

Improving Support of Appropriate Executive Decisions by Combining Artificial Immune Systems and Fuzzy Logic

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Abstract

This paper presents a novel approach to support appropriateness of executive decisions by using combined principles of Artificial Immune System (AIS) and Fuzzy Logic (FL). The main goal is to show that more Appropriate Executive Decisions (AED) may be obtained if strategic decision makers are equipped with supportive tools based on AIS and FL (Fuzzy-AED). In addition, this work aims at improving the quality of the system response by adding new features to the original version of the AED model. A proof of concept for Fuzzy-AED is also included here along with experiments carried out within a real business environment. Experimental results suggest that this hybrid approach to executive decision making could be used to assemble helpful executive decision systems that may be easily deployed to reduce some of the risks inherent in strategic decision making.

1. Introduction

The organizational environment is governed by constant changes in its own dynamics. Hence, decision makers must deal with ever changing complex scenarios upon which they must analyze an increasing number of variables and strive to minimize the risks inherent in most executive decisions. As a complicating factor there is the short response time associated with some decisions in the face of a mounting global competition [1], [2]. The time to perceive, to analyze and to decide is frequently exiguous; thus the decision-making process is error prone, even for seasoned executive officers.

As with the Biological Immune System (IS) [11], organizations need intelligent mechanisms that produce speedy “decision homeostasis” to tackle the challenges of executive decision making. It should be emphasized that uncertainty is no stranger to the entrepreneurial routine [3], [4], [5].

Computational Intelligent (CI) techniques are widely used in real world applications, some of them highly successful in decision making support. Among CI techniques, AIS, drawing their inspiration from the IS

[16], contain interesting mechanisms that are deemed to be useful in tackling the difficult aspects of executive decision making namely, producing solutions to external threats. In a figurative way, it is possible to draw a parallel between the IS and organizations. In animals, pathogenic agents must be fought effectively by the IS [11]. In an organization, external inputs (*i.e.* information) feed the decision-making process, which drive deliberations into actions. These actions may result in success or failure depending on the quality of information gathered during the problem formulation phase [4], [5]. Analogously, success or failure in dealing with pathogens may also be achieved by the IS [11]. Appropriateness and velocity of responses are seminal in both systems.

Crisp evaluations of a factor in search of suitable decisions can be applied successfully in selected programmed decisions on structured problems. However, in most cases, crisp evaluation is not possible or even the best choice to deal with (i) unforeseen data and (ii) unstructured problems, especially those that present dynamic behavior [4], [13].

This paper presents an algorithm capable of: (i) evaluating appropriateness of prototypes of decisions and (ii) dealing with some of the existing uncertainties in executive decision making.

This paper is organized as follows: section 2 subsumes the background concepts necessary for understanding this paper: (2.1) artificial immunologic systems, (2.2) executive decisions, (2.3) Fuzzy Logic and (2.4) Appropriate Executive Decisions (AED). Section 3 details the proposed model and algorithm, Fuzzy-AED. In section 4, all experiments carried out are explained. Results are presented, commented upon and discussed in section 5. Finally, section 6 lists all conclusions drawn from the experiments.

2. Background

2.1. Artificial Immune System

Artificial Immune Systems (AIS) are inspired in the human immune system [18]. They try to mimic biological

behavior in order to solve real problems. This new paradigm is proving to be successful as a growing number of works have been published to a wide range of knowledge areas [15], [16], [17], [18].

The AIS approach aims at developing computational models which preserve some of the important characteristics of the IS. In general, there are three main components in immunologic engineering: (i) the model for representing elements of the system; (ii) mechanisms to evaluate the affinity between antigen and antibodies; and (iii) algorithms/models used for system control. Regarding to the latter, there are: (a) bone medulla, (b) negative selection algorithm, (c) clone selection algorithm and (d) immunologic network models [16], [18].

The Negative Selection algorithm is inspired in the process of cell recognition as it happens in the immune system (in the Thymus), where most of 'self' proteins are stored. Relating to this principle, in the AED algorithm, specific memory cells created to deal with a problem are saved during the training phase. These specific cells are recovered and stimulated to produce clones according to the affinity with the decision to be taken, in order to obtain a generic decision cell to this problem. The generated clones are not equal between themselves, because their receptors can be organized in different positions. The negative selection algorithm (NSA) proposed by Forrest *et al.* [19] was adapted according to specific purposes for clone generation to create appropriate decision cells [14], [20].

