Integrating Evolutionary Computing and the SADDE Methodology

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ABSTRACT

This paper introduces a methodology to help the programmer in the transition from a set of desired global properties expressed as an equation-based model (EBM) that a Multi-Agent System (MAS) must fullfil to an actual society of interacting agents. We report the use of evolutionary programming techniques to tune the parameters of the populations of agents so their aggregated behaviour maximaly approaches the desired global properties as specified by the EBM.

Categories and Subject Descriptors

I.2 [**Computing Methodologies**]: Artificial Intelligence; D.2 [**Software**]: Software Engineering; I.2.11 [**Artificial Intelligence**]: Distributed Artificial Intelligence—*intelligent agents, multiagent systems*

General Terms

Experimentation

Keywords

Evolutionary computing, MAS specification methodology

1. THE SADDE METHODOLOGY

We take the stance that in order to build a model for a society containing thousands or millions of agents, the general view provided by an Equation-Based Model provides succint descriptions of population-level behaviours which we then attempt to replicate building models consisting of a society of individual interacting agents, that is, an Agent Based Model (ABM). Our proposed lifecycle is graphically depicted in Figure 1.

An important characteristic of MASs design from a software engineering perspective is the decoupling of the interaction process between agents from the deliberative/reactive activity within each agent, [1, 5]. The notion of *electronic institution* [2, 3] plays this role in our methodology by establishing a framework that constraints and enforces the acceptable behaviour of agents.

The different phases within SADDE are:

[Step 1] **EBM − Equation-Based Model**. In this first step, a set of state variables and equations relating them must be identified. These equations have to model the desired global behaviour of the agent society and will not contain references to individuals of that society. Typically these variables will refer to values in the environment and to averages of predictions for observable variables of the agents. We model yet-to-exist artificial systems. The EBM is the starting point of the construction of a system that later on will be observed. Thus, a comparison between the EBM predicted behaviour and the actual ABM behaviour will be obtained.

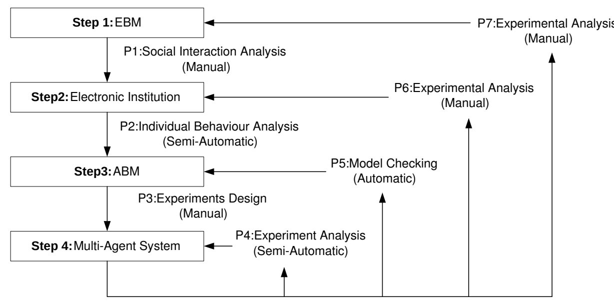

Figure 1: SADDE Methodology

[Step 2] **EIM − Electronic Institution Model**. In this step the interactions among agents are the focus. It is a first "zoom in" of the methodology from the global view towards the individual models. This step is not a refinement of the EBM but the design of a set of social interaction norms that are consistent with the relations established at Step 1.

[Step 3] **ABM − Agent-Based Model**. Here, we focus in the individual. We have to decide what decision models to use. This is the second "zoom in" of the methodology. New elements of the requirement analysis (new variables) will be taken into account here. For instance, some rationality principles associated to agents (*e.g.* producers do not sell below production costs), or negotiation models to be used have to be selected.

[Step 4] **Multi-Agent System**. Finally, the last step of our methodology consists on the design of experiments for the interaction of very large numbers of agents designed in the previous step. For each type of agent the number of individuals and the concrete setting for the parameters will be the matter of decision here. The results of these experiments will determine whether the requirements of the artificial society so constructed have been consistently interpreted throughout the methodology and thus whether the expected results according to the EBM are confirmed or not.

AAMAS'03, July 14–18, 2003, Melbourne, Australia.
ACM 1-58113-683-8/03/0007.

Once the experiments designed at Step 4 are run and analysed, several redesigns are possible as shown schematically in figure 1. Further details on the SADDE methodology can be found at [4].

2. EVOLUTIONARY PROGRAMMING IN SADDE

We have investigated the use of Evolutionary computing to explore the space of possible configurations of MAS populations. Figure 2 illustrates it graphically. We want to use as the initial population of the evolutionary computation algorithm a set of MASs that fit with the schema obtained through the SADDE methodology, and then use evolutionary computation to obtain a set of MASs that fit optimally with the EBM.

