

Multi-Objective Intrinsic Evolution of Embedded Systems (MOVES)

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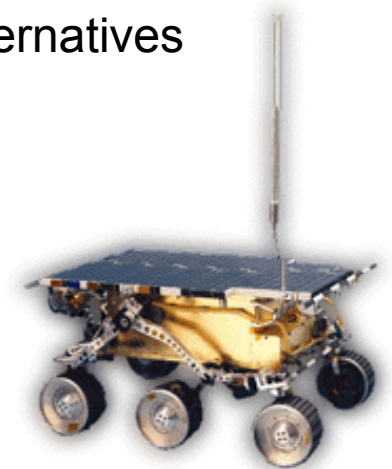
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Outline

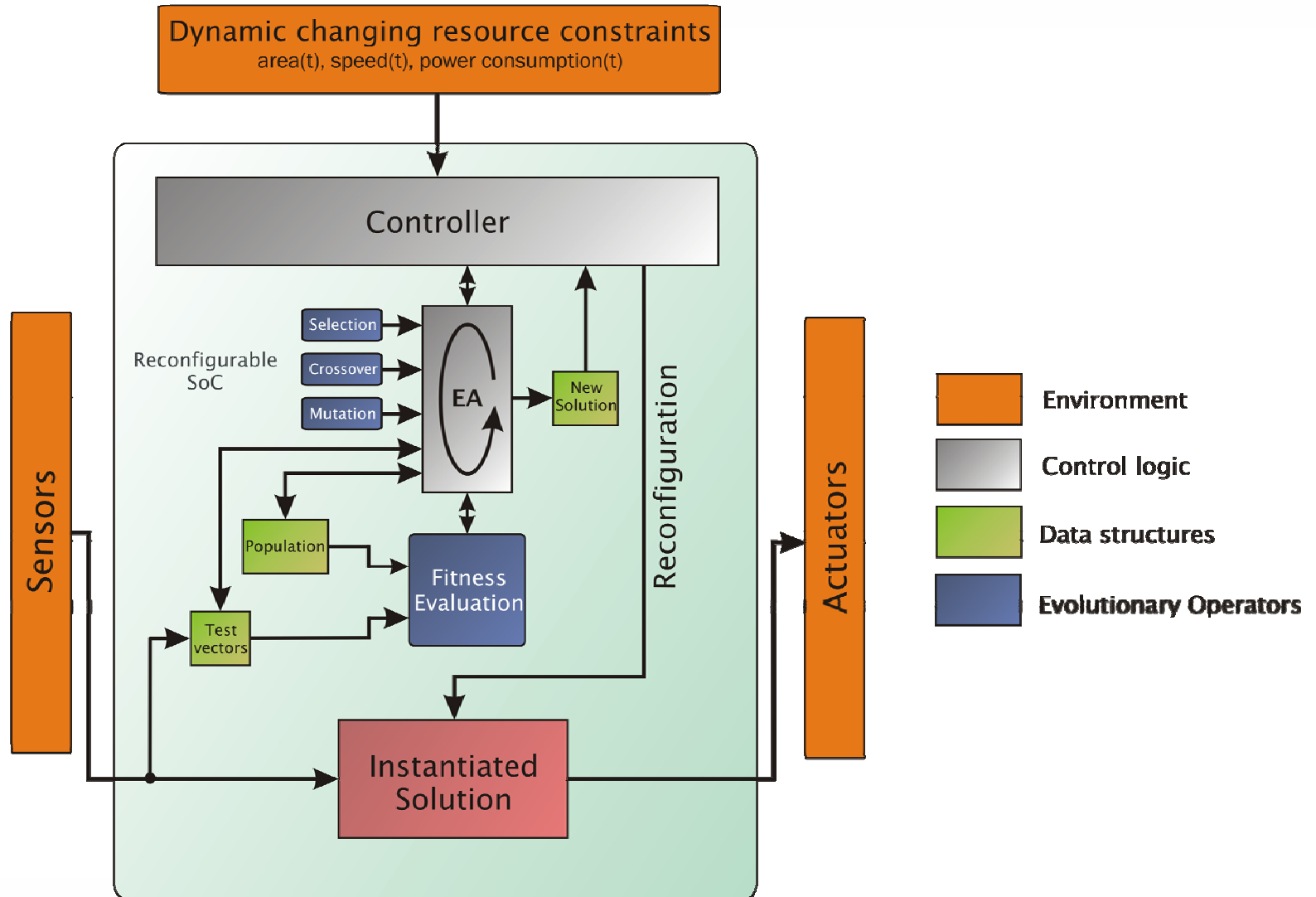
- motivation/vision/approach
- work done
 - hardware representation model
 - evaluation framework
 - evolving circuits with multi-objective optimizers
 - results so far
- ongoing work
 - improving scalability
 - implementing resource-aware EA on Virtex-4
 - cooperation in evolvable hardware

