Post-compiler Software Optimization for Reducing Energy

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Abstract

Modern compilers typically optimize for executable size and speed, rarely exploring non-functional properties such as power efficiency. These properties are often hardware-specific, time-intensive to optimize, and may not be amenable to standard dataflow optimizations. We present a general post-compilation approach called Genetic Optimization Algorithm (GOA), which targets measurable non-functional aspects of software execution in programs that compile to x86 assembly. GOA combines insights from profile-guided optimization, superoptimization, evolutionary computation and mutational robustness. GOA searches for program variants that retain required functional behavior while improving non-functional behavior, using characteristic workloads and predictive modeling to guide the search. The resulting optimizations are validated using physical performance measurements and a larger held-out test suite. Our experimental results on PARSEC benchmark programs show average energy reductions of 20%, both for a large AMD system and a small Intel system, while maintaining program functionality on target workloads.

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1. Introduction

From embedded systems to large datacenters, extreme scales of computation are increasingly popular. At such extremes, properties such as energy consumption [10] and memory utilization can be as important as runtime. For example, data centers are estimated to have consumed over 1% of total global electricity usage in 2010 [28]. However, there are few program optimizations targeting these *non-functional* [19] performance requirements. The few existing methods must cope with complex architectures and workload interactions [62]. Although techniques such as voltage scaling and resource hibernation can be applied at the hardware level to reduce energy consumption [43], software optimizations tend to focus on cycle counts and instruction scheduling [35] for consecutive instructions to lower the switching activity [47, § 4.3.3].

Software engineers are studying methods that trade the guarantee of semantic preservation [11, 15, 22, 27, 65] for greater reliability and robustness [2, 8, 49, 58], availability and security [50], compile-time algorithmic flexibility [5], or performance and quality of service [6, 39, 40]. Interest in such tradeoffs spans domains as diverse as computer graphics [59] and networked servers [50].

Stochastic search methods are increasingly successful at evolving and repairing off-the-shelf software [14, 26, 33, 42, 65]. Similar to profile-guided optimizations, such techniques leverage existing test suites or annotations [64] to ensure that proposed modifications preserve required functionality. Analysis of the test-based stochastic searches suggests that software is *mutationally robust*, i.e., simple randomized program transformations often produce semantically distinct program implementations that still meet functional requirements [54]. This surprising result suggests an approach to optimizing non-functional properties of programs.

We propose a post-compilation, software-based "Genetic Optimization Algorithm" (GOA) for discovering optimizations and managing tradeoffs among non-functional software properties. We illustrate the approach by focusing on the example of energy usage, which combines runtime and other more difficult-to-measure properties. GOA maintains a population of randomly mutated program *variants*, first

selecting those that retain required functionality, and second looking for those that improve a non-functional property (encoded in an objective function). Our approach leverages ideas from evolutionary computation (population-based stochastic search), mutational robustness (random mutations yield independent implementations of the same specification), profile-guided optimization (performance measured on workloads) and relaxed notions of program semantics (customizing software to particular runtime goals and environments provided by a software engineer). Evolutionary algorithms such as GOA are well-suited for exploring difficult search spaces [29]. As input, GOA requires only the assembly code of the program to be optimized, a regression test suite that captures required functionality, and a measurable optimization target.

We demonstrate GOA on the problem of reducing energy consumption for the PARSEC [9] benchmark programs running on both desktop-class Intel and server-class AMD hardware. We define an efficient and accurate architecture-specific linear power model, which is parameterized by hardware counters. This model provides the objective function used by GOA; we validate results found by the model using physical wall-socket measurements. Experimentally, GOA discovers both hardware- and workload-specific optimizations, and reduces energy consumption of the PARSEC benchmarks by 20% on average compared to the best available compiler optimizations.

The main contributions of this paper are as follows:

- GOA, a post-compiler method for optimizing non-functional properties of assembly programs.
- A specialization of GOA that incorporates efficient predictive models to optimize energy consumption in assembly programs.
- An empirical evaluation using PARSEC benchmarks across two microarchitectures. We find that GOA reduces energy consumption by 20% as compared to the best available compiler optimizations, generates optimizations that generalize across different size workloads, and in most cases fully retains program functionality even against held-out test cases.

The next section provides three examples of optimizations found using GOA. We then describe the GOA algorithm more formally (Section 3), report experimental results (Section 4) discuss the relevant background material and related work (Section 5), and discuss the significance of our results and conclude (Sections 6 and 7).

2. Motivating Examples

This section describes three illustrative examples of energy optimizations found by GOA in the PARSEC benchmark suite.

`blackscholes` implements a partial differential-equation model of a financial market. Because the model runs so quickly, the benchmark artificially adds an outer loop that executes the model multiple times. These redundant calculations are not detected by standard static compiler analyses. GOA has discovered multiple ways to avoid this redundancy by making slight random variations on the original assembly code. For example, some variations can change the number of floating point operations or cache accesses. Each candidate is validated dynamically on the regression test suite, and if it passes all tests, retaining required functionality, it is then evaluated for energy efficiency using a linear combination of hardware performance counters. Over time, the best variants are subject to further modifications, until a stopping criterion is reached, and the most energy-efficient variant found is validated using physical energy measurements.

The validated `blackscholes` optimization returned by GOA discovered and removed the redundant calculation on both AMD and Intel hardware. However, the optimization strategy differed between the two architectures. In the Intel case, a "subl" instruction was removed, preventing multiple executions of a loop, while in the AMD case a similar effect was obtained by inserting a literal address which (due to the density of valid x86 instructions in random data [7]) is interpreted as valid x86 code to jump out of the loop, skipping redundant calculations.

GOA also finds hardware-specific optimizations in the `swaptions` benchmark, which prices portfolios. On AMD systems, GOA reduces the total `swaptions` energy consumption by 42% from the value produced by the least-energy combination of flags to `gcc` (Section 4.1). We believe this improvement is mostly due to the reduction of the rate of branch miss-prediction. Although it is not practical for general compilers to reason about branch prediction strategies for every possible hardware target, GOA can find these environment-specific specialized adaptations.

