AN ABSTRACT OF THE DISSERTATION OF

Joseph R. Piacenza III for the degree of Doctor of Philosophy in Mechanical Engineering presented on May 27, 2014.

Title: Design of Robust Infrastructure Systems Incorporating User Behavior.

Abstract approved:

Irem Y. Tumer Christopher J. Hoyle

Infrastructure systems are a critical component supporting today's modern society. From power grids to traffic networks, we rely on these systems to perform as intended, despite the various sources of uncertainty present in their operation. Designing for system robustness can help mitigate the impact of failures caused by unexpected events. However, this poses a challenge as the distributed topology and complex heterogeneous nature of infrastructure systems causes unanticipated behavior when subjected to a single failure event. In addition, infrastructure systems often require multiple individuals (i.e., humans) to control nominal operation, as well as minimize performance loss due to failures. This human in-the-loop system interaction further increases complexity when designing these systems. This dissertation presents a concept-stage framework for robust infrastructure system design that explores emergent behavior due to network topology, subsystem interactions, and the impact of human behavior driving these interactions. Motivated by historical failures in the North American Power Grid, several case studies are presented that illustrate the methods. First, subsystem/system interactions are

modeled by examining user preferences for sustainable building designs, capturing how energy conservation mandates influence system-level robustness. Next, system topology is optimized, which minimizes performance losses from cascading failures, expanding the model. Finally, the impact of human decision-making within an infrastructure system is incorporated, to further increase robustness. In summary, this research demonstrates a concept-stage design framework for creating robust infrastructure systems by minimizing performance variability due to uncertain events and user behavior.

Design of Robust Infrastructure Systems Incorporating User Behavior

by

Joseph R. Piacenza III

A DISSERTATION

submitted to

Oregon State University

in partial fulfillment of

the requirements for the

degree of

Doctor of Philosophy

Presented May 27, 2014

Commencement June 2014

Doctor of Philosophy dissertation of Joseph R. Piacenza III presented on May 27, 2014

APPROVED:

Co-Major Professor, representing Mechanical Engineering

Co-Major Professor, representing Mechanical Engineering

Head of the School of Mechanical, Industrial, and Manufacturing Engineering

Dean of the Graduate School

I understand that my dissertation will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my dissertation to any reader upon request.

Joseph R. Piacenza III, Author

ACKNOWLEDGEMENTS

I express my sincere appreciation to my Ph.D. advisor, Dr. Irem Tumer, for her guidance, research vision, and career inspiration during my four years here at Oregon State University. She has been an excellent advisor, and I am especially grateful for the opportunity to work in her lab after being away from academia for several years. I would also like to thank my co-advisor, Dr. Christopher Hoyle, for his ongoing technical insights, in addition to the exposure he provided to unique research opportunities and computational methods. My graduate school experience was well rounded as a result of having two primary advisors, and each motivated me to also pursue an academic career.

I would like to thank all of the members (past and present) of the *Design Engineering Lab* for their valuable research feedback and support, including Ryan Arlit, Brady Gilchrist, Brandon, Haley, David Jensen, Matthew McIntire, Hoda Mehrpouyan, Bryan O'Halloran, Sarah Oman, and Douglas Van Bossuyt. I also owe a special thanks to my manuscript co-authors, especially Mir Abbas Bozorgirad, John Fields, and Eduardo Cotilla-Sanchez, who made Chapters 4-5 possible. I would like to acknowledge professors Matthew Campbell, Bryony DuPont, Karl Haapala, Robert Stone, and David Ullman, who were all great collaborators, and provided me exposure to a wide breadth of research and teaching styles.

I would like to thank my family and friends for their continued support and ongoing encouragement to pursue my goals. Finally I want to give a special thanks to my wife, Susie, my newborn son, Fletcher, my sister, Teresa, and my friend (and brother-in-law), Matt, for their continued academic inspiration. I couldn’t have done it otherwise.

CONTRIBUTION OF AUTHORS

Irem Tumer and Christopher Hoyle provided the majority of the research vision/guidance and editing assistance throughout this dissertation. The work in Chapter 4 was conceptualized and written in collaboration with John Fields and Christopher Hoyle, with a large portion of data collection and organization also performed by John Fields. Chapter 5 was written in collaboration with Mir Abbas Bozorgirad, Christopher Hoyle, and Irem Tumer. The method presented in this chapter was developed through the interdisciplinary efforts of Mir Abbas Bozorgirad and Christopher Hoyle. Chapter 5 was another interdisciplinary collaboration with Mir Abbas Bozorgirad, Christopher Hoyle, Eduardo Cotilla-Sanchez, and Irem Tumer. Eduardo Cotilla-Sanchez provided key power systems specific insight on this research.

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CHAPTER 1: INTRODUCTION

1.1 Overview

This dissertation presents a concept-stage framework for infrastructure system design that explores emergent behavior due to subsystem interactions, and the impact of "human in-the-loop" behavior driving these interactions. Because of the heterogeneous topology inherent in infrastructure systems, a single initiating failure event can propagate throughout the network uncontrollably, resulting in either severely degraded performance or complete failure. This issue is addressed directly by exploring a robust design strategy to mitigate performance reduction due to cascading failure. Current literature identifies two distinct paths for considering cascading system failure: network analysis and physics based modeling. However, each approach has limitations in the infrastructure systems domain. Network analysis performance metrics (e.g., node degree, centrality measures) can be too far abstracted from the systems they represent to accurately predict behavior. Conversely, physics based models rely on calculations from component level interactions, which may be infeasible to represent when addressing scalability. *Specifically, there is a gap in concept-stage infrastructure system design for capturing elements of both network analysis and physics based modeling, which allows flexibility across multiple domains.* This research presents several case studies motivated by historical reliability issues with the North American power grid (NAPG). However, the applications of the framework developed extend beyond the test cases applied, and are intended to explore other infrastructure system objectives.

1.2 Dissertation Organization

This dissertation is presented in accordance with the Manuscript Document Format option. It is organized into a number of chapters; three of which the manuscripts have been submitted as journal articles. Chapter 2 provides a broad background of the literature relating to the framework developed, which includes highlights such as cascading failures and optimization of complex systems, robust design, and human in-the-loop design. Chapter 4 was submitted to the *Journal of Energy and Buildings* in April 2014 and introduces *user preferences for sustainable building design*. Chapter 5 outlines a *robust optimization strategy for infrastructure system design* and was submitted to the *Journal of Mechanical Design* in December 2014. Chapter 6 evaluates the *impact of human in-the-loop decision-making in robust design* and was submitted to the *IEEE Transactions on Power Systems* in May 2014. Finally, the dissertation's collective conclusion is discussed in Chapter 7, along with future work pertaining to each journal article submission.

1.3 Intellectual Merit

The focus of this research is to create a concept-stage framework that links together several key attributes of infrastructure system design including topology, human interaction, and robustness. The Intellectual Merit is to formalize a hybrid approach that integrates robust design techniques with system specific network analysis to enable novel design strategies for robustness in infrastructure systems. This approach characterizes robustness as the ability of a system to operate in a degraded state, minimizing resultant performance variability due to cascading failure effects. The research presented aims to quantify the impact of operator (i.e., human) decision making at both the subsystem and system level. This outcome is achieved by examining both post occupancy energy usage in commercial buildings (i.e. subsystem level), and operator control decisions during a failure event (i.e., system level). This dissertation provides a framework for concept-stage complex infrastructure design decisions by identifying critical trade offs between network topology, system robustness, and operator influence.

1.4 Broader Impacts

The Broader Impact of this dissertation includes the addition of novel strategies for designing and optimizing infrastructure systems, which are applicable across multiple domains. Promoting system robustness by mitigating performance variability after a cascading failure could provide a significant advantage over existing methods during the early design phase. Incorporating robustness as a design objective will increase the knowledge of a system's invariability to uncertain failure events, and allow designers to make informed decisions that extend beyond cost. In addition, the case studies presented provide a rich environment for collaboration opportunities because of the large breadth of current research topics in the field of concept-stage system design. This collaboration will further refine the framework presented, drawing from various interdisciplinary backgrounds. Speaking to the case studies presented, the framework developed will aid in the design of reliable power grid networks, specifically when designing topology to meet the needs of an increasingly distributed society. The success of this research will also benefit a combination of regional and national electrical utility providers, as well as the various stakeholders affected by sustainable building mandates.

1.5 Motivation

The framework presented in this dissertation is motivated by the overarching challenge of understanding, and subsequently designing infrastructure systems. Catastrophic failures such as the Blackout of 2003 and the Deepwater Horizon disaster of 2010 highlight their vulnerability, and support the need for research of high-level system interactions and design strategies to mitigate failure events. This is of particular interest in early design, as infrastructure systems are often operated near maximum capacity. For example, data provided by the North American Electric Reliability Council (NERC) shows that the frequency of large-scale propagating blackouts in the North American Power Grid (NAPG) has not decreased over the past 25 years [1, 2]. In addition, both of these case studies illustrate the consequences of cascading failures due to operator (i.e., human) decisions made during an emergency failure event [3, 4]. In the Deepwater Horizon case, the National Commission on the BP Deepwater Horizon Oil Spill and Offshore Drilling report acknowledges a combination of cascading mechanical, electrical, and decision based failures ultimately leading to the oil rig explosion [5]. This research illustrates progress toward an end goal of understanding concept-stage design trade offs between complex system performance, robustness, and the impact of human in-the-loop interactions.

1.6 Nomenclature and Terminology

Domain specific nomenclature and technical terms are used repeatedly throughout this research, and are presented in the context of infrastructure system design. Additionally, related terms often used in other system engineering domains (e.g., failure resilience, failure resistance) are included for completeness. While some definitions may vary in different contexts, these terms will be used as defined in Table 1.1 and 1.2 throughout the dissertation.

Table 1.1 Relevant terminologies used throughout this work

Term	**Definition**
Complex System	A system composed of multiple, interacting subsystems.
Complex Infrastructure System	A complex system characterized by its distributed topology.
Degraded System	A system operating successfully at a reduced performance level.
Emergent Behavior	Behavior that exists when multiple different behaviors interact with one another.
Failure Event	A single unintended failure within a system.
Failure Resilience	The ability of a system to recover to the original intended operation after a failure.
Failure Resistance	A system that can operate in a degraded state, but not recover from a failure
Human In-the-Loop	Human interaction required to operate a system.
Model	The representation of key behaviors or functions of an abstract system.
Operator	A required human component of a complex system whose actions can influence emergent system behavior.
Reliability	The probability of a system to perform as intended.
Robustness	A system’s invariability to uncertain failure events.
Simulation	The imitation of the operation of a real-world process or system over time.

Table 1.2 Nomenclature used throughout this work

C_L	network performance
n_G	number of generation nodes
n_D	number of demand nodes
n_G^i	number of generation units able to supply flow to distribution vertex
E	average network path efficiency
G	interaction matrix
ϵ_{ij}	network path efficiency
i	row node in an adjacency matrix
j	column node in an adjacency matrix
N	number of elements in a specific row or column of an adjacency matrix
e_{ij}	value of an adjacency matrix element
N_g	number of generation nodes
N_d	number of demand populations
C_{Tot}	transmission line cost
A	adjacency matrix
L_{ij}	unit length between all pairs of nodes
$C_{N\times N}^{Length}$	cost per unit length
L_{Load}	amount of power flowing through an arc

D_i	demand that has to be satisfied by the shortest path i
L_{Cap}	maximum power that can flow through an individual arc
α	arc factor of safety
D_f	resultant demand that is satisfied after a failure has occurred
D_E	average of resultant demand values that are satisfied after a failure has occurred
$L_{Load}\ (t)$	initial arc load at a given time t
t	instantaneous time associated with an arc load
N_{Comp}	number of disconnected components of a network
$\sigma_{D_E}^2$	expected demand variance
Obj_n	objective function value
$IEEE14_n$	objective value from the original IEEE 14 test bus
PF_{conn}	penalty function for disconnectivity
P	probability a solution will be selected for the continuation of the simulated annealing algorithm
A_x	initial adjacency matrix in simulated annealing algorithm
A_y	solution obtained by perturbing the adjacency matrix A_x
N_{SA}	number of objective functions in simulated annealing algorithm
T	temperature at each iteration of the simulated annealing algorithm
$C_{N\times N}^{Int\_Length}$	cost of interconnection arc

CHAPTER 2: LITERATURE REVIEW AND RELATED WORK

This chapter presents a general overview of existing literature pertinent to the three elements of the Design Framework developed for this dissertation (Figure 2.1). This framework will expand the knowledge base of infrastructure system design, considering interactions over a large breadth of system and subsystems components. Much of this information is repeated in upcoming chapters in order to keep the manuscripts as close to the original, submitted copy of the journal articles. The information is included here for completeness and ease of reference.

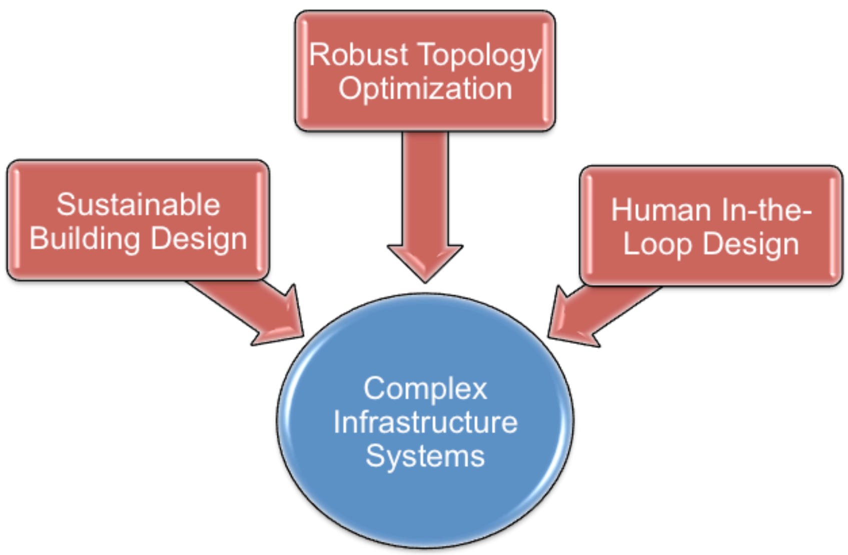

Figure 2.1: Elements of literature review

2.1 Sustainable Building Design

As building standards such as LEED become more complex, designers must explore a greater breadth of feasible solutions for meeting these requirements. In addition to LEED, more complex certifications such as the Living Building Challenge (LBC) have additional requirements such as net-zero energy and water [6]. To achieve a net-zero requirement, each building subsystem (e.g., energy collection, water collection, and heating, ventilation, air conditioning (HVAC)), as well as their interactions, must be considered [7]. By shifting the traditional architectural building design paradigm from a top-down approach to an integrated approach, these system interactions can be better evaluated and subsequently optimized. This integrated optimal design methodology is often found in aerospace, automobile, and other complex systems [8-10].

Current literature shows various techniques that have been explored to achieve optimized solutions for complete building designs. Geyer proposed a methodology using multidisciplinary grammars to optimize building components by linking qualitative design characteristics with a quantitative analysis [11, 12]. Wang et al. use a genetic algorithm to determine floor shape in buildings for optimizing envelope-related design variables such as window-to-wall ratios and shading, which were then linked to life-cycle cost measures [13, 14]. Christensen et al. examine a component selection driven process where minimum required values are calculated to achieve net-zero energy such as insulation, glass type, and foundation insulation [15]. This type of multi-objective optimization approach can lead to a wide selection of feasible designs [16]. A sensitivity analysis by Heiselberg et al. showed that HVAC systems are the primary energy consumers in sustainable buildings, with lighting having the next greatest effect [17].

Beyond building mechanical system optimization, there have been various research paths exploring the social, economic, and environmental effects of sustainable building design. For example, the five categories for sustainable design outlined to achieve LEED certification include *Sustainable Sites, Water Efficiency, Energy and Atmosphere,* *Material and Resources,* and *Indoor Environmental Quality* (IEQ). These categories are highly quantifiable, with the exception of *IEQ*, which contains subjective attributes such as interior lighting, presence of sunlight, and thermal comfort [18]. During the schematic design of the Oregon Sustainability Center (OSC), user preferences and building interactions were considered for quantification of energy consumption [7, 19]. Building users are playing a more prominent role in modern building design as literature has shown measurable effects on individuals' well-being, productivity, and creativity as a result of their indoor environment [20-22]. Reinhart et al. have examined differences in static versus dynamic daylight performance metrics using existing several daylight simulation programs, but do not arrive at a clear metric to quantify these effects [23]. Similar research using Sensor Placement Optimization Tool (SPOT) software was used to create discrete building geometries to achieve energy efficient building designs, although quality of daylight designs do not involve the building user [24].

