Prediction of Energy Consumption in a NSGA-II-based Evolutionary Algorithm

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ABSTRACT

A deeper understanding in how the power consumption of evolutionary algorithms behaves is necessary to keep meeting high quality results without wasting energy resources. This paper presents a black-box model for predicting the energy consumption of the NSGA-II-based *Parallel Islands approach to Multiobjective Feature Selection* (pi-MOFS). We analyzed the power usage of each stage in pi-MOFS when applied to a brain-computer interface classification task. Fitness evaluation showed as the most relevant stage for the case study presented in time and power consumption. The results showed a 98.81% prediction accuracy for the eight experiments designed. We believe that our findings and methodology can be used to apply pi-MOFS, NSGA-II and other EAs to current optimization problems from an energy-aware perspective.

CCS CONCEPTS

- **Computing methodologies** → **Parallel algorithms**; **Model development and analysis**;

KEYWORDS

Black-box model, energy-aware computing, parallel computing, evolutionary algorithm, NSGA-II, fitness evaluation

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1 INTRODUCTION

Despite the usefulness of evolutionary algorithms (EAs) in optimization problems – even in the *Green Computing* trend – energy awareness in EAs is not frequently considered. To the best of our knowledge, only F. Fernandez de Vega et al. [3] have taken a first step by studying the overall energy-related behavior of a genetic programming algorithm across various machines. In this paper we present a black-box model for predicting the energy consumption of the NSGA-II-based *Parallel Islands approach to Multiobjective Feature Selection* (pi-MOFS) [1, 2].

2 CASE STUDY: PI-MOFS

pi-MOFS is a parallel multiobjective EA oriented to a feature selection optimization in a EEG-signal classification task. This task consists on finding the best set of features (up to 30 characteristics from an overall of 3600) across a reduced dataset with just 178 entries to learn from. The multiobjective approach sets in Pareto front the best solutions according to its accuracy and Cohen's kappa values. It also distributes the initial population into the several workers – or *islands* – available in the system. Since it is based in the famous NSGA-II, it shares the same main stages for evolving the initial population to a final set of solutions: *initialization*, *fitness evaluation*, *non-dominated sort*, *tournament selection* and *genetic operations* [1].

The objective was to predict the energy usage of pi-MOFS from a black-box model that only relies on configurations parameters, namely *population size*, *number of generations* to evolve, and the *number workers* where the population is distributed. Eight experiments were designed with all the available configurations with {160, 320} of population size, {50, 100} generations to evolve and {4, 8} workers. The eight experiments were executed 10 times to mitigate the impact of random variations during runtime.

Time measures of stages were obtained with MATLAB during program execution; energy consumption was obtained simultaneously with Arduino Mega and a YHDC-SCTD010T

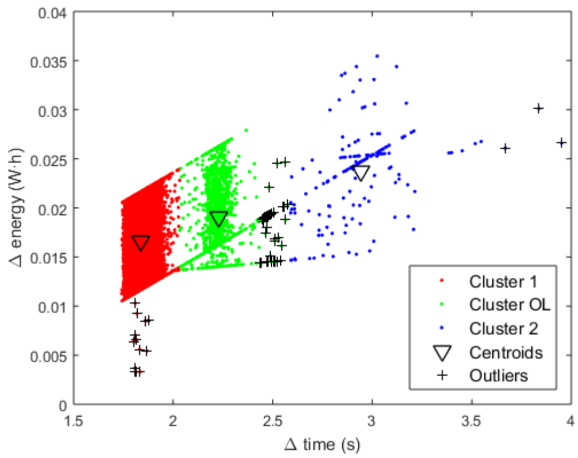

Figure 1: Energy and time consumption for FEs in experiment #5 (4 workers, 320 population size, 50 generations)

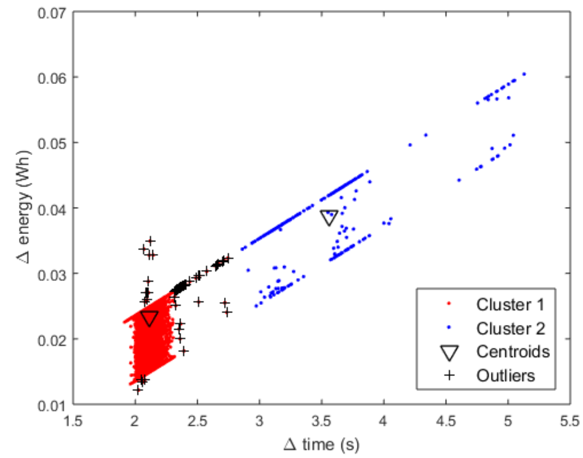

Figure 2: Energy and time consumption for FEs in experiment #6 (8 workers, 320 population size, 50 generations)

amperimeter with 1Hz as sampling frequency, directly attached to the server's power source.

We assumed an additive model where:

$$E_{piMOFS}\left(t\right) = E_T\left(t\right) - \bar{E}_{OS}$$

where E_T is the total energy consumption measured with Arduino, the operating system (OS) has an idle consumption $\bar{E}_{OS} = 65,38 \pm 0,08\ W \cdot h\ /\ sample$ (4764 samples at 1Hz, more than one hour), and E_{piMOFS}, the energy consumed by the EA pi-MOFS, is the excess of energy compared to the energy consumption of the OS in idle state.

3 RESULTS

In average, fitness evaluations (FEs) represented 96.65% of the total time and 97.07% of the overall power consumption for the 8 experiments. The relevance of FEs made the energy-consumption prediction model depend exclusively on this stage, thus setting aside the rest of stages of pi-MOFS.

We found different energy-consumption behaviors depending on the number of workers where the initial population was distributed. Executing the same routine in 8 workers consumes, in average, 57.40% of the total time and 71.26% of total energy used in 4 workers. Figure 1 represents the behavior found in the 4-workers experiments, showing two increasing patterns overlapped across the scatter-plot. In contrast, Figure 2, which represents the 8-island experiments, does not contain this overlapped behavior. We hypothesize that the secondary increasing pattern in 4-island experiments was caused by context switches since the secondary increasing pattern has less slope than the main tendency of the rest of data, that is, for the same power consumption, the CPU has invested more time (context switch involved) in the FEs of the solutions conforming the secondary behavior.

We separated the data with k-means clustering to distinguish the overlapping pattern in four-island experiments. Four-island experiments were divided in three clusters (*Cluster 1*, *Cluster OL* and *Cluster 2*). Eight-island experiments were divided in two clusters (*Cluster 1*, and *Cluster 2*). This was also useful to separate the more dense part of the data (*Cluster 1*) data from the more disperse (*Cluster 2*).

Our model leveraged the clustered distribution of data and used it as main input with the configuration parameters for experiments. We built the model from the FEs in the first nine repetitions of the 8 experiments designed; then we tested it with the tenth repetition of each experiment. We obtained a 98.81% prediction accuracy.

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