Creation of Creative Work Teams using Multi-Agent based Social Simulation

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Abstract: Over the past decades, advances in Artificial Intelligence (AI) techniques have investigated the modelling of complex systems. In particular, the use of Multi-Agent Systems (MAS) opened new possibilities for studying different domains using social simulation. In the present work we have implemented and empirically evaluated a Multi-Agent Based Social Simulation (MABSS) system to support the formation of creative work teams. Based on existent psychological and organizational creativity studies, we have modelled a set of personal characteristics and contextual factors to represent and analyse their influence on creativity at both: the individual and the group level. The obtained initial results were significantly better than the results obtained with a pure stochastic model (average improvement of 8.2%). Additionally, we empirically confirm some hypothesis about group formation from the organizational studies.

1 INTRODUCTION

Simulation systems have been applied since 1950's in several research domains, such as Political Sciences (Yamakage et al., 2007), Economics and Social Sciences (Phan & Varenne, 2010), Environmental Science (Gernaey et al., 2004) and Natural Resource Management (Galán et al., 2009) to name a few.

A particular simulation technique that has been widely used in recent years is the known as Multi-Agent Based Simulation (MABS). Some of the main reasons behind the growing popularity of this kind of systems are that they offer (*1)* the possibility to carry out "what-if" scenarios to better understand the domain under analysis at lower costs and, (*2)* the flexibility to simulate wide combinations of behaviours observed in the real world. In MABS, an agent represents a real world entity that perceives events (such as interactions with other agents) and autonomously reacts according to their mental state.

One of the domains where MABS is more frequently applied is Social science, resulting in the so-called Multi-Agent Based Social Simulation (MABSS) (Davidsson et al., 2006). The MABSS field is frequently used to analyse the properties and effects at social level of a set of attributes modelled in the individuals within an organizational structure.

The agent-based model described in this paper makes use of MABSS to analyse the creativity process in a work team. In particular, our model is focused in the abstract representation of a work team to better understand the influences of the individual team members' characteristics and their interaction on the group creativity.

The rest of this paper is organized as follows: **Section 2** presents the related work developed in the fields of creativity and agent-based Social Simulation Models. **Section 3** describes our proposed model whereas **Section 4** describes its implementation. **Section 5** discusses the initial evaluation of the model through the obtained results of the simulations. Finally, **Section 6** presents the conclusions and the future work.

2 RELATED WORK

The design and implementation of MABSS simulations for the analysis of complex behaviours have been used over quite different domains such as military applications (Luscombe & Mitchard, 2003), police and criminal behaviours (Melo et al., 2006)

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and management of health emergencies (Benkhedda & Bendella, 2012) among others.

A common characteristic of these works is the study of human behaviours within a group. In this line some MABSS have been specialised in the simulation of teamwork characteristics. Some authors have simulated teamwork behaviours through the representation of specific features such as shared mental models, collaborative behaviours, communicative behaviours and others. A close related work to our proposed model is the Dong et al. (2008) approach, where they evaluated the relationships between members of a workgroup based multi-agent model. Whereas this model is focused on the study of group efficiency, our model is on the analysis of group creativity.

From all the existent models, just a few have as the main objective the analysis of individual, social and contextual factors behind creativity behaviours. One of them is the model developed by (Sosa & Albarran, 2008) which is focused on team formation based on the social tie strength to improve teamwork practices in creative activities. With their model, the authors tried to respond if teams with strong ties (teams of friends) and teams with weak ties (teams of strangers/partner) produce different creative processes and solutions. The results concluded that teams of friend produced more quality solutions and teams of strangers produced more creative solutions.

A similar work is described in (Martínez-Miranda, 2010) where the development of an agent-based simulation model to support the formation and configuration of work teams is presented. This model represents and analyses the performance of the team as a consequence of four human attributes: *personality* type, *emotional* state, *social*-related skills and *cognitive* abilities (including creativity). This model considers the individual creativity as an influential variable on work team performance but it is static and the model does not calculate or modify it, a key difference with our proposed model.

3 MODELING CREATIVITY IN A WORK TEAM

3.1 Scenario Description

The scenario is composed of a Manager agent and N Worker agents. Each of these Worker agents represents a different role within the work team: Director, Assistant, Technician and Scholar. Additionally, they have individual characteristics (see section 4.2) that lead to significant differences between them. Worker agents aspire to have a job on the working group that the Manager agent is forming, whereas the Manager agent receives a proposal to create a working group as creative as possible.

