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THE COGNITIVE COMPLEXITY IN MODELLING THE GROUP DECISION PROCESS

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Abstract. The paper investigates for some basic contextual factors (such us the problem complexity, the users' creativity and the problem space complexity) the cognitive complexity associated with modelling the *group decision processes* (GDP) in e-meetings. The analysis is done by conducting a socio-simulation experiment for an envisioned collaborative software tool that acts as a stigmergic environment for modelling the GDP. The simulation results revels some interesting design guidelines for engineering some contextual functionalities that minimize the cognitive complexity associated with modelling the GDP.

Keywords: *group decision support systems, facilitation, social simulation*

1. Introduction

Group Decision Support System (GDSS) is defined as an interactive computer-based environment that supports concerted and coordinated team effort towards completion of joint tasks [1]. A GDSS is composed of a set of highly configurable "tools" (e.g. brainstorming, voting and ranking, multi-criteria analysis etc.) that requires a high level of expertise for an effective use for complex decisions [2]. The strong relationship between the GDP outcome and the presence of a skilful facilitator to direct the joint decision process is thoroughly presented in many field studies of GDSS research [3]. To reduce the dependence on the facilitator, the participant-driven GDSS was proposed as the most promising research direction to leverage the skills and abilities of each group member [4]. However, this approach is highly constrained by the cognitive complexity associated with the construction, coordination and execution of GDP by inexperienced users.

To overcome the problem of cognitive complexity Briggs and de Vreede [5] introduced the *thinkLet* (TL) concept as a discrete facilitation unit that integrates a specific tool, its configuration and a script to use it - a predefined interaction protocol, mediated and enforced by a specific collaborative tool, among users. The TLs are considered to be the smallest piece of essential knowledge to design collaborative processes.

The paper investigates from a cognitive stance the complexity associated with modelling the GDP in relation with some basic contextual factors such us the problem complexity, the users' creativity and the problem space complexity. The remaining part of this paper is organized as it follows. The next section describes the main components of an envisioned collaborative software tool that act as a stigmergic environment for modelling the GDP. These components are implemented and tested in a socio-simulation experiment which is described in Section 3. The experimental results show clear self-organizing capabilities as in many field studies of GDSS research, but simultaneously high dependability of GDP modelling performance on the contextual factor. From the engineering standpoint of constructing purposeful facilitation tools for e-meetings, these results are discussed and concluded in the last section.

2 The simulation model for modelling the group decision process

Analogous with the collaborative way in which CAD software is used in architectural design [6], the development of the socio-simulation model is based on the view of seeing the collaborative software tool as a stigmergic environment to co-design the GDP It basically mimics the users' conceptual 'navigation' over the semantic structure of the problem space composed of TLs. From the socio-simulation perspective the approach implies two design concerns: 1) the population of agents, and 2) the shared environment where the agents are localized and moved over it. For the GDSS domain, the environment is the conceptual problem space that comprise all the TLs discovered and documented by a community of users (so far there are over 70 TLs acknowledged in literature [7]), while the agents are the users responsible to define, execute and evaluate a GDP (a path through the conceptual space of the available TLs).

2.1 The semantic environment for modelling the GDP

According to Parunak [8], a stigmergic environment assumes the definition of three main components: 1) topology, 2) states and 3) process. Structurally, the *topology* may be viewed as a fully connected weighted graph that codifies the facilitation knowledge of group decision in e-meetings. This knowledge presumes correlated information among the users and the TLs, reflecting the users' evaluation of the performance for a TL (a node in the graph) relative to a problem type. The performances are stored for each problem type in a variable associated with each edge of the graph. The problem type is simply codified through a unique ID to distinguish among different performances when they are read, during the modelling phase of the GDP, or modified, after the GDP has been executed and evaluated by agents. Evaluation of a GDP model entails a subjective assessment of the model, after its execution, against some performance criteria.

