

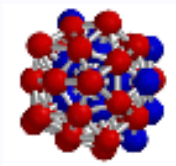
# Silicon Cluster Optimization Using Extended Compact Genetic Algorithm (ECGA)

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**MatSE 385**  
**ATOMIC SCALE SIMULATION**

## Outline

- Motivation
- Overview of ECGA
- Marginal Product Models and BBs
- Silicon Potential
- Algorithm Implementation
- Results
- Conclusions

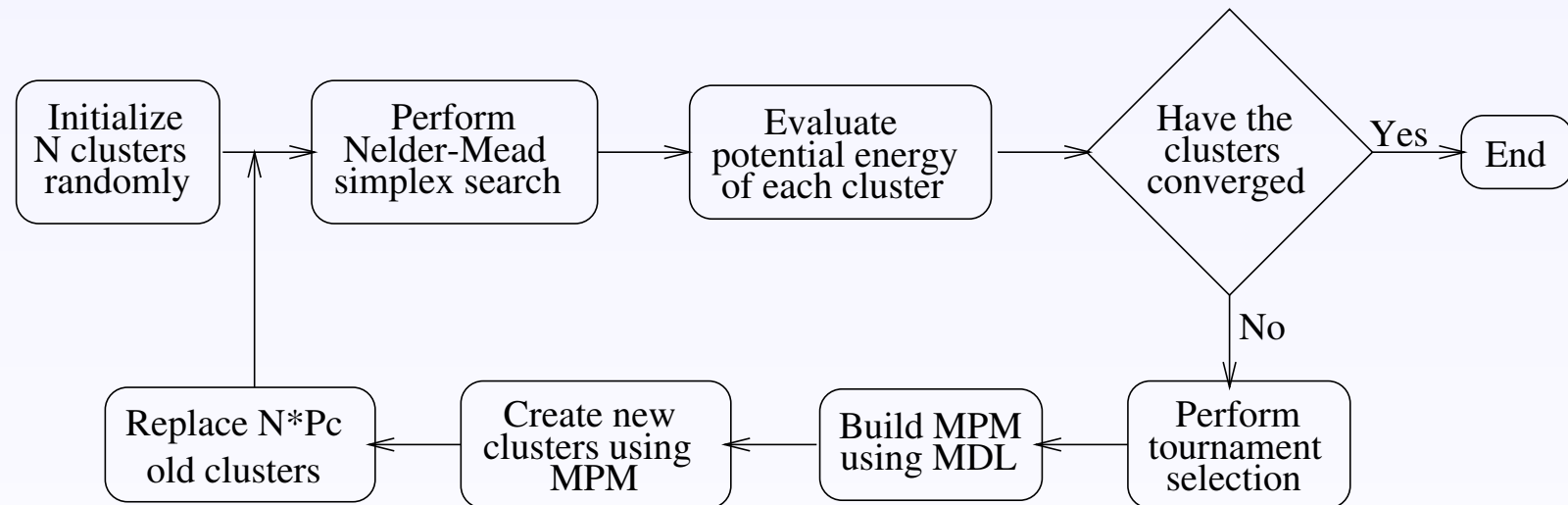
## Motivation

- Existing algorithms use “not-so-good” operators
  - Proportionate selection
  - Single point crossover
- Increased interest in competent GAs
  - Solves hard problems quickly reliably and accurately
- An interesting competent GA is ECGA (Harik, 1999)
  - builds models of good data as linkage groups
- Cluster optimization is a NP-hard problem (Wille and Vennik, 1985)

