch vehicle using finite element methods with localized PSO algorithm.

In the second chapter, the numerical schemes implemented in the optimization module are discussed. design objects are was decoupled by localized systems. To do that, PSO procedure are revised to global-local PSO algorithm. In the third, fourth and fifth chapters, various numerical simulation examples are solved using global-local PSO optimization module. Stiffened shell and launch vehicle FEM model are solved by the module. All of results are compared with standard PSO algorithm.

2. Development of Global-Local PSO Module

PSO module with global-local optimization (global-local PSO module) are developed based on C++ language. The module was integrated in the DIAMOND/IPSAP, which is pre/post processor of structural analysis solver IPSAP. PSO algorithm in the DIAMOND/IPSAP are revised with global-local scheme.

2.1. Structural Design Optimization

General structural optimization problems can be described as follow.

$$
\begin{aligned}
&\text{Minimize } M(x_1, x_2, \ldots, x_N) \\
&\text{Subject to} \\
&\qquad C(\vec{x}) \leq 0 \\
&\qquad \max(f(\vec{x})) < \frac{1}{S.F} \\
&\qquad \lambda \geq S.F
\end{aligned}
\tag{1}
$$

while M is mass, $S.F$ means safety factor and $\vec{x}$ is variable vector, Major objective function of structural optimization is minimize mass. Constraint functions are consist of geometrical constraints of design variables $C(\vec{x})$, failure index f and critical buckling load coefficient λ. Maximum failure index of whole domain should be smaller than unit meanwhile first mode of buckling analysis should be larger than unit.

In the aerospace industry, most of structures are consist of thin wall strucure with stiffener as aircraft wing panel, launch vehicle skin. For this reason, thickness of a shell affects small effects to other shell beyond stiffener. Buckling mode also localized for the same reason. The optimization problem was approached by separating the global and the local based on these concepts. Global-local optimization problem can be described as follow.

Global Optimization:

$$\begin{aligned} &\text{Minimize } M(x_1, x_2, ..., x_n, t_1, t_2, ..., t_m) \\ &\text{Subject to} \\ &\qquad C(\vec{x}, \vec{t}) \le 0 \end{aligned} \tag{2}$$

Local Optimization:

$$\begin{aligned} &\min_{\vec{t_j}} \left(M_j(t_j) + f_i(t_j) + \frac{1}{\lambda_j(t_j)} \right), \; j = 1, 2, 3, ..., m \\ &\text{Subject to} \\ &\qquad f_j(t_j) < \frac{1}{S.F} \\ &\qquad \lambda_j(t_j) \ge S.F \end{aligned} \tag{3}$$

while $\vec{x}$ is global variable vector, $\vec{t}$ is local veriable vector. Total number of design variable is N, the number of global design variable is n, the number of local design variable is m. Objective functions and constraint function is divided respectively into global and local optimization. As before, Objective function in global optimization is minimize mass. Geometrical constraints is remained by constraint functions of global optimization. For local optimization, objective function is minimize the sum of failure index and the inverse of critical buckling load for j-th local variable t_j. Constraint function is failure index and critical buckling load coefficient of j-th local area while global variable vector $\vec{x}$ is fixed.

Approaching with global-local scheme, three effects can be expected. First, constraint function which critical buckling load is separated. A buckling analysis for the global area is performed for applying the critical buckling load constraint on the general structural optimization problem. In order to determine the critical buckling load in the optimization problem, static buckling analysis is repeated until the eigenvalue comes out positive from the first buckling mode. If positive eigenvalue comes out lately, it needs much time for buckling analysis. Especially, change in the thickness sensitively affects the buckling mode. The buckling mode can be disappear while changing the thickness. In this case, buckling analysis is performed from beginning and it is a time-consuming work. On the other hand, buckling occurs locally in structure which consist of stiffener and shell. By separating the local area which only a compressive force is applied and performing buckling analysis, the time required for optimization can be shorten. A prerequisite is that the displacement in the boundary of the local area is substantially same when the thickness of local area is changed.

The second effect will be expected to lower the dimension of the search space. It is particularly effective in the population-based method such as genetic algorithm or PSO algorithm. These algorithms generate randomly candidate solutions called particles and trying to improve them with regard to a given measure of quality. The convergence speed and optimization quality is influenced depending on the quality of the particle generated at the initial step. When the particle finds the optimality region, a small volume of the search space surrounding the global optimum, it can be able to see that optimized. Simply, the probability of generating a particle indise the optimality region is the volume of the optimality region divided by the volume of the search space. Increasing the volume of the search space, this probability will decrease exponentially[11]. Reducing the dimension of the search space by separating design variables into the global area and the local area can be expected to have a positive impact on the convergence speed.

The last effect is to break the relationship between the design variables. The particles are composed of a vector of design variables in the PSO algorithm. Since fitness evaluation of the particle is performed, the sensitivity of the individual design variable are not evaluated. Although it appears that the design variable have a relationship with other design variables, it is not. So, the design variables which have low sensitivity are hard to move optimal position than high sensitive design variables. It makes the PSO algorithm to find the optimal position difficult in the early step. Since the sensitivity of fitness evaluation of local area is depend on the local design variable only, it can be expected that the local design variables are not affected by the sensitivity of the global design variables.

2.2. Overview of Particle Swarm Optimization

In 1995, Kennedy and Eberhart introduced the PSO algorithm. It is a heuristic search technique such asd the genetic algorithm, simulated annealing. Heuristics are typically used to solve complex(large, nonlinear, nonconvex) multivariate combinatorial optimization problems that are difficult to solve to optimality. Heuristics are good at dealing with local optima without getting stuck in them while searching for the global optimum.

The behavior of the PSO algorithm is based on the influence of the attraction index which towards the global best position (gbest) and local best position (pbest) and some irregulars. It is described as equation (4).

$$\boldsymbol{v}_i^{k+1} = a\boldsymbol{v}_i^k + b_1 r_1 \left(\boldsymbol{p}_i^k - \boldsymbol{x}_i^k\right) + b_2 r_2 \left(\boldsymbol{q} - \boldsymbol{x}_i^k\right) \tag{4}$$

Here, $\boldsymbol{v}_i^{k+1}$ is a velocity of i−th particle in next step, k is current step. a is momentum coefficient to control the effect of a current velocity. Attraction coefficients, b_1 and b_2, affect on the attraction toward optimal position. r_1 and r_2 are uniformly distributed random numbers between 0 and 1. $\boldsymbol{p}_i^k$ is the optimal position of i−th particle in current step. $\boldsymbol{q}$ is the best position of the swarm. In equation (4), the velocity of the particles in next step is determined by the current velocity, $\boldsymbol{p}_i^k$, $\boldsymbol{q}$. These are affected by momentum coefficient, attraction coefficient and random number coefficient respectively. The position of the particle is determined by equation (5).

$$\boldsymbol{x}_i^{k+1} = c\boldsymbol{x}_i^k + d\boldsymbol{v}_i^{k+1} \tag{5}$$

In each step, the position of the next step is affected by current position and the velocity of the next step. In here, c is the position affect coefficient, d is the velocity affect coefficient. The behavior of the standard PSO(SPSO) algorithm is shown in figure 1.

