TOWARDS A NEW EXPERIMENTAL ECONOMICS.
Complex Behaviour in Bargaining.

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"Approximating the strategies used by players...will be the area of future research in which low-rationality adaptive game theory will need to interact most closely with cognitive theory"

Erev et al (1998)

ABSTRACT

Game theory has provided a rigorous conceptual support to analyse strategic decisions and bargaining behaviour. But it shares with competitive equilibrium three basic assumptions. The players are fully rational; they comprehend the faced situation; and they know all the relevant institutional parameters. In this paper we deal with players that are bounded rational. The bounded rational behaviour is empirically obtained from a laboratory experiment with human players. Then we demonstrate that the observed behaviour can be captured in a cognitive multiagent modelling with artificial agents, and we replicate the observed results in a natural way. The model accommodate, both declarative and procedural rationality: i.e rationality as a process and as a product of learning.

KEYWORDS. Computational Organization. Complex Behaviour in Bargaining. Multiagent Systems. Market engineering.

JEL classification codes: C63, C92, D83, L14.

1.-INTRODUCTION.

The paper reports work in progress on the application of MAS to the design and engineering of economic institutions, which began with the first author Ph.D., López (2000). Economics is the science which deals with social organizations in relation to the well-getting wealth using and its distribution. Yet when Economics' methods are exported to other sister social sciences, from law to politics or to the bedroom relationship, it was reconverted in the study of the allocation of scarce resources among competing uses. In this way rational behaviour was narrowed to optimization, under suitable analytical constraints, thus clearing the field of any other dimension of human behaviour. No attention is given to motivations, emotions or social learning. The basic inquire of any science, *the true nature of things,* is substituted for predictive performance. Neoclassical Economics assumes that people are highly rational and can reason their way out through the complexity of the Economy. No wonder Economics does not catch up with the Economy under this *"as if"* approach, Hernández et al (2000).

The Economy is *complex* because we observe just real aggregated data, that comes from simple agents' myriad interactions. So that from a macro observation post, the mathematical approach may be very difficult or computationally intractable. But if we adopt a micro definition of even heterogeneous but human agents, the resulting MAS model may be generated in a reasonable and realistic way. In Hernández et al. (1999) and (op.cit.) we examined this issue. We showed that a posted offer auction with many buyers (300) and some sellers (15) can be generated from heterogeneous agents with cognitive capacities. They have limited memory and limited deliberation-action time; partial knowledge, emotions and reputation. We looked for regularities that emerged from the interaction of the agents, and to what extent market efficiency is improved by engineering organization technology: a board (Internet) where sellers, buyers and producers (airline companies) put their bids, asks and reputation. **But there were not strategic interactions between the agents.**

In this paper we deal with the other source of complexity and bounded rationality in Economics. Bounded rationality is understood as rationality exhibited by actual economic behaviour. This means that we have to consider the behavioural limitations and emotional positions of heterogeneous agents that have to learn from each others decisions and actions and that think strategically. We present a procedure for modelling complex behaviour in bargaining. First an experiment is conducted in the Laboratory of the E.T.S. Industrial Engineering, with both fifth year undergraduates and young teachers. They played a repeated game with asymmetric information, for thirty rounds. The revealed patterns and corresponding gains are then classified and used to endorse artificial behavioural agents, using a **cognitive** model language, SMDL. The results of the artificial MAS simulations confirm that we are able to reproduce reasonably well the observed human behaviour, and they open a promising alternative to simulate and engineer the strategic competition.

Some comments are due to fix up the terms of this research. The application of game theory has been an important development in microeconomics. It is conventional wisdom to use it to understand how markets evolve and operate, and how managers should think about the strategic decisions they continually face. For instance, the prisoner`s dilemma when repeated over time clears some of the logical inconsistencies of Cournot, Bertrand or Stackelberg oligopolies. It allows us to show how firms can make strategic moves that give them an advantage over their competitors or the edge in a bargaining situation. How firms can design pay off matrices that allow to develop credible threats, promises, or deter entry by potential competitors. Nevertheless game theory is concerned with the following question: *If I believe that my competitors are rational and act to maximize their own profits, how should I take their behaviour into account when making my own profit-maximizing decisions*?. This question is in itself difficult to answer, even under conditions of complete symmetry and perfect information.

When trying to advance an equilibrium solution one has to assume some kind of intuitive plausible information and learning strategy, plus the most likely emotional response of the contenders. The outcome of a repeated play of a game is path dependant and should be found through a process modelled using some form of learning theory. But since not such a learning theory is available, one has to enforce some mechanical replicator mechanism Peyton (1998), or to model observed behaviour, from controlled experiments (reinforcement learning Erev at al., op.cit., recommended play Brandts et al., 1995, etc). Experimental economics has shown that simple but robust learning and coordination models can predict observed experimental outcomes And the outcomes of these experiments are frequently at odds with rational game theory predictions.

An empirical-based general theory of learning under bounded rationality remains a formidable task for the future, but a claim is gaining acceptance. ***"Approximating the strategies used by players... will be the area of future research in which low-rationality adaptive game theory will need to interact most closely with cognitive theory",*** Erev et al. (1998) and Selten for related work. We would like to consider our paper as a contribution in this direction. We replace learning procedures as used in adaptive game theory, based on mechanical and optimizing players, for cognitive learning agents whose decisions are agenda based.

Although the approach can be labelled as ACE or MAS i.e computational organization, there is a subtle difference with some works in the field. The agents have cognitive capacity and emotions. Thus object oriented programming languages will not be sufficient, since our agents are not objects. They request actions to be performed. In the object-oriented case, the decision lies with the object that invokes a method. In the agent case, the decision lies with the agent that receives the request. *Objects do it for free; agents do it for money*, could be a sharp slogan to indicate the difference.

The assumption of perfect rationality is an imperfect description of real human behaviour. Experimental studies of decision-making (see Camerer´s,1995 and Conlisk´s ,1996 surveys) find inconsistencies with the *SEU* version of rational choice. Models that embody SEU theory are incapable of fully explaining economic activities like incomplete contracts, advertising, transfer pricing etc. This situation led some researches, from Simon (1982) to demand models in which players are bounded rational. Should we consider from now on NASH rational equilibrium as futile armchair economics? Certainly not, as Myerson (1999) cleverly argues.

First as indicated above, an empirically based general theory of bounded rationality (if such generality makes sense) remains a task for the future. A second reason is that the functional goal of social science is not just to predict human behaviour in the abstract, but in relation to a particular social institution and in a contingent context. And to separate, the inefficience of the institutional setting from the inefficiency of agents behaviour will be even more difficult. Thus applied social theorist and market engineers, should find useful to analyse social institutions under the assumption that every member of that society will act, within their domain of control, to maximize welfare as they evaluate it, given the likely behaviour of others.

"*Notice that this argument does not prove that Nash equilibrium should be the only methodological basis for analysis of social institutions. But it does explain why studying Nash equilibria should be a fruitful part of the critical analysis of almost any kind of social institution*" (Myerson, op.cit.)

Thus in spite of the efforts of research like this work, Nash rational equilibrium will be with us for a long time.

2.-ARTIFICIAL AGENTS TO DEAL WITH BOUNDED RATIONALITY AND COMPLEXITY.

The Economy is indeed a **miserable experiment**. That is why we have to simulate and grow up stable aggregated behaviour. We have short data records, that sometimes are of low reliability. It is difficult to test hypotheses concerning the process from individual behaviour to aggregated regularities, in the usual way. In some areas, it may be that simulating economic processes with well founded cognitive models by trial and error procedure, is really the best we can do.