We found that no single edit (or small subset of edits) accounted for this improvement. Rather, many edits distributed throughout the `swaptions` program collectively reduced mispredictions. Typical edits included insertions and deletions of `.quad`, `.long`, `.byte`, etc., all of which change the absolute position of the executing code. Absolute position affects branch prediction when the value of the instruction pointer is used to index into the appropriate predictor. For example, AMD [25, § 6.2] advocates inserting `REP` before returns in certain scenarios.

Finally, GOA finds unintuitive optimizations. In the `vips` image processing program, it found an optimization that reduced the total energy used by 20.3% on the Intel system. The optimization actually increased cache misses by 20× but decreased the number of executed instructions by 30%, in effect trading increased off-chip communication for decreased computation.

In each example, neither the PARSEC-provided compiler flags nor the usual `gcc` "–Ox" flags produced these optimizations. These examples show that beneficial energy op-

timizations exist that are not exploited by common compilers, suggesting the need for a technique to automatically find them.

3. Genetic Optimization Algorithm (GOA)

This section describes the Genetic Optimization Algorithm (GOA) for optimizing non-functional behavior of off-the-shelf assembly programs. The main components of GOA are depicted in Figure 1. GOA takes as input the original program source, a regression test suite capable of exercising program executables, and a scalar-valued objective (or *fitness*) function. The objective function takes as input any program variant that passes the regression test suite and assesses its non-functional behavior.

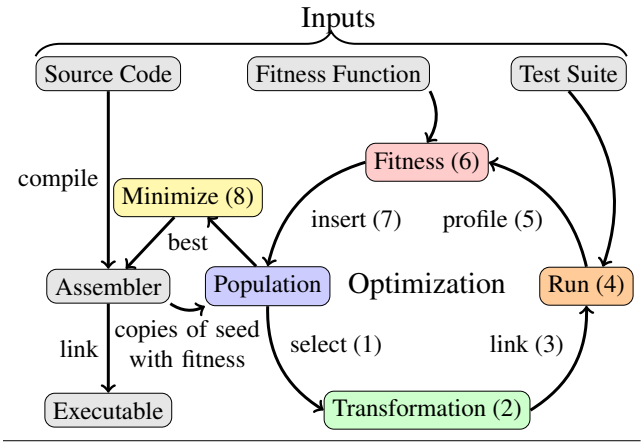

Figure 1. Overview of the program optimization process.

During compilation and linking, the intermediate assembly code representation of the program is extracted from the build process (Section 3.1) assigned a fitness as in steps 4, 5, 6 below and used to seed a population of mutated copies of the program (Section 3.3). An evolutionary computation (EC) algorithm (Section 3.2) then searches for optimized versions of the original program. Every iteration of the main search loop: (1) selects a candidate optimization from the population, (2) transforms it (Section 3.3), (3) links the result into an executable, (4) runs the resulting executable against the supplied test suite, (5) collects performance information for programs that pass all tests, (6) combines the profiling information into a scalar fitness score using the fitness function (Section 3.4), and (7) reinserts the optimization and its fitness score into the population. The process continues until either a desired optimization target is reached or a predetermined time budget is exceeded. When the algorithm completes, a post-processing step (8) takes the best individual found in the search and minimizes it with respect to the original program (Section 3.5). Finally, the result is linked into an executable and returned as the result.

The remainder of this section details the particulars of this process.

3.1 GOA Inputs

The program to be optimized is presented as a single assembly file, which can either be extracted from the build process, or provided directly, for example, using `gcc`'s "–combine" flag for C. For C++, manual concatenation may be required. In practice this was straightforward for the PARSEC programs used as benchmarks in this work. Any performance-critical library functions must be included in the assembly file, because GOA optimizes only visible assembly code and not the contents of external libraries.

The algorithm also takes as input a test suite or indicative workload that serves as an implicit specification of correct behavior; a program variant that passes the test suite is assumed to retain all required functionality [65]. There are two well-known costs associated with adequate test suites—the cost of creating the test suite, and the cost of running it. Both are costs that GOA shares with profile-guided optimization [45], and we view the task of efficient testing as orthogonal to this work. For test suite construction, we note that many techniques for automated test input and test suite generation are available (e.g., [16]). Our scenario allows us to use the original program as an oracle, comparing the output of the original to that of the modified variant, which dramatically reduces costs. For the cost of running the test suite, we note that our approach is amenable to test suite reduction and prioritization (e.g., [60]).

The final input is the fitness function, detailed in Section 3.4, which evaluates behavior on the non-functional properties of interest.

3.2 Genetic Optimization Algorithm

Unlike recent applications of evolutionary computation to software engineering (e.g,. [33]), we use a *steady state* EC algorithm [36]. This means that the population is not completely replaced in discrete steps (generations). Instead, individual program variants (candidate optimizations) are selected from the population for additional transformations, and then reinserted. The steady state method simplifies the algorithm, reduces the maximum memory overhead, and is more readily parallelized.

The pseudocode for GOA is shown in Figure 2. The main evolutionary loop can be run in parallel across multiple threads of execution. Threads require synchronized access to the population Pop and evaluation counter $EvalCounter$.