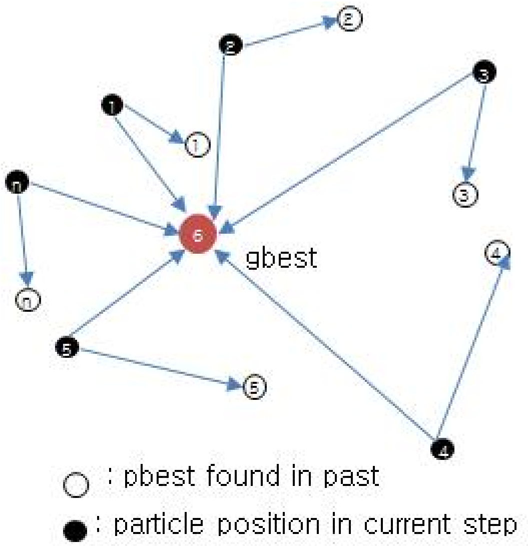

Figure 1. Particle behavior in SPSO.

Figure 2 illustrated the flowchart of SPSO. The swarm is initialized with random−valued particles. In here, the velocity and position of the particles are determined. Initial position and velocity is randomly generated within a range of design variable. To prevent over−range, Maximum velocity is limited to 10% of a range of design variable. In the next, the velocity and position of the particles are updated. Verify that the generated particles are satisfied with the range and constraint in following step. If the particle is not available, this particle is regenerated. In order to determine the gbest and the pbest, fitness is evaluated by objective function. After the gbest and the pbest are updated, termination condition is checked. There are a tolerance and a number of step for termination condition. All the progress iterative until satisfying the termination condition.

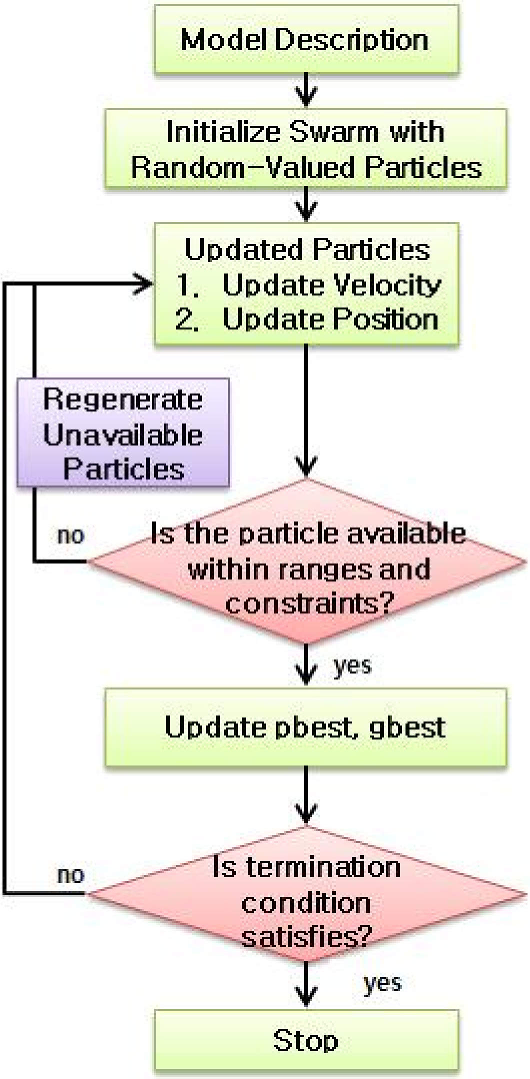

Figure 2. Flow chart of SPSO.

2.3. DIAMOND/IPSAP

DIAMOND/IPSAP is the integrated pre/post processor of structural analysis using solver IPSAP which is developed by Aerospace Structures Laboratory of Seoul National University. DIAMOND is the software based on MFC and IPSAP is the solver of DIAMOND. DIAMOND provides functions of pre/post process, automatic mesh generation module, aircraft generation module, optimization module. IPSAP is the sovler based on FEM. It has linear static analysis, vibration analysis, buckling analysis, thermal analysis and acoustic analysis[12]. To solve the linear static analysis and static buckling analysis, the global-local PSO module is developed as optimization module of DIAMOND/IPSAP.

DIAMOND/IPSAP use the multi-frontal method for linear solver and the block Lanczos algorithm for eigen solver. In the frontal method, global stiffness matrix is not constructed in the sequence of computation, while other general methods assemble it. Stiffness matrix of element is expressed as equation (6),

$$\begin{bmatrix} K_{11} & K_{12} \\ K_{21} & K_{22} \end{bmatrix} \begin{Bmatrix} u_1 \\ u_2 \end{Bmatrix} = \begin{Bmatrix} f_1 \\ f_2 \end{Bmatrix} \tag{6}$$

In here, subscript 1 is assembled parts and subscript 2 is the others. If assembled parts are removed,

$$(K_{22} - K_{21}K_{11}^{-1}K_{12})u_2 = f_2 - K_{21}K_{11}^{-1}f_1 = \overline{f_2} \tag{7}$$

equation (7) is derived. Like this, frontal method assemble the stiffness matrix of each element and then decrease the degree of freedom by removing the assembled terms. In the parallel multi-frontal method, each CPU processor assembles frontal independently and then communicates each other to remove all boundary degree of freedom between frontal. Domain-wise multi-frontal method is depicted in figure 3 briefly, and it is applied in IPSAP[13].

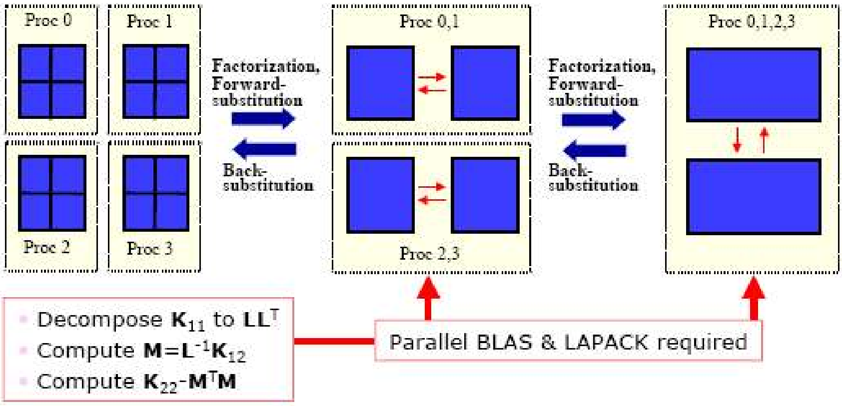

Figure 3. Parallel implementation of the domain-wise multifrontal method [14]

2.4. Global-Local Particle Swarm Optimization Module

As referred in the previous section, the global-local PSO module was developed in DIAMOND/IPSAP. Construction and details of the global-local PSO algorithm were described in this section.

