Evolving Power-Efficient RNGs

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39th CREST Open Workshop
Tuesday 24th February 2015

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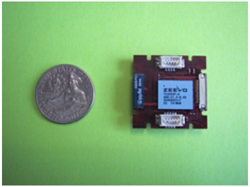
My First Paper

This work was my first paper, at GECCO 2008.

Followed by work on non-functional properties with GP and a collaboration with Andrea Arcuri.

Some of the earliest work on using GP to optimise non-functional properties.

Resource Efficient Software: Target Platforms



WSN Motes

RFID Tags

- Hardware limited (e.g. 64KB, 12MHz Mote)
- Multiple, demanding, requirements
- Interdependence between requirements
- What happens when you just don't have enough resources?

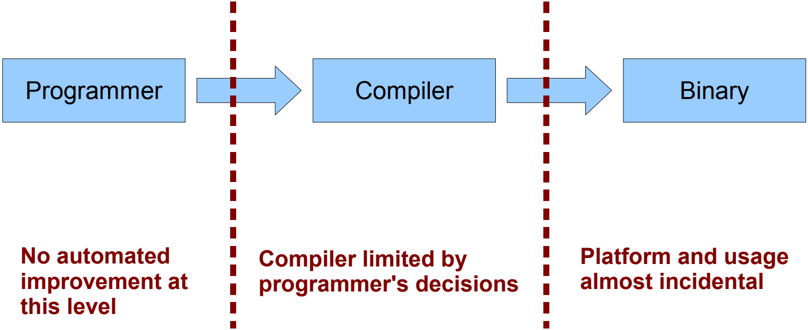
The Difficult of Manual Power Optimisation

AKA "the loneliness of the long-distance embedded systems programmer."

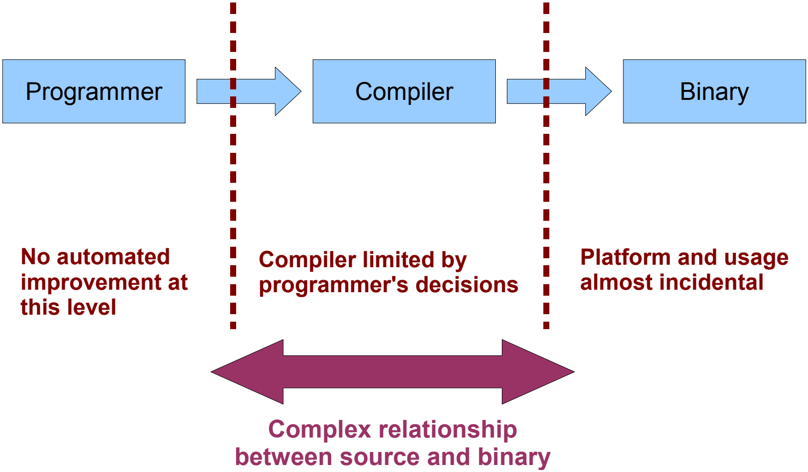
> *"The internals of a modern processor are complete chaos".*
>
> Anonymous RTS Professor

Standard Programming

Standard Programming: Limitations



Standard Programming: Limitations



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Why RNGs?

A common component; small and frequently executed.

We were interested in trade-offs, not solely optimisation.

AnyScale Apps

Proof of Concept: Resource-Efficient PRNGs

Lamenca-Martinez et al. [2006] evolved PRNGs with a view to efficiency, building on work by Hernandez et al. [2004].

Tried to ensure efficiency through choice of function set.

See also Koza [1991], Jannink [1994], Sipper and Tomassini [1996].

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Measuring Fitness

Quality was measured using the Strict Avalanche Criterion as per Lamenca-Martinez et al. [2006].

Power efficiency was measured using the Sim-Wattch Simulator [Brooks et al., 2000].

Wattch

Cycle-level power simulator based on SimpleScalar simulator.

Estimates power usage through approximation for each logic unit:

$$P_d = CV_{dd}^2 af \tag{1}$$

C is the load capacitance; V_{dd} the supply voltage, f the clock frequency and a an activity that estimates the amount of transistor switching.

Partly estimated, validation given by Brooks et al. [2000].

Problems

Simulation is (allegedly) inaccurate and expensive.

For our purposes it only has to be *relatively* accurate, *most of the time*.

We reduced the sample size compared to previous work, to increase speed.

Could we have just used execution time as a proxy?

