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A HYBRID MODEL OF MULTIPLE TEAM MEMBERSHIP AND ITS IMPACTS ON SYSTEM DESIGN

Andrew J. Collins
Sheida Etemadidavan

Department of Engineering Management and Systems Engineering
Old Dominion University
5115 Hampton Blvd
Norfolk, VA 23529, USA

ABSTRACT

Within an organization, Multiple Team Membership (MTM) occurs when employees are working in multiple teams simultaneously. Approximately 65% of all knowledge workers are working in an MTM environment; however, research into MTM has only begun to emerge over the last decade, with no application of simulation to date. The extant research studies, using human subject studies, have focused on the impact of utilizing MTM on productivity and effectiveness of individuals or teams, effectively looking at micro-level phenomena. This paper outlines the first attempt to understand the macro-level phenomena of MTM using quantitative means. The scenario under consideration is a large system design project that requires multiple interdependent teams of engineering designers. An agent-based simulation of this scenario was created. The results from a simulation experiment indicate that using MTM helps in more complex design projects, i.e., it increases the performance of finding a feasible design solution when coupling is introduced.

1 INTRODUCTION

Multiple team membership (MTM) occurs when individuals belong to multiple teams simultaneously (Margolis 2020). It has been estimated that over 65% of all knowledge workers are in MTM environments (O'leary et al. 2011). The multiteam systems (MTS) paradigm has been used to study teams, but the focus has been on disjoint teams (Margolis 2020). An example of disjoint MTS is shown in Figure 1(a). In contrast, MTS that incorporate MTM have interdependencies across teams (O’Leary et al. 2012), as shown in Figure 1(b). MTM has been shown to affect productivity and effectiveness at the individual level (micro-level) (Bedwell et al. 2014; O'leary et al. 2011); however, few quantitative studies have been conducted at the project level (macro-level) (O’Leary et al. 2012). This paper presents the findings, from a prototype simulation experiment, of an investigation into the effects of MTM on the overall performance of a large systems design project.

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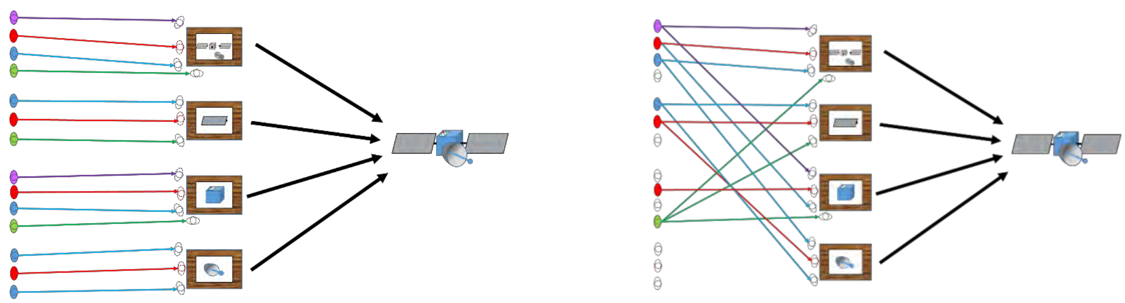


(a) Disjoint MTS design project (b) MTS incorporating MTM design project

Figure 1: Representations of a multiteam system (MTS) design project involving different engineering specialties that have (a) disjoint teams or (b) multiple team membership (MTM).

Simulation is a powerful tool to gain insight into complex systems (Miller and Page 2007). Other techniques, like mathematical programming or analytical modeling, are insufficient to capture all the required complexities (Law 2015; Salt 1993). Simulation easily allows the exploration of alternative scenarios while controlling experimental conditions (Law 2015). Simulation also enables a deep understanding through a dynamic exploration of varying conditions (Epstein 2008).

Human experiments or observations have been conducted to investigate MTM effects at the individual level (Margolis 2020). However, MTS are difficult to study using human subject research at the project level due to large resource and time requirements (Aiken and Hanges 2012). Simulation does not have these limitations and is also able to simulate what would happen over years of real-time in a matter of hours (Banks 1998).

In this research, a simulation is used to investigate the effect of MTM on design task performance, both in cost and time, through a specific scenario of a parametric design project. This requires the development of a hybrid agent-based modeling simulation.

Our research questions are: given an MTS structure, how does incorporating MTM affect a design team's performance at the project level? How do these results vary for different design task complexity?

