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Emotional Decision Making in System Dynamics

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Abstract

This paper is about decision making agents in system dynamic models. Decision makers control the rate variables. The decision is made based on the information of the up- and down-stream levels of each rate received at the decision points. Inspired by the similar concepts created for servo-mechanisms, in socio-economic dynamic systems it is common practice to assume that decisions are made according to a definite law or a guidance table or graph. This *deterministic* approach is hardly able to model systems in which decisions are taken by humans. Since humans may decide differently in the same conditions not because they are rational but because they, sometimes, decide emotionally. Rationality is assumed to be independent of persons; therefore understandable for all, i.e., the decision maker is always trying to maximize her/his explicit profits by taking decisions that are known to the modeler. On contrary, emotionality is very personal and often leads to un-justifiable decisions. To capture the nature of decisions made by people we have to consider the characteristics and personality of the person who is in charge. This way, the *rational* decision maker may be replaced by a *rational-emotional* one. Following efforts to build emotional robots, in this paper an emotional decision maker, which is called sometimes an *agent*, is integrated into a socio-economic system dynamic model. This agent receives information from the environment and decides in-line with its personality. The environment is being changed by the decisions made. So the agent faces a new condition to decide in. The environment also *encourages* or *punishes* the agent by the result of the decisions taken. Therefore, the personality of the agent is a set of dynamic levels under the influences of the environment. However, these levels may accept rapid changes that cannot be given by the integral equations common in socio-economic models. To consider this, emotions are modeled as fuzzy mapping functions. Over longer periods the fuzzy values of the agent's emotions change according to the experiences gained by decisions.

1. Introduction

It was probably in 1981 that, for the first time, Sloman and Croucher interpreted the achievements of *naive* psychology to conclude that "the need to cope with a changing and partly unpredictable world makes it very likely that any intelligent system with multiple motives and limited powers will have emotions". Therefore, the belief that emotions and intellect are somehow quite separate is mistaken. They identified some of the constraints on intelligent systems as "recognition often requires the use of structural descriptions", "the collection of motives is not static", "the environment is not static", "the complexity of the environment often leads to mistaken beliefs, plans, and actions", and "different motives in the same individual may be inconsistent". To develop a general grammar of emotional states they suggest that "an emotional state normally involves having at least one fairly strong motive", "the combination of motive and belief (or uncertainty) must be capable of producing a *disturbance,* i.e. continually interrupting thinking and deciding, and influencing one's decision-making criteria and perceptions", "the disturbance may or may not involve specific new motives", "new motives need not be selected for action",

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“some emotional states arise out of actions performed by the individual”, “sensory detectors may record local changes produced by the interruptions, and the system’s perception of its own state will be changed. … and… the ability to discriminate and recognize complex internal states may have to be learnt, and may involve complex perceptual processes”. To introduce a concept of emotions that can be used in a dynamic system, Sloman [2004] proposes that “what are normally called emotions are a somewhat fuzzy subset of a larger class of states and processes that can arise out of interactions between different mechanisms in an architecture”.

Decision makers change their behavior according to the information they receive. Those active objects that take in and manipulate information and vary their behavior as a result of processing information are called *agents*. Autonomous agents generate their own motivations. Each agent type has an associated collection of rule-sets. Each rule-set is a collection of condition-action rules that interact via ‘databases’ or working memories internal to the agent. Thus one rule-set might be concerned with interpretation of low level sensory information, another with generating motivators in response to the formation of new beliefs, another concerned with assessing the importance of motivators, another concerned with planning, and so on. Within an agent, learning or developmental processes may change individual rules, or introduce new rule-sets, or introduce new interactions between rule-sets, e.g. by adding new communication channels [Davis et al, 1995].

Most autonomous agents are situated in a social context and need to interact with other agents (both human and artificial) to complete their problem solving objectives. There are many potential decision making functions which could be employed to make the choice. Each such function will have a different effect on the success of the individual agent and of the overall system in which it is situated. Therefore, Kalenka and Jennings [1997] examine agents’ decision making functions to ascertain their likely properties and attributes.