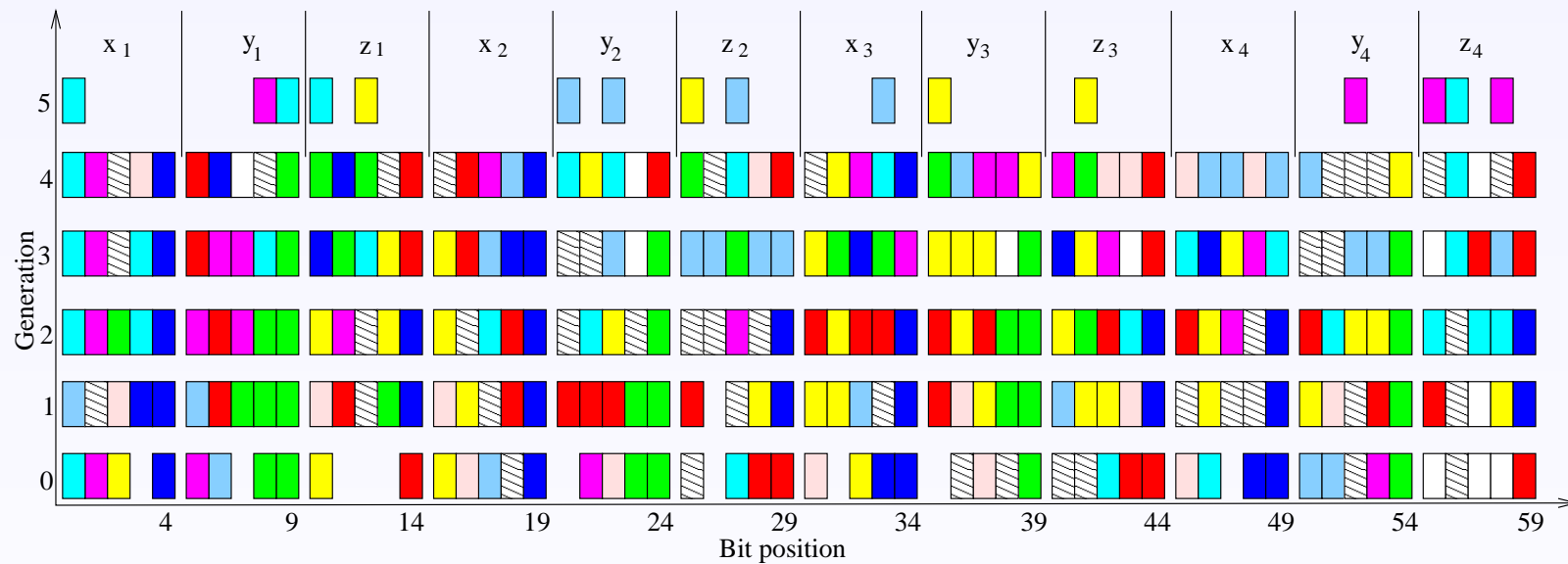
## Overview of ECGA

- **Key Idea:** Good probability distribution  $\equiv$  *Linkage learning*
- Probability distribution: *Marginal Product Models* (MPM)
- Quantified based on *Minimum Description Length* (MDL)
- **MDL Concept:** Simpler distributions are better

## Flowchart of Optimization Algorithm



## MPM and Building Blocks



## Marginal Product Models

- Product of marginal distributions on a partition of genes
- Similar to CGA (Harik et. al;1998) and PBIL(Baluja;1994)
- Represent more than one gene in a partition
- Make exposition simpler
- Gene partition maps to linkage groups

## Minimum Description Length Models

- **Hypothesis:** Good distributions are those for which
  - Representation of the distribution is minimum (*model complexity*,  $C_m$ ).
  - Representation of population compressed is minimum (*compressed population complexity*,  $C_p$ ).
- Penalize complex models
- Penalize inaccurate models
- Combined complexity,  $C_c = C_m + C_p$



## Building MPM using MDL

Uses a steepest ascent search:

1. Assume all the genes to be independent ( $[1],[2],\dots,[L]$ ) and compute  $C_c$ .
2. Form all possible combinations ( $N_{bb}(N_{bb}-1)/2$ ) of merging two subsets. eg., ( $[1,2],[3],\dots,[L]$ ),  $\dots$ , ( $[1],[2],[3],\dots,[L-1,L]$ ).
3. Select the set with minimum combined complexity ( $C'_c$ ).
4. If  $C_c > C'_c$  go to step 6.
5. Use the set with  $C'_c$  as the current MPM and go to step 2.
6. Merging is not possible, exit with set from step 2 as MPM.

