Optimal Partitioning and Coordination Decisions in Decomposition-based Design Optimization

by

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to Ellie, Jonathan, Brian, and Michael

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$\circ$	Hadamard product
β	method of multipliers penalty function multiplier parameter
γ	method of multipliers penalty function threshold parameter
$\boldsymbol{\pi}$	optimal value function for all ALC subproblems
$\boldsymbol{\pi}_i$	optimal value function for ALC subproblem i
ϕ	augmented Lagrangian penalty function
$\boldsymbol{\theta}_{ij}$	consistency constraint vector between subproblems i and j
$\boldsymbol{\Theta}$	consistency constraint matrix
υ_i	number of subproblems linked by the i-th external linking variable
ζ_{ij}	data persistence metric
$\mathbf{a}$	vector of all analysis functions for a system
$\mathbf{a}_i$	i-th analysis function
$\hat{\mathbf{a}}_i$	analysis function vector that corresponds to $\hat{\mathbf{y}}_i$
$\mathbf{A}$	reduced adjacency matrix
$\bar{\mathbf{A}}$	subproblem graph adjacency matrix
B_m	m-th Bell number
B_{allow}	maximum allowed subproblem size imbalance
C	coordination decision problem
$\mathbf{c}_i$	ATC consistency constraint for subproblem i
$\bar{\mathbf{c}}_{ij}$	ALC external consistency constraint between subproblems i and j
$\mathbf{CM}$	correlation matrix
CS	coordination problem size
$\mathscr{C}$	set of consistency constraint graphs for all external shared design variables
$\mathbf{DSM}$	design structure matrix
f	design objective function
$\mathbf{FDT}$	functional dependence matrix
$\mathbf{g}$	inequality design constraint vector
$\mathbf{g}_i$	inequality design constraint vector for subproblem i
G_c	consistency constraint graph
$\mathbf{h}$	equality design constraint vector

$\mathbf{h}_{\text{aux}}$	auxiliary equality constraint vector
$\mathbf{h}_i$	equality design constraint vector for subproblem i
m	number of analysis functions in a system
n	number of design variables in a system
n^s	stage depth
n_{ai}	number of analysis functions in subproblem i
n_{P_i}	number of subproblems that share i-th external shared variable
$n_{x_\ell i}$	number of local design variables in subproblem i
$n_{\bar{x}_s}$	number of external shared design variables
$n_{\bar{x}_s ci}$	number of consistency constraints for external shared variables in subproblem i
$n_{\bar{x}_s i}$	number of external shared design variables in subproblem i
$n_{\bar{x}_s m}$	approximate number of external shared design variable consistency constraints
$n_{\bar{y}_f}$	number of external feedback coupling variables
$n_{\bar{y}_f i}$	number of external feedback coupling variables for subproblem i
n_{yi}	number of internal coupling variables in subproblem i
$n_{\bar{y}i}$	number of consistency constraints for external coupling variables in subproblem i
$n_{\bar{y}Ii}$	number external input coupling variables for subproblem i
n^z	number of subproblems linked by linking variable z
n_z	number of external linking variables
N	number of subproblems
$\mathbf{o}$	analysis function sequence vector
$\mathbf{o}_s$	subproblem sequence vector
$\hat{\mathbf{o}}$	genotype analysis function sequence vector
$\mathbf{p}$	partition vector
$\hat{\mathbf{p}}$	genotype partition vector
p_{ij}	path from vertex i to vertex j
P	partitioning decision problem
P/C	partitioning and coordination
P_i	subproblem i
RM	relation matrix
$\mathbf{r}_{ij}$	ATC responses from subproblem j to subproblem i
$\mathbf{S}_{ij}$	$\mathbf{a}_i$ selection matrix for $\mathbf{y}_{ij}$
SM	structural matrix
SS_i	size of subproblem i
$SS_{\max}$	maximum subproblem size
$\bar{S}S_{\max}$	average maximum subproblem size for each stage