Marcia Macas et al. [2001] also stress on the point that efficient decision-making depends heavily on the emotions underlying mechanism and that alternative courses of action in a decision-making problem are emotionally (somatic) marked as good or bad. These emotional marks not only guide the decision process, but also prune the options leaving only the positive ones to be considered for further scrutiny.

Noting that, to date, the field of Artificial Intelligence has largely ignored the use of emotions and intuition to guide reasoning and decision making, Velásquez’s [1998] contribution is to show “how drives, emotions, and behaviors can be integrated into a robust agent architecture, that uses some of the mechanisms of emotions to acquire memories from past emotional experiences that serve as biasing mechanisms while making decisions during the action-selection process”. The flexible agent architecture presented integrates drives, emotions, and behaviors and focuses on emotions as the main motivational system that influences how behaviors are selected and controlled. It is shown how the mechanisms of primary emotions can be used as building blocks for the acquisition of emotional memories that serve as biasing mechanisms during the process of making decisions and selecting actions. This work is derived from a previous research of Velásquez [1997] on computational models of emotions.

Seif El-Nasr and Skubic [1998] rely on Demasio's suggestion that emotions lead an active role in guiding the decision-making process by providing a selection mechanism for eliminating bad alternatives. Decision-making is then simplified, because there are fewer choices left to be evaluated. They investigate the use of emotional agents in the decision-making process of a mobile robot. They have expanded the traditional Intelligent Agent (IA) framework to incorporate the emotional or the internal state features. In the traditional IA model, the world belief and goals are the determining factors of actions that the agent takes. In contrast, in this model the goals shape the expectation levels of the events. The expectation levels, along with environmental inputs, determine the mixture of emotions and their intensities. They propose "a fuzzy logic model that captures the inherent uncertainty of emotions. The model is used to generate decisions based on both internal and external states and incorporates the use of sensory information to extract environmental conditions". In this way, the agent will react to a changing environment and can take an action according to a mixture of emotions generated by multiple states. Later, Seif El Nasr et al. [2000], develop a model that is using fuzzy-logic representation to map events and observations to emotional states. The model also includes several inductive learning algorithms for learning patterns of events, associations among objects, and expectations.

Gmytrasiewicz and Lisetti [2002] use the principled paradigm of rational agent design to formally define the emotional states and personality of an artificial intelligent agent. The emotional states are viewed as "the agent's decision making modes, predisposing the agent to make its choices in a specific, yet rational way". Personality is defined as consisting of the agent's emotional states together with the specifications of transitions taking place among the states.

In the present work a system dynamic model is examined in which rate variables can be controlled by emotional decision makers. The personality of each decision maker is modeled by a set of fuzzy mapping functions. Each decision, in long-term may result in a profit or loss for the agent. Therefore, the punishment (encourage) due to loss (gain) will weaken (strengthen) the emotion that caused that decision.

2. Decision Agents

The purpose of a decision is to maximize, in long term, the rewards gained for the decision maker. Classic economics defines different rational rules to model the society trend and even to get the best decision in each situation for a DM. Thus, the decision made in a system is independent of the agent, and of the environment which is not overtly integrated into the system. Therefore, it is not wrong to describe "rational decision making" as "deterministic". This approach may fail, however, to explain the diversity of decisions made by different agents or in different environmental conditions, unexpected decisions, the speed a decision is made by, and the importance of suggestions made by a specific agent, i.e., a new manager or salesman.

To build a more general framework for decision making, the personality of a decision maker can be integrated into the model as the agent's emotions. A rational decision is considered as an optimum solution to maximize the reward subject to a set of constraints. Thus, in most cases, it can be left to a computer to find the solution, if the objective function and constraints can be defined properly using mathematical terms. It turned out, however, that to find a solution for a multivariable function under a large number of constraints by known methods may take much longer, even by the fastest computers, than it takes by a human. In one hand, it can be referred to a very high processing speed or parallel computing abilities of the brain. On the other hand one can think of an alternative approach that humans use to find the solution. This alternative is not contradicting any assumption for trial and error learning that may also explain the diversity of decisions due to different history each agent has had. The ability to avoid wrong decisions and to find the best solution can be personal and improving. The set of characters that form this ability is thought of, in recent literature, as *emotions*. Emotional decision making is believed to be in harmony with what has been called rational thinking so far.