Our approach to modeling this situation is to construct a hybrid simulation model that combines the design matrix approach of Grogan and de Weck (2016), with the KABOOM agent-based modeling approach to design teams by Lapp et al. (2019). This hybrid simulation provides the foundation to which MTM can be incorporated and investigated.

2 BACKGROUND

In this section, we provide further background to MTM and introduce the agent-based simulation paradigm.

MTM allows for an individual's specialist knowledge to be shared over multiple teams. This is especially important in an engineering design project where teams might require heterogeneous engineers to work together, e.g., Integrated Project Teams (Creekmore et al. 2008). In theory, multiple specialists of a certain type could be employed for each team, as shown in Figure 1(a), but this could lead to a high level of redundant manpower effort, especially when the workload requirements for a given individual are low. When individuals are placed on multiple projects, their total level of effort is high. Thus, MTM allows for a high level of manpower efficiency (O'leary et al. 2011).

2.1 Research on Multiple Team Membership

Research has shown that the number of teams an employee belongs to affects effectiveness (O'leary et al. 2011), productivity (Fricke and Shenhar 2000), and workload capacity (Bedwell et al. 2014). In all these cases, optimal results were achieved when employees were in two to three teams. O'Leary et al. (2012)

advocate that there are challenges in studying MTM at the systems level and that managers do not recognize the benefits, and problems, that MTM can bring.

The majority of MTM research relies on data-collection methods (Margolis 2020), like surveys (Cummings and Haas 2012) or case studies (Fricke and Shenhar 2000). Conducting a controlled human experiment that involves MTM, even for just one project scenario, is highly time-consuming and would require multiple teams to be formed for each trial. A real-world project that involves MTM could take years to run, making an observation approach extremely time-consuming and difficult to implement. As a result of these limitations, the research into MTM has mainly focused on the individual and team levels.

The use of simulation within Systems Engineering Design (SE&D) research studies at the system or project level has risen in recent years because the "practical challenges of access, limited observation scope, and long timescales limit the empirical study of SE&D phenomena" (Szajnfarber et al. 2020). These challenges are exacerbated with MTM, where it becomes difficult to determine how much effort an individual has put into each team's task; self-reporting is limited in providing this information, and continual observation is impractical. Simulation can be scaled to the required situation. Simulation modeling provides a tool to investigate phenomena related to scenarios that involve several individuals dispersed over multiple teams, which have inter-team effects. This paper discusses the first agent-based simulation that investigates the inter-team effects of MTM on the final system design.

2.2 Agent-based Simulation

Simulation as a research tool has been successfully used to study teams, including those focused on design tasks (Lapp et al. 2019). The specific simulation approach for this proposed project is agent-based modeling (ABM), which is popular for modeling social systems (Gilbert 2004). Simulation modeling has been used to understand phenomena related to design teams, but this application tends to focus on the intra-team efforts, i.e., the effects individuals have on the overall team's design performance (Crowder et al. 2012; Lapp et al. 2019; Perišić et al. 2016) or individuals' collaboration and communications impact on the teams' performance (Yilmaz 2007; Zou and Yilmaz 2012). We propose to use ABM to understand the effects of inter-team phenomena. ABM can capture emergence and dynamics of team's processes while the traditional models such as survey, experiment, and observation fail to capture that, because they are static (Kozlowski and Chao 2018). Several studies have used ABM to study teams in general (Bergner et al. 2016), and some have focused explicitly on engineering design teams (Crowder et al. 2012; Garcia 2005; Lapp et al. 2019). Though most examples only model a single design team focusing on intra-team effects, some do consider multiple teams to understand inter-team effects (Lapp et al. 2019; Soria Zurita et al. 2017). Of the research that has used ABM, some have been developed to support design teams using artificial intelligence methods (Hulse et al. 2019; Soria Zurita et al. 2017); while others demonstrate the ability of ABM to model design teams (Crowder et al. 2012; Garcia 2005). Others still have been used to study specific phenomena relating to design teams like delegation (Vermillion and Malak 2015) or cognitive style (Lapp et al. 2019) using existing theory.

Except for ABM, other computational models were used to study project teams' design and management, like virtual design team model, which was built based on the empirical data to give predictions about the cost and duration of projects based on communication, rework, and waiting (Levitt 2012). Another study on team performance based on Marks et al. (2001) model and empirical data to examine different types of interventions on the team performance and then using genetic algorithms to find the optimal team performance (Kennedy and McComb 2014). The main advantage of ABM compared to other computational models in the team context is that those that we mentioned need empirical data or complex rules to study project level phenomenon or only consider limited number of teams to study, but ABM only involves simple rules while enabling a researcher to study emergent phenomenon in a complex system with larger number of teams.

