Artificial Intelligence

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Lecture 10
Genetic Algorithm

- Evolution
- Steps of Genetic Algorithm
- Roulette wheel selection
- Crossover operator
- Mutation operator
- GA case studies

Evolution

- On 1 July 1858, Charles Darwin presented his theory of evolution.
- **Evolution**: The process by which organisms change over time. Changes that allow an organism to better adapt to its environment will help it survive and have more offspring.
- Evolutionary **fitness** is a measure of the organism’s ability to anticipate changes in its environment.

Genetic Algorithm (GA)

- In the early 1970s, John Holland introduced the concept of genetic algorithms.

- Darwin's classical theory of evolution, together with Weismann's theory of natural selection and Mendel's concept of genetics, now represent the **neo-Darwinian** paradigm.

- Optimization iteratively improves the quality of solutions until an optimal, or at least feasible, solution is found.

- Genetic algorithm simulates natural evolution by creating a population of individuals, evaluating their fitness, generating a new population through genetic operations, and repeating this process a number of times.

- 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

- The GA measures the **fitness** of individual chromosomes.
- As reproduction takes place, the **crossover** operator exchanges parts of two single chromosomes, and the **mutation** operator changes the gene value in some randomly chosen location of the chromosome.

Steps of Genetic Algorithm

- **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. The fitness function establishes the basis for selecting chromosomes 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:

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

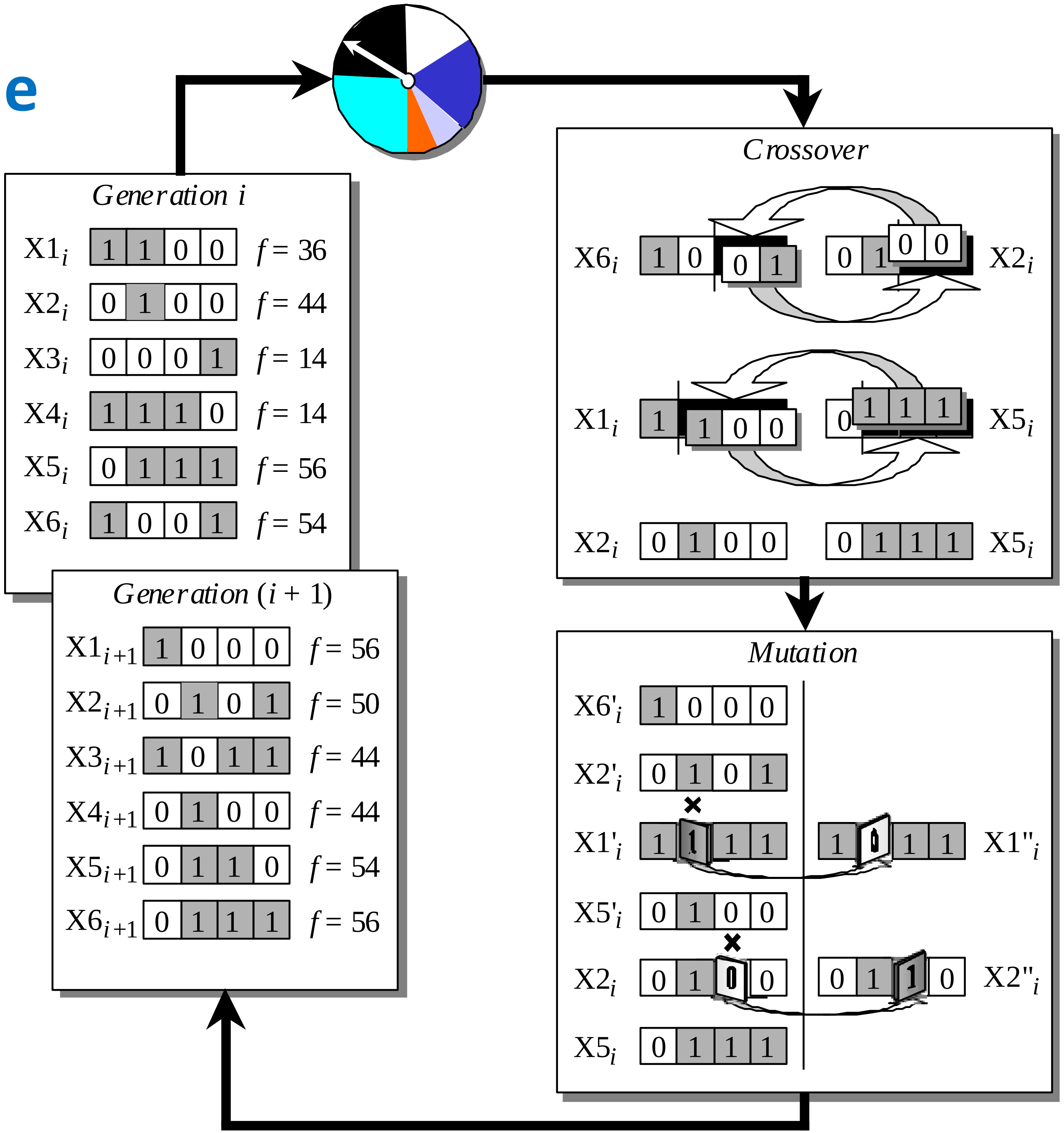
- **Step 5**: Select a pair of chromosomes for mating from the current population. Parent chromosomes are selected with a probability related to their fitness.
- **Step 6**: Create a pair of offspring chromosomes by applying the genetic operators - **crossover** and **mutation**.
- **Step 7**: Place 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.

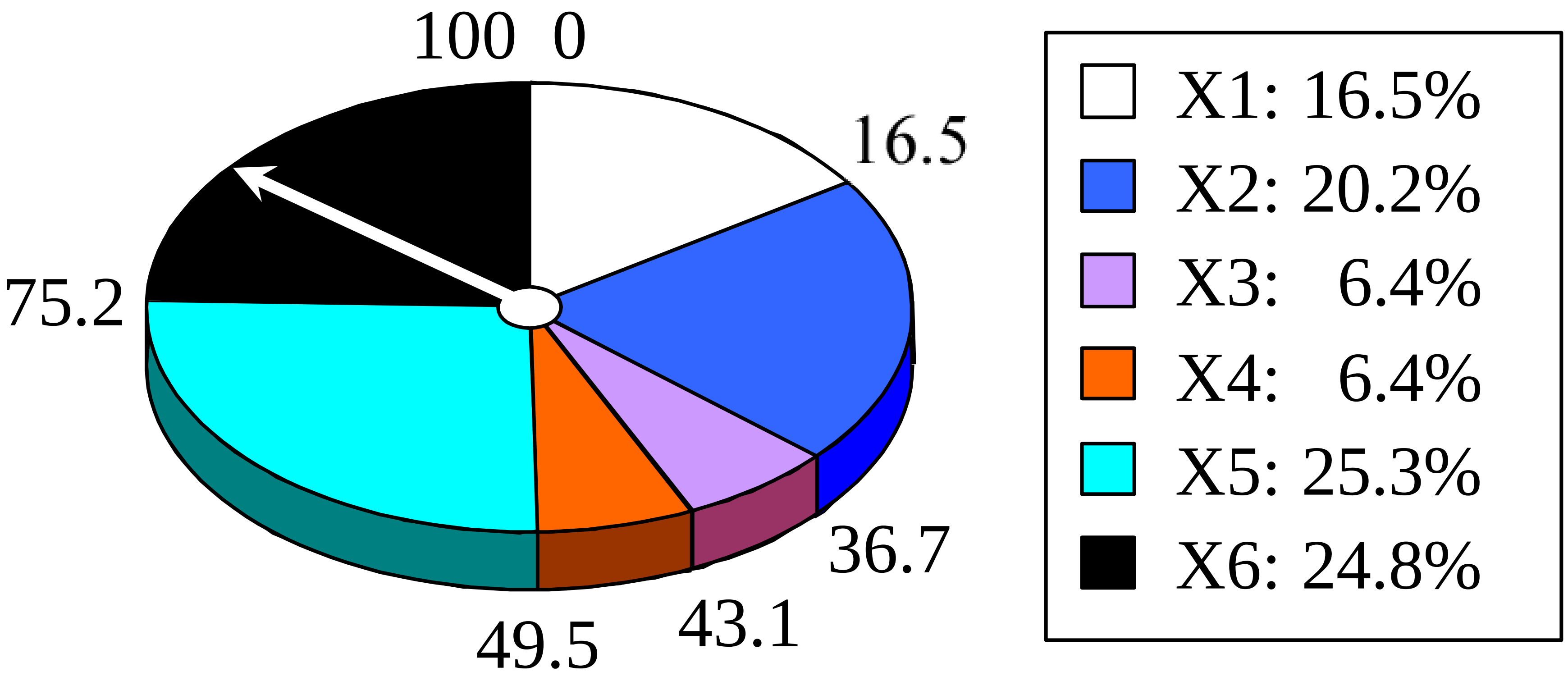
- ➢ GA represents an iterative process. Each iteration is called a generation. A typical number of generations for a simple GA can range from 50 to over 500. The entire set of generations is called a run.
- ➢ A common practice is to terminate a GA after a specified number of generations and then examine the best chromosomes in the population. If no satisfactory solution is found, the GA is restarted.

