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A Study on the Influence of Software and Hardware Features on Program Energy

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ABSTRACT

Software energy consumption has emerged as a growing concern in recent years. Managing the energy consumed by a software is, however, a difficult challenge due to the large number of factors affecting it – namely, features of the processor, memory, cache, and other hardware components, characteristics of the program and the workload running, OS routines, compiler optimisations, among others. In this paper we study the relevance of numerous architectural and program features (static and dynamic) to the energy consumed by software. The motivation behind the study is to gain an understanding of the features affecting software energy and to provide recommendations on features to optimise for energy efficiency.

In our study we used 58 subject desktop programs, each with their own workload, and from different application domains. We collected over 100 hardware and software metrics, statically and dynamically, using existing tools for program analysis, instrumentation and run time monitoring. We then performed statistical feature selection to extract the features relevant to energy consumption. We discuss potential optimisations for the selected features. We also examine whether the energy-relevant features are different from those known to affect software performance. The features commonly selected in our experiments were execution time, cache accesses, memory instructions, context switches, CPU migrations, and program length (Halstead metric). All of these features are known to affect software performance, in terms of running time, power consumed and latency.

1. INTRODUCTION

With rising energy costs and the need for environmental improvements, one of the key challenges faced by the ICT industry now and in the coming years will be reducing its carbon footprint and energy consumption while still delivering the performance and quality that users expect. Energy consumption is not only an issue for the mobile embedded systems domain, but also for servers, desktops and laptops which constitute more than a third of ICT energy consumption [38].

Measuring and managing the energy consumed by a software is, however, a difficult challenge due to the large number of factors affecting energy consumed – namely, characteristics of the processor (clock frequency, voltage, pipeline depth), memory (instruction and data cache reads, writes and misses), communication network, GPU, sensors for mobile devices, compiler and optimisations enabled, features of the program and workload running (number of instructions, input data, number of branches, number of operators and operands, algorithmic complexity, multi-threading), among others. Before we embark on proposing optimisations for software energy consumption, we believe it is imperative to first identify and understand the factors that contribute to energy consumption. Our ultimate goal is to use this understanding to guide techniques in choosing factors to optimise for energy. We would also like to ascertain if the factors affecting software energy are the same as those affecting software performance, in which case there is no need to propose new optimisation techniques specifically targeting energy. Existing optimisation techniques targeting performance may also be adequate for energy.

Existing literature, particularly in the embedded systems domain, has estimated energy consumption based on several architectural features [44, 47, 42]. Recent literature in the mobile devices domain estimated energy consumption using features related to the application and several other integrated hardware components [26, 21]. The goal in all of these studies has been to profile or estimate energy based on architectural and, in some cases, application features [43, 47]. Our empirical study does not aim to estimate energy but instead tries to understand the statistical relevance of features, both architectural and program specific when taken together, to energy consumed. We then select the relevant features as targets for energy optimization techniques. The selection technique we use takes interaction between features into account and eliminates redundancy in the selection.

Our empirical study has the following salient features

• We collect data on energy consumption and over a hundred features, static and dynamic, related to the architecture and the program.
• Our data is collected using 58 subject programs, each with their own workload, from different domains. Many of these programs are part of industry standard benchmarks.

• We use a statistical machine learning technique called feature selection to select the features relevant to energy consumption.
• We analyse the features selected, discuss their use as potential targets for optimisation and determine if they are different from optimisations proposed for software performance.

The feature selection technique we use is the LASSO technique [48]. To validate the usefulness of the features selected by Lasso, we compared accuracy of energy predictions using
only the selected features against energy predictions from a linear regression model using all the features. We found the features selected in our study were the same as known features in existing optimisations for execution time.

Our paper is organised as follows. Section 2 discusses related work. In Section 3 we describe the experimental setup to gather hardware and software features over different programs. We detail and discuss the results of our experiments in Section 4. We provide more insights into the features selected by our experiments, and the effect of existing optimisations in Section 5. Threats to validity in our experiment and conclusions are presented in Sections 6 and 7.

2. RELATED WORK

Monitoring and modeling energy consumption of applications has been and still is an active research area. As stated earlier, the goal in our work is not to model or estimate energy but to understand the relevance of many hardware and software features, when taken together, to energy to guide optimisations. Nevertheless, we present relevant literature on energy modeling since that is the most closely related body of work.

Previous work in the embedded systems domain has focussed extensively on estimating power consumed by the processor [49, 44, 47]. The estimations rely on a complete characterisation of the underlying instruction set architecture and inter-instruction effects to estimate power consumption.

Cycle-accurate simulators developed to estimate power can simulate the actions of a processor at an architecture-level [9, 34, 52]. They identify the architectural blocks that are active in each clock cycle and record the input operands seen by each architectural block. Power consumption is then estimated for each architectural block as a function of the input data values. Both instruction-level characterisation and cycle-accurate simulator estimation methods are slow, compute-intensive, and infeasible for applications outside the embedded systems domain.

Several tools have been developed to estimate energy using hardware component characteristics. pTop [16] estimates energy consumption using a model based on the characteristics of hardware components (such as CPU, hard disk, ethernet). PowerAPI and BitWatts [11] use hardware performance counters to learn the energy model of hardware components. They build the model by benchmarking the computer and collecting power measurements using a power meter. Jalen [32] is built on top of PowerAPI’s energy models and maps energy estimations to an application’s source code. In [43], Seo et al. estimate energy consumption of distributed Java applications by benchmarking Java bytecode and native methods, measuring their energy consumption with a multimeter. Collected results are then used to construct an energy model for Java components and applications.

