Equilibrium Dynamic Systems Intelligence

Marius-Constantin O.S. Popescu, Onisifor V. Olaru and Nikos E. Mastorakis

Abstract— Most work in Artificial Intelligence reviews the balance of classic game theory to predict agent behavior in different positions. In this paper we introduce steady competitive analysis. This approach bridges the gap between the standards of desired paths of artificial intelligence, where a strategy must be selected in order to ensure an end result and a balanced analysis. We show that a strategy without risk level is able to guarantee the value obtained in the *Nash* equilibrium, by more scientific methods of classical computers. Then we will discuss the concept of competitive strategy and illustrate how it is used in a decentralized load balanced position, typical for network problems. In particular, we will show that when there are many agents, it is possible to guarantee an expected final result, which is a 8/9 factor of the final result obtained in the Nash equilibrium. Finally, we will discuss about extending the above concept in Bayesian game and illustrate its use in a basic structure of an auction.

***Keywords*—**Artificial intelligence, *Nash* equilibrium, Bayesian game.

I. INTRODUCTION

Deriving concept solutions for Multi-Agent represents a major challenge for researchers from various disciplines.

The most famous and popular concept solution in economic literature is the *Nash* equilibrium. Although the Nash equilibrium, expansions and modifications are powerful means of description, and even though they were used in artificial intelligence literature [5], [12], [18], the call from their perspective regulation of artificial intelligence is somewhat less satisfactory.

We want to team up an agent with an action (process) so that we ensure the desired effect or at least to wait for the utility, all that without relying on the rationality of other agents. The most important examples were introduced by Aumann in 1982. He shows 2 people-2 variants (2*2) *g* game, where the strategy of the most secure level (probably the maximum level) of the game is not Nash's equilibrium, but it produces a final result of the Nash equilibrium of *g*.

This observation may have a significant positive offset from the perspective of a creative agent.

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If a strategic security level of an agent guarantees a final result which is also the final result expected in the *Nash* equilibrium, then it can serve as a desired protocol, for an agent. We are interested to see whether or not a strategy of the optimum level of safety leads to a final expected result, similar to the one obtained in a *Nash* equilibrium of simple games, represented by variations of the basic scientific problems of classical computers. This is the case of Game 2*2 capturing simple variations in a stew of classical balance and leadership issues in the election of problems. In theory we consider a 2 people game set and we show that if a theoretical set of a *g* - game has defective mixed strategy equilibrium, then the safe level for a player in this game involves equal result obtained in this balance.

Definition: A strategy will be called a safe *C* competitive strategy if it ensures an end result which is 1/*C* of the final result, obtained in Nash equilibrium. We show this in an expected decentralized load balance which sets 9/8 of the existence of competitive strategy, when the number of players is too large.

The 4/3 report can be obtained when we allow an arbitrary speed between 2 lines connecting the source to the target. Furthermore, we use the notation: *k* regular network, where *k* is the ratio of average communication speed and the smallest communication speed, to show the existence of a reliable competitive *k* strategy for general *k*-regular networks.

Afterwards, we discuss the competitive *C* strategies of the Bayesian game and show the existence of e-safe strategy for a first competitive price of classic organized auction. Imagine an agent designed with the communication of a user with different targets (tasks).

Selecting a route for the messages of a multi-agent system is a task not an easy task. The efficiency of an agent depends on the actions of other users (and their agents), while also trying to communicate with similar targets (tasks).

In such cases, the analysis of game theory can identify the Nash equilibrium that may arise in these configurations [2]. However adopting the strategy prescribed by the *Nash* equilibrium can be quite dangerous for our agent. Other agents may fail in choosing the strategy prescribed by this balance, and as a result our staff may turn to be completely penniless. It would have been much better if the agent could have provided similar outcome as that achieved in *Nash* equilibrium, without having to rely on the behavior of other agents.

Our work can be considered a complementary way, which compares the value of the saved level of an end result of an agent in *Nash* equilibrium [3] and [4].

The rest of the paper will be organized as follows:
- section 2: definitions and basic notations;
- paragraph 3-4: simple variations of a balanced task and of the chosen leader;
- section 5: 2*2 games;

- section 6: other extended distributions of games;
- section 7: increasing the complexity level (more agents with more possible variants),
- section 8: the use of competitive analysis, saved in games with incomplete information;
- section 9: the bayesian interpretation of probabilities and statystics;
- section 10: certain competitive analysis in bayesian game;
- section 11: using bayesian networks in evaluatin risks.

II. DEFINITIONS AND IMPORTANT NOTATIONS

Definition 1**:** A game is a triple

$$G = \left\{ N = \{1,\dots,n\}, \{S_i\}_{i=1}^{n}, \{U_i\}_{i=1}^{n} \right\},$$

where: N - a set of n players and S_i - a limited set, defined by pure strategies available to i players;

Definition 2: A game with n players is a sequence of decisions and random events, that can either be simultaneous or not, and that complies with a specific structure of earnings, given by procedure rules (rule of the game).

The S_i random event implies a probability distribution over a field of events $\Delta(S_i)$.

Definition 3: The strategy of a player is a feasible (possible) action that a player can choose during the game. All game strategies are $S = S_1 * S_2 * \dots * S_n$, where n is the number of players. In some situations, nature (hazard) is the (n +1) player.