The performances from all the graph's edges describe the state of the environment over time. Usually, the environment executes a set of processes on the variables (as aggregation end evaporation in the case of ants [8[). For our case, we apply a simple additive rule to simulate the aggregation of *performances*. After the evaluation of a GDP model that corresponds to a certain problem type, a path through a number of n nodes $TL_1, \ldots, TL_n$, the aggregation rule may takes the following form:

$$P_{j,k}(TL_k,t) = P_{j,k}(TL_k,t-1) + P_{j,k}(TL_k)/\lambda \qquad (1)$$

where t represents the temporal component of the model which is incremented by one for each successive use of the GDSS; k is the TL's identification index from the set of TLs used to model the GDP; $P_{j,k}(TL_k)$ - is the performance of the k-th TL evaluated from the side of TL_j; $P_{j,k}(TL_k,t)$ and $P_{j,k}(TL_k,t-1)$ are the new and previous values of the performances stored on the edge between the TLs j and k; and λ is a tuning parameter, arbitrary chosen, to weight the impact of the last evaluation.

2.2 The agents' behaviour over the semantic environment

The agents are the users who interact with the collaborative tool to model a GDP. Conceptually, in any point in time an agent is "located" in a node (TL) of the cognitive environment, performing one of the following basic actions: 1) evaluating the preference for the next possible TL (or TLs) that are going to be executed given the current context of GDP implementation; 2) selecting the next best TL (or a group of TLs) for further completing the GDP model; 3) executing the TL (or the group of TLs) from the model, and finally; 4) evaluating the performance for the executed TLs. The evaluation activity is simulated using the formula (1), while the first three actions with Luce's selection axiom [9]:

$$p_{j,k} = e^{P_{j,k}(TL_k)/T} / \sum_{i=1}^{m} e^{P_{j,i}(TL_i)/T} \qquad (2)$$

where p_{jk} represents the preference for an alternative TL, i.e. the selection probability of the TL k from the TL j; i is the index of TLs connected from the side of node j (in fact all the m TLs available in the problem space as long the graph is fully connected); and T is a positive subunitary parameter used to define the deviation from a pure rational behaviour (for $T = 1$ we have a random selection behaviour, while for $T = 0$ a deterministic one).

The above formula is the most common model of stochastic decisions due to its correlation with the psycho-social observations of human behaviour in several domains. As a result of normalization, the preferences for the unexploited TLs are diminishing after each performance update. This mechanism replicates the pheromone evaporation process of the real ants (e.g. even if a TL has been positively evaluated after an execution of a GDP model, the associated preference will decrease once a better alternative is discovered and more frequently used). Under complex circumstances - when TL's selection depends on other users, the performances available on the edges are uncertain or incomplete, or there is impossible to evaluate the performance of a TL) - we consider the user who models the GDP to have limited cognitive capacity (bounded rationality). Note that Luce's selection axiom does not specify the reasons for the "bounded rationality"; instead, it tries to generalize the selection behaviour of human decision-makers through the parameter T which may be interpreted as the evaluation costs or uncertainty associated with the quantification of TLs' performance.

2.2 Experimental results

To evaluate the cognitive complexity for modelling the GDP we conducted a virtual experiment implemented in the Netlogo multi-agent simulation environment [10]. The experiment presumes the users are facilitating the e-meeting by defining the GDP model for a problem type by mentally moving in the conceptual graph of TLs. While the TLs' performance for a problem type has a randomly assigned value, the user is trying to find the right sequence of TLs that maximise the performance for this GDP model.

The section presents the normalized entropy for 100 successive explorations (iterations) in relation with three factors that potentially could impact over the GDP models' performance: 1) *problem complexity* (PC) - defined as the number of distinct TLs that compose a GDP model; 2) *social temperature* (T) - which stands for the T parameter from the Eq(2); and 3) *complexity of the problem space* (PS) - defined as the total number of TLs that compose the GDP modelling space. An exploration stands for a complete execution cycle of a GDP. It includes three consecutive phases: 1) finding a suitable model through the successive selection (using the Eq(2)) of TLs that compose the GDP for the given problem type; 2) executing the identified model and assessing its performance by reading and averaging the predefined performance values of all the TLs that compose the GDP model; 3) evaluating the model by updating the performances values (using the Eq(1)). The statistics are aggregated from 30 experiments for a relatively simple set of experimental values for the observed parameters.

The auto-organization of relations between TLs (i.e. the performance update after successive evaluations) entails a decrease of freedom due to the emergence of contextual constraints that reduce the probability to select some

TLs (i.e. the preference for the available TL as defined in Eq(2)). For a problem type, the degree of freedom corresponds to the probabilistic distribution of preferences for the selection alternatives that is equivalent with the Shannon normalized entropy [11][12]. The Shannon normalized entropy for the selection of a TL is given by:

$$E(p_{j,k}) = -\sum_{k=1}^{m}(p_{j,k}ln(p_{j,k})/ln(m)) \tag{3}$$

where p_{jk} - represents the preference, the selection probability of the TL k from the TL j; i - is the index for the TLs connected from the node j (in fact, all the m TLs available in the problem space).

