# Designing Like Mother Nature

## An Introduction to Genetic Algorithms

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Linden Innovation Research LLC

## About the Speaker, Derek Linden

- B.S., USAF Academy, 1991, Applied Physics (Elec. Systems)
- M.S., MIT, 1993, EE (Solid State Devices/Superconductivity)
- Rome Lab, 1993 - 1996, basic research on superconductors at microwave frequencies, antennas, GAs
- Ph.D., MIT, 1997, Thesis: "Automated Design and Optimization of Wire Antennas Using Genetic Algorithms"
- Current research: Increasing GA efficiency, applying GAs to new problems
- Linden Innovation Research LLC
  - Automated Design and Optimization Consulting, Training and Software

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# Introduction to GAs: Overview

- Goal: to introduce the fundamental concepts of a GA
  - What is a GA?
  - GA basics
  - Examples

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# What is a GA?

- A probabilistic, iterative search and optimization strategy
- Mimics biological intra-species adaptation and evolution through mating and survival-of-the-fittest
- Finds optima for many types of numerical problems
- Requires:
  - A coding strategy
  - An objective function
  - A mating and mutation scheme

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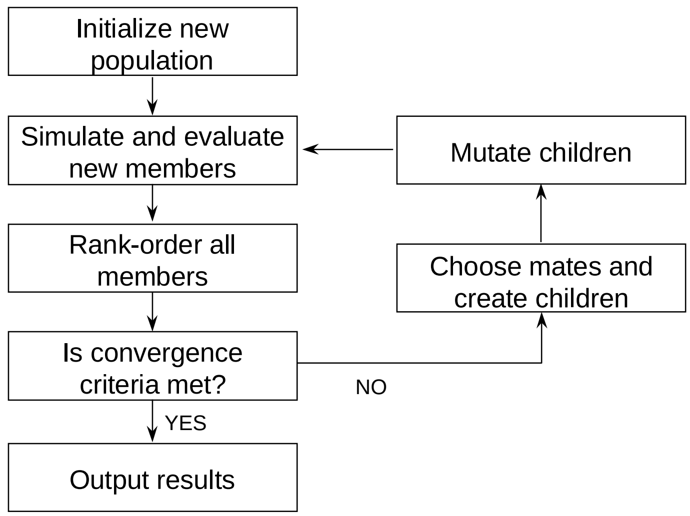
# The GA Iterative Process

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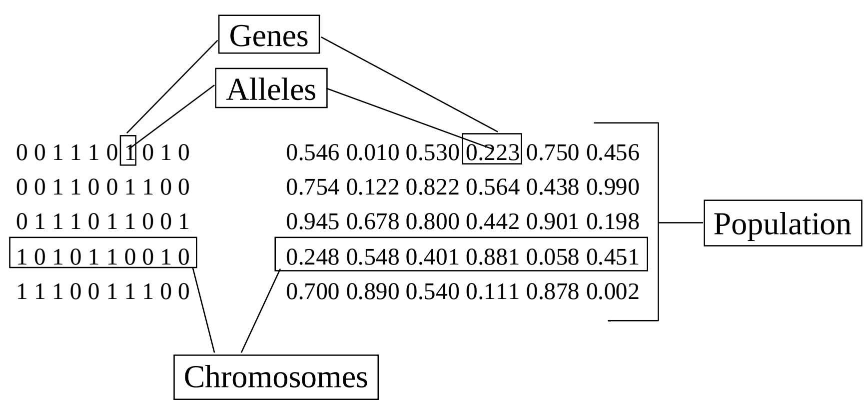
# GA Terms

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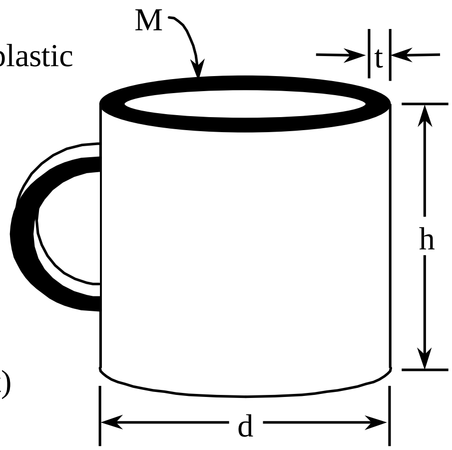
# An Example Design Problem

4 Variables, with Constraints:
- Material: ceramic, glass, plastic
- Diameter: 2”-5”
- Height: 3”-6”
- Thickness: 0.1”-0.5”

Dependent constraint:
- Weight < 1.5 lbs.