The KABOOM model was developed by Lapp et al. (2019) to investigate the effects of cognitive style in an engineering design MTS. The cognitive style was modeled using the Kirton Adaption Innovation inventory, with a focus on an individual's efficiency, sufficiency of originality, and group conformity (Kirton 1976). KABOOM models multiple teams on a system design project; the teams interact through project meetings as well as one-on-one meetings between individual designers on different teams. It is this framework that was used in our simulation model.

We should note that the difference between our hybrid model and other modeling approaches in the MTM context is that our model is the first utilization of simulation that studies the application of MTM on the project-level performance. Other modeling approaches either studied individual-level performance or a small number of teams to investigate intra-team effectiveness and productivity while our hybrid model focus on inter-team.

2.3 Parametric Design

The engineering design process can be considered a multi-staged process that encompasses many steps (Asimow 1962). Though it is feasible to conceptualize and abstract the whole design process into an ABM (Crowder et al. 2012), we feel it is prudent to focus on the parametric design stage due to its quantitative focus. Though not explicitly mentioned, KABOOM focuses on the parameter design process in its model. Grogan and de Weck (2016) represented the parametric design space as a linear mapping from a vector of design parameters $\boldsymbol{x}$ to design output $\boldsymbol{y}$ using a matrix approach:

$$Mx = y \tag{1}$$

Since the matrix M is assumed to be orthonormal, there exists a unique x for each y. In parametric design, the design variables represent dimensions or tolerances, but they may also represent a material, heat treatment, or surface finish applied to the component (Dieter and Schmidt 2021). If there is some error tolerance ε which all functional requirements y* must satisfy, then the parametric design problem becomes finding a feasible x such that:

$$\left|\sum_j m_{ij}x_j - y_i^*\right| < \varepsilon \tag{2}$$

Representing the parametric design problem in this form allows it to be embedded into a quantitative method like the agent-based simulation model.

Another reason to consider parameter design is that it readily enables the modeling of couplings between design teams. By coupling, we mean that the design output of a team is dependent on other design teams. Obviously, in an MTM environment, coupling will occur due to individuals being in multiple teams. However, in parameter design, coupling can occur due to the distinct teams' design solutions influencing each other's ability to meet requirements.

2.3.1 Parametric Design Matrix

We adapt the Grogan and de Weck (GW) (2016) matrix model for our research. This approach allows for a high level of control of the coupling across outputs. The original GW model focused on the coupling of design output across tasks; our model includes the coupling effects of membership across multiple teams. In the GW model, each design parameter and output is assigned to an individual. A single individual might be assigned into multiple design inputs and outputs. In our model, we replace each individual with a team. Since a single individual can be in multiple teams, our model allows us to investigate coupling effects due to both MTM and parameter dependency.

The allocation of individuals to teams is represented by a binary matrix $\boldsymbol{G} \in \{0,1\}^{N\times S}$ where N is the number of individuals and S is the number of teams. The matrix $\boldsymbol{G}\boldsymbol{G}^T$ shows the number of teams that two individuals share. The allocation of P design parameters and Q design outputs to the teams can be represented by $\boldsymbol{A} \in \{0,1\}^{S\times|P|}$ and $\boldsymbol{B} \in \{0,1\}^{S\times|Q|}$, respectively. The matrix $\boldsymbol{D} = \boldsymbol{BMA^T}$ represents coupling between inputs and outputs, where a non-zero value for d_{ij} means that team i's input affects team j's output. We can extend this with the matrix $\boldsymbol{GD}$, which shows individual effects on a given team's output; and, more generally, $\boldsymbol{GDG^T}$ shows which individuals affect which other individuals' output.

Our approach can also represent the disjoint MTS situation. If $\boldsymbol{G^T}$ is a concatenation of a standard basis, then it represents a many-to-one relationship between the individuals and teams where each individual is in one, and only one, team. A breakdown of the integrated base MTS model is shown in Figure 2.

