An Intelligent Decomposition Approach for Efficient Design of Non-Hierarchic Systems

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Abstract

The design process associated with large engineering systems requires an initial decomposition of the complex system into subsystem modules which are coupled through transference of output data. The implementation of such a decomposition approach assumes the ability exists to determine what subsystems and interactions exist and what order of execution will be imposed during the analysis process. Unfortunately, this is quite often an extremely complex task which may be beyond human ability to efficiently achieve. Further, in optimizing such a coupled system, it is essential to be able to determine which interactions figure prominently enough to significantly affect the accuracy of the optimal solution. The ability to determine 'weak' versus 'strong' coupling strengths would aid the designer in deciding which couplings could be permanently removed from consideration or which could be temporarily suspended so as to achieve computational savings with minimal loss in solution accuracy. An approach that uses normalized sensitivities to quantify coupling strengths is presented. The approach is applied to a coupled system composed of analytical equations for verification purposes.

Introduction

Several decomposition approaches have recently been demonstrated to be applicable for performing optimization in non-hierarchic engineering systems [1-3]. However, substantial room for improvement and advancement on these methods exist. One possibility of improvement lies in the incorporation of a knowledge-based system to assist in the determination of subsystem interactions, participating disciplines, and order of execution of the decomposed subsystems. An intelligent decomposition approach, based on Rogers' DeMAID (*Design Manager's Aide for Intelligent Decomposition*) [4], is presented which incorporates artificial intelligence and data management techniques in such a manner to achieve an efficient integrated design capability. This approach has applications in any highly coupled environment in which the input and output information associated with each participating analysis can be quantified. A human interaction capability allows for inclusion of problem-dependent heuristics and designer experience. A system sensitivity analysis provides information corresponding to analysis coupling strengths, thus permitting intelligent choice of participating analyses, according to their impact on the overall system solution. The identification of 'weak' versus 'strong' couplings is made based on normalized sensitivities associated with the Global Sensitivity Equation (GSE) Method [1].

Intelligent Decomposition Approach

A non-hierarchic system is one in which the interactions among subsystem modules cannot be distributed in a traditional top down hierarchy. Non-hierarchic systems are characterized by subsystem analyses coupled through transference of output data, creating a complex network. The solution for such systems begins with a decomposition approach which effectively breaks large intractable problems into smaller subproblems, while maintaining the couplings among them. Such an approach is particularly amenable to the design organization setting in which engineers work in groups divided by task and disciplinary specializations, thus taking advantage of the division of labor, while permitting the concurrency of operations. A representative non-hierarchic system is shown in Figure 1, where three subsystems interact.

Each participating discipline or analysis in the complex system can be modeled as a subsystem for which inputs and outputs are identifiable. The complex system of Figure 1 can be represented as a square design structure matrix [5], wherein each of the subsystems is denoted as a box along the diagonal. The influence of one subsystem upon another depends on the location of the interface between the two subsystems, with feedforwards in the upper diagonal and feedbacks in the lower. A module with a feedback requires information before it is actually available, thus necessitating initial guesses with an associated iterative framework to achieve convergence. Therefore, it is beneficial to minimize the number of feedbacks by reordering the modules along the diagonal. Applying DeMAID to the analytical system of coupled subroutines associated with the system of Figure 1 results in the ordering shown in Figure 2. Each subroutine is denoted by a reference to its subsystem and to the output associated with it. Modules pertaining to the design variables are included to make the identification of subsystem inputs easier.

