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TOWARDS AGENT-BASED MODELING FOR OPERATIONAL CLASH DETECTION IN CONSTRUCTION OPERATIONS

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Abstract: Current clash detection models view the crews as plain objects with a predefined and fixed performance. Such an assumption, though being logical in measuring the impact of certain clashes in the workspace (by maintaining the rest of the factors constant); is not entirely correct. Crews are either people or equipment controlled by workers, which are in both cases intelligent agents with variable performances. Performance of these agents can significantly affect the impact of clashes. This paper proposes a conceptual framework that models crews as intelligent agents, by defining three major decision variables: worker as a unique agent (carrying own traits); team selection strategy; and influence of the management style on the team performance. Existing models are amended to capture the three components referred to above in construction. The paper presents the starting phases of employing agent based modeling in clash detection models.

1 INTRODUCTION

Most construction projects suffer from spatial temporal clashes, defined as the intersection of two or more workspaces in a location at a certain time. Each clash has a certain magnitude, which can be estimated according to the clash's properties. Examples of such properties include duration, size and type of the clash, and the criticality (in terms of cost or time) of impacted activity. Such clashes can have serious impacts on an activity's performance, and hence on the overall project status (Akinci et al., 2002, Guo, 2002, Hosny 2013, Mallasi, 2006, Song and Chua, 2005, Wu and Chiu, 2010). Taking Hosny, 2013 model as an example, Figure 1 shows the formulation of space-clash types. Models previously developed to capture, measure and evaluate such clashes are summarized in Table 1.

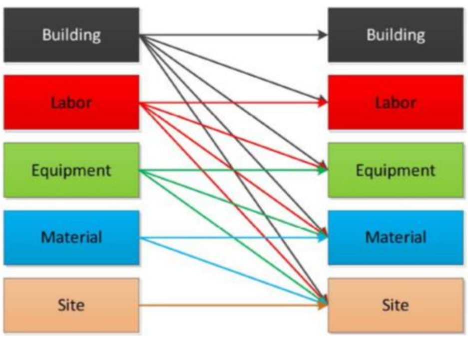

Figure 1 Hosny et al., 2013 classification of workspaces and clashes

Table 1 Review of previous clash detection models

Author	Measure	Different workspace types	Conflict volume analysis	Different clash types	Clash ranking	Accounts for activity criticality	Visualization medium	Optimization approach
Thabet and Beliveau (1994)	Space Capacity Factor	No	Yes	No	No	No	CAD	N.A
Akinci et al (2002)	Conflict Ratio + Clash Ranking	Yes	Yes	Yes	Yes	No	4D CAD	N.A
Guo (2002)	Interference Space Percentage / Interface Duration Percentage	Yes	Yes	No	No	No	4D CAD	Manual Rescheduling
Song and Chua (2005)	Conflict Ratio	Yes	No	No	Yes	No	3D CAD	N.A
Winch and North (2006)	Spatial Loading	Yes	Yes	No	No	Yes	31 / 2D*	Brute force Algorithm
Mallasi (2006)	Space Criticality Factor	Yes	Yes	Yes	Yes	Yes	4D CAD	Genetic Algorithm
Wu and Chiu (2010)	N.A	Yes	No	Yes	No	No	4D CAD	N.A
Hosny, (2013)	First level Check (Days) + Clash Magnitude Estimator (activities)	Yes	Yes	Yes	Yes	Yes	4D CAD	N.A

* See the reference for more info

Most models included in Table 1 aimed to measure the magnitude of a clash on an activity's objective function of cost, time and quality. The output of these models is deterministic. In multiple rounds of simulation, if the initial settings are preserved, the same clash, with the same magnitude. Although such outcomes can be acceptable for building–building and site–site clashes (types of clashes which are normally detectable by commercialized/off-the-shelf software tools); they may not truly capture other forms of clashes highlighted in Figure 1. Other clashes, which directly involve the labours or equipment operators, will depend on human behaviour and performance, which may dynamically change throughout the project lifecycle. To model this dynamic environment, human actors are represented by intelligent agents (Barry and Stewart 1997, Hunter et al., 1990).