Measuring Randomness: Strict Avalanche Criterion

Trying to create a function $r(a_0 \ldots a_7)$

Maximise nonlinearity of this function:

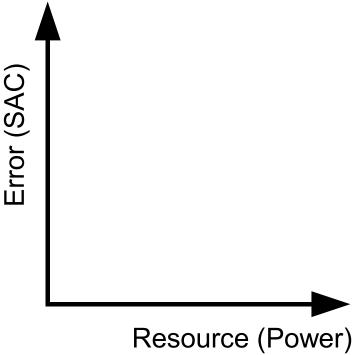
1. Create a random input $a_0 \ldots a_7$
2. Evaluate $o_1 = r(a_0 \ldots a_7)$
3. Flip one bit of input to create $b_0 \ldots b_7$
4. Evaluate $o_2 = r(b_0 \ldots b_7)$
5. Record hamming distance $H(o_1, o_2)$

Measuring Randomness: Strict Avalanche Criterion II

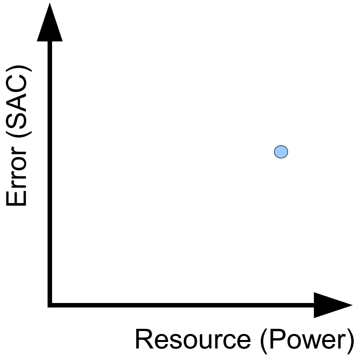
Compare the distribution of bit flips to the binomial distribution:

$$\sum_{i=0}^{n} \frac{(C_i - E_i)^2}{E_i}$$

Our Objective Space



A Single Program



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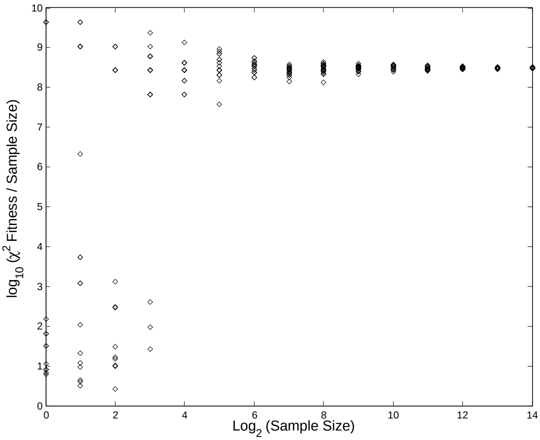
Experimental Method

Replicated work by Hernandez et al. [2004] and achieved similar results.

Used reduced sample size.

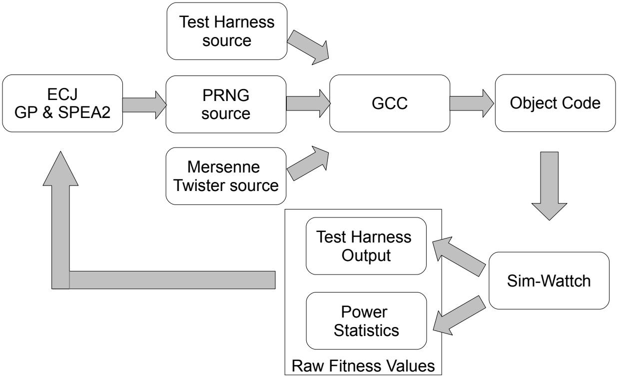
Searched using ECJ and SPEA2.

Variance of Fitness Measures



Repeated for other programs and power consumption measure.

Experimental Framework



Parameter Settings

Function set	MULT, AND, SUM, NOT, OR, XOR, Logical Shift Left (LSL), LSR, Circular Shift Left (CSL), CSR

Parameter settings left to their defaults in ECJ, as specified by koza.params.

All non-default settings taken from previous work, except for MOO-specific settings.

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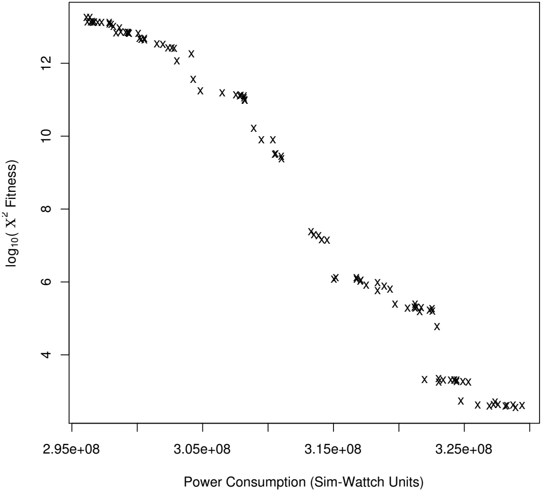
Evolution of the Pareto Front

