INVESTIGATING EFFECT OF ORGANIZATION STRUCTURE AND COGNITIVE PROFILES ON ENGINEERING TEAM PERFORMANCE USING AGENT BASED MODELS AND GRAPH THEORY

by

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To my Wife Carole and my sons Alexander and William Estes

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Judson B. Estes

PREFACE

In my work as a Systems engineer, I diagnose systems and apply corrective actions to optimize their performance. The often-used metric of effectiveness is a decrease in warranty claims. I have worked on many projects across many continents. I have found that people in distress are the most motivated to try methods they have never seen before. How can I best assemble a group to find and solve problems faster, with better solutions and better results? This motivation drives me forward. This research using an Agent-based model with relationships modeled as a graph is not just a theoretical exercise but, quite applied to me.

I hope that my experience in teaching classes, leading teams and adjusting my role to fit into the team and manage them forward is improved by the work done here to understand the interplay of relationships, agents and communication in modern engineering teamwork.

ABSTRACT

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Advisor: Vijitashwa Pandey, PhD

Engineering organizations have to maximize return on investment (ROI) on the products they design and market. Involvement of human decision makers complicates the design process because not only their technical skills affect the results, but also their other cognitive skills *in addition* to their role and seniority in the organization. These cannot be studied easily within existing organizations for logistical reasons, while at the same time human-subject research is time consuming and difficult. An agent-based model, building upon previous research, is employed in this work which addresses both the above issues.

The contributions of this work include an agent-based framework for modeling and simulating engineering design as informed by the organization structure which is represented by a network graph. In particular, the model uses a scale-free network using the Barabasi-Albert algorithm. Using the undirected graph thus generated, we use the eigenvector centrality to depict the relative influence of a team-member on design decisions. This comprehensive model allowed us to investigate a wide variety of problem settings and the effect of cognitive profiles on the engineering design process. Individuals'

intrinsic and organization-induced cognitive skills were incorporated into the model. The model also allowed for the individuals' cognitive profiles to affect and be affected by their experience in the team design effort. Based on our results, we were able to show that organizations that promote collaborative work, particularly with the aim of engaging skilled individuals, are more likely to come up with better designs and/or converge to designs faster.

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LIST OF ABBREVIATIONS

ABM	Agent Based Models
GA	Genetic Algorithm
IRB	Institutional Review Board
KABOOM	Kirton Adaption-innovation inventory agent Based Organizational Optimization Model proposed by other researchers
KAI	Kirton Adaption-Innovation Inventory
MBTI	Myers-Briggs Type Indicator
PPD	Product and Process Development process
NP-hard problems	NP stands for Nondeterministic Polynomial time. NP-hard problems are at least as hard as the hardest problems in NP.
Model A	In this dissertation, in model A, the cognitive attributes of the designers are assumed to be constant throughout the design process.
Model B	In this dissertation, in Model B, the cognitive attributes of leadership and creativity are expected to change over the various design iterations.

NOMENCLATURE

n_c	The number of components in the decision vector $\boldsymbol{x}$.
n_v	Each component has number of possible variants
$f(\boldsymbol{x})$	Objective Function, the value of the solution.
$f_0(\boldsymbol{x})$	The distance of the solution from the local minimum.
$h(\boldsymbol{x})$	The distance of the solution from the global minimum.
h_{crit}^{high}	A user-specified scalar that determines that the solution is “close” to the global minimum.
h_{crit}^{low}	A user-specified scalar that determines that the solution is “in the vicinity of” the global minimum.
α_1	A under-defined parameter used to ensure the function $f(\boldsymbol{x})$ falls within the desired bounds
α_2	A under-defined parameter used to scale $f_0(\boldsymbol{x})$
Ω	The frequency of the sinusoidal noise introduced to the objective function.
$\mathbf{x}_l^*$	The local minimum.
$\mathbf{x}_g^*$	The global minimum.
l^A	The value of leadership cognitive attribute in Model A.
l_o	Organization-endowed leadership skills, Model B.
$l_i(s)$:	Innate leadership skills, Model B.
l^B	The overall leadership attribute in Model B.
k_{lo}	A scalar between 0 and 1, that measures the emphasis the organization places on the organizational rank of the individual

k_{li}	A scalar between 0 and 1, that measures emphasis the organization places on encouraging individual leadership skills
$l^B(s)$	the overall leadership value, when variable, Model B.
$\eta(s)$	The interaction function, which changes based on the times an individual is called upon in the conversation
l_{max}	The maximum fractional increase in leadership possible
R_1	A uniformly distributed random variable between 0 and 1 and is a tunable scalar.
R_2	A uniformly distributed random variable between 0 and 1 and is a tunable scalar.
α_2	A uniformly distributed random variable between 0 and 1 and is a tunable scalar.
κ	The creativity value, is a scalar between 0 and 1. It is kept constant throughout the design process in Model A.
κ_{max}	The maximum fractional increase in creativity possible.
n_{pop}^{max}	The maximum fractional increase in the population size the model allows.
n_{pop}^{base}	The base population size in the model.
t	The intrinsic attribute of technical ability.
l_i^A	A probability proportional to their relative leadership skill.
ψ	A scaling parameter to measure how collaborativeness drops with distance on the graph.

NOMENCLATURE
continued

n	The number of team members.
c_{int}	The intrinsic collaborativeness exhibited by the individual
c_{org}	The collaborativeness induced by the organizational culture.
k_{int}	The scaling constant that measures the relative impact of the intrinsic personality traits and lies between 0 and 1.
k_{org}	The scaling constant that measures the relative impact of the personality traits induced by the organizational culture and lies between 0 and 1.
l_o	The organization-endowed leadership skills.
λ_{max}	The eigenvector associated with largest eigenvalue of the adjacency matrix.
l_o	The value is derived from the eigenvector centrality associated with the node.

CHAPTER ONE

INTRODUCTION

1.1 Introduction

Engineering organizations are constantly looking to maximize return on investment and achieve clarity on the expected cost, time taken, and the expected performance of the product or process they will realize at the end (Joel and Oguanobi, 2024; Jiao et al., 2021). Unfortunately, there are many impediments to designing and executing such projects ranging from technical, managerial, all the way to legislative and market influences (Hutchinson et al., 2014). A major contributor to these challenges stem from the diversity of viewpoints and skills of the individuals that comprise the organization (Ceci and Williams, 2022). This dissertation is an attempt to improve our understanding in this regard so engineering organizations can better assemble design teams.

Numerous techniques have been developed in the literature to address various aspects of the systems realization process considering the resources available to the organization. For example, systems engineering (SE) tools such as the VEE model which is a graphical representation of system development lifecycle, provide a structure to the product and process development (PPD) process (Wymore, 2013; Nielsen et al., 2015). Unfortunately, they struggle to predict the development time and cost accurately since they do not have the element of project management. On the other hand, prevalent project management tools focus on time and resources but there is little focus on the technical methods that affect product performance. For example, de Melo et al (2022) discuss the dynamics of engineering design rework process, identify the causes and suggest various solutions. The approach they recommend for this type of analysis is *soft systems thinking* with specific recommendations such as better requirements planning, reusing past design information, and – in the context of this work – ensuring that interdependent development teams maintain a clear visibility of the development activities. Other research works also echo the importance of better communication in team members (Akhavan et al, 2019 and Moor and Drake, 2001).

Involvement of human decision makers further complicates the engineering design process (Driscoll et al., 2022 and Noyes et al., 2012). Almost all the research identifies that decision making in organizations is a challenging and multifaceted challenge with far reaching consequences in domains such as engineering design (Koopman et al, 2013). In this work, therefore, we aim to understand team dynamics in the context of product development, or, more precisely, how a product or a system can be designed when different "human" aspects of cognitive skills and collaborative efforts are at play.

Figure 1.1 gives a few examples of how different cognitive skills in team members can facilitate different project development steps. Understanding these allows us to improve the process in terms of the resources that need to be invested, in terms of money, time and individuals and to realize the "ideal" design performance. It may also help us to inform ideal organizational structure (whether formal or informal) and team compositions for complex design projects. This dissertation deals with the project initiation and design definition phases of the process, as highlighted in the figure.

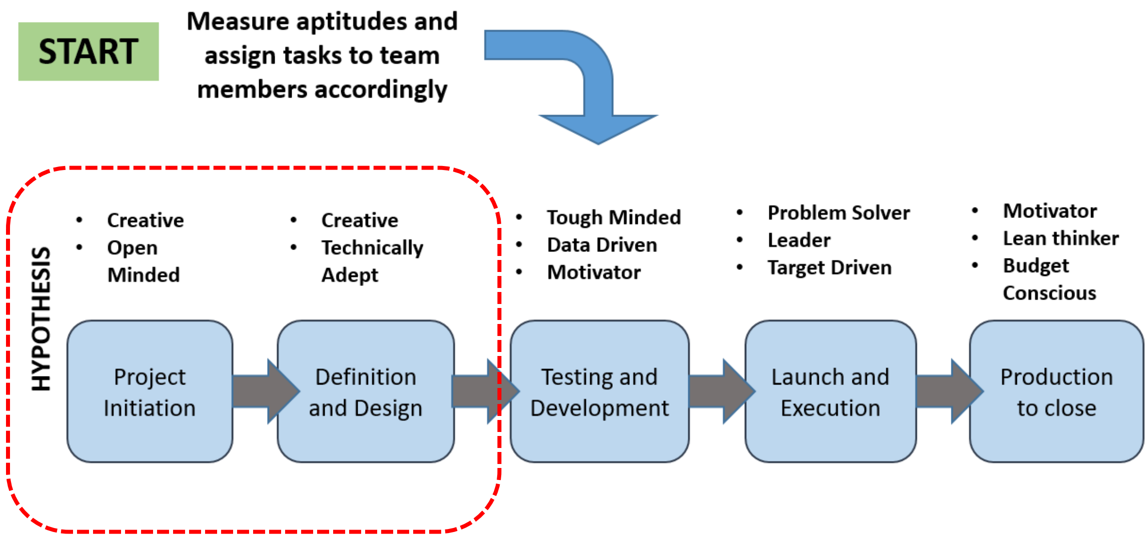


Figure 1.1: A typical engineering project and associated stages. This work focuses on the first two stages highlighted using the rounded rectangle.

1.2 Engineering Design

Engineering design has been explored from various different perspectives, including *optimization techniques* where the designers use mathematical optimization tools to achieve the best design given a set of engineering constraints (Cao et al., 2023; Lin et al., 2022; Drignei et al., 2014; Pandey et al, 2020, Zhao et al., 2010; Ding et al., 2022), *reliability* where one looks at the long-term probability of failure and investigates the techniques to mitigate it (Elshahhat et al., 2023, Mendez-Gonzalez et al., 2023; Daniels and Pierre, 2023; Pandey and Mourelatos, 2012), manufacturability to make sure that a given design is feasible to produce (Zhang et al, 2021; Raza et al., 2021) and decision making where the preferences of the stakeholders are directly incorporated in to the design decisions (Slon et al, 2019, Renzi et al., 2017; Naranjo et al, 2016), among others. However, there are limited studies of the human dynamics that are inherent to, an profoundly affect, the decision making in engineering organizations.

To gain a better understanding of engineering project management, we clearly need to model the processes and people involved in executing them. We must also model the organizational structure so that the relationships between individuals are better understood (Chaudhari et al., 2022; Gyory et al., 2022). Additionally, we also need to be able to propagate these inputs through a typical system design process and predict outcomes in terms of the quality of the designs produced. To this end, we propose a framework to incorporate organization structure using a graph representation. This is then used to inform an agent-based model where team dynamics are simulated, to understand the effects of cognitive attributes and team member relationships. This model is then implemented on an engineering design optimization problem with specific characteristics. Within the design problem, the selected team progresses through the design steps governed by their interaction, inherent and organization-induced cognitive attributes, in conjunction with the engineering optimization problem's objective function and constraints. We then investigate the effect of the make-up of the design teams (for example, the relative distance between individuals within the organization, their skill level etc.) on the quality of the designs produced and present results. Through the framework proposed, in future work, researchers can investigate scenarios such as additional factors affecting team composition (e.g. experience level), various graph realizations, among others, with hopes to make recommendations on organization structures and team formation in a general setting. A high-level overview of the proposed process is shown in figure 1.2.

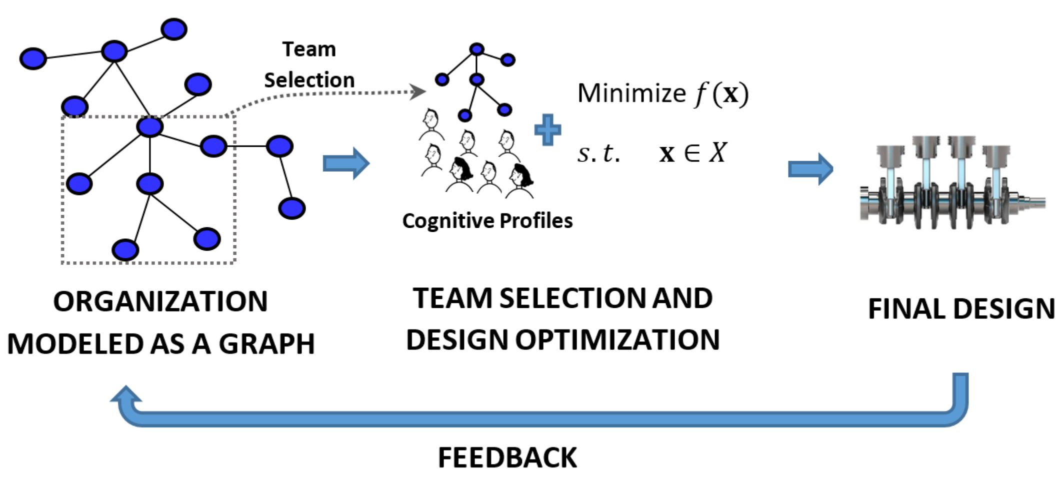


Figure 1.2: Schematic of the proposed method for team design in organizations.

1.3 Background

In all types of organizations and at almost all levels, collective decision making is prevalent. This is done to be able to leverage the various skills and experiences these various decision makers can bring. In response to this, it is recommended, and many organizations are increasingly doing this, to hire teams as opposed to individuals (Kaul, 2022; Gizerenger et al. 2022). This allows the organization to organically have access to individuals with the necessary complementary skills, who can collectively perform the tasks needed.

Several studies have considered team member cognitive skills and their impact on the team's performance (Pandey et al., 2022; Fritz et al., 2018; Converse et al., 1991; and Westli et al., 2010). In their work, Fritz et al, (2018) performed a team design experiment with human subjects and interpreted their cognitive states using electroencephalography (EEG). They were able to identify using EEG neural correlates of the decision-making processes in individual and team settings. In contrast to this, Pandey et al. (2022), which is the precursor to this work, used an agent-based model to be able to learn generalized insights.

It is argued that team members can have shared mental models that help form accurate explanations and expectations for a task, when they are working together. Another study, consisting of employees from different disciplines of an organization, posited that focusing on merely team cognition may not be sufficient (Bierhals et al, 2007) and instead recommended that one must also investigate the motivational aspects. Team dynamics have also been investigated in this context by several other researchers. For example, Buffinton et al. (2002) used the Kirton Adaption–Innovation Inventory

(KAI, Kirton, 1999) to determine cognitive styles. They concluded that cognitive style theory may be applied to characterize and better understand the personal dynamics of individuals working in teams. Jablokow et al. (2019) used cognitive characteristics along with interaction behaviors to model the engineering problem-solving process. Detailed surveys of the literature can be found in Fritz et al. (2018) and Jablokow et al. (2019). In this work, we include personality traits similar to that from Pandey et al. (2022) as the factors that influence team performance with substantial improvements both in how the they are implemented and how they evolve.

A limitation in much of the literature in this area is that team member cognitive profiles are assumed in a simplistic fashion in that they are static and are not affected by organization culture (Pandey et al., 2022). Both of these are major simplifications that we remove in this work. The cognitive profiles, where applicable are a function of the intrinsic characteristics of the individuals and that endowed by either the organizational structure or the organizational culture. Additionally, in most of the existing literature, organization structure is not explicitly considered, which clearly directly affects how team members interact with each other as a function of their status of location in the department. The organization's structure deeply affects whether certain team members have a working relationship (which could be negative) or not, or how new ideas propagate through teams and eventually organizations. There is a large body of literature on the study of business organizations where graph and network theory has been applied (Hunter, 2016). However, it is disconnected from engineering projects and product development. In this work, we address all these limitations together. In this work, the organization graph directly affects the team simulation model. This also provides us with a way to feed back to the organization what is learned as part of the product development process. The overarching goal is to make recommendations regarding team formation and organization structures that best facilitate engineering projects.

1.4 Agent-Based Models

Although experimentation with human subjects can be considered more realistic (Fritz et al., 2018), it expectedly poses huge survey and data collection challenges. This comes not only in the form of the necessary Institutional Review Board (IRB) approvals to ensure that the process is safe for human subjects and protects their personal information, but also the challenge of involving individuals with a given set of cognitive traits. Additionally, the results are almost never generalizable because they are deeply affected by the traits of the participants involved and the specific design problem considered. It also becomes prohibitive to investigate a large number of scenarios because the number of participants that can be realistically included in the study becomes limited and the time commitments from the participants rises exponentially. Many researchers, at least in academic institutions, often include students into their studies (Wendell et al., 2017; Fang, 2020; van Diggele, 2022 and, Copp et al., 2021). The benefit of doing so is that a large number of participants become available since organizing the studies on university campuses is relatively straightforward. However, the obvious shortcoming is that not only are the students not at the same experience level as actively working engineers, the team dynamics that are encountered in student teams will scarcely match that found in real life organizations where the decisions can have far reaching consequences on the organization and by extension, the individuals themselves.

For this reason, many researchers have resorted to mathematical or computer modeling and simulation of realistic experiments (Tohidi et al., 2017). An agent-based model (ABM) creates a representation of sentient decision makers on the computer that follows some given rules for their behavior (De Marchi and Page., 2014). Doing so frees us from the logistical challenges of human subject researchers while providing infinite flexibility in the various scenarios that can be considered.

For ABMs to be a useful simulation and prediction tool, one must not explicitly assume the interaction dynamics of the system. In contrast, one simulates multiple such agents (individuals or entities) that interact using simple rules and measures the emergent behavior of the entire system – which may be very different from expected based on the simple interaction rules. An example of this is the work by Lapp et al. (2019) who present KABOOM (Kirton Adaption–Innovation Inventory agent-based organizational optimization model) – an agent based model for simulating cognitive style in team decision making.

Clearly, the issue of validation remains in ABM. In general, the outcomes of ABMs are not of the type we encounter in engineering simulation where the output provides physically meaningful decisions (e.g. select the number of teeth in a gear as 32) and the expected output (maximum torque transmitted is 200 Nm). Instead, one gets general insights or directions one should take in improving a process. Despite so, a benchmarking process is generally undertaken. For example, one examines a few general trends and observes if the output of the model matches what one would expect in real life. Once confident that the ABM can actually model the dynamics of the problem at hand in simple cases, we can extrapolate it to other more complex scenarios. This allows us to be able to come up with generalized recommendations and can inform policy in engineering organizations. Finally, an ABM also gives us insights into what particular scenarios could be further investigated in a later study whether in a real-life scenario or through simulation.

1.5 Objectives of this Dissertation

The objectives of this dissertation are:

1. Create a framework for representing engineering organizations mathematically through a graph with suitable characteristics so that relevant interactions can be modeled.
2. Devise design scenarios where the cognitive profiles of the team-members and organized-induced effects affect the design process simultaneously.
3. Devise scenarios to model how the dynamics of team interaction affect design process in terms of the design's expected performance and also to simultaneously use the information to influence team traits.
4. Run the simulation model for various input parameter combinations and collect data.
5. Analyze the results obtained to draw conclusions about team decision making in engineering organizations and find avenues for future extensions of the proposed work.

1.6 Organization of this Dissertation

This dissertation is organized into six chapters. In the next chapter, we discuss the motivation, problem setup, along with necessary mathematical background so that we can set the stage for model development. Thereafter, Chapter 3 presents the mathematical implementation of the proposed approach and also provides information about the agent-based simulation model developed. Chapters 4 and 5, present the results from running the simulation for various combinations of inputs. Finally, Chapter 6 summarizes and identifies avenues for future research.

CHAPTER TWO

BACKGROUND, MOTIVATION AND PROPOSED APPROACH

2.1 Introduction

In this chapter, we provide the motivation and a detailed explanation of the underlying theory and agent-based model used in this work. In a nutshell, as presented in figure 1.2, the proposed approach can be divided into the following steps: we first model a representative engineering organization as a graph with given properties e.g. a scale-free graph – explained later in the chapter. Algorithms to create a random scale free graph may introduce unconnected elements which are then removed so that we have a cohesive organization. We then select a suitable engineering design problem that the proposed design team will work on. Each node in the graph represents an individual with a specific set of inherent cognitive attributes and those inherited from the organization. Using the design team selected from the graph and the design problem at hand, we simulate a sequence of team decisions and their effect on the product performance as well as the feedback effect on the team itself. The results are acquired, compiled and conclusions are drawn. Details are provided in the remainder of this chapter of the various technical concepts used and the associated motivations for using them.

2.2 Graphs

A graph is a mathematical construct that captures the pairwise relationship between a set of entities (Erciyes, 2021). Formally speaking, a graph is defined as an ordered pair

$G = (V, E)$, where V is the set of vertices (also referred to as nodes or points in the graph) and E is the collection of the edges of the graph. More specifically, the set E can be defined the following fashion:

$$E \subseteq \{(x, y) | (x, y \in V \text{ and } x \neq y\} \tag{2.1}$$

where x and y denote nodes of the graph. The above set described on the right-hand side is a collection of all possible edges between two distinct vertices in V. The subset E encodes the edges that actually exist between pairs of nodes for a given graph. In undirected graphs, the direction of the edge does not matter, while in directed graphs, it matters where the edge originates and where it terminates – with distinct properties and application areas associated with each type of graph. In problems involving some notion of flow (of information, material etc.) directed graphs are used while when no such directionality exists or is desired, we use undirected graphs.