The genetic algorithm cycle



Roulette wheel selection

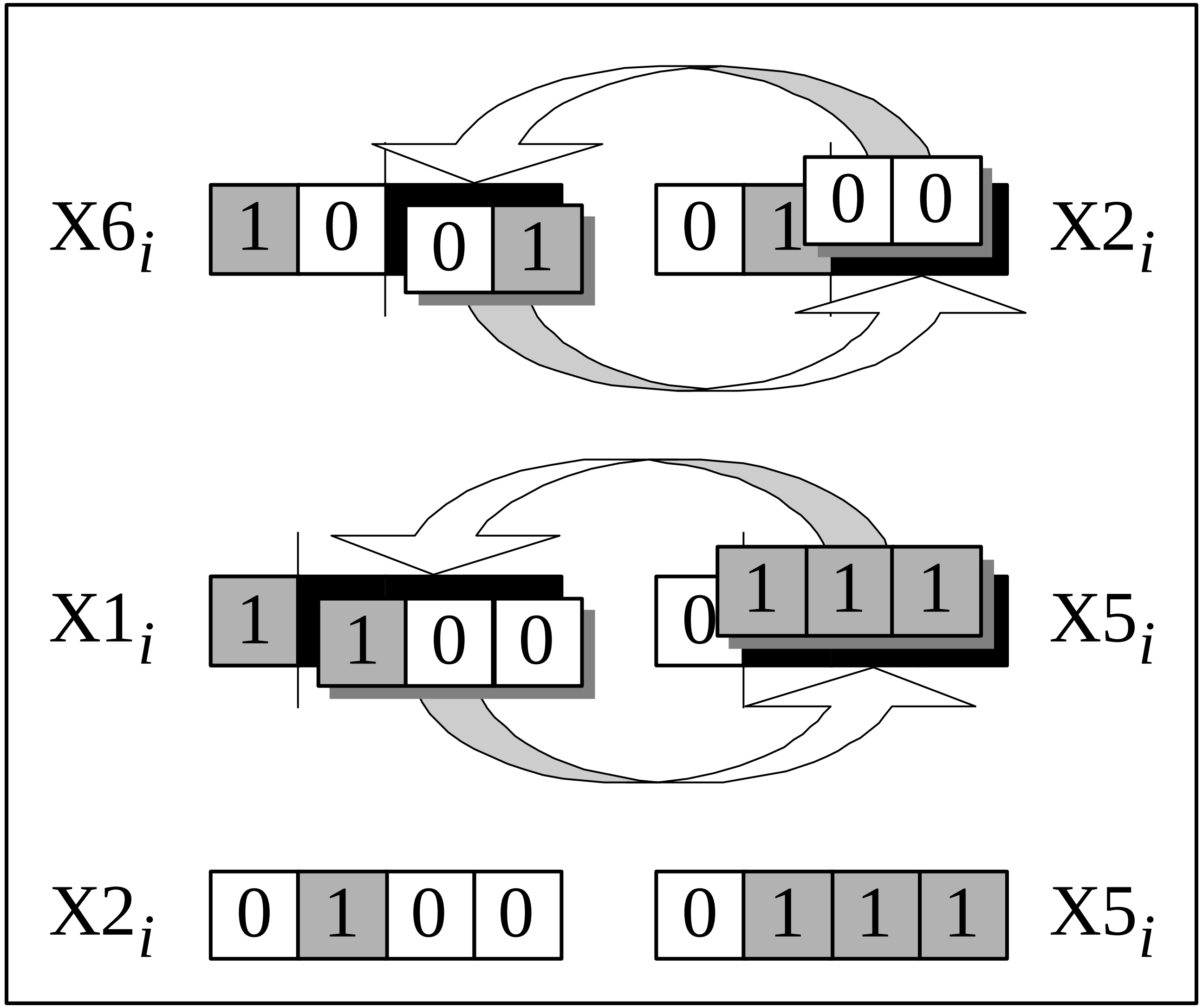
The most commonly used chromosome selection techniques is the roulette wheel selection.



Crossover operator

- 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 cross over, then the chromosome **cloning** takes place, and the offspring are created as exact copies of each parent.

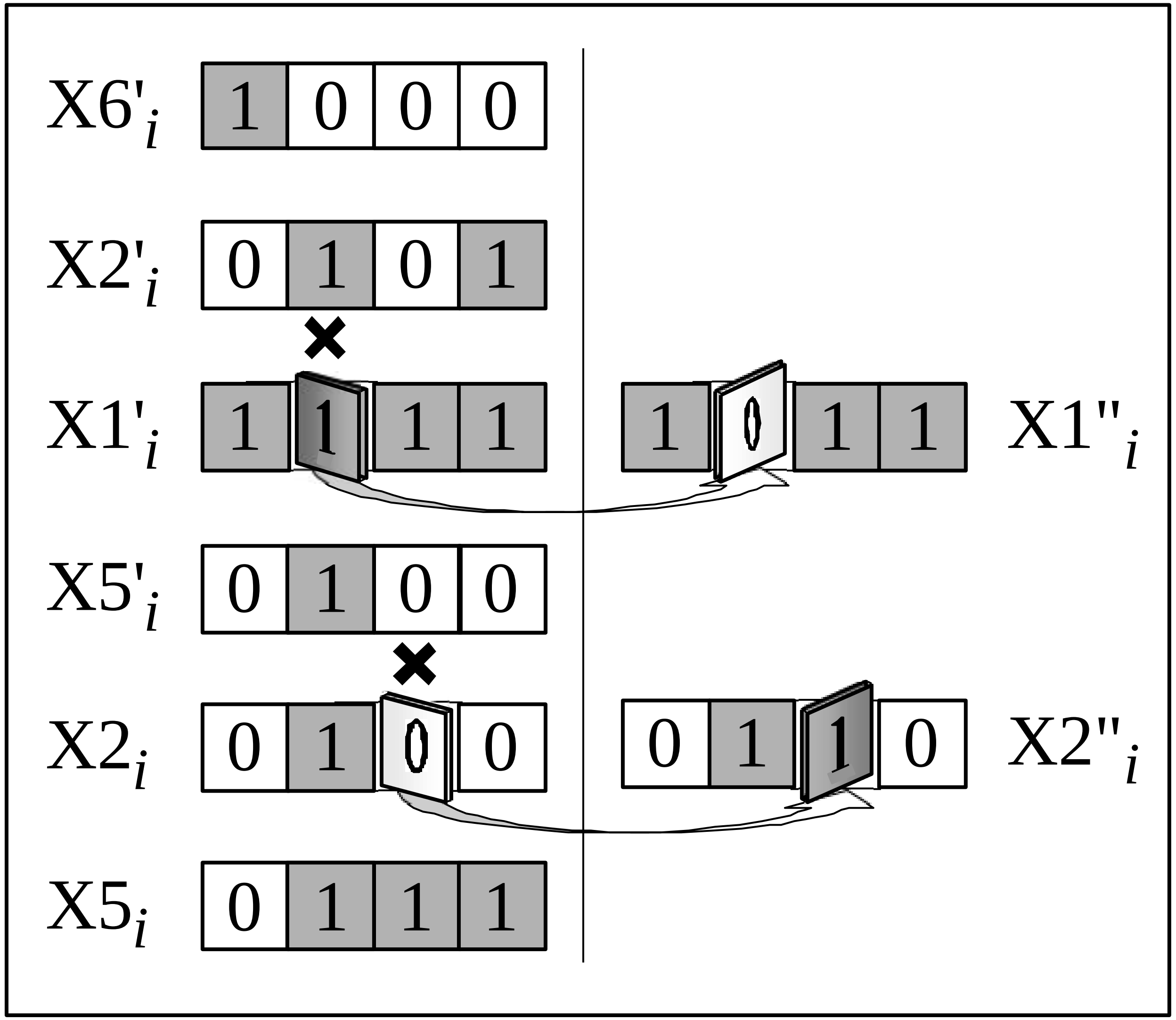
Crossover



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'$_i$
1 1 1 1
1 0 1 1
X1"$_i$
X5'$_i$
0 1 0 0
X2$_i$
0 1 0 0
0 1 1 0
X2"$_i$
X5$_i$
0 1 1 1

