Chapter 4
EFWA as a Method of Optimizing Model Parameters:
Example of an Expensive Function Evaluation

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ABSTRACT

The Fireworks Algorithm (EFWA) is studied as a method to optimize the noise covariance parameters in an induction motor system model to control the motor speed without a speed sensor. The authors considered a system that employs variable frequency drives (VFDs) and executes an extended Kalman filter (EKF) algorithm to estimate the motor speed based on other measured values. Multiple optimizations were run, and the authors found that the EFWA optimization provided, on average, better solutions than the Genetic Algorithm (GA) for a comparable number of parameter set trials. However, EFWA parameters need to be selected carefully; otherwise, EFWA's early performance advantage over GA can be lost.

INTRODUCTION

In industrial applications, it is often desired to set the values of design variables to optimize performance. However, the quantitative relationship between a performance criterion and design variables may not be well known. In many applications, the exact mathematical expression of the quantitative performance measure of interest as a function of design variables is unknown, and the numerical value of the performance measure for a given set of design variables can only be estimated through simulation or experimentation. Evaluating performance for the purpose of optimization can be costly because this type of experimentation can be expensive and the simulation may require a large amount of computational resources. Therefore, in order to employ an evolutionary algorithm for such an application,

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one of the primary concerns is to obtain a good solution after a small number of function evaluations. In this chapter, the authors intend to exhibit use of the enhanced fireworks algorithm (EFWA) for such optimization (Tan, 2015; Zheng, 2013). The authors will present EFWA's performance for optimally choosing model parameters for controlling the speed of an induction motor. Industry uses induction motors (IMs) extensively to drive mechanical loads, so the optimization problem presented is a concrete, real-life example. Due to the high cost of evaluating the performance function, the focus of the chapter will be on how fast the algorithm improves the best candidate solution's performance as the number of function evaluations increases, rather than convergence to the optimal solution.

In order to convey the nature of the optimization problem, the speed control system for the induction motor will be explained for general audiences in the following section. The objective of speed control is to match the actual speed of the motor to the speed command schedule. When speed sensors are used, feedback control schemes can be employed; however, having speed sensors in the system has its disadvantages, and speed sensors are not installed in the example application being studied. Instead of measuring speed, it is estimated based on other measured values. The extended Kalman filter (EKF), a well-known technique to estimate the speed, was used for this purpose (Crassidis & Junkins, 2011). To apply the extended Kalman filter, the covariance values of the process and measurement noise are required for computation. These statistics are not known a priori, but they can be determined through experimentation or simulation as model parameters prior to the actual operation of the motor.

In the application to be presented in this chapter, the performance measure is the mean-square error in the motor speed estimate. To be specific, the performance objective function is the expected value of the square of the difference between the speed of the motor at a given time and the estimation of that speed computed by the estimator, which is a part of the system. Note that the speed of the motor is a randomly time-varying signal, and the mean-square error, as a function of the model parameters, is not known and can only be approximately evaluated through extensive simulation or experimentation. A natural method of estimating the performance value corresponding to a set of parameter values is to take the time average of the square of the difference between the actual speed and the estimator's estimation of the speed. Time averaging requires collection of many samples of the actual speed through experimentation or simulation, and this process can be costly. The next section will present more details on this point.

In earlier work, other researchers used a genetic algorithm (GA) to optimize covariance values as model parameters through simulation and experimentation (Shi et al., 2002). The objective of the authors' research was to gain more knowledge about the EFWA's performance for optimizing the model parameters for the induction motor's speed estimation.

It was found, as expected, that the best candidate solution's performance (the mean square error of motor speed for the example problem studied in this chapter) in the EFWA tends to eventually converge to the value to which the GA converges as the number of generations increases. An interesting observation was that for many different sets of algorithm parameter values, the EFWA's best performing solution tended to improve more quickly, in the initial few generations, than the GA's. The early improvement is important for applications with high function evaluation cost. In the following sections, detailed results are presented from the accumulated data obtained and the statistical significance of EFWA's faster improvement observed at early generations of the algorithms is analyzed.

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