There are many application areas for graph models, including biological networks (Pavolpoulos et al., 2011, Koutrouli et al., 2020), communication networks (Tamura et al., 2011), epidemiology (Rao, 2020), chemistry (Wagner and Wang, 2018), engineering (Harrison, 2016), social networks, (Majeed and Rauf, 2020; Arnaboldi et al., 2015), and Operations Research (Guze, 2014; Wagner and Neshat, 2010; Wilson et al, 2024). In engineering in particular, they are used to study computer networks, product architectures, as well as many other applications. Many properties of graphs and mathematical results associated with them become available to us if a graph model is found to be suitable for a particular application - as the various application areas identified above demonstrate. The reader is referred to (Wilson et al. 2023) for a detailed exposition of various graph theory applications explored in the last 100 years.

2.2.1 Adjacency Matrices

Adjacency matrices are an alternate representation of graphs (Gross, et al. 2018) and allow us to use powerful techniques from linear algebra. They are square matrices used to represent a finite graph. The entries of the matrix denote whether the node associated with the column is adjacent or connected to the node associated with the row or vice versa. In the simplest case, it can be a (0,1) matrix. denoting the existence or lack of connection between node pairs:

$$a_{ij} = \begin{cases} 1 & if\ an\ edge\ exists\ between\ i\ and\ j \\ 0 & otherwise \end{cases} \tag{2.2}$$

Such graphs have zeros on their diagonal, indicating that a node is not connected to itself (except in the case of *loop graphs*, which we encounter in Markov Chains and some neural networks, see Pira, 2021, for example). Undirected graphs have symmetric adjacency matrices, as expected because the direction of the connection does not matter.

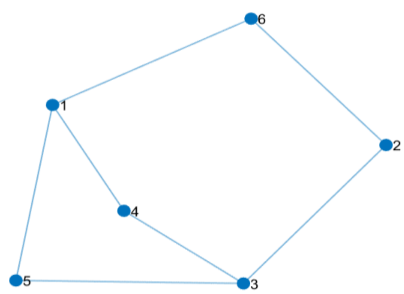
2.2.2 Graph Laplacian

Another type of matrix that is defined, and is relevant for our work is the graph Laplacian (Gross, et al. 2018). The Laplacian, **L**, of a graph is defined as:

$$\mathbf{L} = \mathbf{D} - \mathbf{A} \tag{2.3}$$

Where, **D** is a diagonal matrix whose diagonal entries are equal to the degree of the associated node (described later in the chapter), while **A** is the adjacency matrix. The graph Laplacian is also sometimes referred to as Laplacian matrix, admittance matrix or Kirchhoff matrix. It can be interpreted as a matrix version of the negative discrete Laplace operator on the graph. The Laplacian of a graph is a powerful tool that helps calculate the number of spanning trees in the graph, has applications in machine learning, determines a graph's spectral layout, and models information flow in the graph, among others (Merris, 1994).

The study of the adjacency and Laplacian matrices (along with others such as incidence, degree matrices etc.) is performed under *spectral graph theory* (Spielman, 2007). The Figure 2.1 below shows an example six-node graph and the corresponding adjacency and Laplacian matrices.



Example 6-node graph

	1	2	3	4	5	6
1	0	0	0	1	1	1
2	0	0	1	0	0	1
3	0	1	0	1	1	0
4	1	0	1	0	0	0
5	1	0	1	0	0	0
6	1	1	0	0	0	0

Graph adjacency matrix

	1	2	3	4	5	6
1	3	0	0	-1	-1	-1
2	0	2	-1	0	0	-1
3	0	-1	3	-1	-1	0
4	-1	0	-1	2	0	0
5	-1	0	-1	0	2	0
6	-1	-1	0	0	0	2

Graph Laplacian

Figure 2.1 A simple 6-node graph and the corresponding adjacency and Laplacian matrices.

2.2.3. Random Graphs

To be able to make general inferences about graphs and the real-life networks represented by them, we often need to consider random graphs (Janson et al., 2011). This is in contrast to selecting a representative set of nodes and connections where any analysis or related recommendations will only apply to the given graph. Random graphs find use in many different research settings, such as, complex systems (van der Hofstad, 2014), statistical physics (Montanari, 2013), biology (Sah et al., 2014), neuroscience (Bessadok et al., 2022) among others.

Formally speaking, a random graph represents a probability distribution over graphs (Janson et al., 2011). In other words, every time we sample from this distribution, we get a new graph realization ideally all with some measure of "similar" properties as defined by us. In a mathematical context, random graphs refer to Erdős–Rényi random graphs, named after the researchers who originally proposed and studied them (Erdos and Renyi, 1959). When we generate random graphs, we are often interested in the properties of the graphs that help them represent a network under question. For example, when analyzing a social network of a certain type, we may be interested in properly modeling the number of hubs, the distance to nodes, etc. Naïvely creating graphs without proper consideration of the application at hand can easily create pathological cases such as disconnected graphs, short-circuiting paths, wildly varying degree distributions, among others (see Chung and Lu, 2002; and Molloy and Reed, 1995 for a detailed exposition of pathologies that can appear). For this reason, algorithmic models such as the Barabasi–Albert and Watts–Strogratz models have been proposed in the literature (Albert and Barabási, 2002; Watts and Strogatz, 1998).

The Barabasi-Albert model of scale free networks uses a *preferential attachment* mechanism (Jeong et al., 2003). This implies that there is a subset of nodes that have unusually large number of connections compared to other nodes. Such nodes are often referred as hubs and are commonly observed in social networks (Amaboldi et al., 2015; De Weck, et al. 2020). In the Watts-Strogatz model, on the other hand, one ends up with graphs with small world properties with high clustering, but hubs do not form (Newman, 2003). In other words, the degree distribution converges to a Poisson distribution as opposed to the power law observed in commonly encountered scale-free networks. Therefore, the Barabasi–Albert model is used in this work because it follows the power law distribution (Albert and Barabási, 2002) and is frequently observed in social networks, as described above. The B-A algorithm works by starting with a seed network, which could be a random graph generated with a small number of networks. Nodes are added one by one and the probability of the node attaching to an existing graph node is proportional to the probability of the graph node's degree. Therefore, it implements the *rich-get-richer* scheme where a node with high degree continues to increase in connections. Over time, the graph develops the scale free property, exhibits low average path length and low clustering – all useful for our work.

2.2.4. Scale-Free Networks

Scale-free networks or graphs are graphs that (asymptotically) follow a power law degree distribution (Evans and Saramaki, 2005). Mathematically speaking, this implies that the fraction $p(k)$ of total nodes in the network with k connections to other nodes can be represented, for large values of k, as follows:

$$P(k) \sim k^{-\gamma} \tag{2.4}$$

where γ is a parameter that defines a particular type of scale-free graph. This is a reasonable expectation in modeling engineering organizations using a graph since we expect certain properties of the organization to stay the same as it grows—particularly what fraction of individuals has a given number of connections. The value of γ is 3 for Barabasi–Albert, the model we select in this work.

It should be noted that simply preferential attachment is not enough to obtain the scale-free property, as growth is also required (Mironov, Sidorov, and Malinskii, 2021) in graphs representing social networks. In fact, both of these can be expected in real-life small- to mid-sized organizations that are increasing in business size and sales, and, therefore, number of employees. The BA model is suited to represent social networks and business organizations, and has been used for this purpose in the literature (for example see de Weck et al., 2020); Kitsak et al., 2010); Borgatti et al., 2013).

The BA network model also nicely mimics the author's real world experience in both the industrial setting and also in social settings. A few years ago, the author worked in Italy for Fiat, Maserciconeati, Alpha Romeo engineering and manufacturing plants and interacted with many engineers. In the many years of living in Italy, a typical saying amongst Italian engineers that the author interacted with was "I know a guy, who knows a guy, that can get that done" . The use of connection or edges, in that organization, was highly prevalent. The author himself was well-aware that he was not a native with a thick network of connections, only the influence of the leadership position he held.

Using this influence he was able to teach, solve and certify others, which allowed him to become a part of their networks since he was able to provide the ability "to get things done" for them.

It should be noted that the clear edges of nodes in graph theory can be blurred by "how many forms of social differentiation (e.g., gender, migrant status, age, ethnicity, and educational/occupational sector)" can exist or fail to exist. (Bolzani et al 2021). The inclusion of available but missing edges is not accounted for in this model. The Bolzani paper shows that edges between nodes can be of many types and far more than organizational structure when we allow social connections to influence the problem solving activity. The missing connections can also be shown to be a source of exclusion. As a path for further work we could consider different types of connections between nodes of this type. It is possible using this model to explore and expand the problem solving aspect of our model beyond the current model bounded by engineering problem solving in small teams.

2.2.5. Centrality Measures

Often times, we are interested in the relative "importance" or "centralness" of different nodes of a graph. Many measures of network centrality exist and some commonly used ones are degree, closeness, betweenness and Eigenvalue centralities – see Klein (2010) for a review. They are briefly defined here:

1. *Degree:* Counts the number of nodes incident on/emanating from a node. This denotes how many direct connections a node has with other nodes. It denotes, for organizations, the direct influences that a node has or alternatively, how

many nodes influence it. This is a straightforward metric of importance of a node, v:

$$C_d(v) = \deg(v). \tag{2.5}$$

The limitation of the degree centrality is that it only measures the strength of *direct* connections of a node and does not take into account the centrality of the nodes it is connected with. In organizations, an individual while not directly connected with many individuals may be connected to hub, *inheriting* their importance.

2. *Closeness centrality:* Measures the average *minimum* distance of other nodes in the network to the given node. Closeness measures the extended influence of a node throughout the network so could be considered more general than degree centrality, however, it does not prioritize connections to more important nodes to less importance ones. For a network with N nodes:

$$C_c(v) = \frac{N-1}{\sum_u d_{min}(u,v)} \tag{2.6}$$

3. *Betweenness centrality:* Measures the number of pairs of other nodes that go through a given node to reach each other. This centrality measure accounts for how often the given node mediates connections between other nodes and can be assumed to be a measure of its importance. The normalized betweenness centrality of a node v is given by:

$$C_B(v) = \frac{2}{(N-1)(N-2)} \sum_{u \neq v \neq w}^{u,w} \frac{\rho_{uw}(v)}{\rho(.)} \tag{2.7}$$

where $\rho_{uw}(v)$ is the number of paths between u and w that go through v, while $\rho_{uw}(.)$ is the number of all paths that exist between u and w.

4. *Eigenvector centrality:* Measures the relative importance or influence of a node by looking at how many influential nodes it is connected to. It looks at the corresponding component of the "principal" eigenvector of the adjacency matrix associated with the graph. Major search engine Google's PageRank uses a version of eigenvalue centrality as a way to identify which search results (websites) should be given priority given their connection to more influential websites (Cicone and Serra-Capizzano, 2010).

These centrality measures can be used to select a project team and to even model their relationships with each other. For example, including a member with high betweenness centrality can help with team cohesiveness since the member will contribute to bringing the team members together because of their already-existing familiarity. Alternatively, it may also be possible that a member with high closeness centrality may negatively affect team progress because they may favor one individual over others and promote their own ideas expecting, often correctly, support from familiar individuals. The idea can also be extended to the idea of sub-teams, especially cross-functional teams, which are short-term teams tasked with a specific purpose. It is expected that expertise and familiarity within the sub-team will need to be balanced for the best results (Lapp, Jablokow, & McComb, 2019; Huikkola, 2022).

2.3. Design Problem Setup

The other element of the proposed approach is the design problem that the team members work on within the agent-based model. Given that multiple individuals with a variety of technical backgrounds and experience are typically involved in engineering teams, we must select a problem that is difficult enough that individuals will take multiple iterations to solve it. This will allow us to create an agent-based model where the impact of various cognitive attributes is readily observed. Many product portfolio problems involve selecting the right combination of components to come up with different product variants. This problem has been explored in the literature for modular products, see for example, Mangun and Thurston (2002); Shao et al. (2018) and Gauss et al., (2021). Even for a product involving a small number of components with a few variants each, one can easily construct problems that are extremely difficult to solve even for sophisticated optimization algorithms. We, therefore, adapt the combinatorial optimization problem (integer program) derived from Pandey et al. (2022) for this purpose.

Integer programs are in the class of NP-hard problems - some of the hardest problems encountered in engineering. Classical methods involving gradient information do not perform well for these problems and continuous relaxation is often fraught with other challenges, such as highly sub-optimal or even infeasible solutions. To this effect, heuristics must be employed to find "good" solutions of the problem (Wolsey, 2020). Genetic algorithms, that exploit the tenets of natural selection, are well suited for this type of problems and are therefore employed here (Goldberg, 1989, Lambora et al., 2019; Darwin and Beer, 1951). They simultaneously provide three advantages:

1. The solution progress is gradual and non-monotonic therefore it properly mimics the way design projects typically proceed in real life where not every design decision necessarily improves solutions and there are many such decisions to be made (Wynn et al., 2017).
2. The fact that Genetic Algorithms proceed in "generations" provides one with a way of keeping track of time or design iterations. This also allows for intermediate steps and designer take between "active" design.
3. They work with a population of solutions, which, again, is typical of design process in engineering firms where a set of candidate solutions exists which are evolved until a suitable one is chosen. This concept has been studied extensively in the context of *set based design* (Singer et al., 2010; and Toche et al, 2020).

Details of the optimization problem and its mapping with the team design process are described in the next chapter.

2.4. Individual Cognitive Profiles

As mentioned earlier, the four cognitive profiles we consider are leadership, technical ability, creativity and collaborativeness of the team members similar to our earlier work in Estes and Pandey (2023) and Pandey et al. (2022). In the following few paragraphs, we explain the connotation for each of these traits that we consider, while their mathematical implementation is explained in the next chapter.

2.4.1. Leadership

The Merriam – Webster Dictionary defines leadership as (1) "the office or position of a leader (2) capacity to lead and (3) the act or an instance of leading" (Merriam-

Webster, 2025). Leadership, in a typical sense, is defined by molding individuals into a team that shares a common goal. In the industrial setting, this team goal is often part of larger plan by a higher leader to achieve larger purposes. An excellent example is that of the past U.S. President John F. Kennedy in the context of the "American Moonshot" efforts of the 1960's where he set out the common goal of landing on the Moon before the decade was out (Stambaugh et al, 2021). This goal was then separated into smaller goals for each team involved in the process. The design teams had a design problem from system level to subsystems to components to individual features and the materials and processes that created them. The team of agents in our models are one example of one such small team that solves a design related problem. The leader is able to coordinate the solution in a team meeting and can be considered a measure of "assertiveness" of the member – and this is the connotation we use.

The leadership style that is most flexible is the *Situational Leadership Style* from Blanchard and Hersey and it can be learned (Hersey and Blanchard, 1997; Avolio, 2005), in the author's experience. He has used this technique for decades in the application of problem solving in industrial settings. The leader analyzes the task at hand and assembles the team in place to solve the problem. According to Blanchard and Hersey "*It is not enough to describe your leadership style or indicate your intentions. A Situational Leader assesses the performance of others and takes the responsibility for making things happen."*. The leaders who are hubs in the organization have an advantage "to make things happen" through closer or even personal connections, between agents or nodes, and allow actions to occur quicker and cleaner than many bureaucratic processes alone would allow. These inform our model in that we combine intrinsic and organization-induced leadership – a departure from previous work.

Leadership in our work depends on the stage of the design process and the leader can be removed, and another individual may step in and the teams will still move forward to achieve the common goal. Since leadership evolves with time, we also consider the growth and decay in leadership abilities over time and experience. The shortened time and speed of solution being emphasized, removes the long-term growth of individual agents from our model.

2.4.2. Technical Ability

According to, again, the Merriam-Webster Dictionary, technical (ability) pertains to "having special and usually practical knowledge especially of a mechanical or scientific subject, marked by or characteristic of specialization" as in *technical* language or relating to a particular subject (Merriam-Webster, 2025). Technical ability is the individual agent's ability demonstrate the application of practical knowledge to the design problem facing the team. This technical ability is a function of natural talent as well as training and can be expected to grow with experience. In our model, it is the ability to compare and judge the quality of a design accurately. Also, as the time frame is shorter in the analysis considered in this work, the growth in technical ability and knowledge is considered negligible in our model. This may be an area of exploration in future work.

2.4.3. Creativity

The dictionary definition of creativity is the ability to create and/or the quality of being creative (Merriam-Webster, 2025). Other synonyms of creativity are cleverness, imaginativeness, ingenuity, originality among others. Similar to prior work, we model the creative variable as an event of change in the design. We allow for both improvement and degradation the design solution based on the creativity value. Where we depart from earlier studies is that we see the changing creative abilities as being driven the social environment, as shown in the student studies previously referenced. As shown in the human subject research when actual humans feel free to express themselves, they are measurably more creative (Balakrishnan, 2022). Allowing this social construct to act on our agents in this way is based in real world studies of teams of students solving problems. Our agent-based model creates a similar environment to those created in real world environments.

2.4.4. Collaborativeness

In our work, the idea of collaborativeness is distinct from prior studies that we build upon. Collaborativeness, generally speaking, is the ability or the willingness to work in a team and to accept different viewpoints. This typically has a positive influence but can also be negative – collaborations between individuals that are not very productive can have deleterious effects. In an earlier work, collaborativeness was an intrinsic trait (Pandey et al, 2022). We introduced the notion of graph induced collaborativeness in Estes and Pandey, (2023) which modeled how familiarity can affect the ability and willingness of an individual to collaborate with another. In this work, we extend it even further. We make it an attribute that on the one hand is influenced by intrinsic traits as well as the organization induced traits, we also make it variable in that it evolves with time based on the individual's experience in the team.

2.5. Team Cognitive Profiles

In further contrast to Estes and Pandey (2023) and Pandey et al. (2022), we assign individuals (or agents) a set of cognitive profiles which are updated based on their position and experience in the organization and this modified profile affects their ability to find solutions to problems and how they interact with each other. Two models are presented here which extend the previous work:

1. *Model A:* Static cognitive profiles: In this scenario, the individuals are assigned cognitive profiles that encompass three attributes of leadership, creativity and technical skill. In contrast with (Pandey et al. 2022), the collaborativeness is a pair-wise construct. In other words, individuals' relative distance from each other determines whether one will relinquish control over a discussion in a meeting or not. As a result, individuals that are closer to each other will exchange the speaking role more easily. In this fashion, we are able to take into account the organization structure.
2. *Model B:* Evolving cognitive profiles: In this model, we change the cognitive profiles of the individuals over the course of the design-development process. While technical skills are expected to stay relatively constant over time, we expect that the experience of the individual over the various interactions during the process will alter leadership and creativity. If the individual's inputs are considered in the meetings, their leadership and creativity scores are expected to go up, versus when they are spurned. We

will use a scaling parameter to model how these attributes vary over time. This is explained further in the next chapter. Finally, in model B we also model leadership and collaborativeness through both intrinsic and organization induced approaches. This makes this model more representative of real-life decision making in organizations.

CHAPTER THREE

PROBLEM FORMULATION AND SIMULATION SETUP

3.1 Introduction: Optimization Problem Formulation.

To evaluate the performance of the team we must select a design problem where the cognitive aspects of the designers affect the design progress so their effects can be evaluated. As an initial requirement, the solution time should be long enough that the dynamics of team interaction can be evaluated. Design *optimization* problems can offer this characteristic if they are not so trivial that a solution is easily found, nor so difficult that one cannot find a solution in a reasonable time. In most design optimization problems, one starts with an initial guess (or a set of initial guesses) and incrementally improves the solution until no further improvement is possible or some other convergence criterion is met (Papalambros and Wilde, 2017; Rao, 2019; Pandey, 2013).

In terms of problem characteristics from an optimization standpoint, the problem should ideally be non-convex. Convex optimization problems are such that the objective function is convex and the constraints together form a convex set (Boyd and Vandenberge, 2004). Non-convex problems, on the other hand, are such that at least one of the two, either the objective function or the constraint set, is non-convex. Many efficient algorithms exist for convex optimization problems which may render the design process, and as a result, our investigation too easy. The non-convexity allows for ideas such as creativity to be applied to finding the optimal solution, or getting the design from being stuck in a local minimum.

Before we settled on the problem we use, some commonly used engineering design problems were considered such as the gearbox design problem presented in (Deb and Jain, 2003) and the welded structure design problem presented in (Deb, 1990). However, these problems will need to be modified and adapted to our problem which leads to the following two issues:

1. The necessary modifications may render the problem no longer sound from an application standpoint, making the entire idea of using a realistic design problem moot, and,
2. The modifications will have to be tailored to the problem and some findings from our analysis may not be generalizable.

Therefore, in this work, we select the notional product design problem investigated earlier in Pandey et al., (2022) and Estes and Pandey (2023) as the starting point for this study. The problem is a combinatorial optimization problem which is known to be computationally difficult, in fact most of them belong to the class of NP-hard problems. The details are provided below.

In the selected problem, we consider a product which is comprised of n_c components. Each component has n_v variants and the objective of the design process is to select the best collection of variants such that the overall product performance is optimized. This is a common tactic used in design of complex systems where a manufacturer designs and produces a family of products on the same platform and the only difference between two products is the component combinations (Simpson, 2004).

Therefore, the decision vector $\mathbf{x}$ is an $n_c \times 1$ vector, with each element representing the corresponding variant and $\mathbf{x} \in \{1, \dots, n_v\}^{n_c}$. The baseline optimization problem which will be modify, both in the setup and the optimization procedure, is presented below:

$$\textit{Minimize } f(\mathbf{x}) = \tag{3.1}$$

$$\begin{cases} \alpha_1 + \alpha_2 \sin\omega f_0(\mathbf{x}) + f_0(\mathbf{x}) & h(\mathbf{x}) \geq h_{crit}^{high} \\ \left(\alpha_1 + \alpha_2 \sin\omega f_0(\mathbf{x}) + f_0(\mathbf{x})\right)/2 & h_{crit}^{low} \leq h(\mathbf{x}) < h_{crit}^{high} \\ 0 & h(\mathbf{x}) < h_{crit}^{low} \end{cases}$$

$$\textit{where: } f_0(\mathbf{x}) = \|\mathbf{x} - \mathbf{x}_l^*\|_2$$

$$h(\mathbf{x}) = \left\|\mathbf{x} - \mathbf{x}_g^*\right\|_2$$

$$\textit{Subject to: } x_i \in \{1, 2, \dots, n_v\} \quad \forall i \in \{1,2, \dots, n_c\}$$

This non-convex optimization problem aims at minimizing the objective function $f(\mathbf{x})$, which exhibits the desired characteristics relevant to this study, as described below. First, two functions $f_0(\mathbf{x})$ and $h(\mathbf{x})$ are defined which measure deviations from the local minimum and the global minimum, respectively. The function $h(\mathbf{x})$ is also referred to as the *modifier function*, and is described later. The sinusoidal noise, with frequency controlled by the parameter ω, shown in the objective function, ensures that the designers cannot trivially find a solution—this is typical of real-life non-convex optimization problems, where each step may marginally improve or worsen a solution even if the general trend is good. The function, $f(\mathbf{x})$, as a result, takes small values near the local minimum, $\mathbf{x}_l^*$ but achieves the lowest value, 0, near the global minimum $\mathbf{x}_g^*$.

