Evolutionary Methods for State-based Testing

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Outline

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- Search-based software engineering
- Metaheuristic search techniques
- Test data generation for state-based testing
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Motivation

- A lot of research has been done in the field of state-based testing:
  - test selection methods for FSMs – the **W-method**
  - **coverage criteria** for state machines diagrams (like all transitions, full predicate, transition pair, complete sequence, disjunct coverage)

- The automatic generation of test cases from extended state machines (state machines diagrams, X-machines, etc.) is not straightforward.
- For example: *which input values to choose for a sequence of methods calls, representing a path in a state machine diagram?*
- Idea: *Why not to use the power of evolutionary algorithms or other metaheuristics to solve state-based testing problems?*
- This answer is given by new field of **Search-based Software Engineering**

Search-based Software Engineering (SBSE)

- **Search-based software engineering (SBSE)** is a relatively new approach to transform the software engineering problems into **optimization** problems, which can be further solved by applying **metaheuristic** search techniques.

- The term of SBSE was first used by Harman and Jones (2001), although there are some previous papers on this topic.
- Repository of publications on SBSE: http://www.sebase.org/sbse/publications/repository.html
- In 2008 there were published more than 100 papers on SBSE.

- Important events:
  - The International Workshop on Search-Based Software Testing, held in conjunction with ICST: 2008 Lillehammer, 2009 Denver
  - The International Symposium on Search Based Software Engineering, 2009 Windsor

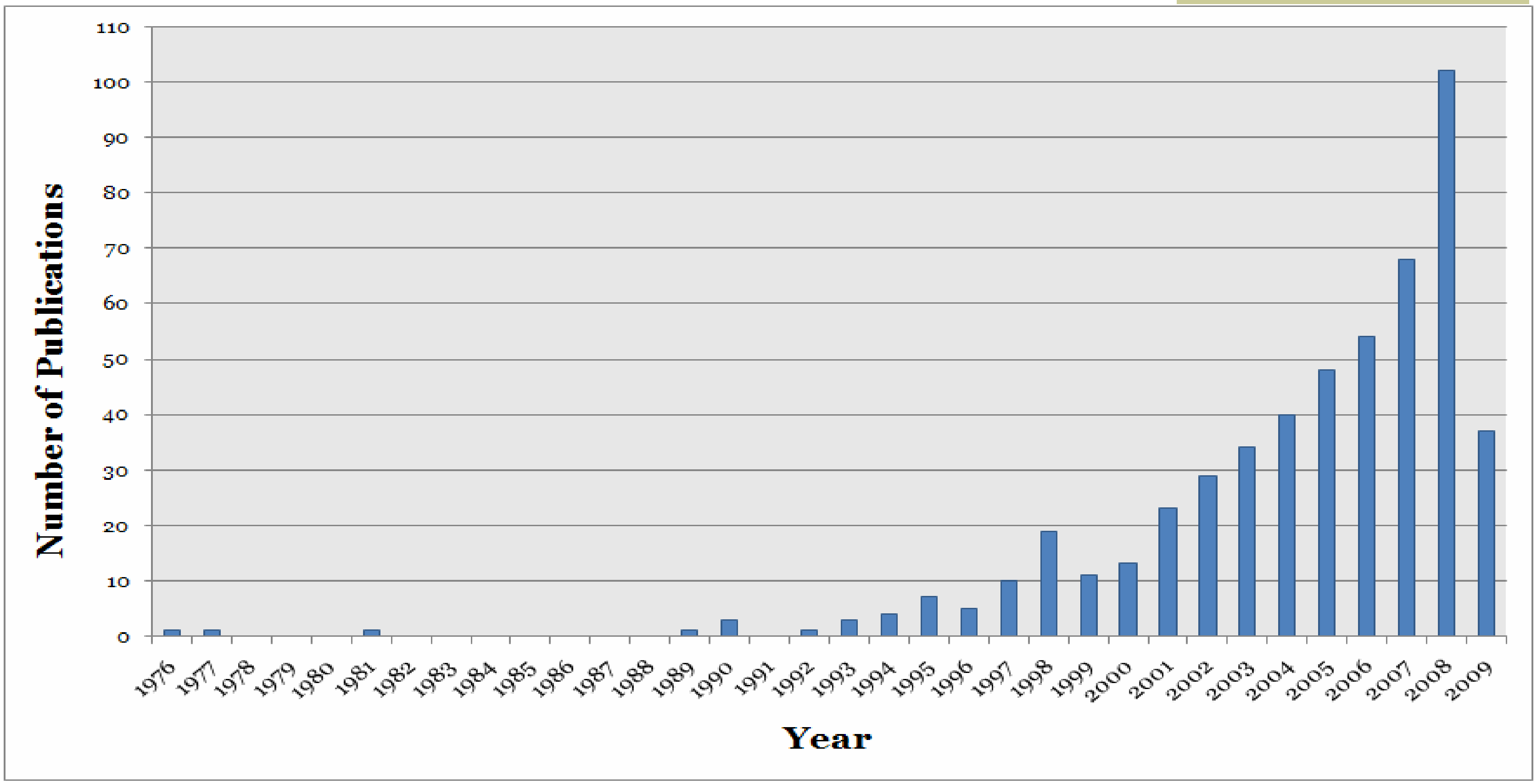
Search-based software engineering (SBSE)

- **Main idea:** Transform the software engineering problems into *optimization problems*, which can be further solved by applying metaheuristics.

