Using Bayesian Networks to Structure the OCC Emotions Model

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ABSTRACT: *This paper presents a new way of modeling the OCC model of emotions. A Bayesian network is employed to represent the structure and the relationship among emotions of the OCC model. In this manner the stochastic behavior, a new characteristic, is inserted in the simulations using the OCC model. Emotions a ect directly the human behavior ff influencing many aspects e.g. decisionmaking, actions and memory. Specially because emotions are not a deterministic variable we propose the use of the Bayesian networks to model them. Bayesian networks are an excellent tool for modeling real problems because they use probabilistic reasoning which differs from the logical reasoning used by the majority of the computational tools. In order to evaluate the proposed model we applied it in a BDI Multi - Agent system. In this system we tested the introduction of emotions in three hypothetical situations and compared how these emotions influence the behavior of the agents.*

Keywords: Bayesian Networks, Emotions, BDI, Agents

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1. Introduction

The human being has been the focus of many studies and served as inspiration in many different areas of knowledge including computing. For example, in the field of Artificial Intelligence (AI) some techniques were inspired in physiology or in individual/ social behavior of human beings.

However, human behavior is determined by many variables. Many of these variables do not have a clear and defined computational simulation method. For instance, emotions affect decisively the human behavior influencing decisionmaking, actions, memory, attention, etc [10]. According to [13], “the term emotion itself is fraught with ambiguities and contrasting definitions. . . emotions are a central aspect of everyday life and people have strong intuitions about them.”

There are various theoretical models that try to formalize the operation of emotions. In [13], a family tree of the most significant models of emotions is presented. Choosing from these models of emotions, in this work we employ the OCC model [17], that is defined as an Appraisal Model [13]. The OCC model relates the emotions to the events that generate them and is composed by 22 emotions. It admits three forms of stimulus: (i) environmental events; (ii) actions of individuals and (iii) objects. The model is based on the principle of di erentiation between positive and negative reactions of valence, i.ff e., from an environmental stimulus. In this way, variables are assigned to determine if the event will have positive or negative impact in the person/agent analysed. It is interesting to note that due to its deterministic nature the OCC model always generates the same emotions from the same valence stimulus.

This paper presents how to transform the OCC model in a Bayesian network structure, adding different characteristics to the model, such as probabilistic variables and values. We postulate that the stochastic component of the Bayesian networks is more appropriated than the deterministic nature of the OCC model for the modelling of emotions. Thus, the simulations with the proposed model should be more realistic than the simulations with the original model.

Bayesian networks are an excellent tool for modeling real problems because they use probabilistic reasoning, which differs from the logical reasoning used by the majority of the computational tools. Bayesian networks can deal with incomplete information which is a very common feature in this type of problem due to the difficulties to collect the information and also owed to the presence of uncertainty.

For practical use and evaluation, we have inserted this hybrid model (OCC and Bayesian networks) in a MultiAgent System.

This kind of system offers the structure for the simulation of different situations based in agents which are able to interact with each other and with their environment. With these characteristics, they become an excellent tool for developers to perform computational simulations of human relationships. We used one example to analyse agents' behavioral changes introduced by the emotions generated from the environmental stimuli. With this scenario it is expected that the agents can behave more similarly to humans.

This paper is structured as follows: in Section 2 the background areas are presented in order to clarify the purpose of this paper. The Section 3 presents the proposed model as a Bayesian network of Emotions to OCC Model. In Section 4 are presented the experiments with one example case and Section 5 concludes the paper and presents some possibilities of future works.

2 Background

2.1 Bayesian Networks

Bayesian Networks (BNs) are a combination of probability theory and graph theory. They are very useful to represent probabilistic relationships between multiple interacting entities. Their nodes represent random variables and its arcs represent dependencies between these random variables. Formally a BN is fully specified by a graphical structure M, a family of conditional probability distributions F and their parameters q, [11].

The graphical structure M is a directed acyclic graph (DAG). DAGs are graphs that have only directed edges between nodes and have no directed cycles. They indicate conditional dependence relations between nodes through their edges. The family of

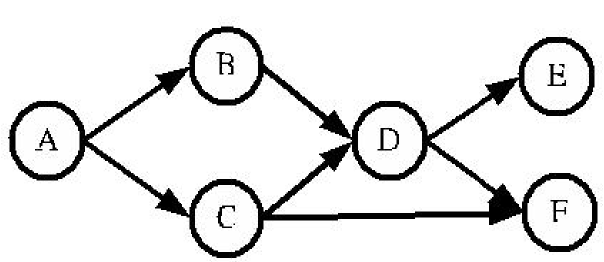

Figure 1. Example of Bayesian Network. This figure presents a Bayesian Network example composed of the set of nodes N = {A, B, C, D, E, F } and edges E= {(A, B),(A, C),(B, D),(C, D),(D, E),(D, F),(C, F)}. Applying the independence relationships depicted by the graph we can write the joint probability P (A, B, C, D, E, F) as P (A)P (B|A)P (C|A)P (D|B, C)P (E|D)P (F |D, C).

conditional probability distributions F and their parameters q specify the functional form of the conditional probabilities associated with the edges, that is, they indicate the nature of the interactions between nodes and the intensity of these interactions.

Figure 1 shows a hypothetical Bayesian network. This network is constituted by the set of nodes N = {A, B, C, D, E, F } where the set of dependencies between them is represented by the set of directed edges E= {(A, B),(A, C),(B, D),(C, D),(D, E), (D, F),(C, F)}. If we have a directed edge from a node A to a node B, then A is called parent of B, and B called the child or descendant of A.

A BN is characterized by a simple and unique rule for expanding the joint probability in terms of simpler conditional probabilities. This follows the local Markov property: A node is conditionally independent of its non descendants given its parents. Thus we can write the chain rule or factorization rule:

$$P (X_1, X_2, ...X_n) = \prod_{i = 1}^{n} P (X_i \mid \pi_M (X_i)) \quad (1)$$

Note that we use the same symbols to represent the nodes and the the random variables that they represent, e.g. (Xi). In the same way the set of parent nodes and the random variables that they represent also have the same symbol, e.g. (ΠM(Xi)). Thus in Equation (1) X1, X2,..., Xn are random variables represented by nodes Xi ∈ 1, . . . , n and ΠM(Xi) is the set of random variables represented by the set of nodes ΠM(Xi) which are the parents of node Xi in the model M.

If we apply Equation 1 to the BN in Figure 2, we obtain the factorization

$$P (A, B, C, D, E, F) = P (A)P (B|A)P (C|A)P (D|B,C)P (E|D)P (F |D, C) \quad (2)$$

A graph provides a scheme for expanding the joint probability into a product of lower complexity conditional probabilities like in Equation (2). In other words, following our example in Figure 2, we apply the chain rule, Equation (1), and we have the product as specified in Equation (2). To specify the complete joint distribution it is still necessary to determine each of the conditional probabilities in the product form, Equation (2).

In this work our interest in Bayesian Networks lies in answering queries of the type P (X|E). In this case X is a node in the graph and E is a subset of nodes in the graph for which we have evidence, i.e., we know its values. This problem is called Belief Propagation and two of the classical algorithms for solving it are Variable Elimination and Junction Tree. The details of theses algorithms are beyond the scope of this article and the interested reader is referred to [12, 1].