A map of DIAMOND/Optimization module is shown in figure

4. Optimization module is performed on the master processor. A description which includes FE model file path, material property, design variable, objective function, constraint function is generated and is delivered to the worker processor. Worcker processor perform the linear static analysis and the buckling analysis which were described on description. The master processor can deal with the various worker processor according to the computation environment.

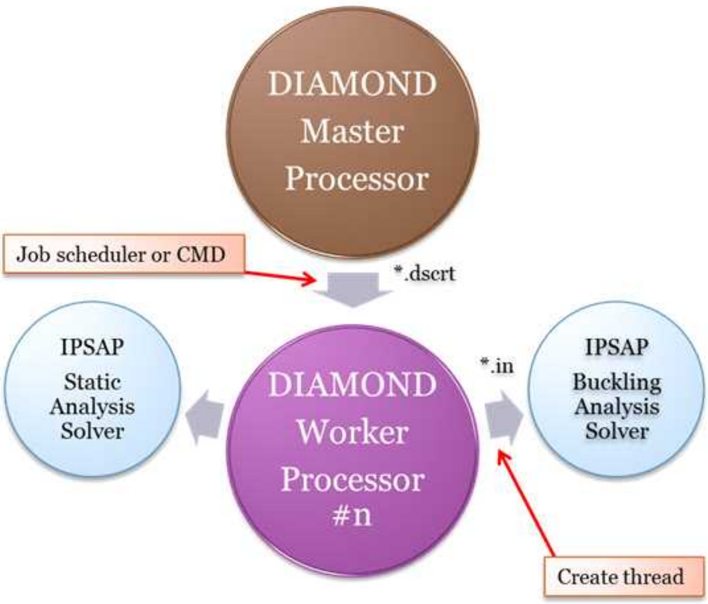

Figure 4. DIAMOND/Optimization module map.

Detail interaction between the master processor and the worker processor is shown in figure 5. In the master processor, the global optimization which deal with the global design variables is performed using the PSO algorithm. Each particles which are generated by the PSO algorithm are evaluated in the worker processor. At the same time, the local optimization is performed using the PSO algorithm in the worker processor. The worker processor perform the linear static analysis with the global FE model which is described in a description. A stress and displacement for each node is output. With these result and description including the local FE model informations which are element ID, the local design variable and optimization functions which are the local objective function and the local constraint functions, the worker processor start the local optimization. The local FE model is generated using local element ID by the worker processor and boundary condition is obtained from the linear static analysis result of the global FE model. The linear static analysis and the static buckling analysis of the local FE model are performed and these results are used for objective function and constraint function of the local optimization. The local fitness is evaluated and the best position of swarm and particles is updated. The local optimization is repeated until satisfying the termination condition. In each repeat, the global FE model and the linear static analysis result are updated with the local design variables which are optimized in current repeat and the boundary condition of the local FE model also updated with the updated displacement. When the termination condition is satisfied in the local optimization, the worker processor pass the evaluation values for the global optimization to the master processor. The master processor update the best position of the particles using evaluation values which were passed by worker processors.

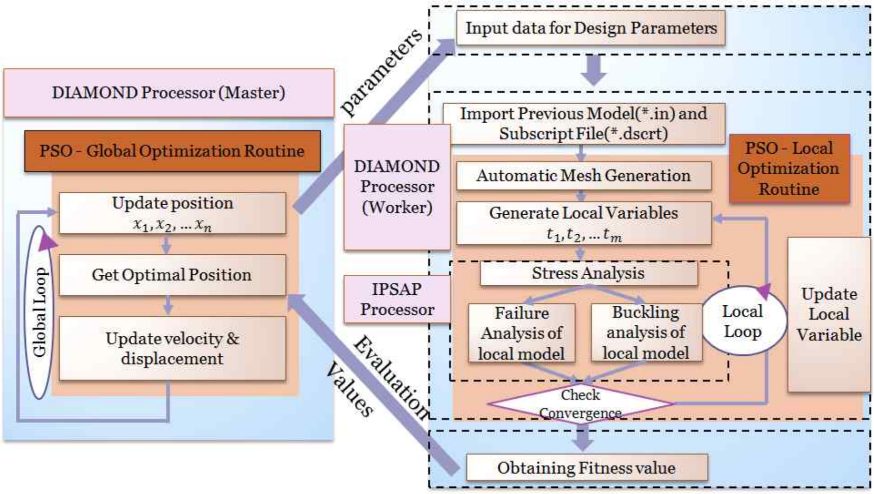

Figure 5. Interaction between master and worker processor.

The global-local PSO module has three interface dialog. It is shown in figure 6. (a) is a dialog for setup the optimization script and enter the design variable. The optimization script is the description which mentioned above. This script includes the FE model file path, the design variables, objective function, constraint function. After setup the optimization script and click 'Setup Variable' button, the maximum and minimum values of the design variable which were described on the optimization script are calculated and are entered in the table automatically. In default, the minimum value is 10% of initial value, the maximum value is 150% of initial value. These values are able to change by the user. The local design variables, element ID of the local FE model, the objective function and contratint function are also entered. To apply all the setup, click ‘Apply’ button. (b) is a dialog for setting the PSO parameter and the termination condition. In default, a number of particle is 30, the momentum coefficient is 0.8, the attraction coefficients are 0.5 respectively. The position affect coefficient and the velocity affect coefficietn are 1.0 respectively. For the termination condition, a number of step is 200 and the tolerance of the design variable is 0.000001 To apply all the setup, click ‘Apply’ button. (c) is a dialog for starting the optimization and monitoring. Clicking the 'Optimization Start' to start the optimization. On the left side of the dialog, the current step and an optimized evaluation value is output. The optimization history graph is output to the center of the dialog. On the right side of the dialog, optimize processes such as the evaluation value and the current generated particles are output. Optimization is continued until it reaches the termination condition entered in (b). A pop-up window will be appeared when the termination condition is satisfied.