- **Search techniques:** *genetic algorithms,* hill climbing, alternating variable method, simulated annealing, genetic programming, particle swarm optimization, artificial immune systems, tabu search etc.

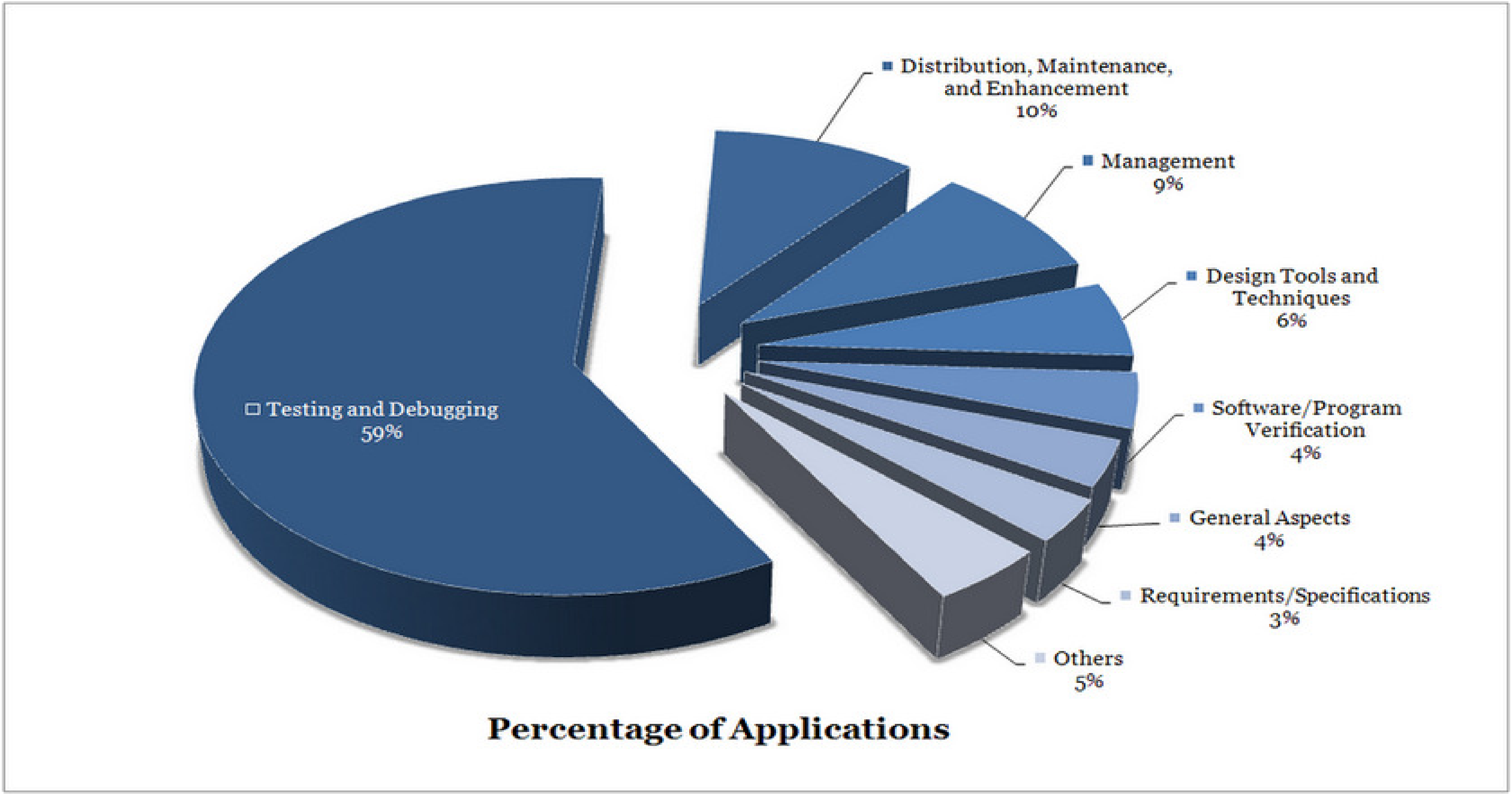
- **Applications:** *software testing*, requirements engineering, automated maintenance, service-oriented software engineering, compiler optimization, quality assessment, project planning and cost estimation.

Number of publications in SBSE, 1976 - 2009



http://www.sebase.org/sbse/publications/

Ratio of SE research fields involved in SBSE



http://www.sebase.org/sbse/publications/

Search-based Software Testing (SBST)

- Characterized by the usage of guided search techniques for *test generation*
- The test aim (cover all branches, obtain the WCET) is first transformed into an optimization problem with respect to some fitness (cost or objective) function.
- **Search space** = the input domain of the test object (program, function).
- The search spaces obtained are usually complex, discontinuous, and non-linear, due to the non-linearity of software
- Therefore metaheuristic search methods are recommended.

Search-based Software Testing (SBST)

- ***Structural testing:*** automatically generate input data for programs written mainly in a procedural paradigm.
- Program = directed graph
- Cover the desired graph elements (nodes, branches or paths)

- ***Functional testing:*** from Z specification, conformance testing, automatic parking system

- Testing of grey-box properties, for example safety constraints

- Testing non-functional properties, such as worst-case execution time

Metaheuristic search techniques

- ***Simulated annealing (SA):*** a random generated ”neighbour” replaces the current solution if it has a better objective value; otherwise, with the probability $p = exp (-\delta / t)$.

