

# **Management of Functional Data Variables in Decomposition-based Design Optimization**

by

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To my family.

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## **Abstract**

The design of highly-sophisticated systems such as electric vehicle (EV) powertrains often requires knowledge from several engineering disciplines, making it increasingly advantageous to implement formal, decomposition-based optimization strategies to facilitate design decisions. In techniques such as Analytical Target Cascading (ATC), this requires systems to be represented as a hierarchy of interacting subsystems. Such behavior is formally captured through coupling variables which ensure that the subsystem design solutions are consistent, or in agreement, with one another. Many times the coupling variables exchanged among the subsystems are few in number and scalar-valued, which readily enables the use of ATC. However, other times the coupling variables may consist of highly-discretized functional data, such as motor performance curves in EV powertrain design. Because each element within these vector-valued coupling variables is treated as a decision variable in ATC, the design problem can become prohibitively large for optimization. Therefore, it becomes necessary to implement reduced dimension representations of the functional data that enable efficient, practical design optimization while maintaining reasonable accuracy.

Based on a literature review and some recent work, a method known as proper orthogonal decomposition (POD) has emerged as a leading candidate for the reduced representation of coupled, functional data within decomposition-based design optimization. However, the full capability of this method in terms of dimensionality reduction and its impact on decomposition-based optimization strategies has never been explored. This dissertation therefore presents a case study which modifies the tuning parameter within POD from its nominal value associated with high accuracy and low dimensionality reduction to progressively lower values and observes its impact on ATC design solution accuracy and optimization efficiency (runtime). Since the high-fidelity POD representation yielded the best design solution in terms of accuracy and

optimization efficiency, it is concluded that such POD representations are most appropriate for coupled, functional data within ATC. In particular, it is found that high-fidelity POD representations possess good accuracy, reasonable dimensionality reduction, and enhance the functional data consistency among ATC subproblems through additional degrees of freedom (reduced representation variables) compared to low-fidelity POD representations, thus leading to fewer ATC iterations and faster runtimes.

Since consistency measures ultimately impact the convergence of ATC, it is critical to implement an appropriate measure for the coupled, functional data. Because the literature has not revealed any well-established functional data consistency measure for decomposition-based design optimization, this dissertation explores the Accuracy and Validity Algorithm for SIMulation (AVASIM) as an alternative to the “standard” root-mean-square error (RMSE) metric. After demonstrating the flexibility of AVASIM in allocating the importance of local versus global functional data accuracy through a newly-developed generalized formulation, a comparative study is conducted examining the impact of the RMSE, AVASIM, and generalized AVASIM consistency measures on ATC performance. The results indicate that the generalized AVASIM consistency measure is ideal for functional data as it provides a clear indication of consistency and led to the most accurate design solution in the least amount of time in the case study. Specifically, the emphasis on the stable global measure within generalized AVASIM enables it to provide more accurate design solutions using fewer function evaluations.

Finally, it is noted that the reduced representation variables often lack physical meaning, making the determination of their applicability boundary beyond simple bound constraints very difficult. This can lead to ill-behaved analysis and optimization, and so it is necessary to implement an appropriate constraint management technique for the reduced representation variables. Since the existing penalty value-based heuristic is inefficient, this dissertation presents an alternative that augments the former approach with support vector domain description (SVDD) and compares the impact of each technique on ATC performance. The results indicate that the SVDD augmentation is the best constraint management approach since it yielded the best design solution in terms of accuracy and efficiency (including SVDD modeling time). In particular, this method