One concern not typically addressed in sustainable building design when designing for IEQ is user productivity. Literature shows employee performance is tied to various metrics, including their response to indoor environments such as temperature and lighting. For example, Jensen et al. examine a Bayesian Network approach to comparing various effects of thermal environment on the mental performance of office workers, suggesting employee performance is increased with thermal sensation, or how an individual feels with respect to his or her environment [25]. Positive effects of natural lighting in the workplace have also been linked to various performance metrics such as well-being, ability to perform, motivation, job satisfaction, and technical competence [26]. While this correlation has been assumed for some time, Juslén has quantified these metrics by conducting field studies on lighting preferences in the industrial workplace and employee productivity [27, 28]. This research outlined a productivity unit increase based on workplace metrics associated with lighting relationships including visual performance, visual comfort, visual ambience, and job satisfaction. In an effort to quantify productivity in terms of financial gain for an organization, Hunter and Schmidt developed a utility function including reduced labor costs and overhead [29].

2.2 User Preferences for Indoor Environmental Quality

Individuals can be affected by their indoor environment, responding to changes in lighting, temperature, and workspace geometry [25, 26]. LEED has recognized this importance by awarding 17 points (out of 100 possible) to their metric for *Indoor Environmental Quality* (IEQ) [30]. LEED's IEQ includes several indoor design attributes including amount of lighting, temperature, air quality, and aesthetic design.

A survey of existing literature shows a long history of positive effects of lighting on individuals in different workplace environments [31, 32]. Romm and Browning presented several case studies where increased lighting in an existing workspace resulted in lower absenteeism, lower productions errors, and higher productivity [33]. This work also reported on new construction buildings, including a Lockheed facility claiming 15% rise in production, and 15% decrease in absenteeism due to architectural natural lighting features throughout the building. Research by Day et al. relate the attributes of building lighting design, in terms of natural lighting, to user satisfaction, health, and occupancy [34]. Hua et al. examine post-occupancy response to lighting conditions in a LEED Gold certified laboratory building [35]. This research combined illuminance measurements on work plane surfaces with rating surveys of long-term occupants, to determine overall user satisfaction of the building.

Related research has explored user preferences based on product attributes, as well as sociodemographic groups. This is done through human appraisal experiments, designed using a Design of Experiments (DOE) methodology. These methods have been refined over several decades by statisticians, and have recently been refined to include specific methods for preference modeling [36, 37]. Chen et al. outlined a method to observe the effect of differing values, of a factor, or user-based attributes, on a response variable [38]. For example, multiple design alternatives can be presented to a customer or product user, and a corresponding rating response can be chosen, ultimately resulting in a single design preference. Individual factor levels and combinations (or interactions) are then identified which will define a design alternative. Hoyle et al. provide a case study of this method, using human appraisal data for automobile seating ergonomics [39]. In this work, both Blocked and Split-Plot statistical analysis are used to capture significant attributes of customer design preferences [40]. Based on the significant factors, a predictive model for customer seating preferences is created, and compared to the actual preference data collected.

2.3 Latent Variable Modeling for System Design

In order to accurately quantify a subjective quantity such as IEQ, latent variable modeling can be used. The term *latent variable* refers to a variable that cannot be observed directly, but is a function of other related variables that are more easily quantified. Previous work by Everitt and Loehlin identifies the ability to capture an individual's attitude toward a specific design through the use of a psychometric survey [41, 42]. Chen et al. have further developed this work, outlining a method identifying user preference indicators, based on specific product attributes [38]. In this work, a case study is presented based on data from J.D. Power's Vehicle Quality Survey, where consumer attitudes on various automobiles were collected, and presented as examples of preference indicators regarding specific vehicle attributes. This methodology can be extended to understand building users' workspace preferences, based on attributes of existing LEED certified buildings.

In the context of sustainable building design, product (building) attributes will be defined as characteristics of the indoor building environment (e.g., temperature, number of windows, workspace geometry). These indicators define an individual's attitude or preference toward design characteristics present in LEED designs or architecture. The latent variables can then used to capture these preferences, quantifying a variable that is typically unobservable. Figure 2.2 displays the latent variable model as it pertains to building indoor environment.

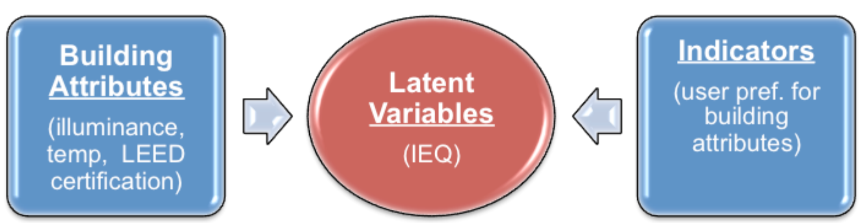

Figure 2.2: Latent variable model for sustainable building design case study

2.4 Robust Design

While there are many methods contributing to failure propagation and reliability in complex systems, these approaches are typically hardware driven and do not address the formalized concept of robustness, and how infrastructure systems can be designed for invariability to uncertain failure events [43-51]. In addition, it is difficult to scale component level failure propagation methods to represent large and distributed networks in terms of computational efficiency. In the context of this research, robust design is defined as the insensitivity to failure due to uncertain events from both internal and external sources [52].

Historically, robust design has been used in manufacturing to minimize unintended consequences (variability) from uncontrollable environmental effects [53]. Expanding on Taguchi's fundamental methods [53], Chang et al. have scaled these principles to complex systems where multiple subsystems must be optimized independently with limited knowledge of other system design parameters [54]. This work outlines the need for an optimization approach accounting for system-level physical and intangible noises that are out of the designer's control. Robust design provides a strategy for designing systems robust to uncertain events, without the need to understand or reduce these events.

The primary issue, however, is creating designs that are robust to the various types of failures and uncertainty present in complex and largely distributed systems. Many system failures occur as a result of external occurrences such as extreme weather conditions, and predicting the effects of these events is challenging, specifically due to cascading failures resulting from a single initiating event. Examining the system topology as a means of increasing design robustness builds on existing approaches, expanding current methods into infrastructure systems, discussed next.

2.5 Network Theory and Topological Graph Models

Based on the distributed nature of many complex infrastructure systems, understanding topological effects is important when designing for system robustness. Current literature addresses the importance of considering topology in network analysis, often drawing from social network theory where networks are represented mathematically, often with an adjacency matrix [55-57]. To address network relationships, several performance indices are studied in the literature, which can be primarily categorized into three major classes: reachability measures, vitality measures, and flow measures. For example, Kinney et al. model a power grid network with an adjacency matrix, where each node represents either a generation or demand component in a network, and arcs connecting the nodes represent connectivity [57]. In this work, failures are examined by removal of a single node, which triggers an overload cascade in the network. Similar methods are used by Leonardo and Vemuru, where connectivity loss $\mathrm{C_L}$, measures network performance [58]:

$$C_L = 1 - \frac{1}{\mathrm{n_D}} \sum_{\mathrm{i}}^{\mathrm{n_D}} \frac{\mathrm{n_G^i}}{\mathrm{n_G}} \tag{2.1}$$

where $\mathrm{n_G}$ is the number of generation nodes, $\mathrm{n_D}$ is the number of demand nodes at the unperturbed network state, and $\mathrm{n_G^i}$ is the number of generation units able to supply flow to distribution (demand) vertex i after disruptions take place. Subsequent averaging is done over every demand node i of the network.

Another method by Ash and Newth examines the optimization of complex networks with respect to the average efficiency of the network [59]. Average efficiency (E) was first introduced by Crucitti et al. and is among the vitality measures, and can be calculated as follows [60]:

$$E(G) = \frac{1}{N(N-1)} \sum_{i \neq j \in G} \epsilon_{ij} \tag{2.2}$$

where ϵ_{ij} denotes the efficiency of the most efficient path between i and j. In this definition, the undirected graph (G) is an $N \times N$ adjacency matrix of (e_{ij}), where $0 < e_{ij} \leq 1$ if there is an arc between node i and node j, otherwise $e_{ij} = 0$.

While these types of topological measures provide valuable information about a specific network, it is important to recognize that these mathematical models are abstractions of infrastructure systems, and may result in misleading information. Hines et al. have explored this issue, comparatively evaluating topological metrics within the same system to predict failure magnitudes in standard test cases [56]. Their work concluded that while exclusively using topological measures can provide general information about a system's reliability, they can be misleading due to the level of abstraction and should be used in conjunction with a physics-based model.

2.6 Human In-the-Loop Considerations for Infrastructure System Design

Minimizing the impact of cascading failure within an infrastructure system is of particular interest, as the distributed topology makes these systems highly vulnerable to propagating failures stemming from a single initiating event. The Blackout of 2003 highlights this vulnerability, where over 45 million people in the Northeast U.S. and Canada lost power due to uncontrollable cascading outages [4, 61]. Beyond hardware and software failures, communication deficiencies between regions was a contributing factor in the Blackout [1, 62]. Since the cascading outage took place over approximately 7 hours, independent regions struggled to obtain operational information from adjacent utilities, forcing system operators to make poor, uninformed decisions to protect their local network. Typical power system protection practices to avoid cascading can include load shedding or intentional islanding [63]. This lack of a comprehensive communication system throughout the NAPG interconnections is primarily a function of federal deregulation policies [64]. From an engineering design perspective, considering the impact of "human in-the-loop" decision making within an existing network could potentially mitigate the system level impact of cascading failure.

The Deepwater Horizon disaster of 2010 also illustrates the consequences of cascading failures due to operator decisions made during an emergency failure event [3]. While news media publications primarily focused on the system's shear ram barrier as the primary source of failure, the National Commission on the BP Deepwater Horizon Oil Spill and Offshore Drilling report acknowledges a combination of cascading mechanical, electrical, and decision based failures ultimately leading to the oil rig explosion [5]. Venkatasubramanian also examines the Deepwater Horizon incident, and addresses the broader perspective of the potential fragility of all complex engineered systems, empathizing the need to understand the commonalities and differences in these types of failures, in order to better design and control such systems in the future [65].

While many cascading system failures begin as a result of external occurrences such as extreme environmental conditions (e.g., excessive well bore pressure on the Deepwater Horizon, above normal summer temperature in the Northeast U.S.), case studies show that human in-the-loop decision-making has the potential to affect the resultant system outcome [66]. The overarching challenge of infrastructure system design is to understand system level interactions, and how an agent (or set of agents) can impact the subsequent emergent system behavior.

Watt's examines this concept from a sociology perspective, citing parallels to engineered systems [67]. In this work, he postulates that individuals in a population exhibit herd-like behavior because they are making decisions based on the actions of other individuals rather than relying on their own information about the problem. This is a concern in agent based control strategies for complex systems, as agents must make decisions based on information about both their local and global network. Hines and Talukdar examine this relationship by developing a method to create a social network of autonomous agents to solve a global control problem with limited communication abilities [68]. This approach uses distributed model predictive control and cooperation to minimize cascading failure in an IEEE test bus. However, it requires an agent to be present at each location (i.e., node) of the system. This solution is not economically efficient, or even possible in many infrastructure systems. Other approaches also draw from social network analysis, where reliability indicators rely heavily on high-level system abstractions [45, 55, 69].

Alternatively, decision based design strategies have also been examined for estimating agent decision-making behavior in complex systems. Sha and Panchal have explored this concept comparing the benefits between generalized preferential attachment, a statistical regression-based approach, and multinomial-logit choice modeling [70]. Both multinomial and nested logit models have been used extensively to predict individual's decisions in a variety of domains including sociology, economics, and civil engineering (e.g., traffic networks) [71]. The barrier to using these methods in early design is the reliance on historical behavior required to generate a utility function capable of predicting behavior.

CHAPTER 3: DISSERTATION OBJECTIVES

The three primary research objectives contributing to the Dissertation Framework are identified in this chapter. The journal manuscripts presented in subsequent chapters meet these objectives.

3.1 Capturing User Preferences for Sustainable Building Design

The first research objective is to understand the demand population (i.e., human) impact on a case study of the North American Power Grid (NAPG), and examined this interaction at the subsystem level. This is achieved by exploring specific design strategies for sustainable building mandates, in an effort to understand user preferences for these designs. The economic, environmental, and social impacts of these strategies are addressed in terms of understanding user preferences for specific building attributes. This research will help bridge the gap between design optimization objectives (e.g., energy conservation) at the system level, and user preferences for sustainable building designs at the subsystem level which could contribute to these objectives. By understanding the trade offs between user preferences, sustainable building mandates, and post occupancy behavior, designers can create repeatable designs that impact system level optimization objectives. A structural equation model (SEM) is used to estimate causal relations between the sustainable building attributes and stated/revealed preferences that drive user behavior. This objective contributes to the understanding of post occupancy user preferences for sustainable building design strategies, as well as their impact on high-level power system optimization objectives.

3.2 Formulate a Robust Topology Optimization Approach for Complex Infrastructure System Design

This objective focuses on mitigating the impact of cascading failure in infrastructure systems, creating robust designs. This work integrates robust topology optimization with network analysis in order to minimize system performance losses due failure propagation stemming from a single initiating event. This novel approach presents design trade offs between performance and performance variability (i.e., robustness) of a degraded complex system, *after* failure has occurred. Using this method, infrastructure system designs can be created that account for uncertain failure events (e.g., natural disasters) often affecting highly distributed networks. Specifically, this research incorporates system specific stochastic failures, and recognizes the importance of a system to meet minimum acceptable performance requirements in a degraded capacity. From a theoretical perspective, the impact of this objective is to provide an understanding of how topological network configurations influence system performance after a cascading failure.

3.3 Evaluate the Impact of Human In-the-Loop Decision Making in Robust Design

This objective is critical when designing infrastructure systems as operators (i.e., humans) can inadvertently make decisions during a cascading failure event that negatively impacts the resulting system performance. Topology constraints and design solutions from *Objective 3.2* are used as a building block to identify critical locations for system operators, as well their domain specific control strategies. This work will consider the stochastic nature of human decision-making within an infrastructure system, and provide insight to how these decisions can affect performance losses due to uncontrollable cascading. From a theoretical perspective, the impact of this objective is to provide an evaluation of how to create robust designs that account for internal human decisions intended to control emergent system behavior.

CHAPTER 4: QUANTIFICATION OF INDOOR ENVIRONMENTAL QUALITY IN SUSTAINABLE BUILDING DESIGNS USING STRUCTURAL EQUATION MODELING

Joseph R. Piacenza, John J. Fields, Christopher Hoyle, Irem Y. Tumer

Journal: Energy and Buildings

Address: http://www.journals.elsevier.com/energy-and-buildings/

Submitted: April 2014

4.1 Abstract

This paper presents an experimental design framework for quantifying Indoor Environmental Quality in sustainable buildings, by estimating causal relations between design attributes, and both the stated and revealed post occupancy user preferences. In this research, a combination of statistical data and qualitative assumptions are used to formulate a structural equation model (SEM) to determine a subsequent latent construct between variables. The SEM is comprised of fixed attributes, observed variables, and latent variables, and is designed to evaluate postulated significant correlations between each. Results show that quantifying relationships among user preferences and built environment attributes will allow designers to consider and incorporate characteristics in early design that support these correlations.

4.2 Introduction

Sustainable building mandates such as the U.S. Green Building Council's (USGBC) Leadership in Energy and Environmental and Design (LEED) are becoming increasingly prevalent as strategies for resource conservation in commercial buildings [72]. With commercial buildings consuming 19% of total energy demand in the United States, sustainable design practices are a creditable consideration for energy reduction [73]. Many commercial institutions, such as universities, have declared all future new construction buildings will meet minimum LEED standards in an effort to reduce energy use and limit their overall environmental footprint. While this may be a viable energy conservation strategy for academic institutions with sufficient funding, additional costs above traditional commercial buildings are a primary barrier for many sustainable building design projects [74].

