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DIVERSITY AND KNOWLEDGE SHARING IN CONSTRUCTION: A MATHEMATICAL MODEL

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Conventional wisdom in the management literature holds that diversity is positively correlated with performance. Yet, the findings from the construction field indicate that this is not always the case. In an effort to study the interaction between diversity and performance in the construction industry, this paper presents the elements of a theoretical mathematical model to explore the relationship between diversity and knowledge sharing which is a precursor of performance. This model includes five dimensions of diversity: ethnicity, age, experience, language and education. At the heart of the mathematical model is a fuzzy based system that generates the probability of knowledge sharing among members with different demographic attributes. The presented fuzzy system will, in future work, become the foundation of an agent based model used to study the impact of worker interactions on productivity.

Keywords: Fuzzy system, Performance, Modeling, Labor management, Demographic.

1 INTRODUCTION AND BACKGROUND

The construction industry often assumes “rational behavior” by workers, and thus project managers tend to focus only on the technical and financial aspects of their projects (Dadfar and Gustavsson 1992). They often fail to acknowledge the socio-technical nature of these projects overlooking the fact that many of the technical and financial problems they face are rooted in the “people”. This is unfortunate in a field, where the human element is a keystone to success. Construction projects are labor intensive environments, where work is accomplished by crews and rarely by individuals. Whenever crews are involved, the issues of coordination and cooperation arise; managers have to constantly question whether crew members are working in harmony or behaving as a dysfunctional unit. This facet of construction management becomes increasingly complex if the crew members are demographically diverse (Lau and Murnighan 1998). Diversity has to be properly managed, and sensitivities must be taken into account if effective work is to be expected (Ling *et al.* 2013).

Demographic differences can affect the rate of social contact among crew members (O’Reilly *et al.* 1989). Team members may want to communicate with those who share their demographic attributes as such communication has lower overhead (Haas and Cummings 2015). For example, two people of the same age are more likely to have successful communication since they share the same values because they have been through similar political and economic cycles (Ryder 1965). In addition, two people with the same educational background will communicate more eloquently since they have similar vocabularies (Haas and Cummings 2015). The effects of demographic diversity on communication and crew operation attracted the attention of multiple construction management scholars. Dadfar and Gustavsson (1992) studied the effect of cultural diversity on communication in Swedish contractors. Along the same lines, Loosemore and Muslmani (1999) investigated the problems arising due to the cultural difference between UK and Persian Gulf nationals. In more recent wok, Ling *et al.* (2013) studied the cultural differences among migrant workers in the Singapore construction industry and generated a set of recommendations for diversity management to avoid diminishing productivity and miscommunication.

These works, however, focus on a single dimension: either culture or age. Other work from the field of management suggests that diversity is a multidimensional construct (Lau and Murnighan 1998). Such a reductionist approach of studying diversity as one-dimensional may lead analysts or managers to neglect other demographic attributes which are actually significant (Lau and Muringhan 1998). When observed as a multidimensional phenomenon, diversity is not only limited to heterogeneity, it also yields faultlines or subgroups (Gibson and Vermeulen 2003). The concept of demographic faultlines is introduced via the example in Table 1. When viewed from the single dimension of cultural diversity, teams one and two are identical. However, when both dimension of age and culture are considered simultaneously, the members of Team 1 show greater cohesion as they belong to both a common ethnicity and age group. Members of Team 2 only share a similar nationality. Faultlines and subgroups have a significant impact on the success of communication among team members. Better communication usually means that there is a better flow of knowledge and information among team members (Gibson and Vermeulen 2003). An improved flow of knowledge means that the members will learn faster and thus will be able to attain the required level of performance faster. However, does this mean that all crew members have to belong to the same age group and ethnicity? The answer is no, since in that case younger members will never get the chance to benefit from the experiences of their older colleagues. What the concept of faultlines suggests is that crews have to be formed and managed while considering the sensitivities associated with such differences. If properly managed, differences could be used to improve communication and foster better performance.

Table 1. Example of faultlines and subgroups.