When the recorded performances are equal for all the available modelling alternatives, the user is considering the entire problem space when he selects a feasible TL (the probabilities from Eq(2) being equally distributed entail an entropy equal with 1). Contrary, when the recorded performances favour a single alternative, the user will have no freedom in the selection of the best TL (all the probabilities from formula 2 being 0 excepting the best alternative that is 1, entails an entropy equal with 0). Thus, the entropy associated with TL's selection is a measure of cognitive complexity for modelling the GDP. Moreover, it is a local metrics that can be computed for each TL's selection activity for modelling the GDP.

Figure 1 shows the cognitive complexity associated with the GDP modelling for different problem complexities. The data are obtained for a problem space composed of 30 TLs with T=0.7. Because this measure is computed on the basis of the local data for each selection action (the performances available on the edges from the current TL), the figures correspond to the average of entropies for all the TL selection actions needed to complete the GDP model (3, 5 and 7 successive TLs depending on the problem complexity). The data from the Figure 1 shows that problem complexity has a great impact over the convergence of entropy (around 190 iterations for a PC=7 while less than 5 are needed for a PC=3). It entails a greater need for experimentation, learning and creative use of the GDSS for more complex problems. These results are contrasting with the real use of GDSS in organizational settings where the complex problems are often less frequent. On the other hand, problem complexity concerns the users' satisfaction in modelling the GDP as well. PC is often a subjective factor that measures the availability of relevant information [13]. The more predictable the GDP modelling is (i.e. the individual entropy

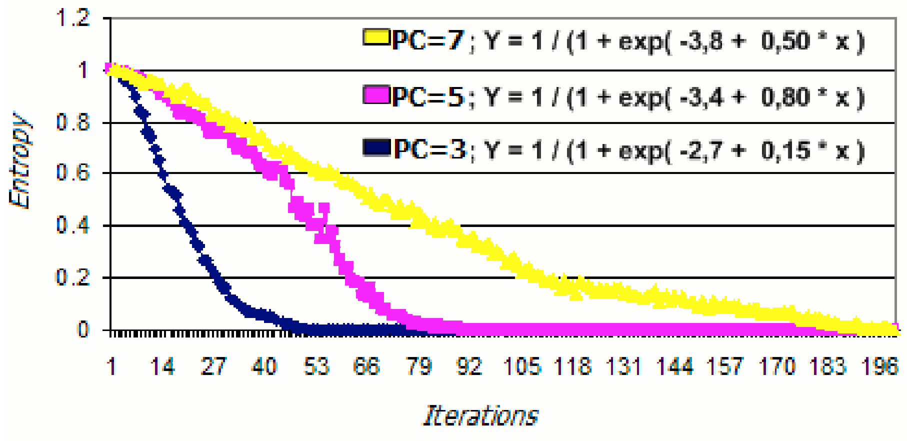

Figure 1: The normalized entropy of the GDP modelling for different problem complexities

smaller), the perceived problem complexity is smaller. Consequently, the cognitive complexity for complex problems may be lessening by incorporating functionalities that provide relevant information for modelling the GDP.

Figure 2 shows the cognitive complexity associated with the GDP modelling for different values of T. The data are obtained for a problem space composed of 30 TLs and a PC composed of 5 TLs. The performances are better for higher values of T as a result of exhaustive exploration of the problem space. Consequently, when the GDP modelling problem is in the learning phase it is preferably to encourage a creative use of the GDSS. Obviously, this issue presumes a high frequency of that problem type and a long-term use of the GDSS in organizational settings. Note that as long the T parameter measures the degree in which the preferences are considered by the users in modelling the GDP, it may be at the same time a post factum measure to quantify the users' creativity.