2.2 Emotions and the OCC Model

There are some proposals for modeling emotions in order to better understand how they work. Most of these proposals offer basic models to simulated emotions in machines [10].

However, the simulation of emotions in the machines is not an easy task. In tasks where emotions play a key role, as decisionmaking processes, many factors, both social and physiological, make the modeling and simulation a very complex process. Another point that makes this work very hard is the difficulty in understanding what emotions are and how they work. There is not a consensus on this definition. According to Del Nero (1997) [9], emotion is a conscious process which together with thought will form the main protagonists on the stage that is the mind.

Damasio [8] says that emotion is a label that designates a set of phenomena or behaviors. He divides emotions between primary (fear, joy, sadness, anger, etc.) and secondary (jealousy, guilt, pride, etc.). Moffat and Frijda [16] argue that emotions are functional, i.e., they have an adaptive value for the organism, contradicting the convention that emotions are not rational. Sloman [22] also concludes that there is not a single definition of emotion, thus, the definition of emotion depends of the individual conceptions of human beings.

About the functioning of emotions we must analyse two characteristics: (i) emotions are physiological processes that are difficult to measure, because they are things that we feel and (ii) emotions are generated by stimuli, though it is impossible to say that the same stimulus will generate the same emotion in two different individuals. This influence of the emotion in an individual depends of several factors which define each person as a different human being.

Many models are proposed for representing the structure of the emotions, however, each one seeks different aspects of the human being. Some try to model psychological aspects, such as perceptions, feelings, experiences, cognition and behavior [16, 5, 17]; others are concerned with physiological aspects, such as heartbeat, blood pressure and sweating [21, 18]. Among the proposed models the model of Ortony, Clore and Collins [17], called OCC, is able to identify, from the stimuli generated in an arbitrary environment, emotions which were generated within a predetermined set of emotions. This is the most widely used model in the computer science field in order to add emotions in artificial agents or to work with the influence of emotions in decisionmaking systems.

The model is based on the principle of di erentiation between positive and negative reactions of valence, i.e., from an environmental stimulus, variables are assigned to determine if the event will have positive or negative feelings to a person.

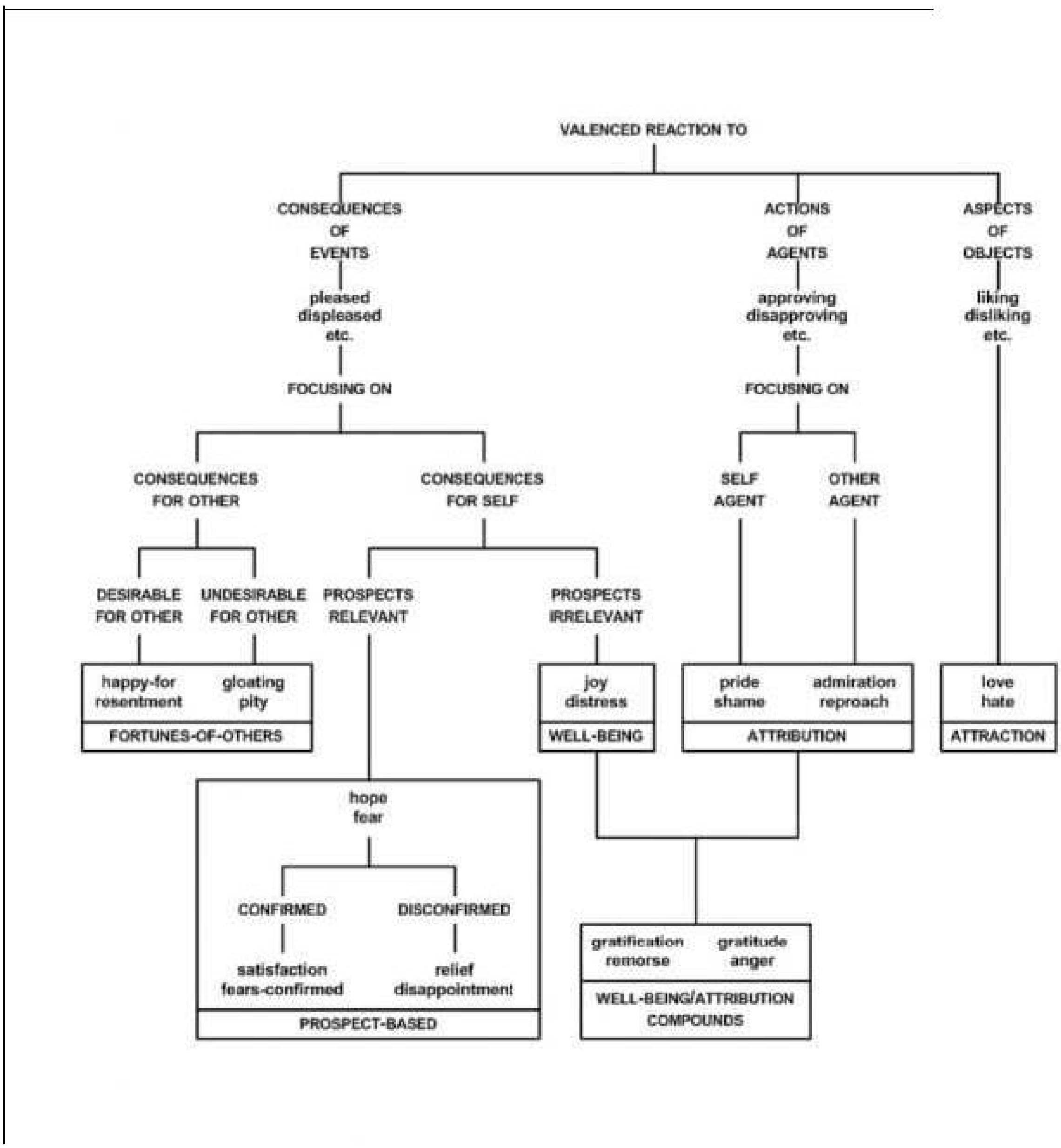

Figure 2. The OCC Model structure [17]

In the OCC model three generators of stimuli for emotions are considered: (i) events, which have their consequences analyzed to generate emotions; (ii) agents, which have their actions considered and (iii) objects, in which aspects and properties are inspected. Every emotion generated in the model is a response to one or more aspects of the environment.

However, for different individuals, a particular stimulus can generate different emotions. This differentiation occurs in the model by the assignment of a positive or negative value as the individual's reaction to a particular situation. This concept becomes clearer when we look for the structure of the model, in Figure 2.

The model structure is divided into three main branches, each corresponding to a type of stimulus generated by the environment. Considering figure 3 the development of emotions from events, actions and objetcs are represented respectively in the left, middle and right branches. Importantly, the structure provides a logical description for the generation of emotions and not a temporal sequence. At the terminal, or leaf nodes, in figure 3 are represented the 22 emotions present in the model.