The action followed by a decision changes the environment. The environment is modeled partly in the system by variables that their *levels* affect the decision making conditions. However the human agents may be influenced by an environment usually larger than the one considered in the model. For example, in the very abstract economic models, the price is determined at the equilibrium point by the levels of the inventory and the demand, while the demand is determined by the price. In reality, the price may change due to the variables that are not considered in the model such as fear of a war, or the rapid changes of the market consumers expect to happen following *breaking news*.

What an agent gains by a decision made may cause changes in the characteristic set of the agent, i.e., its emotions. If the agent is gaining (losing) by taking a risk, this gain (lose) strengthens (weakens) the agent's level of accepting risks. This can be interpreted as the *reinforcement learning* of the agent. It is important to note that the adjustment time of a personal characteristic may be different than the time the system state or environmental conditions change. Therefore, the decision maker receives information of the state of the system and a broader environment according to which the decisions are made and the emotional levels are adjusted in different time scales. Figure 1 shows a schematic of a system dynamic model in which the decision maker personality is influenced by the environment and the reward.

Reward is a personal measure of the consequences of a decision made by the agent. A multivariable averaging function of all levels at each time step by different weights assigned by the agent determines reward. The interested reader is invited to compare the differences of the reward function as defined in this paper with similar definitions [Sutton and Barto, 1998].

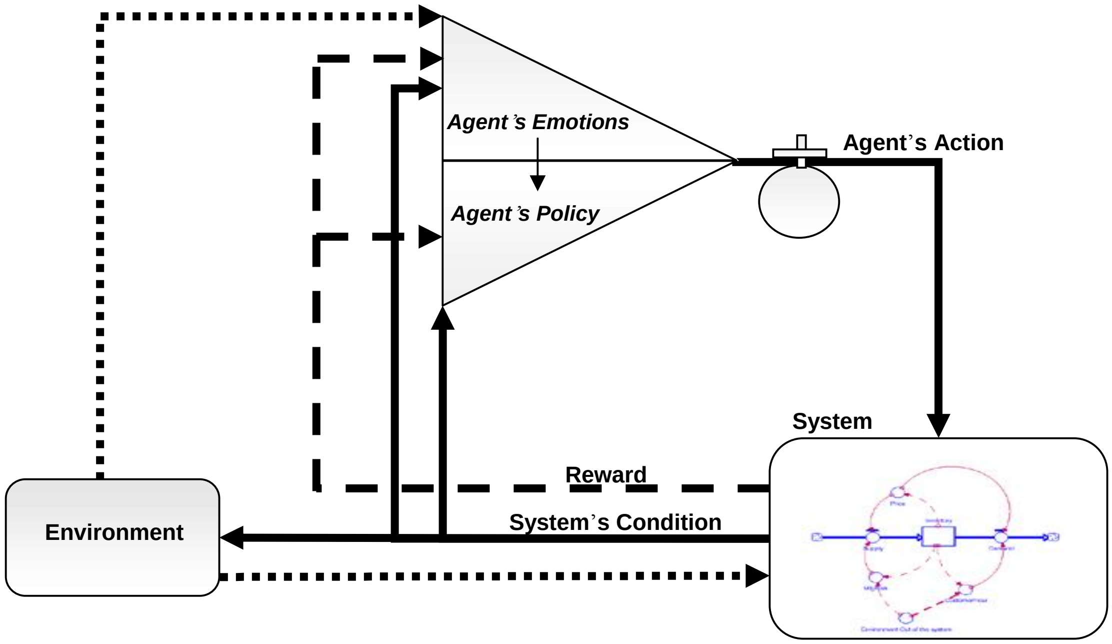

Figure1 Schematic of a system dynamic model in which the decision maker personality is influenced by the environment and the reward.