## Generation of New Population

- Transfer  $N_p * (1 - P_c)$  best individuals to the next generation
- The rest  $N_p * P_c$  individuals are generated as follows:
  - Take each of the subset of MPM from one of the individuals.
  - Similar to multiple point crossover.
  - Number of crossover points =  $N_{bb}$ .
  - Instead of two parents we have  $N_{bb}$  parents.

## Silicon Potential

### Gong Potential

- Gong, X.G. *Phys. Rev. B* **47**, 2329 (1993)
- Empirical three body potential
- Based on Stillinger Weber potential
- Reflects both tetrahedral ( $\sim 109^\circ$ ) and preferred bond angles ( $\sim 60^\circ$ )
- Accurate for predicting structural properties

## Gong Potential: Equations

$$U_{\text{tot}} = \sum_{i < j}^n v_2(i, j) + \sum_{i < j < k}^n v_3(i, j, k)$$

$$v_2(i, j) = A (B r_{ij}^{-p} - r_{ij}^{-q}) \exp \left[ (r_{ij} - a)^{-1} \right], \quad |r_{ij}| < a$$

$$v_3(i, j, k) = h(r_{ji}, r_{ki}) + h(r_{kj}, r_{ij}) + h(r_{ik}, r_{jk})$$

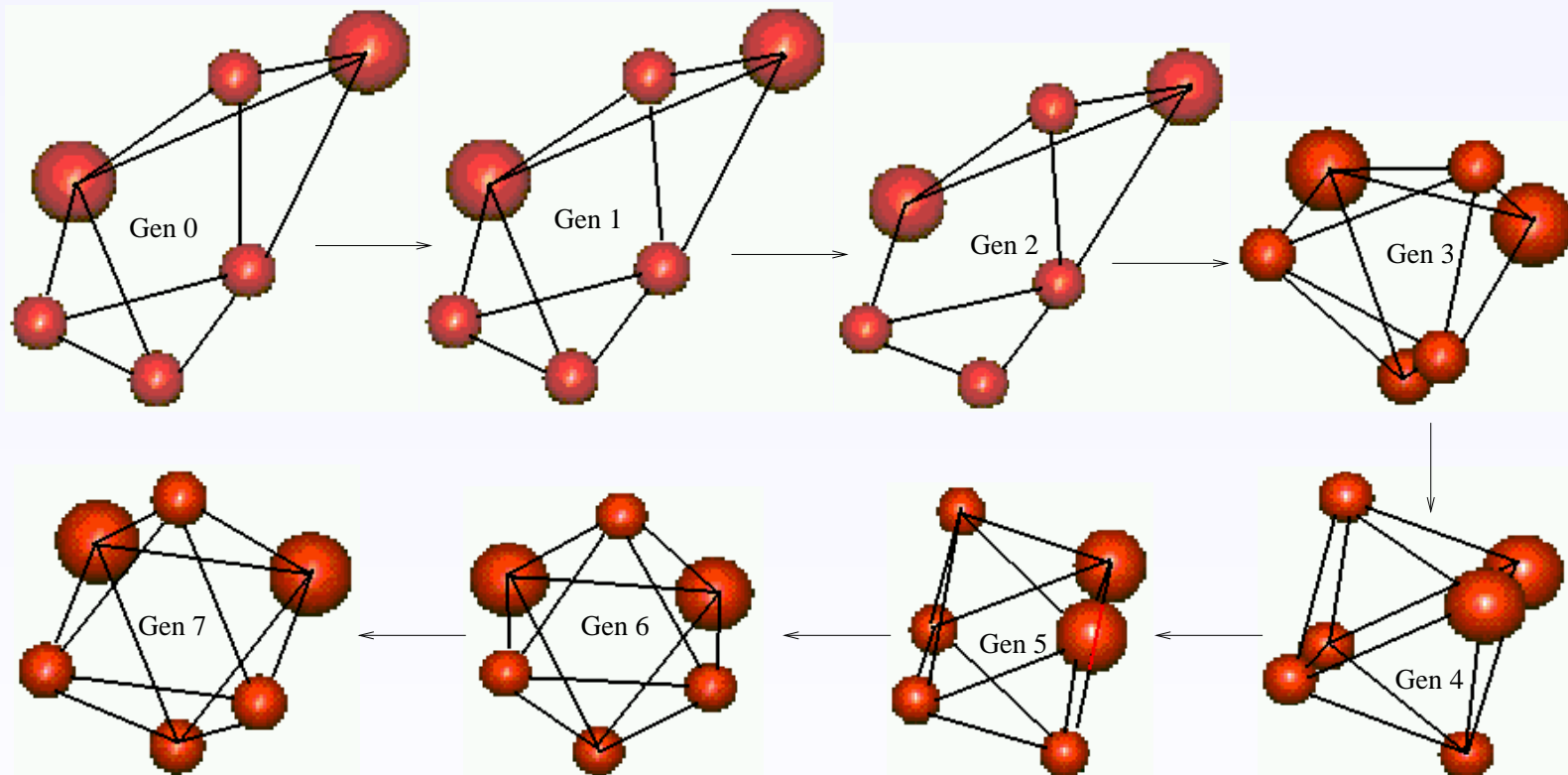
$$h(r_{ji}, r_{ki}) = \begin{cases} \lambda \exp \left[ \gamma \left( (r_{ij} - a)^{-1} + (r_{ki} - a)^{-1} \right) \right] & |r_{ij}| < a \\ \left( \cos \theta_{jik} + \frac{1}{3} \right)^2 \left[ (\cos \theta_{jik} + c_0)^2 + c_1 \right] & |r_{ki}| < a \end{cases}$$