The population is initialized with a number of copies of the original program (line 1). In every iteration of the main loop (lines 3–15) the search space of possible optimizations is explored by transforming the program using random mutation and crossover operations (described in the next subsection). The probability $CrossRate$ controls the application of the crossover operator (lines 6–8). If a crossover is to be performed, two high-fitness parents are chosen from the population via *tournament selection* [46, § 2.3] and combined to form one new optimization (line 8). Otherwise, a

Input: Original Program, P : $Program$
Input: Workload, Run : $Program \rightarrow ExecutionMetrics$
Input: Fitness Function, Fitness : $ExecutionMetrics \rightarrow \mathbb{R}$
Parameters: $PopSize$, $CrossRate$, $TournamentSize$, $MaxEvals$

Output: Program that optimizes Fitness
1: **let** $Pop \leftarrow PopSize$ copies of $\langle \mathsf{P}, \mathsf{Fitness}(\mathsf{Run}(P)) \rangle$
2: **let** $EvalCounter \leftarrow 0$
3: **repeat in every thread**
4: **let** $p \leftarrow$ null
5: **if** $\mathsf{Random}() < CrossRate$ **then**
6: **let** $p_1 \leftarrow \mathsf{Tournament}(Pop, TournamentSize, +)$
7: **let** $p_2 \leftarrow \mathsf{Tournament}(Pop, TournamentSize, +)$
8: $p \leftarrow \mathsf{Crossover}(p_1, p_2)$
9: **else**
10: $p \leftarrow \mathsf{Tournament}(Pop, TournamentSize, +)$
11: **end if**
12: **let** $p' \leftarrow \mathsf{Mutate}(p)$
13: $\mathsf{AddTo}(Pop, \langle p', \mathsf{Fitness}(\mathsf{Run}(p')) \rangle)$
14: $\mathsf{EvictFrom}(Pop, \mathsf{Tournament}(Pop, TournamentSize, -))$
15: **until** $EvalCounter \geq MaxEvals$
16: **return** $\mathsf{Minimize}(\mathsf{Best}(Pop))$

Figure 2. High-level pseudocode for the main loop of GOA.

single high-fitness optimization is selected. In either case, the candidate optimization is mutated (line 12), its fitness is calculated (by linking it and running it on the test suite, see Section 3.4), and it is reinserted into the population (line 13). The steady state algorithm then selects a member of the population for eviction using a "negative" tournament to remove a low-fitness candidate and keep the population size constant (line 14). Fitness penalizes variants heavily if they fail any test case and they are quickly purged from the population. Eventually, the fittest candidate optimization is identified, minimized to remove unnecessary or redundant changes (Section 3.5), and is returned as the result.

We report results using a population of size $MaxPop = 2^9$, a crossover probability of $CrossRate = \frac{2}{3}$, a tournament size of $TournamentSize = 2$ for both selection and eviction, and a total of $MaxEvals = 2^{18}$ fitness evaluations. In preliminary runs these parameters proved sufficient to find significant optimizations for most programs with runtimes of 16 hours or less (using 12 threads on a server-class AMD machine), meeting our goal of "overnight" optimization.

3.3 Program Representation and Operations

Each individual program in the population is represented as a linear array of assembly statements, with one array position allocated for each line in the assembly program [52]. Programs are transformed by mutation and crossover operators defined over the arrays of instructions. Argumented instructions are treated as atomic in the sense that arguments to individual instructions are never changed directly. This potentially limits the search, but in practice most useful instructions are available to be copied from elsewhere in the program. This decision avoids the "problem of argumented instructions" (cf. [61]) when modifying assembly code.

The mutation step selects one of the three mutation operations (*Copy*, *Delete* or *Swap*) at random and applies it to locations in the program, selected uniformly at random, with replacement. When crossover is performed, two program locations are selected from within the length of the shorter program to be crossed. Two-point crossover is then applied at these points to generate a single output program variant from the two input program variants, as shown in Figure 3.

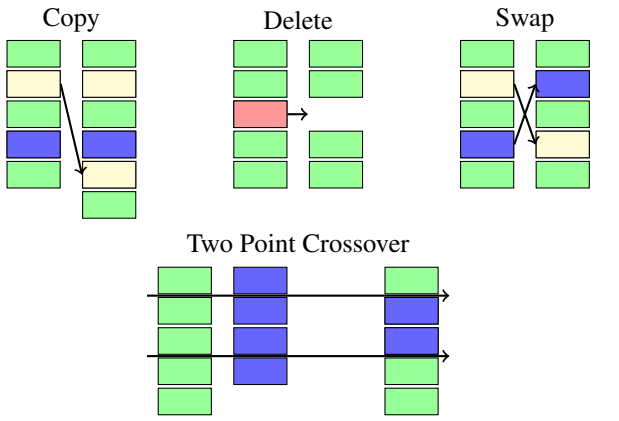

Figure 3. Mutation and Crossover operations on programs represented as linear arrays of argumented assembly instructions.

The mutation operations are not language or domain specific, and they never create entirely new code. Instead, they produce new arrangements of the argumented assembly instructions present in the original program. Our operators are reasonable extensions of the standard EC mutation and crossover operations, which are typically defined over bit-strings. Mutation operators explore the search space through small local changes, while crossover can escape local optima, either by combining the best aspects of partial solutions or by taking long jumps in the search space.

3.4 Evaluation and Fitness

The goal of GOA is to optimize a given fitness function. In our energy-optimizing implementation, the fitness function uses hardware performance counters [18] captured during test suite execution and combines them into a single scalar using a linear energy model (Section 4.3) defined over the values of those counters. Although we demonstrate GOA using this complex fitness function, it could also be applied to simpler fitness functions such as reducing runtime or cache accesses.

Test input data were selected to fulfill two requirements: (1) minimize the runtime of each evaluation, and (2) return sufficiently stable hardware performance counter values to allow reliable fitness assessment. The full test suite, which

validates that candidate optimizations retain required functionality, need not be the same as the abbreviated test data used to measure non-functional fitness.

3.5 Minimization

The randomized nature of EC algorithms sometimes produces irrelevant or redundant transformations. We prefer optimizations that attain the largest fitness improvement with the fewest changes to the original program. To accomplish this, we include a final minimization step to remove changes that do not improve the fitness. Minimization allows us both to focus on mutations that produce a measurable improvement (Section 4.4) and to avoid altering functionality that is not exercised during the fitness evaluation.

