

Analytical Target Cascading Optimization of an Electric Vehicle Powertrain System

by

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ABSTRACT

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In optimizing large-scale, complex design systems, decomposition-based methods such as analytical target cascading (ATC) are frequently used to solve these problems. This decomposition introduces consistency constraints, which contain design variables that are shared between adjacent subproblems and thus link them together. In general, this procedure increases the size of an individual subproblem because it consists of variables that are local to the subproblem as well as variables that couple the adjacent subproblems. When the coupling variables are scalar-valued, the problem size does not increase appreciably, and efficient optimization of the system is still feasible. However, when the coupling variables are vector-valued, as is the case for vector-valued functions (VVF), the problem size can increase dramatically, making optimization of the system inefficient and impractical. Therefore, it is necessary to represent VVF coupling with fewer, surrogate variables that will reduce the problem size while maintaining an acceptable level of fidelity with respect to the original representation.

This study specifically aims at identifying the best VVF reduced representations for maximum and minimum motor torque curves and motor power loss maps produced by an electric vehicle (EV) powertrain system. Three representation techniques, namely radial-basis

function (RBF) neural networks, proper orthogonal decomposition (POD), and hybrid POD/image warping, are investigated, and the first two methods are developed and implemented in an ATC problem formulation. After solving the optimization problems, each VVF reduced representation is assessed in terms of efficiency (design vector dimensionality) and accuracy.

The results from these assessments, as well as from the subsequent optimization problem execution, indicate that neural networks are the best VVF reduced representation for this application as it provides the greatest efficiency with the least approximation error. However, using this technique creates a redundancy between local and coupling variables of the bottom level ATC subproblem. This redundancy implies that the same optimization problem could be solved as an all-in-one (AiO) problem exclusively. Therefore, other VVF reduced representations may be explored. Finally, VVF reduced representation accuracy is more important than its efficiency, since the motor performance information (torque curves and power loss map) significantly impacts the success of the powertrain simulations and hence the optimization solution.

To my family.

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CHAPTER I

INTRODUCTION

In formulating a design optimization problem for complex systems, it is often practical to separate the system into simpler, more manageable subsystem configurations. Decomposition-based optimization algorithms are typically used to solve these design problems, which require that partitions be made between the various subsystem models. Although these design problems are separated into individual subproblems, they are all linked together through consistency constraints that ensure a feasible design solution. These consistency constraints contain design variables that are shared between adjacent subproblems, thus linking the problems together. In general, this procedure increases the size of an individual subproblem because it consists of design variables that are local to the subproblem as well as design variables that couple adjacent subproblems. When these linking variables consist of a finite number of scalars, the problem size does not increase appreciably, and efficient optimization of the system is still feasible. However, in more complex decomposition-based optimization problems, it might be necessary to include linking variables that consist of functions, which are infinite-dimensional variables. This might occur, for example, in a vehicle powertrain system design problem that includes engine performance maps coupled between vehicle and engine design subproblems [2]. In such cases, ensuring consistency between two infinite-dimensional variables is not practically possible due to their high dimensionality. Therefore, discretization is typically applied to these functions,