Genetic algorithms: case study

- 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

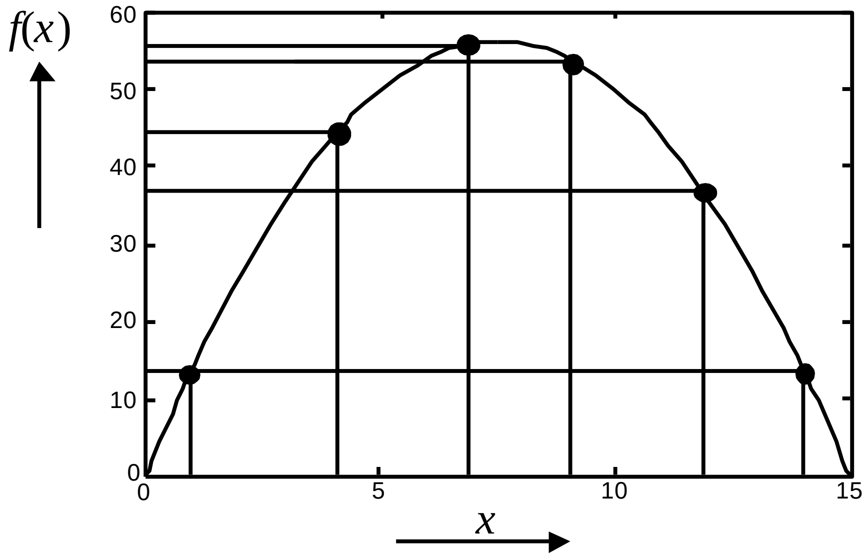
Suppose that :

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

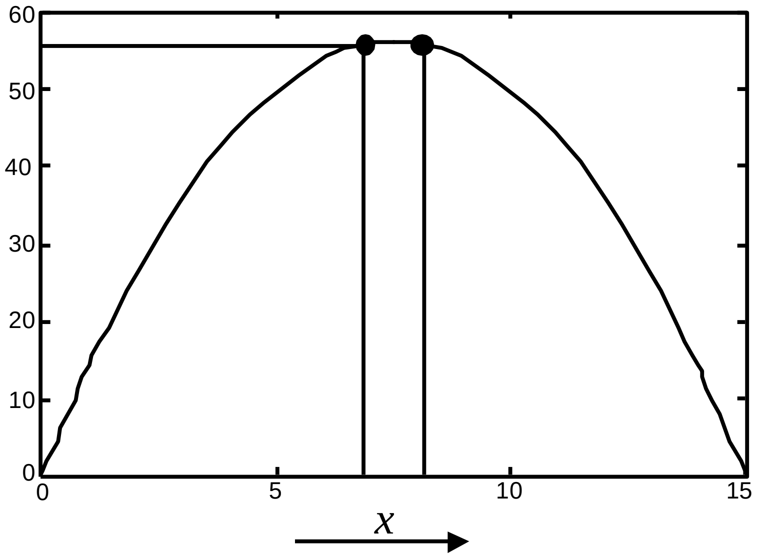
$$f(x) = 15x - x^2$$

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.

- The size of the GA's chromosome population, unlike nature, remains unchanged from one generation to the next.

- The last column in Table shows the ratio of the individual chromosome's fitness to the population's total fitness, **fitness ratio**. This ratio determines the chromosome's chance of being selected for mating. The chromosome's average fitness improves from one generation to the next.

- The algorithm repeats fitness calculation, chromosome selection, crossover, and mutation until the termination criterion is satisfied.

Genetic algorithms: another case study

- Suppose it is desired to find the maximum of the "peak" function of two variables:

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

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	and	0	0	1	1	1	0	1	1

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

$$(10001010)_2 = 1\times 2^7 + 0\times 2^6 + 0\times 2^5 + 0\times 2^4 + 1\times 2^3 + 0\times 2^2 + 1\times 2^1 + 0\times 2^0 = (138)_{10}$$

and

$$(00111011)_2 = 0\times 2^7 + 0\times 2^6 + 1\times 2^5 + 1\times 2^4 + 1\times 2^3 + 0\times 2^2 + 1\times 2^1 + 1\times 2^0 = (59)_{10}$$

- 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:

Real range

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

Chromosome range

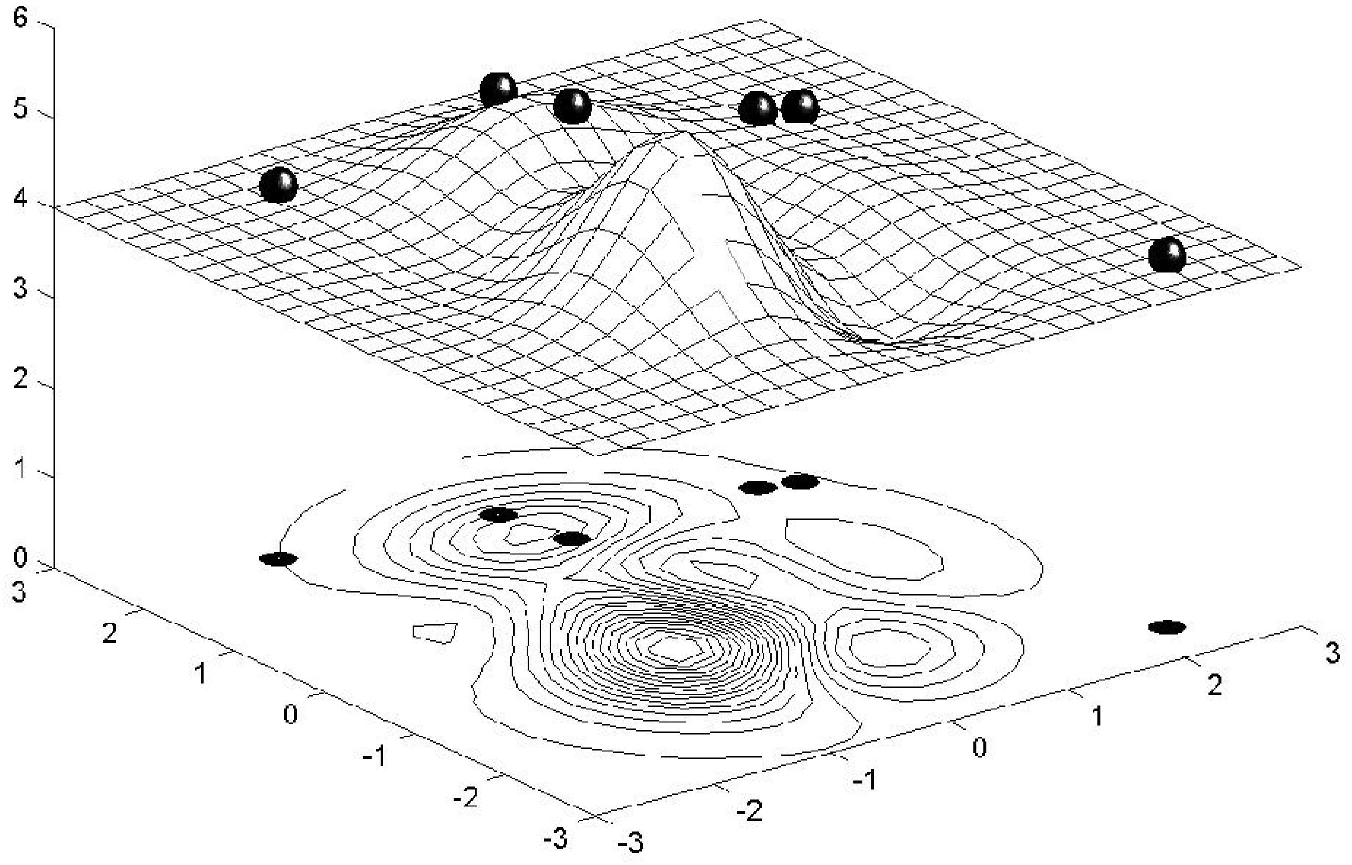
- To obtain the actual values of *x* and *y*, we multiply their decimal values by 0.0235294 and subtract 3 from the results:

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

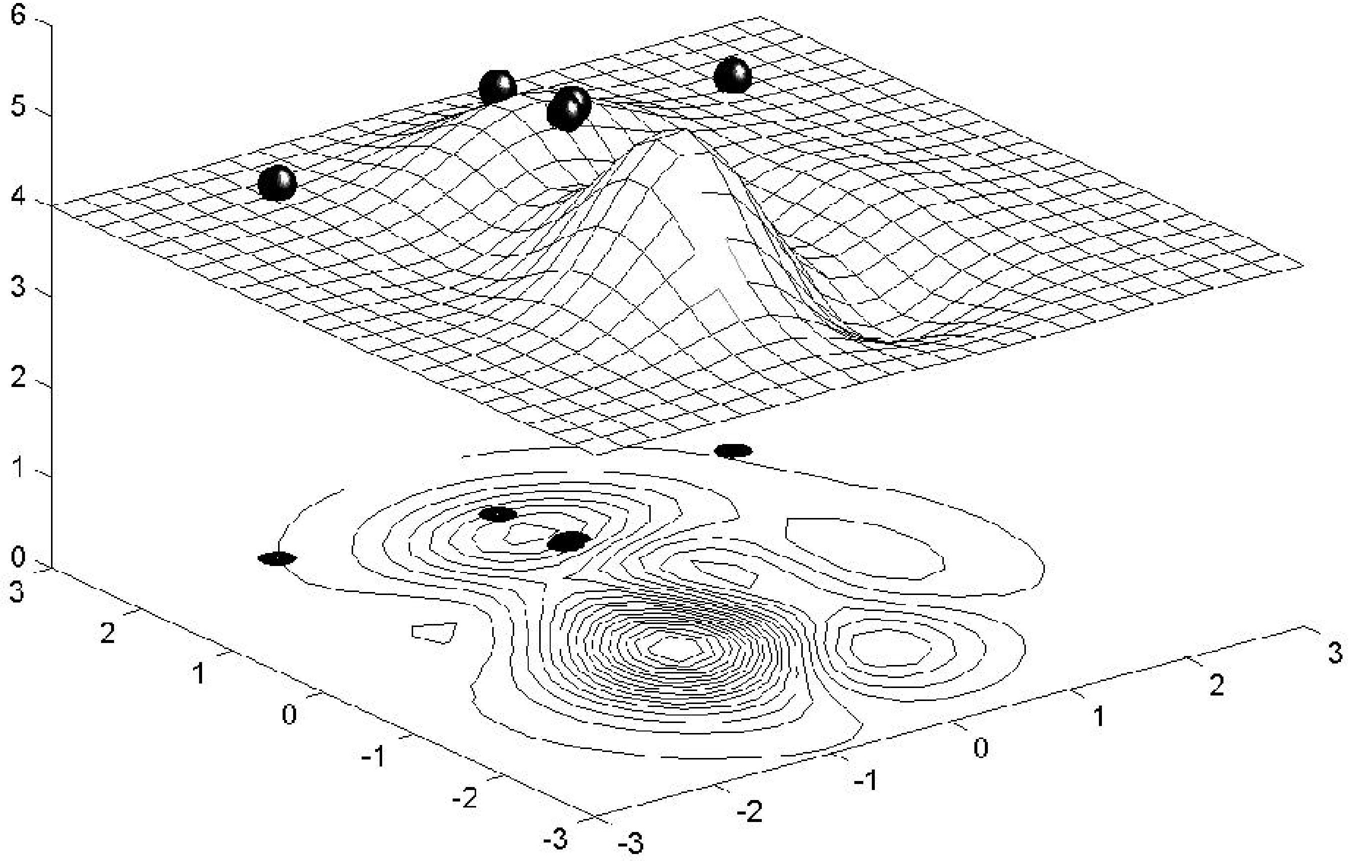
and

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

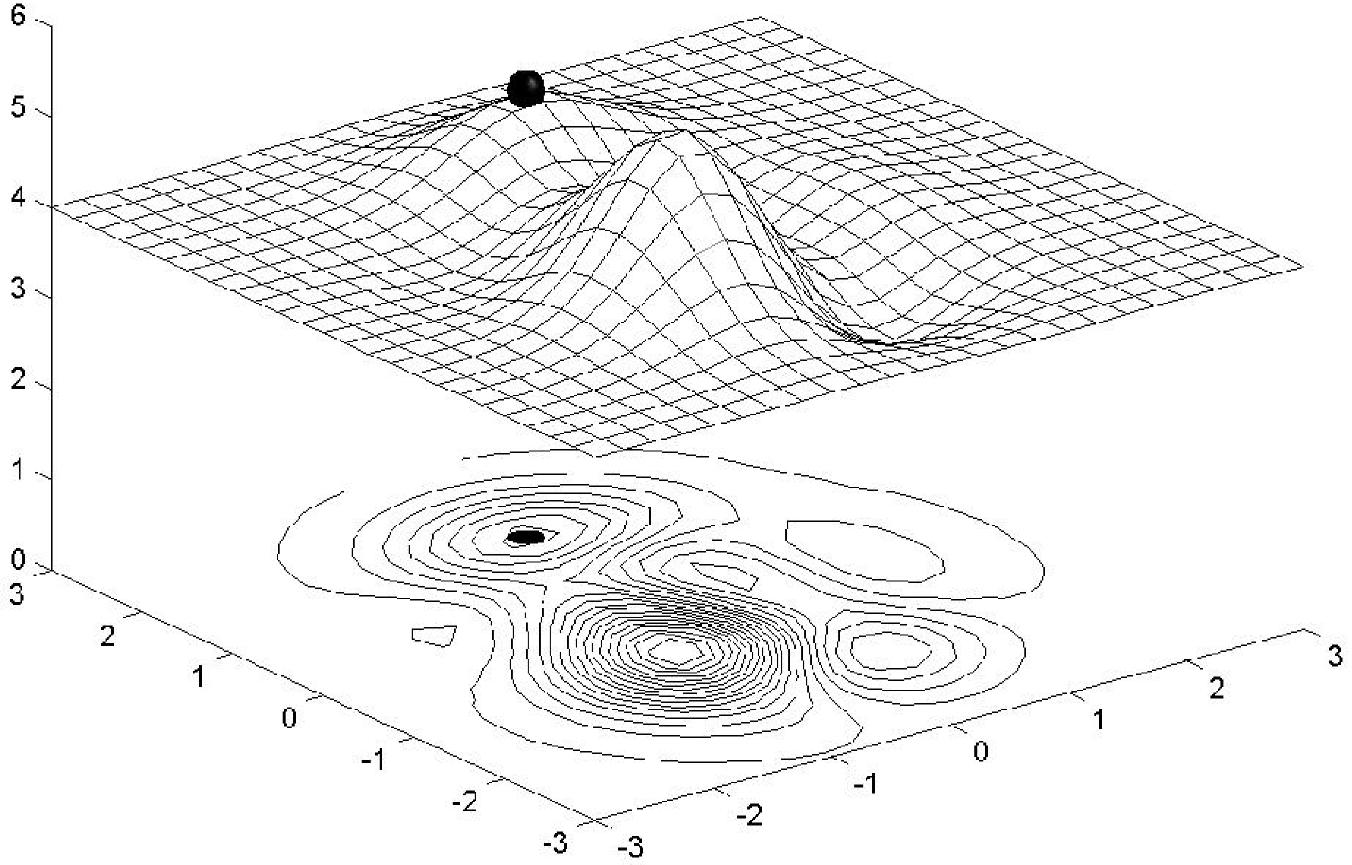
Chromosome locations on the surface of the "peak" function: initial population