Our minimization algorithm is based on Delta Debugging [67]. Here, Delta Debugging takes a set of deltas (edit operations) between two versions of a program and determines a 1-minimal subset of those deltas that cause the first program to act identically to the second. We reduce the best optimization found by the evolutionary search to a set of single-line insertions and deletions against the original (e.g., as generated with the `diff` Unix utility). We then use Delta Debugging to minimize that set with respect to the fitness function. If the application of a particular delta has no measurable effect on the fitness function, we do not consider it to be a part of the optimization. Experimentally, we find that eliminating such superfluous deltas reduces problems with untested program functionality. We apply the minimal set of changes identified by Delta Debugging to the original program to produce the final optimized program.

3.6 Algorithm Summary

GOA maintains a population of linear arrays of assembly instructions, mutating and combining them with the goal of optimizing a given objective function while retaining all required functionality as indicated by a test suite. In the next section we evaluate the effectiveness of GOA by applying it to the problem of reducing energy consumption.

4. Experimental Evaluation

Our experiments address three research questions:

- Does GOA reduce energy consumption? (RQ1)
- Do our results generalize to multiple architectures and held-out workloads? (RQ2)
- Do GOA optimizations retain required functionality? (RQ3)

Recall that GOA requires three inputs: a program to be optimized, a fitness function, and a workload or test suite. We evaluate effectiveness and usability against the PARSEC benchmark suite (Section 4.1). For a fitness function, we develop an efficient energy consumption model, based on hardware counter values (Section 4.3). The test suite was chosen by selecting from the PARSEC suite the smallest inputs that generate a runtime of at least one second on each hardware platform. After running GOA, we evaluate the optimized program using physical wall-plug measurements of energy. All software tools described in this work, including installation and usage instructions, are publicly available at `https://github.com/eschulte/goa/tree/asplos2014`.

Program	C/C++ Lines of Code	ASM Lines of Code	Description
blackscholes	510	7,932	Finance modeling
bodytrack	14,513	955,888	Human video tracking
ferret	15,188	288,981	Image search engine
fluidanimate	11,424	44,681	Fluid dynamics animation
freqmine	2,710	104,722	Frequent itemset mining
swaptions	1,649	61,134	Portfolio pricing
vips	142,019	132,012	Image transformation
x264	37,454	111,718	MPEG-4 video encoder
total	225,467	1,707,068	

Table 1. Selected PARSEC benchmark applications.

4.1 Benchmark Programs and Systems

We use the popular PARSEC [9] benchmark suite of programs representing "emerging workloads." We evaluate GOA on all of the PARSEC applications that produce testable output and include more than one input set. Testable output is required to ensure that the optimizations retain required functionality. Multiple input sets are required because we use one (training) input set during the GOA optimization and separate held-out ("testing") inputs to test after GOA completes (Section 4.2). The eight applications satisfying these requirements are shown with sizes and brief descriptions in Table 1. Two PARSEC applications were excluded: `raytrace` which does not produce any testable output, and `facesim` which does not provide multiple input sets.

We evaluate on an Intel Core i7 and an AMD Opteron. The Intel system has 4 physical cores, Hyper-Threading, and 8 GB of memory, and it is indicative of desktop or personal developer hardware. The AMD system has 48 cores and 128 GB of memory, and is representative of more powerful server-class machines.

We compare the performance of GOA's optimized executables to the original executable compiled using the PARSEC tool with its built-in optimization flags or the `gcc` "–Ox" flag that has the least energy consumption.[1]

4.2 Held-Out Test Suite

We use a large held-out test suite to evaluate the degree to which the optimizations found by GOA customize the program semantics to the training workload. For each benchmark besides `blackscholes`, we randomly generated 100 sets of command-line arguments (and argument values, as

[1] PARSEC includes a version of `x264` with non-portable hand-written assembly. To compare fairly against both Intel and AMD, we report `x264` numbers using the portable C implementation.

appropriate) from the valid flags accepted by the program. `blackscholes` accepts no flags, but instead requires a fixed sequence of arguments, one of which indicates an input file containing a number of independent records. We generated 100 test input files for `blackscholes` by randomly sampling between 2^{14} and 2^{20} records from the set of all records in any of the available PARSEC tests.

Each test was run using the original program and its output as an oracle to validate the output of the optimized program. If the original program rejected the input or arguments (e.g., because some flags cannot be used together), we rejected that test and generated a new one. We also rejected tests for which the original program did not generate the same output when run a second time, or for which the original program took more than 30 seconds to run.

The optimized programs were evaluated by running them with the same inputs and test data, comparing the output against the oracle. In most cases, we used a binary comparison between the output files. However, for `x264` tests producing video output, we used manual visual comparison to determine output correctness.

4.3 Energy Model

Our fitness function uses a linear energy model based on process-specific hardware counters similar to that developed by Shen *et al.* [57]. We simplify their model in two ways:

- We do not build workload-specific power models. Instead, we develop one power model per machine trained to fit multiple workloads and use this single model for every benchmark on that machine.
- We do not consider shared resources.

Incorporating these simplifications gives the following model:

$$power = C_{const} + C_{ins}\frac{ins}{cycle} + C_{flops}\frac{flops}{cycle} + C_{tca}\frac{tca}{cycle} + C_{mem}\frac{mem}{cycle} \quad (1)$$

$$energy = seconds \times power \quad (2)$$

Total energy (Equation 2) is given by the predicted power (Equation 1) multiplied by the runtime. The values for the constant coefficients are given in Table 2. They were obtained empirically for each target architecture, using data collected for each PARSEC benchmark, the SPEC CPU benchmark suite, and the `sleep` UNIX utility. For each program, we collected the performance counters as well as the average Watts consumed, measured by a Watts up? PRO meter. We combined these data in a linear regression to determine the coefficients shown in Table 2.

