Evolutionary Computation:
Genetic algorithms

- Can evolution be intelligent?
- Simulation of natural evolution
- Genetic algorithms
- Case example

Can evolution be intelligent?

- **Optimisation**
  - iteratively improves the quality of solutions until an optimal, or at least feasible, solution is found
- **Intelligence**
  - the capability to adapt its behaviour to ever-changing environment
- **Evolutionary computation**
  - capable of learning to predict changes in its environment over successive generations through inductive inference based on computational models of natural selection and genetics
  - introduced in the 1960s by I. Rechenberg

Simulation of natural evolution

- **theory of evolution**
  - ✓ presented by **Charles Darwin** on 1 July 1858
  - ✓ marks the beginning of a revolution in biology
- **neo-Darwinian paradigm**
  - ✓ represented by Darwin's classical theory of **evolution**, together with Weismannk's theory of **natural selection** and Mendel's concept of **genetics**

Neo-Darwinism

based on processes of reproduction, mutation, competition and selection.

- **reproduction**

  an essential property of life.

- **mutation**

  guaranteed in any living organism that reproduces itself in a continuously changing environment.

- **competition and selection**

  take place in the natural world, where expanding populations of different species are limited by a finite space.

- **Evolution**
  - a process leading to the maintenance of a population's ability to **survive** and **reproduce** in a specific environment.
- **Fitness**
  - quantitative measure of the ability to predict environmental changes and respond adequately
  - can be considered as the **quality that is optimised in natural life**.
- **Evolutionary fitness**
  - viewed as a measure of the organism's **ability to anticipate changes in its environment**.

How is a population with increasing fitness generated?

- Rabbits with **superior fitness .**
  - ✓ a population of rabbits are faster than other rabbits
  - ✓ have a greater chance of avoiding foxes, surviving and then breeding.
  - ✓ Over time the entire population of rabbits becomes faster to meet their environmental challenges in the face of foxes.
- Two **parents** have superior fitness
  - ✓ a combination of their genes will produce an **offspring** with even higher fitness.

Simulation of natural evolution

- create a population of individuals
- evaluate their fitness
- generate a new population through genetic operations
- repeat this process a number of times

Genetic Algorithms

- **John Holland** introduced the concept of genetic algorithms in the early 1970s.
- **make computers do what nature does**
- concerned with algorithms that manipulate **strings of binary digits**.
- Each artificial "**chromosomes**" consists of a number of "**genes**", and each gene is represented by **0 or 1**:

1	0	1	1	0	1	0	0	0	0	0	1	0	1	0	1

- Nature has an ability to **adapt and learn** without being told what to do.
- Nature finds good chromosomes **blindly.**
- GAs do the same by using two mechanisms to link GA to the problem: **encoding and evaluation**.
- GA uses a measure of **fitness of individual chromosomes** to carry out reproduction.
- **crossover** operator exchanges parts of two single chromosomes
- **mutation** operator changes the gene value in some randomly chosen location of the chromosome.

Basic genetic algorithms

Step 1: Represent the problem variable domain as a **chromosome of a fixed length**, choose the **size** of a chromosome population N, the **crossover probability** p_c and the mutation probability p_m

Step 2: Define a **fitness function** to measure the performance, or fitness, of an individual chromosome in the problem domain that will be mated during reproduction.

Step 3: Randomly generate **an initial population** of chromosomes of size N:

$x_1, x_2, \ldots, x_N$

Step 4: **Calculate the fitness** of each individual chromosome:

$f(x_1), f(x_2), \ldots, f(x_N)$

Step 5: **Select a pair of chromosomes** for mating from the current population. Parent chromosomes are selected with a **probability** related to their **fitness**.

Step 6: Create a pair of **offspring** chromosomes by applying the genetic operators – **crossover** and **mutation**.

Step 7: Place the created offspring chromosomes in the **new population.**

Step 8: Repeat *Step 5* until the size of the new chromosome population becomes equal to the size of the initial population, ***N***.

Step 9: Replace the initial (parent) chromosome population with the new (offspring) population.

Step 10: Go to *Step 4*, and repeat the process until the **termination criterion** is satisfied.

- GA represents an iterative process. Each iteration is called a **generation**.
- A typical number ofgenerations for a simple GA can range from 50 to over 500.
- The entire set of generations is called a **run**.
- Because GAs use a **stochastic search** method, the fitness of a population may remain stable for a number of generations before a **superior** chromosome appears.
- If no satisfactory solution is found, the GA is restarted.

Genetic algorithms: case study

A simple example will help us to understand how a GA works. Let us find the maximum value of the function $(15x - x^2)$ where parameter x varies between 0 and 15. For simplicity, we may assume that x takes only integer values. Thus, chromosomes can be built with only four genes:

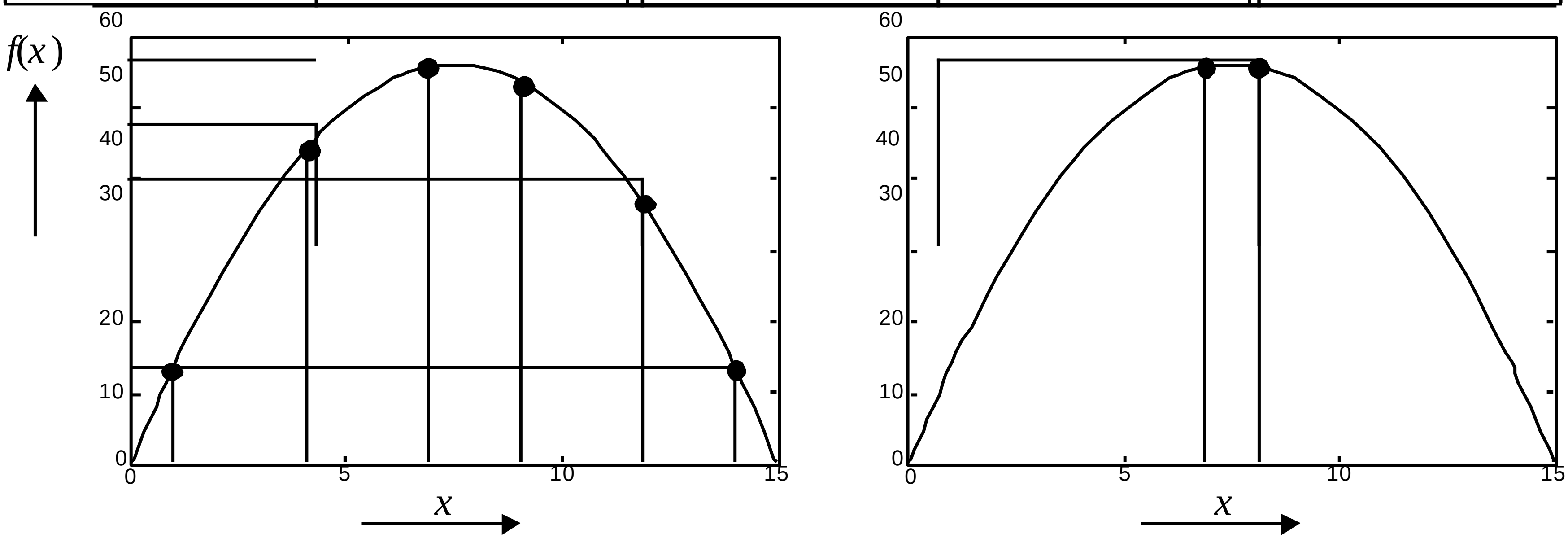
Integer	*Binary code*	*Integer*	*Binary code*	*Integer*	*Binary code*
1	0 0 0 1	6	0 1 1 0	11	1 0 1 1
2	0 0 1 0	7	0 1 1 1	12	1 1 0 0
3	0 0 1 1	8	1 0 0 0	13	1 1 0 1
4	0 1 0 0	9	1 0 0 1	14	1 1 1 0
5	0 1 0 1	10	1 0 1 0	15	1 1 1 1

Suppose that the size of the chromosome population N is 6, the crossover probability p_c equals 0.7, and the mutation probability p_m equals 0.001. The fitness function in our example is defined by

$$f(x) = 15\,x - x^2$$

The fitness function and chromosome locations

Chromosome label	*Chromosome string*	*Decoded integer*	*Chromosome fitness*	*Fitness ratio, %*
X1	1 1 0 0	12	36	16.5
X2	0 1 0 0	4	44	20.2
X3	0 0 0 1	1	14	6.4
X4	1 1 1 0	14	14	6.4
X5	0 1 1 1	7	56	25.7
X6	1 0 0 1	9	54	24.8