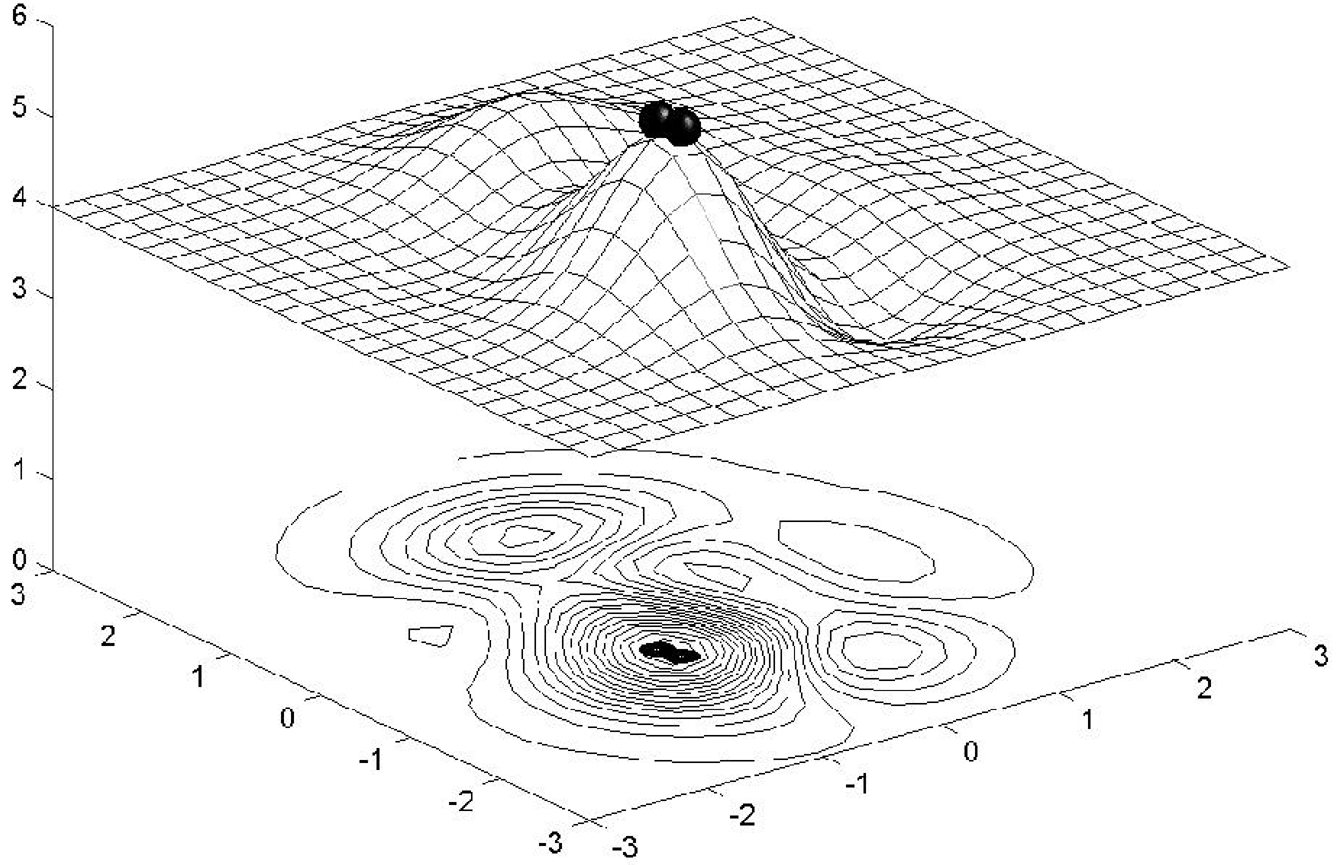
Chromosome locations on the surface of the "peak" function: initial population



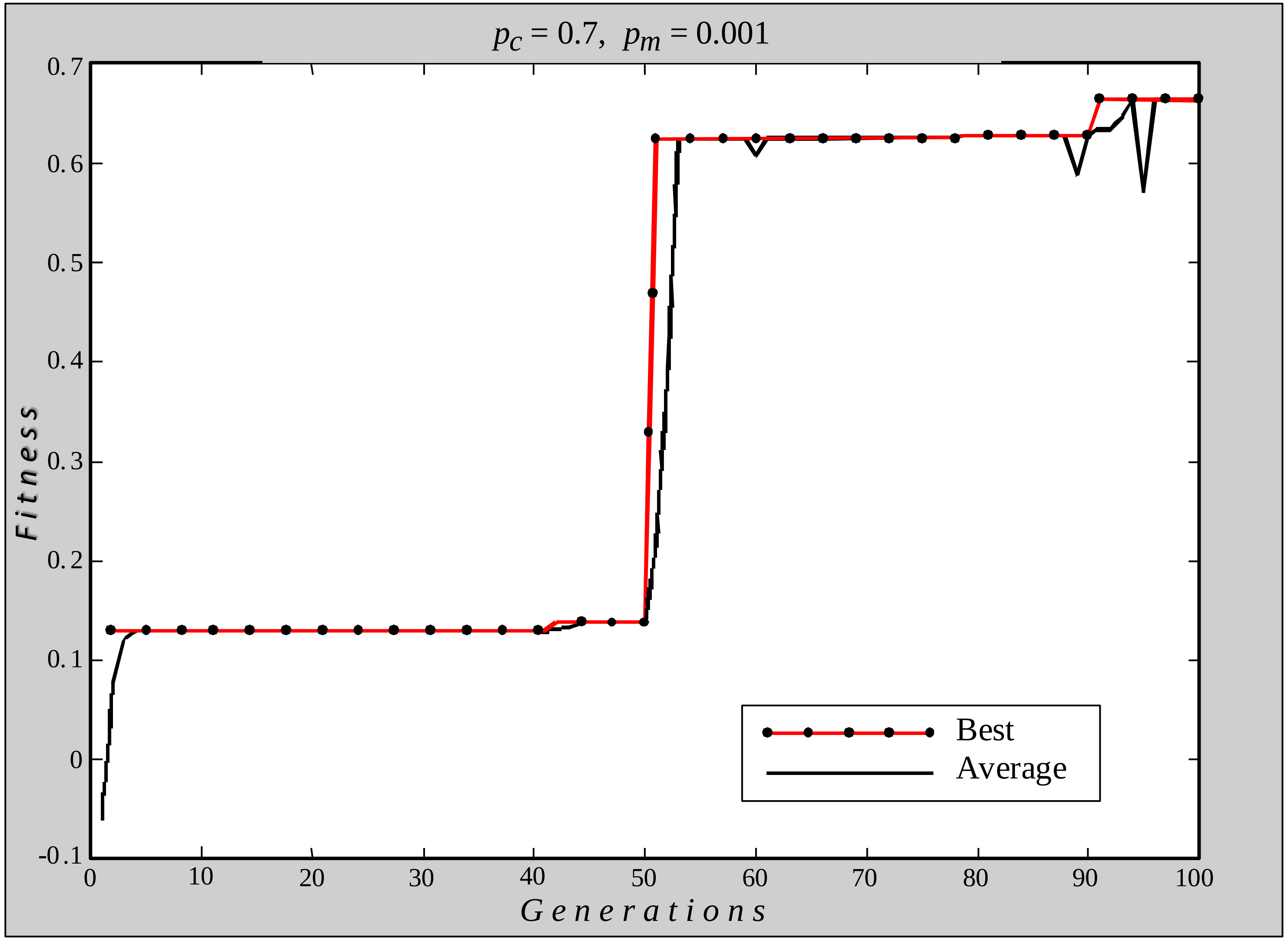
Chromosome locations on the surface of the "peak" function: initial population



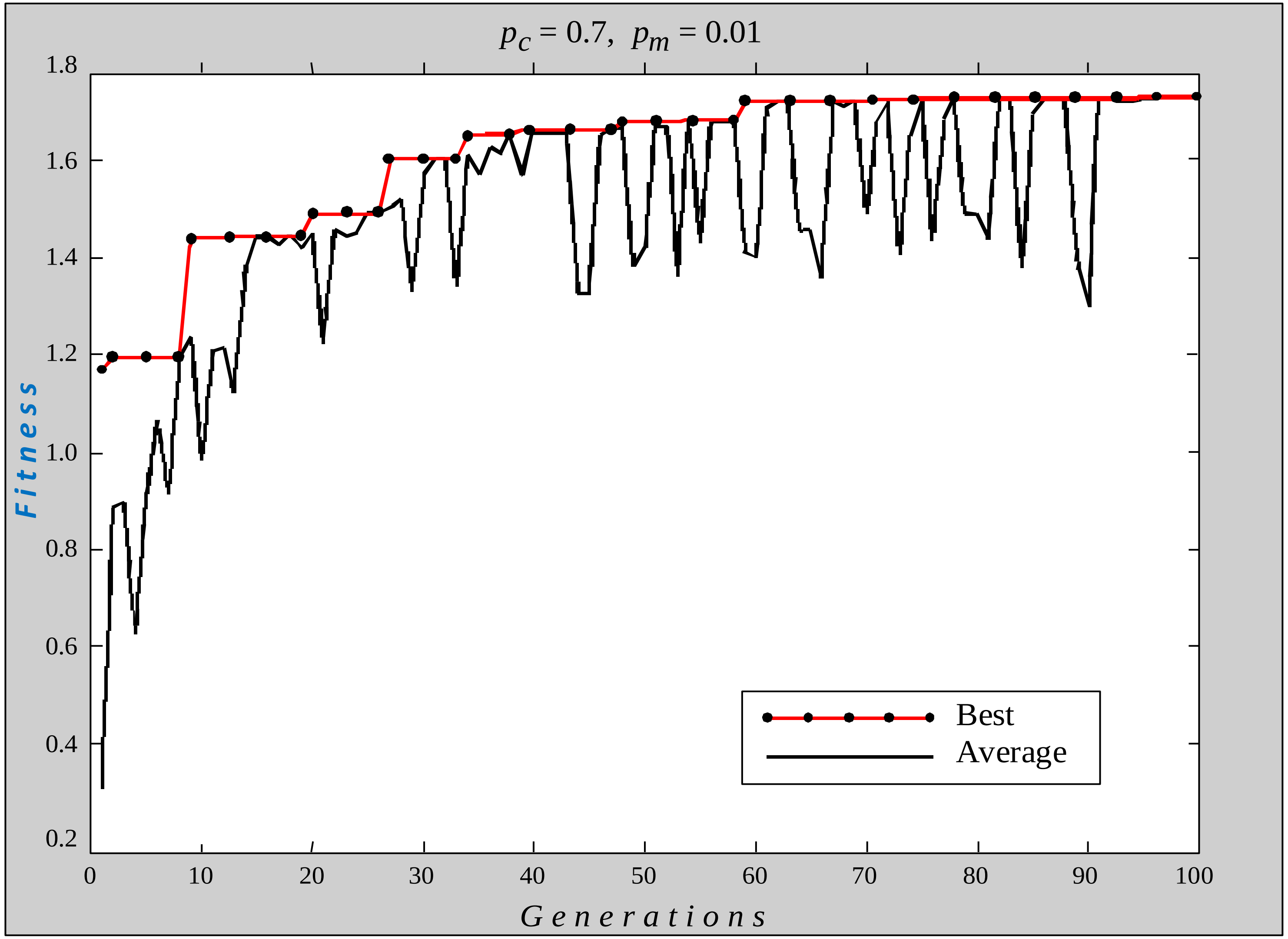
Chromosome locations on the surface of the "peak" function: initial population