Normalized Sensitivities for Determining Coupling Strengths

In this work, coupling strengths are defined in terms of local normalized sensitivities. These local sensitivities are used in the GSE to obtain total behavioral response derivatives with respect to the design variables. The local derivatives are thus already available to the designer. The GSE approach involves defining total derivatives of the output response quantities in terms of local sensitivities of the outputs of each subsystem with respect to that subsystem's inputs. For example, for the coupled system of Figure 3 in which two subsystems, A and B, interact through transference of output information, local sensitivities would be $\partial Y_A/\partial Y_B$, $\partial Y_A/\partial X_A$, $\partial Y_B/\partial Y_A$, and $\partial Y_B/\partial X_B$. Since the components of the output response vector Y and the design variable vector X are of varying magnitudes, a normalization scheme [6] is implemented to ensure that the conditioning of the system is such that accuracy of the solution is not threatened. The local subsystem sensitivity information can be used to quantify the strengths of participating analysis couplings. Such information can then be used to provide the basis for developing heuristics that will indicate which couplings are "weak" enough to be temporarily or permanently suspended. Obviously, in a complex problem involving computationally expensive analyses which must be performed within an iterative framework (such as structural finite element analyses) the ability to reduce the system complexity without sacrificing solution accuracy is of utmost importance. The question then becomes, "to what extent may solution accuracy be compromised in order to achieve solution efficiency?"

Application to Analytical System

Figure 4 graphically identifies the "largest" and "smallest" normalized sensitivities associated with the couplings for the analytical system and aids in the determination of which couplings to remove or temporarily suspend during the optimization process. From Figure 4 it can be seen that the smallest absolute value of the normalized sensitivities is associated with module number 16, which corresponds to output z_3. Both the feedbacks associated with z_3 are considered to be small in comparison with the system's other normalized sensitivities. Therefore, it can be hypothesized that z_3 could be either removed from the analysis altogether or suspended for some number of cycles during the optimization, which turns out to be the case. When the analysis associated with z_3 is removed altogether, the percent differences in the system solution is uniformly less than 1%. Figure 4 also demonstrates that the output z_2 (module 10) has small normalized sensitivities in comparison with the other output analyses. Two of its four interactions are considered very small while two others are in a medium range. Therefore, one might hypothesize that removal of z_2 would result in percent differences that are slightly higher than those associated with the removal of z_3, which Figure 5 demonstrates. The largest percent difference in subroutine solutions was for w_2 in which a 7.153% difference was calculated, with the next associated with y_1, while all other differences were less than 1%. The final possibility for simplifying the system is with respect to the subroutine for z_1 (module 15). With only one of its three feedbacks considered weak, however, one would not expect to obtain a high level of system solution accuracy with its elimination. Furthermore, one can see that z_1 is a feedback into y_3 and w_1. Both of these modules have large normalized sensitivities associated with their outputs. This increases the chances of large errors associated with the remaining analyses if z_1 were to be eliminated. Figure 6 demonstrates that an almost 21% difference in the y_1 solution results with elimination of z_1. The heuristics previously developed regarding removal of modules was incorporated into an analytical optimization problem to determine the potential effects on the optimal solution. Figure 7 shows the convergence history associated with the elimination of z_3 from consideration as a changing output. It demonstrates that the difference in optimal solutions is minimal, with the convergence history paralleling the original path.

Concluding Remarks

Large coupled systems are not amenable to traditional top-down hierarchies and require a framework which permits the exploitation of discipline-dependent technologies and computer facilities that correspond to groups within a design organization setting. An intelligent decomposition approach was presented which uses technologies of artificial intelligence and concurrent information management to facilitate use in a design organization setting. A system sensitivity analysis was introduced which provides information corresponding to analysis coupling strengths, thus permitting intelligent choice of participating analyses in the optimization process. The approach was applied to a coupled system composed of analytical equations for verification purposes. Results obtained demonstrated that elimination and/or suspension of couplings can be achieved with minimal loss of solution accuracy. Numerous areas for future work exist. Two of these include application of the approach to a physical problem and incorporation of an embedded knowledge-based system to control the decision-making process regarding participating disciplines or subsystems.

References

1. Sobieszczanski-Sobieski, J., "On the Sensitivity of Complex, Internally Coupled Systems", AIAA Journal, Volume 28, No. 2, pp. 153-160.

2. Sobieszczanski-Sobieski, J., "Optimization by Decomposition: A Step from Hierarchic to Non-Hierarchic Systems", Recent Advances in Multidisciplinary Analysis and Optimization, NASA CP-3031, 1988.

