INTELLIGENT COMPUTING FOR EVOLVING SYSTEMS

Marilena DONCEAN[1]

e-mail: doncean_marilena@yahoo.com

Abstract

The intermediate results of this study add to specialised, relatively restricted, research focus of the field, which seeks to ascertain the mechanisms behind modern approaches in intelligent computing for evolving systems, based on theoretical and practical foundations and considering the fact that we are heading towards a liberal knowledge-based economy. The knowledge-based economy is a challenge for the future. The mathematical modelling of time-evolving systems is a method of the future. Due to short decision-making time, ever more companies resort to intelligent systems to assist managers in making key decisions. In the new knowledge-based economy, the importance of information derives from the advantages it offers in a deeply competitive society.

Key words: economic decisions, intelligent computing, evolving system, artificial intelligence, fuzzy computing.

Given the existence of numerous optimisation problems, pertaining to the modelling of complex processes that unfold over several periods, each one demanding the optimal solution, the static perspective can act as a drawback. It is clear that the sequence of solutions cannot be determined solely based on the parameters of each examined period separately and that it is necessary to identify a series of solutions that optimise the entire examined process.

Evolving problems, which demand a series of sequential decisions, are characterised by the fact that a decision adopted in a certain period has both an immediate effect, as well as a long-term effect, influencing other stages.

As is well known, many real problems require the simultaneous optimisation of several target functions. Typically, there is no single solution for these applications. Up until now, in order to solve such problems, evolutionary and technical algorithms, proposed as early as 1985, have been applied. The literature in the field describes many successful applications, however the methods based on evolutionary algorithms are not yet widely available.

Because of the short decision-making timeframes, increasingly more companies turn to intelligent systems to assist managers in making key decisions.

In the new knowledge-based economy, the importance of information stems from the advantages it brings to a deeply competitive society.

MATERIAL AND METHOD

For the purposes of conducting the present research, I consulted the most recent and important works of literature in the country and abroad. The methodology of the research of the paper relies on the utilisation of methods such as descriptive analysis, comparative analysis, induction, deduction, synthesis, comparison, correlation, evaluation, and on formal and symbolical constructions and solutions (figures).

Intelligent computing is an area of Artificial Intelligence, grouping techniques aiming to solve "ill-posed" problems or those for which formal models lead to particularly costly algorithms.

Intelligent computing includes the following main directions of research (Tacu A.P. et al, 2003):

• ***Neural computing*** - mainly employed in solving association problems (classification, approximation, prediction, etc.), relies on retrieving a model from examples by means of learning. Its source of inspiration is the structure and functioning of the brain.

• ***Evolutionary computing*** - mainly applied to solve problems based on searching for solutions in a large pool of potential solutions (in particular in solving optimisation problems). Its inspiration lies in the Darwinian evolutionary principles.

• ***Fuzzy computing*** - used when the data of the problem (i.e. the relationship between them) cannot be described accurately and there is a degree of uncertainty ("fuzziness"). The basic idea is to replace the exact values ("crisp") with "fuzzy values" described by membership functions.

Each of the three above-mentioned directions involves alphanumeric processing, requiring a proper numerical encoding of the problem. On the other

[1] Romanian Academy – Iaşi Branch, Gh. Zane Institute of Economic and Social Research, Iasi

hand, each of the above directions attempts to simulate intelligent behaviour, which drives the presence of the intelligent term.

The fundamental principle behind the evolutionary and neural computation is to develop intelligent computation systems starting from the implementation of simple rules, while the complex behaviour of these systems deriving in parallel and interactively the application of these rules. This bottom-up approach is in contrast with the **"top-down"** approach typical of other Artificial Intelligence approaches.

Neural and evolutionary computing are part of the broader spectrum of natural computation which relies on taking cues from natural systems (physical, chemical, biological, ecological) in order to solve problems.

The main objective of natural computing is to develop natural methods of solving ill-posed problems and problems that are unsolvable by traditional methods (e.g., solving NP-complete problems in polynomial time).

In addition to the previously mentioned components, natural computation includes:

•molecular computing (DNA Computing)
• Membrane Computing
• Quantum Computing.

RESULTS AND DISCUSSIONS

Evolutionary computation provides search mechanisms, within the framework of solutions based on the principles of natural Darwinian evolution.

In order to find the solution, a research population is used. This population is subject to an evolutionary process, which involves **selection, crossover, mutation**.

Depending on how the population is built and how evolution is implemented, the evolutionary computing systems fall into one of the following categories:

• **Genetic algorithms -** mainly used to solve discrete optimization problems. The population is represented by binary coded states of the space of the problem (an element of the population is encoded as a string of bits), and the main operators are crossover and selection, while mutation operators have a low probability of application. Genetic algorithms were initially proposed by Holland.