- $A = 7.0496$ ,  $B = 0.6022$ ,  $a = 1.8$ ,  $p = 4$ ,  $q = 0$ .
- $\lambda = 25$ ,  $\gamma = 1.2$ ,  $c_0 = -0.5$ ,  $c_1 = 0.45$

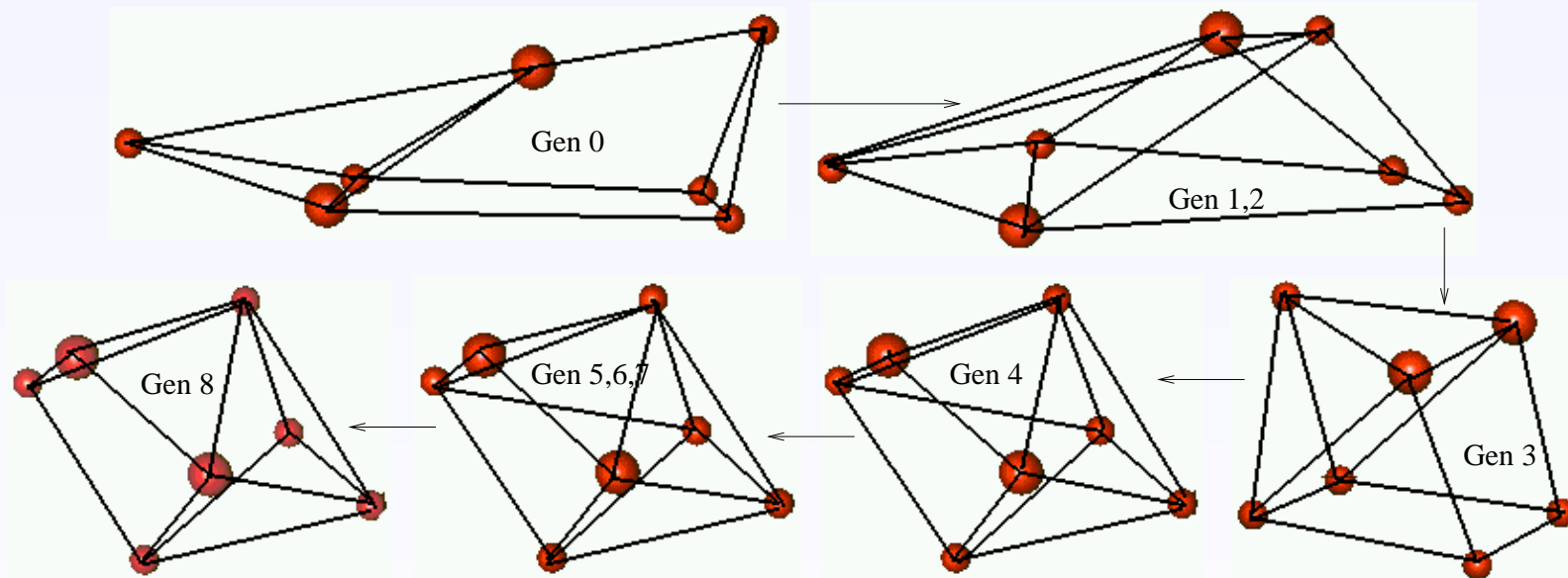
## Algorithm Implementation

- Variables are fixed-space Cartesian coordinates
- Each coordinate is encoded by 5-bit binary
- 25 independent runs,  $p_c = 0.8$ , 4-11 atoms
- Nelder-Mead simplex: Press et al
- Termination criteria:
  - Fitness variance  $\leq 0.1$
  - Population variance  $\leq 0.1$
- At most one failure allowed

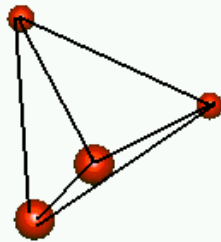
## Results: Single GA Run



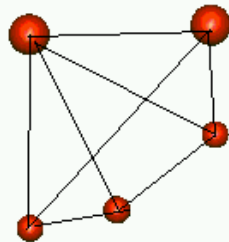
## Results: Single GA Run



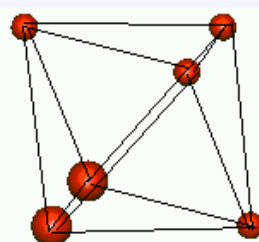
## Results: Optimal Structures



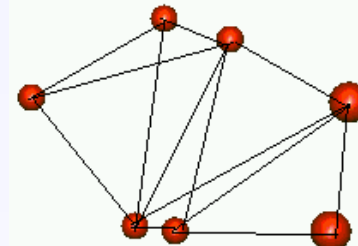
Tetrahedron  
 $U = -4.0016$



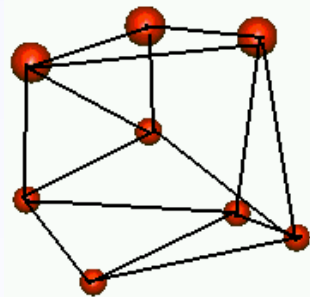
Compressed trigonal  
bipyramid,  $U = -5.7518$