3. Fuzzy sets

If the value of a level is given by rather a qualitative expression, any deterministic one-to-one deduction may not be justified for a decision. To capture the uncertainty inherent in the information given to the decision maker, also the deduction rules the decision maker employs, fuzzy sets are used to define the emotional personality of the decision maker. The core idea is to quantify this uncertainty which is due not to chance but to the absence of sharply defined criteria of class membership. Fuzzy sets are classes with uncertain borders that pervade human language and thinking [Sangalli, 1998]. They can be used to quantify the qualitative expressions usually given for emotions, e.g., the fear of the agent or the level he/she accepts risks can be 'high' 'moderate', or 'low'. Fuzzy sets are also useful to construct the system's input and output space vectors in each step of time.

An important feature of using fuzzy sets to quantify emotions is that they are able to be adapted to new values according to the learning mechanisms inserted in the model.

When the decision making rules in different environmental conditions/system states are defined by an expert team or using tools such as Neural Networks, Genetic Algorithms, or Genetic Programming [Castillo 2001, Ishibuchi 2002], a fuzzy inference is designed so that it can model the past of the system or satisfies the expectations of the expert team for different input conditions. ANFIS (Adaptive Neuro-Fuzzy Inference System) is one example of proper tools to do this job [Jang,1991].

When the fuzzy system is designed, the initial state of the agent is determined by levels defined in the system and levels that determine fuzzily the agent's emotional state. Using the fuzzy inference the agent can make a decision. The decision results in changing the state of the system and the environment. The reward is calculated and reported to the agent. It can be an indication of closeness of the reality to the expectations of the agent.

Therefore, the membership functions are adapted accordingly. The new emotional state of the agent depends on levels of the system and the agent in earlier time steps, and on the environment. The system state may be affected by decisions made by other agents. The environment also may change unexpectedly. The agent is facing the new conditions and decides. In reality, different agents in a system with different rules play a game to maximize their own profit. Their interaction defines the state of the system in time.

4. Example

A simple demand-supply system, figure 2, is considered [Whelan and Msefer, 1996]. A step increase in demand causes a decrease followed by an overshoot then by a diminishing oscillation in the inventory to reach a new equilibrium state. Although the levels included in the model remain stable at the equilibrium conditions, all the human decision makers in the system are influenced by the changes independently happen in the environment. This deterministic model, in which decision to buy or sell is determined independently according to Table1, cannot explain the mechanism the system interact dynamically with the decisions made by the agents to react to the environmental changes. Emotional decision model however is designed specifically to reflect to the environment and represent the personal differences of decision makers.

Figure 3 shows an emotional agent-based demand and supply system. Each of the two agents, that regulate supply and demand, aims to maximize its own profit. Their decisions are rooted in their experiences and the information they receive of the environment. The fuzzy system that is pre-defined is used to make a decision. Although, the membership functions are history-dependent and are changed by experience, i.e., the agents learn how to play to gain higher values in long run. Figure 4 shows how the system react when a rumor, say collapse of a competitor or fear of war or a sudden heat wave, is spread through the market during time distance of (20,60). This shows a sharp increase in demand followed by a permanent positive step despite the price is increased. The reason is obviously the customer fear. There is no punishment or encourage for the agents in the long term since the rumor did not come true. Authors, in another paper [2004] show how the system behave if the rumors come true, i.e., the supply for any reason is really decreased, and how the emotional membership functions change in response to the gaine or lose.

Table 2 defines different rules that are used in this example to define the fuzzy emotional conditions of the agents. Figure5 shows different choices of the supplier with moderate risk at system states: demand and price. This cannot be explained by classic economics in which the demand and supply are functions of only the price but not the agent.

5. Conclusion

In this paper a new model for dynamic systems is presented in which rates can be controlled by emotional agents who are sensitive to the environment. The deterministic decision making which is not a good model of reality is replaced by fuzzy, learning, and interactive decision making. Rules can be defined initially according to the history of each agent and are left to the computer to adapt/correct them using the reward gained by agents.

This model can be developed to multi-agent systems to predict market trend and so on.

