



## Multi-Criteria Distributed Decision-Making System Based on Genetic Algorithms

Ana Țurcan <sup>1</sup>, Olesea Borozan <sup>1</sup>, Silvia Munteanu <sup>1</sup>, Constantin Ababii <sup>1,2</sup>, Ana Nistiriuc <sup>1,3</sup>, Andrei Șestacov <sup>1,4</sup>, Vadim Struna <sup>1</sup>, Victor Lașco <sup>1</sup>

<sup>1</sup> Technical University of Moldova, Computer Sciences & Systems Engineering Department, Chisinau, Republic of Moldova, http://www.utm.md

<sup>2</sup> ICG-Engineering LTD, Chisinau, Republic of Moldova, <a href="http://www.icg-engineering.com">http://www.icg-engineering.com</a>
<sup>3</sup> HANSA TELECOM LTD, Riga, Latvia, <a href="http://www.hansatelecom.com">http://www.hansatelecom.com</a>
<sup>4</sup> Armed Forces Military Academy "Alexandru cel Bun", Chisinau, Republic of Moldova, <a href="https://www.academy.army.md">https://www.academy.army.md</a>

Corresponding Author: ana.turcan@fcim.utm.md

Abstract—This thesis comprises the results of designing a distributed decision-making system in multi-criteria areas. The distributed decision-making system is the architecture of homogenous data-processing devices that form a Wireless network with Mesh topology. The decision-making process is based on finding an optimal solution that is implemented through the use of genetic algorithms. Aiming to identify the initial population of the genetic algorithm, there shall be calculated the partial derivative for each variable for the ordered process. The results of partial derivative serve as an identifier of values from the Chromosome structure.

There have been developed in this thesis: general algorithm of system functioning; population structure formed of Chromosomes and Genes; methodology of calculation of component values of the initial population; and an example of implementation of the distributed decision-making system based on Node MCU ESP32 devices.

Keywords—distributed computing; decision-making systems; multi-criteria optimization; genetic algorithms.

### I. INTRODUCTION

The notion of artificial life predominates more and more often in the course of development of decisionmaking systems for solving complex problems.

The phenomenon of artificial life is based on the fundamental elements, which are specific to biological life, such as: reproduction, evolution, adaptation, self-organisation, parasitism or exploitation of others, cooperation and competition/concurrence.

The model of evolutive calculation [1], which was based on genetic algorithms, was proposed in the last century to optimise certain complex processes,

particularly, multi-criteria ones [2]. Such models were based on treating nonlinear functions as genotypes, which were subject to the operations of mutation, crisscrossing, coupling and selection that were specific to natural evolution of live biological species [3,4,5].

An important role in development of distributed calculation systems used to collective decision-taking is provided by the possibility to standardise the data processing nods. This factor may be compared with object-oriented programming technology, where the same object may be used in different events and circumstances, thus providing a considerable reduction of costs for an implementation process. Thus, there may be also reduced the algorithmic and architectural complexity of calculation systems, through uniform distribution of data processing tasks [6].

An example of development of decision-taking systems is provided in this thesis [7], where there are applied the optimisation techniques aimed to implementation in complex systems, which are the emerging phenomena formed of a collection of interacting objects that can be self-organised and adapt their behaviour depending on their history and feedback.

Complex systems are a large class of processes, for instance: social, economic, technological and manufacturing ones, industrial companies and enterprises, and so on. All the above can be defined as multi-criteria decision-making systems, where decision-making factors shall comply with certain global quality criteria (global minimum or global maximum) [8,9,10,11].



Since complex multi-criteria systems have a distributed and concurrent nature, they need methods of parallel data processing to be applied. Such performances for parallel data processing may be reached through use of model based on genetic algorithms [12]. Genetic algorithms are adaptative algorithms of heuristic search, based on evolutive ideas of natural and genetic selection. The main concept of genetic algorithms is to simulate processes of the natural system, which are required for evolution, particularly those ones that follow the principles of survival of the best individuals [13].