Optimize for:
- Heat Retention = f(M,d,h,t)
- Cost = f(M,d,h,t)
- Volume = f(d,h)

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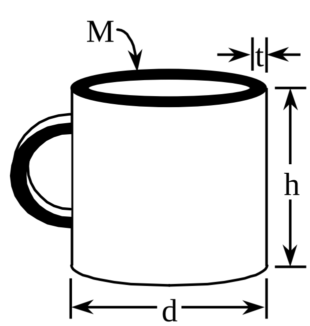
# Setup for GA Optimization

Chromosome:

| Material | Diameter | Height | Thickness |
|---|---|---|---|
| 01 | 1010 | 0100 | 1101 |
| Glass | 4.0” | 2.8” | 0.447” |




Objective Function =

Heat Retention + Volume - Cost - Penalty * Weight

(Penalty is non-zero only if Weight above 1.5 lbs.)

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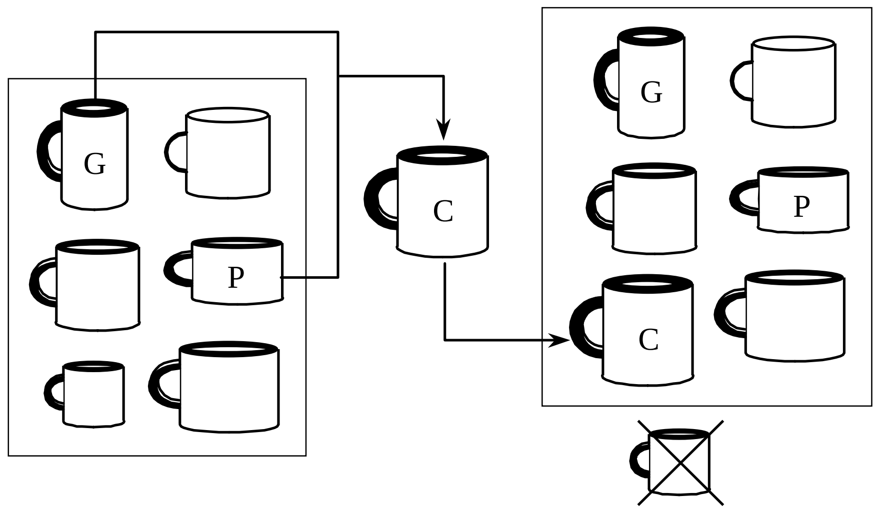
## Snapshot During the GA Process

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## Brief History

- Before the GA, algorithms based on mutation were tried
- John Holland (University of Michigan)
  - Holland had the basic GA by the mid-1960s
  - Monograph in 1975—“Adaptation in Natural and Artificial Systems”
  - Purpose: to understand adaptive processes in natural systems and design artificial systems that mimic natural system behavior
- David Goldberg—textbook in 1989

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# Current Areas of Application

- Mechanical Engineering
- Software Design
- Electromagnetics
- Electrostatics
- Artificial Intelligence/Artificial Life
- Robotics
- Aeronautical Engineering
- Financial

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# The GA Process

- Set up simulator/equations to evaluate members of population
- Define problem—constraints, unknowns, variables
- Determine objective function
- Determine chromosome mapping
- Determine genetic algorithm characteristics
  - mating selection, crossover, mutation, population size, etc.
- Run the GA optimization process
- Output the optimal design characteristics

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# Objective Function

- Gives a single score based on simulation results
- Used to rank-order the members of the population
- Single criteria or multi-criteria
- Include any penalty terms for violating constraints

Fitness = -c1 * gain + c2 * mismatch + c3 * distortion
+ c4 * (amount of power violation)

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# 1-D Binary and Real Chromosomes

- Binary:
  0 0 1 1 1 0 1 0 1 0
  – Usually each variable consists of several bits
  – Most commonly used by far, good for most problems
- Real:
  0.546 0.010 0.530 0.223 0.750 0.456 0.555
  – Usually each variable consists of only one number
  – Use for problems involving mostly real, continuous variables