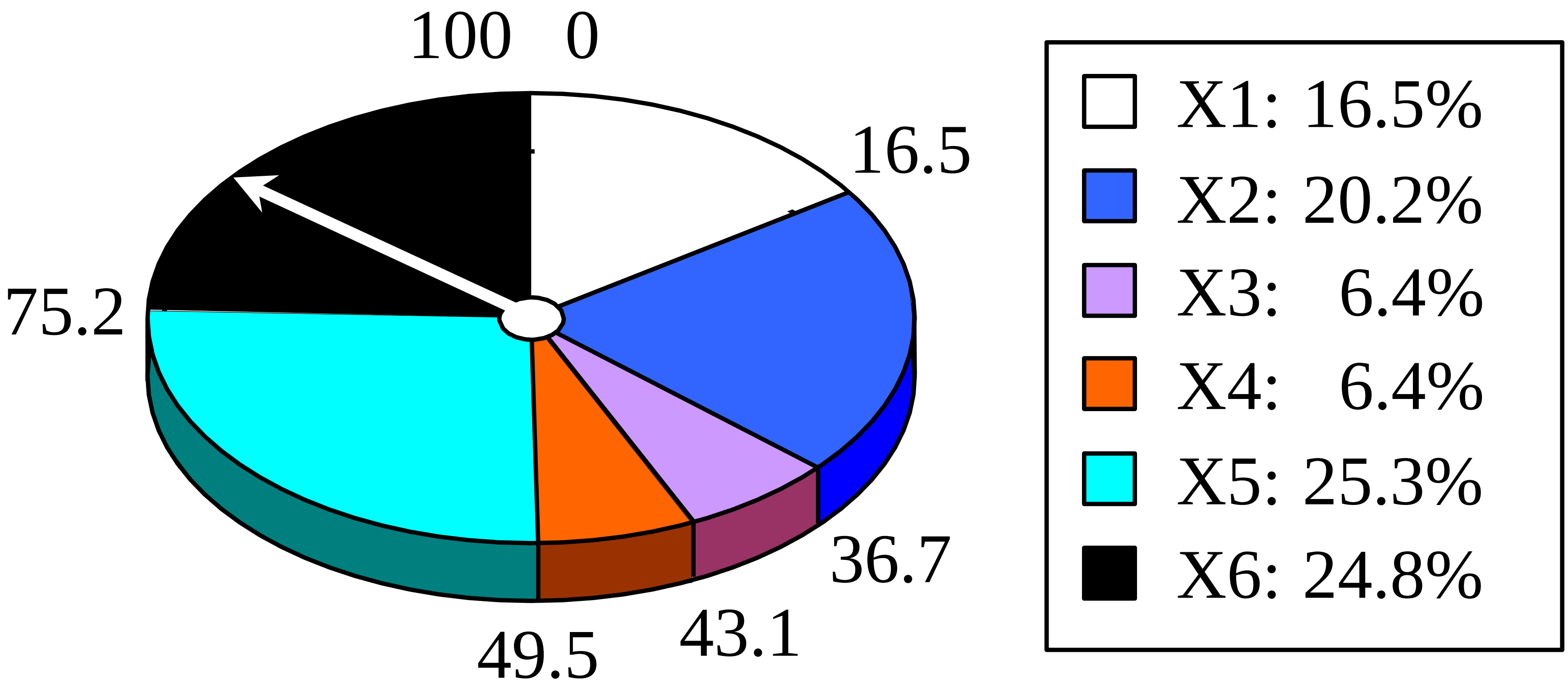
(*a*) Chromosome initial locations.

(*b*) Chromosome final locations.

- In natural **selection, only the fittest species can survive, breed, and thereby pass their genes on to the next generation.**
- GAs use a similar approach, but unlike nature, the **size** of the chromosome population remains **unchanged** from one generation to the next.
- The last column in Table**,** **fitness ratio**, shows the **ratio of the individual chromosome's fitness to the population's total fitness**. This ratio determines the chromosome's chance of being selected for **mating**.
- The chromosome's **average fitness improves** from one generation to the next.

Roulette wheel selection

the most commonly used chromosome selection techniques

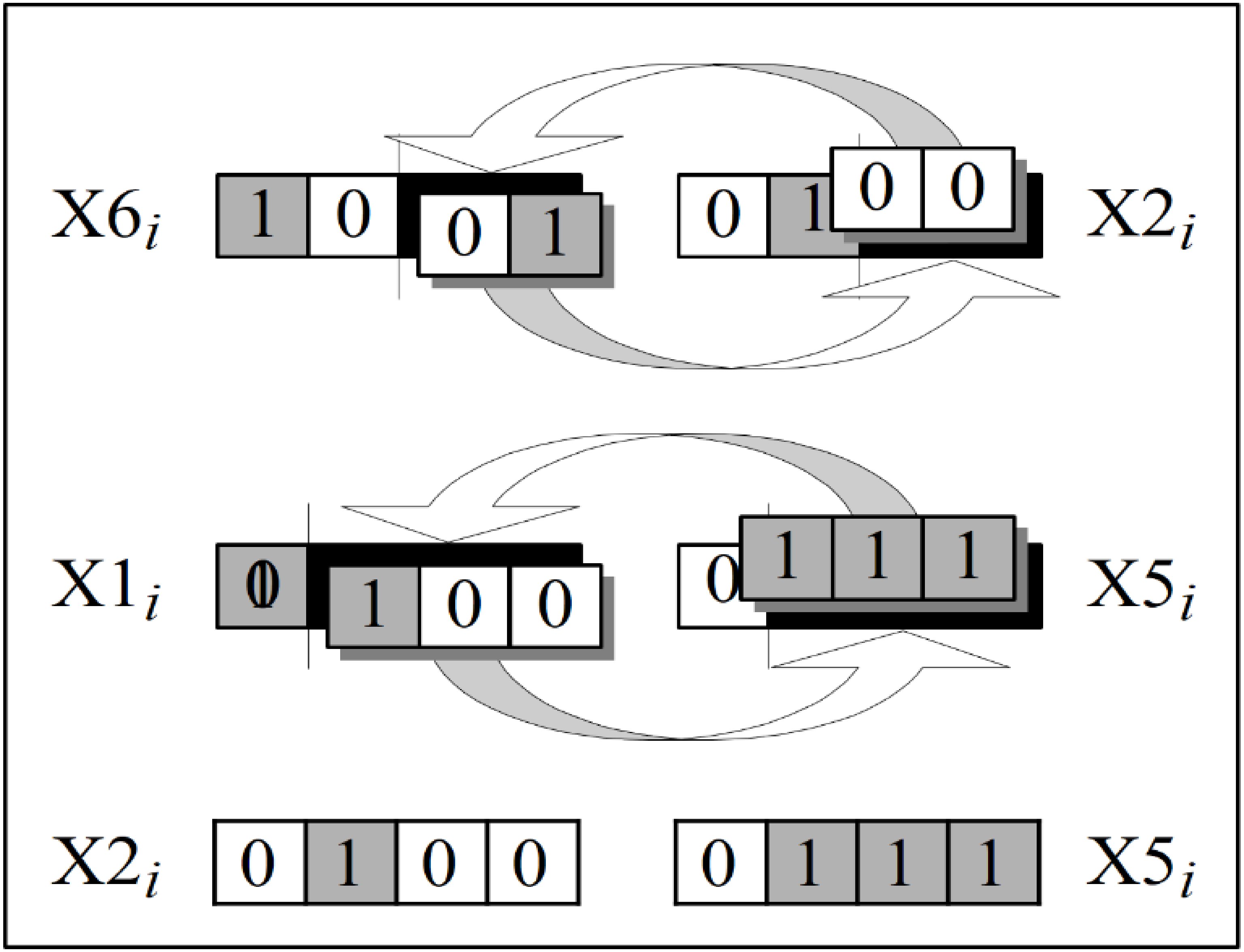


Crossover operator

- we have an initial population of **6** chromosomes. Thus, to establish the same population in the next generation, the **roulette wheel** would be **spun six times**.
- Once a pair of parent chromosomes is selected, the crossover operator is applied.

- First, the crossover operator randomly chooses a **crossover point** where two parent chromosomes "break", and then **exchanges the chromosome parts** after that point. As a result, two new offspring are created.
- If a pair of chromosomes does not crossover, then the chromosome **cloning** takes place, and the offspring are created as **exact copies** of each parent.