For mobile devices, integrated hardware components, such as the GPS, screen, or the 3G communication interface, introduce additional complexity into the energy models. Recent literature [36, 26, 21] has focussed on energy models for mobile devices. Eprof [36] maps back energy consumption of hardware components to applications by adopting a last-trigger policy. For example, it associates tail energy drains of a hardware component 1 to the last application that triggered the usage of that component. Hao et al. [21] and Li et al. [26] propose an approach called bLens to estimate energy usage at the source code level. They estimate the energy consumption of mobile applications using program analysis and linear regression analysis. Applications

3. EXPERIMENT DESCRIPTION

The experiment we conducted is comprised of two phases, Phase 1: Data Collection - We ran a series of experiments on programs from three different benchmark suites to measure energy consumed and features related to the hardware and program. The benchmarks, features measured, and tools used for measurements are explained in the following sections.

Phase 2: Prediction Models - Using the measurements in the data collection phase, we trained our model to select features that are relevant to the energy consumed. The statistical feature selection technique we use is Lasso regression and is described in Section 3.4. In order to validate the accuracy and usefulness of the selected features, we also trained and constructed a linear regression model using all the features. We then compared the energy prediction error of Lasso regression (with the selected features) against that of Linear regression using all the features.

Phases 1 and 2 are described in the following sections.

We ran our experiments using a desktop computer powered by an Intel Core 2 Duo E8400 processor at 3 GHz, 2 GB of DDR2 memory at 800 MHz, 128 KB of L1 cache and 6 MB of L2 cache. The machine was running Ubuntu Server 14.04 with Linux kernel 3.16.0.33.

Phase 1 - Data Collection

3.1 Benchmarks

The programs in our experiments are from a range of application domains such as image processing, biomolecular simulation, networking, automotive, fluid dynamics, operating system, signal processing among others. The programs perform diverse tasks varying in the type and intensity of computation, file I/O, amount and frequency of memory operations, and several other features. For test cases and benchmarks that run in just a few milliseconds, we run them in a loop (ranging from 1 to 10,000 cycles) to get execution times that are large enough for measurement. Collected data is then averaged for a single program run and compared with the other programs. The programs and benchmark families used in our experiments are as follows.

3.1.1 SIR

We used 9 programs from the SIR (Software-artifact Infrastructure Repository) repository [15]. Programs include GNU projects (gzip 1.0.7 and sed 1.17), two lexical analysers (printtokens and printokens2), two priority schedulers (schedule and schedule 2), a pattern matching program (replace), a statistics program (totinfo), and an aircraft collision avoidance system (tcas). Test cases were either provided, or generated using the Make-test-script program and test plans described in universe files. The test cases exercise the parameters and behaviour of the programs as described in [15]. We run our experiments and collected metrics for test cases over each SIR program. We performed two different analysis on the SIR programs, (1) For each SIR program, we used 300 randomly selected test runs to collect observations. We performed feature selection over these observations for each SIR program, (2) We randomly selected 30 test runs for each SIR program, resulting in a total of 270 observations on all 9 SIR programs. We then performed feature selection across observations over all SIR programs. We limited the test runs in order for the total number of

1Tail energy happens when a component, such as the GPS, continues to be active and consumes energy even after the application that triggered its usage has ended.

2Features in our estimation model refers to the hardware and program related metrics.
observations per benchmark family to be comparable. It is worth noting that each observation in our context is a record of the energy consumed along with measurements of the different hardware and program features for that test run.

3.1.2 Parboil Benchmark

We used all 11 programs from the Parboil benchmark [46], which is an open source benchmark suite with benchmarks collected from throughout computing application researchers in many different scientific and commercial fields including image processing, biomolecular simulation, fluid dynamics, and astronomy. Applications in the benchmarks perform a variety of computations including ray tracing, finite-difference time-domain simulation, magnetic resonance imaging, 3-D stencil operation. Parboil provides applications implemented as both serial C++ and OpenMP, along with workloads specific to the programming model. We run both the base and parallel OpenMP versions of these programs. We collected 51 observations over all the programs in Parboil.

3.1.3 EEMBC Benchmark

Embedded Microprocessor Benchmark Consortium (EEMBC) [37] provides a diverse suite of processor benchmarks organised into categories that span numerous real-world applications, namely automotive, digital media, networking, office automation and signal processing, among others. There are a total of 38 programs – 17 from automotive domain, 6 from consumer, 4 in networking, 5 in office, and 6 from telecom. We used the workload in the benchmarks to generate a total of 304 observations over all 38 programs.

The features measured and tools used are explained in the next section.

3.2 Measurements

For every run of every program, we used existing run time monitoring and program analysis tools to measure,

**Hardware performance features** reflecting CPU, cache and memory performance. We measure these features since they are known to impact power and energy [9, 13, 16, 18].

**Dynamic program features** relating to types of program instructions generated, memory operations performed, and register utilisation. Different types of instructions are associated with different base energy costs [49]. Inter-instruction effects, and operands also affect the energy consumed. Memory operations are also associated with high energy costs. Finally, effective register utilisation during machine code translation is shown to help improve energy efficiency [42].

**Static program features** such as number of basic blocks, number of loops, branches, global variables, cyclomatic complexity. We measure these high-level program features since they have been shown to be useful in estimating energy consumed by software [47], and are the primary guide in creating and measuring adequacy of test runs (over which execution time and energy are measured) [45, 22, 41].