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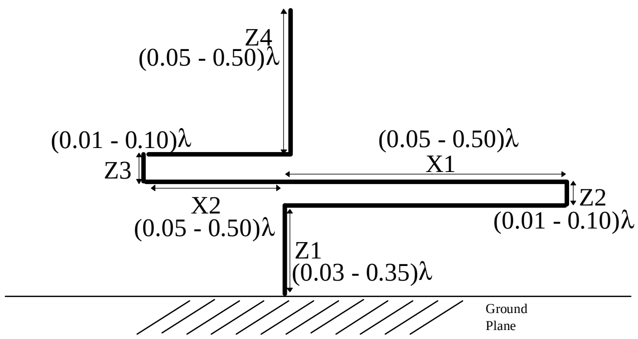
# Chromosome Mapping: Example




| | | | | | | |
|---|---|---|---|---|---|---|
| Binary 1-D | 00000 | 11111 | 00000 | 11111 | 00000 | 11111 |
| | Z1 | Z2 | Z3 | Z4 | X1 | X2 |
| Real 1-D | 0.452 | 0.335 | 0.102 | 0.873 | 0.525 | 0.651 |

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# Mating Process

- The basic mating process:
  - Eliminate poor performers (total population remains constant)
  - Choose chromosomes to mate
  - Create offspring
- Simple GA: replaces whole population with new children, though some are copies of parents
- Steady-State GA: saves a portion of the population each generation
- Elitist: saves top chromosome

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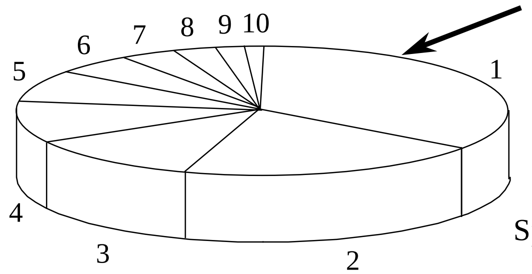
# Mating Selection

- In biology, mates are chosen through natural selection
  - Brightest flower, strongest male, most attractive call
- Most common GA method: weighted roulette wheel




1 = Most fit member

10 = Least fit member

Spin 1: First Parent

Spin 2: Second Parent

- Usually weighted by fitness, or qualities like similarity

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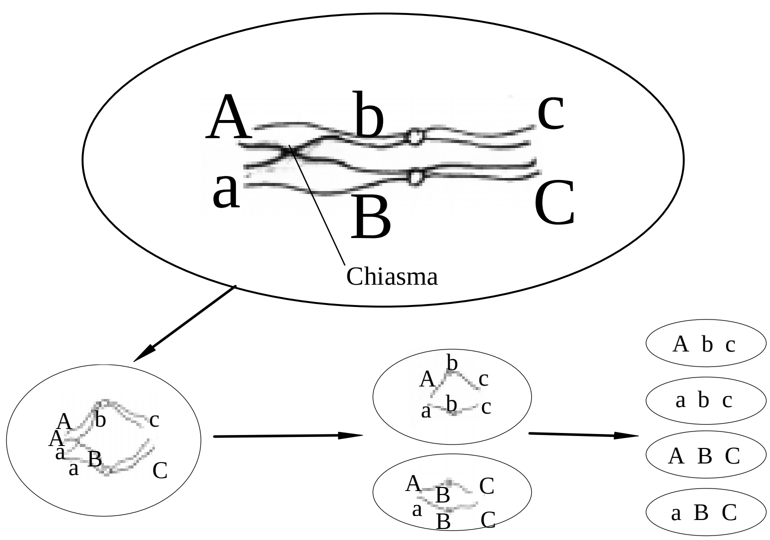
# Concept: Crossover

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# 1-D Binary Mating—Single-Point Crossover

- Parent chromosomes:

  [00011110]

  {11001100}
- Let the crossover point be between the 5th and 6th bit (but could be between any two bits)
- Children: [00011]{100}

  {11001}[110]
- Works the same way for real chromosomes, except no functional genes are able to be split

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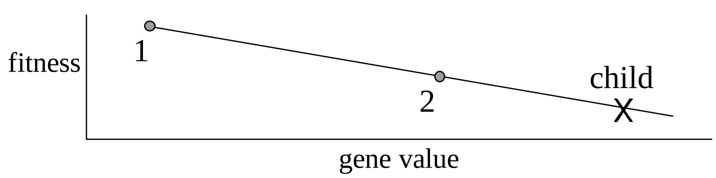
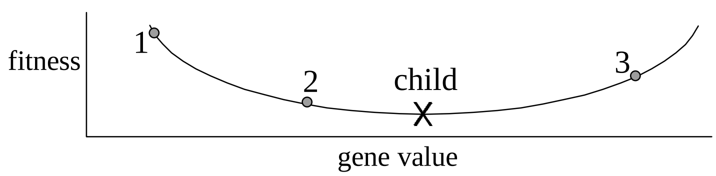
# 1-D Real Chromosome Mating