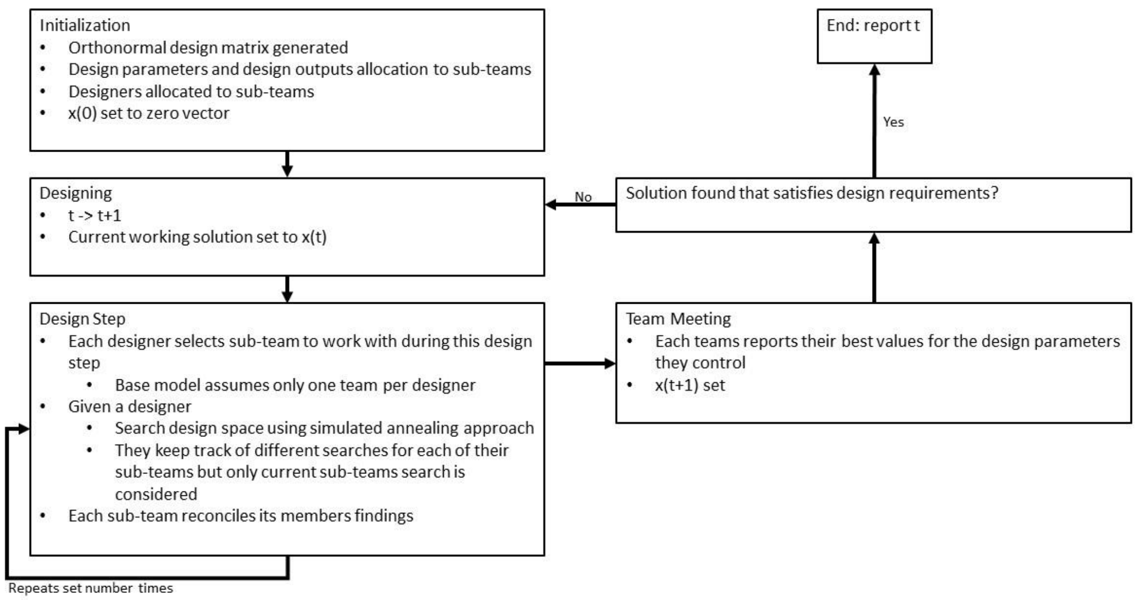


Figure 2: Flow diagram of the base disjoint MTS model.

3 MODEL

The modeling scenario is of a design project scenario, which requires three teams, with each team requiring two design engineers (agents). We consider the disjoint MTS case, where each position is filled with a unique agent (for a total of six agents), and the MTM case where each agent fulfills two positions in two different teams (for a total of three agents).

Each team is responsible for two design inputs and two design outputs. This represents the team's focal concern. For example, in the context of aircraft design, a team might be responsible ensure the airplane's range meets a minimum fresh hold (output), through the design dimensions of the fuel tank (input). A team's output could be affected by other team's input, e.g., other parts of the airplane's design could increase the airplane's weight, thus decreasing its range. This interaction between teams is known as coupling. We represent coupling in our model through the design matrices. Examples of the design matrices are given in the figure below.

$$\begin{pmatrix} 0.5 & 0.5 & 0 & 0 & 0 & 0 \\ 0.5 & 0.5 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.5 & 0.5 & 0 & 0 \\ 0 & 0 & 0.5 & 0.5 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.5 & 0.5 \\ 0 & 0 & 0 & 0 & 0.5 & 0.5 \end{pmatrix}$$

(a)

$$\begin{pmatrix} 0.7 & 0.7 & -0.1 & -0.1 & -0.1 & -0.1 \\ 0.7 & 0.7 & -0.1 & -0.1 & -0.1 & -0.1 \\ -0.1 & -0.1 & 0.7 & 0.7 & -0.1 & -0.1 \\ -0.1 & -0.1 & 0.7 & 0.7 & -0.1 & -0.1 \\ -0.1 & -0.1 & -0.1 & -0.1 & 0.7 & 0.7 \\ -0.1 & -0.1 & -0.1 & -0.1 & 0.7 & 0.7 \end{pmatrix}$$

(b)

Figure 3: Examples of design matrices for (a) uncoupled and (b) coupled scenarios

3.1 Coupling

The matrices shown in Figure 3 show design matrices for the uncoupled and coupled scenarios. By coupled, we mean that a given team's input could affect the outputs of the other teams. To give an example, in our aircraft design example, if the team in charge of designing the fuel tank produces a design that increases the fuel tank's weight, then the team in charge of lift will probably need to increase the wingspan to produce more lift for this extra weight. Coupling brings an extra level of complexity to the design problem as it cannot be reduced into disjoint parts. The uncoupled scenario could be decomposed into three problems, i.e., since the first team is responsible for inputs one and two and outputs one and two then these inputs and outputs are not affected by any other team's design.