Motivation / Vision

- investigate intrinsic evolution as a mechanism to achieve self-adaptation and –optimization for autonomous embedded systems
- an embedded system ...
 - adapts to **slow changes** by simulated evolution
 - typically, change of environment
 - adapts to **radical changes** by switching to pre-evolved alternatives
 - typically, change in computational resources
 - requires intrinsic evolution for autonomous operation



Architecture



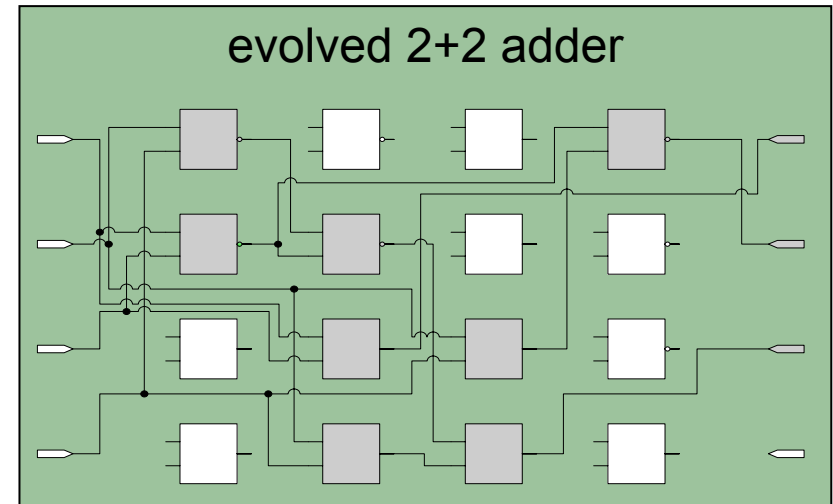
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Hardware Representation Model

- adapted Cartesian Genetic Program (CGP) model
 - array of combinational blocks connected by feed-forward wires
 - chromosome defines configuration of the array
 - model similar to [Miller & Thomson, '96]
 - advantage: matches well FPGA architectures
 - challenge: scalability

- adapted embedded CGP (ECGP) model [Miller & Walker, '04]
 - automatically identify larger building blocks
 - reuse of building blocks
 - implemented, experiments to be done

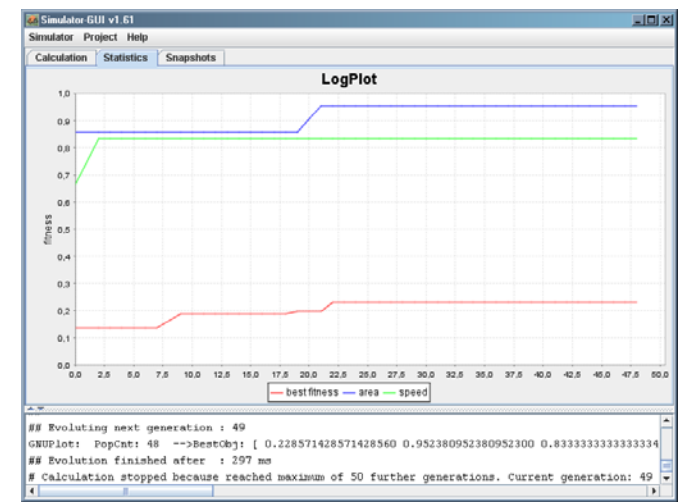
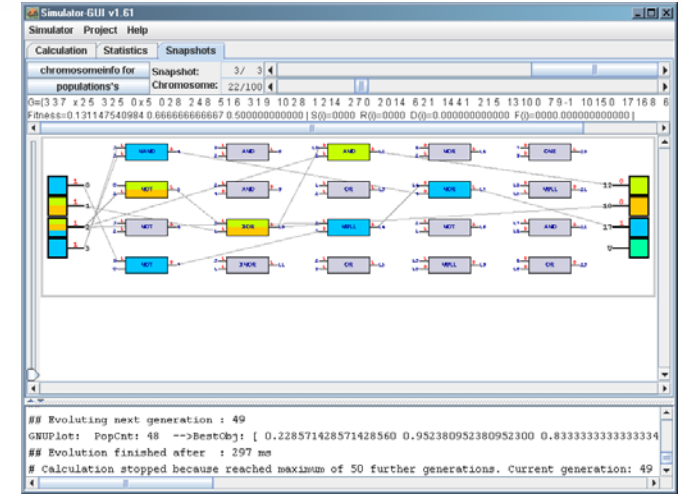