The objective of the Manager is to form a work group (initially empty) with the maximum creativity constrained to the limitations of the proposal (e.g. budget of the project or team size). Using a configurable selection criterion, the Manager agent performs the negotiation by selecting the most promising candidate. After creating the working group, the Manager agent could make replacements in order to achieve a more creative group.

The main hypothesis that our model aims to study is whether the inclusion of a highly creative individual outperform directly the work team's creativity.

3.2 Creativity Assessment

The function that models the creativity of the group (*CF_Group*) is the most important function in the model and it is the objective function to be maximised by the simulation. This evaluation function depends on the individual creativity function (*CF_Individual*), the group characteristics (*GroupFactors*), and the relationships of the members in the group (*RelationalFactors*).

3.2.1 CF_Individual

The calculation of individual creativity (*CF_Individual*) is based on six *positive* and two *negative* (creativity hinders or as defined in Amabile (1998) *creativity killers*). The negative factors are those identified by (Batey et al., 2010) and the positive factors are taken from (Carroll et al., 2009) summarised in the Table 1. The eight factors are classified into cognitive capabilities, social skills, emotional states and personality traits similarly as in (Martínez-Miranda, 2010).

Using the factors listed in Table 1 we define the individual creativity function as a weighted sum of the positive and negative individual factors (see equation 1).

The range of the factors is [0, 1] and the range of weights (randomly assigned) is [0, 7]. The sum of the weights must be 28. In the code, we apply a normalization to the *CF_individual* function so the range is [0, 1].

Table 1: Factors to calculate the individual creativity.

Index	Factor	Category	Effect
1	Exploration	Cognitive-Related Capabilities	Enabler
2	Immersion		Enabler
3	Results Worth Effort		Enabler
4	Collaboration	Social-Related Skills	Enabler
5	Expressiveness		Enabler
6	Enjoyment	Emotional State	Enabler
7	Agreeableness	Personality Traits	Killer
8	Conscientiousness		Killer

$$\boldsymbol{CF_{individual}} = \sum_{i=1}^{6} F_i W_i + \sum_{i=7}^{8} F_i(-W_i) \quad (1)$$

3.2.2 CF_Group

For calculating group creativity (*CF_Group*) we have based our model on a simplification of the work presented in (Woodman et al., 1993) concentrating our model only at the individual and group level and discarding the organisational level. The *GroupFactors* function refers to aspects of composition / characteristics of the group as number of leaders, longevity, composition, cohesion or structure (Payne, 1990), (King, 1990). In our model, we always create new teams (i.e. without longevity) and the user sets the team size and the required roles. So the only variable that we use to calculate the *GroupFactors* function is the cohesion. The cohesion is the commitment of the group members to work together to complete their shared tasks and accomplish their goals (Guzzo & Salas, 1995).

The last factor used is the *RelationalFactors* function which refers to aspects of communication and relationships between the team members. This is an important factor identified by several authors such as (Payne, 1990), (King, 1990), (Carroll et al., 2009) or (Woodman et al., 1993). Our model establishes randomly *good* or *bad* individual perceived relationship between all team members. Hence, we define the group creativity as a weighted sum of the N individual creativities, the group factors and the relationship factors (equations 2, 3, 4, 5). We normalize to the *CF_Group* function in order to obtain a bounded range [0, 1]:

$$\begin{aligned}\boldsymbol{CF_{Group}} = \;& IndividualFactors * W_{IndividualFactors} \\ &+ GroupFactors * W_{GroupFactors} \\ &+ RelationalFactors * W_{RelationalFactors}\end{aligned} \quad (2)$$

$$\boldsymbol{IndividualFactors} = \sum_{i=1}^{N} CF\_Individual_i \quad (3)$$

$$\boldsymbol{GroupFactors} = \sum_{i=1}^{N} IndividualCohesion_i \quad (4)$$

$$\begin{aligned}\boldsymbol{RelationalFactors} = \;& \sum_{i=1}^{N} GoodRelationships_i * W_{GoodRelationships_i} \\ &- \sum_{i=1}^{N} BadRelationships_i * W_{BadRelationships_i}\end{aligned} \quad (5)$$

3.3 Agent Communication

Communication takes place only between the manager and the worker agents. The communication process is supported by a negotiation protocol (Figure 1) in order to construct the better work team in terms of creativity.