Definition 4: The gain function of the game is $U = (U_1, U_2, \dots, U_n)$ and is made out of the functions of each player.

If we note each gain function of a player with U_i and the gain functions of other players with U_i, then the gain function of the game is

$$U_i S \rightarrow R,\ U = (U_i, U_i).$$

Definition 5: An optimum strategy is that which maximizes the gain of a player i, regardless of the strategies chosen by other players.

Notations:

• Given S_i, we see a set of probabilities distributed on the elements S_i and $\Delta(S_i)$;

• $t \in \Delta(s_i)$ - a interblended strategy of player i;

Pure strategy = if S_i item is given the 1 probability.

Strictly mixed strategy = if we declare a positive probability for each S_i element.

• A triple - $t = \{t_1,\dots,t_n\} \in \pi_{i=1}^{n} \Delta(S_i)$ is a profile strategy;

• We note with $U_i(t)$ - the gain of players i which have a strategy profile t;

• The profile strategy $t = \{t_1,\dots, t_n\}$ is S *Nash* equilibrium if for any $i \in N$, $U_i(t_1, t_2, \dots, t_{i-1}, t_i', t_{i+1}, \dots, t_n)$ for each. $t_i' \in S_i$.

• *Nash* equilibrium $t = \{t_1, \dots, t_n\}$ is defined as a pure strategy *Nash* equilibrium if, for all $i \in N$ we have $-t_i$ strictly mixed strategy;

• Given a g game and a mixed strategy of i players, $t \in \Delta(S_i)$, the most reliable value of the obtained i level when we choose t in the g game, indicated by *round* (t, i, g), is the minimum result expected from the i player, when using t arbitrary strategy profile of other players.

A t strategy for an i player, for which *round* (t, i, g) is maximum, is called a security strategy (or a maximum of probability) of the player. Hence, a security strategy for an agent i, $S_{safe} \in \Delta(S_i)$, gratifies the condition [1], [6]:

$$S_{safe} \in arg\ max_{S \in \Delta(S_i)} min_{(s_1, s_2, \dots, s_{i-1}, s_{i+1}, \dots, s_n) \in \pi_{j \neq i} s_j} U_i(S_1, S_2, \dots, S_{i-1}, S, S_{i+1}, \dots, S_n) \quad (1)$$

A $e \in S_i$ strategy dominates a $f \in S_i$, strategy, if for any

$$(S_1, S_2, \dots, S_{i-1}, S_{i+1}, \dots, S_n) \in \pi_{j \neq i} \Delta(S_j),$$

where

$$U_i(S_1, \dots, S_{j-1}, e, S_{j+1}, \dots, S_n) \geq U_i(S_1, \dots, S_{j-1}, f, S_{j+1}, \dots, S_n)$$

with a strict inequality for at leat one triple.

A game is called irreducible, if there is no $e, f \in S_i$, for every $i \in N \Rightarrow e$ dominating on f.

A game is called *generic* (general) if for any $i \in N$, the pair of e strategy, $f \in S_i$ and

$$(S_1, S_2, \dots, S_{i-1}, S_{i+1}, \dots, S_n) \in \pi_{j \neq i} \Delta(S_j),$$

we have the following relationship [8]:

$$U_i(S_1, \dots S_{j-1}, e, S_{j+1}, \dots S_n) \geq U_i(S_1, \dots, S_{j-1}, f, S_{j+1}, \dots, S_n) \quad (2)$$

if and only if e and f coincide.

In a general game the strategies of i players are different; a strategy profile is set for the remaining players, that can lead to other final results.

The conclusion of this simple property is that different strategies of i players and can lead to different end results (e.g. the result of costs, consequences).

A game is a game called a 2*2 game if n=2 and $|S_1| = |S_2| = 2$.

III. THE DECENTRALIZATION BALANCED LOADED POSITION

In this section we consider the decentralization of the balanced, loaded position, where 2 rational players must submit to messages through a simple communication network, a network between 2 parallel lines of communication e_1 and e_2, connecting nodes s and t.

Each player has a message that has to be sent from s to t and he must decide which path to choose.

The e_1 communication line is faster, therefore the values of transmission for a single message over e_1 are α X> 0.

The values of transmission of a single message for e_2 are 0.5 <X <1.4.

Each player must decide what line of communication to use for transmitting messages from *s* to *t*.

If both players choose the same line of communication, then the value for each of them falls within a factor of 2 (a player will receive X/2 if both players have chosen e_1, and αX/2 if e_2 is elected).

By using a matrix, the game will have the following form [14]:

$$\mathbf{M} = \begin{pmatrix} \frac{X}{2}, \frac{X}{2} & X, \alpha X \\ \alpha X, X & \frac{\alpha X}{2}, \frac{\alpha X}{2} \end{pmatrix}. \quad (3)$$

Sentence 1: The safest value of the optimal level for a player is the decentralized load balance in a game that expects the same final result in a balance of strictly mixed strategy game.

The sentence states that an agent can guarantee himself a final result that is equal to the final outcome in *Nash* equilibrium of the balance decentralization loaded game.

IV. CHOOSING LEADERSHIP -DECENTRALIZATION VOTES

In setting the leading choice, the players vote on which player identities are bosses for a particular task. A failure in the agreement governing the production is bad and we can shape it if the end result is 0.