Evaluation Framework

- implemented toolbox for experimenting
 - interactive and batch modes
 - stop/resume evolutionary process
 - graphical array representation and analysis tools, e.g. fitness plots, statistics,

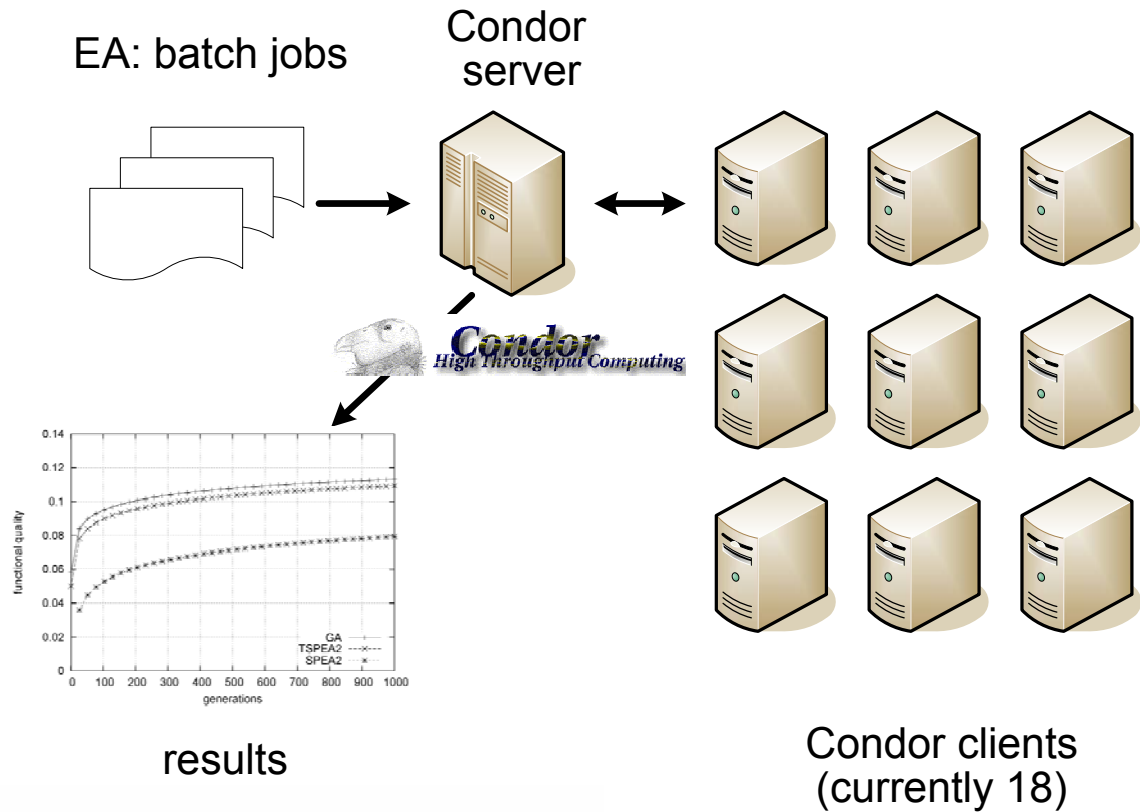
- GCP model parametrizable
 - array dimensions
 - block complexity and functions
 - interconnect