The form of coupling described is what we call *coupling by the team*. Grogan and de Weck (2016) considered this type of coupling along with *coupling by input* (where multiple inputs affect a given output). When considering MTM, having an individual on multiple teams means there is a coupling, through that team member, on outputs of their teams, which we will call *coupling by member*. In the research presented in this paper, all three types of coupling are considered.

3.2 Overview of Model Processes

Based on the design project task described above, a process of design task was developed and used within our simulation. An overview of this process is shown in Figure 4. The process follows the designers (agents) trying to improve the current team's best design, and, periodically, the teams come together in a team meeting to share their current design solutions. This approach to modeling the design tasks follows the main approach from the KABOOM model (Lapp et al. 2019), which also used project meetings to update the overall design solution.

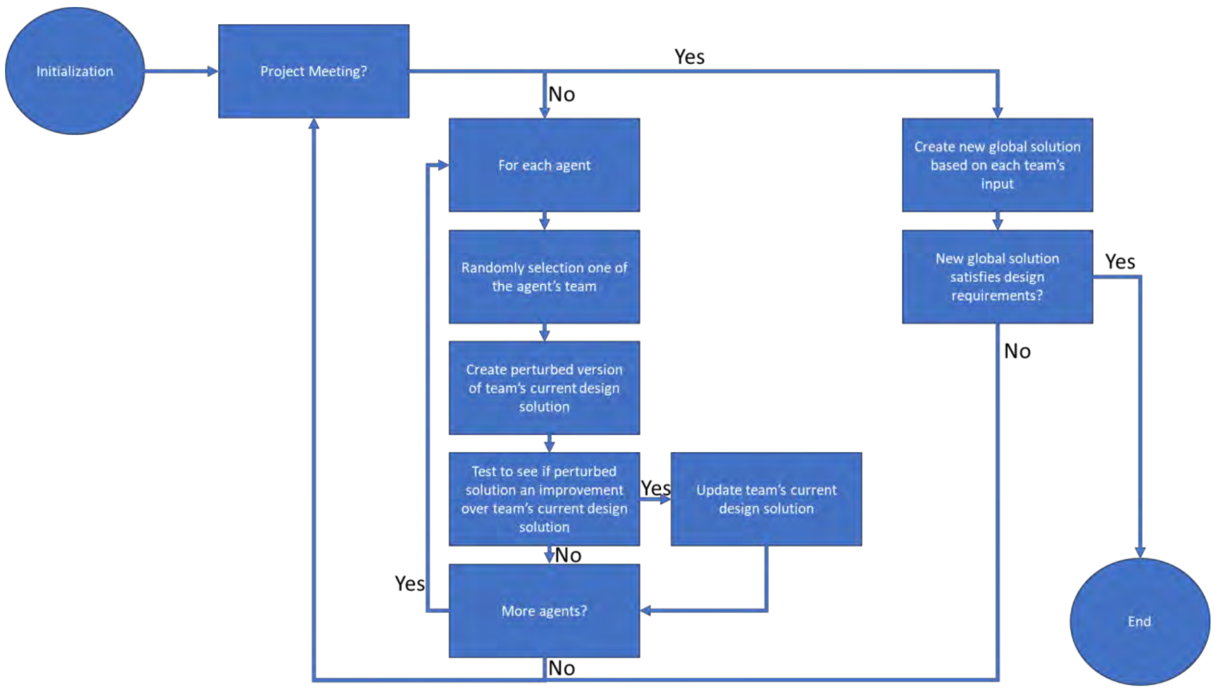


Figure 4: Process diagram of the design project's dynamics.

In the simulation model, all the designs and outcomes had to be represented in a numerical way. The design solutions are input vectors, which are initialized as the zero vector. The design requirements are an output vector, which is made of all ones. Given the two design matrices above, an optimal solution would be an input vector of all ones (the example design matrices are not orthonormal, so the uniqueness of the solution is not guaranteed). In this model, the way the agents find better solutions is through a random walk process (± 0.1 randomly added to each element in the input vector). In future versions of the model, simulated annealing will be used to emulate this process, as was conducted by Lapp et al. (2019).

