TWO AEROSPACE APPLICATIONS OF EVOLUTIONARY ALGORITHMS

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1.1 ABSTRACT

In this paper, we present two applications of genetic algorithms to two problems of interest to aerospace engineers. In the first application, the primary objective is the design, implementation, and analysis of genetic algorithms (GAs) as an input selector for a radial basis function neural network (RBFNN) used to predict aircraft engine performance. The role of the RBFNN is to capture the relationship between measured and unmeasured variables, and ultimately to model engine performance characteristics. Since the engine performance estimation is computationally intensive, the reduction in the number of inputs into the estimator helps to reduce the computational complexity. The second application is the development of a tool for optimizing large-scale air combat tactics using genetic algorithms. The tool's capabilities are demonstrated through the optimization of blue team formation and intercept geometry in a series of tactical engagements. The tactics implementation uses a hierarchical concept that builds large formation tactics from small conventional fighting units, facilitating the design of tactics compatible with existing air combat principles. Excellent blue team performance is demonstrated in scenarios where both sides are matched in terms of formation size and aircraft/weapons capabilities.

1.2 APPLICATION 1: ENGINE PERFORMANCE ESTIMATOR

One of the common objectives of aircraft engine control is to enhance engine performance under deteriorated conditions. To maximize engine performance efficiently under degraded conditions, a fault tolerant engine control scheme can be applied. The first step to implement the fault tolerant engine control architecture is developing an engine performance estimator. This application focuses on developing an engine performance estimator using a combination of a genetic algorithm (GA) and a radial basis function neural network (RBFNN) for the implementation.

Several engine performance estimation structures have been implemented such as the Kalman filter estimator in Performance Seeking Control (PSC) [2, 3, 4], the neural network-based propulsion system model [5], and neural network and fuzzy system estimators in Intelligent Fault Tolerant Engine Control [1].

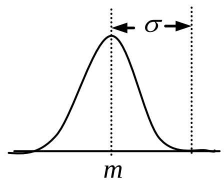

Figure 1. RBF for Scalar Inputs

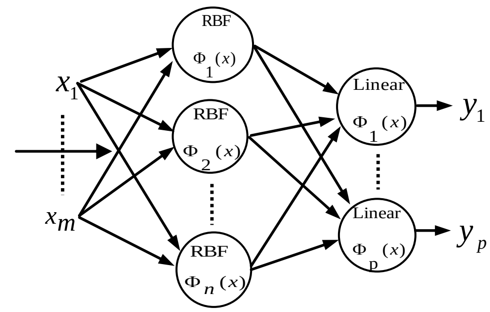

Figure 2. RBF Network

Generally, a traditional engine performance estimation, such as a Kalman filter estimator [3], involves intensive computational procedures because of engines' physical complexity which requires a large number of measurements to be taken and processed.

To overcome computational complexity, model estimation using neural networks has emerged. This emergence comes from a wide variety of application areas and computationally moderate procedures. Neural network-based model estimation has been applied to areas such as optics, robotics, and system control. Typically, the computational strategy of a neural network involves input-output mapping, specifically, a pattern recognition scheme. Only tabulated interconnected synaptic weights are needed for mapping. A RBFNN, which uses a Radial Basis Function, is one of the neural network classification schemes. The RBFNN learning is faster than the traditional back-propagation scheme. Additionally, the RBFNN is effective for highly clustered, large amounts of data [6].

Attracted by the advantages of neural networks, the recent studies of fault tolerance have employed neural network architectures [1, 8, 9]. In these studies, the input selection is executed by simple inspection of data files. This manual inspection can be replaced by automatic inspection as employed in this study.

To apply GAs to an optimization problem, the parameter performance can be evaluated by an objective function (also, a performance index, PI). Regularly, a quadratic error measure is used for the objective function. The error is defined as the difference between desired performance measures and GAs' performance outputs. The following equation represents the least square error scheme.

1.2.1 Engine Details

A schematic of the XTE46 turbofan engine is shown in Figure 3. The XTE46 consists of a fan, a compressor, burners, turbines, an afterburner, and an exhaust nozzle. As shown in Figure 3, the engine's components are described as a combination of alphabets and numbers. For example, P and T stand for total pressure and temperature, and 2 and 3 stand for positions at the inlet and outlet of the fan, respectively. Similarly, engine component's sections are divided into numbers 3-4 for the compressor, 4-5 for the burners, 5-6 for the turbines, 6-7 for