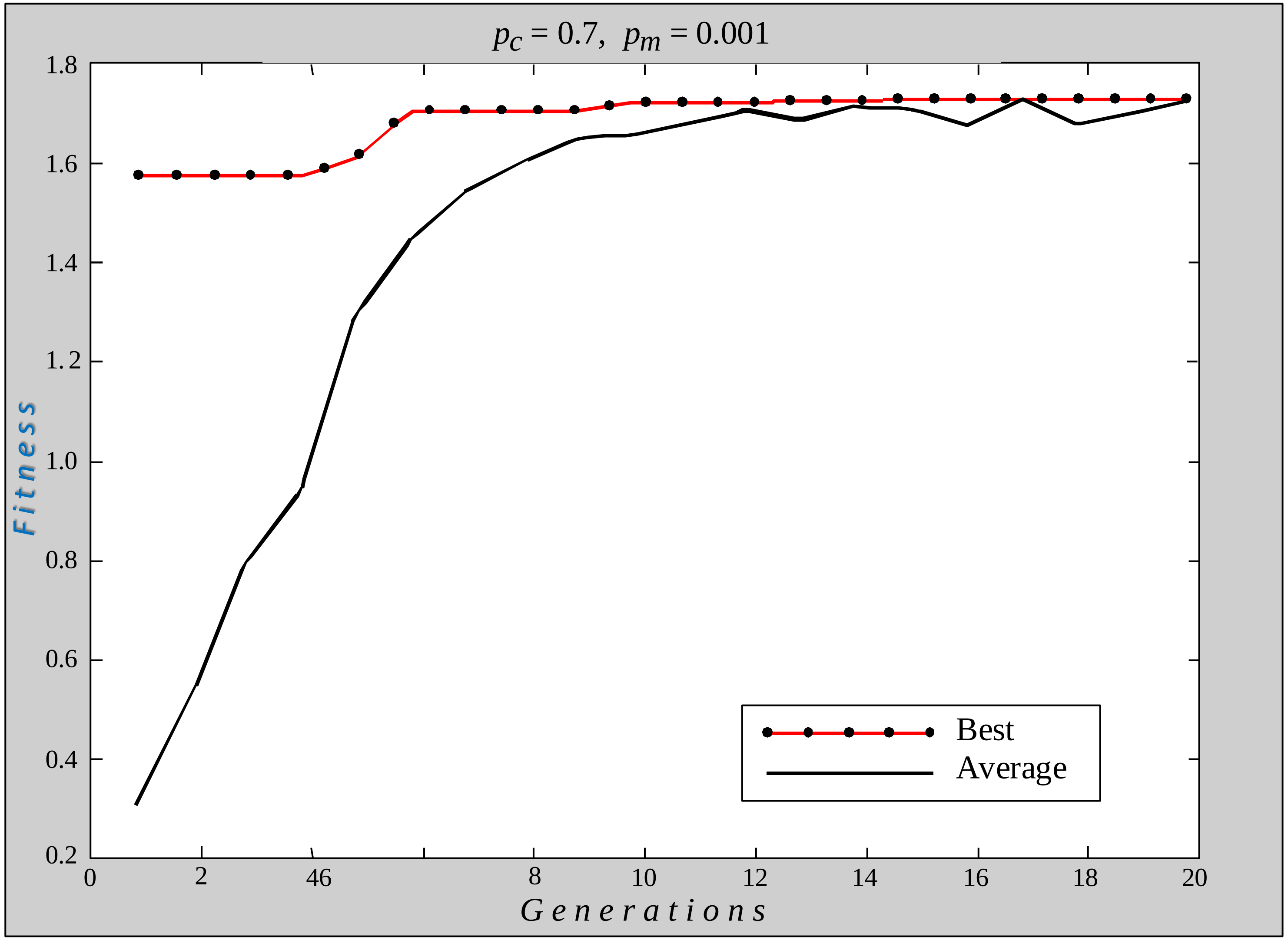
Performance graphs for 100 generations of 6 chromosomes: local maximum



Performance graphs for 100 generations of 6 chromosomes: global maximum



Performance graphs for 20 generations of 60 chromosomes



Case study: Scheduling of 7 power 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.