At each step of a simulation run, one of two events can occur: a project meeting or the search for a better solution by each agent. Every ten steps, a project meeting occurs. In the model, this is represented by allowing each team to provide an update of its latest design solution, i.e., the value of the inputs that the team is responsible. These inputs are combined to provide a new starting point for the teams to use for the next ten iterations. If the resultants design output has an error value below a certain threshold ($\varepsilon < 0.01$), as determined by equation 2, then a feasible solution has been found, and the simulation stops.

During each non-project-meeting step, the agents try to find a better design solution. This is achieved by each agent evaluating a randomly perturbed design solution from the team's current design solution and evaluating it. If the new design solution produces an error lower than the team's current design solution, then it becomes the team's current design solution. This process is repeated for each agent. Note that each team is only evaluating their design solutions so that they minimize the error of the design outputs that they are responsible. If the model includes MTM, then at the start of each agent's turn it randomly chooses which of its teams to work on.

The simulation's output of interest is the cost. We simply define cost as the number of steps times the number of agents. Since a simulation will only stop during a project meeting, the number of steps is always a factor of ten. This means for the case when there are six agents, the cost jumps in increments of 60; and when there are three agents, it is an increment of 30.

Using this model, a series of batch runs was completed to determine the impacts of MTM on system design. The simulation was built in the Netlogo agent-based software package (Wilensky 1999).

4 METHODOLOGY

Our approach is to simulate, using ABM, a multiteam design project that incorporates MTM. The agents of the model represent the individual project members who have been allocated to multiple design tasks and teams. We will first develop a base model of a disjoint MTS and then adapt it to include MTM effects. The base model will be constructed using a parametric design matrix (Grogan and de Weck 2016) and KABOOM models (Lapp et al. 2019), which include the parametric design task model and design team behavior, respectively. Various scenarios will be considered to investigate the effects of MTM on overall system design performance. In future research, the agents will have dynamic autonomy over their effort allocation.

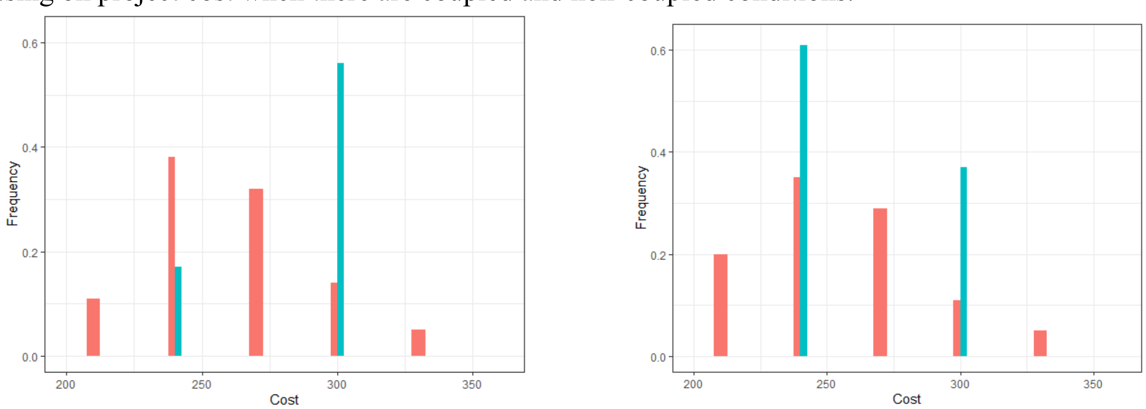
The simulated design of each component is assumed to occur through an iterative process, with different design solutions being proposed at regular intervals and the best overall design being selected at each interval. The components are assumed to be interdependent, and these interdependencies affect both the component's team's design output and the overall design output. Team members are assumed to aid in the search for the best design, as outlined in KABOOM (Lapp et al. 2019).

4.1 Experimental Design

Our approach is to conduct computer simulation experiments to generate empirical distributions of the phenomena of interest and draw conclusions from analyzing them. There are two different dichotomous variables considered: coupled vs. uncoupled design problem, and MTM (with only three designers) vs. disjoint MTS (with only six designers) project team organization. Each of the four possibilities was run 100 times are overall cost data was collected.

5 RESULTS

We have created a prototype of this project and compared the MTM case against the disjoint MTS case, focusing on project cost when there are coupled and non-coupled conditions.



(a) (b)

Figure 5: Empirical discrete cost distribution of MTM (red) vs. MTS (blue) in (a) coupled and (b) non-coupled scenarios.