- ***Genetic algorithms (GAs):*** a class of *evolutionary algorithms*, that use selection, recombination (crossover) and mutation, applied on a population of potential solutions, called *chromosomes* (or *individuals*)

- ***Particle swarm optimization (PS):*** a population of random solutions, called *particles*, which maintain their current position, velocity and best position explored so far, fly through the problem space by following the current optimum particles

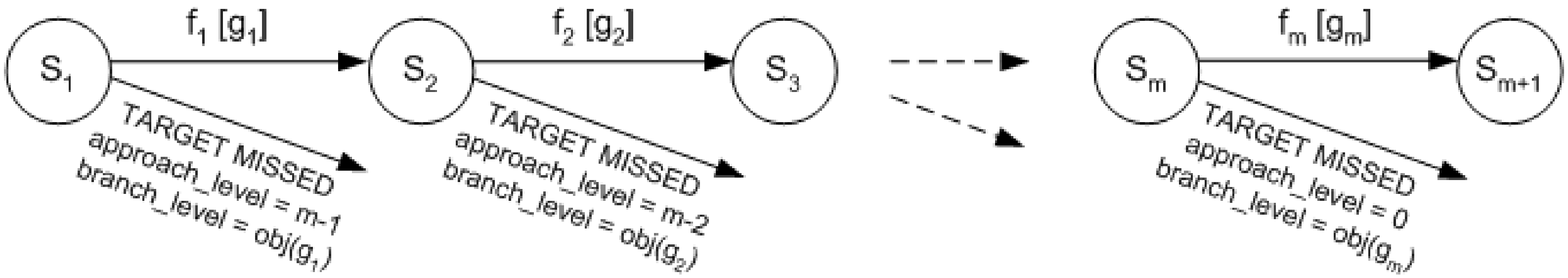
Test data generation for state-based testing

- Given: some ***paths*** in the state machine (obtained according to a certain coverage criteria)

- Use metaheuristic search techniques to find for each method sequence the input values for the parameters, which satisfy the corresponding guards (pre-conditions)

- Questions:
  - Encoding: $x = (x_1, x_2, \dots , x_n)$
  - Fitness function
  - Search technique

Fitness function calculation



$$fitness = approach\_level + normalized\_branch\_level$$

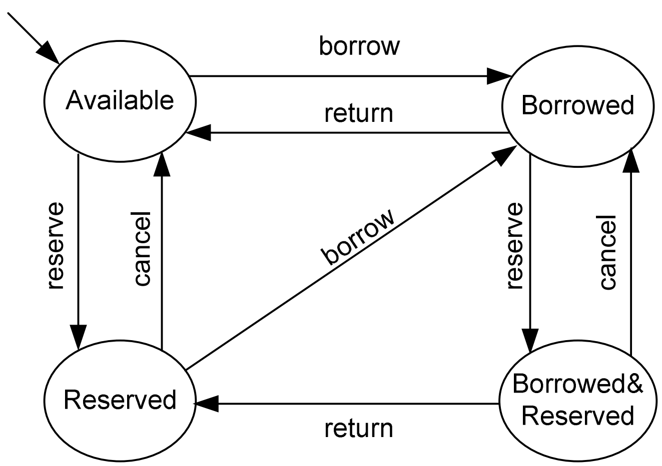
$$approach\_level \in \{0,1,\ldots,m-1\}$$

