HYBRID-AGENT ORGANIZATION MODELING: A LOGICAL-HEURISTIC APPROACH

Ana Marostica, Cesar Briano and Ernesto Chinkes
School of Economics, University of Buenos Aires, Argentina

Abstract. This paper describes a hybrid-agent organization model from a logical-heuristic point of view. The organization model is an ordered set composed by an environment (or domain), the hybrid agents as elements of the environmental structure, and some connecting functions. A hybrid-agent in an organization structure is composed by a heuristic-decision support system (HDSS) and the decision-maker (the user) as a unit. By using this hybrid-agent organization modelling, we can provide instruments to help when making decisions in a financial organization such as a commercial bank.

1.Introduction

This paper describes a hybrid-agent organization model if we understand a model as a frame for the structure of an organization. Our organization modelling tries to capture, in a flexible way, the main part of an organization used by a team of hybrid-agents to satisfy their goals.

From a logical-heuristic point of view, the organization model *M* is an ordered set composed by an *environment* or domain, *hybrid agents* as elements of the environmental structure, and *some connecting functions*.

M = (environment, hybrid agent, function).

Organizational decisions often have important consequences. In order to succeed, organizations (such as commercial banks), try to maintain a high level of performance while minimizing the occurrence of mistakes, due to either excessive optimism or pessimism in interpreting the information coming from the environment.

By using a hybrid-agent organization modelling, where the hybrid-agent is composed by a heuristic-decision support system (HDSS) and the decision-maker as a unit, we can provide instruments to help when making decisions in a financial organization such as a commercial bank.

The remainder of this paper is organized as follows. Section 2 describes the different types of environments. Section 3 briefly explains what is a hybrid decision support system (HDSS). Section 4 deals with the structure of the decision-maker's mind. Section 5 presents hybrid agents. Section 6 explains the connecting functions. Section 7 presents an example of hybrid agents in a financial organization. Finally, Section 8, contains our concluding remarks.

2. Organizational environment

The environment is the domain where the agents act. We can distinguish two main types of environments, the physical and the semiotic environment. The usual physical things compose the physical domain. The semiotic environment is composed by all the meanings the agents has of physical and mental things. The physical environment can be understood as the things (i.e., physical and human) the agent interacts with comprising everything outside the agents. For example, the decision-maker in a financial organization, such as a commercial bank, interacts mainly with the financial world.

Even though all the things outside the agent compose the environment, it is also true that an environment has some meaning for the task of the user. This is why we can introduce the term *scope of the environment*. It is related to the different domains the environment could have. We could have a *wide scope* that for us is almost equivalent to the physical environment and a *narrow scope* that is equivalent to the semiotic environment related to the topic under consideration.

To explain what me mean by *semiotic environment* let us use some ideas of one of the creators of scientific semiotics: Charles S. Peirce [13]. Peirce conceived the whole universe as a frame of signs. Those signs have, among other things, meanings. Those meanings can be arranged in a semiotic tree [8]. This new type of arrangement (i.e., these semiotic trees) is based upon Peirce's semiotic trichotomies [13], Marty's Peircean lattices [11], a transformation of a lattice into a tree structure, and a simplification algorithm (i.e., Shapiro & Sterling "divide and query") [8].

In Peirce's semiotics, a combination of all the ideas presented before, have given rise to Peirce's semiotic trichotomies. However, these semiotic trichotomies are, from the mathematical point of view, combinations with repetitions of three elements taken *n* at a time, where *n* could be (4+0)-1, (4+3)-1, (4+3+4)-1, etc. In connection with these combinations of elements (i.e., 1, 2, and 3) we find the principle at the base of these combinations. The principle in question is that whatever is a 1 determines only a 1; whatever is a 2, determines a 2 or a 1; and whatever is a 3 determines a 3 or a 2 or a 1.

Changing the order of Peirce's numbering of these trichotomies, we can generalize these combinations and obtain further semiotic trichotomies that will show new aspects of the meanings of a sign. R. Marty by using the theory of lattices and Peircean semiotics has shown that the semiotic trichotomies for n=3, 6, and 10, can be arranged in a natural way as the formal elements of lattice structures [11]. As in the case of Peirce's trichotomies, Marty's lattices were generalized in order to introduce a new arrangement [8].