2.3 MutiAgent Systems and BDI agents

The agents, according to Bordini et al. [4], are able to sense the environment extensively or partially and take actions that can modify it. In contrast to procedural programs agents are endowed with certain autonomy to realize these actions besides being able to communicate and organize themselves. MultiAgent Systems (MAS) are inhabited by various agents that are capable of interacting, exchanging information, are sensitive to perceptions, adapt to changes, have knowledge of the environment (full or partial) and can take actions (coordinated with each other or not) to modify it within the called sphere of influence [2].

According to [20], the modeling of MultiAgent Systems and their simulations require some characteristics: the agents must be autonomous; agents' behavior must be represented at a high level of abstraction; agents must be flexible, having characteristics of proactive and reactive behavior; agents can perform tasks that require realtime performance; agents should execute distributed applications; agents must have the ability to work cooperatively.

The MAS can be classified as Reactive or Cognitive, the latter being the model adopted in this work. One aspect that may di er a cognitive MAS from a Reactive MAS is the fact that it usually works with less agents but are more complex ff and robust. Also, what characterizes a cognitive MAS is the fact that agents have beliefs, perceptions, communication, the ability to organize themselves in groups, goals to be achieved, plans to achieve these goals, i.e., they interact, and knowledge and actions to modify the environment.

The BDI architecture [19] (Beliefs, Desires and Intentions) is characterized by its cognitive aspect. Beliefs represent the information that the agent has about other agents and the environment; the desires expressing goals that the agent intends to achieve; and the intentions are the goals that the agent is committed to achieve.

3. The Bayesian Network of Emotions

The OCC model is a quite comprehensive model that has a structure of simple computational translation. This characteristic led to its choice as the basis for Bayesian network of emotions.

The OCC model by itself is not a model that considers human unpredictability, hence, it always reaches the same emotional result from a particular event or action. Thus, our model proposes the construction of a Bayesian network that has the structure equivalent to the OCC model and introduces uncertainty to the simulation model.

In [13] a generic model of computational appraisal models of emotions (see Figure 1) is presented. In this model, the information flows in a cycle: some representation of the personenvironment relationship is appraised; this leads to an a ective response of some intensity; the response triggers behavioral and cognitive consequences; these consequences ff alter the personenvironment; this change is appraised; and so on. In our work, there is an integration of the "Appraisal Derivation Model" and the "Appraisal variables" components, that represent the Bayesian network of emotions (OCC Model); the other components are represented by the MultiAgent System.

There are some works that uses Bayesian networks and OCC model together to treat emotions, e.g. [3, 14, 6, 15]. However, the Bayesian network in these works is used in "Affect Derivation Model" or "Affect Intensity Model" components of Generic Model (see Figure 3). In this way, the Bayesian networks receive the values obtained from the previous module (Appraisal variables) to define the model and the intensity of emotions to be performed by a cognitive model. In our proposal, the MultiAgent System receives the values calculated by the Bayesian network to choose the emotion to use in the simulation. Moreover, in our approach we can create different profiles of individuals by modifying the initial values of the network. In this way, our approach is more generic.

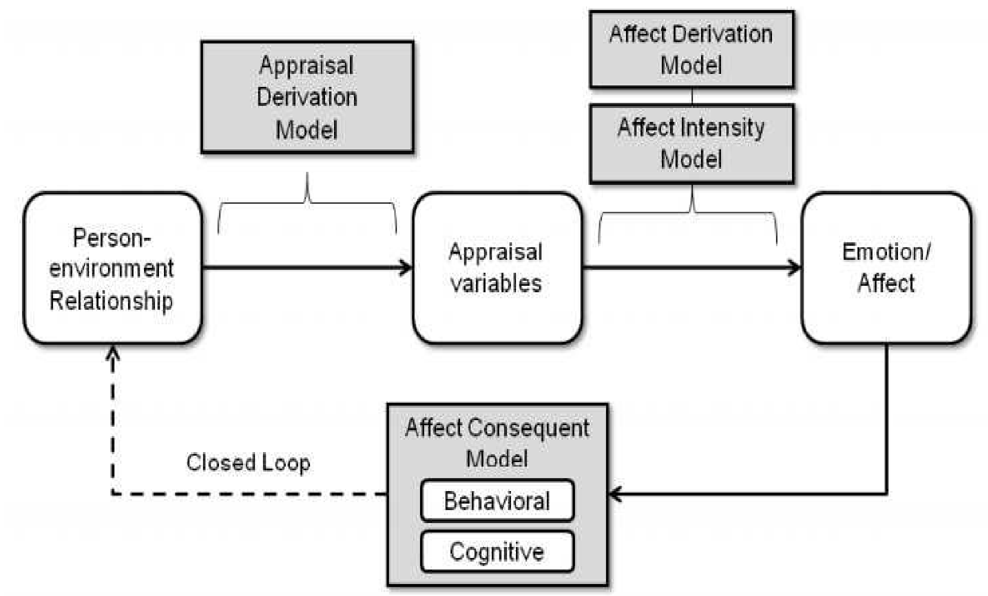

Figure 3. Generic Model of Computational Appraisal Models of Emotion [13]

In order to build this Bayesian network of emotions some conditions for operation and validation are needed. It is necessary the creation of an environment capable of simulating the human reality where stimuli are generated in the environment resulting in emotions in the individuals who inhabit it. Considering the social and individual capabilities of the agents, it is proposed the application of the Bayesian network as a structure able to generate emotions for agents on a multiagent environment.

3.1 Modeling the Network

Based on the structure of the OCC model, the Bayesian network of emotions aims to transform stimuli from an environment in emotions of an individual. For its construction and analysis we have used the software called JavaBayes. Developed by Cozman [7], JavaBayes allows the construction, visualization and graphical analysis of Bayesian networks through a simple interface. The software allows the construction of networks of any structure with an indefinite number of nodes, edges and variables. Furthermore, it provides various functions, for example, the selection of the algorithm for the calculation of the probabilities between the variable elimination method and the junction tree method, and the possibility of displaying the probabilities of all the variables of the network from the observation of one or more of their nodes.

As the OCC model of emotions consists primarily of a sequence of conditional branches that allows the determination of which emotion is activated from certain conditions, the Bayesian network based on its structure was constructed by translating each of these deviations in a set of nodes, variables and edges, where each node represents a deviation: each variable represents one of the states that satisfy the deflection and each edge connects each branch to the next condition to be analyzed. The result of this translation is presented in the Figure 4.

By observing the network structure we can see that like the OCC model of emotions it is also divided into three distinct areas according to the source of the stimulus from the environment. Nodes at left represent stimuli generated from events occurring in the environment; the central area comprises nodes relative to stimuli generated from the actions of other individuals; the right area refers to emotions generated from the individual relation with di fferent objects.

At the bottom of the network are located the nodes that represent each one of the 22 emotions modeled by the system: Happyfor, Resentment, Gloating, Pity, Hope, Fear, Joy, Distress, Satisfaction, Disappointment, Fearsconfirmed, Relief, Pride , Shame, Admiration, Reproach, Love, Hate Gratification, Remorse, Gratitude and Anger.