2.2. Executive Decisions

Life or death of organizations can be essentially decided by good or bad executive decision. An executive decision is a complex process which comprises: (i) problem understanding and characterization, (ii) comprehension about internal and external factors and (iii) knowledge about decision consequences to the organization [10]. Although possible to be inferred early, the real effect of strategic decisions can only be perceived after a medium to long-time intervals. Needless to stress that an organization can be severely affected by non-appropriate strategic decisions, which must be avoided at all costs [4], [7].

Executive decisions are complex especially because of their characteristics, namely, (i) problems dealt with are unstructured and infrequent; and (ii) data available to support decision making is mostly: qualitative, of uncertain reliability, imprecise, and obtained from either internal and external sources [8]. The complexity of executive decision making is further aggravated because most executive officers are constantly migrating between different organizations [6], [9].

Even though it is possible to establish a pattern procedure to repetitive decisions, it is very challenging to derive rules or guidelines for non-recurrent decisions. Therefore, best practices of decision theory together with intelligent computing approaches such as AIS, may be the answer to overcome the challenges of executive decision making [2], [4].

2.3. Fuzzy Logic

Executives frequently face situations in which they must make a decision without any extensive/external sources of information or help from any system of support. This problem is further aggravated because the information available is, more often than not, imprecise [4], [5].

Human-computer interaction is a highly relevant issue in information systems and can be considered a critical factor in the acceptance or not of executive information by its user. Thus a metaphor that can simplify the communication between executive and system is highly desirable [4].

Fuzzy Logic, created by Lotfi Zadeh [13] as an extension of Aristotelian Logic, presents the following main characteristics: (i) it deals well with imprecision in its input variables; (ii) it works internally with linguistic variables and degrees of membership; and (iii) it performs inference over a rule set obtained (frequently) from a human specialist. Thus, a natural application of Fuzzy Logic is to simplify the Human-computer interaction.

Because of its characteristics, Fuzzy Logic has been used in a wide range of applications and has achieved success, particularly in situations where Aristotelian logic does not work well. For example, the boundary between an appropriate and a more appropriate decision is not easily detected. Hence, a method that can tackle flexible boundaries in decision making has a good chance of outperforming traditional methods. In addition, complex processes that can be modeled through a rule set are candidates for receiving back up from Fuzzy Logic [12].

In this study, Fuzzy Logic was employed with a two-fold purpose: (i) to benefit from a specific rule set to support executive decision making and also (ii) to improve the quality of these decisions, since the semantic gap between how the executive thinks (to draw conclusions) and how the system operates can be significantly reduced.

2.4. Appropriate Executive Decisions (AED)

AED – the original proposal of Caldas *et al.* [22] was the creation of an analogy between the IS and the information system of an organization. Its main contributions (and how AIS are seminal to AED) were:

1) The formal definition of a model to correlate the biological and organizational domains. Figure 1 shows the immunologic response for an organism (affected by a non-appropriate agent) and equivalent homeostatic response for organizations (through the action of external information).

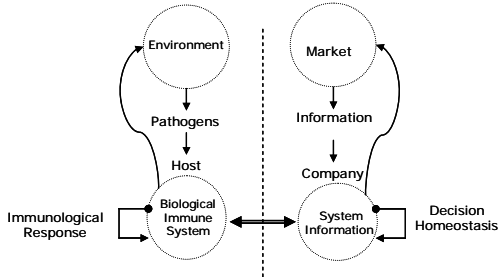


Figure 1. Analogy between the IS (left) and a decision system of a company (right). Immunological responses to environment attacks are compared with decisions taken by executives of companies in response to market demands as proposed by Caldas *et al.* [22].

2) According to Simon [5], the decision process encompasses four phases: (i) problem perception, (ii) problem formulation, (iii) evaluation of alternatives and (iv) alternative selection and subsequent implementation. Figure 2 (left) presents the relations between phases of IS [11] and equivalent phases of a decision process (right). The AED algorithm contributes as a supportive tool for decision makers, in each of the three points indicated by AED in the Figure (on the far right).