Since we need to explain some meaning related to inductive arguments, we need to transform the semiotic lattices into a tree structure because we need to use a decision tree in that type of algorithm (e.g., Quinlan's ID3). In order to transform Marty's lattices into a tree structure, we have to do the following: Duplicate each branch of a tree where there is a node with two ancestors. This is why we repeat twice each branch with two ancestors in the transformation [8].

In the economic field, inductive inferences are very important. They are indicative types of processes. In inductive generalizations used in economics and financial fields, the random sample is an index of what we will find in the population. This is because we must classify properly the elements of that sample. Consequently, it is very important to detect and to analyse the meanings of all the indices involved for making further decisions. We can do that in the tree presented above. Of course, according to the topic at hand, we can use trees more complex (where in the corresponding lattice have 10, 28, 64, etc, elements).

In order to classify and simplify the trees, we have to eliminate all the nodes that do not correspond to indexical meanings. To begin this operation, we may use a modification of the heuristic technique *divide and query* that Shapiro and Sterling used in PROLOG [14].

By using credit risk assessment in a bank as an example of the semiotic of meaning classification, the following reduced tree, (to indicate meanings of the signs where the elements are 28), shows the advantage of this type of taxonomy. In this example, we have the meaning of concepts such as *Income*, *Salary*, *Debt* (i.e., size of the loan asked), *Credit Risk*, etc. In order to classify these types of indexical meanings, we cannot use the tree structure corresponding to the three Peirce's trichotomies (i.e., where n=3) because this classification does not involve a process [8]. However, concepts involved in business represent processes. Therefore, we need a tree in which the concepts involved represent processes, too. The six-lattice (where n=6, and the elements are 28) and its corresponding tree structure will give us the adequate semiotic classification in this semiotic domain. In this structure, the concepts with their meaning evolved from the past to the present, and the future meaning.

Turning back to our concrete example of a semiotic environment related to credit risk analysis, we will use only the branch we need in the tree. See Figure 1. There, the nodes of the six-tree structure (where n=6), that serves to illustrate our claim, are the following: 25, 24, 23, 16, and 11.

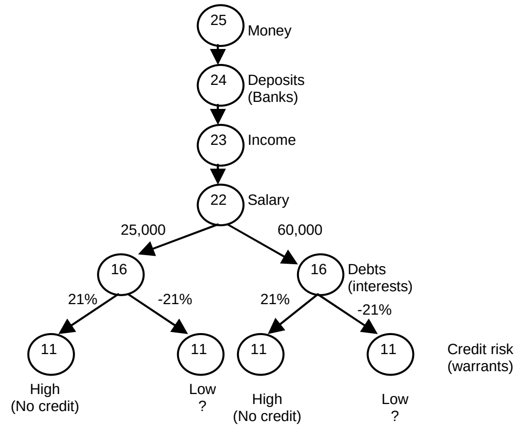

Figure 1. **A semiotic tree**

25: It is a concept of a general state of facts [17]. Example: *Money* is a type of social relationship. It is used as a medium of exchange. Nowadays, it is a paper note authorized to be used as a medium of exchange. It is symbolic or conventional. It is an abstract unit of exchange.

24: It is a general state of facts that evolves from conventions or symbols. In effect, symbols, like those of a language, are conventions among people. Example: Money *deposited in a bank*. Money a person has in a bank. It indicates a person's capacity to pay a loan.

23: It is an index of a general state of facts. Example: *Income* is the money a person receives periodically for services or for realized works (like a salary), or for an investment or the rent of properties.

22: It is an index of a particular state of facts. Example: *Salary* is the monthly (or in a certain period of time) payment for realized work. This payment could be from the government, private corporations or other persons.

16: An index indicating a singular state of facts. However, in the future there is a fact that will determine the whole state of facts. Example: Debt (the money a person is asking for in the way of a loan). It indicates a contract or agreement to do something, put in writing and enforceable by law. A person that borrows money has to pay *interest* on it. The repayment instalment is in the future and is an important part of the loan that the person has asked for.

11: It is an index indicating a state of facts that in the present and in the future can be determined by a particular fact. Example: *Credit Risk* is an index of uncertainty that could adversely affect the financial agreement. In order to reduce the uncertainty banks and financial institutions have to diversify risks. In order to avoid losses, banks have to ask for collaterals. This protection reduces the uncertainty and possible losses due to credit risk.