Each node has a variable that can assume two states which are "true" and "false" even for the nodes who represent the emotions. The "true" is an active state, it is the confirmation of a condition or the effectiveness of an emotion and "false" means the opposite. The exceptions to this rule are the three top nodes to each of the previously mentioned areas: Consequences of Events, Actions of Agents and Aspects of Objects.

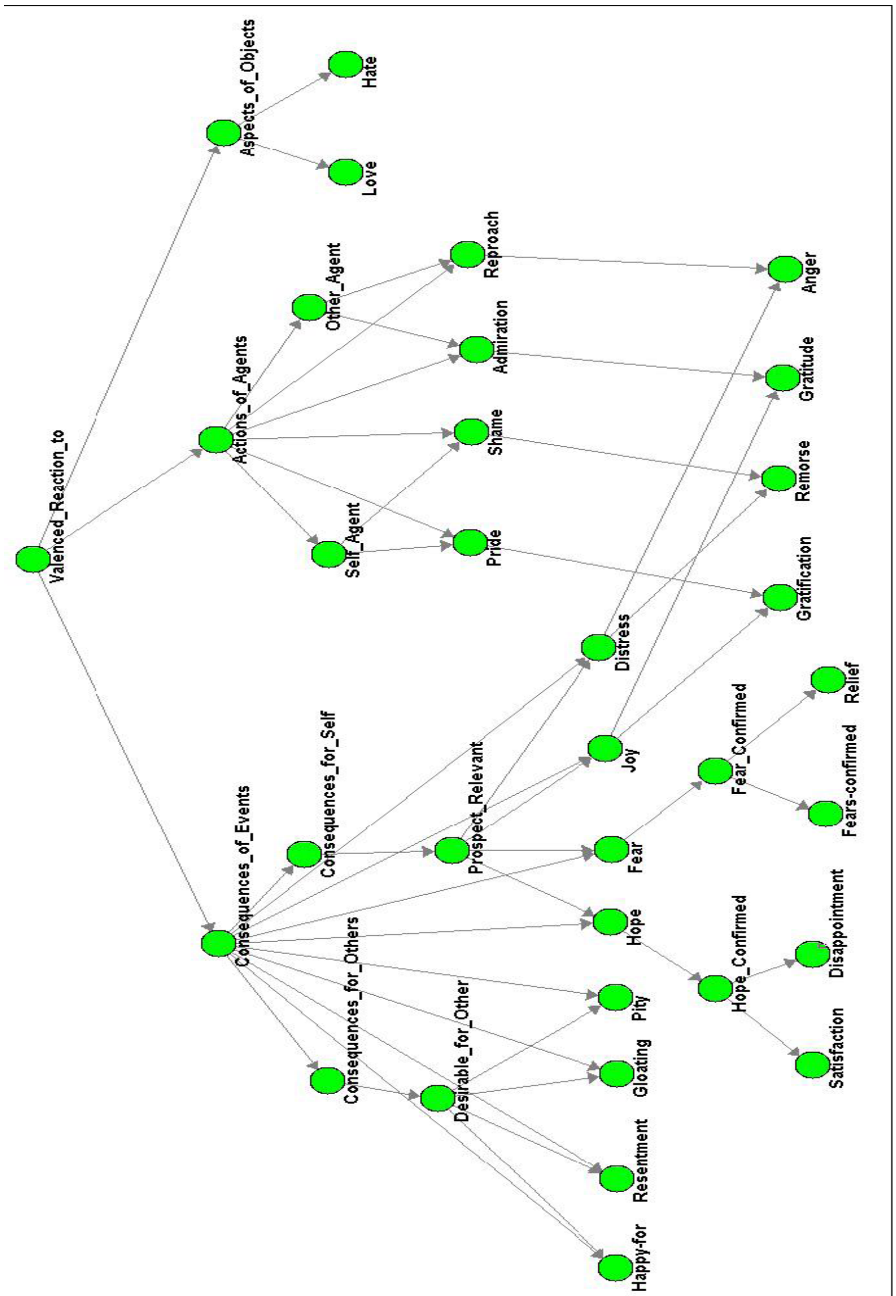

Figure 4. Bayesian network developed. Inspired by the OCC model of emotions, each node represents a conditional branch in the original model and the edges represent the parentchild dependencies between these nodes.

For these three top nodes the states and variables are distinct from the others: the variable of the node Consequences of Events can assume the states “Pleased” and “Displeased”, which indicates respectively a desirable or undesirable event for the individual on the environment. The Actions of Agents node variable can assume the values “Approving” or “Disapproving” which indicates whether the individual is in agreement or not with the action of an individual who triggered the node. The variable associated with the node Aspects of Objects can assume the states “Liking” and “Disliking” that indicates whether the individual likes or dislikes the object that stimulates the Bayesian network.

After defining the possible states for the variables of each of the nodes it is necessary to define the probabilities of activation of each of the states following the dependencies between parents and children nodes and respecting the conditions presented by the OCC model. The network presents two situations, nodes that have one or two parents. For the first case the states of the variable may have weak or strong dependence on the parent node depending whether the child node is a leaf node or not. Strong dependence occurs when the child node is a leaf and weak dependence when it is not a leaf.

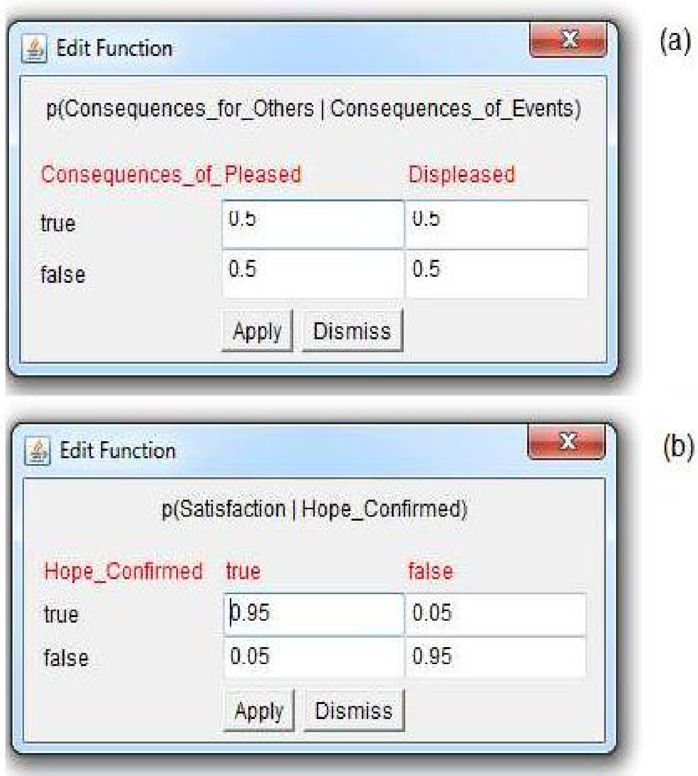

Figure 5. Example of the determination of probabilities for the states of nodes with a parent. (a) Node Consequences for Others not depend on the states of Consequences of Events, “Pleased” and “Displeased”. (b) Node Satisfaction depends on the states of Hope Confirmed, when the father is true the child has 95% chance of also being, as well as otherwise.

In this way, when the dependence is weak, their probabilities were defined as 50% of any of the states to occur, whatever the state of the parent node. An example of this can be viewed on Figure 5(a).