Figure 5 shows the empirical distributions generated from 100 simulation runs in each of the four cases. The spread of the columns is due to the project meeting timing, i.e., a final design solution could only be realized in the meeting. In general, MTM cases tend to produce a lower amount of cost rather than base MTS with the majority ranging from 225 to 250. The majority range for the base MTS case also occurs between 225 to 250 for the non-coupled scenario but is higher for the coupled scenario.

It is shown in Figure 5(a) that MTM works more efficiently with regard to the overall cost. Figures 5(a) and 5(b) suggest that MTM works almost the same in both coupled and non-coupled environments, while the disjoint MTS costs more in the coupled environment.

Table 1: Unpaired t-test results.

	Not coupled	Coupled
p-value	0.223	0.673
t-value	-1.219	0.422

An unpaired t-test (independent) was conducted to check whether there is a significant difference between the average costs of these two environments (Table 1). Because the p-values are greater than the confidence level (0.05), we cannot conclude that there is a significant difference between the mean costs of the MTM and disjoint MTS cases. Additional investigation will be needed in order to have more robust findings. Chi-squared testing for goodness-of-fit was not used due to data limitations.

The results presented only represent a single case-study of a particular MTM scenario: three or six agents distributed over three teams that are conducting coupled or uncoupled simultaneous design tasks. Within this scenario, there is scope to conduct a variety of sensitivity analysis. The focus of our sensitivity analysis was on the design matrix and time between meetings. When we slightly varied the values in the design matrix (e.g., -0.15 in place of -0.1), but the results produced the same non-significant findings. Similar results were observed with varying the time between meetings.

6 FURTHER RESEARCH

The work presented in this paper only represents the beginning of the use of simulation to investigate the impacts of MTM on overall effectiveness of finding feasible solutions in a large design project. Only one scenario was considered in this prototype (i.e., three homogeneous teams); the next stages are to consider a wider variety of scenarios, for example, more teams and varying number of agents required per team. Another variation that might be considered is heterogeneous teams, where they vary by both size and tasks (i.e., variation in the design matrix). Obviously, the homogeneous case needs to be well-understood before moving onto the heterogeneous case.

Ideally, each team would be allocated adequate resources to effectively complete their tasks both in terms of expertise provided and time allocated to team members to complete the design; however, in practice, there is competition for acquiring adequate resources by both team leaders and project managers (Kaulio 2008). We will investigate this competition in the later phases of our research.

We have used a matrix approach to modeling the design task complexity and coupling based on the work of Grogan and de Weck (2016). Another approached could have been the NK models, which was originally suggested for biological applications (Kauffman and Weinberger 1989) and later adapted to design situations (Levinthal 1997; Rivkin and Siggelkow 2007). The approach models the performance landscape by mapping binary decision vectors to randomly generated contributions of those decisions; it is able to model coupling and complex decision landscapes and has the advantage, over our approach, not requiring to concerned about matrix orthogonally. However, as part of intent is to compare our results to those of Grogan and de Weck (2016), we will continue using the matrix approach and later do a comparison of the two approach in a similar scenario setting.

7 CONCLUSION

Our agent-based model provides some insights into MTM. In particular, it indicates the MTM might be more effective in complex design scenarios. The complexity level used in our scenario was driven by coupling effects. Understanding the relationship between complexity and team organization will enable design engineering and human resource managers to allocate their staff to projects. This could also inform the development of future human subject research projects to understand the effects on design team staffing.

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AUTHOR BIOGRAPHIES

ANDREW J. COLLINS is an assistant professor at Old Dominion University in the Department of Engineering Management and Systems Engineering. He has a Ph.D. in Operations Research from the University of Southampton, and his undergraduate degree in Mathematics was from the University of Oxford. He has published over 80 peer-review articles. His projects have been funded to the amount of approximately $7 million. Dr. Collins has developed several research simulations, including an award-winning investigation into the foreclosure contagion that incorporated social networks. His email address is: ajcollin@odu.edu . His website and full resume are at www.drandrewjcollins.com.

SHEIDA ETEMADIDAVAN is a Ph.D. student at Old Dominion University in the Department of Engineering Management and Systems Engineering. Her research interests is to conduct research on strategic relations using modeling and simulation techniques to optimize efficiency and decision-making at the industry level, specifically buyer-supplier relation. Her email is setemadi@odu.edu.