$\mathbf{t}_{ij}$	ATC targets from subproblem j to subproblem i
$\mathbf{v}$	linear penalty weights
$\mathbf{v}_i$	linear penalty weights for subproblem i
$\mathbf{w}$	quadratic penalty weights
$\mathbf{w}_i$	quadratic penalty weights for subproblem i
$\mathbf{x}$	design variable vector
$\mathbf{x}^*$	optimal design variable vector
$\mathbf{x}_i$	design variables input to $\mathbf{a}_i$
$\mathbf{x}_{\ell i}$	design variables local to $\mathbf{a}_i$
$\mathbf{x}_{si}$	shared design variables associated with $\mathbf{a}_i$
$\bar{\mathbf{x}}_i$	design variables input to subproblem i
$\bar{\mathbf{x}}_i^{(j)}$	copy of $\bar{\mathbf{x}}_i$ local to subproblem i
$\bar{\mathbf{x}}_{\ell i}$	design variables local to subproblem i
$\bar{\mathbf{x}}_{si}$	external shared design variables associated with subproblem i
$\bar{\mathbf{x}}_s^{ij}$	design variable copies shared between subproblems i and j, local to subproblem i
$\bar{\mathbf{x}}_{s\mathscr{C}_i}$	external shared design variables associated child elements of subproblem i
$\hat{\mathbf{x}}_i$	internal shared design variables for subproblem i
$\mathscr{X}$	set of feasible design points
$\mathbf{y}$	coupling variable vector
$\mathbf{y}_p$	consistent coupling variable vector
$\mathbf{y}_{ij}$	coupling variable vector form $\mathbf{a}_j$ to $\mathbf{a}_i$
$\bar{\mathbf{y}}_i$	external coupling variables input to subproblem i
$\bar{\mathbf{y}}_{ij}$	coupling variable vector from $\mathbf{P}_j$ to $\mathbf{P}_i$
$\bar{\mathbf{y}}_{\mathscr{C}_i}$	external coupling variables associated child elements of subproblem i
$\hat{\mathbf{y}}_i$	internal coupling variable vector for subproblem i
$\mathbf{z}_i$	vector of linking variables associated with $\mathbf{a}_i$
$\bar{\mathbf{z}}$	vector of all external linking variables
$\tilde{\mathbf{z}}$	vector of all copies of linking variable z
$\bar{\mathbf{z}}_i$	vector of external linking variables associated with subproblem i
$\bar{\mathbf{z}}_{ij}$	external linking variables between subproblems i and j
$\bar{\mathbf{z}}_{\bullet i}$	subproblem i output vector

Abstract

Successful design of complex modern products is a grand challenge for design organizations. The task is becoming increasingly important due to economic competition and concern over safety, reliability, and energy efficiency. Automotive and aerospace products, for example, are composed of numerous interdependent subsystems with a level of complexity that surpasses the capability of a single design group. A common approach is to partition complex design problems into smaller, more manageable design tasks that can be solved by individual design groups. Effective management of interdependency between these subproblems is critical, and a successful design process ultimately must meet the needs of the overall system. Decomposition-based design optimization techniques provide a mathematical foundation and computational tools for developing such design processes. Two tasks must be performed so that decomposition-based design optimization can be used to solve a system design problem: partitioning the system into subproblems, and determining a coordination method for guiding subproblem solutions toward the optimal system design. System partition and coordination strategy have a profound impact on the design process. The effect of partitioning and coordination decisions have been studied independently, while interaction between these decisions has been largely ignored. It is shown here that these two sets of decisions do interact: how a system is partitioned influences appropriate coordination decisions, and vice versa. Consequently, addressing partitioning and coordination decisions simultaneously leads to improved system design processes. The combined partitioning and coordination decision problem is a difficult combinatorial problem. An evolutionary algorithm that solves this decision problem effectively is presented. The set of all partitioning and coordination options for a specific formulation framework, augmented Lagrangian coordination (ALC), is derived, and a method for choosing Pareto-optimal solutions from amongst these options is described. Concepts and techniques are demonstrated using several engineering example problems. A detailed model for an electric vehicle design problem is presented that considers three vehicle systems: powertrain, chassis, and structure, and partitioning and coordination decisions for this problem are analyzed.