The representative agent is not a realistic assumption to start with. We have to deal with bounded rational agents, with finite processing capacity and without explicit utility functions. They adapt and settle for satisfaction under rules of thumb. They have emotions. And they are rather heterogeneous. Even if the resulting model with a representative full rational agent has high predictive capacity, it is still important to replicate the observed patterns from models with heterogeneous and bounded rational agents.

The method we use, MAS, can help to overcome the lack of capacity of Economics to explain the Economy as a process. General equilibrium theory and its more rigorous game theory approach to strategic firm behaviour, have been concerned mainly with static equilibria, ignoring process dynamics. MAS and computational organization, we claim, is a natural and very soon popular methodology for studying dynamics in social systems.

The following comments on complexity and rationality will be conditioned by our generative approach. The aim is to provide initial micro specifications for the artificial agents, environment, and production rules that are sufficient to generate the macrostructures of interest. We shall not enter into other philosophical discussions, on rationality or complexity.

Complexity is a term used in many ways according to different schools; see Barkley (1999) for a recent survey. Most users come from the field of nonlinear dynamic models as applied to Economics. Complexity is then, the fourth C in this line of research: cybernetics, catastrophe, chaos and complexity. But the field of complexity is controversial and unsettled. And there is no accepted definition of the term. There have been two prevailing views . A dynamical system is complex if it endogenously does not tend asymptotically to a fixed point, a limit cycle, or an explosion. Alternatively a situation exhibits complexity when there is an extreme difficulty of calculating solutions to optimization problems. We use this view of complexity, that in turn comes from two sources.

From the aggregate outcome of simple agents´ myriad interactions taking notice of each other agents´actions: institutional complexity. In these interactions, agents relate to each other and with the environment through agent-environment production rules, and agent-agent rules. We release an initial population of agents into the simulated environment and watch for macroscopic spontaneous order. This was the problem we addressed in Hernández et al. (1999, 2000 op.cit.)

From agents trying to model other agents modelling of them, modelling those agents, ad infinitum. This is the main source of complexity in game theory. Expectations about other agents strategic behaviour. This is the view we take in this paper.

Some selected facts on bounded rationality.

To endorse our artificial agents with instruments for unbounded rational, but consistent behaviour, one has to recall some facts.

(i) <u>The basic dimensions</u>. Following Selten (1998), the mental bounded rationality process comes from the interaction of, motivation (the driving force) adaptation (routine adjustment without reasoning) and cognition (reasoning and deliberation). Thus our cognitive approach has to accommodate a process for reasoning and a process for adaptation. An this implies that unbounded rationality goes far beyond "the imitation paradigm" as in Vega-Redondo (1999).

(ii) <u>Bounded rational agents are computationally strong</u>. Full rational decision -making methods (the usual methods drawn from logic, mathematics, and probability theory) are computationally weak: incapable of solving the natural adaptive problems.

"Despite widespread claims to the contrary, the human mind is not worse than rational (e.g. because of processing constraints) but may often be better than rational. On evolutionary recurrent computational tasks, such as object recognition, grammar acquisition, or speech comprehension, the human mind greatly outperforms the best artificial problem-solving systems that decades of research have produced... How can this be? General-purpose systems are constrained to apply the same problem-solving methods to every problem and can make no special assumptions about the problem to be solved. Specialized problem-solvers are not handicapped by these limitations... Natural selection could equip humans´ cognitive specializations. For the problem domains they are designed to operate on, specialized problem-solving methods perform in a manner that is better than rational". Cosmides et al. (1994).

The departure from rationality does not at all imply that we retreat, *malgré nous*, to second best outcomes. Thus individual adaptive and satisfying learning does not necessary lead to inferior emergent results.

(iii) <u>Spontaneous order and the social component</u>. The wide variety of situations where the social interaction outcome was surprisingly different from individuals motivations and expectations, first shown in Economics by Schelling (1995) and then in the wide literature of experimental economics, underlies the fact that institutional rules themselves matter and change as a result of myriad of individual actions. This causes the spontaneous order as outcomes from bounded rational agents which can be more efficient than expected from rational agents. Thus learning and knowledge acquisition has a social component. Our instruments for bounded rational agents, explicitly should make methodological individualism and social knowledge compatible views.

(iv) <u>Simons´ Ltd</u>. Bounded rational modelling should then include: motivations (and perhaps emotions), adaptation to accommodate social learning (can I name them knowledge externalities?) and cognition. But is there a place where we could find such desirable stock of tools to model our bounded rational agents?. The answer is yes, surely. The concepts warehouse is Simons´ Ltd. , the premises to be located in his collected work, Simon (op.cit.). The cognitive facilities to assemble his ideas of procedural and substantive rationality are available in recent developments by Anderson (1993). The convergence of these two contributions allows for a consilient unification of the social science with a reasonable balance of relevance, realism and rigour.

In a nutshell Simon distinguishes between *substantive rationality* —we prefer to call it declarative knowledge, taking from Anderson (op. cit.)— and *procedural rationality*. Substantive rationality refers to behaviour that is appropriate to the achievement of given goals within the limits imposed by given conditions and constraints. On the other hand, behaviour is procedural rational when it is the outcome of appropriate deliberation. It is the outcome of some strategy of reasoning within the repository of valid rules, and it is selected among those credited as the best so far.

The following classroom example, Pindyck et al. (1995) will help to clarify the two concepts. Three contestants A. B and C, each have a balloon and a pistol. From fixed positions, they fire at each others balloon. When a balloon is hit, its owner is out of the game. When only a balloon remains, his owner is the winner and receives a $1000 prize. At the outset, the players decide by lot the order in which they will fire, and each player can choose any remaining balloon as his target. Everyone knows that A is the best shot and always hits the target; that B hits the target with probability 0.9 and C with probability 0.8. Which contestant has the highest probability of winning the $1000? When asked to advance an answer within five minutes, some will come up with a reasonable and correct one: Contestant C.

The intuitive argument —cognitive efficient— is that, as in real life, under perfect rationality , the observed fact is that mediocre are the winners as well: this is procedural rationality. Of course, in this case, declarative learning will lead to the same answer that substantive one. Ancillary assumptions about the emotional attitudes of the contestants: aggressive selfishness are needed. There is a well specified protocol for the game, a sequentially random order.

In the rest of the paper we shall describe how these ideas have been implemented in a two players repeated game with asymmetric information. First the observed behaviour is taken from a Lab. experiment with human players. Then the artificial agents are modelled using the SDML as developed by Moss et al. (1998). Simulations with this last model do reproduce the observed strategies in the real experiment. For full details see López op.cit. [chapter 4].

3.-EXPERIMENTAL ECONOMICS: A TWO STAGE REPEATED GAME.

To obtain knowledge of the players strategic behaviour, an experiment was conducted at the Lab with students in their fifth year and young teachers of the Department of B.& Ec. There are two players. P1 takes his decision with information about a state of nature. But then P2 has to make his choice without knowing the true state of nature. Perhaps P1 supplies to P2 a product-service of alternative quality, say H or L. The associated probabilities for states H and L are 2/3 and 1/3 and are known to both players. P1 can take either action A or B, once he knows about the true state of nature (H, L). Then P2 knowing the action that P1 took, makes his decision, C or D. The payoff matrix is as in figure 1.