Price	Quantity Demanded (per week)	Quantity Supplied (per week)
$50	10	100
$45	14	97
$40	18	94
$35	22	89
$30	28	84
$25	35	77
$20	45	68
$15	57	57
$10	73	40
$5	100	0

Table 1 Demand and Supply Schedules

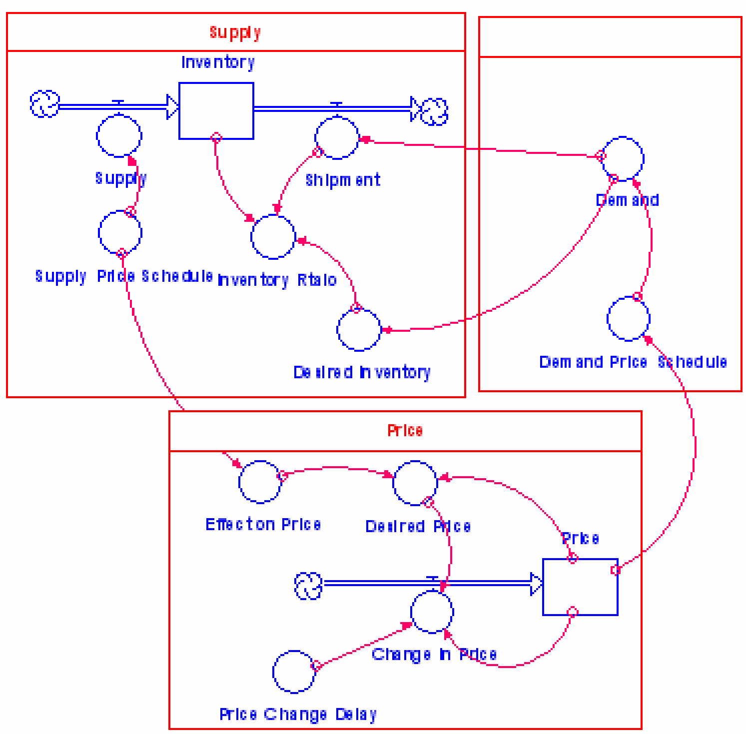

Figure2 Traditional System Dynamic Model of Supply and Demand

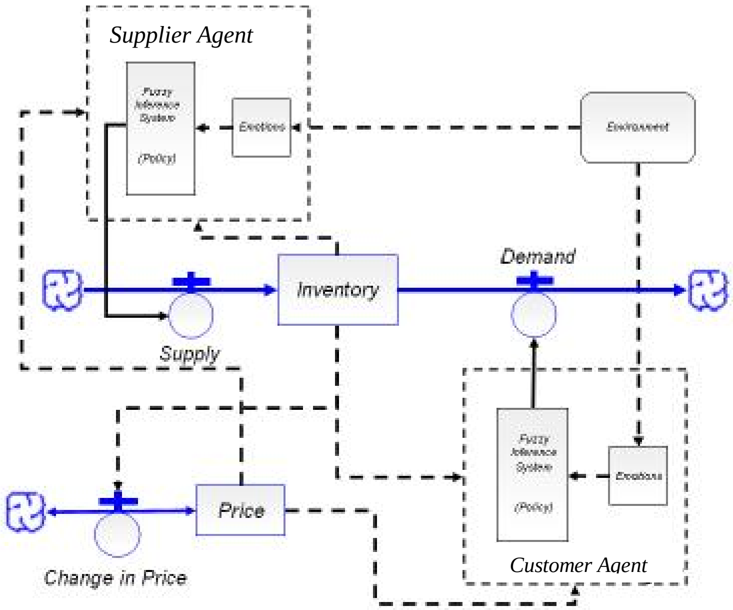

Figure3 Agent-based Model of Supply and Demand

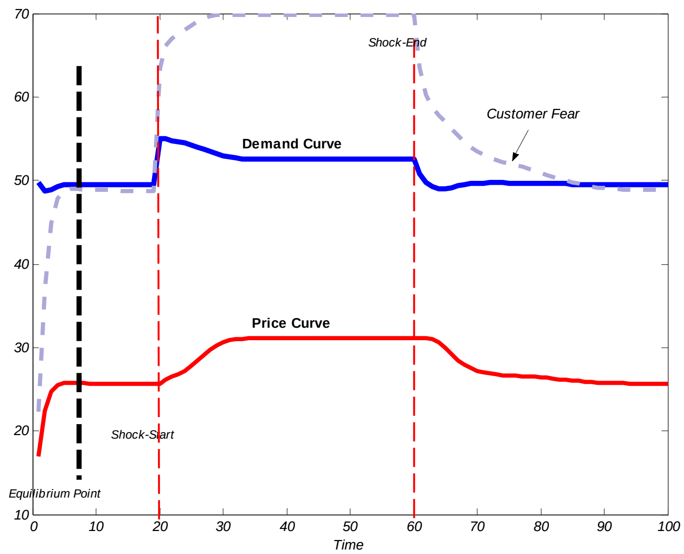

Figure4 Demand increases sharply following a rumor (information) at time 20. When the rumor is denied at time 60 the demand goes back to the normal. The same happens for the price. The customer fear, that causes the changes, is also back to normal.

Supplier	Customer
1. If (Price is Low) then (Supply is Low) (0.8)	*1. If (Price is Low) then (Demand is High) (0.8)*
2. If (Price is High) and (Inventory is not High) then (Supply is High) (0.9)	*2. If (Price is Normal) then (Demand is Medium) (0.8)*
3. If (Price is Normal) then (Supply is Medium) (0.8)	*3. If (Price is High) then (Demand is Low) (0.8)*
4. If (Supplier Risk is Low) and (Inventory is Low) then (Supply is High) (1)	*4. If (Customer Fear is Low) then (Demand is Low)(New Customer Fear is Low) (0.65)*
5. If (Supplier Risk is High) and (Inventory is High) then (Supply is Low) (1)	*5. If (Customer Fear is High) then (Demand is High)(New Customer Fear is High) (0.65)*