Animation

Example Pareto Front



A Fantastically Low Power RNG

int genRand (int a0, int a1, int a2, int a3, int a4, int a5, int a6, int a7) {
    return $\neg(\neg(1997453768ul))$;
}

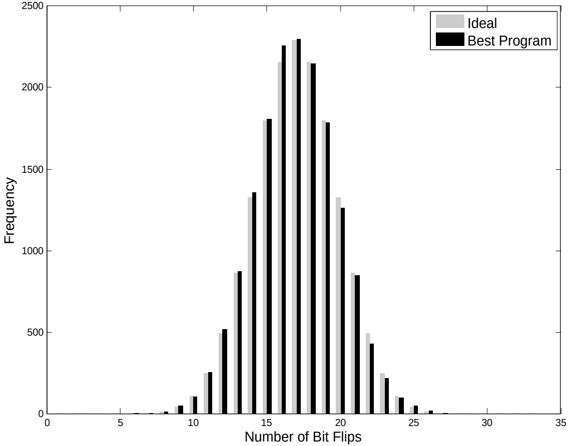
A Middle Ranking Low Power RNG

int genRand (int a0, int a1, int a2, int a3, int a4, int a5, int a6, int a7) {
return $a2 \vee \neg(((a2 + a0) * ((a4 \oplus ((a6 + a5) \oplus a7)) + (a1 \oplus a3))) \wedge \neg(\neg(1997453768ul)))$;
}

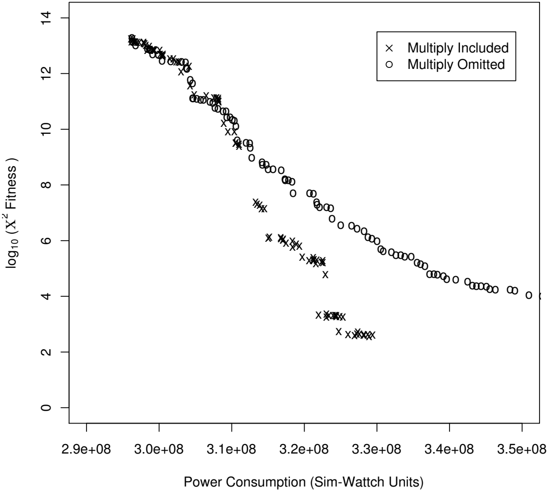
An Excellent Low Power RNG

int genRand (int a0, int a1, int a2, int a3, int a4, int a5, int a6, int a7) {
$(2307363674ul \oplus (a2 * a6)) + ((\neg((((((a2 * a6) \oplus (a7 \oplus a1)) * (a0 \oplus a3)) \oplus (a2 * a6)) + (a5 * a4)) >> 2307363674ul) \oplus (a0 \oplus a3)) + \neg((a5 * a4) * ((2307363674ul \oplus (a7 \oplus a1)) + (a0 \oplus a3))));$
}

Bit Flip Distribution for Best Individual



The Impact of the Mult Function



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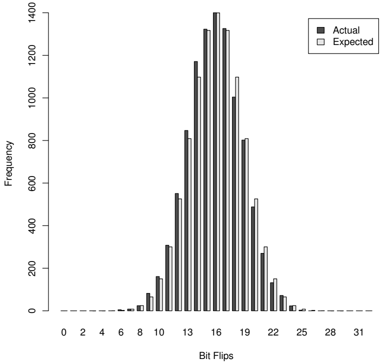
Conclusions

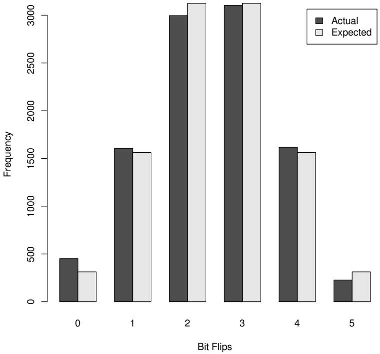
This is about more than straightforward optimisation.

Multiple solutions vs a single, tunable, scalable algorithm.

More radically, consider manipulation rather than optimisation.

Postscript: Time Avalanche Criterion





See White et al. [2010]

Acknowledgements

My coauthors John Clark, Jeremy Jacob and Simon Poulding.

Andrea Arcuri for his collaboration.

Juan E. Tapiador and Julio Cesar Hernandez-Castro, for inspiration and creative discussion.

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Genetic Improvement Workshop
(at GECCO 2015)
Submission deadline: April 3, 2015
geneticimprovement2015.com

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