An example of node that has a strong dependence on its parent node is the node Satisfaction, which has its states directly dependent of the states of Hope Confirmed. In this case, one of the states of the parent causes the child to have a 95% chance of having a certain state, while its opposite state causes its child node 95% chance of having the opposite state. This example can be seen in Figure 5(b).

When a node has two parent nodes it always depends directly on the states of these two parents. In this case the child node has 95% of owning one of their states when a given state for each of their parents. When the states of the parents are reversed, the child node has a 95% chance of also having its inverted state. In the case one of the parents having their inverted state, the child node has a 50% chance of having each of its states. An example of this can be viewed on Figure 6.

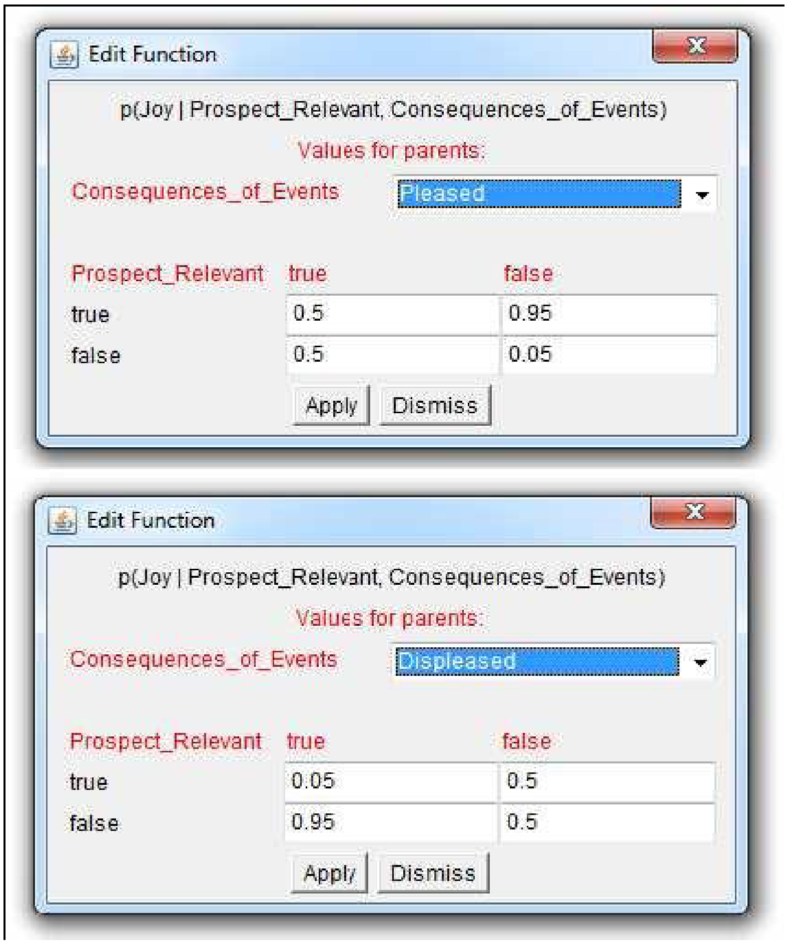

Figure 6. Demonstration of probabilities defined for Joy node according to the possible states of their parent nodes, Consequences of Events and Prospect Relevant.

3.2 Adding the network to a multiagent environment

As mentioned before, in order to be able to evaluate the functioning of the Bayesian network of emotions we have applied it to a multiagent environment. In this case, the environment used is Jason, a multiagent environment [4].

The software works with an environment based on a model of cognition environment founded on BDI architecture. In its standard database, Jason o ers a number of examples of multiagent models that simulate di erent situations. We have chosen the “cleaning robots” example for the experiments presented in this work.

In this example, two robots, R1 and R2, collect and dispose garbage on Mars. The R1 robot walks on the soil of the planet looking for Garbage units. When it finds a garbage, it collects this garbage and takes it to the point where R2 is located. After, R1 returns to the spot where it found the unit to continue the search. The robot R2 is positioned next to an incinerator and when it receives a unit of garbage it burns the garbage immediately.

The Figure 7 presents an overview of the graphical interface of the simulation environment. The garbage units, represented by G on the map are placed in random positions in the grid at the beginning of each simulation. The R1 agent always starts in the upper left position, conducting its search through all the positions on the map, line by line and always from left to right.

The R2 agent always starts in the center position of the map and it is fixed the entire simulation in same position.

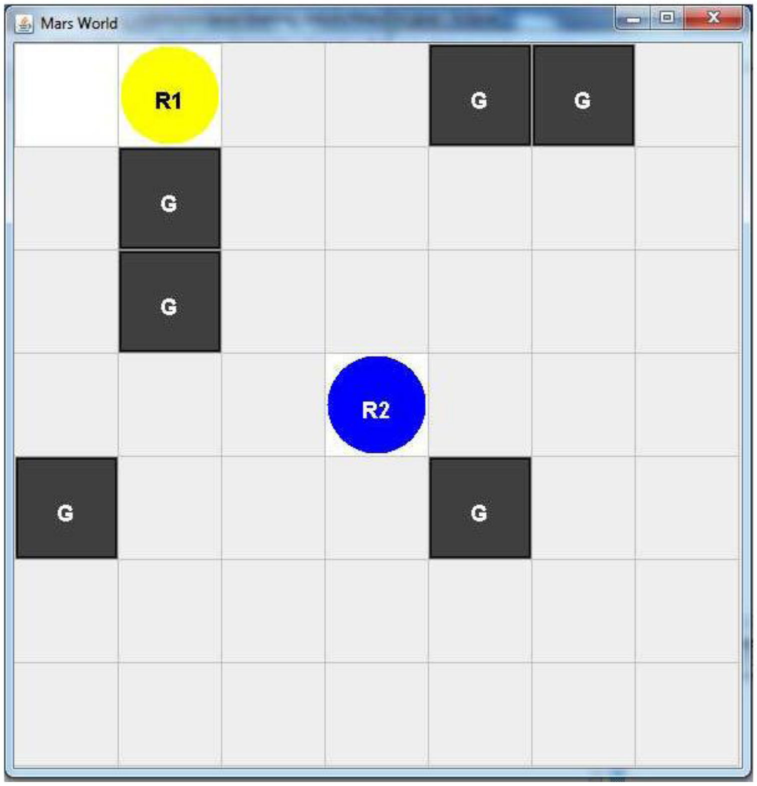

Figure 7. Graphical interface for the example cleaning robots in the Jason tool, presenting R1 and R2 agents.

With the example chosen, the next step is to add the Bayesian network of emotions. In this way with the creation of the environment an instance of the network is created for each of the agents selected. In this example, just R1 received a network of emotions.

After the network has been created, it is necessary to determine how it will receive the influences of the environment. To achieve this it is necessary to analyze each of the available actions in the model that are defined in its code. The agent R1 performs four di erent actions: nextSlot, moveTowards, pickGarb and dropGarb. The R2 agent performs only the ff burnGarb action.

The nextSlot action is responsible for moving R1 to the next search position either the position immediately to its right or the first position of the next line which occurs when R1 is in a position of the right edge of the map.