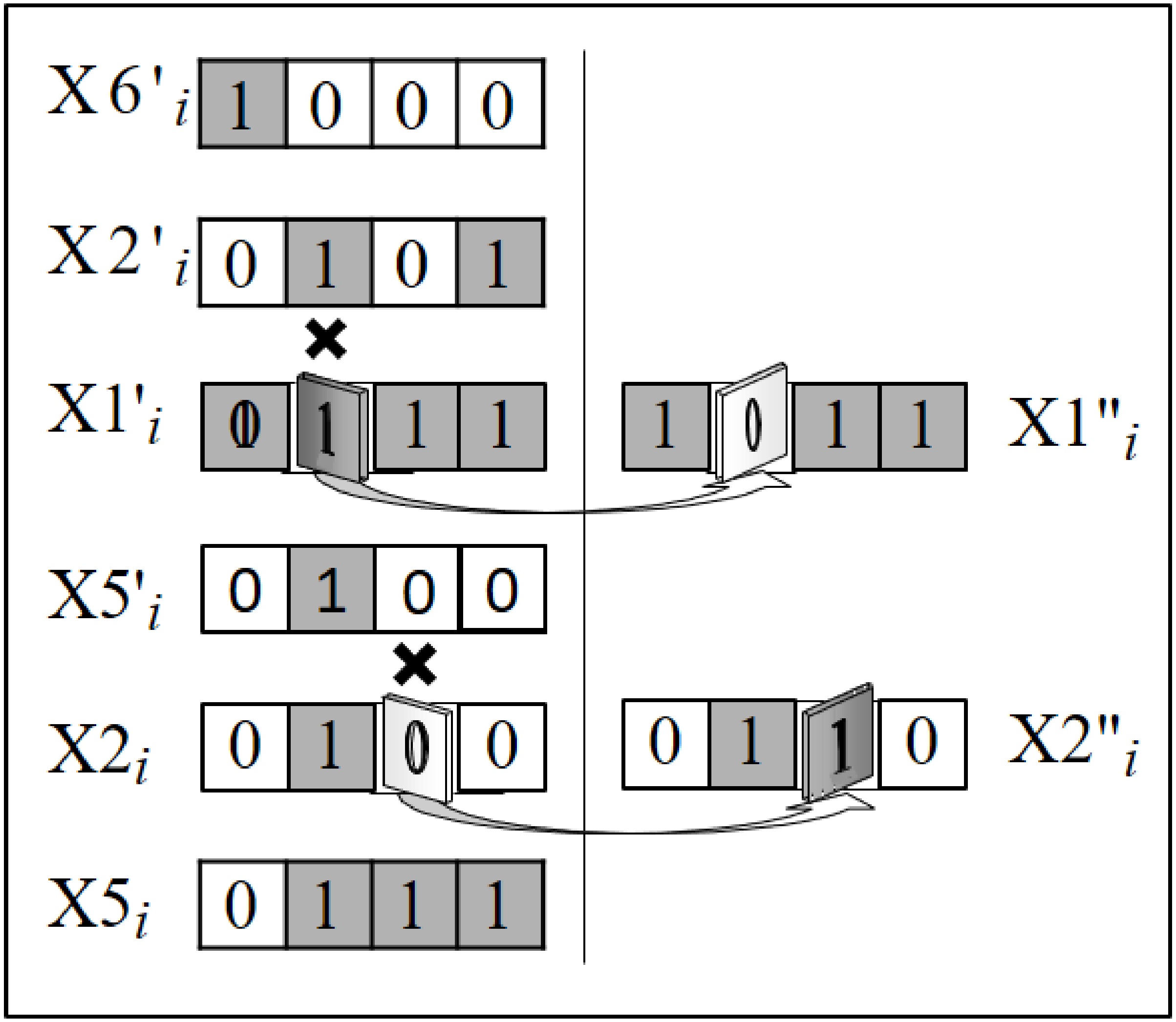
Crossover



Mutation operator

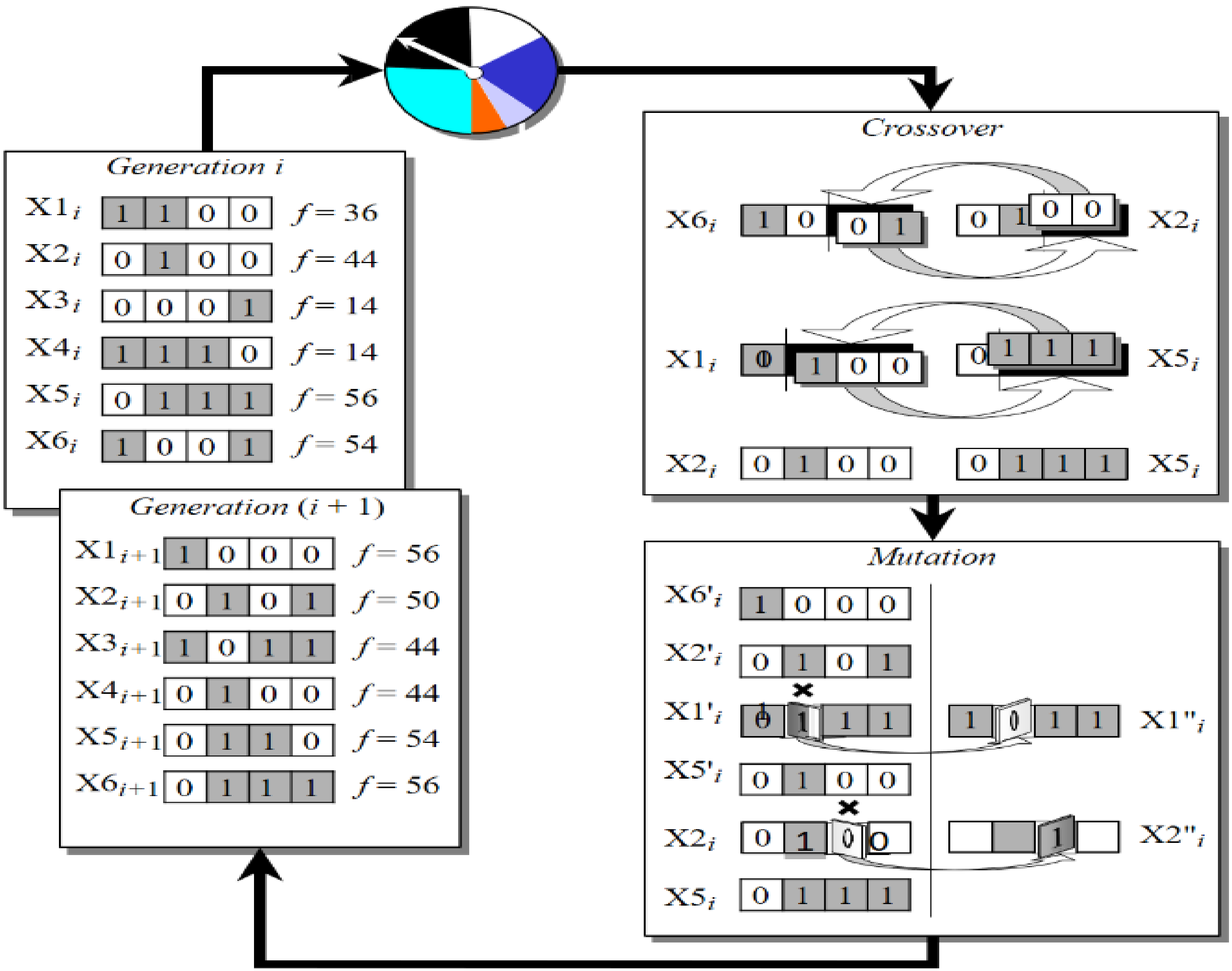
- Mutation represents **a change in the gene**.
- Mutation is a background operator. Its role is to provide a guarantee that the search algorithm is **not trapped on a local optimum**.
- The mutation operator **flips a randomly selected gene** in a chromosome.
- The **mutation probability** is quite small in nature, and is kept low for GAs, typically in the range between 0.001 and 0.01.

Mutation



X6'i
1 0 0 0
X2'i
0 1 0 1
X1'i
0 1 1 1
1 0 1 1
X1"i
X5'i
0 1 0 0
X2i
0 1 0 0
0 1 1 0
X2"i
X5i
0 1 1 1

The genetic algorithm cycle



Genetic algorithms: case study

$$f(x, y) = (1 - x)^2 e^{-x^2-(y+1)^2} - (x - x^3 - y^3)e^{-x^2-y^2}$$

- where parameters ***x*** **and** ***y*** **vary between –3 and 3**.
- The first step is to represent the problem variables as a chromosome – parameters *x* and *y* as a concatenated binary string:

$$\underbrace{\boxed{1}\boxed{0}\boxed{0}\boxed{0}\boxed{1}\boxed{0}\boxed{1}\boxed{0}}_{x}\underbrace{\boxed{0}\boxed{0}\boxed{1}\boxed{1}\boxed{1}\boxed{0}\boxed{1}\boxed{1}}_{y}$$

- We also choose the size of the chromosome population, for instance 6, and randomly generate an initial population.
- The next step is to calculate the fitness of each chromosome. This is done in two stages.
- First, a chromosome, that is a string of 16 bits, is partitioned into two 8-bit strings:

1	0	0	0	1	0	1	0

0	0	1	1	1	0	1	1

- Then these strings are converted from binary (base 2) to decimal (base 10):