• **Genetic programming –** is used to develop calculation "models" (simple programs). The population is represented by programs that contribute to solving the problem. These tend to be described as derivation trees of the word that they represent in the language in which it is written and not as lines of code; for example, "the expression-program a + b * c" is (+ a (* bc)). Crossover is performed by means of random selection sub-trees from the tree associated with parent programs and performing interchanges. As with genetic algorithms, the mutation has a limited weight. Koza is widely regarded as the founder of genetic programming.

• **Evolving strategies -** were originally designed to solve technical optimisation problems, aiming to solve continuous optimisation issues. The population consists of elements of the definition field of the target function. The main operator is mutation, however recombination is also employed. Adaptation schemes for control parameters (self-adaptation) have been developed for evolutionary strategies. Rechenberg and Schwefel have made significant contributions to the development of evolutionary strategies.

• **Evolutionary programming -** is used both for the optimisation and the development of certain computing (automated) structures. The main operator is mutation. The foundations of the field were laid by Fogel.

All these methods rely on the simulation of the evolution of a set (population) of information structures (configurations or individuals) under the action of processes similar to those of natural evolution, namely: **selection, mutation and crossover**.

The action of these processes is controlled by means of a performance function ("fitness function"), which measures the adequacy each individual to the environment it belongs to. For example, when solving an optimisation problem (maximisation), the "fitness" function is essentially the target function of problem.

Genetic algorithms are part of the class of evolutionary computation techniques, being stochastic search algorithms inspired by natural selection and genetics. The underlying principle is that there is a population made up of individuals, that make up the potential solutions to the problem and, in metaphorical terms, individuals are asked to compete against one another for survival. After evaluating each individual, the stronger ones are assigned a greater chance of participating in the reproduction process than the less powerful, which may not even be involved at all.

Genetic algorithms typically involve the following steps:

1. Random generation of an initial population of **n** acceptable solutions to the problem, represented by **n** chromosomes.

2. The evaluation of a suitability function **f (x)** for each chromosome x in the population.

3. Creating a new population by repeating the steps below until the new population is complete:

a. Selection: select a pair of parent chromosomes according to their suitability (the more suitable being more likely to be chosen for reproduction)

b. Crossover: based on a given crossover probability parents are crossed with each other to generate a pair of descendants (if there is no crossover, descendants are identical copies of the parents).

c. Mutation: based on a given probability certain positions are changed, i.e. genes in descendants' chromosomes.

4. The generated population replaces at least in part the old population and the resulting population is used to go step by step through the same algorithm.

5. If the stopping condition is reached, the algorithm ends and retains the best solution in the current population, which is also the last.

6. If the stopping condition is not reached, the evaluations at step 2 are resumed.

The outline of genetic algorithms given above has varied consequences. One issue, as noted above, refers to creating chromosomes, to perform the encoding of individuals in a particular population. Based on the shape chromosomes, the two basic operators of genetic algorithms are defined, i.e. combining- crossover and mutation.

The theoretical advances over the past two decades in the area of artificial intelligence increasingly suggest the attempt to abandon traditional ways of approaching and solving practical problems in various fields not limited to technical ones (economy, finance, social, etc.). In contrast to the (logical-symbolic paradigm (with applications found in intelligent software focusing on highly complex problems, yet in a strictly defined field – such as chess for example), the connexionist paradigm introduces the concept of neural computation and has given rise to **artificial neural networks** (ANN) - which are models inspired by the human brain structure (Docean G. and Docean M., 2012).

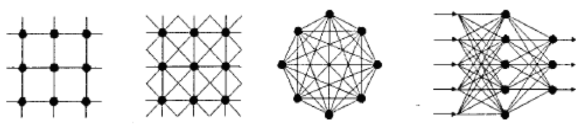

Figure 1. **Neural networks**

Artificial neural networks learn to solve a given problem, developing a memory that is able to associate a large number of input data sets with corresponding sets of results or effects. They have the ability to learn from the examples they are presented with, without knowing anything about the mathematical model and solution algorithm behind the model. Moreover, even if the practical problem is so complex that does not permit the development of a sufficiently coherent mathematical model (and therefore cannot be approached by traditional computing means, regardless of the performance of the computer and the time available), a properly built artificial neural network can solve the problem satisfactorily, provided only there are enough examples of input-output data, which can serve to teach it.

In a broader context, such networks may be integrated into "**artificial intelligence**"-type computational structures, that also draw on other recent techniques such as genetic algorithms, evolutionary programming, simulated tempering and fuzzy systems theory (Beiseln E.P, 1987).

Fuzzy computing allows the handling of vague concepts that cannot be modelled by exact mathematical concepts (classic numbers, sets or functions). Problems in which vague concepts occur arise in control theory when systems are nonlinear character and their states can be described accurately only by means of statements, which have a degree of ambiguity.

Neural and evolutionary computing are part of a broader ***natural computing*** whose principle is to draw ideas for problem solving from natural systems (physical, chemical, biological, ecological). The main objective of the natural computing is to develop methods of solving ill-posed problems and those that are unsolvable by traditional methods.