We can verify that a rational player will order his preferences as follows:

B – C > A – C >> A – D > B – D

If we compute the different cases:

Option B – C: Ing P2 B – C = 120•1/3 + 140• 2/3 = 133.33 u.m.
Option B – D: Ing P2 B – D = 80•1/3 + 60• 2/3 = 66.67 u.m.

Option A – C: *Ing P2 A – C = 140•1/3 + 120• 2/3 = 126.67 u.m.*
Option A – D: *Ing P2 A – D = 60•1/3 + 80• 2/3 = 73.33 u.m.*

The intuitive equilibrium of this new game predicts that P1 will always select B and P2 select C. With this form of decision, both players obtain half the maximum possible payoff during the session. Nevertheless, since there are no negative payoffs, there will be a bias towards higher risk bearing, particularly for P2.

P1 can initially take a selfish attitude: choose A when the product is L and decide B when the product is H. This conduct will induce P2 to play strategically most of the time. On the other hand if P2 tries to play to guess if the state is H or L, he will play C if he thinks is facing H and D if he thinks is facing L. This risk taking is not considered in game theory models and it is a human attitude that can not be ignored. If P2 plays and he is right he will get 125 units in each round, independent of P1`s decision. If he is wrong he will be short of 50 units. But when he is correct he will get the maximum payoff. Even more he will have the extra satisfaction to go over P1`s payoff, who having more information is initially favoured by the payoff matrix.

If P2 plays strategically and adventurously, P1 may suffer a substantial decrease in his earnings. He could react doing nothing or trying to gain advantage of P2 mistakes. Thus he will play sometimes A and sometimes B.

The result of the experiment after thirty sessions (with an average of twenty-five rounds per session) indicates that the most repeated decisions are B-D and A-C (see table 1).

		P2	
	%	C	D
P1	A	32 %	20%
	B	12%	36%

Table 1. Real players' decisions.

After a certain amount of sessions, a stable decision pattern seem to emerge. The players tended to repeat their decisions till the end of the game. The most relevant result is of course the wide variation of outcomes, at odds with a rational behaviour (optimizing) of both agents. If the objective of the experiment would have been to discover useful guides for strategic behaviour in this type of game, to perhaps compare them with similar experiments, we should have controlled for real gain and losses. But since what we want is to show that the strategic behaviour can be modelled under a cognitive MAS, this is not a relevant question.

4.-MODELLING THE BEHAVIOUR OBSERVED IN THE LAB-EXPERIMENT.

The complexity of this problem is not due to a lack of information about the environment, but about the characteristics of each participant. Each player knows that he can classify his opponent as being one of the following types: altruistic, co-operative, normative or perverse. This taxonomy allows to establish an initial decision making behaviour for each agent. Furthermore, during the sequential process, each agent creates his own model of the others and uses this information before taking his decision (see Cesta, et al., 1996 for a study of the interactions between different attitudes). The taxonomy that we have finally adopted is very similar to that introduced by Rizzo et al. (1998).

This taxonomy allows us to recover an important feature of the experiment. The results and the decision-taking vary according to the idiosyncrasy of each participant. The description of the characteristics of the four previous groups can be briefly described as follows:

An altruistic agent is always concerned with the general well-being; his desire to help includes sacrificing his own particular goals. It is not absolutely important to him what strategy his opponent adopts as he works to select a strategy, taking into account the advance information, which is better for both; him and his opponent. He is never trying to change the attitude of his opponent, and he will not alter his own emotional state even when he knows his adversary is of a perverse type, trying to fool him.

A co-operative agent is always keen to help the group, so long as his helping does not cause damage to him and he will be corresponded. He will even try to modify the behaviour of the other player, to induce him towards a coordinated higher payoff. His emotional state could be affected by "opportunist" conduct from the other players. He is ready to partially lowering his rewards in order to obtain a better sharing of the total payoff and achieving stable cooperation.

A normative (egoistic) agent is fundamentally concerned with getting the maximum profit from the opportunities at his disposal. He will solely look for deals or agreements only when these can bring any extra benefits. His emotional state can be affected by the relative distribution of earnings, according to the situation of every participant in the business.

A perverse agent especially enjoys doing bad things to others, interfering in their plans and, in general, harming others. The satisfaction he gains from economic earnings (for example) is less than that gained from harming his opponent. He fixes his strategy according to this spitting principle.

These four types of behaviour are essential in the development of the decision-making process and expectations formation. Every participant will construct and modify his conception about the others based on a series of initial beliefs as well as the decisions and results obtained.

The complexity of the system studied is generated by the possibility of the participants' choice, aided in part by the ignorance of the opponent. There exists in the model another source of uncertainty: the lack of information that player P2 has about the quality of the product that player P1 receives. Although he knows that approximately two thirds of the time, the quality is high; he does not have information on the actual probability distribution.

Both participants know the rest of the information about the problem. For the individual participants in the experimental sessions, the difficulty of taking a decision has different origins. Player P1 does not know what type of agent P2 is. Player P2 does not know neither what type of agent P1 is, but he places more importance on knowing the quality of the product, which is information that P1 has.

We would like to note that although we are well aware that real individuals have a distinct form of reacting when they are confronted with losses instead of earnings, the lack of experimental evidence in this respect does not allow us to use this characteristic in this first exercise. However, it will not be complicated to incorporate this aspect of the problem later. The modularity of the models that we use and their easy extensibility is one of the fundamental properties of the methodology of the programming language that we have selected.

In addition to the experimental results, the participants were asked to explain formally their strategy all along the bargaining game. We grouped the revealed behaviour in several types, detailed in López (2000, op.cit.). We further consolidated these patterns into the four types we set-up before. The result could be directly correlated with the type of players, since it looked as if most of them are normative or cooperative players (see table 2).

Player/Type	Altruist	Cooperative	Normative	Perverse
P1	8%	21%	62%	9%
P2	5%	26%	55%	14%

Table 2. Extrapoled human participants' behaviour.

We observe that for P2 will have the largest percentage of possible perverse behaviour because the game is asymmetric e, and P2 appears to be disfavoured in the payoff matrix as compared with P1.

It will also be important to report about the level of satisfaction achieved from the results of the game. Approximately 60% of the participants are dissatisfied with the results and their opponents decisions.

These two characteristics are considered fundamental to allowing a modelling of agents more realistic than that of conventional models in game theory because of the difficulty of a mathematical treatment:

a) Emotional state: happy, angry or indifferent; the same for P1 as for P2

b) Character or initial conduct: aggressive and/or benevolent for whichever of the participants. Two players with aggressive character fell nearly irremediably into a“fight” that either led to undefined situations B-D, or to random choices from all the four alternatives A-C/A-D/B-C/B-D. In all of the sessions where P2 has a benevolent character he will end up at situation B-C. In all sessions that P1 has a benevolent character he will end up at situations A-C/A-D.

Nearly 90 % of the participants have a very limited “computational rationality”. Only eight to ranked their decisions on initial calculations. The majority opt to start taking decisions of an accidental or intuitive way, and modify these adaptively, based on past results.

5.-MODEL STRUCTURE.

To build a good agent based model using SDML [1], one should begin with a detailed and complete definition of the structure of the model.. The multiple heritage property is a clear advantage that will improve the efficiency of the system if it is part of a well-defined structure. The first thing to do is to define the hierarchy container and the time levels. The system that we will develop has the following elements:

The market with its given fixed rules, is where the distribution of profits (or payoffs) takes place, at the end of each bargaining round and is the source of the information to each player. And of course where the decision-making takes place.