In order to determine the fitness function we have to put in relation global EBM properties with individual variables so that by selecting MASs that maximize some functions over those variables we approach the desired global behaviour. In general, we might have a set of properties that we want the MAS to satisfy along time. Each property can be modeled as a function over a vector $\mathbf{X}$ of state variables in the EBM and over a vector $\mathbf{Y}$ of state variables in the ABM. Vectors $\mathbf{X}^t$ and $\mathbf{Y}^t$ represent the values of the variables at instant t of time. That is, a comparison function φ is defined as:

$$\varphi\left(\mathbf{X}, \mathbf{Y}\right) = g\left(h_X\left(\left(\mathbf{X^t}\right)_{t\in T}\right), h_Y\left(\left(\mathbf{Y^t}\right)_{t\in T}\right)\right)$$

where h_X is a function that given the temporal evolution of $\mathbf{X}$ transforms it into a value to be compared, by means of g, with the transformation made by h_Y to the temporal evolution of $\mathbf{Y}$. For instance, to apply a quadratic means error comparison, we must take $h_X = h_Y = id$ and

$$g\left(\mathbf{X}, \mathbf{Y}\right) = \sqrt{\sum_{i\in I}\omega_i \cdot \sum_{1\le t\le T}\left(X_i^t - Y_i^t\right)^2}$$

where g's range must be, obviously, the real line and ω_i is a normalizing parameter.

Thus, we can define the fitness function for a given instance of an EBM model ($\mathbf{X}$) as:

$$f(\left(\mathbf{Y^t}\right)_{t\in T}) = h(\varphi(\left(\mathbf{X^t}\right)_{t\in T}, \left(\mathbf{Y^t}\right)_{t\in T})$$

where h maps the range of g over $[0, 1]$.

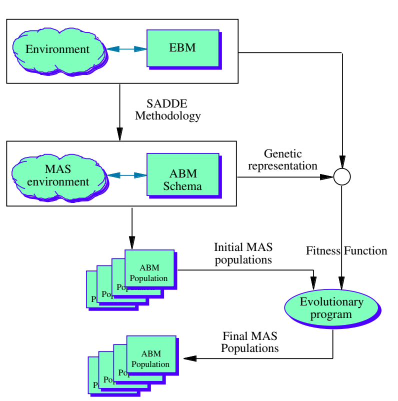

Figure 2: Evolutionary computing within SADDE.

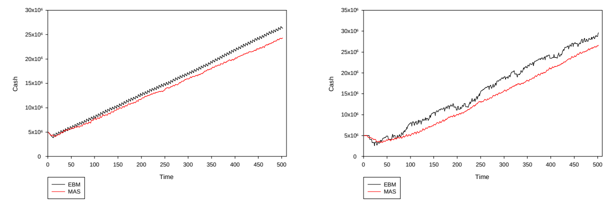

Figure 3: EBM evolution of Cash1 (left) and Cash2 (right) and comparison with the best found MAS.

3. EXPERIMENTAL RESULTS

The application of the SADDE methodology to a supply chain scenario has shown the feasibility of the approach. In some of our experiments the comparison function is the minimum of the difference of the slope of the regression lines obtained from $\mathbf{X} = \langle Cash_1, Cash_2\rangle$ and $\mathbf{Y} = \langle SumCash_1, SumCash_2\rangle$. Where $Cash_1$ and $Cash_2$ are the global variables used in the EBM to represent the amount of cash at two levels of a supply chain and $SumCash_1$ and $SumCash_2$ are the summation of the Cash of all agents at those two levels. That is,

$$\begin{aligned}\varphi(\mathbf{X}, \mathbf{Y}) = \max\ (&|slope(t, Cash_1^t) - slope(t, SumCash_1^t)|,\\ &|slope(t, Cash_2^t) - slope(t, SumCash_2^t)|)\end{aligned}$$

and the fitness function is defined as:

$$f(\mathbf{Y}) = e^{-0.2\cdot\varphi(X,Y)}$$

As an example of the results obtained you can see the evolution, in one of the experiments, of the variables $Cash_1$ and $Cash_2$ of the EBM and of the best MAS found by the GA in Figure 3. This experiment shows that the ABM obtained the same behaviour that the EBM predicted.

4. ACKNOWLEDGEMENTS

This work has been partially supported by the Spanish CICYT project eINSTITUTOR (TIC2000-1414), and by the European research project SLIE (IST-1999-10948).

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