$(10001010)2=1\times2^7+0\times2^6+0\times2^5+0\times2^4+1\times2^3+0\times2^2+1\times2^1+0\times2^0 = (138)_{10}$

and

$(00111011)2=0\times2^7+0\times2^6+1\times2^5+1\times2^4+1\times2^3+0\times2^2+1\times2^1+1\times2^0 = (59)_{10}$

- Now the range of integers that can be handled by 8-bits, that is the range from 0 to ($2^8 - 1$), is mapped to the actual range of parameters *x* and *y*, that is the range from –3 to 3:

$$\frac{6}{256 - 1} = 0.0235294$$

- To obtain the actual values of *x* and *y*, we multiply their decimal values by 0.0235294 and subtract 3 from the results:

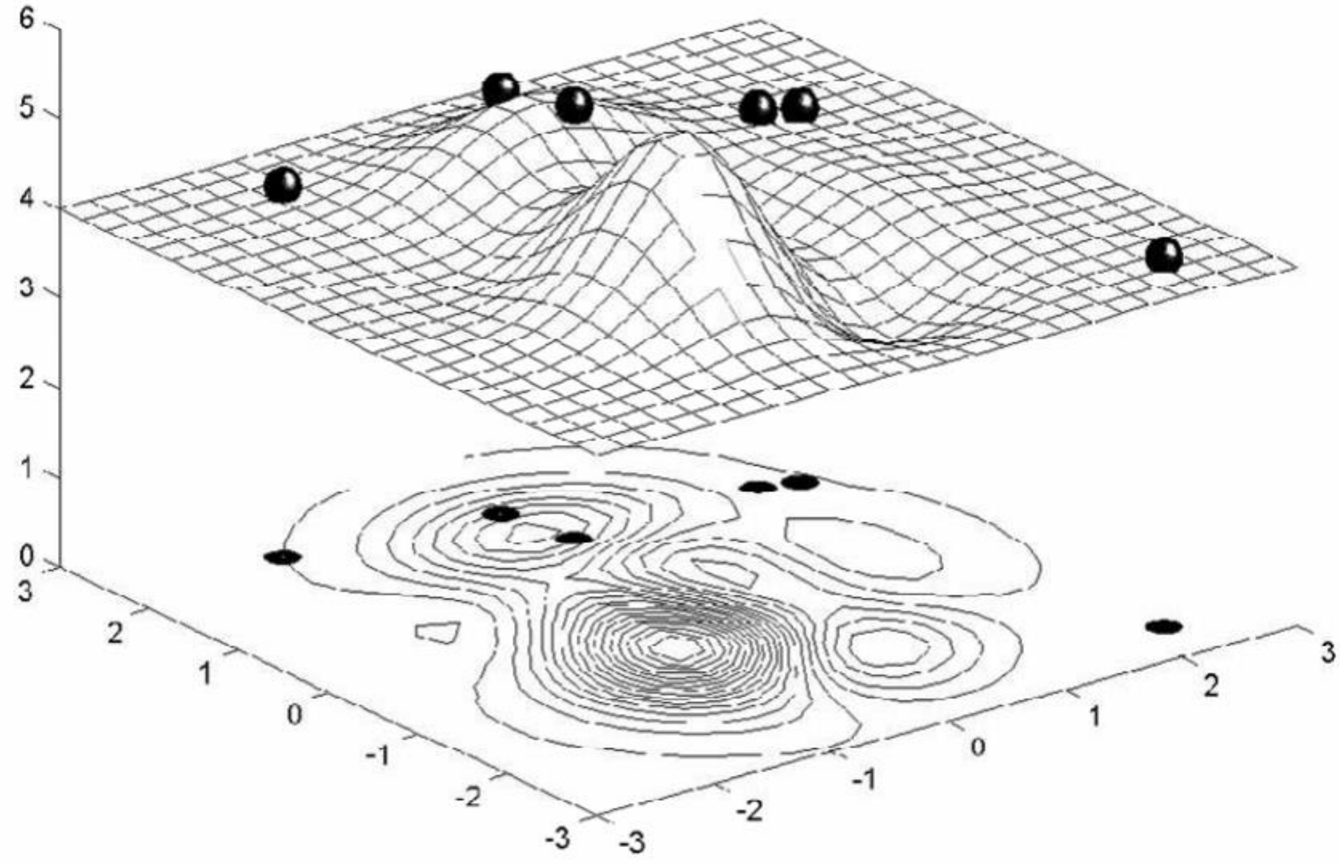
$$x = (138)_{10} \times 0.0235294 - 3 = 0.2470588$$

and

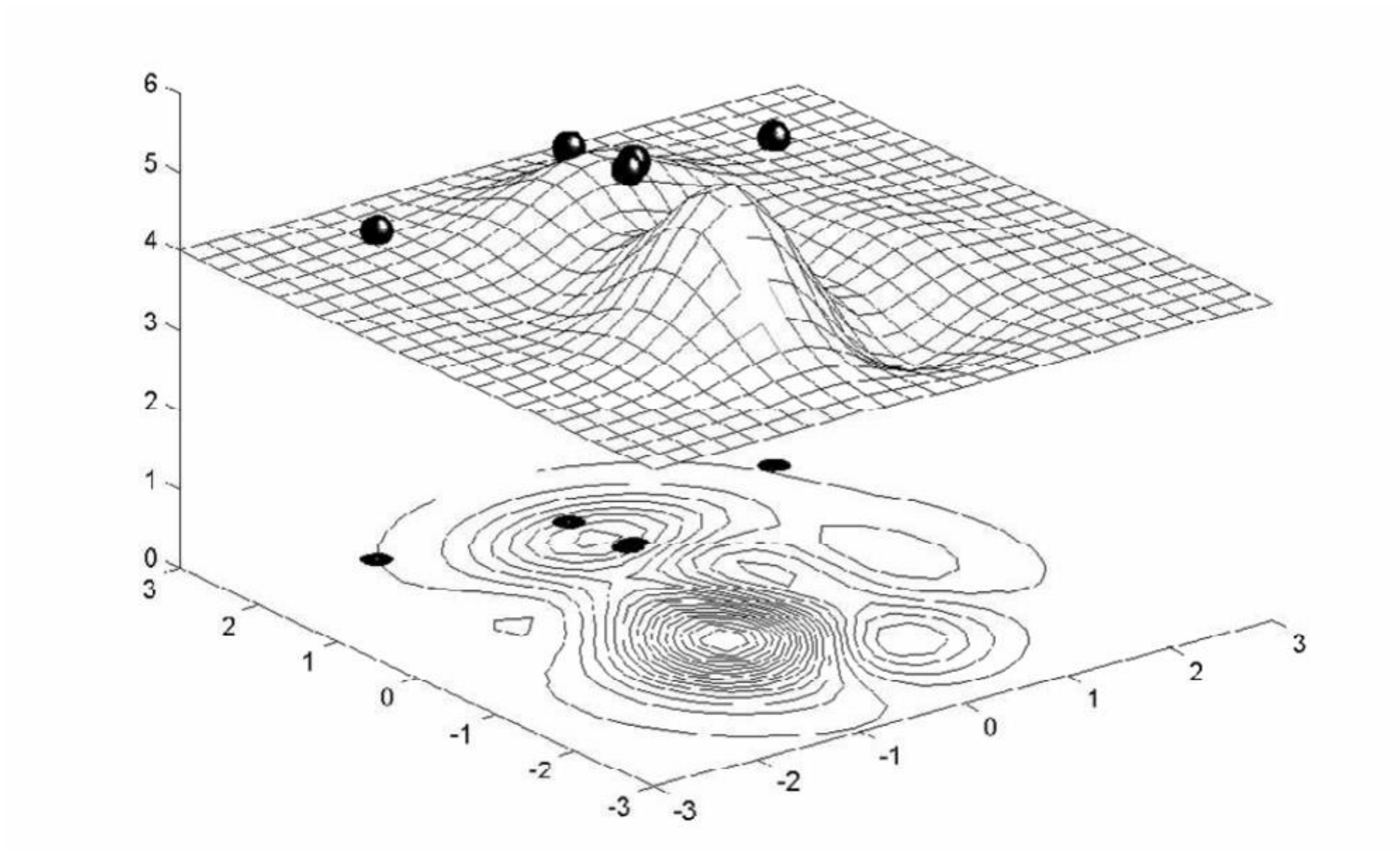
$$y = (59)_{10} \times 0.0235294 - 3 = -1.6117647$$

- Using decoded values of *x* and *y* as inputs in the mathematical function, the GA calculates the fitness of each chromosome.
- To find the maximum of the "peak" function, we will use crossover with the probability equal to 0.7 and mutation with the probability equal to 0.001. As we mentioned earlier, a common practice in GAs is to specify the number of generations. Suppose the desired number of generations is 100. That is, the GA will create 100 generations of 6 chromosomes before stopping.