The decision-taking agents: player-agent P1 and player-agent P2. Each one will have an individual rule base, although they will share many parameters and characteristics .

We need at least two levels of time. The complete session starts with agent P1 receiving information about the quality of the product and ends when the payoffs are distributed once P2 made his choice.

Stages exist in each session as to the sequence of the distinct processes that take place. P1 receives information; P1 thinks; P1 takes a decision; and P1 sends his choice to P2. P2 receives the information from P1; P1 thinks, and P2 takes a decision. "Market" processes the decisions. "Market" sends the results to P1 and P2. "Market" continues or stops the sessions.

Once we know the agents that are part of our model ("Market", P1 and P2) we define the hierarchy of types (see figure 2)

[1] SDML stands for Strictly Declarative Modelling Language. SDML has been developed by the Centre for Policy Modelling of the Manchester Metropolitan University.

"Market" is an entity that contains various agents and that will process and transmit information to the agents it contains. Therefore, the market is an entity that is a type of container, without cognitive capacity and that will not take pro-active decisions. On the other hand, P1 and P2 will take sequential decisions, firstly P1 then P2. Both have a cognitive capacity that they will inherit from the Cognitive agent hierarchy of types. Because P1 and P2 have many common features, it is convenient to have duplicated rules, predictions and various objects that can be used for both. For this reason, it is convenient to define an intermediate type that we have named as Player, whose common characteristics are inherited by both.

The hierarchy structure can support Rule bases and data bases associated with different levels of defined time. Besides the agents observed in the hierarchy, we observe that there are other entities that inherit Object Type, including: Strategy, Behaviour, Play, Emotions, Endorsement and Endorsement Scheme. These entities are Objects and therefore they cannot have Rule bases or have their own behaviour. They are used with this type to define instances that permit identification of associated concepts. Thus, the object Behaviour will have four defined instances: altruist, co-operative, normative and perverse.

After the definition of the container hierarchy, and the definition of the hierarchy of types, we introduce into the model the hierarchy of levels of time. In our case, it is necessary to add two instances of Time Level: session and round, and activate them within the Universal Agent, in the Rule base corresponding to Initial Eternity.

This is a starting point for programming the model through the introduction of rules for each agent, grouped within categories and within the corresponding levels of time. The rules consist of antecedents and consequents and can be fired forwards or backwards. Therefore, the antecedents, like the consequents, can be simple and can have just one or several clauses. The clauses are defined by the user from the available predicates. Normally the user will define, besides the predicates and primitives that are available (clustered by categories) his own predicates, with forward or backward chaining.

We should proceed with the programming of our agents P1 and P2 in the following way. Both will have declarative knowledge of the system, a priori information and behavioural patterns, that are stored in a set of rules. Furthermore, both will have a capacity to learn and develop procedural knowledge about the rules that performed better. This capacity is given by the set of predicates that have been inherited from the Cognitive agent and stored in the Endorsement category. For this to be effective, one has to decide the instances that we want to reinforce (objects of Endorsement type). For example the agent has his model of the other player and this model changes as new information is available from each round in response to his own choice.

In figure 3 we show the instances of Endorsement type given in our model under Player type, that are common to P1 and P2 players.

The representation of the elements introduced till now is the following. **Each agent is characterised as follows**:

— The entities of the type of container in which they are contained: **CC** (Container Constraints)

— The type of heredity, receiving predicates, rules and object instances: **ST** (Super Types)

— The predicates, they use by forward or backward chaining: **CS** (clause sets)

— The Rulebases stored in Content and the ones corresponding to the different Initial and Final levels of time: **RB** (Rulebases)

— The instances defined in Object: **O** (Objects)

We can therefore represent an agent by the following tuple:

$$\mathbf{Agent^k\ \{CC^k\ ,\ ST^k,\ CS^k,\ RB^k,\ O^k\ \}}$$

This agent's description will allow an easier understanding of what our agents consist of. This will also help other researches to reproduce our models, perhaps using other programming languages.

In this model, each simulation will have only one instance of Agent Market, another of Agent First and another of Agent Second. In other models like that presented in Hernández et al. (1999 op.cit.) there are multiple instances of each one of the types Buyer and Seller to allow a replicate of the functioning of the market.

6.-CODING THE BEHAVIOURAL RULES.

The programming of our agent-based model is carried out within the categories defined under the hierarchy of types to support them. Thus we will carry out the programming of Market, Player, First and Second.

The programming is done at two levels. Firstly, we define the Object types that will be necessary for our Rules and the predicates that will be part of the rules that will feed each agent's Rule base. Then new rules keep feeding the Rule bases, from these more elemental blocks.

For each agent the Rule base has various levels associated with distinct temporary blocks defined in the model. The fundamental programming is done in the Content Rule base and in the initialisation of attributes and necessary values like parameters, for the distinct temporary levels associated with Initial. Finally, we introduce rules into the Rule base that is associated with the Final to present results and other output data for each of the different temporary levels.

6.1 The Market Type

Programming the market is carried out under Market Type. In the types hierarchy we can see the legacy of Serial Composite Agent and Looping Agent. The first relation permits to construct the Market under the Entity where other agents exist and start their Rule base in sequential form. The second relation allows the Market, and all the entities included in it, to activate Rule bases at different levels of time.

The representation of the Market is: $Agent^{Market}$ {CC^{Market}, ST^{Market}, CS^{Market}, RB^{Market}, O^{Market}} where:

CC^{Market} = [ ]. The instance or agent Market, that will be contained directly under universe.

ST^{Market} = [LoopingAgentSerial | CompositeAgent]. These types will be contained directly under the module Standard and are a part of the standard SDML platform.

CS^{Market} = [backward rules | parameters | players | time]. Each of these categories has defined predicates that are necessary to construct rules (see the predicates defined in figure 4).

RB^{Market} = [communication (Content) | final experiment (Content) | report (Content) | reward information (Content) | set-up game (Initial Eternity) | set-up players (Initial Eternity) | set-up time level (Initial Eternity)].

O^{Market} = [Behaviour | Choice | Emotions | Endorsement Scheme | Quality | Strategy]. Different instances exist defining each one of these types.Thus for example, we define four types of behaviour {altruist, cooperative, normative, perverse}; four for choice {a, b, c, d}; three for emotions {angry, happy, neutral}; three for Endorsement scheme {behaviour Endorsement scheme, strategy Endorsement scheme, emotions Endorsement scheme}; two for quality {high, low}; and four for Strategy {deliberative, reactive Downing, reactive Tit for Tat, retaliator}.

6.2 The Player Type

Player is a category created to construct objects, predicates and rules that are common for the agent P1 (or first) and for agent P2 (or second). Therefore, there cannot be an instance of an agent during the simulations reproducing a Player-type entity. Following this notion then, the Player entity is represented by: $Agent^{Player}$ {CC^{Player}, ST^{Player}, CS^{Player}, RB^{Player}, O^{Player} }.

CC^{Player} = [Market]. It allows for every instance of Player, and for those of its subtype, to directly read the information contained in the Database (associated with the distinct temporary levels) for the instances that we define as the Market type. Any clause or object that is defined under the Market is inherited by Player and its subtypes.

ST^{Player} = [Cognitive Agent]. Cognitive agent is the agent type defined under the Cognitive module. Player and its subtypes ,First and Second, inherit all of the characteristics of the Cognitive Agent (and therefore of EndorsingAgent) besides the heritage of properties gained from the hierarchy of modules.