This contributes to it becoming a deceptive optimization problem where an optimization algorithm is misled into converging to suboptimal solutions. Since the problem has multiple local minima, classical gradient based optimizers typically struggle. These types of problems have been studied extensively when testing heuristic optimization problems such as Genetic Algorithms (Goldberg et al, 1992).

3.2. The Modifier Function, $h(\mathbf{x})$

The modifier function allows one to define regions in the feasible set of solutions, based on the value of $h(\mathbf{x})$. If the current solution, **x**, is far from the global optimum, $h(\mathbf{x}) \geq h_{crit}^{high}$, where h_{crit}^{high} is a user-specified scalar, the modifier function does not affect the objective and the objective simply is a function of $f_0(\mathbf{x})$ and the sinusoidal noise. For modifier function values between h_{crit}^{low} and h_{crit}^{high}, the objective function is halved. This serves to reward the knowledge or intuition regarding the location of the global minimum. Finally, when this distance is less than h_{crit}^{low}, the objective function drops to 0. This is similar to being in the *basin of attraction* in the case of an optimization problem because finding the global optimum when so close to it is typically easy. This is also observed in practice that when nearly all aspects of a design are understood, finding the best solution becomes trivial. This is shown visually in Figure 3.1.

It should be noted that the number of components that a product we select determines the dimensionality of the feasible space. As a result, even a solution that appears close has may be far in the 2-norm sense which is what both $f_0(\mathbf{x})$ and $h(\mathbf{x})$ are defined with. As a selection, the values of h_{crit}^{low} and h_{crit}^{high} must be fine-tuned to the other parameters of the optimization problem. This will ensure that the global optimum is elusive for a search algorithm but not impossible to find.

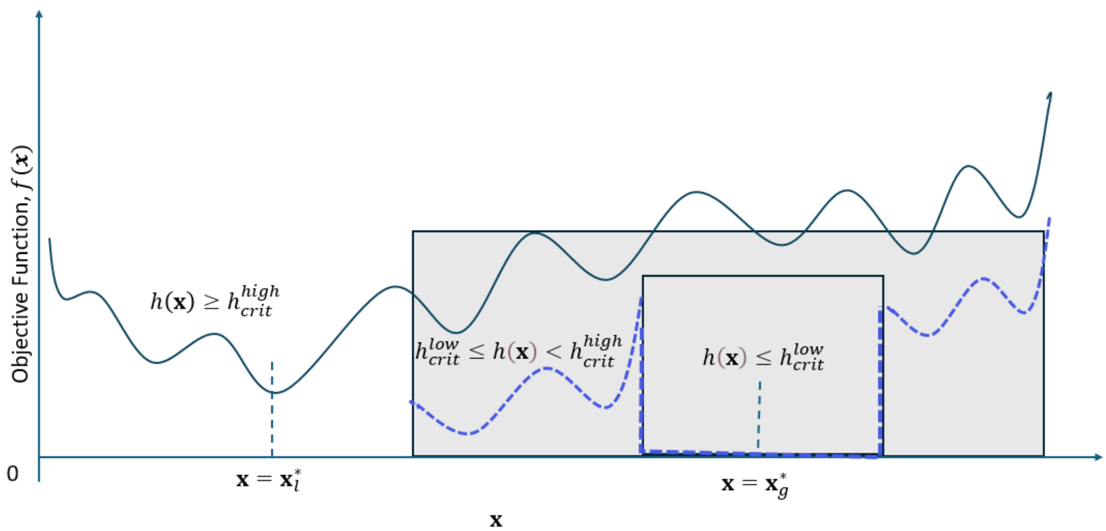


Figure 3.1: Description of how the modifier function affects the objective function value depending on the distance from the global minimum.

3.3. Cognitive Attributes and their Implementation

As described earlier, within each region of the feasible space, the objective function value is a function of $f_0(\mathbf{x})$, the distance from the local minimum, which is then modified by $h(\mathbf{x})$. Here we present how we update the optimization problem and the solution process to incorporate the impact of a decision maker's cognitive attributes and their position in the organization on their ability to find the local or the global minimum. The cognitive attributes are all modeled as scalars between 0 and 1. Two simulation models are created as introduced in Chapter 2 and briefly described below:

Model A - static model: In Model A, the cognitive attributes of the designers are assumed to be constant throughout the design process.

Model B – dynamic model: In Model B, the cognitive attributes of leadership and creativity are expected to change over the various design iterations.

The mathematical implementation of cognitive attributes, while the cognitive attributes have been explained in the previous chapter conceptually, here we present their mathematical implementation.

3.3.1. Implementing Leadership

In both the models, the leadership ability of a team member is defined as a scalar between 0 and 1. In model A, similar to the work presented in (Pandey et al, 2022) and (Estes and Pandey, 2023), it is kept constant. In this case, we denote it with the variable l^A. In model B, in contrast, we make it time-dependent and make it a function of the following two aspects:

1. *Organization-endowed leadership skills, l_o:* An individual that is part of an organization usually has a certain rank or seniority associated with their

position which provide certain powers and privileges. As a result, an individual may be more or less assertive as a result of their status in the organization, particularly relative to the other individuals in the team.

2. *Innate leadership skills,* $l_i(s)$*:* An individual, because of their personality and experience, may have some innate leadership skills. It is well-known that even under similar circumstances and training, some individuals are more likely to exhibit leadership and assertiveness traits compared to their peers. This innate leadership ability is also expected to be affected by the individual's experience in the team. In other words, individuals who are able to contribute to team discussions are likely to increase in confidence and speak up more compared to their peers.

The overall leadership attribute is created using the multilinear function as follows:

$$l^B = k_{lo}l_o + k_{li}l_i(s) + (1 - k_{lo} - k_{li})l_o l_i(s) \tag{3.2}$$

Where k_{lo} and k_{li} are scalars between 0 and 1, that measure the emphasis the organization places on the rank of the individual or the emphasis the organization places on encouraging individual leadership skills, respectively. It is easy to see that the overall leadership value $l^B(s)$ is also scaled between 0 and 1 as a result. This type of model is routinely used in the multilinear utility analysis research (Pandey et al, 2020) when combining the influence of multiple factors. In this model, the leadership value is considered time-dependent and is affected by their experience in the team. The leadership update model using the modified logistic function is given below:

$$l^B(s) = \max\left[\min\left[l^B\left(\frac{2l_{max}}{1+e^{-\eta(s)}} + 1 - l_{max}\right), 1\right], 0\right] \tag{3.3}$$

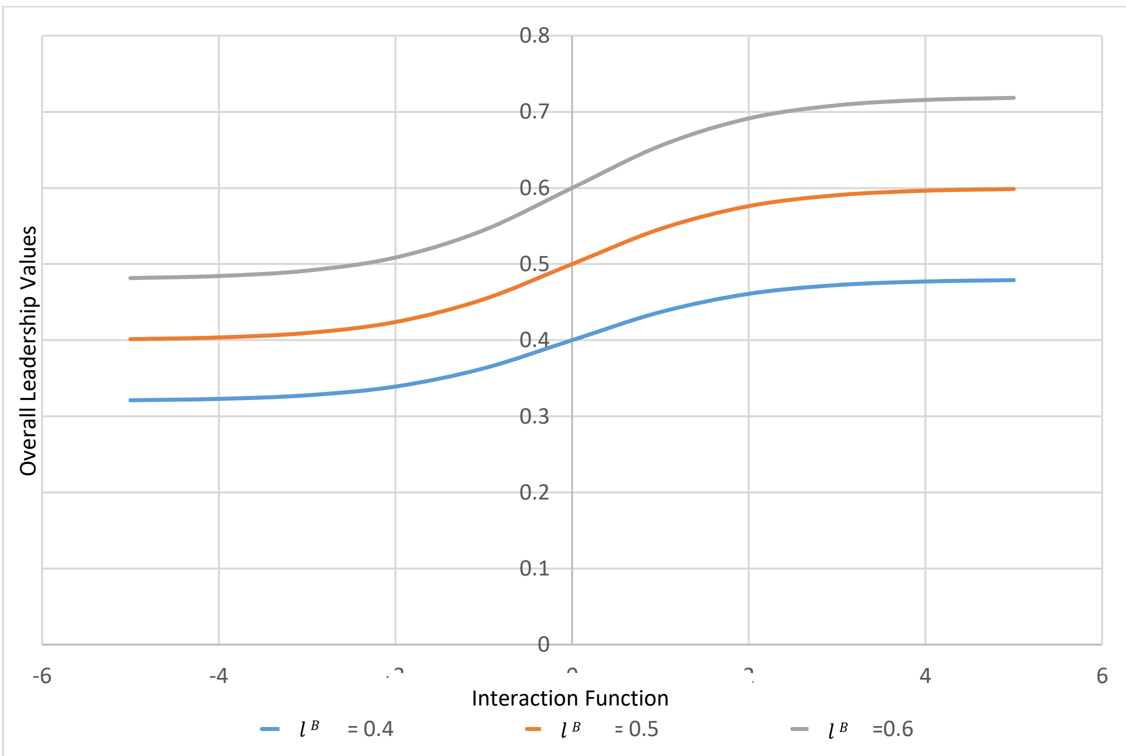


Figure 3.2: Leadership evolution as a function of number of opportunities an individual gets to contribute to the team meeting.

Where, $\eta(s)$ is the interaction function, which increments by 1 every time an individual is called upon in the conversation and decrements by 1 every time that are not called upon in the conversation, while l_{max} is the maximum fractional increase in leadership possible. We investigate the effects of these parameters in the results section later in the dissertation. An example plot of the function for various values of $\eta(s)$ and $l_{max} = 0.2$ is shown in Figure 3.2. As we can see from the figure, that the logistic function allows increase and decrease from the nominal but the rate of change diminishes as $\eta(s)$ increases or decreases to account for the fact that the effect diminishes after a few steps.

3.3.2. Implementing Technical Ability

A decision maker with a high technical aptitude will approach design optimization systematically, which may be compared with the approach by gradient-based or classical optimization algorithms. These algorithms start with an initial guess and iteratively approach the minimum using a the locally available information such as the gradient and the hessian of the objective function. To implement the effect of technical ability, similar to the work presented in (Pandey et al, 2022) and (Estes and Pandey 2023), we add a noise to the objective equal to $\alpha_2 R_1(1-t)$. Where R_1 is a standard normal random variable between 0 and 1 and α_2 is a tunable scalar so that we can amplify the effect of an individual's technical ability. It is easy to see that a technically sound individual will experience a smaller noise in the objective function and is more likely to find the true solution. The effect of technical ability is presented similarly in both Model A and Model B. Since technical ability and creativity affect the optimization problem together, the entire updated problem is presented later in the chapter.

3.3.3 Implementing Creativity

As we mentioned before, a creative decision maker is expected to intuitively find a solution that evades other decision makers. More specifically:

1. They are more likely to find the global minimum as they can explore the entire solution space better.
2. They are able to consider many more solutions simultaneously and thus can combine them creatively to find the solution faster.

Creativity in Model A: In this case the creativity value, κ, is a scalar between 0 and 1. It is kept constant throughout the design process and is considered the intrinsic capacity of the individual.

Creativity in Model B: In this case, creativity is considered time-dependent and is affected by their experience in the team. Similar to the leadership function, the creativity update model uses the modified logistic function given below:

$$\kappa(s) = \max\left[\min\left[\kappa_0\left(\frac{2\kappa_{max}}{1+e^{-\eta(s)}} + 1 - \kappa_{max}\right), 1\right], 0\right] \tag{3.4}$$

Where, as before, $\eta(s)$ is the interaction function, which increments by 1 every time an individual is called upon in the conversation and decrements by 1 every time that are not called upon in the conversation, while κ_{max} is the maximum fractional increase in creativity possible.

Furthermore, we also investigate intrinsic and learned creativity described below. Innate creativity is the creativity that allows an individual to have an insight into the problem. Similar to earlier approaches this type of creativity allows the designer to be able to have a higher probability of finding the global optimum.

In the learned creativity model, we update the population size for the genetic algorithm that the individuals use to solve the problem when working on it alone. Ulrich and Eppinger (2011) argue that one of the ways one can get new ideas during design concept generation is through internal and external stimuli. This translates to looking at many different design solutions, which provide a pathway for improvements in the solution process. In the genetic algorithm-based optimization process we use in this work; we increased the population size that the designer uses based on the following modified logistic model:

$$n_{pop} = n_{pop}^{base}\left(\frac{2n_{pop}^{max}}{1 + e^{-\kappa_0}} + 1 - n_{pop}^{max}\right) \tag{3.5}$$

Where n_{pop}^{max} is the maximum fractional increase in the population size the model allows. As before, we will investigate the sensitivity of the solution to this parameter.

The modified optimization problem considering both creativity and technical skills is given in equation 3.6.

$$Minimize\ f(\mathbf{x}, s) \tag{3.6}$$

$$= \begin{cases} \alpha_1 + \alpha_2 R_1(1-t) + \alpha_3 \sin\omega f_0(\mathbf{x}) + f_0(\mathbf{x}) & R_2 > \kappa(s) \\ \big(\alpha_1 + \alpha_2 \sin\omega f_0(\mathbf{x}) + f_0(\mathbf{x})\big)/2 & h_{crit}^{low} \leq h(\mathbf{x}) < h_{crit}^{high} \cap R_2 \leq \kappa(s) \\ 0 & h(\mathbf{x}) < h_{crit}^{low} \cap R_2 \leq \kappa(s) \end{cases}$$

where: $f_0(\mathbf{x}) = \|\mathbf{x} - \mathbf{x}_i^*\|_2$

$$h(\mathbf{x}) = \left\|\mathbf{x} - \mathbf{x}_g^*\right\|_2$$

$$\kappa(s) = \max\left[\min\left[\kappa_0\left(\frac{2\kappa_{max}}{1+e^{-\eta(s)}} + 1 - \kappa_{max}\right), 1\right], 0\right]$$

Subject to: $x_i \in \{1, \dots, n_v\} \quad \forall i \in \{1, \dots, n_c\}$

3.4. Implementing Individual Attributes in Individual and Team Settings

As in the models explored in the previous work, the designers first solve the problem separately (individually), with their performance being a function of their intrinsic attributes of technical ability, t, and creativity, $c(s)$. They then bring their best solutions to a team meeting, where they again solve the problem; however, their leadership level and ability to collaborate influences the performance of the team. The cognitive attribute of collaborativeness is also a scalar between 0 and 1 similar to the other attributes we consider and the ability to collaborate is a function of the level of the intrinsic attribute level, the organizational architecture and culture. We describe the details below.

Individual setting: In this stage, individuals independently solve the optimization problem. For each individual, we first randomly select the modality the decision maker uses to solve the problem: technical ability or creativity. The probability that the creativity modality is selected is equal to their creativity score, $\kappa(s)$, i.e., a more creative decision maker will be able to preferentially select a creatively derived solution over a technically derived solution. If a technical solution pathway is selected, then we add noise to the objective function equal to $\alpha_2 R_1(1-t)$ in the case that $h(\mathbf{x}) \geq h_{crit}^{high}$, where R_1 is a standard normal random variable and t is the individual's technical proficiency; as described before. Therefore, a technically adept but creatively limited individual will select a technical solution pathway and is likely to end up with the locally optimal solution. When the decision maker selects a creative pathway, the objective function is kept the same as before in the case that $h(\mathbf{x})$ is between h_{crit}^{low} and h_{crit}^{high}; and the objective function is 0, i.e., the global minimum, when $h(\mathbf{x}) < h_{crit}^{low}$. This ensures that when a creative decision maker is close to the globally optimal solution, they quickly find it.

It should be noted that in Model A, since creativity is constant, the individual's solution efficacy does not change in the individual setting. On the other hand, in Model B because the creativity score can go up and down with the number of cycles based on their experience in the team, even their individual performance can suffer or be enhanced over time. This can serve to show that encouragement can have long lasting impact on the performance of an individual and can affect the outcome of a design process.

<u>*Team setting:*</u> The optimization process that happens in the team setting is implemented differently in each model. In model A, the extrinsic attribute of familiarity, or closeness, is derived from the graph and is a function of the matrix of distances between pairs of individuals. This allows for the optimization problem to be solved in a team setting, where the relative familiarity between individuals plays a part. In terms of implementation, in the team setting, an individual (individual *i*) begins the discussion with a probability proportional to their relative leadership skill, l_i^A, compared to other team members. This implies that the objective function we use in the design optimization problem corresponds to the individual.

Subsequently, after one GA generation, they hand over the discussion to another individual (individual *j*) with a probability $\frac{l_j^A e^{-\lambda d_{ij}}}{\sum_{k=1}^{n} l_k^A e^{-\lambda d_{ik}}}$, where λ is a scaling parameter, and n is the number of team members. This functional form is selected because it implements the following logic. An individual has a chance to talk and influence the solution to the design problem with a probability proportional to their intrinsic leadership level and inversely proportional to the distance (which is the number of hops it takes to get to the other individual on the graph) from the previous speaker. In other words, individuals not familiar with each other are not as likely to hand over the discussion to each other unless the other individual has a high leadership level. The value of the parameter λ controls how quickly the probability drops as a function of distance between individuals.

In model B, the leadership attribute is implemented similarly to model A except that the leadership variable is a function of the organization induced and intrinsic leadership values. For the creativity attribute, if an individual gets an opportunity to speak at the team meeting, the individual is likely to feel encouraged and to reflect this, their creativity score goes up, similarly when they are not allowed to speak their creativity score goes down. This is presented earlier in the section where we discuss the implementation of the cognitive attributes. Finally, collaborativeness is implemented in two steps. In the first step, we consider the intrinsic collaborativeness exhibited by the individual, c_{int} and that induced by the organizational culture, c_{org}. We again use the multilinear function for this as follows:

$$c = k_{int}c_{int} + k_{org}c_{org} + \left(1 - k_{int} - k_{org}\right)c_{int}c_{org} \tag{3.7}$$

An individual leading the conversation at a given stage gives up the discussion with the above probability. The scaling constants k_{int} and k_{org} measure the relative impact of the intrinsic personality traits and that induced by the organizational culture and lie between 0 and 1. It is easy to see that since, c_{int} and c_{org} are also scaled between 0 and 1, the value of c is also similarly normalized, as is expected of a probability value.

In the second step, we implement the handover probability in the same fashion as in Model A.

3.5. Deriving the Organization-Endowed Leadership Skills, l_o

There are many possible ways to interpret or even impose the leadership level of an individual in an organization when looking at its graph representation. One of the possible ways is to use directed graphs and the direction of the edge from one individual to another can determine the supervisor-supervisee relationship. However, this relationship does not necessarily exist between two individuals who are not in the same branch of the network – for example, consider two individuals who hold the same rank in different units of a large institution. In such cases, it may not even matter that the individuals are not at the same seniority level. For example, a node with lower rank derived in such way may be more influential in the organization because of their proximity to powerful figures. To remedy this, the value of l_o is derived from the eigenvector centrality associated with the node. Mathematically, the eigenvector centrality of the i-th node is calculated as follows. First, we find the eigenvector associated with largest eigenvalue, λ_{max} of the adjacency matrix A. Since it is an eigenvalue, it has to satisfy the eigenvalue equation:

$$A\mathbf{x} = \lambda_{max}\mathbf{x} \tag{3.8}$$

The eigenvector centrality is now simply the i-th element of the eigenvector $\mathbf{x}$. This centrality can also be calculated using the power iteration method, where starting with a non-zero vector (e.g. a vector of ones), we repeatedly left-multiply with A and normalize at each step. Since this serves to amplify the eigenvector associated with the largest eigenvalue of A, we get the same result.

3.6. Information Flow in Graphs

One of the aspects of design decisions is how easily they can be propagated throughout the organization. This is an important consideration because if the designers are not well connected with the rest of the organization, they may not be able to convey the merits of the design to the rest of the organization. This type of information flow can be modeled using the Laplacian of the graph as we described before in the chapter. Information flow through the graph can be modeled using the simple differential equation below:

$$\frac{d\mathbf{x}}{dt} = -\mathbf{L}\mathbf{x} \tag{3.9}$$

Where $\mathbf{x}$ is the vector of the information at each node. The above equation can be used to incrementally evaluate which nodes the information diffuses starting from an initial point.