6. If (Inventory is High) then (New Customer Fear Low)(New Supplier Risk is High) (0.85)	*6. If (Customer Fear is Medium) then (Demand is Medium)(New Customer Fear is Medium) (0.65)*
7. If (Inventory is Low) then (New Customer Fear High)(New Supplier Risk is Low) (0.8)	*7. If (Inventory is Medium) then (Supply is Medium) (0.45)*
8. If (Supplier Risk is Low) then (New Supplier Risk is Low) (1)	*8. If (Customer Fear is Low) then (New Customer Fear Low) (1)*
9. If (Supplier Risk is Medium) then (New Supplier Risk is Medium) (1)	*9. If (Customer Fear is Medium) then (New Customer Fear Medium) (1)*
10. If (Supplier Risk is High) then (New Supplier Risk is High) (1)	*10. If (Customer Fear is High) then (New Customer Fear High) (1)*
11. If (Supplier Risk is Low) then (Supply is High)(New Supplier Risk is Low) (0.7)	
12. If (Supplier Risk is Medium) then (Supply is Medium)(New Supplier Risk is Medium) (0.7)	
13. If (Supplier Risk is High) then (Supply is Low)(New Supplier Risk is High) (0.7)	

Table 2 Rules are defined by an expert team.

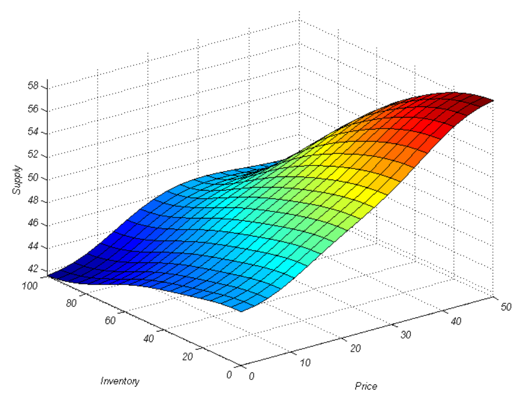

Figure5 shows different choices of the supplier with moderate risk at system states: demand and price.

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