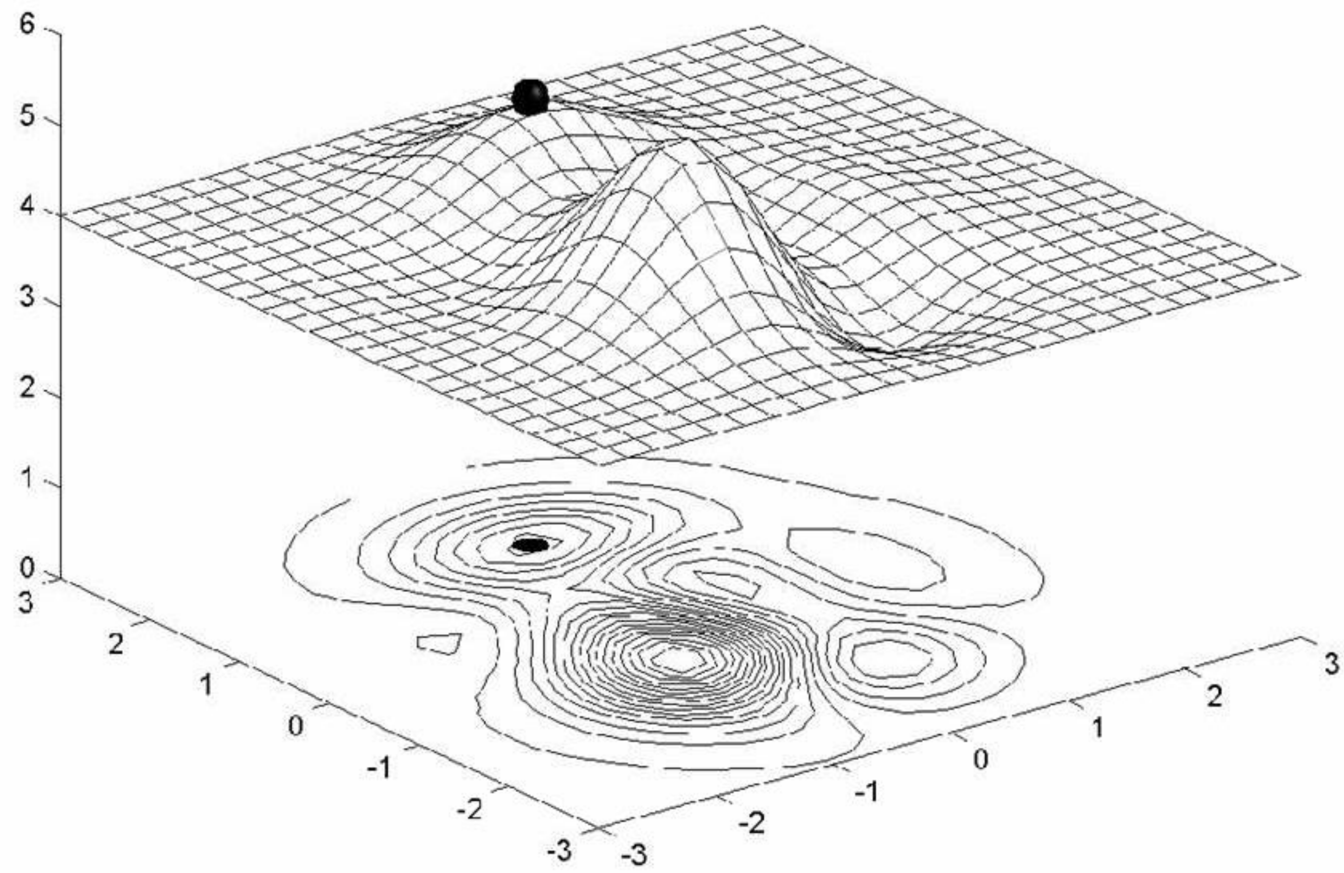
Chromosome locations on the surface of the "peak" function: initial population



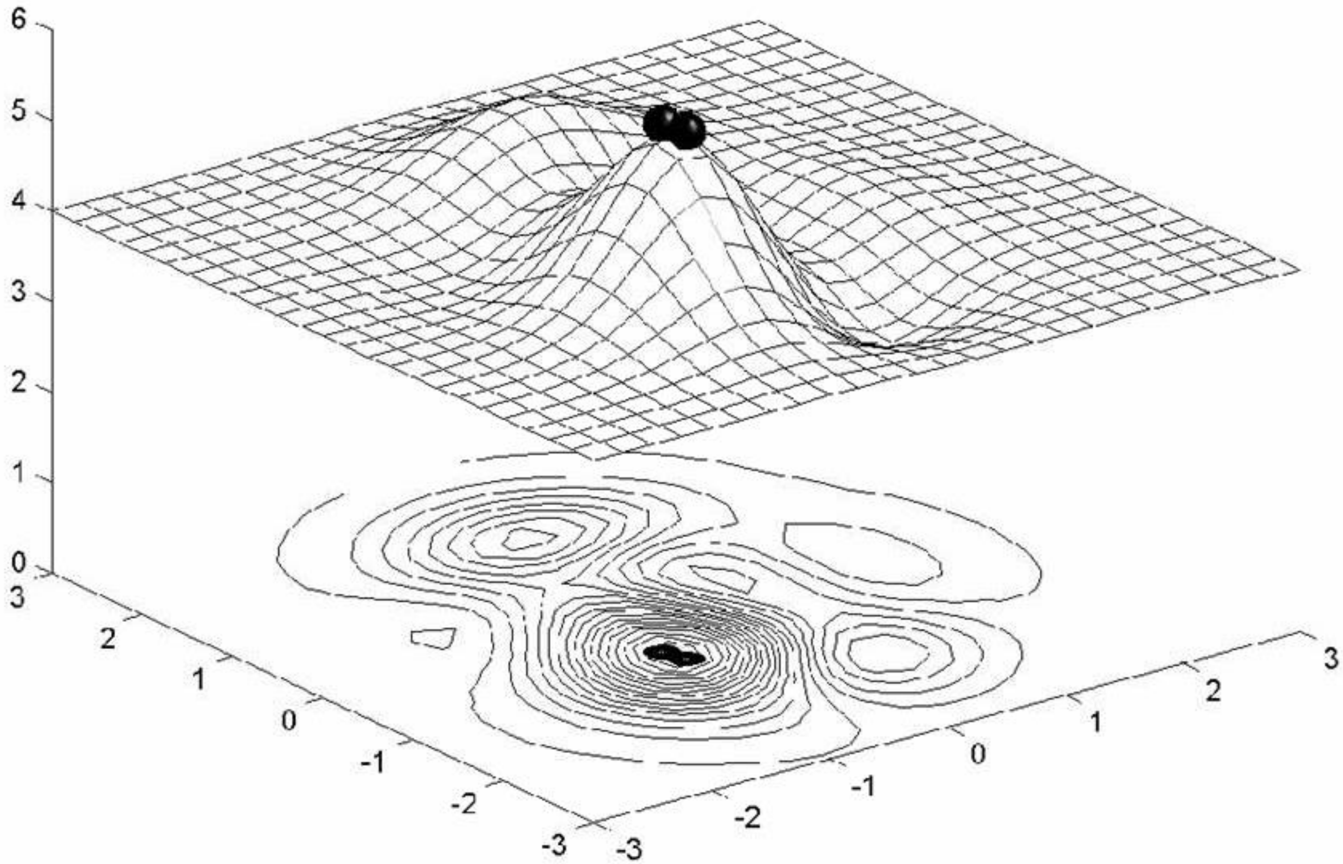
Chromosome locations on the surface of the "peak" function: first generation