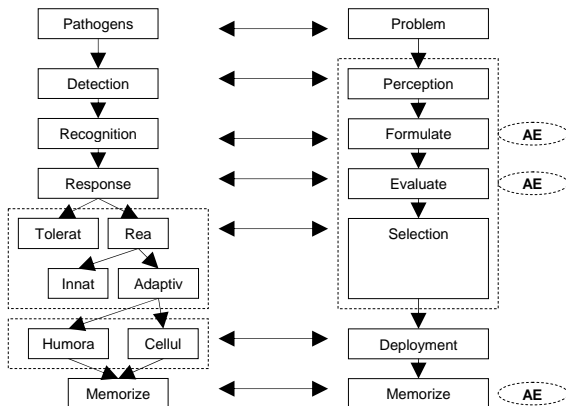


Figure 2. Relation between IS (left) [13] and decision process (right) [5], highlighting AED contribution in each phase of the task.

According to the view of Chiavenato on Decision Theory [4], every administrative problem is equivalent to a decision process. In line with that AED supports the decision maker by generating appropriate decision cells, or evaluating decision cells informed by the user. That is, AED is capable of memorizing the judgment of a decision maker about past decisions.

During the creation of decision cells (*i.e.* training phase of AED), receptors are allocated according to their priority, informed in the interval {1-10} by the decision maker.

3) The concept proposed by Oliveira *et al.* [21] was extended and adapted to create a specific hierarchy for strategic decision. This hierarchy inspired an abstract model to relate receptors and lymphocytes presented in Figure 3. The specificity of lymphocyte B is correlated with decision receptors of the problem at hand, in the sense of neutralizing the evaluated information. The use of the AED algorithm in different domains is only a matter of training, as appropriate cells concerning each specific task will be memorized for every given task (*i.e.* different decision problems).

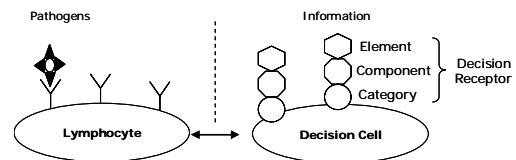


Figure 3. Analogy between lymphocyte (left) and a decision cell (right) as proposed by Caldas *et al.* [22].

4) In the training phase of the AED algorithm, see Figure 4, appropriate cells of a certain type (*e.g.* tasks such as buying, selling and marketing) were saved after being evaluated by the decision maker. In the operational phase, according to the type of cell requested by the decision maker, clones of memory cells are randomly generated according to the quantity of receptors in each memory cell. The main purpose is to generate a number of clones with diverse characteristics among themselves that are within the affinity range proposed by the decision maker. The information affinity is measured using the Hamming distance between the clones, and each memory cell selected in the repository (*i.e.* the artificial thymus). The objective of that is to identify clones which have more appropriate receptors (*i.e.* pieces of information) according to the problem presented. In case of cell evaluations performed in AED-Fuzzy, only affinity and participation are calculated, as will be described next.

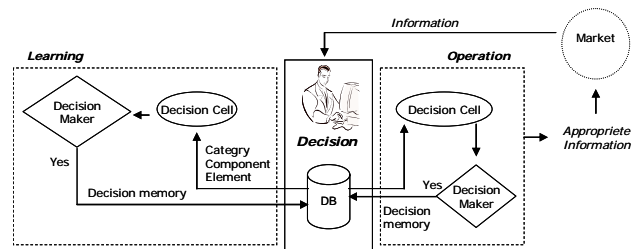


Figure 4. Overview of the original AED algorithm.

3. Fuzzy-AED

Fuzzy-AED extends AED by incorporating support to linguistic variables of the decision maker. Figure 5 presents the proposed architecture for combining AIS and Fuzzy Logic. The executive officer inputs a decision cell *e.g.* the tuple {Price, Quality, Customer Support}, participation of decision receptors and the certainty level he/she has on this decision input cell; the interval used was {0..10}. The AED System, then, calculates the affinity levels of the input cell in relation to all stored memory cells.

Next, participation, affinity and certainty are evaluated by a fuzzy classifier, which presents the decision evaluation as output. This evaluation can result as one of the following classes: (i) Appropriate+, (ii) Appropriate or (iii) Appropriate-.

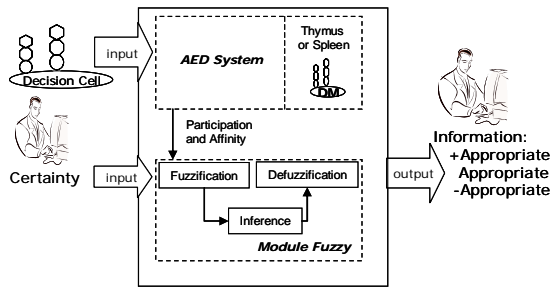


Figure 5. Overview of the proposed Architecture.