In addition to LEED, more complex certifications such as the Living Building Challenge (LBC) have additional requirements such as net-zero energy and water [6]. To achieve a net-zero requirement, each building subsystem (e.g., energy collection, water collection, and heating, ventilation, air conditioning (HVAC)), as well as their interactions, must be considered [7]. By shifting the traditional architectural building design paradigm from a top-down approach to an integrated approach, these system interactions can be better evaluated. This integrated design methodology is often found in aerospace, automobile, and other complex systems where optimal designs are required [8-10]. By applying optimization methods typically used in complex system design to sustainable building strategies, designers can explore important subsystem trade-offs. These trade-offs can then be evaluated, and the best design selected based on project requirements (e.g., LEED certification, cost) and designer preferences.

One approach to mitigate the additional costs associated with sustainable building design is to consider post occupancy user interactions within the built environment. The literature has shown that individuals can respond positively to various characteristics of their indoor environment, citing qualitative preferences for lighting, temperature, and workspace geometry [25, 26]. In industrial manufacturing environments, these preferences have been linked to motivation, job satisfaction, and technical competence [34]. The USGBC has recognized the value of designing for these preferences by awarding 17 points (out of 100 possible) to a metric described as *Indoor Environmental Quality* (IEQ), toward their LEED certification [30]. Currently, LEED's IEQ mandate includes 15 metrics, however, they are primarily focused on material selection and environmental control strategies. In addition, this standard does not directly address the long-term post occupancy effect of a building design on its users. By quantifying the benefit of an individual's indoor environmental response to sustainable buildings, the building attributes can be replicated, supporting engineering design. Specifically, if an individual's cumulative positive response to their environment resulted in behavioral changes, such as increased productivity, this productivity increase could offset additional costs incurred in meeting sustainable building standards.

The approach presented in this paper focuses on understanding the impacts of sustainable building design on an individual's stated and revealed preferences for the built environment, and how each of these preferences affect post occupancy behavior. Brownstone et al. observed the importance of capturing both of these metrics as consumers' stated preferences don't always align with their actual choices [75]. By understanding the sustainable building design characteristics that drive user preferences, and the effect these designs have on their behavior, designers can incorporate building characteristics that support these correlations.

4.3 Background

As building standards such as LEED and LBC become more complex, designers must explore a greater breadth of feasible solutions for meeting these requirements. Building users are playing a more prominent role in modern building design as literature has shown measurable effects on individuals' well-being, productivity, and creativity as a result of their indoor environment [20-22]. During the schematic design of the *Oregon*

Sustainability Center for example, user preferences and building interactions were considered for quantification of energy consumption [7, 19]. As previously discussed, LEED's rating for *Indoor Environmental Quality* (*IEQ*) assigns a point system based on metrics potentially influencing a user's response to his or her environment. Unlike other LEED categories such as *Water Efficiency*, satisfying the *IEQ* requirement does not result in a quantifiable resource reduction (e.g., water, energy, cost).

The literature regarding the effect of indoor environment on a user's behavior has shown various methods attempting to quantify this relationship. Positive behavioral changes such as decreased absenteeism, and increased employee efficiency and productivity have been recognized. Jensen et al. examine a Bayesian Network approach comparing various effects of thermal environment on the performance of office workers [25]. This work explores causal relationships between temperature related variables and subsequent mental performance of workers. These included indicators such as air velocity, thermal sensation, individual clothing type, and ventilation type. In addition to temperature, effects of natural lighting in the workplace have also been linked to various performance metrics such as well-being, ability to perform, motivation, job satisfaction, and technical competence. Research by Juslén has quantified a productivity unit increase based on workplace metrics associated with lighting relationships including visual performance, visual comfort, visual ambience, and job satisfaction [27]. Figure 4.1 displays a graph summarizing several historic studies mapping interior lighting levels (illuminance) with employee productivity.

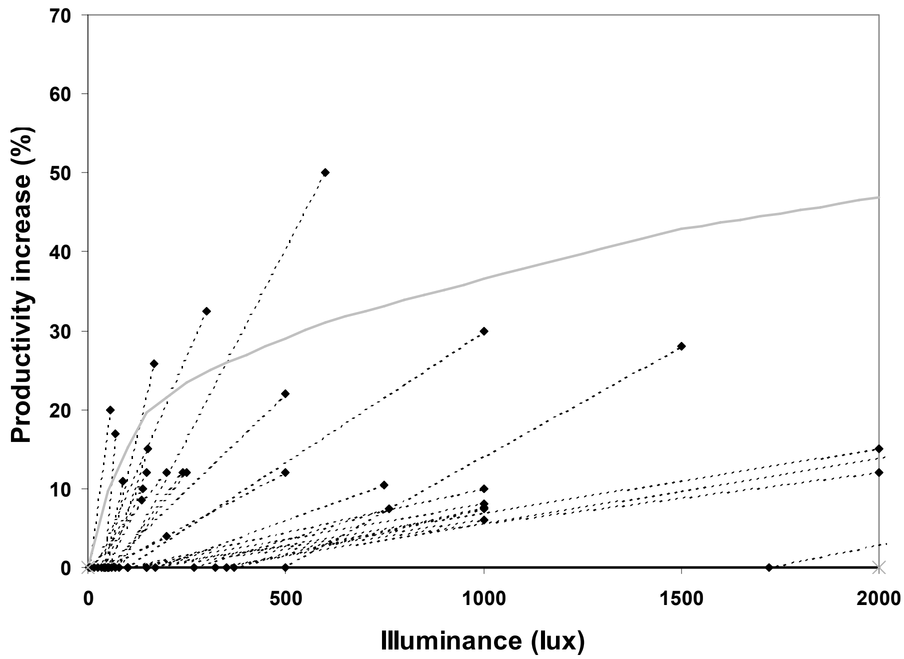

Figure 4.1: Employee productivity as a function of illuminance level in an industrial manufacturing setting [27]

Understanding a user's response to their indoor environment is beneficial, specifically in terms of climate and lighting, as these factors contribute heavily to energy usage. A sensitivity analysis performed by Heiselberg et al. shows lighting and HVAC systems are the two single highest users of energy in commercial buildings, and should be a primary concern during sustainable building design [17]. By designing lighting and HVAC systems with the building user in mind, trade-offs could be explored between energy efficiency and increases in productivity.

While productivity is often defined in terms of a ratio of total output per unit of input, it can also be evaluated in terms of reduced labor costs. It is inferred that there is an inverse relationship between employee productivity and salary per hour, postulating that if an employee on a fixed salary has a greater productivity than expected, he or she has a lower net cost (C_{NE}) to the organization [76]. These relationships are defined in Eq. 4.1 and 4.2:

$$PI = P_E + (P_E * P_C) \tag{4.1}$$

$$C_{NE} = \frac{\frac{Salary}{hr}}{PI} \tag{4.2}$$

where *PI* is the Employee *Productivity Index*, P_E is the *Expected Productivity Value*, P_C is the *Change in Productivity*, and C_{NE} is *Net Employee Cost* (*$/hr*). Hunter and Schmidt proposed a similar metric for productivity increase using meta-analysis, indicating it correlates to a reduction in both labor costs and overhead [29]. In their method, assigning different savings coefficients for labor and general overhead costs compounded financial gains. Figure 4.2 supports this approach displaying cost comparisons between various building expenses, citing salary as the largest annual expense [77].

In addition to productivity, this research aims to explore both stated and revealed user preferences for design attributes commonly used in LEED buildings. This is done through human appraisal experiments, designed using a Design of Experiments (DOE) methodology. These methods have been refined over several decades by statisticians, and have recently been refined to include specific methods for preference modeling [36, 37]. Chen et al. have outlined a method to observe the effect of differing values of a factor, or user-based attributes, on a response variable [38].

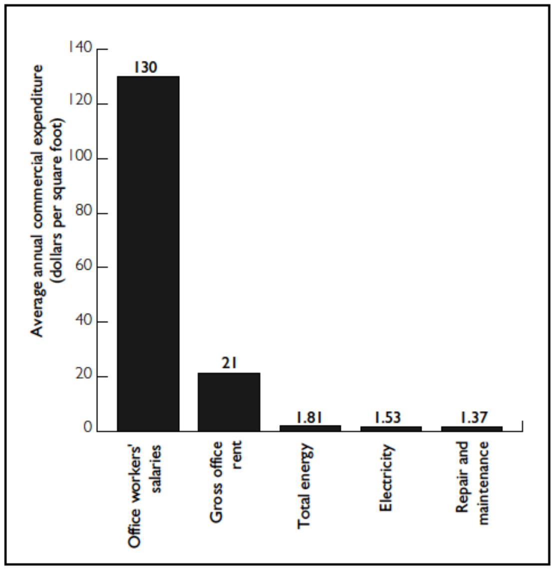

Figure 4.2: Cost comparison of post occupancy building expenses [77]

For example, multiple design alternatives can be presented to a customer or product user, and a corresponding rating response can be chosen, ultimately resulting in a single design preference. Individual factor levels and combinations (or interactions) are then identified which will define a design alternative. Hoyle et al. provide a case study of this method, using human appraisal data for automobile seating ergonomics [39]. In this work, both Blocked and Split-Plot statistical analysis are used to capture significant attributes of customer design preferences [40]. Based on the significant factors, a model for customer seating preferences is created, and compared to the actual preference data collected.

Since LEED buildings are based on energy efficiency design mandates, typical design qualities include passive energy savings features such as large window-to-wall ratio, passive air ventilation, and an open floor plan. These architectural attributes consequently end up satisfying constraints for energy efficiency, but do not actively contribute to improving the workspace preferences that LEED's *IEQ* metric attempts to capture. However, research by Fisk corroborates LEED design strategies, suggesting that energy efficiency and *IEQ* are not mutually exclusive, since many sustainable buildings address both considerations [78].

Existing literature shows a long history of positive effects of lighting on individuals in different workplace environments [31, 32]. Romm and Browning have presented several case studies where increased lighting in an existing workspace resulted in lower absenteeism, lower productions errors, and higher productivity [33]. This work also reported on new construction buildings, including a Lockheed facility claiming 15% rise in production, and 15% decrease in absenteeism due to architectural natural lighting features throughout the building. Research by Day et al. relate the attributes of building lighting design, in terms of natural lighting, to user satisfaction, health, and occupancy [34]. Hua et al. examine post-occupancy response to lighting conditions in a LEED Gold certified laboratory building [35]. This research combineds illuminance measurements on work plane surfaces with rating surveys of long-term occupants, to determine overall user satisfaction of the building.

4.4 Contributions

This paper presents a novel approach to sustainable building design that identifies key relationships between user preferences and building design characteristics (e.g. LEED mandates). A framework is developed for quantifying IEQ in sustainable buildings by estimating the causal relations between design attributes and both the stated and revealed user preferences for these designs. The metrics in this framework are based on post-occupancy user preferences for the indoor environment of sustainable buildings (e.g., LEED certified). Structural equation modeling (SEM) is used to evaluate postulated significant correlations between fixed attributes, observed variables, and latent variables. Within this model, latent variables uncovered in the statistical analysis represent emergent preferences resultant of a building's indoor environment. This approach will enable designers to explore tradeoffs between fixed costs, operational costs, and cost savings due to sustainable building mandates.

The stated preference metric employs a psychometric survey designed for building users who frequently occupy LEED buildings on a university campus. This survey evaluates building preference information from frequent users, including studying and socializing habits, temperature, and lighting. For this research, the survey was administered to university students who were familiar with the buildings selected. A statistical factor analysis was performed resulting in multiple distinct factors, or latent variables, correlating building attributes with user preference indicators. This analysis resulted in the identification of latent variables pertaining to *Personal Building Preference, Building Design,* and *Building Usability*.

The revealed user preference metric aims to validate these stated preferences by capturing the relationship between user occupancy and lighting levels in LEED certified buildings. This experimental procedure concurrently measures illuminance and number of occupants in a public workspace over a given period of time. This is accomplished with time-lapse photography, light meters, and data loggers. A generalized linear model identifies significant individual treatment effects, as well as treatment interactions. A nested split-plot design technique is utilized to mitigate randomization restrictions from collecting data over multiple days. The analysis of this experiment results in a statistical numerical interpretation between illuminance and occupancy, while evaluating the effects of experimental restrictions and noise.

The approach presented in this paper directly addresses deficiencies in how sustainable building mandates identify design characteristics that measurably influence user preferences. Specifically, existing IEQ metrics do not accurately capture the building design attributes that drive post occupancy user preferences for the built environment,. Quantifying the impact of sustainable building attributes on these user preferences will allow designers to trade off IEQ with other performance metrics (e.g., energy use, cost, environmental impact) when creating optimal building designs.

4.5 Methods for Quantifying User Preferences

4.5.1 Structural Equation Modeling and Latent Variables

This research aims to understand post occupancy user preferences for sustainable buildings, and how these preferences are influenced by the building designs. The motivation for this work comes from literature citing positive relationships between users and their indoor environments, specifically physical characteristics such as natural lighting, temperature, and design geometry [20, 78]. As sustainable mandates become more prevalent as a means to reduce energy consumption, novel design strategies must be applied to satisfy user requirements. One technique, behavior modification, has been explored as a method for reducing energy demand within a building [79]. A barrier to this strategy is the inability of the designer to accurately quantify potential energy savings from user behavior based solely on building characteristics or attributes. Subjectivity about what affects an individual's behavior makes it difficult to create repeatable designs that rely on users to meet energy demand requirements. The following framework was developed to help designers understand user preferences of existing sustainable buildings, so future design decisions can be made considering attributes preferred by post-occupancy users.

In this paper, a structural equation modeling (SEM) approach is explored as a viable strategy for understanding the effects of sustainable building mandates on building users. This approach estimates causal relations by combining different types of performance metrics including empirical measurements, categorical survey evaluations, and causal assumptions. SEM strategies are primarily used in sociology and medicine where a combination of several observed variables are needed to assess the nature of a latent variable construct [80]. The term *latent variable* refers to a variable that cannot be observed directly, but is a function of other related variables that are more easily quantified. Wheaton et al. originally formulated this approach based on a need to determine an underlying "true score" variable that measured two or more points in time [81]. A primary function of SEM is the ability to correlate a combination of fixed attributes, observed variables, and latent variables [82]. This approach is slowly gaining momentum in the design community, specifically when trying to identify driving customer preferences for product design. Hoyle et al. use utility theory to extract design preferences from individuals by analyzing product attributes, sociodemographic factors, and customer survey responses [39]. The importance of customer feedback is described in previous work by Everitt and Loehlin, identifying the ability to capture an individual's attitude toward a specific design through the use of a psychometric survey [41, 42]. Chen et al. have further developed this work, outlining a method identifying user preference indicators, based on specific product attributes [38]. In their work, a case study is presented based on data from J.D. Power's Vehicle Quality Survey, where consumer attitudes on various automobiles were collected, and presented as examples of preference indicators regarding specific vehicle attributes.

In the context of sustainable building design, latent variables for stated customer preferences are formulated by statistically combining building attributes with associated indicators that describe user preferences. Building attributes are defined as characteristics of the indoor building environment (e.g., lighting, temperature, number of windows, amenities). The indicators will be defined as an individual's attitude, or preference, toward design characteristics present in existing sustainable building architecture. The latent variables are then used to capture these preferences, quantifying a variable that is typically unobservable. Figure 4.3 displays the latent variable model as it pertains to building indoor environment or usability.

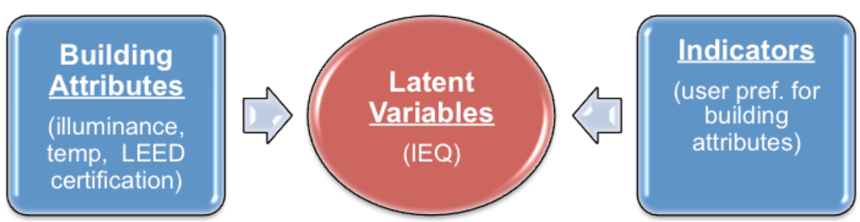

Figure 4.3: Latent variable model for indoor environmental quality (IEQ)

The method presented in this paper expands the application of existing approaches cited in the literature, attempting to understand the complex relationship between sustainable building design mandates and an individual's response to these indoor environments. The flexibility of SEM will be used to quantify these responses by correlating relationships between building attributes, psychometric survey responses, and empirically determined revealed preferences.