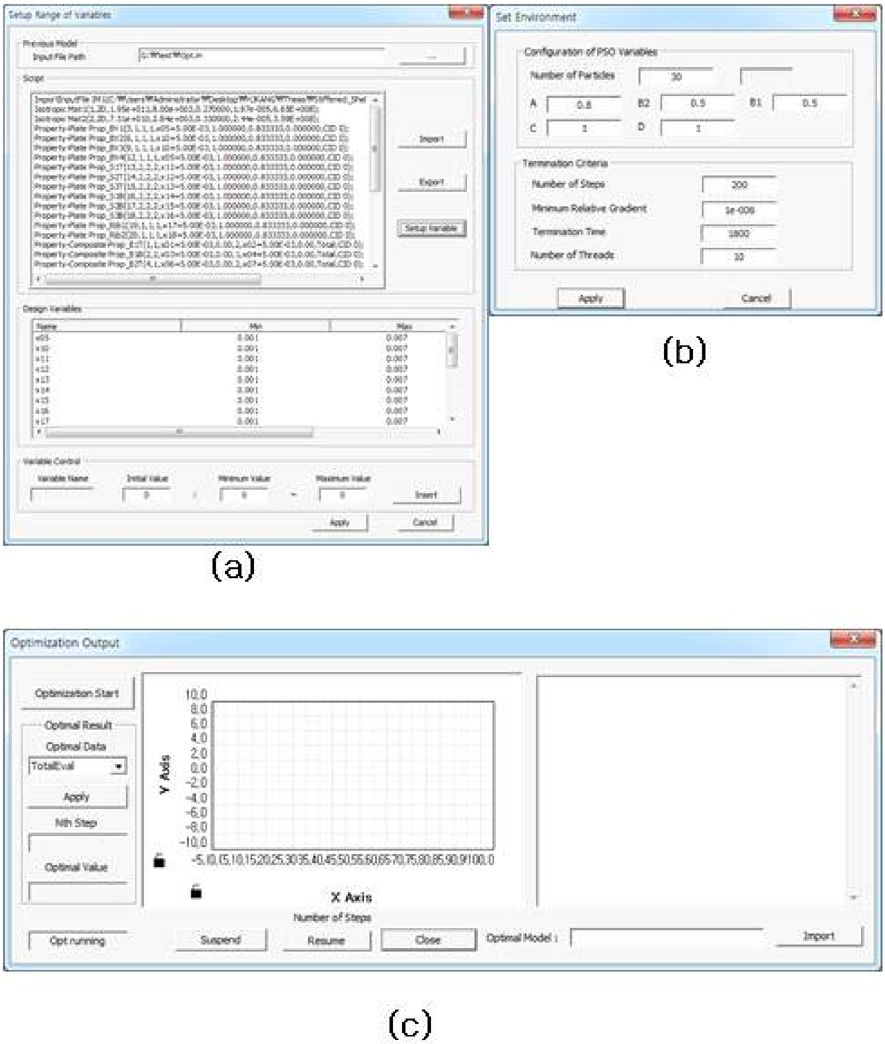

Figure 6. Preprocessor for optimization module in DIAMOND. (a) setup range of variables dialog, (b) set environment dialog, (c) optimization output dialog

2.5. Objective Function and Constraint

In this chapter, formulation of objective function and constraints are derived. Static failure analysis and buckling analysis are considered for that.

2.5.1. Objective Function

In the structural optimization problems, mass is typically used as objective function. In the case of finite elements are used, it can be obtained as sum of each element mass. It can be expressed as follow

$$\text{minimize} \qquad M\left(\overrightarrow{x}_i^k\right) = \sum_{e=1}^{N} \rho_e V_e \qquad (8)$$

where ρ_e is density of element and V_e is volume of element. In the every step of optimal process, thickness of shell and cross section information of beam can be changed. Above equation is necessary because mass should be minimized for most of structural optimization.

2.5.2. Constraint: Critical Buckling Load

The cross sections of aerocraft/launch vehicle structure tend to consist of an assembly of thin plates. When the plates is subjected to large compressive stresses, the thin plates that make up the cross section may buckle before the full strength of the member is attained if the thin plates are too slender. When a cross sectional element fails in buckling, then the member capacity is reached. Therefore, local buckling becomes a limit state for the strength of the structure subjected to compressive stress rather than strength−based failure criteria.

In this chapter, constraints about buckling analysis is derived. In advance, governing equation of static buckling analysis is expressed as follow

$$[[K_s]+\lambda_i[K_g]]\{\delta\}=\{0\} \tag{9}$$

where K_s is stiffness matrix which is referred in the previous chapter. K_g is geometric stiffness matrix. δ is nodal displacement vector. This problem is general form of eigenvalue problem. The first mode of equation (15) is critical buckling load coefficient. K_s is described as follow.

$$[K_s]=\int_{\overline{V}}[B]^T[C][B]|J|d\xi d\eta d\zeta \tag{10}$$

where B is an interpolation matrix obtained by imposing the considered set of shape functions, C is constitutive matrix, J 는 the determinant of the Jacobian matrix.

Otherwise, K_g is formulated as follow

$$\begin{aligned}[K_g]=&\iint[G_i]^T[\sigma_{0a}][G_i]h|J|dA_e\\&+\iint[G_b]^T[\sigma_{0b}][G_b]h|J|dA_e\\&+\iint[G_{s1}]^T[\sigma_{0b}][G_{s1}]\frac{h^3}{12}|J|dA_e\\&+\iint[G_{s2}]^T[\sigma_{0b}][G_{s2}]\frac{h^3}{12}|J|dA_e\end{aligned} \tag{11}$$

where h is shell thickness. It is consists of in-plane, bending and transverse shear terms, this equation is effective only for shell elements.

After obtaining stress vector from static analyis results, geometric stiffness matrix can be assembled by above equation. Then the equation (15) can be solved by eiqen solver like block lanczos algorithm. If the structure is subjected to tensile load, their eigen value will be smaller then zero. Therefore, it should be iterated until smallest positive eigen value is found. λ of equation (1) is the eigen value of static buckling analysis results.

2.5.3. Constraint: Failure Index

In structural problems, where the structural response may be beyond the initiation of nonlinear material behaviour, material is of profound importance for the determination of the integrity of the structure. For ductile materials, yield criteria like von Mises yield criterion or maximum stress/strain criterion is commonly used. For anisotropic material like composite material which is frequently used for aerospace systems, quadratic failure criterion also can be considered. Hashin, Tsai-wu, Tsai-hill are popular failure criteria.