In order to test the approach presented, a custom-made executive decision system was implemented, according to the algorithm presented in Figure 6.

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//Appropriate Executive Decisions Fuzzy
AEDFuzzy(a,dc,c)
a: decision type
dc: decision cell
c: certainty
//Learning stage – finished
while decision maker is not satisfied
  Module AED
    input ( a, dc )
    output (Participation and Affinity)
  Module Fuzzy
    input ( Part., Affin. and Certainty)
    fuzzification
    inference
    defuzzification
    output(+Appro. or Appro. or -Appro.)
end while

```

Figure 6. Pseudocode for the new Fuzzy-AED algorithm.

Three linguistic variables were included, each with three fuzzy sets. It is important to mention that the number of variables as well as fuzzy sets can be increased according to the application need. In this example, the variables considered were:

1) Information Participation: the frequency of occurrence of each decision receptor in the permanent

repository (*i.e.* artificial thymus) in the AED System. Information Participation indicates how much receptors presented in a decision cell are aligned with the organizational culture.

2) Information Affinity: the distance between the input decision cell and all other memory cells, and it is equal to the smallest distance (bigger affinity) to all decision cells in the repository (artificial thymus). The affinity indicates how close the informed cell is, in relation to the pattern established by the organization.

3) Information Certainty: indicates the degree of confidence the executive has in all information contained in the decision input cell.

The Fuzzy Module employed triangular membership functions for input and output. It was used three functions for each considered I/O category, in the following order: (i) low, medium and high for Information Participation and Certainty, (ii) high, medium and low for Information Affinity (*i.e.* an inversely proportional metric) and (iii) the only output – Appropriateness – was classified as Appropriate(-), Appropriate and Appropriate(+). The inference method used was Takagi-Sugeno [23], using weighted-average for defuzzification. Table 1 presents rules drawn from the rule matrix, *i.e.* a total of 27 rules.

Table 1: Rule Matrix used in the Experiment

Decision order	Fuzzy variables			User answer
	Participation	Affinity	Certainty	
01	Low	Low	Low	A(-)
02	Low	Low	Medium	A(-)
03	Low	Low	High	A
04	Low	Medium	Low	A(-)
05	Low	Medium	Medium	A(-)
06	Low	Medium	High	A
07	Low	High	Low	A(-)
08	Low	High	Medium	A(-)
09	Low	High	High	A(+)

Further details on the rule matrix and AED Training are given in the next section.

4. Experiments

A field research was conducted to collect appropriate decision information from a group of 20 executive officers working with strategic purchase decisions in the IT sector in the northeast of Brazil.

Since the information deals with critical processes of each organization, the data had strong confidentiality constraints. Some executive officers (not included in this study) totally refused to disclose their purchase strategy. Notice that the experiment carried out here is a proof of concept for Fuzzy-AED, so qualitative aspects are more important than quantitative ones. This fact does not diminish the value of the experiment, since its main goal

was to verify whether Fuzzy-AED is able to produce useful executive decision support.

In order to guarantee information quality, each of the executives was chosen from the upper echelons of medium-to large established organizations (*i.e.* all of them operating in the abovementioned market/region for more than 10 years).

Data acquisition and manipulation for the simulation comprised the following activities:

- 1) Gathering of information from executives, respecting their preferences and priorities regarding information participation and certainty of purchasing;
- 2) Fuzzy-AED training;
- 3) Generation of the rule matrix for the Fuzzy classifier;
- 4) A questionnaire was prepared with 20 distinct solutions for solving a given problem. To create this questionnaire, 20 decision cells and certainty levels were randomly generated by AED.
- 5) Five executive officers were then randomly selected to take part in the next phase. That is, each executive was asked to evaluate each of the 20 solutions as Appropriate(+), Appropriate or Appropriate(-).

A small excerpt of possible answers contained in the questionnaire is shown in Table 2. Decision cells (rows in the table) had 3 to 10 priority levels. Certainty assumed values from 5 to 10.

Table 2: Excerpt of possible answers to the questionnaire applied to the executive officers. Each row contains an example of decision cell and certainty level.