3. Heuristic decision support systems

An agent, according to some authors, is a computational entity such as a software program or a structure that can be viewed as perceiving and acting upon its environment. In addition, it is an autonomous intelligent entity. This is because its behaviour is at least partially dependents on its own experience [17]. Agents can accomplish individual and broader goals. Within a financial organization, our *hybrid agents* (i.e., the heuristic system HDSS and the user of the system as a unit) play roles required by their specific goals.

Let us see the components of these hybrid agents separately. A common decision support system (i.e., a DSS) generally is described as having five parts:

1. The User interface,
2. The Model-Based Management System,
3. The Knowledge Engine,
4. The Data Management System,
and
5. The User.

These five parts are the ones recognized by some authors (e.g., [3]). All these parts correspond, more or less, to the parts we find in an information system [6] with the exception of the Model-Based Management System. This software includes different types of models, for example, financial, statistical, management, etc., which give the system analytical capability and appropriate administration of the software. For more details of a common DSS go to [3] and [6].

The heuristic tools, in our system, set first precise definitions of the ambiguous variables and a kind of boundary for the vague or fuzzy variables [9]. The architecture specified in Figure 2 shows the two parts of a heuristic-decision support system (HDSS). The left part is the DSS itself mentioned above, and the right part of the figure is a heuristic-data mining mechanism that is a complement of statistical data mining. This heuristic part of the architecture is embedded into the original DSS. See Figure 2.

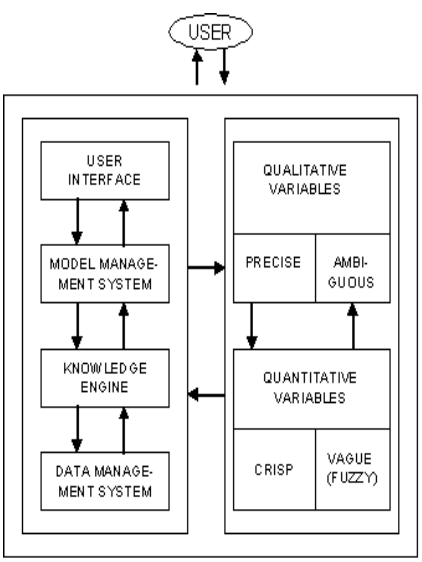

Figure 2. **A heuristic-decision support system**

We consider a *decision* as the conclusion of an inference, and its premises are the *alternatives*, *possible consequences* related to expected utility hypothesis, *weak preferences* related to the principle of rationality or optimality, and the *state of the environment* related to subjective probabilities. For example in a financial context, ambiguity could arise when decisions related to a prescription that the Central Bank should vary reserve requirement in order to allow a “smooth functioning of the banks” could call for either and increase or a decrease in the requirements according to the circumstances.

In the information we find in a HDSS, after giving precise definitions, it is possible to check the status of each variable (i.e., our n-adic predicates) to see if it is ambiguous or not by using the following algorithm:

Algorithm: AMBIGUITY
1. Evaluate type of variable in the set of alternatives
2. IF the variable is quantitative or precise, GOTO 4
3. For I = 1, 2, …, N Do
    a. Select M(I)
    b. Evaluate M(I)
    c. If M(I) ≠ PM(I)
    End IF
Next
4. IF there are more variables, GOTO 1
5.END

The symbol PM(I) represents the “precise meaning” of a node I (i.e., the variable I). Calling AMBIGUITY recursively, it performs the algorithm. SELECT is a procedure that chooses an element out from a set of nodes, such that, this element obeys a set of conditions, for example, to choose precise qualitative variables instead of ambiguous ones. For more details, see [4].

Since decision-making involves the selection of the best available alternative, according to the rationality principle, sometimes the set of alternatives, which contains a solution to a decision-making problem, cannot always be defined explicitly because it contains *vague* or *fuzzy* variables. Vagueness is a quantitative problem, and has to do with representations of the world through natural languages. Decision-making in finances, for instance, used natural languages where we have the problem of vagueness. In order to use fuzzy set theory as a tool for vagueness it is necessary to explain fuzzy membership functions [15]. In decision inferences, we can say that the fuzzy membership function of a decision or goal in a decision problem is:

$$F(x) = A \rightarrow [0, 1] \qquad (1)$$

A, in this formula, represents a set of possible alternatives that contain a solution to a decision-making problem we are considering. A fuzzy decision D is a fuzzy set on A characterized by the above membership function, which represents the degree to which the alternatives satisfy the specified decision goal. In general, a fuzzy decision indicates that the target should be obtained, but also quantifies the degree to which the target is fulfilled [15]. The fuzzy sets call sometimes “fuzzy categories” are constructed according to the following algorithm:

Algorithm: VAGUENESS
1. Define the type of variable in the set of alternatives
2. IF the variable is qualitative or crisp, GOTO 4
3. IF the variable, or set, is fuzzy
   a. Create fuzzy subsets or fuzzy categories (given by experts)
   b. Determine the relative membership of elements of the original fuzzy set
   c. Return the relative membership of those elements
   END
4. IF there are more variables, GOTO 1
5. END.

The following algorithm performs the relationship between the DSS and the Heuristic-data mining:

Algorithm: HEURISTIC-DSS
1. Define the type of variable by using AMBIGUITY and VAGUENESS algorithms
2. IF the variable is an n-adic predicate where
   n = 4, 5,…,
      a. Apply Reduction Principle
3. IF there are more variables, GOTO 1
4. END

Peirce's *Reduction Principle* [13] roughly says that any n- adic predicate (i.e., where $n > 3$) can be reduced to some n-adic predicates (i.e., where $n \leq 3$). Monadic, dyadic and triadic predicates are irreducible.

4. The structure of the decision-maker's mind

We will analyze now the user as a complex architecture. From a logical-heuristic point of view, the architecture of the mind when thinking uses different types of processes to solve problems or to make decisions.

The main types of processes of the mind are the following: *abductive explanation*, which is the most plausible explanation found (according to the circumstances) for an anomalous fact. After the abductive process, we find *deductive predictions* of the consequences related to that previous explanation. Following the deductive process, we have the *quantitative inductive* process, which consist in checking those consequences against real data.

Since the world evolves, the mind must create worldviews (simplified *scientific models*) in order to extract uncertain information from evolving data. This is precisely the job fulfilled by qualitative induction that creates the *models* and *controls* the information received by the mind. With its model generator role, qualitative induction solves the first part of the problem because it allows the scientist to create a framework for the best plausible explanation of an anomalous fact. That is, how to do things properly. Under any circumstance, the possible "correct things" are not in the majority of cases, the "optimum things" but the "appropriate ones" under given circumstances.

Qualitative induction through its *principles* provides the limits of the mind processes to be controlled. In addition, the activity of qualitative induction can be adapted continuously in order to respond to the process changes through time. In qualitative induction, these changes are heuristic approximations.

The *two principles* involved in qualitative induction can be considered as heuristic principles. For example, the first one performs a heuristic search among the explanatory hypotheses arrived at by abduction. Since qualitative induction is

When the most promising hypothesis has been selected, qualitative induction activates deduction in order to predict observable consequences related to that explanatory hypothesis. After that, it activates quantitative induction for checking the most promising predictions. If the evaluation of the checking of all elements of the sample set is considered successful, then qualitative induction allows quantitative induction to generalize for the population. The last part of this work is performed by a *second heuristic principle* that qualitative induction has. This second principle supervises, the partial checking of the likely elements of the sample related to the most promising explanatory hypothesis.

To sum up the heuristic work (or "things to do") performed by this controller, we could sketch it in the following algorithm:

Procedure: (**Qualitative inductive controller**)
1. Begin
2. Analyze anomalous fact
3. Create a model for that fact
4. Activate abduction
5. Select the first plausible explanatory hypothesis
6. Activate deduction
   Allow observable predictions
7. Activate quantitative induction
   Allow generalization and checking with the environment
8.If checking is OK
   Successful end
9. Select the next plausible explanation
10.If that is the last hypothesis
   Dead end
   Else
   Goto step 6.

After that, the mind creates the model or appropriate frame where the most plausible explanatory hypothesis must be presented. With abduction, we start with new ideas. It must create the explanation for the anomalous fact.The following algorithm summarizes the main activity of abduction:

Procedure: (**Abductive explanatory hypothesis**)
1. Begin
2. Write the anomalous fact in statement form
3. Accept the model given by qualitative induction
4.Search for information in the predicate of the anomalous fact for finding an explanation
   Use *Reduction Theorem* when needed
5. If It is an adequate explanation for the anomalous fact
   Success end

6. Else go to step 2.

Once we have settled down the best possible explanation for the anomalous fact, the mind process continues with the deductive part, namely the *prediction* of the most important consequences related to that explanatory hypothesis. In deduction, with formal procedures we can arrive at the conclusion of an inference, which is a logical consequence of the premises.