Assuming that the player's strategy is either "vote for 1" or "vote for 2", indicated by a_1 and a_2, and U_i (a_j, a_k) >0, where $i, j, k \in \{1,2\}$, $j=k$. Using a matrix where $a, b, c, d > 0$ we can represent this problem as follows:

$$\mathrm{M} = \begin{pmatrix} a,b & 0,0 \\ 0,0 & c,d \end{pmatrix}. \quad (4)$$

Sentence 2 (theorem): The optimal solution of the certain level for a player in a winning game, the final result is expected to draw mixed strategy equilibrium of the game.

An agent can guarantee that the expected end result is equal. Thus we can achieve a different strategy from the strategies of *Nash* equilibrium [7], [13].

V. THE SAFE LEVEL IN A 2*2 PLAY

There are 2 people with 2 answers to a problem that are produce in a computational context. By giving 2 encouraging results in these important settings, we can consider 2 types of extensions.

1. Generalization of the results in a large family of simple games;
2. Generalize of results to more general settings of the relationship *CS*, playing in particular with more players.

The following part refers to the first point. Later, and particularly in stage 7, we will be referring to the second point. We have an interest in scaling the results obtained in stages 3 and 4, so we are able to expand to other 2*2 games forms.

Load balance and the settings of the choosing lead may be represented as a generic 2*2 game.

Aumann's representation:

$$\mathrm{M} = \begin{pmatrix} 2,6 & 4,2 \\ 6,0 & 0,4 \end{pmatrix}. \quad (5)$$

General irreducible games have an attractive concept. Dominant strategies in the game do not mean understanding the interaction because sure strategies can be ignored [15].

Theorem 1: We have a *G* irreducible 2*2 game. Assuming that the minimum optimal value of a player is best achieved with a strictly mixed strategy, and then this value coincides with the end result produced a player in the *Nash* equilibrium of *G*.

The best strategy level. In general, in the context of artificial intelligence, the discussion (comment) is a mixed strategy, where the probability of operation is not considered.

Of course, the strategy of maximum probability is much stronger, and in many cases a safe level is only achieved through a mixed strategy and not by simple strategy. There is a generic irreducible 2*2 game, where the optimal strategy level for a player is pure, and the final result for this player is lower than the final outcome in all *Nash* equilibrium for *g*.

Considering a *g* game, where:

$$\begin{aligned} &U_1(1,1) = 100; \quad U_2(1,1) = 100; \\ &U_1(1,2) = 40; \quad U_2(1,2) = 210; \\ &U_1(2,1) = 60; \quad U_2(2,1) = 200; \\ &U_1(2,2) = 50; \quad U_2(2,2) = 90; \end{aligned} \quad (6)$$

With a matrix, the game looks like this:

$$\mathrm{M} = \begin{pmatrix} 100,100 & 40,210 \\ 60,200 & 50,90 \end{pmatrix}; \quad (7)$$

It is very easy to see that g is generic and irreducible.

In particular, there is no dominant strategy and the final result obtained by each player for the profile of various different strategies is different from the result of other players.

The game has no pure *Nash* equilibrium. In a mixed equilibrium strategy, the probability that in a *g* game, player 2 will choose a_2, should satisfy the following condition:

$$\begin{aligned} &100q + 40(1-q) = 60q + 50(1-q) \Rightarrow \\ &\Rightarrow 60q + 40 = 10q + 50 \Rightarrow q = 0{,}2; \end{aligned} \quad (8)$$

In this equilibrium, the probability that player 1 chooses a_1 is p=0,5 and the final result of player 1 is:

$$100q + 40(1-q) = 52.$$

The safe strategy for player 1 is to perfect a_2, ensuring that the final result is equal to 50, knowing that (a_1, a_2) is a difficult point in a zero sum game, where the final result of player 2 is the complement of 0 to the final result of the player 1, thus the sure level strategy for player 1 is 50 <52.

VI. GAMES OVER 2*2

The theoretical game set: In a theoretical set of games, the set of strategies available to players is the same and the final outcome for each player is determined by a unique set of strategies by each player.

For example, in a theoretical precise 2 player game, we have:

$$U_1(s,t) = U_1(t,s), \text{ for each } s,t \in s_1 = s_2 ;$$
$$U_2(s,t) = U_2(t,s) . \quad (9)$$

It is important to note that in a theoretical precise game, the context is very important [16].

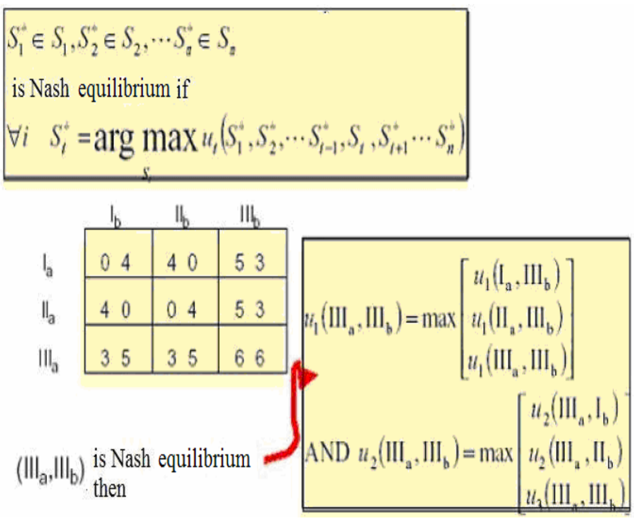

Fig.1: *Nash* equilibrium.