- Heuristic crossover




- Quadratic crossover




Adewuya, 1996

- Many other methods exist

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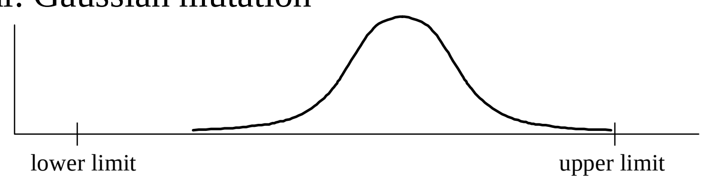
# 1-D Binary and Real Chromosome Mutation

- Binary: Bit flip
  - Flip a randomly selected 1 ➔ 0 or 0 ➔ 1
- Real: Uniform mutation


- Real: Gaussian mutation

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# The GA Parameters

- Population Size: 30 - 10,000
  (most I've heard of: 1,000,000)
- Parent pool size (overlap): 10%-50%
- Probability of mutation: < 2%
- Convergence criteria:
  - # generations
  - # simulations
  - non-improvement
  - loss of diversity
  - when I choose to stop it

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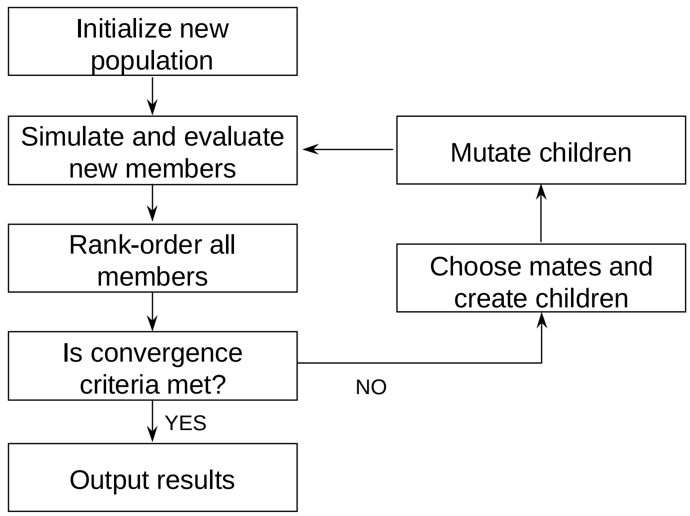
# Putting the Process Together

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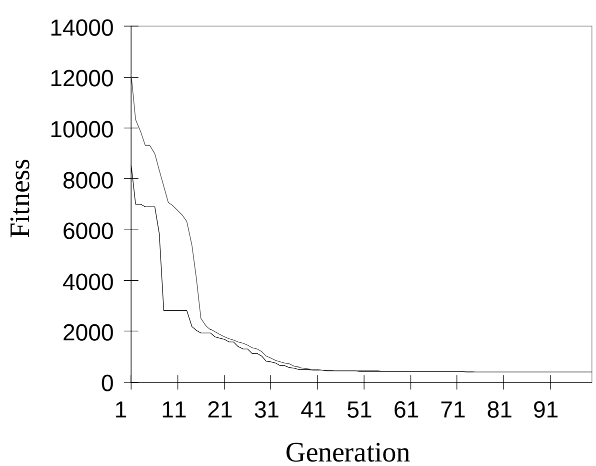
# Typical GA Behavior: Fitness

- Best fitness, Average fitness vs. Generation

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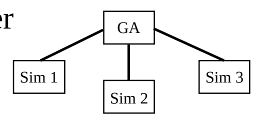
# GA Advantages

- Properly implemented, it can lead to optimal solutions relatively rapidly and efficiently
- Prevents the solution from getting trapped in local minima through parallelism
- Is zeroth-order/blind—requires no information other than the objective function value for each chromosome
- Can optimize very complicated systems with no human intervention (not even an initial guess!)
- Very robust to parameters, coding, etc.
- Able to be implemented in a parallel manner

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# GA Examples

- Discrete problems
  - Truss topology design
  - VLSI connection design
  - Job Shop Process Planning
- Continuous problems
  - Turbine engine design
  - Pattern nesting (Parts layout)
  - Simple wire antenna
  - Folded monopole & Crooked-wire antennas