In addition to the above features, we also measured the execution time and energy consumed by each of the program runs.

3.2.1 Hardware Features

We use Linux’s Perf tool [2] to collect 37 hardware features. Perf uses special-purpose CPU registers to count the number of events, such as CPU misses or mispredicted branches. Perf runs in the user space and is part of the kernel. It has a low overhead compared to instrumenting profilers [51]. The hardware features collected with Perf are as follows:

**Performance features.** We collected 8 features that provide CPU performance information for the program, such as the number of instructions executed between each performance sampling, total CPU cycles, total bus cycles, the total time spent by the application or its tasks on the CPU (CPU clock and task clock). Additional metrics include the number of context switches and the number of CPU migrations. Number of context switches corresponds to the number of times the CPU restored the context (e.g., state) of a process or thread. Context switches can invalidate some TLB entries, since the virtual-to-physical address mapping is different. This results in misses in the TLB for a memory reference. The number of CPU migrations counts the number of times the executing process has migrated to a new CPU or a new CPU core.

**Branch Instruction features.** We collected 4 features that count the number of executed branch instructions, mispredicted branch instructions, number of branch instructions with a load access, and the number of those loads that resulted in a cache miss.

**Cache Related features.** Cache effects are known to have a significant impact on performance [18]. We collected 19 features that record the number of loads and stores (in addition to load misses and store misses) for Level 1 Cache (L1), Last Level Cache (LLC) and Translation Lookaside Buffer (TLB). For L1 cache and TLB buffer, we collect separate metrics for data and instruction cache.

**Page Fault features.** We collected 6 features including, total page faults, minor and major page faults, alignment and emulation faults. When a page fault occurs, the thread that experienced the page fault is put into a Wait state while the operating system finds the specific page on disk and restores it to physical memory. Page faults can cost millions of CPU clock cycles because of disk access and, as a result, severely affect performance.

In addition to the above hardware features, we also measured execution time of the program using the “time” Linux command.

3.2.2 Dynamic Program Features

We use the Pin tool [28] (version 2.14) to collect 42 dynamic program features. Pin is a dynamic binary instrumentation framework where instrumentation is performed at run-time on the compiled binary files. We built instrumentation tools in this framework to collect features in the following categories:

**Program Instructions.** We used 4 features to count the number of executed instructions, the number and size of basic blocks executed, and the number of threads.

**Memory Instructions.** We used 6 features counting the number of times instructions were read or written from/to memory, and the number of malloc/realloc/calloc and free calls.

**Processor Registers.** We used 32 features to count the number of read and write accesses to the different processor registers.

3.2.3 Static Program Features

We collect 25 static program features using Frama-C’s [5] metrics plugin [1] (Sodium release). The Frama-C platform helps analyse the source code for C programs. We collect the following metrics:

**Halstead Complexity measures** [20]. We have 13 features that count the total and distinct number of operators and
operands, the program length (which describes the size of
the abstracted program by removing everything except op-
erators and operands), the program volume (which mod-
els the number of bits required to store the abstracted pro-
gram), and program level (which defines the ratio between
the program volume and the volume of its most compacted
implementation).
McCabe’s Cyclomatic complexity [29]. We use this feature
to provide an indication of the complexity of a program by
measuring the number of linearly independent paths in a
program.
Other static progam features. We have 11 features represen-
ting the number of source lines of code, number of loops,
ifs, Gotos, functions declared, exit points (e.g., return state-
ments), the number of decision points, global variables and
the number of pointer dereferences.

3.2.4 Energy Metric
We measure the energy consumed by the computer for
each program run using a Watts Up? .Net power meter [4].
The power meter is connected to another computer that col-
lects energy observations at runtime. We also measured and
continuously monitored the idle energy of the computer. We
used the server edition of Ubuntu as our operating system
with no additional services running. Energy consumption of
a program run is the difference between the measured en-
ergy and idle energy. It is also worth noting that our energy
measurements do not include the energy consumed by the
monitor since the monitor we use has its own independent
power supply.
In summary, we observed a total of 106 features, both
hardware and program specific, that we believed will be rel-
levant to the energy consumed by the program. In the next
sections, we describe the regression models and feature se-
lection technique we use in our experiments.

Phase 2 - Prediction Models
3.3 Linear Regression
One of the most widely used regression models is linear
regression. This asserts that the response we wish to predict,
y ("dependent variable") is a linear function of the input
vector x (“independent variables” or features). In this paper,
x is a vector of hardware and software features measured
over the program that is used to compute y, the energy
consumed by the program. Linear regression is expressed
by Murphy et al. [31] as

$$ y(x) = w^T x + \epsilon = \sum_{j=1}^{D} w_j x_j + \epsilon $$

where $w^T x$ represents the scalar product between the input
vector x and model’s weight vector w, also referred to as
vector of coefficients for x. $D$ is the length of input vector
x. $\epsilon$ is the residual error between our linear predictions
and the true response. Now given this regression model and a
training data with $N$ number of observations, we need to
find an optimal setting of the coefficients vector, w, for best
predicting y from x. This optimisation is typically done by
minimizing the residual sum of squares (RSS) or sum of
squared errors (SSE) as defined by,

$$ RSS(w) = \sum_{i=1}^{N} (y_i - w^T x_i)^2 $$

This method is referred to as least squares. The values of
$w_i$ computed for minimal RSS represent the regression co-
efficients to be used in the model. We used the WEKA
(Waikato Environment for Knowledge Analysis) tool [19] to
build the Linear regression models.