CHAPTER FOUR

SIMULATION RESULTS: MODEL A

4.1. Introduction

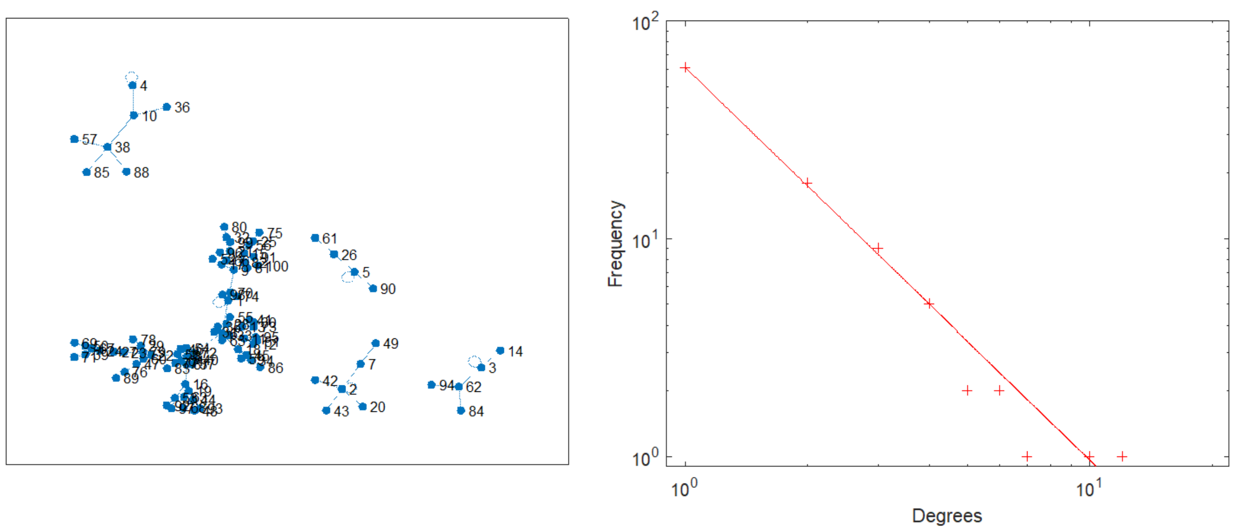
In this chapter, we present the results of the simulation model developed as part of this work. We will first present the simulation results for the baseline cases to understand some basic trends. Then we present results derived using Model A where the cognitive attributes of the team members remain constant throughout the design process however, the team members' location on the organizational graph varies. This model serves to verify the feasibility of including the factors from the organization structure into the process.

For convention, results are described in terms of cases, where each case is comprised of a set of team members, their cognitive attributes and locations on the organizational graph, and a set of relevant model parameters.

4.2 Generating the Representative Organization

For this portion of the work, we selected a 100-member organization. A 100-member organization is classified as a small or midsize business, depending on the classification system or local jurisdiction. Organizations of this size start developing characteristics of a large business such as different internal divisions and large inter-member distance, without becoming as intractable to analyze as a much larger organization with thousands of employees would be. Additionally, in accordance with the growth and preferential attachment requirement for the scale-free property of a graph, a small to midsize organization is generally expected to increase in size in the future while still retaining these properties, making the analysis scalable.

The initial network, representing this organization was generated in MATLAB using the in-built graph theory toolbox. As described earlier, to model the organization's architecture, we selected an initial Barabasi–Albert scale-free network as shown in Figure 4.1a below. Figure 4.1b confirms the scale-free property of the network, with the connections following a power law degree distribution, which points to the generalizability of the results to larger size organizations.



(a) **(b)**

Figure 4.1 (a) Random Barabasi–Albert graph generated with 100 nodes; (b) random Barabasi–Albert graph shows the scale-free property of the network.

To make the organization structure more representative of real-life organizations, disconnected subgraphs and self-loops were then removed from the initial graph and the largest connected subgraph was derived, as shown in the following Figure 4.2. This is because in organizations, while there may be divisions that are separate with a certain degree of autonomy, it is highly unlikely that they have no connection with the rest of the organization whatsoever. Self-loops were removed as they indicate individual-to-same-individual connection, and we are interested in interpersonal relationships. Looking at the structure generated, we see that it also appears representative of a typical organization with three “main” divisions denoted by the locations of hubs. Note that this description of hubs is informal, we propose the use of eigenvector centrality to define it formally. This largest connected subgraph of the original graph generated was then used for further analysis, as we discuss below.

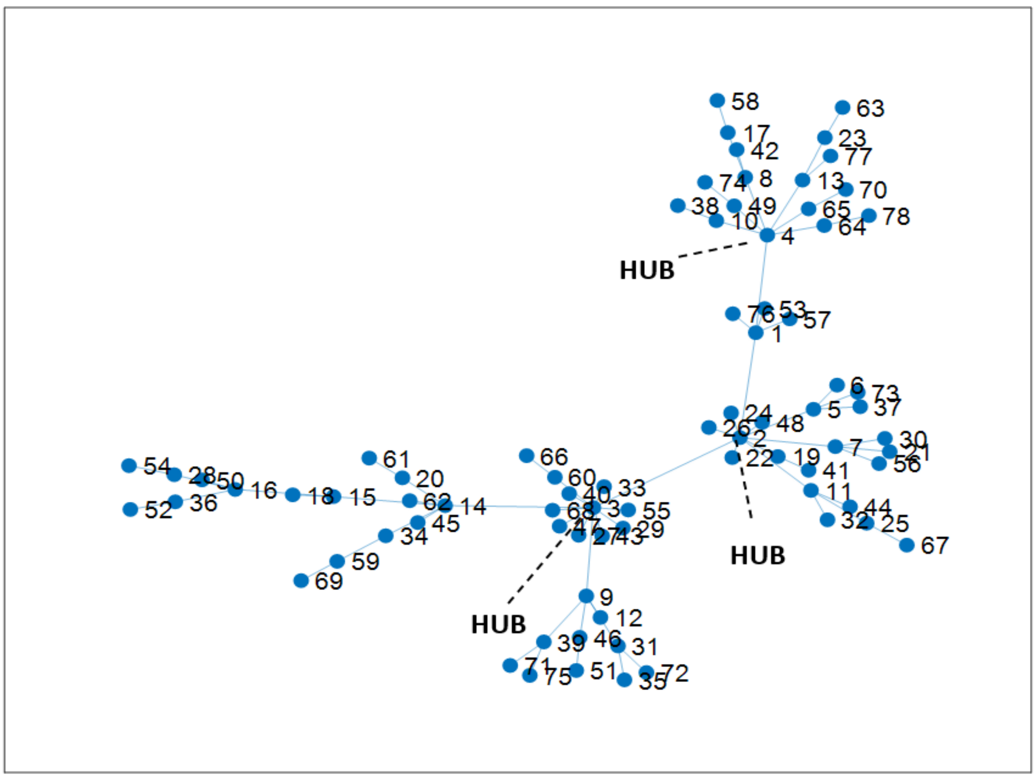


Figure 4.2: Largest Connected Subgraph of the Initial Network from Figure 4.1. Self-Loops were also Removed.

4.3 Simulation Setup

The following table 4.1 shows the values of the various parameters used in the simulation as described in chapter 3. These values were selected after running trials of the simulation model multiple times to ensure that the trends we expect are properly represented. It should be noted that given the type of simulation where we intentionally stop the solution progress to demarcate individual and team meetings, these parameters can only be determined empirically for a particular problem.

Table 4.1: Baseline Values of Simulation Parameters.

Variable	**Value**
α_1	1
α_2	20
α_3	1
h_{crit}^{low}	12.5
h_{crit}^{high}	18
n_v	10
n_{comp}	20
l_{max}	0.2
κ_{max}	0.2

Table 4.2: Cognitive Attributes Associated with Homogenous Teams.

Case	Leadership	Technical	Creativity	Collaborativeness
0a	0.9	0.1	0.1	0.1
0b	0.1	0.9	0.1	0.1
0c	0.1	0.7	0.7	0.1
0d	1	1	1	1

4.4 Model A Results

In model A, team members' cognitive attributes are held constant throughout the design process. This allows for verification of the effects of intrinsic cognitive attributes of the team members and the impact of their locations in the organizational graph. We present to cases, Case 0 and Case 1 which quantify these influences.

4.4.1 Case 0: Homogenous Team Members

To begin, we ran the simulation for homogenous teams with constant intrinsic characteristics as shown in table 4.2. The objective of this step is to verify that the simulation provides expected results for the "corner" cases. Case 0a consists of 6 members that are all high on leadership but low on other attributes. Case 0b consists of members that are all high on technical ability. Case 0c consists of members that are high on technical and creative ability while Case 0d consists of individuals that are perfect on all the four attributes.

Figure 4.3 presents the outputs of these runs using the average of objective function, $f(\mathbf{x})$, values in the final team population and the 20^{th} percentile. Note that the team members were acting to minimize their individual objective function as influenced by their creativity and technical ability, $f(\mathbf{x}, s)$. The simulation was run 30 times and averaged with each run including 20 cycles of optimization happening alternately in individual and team settings. We use the 20^{th} percentile value because it gives a measure of how well the GA optimizer performed and is not as biased a measure as the minimum. In other words, using only the minimum is susceptible to simulation noise since GA, being random search algorithms, can sometimes get lucky and stumble upon the solution as defined by the true objective function skewing the results.

Figure 4.3 confirms the expected trends in that the team with only leaders does not perform well, since their ability to find the optimum is limited on account of lower technical ability and creativity. The team with only high technical ability performs better, but not as well as the team with both technical and creativity skills. Finally, the team with the highest value possible for each attribute performs the best, as expected. This confirms, at least empirically, that the model can identify trends and the relevant attributes affect the solutions as expected in the corner cases. Note that collaborativeness does not matter in these runs since whether or not the designers collaborate, it does not change the solution process materially since all individuals have the same set of cognitive attributes.

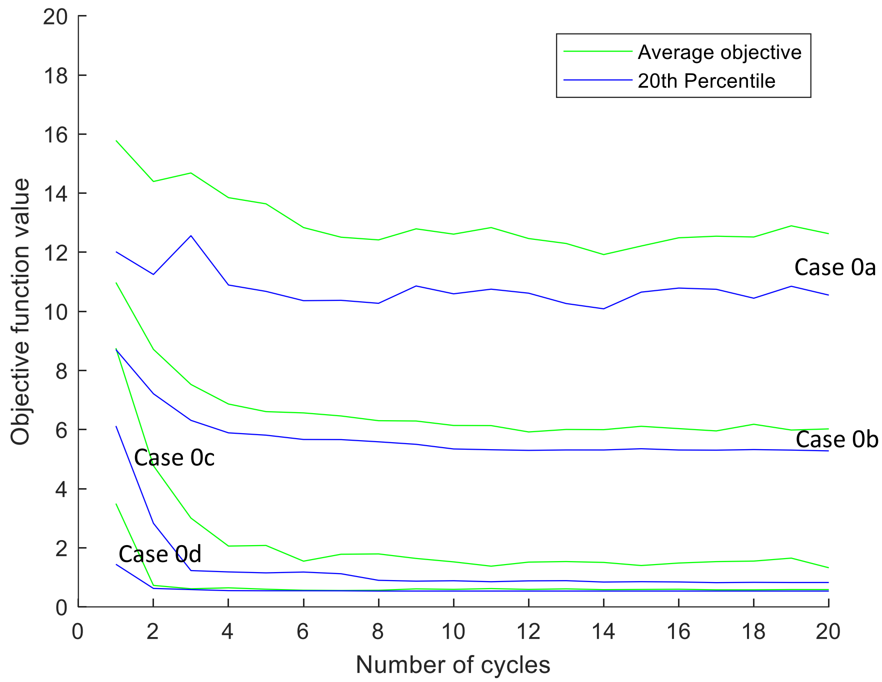


Figure 4.3: Evolution of the Solution Over Time Comparison of Homogenous Teams with Cognitive Profiles as Given in Table 4.2.

To verify that the trends shown in Figure 4.4 are indeed there and not just an artifact of stochastic behavior, we use the concept of stochastic and deterministic dominance used commonly in decision analysis (Pandey, 2013). In deterministic dominance, no realization of one option can be worse than any realization of another option i.e. CDF of the former goes from 0 to 1 while the other is still at 0 (or 1 in case of maximization problems). In the case of stochastic dominance, we check to see that there is no intersection of the CDF indicating that for each realization of the random variable one option has a higher likelihood of performing better.

We see that Case 0d stochastically dominates the other cases. Similarly, Case 0c dominates Case 0b and Case 0a stochastically, while Case 0b dominates Case 0a stochastically.

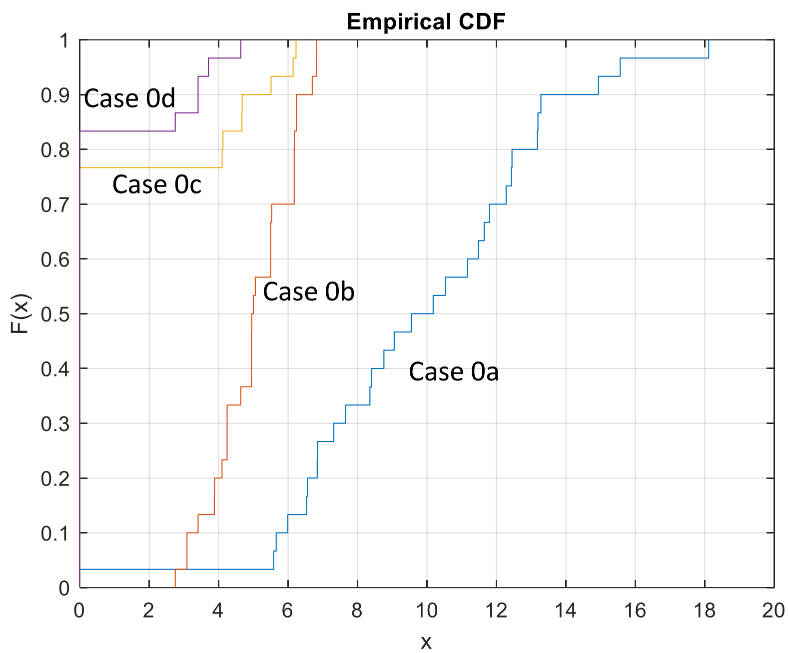


Figure 4.4: Comparison of Empirical CDF of Objective Values of the Four Cases with Homogenous Cases (0a – 0d).

Since the teams selected were homogenous, the individuals all participated in the conversation equally. This is shown in figure 4.5 with a pie chart of who was the selected speaker in team meetings for Case 0d. Other teams exhibited similar trends, further confirming the validity of the model.

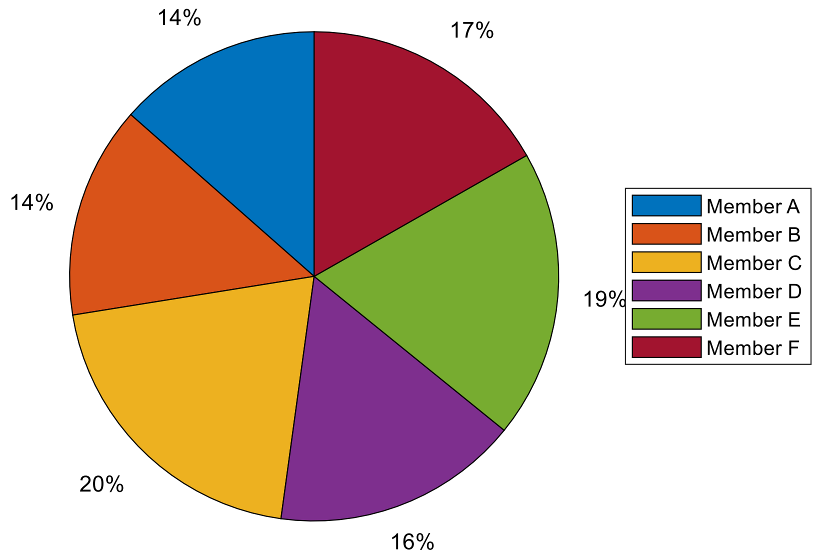


Figure 4.5: Relative Proportion of Time an Individual Leads the Design Effort for the Homogenous Teams (Case 0a – 0d) Showing that the Individuals Led the Design Discussions Equally in Team Meetings.

4.4.2 Case 1: Effect of Distance Between Leaders and Skilled Individuals

Using the pairwise distance between nodes, we selected a six-member team with an individual with strong leadership skills, another with high technical and creativity skills, as well as four other members with smaller values. The team thus selected comprised members with indices {54, 28, 8, 4, 17, 58}; they are also labeled A–F for ease of reference later. It should be noted that the intrinsic collaborativeness value does not affect the solution in Model A as it is just a function of location on the graph.

Table 4.3. Intrinsic cognitive profiles of the team members selected for Case 1.

Team Member	Leadership	Technical Ability	Creativity	Collab.
A	0.9	0.1	0.1	0.1
B	0.2	0.7	0.7	0.1
C	0.2	0.2	0.2	0.2
D	0.2	0.2	0.2	0.2
E	0.2	0.2	0.2	0.2
F	0.2	0.2	0.2	0.2

It can be verified from the graph presented earlier (Figure 4.2) and the distance matrix shown in Table 4.4 below that the intrinsic leader (A) and the most technically skilled member (B) are close to each other, while the other members are distributed over the graph. This effect of inter-member distance is implemented in the simulation as follows. In the team optimization setting, an individual is initially selected with a probability proportional to their leadership value. In the subsequent GA generations, this probability was updated to include the distance from the individual selected in the first generation, as presented in Chapter 3. This process repeats and enforces the notion that individuals are more likely to hand over discussion to people they are more familiar with. When an individual is selected, the entire team performs one generation of evolutionary optimization using that individual's objective function. Recall the using an individual's objective function essentially means that the impact of their cognitive attributes, particularly technical ability and creativity momentarily represent that of the entire team. This continues until the next individual speaks, which is representative of how design team meetings take place in organizations.

Table 4.4. Distance matrix for the members chosen for Case 1a.

CASE 1a		Team Members					
		54(A)	**28(B)**	**8(C)**	**4(D)**	**17(E)**	**58(F)**
Team Members	**54(A)**	0	1	9	8	10	11
	28(B)	1	0	8	7	9	10
	8(C)	9	8	0	1	1	2
	4(D)	8	7	1	0	2	3
	17(E)	10	9	1	2	0	1
	58(F)	11	10	2	3	1	0

We repeated the same study with member locations given by vertices {26, 28, 8, 4, 17, 58}. In this case, the leader (member A) and most technically skilled person (member B) are farther from each other in node-to-node distance but possess the same intrinsic cognitive profiles (same individuals) as before and are again labeled A-F for comparison purposes. The distance matrix is presented below in Table 4.5.

Table 4.5. Distance matrix for the members chosen for Case 1b.

CASE 1b		Team Members					
		2(A)	28(B)	8(C)	4(D)	17(E)	58(F)
Team Members	26(A)	0	6	4	3	5	6
	28(B)	6	0	8	7	9	10
	8(C)	4	8	0	1	1	2
	4(D)	3	7	1	0	2	3
	17(E)	5	9	1	2	0	1
	58(F)	6	10	2	3	1	0

Figure 4.6 shows the result of the simulation of the above two teams. Again, we report both the average and 20th percentile objective values in the solution population. The simulation completed 20 individuals and then team optimization cycles. To reduce the noise from individual simulations, we averaged the values over 30 runs. We notice that there is a significant improvement in the beginning few cycles followed by a slower improvement, as expected, in each case. We also notice that despite the fact there were individuals with relatively little in the way of skills, they were still able to improve the solutions, possibly because the handoffs inherent in the model.

We notice in Figure 4.6 that the progress in Case 1b is slower and the final solution is also inferior Case 1a. This can be verified by comparing the objective values at various points of the simulation. As the team members selected were identical for both Case 1a and Case 1b, this difference in performance hints towards the conjecture that since the graph distance between the technically adept member and the leader is larger, it is difficult for the technically adept member B in this case to influence the team, especially because their own leadership levels are lower.

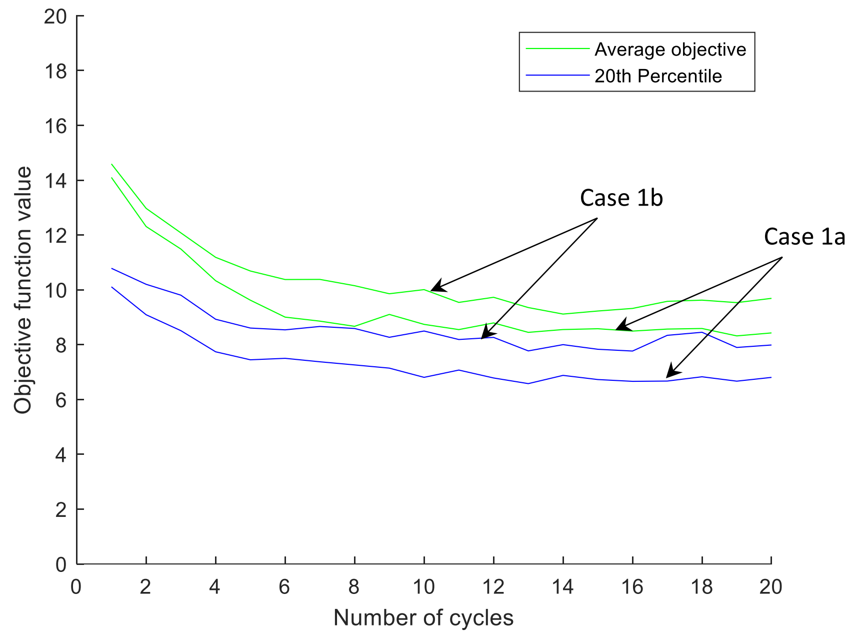


Figure 4.6: Evolution of the Solution Over Time when the Most Technical Member is Close to the Leader (Case 1a) and when the Most Technical Member is far away from the Leader (Case 1b).

As before, we compare the empirical CDFs (Figure 4.7) in the two cases showing that stochastic dominance in the objective function value of the team's proposed designs indeed between the two cases. In other words, in organizations where the leader themselves are not technically adept, it is important to reduce the distance between them and the technically and creatively skilled people.