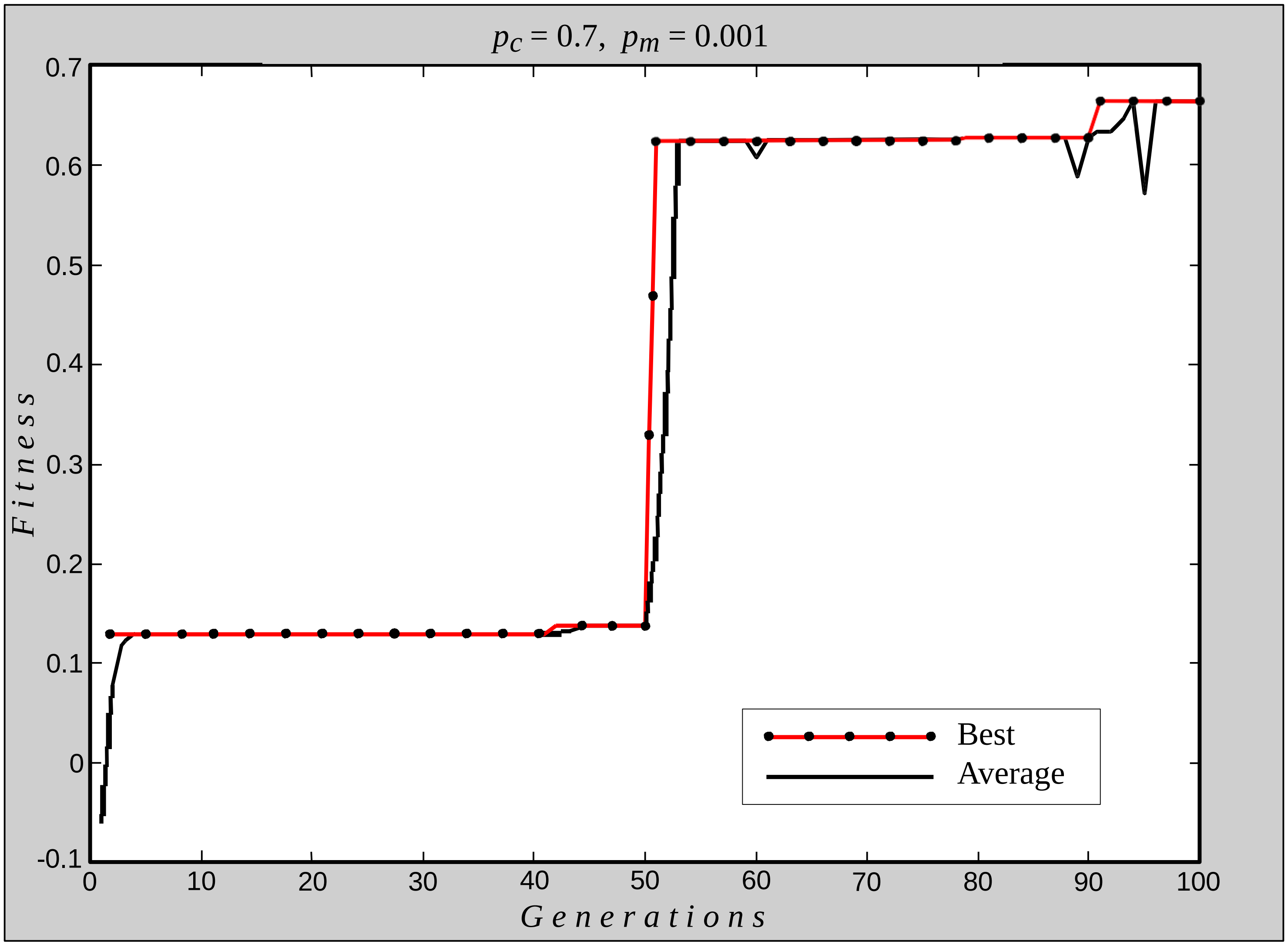
Chromosome locations on the surface of the "peak" function: local maximum



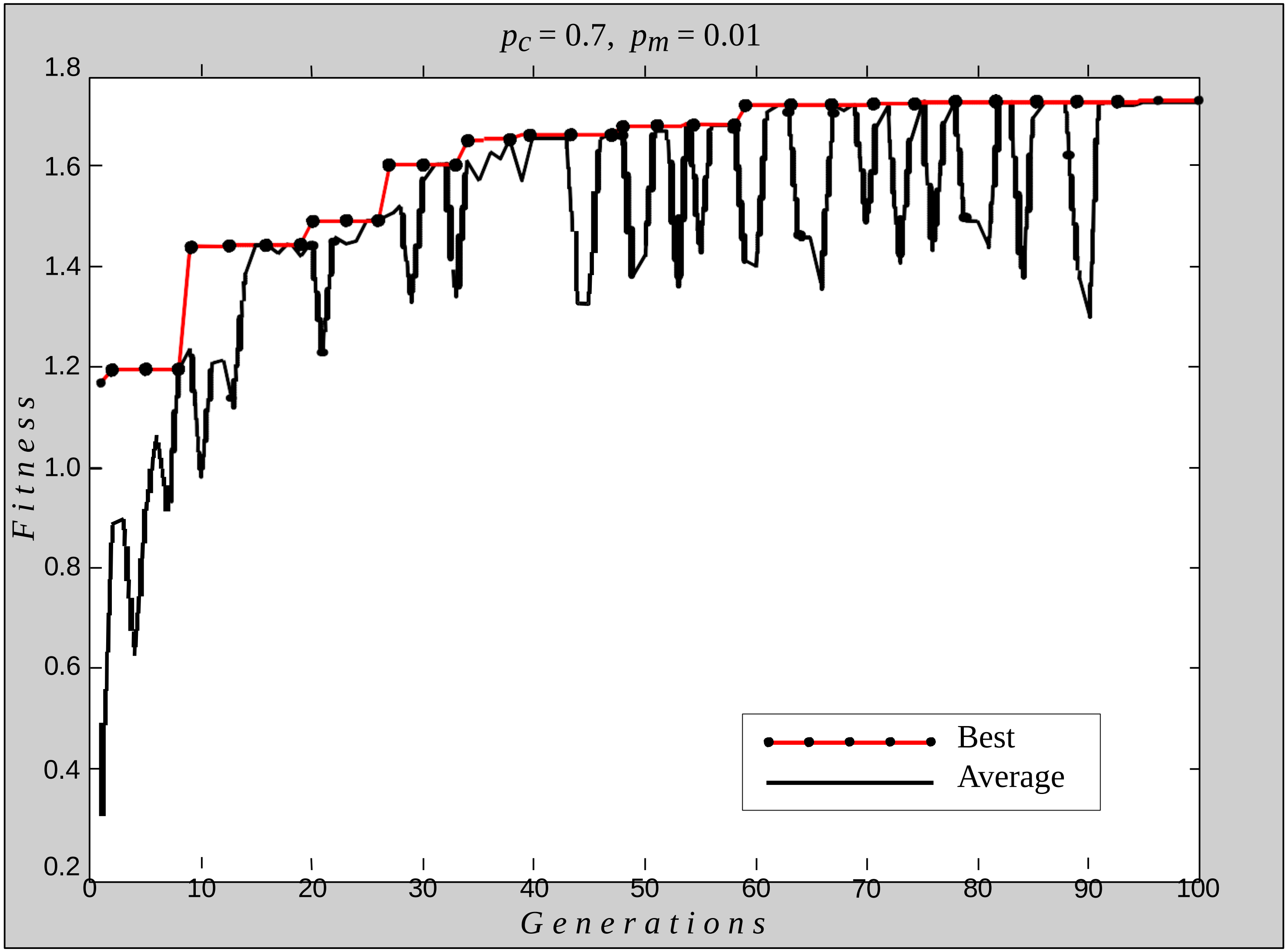
Chromosome locations on the surface of the "peak" function: global maximum



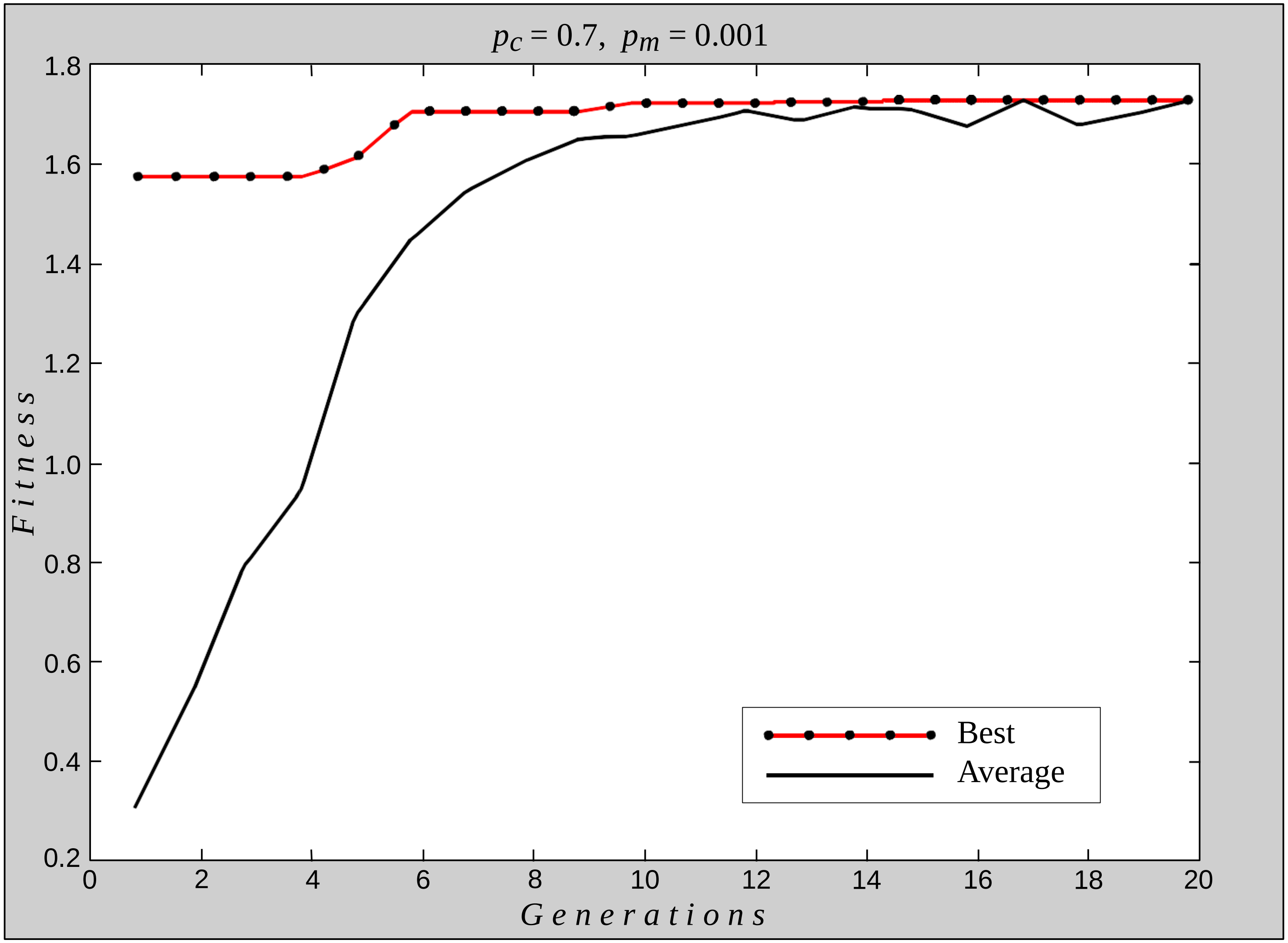
Performance graphs for 100 generations of 6 chromosomes: local maximum



