Separating Engineering Design Optimization Problems

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Motivation: Reducing the Cost of Optimization

Design optimization determines values for design variables such that an objective function is optimized while performance and other constraints are satisfied. The use of design optimization in engineering design continues to increase, driven by more powerful software packages and the formulation of new design optimization problems motivated by the decision-based design framework.

The difficulty of solving large scale optimization problems and multidisciplinary optimization (MDO) problems, especially in the area of aerospace systems, has motivated various decomposition approaches.

In general, these decomposition approaches require multiple iterations to converge to a feasible, optimal solution, which can require extensive computational effort in some cases.

Approach: Separation, not Decomposition

Our approach, which we call ***separation***, replaces a large design optimization problem with a sequence of subproblems, solves each subproblem once, and produces a feasible solution without iterative cycles.

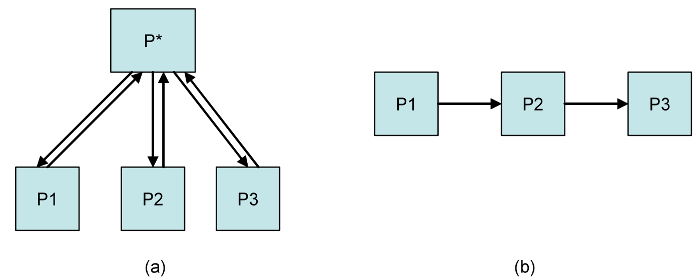

Figure 1. (a) A typical decomposition scheme has multiple first-level subproblems (P1, P2, P3) that receive inputs from a second-level problem (P*), which also coordinates their solutions. (b) Separation yields a sequence of subproblems. Solving one provides the input to the next.

Application: Motor Design

The optimization model for the universal electric motor problem includes nine design variables, twenty-three intermediate engineering attribute calculations, six constraints, and four customer attributes. We created four separations in order to find the most profitable solution.

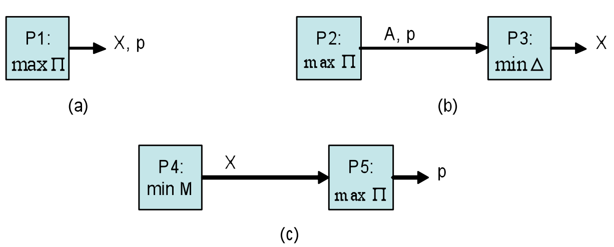

Figure 2. Decision networks for the motor design problem. (a) The integrated design optimization problem S1 maximizes profit. S2 includes power and torque constraints. (b) Separation S3 finds the most profitable attribute values and price and then sets the design variables to satisfy them. (c) Separation S4 finds the best design and then sets the price to maximize profit.

Results and Conclusions

Separation	Scenario	Average Number of Function Evaluations	Profit ($)	Deviation from S2 (%)
S1		579	4,000,518	0.29
S2		65037	3,989,027	-
S3	CS1, $\overline{C}$ = 1.5	181	3,317,975	16.82
	CS1, $\overline{C}$ = 2	168	3,580,730	10.24
	CS2, $\overline{C}$ = 1.5	306	3,935,065	1.35
	CS2, $\overline{C}$ = 2	306	3,935,521	1.34
S4	Max Efficiency	312	3,040,692	23.77
	Min Material Cost	554	3,379,202	15.29
	Min Mass	834	3,379,029	15.29

The motor design results demonstrate the tradeoffs between different separations. The separations that found the best solutions took the most effort. The right separation can find a very good solution with less effort; poor separations find low-quality solutions.

Ongoing work is studying the conditions under which a separation yields an optimal solution. Ultimately, the mathematical analysis of separations will indicate when a separation is a reasonable way to design a product or system, provided that the subproblems are appropriately formulated.