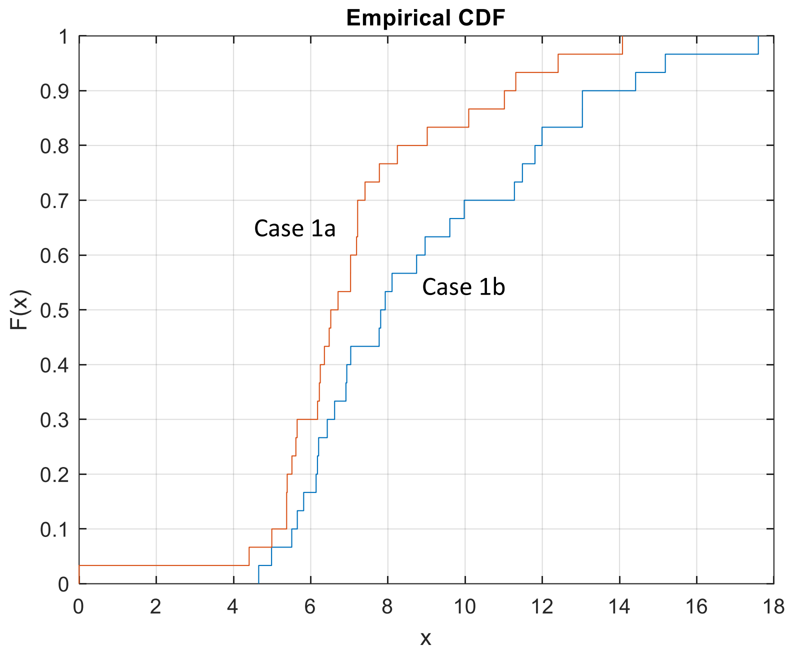


Figure 4.7: Comparison of Empirical CDF of Objective Values When the Most Technical Member is Close to the Leader (Case 1a) and When the Most Technical Member is Far Away from the Leader (Case 1b).

We now investigate why the above results happened in detail by comparing the number of times over the 20 cycles each individual contributed to the team discussion. This is shown in Figure 4.8. We notice that in the case of team 1, individual B, because of their closeness to the leader was able to talk more and thus contribute to the improvement in the solution compared to team 2. This effect is further amplified in team 2 where the individuals with limited skills contributed more to the discussion and therefore caused the objective values to worsen.

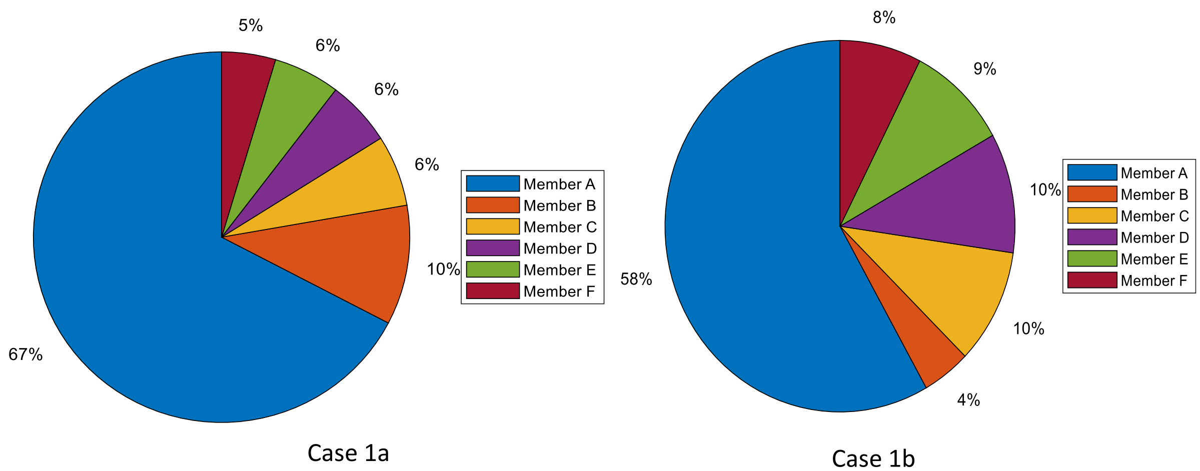


Figure 4.8. Relative Proportion of Time an Individual Leads the Design Effort in the Team Meeting When the Most Technical Member is Close to the Leader (Case 1a) and Far from the Leader (Case 1b).

Finally, we report the destruction events in the team meeting, which we define as the number of times the objective function value got worse from speaker to speaker within a team meeting (Figure 4.9). This value keeps relatively constant as we can see with sporadic improvements and worsening in Case 1a. In a team where multiple handoffs happen between skilled and unskilled workers, one would expect to see many destruction events. However, it should be noted that a solution gets worse both because of the skill of the individual leading the discussion and also because of random chance inherent in Genetic Algorithms.

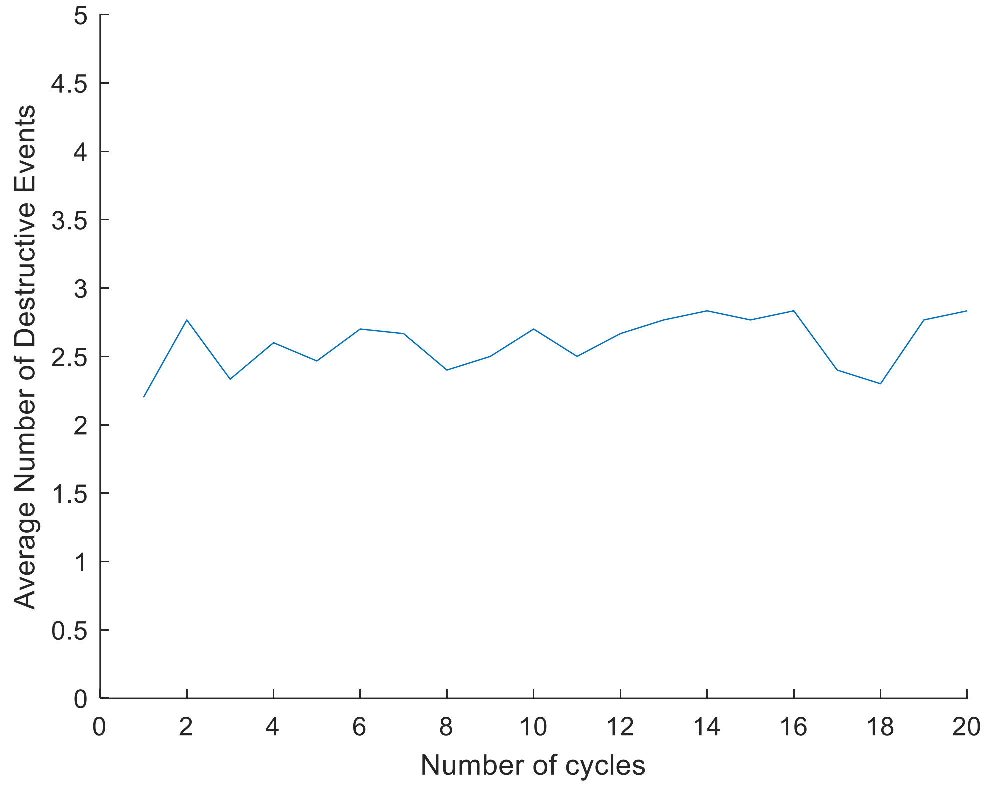


Figure 4.9: Solution Destruction Events, or Design Iterations where the Average Objective Value of the Population Worsens Time when the Most Technical Member is Close to the Leader (Case 1a).

With the results from Case 1, we see that the graph model for organizational relationships, coupled with the agent-based model that includes personality profiles in three dimensions (leadership, creativity and technical skill), is able to model expected team dynamics and predict trends. Furthermore, we see that, all else being held constant, placing highly technical individuals close to intrinsic leaders improves the design process results.

CHAPTER FIVE

SIMULATION RESULTS AND ANALYSIS

5.1 Introduction: Centrality Analysis of Graph Nodes

We discussed in Chapter 3 that Model B incorporates evolving cognitive attributes as a result of team interaction as well as incorporation of organization-induced and intrinsic attributes. Model B also allows us to investigate the effects of the organization's culture on how it promotes leadership, creativity, and collaborativeness. Additional analysis include the dispersion of a design through the organization graph via the Laplacian of the graph and investigation of intrinsic versus trained creativity.

Since Model B assigns leadership values partly based on the organization structure, in particular, the eigenvector centrality associated with each node, we begin with the centrality analysis of the network we generated in the last chapter. The various centrality values associated with each node are presented in detail in the appendix in table A1. Here we present the salient features we observe.

Figure 5.1 shows the plot of each of the five centrality scores calculated for each node. The eigenvector centrality is shown in darker shade to help its identification better. We see that the highest eigenvector centrality values we get are for nodes 3, 2, 14, 9, 1 and so on, in that order. From Figure 4.2, we can see that these nodes are indeed the ones which "hub" like characteristics. It is important to note that node 9 while itself not a big hub, is connected directly to node 3, the node with highest centrality, and therefore is able to inherit its importance in the network.

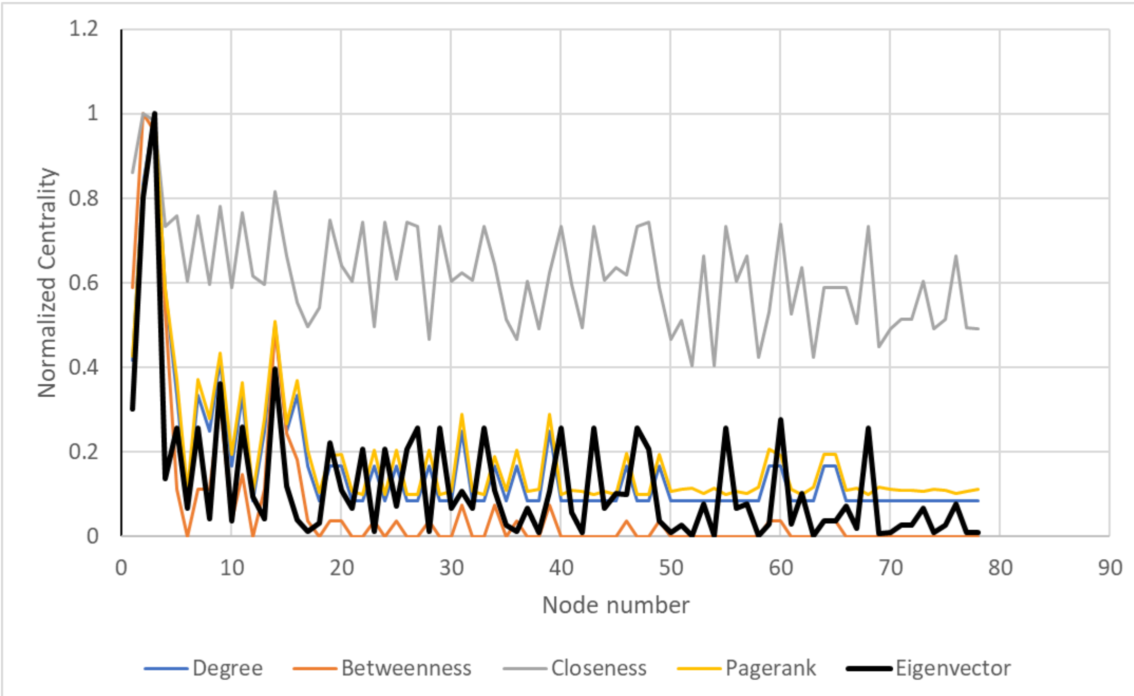


Figure 5.1: Graph Centrality Values Associated with all the Nodes in the Organization Considered (Eigenvector Centrality Highlighted).

We also investigate the correlation between the various centrality measures and the results are shown in table 5.1. We see that the eigenvector centrality shows a reasonably strong (but not extremely high) correlation with other centrality measures. This is expected because all of them measure the importance of the node. It should be noted that the closeness centrality which shows the highest correlation with the eigenvector centrality can be misleading because despite the high correlation, it does not distinguish *between* the nodes as much (see Figure 5.1). In other words, the trends are similar to eigenvalue centrality but almost all nodes are considered somewhat equally important. This is in contrast with the eigenvalue centrality that truly amplifies the effect of hubs. Based on this discussion, we conclude that eigenvalue centrality is the best measure of the influence of an individual in an organization.

Table 5.1 Correlation Values Between the Different Centralities Considered.

	Degree	Betweenness	Closeness	Pagerank	Eigenvector
Degree	1	0.957	0.608	0.998	0.762
Betweenness	0.957	1	0.622	0.945	0.777
Closeness	0.608	0.622	1	0.580	0.876
Pagerank	0.998	0.945	0.580	1	0.739
Eigenvector	0.762	0.777	0.876	0.739	1

5.2. Case 2: Heterogeneous Teams

In this part of the work, we run model B to investigate heterogeneous teams and also incorporate the portion where the cognitive attributes of leadership and creativity evolve based on the experience of the team members. The goal of the comparison is to investigate the impact the organization location has on a heterogeneous team. As before, we select 6 team members for Case 2 distributed across the organization as shown in figure 5.2. The team members' pair-wise distance from each other is shown in Table 5.2, while the eigenvector centrality values (normalized) of the team members are shown in Table 5.3.

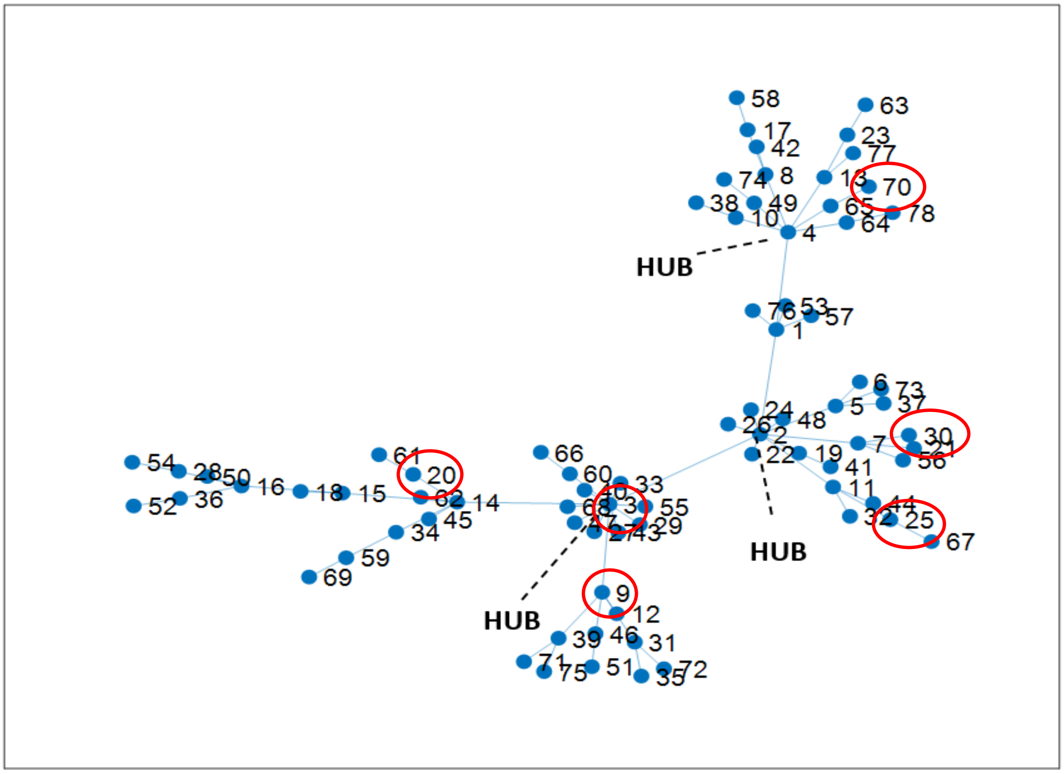


Figure 5.2: Team Member Locations on the Organizational Graph for Case 2.

Table 5.2: Pairwise Distance Between Team Members in Case 2a.

	CASE 2	Team Members					
		3(A)	**9(B)**	**20(C)**	**25(D)**	**30(E)**	**70(F)**
Team Members	**3(A)**	0	1	2	3	3	5
	9(B)	1	0	3	4	4	6
	20(C)	2	3	0	5	5	7
	25(D)	3	4	5	0	4	6
	30(E)	3	4	5	4	0	6
	70(F)	5	6	7	6	6	0

Table 5.3: Normalized Eigenvector Centrality of the Team Members in Case 2a.

CASE 2a	Team Members					
	3(A)	9(B)	20(C)	25(D)	30(E)	70(F)
Eigenvector Centrality	1.000	0.362	0.109	0.071	0.066	0.010

The member proficiencies of the team are given in table 5.4 below. We notice that member A in this case has a high technical ability but suffers in the other attributes. Member B is high in leadership and collaborativeness, while member C has high technical and creativity values. Members D, E and F progressively have diminishing values of each of the attributes.

Table 5.4. Intrinsic Cognitive Profiles of the Members Selected in Case 2.

Team Member	Leadership	Technical Ability	Creativity	Collab.
A	0.1	0.9	0.1	0.1
B	0.75	0.1	0.1	0.75
C	0.2	0.7	0.7	0.1
D	0.6	0.6	0.6	0.6
E	0.2	0.2	0.2	0.2
F	0.1	0.1	0.1	0.1

We also select 6 team members distributed across the organization in the reverse order of Case 2a in terms of their location, which we call Case 2b. In other words, this case maintains the cognitive attributes of its team members but reverses the location of the members. The new eigenvector centrality values (normalized) of the team members are shown in Table 5.5. This has the profound of changing the leadership endowed by the organizational structure.

Table 5.5: Eigenvector Centrality of the Team Members in Case 2b.

CASE 2b	Team Members					
	3(A)	**9(B)**	**20(C)**	**25(D)**	**30(E)**	**70(F)**
Eigenvector Centrality	0.010	0.066	0.071	0.109	0.362	1.000

We now provide some comparison results in the two cases. We begin by noticing that Case 2a performs better than Case 2b. This is shown in the empirical CDF plots of the two teams' performance after 20 cycles, demonstrating stochastic dominance of Case 2a over Case 2b (see Figure 5.3).

Figures 5.4a and 5.4b show the design presentation count for both the team types over time. We notice that in Case 2a, member A leads the discussion the most followed by member C. As a result, the end result is better because members A and C are skilled in technical and/or creativity which affect the design process. When we compare this with Case 2b, we see that not only is an unskilled individual able to lead the discussion more (member F), they are also progressively more likely to do that as the time progresses. This is a direct effect of evolving profiles that are inherent to model B. As a result, the solution has a diminished chance of getting better if this runaway effect happens – something we see commonly in group decision making settings in engineering organizations. This is further confirmed in Figures 5.5a and 5.5b which shows the totals for each team member. In future work, one may take into account interventions that are possible to mitigate this effect.

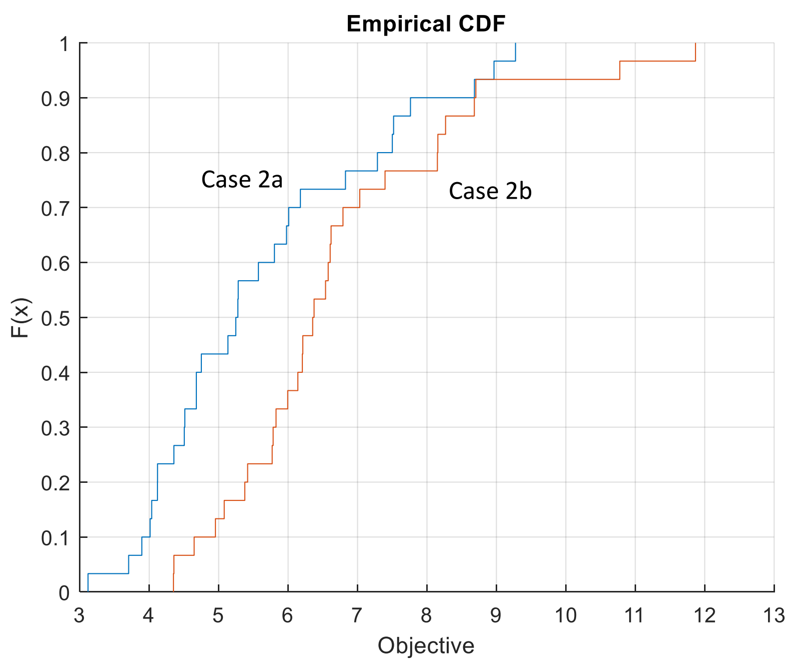
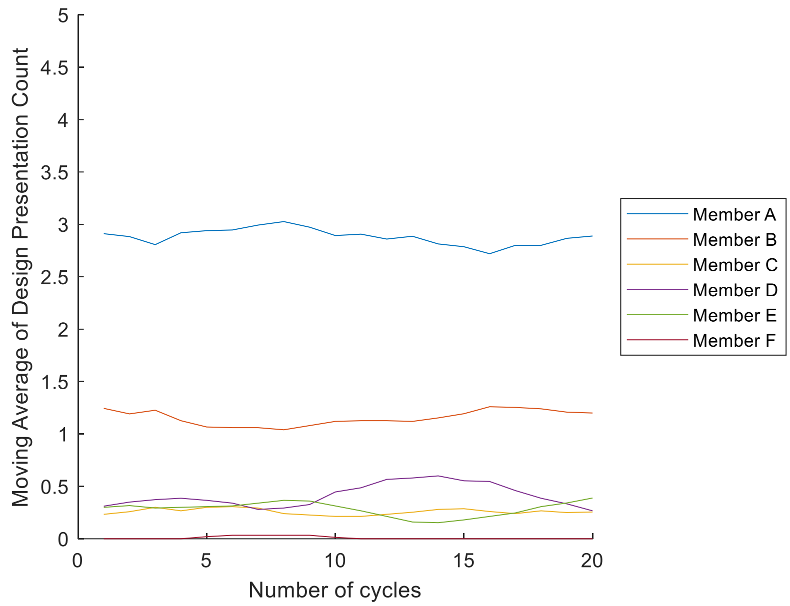
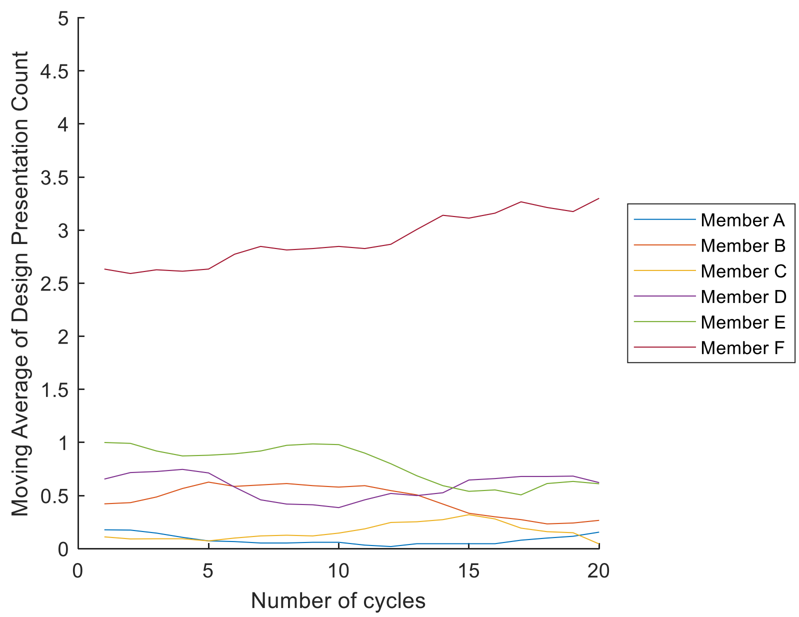


Figure 5.3: Comparison of Empirical CDFs of Objective Values for a Heterogeneous Team with One Organizational Position (Case 2a) and the Opposite Locations (Case 2b).