The disparity between the AMD and Intel coefficients is likely explained by significant differences in the size and class of the two machines. For example, the $13\times$ increase in idle power of the AMD machine as compared to the Intel machine is reasonable given the presence of 12 times as many cores, and 15 times as much memory.

Coefficient	Description	Intel (4-core)	AMD (48-core)
C_{const}	constant power draw	31.530	394.74
C_{ins}	instructions	20.490	-83.68
C_{flops}	floating point ops.	9.838	60.23
C_{tca}	cache accesses	-4.102	-16.38
C_{mem}	cache misses	2962.678	-4209.09

Table 2. Power model coefficients.

Even without our simplifications, the predictive power of linear models is rarely perfect. McCullough *et al.* note that on a simple multi-core system, CPU-prediction error is often 10–14% with 150% worst case error prediction [38]. We checked for the presence of overfitting using 10-fold cross-validation and found a 4–6% difference in the average absolute error, which is adequate for our application. Since we ultimately evaluate energy reduction using physical wall-socket measurements, our energy model is required only to be accurate and efficient enough to guide the evolutionary search.

We find that our models have an average of 7% absolute error relative to the wall-socket measurements. Collecting the counter values and computing the total power increases the test suite runtime by a negligible amount. Thus, our power model is both sufficiently efficient and accurate to serve as our fitness function.

The Intel Performance Counter Monitor (PCM) counter can also be used to estimate energy consumption. We did not use this counter because the model used to estimate energy is not public, and because it estimates energy consumption for an entire socket and does not provide per-process energy consumption. Relying on the PCM would reduce the parallelism available to our GOA implementation.

4.4 RQ1 — Reduce Energy Consumption

Table 3 reports our experimental results. The "Energy Reduction" columns report energy reduction while executing the tests by the GOA-optimized program, as measured physically and compared to the original. For example, if the original program requires 100 units and the optimized version requires 20, that corresponds to an 80% reduction.

GOA found optimizations that reduced energy consumption in many cases, with the overall reduction on the supplied workloads averaging 20%. Although in some cases—such as in `bodytrack` on AMD or `bodytrack`, `ferret`, `fluidanimate`, `freqmine` and `x264` on Intel—GOA failed to find optimizations that reduced energy consumption, it found optimizations that reduce energy consumption by an order of magnitude for `blackscholes` and over one-third for `swaptions` on both systems. We find that CPU-bound programs are more amenable to improvement than those that perform large amounts of disk IO. This result suggests that

	Program Changes				Energy Reduction				Runtime Reduction		Functionality	
	Code Edits		Binary Size		Training		Held-Out		Held-Out		Held-Out	
Program	AMD	Intel	AMD	Intel	AMD	Intel	AMD	Intel	AMD	Intel	AMD	Intel
blackscholes	120	3	-8.2%	0%	92.1%	85.5%	91.7%	83.3%	91.7%	81.3%	100%	100%
bodytrack	19656	3	-38.7%	0%	0%	0%	0.6%	0%	0.3%	0.2%	92%	100%
ferret	11	1	84.8%	0%	1.6%	0%	5.9%	0%	-7.9%	-0.1%	100%	100%
fluidanimate	27	51	-3.3%	11.4%	10.2%	0%	—	—	—	—	6%	31%
freqmine	14	54	18.7%	34.9%	3.2%	0%	3.3%	-1.6%	3.2%	0.1%	100%	100%
swaptions	141	6	27.0%	18.5%	42.5%	34.4%	41.6%	36.9%	42.0%	36.6%	100%	100%
vips	57	66	-52.8%	0%	21.7%	20.3%	21.3%	—	29.8%	—	100%	100%
x264	34	2	0%	0%	8.3%	0%	9.2%	0%	9.8%	0%	27%	100%
average	2507.5	23.3	3.4%	8.1%	22.5%	17.5%	24.8%	19.8%	24.1%	19.7%	78.1%	91.4%

Table 3. GOA energy-optimization results on PARSEC applications. The "Code Edits" column shows the number of unified diffs between the original and optimized versions of the assembly program. "Binary Size" indicates the change in size of the compiled executable. The "Energy Reduction" columns report the physically measured energy reduction compared to the original required to run the tests in the fitness function ("Training Workload") or to run all other PARSEC workloads for that benchmark ("Held-Out Workloads"). The "Runtime Reduction" columns report the decrease in runtime compared to the original. In some cases, the measured energy reduction is statistically indistinguishable from zero ($p > 0.05$). Note that for some benchmarks (e.g., `bodytrack`), although there is no measured improvement, the minimization algorithm maintains modeled improvement, resulting in a new binary. We do not report energy reduction on workloads for which the optimized variant did not pass the associated tests (indicated by dashes). The "Functionality" columns report accuracy on the held-out test suite.

GOA is likely better at generating efficient sequences of executing assembly instructions than at improving patterns of memory access. Overall, when considering only those programs with non-zero improvement, average energy reduction was 39%. The increased improvement on held-out workloads compared to training workloads was expected given the increased comparative size and runtime of most held-out workloads.

In most benchmark programs energy reduction is very similar to runtime reduction (see Columns "Energy Reduction" and "Runtime Reduction", Table 3). This is not surprising given the important role of time in our energy model. However, in some cases (e.g., `ferret`) energy was reduced despite an increase in runtime.

Although some optimizations are easily analyzed through inspection of assembly patches (e.g., the deletion of "`call im_region_black`" from `vips` skipping unnecessary zeroing of a region of data), many optimizations produce unintuitive assembly changes that are most easily analyzed using profiling tools. Such inspection reveals optimizations (Section 2) that run the gamut from removing explicit semantic inefficiencies in `blackscholes` to re-organizing assembly instructions in `swaptions` and `vips` in such a way as to decrease the rate of branch mispredictions. The AMD versions of `fluidanimate` and `x264` seem to improve performance by reducing idle cycles spent waiting for off-chip resources.

4.5 RQ2 — Generality

We evaluate the generality of our results on the two architectures and using the held-out test cases described earlier.