As results of failure analysis, failure index can be obtained. Failure analysis is composed of performing stress analysis and applying failure criterion. Following linear equation is typical static analysis problem.

$$\boldsymbol{Ku} = \boldsymbol{F} \tag{12}$$

where $\boldsymbol{K}$ is stiffness matrix, $\boldsymbol{u}$ is displacement vector, $\boldsymbol{F}$ is force vector. $\boldsymbol{K}$ matrix can be assembled by structural domain and boundary condition. If external force is exist, $\boldsymbol{F}$ is given. Then $\boldsymbol{u}$ vector can be obtained by inversing the stiffness matrix. Design variables of structural optimization problem are used for calculating the stiffness matrix.

Strain−displacement relationship can be expressed as following equation (13).

$$\epsilon_{ij} = \frac{1}{2}\left(\frac{\partial u_i}{\partial x_j} + \frac{\partial u_j}{\partial x_i}\right) \ (i,j = 1,2,3) \tag{13}$$

where ϵ_{ij} is strain tensor. u_i is tensor notation of $\boldsymbol{u}$ vector and x_i is tensor of nodal position. Finally, stress can be obtained by stress−strain relationship as equation (14)

$$\sigma_{ij} = \sum_{k=1}^{3}\sum_{l=1}^{3} c_{ijkl}\epsilon_{kl} \ (i,j = 1,2,3) \tag{14}$$

where σ_{ij} is stress tensor and c_{ijkl} is elasticity tensor. Stress tensor can be expressed engineering notation as follow.

$$\sigma_i = C_{ij}\epsilon_j \ (i,j = 1,2,3,...,6) \tag{15}$$

It is composed of three normal stress components and three shear stress components. For beam elements, only axial stress exist while shell element has two component of normal stress and one shear stress component.
For two dimensional elements, failure criterion can be expressed as follow.

Maximum Stress Failure Criterion:

$$f = \frac{\sigma_1}{X_t} < 1 \text{ when } \sigma_1 > 0 \tag{16a}$$

$$f = \frac{|\sigma_1|}{X_c} < 1 \text{ when } \sigma_1 < 0 \tag{16b}$$

$$f = \frac{\sigma_2}{Y_t} < 1 \text{ when } \sigma_2 > 0 \tag{16c}$$

$$f = \frac{|\sigma_2|}{Y_c} < 1 \text{ when } \sigma_2 < 0 \tag{16d}$$

$$f = \frac{|\sigma_6|}{S_{12}} < 1 \tag{16f}$$

where σ_1 and σ_2 are normal stress of each direction. σ_6 is shear stress. X_t, Y_t are tensile strength of each direction while X_c, Y_c are compressive strength. If the value of f exceed unit, failure is occurred. Maximum stress failure criterion is simplest form of failure criteion and no interaction between the stress components are considered. If it is assumed as isotropic material, all strength normal direction strength will have same value and then only two strength components, normal direction and shear direction strength, are required.

On the other hands, Tsai-Wu failure criterion can be expressed as following equation

Tsui-Wu Failure Criterion:

$$F_i\sigma_i + F_{ij}\sigma_i\sigma_j \le 1 \tag{17}$$

where σ_i, σ_j are stress tensor, F_i, F_j are strength components. When the left side of equation (17) exceed unity, then failure is occurred.

For isotropic material like metal, maximum stress or von Mises failure criterion can be used rather than quadratic form. For applied failure criterion, maximum component of failure index can be obtained. constraint function $f(\vec{x})$ of equation (1) indicate the index. Therefore, one failure index per load case is obtained.

3. Optimization of Stiffened Shell Box using Global-Local PSO

3.1. Optimization of Stiffened Shell Box

As referred in section 2.1, the global-local scheme can be applied on the structural optimization which constructed with the stiffener and the shell. In this section, the mass minimization of the stiffened shell box, which is a simple shape of the part of flight wing box, is considered. The stiffened shell box is consist of 4 spars, 2 ribs and 6 panels.

A fixed boundary condition is applied on 4 node in a corner the back. Vertical upward force of 5400 N at node in corner the front. The stiffened shell box FE model is shown in figure 8. Table 2 shows a material property of this example.

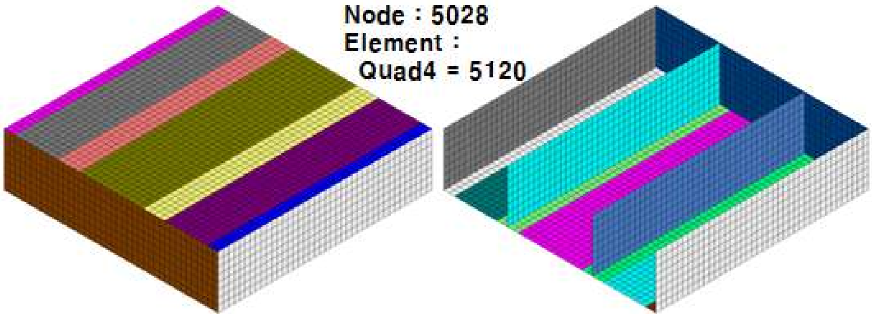

Figure 7. Finite element model of stiffened shell box.

Table 2. Material properties of stiffened shell box FE model.

	Young's modulus (Pa)	Poisson's ratio	Density (kg/m^3)	Tensile Strength (Pa)
Panel	7.31E+10	0.33	2.84E+03	3.59E+08
Rib, Spar	1.95E+11	0.27	8.00E+03	6.65E+08

The design variables are the thickness of spars, ribs and panels. The initial values for the thickness and a range is shown in table 3. Constraints are imposed in terms of failure index of each element and critical buckling load coefficient. The allowable failure index is 0.5 applying 1.0 of M.O.S (margin of safety). The allowable critical buckling load coefficient is unit. For the global-local PSO algorithm, each panel has been set to a local area for the local optimization.

The thicknesses of panels are the local design variables. Failure index are constraints for the global optimization and the local optimization. Critical buckling load coefficient are constraints for the local optimization in upper surface panels only. Because of three panels which located on upper surface are subjected to compressive stress. Table 3 shows the design variables of stiffened shell box FE model. A number of particles is 100 and a number of steps is 200. For the global−local PSO algorithm, a number of particles in the global optimization is 48, a number of particles in the local optimization is 7 for each local area. Total number of particles is same with the SPSO algorithm. Parameter a is 0.8, b_1 and b_1 are 0.5, c and d are 1.

Table 3. Design variables of stiffened shell box FE model.

	Design Variable (Thickness)	Min (m)	Max (m)	Init (m)
Local Variables	Upper Surface $t_1 \sim t_3$	0.0005	0.0075	0.005
	Lower Surface $t_4 \sim t_6$	0.0005	0.0075	0.005
Global Variables	Stiffener $x_1 \sim x_{12}$	0.0005	0.0075	0.005

3.2. Optimization Results

Table 4 and 7 show the optimization results of the stiffened shell box FE model. The optimized mass using the SPSO algorithm is 84.6 kg. The optimized mass using the global-local PSO algorithm is 82.1 kg. The elapsed time per particle using the SPSO is shorten than the global-local PSO algorithm. But total elapsed time using the global-local PSO algorithm is much faster than the SPSO algorithm. The mass optimization history is shown in figure 8. It can be seen that a lot of mass is dropped in early step in the global-local PSO algorithm. This effect can be seen as the local optimization.