Sentence 3: Given a theoretical precise game g, with 2 people and a mixed *Nash* equilibrium strategy, then the optimal value for a good strategy of a player is the expected and equal result (Fig.1, Fig.2, Fig.3 and Fig.4).

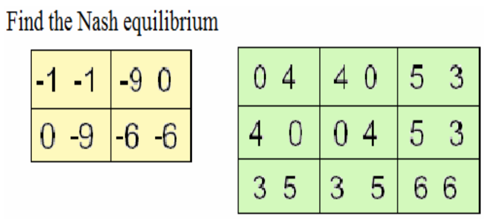

Fig.2: If (S_1*, S_2*) is a *Nash* equilibrium, then player 1 will not offer player 2 the possibility to make the S_2 move.

If (S_1*, S_2*) is a Nash equilibrium, then player 2 will not offer player 1 the possibility to make S_1 move.

Is there always equilibrium?

Can there be more than one?

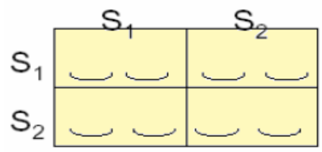

Fig.3: An example of *Nash* equilibrium from pure strategy.

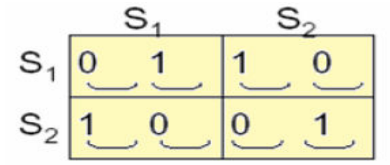

Fig.4: An example without *Nash* equilibrium from pure strategy.

VII. THE COMPETITION OF SAFE STRATEGIES

Let S be - a set of strategies. Considering a family of games $(q_1, q_2, \ldots, q_j, \ldots)$, where i is a player for each of these families, the set of strategies for each game is S, there are j players, in addition to i, in q_j.

An example is the family of balanced loaded position states. We have (n-1) games, resulting in n players and one of them being i. Players present their messages through e_1 and e_2.

The final result of player i, where there are n people, is

$$\frac{X}{K} \text{ (and } \frac{\alpha X}{K} \text{)} \quad (10)$$

if you chose e_1 (respectively e_2) and additional K-1 participants have chosen the same line of communication.

A joint strategy $t \in \Delta(S)$ will be called C- safe strategy competitions if there is a constant C> 0 such that:

$$\lim_{j \to \infty} \frac{nash(i, g_i)}{round(t,i,g_j)} \le C , \quad (11)$$

where:

- $nash(i,g_i)$, is the lowest result of the player i which can be obtained by any balance of the g game;
- $round(t,i,g_j)$, is the expected result, guaranteed by i, that chooses t in the game g_j.

Theorem 2: There is $9/8$ safe competitive strategy for the settings of the secure, balanced, loaded position. [17].

Extension: arbitrary success and m- links. The case where we have m parallel communication lines run by the source target.

The value obtained by the agent when the i line messages are presented, where officials decide whether the messages on this line are given by:

$$\frac{X - 2i}{n_i} , \quad (12)$$

where $1 = \alpha_1 \ge \alpha_2 \ge \ldots \ge \alpha_m \ge 0$.

Theorem 3: There is

$$\frac{\sum_{i=1}^{m}\alpha_i\sum_{i=1}^{m}\pi_{j\neq i}\alpha_j}{m^2\pi_{i=1}^{m}\alpha_j},$$

a competitive strategy for a secure broad decentralization when we allocate m parallel lines of communication, and arbitrary α_i;S [19].

VIII. THE DYNAMICS OF INTELLIGENT SYSTEMS

The Bayesian probability of an "*X*" event represents a person's degree of trust that the event will take place, whereas in classical probability it represents physics propriety [17]. We will refer to the classical probability of an event as the physical possibility of the events occurrence and the Bayesian probability will be referred to as the degree of trust that the event will occur [19].

One important difference between the classical probability and the Bayesian one is that for the second one experiments must not be repeated. For example, let us imagine the consecutive throws of a sugar cube on a wet surface. Each time we throw the cube, its dimensions change. Therefore, although in classical statistics it is very hard to measure the probability of a cube falling face up, in Bayesian probability our attention is directed only to the next throw, which is attributed a certain probability. One critic that is often brought to Bayesian probability is that it seems arbitrary [11].

A series of studies have suggested different sets of proprieties which should be satisfied by the degree of trust [18]. These sets of proprieties all lead to the same rules: the rules of probability. Each probability set, no matter how different from one another, actually lead to the probability rules, thus giving us a strong argument towards using probability to measure trust.

The measurement scale can be established considering the fact that people often find it easy to say that two events are almost the same. Usually, the process of measuring the degree of trust is known as the probability of evaluation [8].

One of the problems linked to evaluation probability is that of precision. In most of the cases, we cannot say for sure that the probability of an x event is 0,802 rather than 0,799. Anyhow, in most cases, probabilities are used to make decisions, which are not influenced by minor probability variations

Another problem linked to evaluation probability is accuracy. For example, the way a certain question is enunciated can lead to an evaluation that does not reflect the true degrees of trust of a person. There are many methods of improving accuracy that are enunciated in the analysis-decision literature. [23] and [24].