Priority 1	Priority 2	Priority 3	Certainty
Price	Quality	Supplier	8
Quality	Price	Waranty	5
Waranty	Quality	Price	10

Executives were instructed to evaluate each decision according to information participation, priority order (of decision receptor) and degree of certainty. Results are shown in the next section.

5. Results

After analyzing the executives' answers to the questionnaire, a high level of dispersion concerning the evaluation of each alternative was detected. This fact can be characterized by different strategic positioning towards the market, which is perfectly acceptable.

In order to make a more significant analysis, in the face of this data distribution, system outputs were compared to those evaluations informed by executives and grouped into three categories: (i) Match, (ii) Conservative and (iii) Aggressive. Examples can be seen in Table 3.

Figure 7 presents the three decision categories of

system evaluation by each executive.

Table 3: Classification results as Match, Conservative and Aggressive.

Executive	AED-Fuzzy	Classification
Appropriate+	Appropriate+	Match
Appropriate-	Appropriate-	Match
Appropriate	Appropriate	Match
Appropriate	Appropriate-	Conservative
Appropriate+	Appropriate	Conservative
Appropriate+	Appropriate-	Conservative
Appropriate-	Appropriate+	Aggressive
Appropriate-	Appropriate	Aggressive
Appropriate	Appropriate+	Aggressive

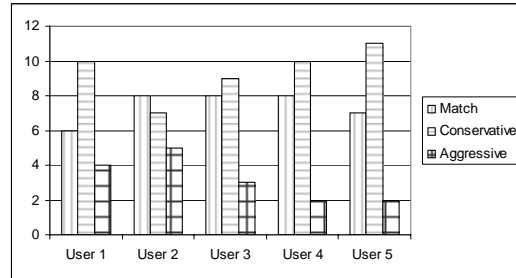


Figure 7. Distribution of the considered categories of assessment

A summary of the results is presented in Table 4. The number of matches was 37% on average. When added to conservative cases, the Fuzz-AED performed well over 70% than worst case scenario. This means that the system was conservative in most cases, which is highly desirable in reducing risks of strategically not appropriate decisions.

Table 4: Result of evaluations of AED-Fuzz by five Executives (Ex.) selected randomly as a control sample

	Ex. 1	Ex. 2	Ex. 3	Ex. 4	Ex. 5	Avg.
Match	30%	40%	40%	40%	35%	37%
Conservative	50%	35%	45%	50%	55%	47%
Aggressive	20%	25%	15%	10%	10%	16%

It is possible, that when the system output presented conservative or aggressive evaluations, it was because it adhered more strictly to its training (repository in thymus) than the executive himself. These answers can warn the executive that he/she may be moving too far from his/her own decision pattern. This can be very useful for maintaining the long-term consistence of decisions. In such cases, an interested executive officer can further analyze his/her current rationale, to avoid risky decisions.

6. Conclusion

This paper presented an enhanced approach to evaluating the appropriateness of executive decisions. It also aimed at improving the quality of executive decision making as well as reducing its inherent uncertainty. The

proposed approach combines immune inspired features with Fuzzy Logic and is capable of learning decision patterns to further coupling them with linguistic variables.

Experimental results achieved an average of 70% decision evaluated in categories conservative and match, when compared to the executive officers' own evaluations. This may suggest that AED-Fuzzy can be reliable enough to support executives in real problems, mainly because it will gradually adapt even further to their cognitive style. Thus, reliability and performance are expected to increase over time. Yet, if executive officers need aggressive decisions, AED is also able to provide.

The executives interviewed deemed the system to be easy to operate, especially since inputs and outputs are at their same communication level. This observation indicates that Fuzzy Logic has achieved its main purpose.

Acquired data presented a great dispersion, in some cases; this variability can be blamed for having misled executives to perceive property level as good, by ignoring the information order of precedence. Fortunately, in these cases the system has consistently presented conservative behavior; thus confirming its usefulness as a supportive tool for helping to reduce inappropriate decisions.

Based on the results obtained so far, we are confident to suggest that a well trained Fuzzy-AED may act as a savvy companion of executive decision makers in their difficult and lonely tasks. The system is capable of offering fast, appropriate and reliable insights during the phases of formulation, evaluation, and memorization of the decision process, indicated in Figure 2.

Future works include the use of extra decision variables such as benefits, impacts and urgency of a decision. Other principles of AIS and different parameterizations of fuzzy sets and rule matrix could also be used to further increase the reliability and quality provided by Fuzzy-AED.

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