The "AMD" and "Intel" columns in Table 3 show results for the two architectures (described in Section 4.1). On both architectures, optimizations fix branch mispredictions in `swaptions` and `vips`; rely on relaxed notions of program semantics, such as by eliminating unnecessary loops in `blackscholes`; or remove redundant zeroing behavior in `vips`.

The GOA technique appears to find more optimizations on AMD than Intel. We hypothesize that the higher overall energy usage of the larger server-class AMD system affords more opportunity for improvement. It is also notable that the two programs with better results on AMD than Intel (`fluidanimate` and `x264`) are also the only two programs for which we find significant failures on held-out test data. This suggests that workload-specific improvements or customizations are more easily accomplished (or more readily rewarded) on the AMD than the Intel system. Despite these differences, GOA substantially reduces energy consumption on both AMD-based server-class and Intel-based workstation-class systems.

We also evaluate generality in terms of held-out workloads. GOA only has access to the supplied workload (Section 3.2). The PARSEC benchmark includes multiple workloads of varying size for each of our benchmark applications. The "Energy Reduction on Held-Out Workloads" columns in Table 3 show how optimizations learned on the smaller workloads apply to the larger held-out workloads.

Overall, we find that performance gains on the training workload generalize well to workloads of other sizes. The energy reduction of 20% on the training workloads is similar to the 22% observed for held-out workloads. However,

when the optimizations customized to the training workload change the semantics on the held-out workload and produce different answers, the energy consumption varies dramatically. On Intel, `fluidanimate` and `vips` consume significantly more energy, while on AMD `fluidanimate` consumes significantly less. We attribute this improvement on held-out workloads to their increased size, which leads to a larger fraction of runtime spent in the inner loops where most optimizations are located. This generalization is important for the practical application of GOA. The training workload must execute quickly, because it is run as part of the inner loop of the GOA algorithm.

Although high-quality training data remains an essential input to our approach, the energy reductions found by GOA in this experiment generalized beyond the particular training data, and no special care was required in selecting training workloads. The defaults supplied as part of the PARSEC benchmark proved sufficient.

4.6 RQ3 — Functionality and Relaxed Semantics

A strength of our approach is its ability to tailor optimizations to the workload and architecture available [17, 45]. In many situations (e.g., if the deployment scenario is controlled, as in a datacenter, or if the available test suite is extensive) this is advantageous, and "relaxed semantics" may be an acceptable tradeoff for improvements to important non-functional properties. However, in some situations it may be more important to replicate original program behavior even in untested scenarios. We constructed a set of held-out test cases (see 4.2) and evaluated untested behavior by measuring the accuracy of the optimizations on these tests (the final columns in Table 3).

Recall that the optimizations are required to pass all available held-in test cases. The "Functionality on" columns show that GOA generally finds optimizations that behave just as the original, even on held-out tests not seen during the optimization process. The exceptions are `x264` (in which the AMD optimization works across every held-out input, but does not appear to work at all with some option flags) and `fluidanimate` (where the optimizations appeared to be brittle to many changes to the input, including workloads of different sizes). Notably, the minimization step (Section 3.5) ensures that changes to parts of the program not exercised by the training set are likely to be dropped (because removing those changes does not influence the energy consumption on the training set). Anecdotally we note that the unminimized optimizations typically showed worse performance on held-out tests than did the minimized optimizations. Although not a proof, this gives confidence that the technique produces optimizations that retain, or only slightly relax, the original program semantics.

Developers concerned with retaining the exact behavior of the original program have several available off-the-shelf random testing techniques (e.g., [16, 20, 32, 56]) that could be used by interpreting the original program's behavior as the oracle. This would restrict the search to considering only optimizations that are even more similar to the original. It would also increase the time cost for running GOA, but does not limit its applicability. As mentioned earlier, there is increasing willingness to trade guarantees of exact semantic preservation for other desired system properties [1, 2, 5, 6, 8, 39, 40, 50, 58, 59]. Taken together, the growing popularity of acceptability-oriented computing [48–50] and the difficulty of manually optimizing for energy [17, 35, 47], suggest that automatically reducing energy and manually focusing on semantics is a profitable tradeoff compared to the traditional converse.

4.7 Threats to Validity

Although the experimental results suggest that GOA can optimize energy, the results may not generalize to other non-functional properties or to other programs. One threat to generality is that energy consumption and our modeling are machine- or architecture-specific, and our optimizations are only individually valid for a particular target architecture. We attempt to mitigate this threat by considering two distinct architectures. We note that this is a general issue for performance optimization [41] and not specific to our approach. A second threat is that energy consumption can differ dramatically by workload—optimizations developed for training test cases may not be as effective when deployed. We mitigate this threat by physically measuring energy reduction on held-out workloads. A third threat is that our approach requires high-quality test cases (or specifications, etc.). If the test suite does not ensure that the implementation adheres to its specification, the resulting optimizations may over-customize the program to the environment and specific workload.

The performance of this post-compiler optimization technique may depend on the compiler used to generate the assembly code. Our evaluation considered only GCC, and it is possible that our results will not generalize to assembler produced by other compilers (e.g., the improvements in branch prediction might not be achieved in code generated by a compiler with better branch prediction capability).

Finally, by embracing relaxed program semantics we acknowledge that our optimizations may change the behavior of the program. Section 4.6 on held-out test suites provides one way to assess this threat in cases where relaxed semantics are undesirable. Earlier studies of a similar approach used for program repair suggest that our minimization step mitigates this threat significantly [34, 55].

5. Background and Related Work

Our approach combines (1) fundamental software engineering tools such as compilers and profilers, (2) mutation operations and algorithms from evolutionary computation, (3) relaxed notions of program semantics to customize software

to a specified environment, and (4) software mutational robustness and neutral spaces.