A Bayesian network with a set of variables $X=\{X_1,...X_n\}$ is made out of [24]:

- a network structure (S) that is encoded by a set of independent conditional propositions regarding the variables of X;
- a set of probabilities (P) linked to each variable.

Together these components represent the distribution of probabilities for X. The network structure (S) is an acyclic undirected graph. The nodes in S correspond one on one with the variables of X. We will use X_i to specify the (X) variable and the corresponded *node*(i), and pay to specify the parents of the nodes and the variables attached to them. In particular, the distribution of probabilities for X, in an S structure is given by *pair*(S,P), that is the all distributions of $p(x)$.

The probabilities used in Bayesian networks can be either Bayesian probabilities or physics probabilities. When networks are being built using previous knowledge, the probabilities will be Bayesian ones. When the Bayesian networks are being "learned" from data, they will be physics ones (values can be uncertain).

The first stage of building a Bayesian network must consider the following: the correct identification of the purpose of the model (explanation, exploration), identifying possible observations that could be relevant in resolving the problem, determining the set of observations useful to the model and organizing observations in variables with exclusive and exhaustive states.

The difficulties that might arise are not specific to Bayesian networks. They are commune problems of all models, but there is a method of building Bayesian networks that does not require ordering variables.

This approach is based on two observations:

- People can easily identify causal relations between variables.
- Causal relationships usually correspond to conditional dependencies of the nodes.

Therefore, in order to build a Bayesian network for a multitude of variables, you must only mark the edges between cause and effect variables. Using this method will result, in any case, in a structure that will satisfy the equation.

Once a Bayesian network has been built, we must determine the necessary probabilities of a functional model and also know the probability of events leading to other events. This probability is not stocked directly in our graph. It must be calculated. This phenomenon is called probability interference.

Because a Bayesian network for X will determine a reunion of probabilities distributed for X, it can be used to calculate any probability.

A remarkable characteristic of Bayesian networks is that they can be used to talk about causality, through mathematics.

For better understanding, we will present an example.

A work security and health specialist wants to know if it is necessary to increase or decrease the means of signaling for danger in order to raise the level of security amongst workers by making them aware of the dangers they can face.

The chosen variables are Signaling(S) and Awareness (A), which indicated if a person has seen or not the signals before they were aware of danger.

A first step would be studying the physics probability that A= True, knowing that S= True and the physical probability that A= True, knowing that S= False.

One way of studying these probabilities is by using an experiment: we choose two similar, random populations we force P to be true in one case and false in another, while we observe S.

This method is quite simple, but it can be very expensive from an implementation point of view.

IX. THE BAYESIAN INTERPRETATION OF PROBABILITIES AND STATYSTICS

One alternative method arises from causal knowledge. In the situation we have chosen, we study the relationship *S→C*.

If we force *S* to be true, or we simply observe that *S* is true for our current population, then we can say that signaling for danger was efficient towards people's acknowledging of that danger. In this case, we will write: $p(c|\bar{s}) = p(c|s)$ *(2.2)*- the physical propriety of *C*= true; knowing that S is not forced to be true in the current population.

We will use the same analogy for: $p = (c|\hat{\bar{s}}) = p(c|\bar{s})$

On the other hand, if we have *S→C* and we force *S* towards one state, C will not be influenced.

To determine if S is the cause of *C*, we will use causal dependency and probability, known as the Markov causal condition, which states that an acyclic undirected graph *C*, is a causal graph for *X* variables, if the nodes in *C* are in one on one correspondence with *X* and there is an arc between *X* and *Y*, if and only if *X* is the direct cause of *Y*. According to the causal condition of Markov, if *C* is a causal graph for *X*, then *C* is a Bayesian network.

Being given the Markov causal condition, we can extract causal relationships out of conditional- independent and conditional- dependent relationships. Assuming that we have learned that physical relationships are not equal, using the Markov causal relationship we will define four simple causal relationships (Fig.5):

a) *S →C*,
b) *C →S*,
c) there is a "hidden" cause for *P* and *C*;
d) *S* and *C* are causes for the selection of data;

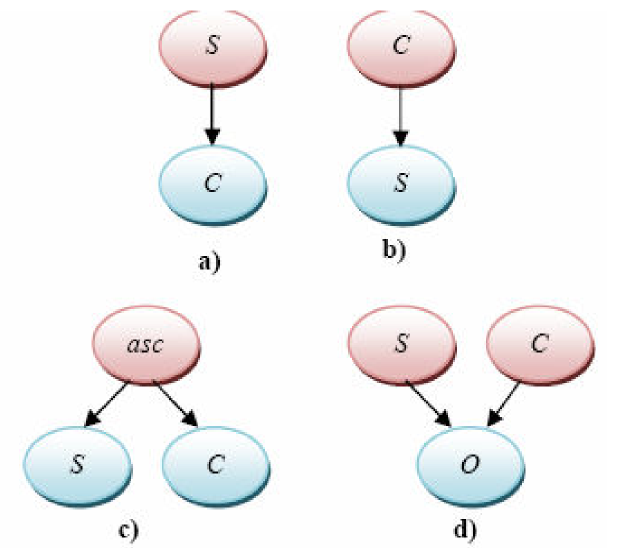

Fig.5: Causal graphs that show four relationships between *S* and *C*. "asc" corresponds to a commune hidden cause for *P* and *C*. The common node *O* indicates that this case has been introduced in the database.