4.5.2 Structural Equation Model Development

A model was constructed using fundamental SEM principles originally outlined by Wheaton et al., applying them in the context of quantifying subjective building design performance metrics such as IEQ [81]. This approach is unique, specifically due to its applications for sustainable building design. In this research, key latent performance metrics are identified by statistically correlating sustainable building design attributes, individual preferences for these designs, and subsequent interactions between the two. First, an initial path diagram was constructed displaying the conceptual ideas behind the actual situation (Figure 4.4). This diagram includes four primary components relative to the model including *categorical variables* (taken from a psychometric survey), *empirical data* (collected within a LEED certified building), explanatory observed variables (building attributes such as window to wall ratio or LEED certification - i.e., *fixed covariates*), and *latent variables* (as described in Figure 4.3).

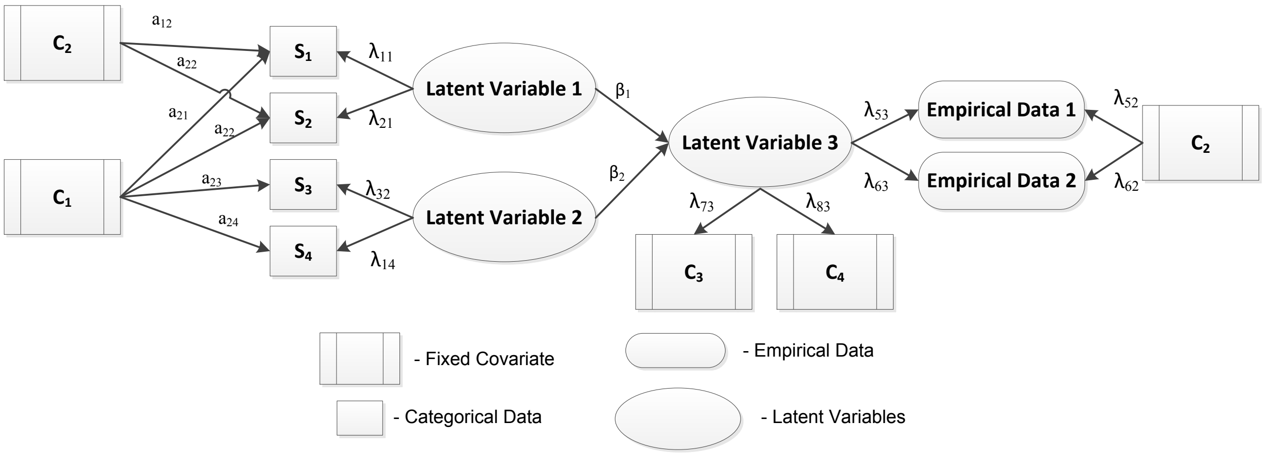

Figure 4.4: Hypothetical path diagram displaying conceptual model relationships

The one-way arrows between each variable represent a postulated significant correlation between one variable and another. The first component captures the latent building characteristics as identified from the *stated preference survey data.* These characteristics represent user's opinions about post occupancy building attributes. While the survey questions for this research are tailored for the built environment, this approach is applicable across various design disciplines. The second component incorporates the *empirical revealed preference data*, which aims to validate the individual's stated preferences. This is done by experimentally identifying which elements of sustainable building design drive occupancy. The third component is the addition of the *explanatory observed variables*, or fixed covariates. These variables provide additional information about the model landscape, reducing the estimation uncertainty for the latent variables [80]. For example, the presence of a LEED certification in a building provides important context for architectural attributes. Finally, *latent variable relationships* are added to the model for both the categorical survey data, as well as the empirical data. For the stated preference survey, these are defined from the factor analysis as outlined in Table 4.1. For the empirical data, latent variables are incorporated based on results from the ANOVA analysis (Figure 4.6). This variable represents the statistical correlations between building occupancy and the associated independent variables. It is predicted that these latent variables from each data set can then be used to identify a higher-level latent variable that is directly influenced by each. This resulting relationship is the key component to identifying a meaningful correlation between data types. The measurement equation for the predicted path diagram is defined by Eq. 4.3:

$$\begin{bmatrix} s_1 \\ s_2 \\ s_3 \\ s_4 \\ e_1 \\ e_2 \\ c_3 \\ c_4 \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \\ a_{31} & 0 \\ a_{41} & 0 \\ 0 & a_{52} \\ 0 & a_{62} \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + \begin{bmatrix} \lambda_{11} & 0 & 0 \\ \lambda_{21} & 0 & 0 \\ 0 & \lambda_{32} & 0 \\ 0 & \lambda_{42} & 0 \\ 0 & \lambda_{52} & 0 \\ 0 & \lambda_{62} & 0 \\ 0 & 0 & \lambda_{73} \\ 0 & 0 & \lambda_{83} \end{bmatrix} \begin{bmatrix} LV_1 \\ LV_2 \\ LV_3 \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \epsilon_3 \\ \epsilon_4 \\ \epsilon_5 \\ \epsilon_6 \\ \epsilon_7 \\ \epsilon_8 \end{bmatrix} \tag{4.3}$$

where $s_{1\ldots4}$ are the factored results of the categorical survey questions, $e_{1,2}$ are empirically sampled variables, $c_{1,2}$ are fixed covariates influencing both of these variables. In addition, $c_{3,4}$ are fixed covariates influencing the latent variables LV_1, LV_2, LV_3 directly, a_{11-62} are regression coefficients, β_1 and β_2 are the factor scores relating LV_3 to LV_1 and LV_2, λ_{11-83} relate the latent variables to each of the observed variables, and $\epsilon_{1\ldots8}$ are the error terms.

4.5.3 Psychometric Stated Preference Survey

Based on relationships identified from the hypothetical path diagram, a psychometric survey was developed to elicit a preference for various sustainable building design attributes by frequent users. This survey is based on a seven point Likert scale, commonly used for quantitatively evaluating social attitudes [83]. The Likert scale is a bipolar scale, containing a neutral preference option, indicating the respondent does not have an opinion on (or is unfamiliar with) the content of the questions [84].

The overall goal of this survey is to determine which architectural attributes of LEED certified buildings are preferred by frequent users. The buildings were chosen based on several characteristics such as departmental usage, age, presence of public workspace, and geometry. The primary common feature among the buildings is a public atrium where students can study or socialize. The atriums share similar stylistic construction features including use of natural lighting, high ceilings, open floor plan, and plentiful seating. In addition, each space has a coffee shop with a selection of food and beverages. To obtain a point of reference on which buildings are being evaluated, respondents are asked to identify which building they are the most familiar with at the beginning of the survey.

This survey was developed to be self-administered, and distributed to university students during a course in which they were enrolled. The questions were tailored around an individual's potential preference for certain building attributes, primarily related to both of their studying and socializing habits. These attributes included features such as lighting, temperature, presence of windows, amenities, and workspace features. The questions were further divided to investigate an individual's specific attitude toward how they interact within the common workspace of the building, and which attributes contribute to this usage. The first question asks how often the respondent uses the building they selected, and is the only question not using the seven point Likert scale. This gives the researchers a baseline for occupant frequency. The survey contains 21 questions, and was administered to 213 students to obtain a quality data set [84]. Extra credit course points were not issued to students agreeing the participate [85]. The finalized questions submitted to the Institutional Review Board (IRB) can be seen in the Appendix [86].

To interpret the results of the preference survey, a factor analysis was performed. The purpose of factor analysis is to describe the covariance relationships among many random variables in terms of a few underlying, but unobservable, random quantities called factors [87]. In the context of this research, the random (latent) variables are unobservable variables such as *IEQ*, while the measurable quantities are indicators such as *lighting type*. The factor analysis model is shown in Eq. 4.4:

$$X_1 - \mu_1 = l_{11}F_1 + l_{12}F_2 + \ldots l_{1m}F_m + \varepsilon_1 \tag{4.4}$$

$$X_2 - \mu_2 = l_{21}F_1 + l_{22}F_2 + \ldots l_{2m}F_m + \varepsilon_2$$

$$X_p - \mu_p = l_{p1}F_1 + l_{p2}F_2 + \ldots l_{pm}F_m + \varepsilon_p$$

where:

X_i = observable (latent) random variable

μ_i = mean of latent variable

l_{ij} = loading of the *i*th variable on the *j*th factor

F_j = *j*th common factor

ε = *i*th specific factor (error)

While there are different methods of factor analysis estimation, the Maximum Likelihood Method for parameter estimation is used since the log-likelihood is additive as opposed to multiplicative [87]. This method assumes factors **F** and specific factors **ε** are normally distributed. To perform the estimation, the statistical software STATA is used [88]. The output result is shown in Table 4.1.

Table 4.1: Output formatting for the factor analysis output

Variable	**Factor 1**	**Factor 2**	**……**	**Factor m**
X1	loading 11	loading 12	……	loading 1m
X2	loading 21	loading 22	……	loading 2m
:	:	:	……	loading 3m
Xp	loading p1	loading p2	……	loading pm

To determine an accurate number of latent variables, the factored correlation matrix is examined, and the convention of selecting factors based on eigenvalues greater than one is used [42]. In order to assist with the intrepretation of factor loading, a factor rotation is performed to position the orthogonal axis where variables load highly [41]. This oblique rotation is nonrigid, leading to a new axis that passes through the most prominent loading clusters [87]. The Varimax rotation, developed by Kaiser, is used based on its ease of loading interpretation [89]. A graphical representation of this method is shown in Figure 4.5, displaying an orthogonal rotation in two dimensions, where $\boldsymbol{x_1}$

and $\boldsymbol{y_1}$ are factors, and the angle of rotation between the original axis *m* and a new axis *n* is $\theta_{m,n}$ [90].

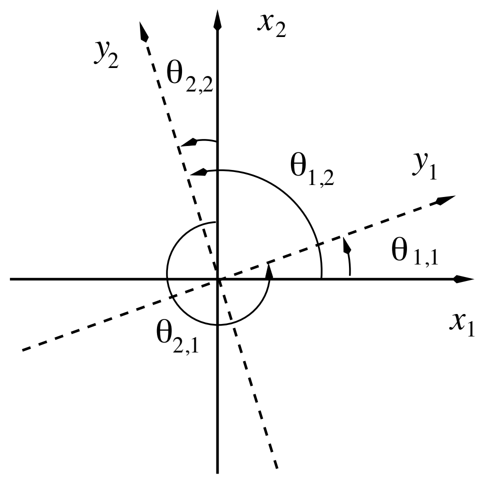

Figure 4.5: Orthogonal rotation diagram [90]

4.5.4 Experimental Design for Revealed Preference

As a way to observe an individual's actual, or revealed preferences for sustainable building indoor environments, an experiment was designed to correlate workspace occupancy as a function of available lighting, or illuminance. This hypothesis is based on the assumption that a user will choose to occupy a publicly accessible workspace based on specific design attributes, such as increased lighting levels due to large window-to-wall ratios (WWR), often present in LEED architectures [91]. While workspace occupancy cannot directly infer causation between a building design and a user's preference for this design, it can be used as an indicator to learn more about the relationship. By identifying a significant relationship between illuminance and occupancy in sustainable buildings, the interaction between building users and their environment can be further understood. This information can be used when attempting to understand design trade-offs between user preferences, energy efficiency, and cost. In this research, the workspaces being evaluated are LEED certified buildings on a university campus, each of which contain an open floor plan common atrium. Since these common workspaces are public, occupancy is based on a user's decision whether or not to use the area for studying, socialization, or the area's amenities.

To measure illuminance, a light meter equipped with a data logger was placed at work plane level, in the atrium seating area. Although there are minor changes in illuminance with increasing distance from the exterior windows, these will not be considered in this experiment. To measure occupancy, a time-lapse digital camera was placed at one end of the atrium, with the ability to capture an image of all users occupying the workspace. Both the light meter and the camera concurrently collected measurements every 15 minutes from 6:00am to 6:00pm, Monday through Friday. The total number of occupants present in the images collected were recorded with the corresponding time of day and illuminance measurements.

Data measurements are taken in different buildings, and randomization restrictions are incorporated in the analysis. Since the goal of this experiment is not to compare buildings against one another, blocking is utilized to address effects on individual building occupancy. In addition, the experiment is conducted during the academic school year, so there is a concern that student schedules could drive occupancy changes. To mitigate these issues, a nested split-plot design is used to analyze the data. A detailed layout can be seen in Figure 4.6.

Day	Time Range	Building 1						Building 2					
		1	2	3	4	5	6	1	2	3	4	5	6
Monday	Illuminance	1 2 . η	1 2 . η	1 2 . η	1 2 . η	1 2 . η	1 2 . η	1 2 . η	1 2 . η	1 2 . η	1 2 . η	1 2 . η	1 2 . η
Tuesday	Illuminance	1 2 . η	1 2 . η	1 2 . η	1 2 . η	1 2 . η	1 2 . η	1 2 . η	1 2 . η	1 2 . η	1 2 . η	1 2 . η	1 2 . η
Wednesday	Illuminance	1 2 . η	1 2 . η	1 2 . η	1 2 . η	1 2 . η	1 2 . η	1 2 . η	1 2 . η	1 2 . η	1 2 . η	1 2 . η	1 2 . η
Thursday	Illuminance	1 2 . η	1 2 . η	1 2 . η	1 2 . η	1 2 . η	1 2 . η	1 2 . η	1 2 . η	1 2 . η	1 2 . η	1 2 . η	1 2 . η
Friday	Illuminance	1 2 . η	1 2 . η	1 2 . η	1 2 . η	1 2 . η	1 2 . η	1 2 . η	1 2 . η	1 2 . η	1 2 . η	1 2 . η	1 2 . η

Figure 4.6: Nested split-plot design layout

This concept is helpful when there are two levels of randomization restrictions within a block [92]. In this design, the experiment is identically performed, Monday through Friday, in each of the buildings. This gives a total of five replicates in each building. The time-lapse camera captured *occupancy*, with images being recorded every 15 minutes, from 6:00 am until 6:00 pm. Illuminance levels are recorded simultaneously during the same time period. The resulting data is then organized in groups of six categorical time ranges, with *illuminance* being measured empirically. Based on initial illuminance testing in each of the buildings, lighting values range from 20 – 4000 *lux*, depending on local weather conditions. Time ranges are grouped as 6:00 am – 8:00 am, 8:00 am – 10:00 am, 10:00 am – 12:00 pm, 12:00 pm – 2:00 pm, 2:00 pm – 4:00 pm, and 4:00 pm – 6:00 pm.

To analyze the data, the statistical program StatGraphics is used [93]. The primary relationship of interest is occupancy as a function of illuminance, however confounding factors from each building, day of the week, and time of day are also examined.

4.6 LEED Certified Building Case Study

To illustrate an application of the methodology described above, a LEED certified building case study is presented. The initial data acquisition and subsequent analysis is included for both the stated and revealed user preferences.

4.6.1 Stated User Preferences

Incorporating the analysis from the psychometric survey is the next step for creating the SEM. This survey was conducted with 213 engineering students, and distributed over three different junior level mechanical engineering design courses. The buildings chosen for the survey were LEED certified new construction, used frequently in by engineering students. The survey results were manually entered in STATA, where a factor analysis estimation was performed. Based on the eigenvalues of the factored correlation matrix, three factors were determined to be significant. To aid in the interpretation of values for factor loading, a Varimax rotation was performed. Table 4.2 displays the variable indicator descriptions, resulting factors (latent variables), and corresponding factor loadings. For clarity, only loadings with an absolute value > 0.3 are shown.

Beginning with Factor 1, the positively loaded variables are associated with *frequency of use, studying preference, socializing preference*, *availability of amenities, work speed, use for homework*, *perceived popularity,* and *"green" construction*. From this data it can be suggested that this factor reflects a latent variable of *Personal Building Preference*, where an individual prefers attributes associated with a familiar workspace where they can work productively, while still interacting socially and having access to amenities.

Factor 2 contains all positive loadings including *lighting quality, temperature quality, seating quality, architecture quality, use of windows* and *color preference.* This latent variable can be described as *Building Design*. Factor loadings infer general positive building preferences for specific architectural features, indicating the user recognizes their importance. The loadings also indicate users prefer comfortable seating, presence of natural light, and a comfortable temperature.