5.1 Compilers and Profilers

Compilers. Optimizing compilers are well-established in both research and industrial practice [3]. Our work provides *post*-compilation optimizations that refine compiler-generated assembly code.

Traditional compiler optimizations consider only transformations that are provably semantics-preserving (e.g., dataflow analysis). In practice, the C language includes undefined behavior which may lead to compiler- and architecture-dependent runtime behavior, often with surprising effects, such as compilers eliding null checks in programs that rely on undefined behavior [63, §3.3.4].

The difficulty of proving transformations to be semantics-preserving, combined with large differences in energy consumption across machines, means that semantics-preserving compiler optimizations to reduce energy consumption remain unlikely in the near future. For example, a feature request that the popular `llvm` compiler add an "–Oe" flag to optimize for energy was rejected with the counter-suggestion to use the established optimizations for speed instead.[2]

Profiling. Profiling techniques are an established method for guiding both automated and manual optimizations [21]. We use hardware counters, allowing for fine-grained measurements of hardware events without requiring virtualization or instrumentation overheads. This allows test programs to operate at native speeds, which is critical in a search that explores hundreds of thousands of program variants. Our prototype implementation uses the Linux Perf [18] framework to collect hardware counters on a per-process basis.

Profile Guided Optimization. Profile guided optimization (PGO) techniques combine test runs with instrumented programs (or, more recently, with hardware counters) to profile program runtime behavior. These profiles then guide the application of standard compiler optimizations to improve runtime performance, especially to reposition code to reduce instruction loads [45].

PGO can be used to tailor optimizations to a particular workload and architecture. However, the actual transformations provide the same guarantees and limitations of traditional compiler passes. That is, PGO typically narrows its search space by focusing on particular parts of the program (e.g., hot paths). By contrast, our work broadens the scope of possible optimizations through randomized operators and relaxed semantics.

Auto-tuning. Auto-tuning extends PGO, providing additional performance enhancements and the ability to aggressively customize an application to specific hardware. It often requires that applications be written in a distinct modular style. For example, the exceptional performance gains found by the popular FFTW [17] required that the fast Fourier transform (FFT) source code be written in "codelets" (small optimized sub-steps) which were then combined into hardware dependent "plans."

Auto-tuning addresses the same problem as this work, namely that "computer architectures have become so complex that manually optimizing software is difficult to the point of impracticality." [17, § 5] Unlike auto-tuning, however, our method does not require that software be written in any special manner.

Superoptimization. Massalin's classic work introducing superoptimization [37] exhaustively tested all possible combinations of instructions in Motorola's 68020 assembly language to find the fastest possible implementation of simple programs up to 14 instructions in length. The more recent MCMC project [51] leverages increased computing power and heuristic search to find optimizations on the same scale of ˜10 instructions in the much larger x86 instruction set.

Despite its impressive results, the MCMC technique is not directly comparable to this work. They focus on very short sequences of assembly instructions while we operate on entire programs (hundreds of thousands of lines of assembly on average). Because of the extremely small size and simple functionality of their benchmark code, they initialize their heuristic search using a *random* sequence of x86 assembly instructions (using all instructions, including vector operations), and work back from these random sequences to functional code. Such an approach is not feasible for larger programs such as the PARSEC benchmarks.

Both approaches to superoptimization use simple tests of random sequences of assembly instructions to find faster assembly sequences than those accessible through traditional compiler optimizations. Although GOA addresses an entirely different scale in terms of functional and size complexity of the programs analyzed, we exploit the same insights that optimal instruction sequences are often not directly accessible through semantics-preserving operations and that tests can restrict attention to desired modifications. Ultimately, we see superoptimization as complementary, possibly being used in conjunction with our technique (e.g., as an alternating phase targeting the hottest profiled paths).

5.2 Evolutionary Computation

Program Repair. Evolutionary computation is one of several techniques for automatically repairing program defects by searching for patches (sequences of edits) [14, 26, 33, 42, 65], including at the assembly level [52, 53]. GOA differs from this earlier work by addressing a different problem with a continuous complex objective function (reducing power consumption), rather than a discrete single-dimensional objective (passing all test cases).

Evolutionary Improvement. Previous work on the evolutionary improvement of software was limited to modifying abstract syntax trees of simple ˜10-line C functions [66].

[2] `http://llvm.org/bugs/show_bug.cgi?id=6210`

While optimizations were found that are not possible using standard compiler transformations, the small program size and simplified build environment suggest that results may not generalize to legacy software.

Exploring Tradeoffs. EC techniques have recently been used to explore tradeoffs between execution time and visual fidelity in graphics shader programs [59]. This work is similar in spirit to ours but lacks an implicit specification through test cases. Instead, all mutants are valid and a Pareto-optimal frontier of non-dominated options with respect to execution time and visual fidelity is produced.

5.3 Relaxed Program Semantics

As mentioned earlier (Section 1), there is increasing interest in the tradeoff between exact semantics-preserving transformations and improving non-functional properties of programs. "Loop perforation" removes loop iterations to reduce program resource requirements while maintaining an acceptable Quality of Service (QoS) [39, 40]. Other systems change program behavior by switching function implementations [5] at runtime in response to QoS monitoring [23]. A formal system has even been developed to prove "acceptability properties" of some applications of the "relaxed" program transformations [11].

We view our work as partially customizing software to particular runtime goals and environments provided by a software engineer. While we do change explicitly programmed behavior (e.g., removing loop iterations, dropping calculations, etc.), we do not rely on QoS, but always give the *exact* right answer on tested inputs.

5.4 Mutational Robustness and Neutral Spaces

Recent work [54] showed that software functionality is surprisingly robust to random mutations similar to those used in this work, with over 30% of mutations producing *neutral* program variants that still pass an original test suite. These results were obtained over a wide variety of software (including both large open source projects and extensively tested benchmarks from the software testing community [24]). Many of these neutral mutations introduced non-trivial algorithmic changes to the program, yielding new implementations of the program's implicit specification.