Until now, the Markov causal condition has not answered our question whether *S* causes *C* or not. We assume that another two important variables will be observed: Person studies (I) and Person senses (M), which represent the studies and acuteness of the workers. By introducing these two variables in our graph, we will obtain the graph in the Fig.6.

Because we are aware of the Markov causal condition, the only explanation we can find for the independent- conditional and dependent conditional relationships of the Bayesian network is that *S* causes *C*.

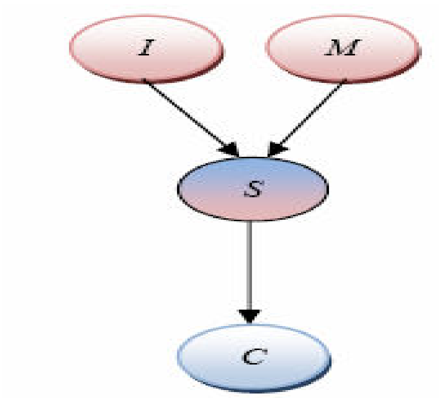

Fig.6: A Bayesian network where *A* causes *B* is the only causal explanation for the Markov causal condition.

X. CERTAIN COMPETITIVE ANALYSIS IN BAYESIAN GAMES

The results presented in the previous section refer to games with complete information. The games that we have studied in this context refer to basic settings in artificial intelligence and game intersection theory. Throughout this section we will be showing that our ideas can be applied for games that lack in information. In a game with incomplete information the final result of a player gives other players private information about him/her. On the other hand to illustrate certain competitive analysis in games with incomplete information, we chose to use a basic mechanism, namely, the first - with the most points takes action. Actions are the fundaments of economic mechanism theory, one that has no dominant strategy assumes independent private action, and the first move is likely to be the most common [9].

We will consider a setting where a good, *g* is for sale and there are *n* potential buyers. Each player knows the maximum he/she can offer for the good, *g*, and that information is estimated in uniformly distributed real numbers of [0,1]. This evaluation represents private information that is available only to the agent. The exact evaluation is only known by the agent, whereas the evaluation of agents is public. Evaluations are independent data. In the first action, every potential buyer is asked to auction for the product. Then we have to make sure that the auction for the g product and the v evaluation are situated in the interval that offers the highest price (in case there is more than one winner, a lottery is held). Auction rules can be defined using the Bayesian game. In this game, the players are perspective buyers and the end result of a player with the *v* evaluation is *v-p* if he/she wins and pays p and 0 if he/she does not want the product. The equilibrium concept can also be extended in the context of Bayesian games.

In his/her self evaluation, the strategy of each player is linked to the maximum price that can be auctioned. A strategy profile will be balanced if the strategy of an agent is the best compared with the strategies of the other agents. More exact, for the balance of the game, the auctioning of players with *v* evaluation is

$$(1-\frac{1}{n})v\,.$$

The final result of an agent with the v evaluation will be:

$$\frac{v^n}{n}\,.$$

The questions are now: can we guarantee the final price, which is proportional with the final price expected for a balance?

We have to make sure that the competitive action of a player is independent from the number of players. On the other hand, the number of players is taken into consideration when it comes to the balance of the game. The main revelation tells us that one can replace the first price offered by the following: each bidder will be asked to report its evaluation and the best will be sold to the bidder who will narrate the best evaluation, if the staff gives the assessment, he/she will be considered a player and will be asked if he/she can pair $(1-\frac{1}{n})v'$. In this mechanism, a player is going to make a bid between $\frac{n}{n-1}v$. He then sends that the true evaluation report in a balance of that auction, producing the same allowance, payment and utility expected from the participants, as in the original auction. It is convenient to consider that the revelation of the mechanism (from the moment we choose the number of participants) is based on the same strategy as the equilibrium auction.

The price of the first set is identified with the games $(g_1, g_2, ...)$ where g_j is a Bayesian game associated with the first price j+1 offered by potential buyers.

C competitive strategy definition can now be applied over the context.

Theorem 4: There is an *e*-competitive strategy for choosing the first price. An interesting observation in this theorem is that the sure level of the strategy is identical to the level of the balanced strategy. This connection is not 0.

It is also interesting to see that when we consider the revelation of the mechanism, the sure level of the strategy is not related to the number of players. Our result can also be obtained if we consider the first price to be the standard one. However, this action gives players the chance to choose that action, knowing the potential number of bidders and when they will exchange with one another in the equilibrium analysis.

XI. USING BAYESIAN NETWORKS IN EVALUATIN RISKS

There are several methods we can use, such as the Analysis of the deterioration of the Tree, which can give very good results if used together with an efficient probability system. The graphic probability models are graphs where the nodes are random variables and the arcs are conditional independence assumptions. As a result, they offer a good representation of probability distributions.