As will be shown later in this paper, using agent-based modeling in clash detection can create a new relationship between the clash magnitude and the objective function and re-define the structure of clash detection problem. This paper presents the initial steps to achieve agent-based simulation in modelling clash detection. The paper presents a conceptual framework for modelling labours as intelligent agents, utilizing the previous models offered by Hsu et al., 2016 and Wang et al., 2015, with amendments to adapt them to measure construction operations. The framework comprises three main aspects: the parameters of an individual worker, the team selection method, and the influence of management strategy on the team performance. The paper suggests additional behavioural factors to be included in future framework development. A case example is presented to express the possible influences of agent based modeling on clash detection, via the proposed framework.

2 LITERATURE REVIEW

As perceived from the introduction above, the main task at hand is modelling labours' behaviour, as intelligent agents, accurately in clash detection. This requires considering several parameters. Firstly, it is imperative to identify the types of crews available. According to Joshi and Roh, 2009, and Hollenbeck et al., 2012, teams can be divided into long-term and short-term teams, where the long and short mainly refer to the time span per project the team members work together on certain goals. It is claimed that long term project teams (those working together for one year or longer) are more stable and would present a better fit for agent based modelling (Joshi and Roh, 2009, Hsu et al., 2016). The next requirement is the set of parameters affecting the team's performance. As per the literature, three main categories are investigated to measure a team's performance: parameters of modelling workers' performance, team selection approaches, and management styles applied to the team.

2.1. Modelling A Single Worker

An early method by Barry & Stewart ,1997, called "Five Factor Approach", suggested that human could be modeled through their: 1. *Extraversion characteristic* (associated with being sociable, gregarious, assertive, talkative, and active); 2. *Agreeableness* (associated with being courteous, flexible, trusting, good-natured, cooperative, and tolerant); 3. *Conscientiousness* (associated with being careful, thorough, responsible, and organized); 4. *Emotional stability* (associated conversely with being anxious, depressed, angry, embarrassed, worried, and insecure); and 5. *Openness to experience* (associated with being imaginative, curious, original, broad-minded, and intelligent). This approach mainly focused on individual's general self-traits and was less concerned with addressing other parameters related to performance (such as the worker's education or job stability), which would have a great impact.

Another approach was that of Wang et al., 2015, which suggested that individuals could be modelled by the magnitude of their intellectual capital (IC). This approach was based upon Stewart ,1998, Bontis ,1999, and Cortini & Benevene ,2010, who explained IC as a combination of personal traits possessed by a certain individual. They classified IC under three main categories: human, social or organizational capital; where *human capital* refers to the personal skills acquired by the individual, *social capital* stands for the relationships the individual has developed with external entities, which could ease the job execution; and *organizational capital* appertains to the level of familiarity the individual has with the organization's workflows, procedures, and methods. Wang et al., 2015, also measured the impact of job autonomy and team cooperation on the overall performance. However, they did not suggest any metrics to evaluate the specific human aspects.

Hsu et al. ,2016, offered eight parameters to be measured in evaluating an individual's performance. Those parameters focused on work-related attributes and included variables such as: *education*; *working experience* (in the specific field/sector); *expertise* (in the specific trade/for the specific activity); *license* (certificates acquired by the individual, relevant to the context of the work), *salary* (which is normally correlated with the other variables mentioned so far); *availability* (fraction of time the individual is available for work); *capacity* (the amount of work the individual is capable of doing); and *interdependence with other workers (team work contribution, giving to others, and receiving from others)*. They also addressed various team selection approaches. Yet, their framework did not capture any social or organizational capitals in the worker's performance. Moreover, some of the dimensions in have correlation or redundancy, if used to model construction operations, such as working experience and expertise. Additionally, the attribute “license” is too specific to their case study which was focused on a design management firms. Also, it can be argued that the “interdependence with other workers” could be under the team selection and not modeling the worker as an individual.

2.2. Team Selection Approaches

Team selection is concerned with the strategy followed by organizations to group workers for projects or specific tasks. There is a clear correlation with such strategies and the nature of the task being performed (Lim and Klein 2006, Hsu et al., 2016). As a result, there are conflicting opinions in the literature on the methods for team selection and grouping workers. However, three major approaches utilized are: *homogenous*, *heterogeneous* and the *interdependence–based*. Such approaches team-up the workers through classification of their traits/behaviours, regardless of the tasks at hand.