Table 4. Optimized design variables of stiffened shell box FE model.

	Design Variable (Thickness)	SPSO	Global-Local PSO
Local Variables	t_1	5.062E-03	2.468E-03
	t_2	5.888E-03	3.381E-03
	t_3	5.917E-03	2.704E-03
	t_4	5.316E-03	5.000E-04
	t_5	4.008E-03	5.000E-04
	t_6	4.460E-03	5.000E-04
Global Variables	x_1	4.295E-03	5.950E-03
	x_2	2.016E-03	2.166E-03
	x_3	4.774E-03	6.489E-03
	x_4	1.996E-03	6.730E-03
	x_5	3.960E-03	5.846E-03
	x_6	5.047E-03	6.186E-03
	x_7	3.211E-03	1.413E-03
	x_8	5.664E-03	6.542E-03
	x_9	2.893E-03	4.243E-03
	x_{10}	5.184E-03	2.226E-03
	x_{11}	2.314E-03	1.426E-03
	x_{12}	4.495E-03	3.157E-03

Table 5. Optimized results of stiffened shell box FE model.

	SPSO	Global-Local PSO
Optimized mass	84.6	82.1
Number of step for optimal position	52	7

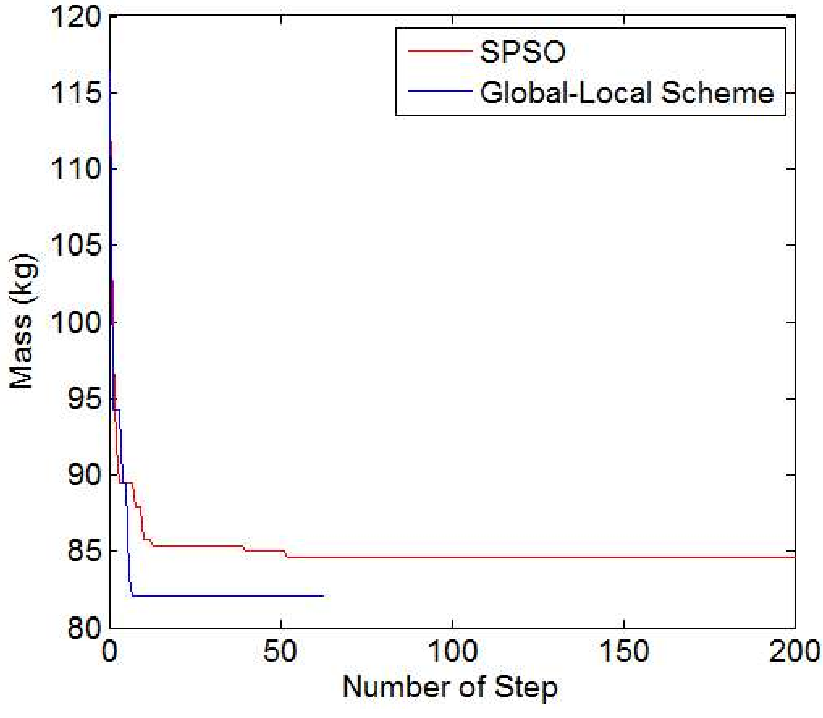

Figure 8. Mass optimization history of stiffened shell box FE model.

4. Optimization Analysis of Launch

Vehicle using Global−Local PSO

4.1. Optimization of Launch Vehicle

In this section, the mass minimization of the launch vehicle, which is a virtual model of the KSLV−II, is considered. The launch vehicle has 2 liquid engine, a kick engine and 4 nozzle in 1st stage rocket. A shape of each engine is simplified to control total degree of freedom. Cylinder which has been reinforced by the stiffener is realized. Table 6 shows a material property of this example.

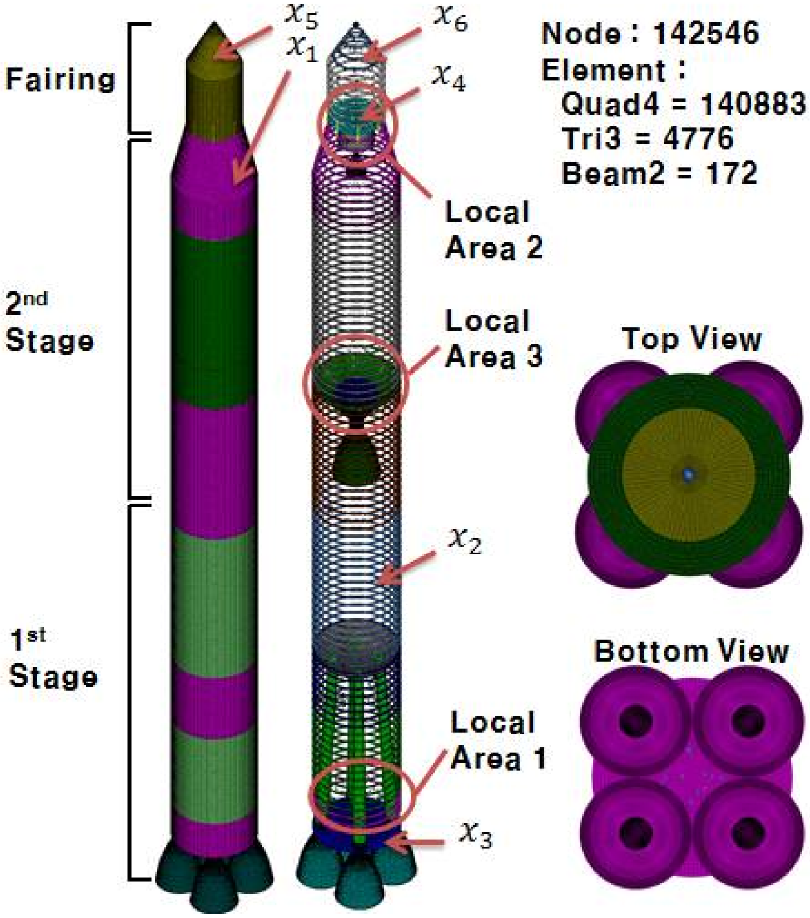

Figure 9. Finite element model of launch vehicle FE model.

Table 6. Material properties of launch vehicle FE model.