3. Bloebaum, C.L., Hajela, P., and Sobieszczanski-Sobieski, J., "Non-Hierarchic System Decomposition in Structural Optimization", 3rd Air Force/NASA Symposium on Recent Advances in Multidisciplinary Analysis and Optimization, San Francisco, California, September 1990.

4. Rogers, J.L., "A Knowledge-Based Tool for Multilevel Decomposition of a Complex Design Problem", NASA TP 2903, May 1989.

5. Steward, D.V., System Analysis and Management (Petrocelli Books, 1981, New York, N.Y.).

6. Hajela P., Bloebaum, C.L., and Sobieszczanski-Sobieski, J., "Application of Global Sensitivity Equations in Multidisciplinary Aircraft Synthesis", Journal of Aircraft, Volume 27, No. 12, 1990, pp. 1002-1010.
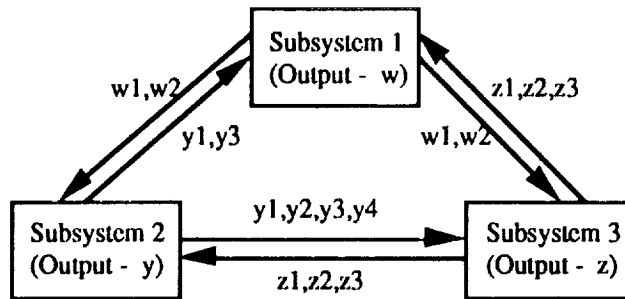
Figure 1. Non-hierarchic analytical system providing testbed for coupling strength comparisons.
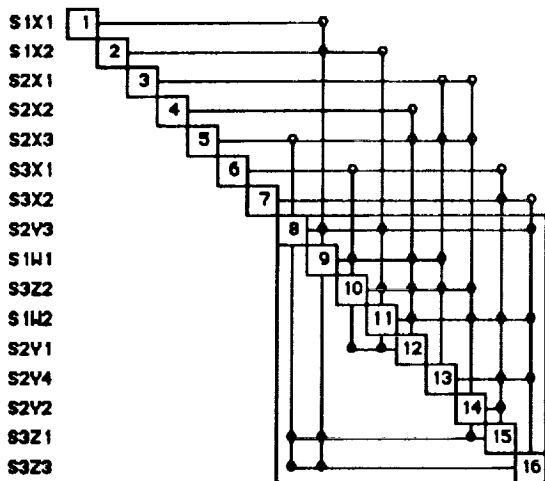

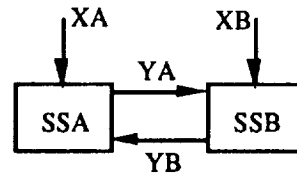Figure 2. Subroutine modules with minimized feedbacks.

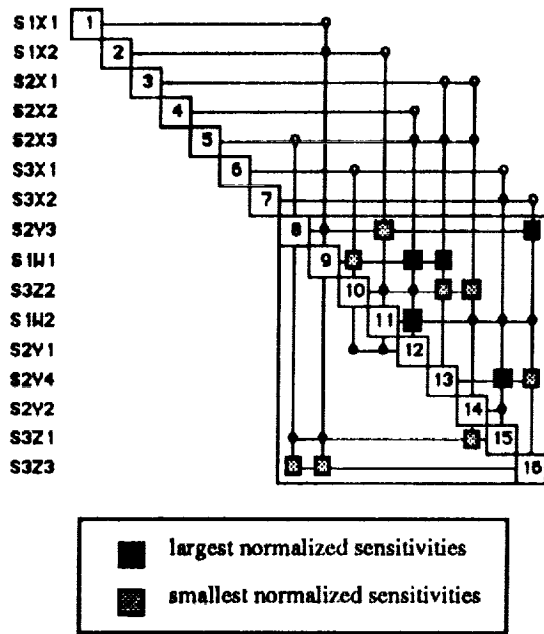Figure 3. Interactions in two subsystem non-hierarchic environment.