2.2.1. Homogenous Approach

Mannix and Neale, 2005, suggested to group individuals into teams based upon similarities among their traits. The assumption was towards the utilization of the combined knowledge in certain areas. Such approach could be useful in repetitive, basic and simple work tasks (Hinds et al. 2000). However, the attributes chosen for the homogenous approach must be chosen properly as they may cause a negative impact on team performance rather than a positive one. For example, grouping more than one individual each with high leadership skills and opinionative could lead the team to many disagreements and loss of function. More importantly, such a grouping strategy may increase the risk of silo effect and its results will lack the multi-disciplinary nature required for achievement of more complex tasks.

2.2.2. Heterogeneous Approach

Contrary to the previous method, and as per Somech, 2006, and Page, 2010, this approach depends on the diversification of the team by grouping together individuals that have different traits. It is believed that such a mixing would enhance the team functionality, robustness, and productivity. In a controlled environment (with a limited number of candidates to choose from), there would be multiple criteria to define and examine the heterogeneity. Researchers have followed various methods to achieve heterogenity in teams’ formation (Millhiser et al. 2011, Curral et al., 2001, Keller, 2001).

2.2.3. Interdependence-based Approach

This method, suggested by Hsu et al., 2016, focusses on forming the teams based upon interdependencies among team-members. As briefly mentioned, Hsu et al., 2016, proposed that this selection can be done by measuring: what each individuals achieves; what they providing to others; and what they need from others. To better explain this approach, let’s assume the example of a heterogeneous / homogenous team developed for formwork crews formed of carpenters and helpers. Over the time of them working together, the team would get accustomed to each other, building certain understandings and interdependence, and hence maintaining a certain performance level. Hsu et al., 2016 argued that replacing the helpers in the team with others of the same traits, would impact the performance. As the new additions might not be able to build the same working relation with their supers (carpenters) or have the same chemistry.

2.3. Management Styles

Soderland, 2011, have introduced nine different schools of project management and various tactics used for scope definition and problem solving. Shenhar and Dvir, 2007, have argued that each project would have its unique way of management based upon the variables introduced at the time of execution. One of the earliest schools was that proposed by Klein and Meckling, 1958, where they assumed two different methods: optimizer and skeptic. In the optimizer approach, issues are tackled, analyzed, and alternative solutions are presented and implemented immediately. In the skeptic approach, however, actions are more conservative and based upon intuitive judgement and past experience. Klein and Meckling, 1958, assumed that the team would better perform with the optimizer approach rather than the skeptic.

Another school of project management classification would be “task-based perspective” vs “organizational perspective”. While the former assumes each project (and the teams involved in it) as independent entities from the organization, the latter assumes a close relation between the team and the base organization. In task-based perspective, the main focus of the project manager and the team is achieving the goals. At the end of the project, the team relations are terminated and do not necessarily return to the organization. It is argued that such an approach increases the loyalty of the team to the project (rather than the organization). This means that the team would always choose what is best for them only, and at the closing stages of the project, the team would lose focus and seek other opportunities to ensure continuity (Anderson, 2016).

On the other hand, the organizational approach acknowledges any project team as a temporary sub-organization established by the base organization to carry out a specific task. Here, the project team acts in the best interest of the organization and not the project (Anderson, 2008, Kenis et al., 2009). In the case where the base organization shares the project’s importance and explains its actions adequately to the project team, it is assumed that this approach would maintain a stronger relation with the team and hence result in better performance.

3 PROPOSED FRAMEWORK

The proposed framework is based on Wang et al., 2015, and Hsu et al., 2016, models, with amendments to existing attributes and extensions of new ones to make it applicable to the modeled construction environment. The framework represents workers through human, social, and organizational capital, using the metrics provided by Hsu et al., 2016 for evaluation of associated factors, and their team selection approach. Then the framework expands the “job autonomy” concept of Wang et al., 2015, to represent the different management strategies common in construction practices, and their influence on team performance.