- modular and extensible to different EAs and representation models
 - currently: variants of GA, SPEA2, TSPEA2 on CGP and ECGP models



Evaluation Framework (2)

- distributed computing environment to speed up experiments
 - installed Condor grid
 - implemented extensions for improved client control and Java support



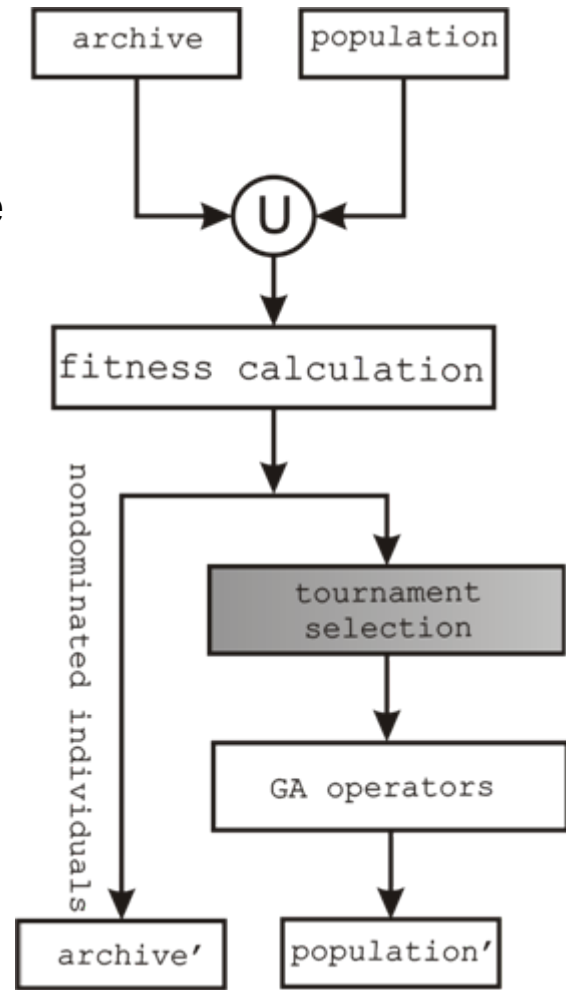
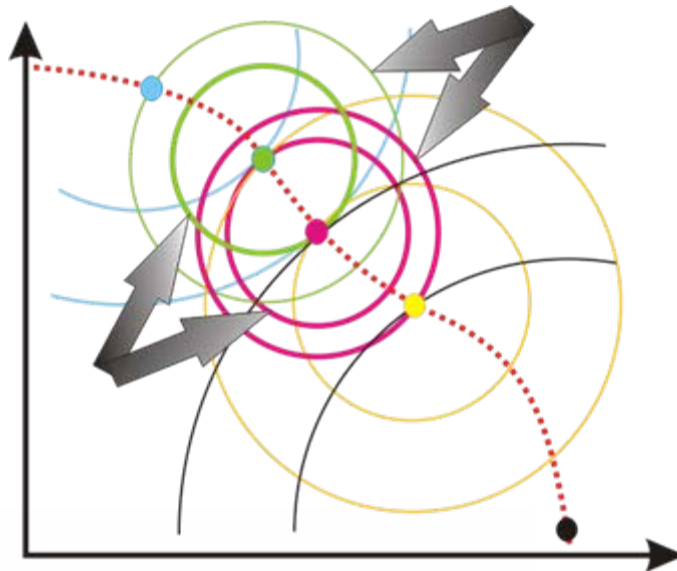
EAs for Multi-objective Optimization

- implemented and experimented with different variants of EAs
 - multiple objectives: functional quality, circuit area, circuit speed
 - experimented with rather simple test functions: adders, multipliers, parity-function, hash functions, etc.