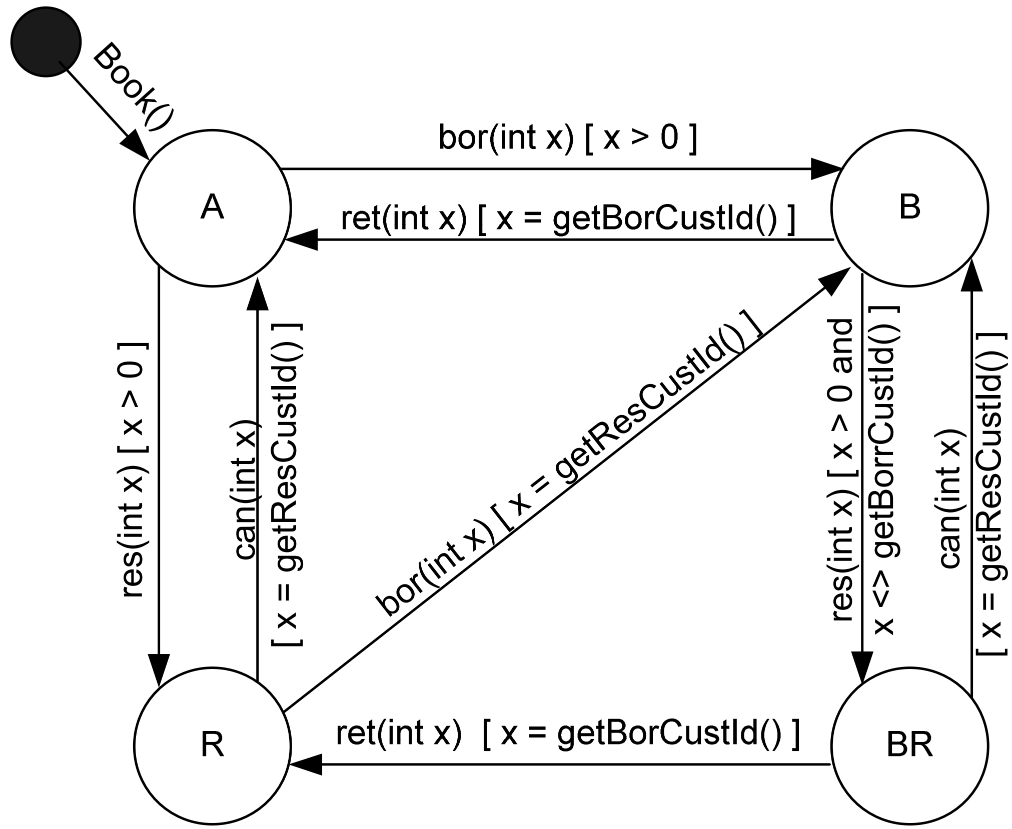
$$normalized\_branch\_level \in [0,1]$$

Tracey's objective functions

Predicate	Objective function *obj*
$a = b$	if $abs(a - b) = 0$ then 0 else $abs(a - b) + K$
$a \neq b$	if $abs(a - b) <> 0$ then 0 else K
$a < b$	if $a - b < 0$ then 0 else $(a - b) + K$
$a \leq b$	if $a - b \leq 0$ then 0 else $(a - b) + K$
$a > b$	if $b - a < 0$ then 0 else $(b - a) + K$
$a \geq b$	if $b - a \leq 0$ then 0 else $(b - a) + K$
Boolean	if *TRUE* then 0 else K
$a \wedge b$	$obj(a) + obj(b)$
$a \vee b$	$min(obj(a), obj(b))$

State machine diagram of a *Book* class





Fitness function landscape

$$A \xrightarrow{[x_1>0]\ \ res(x_1)} R \xrightarrow{[x_2=getResCustId()]\ \ bor(x_2)} B$$

