Novell Methods for Engineering Optimization

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Recently, various optimization algorithms have been successfully applied in a number of engineering disciplines. However, for a large number of design variables and objective functions that need to be extremized simultaneously, traditional approaches become progressively too costly. To reduce the computing time significantly, we are developed a set of unique algorithms for complex technical systems optimization. These optimization algorithms that we propose are modified versions of an indirect method of optimization based upon self-organization (IOSO).

Parallel optimization algorithm

One of the possibilities to reduce the elapsed (clock) computing time for complex optimization problems is to use multiple processors in parallel. The reduction of the clock time can then be achieved through reduction of mathematical model solution time by means of parallel computations "inside" the model, as well as by adaptive organization of the optimization process for parallel computations. The first approach supposes the use (or development) of mathematical analysis models suitable for computations using parallel processors. The latter makes it necessary to develop the corresponding optimization methods. The scheme of the developed optimization algorithm is shown in Fig. 1.

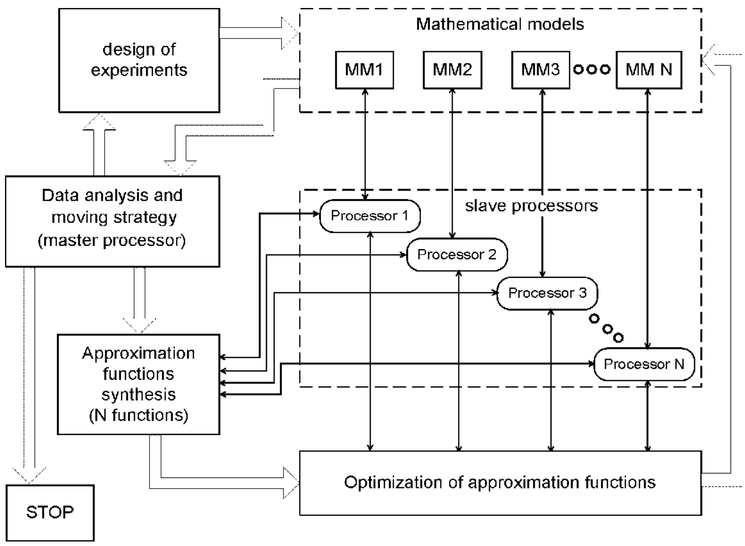

Fig. 1. IOSO parallel algorithm scheme.

Example of parallel optimization algorithm usage

The design variable set defines the geometry of the turbine blade coolant passage including blade wall thickness distribution and blade internal strut configurations. A parallel three-dimensional thermoelasticity finite element analysis (FEA) code from the ADVENTURE project at the University of Tokyo was used to perform automatic thermal and stress analysis of different blade configurations. The same code can also analyze nonlinear (large/plastic deformation) thermoelasticity problems for complex 3-D configurations. Convective boundary

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conditions were used for the heat conduction analysis to approximate the presence of internal and external fluid flow. The objective of the optimization was to make stresses throughout the blade as uniform as possible. Constraints were that the maximum temperature and stress at any point in the blade were less than the maximum allowable values.

The optimization run was performed on a commodity component based PC cluster with 54 Pentium II 400 MHz processors. A total of 12 analyses were performed concurrently where each parallel thermoelastic FEM analysis used 4 processors. A converged result was found by the IOSO optimizer in 70 iterations after consuming approximately 12 hours of total computer time.

The temperature distributions for the initial and optimal designs are shown in Fig. 2, 3.

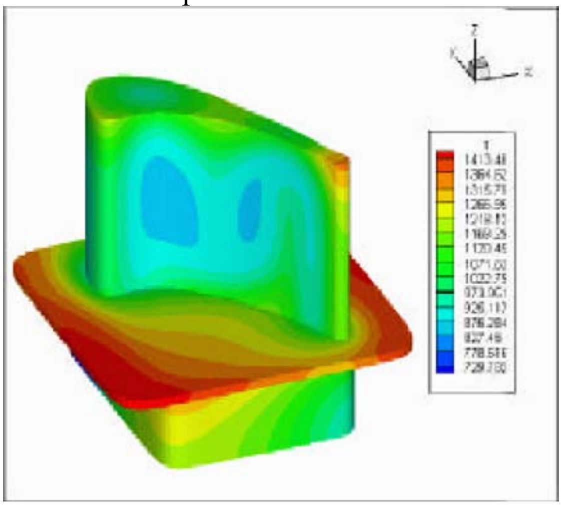

Fig. 2. Temperature contours for initial design.

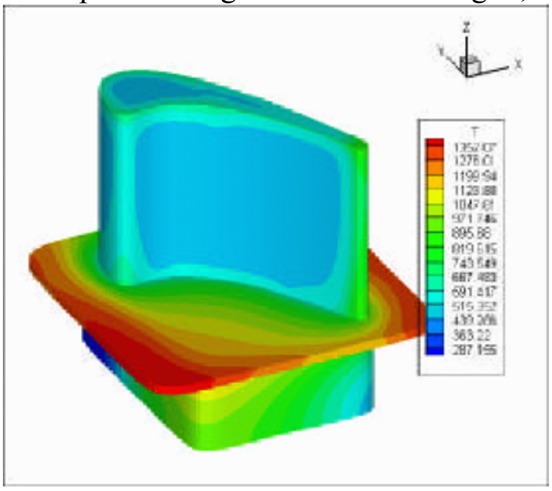

Fig. 3. Temperature contours for optimized design.