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

Total capacity : 20+15+35+40+15+15+10 = 150 MW

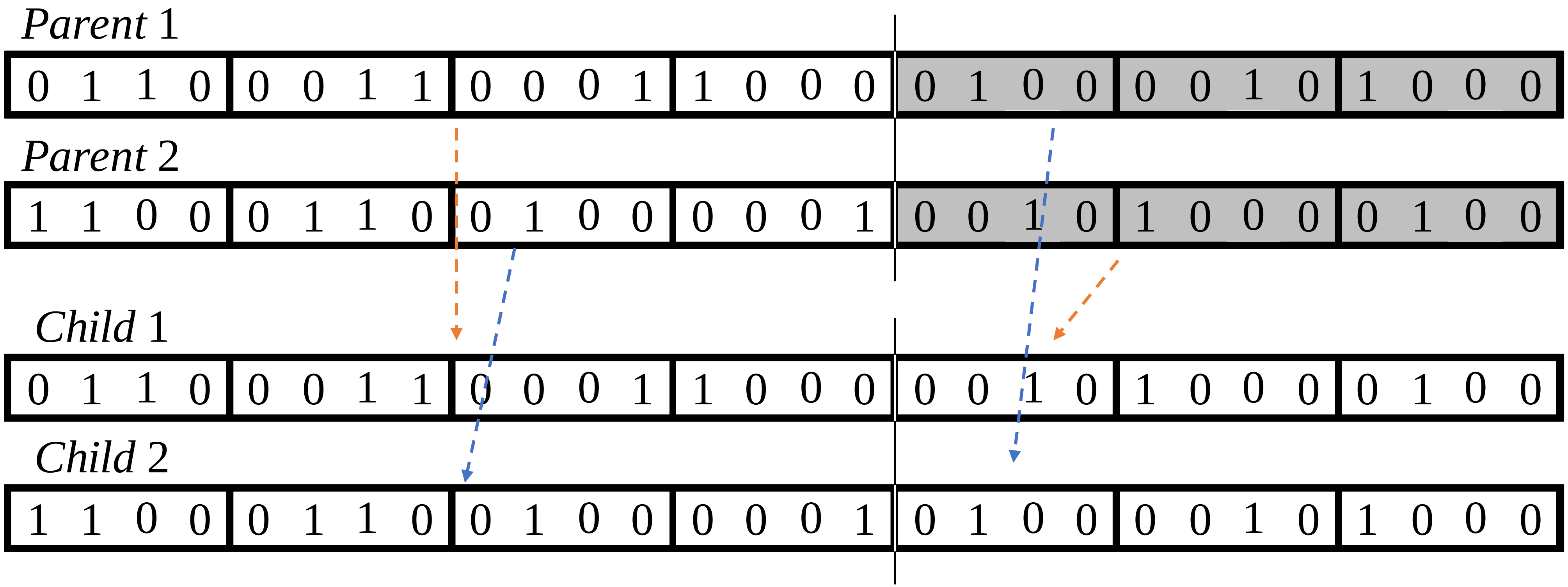
Unit gene pools

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

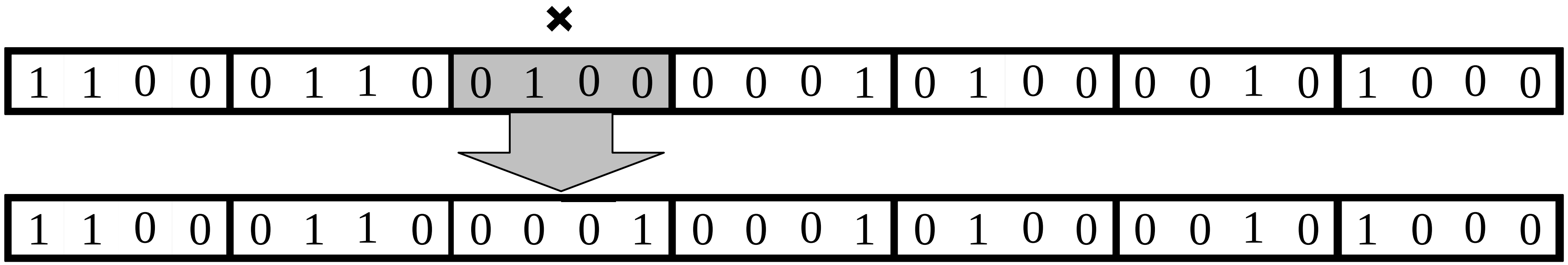
Chromosome for the scheduling problem

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

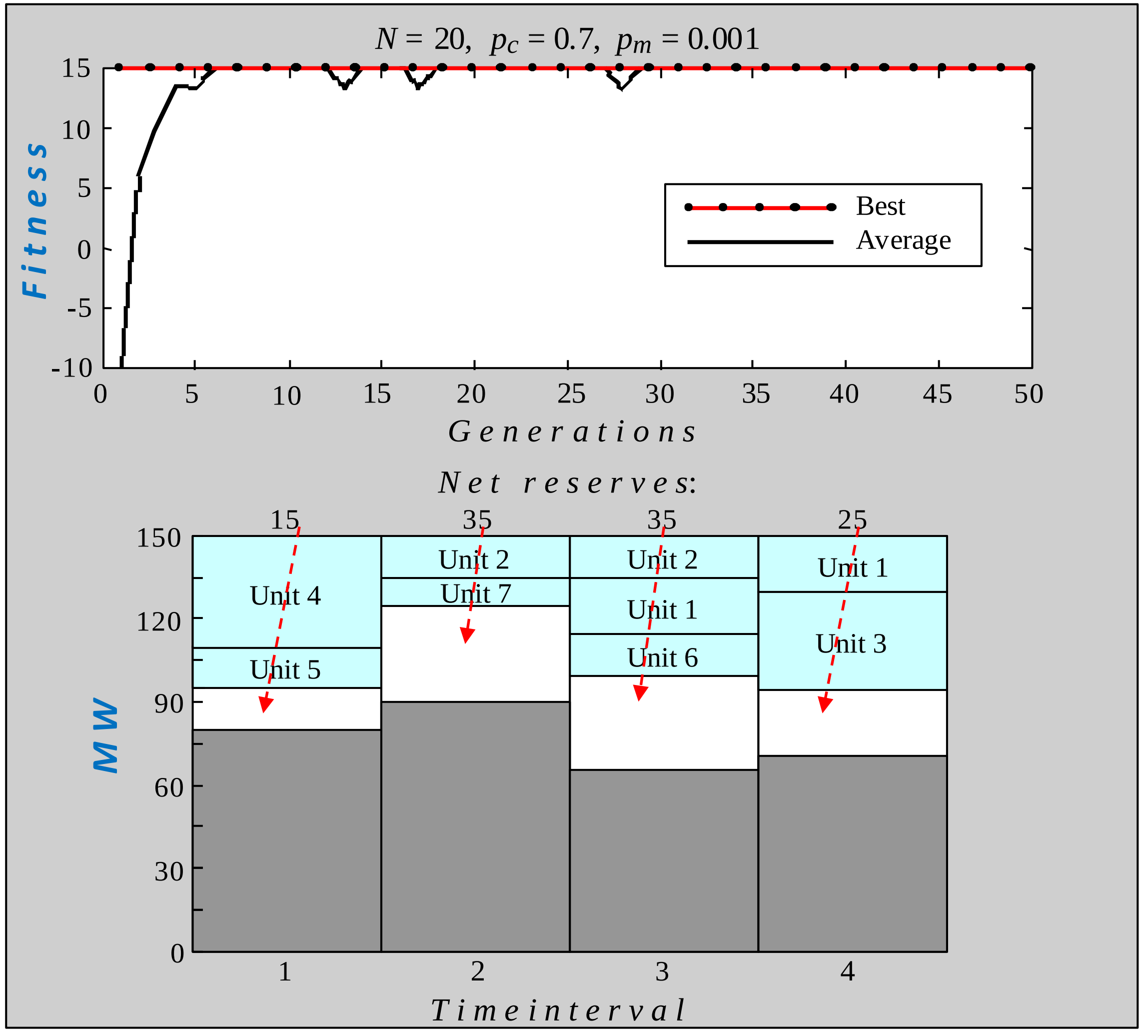
The crossover operator



The mutation operator

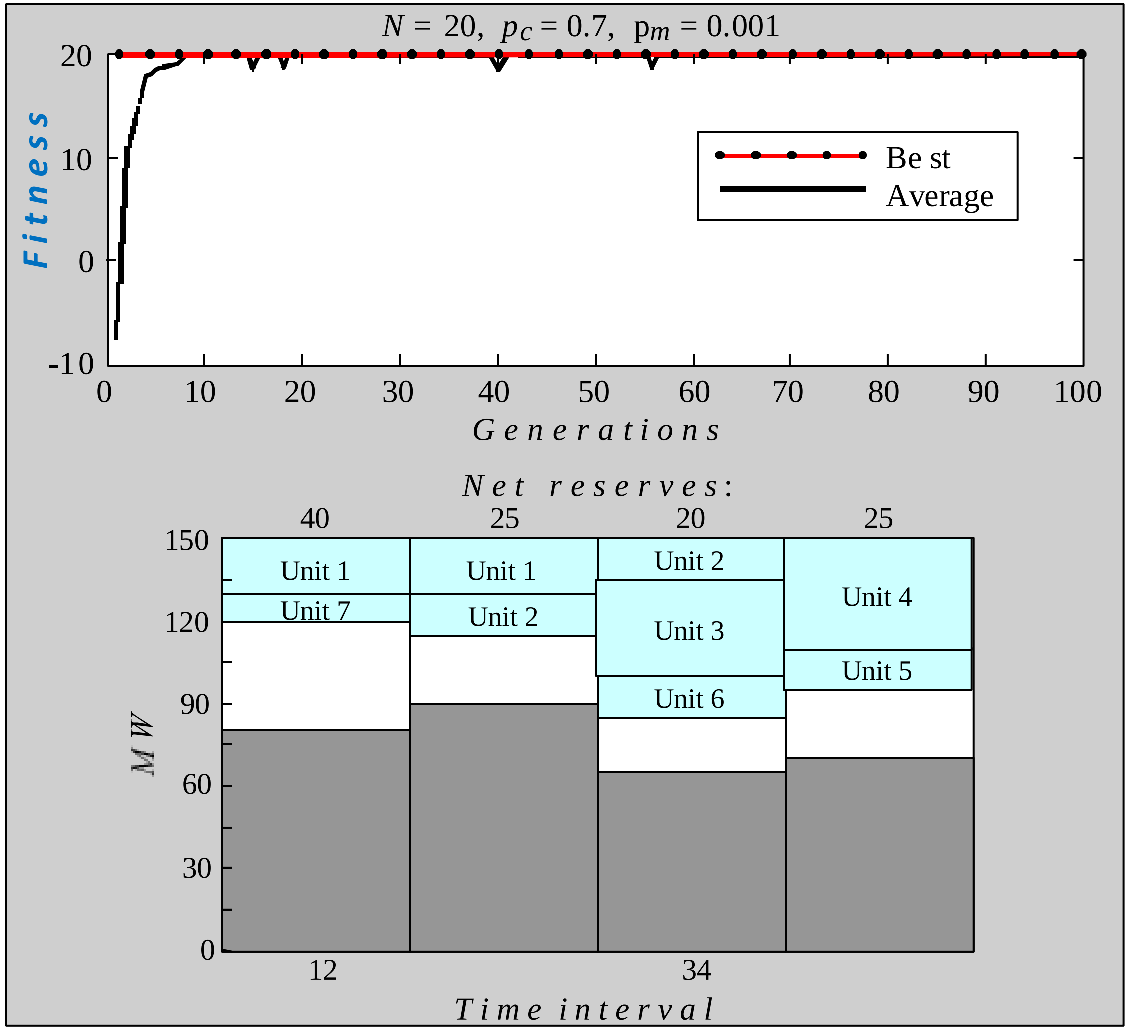


Performance graphs and the best maintenance schedules created in a population of 20 chromosomes



