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OPTIMIZING CONSTELLATION DESIGN USING KNOWLEDGE-DRIVEN OPTIMIZATION: TAT-C ML'S TRADESPACE SEARCH EXECUTIVE

Abstract

Distributed Spacecraft Missions (DSM) are becoming increasingly popular for Earth observation, because of their capability to get frequent and diverse global measurements, among other reasons. With multiple simultaneous measurements, their science return may increase significantly, but so does their complexity and interdependencies between design variables. This makes designing DSMs more challenging. Hence, there is a growing need to develop tools for designing and evaluating DSM architectures. NASA's Tradespace Analysis Tool for Constellations (TAT-C) is a pre-phase A constellation mission analysis tool which provides a framework to enumerate and evaluate architectures taking into account coverage, cost, and risk considerations. TAT-C's initial version performed full factorial enumeration of the design space. However, with a large number of design variables and their couplings, the design space grows combinatorially, which makes efficiently exploring and optimizing it difficult and time consuming. Therefore, it was proposed that TAT-C (now, TAT-C ML) be augmented with a machine learning module to explore the design space more efficiently. As a result, a new Tradespace Search Executive (TSE) module was developed to reduce the number of function evaluations required to achieve a certain level of performance in the optimization. TSE is based on a multi-objective evolutionary algorithm to guide the search towards promising architectures. It also employs machine learning techniques to further improve the computational efficiency by extracting and incorporating expert knowledge. In addition to the full factorial enumeration strategy that existed in TAT-C's previous version, TSE uses three types of search strategies to explore the tradespace - 1) Multi-Objective Evolutionary Algorithm (MOEA): a population of solutions is evolved using typical domain-independent evolutionary operators, like crossover, to approximate the Pareto optimal set, 2) Adaptive Operator Selection (AOS): extends MOEA by adding a pool of domain-specific operators, and using simple reinforcement learning techniques to learn which operators work best for the problem at hand, and 3) Knowledge-Driven Optimization (KDO): applies data mining techniques during optimization to extract common features in high-quality designs and creates new operators from the most common "good" features found so far. This paper describes the TSE module focusing on the search strategies described above. Emphasis is put on describing how the TSE leverages domain-specific knowledge to guide the search towards optimal architectures, performs exploitation vs exploration decisions and extracts new knowledge using data mining algorithms. A case study is used to illustrate the features of the TSE Module and benchmark the performance of the three search strategies.