These results help explain how random mutations can modify programs without "breaking" them, and it provides a rationale for why GOA succeeds in building "smart" optimizations from "dumb" program transformations.

6. Discussion

The experimental results support the claim that GOA can significantly reduce energy consumption on PARSEC benchmark programs in a way that generalizes to multiple architectures and to held-out workloads and tests. We next discuss the relationship between our work and traditional biological notions of trait selection (optimization), and we outline promising directions for future work.

6.1 Mathematical models of evolution

GOA's evolutionary computation algorithm is inspired by widely accepted theories of biological evolution, a field with a mature literature of mathematical results. Insights from the *Breeders Equation* guided our design of the linear power model fitness function, and analyses of Darwinian selection suggested larger population sizes and higher recombination rates than those used in similar applications to software engineering [33, 59].

Predating Darwin's Origin of Species [13], breeders used the *Breeder's Equation* to measure the effectiveness with which they could select for particular traits. The modern formulation of this classic model helped us analyze heritability and dependencies between traits. In our work, fitness is directly measurable in kilowatt hours, and hardware counters measure *phenotypic traits*. Analysis using biological theory pointed directly to the choice of a simple energy model based on hardware counters (Section 4.3). We used the fitness function to create a selection gradient analogous to β in Equation 3 and derived in the same way. This equation decomposes the effect of natural selection into measurable phenotypic traits by regressing phenotypic traits β against fitness [12, Chpt. 4].

The *Multivariate Breeder's Equation* is shown in Equation 3, where $\Delta\hat{Z}$ is a vector representing the change in phenotypic means, G is a matrix of the additive variance-covariance between traits and β is a vector representing the strength of selection. This equation quantifies the notion of heritability and the likely side effects of optimizing a given phenotypic trait in terms of other uncontrolled traits. The mathematical foundation provided by the Breeders Equation will provide a starting point for designing fitness functions for other GOA applications, for example, as outlined in Section 6.3.

$$\Delta\hat{Z} = G\beta \tag{3}$$

6.2 Fault Localization

Previous applications of EC to software engineering have relied on fault localization techniques as a way to limit the space of possible code modifications to the execution paths of the given test suite [33, 34]. In this paper we did not impose that restriction, and we discovered that minimized optimizations often did not modify the instructions executed by the test cases. We speculate that these optimizations may operate through changes to program offset and alignment, or by modifying non-executable data portions of program memory.

6.3 Future Work

Other Architectures. To date, we have applied GOA only to x86 assembly code. Our program representations and mu-

tation operations are quite general, and we believe that GOA would apply equally well to other instruction sets, such as ARM [52] or Java bytecode [44]. We note, however, that the high density of x86 instructions in random data [7] may have played a role in our results (Section 2),

Co-evolutionary Model Improvement. GOA could be extended to iteratively refine the models that predict measurable values from hardware performance counters (such as the energy model used in this work). At a high level, the approach would be as follows:

1. Build an initial model from hardware counters and empirical measurements across multiple benchmark programs.
2. Evolve benchmark variants that maximize the difference between the model and reality.
3. Re-train the model using the evolved versions of benchmark programs.

Assuming that the measurable quantity predicted by the model (e.g., energy) can be changed only a limited amount, the evolutionary process would likely find and exploit errors in the initial model. Adding individuals to the training data that exploit these errors would improve subsequent versions of the model. Over multiple iterations, this *competitive co-evolution* [4] between the model and the candidate optimizations could improve both the model and the final optimizations.

Mathematical Analysis. Our energy reduction optimizations of `vips` on both systems produce optimized versions that (despite running for fewer cycles) generate significantly more page faults than the original. It would be desirable to predict unintuitive results of optimization such as these, i.e. program features that are not included in the fitness function or energy model.

The concept of *Indirect selection* [12, Chpt. 6] suggests an approach for predicting some side effects of the search. Indirect selection is defined as the impact of selection on properties (traits) that are not themselves targets of selection but are strongly correlated with the selected traits. Variance-covariance matrices (G in Equation 3) could be used to predict the effects of optimization on program characteristics that are not included directly in the fitness function but likely affected by the optimization process. This would require constructing and analyzing the program's variance-covariance matrix of traits of neutral mutations before the optimization run.

Compiler Flags. Finding effective combinations and orderings of compiler passes is an open research question, and it is known that no single sequence of compiler passes is optimal for all programs [30] or even for all methods in a single program [31]. GOA could be extended to include multiple populations, each generated using unique combinations of compiler optimizations. By allowing each population to search independently for optimizations and occasionally exchanging high-fitness individuals among the populations, it may be possible to mitigate this problem.

7. Conclusion

We present an automated post-compilation technique for optimizing non-functional properties of software, such as energy consumption. Our Genetic Optimization Algorithm (GOA) combines insights from profile-guided optimization, superoptimization, evolutionary computation and mutational robustness. GOA is a steady-state evolutionary algorithm, which maintains a population of candidate optimizations (assembly programs), using randomized operators to generate variations, and selecting those that improve an objective function (the power model) while retaining all required functionality expressed in a test suite.

We describe experiments that optimize the PARSEC benchmarks to reduce energy consumption, evaluated via physical wall-socket power measurements. The use case is an embedded deployment or datacenter where the program will be run multiple times. Our technique successfully reduces energy consumption by 20% on average. Our results show that GOA is effective on multiple architectures, is able to find hardware-specific optimizations and to correct inefficient program semantics, that the optimizations found generalize across held-out workloads, and that in most cases the optimizations retain correctness on held-out test cases.

To summarize, GOA is: *powerful*, significantly reducing energy consumption beyond the best available compiler optimizations and capable of customizing software to a target execution environment; *simple*, leveraging widely available tools such as compilers and profilers and requiring no code annotation or technical expertise; and *general*, using general program transformations from the EC community, able to target multiple measurable objective functions, and applicable to any program that compiles to x86 assembly code.

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