Figure 3 shows the cognitive complexity associated with the GDP modelling in a problem space with a different number of TLs. The data are obtained for a simple problem type composed of three TLs with T= 0.7. It may be seen that the complexity of the problem space has basically no impact over the convergence of the entropy function. This is one of the core arguments for employing stigmergic coordination mechanisms for global optimization problems based solely on local interactions which that remains effective in open, dynamic and

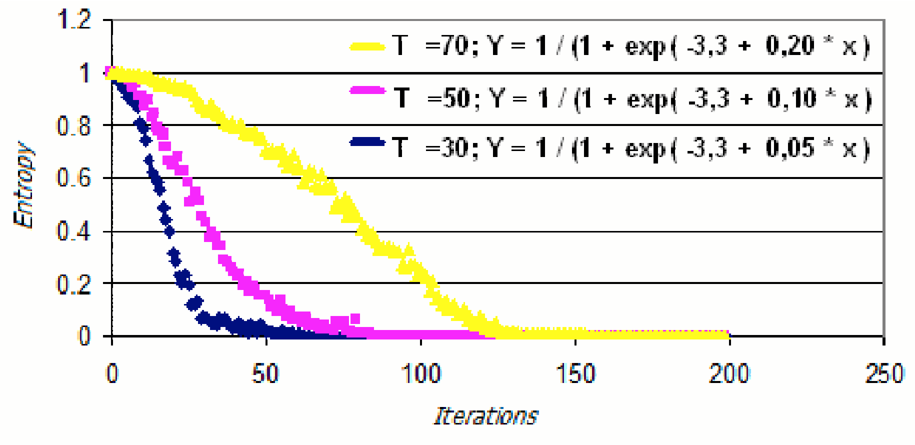

Figure 2: The normalized entropy of the GDP modelling for different T values

uncertain environments. On the other hand, an increase of available TLs for modelling the GDP will automatically result in an increase of alternatives to model it. It has been experimentally shown that as the number of decision alternatives is higher the decision makers are tempted to consider less of them (Poole and Roth, 1989). This implies an accelerated discrimination among possible alternatives through the intensification of GDP model evaluation.

3 Conclusions

The paper investigated some of basic contextual factors (such us the problem complexity, the users' creativity and the problem space complexity) that usually have a significant impact over the cognitive complexity associated with modelling the GDP in e-meetings. The investigation has been conducted by implementing and testing in a socio-simulation experiment an envisioned collaborative software tool that act as a stigmergic environment for modelling the GDP.

The results show that the most dominant factor remains the problem complexity. It may be lessening by incorporating functionalities that provide relevant information for modelling the GDP (i.e. the knowledge resulted from the subjective evaluation of each GDP from a large community of users) that entails a greater need for experimentation, learning and creative use of the GDSS. Moreover, the performances are better for higher values of the social

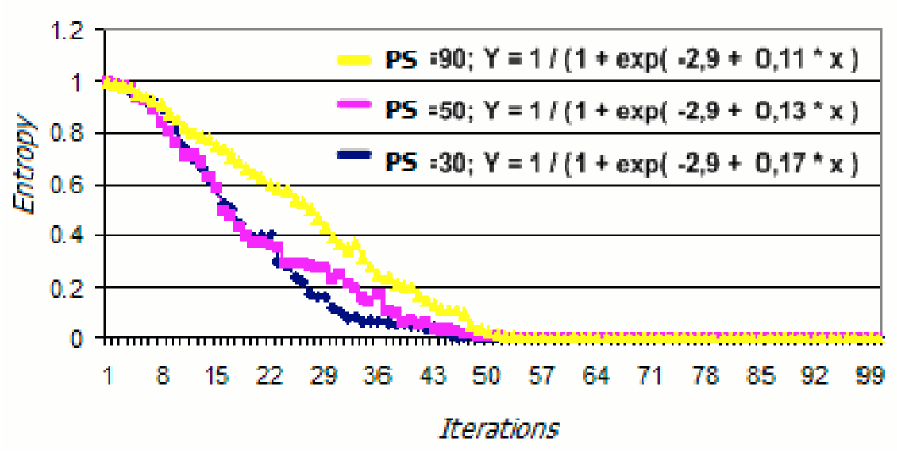

Figure 3: The normalized entropy for the GDP modelling in a problem space of different complexities

temperature as a result of exhaustive exploration of the problem space. Consequently it is preferably to encourage a creative use of the GDSS when the GDP modelling problem is in the learning phase. Conversely, the complexity of the problem space has basically no impact over the cognitive complexity associated with modelling the GDP. It shows why the emergent functionalities of a facilitation tool for modelling the GDP should be engineered around some simple stigmergic coordination mechanisms.

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