Multilevel optimization algorithm

The typical situation when solving a real life multi-objective Multi-disciplinary Design Optimization (MDO) problem is that a designer has several tools available for performing the analysis. These analysis tools differ according to their levels of complexity and accuracy. The low-fidelity analysis models allow us to carry out optimization, but the validity of the obtained results can be rather low. The high-fidelity analysis tools can be the detailed non-linear mathematical models or even the experimental samples of the system or its components. However, the exclusive use of such high-fidelity tools in multi-objective MDO is associated with significant time expenditures.

We propose to use a combination of various analysis tools with different levels of sophistication in the multi-objective MDO of complex systems. The proposed approach is intended to minimize the use of the time consuming highly sophisticated analysis tools. The simplified scheme of such procedure is depicted in Figure 4.

Example of multilevel optimization strategy usage

This problem consisted of a search for multi-stage axial compressor optimum design parameters to improve its efficiency at two operating modes, namely, at the design-point operating mode, corresponding to maximum thrust of the GTE, and at the cruise operating mode, corresponding to minimum specific fuel consumption. As these objectives could be mutually contradictory, the problem was in determining the set of Pareto-optimal design parameter vectors. Let us consider a specific example for a four-stage axial compressor.

The variable parameters: inlet and exit flow angles of 7 blade rows at 3 spanwise locations each.

The objectives: maximize GTE efficiency at two operating modes.

The constraints: stall margins at two operating modes; objective function computability.

High fidelity analysis tool: quasi-3D rotor-stator aerodynamic flow-field analysis with viscosity effect.

Low fidelity analysis tool: 2D axisymmetric throughflow analysis.

During the first iteration, 10 Pareto-optimal vectors of the design parameters were found using the low fidelity analysis model. After verifying this set with the use of high fidelity model it appeared that 2 of the vectors were out of computability region (that is, the high fidelity model could not compute the objective functions and constrained parameters). Another 8 vectors did not satisfy the stall margin constraints. Thus, the first iteration did not provide any admissible solutions. Meanwhile, the obtained results were used for the identification (improvement) of the low fidelity model, and 3 more iterations were conducted. The results of Pareto-optimal solutions set transformations are presented in Fig. 5. Notice the relatively uniform distribution of the Pareto-optimized solutions along the Pareto front. Also, notice that the total number of high fidelity (expensive) analysis was only 32 which is fewer than the number of design variables which was 42!

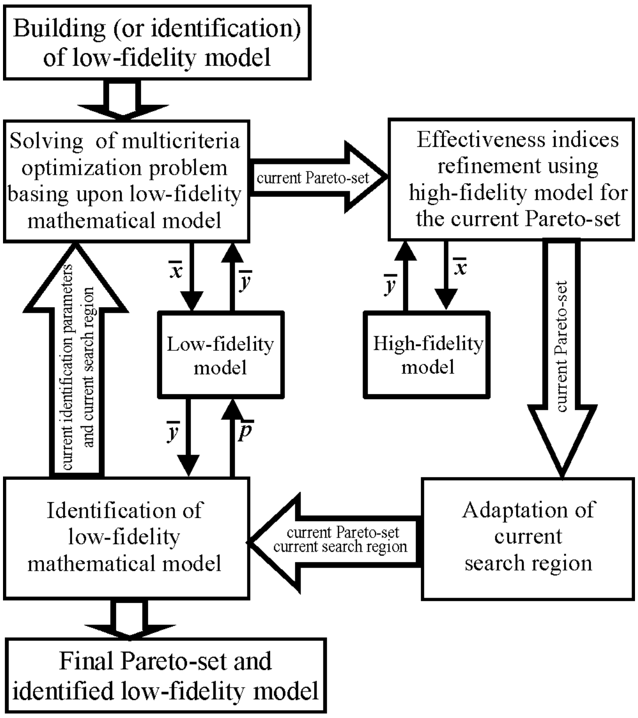

Fig.4. The simplified scheme of multi-level optimization procedure.

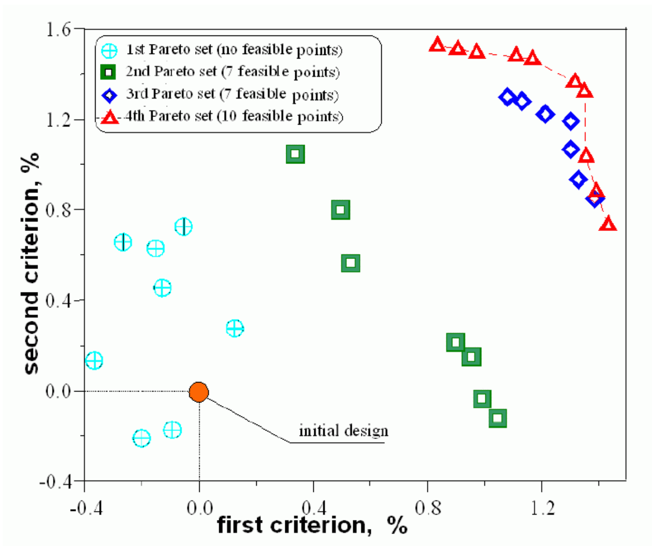

Fig. 5. The results of Pareto set transformation.