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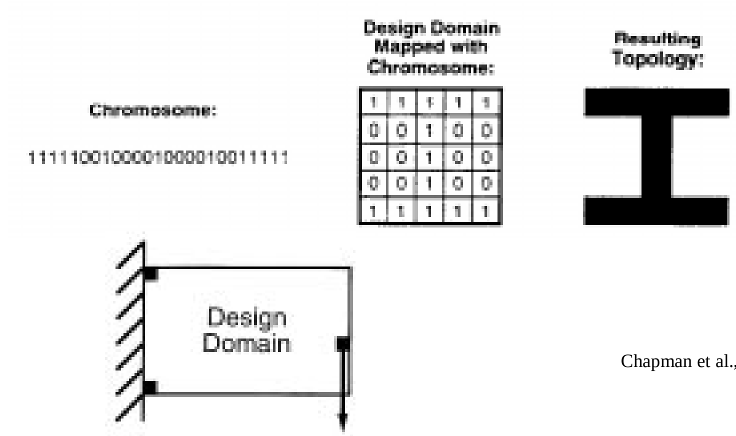
# Truss Topology Design

- Use a GA to determine an optimal truss structure with the least amount of material given a load




Chapman et al.,1994

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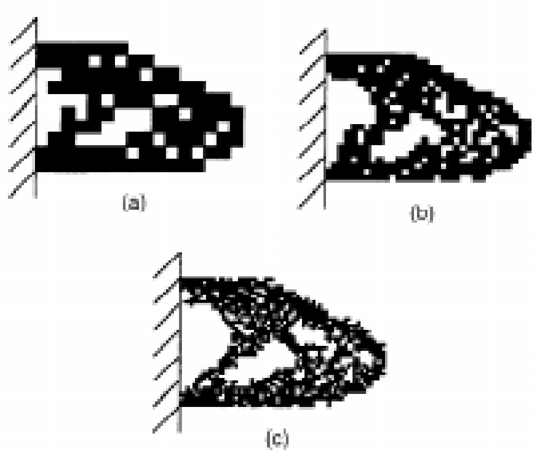
# Truss Topology Design

- Example optimized designs at differing resolutions

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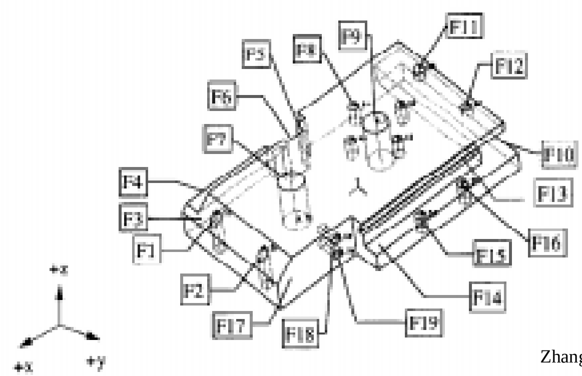
# Job Shop Process Planning

- Minimize the cost and hassle in machining custom parts
- Many different combinations of machine, tool, and setup are possible to create the same part




Zhang, et al.,1997

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# Job Shop Process Planning

| Minimize | Machine | Setup | Tool | Cost |
|---|---|---|---|---|
| Machine | 0 | 11 | 13 | 2664 |
| Setup | 8 | 0 | 10 | 3799 |
| Tool | 12 | 5 | 0 | 5014 |
| Cost | 1 | 3 | 8 | 1739 |

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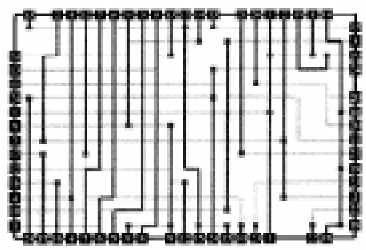
# VLSI Connection Design

- Rather complex GA technique compared with 2-4 other standard VLSI techniques in each of 10 classic benchmarks
- GA was best method for each benchmark in numbers of vias
- Best for overall wire length in 7 of 10 benchmarks
- 2nd best in the other 3 benchmarks, and usually a close second
- Crosstalk requirements can be added, which none of the other techniques can handle



Leinig, 1997

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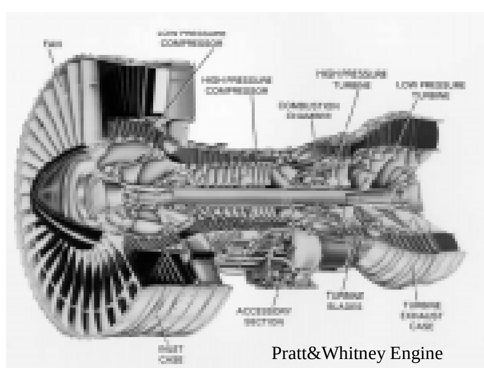
# Turbine Engine Design