CS^{Player} = [parameters | players]. Within this category of parameters (inherited from the hierarchy of containers), we define new predicates under Player, which are shown in figure 5.

RB^{Player} = [endorsement (Content) | compute performance (Content) | set-up experiment (Initial Eternity) | endorsement (Initial Eternity) | set-up experiment (Initial Session)]. In figure 6 we observe the grouping of rules into their categories in accordance with the temporary level of the Rulebase in which they are constructed.

O^{Player} = [Endorsement | Player]. There exists multiple defined instances of the Endorsement Type that allows to construct the endorsement scheme from the rules " endorsement For + Object + Type + [+ Ground Term]". With the rules we define various instances of Endorsement for the types: Behaviour, Emotions and Strategy.

Thus each agent will construct and modify his mental model of his opponents' behaviour; build and vary his emotional state; and select the strategy he considers most appropriate at each moment. The Play Objects {choice A, choice B, choice C, choice D, randomly, repeating} define each player choices in each session.

6.3 The First and Second Types

The player P1 will be an instance of the First Type in our model. The representation of this agent will be the following: $Agent^{First}$ $\{CC^{First}, ST^{First}, CS^{First}, RB^{First}, O^{First}\}$

Similarly, player P2 will be: $Agent^{Second}$ $\{CC^{Second}, ST^{Second}, CS^{Second}, RB^{Second}, O^{Second}\}$

Agent First and Agent Second share various elements of their representation:

$CC^{First} = CC^{Second}$ = [Market], from their definition as, Player, which elects Market as the Container
$ST^{First} = ST^{Second}$ = [Player].
$O^{First} = O^{Second}$ = [ ]. There is not an object, or some kind of instance, which could be specific to a player. All the instances of Object have been inherited from the super type and from the container.

The differences between P1 and P2 are fundamentally part of the decision rules that both use. This means that specific clauses for each agent exist as well, although not many. These clauses are shown in figure 7.

We extracted the rules of thumb used by the participants in the experimental sessions, from their on description , after the experiment ended. Some of these rules are shown in tables 3, 4 and 5.There you can find the description of the rules, their antecedents as well as their consequents. All of the rules used in the model have been obtained from the “natural conduct” of the participants in the experiment.

<table>
<tr><td colspan="2">Description: quality-past_decisions memory.
P1 intends to relating P2´s decisions with decisions he has made, and differentiate if the quality was high or low when he decided on A or B. This rule gives us a predicate that P1 will use to proceed to a different endorsement.</td></tr>
<tr><td>Antecedents</td><td>Consequents</td></tr>
<tr><td>and
time session ?ts\
time round 1\
quality ?quality\
last session (fullListOfChoices ?oldList)\
sortedList ?setChoices ?group
(and
includes ?oldList ?item\
= ?item [?pair ?quality]\
occurrences ?oldList [?pair ?quality]
?num\
= ?group [?num ?pair])\</td><td>memoryOfChoices ?setChoices\</td></tr>
</table>

Table 3

<table>
<tr><td colspan="2">Description: my opponent is not looking for a compromising strategy for both of us (he endorses common defection).
P1 uses the information from the rule above, to know how many times P2 has deceived.</td></tr>
<tr><td>Antecedents</td><td>Consequents</td></tr>
<tr><td>and
time session ?ts\
memoryOfChoices ?setChoices\
total ?value ?num
includes ?setChoices [?num [?a d]]\
is ?half ?ts / 2\
greater ?value ?half\
includes [pervers normative angry]\</td><td>all session (endorsementFor ?endorsement commonDefection ?ts)\</td></tr>
</table>

Table 4.

The second rule states that if P2 has chosen D more than half the time, then P1 considers that P2 is perverse or egotist (normative). Beside this, P1 alters his emotional state, being very disgusted with P2´s attitude.

An example of a rule used for individuals who participate in the game as a P2 did, using a “retaliator” strategy, is the selection of C or D guessing if the quality of the product was high or low. This strategy forces P2 to discover the correlation between the decisions of P1 and the quality that he in fact received.

<table>
<tr><td colspan="2">Description: correlation of P2 decisions and product quality.
P2 mentally estimates the correlation between P1´s previous decisions and the quality of the product</td></tr>
<tr><td>Antecedentes</td><td>Consecuentes</td></tr>
<tr><td>and
last session (fullListOfChoices ?oldList)\
pairList ?oldList ?reducedOldList ?otherList\
pairList ?reducedOldList ?firstList ?secondList\
pairList ?finishList ?otherList ?firstList\
sortedList ?averageList ?cumulo
(and
index [a b] ?i ?elem\
occurrences ?finishList [?it ?elem] ?ex\
= ?cumulo [?elem [?ex ?it]])\</td><td>listOfChoiceAndQuality
?averageList\</td></tr>
</table>

Table 5.

7.- MAIN RESULTS AND CONCLUSIONS.

The simulation was set up so that both participants were “artificial decision makers”. It would not be a problem to substitute either of them for a human decision-maker. Furthermore, it was simpler to think of only constructing an artificial agent that was the first or second decision-maker, whilst the other was a human player.

The number of sessions for each simulation run is introduced by the model’s user. A minimum of 15 sessions is recommended to allow the emergence of certain patterns in the player’s decision making.

We run approximately 120 simulations of the repeated game, whose average running time was five minutes each. We set up the simulation sessions, to analyse the following dimensions of the problem:

a) ***Path dependency***. The importance of the sequence of the states of nature (quality product values: high/low), with the same pair and types of players. If the length of the game is not too long, as in real strategic competition, path dependence should be important. Four fixed sequences were used, to control for this feature.

b) The relevance of the combination in pairs of ***different players' behaviour***, for a given quality states sequence.

c) The effect of N , the ***number of times*** the game is played.

In the figure 8 we can see the sequences of quality in four different scenarios. In the figure 9 we show the evolution of the decisions in different simulations with some pairs of normative players.

In general terms, the human players agreed that they have been influenced by path dependency in a similar way that in our artificial experiment for pair of normative players. If for the same sequence of quality, they tend to be very "learning", they show an unstable strategy, which led to poorer rewards towards the end of the game.

If the initial variability of the players is not high, for the same quality sequence, the players settle down very early in the game and stay there repeating their moves.

If the quality sequence is very variable, and either of the players reaches a negative emotional state, the evolution of the game is that P2 repeats taking D whilst P1 also repeats the same decision. Both players lose interest in obtaining a good result and focus on getting better rewards than their opponent.
P2 's negative attitude normally means repetition of decision D, independently of what P1 might do or the quality state. This harms P1 more because his earnings diminish substantially.

In general terms, the comparison leads us to conclude that if the two players have normal (egotist) behaviour, P2 gets more earnings than P1, contrary to what one could expect from normal analysis with rational players in a purely expected utility optimization.

Total earnings are less than we possibly expected, and although both players approximately get half of the total profits (on average over all the simulations), P2 will do better than P1, at odds with the prediction of a normative theory (see figure 10).

We think that the following are some reasonable conclusions.

We totally agree with Erev's statement, that to approximate the strategies used by players, will be the area of future research in which low-rationality adaptive game theory will need to interact most closely with cognitive theory. Our paper shows a possible way to achieve this goal. Evidence can be taken from, actual competing strategies observed in real cases, or from experimental Lab. sessions with human agents. Then different behavioural patterns can be looked for by simulating with artificial agent cognitive models like the one used in here.