3.1. Worker’s Individual Modelling

Table 2 shows the factors considered in modelling worker’s performance from the previous models (Hsu et al. 2015, Wang et al. 2014) and the modifications introduced. Starting with Education which is a human aspect, it has been modified from Hsu et al., 2016, categories to account for illiteracy, since, especially in developing countries, workers could have learnt trades by practice, without competencies in reading and writing. It is assumed that education would have a direct relation to performance as long as the salary is suitable for the level of education. Otherwise, if the education level is not suitable with the salary, then the education might have an inverse relation to performance. Then, the working experience and expertise of Hsu et al., 2016, are merged into one factor in the framework called working experience. Where this factor considers the overall experience years, number of professions / fields worked in and spent on each, as it is assumed that these (given that each profession has a duration longer than one year) would have a direct relation with performance. After that, the availability in both models (Hsu et al. (2016) and Framework) are the same, except that

the framework account for the case of construction which is 26 days a month not 22 and account for the possibility of sickness / annual vacations as well.
Leadership, communication skills, presentation skills, and the appetite for learning are added in the model to account for the social capital. Clearly, the higher these factors are, the higher social capital a worker has and hence the better his/her performance is. As well, job stability factor is added to measure worker's knowledge of organization procedures. It is assumed that the longer the period of service a worker has in his organization the higher his/her performance. However, the lesser duration left in the contract, the lower the performance, as the worker is no longer motivated to perform the task at hand. The salary has been placed to allow for the comparison of other factors versus it to check for the suitability and hence the motivation of the worker. The capacity factor accounts for other parameters that interfere with the volume of work performed by the worker

Table 2 Comparison between Hsu et al. (2016), Wang et al. (2015) and suggested framework.

Wang et al. (2015)	Hsu et al. (2016) Factor	Hsu et al. (2016) Description	Suggested Framework Factor	Suggested Framework Description
Human Capital	Education	Post-secondary graduate; College; High school	Education	Illiterate; Elementary/ High school; College graduate
	Working Exp.	No. of years in a specific field	Working Experience	No. of years spent overall + No. of years in each occupation to measure diversity
	Expertise	Knowledge in particular areas		
	License	Valid (PE)	Not considered	
	Salary	Worker's periodic remuneration	Salary	Worker's periodic remuneration
	Availability	8 hours * 22 days / month	Availability	(Typical 6 days per week * 52 weeks) – (Annual Vacations + sickness Leaves / (Typical 6 days per week * 52 weeks)
	Capacity	1.6 to 2.5 of salary	Capacity	Defined based on other personal attributes of the individual
Social Capital	Inter. with Others	Cooperation between team members	Leadership Communication Presentation Appetite to Learn	Leader Vs. follower High Vs. Low Introvert Vs. Extrovert Fast Vs. Slow Learner
Organizational Capital	Not Considered		Job Stability	# of Years with same organizations and # of years remaining in contract

3.2. Team Selection Approaches

The three approaches of homogenous, heterogeneous and interdependence-based selection suggested by Hsu et al., 2016, for team selection are considered in the proposed framework. Education, working experience and salary are the factors considered for the homogenous approach. For the heterogeneous, the equity-based approach of Simmons & Rowland, 2011, is used. As for the interdependence the model of Hsu et al., 2016, is utilized.

3.3. Management Styles

Similar to the job autonomy concept, offered by Wang et al., 2015, this framework accounts for the effect of the various management styles on the team performance. It is assumed that management would have a range of behaviour from Skeptic (no clear vision, minimum empowerment, authoritarian attitude), to motivational (clear path, sharing of ideas, empowerment of team).

3.4. Additional Considerations

This section presents additional parameters to be added to the framework in light of future findings. The first area would be internal factors, where parameters such as "health" and "Mental stability" are required to account for the workers' physical and psychological condition which has a direct effect on their performance. For example, workers with recent experience of a close relative loss might suffer from some form of depression, and hence would lose motivation and focus for a while, which results in a lower performance. On the opposite side, joyful news may motivate the workers and positively influence their performance. Another parameter is rewarding and evaluation system applied by management. Normally, the worker / team performance would be higher when knowing that they are being monitored and are under evaluation; and may be lower if they know that management awarded others than them. Other parameters could account for the impact of external factors, such as weather and job site conditions, on the team performance.