This thesis proposes to design and to carry on functional research of a distributed decision-making system for multi-criteria areas, as based on genetic algorithms. The system architecture is composed of a lot of devices for parallel data processing [14,15,16], which interact and settle the problem of finding an optimal value for the activity area [17,18].

### PROBLEM FORMULATION

Whether in a multicriteria space, the process is defined  $P = \{X, U, t\}$ , where:  $P \in \mathbb{R}^N$  and N are the number of process definition criteria P;  $X = \{x_i, \forall i = \overline{1, N}\}$  the state vector of the process P and  $X \subset \mathbb{R}^{\mathbb{N}}$ ;  $U = \left\{ u_i, \forall i = \overline{1,N} \right\}$  - the decision vector for the process command P and  $U \subset \mathbb{R}^N$ ;  $t \in [0,T]$  - the time parameter that determines the activity interval of the process P.

For the process command P the mathematical model (1) that generates the decision vector U is defined to ensure conditions (2) and (3), if necessary.

$$U = g\left(X^{Opt}\right) \tag{1}$$

Where:  $X^{Opt} = X^{\min} \cup X^{\max}$  are the values of the optimal state of the process P ,  $X^{\mathrm{max}}$  and  $X^{\mathrm{min}}$  are respectively the maximum or minimum state values; g are the set of decision-making functions for action on the process P.

$$f(X^{\min}) = \min_{X \in \mathbb{R}^N} (f(X)), \tag{2}$$

$$f\left(X^{\max}\right) = \max_{X \in \mathbb{R}^N} \left(f\left(X\right)\right),\tag{3}$$

where: f(X) - non-linear function that ensures the selection of optimal decision solutions for process control *P* .

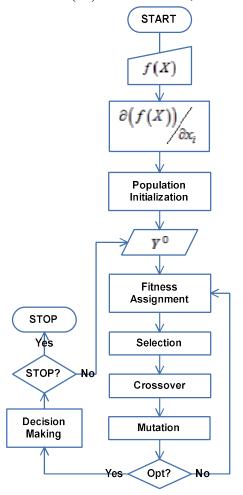
#### III. SYNTHESIS OF THE ALGORITHM OF OPERATION OF THE DECISION-MAKING SYSTEM

The sequence of operations performed by the distributed decision-making system based on genetic algorithms is shown in Figure 1, where the following are mentioned:

f(X) - defining the non-linear function that will ensure the selection of the optimal decision solutions for process control P;

 $\partial (f(X))/\partial x_i$  - calculation of the partial derivative

of the function f(X) on the variable  $x_i$ ,  $\forall i = 1, N$ ;



The operating algorithm of the decision-making system)

Population Initialization - application of the initial population calculation algorithm  $Y^0$ ;



 $Y^0$  - the initial population for the genetic algorithm, where:

$$Y^0 = \left[ Y_i^0, \forall i = \overline{1, N} \right]^T$$
 - the set of Chromosomes

of the population  $Y^0$ ;

$$Y_i^0 = \left[ y_{i,j}^0, \ j = \overline{1, M} \right], \forall i = \overline{1, N}$$
 - the set of

Genes M which forms the Chromosome i;

Fitness Assignment - The fitness function determines how fit an individual is. It gives a fitness score to each individual. The probability that an individual will be selected for reproduction is based on its fitness score;

Selection - the idea of selection phase is to select the fittest individuals and let them pass their genes to the next generation. Two pairs of individuals (parents) are selected based on their fitness scores. Individuals with high fitness have more chance to be selected for reproduction;

Crossover - Crossover is the most significant phase in a genetic algorithm. For each pair of parents to be mated, a crossover point is chosen at random from within the genes;

*Mutation* - In certain new offspring formed, some of their genes can be subjected to a mutation with a low random probability. This implies that some of the bits in the bit string can be flipped;

Opt? - The iteration terminates if the population has converged . Then it is said that the genetic algorithm has provided a set of solutions to our problem;

Decision Making - calculation of decisions U for action on process P;

Stop? - Checks the expiration of the time interval  $t \in [0,T]$  of the process activity.