3.4 Feature Selection using Lasso
We use a machine learning technique, called feature se-
lection, to select a subset of statistically relevant features
to improve the overall performance of the learning model by
preventing overfitting. In the context of this paper, we apply
feature selection to (1) understand the relationship between
the features and energy consumed, and (2) to select the set
of relevant features (among all hardware and program fea-
tures) that can provide insight on where to target energy
optimisation efforts. Note that we are interested in the ef-
fect of features taken together, rather than individually, on
the energy consumed. Feature selection also eliminates the
need for measuring features that are not relevant, or are
redundant to the energy consumed. We use an $L_1$ regular-
ization method called LASSO to apply feature selection in
the linear regression model [31], [48]. Lasso is an embedded
algorithm performing feature selection as part of the model
construction process. Regularization methods introduce a
penalty term for the size of the weights that is tuned em-
pirically for minimizing the RSS. Lasso regression is often
preferred because it produces sparse models effectively, i.e.,
the regression coefficients for most irrelevant or redundant
features are shrunk to zero, thereby achieving feature selec-
tion [27]. Interactions among features are also taken into
account by Lasso. We achieve Lasso feature selection in
our experiments using the ‘glmnet’ package [17] in R [40], a
software environment for statistical computing.

3.5 Validation
We use cross validation, in particular, Leave-One Out
Cross Validation (LOOCV) to evaluate the performance
of the different prediction models. Cross validation tech-
nique works as follows; suppose the original dataset has $N$
observations, then, for each $i \in \{1, ..., N\}$, we train the re-
gression model on all except the ith observation, test the
model on the ith observation and compute the error. This
process is repeated in a round-robin fashion and the error
averaged over all $i$, i.e, $N$ validation runs. In our case, every
test case run from every program results in an observation
of vector x of features and response y of the energy consumed.
For each regression model, we compute, using LOOCV, the
Root Mean Squared Error,

$$ RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2} $$

which is the square root of the mean of the squared errors
over n different predictions. We then normalize the RMSE
to the range of the observed response using the minimum
and maximum actual response, i.e., Normalised RMSE

$$ NRMSE = \frac{RMSE}{y_{max} - y_{min}} $$

NRMSE is a popular error metric to compare numerical pre-
diction errors between models. Compared to mean absolute
error, RMSE amplifies and severely punishes large errors,
such as those from outliers.

4. EXPERIMENTAL RESULTS AND
ANALYSIS
We collected observations of energy and features for pro-
grams with their respective workloads in the three bench-
mark families as described in Section 3. The results are
organised and analysed as follows.
1. Per SIR program. We conducted analysis separately
for each of the 9 SIR programs.

$$ y_{max} - y_{min} $$

NRMSE is a popular error metric to compare numerical pre-
diction errors between models. Compared to mean absolute
error, RMSE amplifies and severely punishes large errors,
such as those from outliers.
2. Per benchmark family. Within each benchmark family, we analysed the results from runs of all programs. Each analysis was carried out as follows: We used the Lasso learning technique to select a subset of features from all the hardware and program specific features observed. We assessed the usefulness of the selected features by comparing the NRMSE for energy prediction using Lasso against that of Linear regression with all features. We list the relevant features selected by Lasso and their coefficients. The coefficient values of the different features cannot be compared directly since the magnitudes and units of the measurements are not comparable. For instance, execution time is measured in milliseconds, while a Halstead metric gives the number of distinct operators and operands.

We did not conduct per program analysis for EEMBC and Parboil benchmarks since the number of test runs available per program was significantly smaller than the number of features measured. Predictions for such programs in our high-dimensional feature space will be highly inaccurate due to the curse of dimensionality [6]. As a result, we only conducted per program analysis for SIR programs that had greater number of test runs than features measured.

4.1 Individual SIR Programs

For each of the SIR programs, we ran 300 randomly selected test cases. The NRMSE results for the individual SIR programs are presented in Figure 1. Lasso regression performs well with a lower NRMSE across all SIR programs. Linear regression has a slightly higher NRMSE (less than 0.2%).

Table 1 lists for each of the 9 SIR programs, the features selected by LASSO for energy estimation. It is important to note that the Lasso feature selection technique will suppress features that are relevant to energy but redundant with respect to another feature selected.

Execution time is a feature selected in all SIR programs. This was to be expected since execution time has a high impact on energy consumption, and aligns with observations in previous investigations [12, 36, 24].

For all the SIR programs, CPU migrations and context switches are among the features selected. Both these features are known to cause overheads in terms of running time [25, 14]. CPU clock and/or task clock are also selected since the time spent in the CPU by the program (CPU clock) and its threads (task clock) is high.

Features related to LLC cache and memory instructions in the source code (malloc/calloc/realloc and free) also appear in Table 1. This is because the programs frequently read and write data resulting in frequent accesses to the cache. Some of these cache accesses result in cache misses that cost extra clock cycles. Static software features are not selected for any of the SIR programs since for runs within each program, these features remain constant. Lasso shrinks the weight of these features to zero since they do not exhibit any deviation between observations.

4.2 Benchmark Families

We now discuss results from runs of all programs within each benchmark family.