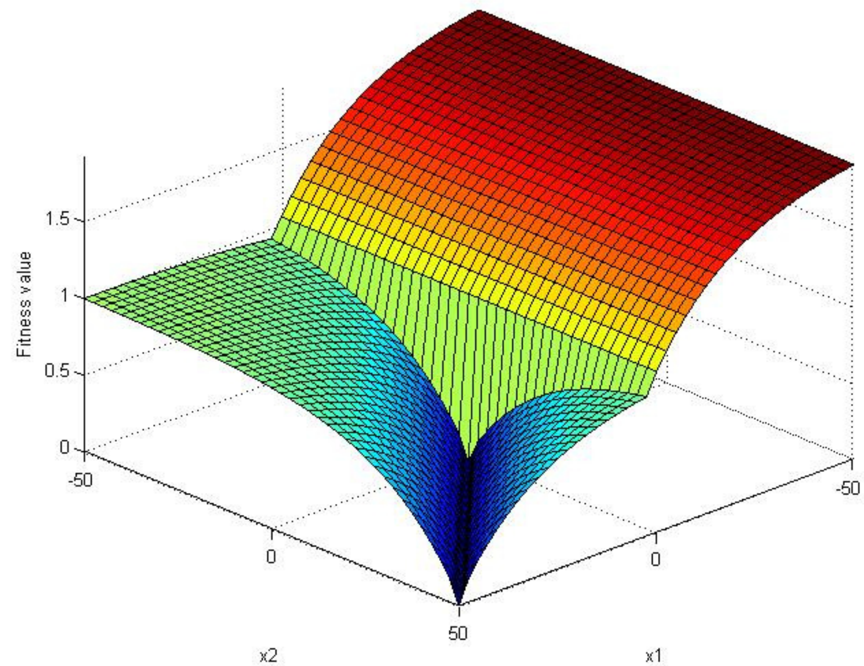
$x_1, x_2 \in [-50,50]$

$x_1 > 0$ and $x_2 = x_1$

Tracey's constant $K = 1$

$norm : [0,101] \to [0,1)$

$norm(d) = 1 - 1.05^{-d}$



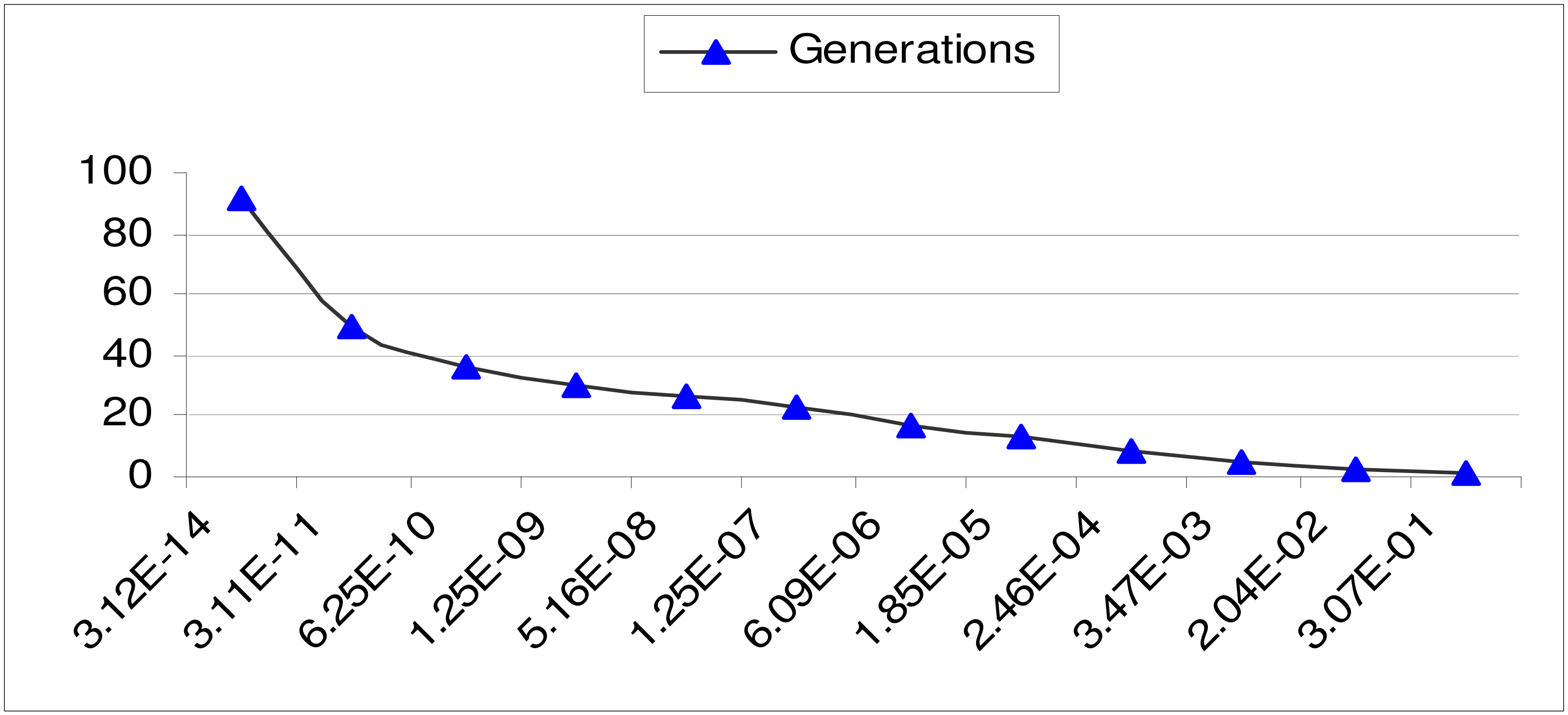
Experiments employing genetic algorithms

- Generating numerical input values for given paths in the state machine, with the *approach level + normalized branch level* fitness function
- GAs had a good convergence rate (max. allowed generations 100)
- Heuristic real value crossover inspired from Michalewicz: $z_i = \alpha \cdot (x_i - y_i) + x_i$, $0 < \alpha < 1$, where $x = (x_1, \ldots, x_n)$, $y = (y_1, \ldots, y_n)$, x fitter than y.

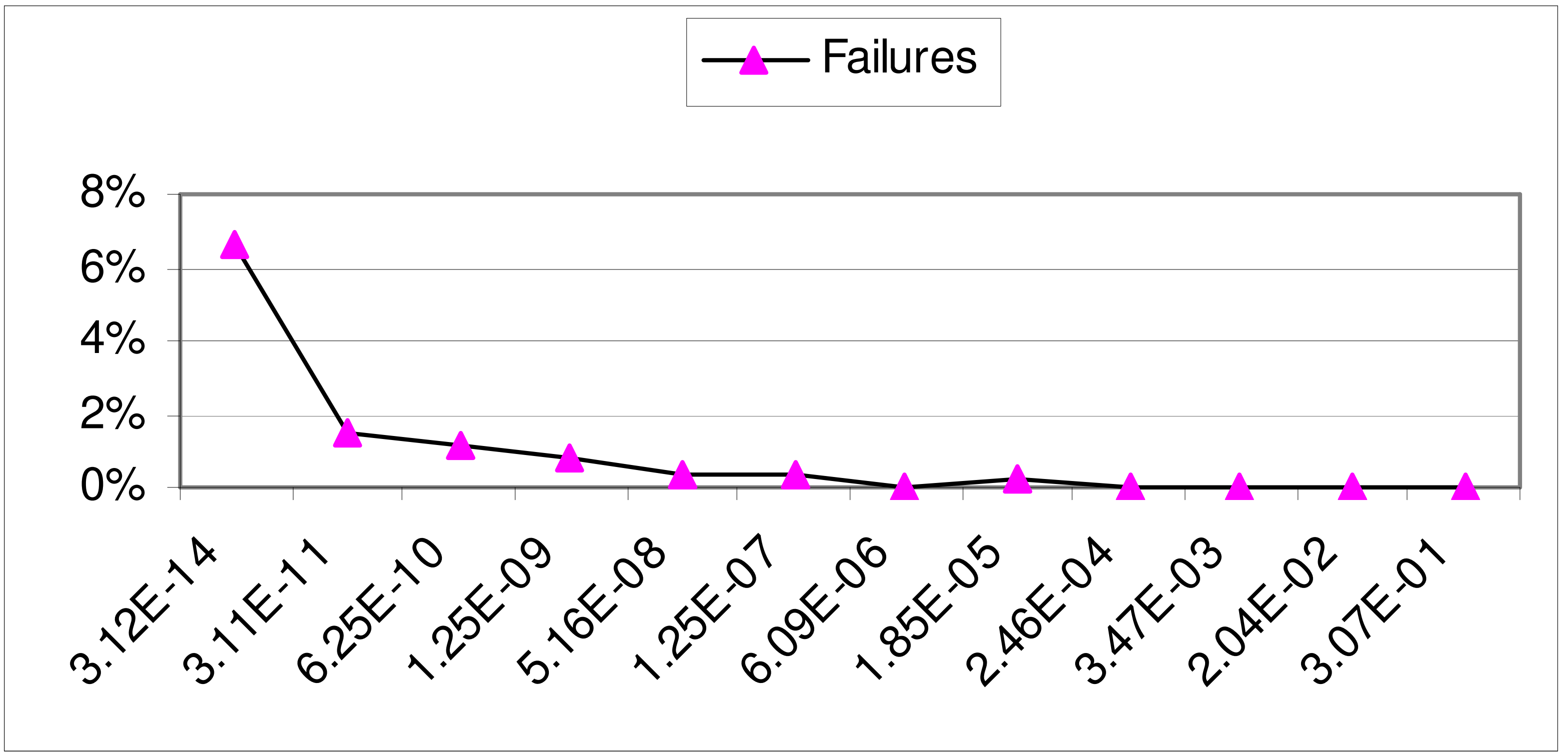
- **Conformance testing:** experiments that used mutation testing and a fitness function of form *pre-condition* $\wedge \neg$ *post-condition.*
- Discovered 72-82% of the mutants in 100 generations. After increasing the maximum allowed evolutions to 200 the rest of unequivalent mutants were detected also.