# IV. The Algorithm for Generating the Initial Population $Y^{0}$

Based on the optimization conditions (2) and (3), the initial populations for the genetic algorithm are also obtained.

Figure 2 shows the general structure of a population.

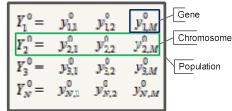


Figure 2. Population structure

Gene 
$$y_{i,j}^0 \in \{0,1\};$$

**Cromosome**  $Y_i^0$  has a series of genes (0 or 1) whose values are calculated based on the algorithm defined by Figure 3;

**Population**  $Y^0$  is the set of Chromosomes defined for the genetic algorithm that will provide optimal solutions in making ordering decisions with the process P.

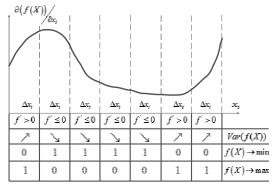


Figure 3. Calculation of gene value

$$\partial (f(X))/\partial x_i$$
 - is the partial derivative of the

function f(X) on the variable  $x_i, \forall i = \overline{1,N}$ . As a result of performing the partial derivation operation we will obtain:

$$\left[ \frac{\partial (f(X))}{\partial x_1} \quad \frac{\partial (f(X))}{\partial x_2} \quad \dots \quad \frac{\partial (f(X))}{\partial x_N} \right]^T \quad ,$$

respectively N graphs (Figure 3) for identifying the value of Genes and Chromosomes;

 $\Delta x_i$  - the step of variation of the variable  $x_i, \forall i = \overline{1, N}$ ;

f' - the value of the partial derivative;

Var(f(X)) - variation of the control function. If the function it increases then  $Var(f(X)) \approx \mathcal{F}$ , else  $Var(f(X)) \approx \mathcal{F}$ ;

 $f(X) \rightarrow \max$  - the value of the Gene identification bit for vector definition conditions  $X^{\max}$ ;

 $f(X) \rightarrow \min$  - the value of the Gene identification bit for vector definition conditions  $X^{\min}$ .

## V. DISTRIBUTED DECISION-MAKING SYSTEM SYNTHESIS

We will consider Figure 4 the structure of the distributed decision-making system consisting of homogeneous computing devices (Node MCU ESP32) configured in a Wireless communication network with

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mesh topology and programmed to calculate decision values based on model (1) taking into account the conditions generated by formulas (2) and (3).

Way of operation. The distributed decision-making system based on genetic algorithms, consisting of Node MCU ESP32 devices, performs identical operations in parallel:

- Acquires the state value  $x_i$ ,  $\forall i = \overline{1, N}$  of the process P forming the state vector X;
- Performs the exchange with the values of the state vector X;
- Process the data according to the algorithm shown in Figure 1;
- Performs the exchange with the values of the set of chromosomes of the population  $Y^0$ ;
- Calculates decision  $u_i$ ,  $\forall i = \overline{1, N}$  for the action on the P process.

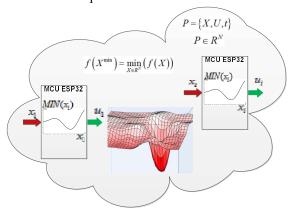


Figure 4. Distributed Decision-Making System Diagram

### CONCLUSION

This thesis provides the results of designing a distributed decision-making system in the course of ordering process, in multi-criteria areas. This system includes a lot of homogenous data-processing devices that form a network with Mesh topology. Aiming to apply genetic algorithms for finding optimal solutions, there is proposed to calculate the partial derivative for each state variable that serves as a generator of initial population.

There are provided in this thesis: general algorithm of system functioning; population structure; methodology of obtaining the population; and a chart of a distributed decision-making system.

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