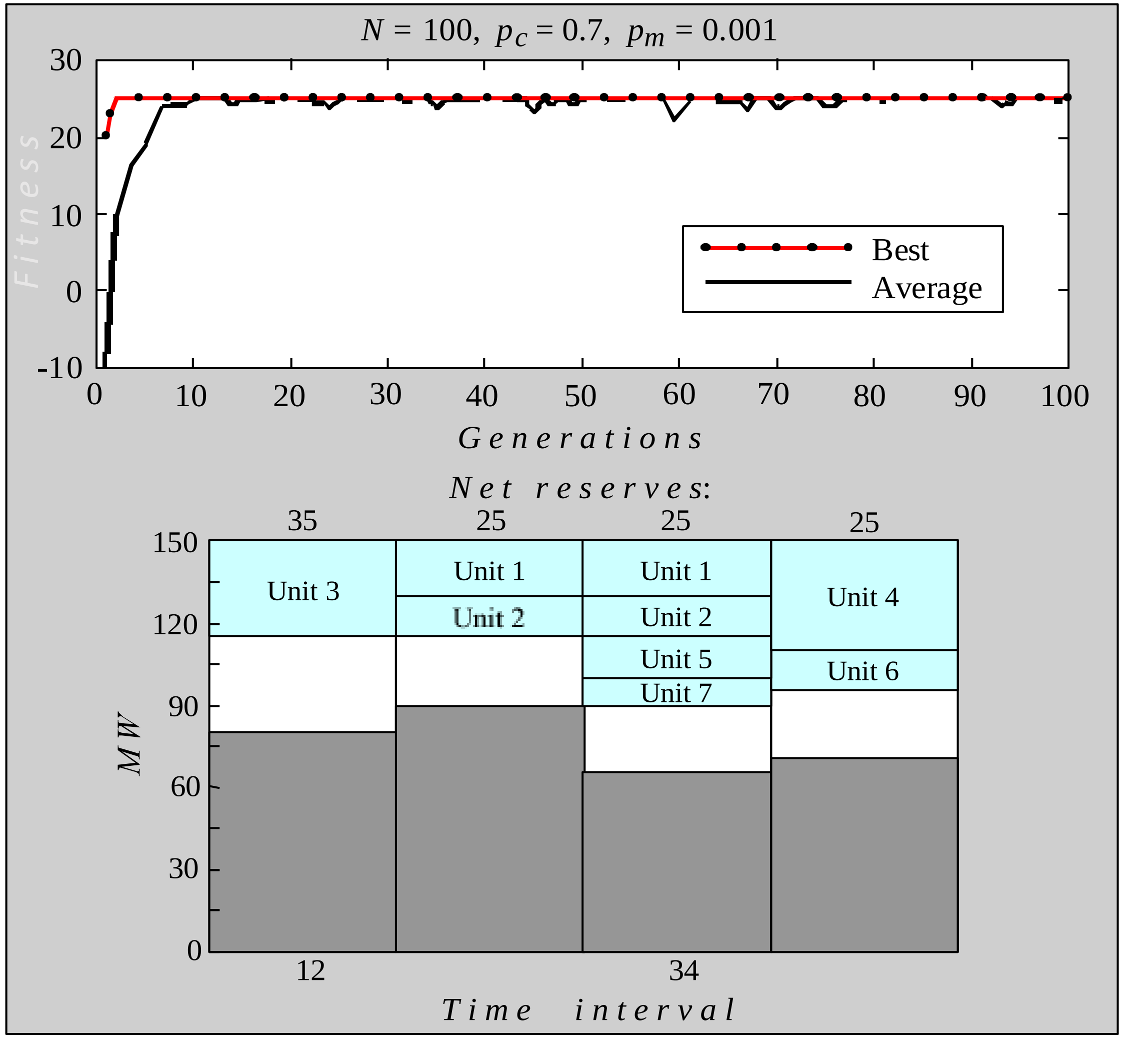
(*a*) 50 generations

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



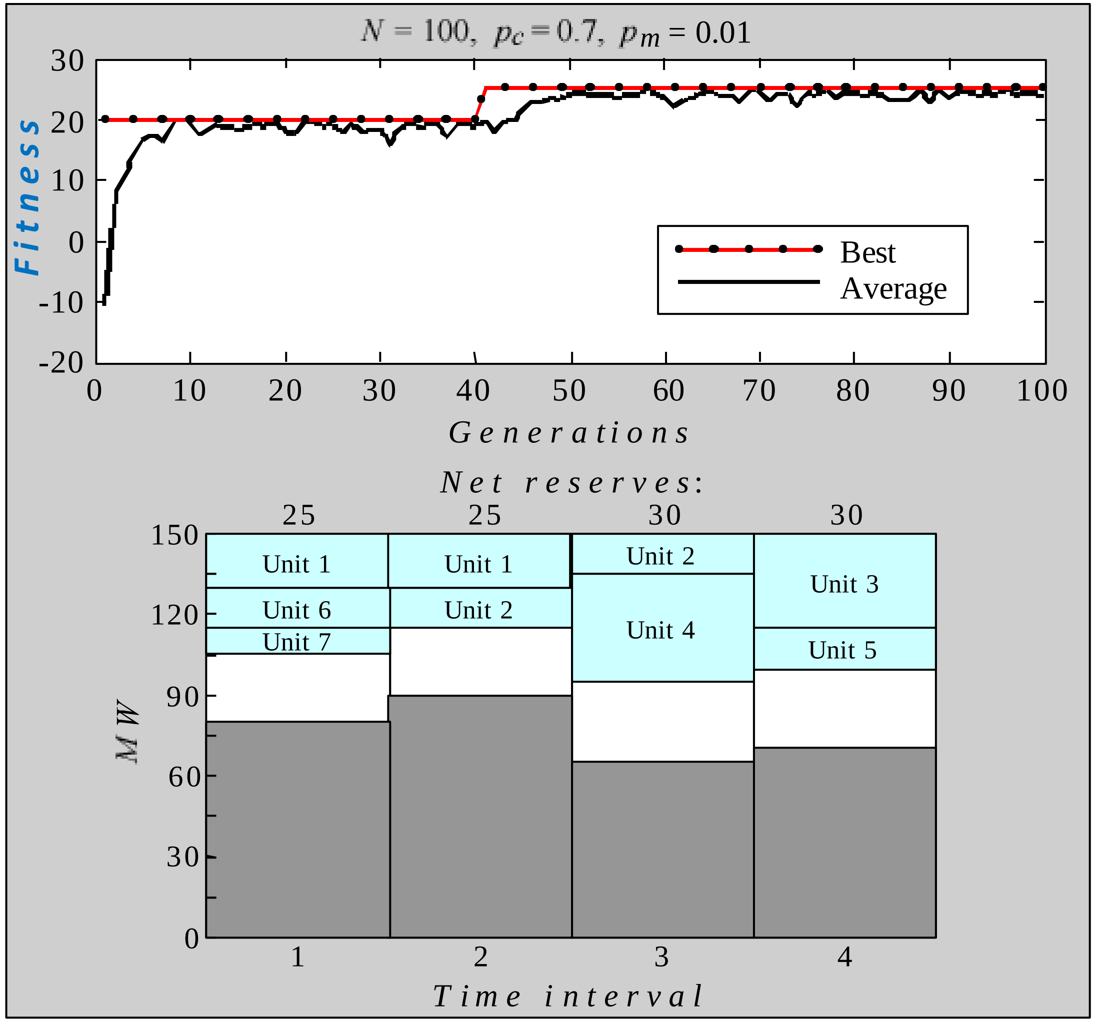
(*b*) 100 generations

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



(*a*) Mutation rate is 0.001

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



(*b*) Mutation rate is 0.01


That's all Folks!