Even though there is not a full decision procedure for the first-order calculus, we can use a *resolution rule* as a single rule to minimize the search problem in deduction. We can take advantage of the already existing logical method used in AI, the *resolution* method. The following algorithm shows the deductive prediction procedure:

Procedure: (**Resolution for deductive prediction**)
1.Begin
2.Symbolize the inference in first-order logic
3.Apply *Reductio ad Absurdum* rule [Take the premises and the negation of the conclusion] to the deductive inference.
4.Eliminate quantifiers of symbolized statements [existential quantifiers are eliminated by *Skolemization*]
5.Transform the expressions into *Horn clauses*
6. Apply resolution rule to any premises with inconsistent clauses
7.If you arrive at the *null* clause
    Success end,
8.Else goto step 2.

Quantitative induction is the last part of the mind processes. Even though, statistical generalization probability of inferences is applied (e.g., by using an interval estimation), we cannot conclude with certainty that the generalization to the population will be true when the sample set has been true. This is because in induction, where the form is not enough to check the correctness of an inference, there is a need for heuristic criteria to check what type of sampling we choose for a specific kind of population. Before we check whether a sample is random, large and varied enough, it is important that the heuristic checking of the meaning of quantitative and qualitative variables involved in population and sample is the most accurate possible. ID3 of Quinlan induces concepts from examples in a top-down way. Quinlan's decision tree induction algorithm, which is an intelligent algorithm, begins with the sample of classified elements of the target properties. ID3 relies heavily on its criteria for selecting the test at the root of each subtree.

Procedure: (ID3 algorithm)
Function induce_tree (sample_set, Properties)
Begin
If all entries in element_set (the properties of the sample set) are in the same class
    Then return a node labeled with that class
    Else if Properties is empty
    Then return node labeled with disjunction of all classes in element_set
    Else begin
        Select a property, P, to test on and make it the root of the current tree;
        Delete P from Properties;
        For each value, V (Yes or No), of P,
            Begin
Create a branch of the tree labeled with V
Let partition$_V$ be elements of sample_set with V for property P;
Call induce_tree (partition$_V$, Properties), attach result to branch V
            End;
        End;
End.

ID3 applies the induce_tree function recursively to each partition and can eventually reproduce a given tree.

If we accept that decision-makers would always behave perfectly rationally based on an immediate and accurate representation of the environment, we may have the *homo economicus*. However, even in financial domains, decision-makers some times make decisions based on emotions. In this paper, we are only concerned with a *logical* type of inferences related to decisions.

Procedure: (**Connection between HDSS and Decision-Maker Architecture**)
Begin
1. Select the problem
2. Activate HDSS and decision-maker structures
3. The decision-maker suggests a possible decision
4. Obtain the appropriate information from the HDSS
5. If decision-maker's possible decision is NOT guaranteed by HDSS
Goto 3
Else
    The decision is confirmed
6. End

The design of a system like this allows producing real interactions between HDSS and its user, the decision-maker.

5. Hybrid agents

Now let us consider *hybrid agents* as singled agents. They are like actors with different abilities. Those capabilities allow agents in an organization to accomplish individual and system-wide goals. Within an organization, agents play roles required by their goals [12]. We consider *goals* as a consistent set of desires (i.e., the state of affairs toward which the agent has a positive disposition).

For us, an agent's *state* is whatever information is available to the agent. We assume that the environment provokes the state in the agent. The agent takes sensory input from the environment and has an internal state, and produces, as out put, actions that affect the environment. The state of a hybrid agent is an instance of the set of the agent states at a point in time. The interaction between the agent and the environment is usually an ongoing, non-terminated one. Different agents may have different goals, actions and domain knowledge according to the type of decisions that in an organization these agents must take [16]. A key pattern of interaction in multiagent systems is goal and task oriented coordination. An organization (such as a commercial bank) possesses at least one goal, one role to accomplish the goal and one agent to play the role where the agent that plays the role must posses the capabilities required by the role. We consider a *role* as an entity that performs some functions within the system. It is similar to the roles played by actors in a typical company structure and have specific capabilities and relationships defined in order to meet the general company goal [12].