The aim of the work was just to show that this goal is not wishful thinking, and to give a detailed account of the steps in cognitive ACE modelling. It can be extended in many ways, since the model is very flexible. Many kinds of controlled learning can be implemented, although we rather think that it is better to see learning growing without a priori assumptions on learning or recommended strategies.

This approach is not incompatible with Nash analysis that it will always convenient as a benchmark. But clearly the process of learning matters.

The relevance of experimental economics for research on market strategies and market design, it will be enhanced by cognitive approaches , as we have shown.

The repeated game with asymmetric information that we have use for our analysis and experimental simulation is rather versatile and generic. Agency theory, advertising and bargaining can be accommodated in our basic model.

We could not finish this report of our ongoing work on cognitive adaptive game simulation without recognizing that the way ahead is long and hard. But **hard** is Economics as a social science. Certainly it is harder than natural sciences. Failing to accept this fact will widen the gap between Economics, as it stands now, and the Economy.

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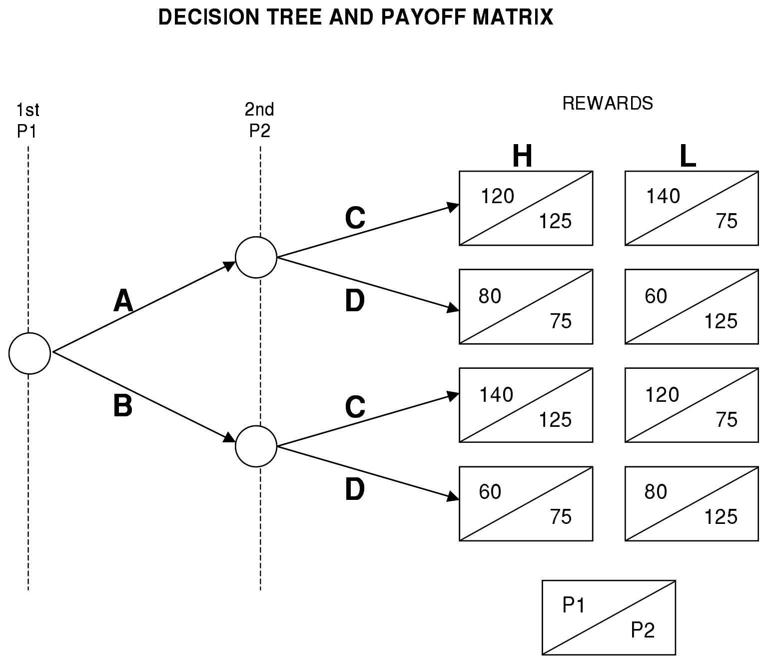

Figure 1 Final payoff real players faced in the experimental sessions with Labex.

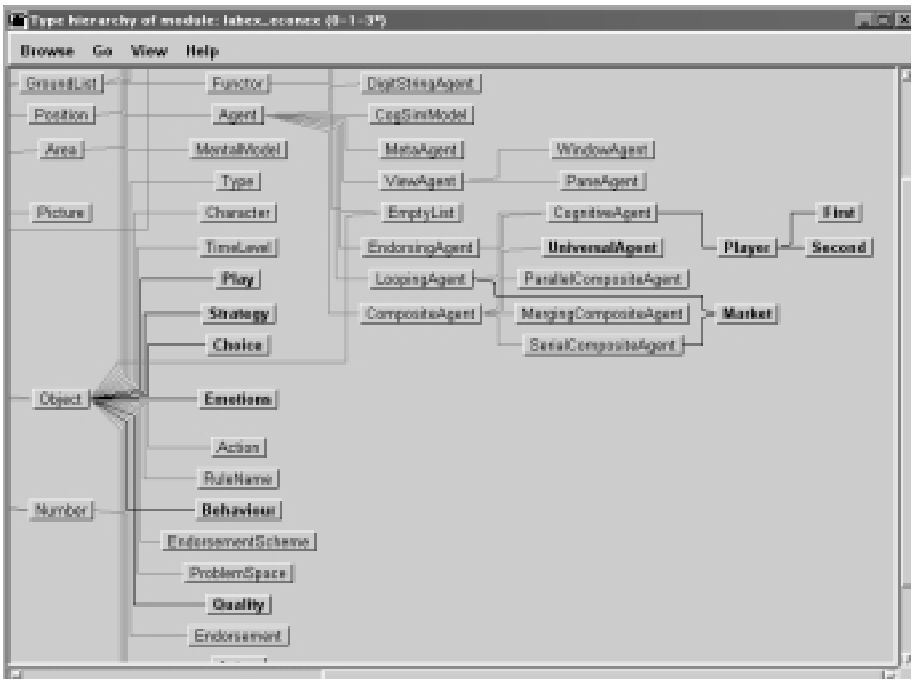

Figure 2 Type Hierarchy for the model.

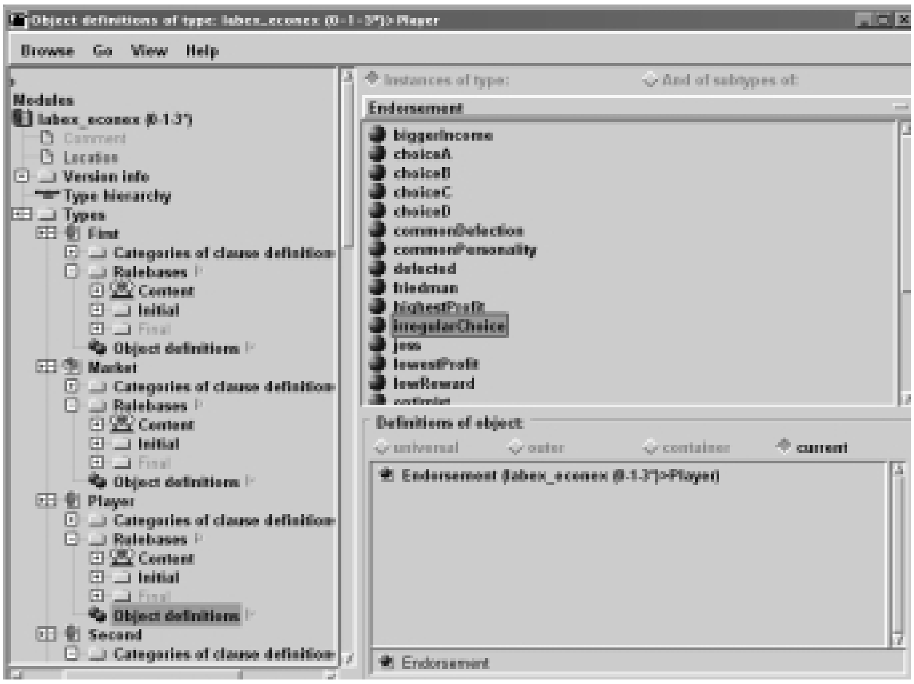

Figure 3 Instances of Endorsement in the model.