At least 100 variables, each with a continuous range

Search space of $10^{387}$ points

Fitness: compliance with about 50 constraints + performance measures



Pratt&Whitney Engine

Engineer: 8 weeks for a satisfactory design
Engineer + Expert system: less than 1 day w/ 2x improvement
GA + Expert system: 2 days w/ 3x improvement over engineer alone

Holland, 1992

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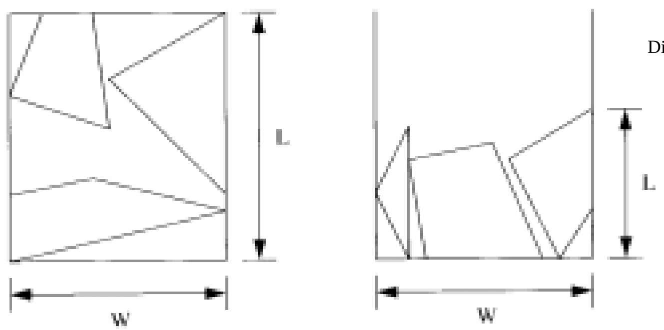
# Pattern Nesting

- Applications in many industries
  - Clothing
  - Shipbuilding
  - Automobile part manufacturing




Dighe & Jakiela, 1996

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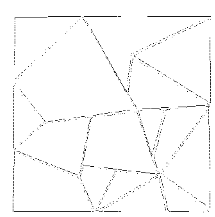
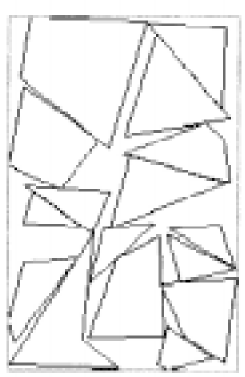
# Pattern Nesting

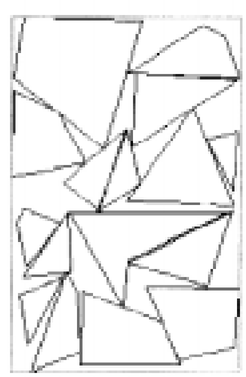
- Minimizing rectangular enclosure



68.4%



69.0%



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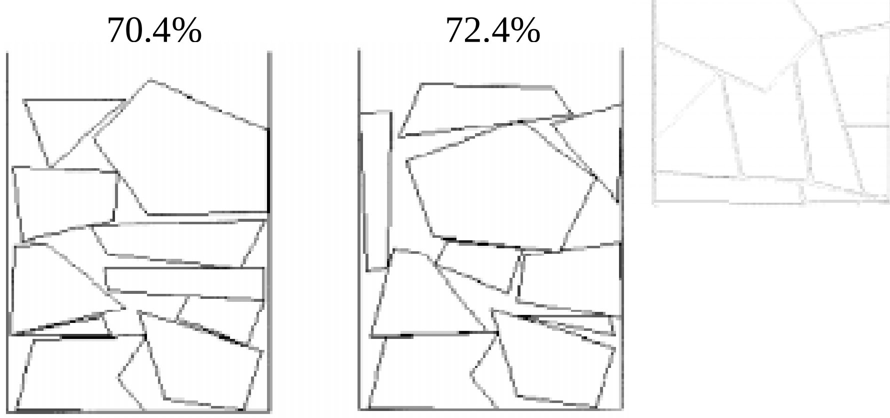
# Pattern Nesting

- Minimizing height

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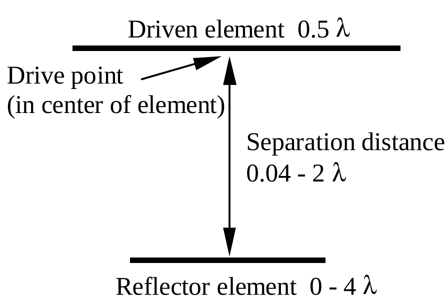
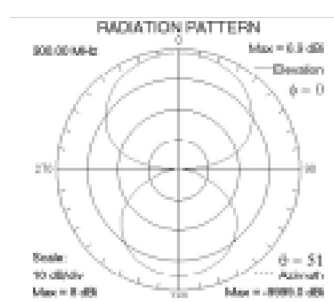
# Simple Wire Antenna