Another important factor in modelling labour as intelligent agents in the proposed clash detection model is the "clash adaptation". Teams may face similar clashes several times, during project delivery. Based upon the learning curve principal, it is assumed that the team performance in later encounters to the clash would increase over time.

4 DISCUSSION

In this section, a benchmark problem, previously introduced by Hosny, 2013, is utilized to further explain how a clash detection model can be improved via agent based modelling. Figure 2 shows the benchmark problem of masonry works for 5 walls and the initial settings of the model. Figure 3 shows a caption of calculations for the magnitude of the clashes based on Hosny's model, 2013. These calculations are based on the following parameters: 1.the ratio between the duration of the clash and the original planned activity duration; 2.the ratio between the clashed volume versus the original planned workspace; 3.the criticality of the activity; and 4.the magnitude of the clash. All of these attributes are subject to change in a dynamic state simulation. Starting with attribute # 3, should the agent-based modelling be used, the capacity of a worker, and hence the team, will be variable. Thus the planned duration of the activity would differ in each simulation, and consequently, the criticality of the activity would be a changing variable (rather than a deterministic value derived from the baseline schedule).

Moving on to the duration ratio, Hosny's, 2013, assumption was that occurrence of a clash would not affect the team's performance. As a result, if an activity has a planned duration of five days and clashes on day three, then the model assumes that the maximum ratio for this case would be 2/5. Again, using agent-based modelling, this ratio would change. The duration taken in the clash would be subject to the team's performance. A high performance shall produce a shorter clash duration (assuming that it would be possible) and vice versa. The same concept applies to the volume ratio, which is affected by the availability of workers.

Additionally, different team compositions would impact such clash attributes. If a homogenous approach is followed in team selection, the team would perform well under typical clashes and would perhaps require less workspace as the team's cumulative knowledge in the same area would optimize their space usage. Nevertheless, if exposed to unusual clashes, the team might not perform well. On the other hand, while a heterogeneous approach may perform better in unusual clashes, the team would have a weaker performance as part of its members may lack the expertise in a specific task.

These points bring us to the magnitude of the clash factor; relation of this factor with the objective function may greatly change under agent-based simulation. Hosny, 2013, assumed it as a fixed constant based on the type of workspaces clashes. The management style of the teams would, however, greatly impact such factor. For example, a team empowered by its manager, may be able to resolve the clash quickly and hence the magnitude is expected to be low and vice versa. Basically, it is assumed that the utilization of agent-based modeling in clash detection would require researchers to revise the relationships between the developed attributes and the objective functions. Understanding the significance of different changes listed above, however, requires further investigation.