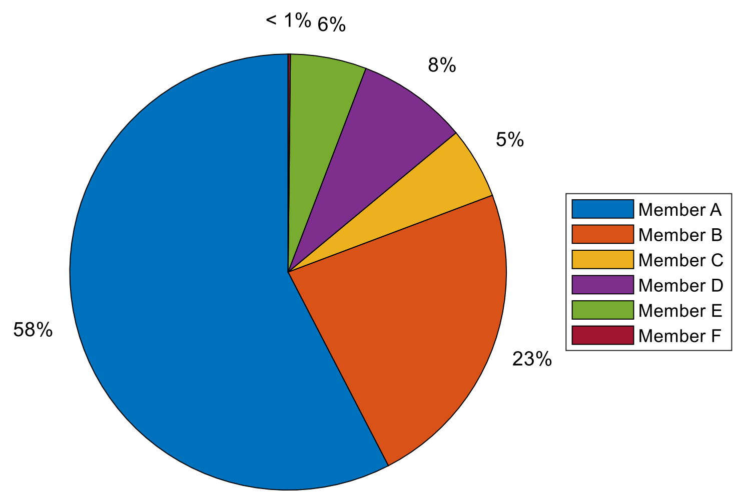


(a)

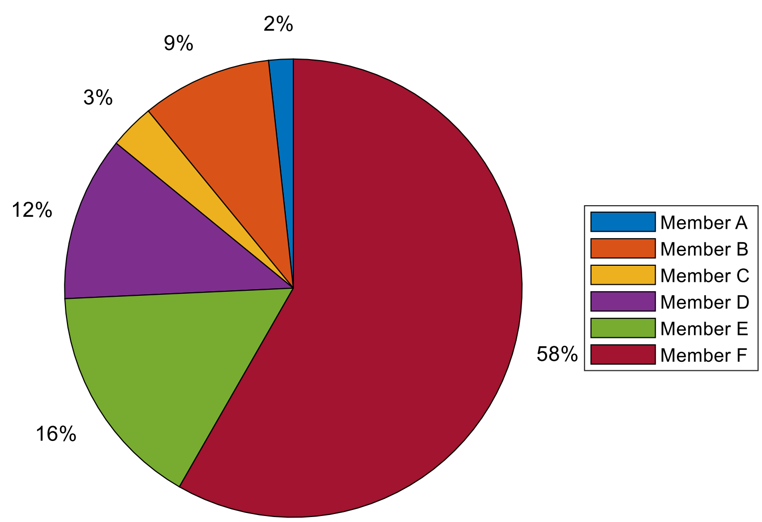


(b)

Figure 5.4: Number of Times an Individual Leads the Discussion in a Team Setting as a Function of Time for a Heterogeneous Team with (a) One Organizational Position (Case 2a) and (b) the Opposite Locations (Case 2b).



(a)

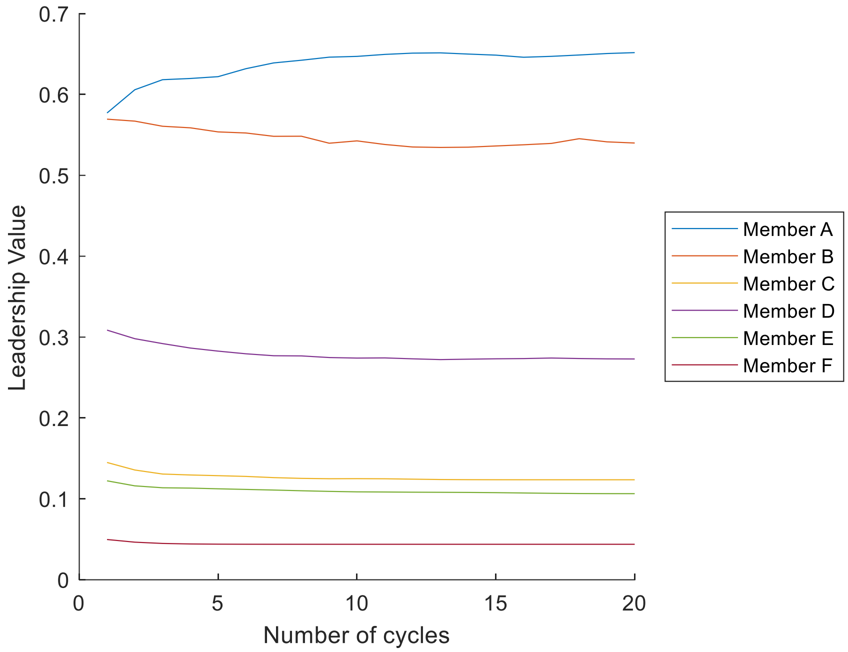


(b)

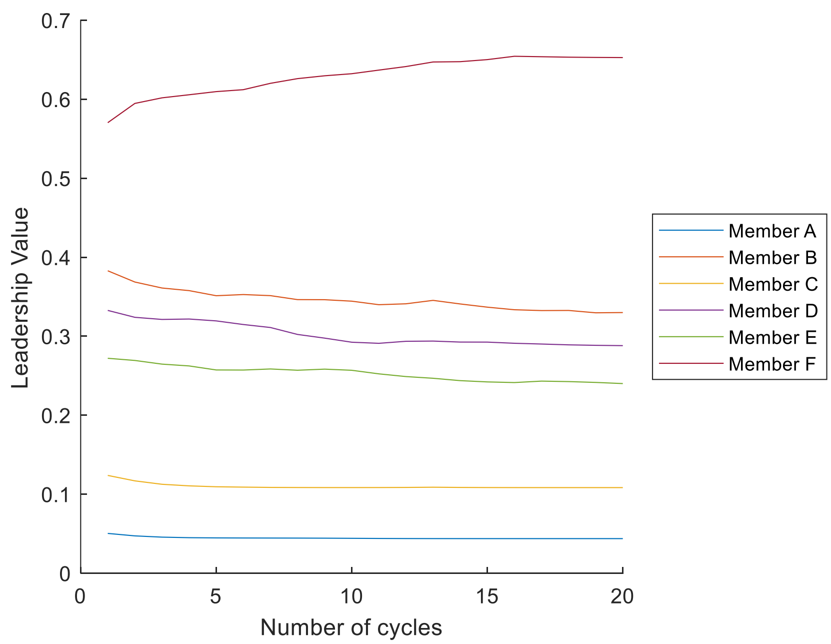
Figure 5.5: Relative Proportion of Time an Individual Leads the Design Effort in the Team Meeting for a Heterogeneous Team with (a) One Organizational Position (Case 2a) and (b) the Opposite Locations (Case 2b).

Figures 5.6 (a and b) and 5.7 (a and b) summarize the effect of the relative number of times each individual leads the discussion. In the case of Case 2a, we notice that because the organizational leadership endowed to them, skilled individuals are able to not only contribute to the team discussions but also over time either increase in leadership and creativity skills or the diminution is not enough to have a deleterious effect on the outcome of the design process.

This is reversed in the case of Case 2b. We find that not only there is a runaway increase in the leadership value of the unskilled member F, even though skilled individuals still exist (for example individual C), they do not get a chance to speak and thus are not able to improve the solution. This redoubles the results from Case 1 wherein it was found that skilled individuals should be placed close to leaders and extends it to skilled individuals should be placed in central positions in organization, if possible.

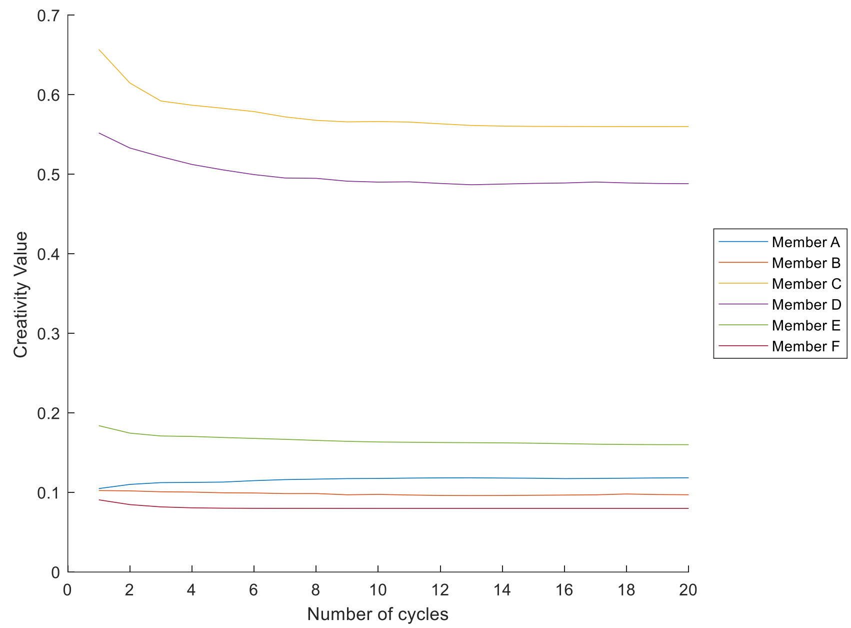


(a)

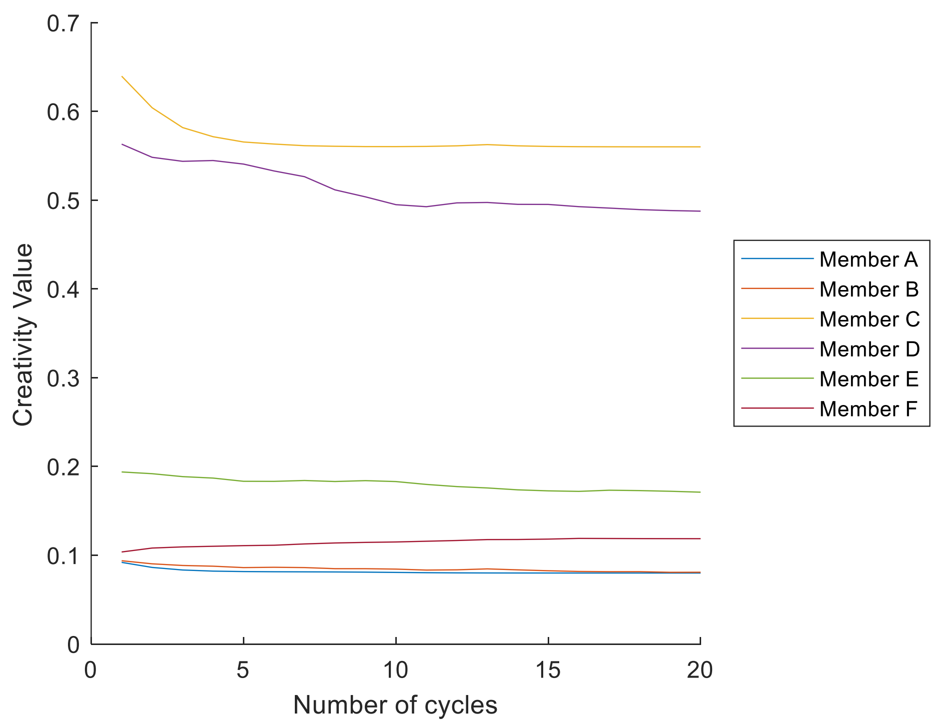


(b)

Figure 5.6: Leadership Evolution of Team Members as a Function of Time for a Heterogenous Team with (a) One Organizational Position (Case 2a) and (b) the Opposite Locations (Case 2b).



(a)



(b)

Figure 5.7: Leadership Evolution as a Function of Time for a Heterogeneous Team with (a) One Organizational Position (Case 2a) and (b) the Opposite Locations (Case 2b).

5.3. Intrinsic Versus Learned Creativity

As discussed in chapter 3, creativity can be both intrinsic, representing an individual who can apply design principles to arrive at a solution that others might overlook, or exhibit learned creativity, where an individual is given tools and training to systematically increase the number of designs they actively consider.

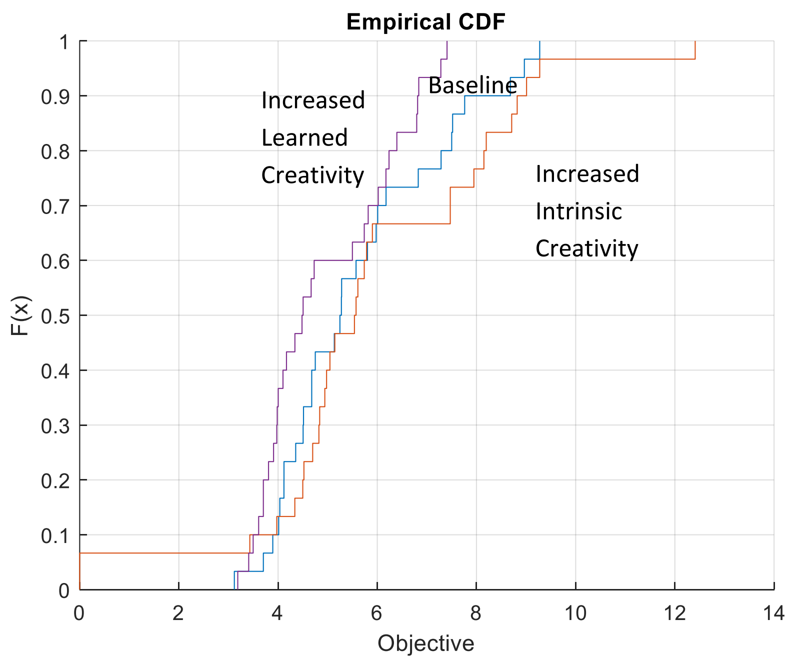


Figure 5.8: Comparison of Empirical CDFs of Objective Values for a Baseline Heterogeneous Team (Case 2a), increased intrinsic creativity and increased learned creativity.

We investigate the effects of both by increasing these different models for creativity in Case 2a by 40%. Figure 5.8 shows the comparison of the baseline Case 2a with both the increased intrinsic creativity and the increased learned creativity. It shows that while intrinsic creativity is necessary for the globally optimal solution where the objective function reaches 0 and increasing intrinsic creativity then allows for more individuals to find it, increasing learned creativity consistently improves the solutions over the baseline. Furthermore, learned creativity is inherently the one which can be influenced by a company through training in systematic problem solving.

5.4. Case 3: Leaves Versus Hubs Comparison

In this part of the discussion, we investigate what happens when the team members are located at the leaves of the network or when they close to being the hubs. This study was done to see what happens when the entire team suffers or benefits from organization induced attributes in the same fashion.

We selected the same cognitive attributes as shown before in table 5.4 and ran two simulation cases, Case 3a and Case 3b, by varying the location of the team members (Table 5.6). It can be easily verified that the individuals in Case 3a are located in the leaves of the graph while the individuals in Case 3b are hubs or close to the hubs of the graph from Figure 4.2. The team distance matrices for Case 3a and 3b, are presented in tables 5.7 and 5.8.

Table 5.6: Locations of Team Members on the Graph for Case 3a and Case 3b.

	A	**B**	**C**	**D**	**E**	**F**
Case 3a	52	54	58	63	69	70
Case 3b	3	2	14	9	1	60

Table 5.7: Pairwise Distance Between Team Members in Case 3a.

CASE 3a		Team Members					
		52(A)	54(B)	58(C)	63(D)	69(E)	70(F)
Team Members	52(A)	0	4	11	11	7	10
	54(B)	4	0	11	11	7	10
	58(C)	11	11	0	6	10	5
	63(D)	11	11	6	0	10	5
	69(E)	7	7	10	10	0	9
	70(F)	10	10	5	5	9	0

Table 5.8: Pairwise Distance Between Team Members in Case 3b.

CASE 3b		Team Members					
		3(A)	2(B)	14(C)	9(D)	1(E)	60(F)
Team Members	3(A)	0	1	1	1	2	1
	2(B)	1	0	2	2	1	2
	14(C)	1	2	0	2	3	2
	9(D)	1	2	2	0	3	2
	1(E)	2	1	3	3	0	3
	60(F)	1	2	2	2	3	0

In terms of the team interaction, we see through the pie charts presented in Figure 5.9 that despite having similar profiles, placing individuals in leaves discouraged discussion and allowed for a few individuals (members B and D) to dominate the team meetings. This is expected because the distance between leaves in the graph is much greater, on average, than the distance between hubs. Interestingly, both Case 3a and Case 3b show a delayed trend in their discussions over time as can be seen in Figure 5.10 which can be attributed the effects of distance between members B and D in Case 3a and to low collaborativeness of member A in Case 3b. This similarly reflects in the evolution of their cognitive attributes, leadership (Figure 5.11) and creativity (Figure 5.12). Even when the formerly repressed individuals more frequently lead the discussion, their attributes are lower than beginning, representing the long-term effects of being under-represented in group discussions.

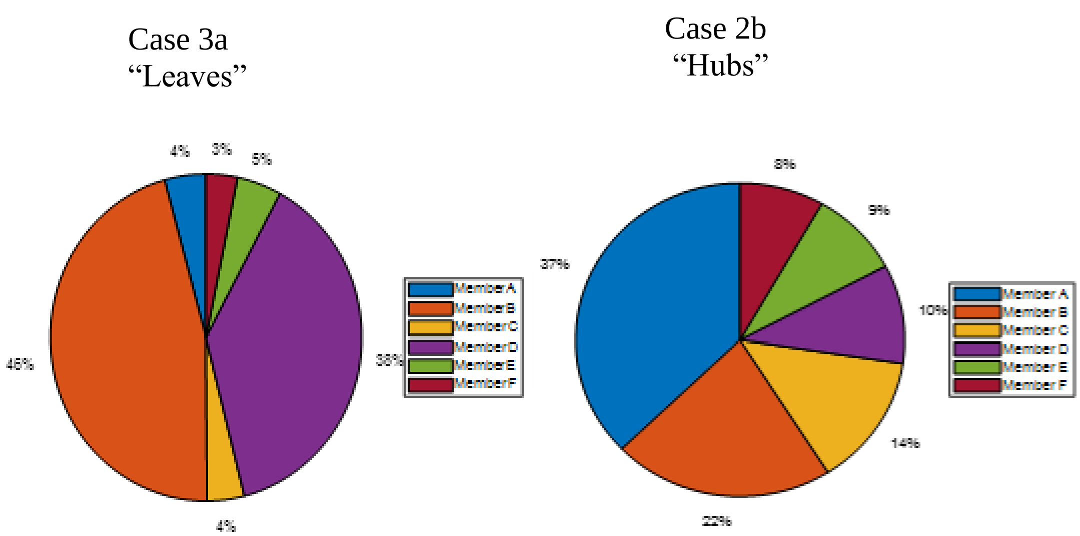
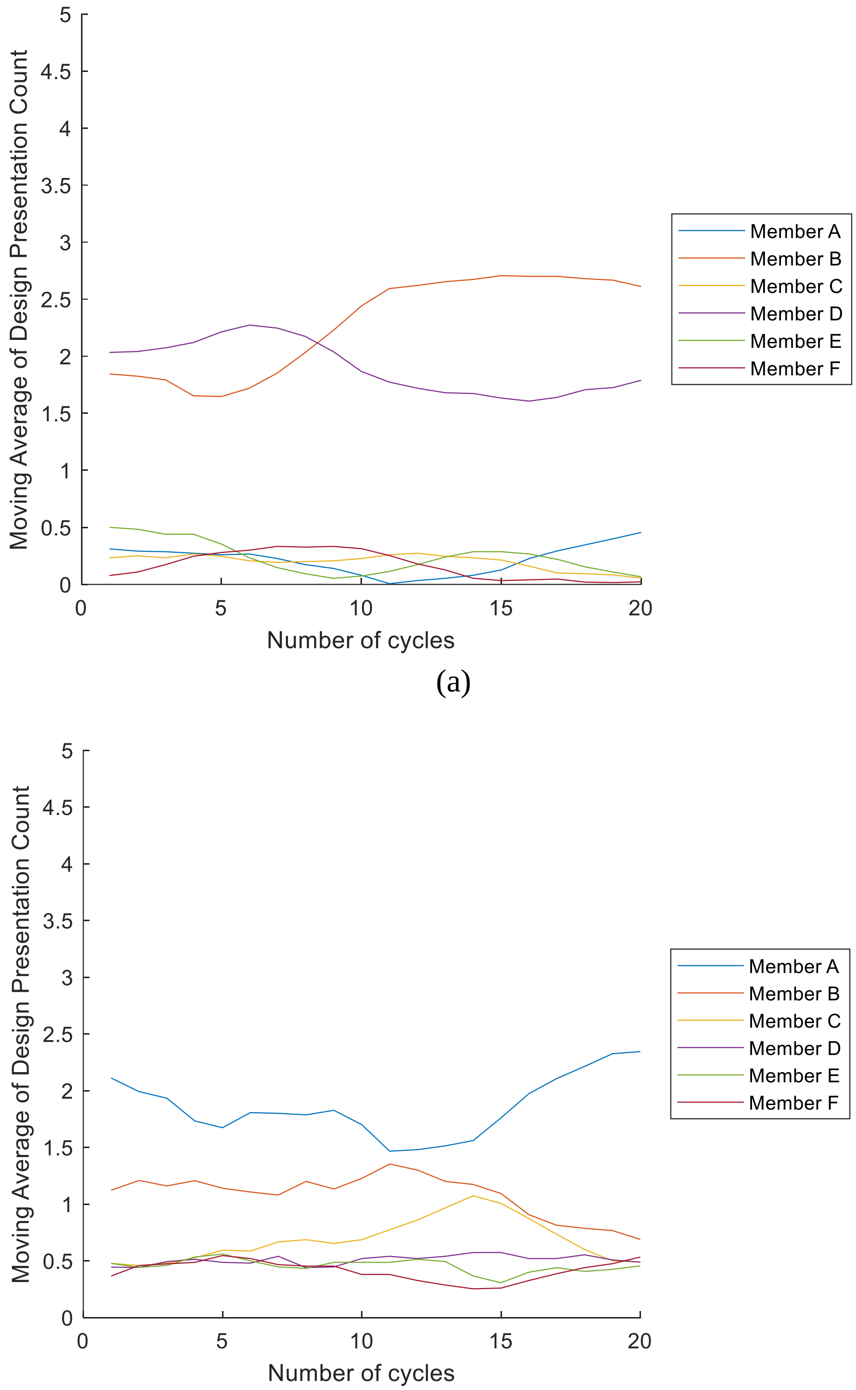


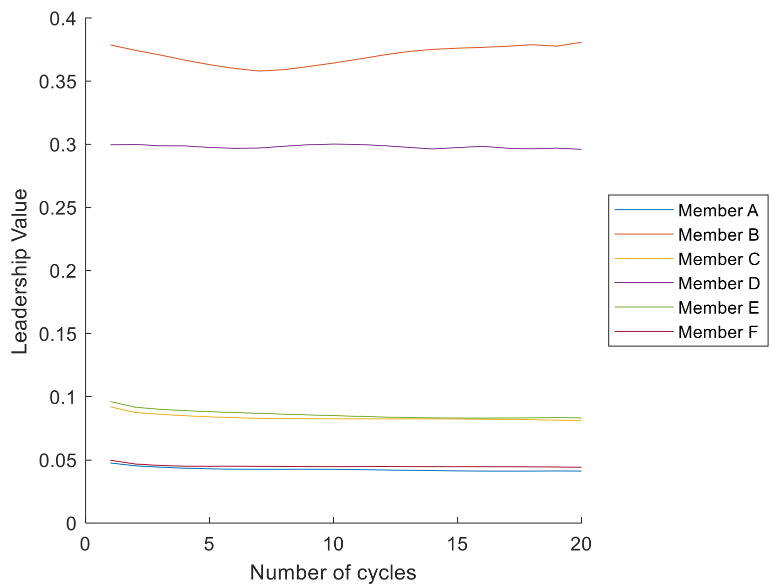
Figure 5.9: Relative Proportion of Time an Individual Leads the Design Effort in the Team Meeting for a Team located at Leaves of the Organizational Graph (Case 3a) and Hubs of the Organization Graph (Case 2b).