Mat ID	Young's modulus (Pa)	Poisson's ratio	Density (kg/m^3)	α (10^{-5}/℃)	Tensile Strength (Pa)
100000002	7.17E+10	0.33	2.81E+03	2.45E-05	4.00E+08
100000005	7.31E+10	0.33	2.84E+03	2.44E-05	3.59E+08
100000008	7.31E+10	0.33	2.80E+03	2.44E-05	4.27E+08
100000011	2.05E+11	0.29	7.85E+03	1.17E-05	5.25E+08
100000014	1.95E+11	0.27	8.00E+03	1.87E-05	6.65E+08
100000015	1.10E+11	0.31	4.43E+03	8.50E-06	9.23E+08

The design variables are the thickness of the propellant tanks, cylinders, stiffeners, nose, ribs and pipes. The initial values for the thickness and a range is shown in table 7. Constraints are imposed in terms of failure index of each element. The allowable failure index is 0.869 applying 0.15 of M.O.S. For the global−local PSO algorithm, the local areas are set as figure 10. The local variables t_1, t_4 and t_6 have the high sensitivity in mass evaluation but not critical in failure index. Failure index are constraints for the global optimization and the local optimization. A number of particles is 60. For the global−local PSO algorithm, a number of particles in the global optimization is 42, a number of particles in the local optimization is 6 for each local area. Total number of particles is same with the SPSO algorithm.

Table 7. Design variables of launch vehicle FE model.

	Design Variable (Thickness)		Min (m)	Max (m)	Init (m)
Local Variables	Local Area 1	t_1	0.001	0.003	0.002
		t_2	0.002	0.006	0.004
	Local Area 2	t_3	0.002	0.006	0.004
		t_4	0.001	0.003	0.002
	Local Area 3	t_5	0.001	0.003	0.002
		t_6	0.002	0.006	0.004
Global Variables	x_1		0.001	0.003	0.002
	x_2		0.002	0.006	0.004
	x_3		0.002	0.006	0.004
	x_4		0.002	0.006	0.004
	x_5		0.002	0.006	0.004
	x_6		0.001	0.003	0.002

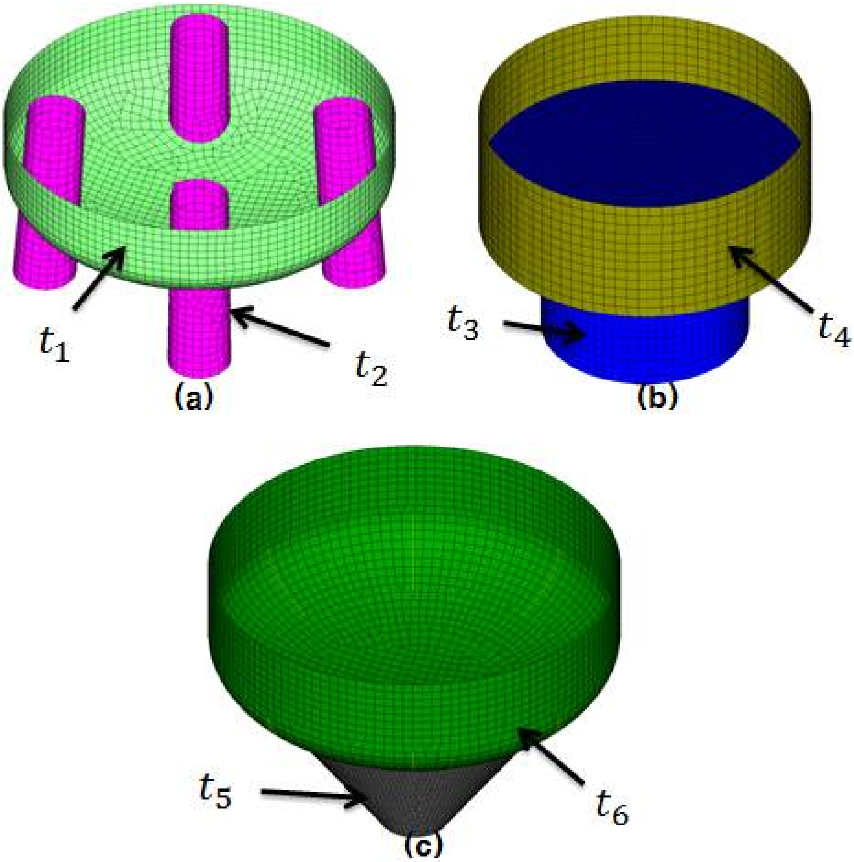

Figure 10. Finite element model of local area. (a) 1st stage, (b) fairing (c) 2nd stage.

In this example, load condition during fligh phase is considered. There are aerodynamic load, aerodynamic heating and acceleration force. To assume the flight environment, the launching history of the KSLV-I is referred. Selection of a total of 9 cases, depending on time was calculated. Pressure distribution and temperature distribution are predicted by aerodynamic analysis and thermal analysis using CFD with [22], [23] and [24]. Acceleration force is calculated by slope of velocity from launching history. At the time of 140 seconds after launch which is most high load case among nine cases, the altitude is 67 km, mach number is 6.25, acceleration is 44.325 m/s^2. Th load of this cases was carried out to optimized the launch vehicle FE model.

4.2. Optimization Results

Table 8 and 11 show the optimization results of the launch vehicle FE model. The optimized mass using the SPSO algorithm is 7550 kg. The optimized mass using the global-local PSO algorithm is 7080 kg. Since the initial mass si 10260 kg, it can be seen that the global-local PSO found a mass which lower than the SPSO. Figure 11 shows the mass optimization history. As the result of the stiffened shell box, it can be seen that a mass is highly dropped by the global-local PSO in early step. Total elapsed time using the global-local PSO is much shorten than the SPSO whereas the elapsed time per particle is not.

Table 8. Optimized design variables of launch vehicle FE model.

	Design Variable (Thickness)	SPSO	Global-Local PSO
Local Variables	t_1	1.000E-03	1.000E-03
	t_2	2.000E-03	2.000E-03
	t_3	2.888E-03	2.000E-03
	t_4	1.468E-03	1.000E-03
	t_5	1.613E-03	1.000E-03
	t_6	4.570E-03	2.000E-03
Global Variables	x_1	1.891E-03	1.978E-03
	x_2	2.173E-03	2.050E-03
	x_3	2.197E-03	4.180E-03
	x_4	3.265E-03	3.529E-03
	x_5	3.485E-03	3.528E-03
	x_6	3.572E-03	2.416E-03

Table 9. Optimization results of launch vehicle FE model.

