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Data-Driven Set Based Concurrent Engineering Method for Multidisciplinary Design Optimization

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Abstract

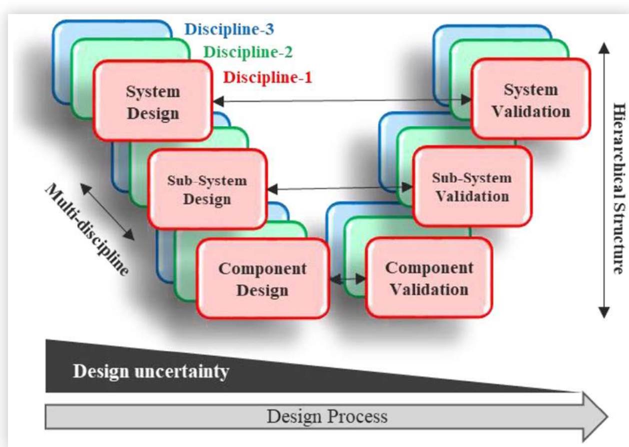
In the development of multi-disciplinary systems, many experts in different discipline fields need to collaborate with each other to identify a feasible design where all multi-disciplinary constraints are satisfied. This paper proposes a novel data-driven set-based concurrent engineering method for multidisciplinary design optimization problems by using machine learning techniques. The proposed set-based concurrent engineering method has two advantages in the concurrent engineering process. The first advantage is the decoupling ability of multidisciplinary design optimization problems. By introducing the probabilistic representation of multidisciplinary constraint functions, feasible regions of each discipline sub-problem can be decoupled by the rule of product. The second advantage is an efficient concurrent study to explore feasible regions. A batch sampling strategy is introduced to find feasible regions based on Bayesian Active Learning (BAL). In the batch BAL, Gaussian Process models of each multidisciplinary constraint are trained. Based on the posterior distributions of trained Gaussian Process models, an acquisition functions that combine Probability of Feasibility and Entropy Search are evaluated. In order to generate new sampling points in and around feasible regions, optimization problems to maximize the acquisition function are solved by assuming that the constraint function is Lipschitz continuous. To show the effectiveness of the proposed method, a practical numerical example of a multi-disciplinary vehicle design problem is demonstrated.

Introduction

With advancement and divergence in vehicle technology, the vehicle design process is becoming more complex. Following future market demands for vehicle technologies such as connectivity, autonomy, sharing, and electronic mobility, increases the complexity of vehicle development. To develop a complex system which has a multi-disciplinary and hierarchical structure, many experts in different discipline fields need to collaborate with each other. In the design process, concurrent engineering (CE) [1,2], also known as simultaneous engineering, is an efficient work methodology emphasizing the parallelization of tasks. Based on the CE, development term and costs can be reduced. In this paper, we propose a data-driven set-based concurrent engineering method which can solve the multidisciplinary design optimization problem concurrently using machine learning.

In order to solve multi-disciplinary system development concurrently, it is required to set appropriate design targets that satisfy all requirements of discipline sub-problems. The development flow of a complex system which has a multi-disciplinary and hierarchical structure can be described by the V-model, which is a way to graphically represent a system development method as shown in Figure 1. In this figure, the

FIGURE 1 V- model of a complex system which has multi-disciplinary and hierarchical structure. The left side depicts the decomposition of multi requirements and the creation of system specifications. The right side represents the integration of parts and their validation. In the top-left stage, it is required to set robust design targets considering design uncertainty.



constraint function is Lipschitz continuous. To show the effectiveness of the proposed method, a practical numerical example of a multi-disciplinary vehicle design problem was demonstrated.

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