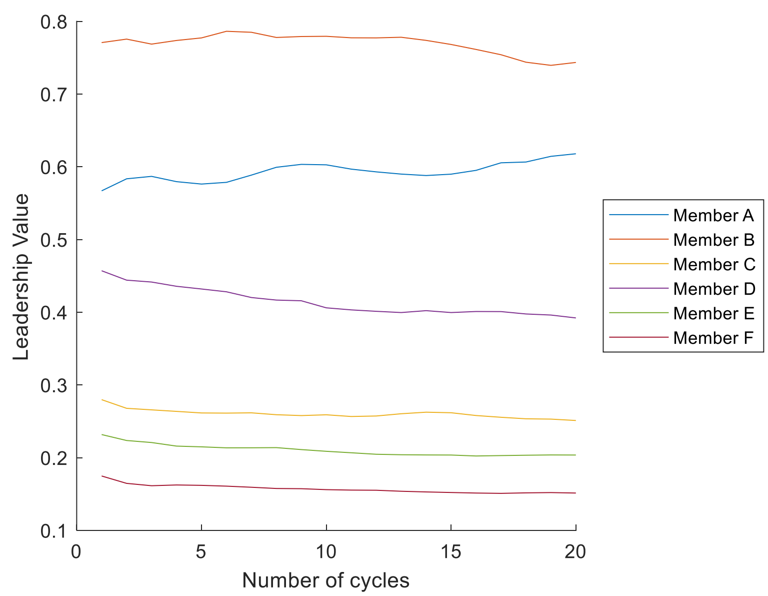
(a)

(b)

Figure 5.10: Number of Times an Individual Leads the Discussion in a Team Setting as a Function of Time for a (a) Team of Leaves (Case 3a) and (b) Team of Hubs (Case 3b).

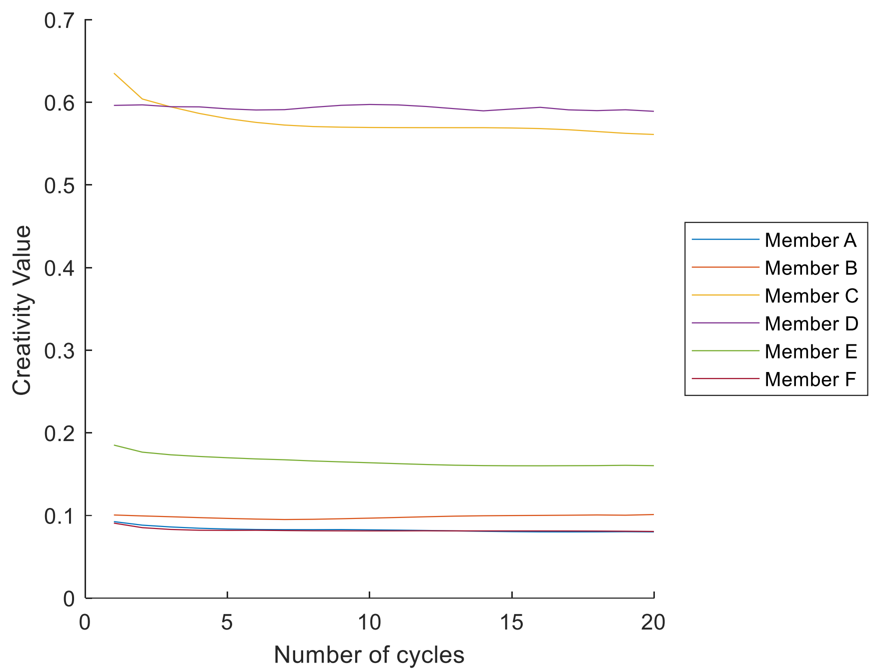


(a)

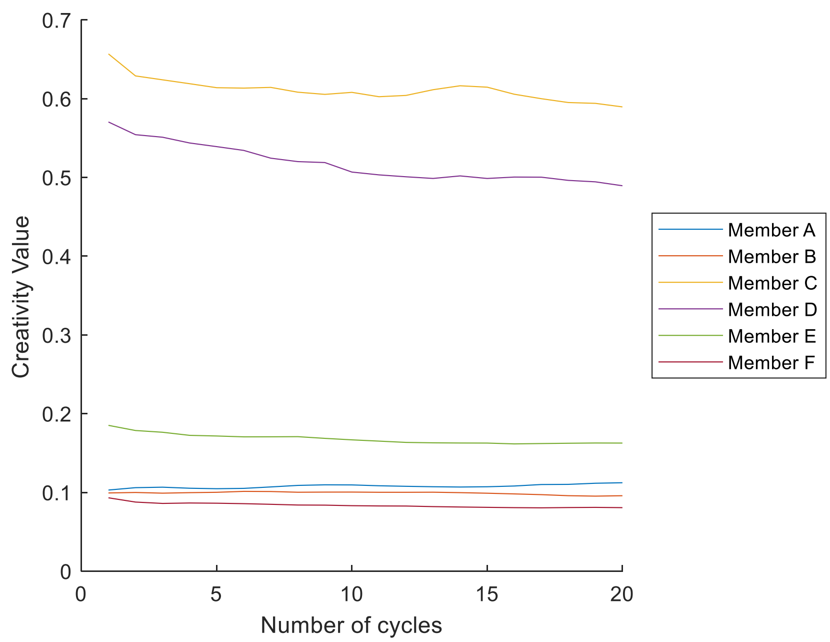


(b)

Figure 5.11: Leadership Evolution of Team Members as a Function of Time for a (a) Team of Leaves (Case 3a) and (b) Team of Hubs (Case 3b).



(a)



(b)

Figure 5.12: Creativity Evolution of Team Members as a Function of Time for a (a) Team of Leaves (Case 3a) and (b) Team of Hubs (Case 3b).

We also notice that the average outcome of the two cases were similar (Figure 5.13), but the variance was much higher for the team of all leaves (Case 3a) than the team of near-hubs (case 3b). This further provides evidence that the plurality of discussion within Case 3b leads to a more robust design process.

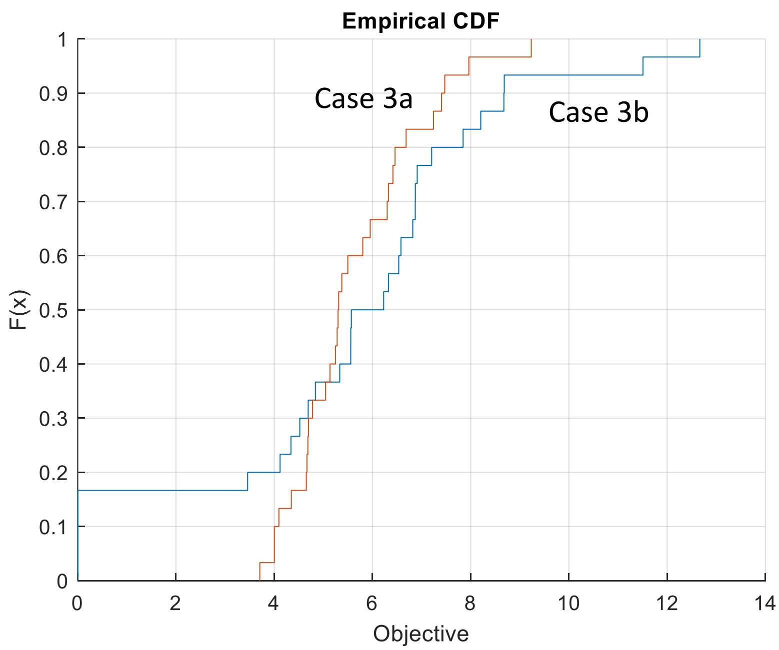


Figure 5.13: Comparison of Empirical CDFs of Objective Values for a Team of Leaves (Case 3a) and Team of Hubs (Case 3b).

5.5. Information Flow in the Organization

The largest difference between a team comprised of leaves in the organization (Case 3a) and hubs of the organization (Case 3b) is in the dissemination of information. Not only does the design need to be complete and provide a low objective value, but that the information needs to be adopted by the organization. We first evaluate the Laplacian of the graph as:

$$\mathbf{L} = \mathbf{D} - \mathbf{A} \tag{5.1}$$

We then define the vector $\mathbf{x_0}$ for Case 3a such that to represent that the members of the team are the only ones aware of the design at the beginning:

$$x_0^i = \begin{cases} 1 \; if \; i \in \{52, 54, 58, 63, 69, 70\} \\ 0 \qquad\qquad\qquad\qquad otherwise \end{cases} \tag{5.2}$$

In Case 3b the vector $\mathbf{x_0}$ is defined as:

$$x_0^i = \begin{cases} 1 \quad if \qquad i \in \{3, 2, 14, 9, 1, 60\} \\ 0 \qquad\qquad\qquad\qquad otherwise \end{cases} \tag{5.3}$$

We then repeatedly perform the following iteration in each case:

$$\mathbf{x}_{n+1} = \mathbf{x}_n - 0.1\boldsymbol{L}\mathbf{x}_n \tag{5.4}$$

Figure 4.22 shows the diffusion for information for Case 3a over a few iterations. Each iteration can be interpreted as passing of time as reports are made to superiors in the company, results are discussed and plans for implementation are made. The peaks represent the initial cycle where only the team members assigned to the design problem have information about the design. Over various iterations, this information diffuses through the graph to other members. Since the team members in this case were leaves in the organization, we see that even after 10 iterations the information has only moved to a few members.

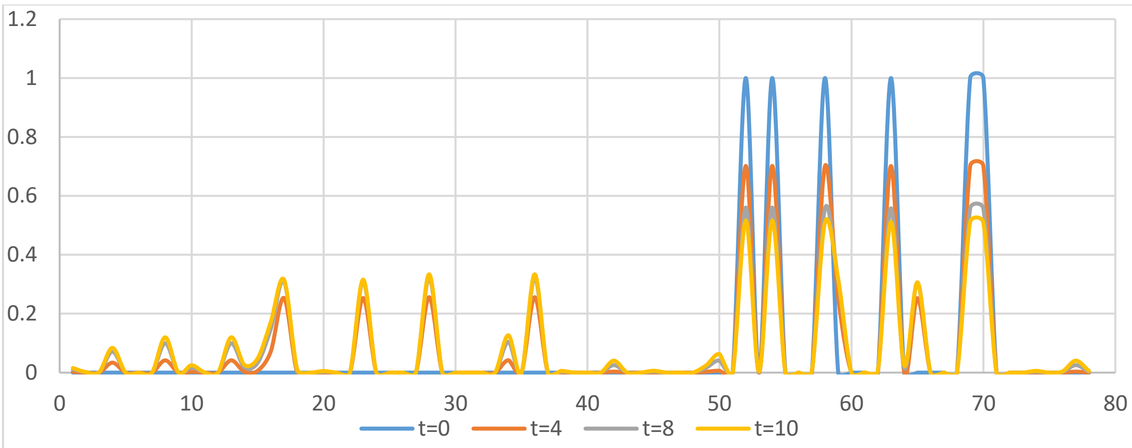


Figure 5.14: Information Diffusion of the Proposed Design Through the Network for a Team located at the Leaves of an Organization (Case 3a).

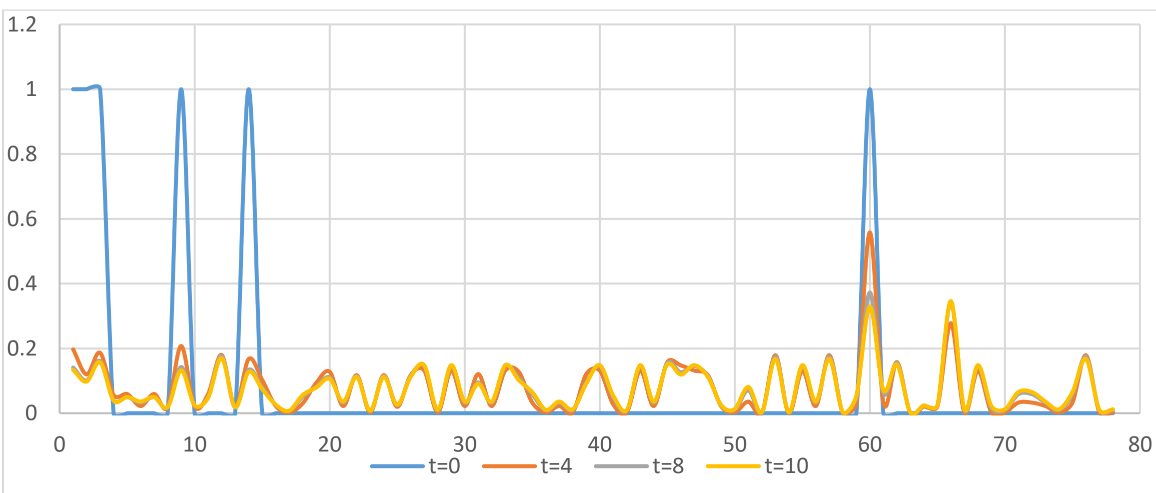


Figure 5.15: Information Diffusion of the Proposed Design Through the Network for a Team located at the Hubs of an Organization (Case 3b).

In Case 3b, on the other hand, because of the centrality of the team members, the information flows much faster to the entire organization. Not only does the information reach more members of the organization, the spread of information is much faster, reaching near-steady state values after only 4 iterations. This leads us to an important conclusion that when forming teams, it is critical to select members that have the ability to influence the adoption of the new design in the organization.

CHAPTER SIX

CONTRIBUTIONS AND FUTURE WORK

6.1. Dissertation Contributions

The overall contribution of this work is an agent-based framework for modeling and simulating engineering design as informed by the organization structure which is represented by a network graph. Through this model, we aimed to understand team dynamics in the context of product development, or, more precisely, how a product or a system can be designed when different “human” aspects of collaboration within an organization are considered.

Engineering organizations have to maximize return on investment and achieve clarity on the expected performance of their products on an on-going basis. Involvement of human decision makers further complicates the process because not only their technical skills affect the results, but also their other cognitive skills (leadership, interpersonal etc.) as well as their role and seniority in the organization. These cannot be studied easily within existing organizations because the recommendations will be limited to the type of organization involved and the design problems considered. While at the same time human-subject research is time consuming and logistically difficult to run for the number of studies we will have to do to derive generalizable results. An agent-based model addresses both the above issues and was employed in this work.

The contributions of this work are summarized below:

1. We developed a model for representing an engineering organization using a scale-free network using the Barabasi-Albert algorithm. Using the undirected graph thus generated, we used the eigenvector centrality measure (of which the PageRank centrality is a variant) to depict the relative influence of a team-member on design decisions. This comprehensive model allowed us to investigate a wide variety of problem settings and the effect of cognitive profiles on the engineering design process.
2. Individuals' intrinsic and organization-induced cognitive skills were incorporated into the model. This allowed us to investigate the combined contributions on how much the corporate culture affects engineering design and how much of it is because of the individual's capabilities.
3. The model allowed for the individuals' cognitive profiles to affect and be affected by their experience in the team design effort.
    a. An individual that does not get a chance to frequently contribute to the design effort exhibits diminished leadership and creativity levels. As a result, their performance can diminish both within the team and when they are working independently.
    b. Conversely, individuals that are encouraged to speak and improve the design are able to perform better in individual and team settings.

4. Based on our results, we were able to show that organizations that promote collaborative work, particularly with the aim of engaging skilled individuals, are more likely to come up with better designs and/or converge to designs faster.

6.2. Empirical Validation

We find empirical evidence in other studies investigating team design efforts that support our work. Scott (2004) showed that the highest success rate was among teams with complementary roles within the problem. This is similar to how we showed that increasing collaboration through strategic placements (division within the organization or through promotion) of skilled individuals led to better outcomes. They also showed that KAI may be too simple and additional behavior scales besides adaptors and Innovators maybe needed to fully represent human problem-solving behavior – which is something we do in our work. The positive effects of encouragement on creativity and leadership has also found mention in previous research (Paulus, 2024). Finally, our results of how learned creativity may obviate dependence on innate talent also finds support in Ulrich and Eppinger (2011).

6.3. Future Work

The presented work can be extended in various ways:

1. Investigate a broader range of organizational structures including models such as small world network (Watts-Strogatz model). Many organizations have a “flat” structure which may lead to different insights.

2. Learning effect: We did not investigate how our technical abilities evolve as we work on more problems of the same type, only leadership and creativity traits were modeled to evolve. Evolving technical ability because of better understanding of the problem may also be investigated in the future.
3. Seek interactions between leadership, technical ability and creativity as a function of the difficulty level of the technical problem. For example, for simple problems some of the cognitive attributes may not present as readily as for more complex problems.
4. Investigate a wide variety of design problems to see if the findings and recommendations hold. This may become challenging for larger problems, however, the approach presented in this work may still be useful.
5. Use modern techniques such as Large Language Models along with Natural Language Processing to help assess the cognitive skills of members. This has the potential to provide more accurate predictions of team performance.
6. Finally, as with all simulation-based results, the recommendations can be enhanced with validation using human subject research.

REFERENCES

1. Akhavan Tabassi, A., Bryde, D.J., Mustafa Kamal, E., Dowson, J. and Michaelides, R., 2019. Challenges for project management in the 21st century. The European Proceedings of Multidisciplinary Sciences.
2. Arnaboldi, V., Passarella, A., Conti, M. and Dunbar, R.I., 2015. Online social networks: human cognitive constraints in Facebook and Twitter personal graphs. Elsevier.
3. Albert, R. and Barabási, A.L., 2002. Statistical mechanics of complex networks. *Reviews of modern physics*, *74*(1), p.47.
4. Avolio, B.J., 2005. Leadership development in balance: Made/born. Psychology Press. Jan 15.
5. Balakrishnan, B., 2022. Exploring the impact of design thinking tool among design undergraduates: a study on creative skills and motivation to think creatively. International Journal of Technology and Design Education, 32(3), pp.1799-1812.
6. Bessadok, A., Mahjoub, M.A. and Rekik, I., 2022. Graph neural networks in network neuroscience. IEEE Transactions on Pattern Analysis and Machine Intelligence, 45(5), pp.5833-5848.
7. Bierhals. R., Schuster. I., Kohler. P., & Badke-Schaub. P. "Shared mental models - linking team cognition and performance". *CoDesign* Vol. 3 No. 1 (2007): pp. 75 - 94.
8. Bolzani, D., Crivellaro, F. and Grimaldi, R., 2021. Highly skilled, yet invisible. The potential of migrant women with a STEMM background in Italy between

intersectional barriers and resources. *Gender, Work & Organization*, *28*(6), pp.2132-2157.

9. Borgatti, S. P., Everett, M. G., & Johnson, J. C. (2013). *Analyzing Social Networks.* SAGE Publications. pp.189-208.

10. Boyd, S.P. and Vandenberghe, L., 2004. Convex optimization. Cambridge university press.

11. Buffinton. K. W., Jablokow. K. W., & Martin. K. W. "Project Team Dynamics and Cognitive Style", *Engineering Management Journal* Vol. 14 No. 3 (2002): pp. 25 - 33.

12. Cao, S., Qian, Q., Cao, Y., Li, W., Huang, W. and Liang, J., 2023. A novel meta-heuristic algorithm for numerical and engineering optimization problems: Piranha foraging optimization algorithm (PFOA). IEEE Access, 11, pp.92505-92522.

13. Ceci, S.J. and Williams, W.M., 2022. The importance of viewpoint diversity among scientific team members. Comment on Clark et al.

14. Chaudhari, A.M., Gralla, E.L., Szajnfarber, Z. and Panchal, J.H., 2022. Co-evolution of communication and system performance in engineering systems design: a stochastic network-behavior dynamics model. Journal of Mechanical Design, 144(4), p.041706.