R. Lefticaru, F. Ipate, "Automatic State-Based Test Generation Using Genetic Algorithms“, *SYNASC2007*

Average number of generations, related to: solutions number / possible solutions number

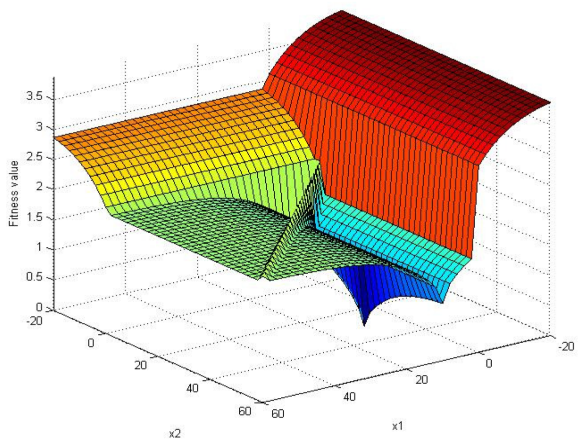


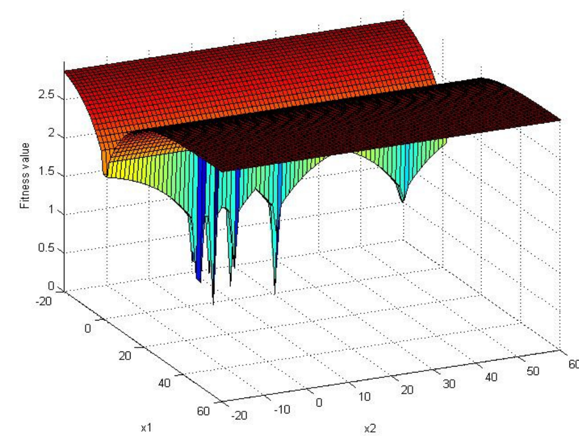
Average number of failures, related to: solutions number / possible solutions number



Experiments employing GAs, PSO, SA

- Aim: generate input values for different state machine paths
- Search techniques: GAs, SA, PSO
- The corresponding fitness landscapes have different complexity: simple (only one minimum), complex (many local minima).