The method moveTowards moves the agent R1 to a certain position. This function is used after the agent finds and picks a unit of garbage so it moves to the position where R2 (and the incinerator) are. After, it returns to the position where the unit of garbage was found.

The pickGarb, dropGarb and burnGarb functions perform respectively the following tasks: R1 picks an existing unit of garbage in its current position; drops the unit of garbage in its possession when he meets R2; and R2 burns the unit of garbage brought to it by R2.

To create the e ects of the environment on the network, it is necessary to evaluate the possibilities into the ff environment which are determined by the functions occurring in it. After that, it is necessary to make some assumptions about the environment. These assumptions should include valid situations for the model that can produce effects on the network.

The effects on the network are simple observations for some of its nodes. The observation function allows the execution of a statement about the current state of a variable of the Bayesian network, changing therefore the probabilities of other variables of the network to assume certain states.

Considering the example presented in this work, we defined three hypothetical situations:

1. When R1 performs five consecutive steps on the map and finds no unit of garbage, it starts wondering if the environment is clean and therefore its work is being done in vain, which discourages it;

2. When R1 finds a unit of garbage the effect is the opposite of the proposal in the previous assumption. Because it is performing the function that will complete its goal the agent increases its motivation;

3. When R1 deposits the unit of garbage in the position where is R2, there is a possibility (a random variable) that R2 thanks it for the good work, this also motivates R1.

After defining the hypothetical situations it is necessary to translate them into observations in the variables of the R1's Bayesian network of emotions. For the first assumption, an event occurs in the environment (lack of garbage units) which is undesirable for the agent translated in the observation of the variable of the node Consequences of Events to a "Displeased" state. Furthermore, this is an event that has consequences for R1 translated into the variable of the node Consequences for Self to be observed in state "true".

The second assumption is similar to the first and involves observations of the same nodes. When the agent finds a unit of garbage, an event of the environment (the existence of units of garbage in the environment) which is desirable for the agent occurs, thus, it enables R1 to perform the function which it is intended to. Therefore, the Consequences of Events node should be observed as "Pleased" while Consequences for Self node must also be observed for the state "true".

The latter assumption is not an event but an environmental action performed by the R2 agent, which is approved by R1. So the Actions of Agents node must have its variable observed for the "Approving" state. As it was an action performed by another agent, Other Agent node must take the state "true".

From these changes, the network begins to undergo a change in the probabilities of its nodes, and these will determine when an emotion is or not producing an effect in the agent. These values can be worked at least in three different ways: (i) the probability at the nodes corresponding to the emotions can be regarded as a probability value of the emotions being really active; (ii) values can be considered as intensity of emotions, 50% being the initial value of emotion with higher values meaning that the emotion is active at a higher intensity and lower values meaning that the emotion is not performing an effect in the agent and (iii) there is the way the values were treated in this work. In this work the set of 11 emotions considered to be positive are: Happy for, Pity, Hope, Joy, Satisfaction, Relief, Gratification, Gratitude, Pride, Admiration and Love. Probability values of the nodes of these emotions are summed and compared to the summed value probabilities of the other emotions that are considered negative which are: Resentment, Gloating, Fear, Distress, Disappointment, Fearsconfirmed, Shame, Reproach, Hate , Remorse, and Anger.

This comparison of values allows observing the current emotional state of the agent. If the values are equal the agent is considered in a stable emotional state (this is the initial state of the agent). If the value of the summed probabilities of positive emotions is greater than the probability of the summed negative emotions, then the emotional state of the agent is considered good, thus, motivating the agent. On the other hand, when the comparison indicates the opposite with the probability of the negative emotions being greater than that of positive emotions, then the emotional state of the agent is considered bad, thus discouraging it.

Having defined how to evaluate the outputs of the network, it is necessary to establish how they influence the actions of the agent. The same way as it is necessary to conduct assumptions about the multiagent environment to create the stimuli on the network, are necessary assumptions about what effects the emotional states cause in the agent.

Assuming that positive emotions will motivate the agent and that the agent works better motivated it was decided that when the emotional state of the agent is good it must increase its efficiency in the search for new units of garbage. On the other hand, if its emotional condition is bad its efficiency will decrease.

To modify the level of efficiency of the agent and obtain a clear way to evaluate the effect of emotions on its actions the addition of a new feature in agent R1 is proposed: different speeds in the search process. The simulation of different speeds is obtained as follows: when the agent is in its stable emotional state or the network of emotions is not considered the agent executes the function nextSlot every two simulation cycles. This means that the agent attempts to perform the task of moving to the next location search at its normal speed. When the agent is in a negative emotional state the process should become slower. In this case every three simulation cycles the agent will perform the action nextSlot. When the emotional state of the agent is positive it needs to become more efficient in performing the search than when it is in a balanced emotional state, which means conducting the search with a higher speed. In this case, it will perform it in every simulation cycle.

4. Experiments

To evaluate the effects of modelling emotions with the Bayesian network it is interesting to note that the default behavior of the agent R1 is unemotional. The best way to evaluate its performance and achieve a measurable value is to observe how many execution cycles are required for the agent to perform a search for units of garbage all over the map.

The execution cycles considered are only responsible for implementing nextSlot function, because this is truly the only function a ected by emotions from the proposed model. Including all the execution cycles could turn the results ff inconsistent and mask the effect of emotions.

Figure 8 shows the values obtained for the runtime in number of cycles to 100 instances of example without using the network of emotions. In this case, the execution time is always the same, 97 cycles. The time is constant because the execution of nextSlot function occurs always in the same way regardless of the variations in the environment.

Considering the first hypothetical situation the fact that the agent does not find units of garbage in a certain period of time demotivate it and activates the network of emotions that cause variations in the performance of the agent, as presented in the Figure 9. In this scenario the simulation was run 100 times. The performance of the agent R1 was much lower and the runtime instance varied between 132 and 140 cycles with an average of 138.77 execution cycles.

Comparing the values obtained from the example with this configuration with the results obtained with the sample without the Bayesian network of emotions the performance is worst. This is due to the fact that the agent is unmotivated.