Team 1			**Team 2**		
Member	Age	Nationality	Member	Age	Nationality
A	20	Chinese	D	29	American
B	25	Chinese	E	40	American
C	27	Chinese	F	55	American

Demographic traits such as age group, ethnicity, and educational background can also be qualitative in nature. What does it mean if to say "Worker A is young" or "Workers A and B share a similar cultural background"? Being young or culturally similar depends significantly on the definition of age-groups and cultural similarity. As such, the two statements embedded in the question above could be both true and false at the same time; and, therefore, they are considered to be "fuzzy". Fuzzy theory allows us to deal with uncertainty and also allows for computing with words (Sivanandam *et al.* 2007). Fuzzy theory therefore permits representing linguistic constructs such as "young", "similar", "big", "late" (Sivanandam *et al.* 2007). Fuzzy logic is an attractive alternative for studying the impact of demographic attributes on communication, since there is a lack of consensus in the literature regarding the effects of these attributes on communication, and thus cooperation in work crews. There is no evidence, for instance, that different demographic attributes have a different impact on communication and learning (Gibson and Vermeulen 2003). Fuzzy logic is suitable to such a problem where there are incomplete or imprecise relationships between the variables of interest (Chan *et al*. 2009). The fuzzy system presented in this paper takes the worker's linguistic or demographic attributes as inputs, and outputs an array of probabilities representing the likelihood of communication with every other individual in the team. The outputs of the fuzzy system will go as inputs to an agent based model that aims at studying the impact of diversity on performance in construction crews. The next section provides a description of the fuzzy logic model in detail, and the last section provides a conclusion with a road map for future research directions.

2 THE MODEL

Figure 1 presents and overview of the fuzzy system.

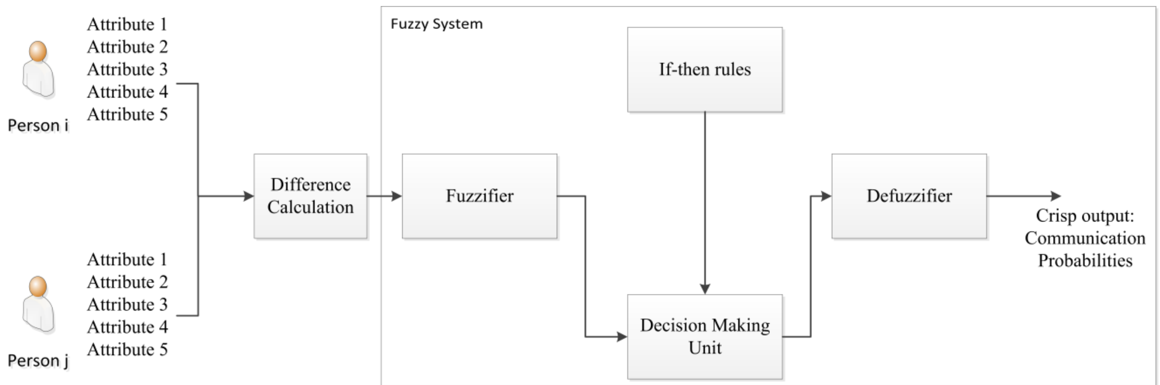


Figure 1. Fuzzy system design.

The fuzzifier takes in the crisp inputs which are the differences of demographic attributes among crew members. For example, if one crew member is 29 years old and the other is 40 years old, then the input to the fuzzier would be the age difference which is 11 in this case. The fuzzifier includes the membership function $\mu_A(x)$, which converts the inputs into a fuzzy number <0, 1>. If the fuzzy number obtained was 1, then the input belongs completely into a certain fuzzy set. Specifically, the fuzzifier takes as input the overlap among individual crew members which is in line with the methodology adopted in Gibson and Vermeulen (2003), who used the overlap among different crew members to calculate the heterogeneity and the strength of the subgroups or faultlines. Three of the five diversity dimensions used in this paper are qualitative or linguistic in nature, and these are nationality, language and education. Regarding the overlap in these dimensions, the following membership function was used:

Perfect Overlap [0.8-1.0]; Good Overlap [0.6-0.9]; Average Overlap [0.3-0.7]; Weak Overlap [0.1-0.4]; Opposition [0.0-0.2].