	PSO	Global-Local PSO
Optimized mass	7550	7080
Number of step for optimal position	161	71

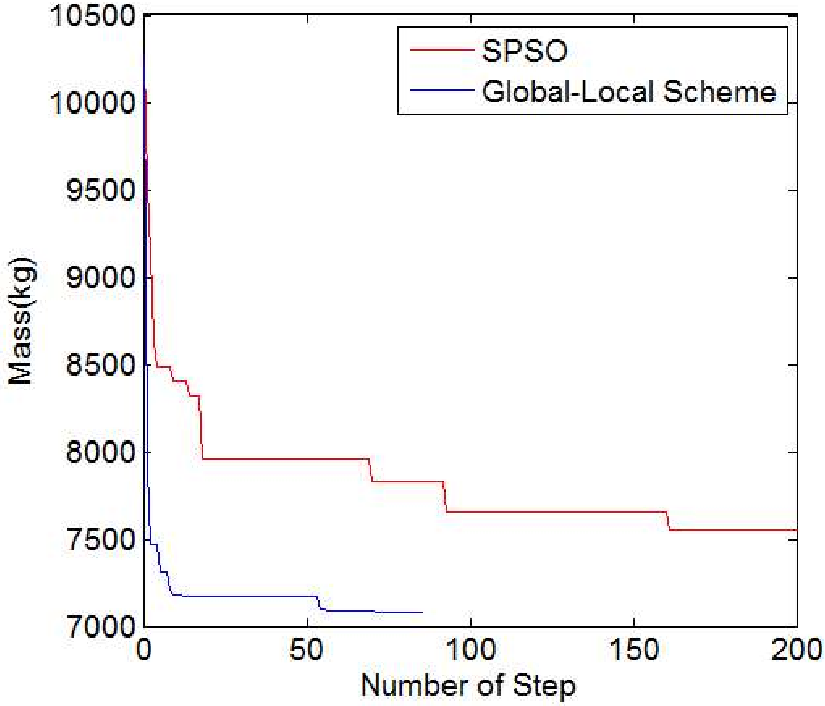

Figure 11. Mass optimization history of launch vehicle FE model.

5. Conclusion

In this study, the global-local scheme was applied into the PSO algorithm for the structural design optimization. And structural design optimizations were performed for stiffened shell box and launch vehicle models. All analysis works were based on DIAMOND/IPSAP.

The conventional structural optimization problem was separated to the global optimization problem and the local optimization problem using the global-local scheme. The global-local PSO module for the global-local PSO algorithm, the PSO algorithm using the global-local scheme, was developed to solve the global-local optimization problem. Failure index and critical buckling load coefficient were consider for constraints. To linear static and static buckling analysis works, IPSAP was used to solve the problem faster and to use the memory effectively. Pre/post processors were developed in order to define the structural optimization problem and monitor the progress.

The stiffened shell box was optimized for mass, with considering thickness as design variable. In this example, the local area was a panel surrounded by the stiffener. Since load path does not change significantly even if the local optimization is performed, stiffened structure is suitable to perform the local buckling analysis because the buckling mode is present in the local area surrounded by the stiffener. Critical buckling load coefficient was used to constraint for the local optimization. Total elapsed time for searching the global optimal position using the global-local PSO algorithm was shorten than the SPSO algorithm even though the elapsed time per each particle was longer. It was confirmed the benefits of dividing the design area by the global and the local. The last example was perform for mass optimization of launch vehicle. The local was divided by three. Each local area has a two design variables. As a result of performing the optimization, mass reduction of 26% by the SPSO algorithm and mass reduction of 30% by the global-local PSO algorithm were output. Total elapsed time for optimal position using the global-local PSO algorithm was 33% faster than the SPSO algorithm.

This study has the significance that it is constructed computational environment for the structural design optimization using the global-local PSO algorithm. By develope pre/post processor for easy handling the structure optimization problem, computational environment is constructed for the optimal design of various structures. Since it provide the reasonable and good solutions determining the initial design, cost and time consumption to develop the aerospace system structures are able to decrease effectively.

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초 록

항공기, 발사체 그리고 인공위성과 같은 항공우주 시스템의 구조물은 비행 중에 구조물이 안정적으로 유지될 수 있도록 설계하고 최적화하는 것이 중요하다. 항공우주 시스템의 구조물들은 대체로 보강재와 판으로 구성되어 있다. 판은 보강재로 둘러 쌓여있기 때문에, 좌굴 해석과 같은 특정 해석에서 국부적인 특성을 보인다. 판과 같이 보강재로 인해서 하중경로가 극적으로 변하지 않는 경우에는 국부 좌굴 해석을 수행하기에 적합하다. 좌굴 해석은 구조 설계 최적화에서 많은 계산 시간을 필요로 한다. 그렇기 때문에 구조 설계 최적화를 효과적으로 수행하기 위해서 최적화 문제를 전역 최적화 문제와 국부 최적화 문제로 분리하는 것이 중요하다.

본 연구에서는 항공우주 시스템의 구조물을 효과적으로 최적화하기 위해서 전역-국부 구조를 최적화 문제에 적용하여 전역-국부 최적화 문제를 구성하였다. 최적화 알고리즘으로는 구조 설계 최적화에 유용한 입자군집 최적화 알고리즘을 사용하였다. 전역-국부 구조를 입자군집 최적화 알고리즘에 적용하기 위해서 최적화 모듈을 개발하였다. 이 모듈을 전역-국부 PSO 모듈이라 칭한다. 이 모듈은 세가지 인터페이스 대화창으로 구성되어 있다. 인터페이스 대화창은 최적화 문제의 셋팅, 최적화 환경변수 설정 그리고 최적화 수행 및 모니터링이다. 위의 모든 기능들은 서울대학교 항공우주구조연구실에서 개발 중인 DIAMOND/IPSAP에 구현하였다.

전역-국부 PSO 모듈을 사용한 입자군집 최적화 알고리즘의 성능을 평가하기 위해서 보강된 쉘 박스와 발사체 모델을 만들고 최적화를 수행하였다. 보강된 쉘 박스의 경우에, 국부 정적 좌굴 해석을 수행하였다. 임계 좌굴 하중을 국부 최적화의 제약조건으로 사용하였다. 마지막 예제는 발사체의 최적화를 수행하였다.

본 연구의 중요성은 전역 영역과 국부 영역으로 나눌 수 있는 구조물의 구조 설계 최적화에 적합한 전역-국부 PSO 알고리즘을 사

용해서 보다 빠른 최적화를 가능하게 했다는 점이다. 또한 고성능 해석기와 전/후처리 툴을 포함한 컴퓨터 이용 공학을 사용함으로써 항공기 윙박스, 발사체 등과 같은 항공우주 시스템 구조물의 최적화에 소요되는 시간과 노력을 효율적으로 감소시키는 효과를 볼 수있었다.

Keywords : 구조 설계 최적화, 입자군집 최적화, 국부화, 발사체, 보강된 쉘

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