4.2.1 SIR Benchmarks

Similar to our observation in individual SIR programs, NRMSE numbers are low across both prediction models (see Table 2). 0.00097 for linear, and Lasso is lower with 0.00082. The features selected with Lasso are marginally more effective in predicting energy than all the features in the linear model. Table 3 shows the features selected by Lasso.

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Table 1: Features selected by LASSO for individual SIR programs (when applying Lasso using all features)

<table>
<thead>
<tr>
<th>Function</th>
<th>Program.level</th>
<th>Gzip</th>
<th>Printtokens</th>
<th>Printtokens2</th>
</tr>
</thead>
<tbody>
<tr>
<td>cpu.migrations</td>
<td>0.234642543</td>
<td>execution.time</td>
<td>execution.time</td>
<td>execution.time</td>
</tr>
<tr>
<td>LLC.load.misses</td>
<td>0.001374207</td>
<td>time</td>
<td>cache.misses</td>
<td>cache.misses</td>
</tr>
<tr>
<td>page.migration</td>
<td>0.000190104</td>
<td>cpu.migrations</td>
<td>context.switches</td>
<td>context.switches</td>
</tr>
<tr>
<td>LLC.store.misses</td>
<td>0.0001386825</td>
<td>cpu.migrations</td>
<td>minor.faults</td>
<td>minor.faults</td>
</tr>
<tr>
<td>replacement</td>
<td>0.000154405</td>
<td>LLC.load.misses</td>
<td>LLC.load.misses</td>
<td>LLC.load.misses</td>
</tr>
<tr>
<td>free</td>
<td>0.000154405</td>
<td>LLC.store.misses</td>
<td>LLC.store.misses</td>
<td>LLC.store.misses</td>
</tr>
<tr>
<td>-</td>
<td>-</td>
<td>malloc</td>
<td>free</td>
<td>free</td>
</tr>
</tbody>
</table>

Table 2: Normalized Root mean square error (NRMSE) for all benchmarks

<table>
<thead>
<tr>
<th>Linear</th>
<th>LASSO</th>
</tr>
</thead>
<tbody>
<tr>
<td>SIR</td>
<td>0.000971891</td>
</tr>
<tr>
<td>EEMBC</td>
<td>0.004287477</td>
</tr>
<tr>
<td>Parboil</td>
<td>0.051841246</td>
</tr>
</tbody>
</table>

Table 3: Features selected by LASSO for all SIR benchmarks

Most of the features present in Table 3, are also present in the selection for individual SIR programs (see Table 1) and the reasons for the selection are similar. Table 3 also...
shows the coefficient values for the selected features. The coefficient value for execution time is $10^2$ to $10^3$ times larger than coefficient values for other features. Although, coefficient values in such models cannot be directly compared due to the different units of measurements, it provides a hint on the importance of execution time for energy prediction in the SIR benchmarks. To assess the importance of execution time for energy prediction, we compared LASSO prediction errors with and without execution time in the feature set. Table 4 lists the NRMSE for LASSO with “All” features, “All - Time”, “Only Software”, and “Only Hardware”. As can be seen, NRMSE increases by 3 times when execution time is removed from the observations. execution.time is, thus, a key consideration, and cannot be approximated by any set of hardware or software features for SIR benchmarks.

Table 4 also shows that prediction accuracy is approximately the same for “All - Time”, “Only Software” and “Only Hardware” with “Only Hardware” being marginally better. For SIR programs, measuring either only the program characteristics or only the hardware features, along with execution time would suffice to predict energy.

A feature that is different from what we saw for individual SIR programs is the size of the program indicated by the Halstead metric, Program.level. This implies that the number of distinct operators and operands in the source code for the SIR programs has an effect on energy. As mentioned earlier, we did not see this static program metric for individual programs since it does not change across runs of the same program. cpu.clock and/or task.clock are selected for all individual SIR programs, but is not seen in the LASSO selection across all programs. The software metrics, Program.level, Function, and calloc have effectively replaced cpu.clock and task.clock. This is confirmed again in Table 4 when we perform Lasso selection with Only Software metrics which has the same prediction accuracy as Lasso using All – Time.

### 4.2.2 EEMBC Benchmarks

For the 38 programs in the EEMBC benchmark, the Linear regression model performs better with an NRMSE of 0.0042 compared to the Lasso model with an NRMSE of 0.0055 (see Table 2). The prediction errors are, however, comparable and as a result, the features selected can be considered further for optimisations.

Table 5 shows the features selected by Lasso. As with the SIR benchmarks, execution time is selected and the coefficient value (without normalising) is larger than the other features. However, execution time is not as significant for energy prediction as in the case of SIR benchmarks. This is evident from Table 6 where the prediction error of Lasso using All features is comparable to Lasso using All – Time features. Only Software and Only Hardware features also have comparable accuracy in energy prediction. This implies that targeting optimisations at one of these sets of features will be effective in achieving energy efficiency.

```
<table>
<thead>
<tr>
<th>Features selected</th>
<th>Absolute Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>execution.time</td>
<td>4.83E22931</td>
</tr>
<tr>
<td>cpu.clock</td>
<td>0.00460450</td>
</tr>
<tr>
<td>task.clock</td>
<td>0.00431552</td>
</tr>
<tr>
<td>context.switches</td>
<td>0.046315249</td>
</tr>
<tr>
<td>cpu.migrations</td>
<td>1.75523195</td>
</tr>
<tr>
<td>branch.misses</td>
<td>6.10E-08</td>
</tr>
<tr>
<td>bus.cycles</td>
<td>1.38E-08</td>
</tr>
</tbody>
</table>
```