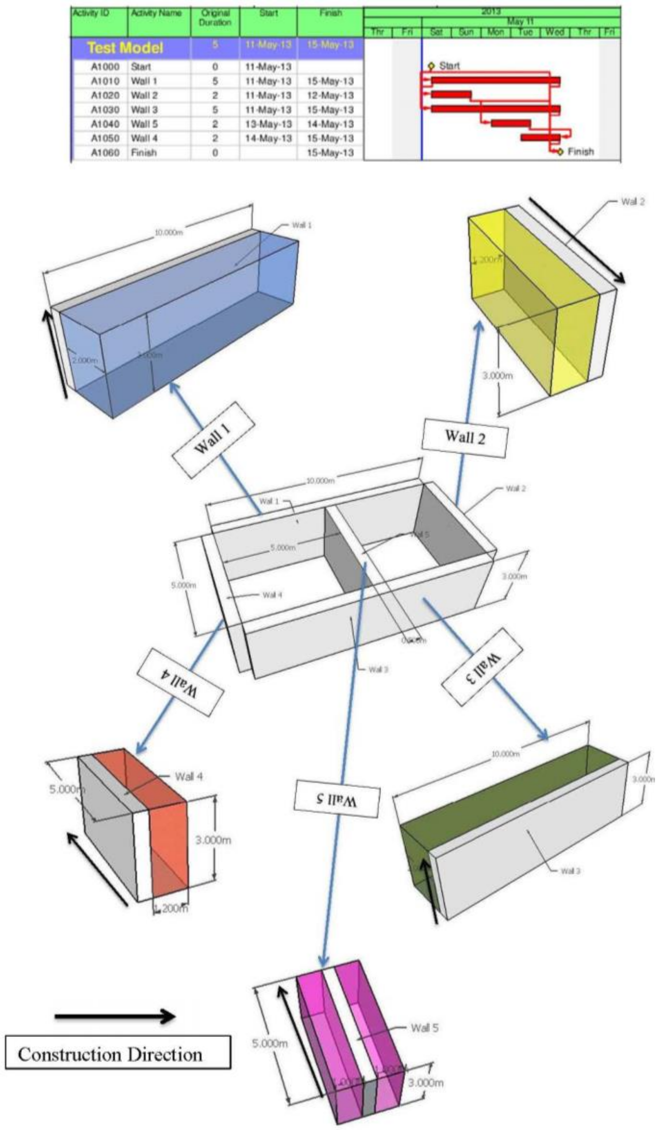

Figure 2 Hosny (2013) Test Model and Initial Settings

The framework must undergo a careful verification and validation procedure to make sure no attribute is double counting, no unneeded correlation or dependency exists between the model parameters. Especially the attributes related to the social capital, which may be perceived as subjective, proper metrics must be developed. Another challenge is the required computational capacity. Simplifying assumptions and smart data processing are required to enable use of the model on large-scale projects.

Activity Name	Clash Dates	Workspace Type	Planned Workspace Volume (m³)	Clashed With: Activity Name / Object Name	Clashed With: Workspace Type	Clashed With: Clash Volume (m³)	Total Float	W1	Vc (m³)	Vp (m³)	W2	Dc (days)	Dp (days)	W3	CF	W4	SF	CME Value
Wall 1	11-May-13	Labor	60	Wall 2	Labor	7.2	0	0.3	7.2	60	0.1	1	5	0.1	0.9	0.5	0.5	0.396
Wall 1	14-May-13	Labor	60	Wall 5	Labor	12	0	0.3	12	60	0.1	1	5	0.1	0.9	0.5	0.5	0.42
Wall 1	15-May-13	Labor	60	Wall 4	Labor	7.2	0	0.3	7.2	60	0.1	1	5	0.1	0.9	0.5	0.5	0.396
Wall 1	15-May-13	Labor	60	Wall 5	Building	3	0	0.3	3	60	0.1	1	5	0.1	0.9	0.5	0.85	0.55
Wall 1 Total																		1.762
Wall 3	12-May-13	Labor	60	Wall 2	Labor	7.2	0	0.3	7.2	60	0.1	1	5	0.1	0.9	0.5	0.5	0.396
Wall 3	13-May-13	Labor	60	Wall 5	Labor	12	0	0.3	12	60	0.1	1	5	0.1	0.9	0.5	0.5	0.42
Wall 3	14-May-13	Labor	60	Wall 4	Labor	7.2	0	0.3	7.2	60	0.1	1	5	0.1	0.9	0.5	0.5	0.396
Wall 3	15-May-13	Labor	60	Wall 5	Building	3	0	0.3	3	60	0.1	1	5	0.1	0.9	0.5	0.85	0.55
Wall 3 Total																		1.762
Wall 4	14-May-13	Labor	9	Wall 3	Labor	7.2	0	0.3	7.2	9	0.1	1	2	0.1	0.9	0.5	0.5	0.63
Wall 4	15-May-13	Labor	9	Wall 1	Labor	7.2	0	0.3	7.2	9	0.1	1	2	0.1	0.9	0.5	0.5	0.63
Wall 4 Total																		1.26

Weights	Values
W1	0.3
W2	0.1
W3	0.1
W4	0.5

Severity Factors		
Workspace	Workspace	Value
Labor	Labor	0.5
Building	Labor	0.85

Criticality Factors	
T.F Range	Value
0≤x<20	0.9

Figure 3 Caption of clash magnitude calculations based on Hosny's (2013) model

5 CONCLUSIONS AND RECOMMENDATIONS

This paper highlights a new conceptual framework that embraces agent-based simulation in clash detection models. The paper highlights the needed amendments and extensions to current agent based simulation models to adapt them to construction and presents an illustrative cases study to display the improvements in attained results. Future work should focus on verification and validation of the framework and on development of suitable metric to measure the subjective parameters related to the social capital.

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