Factor 3 was positively loaded for preferences pertaining to *importance of lighting, importance of temperature, traditional workspace* (desk instead of couch), *quiet environment, fresh air importance, and color preference.* This factor can be associated with *Building Usability*. For this factor, stated user preferences described a practical workspace with specific requirements. These individuals indicate a preference to work in a practical, productive environment, free from distractions.

Table 4.2: Factor loadings for stated user preferences

Indicator Description	Factor 1	Factor 2	Factor 3
	Personal Building Preference	Building Design	Building Usability
Frequency of Use	0.5364		
Studying Preference	0.8009		
Socialize Preference	0.5012		
Lighting Quality		0.6976	
Temperature Quality		0.4129	
Seating Quality		0.3892	
Architecture Quality		0.4064	
Availability of Amenities	0.3565		
Use of Windows		0.4868	
Work Speed	0.6642		
Use for Homework	0.7771		
Perceived Popularity	0.5573		
Importance of Lighting			0.5689
How Others Use Space			
Environment Familiarity			
Importance of Temperature			0.3562
Traditional Workplace			0.4689
Quiet Environment			0.3783
Fresh Air Importance			0.3411
"Green" Construction	0.3167		
Color Preference		0.3978	0.3125

Based on this analysis, each latent variable describes a distinct workspace attribute that would otherwise be difficult to quantify on its own. These three factors are imported into the SEM, representing empirical input variables for the model. By extracting distinct user requirements from stated preferences, latent variable analysis can help designers tailor building attributes for specific workspace objectives.

4.6.2 Empirical Evidence for Revealed User Preferences

The last step in creating the SEM is the incorporation of the empirical data. For this analysis, data was collected at two buildings on the Oregon State University campus. Both are LEED Gold certified new construction, and used for engineering. These buildings were selected based on several common design characteristics including frequency of engineering student use, presence of an atrium style public workspace, amenities (coffee shop), open seating area, and window to wall ratio over 0.30. For research consistency, both the psychometric survey and data collection referenced the same buildings. Occupancy was captured using time-lapse images, and manually extracting by count the current number of occupants during a designated time frame. Figures 4.7a and 4.7b respectively display images from both Buildings 1 and 2.

First, a cursory linear regression analysis of the raw *occupancy* and *illuminance* data was performed to gain an understanding of the relationship between these two variables. Based on these results, a logarithmic transformation was applied to the *illuminance* values, and a square root transformation was performed to *occupancy* values to stabilize the variance [92]. Figure 4.8 displays the results of the linear regression analysis of these elements, for both Building 1 and 2. Since these data sets have not been normalized, the range of *occupancy* values are different. This is because the total occupancy for Building 1 is greater than Building 2.

Figure 4.7a: LEED certified Building 1 workspace

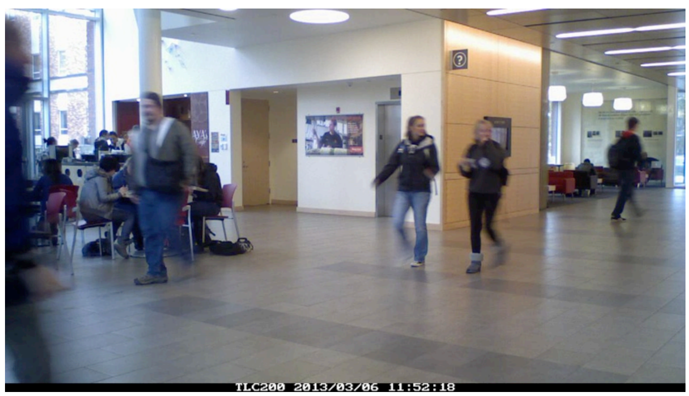

Figure 4.7b: LEED certified Building 2 workspace

Next, a generalized linear model was created in StatGraphics to determine the statistical significance between *illuminance* and *occupancy*. In addition to the empirical data collected, this also model also incorporates the categorical effects of *time range* and *day of week* to address randomization restrictions.To capture potential external effects due to scheduling, interactions between each variable were also considered during the analysis. Based on the results shown in Table 4.3, statistically significant effects (based on a *p*-

value ≤ 0.05) on *occupancy* are *time range,* the *building,* and *illuminance*. Significant interactions include every two and three factor interactions between each variable with the exception of the interaction between *illuminance* and *building.* This reinforces the hypothesis that occupancy is truly a function of sustainable building design characteristics, and not a specific building itself.

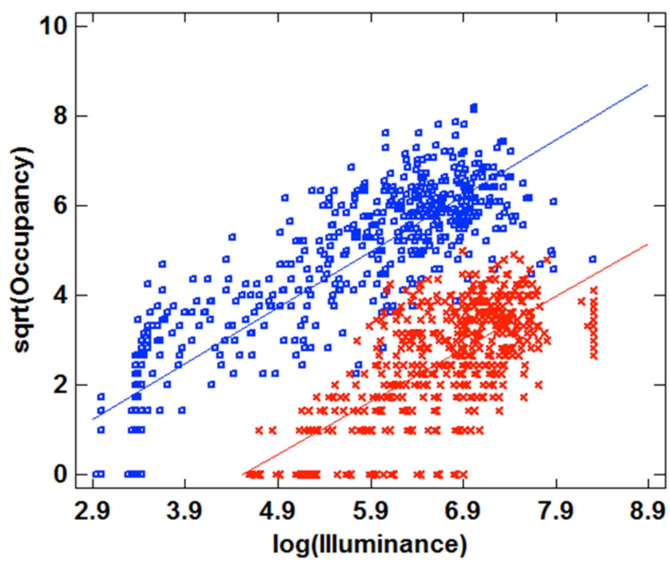

Figure 4.8: Square-root of occupancy versus log transformed illuminance

Based on this analysis, user occupancy in each LEED certified building varies significantly as a function of lighting level. This relationship occurs in both buildings, independently of potential confounding factors such as student class schedules or day of the week. From these results, design variables for *illuminance* and *time of day* are incorporated into the SEM.

Table 4.3: ANOVA results for revealed preferences

Source	Sum of Squares	DF	Mean Square	F-Ratio	P-Value
Time Range	7238.37	5	1447.6700	41.6100	0.0000
Day of Week	161.988	4	40.4969	1.1600	0.3252
Building	3218.81	1	3218.8100	92.5100	0.0000
Illuminance	169.938	1	169.9380	4.8800	0.0271
Time Range*Day of Week	1220.92	20	61.0459	1.7500	0.0212
Time Range*Building	1548.63	5	309.7270	8.9000	0.0000
Time Range*Illuminance	2817.29	5	563.4590	16.1900	0.0000
Day of Week*Building	354.939	4	88.7347	2.5500	0.0378
Day of Week*Illuminance	388.742	4	97.1855	2.7900	0.0252
Illuminance*Building	129.708	1	129.7080	3.7300	0.0535
Time Range*Day of Week*Building	2027.81	20	101.3900	2.9100	0.0000
Time Range*Day of Week*Illuminance	1644.99	20	82.2494	2.3600	0.0007
Day of Week*Building*Illuminance	741.099	4	185.2750	5.3200	0.0003
Time Range*Building*Illuminance	1095.01	5	219.0010	6.2900	0.0000
Residual	35071.8	1008	34.7935		
Total (corrected)	233777	1007			

4.7 Structural Equation Model Results

Based on the results of each independent data analysis from the psychometric survey and the empirical data, a SEM was constructed within the R computing environment [94] After many iterations stemming from the initial path diagram hypothesis, the resulting diagram is shown in Figure 4.9.

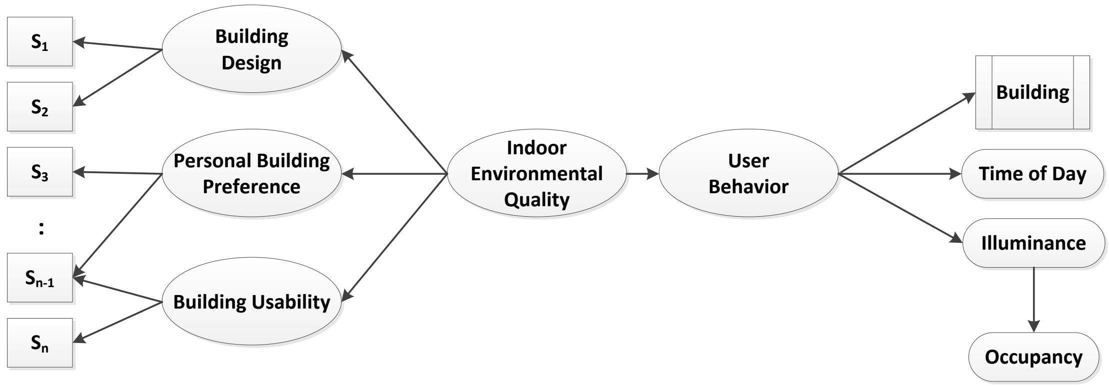

Figure 4.9: Evaluated structural equation model

In this model, the three factors resulting from the *categorical variable* (survey) analysis are represented as indicators corresponding directly to a top-level latent variable which can be represented explicitly as *Indoor Environmental Quality (IEQ)*. In addition, *IEQ* is also predicted by an independent latent variable characterized as *User Behavior*. This variable describes post occupancy user response to specific building design attributes, and includes indicators for lighting levels, the unique design of a specific building, and the time range a building is used. After performing the analysis in R, the results of this model are statically supportive of the path diagram (Table 4.4).

Table 4.4: Structural equation model fit comparison

SEM Performance Metric	Experimental Value	Acceptance Value
Goodness-of-Fit	0.99236	> 0.90
Adjusted Goodness-of-Fit	0.98568	> 0.90
RMSEA	0.02688	< 0.10
Non-Normed Fit	0.92672	> 0.90

The most relevant metric to validate this case is the Root Mean Squared Error Approximation (RMSEA) index, which is significantly below the acceptance value of 0.10 [95]. This measure indicates how accurately the model describes the correlations within the data using optimal model parameters. Both Goodness-of-Fit and Adjusted Goodness-of-Fit indices are well above the acceptance level of 0.90, describing the model's ability to recreate observed variances between observations. The Non-Normed-Fit index, which has an acceptable value above 0.90, suggests that further refinements could be used to improve model fit, specifically the inclusion of additional latent variable indicators [95]. In addition, increasing the size of the input data sets will also increase model fit.

Based on this cursory analysis, the impact of various building design attributes (Figure 4.3) on user preferences can be used to quantify IEQ. It is demonstrated in this case study that illuminance affects post occupancy building usage, however additional work is needed to validate the use of IEQ as a performance metric. For example, IEQ could now be incorporated into a building optimization objective function, and could be traded off with other environmental considerations (e.g., heat loss, energy use).

4.8 Conclusions and Future Work

As sustainable building mandates such as LEED and LBC become more prevalent, designers must look for novel solutions to meet design requirements, while maintaining cost expectations. This paper presents a novel approach for quantifying the U.S. Green Building's performance metric of IEQ, by estimating causal relations between design attributes, and both the stated and revealed user preferences for these buildings. Understanding an individual's preferences for sustainable design characteristics could lead to repeatable designs that would offset additional costs required to meet these mandates. The experimental design framework presented could be implemented in design optimization strategies, examining trade-offs between building standards, users, and cost. Sustainable building design costs could be mitigated by recognizing the relationship between building designs, and user behavior (e.g., occupational productivity, energy usage) as a result of these designs.

A key benefit of this approach is flexibility, allowing it to be applied to design problems across multiple disciplines where user and product interaction, and subsequent behavior are influenced heavily by the design characteristics. For example, existing hybrid-electric vehicles only account for a small portion of the automotive market. This is because their design only appeals to a narrow segment of the population due to personal preferences, despite comparable functionality within their class (e.g., mid-size sedan, SUV). Understanding which design attributes drive latent preferences in hybrid-electric vehicles could expand their market share, resulting in reduced natural resource consumption.

While the approach developed for this paper shows merit, additional research is needed to increase accuracy. In the LEED building case study presented, additional empirical measurements could be included such as indoor temperature, humidity, and air quality. In addition, the input data size should be increased by including measurements from additional LEED buildings to verify consistency. Finally, LEED buildings and users outside of a university campus could be analyzed to address any biases present in an academic institution.

4.9 Acknowledgment

The authors would like to thank Oregon State University facility services for approval of building use.

CHAPTER 5: ROBUST TOPOLOGY OPTIMIZATION OF COMPLEX INFRASTRUCTURE SYSTEMS

Joseph R. Piacenza, Mir Abbas Bozorgirad, Christopher Hoyle, Irem Y. Tumer

Conference: Int. Mechanical Engineering Congress & Exposition, November 2013

Address: http://www.asmeconferences.org/congress2013/

Journal: Mechanical Design

Address: http://mechanicaldesign.asmedigitalcollection.asme.org/journal.aspx

Submitted: May 2014

5.1 Abstract

Optimizing the topology of complex infrastructure systems can minimize the impact of cascading failures due to an initiating failure event. This paper presents a novel approach for the concept-stage design of complex infrastructure systems by integrating physics based modeling with network analysis to increase system robustness. This approach focuses on system performance after cascading has occurred, and examines design trade-offs of the resultant (or degraded) system state. In this research, robustness is defined as the invariability of system performance due to uncertain failure events. Where a robust network has the ability to meet minimum performance requirements despite the impact of cascading failures. This research is motivated by catastrophic complex infrastructure system failures such as the August 13th Blackout of 2003, highlighting the vulnerability of systems such as the North American Power Grid (NAPG). A mathematical model was developed based on the IEEE 14 test bus using an adjacency matrix, and uncertain failure events are simulated by removing a network connection. Performance degradation is iteratively calculated as failures propagate throughout the system, and robustness represents the lack of performance variability over multiple cascading failure scenarios. The overarching goal of this research is to understand key system design trade-offs between robustness, performance objectives, and cost. In addition, optimizing network topologies to mitigate performance loss during concept-stage design will enable system robustness.

5.2 Introduction

Current literature shows many existing approaches available to understand the effects of failure propagation in complex infrastructure systems. However, as these systems become increasingly heterogeneous and distributed (e.g., smart grids, electronic data networks, transportation networks), they become more susceptible to failures despite continued advances in system specific technology [56, 59, 96]. Since complex infrastructure systems operate in highly stochastic environments, it is not cost-effective (or even possible) to design for total immunity to uncertain failure events. Alternatively, this research asserts that systems must be designed for system robustness by incorporating the effects of fault propagation into optimization objectives, evaluating the performance of the resultant degraded system state.

This strategy of optimizing for degraded performance is applicable over a wide range of complex infrastructure systems. In a traffic network for example, if a bridge between two densely populated regions is unavailable due to a vehicle accident, commuters will automatically begin taking the next fastest (or shortest path) alternative route. To avoid subsequent vehicle accidents, the traffic network must be able to support increased commuter volume without exceeding the intended route capacity. Alternatively, designing for system robustness is equally important in infrastructure systems with less tangible material flows such as energy (e.g., power grid) or information (e.g., communication network). Imagine a network of Unmanned Aerial Vehicles (UAVs) that must gather information, and successfully transfer it to each other at a desired bandwidth. If a single UAV is unable to transmit data due to unexpected failures, the remaining vehicles must still be capable of accurately communicating system level information, even at a reduced rate [97].

This paper introduces a concept-stage topology optimization approach for the robust design of complex infrastructure systems. The IEEE-14 power system test case is used to demonstrate their vulnerability. For example, if a single transmission line is broken due to a falling tree, the existing power is immediately redistributed, potentially triggering a cascading failure. The primary goal of this research is to facilitate an understanding between design trade-offs in system performance and robustness. For example, if the system optimization objectives were purely performance driven, a traditional optimization approach would suffice. Conversely, if the optimization objectives also contained the need for invariant performance with respect to all potential failure scenarios, a robust design strategy could be implemented. Robust optimization examines trade-offs between performance and robustness, considering the impact of uncertain failure events.