The simulation starts with a work team proposal that the manager should form. The work team proposal is defined by a set of requirements such as the number of agents to form the group, the number of different roles within the group and the available budget for hiring agents. Following these requirements, the manager generates an offer and sends it to the workers. An offer has two attributes: the *wage* and the *current team creativity*. The *wage* is set by the manager depending on the role for which the offer is made up. The *current team creativity* indicates the creativity of the team in which the agent will become a member (initially *CF_Group*=0).

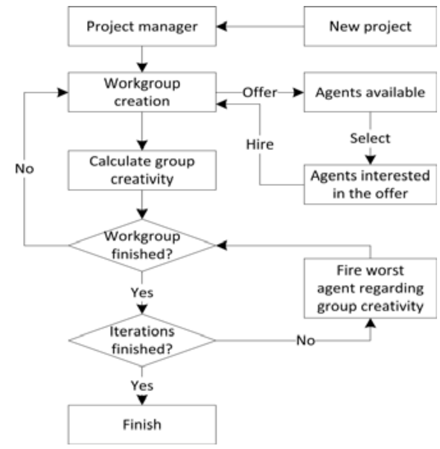


Figure 1: Negotiation protocol for a work team creation.

According to its personal preferences, each agent accepts the offer or ignores the proposal based on the satisfaction degree related with the offer (see details in section 4.2.3). Each agent has different preferences: while some agents are more motivated by the economic aspect, others give more importance to the team creativity level. Thus, a score is computed for each agent, indicating the degree of satisfaction with the offer. This score is then used in the *CF_Group*, particularly in equation (4), as *IndividualCohesion*.

After the offer evaluation, a list of candidate agents is filled with those agents that accept the offer. Then, the manager selects the highest creativity agent and includes it into the team.

4 MODEL IMPLEMENTATION

From the available platforms used for the development of agent-based models and simulations, we selected the Repast Simphony software (http://repast.sourceforge.net/repast_simphony.html) which is an open source software with a good documentation and support. The following subsections describe the classes implemented in the model.

4.1 General Purpose

4.1.1 Work Team

The *work team* class represents the current work team in every simulation step. This class stores the list of agents belonging to the work team and provides the method to compute the team creativity (equations (2), (3), (4) and (5)). Weights used in the equations are summarized in Table 2.

Table 2: Weights for the work team creativity attributes.

Weight	Value
Individual weight	0.3
Group weight	0.4
Relational weight	0.3
Good relations weight	0.4
Bad relations weight	0.6

4.1.2 Offer

The *offer* class represents an instance of a job offer that the manager sends to the workers. The offer has two attributes:

1. Pr*oposed wage*
2. *Current work team creativity*

This class is used as a message within the communication protocol during the negotiation process. Each agent evaluates the content of this class in order to accept or reject the offer.

4.1.3 Project

The *project* class represents the work team restrictions that the manager should met when forming the team. The attributes of this class which can be set through the developed GUI are:

1. Current budget
2. Initial budget
3. Number of work team members
4. Required roles

4.2 Worker Agent

Worker Agents store a set of methods and attributes, each of them representing different features and behaviours that workers must have. These attributes and methods are divided in the following groups:

1. Creativity skills.
2. Agent relations.
3. Negotiation.

Different types of agents have been implemented in terms of the role it plays in the system (*Director, Assistant, Technician* and *Scholar).* Each role inherits from the Agent class and represents a type of worker with a similar behaviour and characteristics. Differences between roles rely in the values that each attribute can get. These attributes can be modified (using the GUI) to analyse how these changes affect the global behaviour of the system.

4.2.1 Creativity Skills

An agent has an individual creativity based on a combination of its creativity attributes and the weights attached to each of them. We implemented these attributes as floating point variables in the [0, 1] range whit 0 referring to the absence of the skill represented by the attribute, and 1 representing the maximum ability in that skill (Table 3). Moreover, several ranges are modified to generate different states from a set of initial conditions.

Thus, an agent randomly initializes its attributes in its specific range defined by ourselves. This implementation allows us to generate a large population of agents of different types, with a high intra-role and inter-role variability. A linear combination of the creativity attributes and their corresponding weights provides the final individual creativity of the agent (see equation 1).

Table 3: Attribute ranges for each agent's role.