15. Chung, F. and Lu, L., 2002. Connected components in random graphs with given expected degree sequences. Annals of combinatorics, 6(2), pp.125-145.

16. Cicone, A. and Serra-Capizzano, S., 2010. Google PageRanking problem: the model and the analysis. Journal of computational and applied mathematics, 234(11), pp.3140-3169.

17. Converse, S. A., Cannon-Bowers, J. A., & Salas, E. “Team Member Shared Mental Models: A Theory and Some Methodological Issues”. *Proceedings of the Human Factors and Ergonomics Society 35th Annual Meeting* Vol. 35 No. 19 (1991).

18. Copp, D.A., Mejia, A.H., Walter, M.E. and Buswell, N.T., 2021, July. Team Formation and Function Decisions and Student Roles on Diverse Engineering Design Teams. In 2021 ASEE Virtual Annual Conference Content Access.

19. Darwin, C. and Beer, G., 1951. The origin of species., 473 pp.

20. De Marchi, S. and Page, S.E., 2014. Agent-based models. *Annual Review of political science*, *17*, pp.1-20.

21. de Melo, É.S., Vieira, D. and Bredillet, C., 2022. Investigating the Dynamics of Engineering Design Rework for a Complex Aircraft Development Project: Lessons Learned From a Soft Systems Thinking Lens. Project Management Journal, 53(6), pp.625-640.

22. De Weck, O., Krob, D., Lefei, L., Lui, P.C., Rauzy, A. and Zhang, X., 2020. Handling the COVID-19 crisis: Toward an agile model-based systems approach. *Systems Engineering*, *23*(5), pp.656-670.

23. Deb, K. and Jain, S., 2003. Multi-speed gearbox design using multi-objective evolutionary algorithms. J. Mech. Des., 125(3), pp.609-619.

24. Deb, K., 1990, April. Optimal design of a class of welded structures via genetic algorithms. In 31st Structures, Structural Dynamics and Materials Conference (p. 1179).

25. Ding, T., Jia, W., Shahidehpour, M., Han, O., Sun, Y. and Zhang, Z., 2022. Review of optimization methods for energy hub planning, operation, trading, and control. *IEEE Transactions on Sustainable Energy*, *13*(3), pp.1802-1818.

26. Daniels, M.W. and Pierre, K., 2023, January. Integrating Reliability Engineering with Model Based Systems Engineering. In 2023 Annual Reliability and Maintainability Symposium (RAMS) (pp. 1-6). IEEE.

27. Drignei, D., Mourelatos, Z.P., Kokkolaras, M. and Pandey, V., 2014. Reallocation of testing resources in validating optimal designs using local domains. Structural and Multidisciplinary Optimization, 50, pp.825-838.

28. Driscoll, P.J., Parnell, G.S. and Henderson, D.L. eds., 2022. Decision making in systems engineering and management. John Wiley & Sons.

29. Elshahhat, A., Alotaibi, R. and Nassar, M., 2023. Reliability and the engineering applications of the generalized half-normal model via an adaptive progressive hybrid censored mechanism. AIP Advances, 13(11).

30. Erdős, P. and Rényi, A., 1959. Some further statistical properties of the digits in Cantor's series. *Acta Math. Acad. Sci. Hungar.*, *10*, pp.21-29.

31. Erciyes, K., 2021. Discrete mathematics and graph theory. Cham, Switzerland: Springer.

32. Estes, J. and Pandey, V., 2023. Investigating the Effect of Organization Structure and Cognitive Profiles on Engineering Team Performance Using Agent-Based Models and Graph Theory. Mathematics, 11(21), p.4533.

33. Fang, A.Q., 2020. Student team decision-making processes and assessment criteria in early stage engineering design (Doctoral dissertation, Massachusetts Institute of Technology).

34. Evans, T.S. and Saramäki, J.P., 2005. Scale-free networks from self-organization. Physical Review E—Statistical, Nonlinear, and Soft Matter Physics, 72(2), p.026138.

35. Fritz, K., Deschenes, L. and Pandey, V., 2018, November. Effective design team composition using individual and group cognitive attributes. In ASME international mechanical engineering congress and exposition (Vol. 52187, p. V013T05A030). American Society of Mechanical Engineers.

36. Gauss, L., Lacerda, D.P. and Cauchick Miguel, P.A., 2021. Module-based product family design: systematic literature review and meta-synthesis. Journal of Intelligent Manufacturing, 32, pp.265-312.

37. Goldberg, D.E., Deb, K. and Horn, J., 1992, April. Massive multimodality, deception, and genetic algorithms. In PPSN (Vol. 2).

38. Gigerenzer, G., Reb, J. and Luan, S., 2022. Smart heuristics for individuals, teams, and organizations. Annual Review of Organizational Psychology and Organizational Behavior, 9(1), pp.171-198.

39. Goldberg, D.E., 1989, Genetic algorithms in search, optimization, and machine learning. Addison-Wesley, 412 pages.

40. Gross, J.L., Yellen, J. and Anderson, M., 2018. *Graph theory and its applications*. Chapman and Hall/CRC.

41. Gyory, J.T., Soria Zurita, N.F., Martin, J., Balon, C., McComb, C., Kotovsky, K. and Cagan, J., 2022. Human versus artificial intelligence: A data-driven approach to real-time process management during complex engineering design. Journal of Mechanical Design, 144(2), p.021405.

42. Guze, S., 2014. Graph theory approach to transportation systems design and optimization. TransNav: International Journal on Marine Navigation and Safety of Sea Transportation, 8.

43. Harrison, W.K., 2016. The role of graph theory in system of systems engineering. IEEE Access, 4, pp.1716-1742.

44. Hersey, P. and Blanchard, K.H., 1997. Situational leadership. In *Dean's Forum* (Vol. 12, No. 2, p. 5).

45. Hunter, S., 2016. If ever the twain shall meet: graph theoretical dimensions of formal and informal organization structure. *Int'l J. Soc. Sci. Stud.*, *4*, p.79.

46. Hutchinson, J., Whittle, J. and Rouncefield, M., 2014. Model-driven engineering practices in industry: Social, organizational and managerial factors that lead to success or failure. Science of Computer Programming, 89, pp.144-161.

47. Huikkola, T., Kohtamäki, M. and Ylimäki, J., 2022. Becoming a smart solution provider: Reconfiguring a product manufacturer's strategic capabilities and processes to facilitate business model innovation. Technovation, 118, p.102498.

48. Jablokow, K., Sonalkar, N., Edelman, J., Mabogunje, A., & Leifer, L. "Investigating the Influence of Designers' Cognitive Characteristics and Interaction Behaviors in Design Concept Generation". *Journal of Mechanical Design* Vol. 141 No. 9 (2019).

49. Janson, S., Luczak, T. and Rucinski, A., 2011. Random graphs. John Wiley & Sons.

50. Jeong, H., Néda, Z. and Barabási, A.L., 2003. Measuring preferential attachment in evolving networks. *Europhysics letters*, *61*(4), p.567.

51. Jiao, R., Commuri, S., Panchal, J., Milisavljevic-Syed, J., Allen, J.K., Mistree, F. and Schaefer, D., 2021. Design engineering in the age of industry 4.0. *Journal of Mechanical Design*, *143*(7), p.070801.

52. Joel, O.T. and Oguanobi, V.U., 2024. Data-driven strategies for business expansion: Utilizing predictive analytics for enhanced profitability and opportunity identification. International Journal of Frontiers in Engineering and Technology Research, 6(02), pp.071-081.

53. Kaul, K., 2022. Understanding Hiring Processes to Improve Diversity on Startup Technology Teams (Doctoral dissertation, Northeastern University).

54. Kitsak, M., Riccaboni, M., Havlin, S., Pammolli, F. and Stanley, H.E., 2010. Scale-free models for the structure of business firm networks. Physical Review E—Statistical, Nonlinear, and Soft Matter Physics, 81(3), p.036117.

55. Klein, D.J., 2010. Centrality measure in graphs. Journal of mathematical chemistry, 47(4), pp.1209-1223.

56. Kirton, M.J., 1999. Kirton adaption-innovation inventory.

57. Koopman, P.L., Broekhuijsen, J.W. and Wierdsma, A.F., 2013. Complex decision-making in organizations. In A Handbook of Work and Organizational Psychology (pp. 357-386). Psychology Press.

58. Koutrouli, M., Karatzas, E., Paez-Espino, D. and Pavlopoulos, G.A., 2020. A guide to conquer the biological network era using graph theory. Frontiers in bioengineering and biotechnology, 8, p.34.

59. Lambora, A., Gupta, K. and Chopra, K., 2019, February. Genetic algorithm-A literature review. In *2019 international conference on machine learning, big data, cloud and parallel computing (COMITCon)* (pp. 380-384). IEEE.

60. Lapp, S., Jablokow, K., & McComb, C. "KABOOM: An agent-based model for simulating cognitive style in team problem solving". *Design Science: An International Journal* Vol. 5 No. 13 (2019).

61. Lin, X., Yu, X. and Li, W., 2022. A heuristic whale optimization algorithm with niching strategy for global multi-dimensional engineering optimization. Computers & Industrial Engineering, 171, p.108361.

62. Majeed, A. and Rauf, I., 2020. Graph theory: A comprehensive survey about graph theory applications in computer science and social networks. Inventions, 5(1), p.10.

63. Mangun, D. and Thurston, D.L., 2002. Incorporating component reuse, remanufacture, and recycle into product portfolio design. *IEEE transactions on engineering management*, *49*(4), pp.479-490.

64. Méndez‐González, L.C., Rodríguez‐Picón, L.A., Pérez‐Olguin, I.J.C., Garcia, V. and Quezada‐Carreón, A.E., 2023. A reliability analysis for electronic devices under an extension of exponentiated perks distribution. Quality and Reliability Engineering International, 39(3), pp.776-795.

65. Merris, R., 1994. Laplacian matrices of graphs: a survey. Linear algebra and its applications, 197, pp.143-176.

66. Merriam-Webster.com Dictionary, Merriam-Webster, https://www.merriam-webster.com/dictionary. Accessed 4 May 2025.

67. Molloy, M. and Reed, B., 1995. A critical point for random graphs with a given degree sequence. Random structures & algorithms, 6(2-3), pp.161-180.

68. Montanari, A., 2013. Statistical mechanics and algorithms on sparse and random graphs. *Lectures on Probability Theory and Statistics. Saint-Flour*.

69. Mironov, S., Sidorov, S. and Malinskii, I., 2021. Degree-degree correlation in networks with preferential attachment based growth. In *Complex Networks XII: Proceedings of the 12th Conference on Complex Networks CompleNet 2021* (pp. 51-58). Springer International Publishing.

70. Moor, S.S. and Drake, B.D., 2001. Addressing common problems in engineering design projects: A project management approach. Journal of Engineering Education, 90(3), pp.389-395.

71. Naranjo, S., Patil, V. and Pandey, V., 2016, August. Preference Aggregation in Lifecycle Decision Making. In International Design Engineering Technical Conferences and Computers and Information in Engineering Conference (Vol. 50145, p. V004T05A033). American Society of Mechanical Engineers.

72. Newman, M. E. J. (2010). *Networks: An Introduction.* Oxford University Press.

73. Newman, M.E., 2003. The structure and function of complex networks. SIAM review, 45(2), pp.167-256.

74. Nielsen, C.B., Larsen, P.G., Fitzgerald, J., Woodcock, J. and Peleska, J., 2015. Systems of systems engineering: basic concepts, model-based techniques, and research directions. ACM Computing Surveys (CSUR), 48(2), pp.1-41.

75. Noyes, J., Cook, M. and Masakowski, Y. eds., 2012. Decision making in complex environments. Ashgate Publishing, Ltd..

76. Pandey, 2013, "Decision Based Design" Taylor and Francis, Boca Raton, Florids USA, 284 pages.

77. Pandey, V., Murthy, S.V. and Corona, S.N., 2022. Work alone then meet: Cognitive attributes and team interaction in engineering design using evolutionary algorithms. Applied Soft Computing, p.108989.

78. Pandey, V., Slon, C., Deschenes, L., Gorsich, D. and Jayakumar, P., 2020. A Decision Based Mobility Model for Semi and Fully Autonomous Vehicles. SAE International Journal of Advances and Current Practices in Mobility, 2(2020-01-0747), pp.2640-2649.

79. Pandey, V. and Mourelatos, Z.P., 2012, August. Evolutionary System Topology Identification and its Application in Product Reuse. In International Design Engineering Technical Conferences and Computers and Information in Engineering Conference (Vol. 45042, pp. 687-701). American Society of Mechanical Engineers.

80. Papalambros, P.Y. and Wilde, D.J., 2017. Principles of Optimal Design, Cambridge Univ.

81. Pavlopoulos, G.A., Secrier, M., Moschopoulos, C.N., Soldatos, T.G., Kossida, S., Aerts, J., Schneider, R. and Bagos, P.G., 2011. Using graph theory to analyze biological networks. BioData mining, 4, pp.1-27.

82. Paulus, P.B., 2024. Fostering creativity in groups and teams. In Handbook of organizational creativity (pp. 165-188). Psychology Press.

83. Pira, E., 2021. Using Markov chain based estimation of distribution algorithm for model-based safety analysis of graph transformation. Journal of Computer Science and Technology, 36(4), pp.839-855.

84. Rao, S.S., 2019. Engineering optimization: theory and practice. John Wiley & Sons.

85. Rao, A.S.S., 2020. Population network structures, graph theory, algorithms to match subgraphs may lead to better clustering of households and communities in epidemiological studies. Epidemiology & Infection, 148, p.e10.

86. Raza, A., Deen, K.M., Jaafreh, R., Hamad, K., Haider, A. and Haider, W., 2022. Incorporation of machine learning in additive manufacturing: a review. The International Journal of Advanced Manufacturing Technology, 122(3), pp.1143-1166.

87. Renzi, C., Leali, F. and Di Angelo, L., 2017. A review on decision-making methods in engineering design for the automotive industry. Journal of Engineering Design, 28(2), pp.118-143.

88. Sah, P., Singh, L.O., Clauset, A. and Bansal, S., 2014. Exploring community structure in biological networks with random graphs. BMC bioinformatics, 15, pp.1-14.

89. Scott, S.K., 2004. Measuring the performance of teams formulated according to problem solving style among undergraduate students. Indiana State University.

90. Shao, C., Zhang, Z.J., Ye, X., Zhao, Y.J. and Sun, H.C., 2018. Modular design and optimization for intelligent assembly system. *Procedia Cirp*, *76*, pp.67-72.

91. Simpson, T.W., 2004. Product platform design and customization: Status and promise. Ai Edam, 18(1), pp.3-20.

92. Singer, D.J., Doerry, N. and Buckley, M.E., 2009. What is set-based design?. Naval Engineers Journal, 121(4), pp.31-43.

93. Spielman, D.A., 2007, October. Spectral graph theory and its applications. In 48th Annual IEEE Symposium on Foundations of Computer Science (FOCS'07) (pp. 29-38). IEEE.

94. Stambaugh, T., Mofield, E. and Kennedy, J.F., 2021. We Choose to Go to the Moon. In Space, Structure, and Story (pp. 128-136). Routledge.

95. Tamura, H., Nakano, K., Sengoku, M. and Shinoda, S., 2011. On applications of graph/network theory to problems in communication systems. ECTI Transactions on Computer and Information Technology (ECTI-CIT), 5(1), pp.15-21.

96. Tohidi, H., Namdari, A., Keyser, T. K., & Drzymalski, J. “Information sharing systems and teamwork between sub-teams: A Mathematical Modeling Perspective”. *Journal of Industrial Engineering International* Vol. 13 (2017): pp. 513 – 520.

97. Toche, B., Pellerin, R. and Fortin, C., 2020. Set-based design: a review and new directions. Design Science, 6, p.e18.

98. Ulrich, K. and Eppinger, S., 2011. *Product Design and Development*. McGraw Hill.

99. van Diggele, C., Roberts, C. and Lane, S., 2022. Leadership behaviours in interprofessional student teamwork. *BMC Medical Education*, *22*(1), p.834.

100. Van Der Hofstad, R., 2014. Random graphs and complex networks. vol. I.

101. Wagner, S. and Wang, H., 2018. Introduction to chemical graph theory. Chapman and Hall/CRC.

102. Wagner, S.M. and Neshat, N., 2010. Assessing the vulnerability of supply chains using graph theory. International journal of production economics, 126(1), pp.121-129.

103. Wasserman, S., & Faust, K. (1994). *Social Network Analysis: Methods and Applications.* Cambridge University Press.

104. Watts, D.J. and Strogatz, S.H., 1998. Collective dynamics of ‘small-world’ networks. nature, 393(6684), pp.440-442.

105. Webster, M., 2014. Merriam webster online. Merriam-Webster Incorporated, 556.

106. Westli, H. K., Johnsen, B. H., Eid, J., Rasten, I., & Brattebø, G. “Teamwork skills, shared mental models, and performance in simulated trauma teams: An independent group design”. *Scandinavian Journal of Trauma, Resuscitation and Emergency Medicine* Vol. 18 No. 47 (2010).

107. Wendell, K.B., Wright, C.G. and Paugh, P., 2017. Reflective decision-making in elementary students' engineering design. Journal of Engineering Education, 106(3), pp.356-397.

108. Wilson, J.J., Bechler-Speicher, M. and Veličković, P., 2024. Cayley graph propagation. *arXiv preprint arXiv:2410.03424*.

109. Wilson, R., Watkins, J.J. and Parks, D.J., 2023. Graph theory in America: the first hundred years. Princeton University Press.

110. Wolsey, L.A., 2020. Integer programming. John Wiley & Sons. 336 pp.

111. Wymore, A.W., 2018. Model-based systems engineering. CRC press.710 pp.

112. Wynn, D.C. and Eckert, C.M., 2017. Perspectives on iteration in design and development. Research in Engineering Design, 28, pp.153-184.

APPENDIX

Table A1. Centrality values associated with different nodes in the graph used for analysis in Chapter 4 (unconnected components were removed).

Node Number	Degree	Betweenness	Closeness	Pagerank	Eigenvector
1	5	1194	0.00389	0.02901	0.03101
2	10	2027	0.00452	0.05584	0.08259
3	12	1940	0.00444	0.06800	0.10310
4	7	1080	0.00332	0.03990	0.01413
5	4	225	0.00344	0.02528	0.02648
6	1	0	0.00272	0.00729	0.00681
7	4	225	0.00344	0.02528	0.02648
8	3	224	0.00270	0.01888	0.00421
9	5	641	0.00353	0.02947	0.03727
10	2	76	0.00267	0.01316	0.00389
11	4	297	0.00346	0.02476	0.02663
12	1	0	0.00279	0.00694	0.00958
13	3	224	0.00270	0.01888	0.00421
14	6	1003	0.00369	0.03450	0.04087
15	3	496	0.00300	0.01814	0.01235
16	4	368	0.00251	0.02502	0.00401
17	2	76	0.00225	0.01394	0.00116
18	1	0	0.00244	0.00706	0.00317
19	2	76	0.00339	0.01301	0.02273
20	2	76	0.00290	0.01323	0.01125
21	1	0	0.00272	0.00729	0.00681
22	1	0	0.00337	0.00668	0.02123
23	2	76	0.00225	0.01394	0.00116
24	1	0	0.00337	0.00668	0.02123

Node Number	Degree	Betweenness	Closeness	Pagerank	Eigenvector
25	2	76	0.00275	0.01380	0.00733
26	1	0	0.00337	0.00668	0.02123
27	1	0	0.00332	0.00673	0.02650
28	2	76	0.00211	0.01390	0.00110
29	1	0	0.00332	0.00673	0.02650
30	1	0	0.00272	0.00729	0.00681
31	3	151	0.00282	0.01970	0.01104
32	1	0	0.00274	0.00718	0.00685
33	1	0	0.00332	0.00673	0.02650
34	2	150	0.00292	0.01280	0.01130
35	1	0	0.00232	0.00750	0.00284
36	2	76	0.00211	0.01390	0.00110
37	1	0	0.00272	0.00729	0.00681
38	1	0	0.00222	0.00751	0.00100
39	3	151	0.00282	0.01970	0.01104
40	1	0	0.00332	0.00673	0.02650
41	1	0	0.00270	0.00745	0.00584
42	1	0	0.00224	0.00727	0.00108
43	1	0	0.00332	0.00673	0.02650
44	1	0	0.00274	0.00718	0.00685
45	1	0	0.00288	0.00682	0.01051
46	2	76	0.00280	0.01343	0.01026
47	1	0	0.00332	0.00673	0.02650
48	1	0	0.00337	0.00668	0.02123
49	2	76	0.00267	0.01316	0.00389
50	1	0	0.00211	0.00724	0.00103
51	1	0	0.00231	0.00762	0.00264

Node Number	Degree	Betweenness	Closeness	Pagerank	Eigenvector
52	1	0	0.00182	0.00783	0.00028
53	1	0	0.00300	0.00685	0.00797
54	1	0	0.00182	0.00783	0.00028
55	1	0	0.00332	0.00673	0.02650
56	1	0	0.00272	0.00729	0.00681
57	1	0	0.00300	0.00685	0.00797
58	1	0	0.00192	0.00785	0.00030
59	2	76	0.00240	0.01408	0.00311
60	2	76	0.00334	0.01310	0.02837
61	1	0	0.00238	0.00754	0.00289
62	1	0	0.00288	0.00682	0.01051
63	1	0	0.00192	0.00785	0.00030
64	2	76	0.00267	0.01316	0.00389
65	2	76	0.00267	0.01316	0.00389
66	1	0	0.00267	0.00750	0.00729
67	1	0	0.00228	0.00779	0.00188
68	1	0	0.00332	0.00673	0.02650
69	1	0	0.00203	0.00791	0.00080
70	1	0	0.00222	0.00751	0.00100
71	1	0	0.00232	0.00750	0.00284
72	1	0	0.00232	0.00750	0.00284
73	1	0	0.00272	0.00729	0.00681
74	1	0	0.00222	0.00751	0.00100
75	1	0	0.00232	0.00750	0.00284
76	1	0	0.00300	0.00685	0.00797
77	1	0	0.00224	0.00727	0.00108
78	1	0	0.00222	0.00751	0.00100