- The design




Linden, 1997

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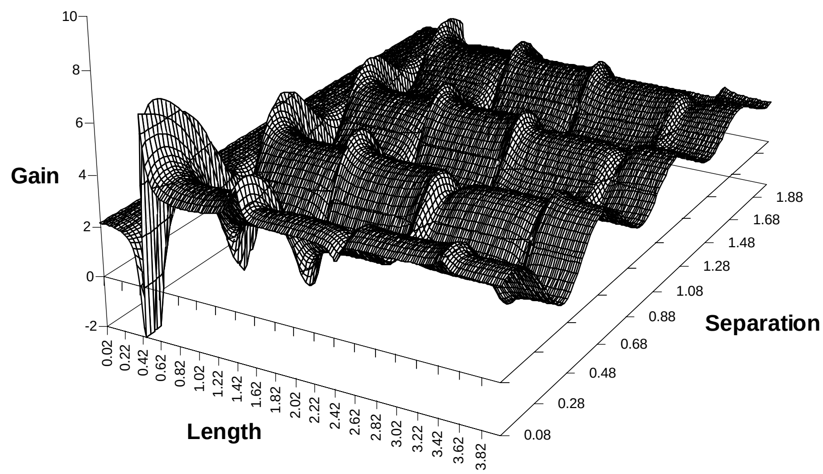
# Simple Wire Antenna

- The search space

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# Simple Wire Antenna

- The objective function
  - Maximize gain in forward direction (already a single number)
- The chromosome
  - Two real values for length and separation
- GA parameters
  - 20 chromosomes, 50% overlap, 0.6% mutation

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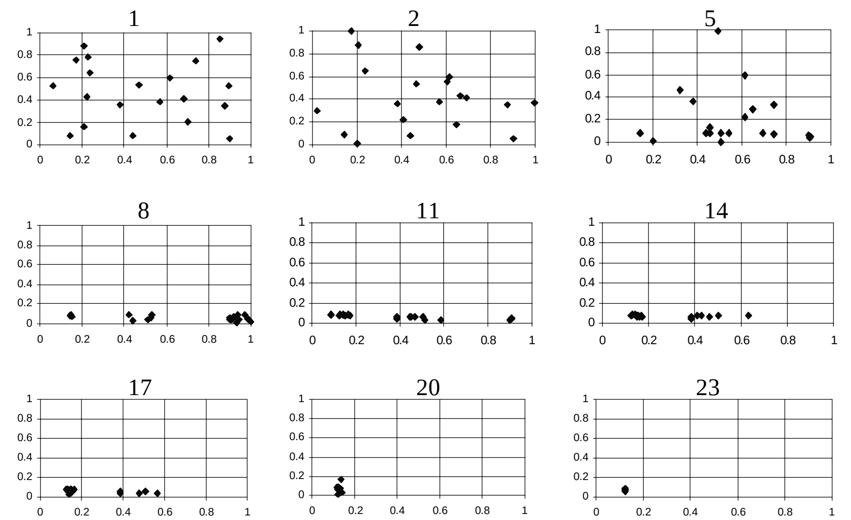
# Simple Wire Antenna

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# Folded Monopole, Crooked-Wire Antennas

- The problem: Our goal in each case was to achieve a single objective: the broadest beam possible over the upper hemisphere

  Score = $\Sigma_{\text{over all } \theta,\phi}(\text{Gain}(\theta,\phi) - \text{Avg. Gain})^2$

  – Folded monopole — power gain only

  – Crooked wire antennas — RH circular polarization gain

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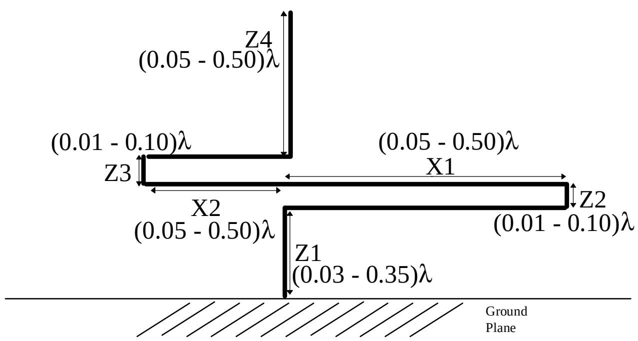
# The Folded Monopole Chromosome

Goal: Hemispherical coverage, regardless of polarization




| | | | | | |
|---|---|---|---|---|---|
| 00000 | 11111 | 00000 | 11111 | 00000 | 11111 |
| Z1 | Z2 | Z3 | Z4 | X1 | X2 |