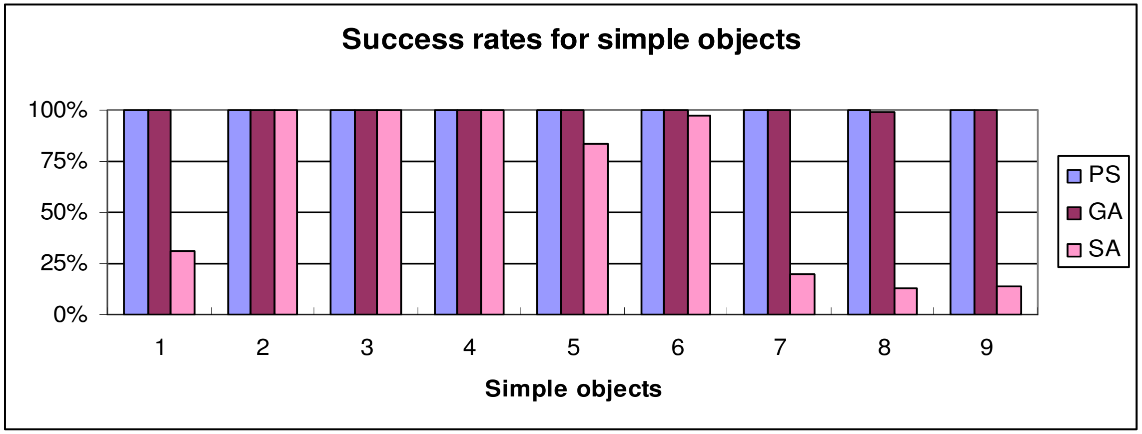


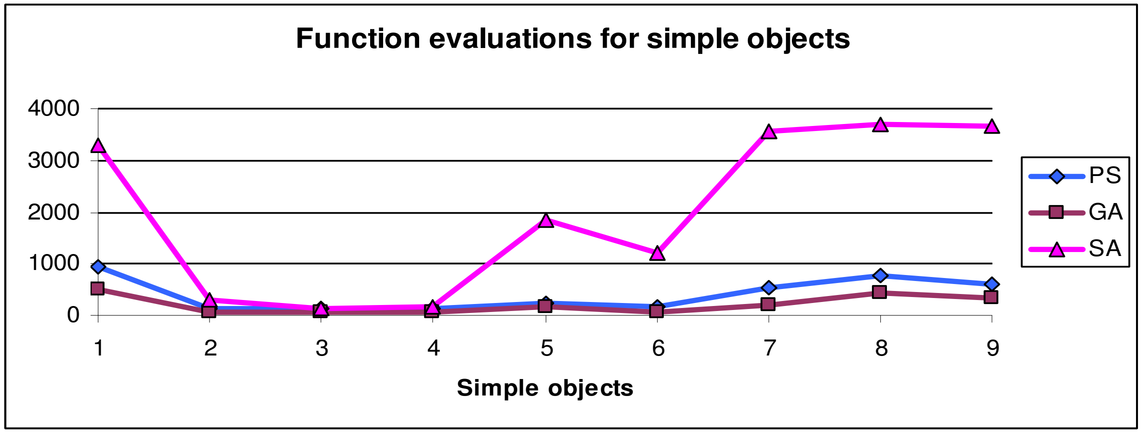


R. Lefticaru, F. Ipate, "Functional Search-based Testing from State Machines", *ICST2008*

Simple objects (one minimum)

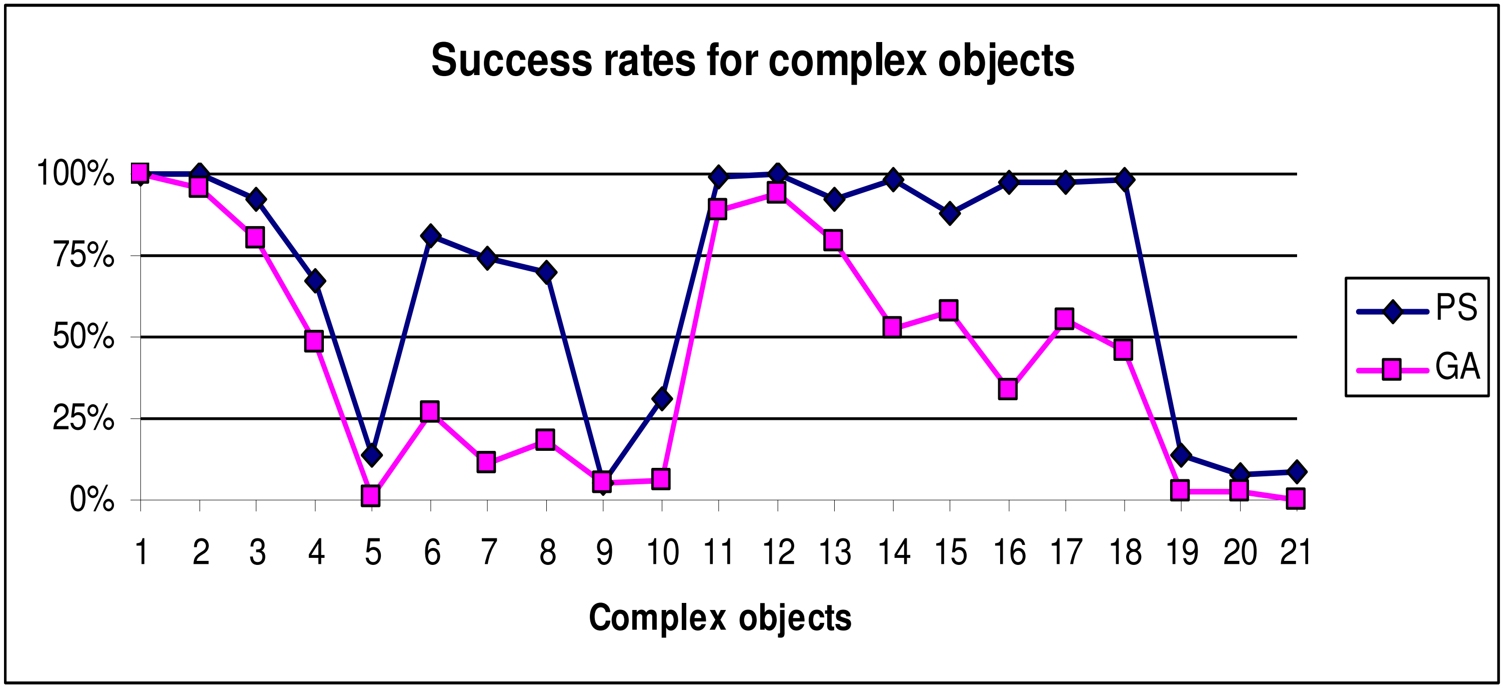
- GAs (with heuristic crossover) achieved better results (9 out of 9 cases) than PSO and SA





Complex objects (more local minima)

- For more complex landscapes, having more local minima, PSO outperformed GAs and the difference was statistically significant for 17 out of 21 test objects (confidence 95%)



Measures to Characterize Search Problems

- Used to characterize the search landscapes, to predict or explain the behavior of search algorithms, to guide the implementation choices to be made.
- Intuitively, some fitness functions might present plateaux along which they provide no guidance.

- **Diameter:** maximal distance between two points in S, in terms of successive applications of a neighbourhood operator N.

- **Autocorrelation:** measures the variation of fitness for points that are at the same distance. It characterizes the ruggedness of a landscape: ***smooth*** (the neighbours have nearly the same fitness value) or ***rugged*** (the fitness values are dissimilar).

- **Fitness Distance Correlation (FDC):** joint variation of distances and costs.