- evolutionary algorithms
 - GA (reference algorithm)
 - conventional, single-objective genetic algorithm
 - uses elitism, tournament selection, uniform crossover, mutation
 - SPEA2
 - TSPEA2

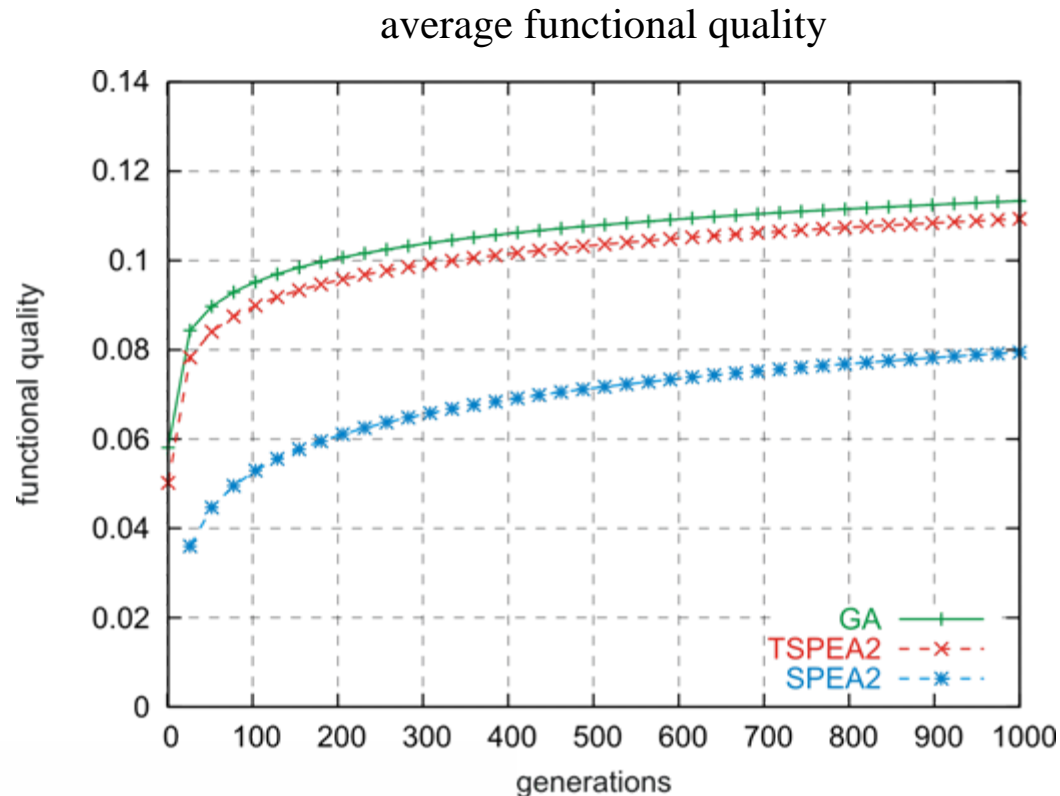
TSPEA2

- Turtle Strength Pareto Evolutionary Algorithm
 - based on SPEA2 [Zitzler et al., '01], which maintains diversity by dissolving Pareto front clusters with k-th nearest neighbor density estimation
 - prioritize a main objective to speed up convergence
 - selection scheme similar to MO-Turtle GA [Trefzer et al., '05]



Example: Hashing Function

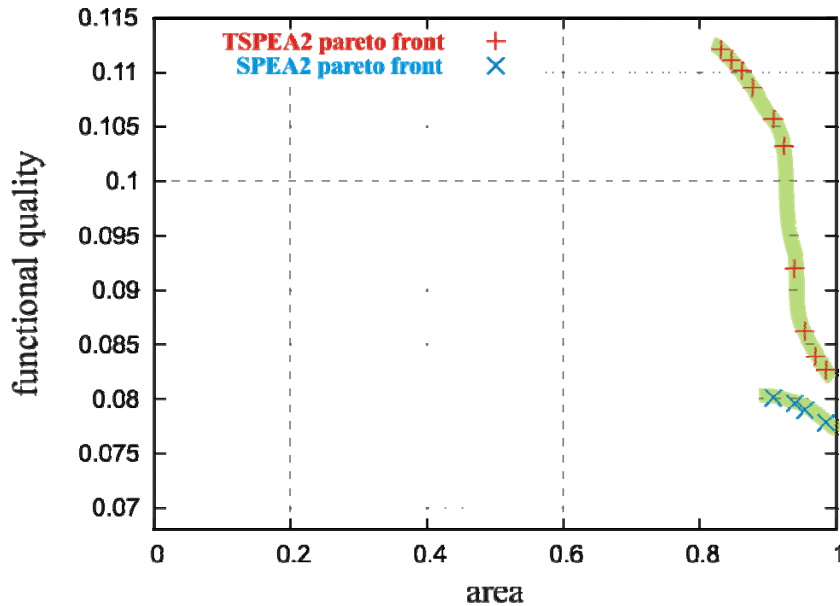
- test function used by [Tettamanzi et al., '98]
 - find a function that maps 4096 16-bit keys to 256 indices
 - no correctness property, just a functional "quality"
 - CGP model: 8x8 4-LUT array, levels back parameter $l=8$