These measures (Perfect-Good-Average-Weak and Opposition), comprise the fuzzy sets to which the overlap between every pair of workers belongs. The numbers shown in parentheses offer a numerical measure of the overlap between every two workers. Thus, if two workers have the same nationality the overlap value would be one and the overlap between these two workers would belong entirely to the perfect overlap set. However, if two workers belong to two countries with similar cultures-one Lebanese and one Jordanian- then the value of the overlap would be in the range 0.8-0.9. The overlap between these two workers would then have 50% membership to the perfect overlap set and 50% membership to the good overlap set. The membership of the differences to the fuzzy sets shown in Figure 2 ranges between 0 and 1. If the membership value is 0, then the difference is entirely excluded from the set, whereas if it was found to be 1, then the difference belongs entirely to a set. Any number in between 0 and 1 indicates partial membership and thus the membership values to every set ranges between 0 and complete. The graphical representation of this membership function is shown in Figure 2. Unlike Gibson and Vermeulen (2003), who assumed a binary alignment among ethnicities, we allow for partial alignment. Thus, rather than assuming that an American and a German national would have zero alignment, we assume that an American would have "some" overlap with the German person due to the shared western culture and other aspects. Fuzzy systems allow the representation of this partial overlap and thus are a viable candidate for studying such complex realities. The same applies to language and education. A worker with a technical degree will have more overlap with a person with basic technical training, than with a worker who can't read or write.

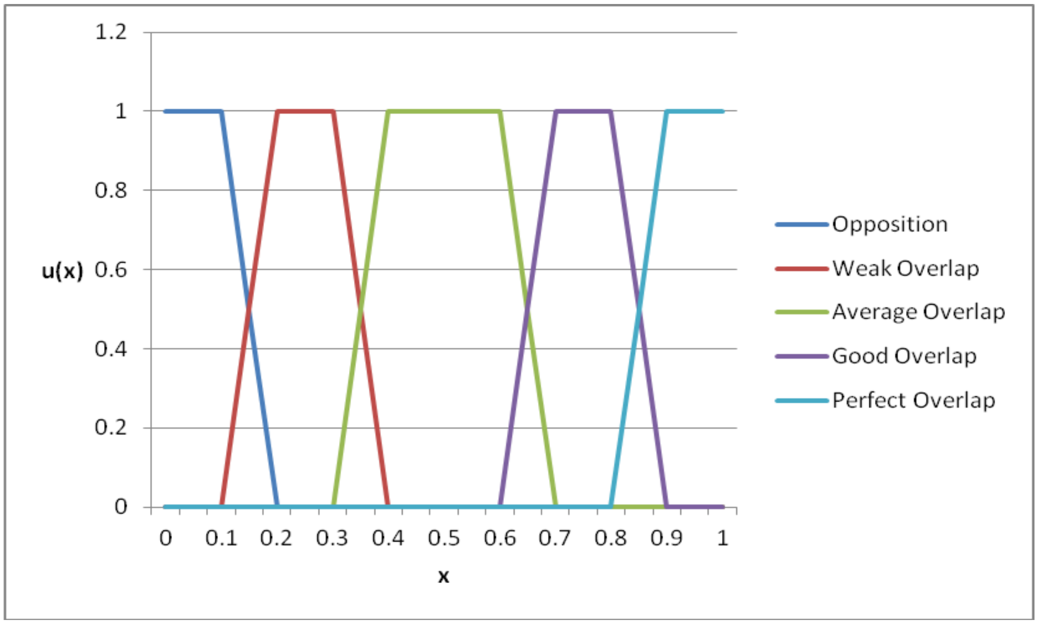
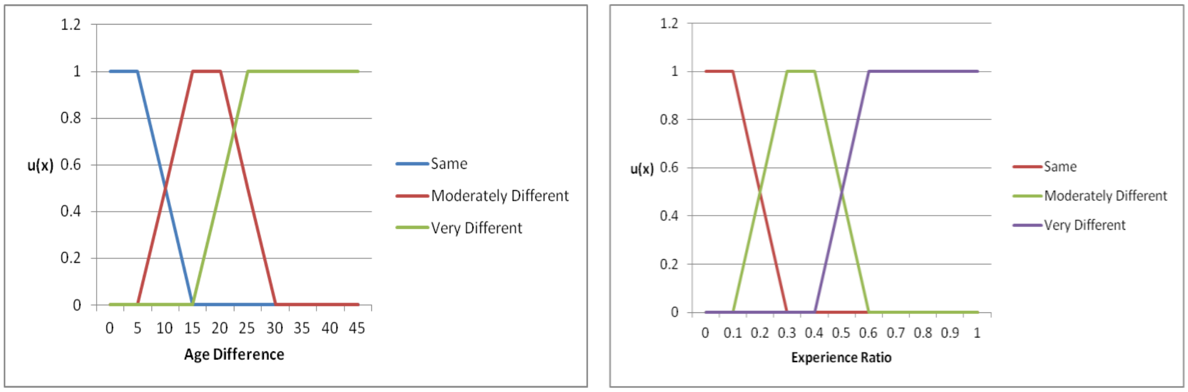


Figure 2. Membership function for linguistic inputs.