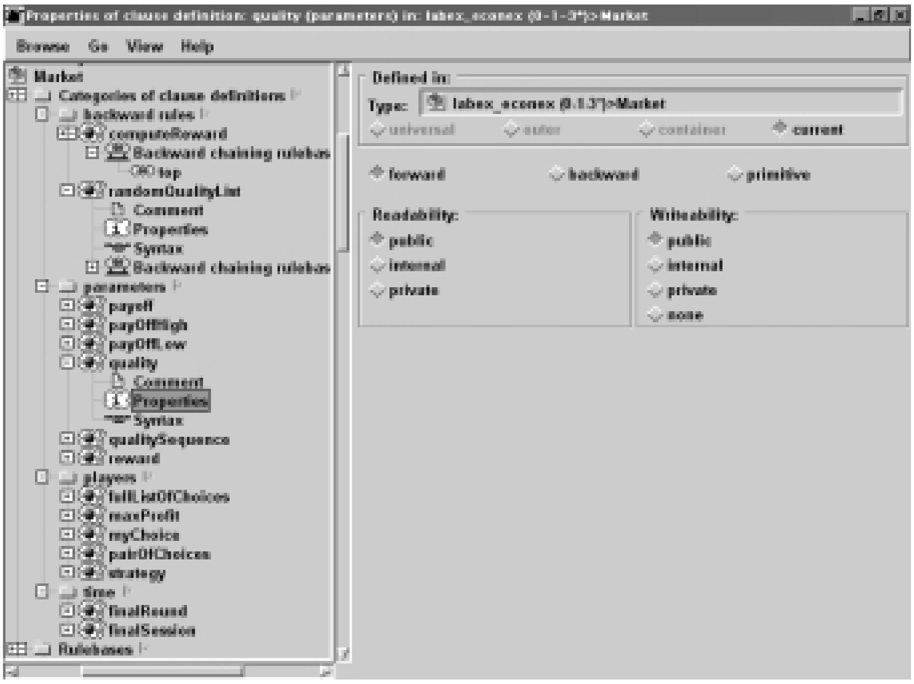

Figure 4 Clauses and predicates into Market type.

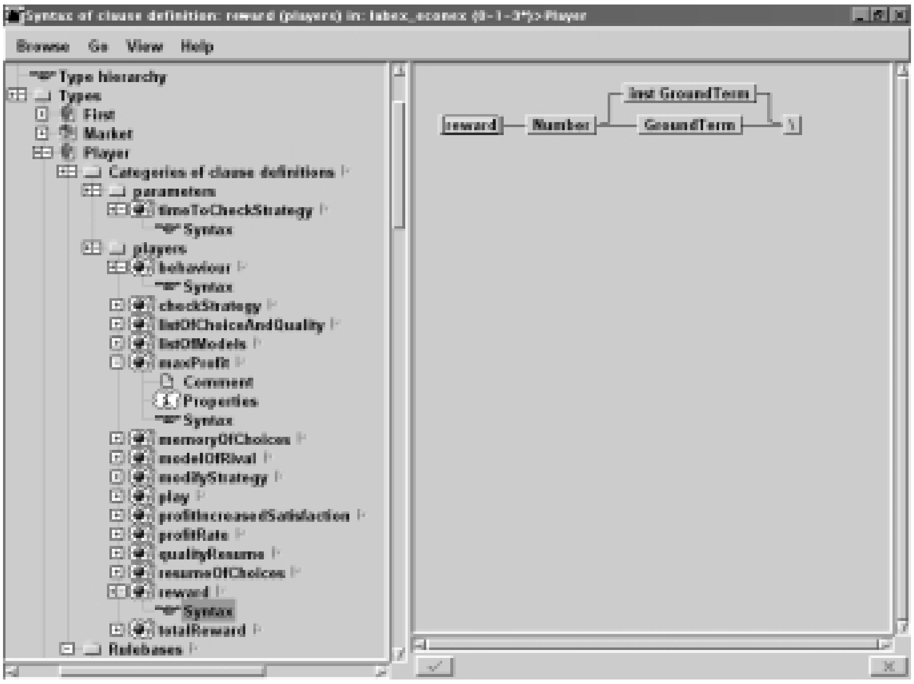

Figure 5 Clauses defined under Player Type. Sintax of a clause: *reward*.

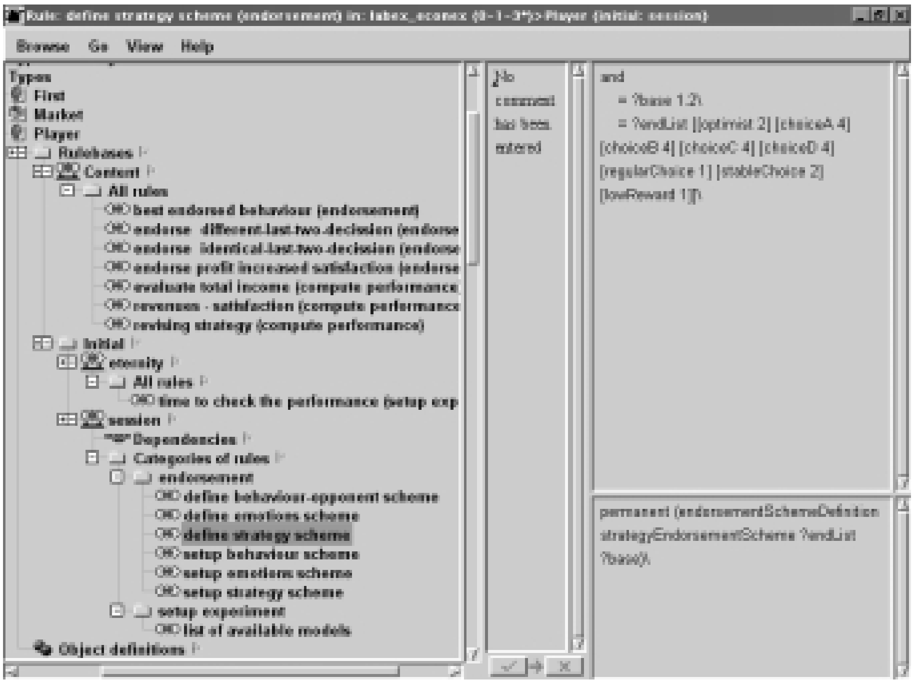

Figure 6 Rulebases of Player Type. Antecedents and consequents for: *define strategy scheme.*

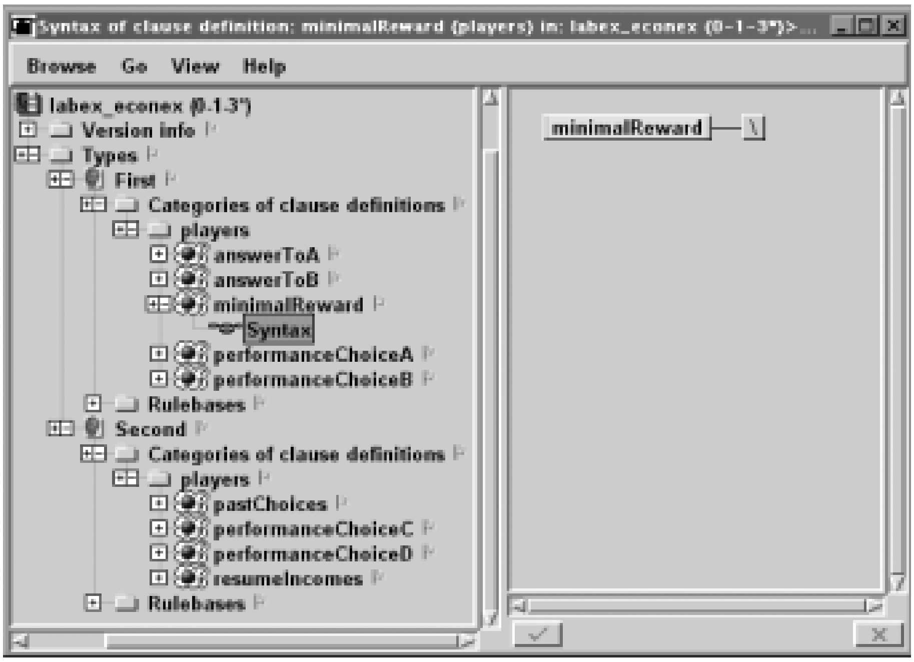

Figure 7 Clauses defined in the Types First and Second.