Attributes	Ranges			
	Director	Assistant	Technician	Scholar
Exploration	[0, 1]	[0, 1]	[0.8, 1]	[0.8, 1]
Immersion	[0.8, 1]	[0, 0.7]	[0.8, 1]	[0, 0.7]
Results Worth Effort	[0.8, 1]	[0, 0.7]	[0.8, 1]	[0, 1]
Collaboration	[0, 0.5]	[0.8, 1]	[0, 0.8]	[0.8, 1]
Expressiveness	[0.8, 1]	[0.8, 1]	[0, 0.5]	[0.5, 0.8]
Enjoyment	[0, 0.4]	[0, 1]	[0.5, 1]	[0.8, 1]
Agreeableness	[0, 1]	[0.8, 1]	[0, 1]	[0.9, 1]
Conscientiousness	[0.8, 1]	[0.4, 1]	[0.5, 1]	[0, 1]

4.2.2 Agent Relations

Social relations are one of the most important factors influencing the work team creativity. Several studies claim that relations within a team can become more relevant to the team creativity than the individual creativity of the members.

In our model, the agent relationships are implemented as individual hash maps in which the key indicates the agent identifier and the value indicates the type of relationship. A positive value means a *good* relationship; while a negative value indicates a *bad* relationship. Each agent has its own hash map initialized with the identifiers of all the agents in the system and a random relation for each of them. Therefore, relations may not be reciprocal. Agent A1 may have a good relationship with agent A2, but agent A2 may have a bad relationship with agent A1. This approach allows us to model the social interactions between agents in order to measure the impact of relationships in the development of worker teams, which is part of the hypothesis that our system tries to corroborate.

4.2.3 Negotiation

The negotiation process is based on two aspects: the economic and the creativity motivations. Economic motivations are based on a *desired wage* and the proposed wage of the offer. The *desired wage* attribute is randomly initialized in a specific range depending on the role, while the *proposed wage* is set by the Manager. Creativity motivations are influenced by the current team creativity in which the agent will become a member. Both parameters (economic and creativity) are weighted by each agent, so the offer evaluation process is performed as follows:

$$\boldsymbol{Individual\ Cohesion} = \left(wageRatio * W_{wage} + CF\_Group * W_{CF\_Group}\right) \tag{6}$$

$$\boldsymbol{wageRatio} = \frac{proposedWage}{desiredWage} \tag{7}$$

$$\begin{aligned} &if\ IndividualCohesion > 0.5 \\ &\qquad \rightarrow Accept\ offer \\ &else \rightarrow Reject\ offer \end{aligned} \tag{8}$$

Both *wageRatio* and *workgroup Creativity* are represented in the [0, 1] range with 0 representing the worst value and 1 referring to the better value. Moreover, these values are weighted with different weights for each agent, modelling the personal preferences in the negotiation process. Finally, if the result of the evaluation is greater than 0.5, (i.e. is more positive than negative), the offer is accepted. Otherwise, the offer is rejected.

4.3 Manager Agent

The manager is a special type of agent whose purpose is to conduct the simulation. Unlike worker agents, the manager has no creativity attributes and only interacts with the agents during the negotiation process. The manager behaviour follows the next steps:

1. Discard an agent (if the group is full)
2. Propose offer
3. Select best candidate
4. Update work team

The manager owns the work team proposal represented by a *project* object. The work team is initially empty but in posterior steps it may be full, so it is needed to check the number of members in the work team, in order to discard an agent if needed. We followed a discard criteria based on the work team creativity loss when an agent is discarded. Thus, each agent is virtually excluded from the work team in order to measure the amount of creativity loss. Following this approach, the worst agent is the one that generates the least loss in the work team creativity. Moreover, it is possible that creativity increases when a member is excluded, e.g. when the member has bad relations within the group.

Once a vacant is generated in the work team, a new agent must be hired. Therefore, the manager proposes an offer for the required role and sends it to the agent population. The offer is then evaluated by the agents and the manager receives a list of candidates. The main hypothesis that our system is trying to verify is whether the inclusion of an agent with a high creativity always increases the team creativity, so the manager must select the best candidate based solely in the individual creativity, ignoring relationships or other attributes. The agent with highest creativity level is then included into the work team.

5 RESULTS

The empirical evaluation of the system have been performed by defining three set of simulations which creates work teams with 50, 10 and 5 workers respectively. For each set of simulations we compared the group creativity obtained by our model algorithm vs. a pure stochastic selection algorithm using a high (500), medium (100) and small (50) agent populations of each role. A summary of the simulations can be seen in the Tables 4-6.

Table 4: Simulation results summary of SET 1 (50 Work Team Size: 15 assistants, 5 directors, 10 scholars and 20 technicians).

	Population size		
	500 (x4)	100 (x4)	50 (x4)
Our Model	0,718	0,712	0,64
Random Model	0,612	0,605	0,611
Improvement	**10,6%**	**10,7%**	**2,9%**

Table 5: Simulation results summary of SET 2 (10 Work Team Size: 3 assistants, 1 director, 3 scholars and 3 technicians).