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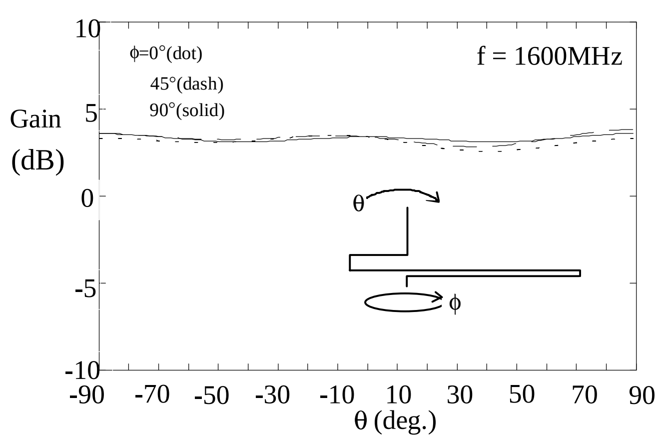
# Folded Monopole Results




Altshuler & Linden, 1997

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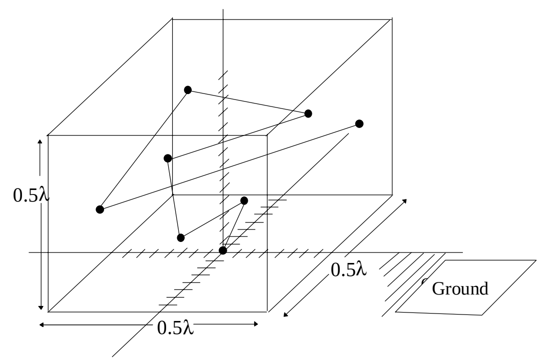
# Crooked-Wire Genetic Antenna Space

Goal: Coverage over hemisphere 10 above the horizon with right-hand circular polarization




(X1,Y1,Z1)(X2,Y2,Z2)(X3,Y3,Z3)...(X7,Y7,Z7) 105 bits

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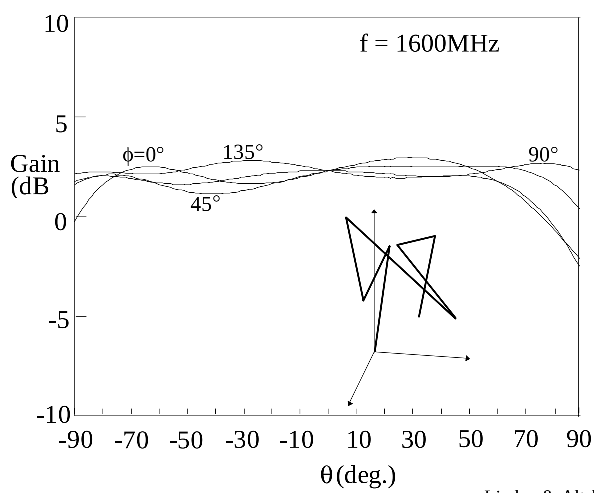
# Crooked-Wire Genetic Antenna Results




Linden & Altshuler, 1996

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# References


- A. Adewuya, " New Methods in Genetic Search with Real-valued Chromosomes," Master's Thesis, Mech. Engr. Dept., MIT, 1996
- C.D. Chapman, K. Saitou, M.J. Jakiela. "Genetic Algorithms as an Approach to Configuration and Topology Design." Journal of Mechanical Design,Vol. 116, December 1994.
- F. Zhang, Y.F. Zhang, A.Y.C Nee. "Using Genetic Algorithms in Process Planning for Job Shop Machining." IEEE Trans. on Evolutionary Computation, Vol. 1, No. 4, November 1997.
- J. Lienig. "A Parallel Genetic Algorithm for Performance-Driven VLSI Routing." IEEE Trans. on Evolutionary Computation, Vol. 1, No. 1, April 1997.
- J.H. Holland. "Genetic Algorithms." Scientific American, July 1992.
- R. Dighe and M.J. Jakiela. "Solving Pattern Nesting Problems with Genetic Algorithms Employing Task Decomposition and Contact Detection." Evolutionary Computation, Vol. 3, No. 3, 1996.
- D.S. Linden. "Automated Design and Optimization of Wire Antennas using Genetic Algorithms." Ph.D. Thesis, MIT, September 1997.
- E.E. Altshuler and D.S. Linden. "Design of a Loaded Monopole Having Hemispherical Coverage Using a Genetic Algorithm." IEEE Trans. on Antennas and Propagation., Vol. 45, No. 1, January 1997.
- D.S. Linden and E.E. Altshuler. "Automating Wire Antenna Design using Genetic Algorithms." Microwave Journal, Vol. 39, No. 3, March 1996.