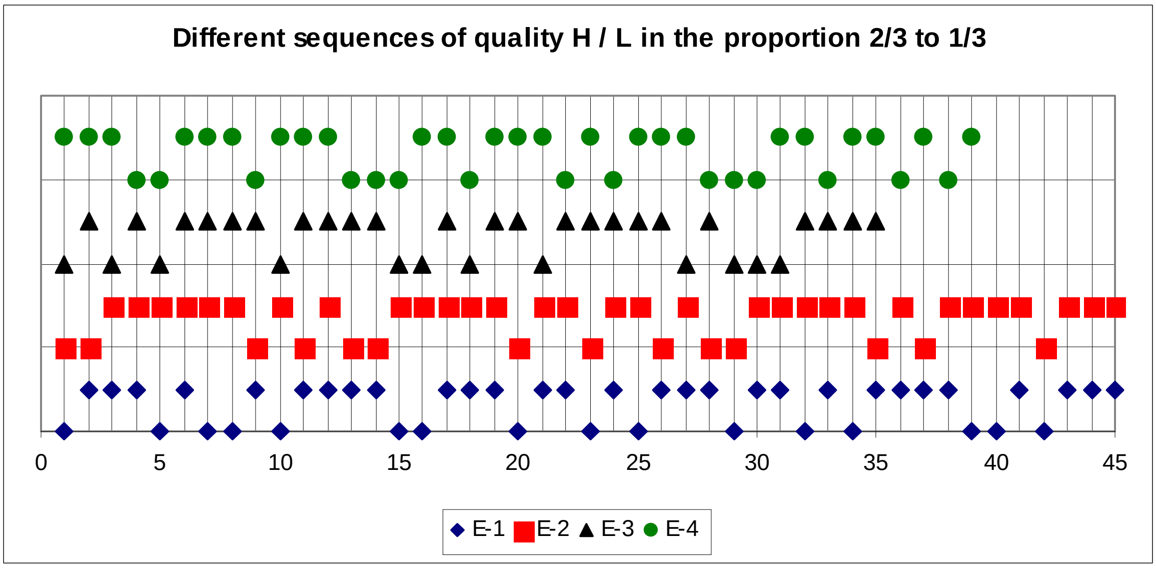

Figure 8 The four sequences [E-1, E-2, E-3 & E-4] we used to evaluate the relevance of path dependency in the sequence H/L for player's decisions.

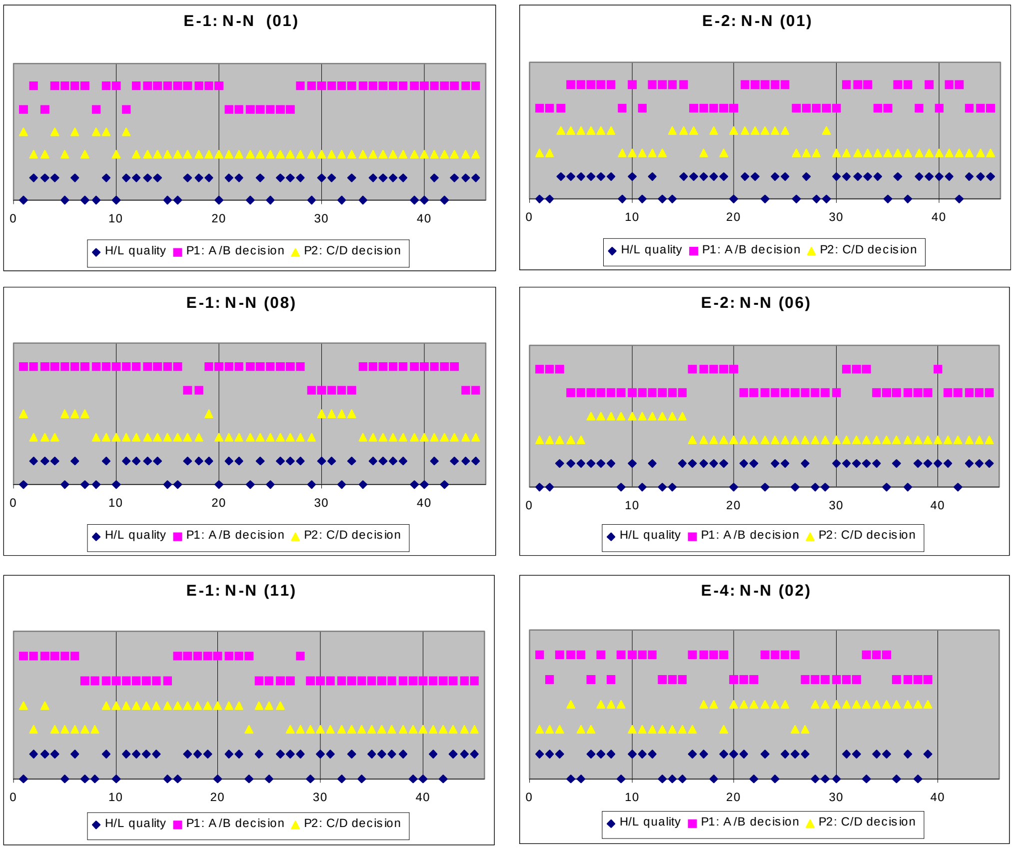

Figure 9 Different simulations with some couple of normative artificial players.

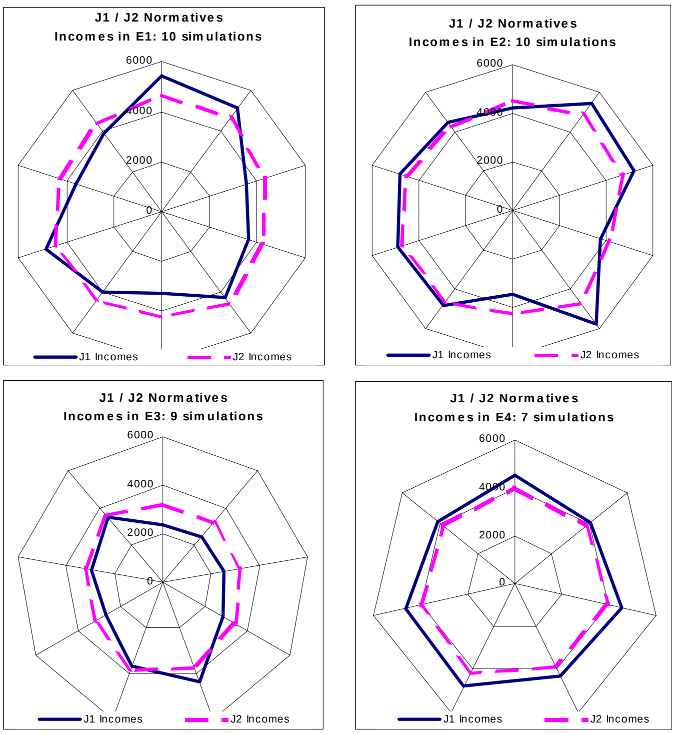

Figure 10 Total earnings obtained by P1 and P2 in different simulations where both players were normal (egoist-normative). Incomes for two 'rational' players would be J1~6000 and J2 ~5000.