The graphic undirected models, known as Markov Random Fields or Markov networks, have a simple independence definition: two nodes *A* and *B* are conditionally independent if, being given another node *C*, all paths between *A* and *B* are separated by a node in *C*. Unlike these models, the oriented ones, known as Bayesian networks, have a more complex definition of independence, which takes in consideration the orientation of the arcs.

Therefore, this type of graphs has more advantages. One advantage is that an arc between *A* and *B* can be interpreted as *A* causes *B*. This can be used as a graph building guide. Moreover, the oriented models can encode relationships and they are easier to learn and implement. The causal structure and conditional relationships which are found in the model, allow the insertion of data through entrance nodes, spreading data throughout the model and modifying the values of exit nodes [11]. This model can be used for both interpretation and diagnosis, thus ensuring a decision making support. Considering what we have mentioned earlier, we have chosen a conceptual model of analysis for the safety functioning of a monitoring system, based on Bayesian networks (Fig.7).

In this analysis we have the safety of the monitoring system and the appearance of testing errors. Causal factors are divided into two categories: the ones related to human quality, which use, design, create and test and those related to the complexity and accuracy of testing. We can see that the major role in establishing causes is played by the causal factors determined by the human resources involved in the creation of the system.

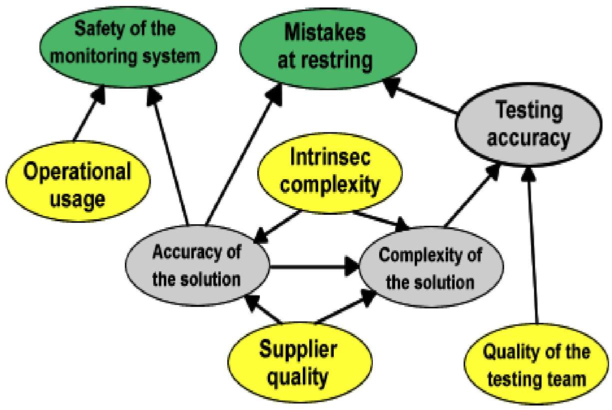

Fig.7: Model of analysis for the safe functioning of a monitoring system, based on Bayesian networks.

To create the logics of a monitoring system for a safety degree, we propose a Bayesian model, presented in fig. 8. Through the implementation of this model we can create an evaluation of a state of danger using several observations. The state in which the system is found at a certain point as well as other causes can lead to a dangerous state of the model.

This state can appear because it has not been eliminated when the model was designed. As a consequence it can be considered the cause of appearance of a residual risk. The manifestation of the residual risk is determined by de dangerous state in which the monitoring system in found, but it can be tempered or eliminated by existing security barriers.

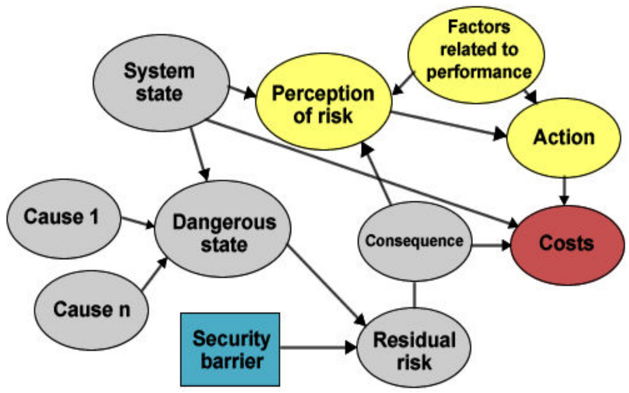

Fig.8: Monitoring risk model based on Bayesian networks.

Fig.9: Evaluating the risk degree.

This action affects the human factor – harming him, as well as loss of materials, loss in production or any other damages. Depending on how the risk is seen, an action can be initiated, which can affect costs either in a positive way or a negative one. Unlike the Analysis of the deterioration of the Tree, Bayesian networks use a wide range of information, all found in the same model, thus enhancing the range of application of the model. Moreover, the relationships between variables of Bayesian networks fall into the probability category instead of the determination one.

Determination relationships are basic characteristics of the Analysis of the deterioration of the Tree model, as well as of other management risk tools. Probability relationships between data allow the encoding of uncertainty. This is very important because it helps represent an uncertain world, very similar to the way people see the world. The method we proposed for evaluating the risk in a Bayesian network is based on creating a Bayesian model that takes into consideration risk related observations about working equipment, work environment, work tasks. Based on these observations we calculate the probability of appearance of an accident. Taking into consideration the fact that risk is represented by the probability of appearance of a dangerous event as well as the gravity of its consequences, we propose a way of evaluation the risk using 4 probability degrees and 4 gravity degrees (Fig.9). Using this method we will cover several stages (Fig.10). In the first stage we identify the causal factors generated by the work equipment, work environment,