5.3 Background

Robustness is typically defined in literature as the ability of a system to behave as intended, despite the effects of uncertainty from both internal and external sources [53, 98]. While the effects of uncertainty on a system can be accurately predicted in some applications (e.g., manufacturing), it is difficult to characterize this behavior in complex infrastructure systems, especially as they become increasingly large and distributed. In addition, systems optimized for performance are particularly susceptible to failures due to uncertainty as they are finely tuned to meet a specific objective (or set of objectives) without considering failure. For example, a single initiating failure can propagate throughout a power system uncontrollably, resulting in severely degraded performance or complete failure. To understand these cascading issues, current methods have employed graph theory and network analysis for evaluating emergent behavior [55, 96]. However, performance metrics such as node degree and centrality measures are too far abstracted from actual infrastructure systems to accurately model the impact of cascading failures. *Specifically, there is no provision to incorporate robustness into complex infrastructure system design to mitigate the effects of cascading failures due to uncertain events.*

5.3.1 Robust Design

While there are various methods contributing to the design of complex infrastructure systems, many approaches are typically focused exclusively on network analysis or modeling component interactions, and do not address the formalized concept of robustness [43-51]. Historically, robust design has been used in manufacturing to minimize unintended consequences (variability) from uncontrollable environmental effects [53]. Expanding on Taguchi's fundamental methods [53], Chang et al. have scaled these principles to design complex systems where multiple subsystems must be optimized independently with limited knowledge of other system design parameters [54]. This work outlines the need for an optimization approach accounting for system-level physical and intangible noises that are out of the designer's control. Incorporating robustness into a system model allows the designer to capture uncertainty, without the need to understand or reduce the source.

The primary issue, however, is creating designs that are robust to the various types of uncertain failures common in highly distributed systems. Many failures occur as a result of external occurrences such as extreme weather conditions, and predicting the impact of cascading failures resulting from a single initiating event is challenging. Examining the system topology as a means of increasing design robustness builds on existing approaches, expanding current methods into complex infrastructure systems, discussed next.

5.3.2 Network Theory and Topological Graph Models

Based on the distributed nature of many complex infrastructure systems, understanding topological effects is important when designing for topological robustness. Current literature addresses the importance of considering topology in network optimization, often drawing from network theory where networks are represented mathematically, often with an adjacency matrix [55-57]. Several network performance indices are studied in the literature, which can be primarily categorized into three major classes: reachability measures, vitality measures, and flow measures. For example, Kinney et al. model the power grid with an adjacency matrix, where each node represents either a generation or demand component in a network, and arcs connecting the nodes represent connectivity [57]. In this work, failures are examined by removal of a single node, which triggers an overload cascade in the network. Similar methods are used by Leonardo and Vemuru, where connectivity loss C_L, measures network performance (Eq. 5.1) [58]:

$$C_L = 1 - \frac{1}{n_D}\sum_{i=1}^{n_D}\frac{n_G^i}{n_G} \tag{5.1}$$

where n_G is the number of generation nodes, n_D is the number of demand nodes at the unperturbed network state, and n_G^i is the number of generation units able to supply flow to distribution (demand) vertex i after disruptions take place. Subsequent averaging is done over every demand node i of the network.

Another method by Ash and Newth examines the optimization of complex networks with respect to the average efficiency of the network [59]. Average efficiency (E) was first introduced by Crucitti et al. and is among the vitality measures, and can be calculated in Eq. 5.2 [60]:

$$E(G) = \frac{1}{N(N-1)}\sum_{i \neq j \in G} \epsilon_{ij} \tag{5.2}$$

where ϵ_{ij} denotes the efficiency of the most efficient path between i and j. In this definition, the undirected graph (G) is an $N \times N$ adjacency matrix of (e_{ij}), where $0 < e_{ij} \leq 1$ if there is an arc between node i and node j, otherwise $e_{ij} = 0$.

While these types of topological measures provide valuable information, it is important to recognize that these mathematical models are abstractions of complex infrastructure systems, and may result in misleading information. Hines et al. have explored these issues, comparatively evaluating topological metrics within the same system to predict failure magnitudes in standard test cases [56]. Their work concluded that while exclusively using topological measures can provide general information about a system's robustness, they can be misleading due to the level of abstraction and should be used in conjunction with a physics-based model.

5.4 Contributions

Current literature in complex infrastructure systems provides several approaches for robust design; however, a gap exists between the two primary research paths identified above. A generalized approach is needed to couple contextual robust design strategies at the component level (i.e., minimizing performance variability), and topological strategies at the network level (i.e., maximizing connectivity). This is a challenge since both of these approaches are mutually exclusive, and each evaluates system robustness at different resolutions of abstraction. For example, component level models are based on physical system properties (e.g., voltage), and network models rely on topology relationships (e.g., node degree). In addition, most current methods focus on failure prevention, instead of the ability of a system to successfully operate in a degraded state. Since most failures occur due to uncertain events, minimizing the degraded performance variability is essential for creating predictable and robust designs.

The research presented in this paper integrates contextual robust optimization with network analysis to minimize the performance variability of cascading failures. A key benefit is the use of both physics-based parameters and topological relationships to create a balanced system abstraction. This novel approach presents design trade-offs between performance and performance variability of a degraded infrastructure system, *after* failure has occurred. Using this method, network topologies can be designed that are robust to uncertain events (e.g., natural disasters) often affecting highly distributed systems. Specifically, this research recognizes stochastic failure events, and accounts for the ability to meet specified requirements, as well as considering cost.

The method presented minimizes the impact of cascading failures through topology design, and optimizes for both performance and performance variability. Motivated by the North American Power Grid (NAPG) case study, a mathematical representation of the IEEE 14 test case is created using an adjacency matrix, where system attributes for power generation, regional demand, and system topology are included [99]. The result is an optimization topology model that suggests alternative power grid network designs based on user data for power generation and demand requirements. Topology optimization is performed with two search algorithms (i.e., genetic algorithm, multi-objective simulated annealing). Scalability is addressed by applying the method to a simulated system composed of three IEEE 14 test bus networks. Specific power systems applications to this approach include microgrid design and existing systems re-works.

5.4 Motivation Case Study – The North American Power Grid

Large-scale cascading failures within the North American Power Grid (NAPG) have remained constant over the past few decades, and there is a need to increase the robustness of these types of complex infrastructure systems [1, 61, 62]. Organizations such as the North American Electric Reliability Council, Edison Electric Institute, and the Electric Power Research Institute (EPRI) attribute this issue to Federal reorganization and deregulation of the NAPG, citing growing discontinuity between transmission and distribution systems [64]. Major system failures such as the Blackout of 2003 highlight the vulnerability of the NAPG, and support the need for strategies to minimize the impact of uncertain failure events [4]. Cascading hardware failures are primarily responsible for system blackouts; however, communication deficiencies also contributed to significant performance loss during the Blackout [61]. Although there have been significant advances in power grid reliability and optimization methods, data provided by the North American Electric Reliability Council (NERC) shows that the frequency of blackouts has not decreased over the past 25 years [2]. Since the NAPG was originally constructed ad hoc based on sprawling population and increasing demand, topology optimization was not a primary consideration [100].

5.4.1 Power Grid Optimization

The field of power grid optimization encompasses a vast array of strategies for achieving system objectives. Currently, probabilistic risk assessment (PRA) methods are considered a best practice for evaluating the types of faults that ultimately lead to system failures, causing measureable system blackouts. The Long Island Power Authority uses a PRA tool, developed by EPRI, to determine likelihood and magnitude of occurrences within their local power system [101]. One issue, however, is the localization of the failure analysis, as this software does not account for propagating failures that occur over multiple utilities, or the optimal design of the power grid with respect to system-level objectives. Understanding subsystem relationships on a system level creates a challenge for researchers in developing computer simulation models that effectively capture significant interactions among these components.

Most uncertain events that trigger power system failures are natural occurrences such as hurricanes, ice storms, and lightning. Although wind and rain accounted for 31.4% of blackouts between 1984-2006, equipment failure was the second greatest source of failure accounting for 19.9% of events [1]. Several accepted hardware solutions have been developed to respond to failure such as the Flexible AC Transmission System (FACTS), introduced by Hingorani [102]. This technology enables the control of power flow on Alternating Current (AC) transmission lines to optimize loading [103]. Lininger et al. have incorporated the FACTS device into a computer simulation using a Maximum Flow algorithm to detect failure types in various outage scenarios [47]. Similar research by Carrers et al. has led to a computer model to replicate power outages due to line outages or losses due to excessive load limits [45]. Pinar et al. have also addressed power grid vulnerability by outlining optimization strategies for power line failure prevention [104]. Pahwa et al. have examined system failure modes by simulating a power grid within a standard network such as the IEEE 300 bus to examine cascading system failures [96]. Mitigation strategies to reduce failures include targeted range-based load reductions and intentional islanding [63].

Examining and modeling system failure due to cascading faults is an area of research intended to predict the probability of outages across regions. Talukdar et al. have focused on power grid failure predictions addressing partial functionality of a grid after a failure event, instead of attempting to find a solution to prevent them [105]. This methodology addresses system uncertainty from dynamic periods of change due to intended switching operations designed to bring systems back online. Fairley comments on this methodology, supporting the premise that failure is a byproduct of such a large complex system and research in mathematical modeling for failure management, instead of elimination, should be a primary strategy for increased robustness [4].

5.4.2 Power System Parameter Design

Applying Taguchi's Parameter Design approach to power systems design illustrates the different sources of uncertainty effect system response (Figure 5.1) [52, 53]. In this approach, the system control factors are elements that can be varied within the system, and noise factors are environmental elements that cannot be controlled. When addressing potential initiating events for fault propagation, both types of factors can be considered. Failures from external events are addressed in the context of Type 1 (Parameter) robust design, which minimizes performance loss from external noise (e.g., weather). Type II (Tolerance) robust design reduces performance losses due to uncertainty from internal control variables within the system (e.g., topology).

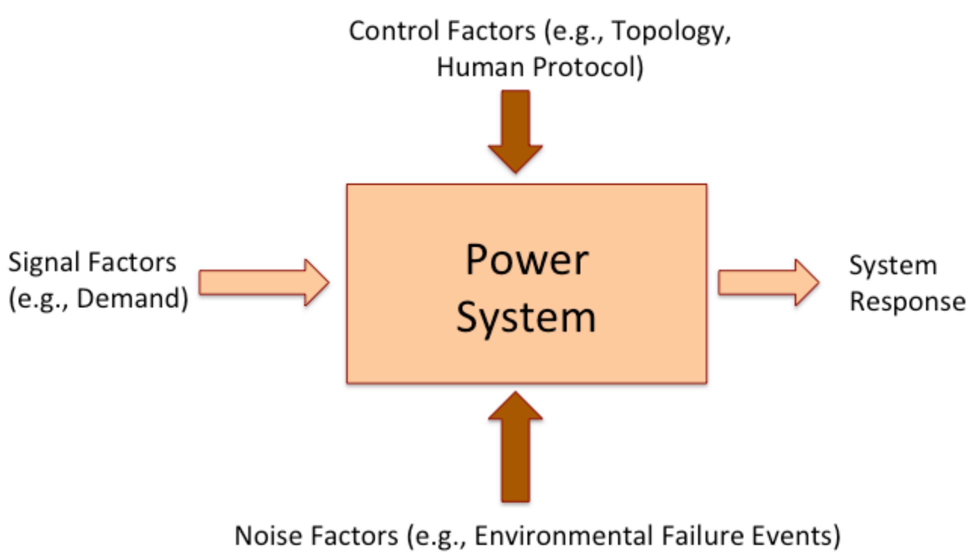

Figure 5.1: Parameter diagram for the NAPG

Lewis et al. combine both Type I and Type II robust design principles and apply them to complex systems, in an effort to address uncertainty from both internal and external environment [106]. The goal of Lewis' formulation is to meet performance requirements, while minimizing the variation about the mean. Figure 5.2 outlines this relationship, displaying how the performance-based optimized solution may exist at the boundary of an objective, where variability is greatest [52, 106]. The objective value of the robust solution is slightly higher, although with less performance variation. Complex infrastructure systems can benefit from applying this method, as uncertainties from both sources are present. However, further research is needed to understand how this application of contextual robust design can benefit complex infrastructure systems, discussed next.

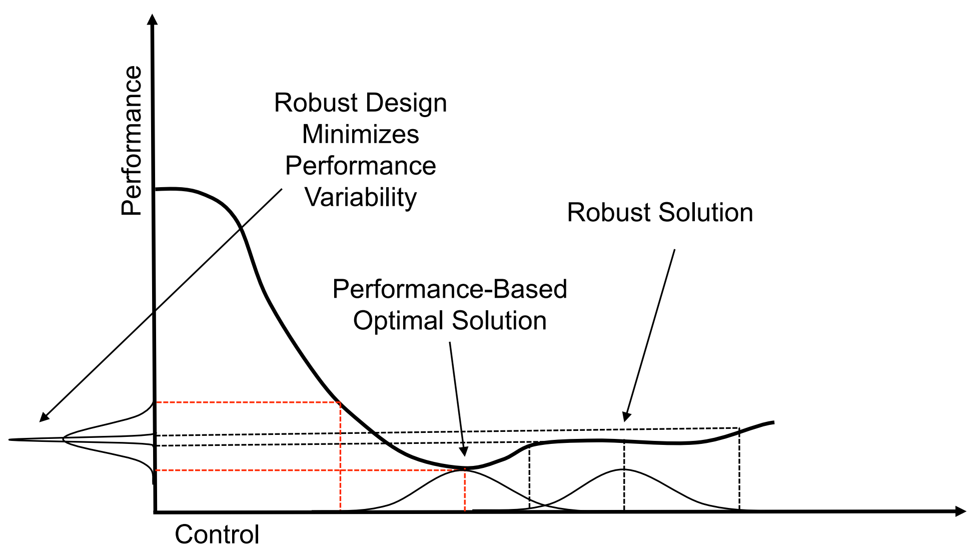

Figure 5.2: Visual interpretation between the performance-based and robust solution

5.5 Methodology

5.5.1 IEEE 14 Test Bus System

The IEEE14 test bus system (Figure 5.3) used for this method consists of 2 power generation stations, and 12 demand connections [99]. Since transmission line capacities are a function physical topology, line lengths were utilized as calculated by the Power Systems Engineering Research Center [107]. This is an important system attribute as line lengths directly drive connectivity costs. Nominal demand node power requirements were also used from the IEEE 14 test bus.

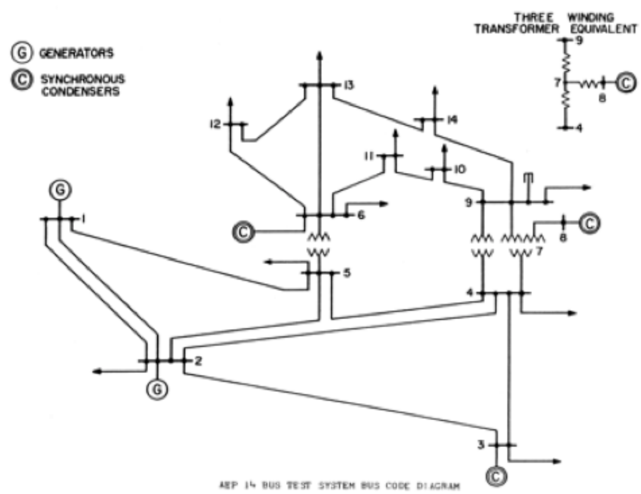

Figure 5.3: IEEE 14 test bus system [99]

5.5.2 Topology Relationships

The IEEE-14 test bus is created in MatLab, represented by an $N \times N$ adjacency matrix, where $N = N_g + N_d$. N_g represents the number of generation nodes and N_d represents the number of demand population nodes. An initial network topology is created randomly, constrained by the fixed node locations from the IEEE-14 test bus. This network topology is then tested for connectivity, as we are assuming each demand population must be serviced (connected) to the network to satisfy nominal performance requirements.

An algorithm based on a Monte Carlo *breadth first search* is used to check the connectivity of the network. Since the goal of this work is to minimize the performance impact of uncertain failure events, it is not assumed that greater system connectivity leads to greater robustness. In addition, it is not economical to incorporate line redundancy between each connection due to transmission line costs. Eq. 5.3 describes the relationship between transmission line cost with respect to length.

$$C_{Tot} = \sum_{i=1}^{N}\sum_{j=1}^{N} C_{ij}^{Length} * L_{ij}A_{ij} \tag{5.3}$$

where A_{ij} is the adjacency matrix, L_{ij} represents the length in units between all pairs of nodes, and C_{ij}^{Length} is the length cost between all pairs of nodes.