Robert Lucas provided the notion of an *economic agent*. This decision agent can be considered as a collection of decision rules and a set of preferences used to evaluate the outcomes arising from particular situation-action combination [1]. The premises of a decision inference are provided by the heuristic decision support system (HDSS) and the conclusion of that process, the actual decision, by the decision maker (or user of the HDSS). In Chen's paper (p.137), he makes a comparison between Lucasian agents and genetic algorithms (e.g., to decision rules correspond strings of binary ones and zeros, to decision rules review corresponds fitness evaluation, etc). We think that improving decision support systems with heuristic tools and notions such as hybrid agents is useful. This is because the important research in genetic programs and multiagent systems in the field of organizations in general and financial ones, in particular, is nowadays applied with restrictions. The traditional decision support systems, in turn, are applied everywhere without restrictions but they lack intelligent tools. In the near future, a research related to this topic of "hybrid agents" taking decisions and considering the decision-maker as the part of the agent that shows intelligence must be considered. In the user's part, we find the mechanisms of natural selection and natural genetics. In this way, the hybrid agent starting with an initial set of random solutions as a whole can converge to the best solution which hopefully represents the optimal or near-optimal solution for a decision problem [2].

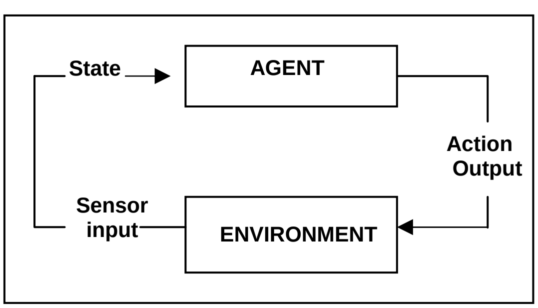

Figure 3. **The agent-environment interaction**

6. Connecting functions

In logic as well as in heuristics, a *function* is a relation that satisfies certain conditions. In the most general sense, a single-value function F(x) of one variable x is a correspondence by which, to each element x of a set X there corresponds a single element y of a set Y. The set X is called the *domain*. It is a function of a member of X taking a member of Y as *value*. Some times a function is called an *operation* on a member of X producing a member of Y. The set Y is the *range* of the function F. In our present case, the function *F* could be the following:

$$F(x) = S_n \rightarrow A_n$$

The stimulus of the environment creates a *state*, S_n, in the agent as input, and generates as output A_n, the agent's *action*. See Figure 3.

Another connective function, *G*, is a transition function among the agent's *states*. This function defines the ability of the agent in an organization. If we have one *agent's internal state* as input, the function *G* gives as output a different *internal state*. The function is as follows:

$$G(x) = S_n \rightarrow S_{n+1}.$$

The domain of both functions is the same, the set of all possible states produced by the stimulus of the environment. However, their range is different, it is the set of all possible actions in the first case, and the set of all possible agent's internal states in the second case.

The joint action of these two functions allows that, given the stimulus of the environment and the agent's internal state, an action is determinate that will change the environment. At the same time, the agent will have another internal state. The function *F* gives the answer of the agent to the stimulus of the environment. The function *G* gives the agent's natural learning (through the decision-maker part of the hybrid agent), which is how to change from one state to another.

7. Hybrid agents in a financial organization

A financial organization contains, in general terms, human and the software information sources. The fusion of data from these sources provides the foundation for the information for decision processes. In the paper, we assume that in a financial organization (e.g., a commercial bank), our hybrid-agents are economically rational. Further, the set of agents may be small, they must have a common language and common problem abstraction, and they must reach a common decision. Agents that follow this protocol create a deal (i.e., a redistribution of tasks). This deal is a joint plan among the agents that would satisfy all their goals. A conflicting deal appears when the agents cannot reach a deal, and the negotiation has to continue [17].

If we consider a limited setting, a decision-maker (i.e., a component of a hybrid-agent involved in a decision process), he will adopt or not a particular decision according to the information given by the correspondent HDSS. For example, in a financial organization such as a commercial bank, a big problem in these types of organizations is the credit-risk problem for physical persons as clients. For example, the main decision-makers must fix the bank policy related to possible loans to clients of that bank. The other decision-makers, directors of the corresponding departments, when a client applies for a loan, they must require the appropriate information from the HDSS about that client before making a decision. Then, they will take the decision of giving or not the money required. However, since credit risk is an index of uncertainty that could adversely affect the financial agreement, in order to reduce the uncertainty, commercial banks use diversification of risks. In order to avoid loses banks have collaterals on some loans. This protection reduces the uncertainty and possible losses produced by decisions related to credit risk.