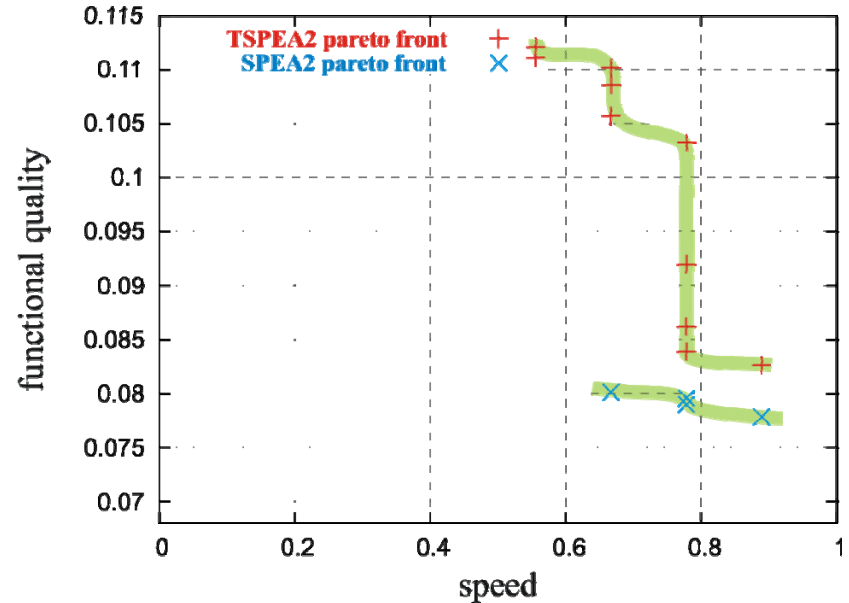
Example: Hashing Function (2)

- Pareto front approximations: SPEA2 vs. TSPEA2

quality vs. area



quality vs. speed



- surprisingly, TSPEA2 outperforms SPEA2 in quality and area and speed

Results so far ...

- for functions with a correctness property (eg. arithmetic functions)
 - functional quality is a constraint (100% required) and needs to be preferred during selection to achieve acceptable convergence times
 - we would expect that this comes at the price of a degraded Pareto front
→ SPEA2 and TSPEA2 generate roughly the same Pareto front

- for functions without correctness property (eg. hashing function)
 - functional quality is an objective, but TSPEA2 beats SPEA2 in both, runtime and Pareto front: possible explanations
 - our objectives are not necessarily conflicting (!)
 - we have experimented with rather small examples
 - there are not too many possible area/speed values

- to evolve more complex circuits, we have to ...
 - move to higher-level hardware representations, automatically identify larger building blocks, utilize domain-specific knowledge,