5.5.2 Physics Based Properties

In the IEEE-14 test bus, generation and demand nodes each have an associated load (in MW) that must be satisfied to perform nominally. Power generation values are based on energy production at that node, and demand values are derived from the total power required to service a given area. It is assumed that, if connected, power can flow unaffected between both types of nodes.

In this model, each line has a maximum available capacity for power transportation, and an associated line load based on the number of nodes which it is transporting power. Line load (L_{Load}) is the amount of power flowing through a line, assuming the load always travels through the shortest path available from a generation node to a demand node. This is calculated based on the number of *shortest path* (SP) connections, and the magnitude of the demand nodes serviced by at least one generation node (Eq. 5.4).

$$L_{Load} = \sum_{i=1}^{SP} D_i \tag{5.4}$$

where D_i is the demand that has to be satisfied by the shortest path i. Line capacity (L_{Cap}) is defined as the maximum power (in MW) that can flow through an individual line before a failure occurs, based on a fixed parameter factor of safety (α) (Eq. 5.5).

$$L_{Cap} = (1 + \alpha) * L_{Load} \tag{5.5}$$

Connectivity relationships are based on previous research by Kirk, where Dijkstra's algorithm is used to determine the shortest path distances between generation and demand nodes, which are used to calculate the loads on the connection lines [27].

Uncertain failure events are modeled by randomly removing a single line from a given topology. This is an iterative process where $L_{Load}\ (t)$ is the initial line load at time t, and its value is based on the demand node values associated with it. In this model, power generation is unlimited, and multiple generators can satisfy a single node demand. Since the remaining lines must support the load from the failure, load redistribution may cause other lines to exceed capacity, initiating a cascading failure. D_f is the remaining demand being satisfied after cascading failure occurs, and the system is operating at a degraded steady state. Arc removal is performed 10 times randomly (without replacement) for a single topology design. *Expected Demand* (D_E) is calculated based on the average of resultant demand for each of the 10 failure scenarios (Eq. 5.6).

$$D_E = \frac{\sum D_{f_{1\ldots10}}}{10} \tag{5.6}$$

A process flow diagram for this model is shown in Figure 5.4

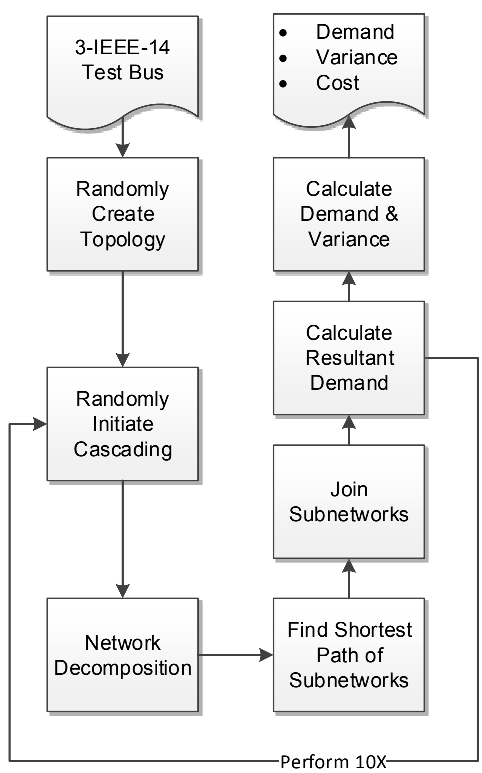

Figure 5.4 Process flow diagram for cascading failure model

For specific applications, arcs will be removed according to the distribution of failure events anticipated based upon historic data using a Monte Carlo simulation approach. For example, complex infrastructure systems are typically reliable, and failures can be minimal or non-existent for long periods. To help identify the likelihood of failure events in the NAPG, Figure 5.5 displays failure occurrences over a one-year period. Future work will include a goodness-of-fit test based on multiple years of reliability data.

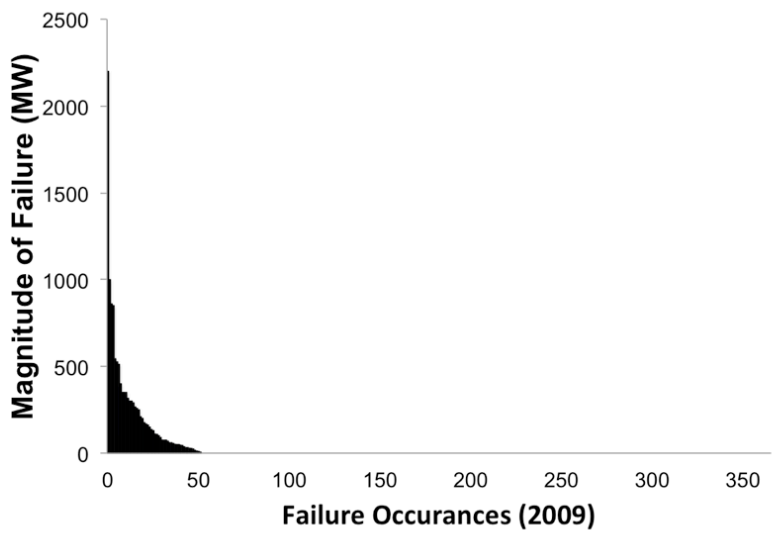

Figure 5.5: Annual failure occurrence data for the NAPG (2009)

5.6 Implementation

5.6.1 Multi-Objective Optimization

The optimization objective developed is based on the ability of a degraded system to predictably satisfy performance requirements after a cascading failure has occurred. Robustness is incorporated into the objective by considering the variation of Expected Demand (D_E) in the solution (Eq. 5.7).

$$\begin{aligned}
&\textbf{find } A \\
&\textbf{minimize} \\
&f_1 = C_{Tot}(A) \\
&f_2 = -D_E(A) \\
&f_3 = \sigma_{D_E}^2(A) \\
&\textbf{subject to} \\
&h_1 : N_{Comp} - 1 = 0 \\
&h_2 : A = \{0,1\}_{N \times N}
\end{aligned} \tag{5.7}$$

where A and N_{Comp} respectively represent the adjacency matrix and the number of disconnected components of the network, and $\sigma_{D_E}^2$ is the Expected Demand variance. The optimization objective is calculated using two search algorithms.

5.6.2 Optimization #1: Genetic Algorithm

First, a genetic algorithm (GA) was used within the MatLab Optimization Toolbox [108]. Since Expected Demand Variability is part of the objective function, values were normalized so the GA could evaluate solutions on the same scale. Values were calculated for Cost, Expected Demand, and Expected Demand Variability from the original IEEE 14 topology configuration. These nominal values were included in the fitness function for each objective (Eq. 5.8). In addition, a penalty function was used to penalize solutions in which the grid is disconnected. This was included to ensure network connectivity after a cascading failure. The resulting objective is stated as:

$$f(x) = \frac{Obj_n}{IEEE14_n} + PF_{Conn} \tag{5.8}$$

where the Obj_n is the value of the objective functions, $IEEE14_n$ is the calculated objective value from the original IEEE 14 test bus, and $PF_{conn}$is the penalty function for disconnectivity. This penalty function represents one element of network theory incorporated into the approach, differentiating it from traditional robust design approaches.

Each solution is represented with the help of the network adjacency matrix. Since the network is undirected, only the upper triangle of this matrix is considered. This triangle is converted to a long bit-string in order to use the matrix as an input to the GA toolbox of MatLab. Details of the GA are as follows:

- Population = 400
- Mutation Probability = 5%
- Crossover Probability = 90%
- Elitism = 10 %
- Selection Method: Roulette Wheel

5.6.3 Optimization #2: Multi-Objective Simulated Annealing Algorithm

Next, a multi-objective simulated annealing (SA) algorithm was implemented as an alternative to the GA to potentially increase computational efficiency. SA is a search algorithm that starts with an initial solution and seeks for possible improvements within its neighborhood [109]. SA avoids getting trapped in local optima by accepting deteriorated solutions, in addition to improved solutions, with a probability less than one.

This acceptance probability is controlled by the 'annealing temperature', and decreases as the temperature drops in the course of the annealing process. Czyzżak and Jaszkiewicz developed Pareto simulated annealing (PSA) to adopt this search for the multi-objective optimization problems [110]. This search is conceptually identical to the single-objective SA but, instead of using one candidate to represent the final solution, PSA uses a set of interacting solutions at each iteration [111]. This set is called the *generating set* and is similar to the concept of *population* in genetic algorithms.

Since the evaluation of individual solutions in this research is a time-consuming process, using a population of solutions at each iteration of the algorithm drastically decreases its efficiency. For this work, SA was performed that perturbs an individual solution at each iteration, instead of using a generating set. If the perturbed solution is not dominated by its preceding solutions, it enters the non-dominated set of Pareto fronts and this set gets updated accordingly. The next seed of SA is selected randomly from the updated set of Pareto fronts. If the perturbed solution is dominated by at least one of its preceding solutions, it will not enter the Pareto front set, but it will still be selected for the continuation of the algorithm with the following probability (Eq. 5.9):

$$P\left(A_x, A_y, T\right) = \min\{1, \exp\left(\frac{\sum_{j=1}^{N_{SA}}\left(f_j(A_x) - f_j\left(A_y\right)\right)}{T}\right)\} \tag{5.9}$$

where the adjacency matrix A_y is the solution obtained by perturbing the adjacency matrix A_x, N_{SA} is the total number of objective functions, and T is the temperature at each iteration. Details of SA algorithm are as follows:

- Initial Temperature = 1000
- Stop Temperature = 1e^{-6}
- Cooling Rate = 0.95

5.7 IEEE 14 Optimization Results

5.7.1 Genetic Algorithm

The resulting plot of Pareto optimal solutions is displayed in Figure 5.6. In this plot, design values are normalized with respect to the performance of the original IEEE 14 network topology. Tradeoffs between each optimization objective are explored within this design space, and an optimal solution is found. The population of the Pareto frontier is sparse due to the finite number of solutions in the IEEE 14 network. However, it can be seen that with a decrease in *Cost*, the ability to satisfy *Expected Demand* after a cascading failure decreases, and *Expected Demand Variability* increases.

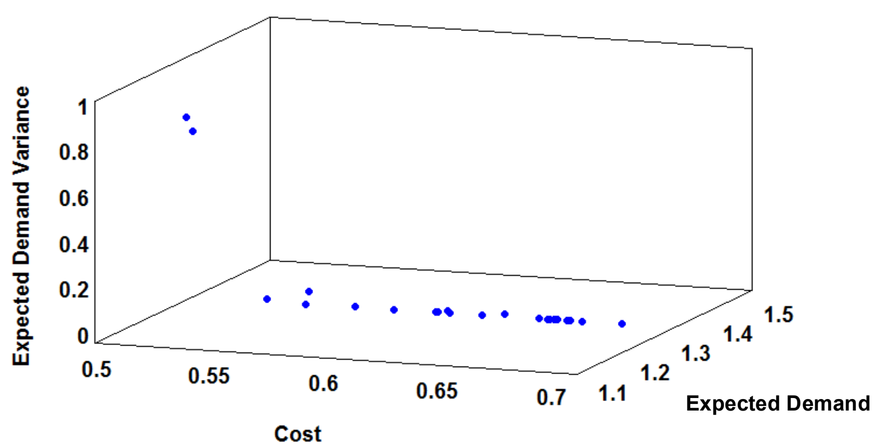

Figure 5.6: Normalized Pareto solutions for the IEEE 14 test bus network using the GA

To illustrate the impact of adding robustness to the objective function, a performance based optimization solution was executed, with the removal of *Expected Demand Variability*. In this version of the solution, only *Cost* and *Expected Demand* are considered, and variance is ignored. All existing constraints remained, and the normalized fitness function values are still based on the original IEEE 14 solution. A comparative results summary from selected Pareto solutions is shown in Table 5.1

Table 5.1: Objective function results for the original, performance optimized, and robust optimized topology of the IEEE 14 test bus using a GA

IEEE 14 Network (GA)	Network Cost	Expected Demand	Expected Demand Variance	Network Lines	Avg. Node Deg.	Max. Node Deg.
Original	1212	182	5738	18	2.6	4
Performance Opt.	**660**	**224**	**769**	17	2.4	6
Robust Opt.	**666**	**235**	**235**	18	2.6	5

The performance-based solution is the least expensive (660), with an *Expected Demand Variance* of 769. However, the robust solution is only slightly more expensive (666), and the variance is reduced by over one third. This is due to both the addition of a single line, and a robust optimized topology. The original IEEE 14 network *Cost* is the highest, most likely since the network was physically constructed based on both population demand and geography.

In terms of network topology, the robust design (Figure 5.7a) consists of 18 transmission lines, versus 17 in the performance-based solution (Fig. 5.7b). Each network is fully connected, with no disconnected demand nodes or sub-networks. The generation nodes (*node marked G*) of the robust solution each have 3 and 5 degrees of connectivity respectively, versus 3 and 4 degrees respectively for the non-robust solution. The non-robust network configuration is a direct result of the *Variability* objective being removed, where the optimal solution focuses exclusively on meeting performance objectives *Cost* and *Expected Demand*. Also, the average node degrees for each solution are similar, typically suggesting a close level of performance in traditional social network analysis [55]. However, since *Variability* is decreased significantly, this infers there are other factors also contributing to system robustness.

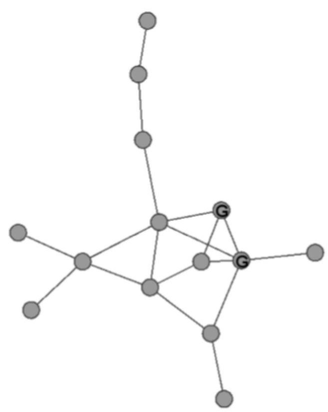

Figure 5.7a: Robust optimized network topology using GA

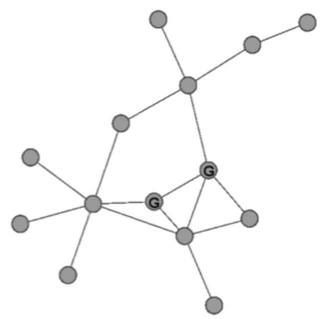

Figure 5.7b: Performance Optimized network topology using GA

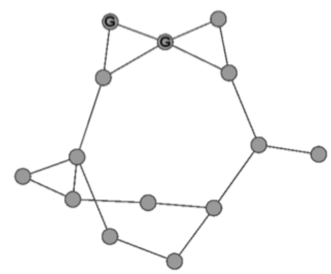

Figure 5.7c: IEEE 14 original network topology

It should be noted that neither model (robust or performance based) currently accounts for physical geographical constraints between nodes (e.g., mountains, rivers, preservation areas), and assumes the shortest path is always available. However, the original IEEE 14 network is constrained by the physical distances between nodes, which were originally constructed around such topology restrictions. To increase model fidelity, these types of geographic constraints can be added for specific applications by penalizing node connections representing various topological features.

5.7.2 Simulated Annealing Results

The simulation was run again using a multi-objective SA algorithm. The Pareto optimal solutions are displayed in Figure 5.8, where the SA algorithm provides a larger breadth of solutions over the GA. The results of SA follow a more traditional Pareto frontier than GA, clearly displaying trade offs between each objective.

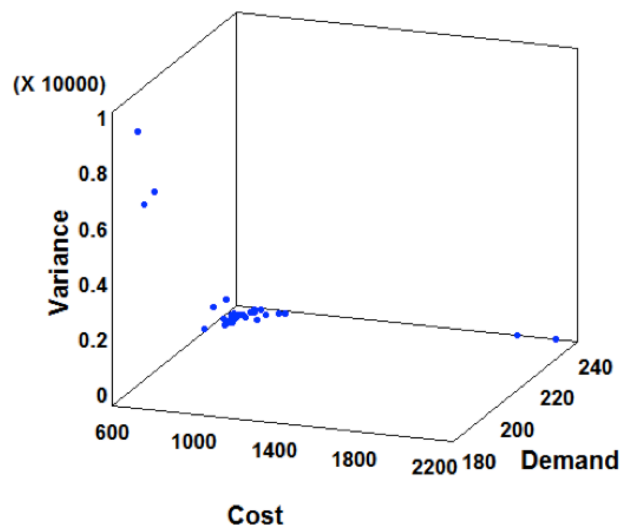

Figure 5.8: Pareto solutions for the IEEE 14 test bus network using multi-objective SA

Table 5.2 displays the comparative results summary based on selected Pareto solutions from the original, performance optimized, and robust optimized solution.