Performance graphs for 100 generations of 6 chromosomes: global maximum



Performance graphs for 20 generations of 60 chromosomes



Case study: maintenance scheduling

- Maintenance scheduling problems are usually solved using a combination of search techniques and heuristics.
- These problems are complex and difficult to solve.
- They are NP-complete and cannot be solved by combinatorial search techniques.
- Scheduling involves competition for limited resources, and is complicated by a great number of badly formalised constraints.

Steps in the GA development

1. Specify the problem, define constraints and optimum criteria;
2. Represent the problem domain as a chromosome;
3. Define a fitness function to evaluate the chromosome performance;
4. Construct the genetic operators;
5. Run the GA and tune its parameters.

Case study

Scheduling of 7 units in 4 equal intervals

The problem constraints:

- The maximum loads expected during four intervals are 80, 90, 65 and 70 MW;
- Maintenance of any unit starts at the beginning of an interval and finishes at the end of the same or adjacent interval. The maintenance cannot be aborted or finished earlier than scheduled;
- The net reserve of the power system must be greater or equal to zero at any interval.

The optimum criterion is the maximum of the net reserve at any maintenance period.

Case study
Unit data and maintenance requirements

Unit number	*Unit capacity, MW*	*Number of intervals required for unit maintenance*
1	20	2
2	15	2
3	35	1
4	40	1
5	15	1
6	15	1
7	10	1

Case study
Unit gene pools

Unit 1:	1 1 0 0	0 1 1 0	0 0 1 1	
Unit 2:	1 1 0 0	0 1 1 0	0 0 1 1	
Unit 3:	1 0 0 0	0 1 0 0	0 0 1 0	0 0 0 1
Unit 4:	1 0 0 0	0 1 0 0	0 0 1 0	0 0 0 1
Unit 5:	1 0 0 0	0 1 0 0	0 0 1 0	0 0 0 1
Unit 6:	1 0 0 0	0 1 0 0	0 0 1 0	0 0 0 1
Unit 7:	1 0 0 0	0 1 0 0	0 0 1 0	0 0 0 1

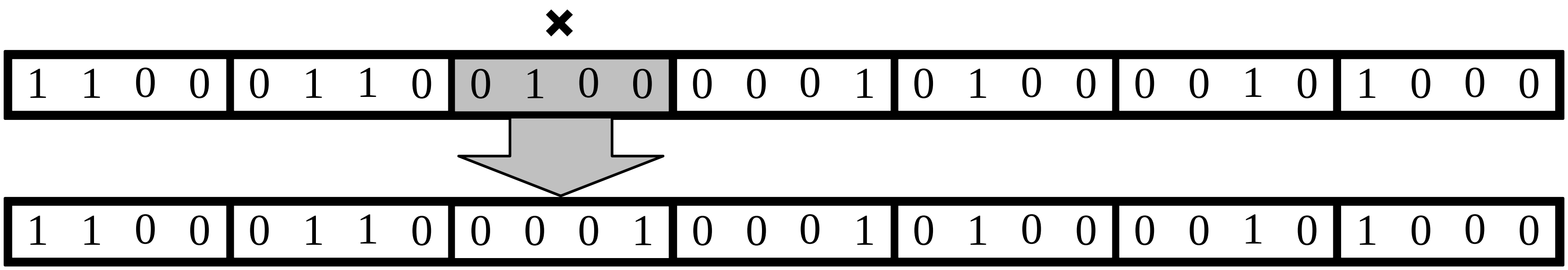
Chromosome for the scheduling problem

Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6	Unit 7
0 1 1 0	0 0 1 1	0 0 0 1	1 0 0 0	0 1 0 0	0 0 1 0	1 0 0 0

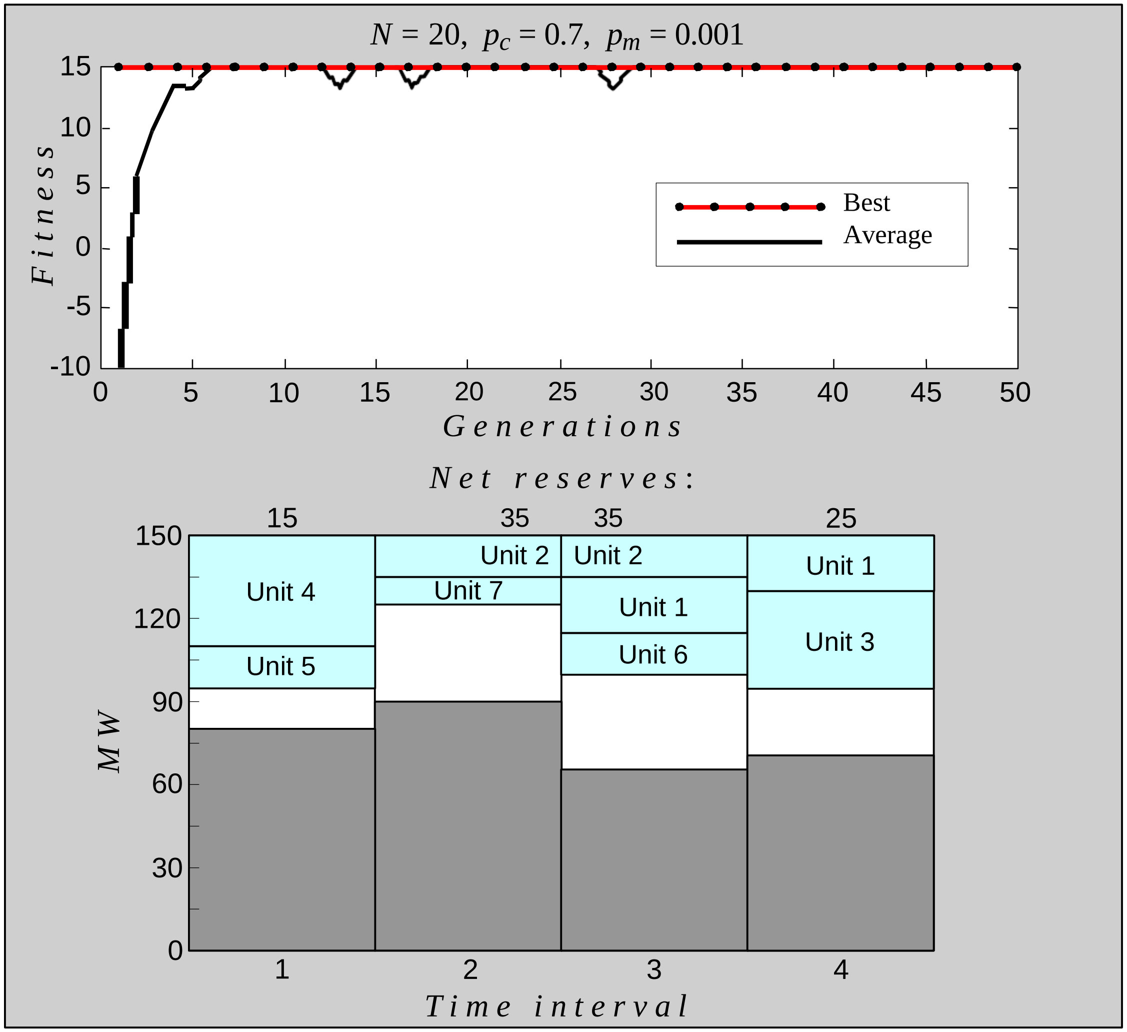
Case study
The crossover operator

Parent 1	0 1 1 0	0 0 1 1	0 0 0 1	1 0 0 0	0 1 0 0	0 0 1 0	1 0 0 0
Parent 2	1 1 0 0	0 1 1 0	0 1 0 0	0 0 0 1	0 0 1 0	1 0 0 0	0 1 0 0
Child 1	0 1 1 0	0 0 1 1	0 0 0 1	1 0 0 0	0 0 1 0	1 0 0 0	0 1 0 0
Child 2	1 1 0 0	0 1 1 0	0 1 0 0	0 0 0 1	0 1 0 0	0 0 1 0	1 0 0 0