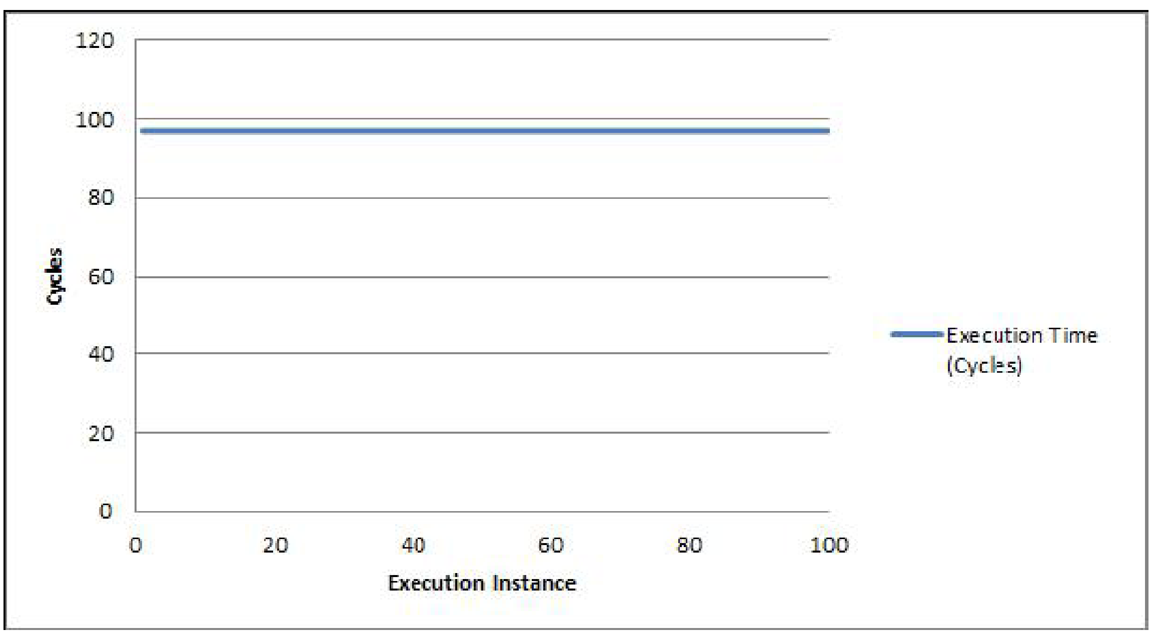

Figure 8. Running time for 100 instances of the example emotionless.

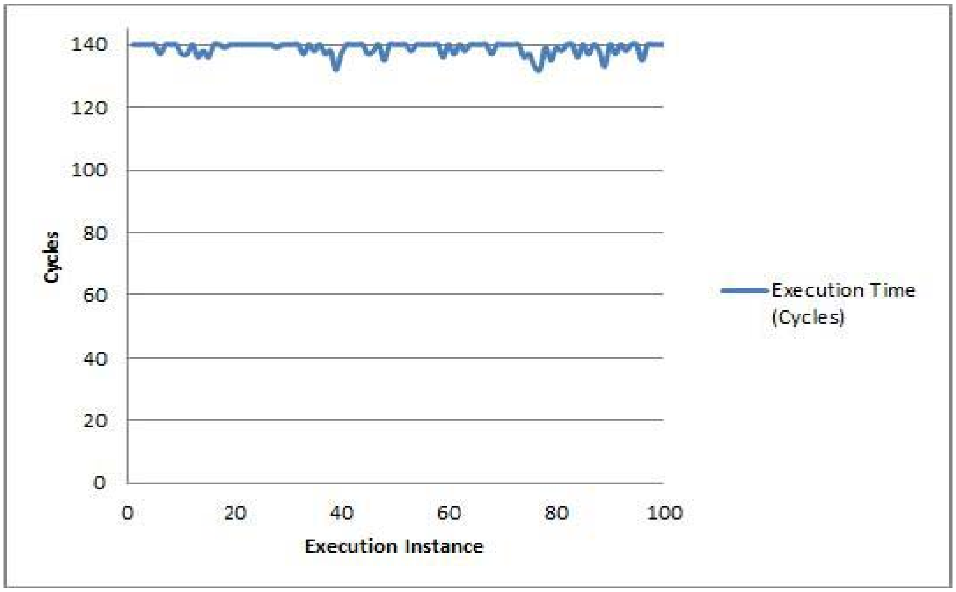

Figure 9. Runtime for 100 instances of the first hypothetical situation.

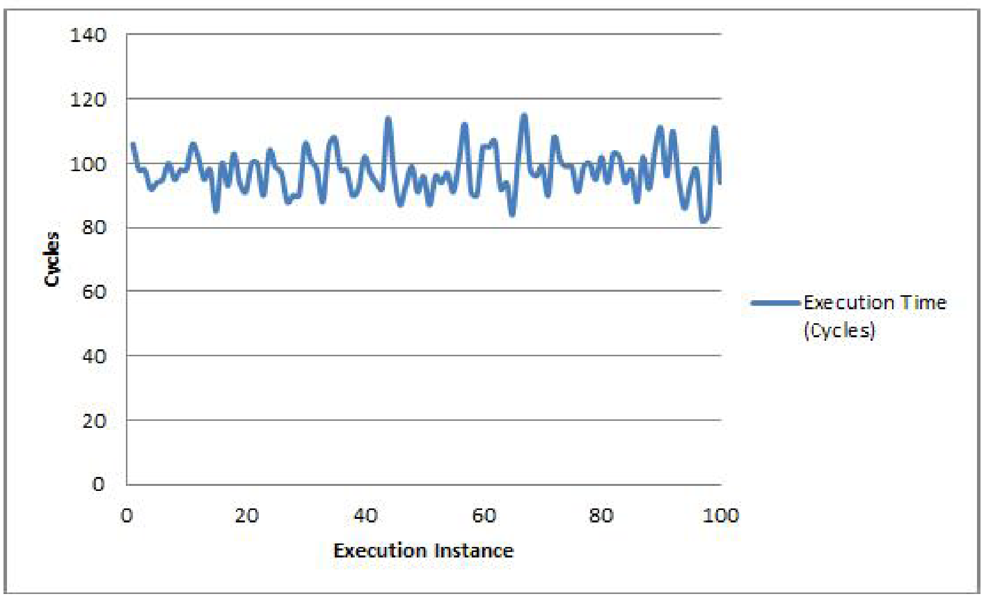

Figure 10. Runtime for 100 instances of the first and second added hypothetical situations.

The study of this example and the network of emotions becomes more interesting by adding the second hypothetical situation to the environment in which the agent finds a unit of garbage and is motivated by the fact that it is working towards its goal. The results obtained after running 100 instances of the example with these conditions is presented in Figure 10.

The example with these two situations of the network presents some interesting results. First, there is a greater variation between the runtime observed ranging between 82 and 115 cycles. This demonstrates that in some instances prevailed a positive emotional state of the agent making these instances faster and more e cient outperforming the results obtained ffi in the case without emotions. In contrast, in other instances the runtime was quite high, revealing that in these executions negative emotions prevailed over the agent. Hence, the agent performance directly depends on the environment configuration which is responsible for providing the stimuli that feed the network of emotions. This is a feature that is also observed in our daily life where actions and events that occur around us cause different emotional reactions.

The average execution time was 97.23 cycles, quite close to the value observed for the sample without emotions. This indicates that, in general, when looking at the sample as a whole, the two proposed situations almost cancelled each other. This is the expected behavior given that the assumptions are based on the same opposite actions.

In order to add in the example the third hypothetical situation (R2 can motivate R1 when it takes the units of garbage to be incinerated) it is necessary to determine how often the proposed iteration occurs. Assuming a 50% chance that R2 interacts with the agent R1 the result obtained is displayed in Figure 11.

For this configuration the example shows a maximum running time of 109 cycles and a minimum time of 69 cycles with an average time 80.27 cycles. In this last scenario there are two positive and one negative inputs. This leads to a lower average runtime when comparing with the previous scenario. However, the highest value in this scenario (109) is bigger than the highest value on the previous scenario (107). This shows that even with favorable inputs the agent can perform poorly.