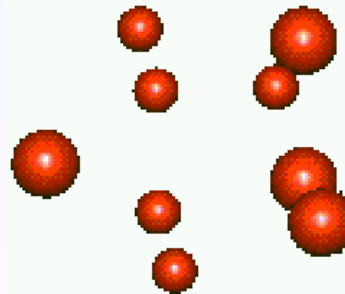
Octahedron  
 $U = -7.6696$



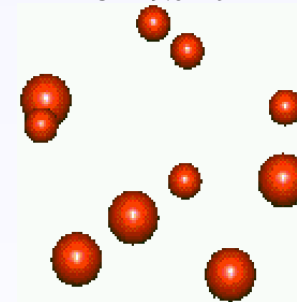
Pentagonal bipyramid  
 $U = -9.6240$



Unicapped distorted  
pentagonal bipyramid  
 $U = -11.5346$



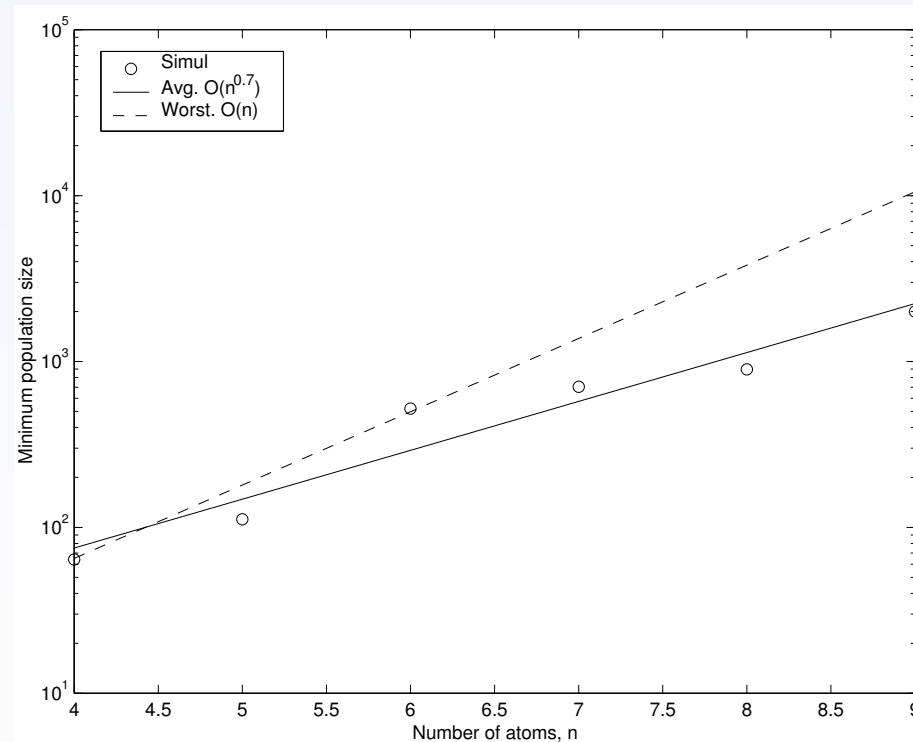
Tricapped trigonal  
prism,  $U = -13.5999$