Table 5: Features selected by LASSO for all EEMBC benchmarks

For the Parboil benchmarks, Linear regression model does better with an NRMSE of 0.0518, as seen in Table 2. Lasso has a slightly higher error of 0.07484. Among the 3 benchmark families seen thus far, NRMSE is highest for Parboil across prediction models. We believe there are two reasons for the high NRMSE values for Parboil, (1) The number of observations available for Parboil is fewer than the other two benchmarks (51 for Parboil versus 304 for EEMBC and 270 for SIR), resulting in the dimensional feature space being much bigger. As a result, the effect of the curse of dimensionality is more significant in Parboil. (2) Parboil benchmarks have both the serial and parallel versions. Number of threads is the only feature in our measurements that reflects the parallel nature of benchmarks. It may be the case that this single feature is inadequate in capturing the effects of parallelism on energy. Table 7 shows the features selected by Lasso and the absolute weights of the coefficients.

The coefficient value of execution time is significantly larger than that of the other selected features. As can be seen in Table 8, prediction error almost doubles when execution time is not included (All – Time) in the observations, reflecting its importance for energy estimation.

![Figure 1: Normalized Root mean square error (NRMSE) for SIR programs](image)
energy optimisation targets. We also go on to discuss if the features (or sets of features) and discuss their potential as repeatedly selected across all our experiments. We list these features with respect to each other or a combination of other selected variables have high coefficient values in the linear regression model but are not selected by Lasso since they are redundant. For instance, features like basic blocks and global spatial locality result in data cache misses being an important aspect of energy estimation.

5. DISCUSSION

From our experiments, we find that the overall accuracy of the Lasso feature selection technique is comparable to the Linear regression model with all the features. The Lasso technique did not always outperform the Linear model and there was no consistent best model across all experiments. Given the high dimensional feature space, we believe comparable prediction accuracy using the Lasso model is a good start and the selected features can be used as a basis for discussion on potential optimisations for energy. It is worth noting that feature selection using Lasso implies they are not redundant with respect to execution time. When correlated features are selected, it implies that the features together better predict energy than any one of them (they are not redundant with respect to each other or a combination of other selected features).

We found that some hardware and program features were repeatedly selected across all our experiments. We list these features (or sets of features) and discuss their potential as energy optimisation targets. We also go on to discuss if the selected features and optimisations are any different from those already known for software performance.

**Execution Time:** Execution time has often been used as a representative for energy [12, 36, 24]. Lasso feature selection over all benchmarks resulted in coefficient values for execution time being 10 to 100 times larger than coefficient values for other features. Although, coefficient values in such models cannot be directly compared due to the different units of measurements, it provides a hint on the importance of execution time for energy. It is clearly valuable to target execution time for energy optimisation. However, it is important to bear in mind that energy is dependent on both execution time and power, and reducing one while increasing the other will offset the gains achieved.

**Cache and Memory instructions:** Our experiments consistently selected cache (L1, LLC, and TLB) features, and dynamic memory instruction features. Missed cache hits, on both the internal and external cache, as well as page faults slow the performance of a program [49, 50] by significantly increasing memory latency and, therefore, execution time. Note, however, that the cache features being selected by Lasso implies they are not redundant with respect to execution time. The selection implies that it is potentially beneficial to optimise cache features in addition to optimising execution time. For instance, if we have a memory intensive process whose performance is limited by the available memory bandwidth (cache and memory access speeds are slower than processor speeds), we will gain limited execution time gains from increasing processor clock frequency. The increased clock frequency will result in increased power consumption that may offset the limited execution time gains. Thus, it may be beneficial to move memory intensive processes to lower frequency cores, while executing less memory intensive processes on higher frequency cores.

To reduce cache misses and memory latency, one can place related data close in memory and use algorithms and data structures that exploit the principle of locality. For instance, elements of std::vector in C++ are stored in contiguous memory and accessing them is more cache-friendly since it exploits spatial locality, than accessing elements in std::list that does not have this feature.

Compiler researchers have also proposed the use of reuse distance as a metric to approximate cache misses [8, 39].

<table>
<thead>
<tr>
<th>Table 4: NMRSE and feature selected by LASSO for SIR benchmarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>NRMSE</td>
</tr>
<tr>
<td>-------</td>
</tr>
<tr>
<td>0.005921402</td>
</tr>
<tr>
<td>0.005999306</td>
</tr>
<tr>
<td>0.006079861</td>
</tr>
<tr>
<td>0.006016273</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 7: Features selected by LASSO for all Parboil benchmarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Features selected</td>
</tr>
<tr>
<td>-------------------</td>
</tr>
<tr>
<td>execution.time</td>
</tr>
<tr>
<td>cpu.clock</td>
</tr>
<tr>
<td>task.clock</td>
</tr>
<tr>
<td>L1.dcache.prefetches</td>
</tr>
<tr>
<td>dTLB.load.misses</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 6: NMRSE and feature selected by LASSO for EEMBC benchmarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>NRMSE</td>
</tr>
<tr>
<td>-------</td>
</tr>
<tr>
<td>0.003193454</td>
</tr>
<tr>
<td>0.003193454</td>
</tr>
<tr>
<td>0.003183806</td>
</tr>
</tbody>
</table>

Authors: [List of authors]
It is evident from Table 9 that the energy gains achieved over SIR benchmarks using Polly for loop optimisations is relatively low, maximum being 6.36% (over printtokens2). This is primarily because in SIR programs, loops are used sparsely with relatively few data and array references within them. As a result, there is not enough opportunity for Polly to improve data locality. For instance, in the case of the tcas program where almost no energy gain was observed, loop structures are not present in the program and as a result Polly has no effect. printtokens, on the other hand, is a program which accepts a file containing a stream of characters and for each character (outer loop) it performs an expensive search to find the corresponding token (inner loop). This loop structure provides relatively more opportunities for Polly to optimise than in the case of tcas, resulting in the higher energy gain of 5.06%. As seen in Table 9, energy gains follow execution time gains for most SIR programs. This is because, improved data locality and thus, reduced cache misses helps reduce execution time and not power.