Case study
The mutation operator



Performance graphs and the best maintenance schedules created in a population of 20 chromosomes



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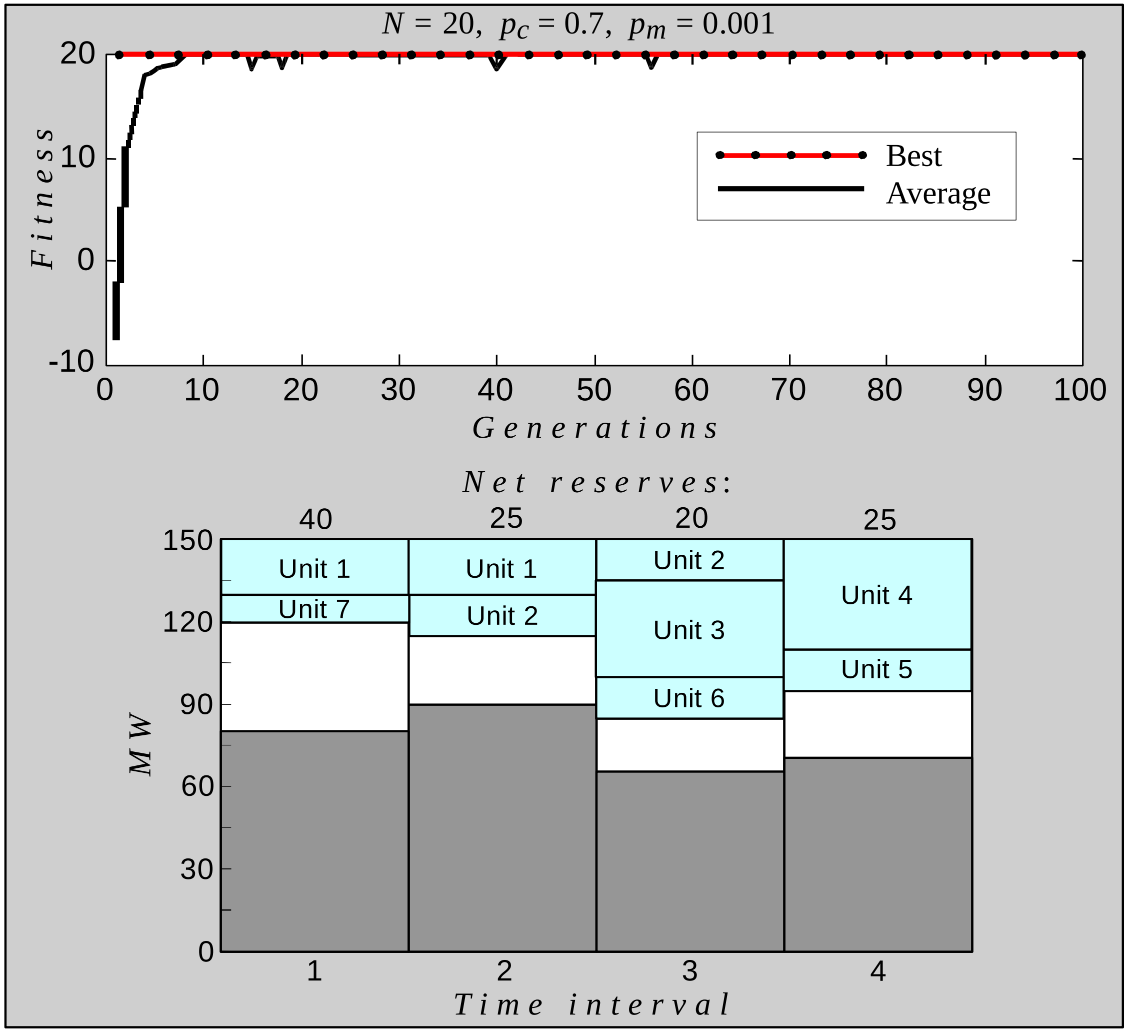
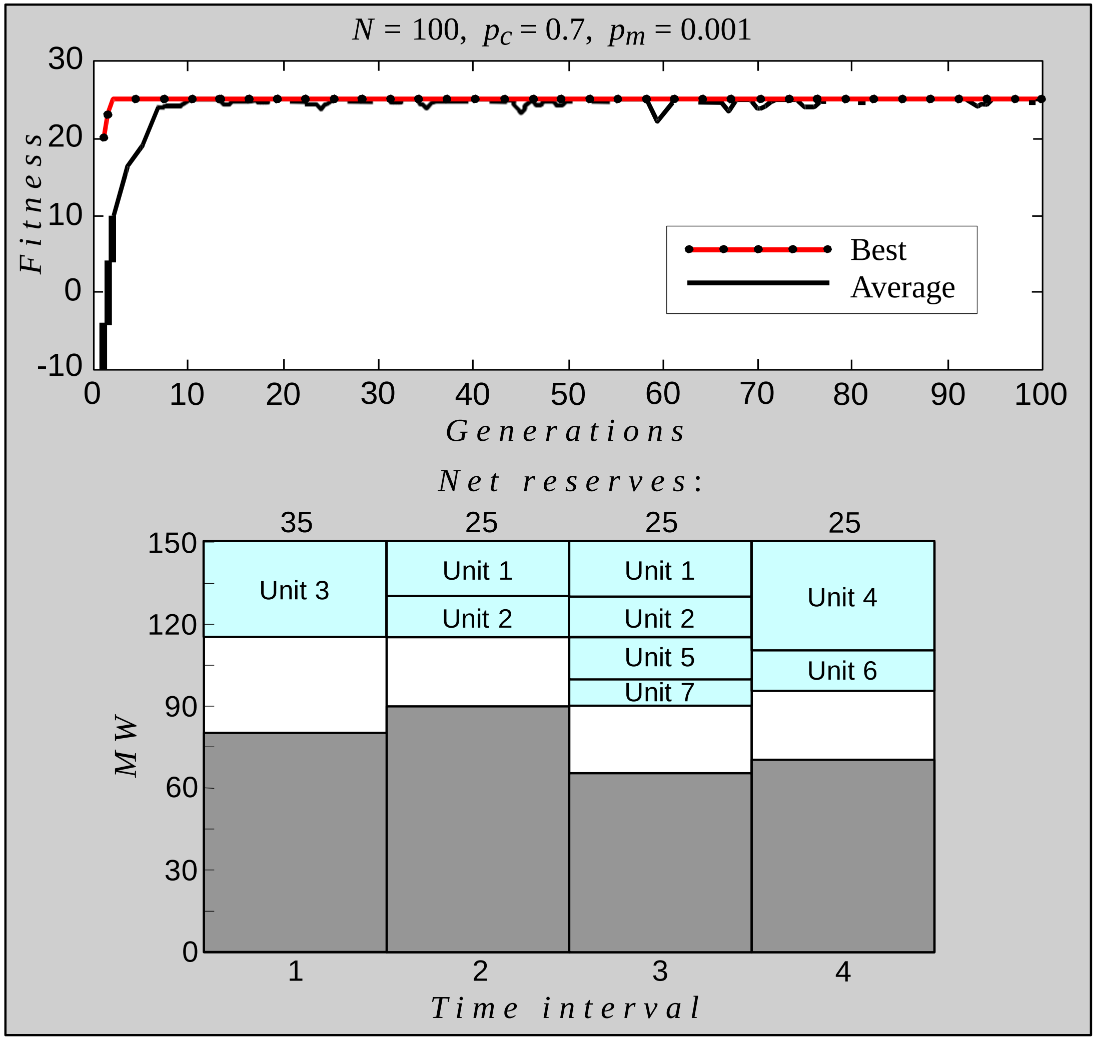


Performance graphs and the best maintenance schedules created in a population of 100 chromosomes



Performance graphs and the best maintenance schedules created in a population of 100 chromosomes