In addition to the previously mentioned components, natural computation includes *molecular computing* (**DNA Computing**), *computing using membranes* (**Membrane Computing**) and **Quantum Computing**. While the first two lines are already established, the last three are still in the early stages of development.

From a practical standpoint, worldwide in the technical field multi-criteria decision analysis (MCDA) and multi-objective optimisation (MOO).

CONCLUSIONS

The goal of reflecting the true qualities and structural relations of economic reality demands a continuous process of development of flexible economic and mathematical models. The emergence of new situations from innovative assumptions marks each time a new step towards reconciling the model with the reality (the real objective reflected by the model).

Viewed in terms of the evolution of their trajectories, intelligent computing for evolutionary systems has gained in adaptability and flexibility and have significantly developed their interdisciplinary focus.

Taking into account the advances of computing technology, existing software capabilities and the constant adaptation to practical requirements, intelligent computing for evolutionary systems lies at the border of organisational economics, mathematics and computing.

The progress made since the emergence of the first modelling, simulation and optimisation works up to the present illustrates the constant concern of specialists to distinguish methods and paths that are as close as possible to economic reality in order to improve decision making. Along these lines, in addition to traditional processes based on intuition and experience, very modern scientific decision making methods are required, with a strong theoretical foundation based on mathematical methods, while maintaining a general, practical and realistic focus.

For these purposes, **intelligent computing for evolutionary systems represents an advanced approach that is a prerequisites for decision making in a liberal knowledge based society.**

REFERENCES

ANDREI, Neculai – "*Software for Mathematical Programming, (Sisteme si Pachete de Programe pentru Programarea Matematica), (in Romanian)",* Technical Press - Bucharest, 2002.

ANDREI Neculai – *„Sisteme şi pachete de programe pentru programarea matematică",* Editura Tehnică, Bucharest, 2002

BEISELN, Ernst Peter – "*Optimierungsmethoden des operations resarch",* Editura Friedrich Vieweg, Braunschweig Wieshaden, 1987.

DONCEAN Gheorghe –*„Modele de evaluare tehnico-economică (technical-economic assessment models)",* Scientific and practical international conference "Creşterea economică în condiţiile internaţionalizării" [EN: Economic growth under the conditions of internationalisation], Section on Economic growth policies and models, 5th ed., 21-22 October 2010, Chisinău, Republic of Moldova, Institute of Economics, Finance and Statistics

DONCEAN Marilena - *"The database of economic phenomena and effects resulting from the establishment of modular inventive structures in research and education institutions",* in the volume "Lucrări Ştiinţifice" – vol. 53/2010, seria Agronomie, Editura Ion Ionescu de la Brad, Iasi, 2010

DONCEAN, Gheorghe, DONCEAN Marilena - *"Puncte critice în evoluţia economico-socială a societăţii sub influenţa factorilor pozitivi şi restrictivi"* [Critical points in the economic and social evolution of society under the influence of positive and restrictive factors], in the volume „Progrese în teoria deciziilor în condiţii de risc şi incertitudine" [Advances in the theory of decision-making under risk and uncertainty conditions],, Editura Performantica, Iaşi, 2007.

DONCEAN, Gheorghe, DONCEAN Marilena. - *"Un model de evaluare şi implementare investiţională într-un sistem economic"* [A model of investment assessment and implementation in an economic system], "Ecoinvent -2007", 19th international inventics conference on „High performance innovative research and technologies" and the International Salon of inventions, research and technology transfer in environmental protection, 3rd ed., Editura Performantica, Iaşi, pp. 205-216

DONCEAN, Gheorghe, Marilena DONCEAN – *"Nanoştiinta la început de mileniu"* [Nanoscience at the turn of the millennium], in the volume "Progrese în teoria deciziilor în condiţii de risc şi incertitudine" [Advances in the theory of decision-making under risk and uncertainty conditions], Editura Tehnopress, Iaşi, 2010

DRUCKER, PETER – *"Eficienţa factorului decizional",* Editura Destin, Deva, 1994, p. 98.

DRUKER, PETER - *"Managing for the future",* Truman Talley Books, New York, 1992.

DUMITRU, V. – *"Programarea Neliniară. Algoritmi, Programe, Rezultate Numerice"*, Editura Academiei, Bucureşti,1975.

NEGRESCU, Cristian – *"Bazele algoritmilor adoptivi de gradient : metode de optimizare",* Editura Universităţii Politehnice, Bucureşti, 1997.

POPA, Monica 2003 – "*Bazele proiectării asistate – Metode de optimiza*re", Editura Universităţii Oradea,

TACU, Al. Puiu; HOLBAN, Ştefan; VANCEA, Romul; BURCIU, Aurel; EXNER, Robert 2003 – *"Intelligente systeme in der optimierung vonentschedungen",* Bonn, Germany.