For the EEMBC benchmarks, we ran the Polly optimiser over the automotive domain comprising of 16 programs and associated workloads. Table 10 lists the energy gains with

<table>
<thead>
<tr>
<th>SIR prog.</th>
<th>Energy gain (%)</th>
<th>Exec.time gain (%)</th>
<th>Power gain (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>gzip</td>
<td>3.38</td>
<td>3.71</td>
<td>-0.37</td>
</tr>
<tr>
<td>printtokens</td>
<td>5.06</td>
<td>4.99</td>
<td>0.28</td>
</tr>
<tr>
<td>printtokens2</td>
<td>6.36</td>
<td>6.10</td>
<td>0.16</td>
</tr>
<tr>
<td>replace</td>
<td>-0.16</td>
<td>0</td>
<td>-0.17</td>
</tr>
<tr>
<td>schedule</td>
<td>0.24</td>
<td>0</td>
<td>0.25</td>
</tr>
<tr>
<td>schedule2</td>
<td>0.22</td>
<td>0.10</td>
<td>0.03</td>
</tr>
<tr>
<td>sed</td>
<td>4.59</td>
<td>4.95</td>
<td>-0.31</td>
</tr>
<tr>
<td>tcas</td>
<td>0.03</td>
<td>0</td>
<td>0.04</td>
</tr>
<tr>
<td>totinfo</td>
<td>-0.04</td>
<td>-0.2</td>
<td>0.12</td>
</tr>
</tbody>
</table>

Table 9: Energy gains in SIR benchmarks from Polly loop optimiser

Polly in complete contrast to the SIR benchmarks, we observed massive energy gains with Polly, ranging from 45.74% to 83.94%. The large gains can be explained by the program structure of the EEMBC benchmarks, predominantly comprising of statements in for loops and array accesses. Polly’s loop tiling and loop fusion optimisations perform extremely well over such program structures. Polly’s data locality optimisations resulted in execution time gains that were similar to the energy gains observed, ranging from 44.96% to 83.53%. Power gains over the EEMBC programs were relatively low, and even negative for 3 of the 16 programs. The observations in Table 10 supports our earlier inference from Table 9 that energy gains are driven by execution time, rather than power, gains when using the Polly optimiser.

Context switches and CPU migrations. Both these features are relevant to energy consumption and are known to cause overheads in terms of running time [25, 14] and power [13]. Switching a process context or migrating it to a different CPU core is a costly task and tends to generate many cache misses (since the process may not find valid data on the new migrated core’s cache). CPU scheduling algorithms have been proposed to help tackle this problem to reduce the power and energy consumed [13]. Some multi-core programming models (like OpenMP and MPI) allow developers to use environment variables that pin processes to CPU to prevent migration to a different core.

Program Level This halstead metric was selected for the SIR benchmark family. It is worth noting that for EEMBC, the linear regression model assigned the highest coefficient value to this feature. Lasso did not select this metric since it was, likely, redundant with respect to execution time. We hypothesize that reducing the number of operators, operands and function calls (that are used to compute this metric) in a program will help

Table 8: NMRSE and feature selected by LASSO for Parboil benchmarks

<table>
<thead>
<tr>
<th>Features</th>
<th>NRMSE</th>
<th>Features</th>
<th>NRMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Execution.time, cpu.migrations, dTLB.load.misses, L1.dcache.pref</td>
<td>0.074839977</td>
<td>Global.variables, goto, cpu.migrations, task.clock, ppoint.dereferencing, rcx.written, rdx.read, assignment</td>
<td>0.277245127</td>
</tr>
</tbody>
</table>