	Population size		
	500 (x4)	100 (x4)	50 (x4)
Our Model	0,763	0,719	0,685
Random Model	0,648	0,64	0,62
Improvement	**11,5%**	**7,9%**	**6,5%**

We used the same seed in all the simulations for reproducibility. The number of iterations used for calculating the results was 200.

Table 6: Simulation results summary of SET 3 (1 Work Team Size: 1 assistant, 1 director, 1 scholar and 1 technician).

	Population size		
	500 (x4)	100 (x4)	50 (x4)
Our Model	0,799	0,754	0,768
Random Model	0,724	0,682	0,671
Improvement	**7,5%**	**7,2%**	**9,7%**

As shown in Table 4, in all cases our algorithm get better creativity levels than the stochastic selection algorithm. Our algorithm runs better with high populations and small work teams. However, the stochastic selection algorithm had similar results in all the tests.

As Figure 2.a shown, in the initial iterations, the evolution of work team creativity is highly variable. At this step, since the work team is not full, the manager only hires agents considering their individual creativity. This can result in work teams where agents have enough bad relations and then unstable work team creativity is obtained. Once the work team is full, the manager should discard the worst agent and include a new one in order to observe the creativity evolution. The discard criterion takes into account the *GroupFactors and RelationalFactors*, besides *CF_Individual*.

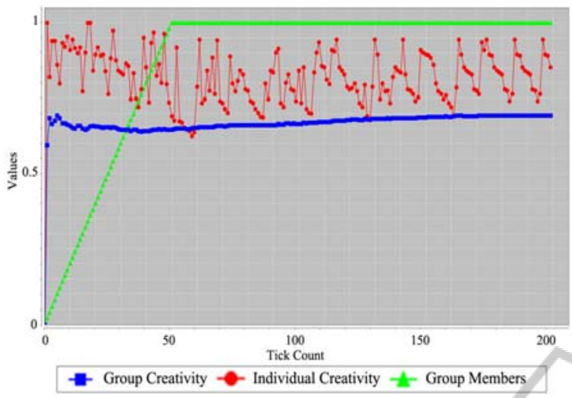
As also represented in Figure 2.a, the work team creativity increases significantly if these aspects are considered (iterations 50 to 200), which is the main hypothesis we want to corroborate. The inclusion of agents with highest individual creativity do not ensures the highest work team creativity. In the simulation (b) no clear differences were seen as in the previous case. All the time the *CF_Group* remains similar because it is only influenced by the *CF_Individual*.

6 CONCLUSIONS

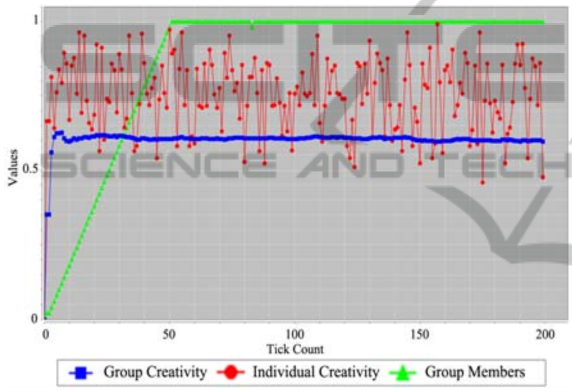
The presented model could be used to empirically support, hypothesise, train and analyse how factors such as cognitive-related capabilities, emotional state, personality and social-related skills can affect individual and group creativity.

As confirmed by the results, our model reaches values higher than a pure stochastic model obtaining a significant difference (until 11.5%). Additionally, we have confirmed the hypothesis that when incorporating an agent with a high of creative individual to a working group, the group creativity is not always positively affected. This is because in the calculation of creativity there are other (group and relational) factors besides the individual factor.

In further improvements, we would follow the approach proposed by Woodman et al. (1993), which states that when an individual becomes part of a group and the group creativity is affected, the individual creativity is also influenced immediately by the group conditions.



Simulation (a): 100 (x4) agents, 50 team members, algorithm selection implemented.



Simulation (b): 100 (x4) agents, 50 team members, stochastic selection.

Figure 2: Two representative simulation examples. The green line shows the total number of agents belonging to the group. The blue line shows the group creativity and the red line shows the individual creativity of the hired agent.

Another necessary improvement is to add an organizational layer designed to assess aspects such as the organizational structure of the working group, an important influence on creativity.

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