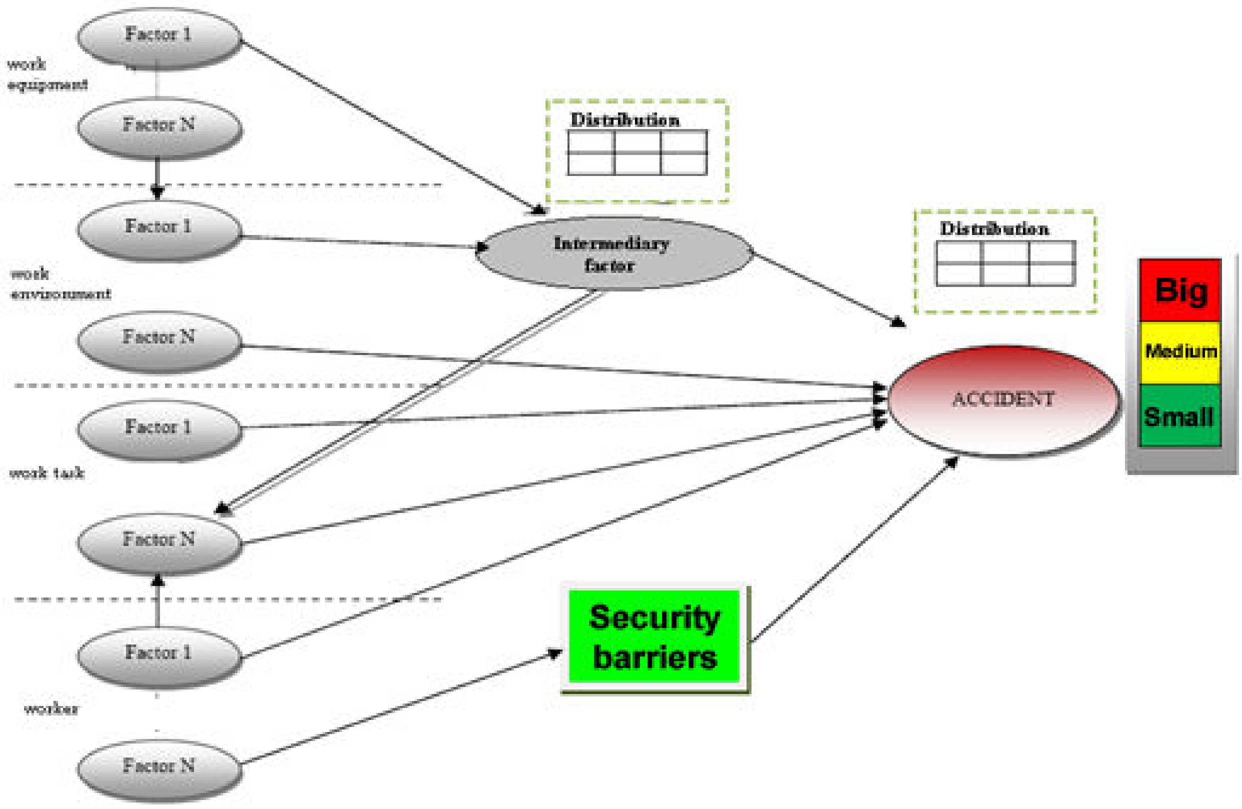

Fig.10: Generalised model of evaluation: a) causal factors identification; b) influence diagram development; c) distribution table asignement; d) risk level calculus.

work tasks or execution of the tasks.

In the next stage, we create an influence diagram, which establishes the relationships between causal factors. In the third stage, we build the Bayesian network, we determine who are the intermediary factors, what are the relationships between them and we make the distribution tables.

The last stage is evaluating the risk level through use of the interface.

XI. CONCLUSION

Some of the earlier work in artificial intelligence has tried to show the potential power of theoretical path which does not talk about the theoretical game of classic analysis.

In particular, work in competitive analysis of computer science theory has been extended, emphasizing on reasoning restrictions, in such a way that it can be applied for multi-agent systems.

We introduce reliable competition analysis, covering the differences between artificial intelligence/ secure regulatory competition and advanced classical equilibrium analysis.

The above notes have shown, thanks to Aumann, that the strategy of the sure level can relinquish the values of the Nash equilibrium which do not have an amount equal to 0, generating a normative power for computers and interesting discoveries in artificial intelligence. It was shown that sure competitive analysis can be used in different contexts.

We show the results of a 2*2 game, as a safe game of numerous participants, by introducing the use of sure competitive analysis in the balanced, loaded position of choosing the winner and the bids. It is very important to realize that this paper implies the regulatory discussion in decision- making for multi- agent systems.

Although the *Nash* equilibrium has many shortcomings, it is still the most powerful concept in the prediction of actions in multi-agent systems. The settings of balanced loaded positions are very important in theoretical games.

This paper suggests the use of protocols and analysis, by underlining the difference between classical decision theory and artificial analysis of equilibrium in game theory.

By analyzing and representing a system with the help of models based on Bayesian networks, we can make a probable evaluation in real time of potential dangerous situations. Depending on security policy, we can also make efficient decisions.

We propose that these models be implemented with the help of computerized technology in order to constantly monitor by observing different parameters. This way we can determine the risk of accidents, which is crucial in security and health management.

The boundaries of this research can be broken, considering the fact that recent studies have shown that this type of mathematics is used by the human brain. The “optimal Bayes” represents the means of reaching correct conclusions, by using probabilities.

Human neurons receive different signals, such as light or sound signals, or any other signals from the surrounding world. When the brain processes these variables, it requires accurate information, which is not necessary contained in those transmitted by our senses.

In this case, the neuron that has to make the decision take into consideration only the set of variables that can be converted and used in a Bayesian calculation.

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