Analysing the fitness landscape

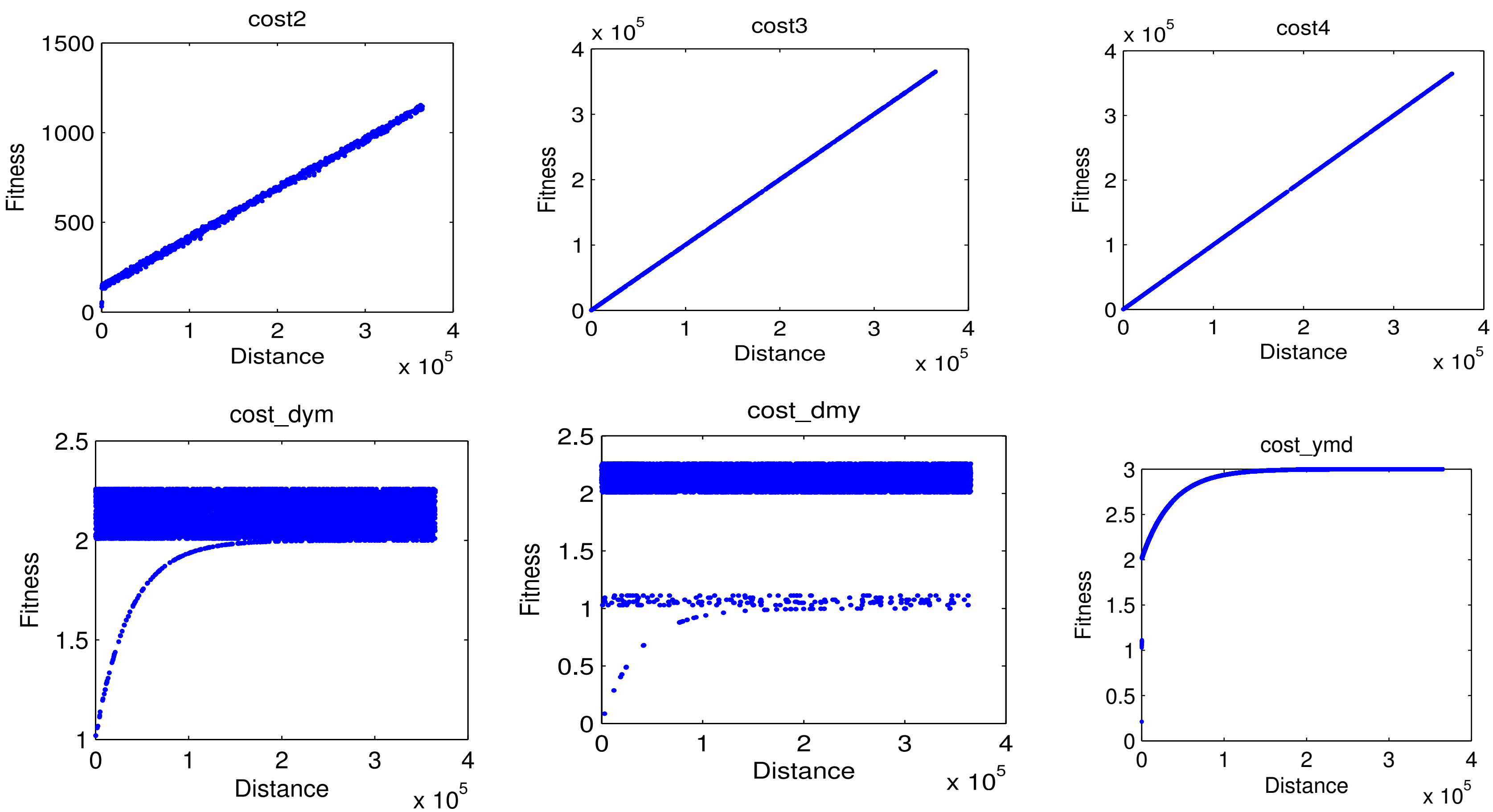
- The general fitness functions *approach level + normalized branch level* (*al + nbl*) may produce results comparable to those produced by fitness functions, designed especially for a particular situation.

- The best results were obtained when using the *al + nbl* functions with GA and PSO.

R. Lefticaru, F. Ipate, "Search-based Testing using State-based Fitness ", ICSTW 2008 (SBST 2008)

R. Lefticaru, F. Ipate, "A Comparative Landscape Analysis of Fitness Functions for Search-based Testing", SYNASC 2008

Fitness-distance scatterplots



Conclusions

- The test data obtained with the *al+nbl* functions can cover difficult paths in the machine.
- A slightly different design (*pre-condition* /\ ¬ *post-condition*) of the fitness function can be used for specification conformance testing.
- For more complex landscapes, having more local minima, PSO outperformed GAs.
- For simpler function, having only one minimum GAs achieved better results.
- Hybridizing SA or GAs with local search techniques improved their effectiveness.
- The general fitness functions *al + nbl* may produce results comparable to those produced by fitness functions, designed especially for a particular situation.

Future work

- Analyzing, on a larger benchmark of classes, the effectiveness and the efficiency of several search techniques.
- Finding categories of problems for which certain search algorithms achieve better results.
- Extending the strategy presented for method parameters with more complex types and multi-class testing.
- Analyzing other variants of fitness functions.
- Derivation of the fitness function from hierarchical and concurrent state machine diagrams.

Question & Answers

Thank you for your attention !