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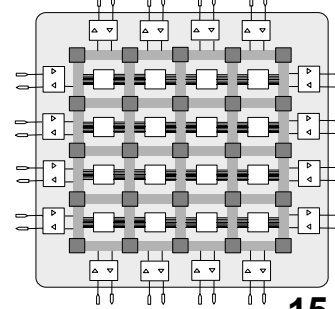
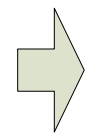
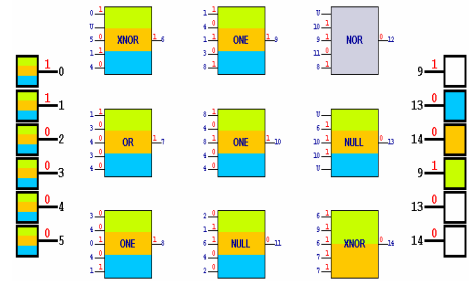
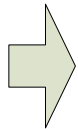
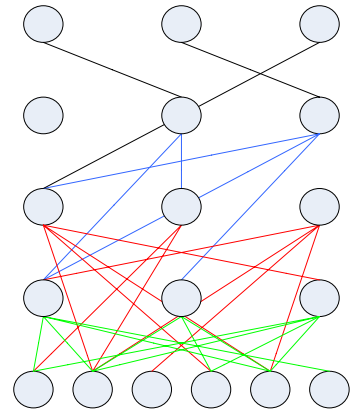
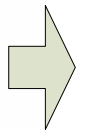
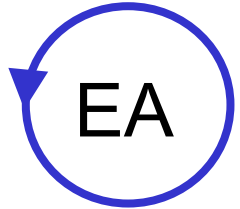
Scalability

- native CGP model too flat for complex problems
- evolving higher-level models is more efficient but increases the effort to map to actual hardware
 - balance the computational resources between evolutionary search and FPGA mapping

```

library ieee;
use ieee.std_logic_1164.all;
entity gates is
    port( in0, in1, in2, in3, in4, in5: in std_logic;
          out: out std_logic);
end;

architecture implement of gates is
begin
    node06 <= in0 xor in5 xor in1 xor in4;
    node07 <= in1 or in3 or in4 or in4;
    node08 <= 1 or in3 or in4 or in4 or in1;
    node09 <= 1 or in1 or in1 or in3 or node08;
    node10 <= 1 or node07 or in4 or node08 or in4 or node4;
    node11 <= 0 and in2 and in1 and node6 and in4 and in2;
    node12 <= node10 nor node9 nor node11 nor node8;
    node13 <= 0 and node6 and node10 and node10;
    node14 <= node6 xnode node9 xnor node6 xnor node7 xnor node7;
end;
    
```



Resource-constrained EA

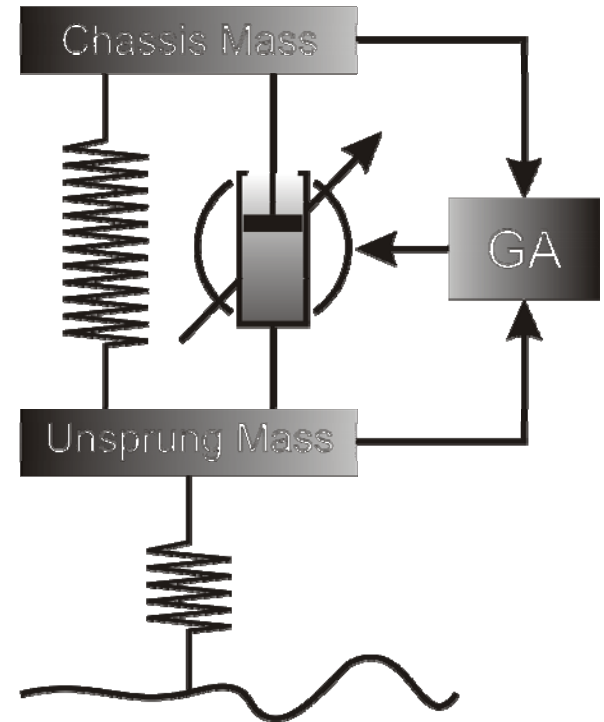
- implement EA on an embedded platform
 - Virtex4 platform FPGA with Power PC core (ML403 board)
 - EA and data structures in software
 - operational circuit and time-consuming computations in hardware
 - fitness evaluation amounts to 75% of EA runtime, density estimation to 12.5%

- challenges
 - what can we achieve under stringent resource-constraints?
 - eg. with population size of only 10, single-parent crossover,
 - mapping to FPGA at runtime
 - utilize dynamic reconfiguration vs. virtual FPGA on FPGA



Cooperation in Evolvable Hardware

- with Prof. Jim Tørresen, University of Oslo
- improving scalability of hardware evolution
 - automatic localization of “building blocks”
 - adding scalability-driven objectives
- investigate potential applications
 - prosthetic hand controller
 - active suspension control



Thank you for your attention!