8. Concluding remarks

We have presented a very simple model of a financial organization from a logical-heuristic point of view. This work is part of an effort of building a more fully useful financial organization based on a multi-agent system that contains hybrid agents as elements of that model. This will allow us to improve decision support systems used in financial organizations (e.g., a commercial bank). Another goal of this type of research is the idea of fully evaluating the effectiveness, for this model, of our organizational reasoning techniques with the hybrid agents involved in it. If a financial organization has become inefficient, then the use of this type of systems can help with a reorganization of the bank activities to improve the efficiency. In the near future, we plan to enlarge the application of this approach to other types of organizations.

Acknowledgements

We want to thank Dr. Daniel Heymann for his helpful comments and suggestions, and Dr. Fernando Tohme for his explanation related to the connecting functions.

References

[1] Chen, S-H. (2001). On the relevance of Genetic Programming to Evolutionary Economics. In J. Aruka (Ed). *Evolutionary Controversies in Economics. A New Transdisciplinary Approach*. Tokyo: Springer.

[2] Chingping, H. and Damronwongsiri, M. (2003]. A Genetic Algorithm Based Supply Chain Inventory and Distribution Cost Reduction Model. *Proceedings 7th Joint Conference on Information Sciences*. Durham, North Carolina: Association for Intelligent Machinery, Inc., pp 1049-1052.

[3] Marakas, G.M. (1999). *Decision Support Systems in the 21st Century*. London: Prentice-Hall International (UK) Limited.

[4] Marostica, A. and Tohme, F. (2000). Semiotic Tools for Economic Model Building. *The Journal of Management and Economics*. 4, pp 27-34.

[5] Marostica, A. (1992). *Ars Combinatoria* and Time: Llull, Leibniz, and Peirce. *Studia Lulliana*, XXXII. 87, pp. 105-135.

[6] Marostica, A. (1997a). A Nonmonotonic Approach to Tychist Logic. In N. Houser, et al. (Eds). *Studies in the Logic of Charles Sanders Peirce*. Bloomington: Indiana University Press, pp. 535-559.

[7] Marostica, A. (1997b). Semiotic Classifications for Inductive Learning Systems. *The Journal of Management and Economics*, 1, www.econ.uba.ar/sevicios/publicaciones/journal/

[8] Marostica, A. (1999). Semiotic Trees and Classifications for Inductive Learning Systems. Ed. By J. Deely et al. Toronto: Peter Lang Publishing, Inc., pp. 114-127.

[9] Marostica, A. and C. Briano. (2002). Towards the Implementation of the Heuristic-Information System. *Proceedings of the 6th International Conference on Complex Systems 2002*. Chuo University, Association for Intelligent Machinery, Inc. pp.1131-1134.

[10] Marostica, A. (2003). Decision-Making Processes in Organizations: A Logical-Semiotic Perspective. *KIMAS 2003*, Boston: IEEE, pp 254-259.

[11] Marty, R. (1989). *L'Algèbre des Signes. Essai de Sémiotique Scientifique d'Apres Charles Sanders Peirce*. Amsterdam: John Benjamin Company.

[12] Matson, E., and DeLoach, S. (2003). An Organization-Based Adaptive Information System for Battlefield Situation Analysis. *KIMAS 2003*, Boston: IEEE, pp 46-51.

[13] Peirce, C.S. (1857-1910). *Manuscripts and Letters. As Arranged in Annotate Catalogue of the Papers of Charles S. Peirce*. Ed. R.S. Robin, Cambridge, MA: University of Massachusetts Press, 1967).

[14] Shapiro, E, *et al*.(1996).*The Art. of PROLOG*: *Advanced Programming Techniques*. Cambridge, MA: MIT Press.

[15] Sousa, JMC, et al. (2002). *Fuzzy Decision Making in Modeling and Control*. London: World Scientific.

[16] Stone, P. (2000). *Layered Learning in Multiagent Systems*. Cambridge, MA: The MIT Press.

[17] Weiss, G. (Ed.) (1999). *Multiagent System. A Modern Approach to Distributed Artificial Intelligence*. Cambridge, MA: The MIT Press. Prologue, pp 1-9.