Table 10: Energy gains in EEMBC benchmarks from Polly loop optimiser

<table>
<thead>
<tr>
<th>EEMBC prog.</th>
<th>Energy gain (%)</th>
<th>Exec.time gain (%)</th>
<th>Power gain (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>idctrn01</td>
<td>83.94</td>
<td>83.53</td>
<td>2.48</td>
</tr>
<tr>
<td>a2time01</td>
<td>45.74</td>
<td>44.96</td>
<td>1.41</td>
</tr>
<tr>
<td>aiffir01</td>
<td>63.73</td>
<td>63.79</td>
<td>-0.18</td>
</tr>
<tr>
<td>aiffir02</td>
<td>66.18</td>
<td>65.91</td>
<td>0.77</td>
</tr>
<tr>
<td>aiffir03</td>
<td>60.65</td>
<td>60.45</td>
<td>0.49</td>
</tr>
<tr>
<td>basefp01</td>
<td>66.50</td>
<td>64.96</td>
<td>4.37</td>
</tr>
<tr>
<td>bitump01</td>
<td>51.82</td>
<td>50.36</td>
<td>2.94</td>
</tr>
<tr>
<td>cache01</td>
<td>51.02</td>
<td>60.70</td>
<td>-0.82</td>
</tr>
<tr>
<td>canrdr01</td>
<td>78.27</td>
<td>78.10</td>
<td>0.76</td>
</tr>
<tr>
<td>iirft01</td>
<td>72.10</td>
<td>71.65</td>
<td>1.58</td>
</tr>
<tr>
<td>matrix01</td>
<td>71.79</td>
<td>72.72</td>
<td>-3.41</td>
</tr>
<tr>
<td>pntrch01</td>
<td>61.95</td>
<td>62.98</td>
<td>-2.79</td>
</tr>
<tr>
<td>pwmm0d01</td>
<td>67.54</td>
<td>67.45</td>
<td>0.25</td>
</tr>
<tr>
<td>rasedc01</td>
<td>63.92</td>
<td>65.82</td>
<td>0.28</td>
</tr>
<tr>
<td>thlok01</td>
<td>49.48</td>
<td>48.54</td>
<td>1.83</td>
</tr>
<tr>
<td>tsprk01</td>
<td>64.79</td>
<td>64.06</td>
<td>2.03</td>
</tr>
</tbody>
</table>
in reducing energy consumption. In a previous study, we
found that optimising design patterns by reducing function
calls improved energy consumption [33].

Optimising for Energy versus Performance.
The features picked by our empirical study that affect soft-
ware energy, namely execution time, cache misses, context
switches, CPU migrations, program length (in terms of num-
er of operators, operands and function calls) are no differ-
cent from those known to affect software performance with
respect to running time, memory latency, and power con-
sumed. Datta and Patel propose CPU scheduling algorithms
to mitigate performance loss, in terms of power, incurred from
context switches, and CPU migrations [13]. David et al.
and Li et at. have also studied the performance over-
head introduced by context switches [14, 25]. Cache misses
are widely known to impact performance in terms of exe-
cution time [33] and existing optimisations for data re-use
like Polly achieve significant energy gains by reducing cache
misses. Compiler optimisations built into existing compil-
iers, like the GCC optimisation flags, attempt to reduce the
code size and execution time of the program [23, 35].
All of the existing optimisation techniques proposed for
performance, either focus on power or on execution time, but
not both. Existing performance optimisations are effective
in reducing energy and this has been observed in several
studies [35, 47, 13, 52, 30, 7, 33]. It is, however, important
to bear in mind that execution time gains do not always
translate to energy gains. An example of this, is frequency
scaling in processors that reduces execution time by running
at full clock speed. This technique, however, proportionally
increases power consumed as seen from the equation,

\[ P = \frac{1}{2} CV^2 f \]  

(5)

where \( C \) is capacitance, \( V \) voltage and \( f \) is the frequency.
Miyoshi et al. observed that scaling CPU frequency, al-
though reducing execution time, can cost more energy than
running at a slower clock speed [30]. Typical techniques
for reducing power are power management software and dy-
namic voltage frequency scaling in processors. Our study
does not consider these techniques since they focus on pro-
cessors rather than a specific application.

The features affecting energy selected in our study lead
us to believe that existing performance optimisations will
suffice if one looks to reduce energy by reducing either only
power consumed or only execution time. To achieve energy
gains that goes beyond existing optimisations, we need to ex-
amine techniques that target both power and execution time.

We plan to explore this problem in our future research.

6. THREATS TO VALIDITY

Our experiments suffer from the following internal threats to
validity,

- We did not enable and examine the effect of standard
compiler optimisations on energy consumption. We
did, however, use Polly for data locality optimisations
in loops. Enabling compiler optimisations has been
shown to reduce energy consumption by reducing pro-
gram execution time [23, 35].
- In our experimental setup, we do not completely con-
trol the services, unrelated to the benchmark being
measured, run by the operating system. We used the
server version of the Ubuntu distribution in order to
limit the number of applications and background ser-
vice running concurrently. However, some operating
system services might still be running (such as check-
ing for - but not performing, new updates). We did
not specifically disable these services.

The external threat to validity in our experiment is using
only a single hardware platform for running benchmarks and
collecting observations. Our results cannot be generalized
to other hardware architectures since the hardware and pro-
gram specific features observed and measured will be very
different. A similar experiment will have to be conducted to
learn the features relevant to energy consumption for each
hardware platform and each application domain. This is a
consequence of the no free lunch theorem [31] that states
that “there is no single best model that works optimally for
all kinds of problems”. The reason for this is that a set of
assumptions that works well in one domain or architecture
may work poorly in another.

7. CONCLUSIONS

We have studied energy consumption of programs and
workloads from three different benchmark families measur-
ing over 100 different software and hardware features. The
feature selection technique, Lasso, effectively picks five to
seven features for each of the benchmark families that are
relevant to energy consumption. The accuracy of energy
predictions with the selected features was comparable to
energy predictions using a linear regression model with all
the features. The features commonly selected in our ex-
periments were execution time, cache accesses, memory in-
structions, context switches, CPU migrations, and program
length (Halstead metric). All of these features are known
to affect software performance, in terms of running time,
power consumed and latency. As a result, we can use exist-
ing performance optimisation techniques that reduce power
or execution time to also achieve energy gains. We confirmed
with the use of Polly, a compiler optimisation for data local-
ity, that significant energy gains were possible by reducing
latency and execution time. We believe the future in energy
optimisation lies in techniques that can reduce both power
and execution time.

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