The age differences are based on a quantitative measure, and thus can be modeled by a mathematical function. The work of Zemke *et al.* (1999) identifies three generations at the current workplace. On average, a generation is the set of people with 16 years age difference. As such, people with an age difference of less than 16 years are considered to belong to the same generation, those with an age difference between 16-32 years are considered moderately different and those with an age difference of more than 32 years are considered to be very different. The membership function for the age difference is shown in Figure 3a.

The last measure for comparing crew members is the level of experience. Experienced workers are more familiar with their tasks and communicate about it easily. Overlap in experience is measured proportionally similarly to Gibson and Vermeulen (2003). The minimum value for experience overlap is zero, and the maximum is one. Thus, if one worker has three years of experience, and the other has five then the overlap is 0.6, the same value would be obtained when comparing a worker with six years of experience and a worker with ten years of experience. The membership function for experience is shown in Figure 3b.



(a) (b)

Figure 3. (a) Membership function for age difference, (b): Membership function for experience ratio.

With the fuzzifier component of the fuzzy based system defined, the next step is to define the if-then rules. These rules are logical statements that provide the intelligent component of the fuzzy system with a recipe to formulate decisions. The intelligent unit in any fuzzy system typically assumes one of two formats, Takagi-Sugeno or Mamdani. Since the input in our system is intuitive and is expected to be done by human experts, the Mamdani paradigm will be applied. Unlike Takagi-Sugeno, the output of a Mamdani fuzzy based system is also fuzzy and thus the need arises for a defuzzifier as depicted in Figure 1. A sample of the if-then rules applied in our system is shown in Table 2. It is worth mentioning that the proposed system has 243 rules; Table 2 shows an example illustrating these rules. What the first rule states is that if nationality, language and education overlap perfectly and the age and experience are the same then the output, or likelihood of communication, is highly probable.

Table 2. Sample fuzzy system if then rules.

Input					**Output**
Nationality	**Language**	**Education**	**Age**	**Experience**	**Probability**
Perfect Overlap	Perfect Overlap	Perfect Overlap	Same	Same	Highly Probable
Average Overlap	Average Overlap	Average Overlap	Moderately Different	Moderately Different	Average
Opposition	Opposition	Opposition	Very Different	Very Different	Improbable

However, what does an output of "Highly Probable" signify? This output is still fuzzy and needs to be converted into a numerical format, since our system is expected to generate numerical probabilities. This is when the defuzzifier comes into play, and it converts such fuzzy terms into numbers. The defuzzification method used in this system is the Centroid method. It was selected since it returns estimates which are at the center of the membership function curve. Therefore, the generated probabilities will not be too high or too low.

3 CONCLUSION

Demographic diversity could have a significant impact on communication and thus knowledge sharing in any industry. This impact could be more severe in the construction industry, where the work is done by crews and not individuals. Workers could be from different nationalities, age groups, experience levels and with varying educational backgrounds. All of these factors lead to the creation of faultlines or subgroups and workers are most likely to communicate with those belonging to the same subgroup. However, given the soft nature of the problem standard mathematical methods fail in quantifying the impacts of these attributes for a multitude of reasons. First, many demographic constructs are loosely defined. Moreover, there seems to be a disagreement on the impact of individual demographic attributes on communication and knowledge sharing. As such, a fuzzy based system was proposed to study this matter. Fuzzy based systems work well with systems that are represented linguistically and with systems that have inputs with a high degree of uncertainty.

The proposed fuzzy based system takes the demographic differences among crew members in as inputs and generates the probabilities of communication among these members. The system has three linguistic inputs, and two numerical or continuous inputs. We used the Mamdani approach while designing the system since it allows for intuitive estimates and for human estimates. Moreover, the defuzzifier uses the Centroid method to generate the outputs. This method was selected due to its popularity and its capability of generating moderate estimates. These probabilities will be used in future work as the theoretical foundation for an Agent Based Model that studies the impact of demographic diversity on knowledge sharing among construction crews.

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