Bicapped tetragonal  
antiprism,  $U = -15.6487$

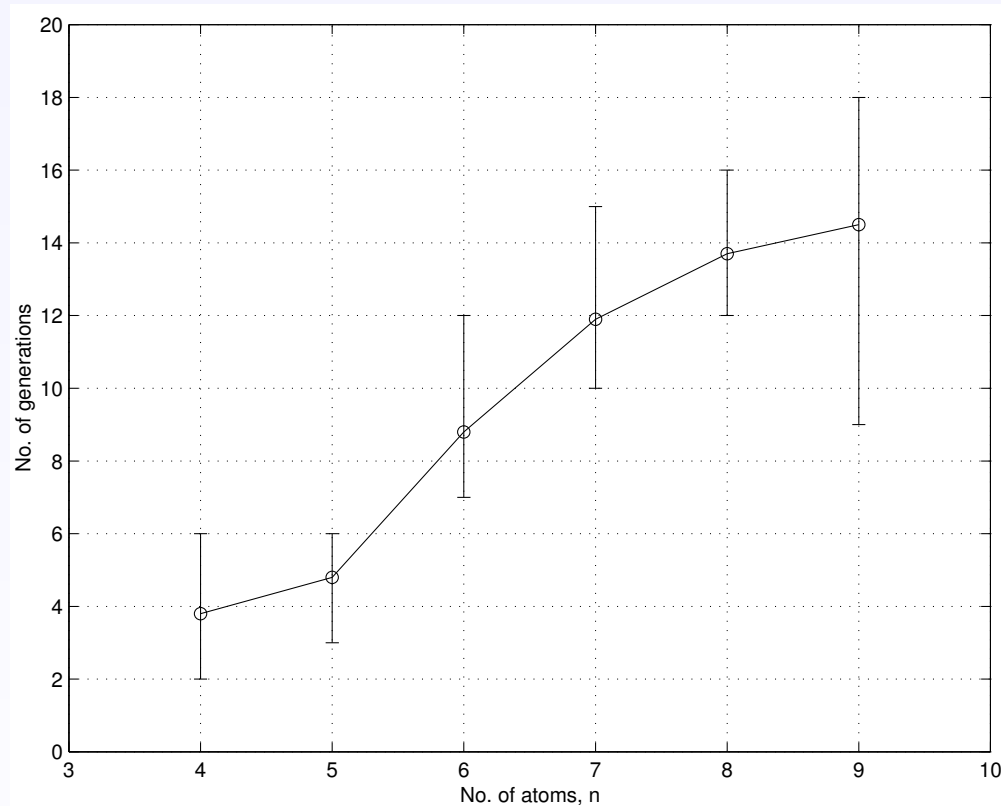


## Results: Population Size

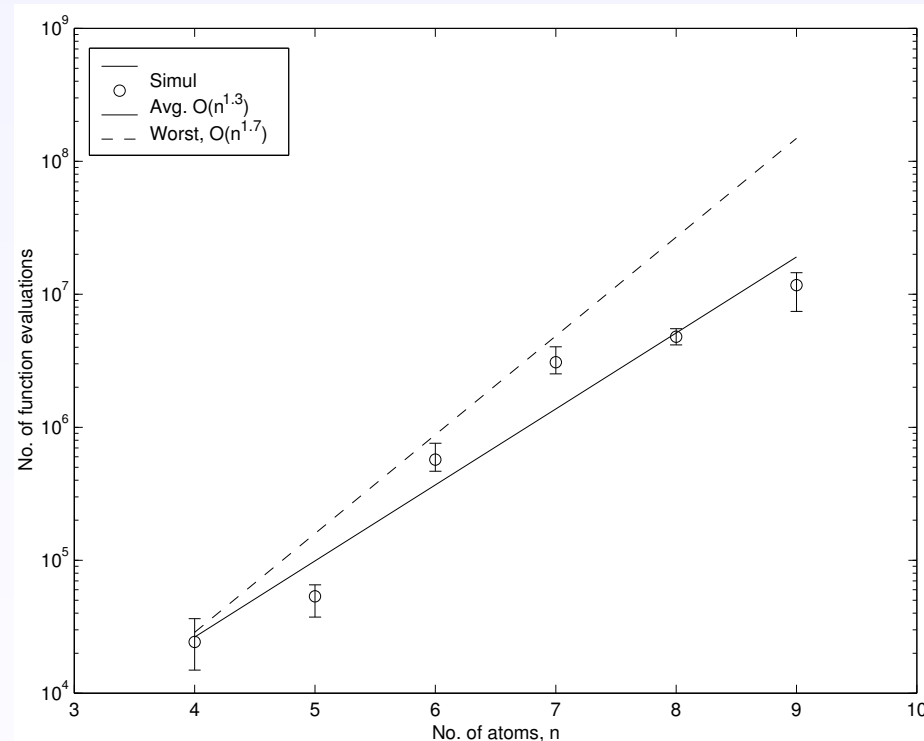


Average Case:  $O(n^{0.7})$ , Worst Case:  $O(n)$ .

## Results: Convergence Time



## Results: Function Evaluation



Average Case:  $O(n^{1.3})$ , Worst Case:  $O(n^{1.7})$ .

## Conclusions

- Optimal structures of small Si clusters found
- Results agree with literature (Iwamitsu, *M. J. Chem. Phy.* **112** (2000))
- Convergence is very fast ( $\leq 25$  generations).
- Population size increases linearly with cluster size
- Polynomial increase of function evaluation
- Results to be confirmed with bigger clusters