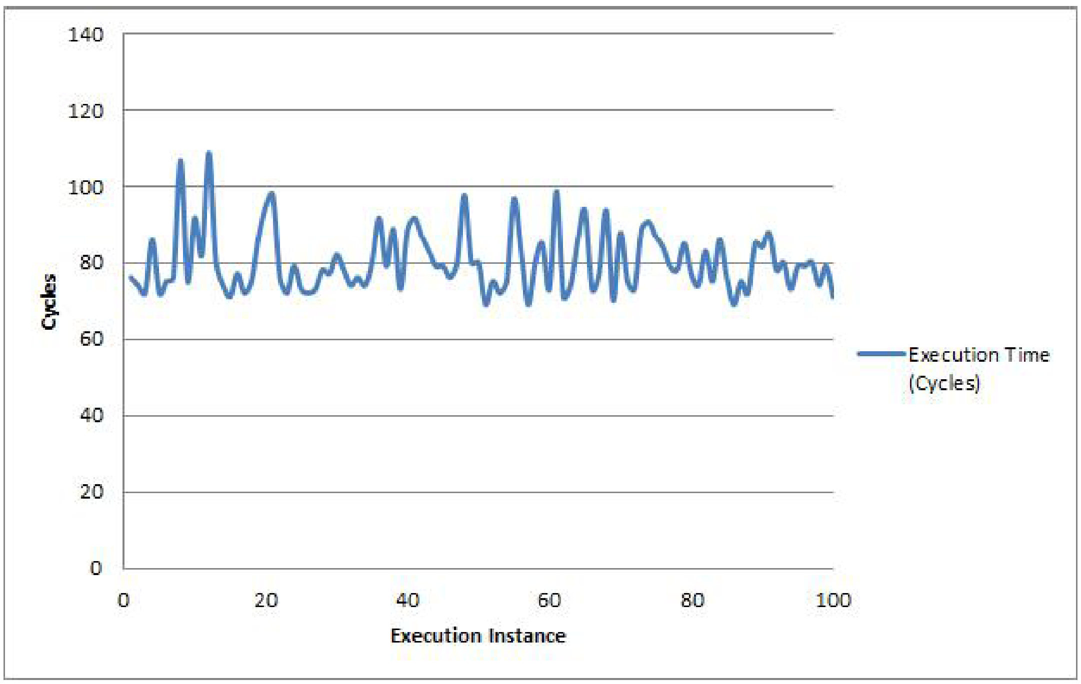

Figure 11. Runtime for 100 instances of the first, second and third added hypothetical situations.

Figure 12 shows all simulated scenarios together. By inspecting all the results together we can draw some conclusions. First, new inputs are added to the example increasing its complexity and unpredictability. The scenario without emotions is constant for 100 runs. Adding the first hypothetical situation the scenario varied only eight cycles between its better and worse results. Adding the second hypothetical situation the scenario presented a variation of 33 cycles between its extremes. Finally, adding the third hypothetical situation the scenario presented the greatest variation with 40 cycles between its better and worse performance.

In these two last scenarios, the difference among the average cycles is 17. This may lead to the false assumption which the third scenario is always better than the second, however this is not true. If we inspect the figure 12 we can see some situations where the third scenario is worse than the second. This is possible because of the randomness introduced by the Bayesian network in the modeling of emotions in agents. Moreover, this randomness is closer to the behavior of humans.

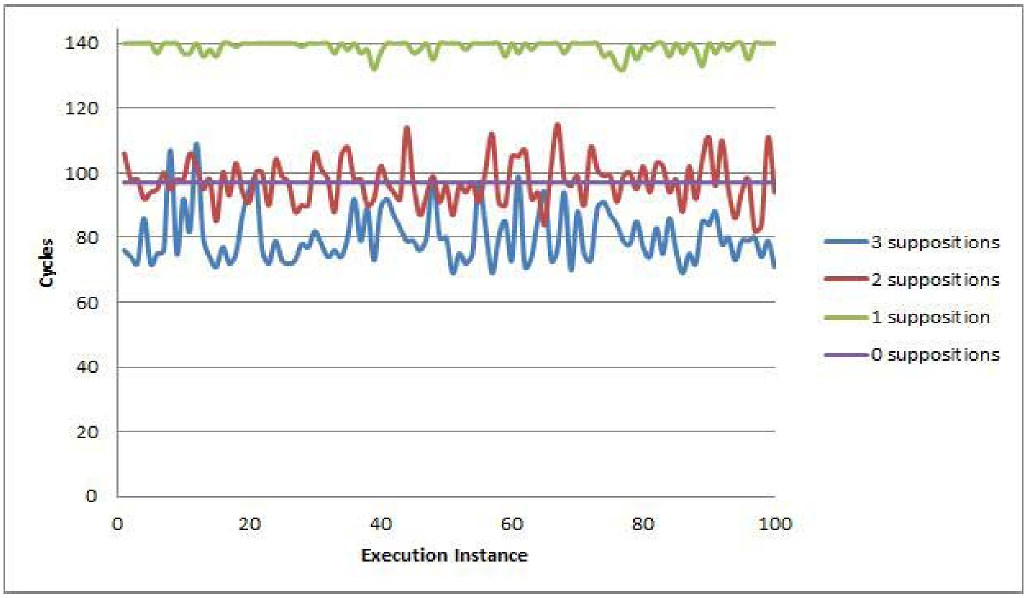

Figure 12. Running time for 100 instances of the example with the four di erent configurations: no emotions, first, ff first and second, first, second and third hypothetical situations (suppositions)

5. Conclusions

Observing the operation of the Bayesian network of emotions proposed in this work we can make some affirmations. First, the use of a Bayesian network for the OCC model application is possible and the manipulation of its variables increases the similarity between the model and the reality given that the original model provides a method of deterministic decision to define how emotion will occur according to an event and the use of Bayesian network can bring the uncertainty to the model. The use of the OCC model in the form of a Bayesian network has another important feature allowing a view of the relationship between the di erent emotions that compose the model and in many situations these relations are hidden by the structure. For example, when the network established the existence of “Anger” emotion, there is an probability increased to “Fear” emotion also occur and the “Happyfor” emotion will have a small probability.

In our study, the example presented is simple. However, it was possible to see the main features of Bayesian network of emotions. In this way, we propose as future work, the application of the network in a more elaborate example, where many agents having their own Bayesian networks of emotions. This example would provide more interactions between the agents and the environment which are inserted and also with each other, enabling a greater amount of stimuli to the network and, consequently greater variation in individual emotions, directly influencing their behavior.

In our approach the proposed model just treat emotional states reducing the individual values of the emotions the two general values, positive and negative. Using our Bayesian network, it is possible extend the approach, i.e., it could work with levels of emotional states. In this way, when the sum amount of positive and negative emotions is very high, the agent should behave differently when this sum is not so high. Taking this into account, the results of the simulations could be greater than three types of reaction (stable, positive and negative).

The use of individual values of emotions is also possible. Although quite complex, because it requires an understanding of the effects of each emotion and how each agent perform the actions. In this context, the agents can have a large quantity of reactions (and an unpredictable complexity).

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