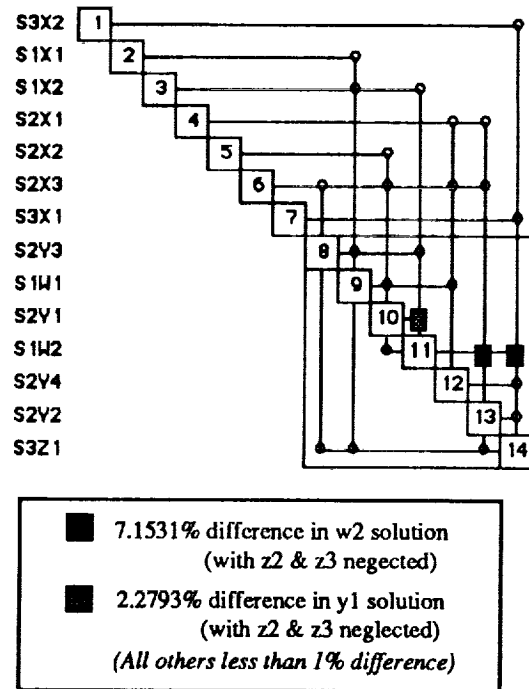Figure 4. Comparison of normalized sensitivities for coupled system.

7.1531% difference in w2 solution
(with z2 & z3 negected)

2.2793% difference in y1 solution
(with z2 & z3 neglected)
(All others less than 1% difference)

Figure 5. Differences in w2 and y1 solutions with removal of z2 and z3.

20.5826% difference in w2 solution (with z1 negected)
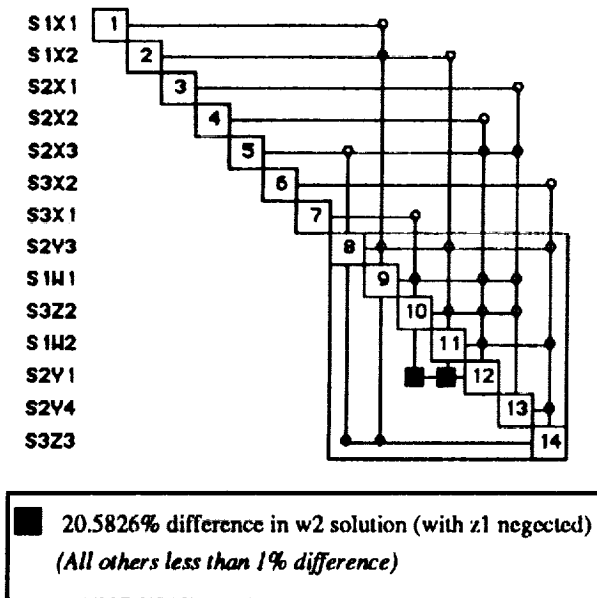*(All others less than 1% difference)*

Figure 6. Percent differences in w2 solution with removal of z1 module.
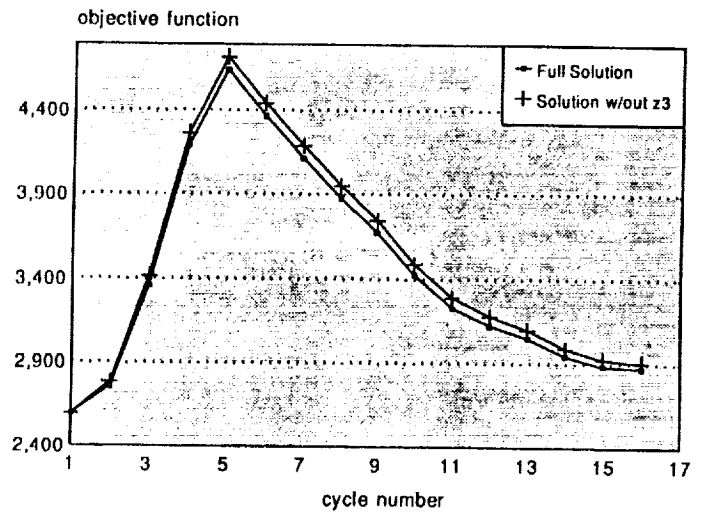

Figure 7. Optimization convergence history for full and modified problem.

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