Table 5.2: Objective function results for the original, performance optimized, and robust optimized topology of the IEEE 14 test bus using SA

IEEE 14 Network (SA)	Network Cost	Expected Demand	Expected Demand Variance	Network Lines	Average Node Deg.	Max. Node Deg.
Original	1212	182	5738	18	2.6	4
Performance Opt.	**629**	**183**	**9380**	13	1.9	4
Robust Opt.	**1991**	**237**	**0**	25	3.6	5

It can be seen that the robust design is the most expensive solution, specifically because of the total number of network connections. Consequently, the robust design also has the largest average node degree, as well as the largest maximum node degree. In the Pareto solution selected, the *Expected Demand Variance* converges to zero, indicating this design is always able to satisfy *Expected Demand* at the same rate (237) after cascading failure has occurred. This robust solution is over three times the cost of the performance-based solution, allowing the designer to explore multiple tradeoffs between *Cost* performance and solution variability. While the intent of this paper is not to compare local search algorithms, the SA algorithm provides a more intuitively logical solution for a network of this size over the GA. This could be a function of system attributes such as the limited number of discrete solutions, where the SA algorithm is more likely to converge on a global optimum over the GA [112]. Topological relationships can be seen for the performance-based and robust solutions in Figures 5.9a, 5.9b, and 5.9c.

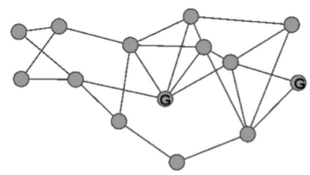

Figure 5.9a: Robust optimized network topology using SA

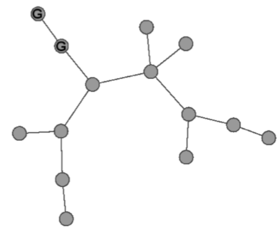

Figure 5.9b: Performance optimized network topology using SA

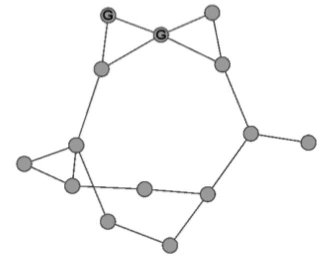

Figure 5.9c: IEEE 14 original network topology

5.7 Scalability to Larger Systems

While the IEEE 14 test bus results show promise, scalability was addressed next to examine the method's applicability to larger systems. Several strategies were explored based on literature in complex systems design. First, a "brute force" approach was considered, which would take advantage of modern parallel computing strategies. For example, the simulation could be performed in an off site computing environment such as the Amazon Elastic Compute Cloud (Amazon EC2) [113]. Next, small world networks were explored as a means of representing the various interconnections of the NAPG, and the links between them [55]. Collaborative optimization was also considered as a way to concurrently optimize several subnetworks within a master network model. This approach has been used previously in complex systems as a way to simultaneously optimize a system by placing constraints (typically resource limits) on each subsystem design [114, 115]. The drawback of this method is the risk of over-specifying or constraining the design, greatly limiting the possibility of novel solutions. This information lead to the exploration of a distributed analysis approach, where the master network was decomposed into various subnetworks based on an identifiable structure of node clustering [116, 117]. These subnetworks are then partitioned and simultaneously optimized independently.

Based on a literature review of the four methods discussed above, elements from each were utilized to develop a supplemental method for addressing system scalability.

5.7.1 Network Decomposition

One limitation of this work the use of a Monte Carlo simulation to find all possible shortest paths in a given network. While this is sufficient for the IEEE 14 test bus, the search time will grow exponentially for larger systems. To address this issue, a matrix decomposition approach was developed to supplement the method presented in Section 5.5. This supplement identifies *subnetworks* within the *master network*, enabling the algorithm to decompose the system into subnetworks and individually determine the shortest paths. Once the subnetworks are identified, the parallel computing function in MatLab is utilized to calculate all of the shortest paths from generation to destination nodes.

This technique is based on the modularity properties of small world networks, as the subnetworks represent regions (or interconnections) of the power grid [55]. In the NAPG, high voltage transmission lines transport power between each region. Figures 5.10 and 5.11 display a visual representation of both the subnetwork relationship and the corresponding adjacency matrix (upper triangular) considered for this method. This visualization represents a scenario with three subnetworks and three interconnection lines between each.

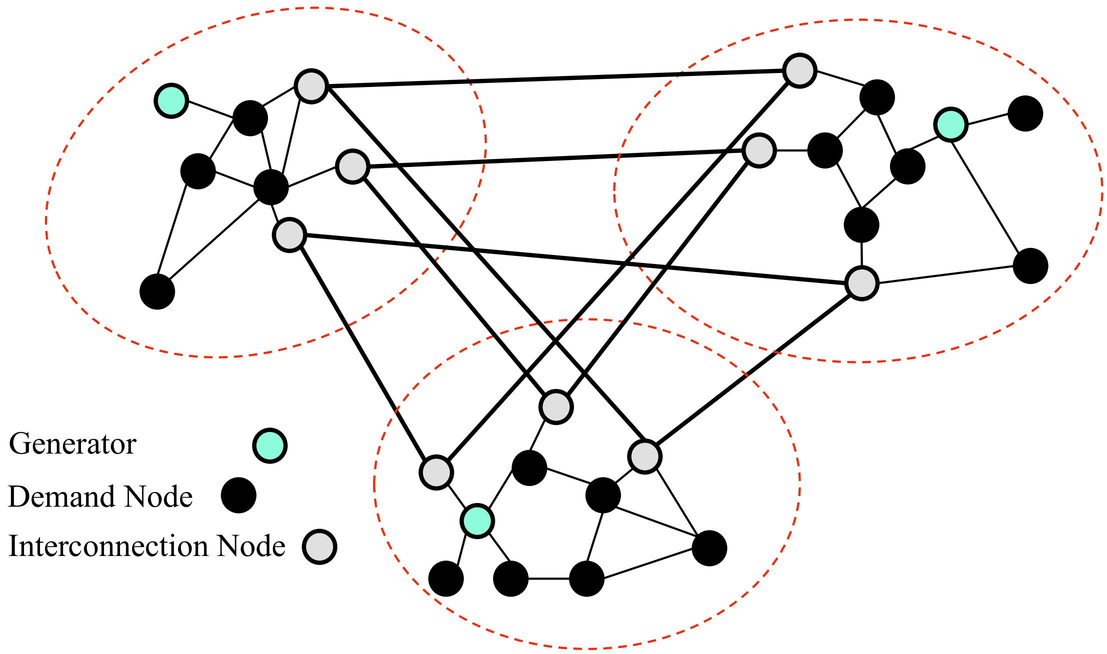

Figure 5.10: Visualization of subnetwork and master network relationship

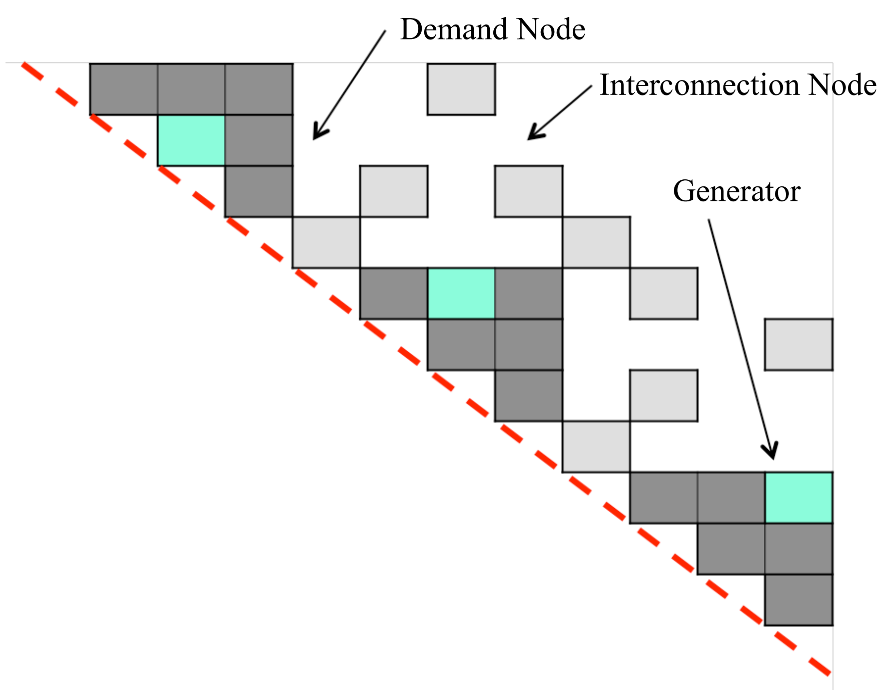

Figure 5.11: Adjacency matrix representing subnetworks and interconnections

5.7.2 3-IEEE 14 Test Bus System

For this case study, three IEEE 14 Test Buses (3-IEEE 14) were composed into a single adjacency matrix ($A_{42\times42}$), and three lines were made available to connect each subnetworks (for a maximum of 9 interconnection lines). All system performance metrics (e.g., line length, capacity, load) from the single IEEE 14 test bus remained the same, Interconnection Line Cost ($C_{N\times N}^{Int\_Length}$) was based on a fixed interconnection line length of 483 km. This distance is a function of the longest line of the IEEE 14 test bus, and was chosen to penalize the algorithm for selecting solutions where demand was satisfied by transporting power between subnetworks.

The updated 3-IEEE 14 model is evaluated using the multi-objective SA for both the performance-based optimization and the robust optimization. Figure 5.12 displays the Pareto frontier of design objective solutions, allowing a designer to select a specific solution based on their risk attitude [118-121].

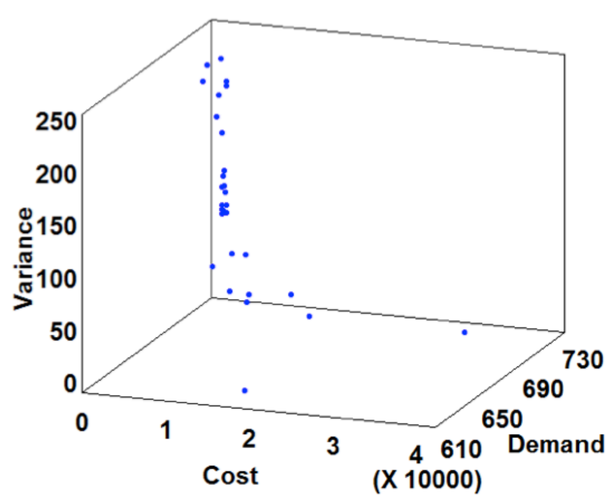

Figure 5.12: Pareto solutions for 3-IEEE-14 network using multi-objective SA

For example, a risk neutral engineer may be willing to accept a slightly higher cost, for a significant decrease in performance variability. However, a risk adverse engineer is willing to significantly increase design cost by almost completely eliminating variability. Table 5.3 displays the results comparison between the performance-based solution, a low risk aversion robust solution, a moderate risk aversion robust solution, and a high risk aversion robust solution. The high risk aversion robust solution resulted in over three times the cost of the deterministic solution, similar to the results of the single IEEE 14 using SA. *Expected Demand Variability* converges to one in the high risk aversion solution, indicating the ability of this network design to consistently satisfy *Expected Demand* at approximately the same value, regardless of which arc is removed from the network.

Figures 5.13a, 5.13b, 5.13c, and 5.13d display the topology results of the performance-based solution, the low risk aversion robust solution, the moderate risk aversion robust solution, and the high risk aversion robust solution respectively. The performance-based solution can be characterized as a sparse network, while the three robust designs provide a solution with at least one redundant arc between nodes.

Table 5.3: Objective function results for performance optimized, low risk aversion, moderate risk aversion, and high risk aversion robust optimization topology of the 3-IEEE 14 test bus using SA

3-IEEE 14 Network (SA)	Network Cost	Expected Demand	Expected Demand Variance	Network Connections	Average Node Deg.	Max. Node Deg.
Performance Opt.	**3753**	**689**	**250**	41	2.0	5
Robust Opt. Low Risk Aversion	**3960**	**702**	**125**	42	2.0	5
Robust Opt. Moderate Risk Aversion	**6194**	**708**	**12**	43	2.0	5
Robust Optimization: High Risk Aversion	**13272**	**712**	**1**	51	2.4	7

However, the average node degrees and maximum node degrees are similar for each solution, indicating traditional network analysis performance metrics (e.g., node degree) may not always indicate system robustness [59, 122]. The moderate risk aversion and the high risk aversion robust design also utilize at least two of the three available lines between subnetworks. This topology solution illustrates the importance of maintaining interconnection lines between regions, so power can be transported from one subnetwork to another after a cascading failure event.

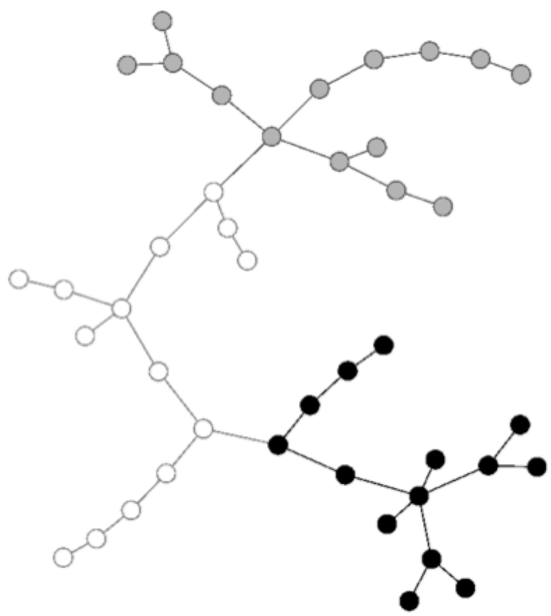

Figure 5.13a: Performance-based optimization of the 3-IEEE 14 network using SA algorithm

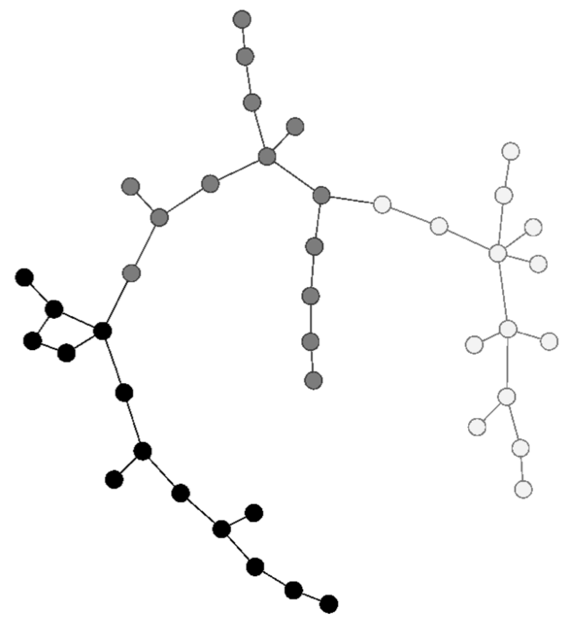

Figure 5.13b: Low risk aversion robust optimization of the 3-IEEE 14 network using SA algorithm

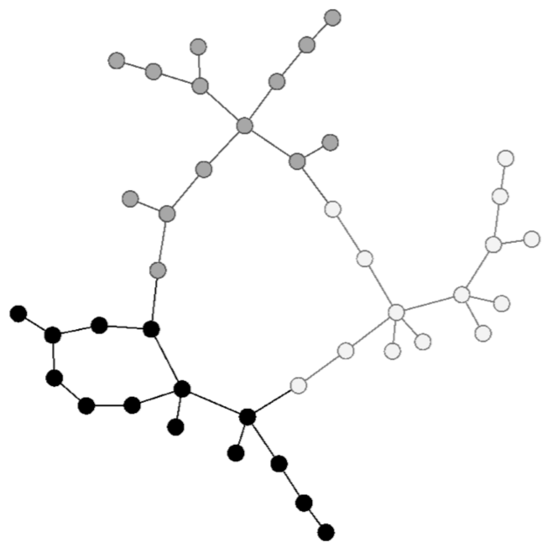

Figure 5.13c: Moderate risk aversion robust optimization of the 3-IEEE 14 network using SA algorithm

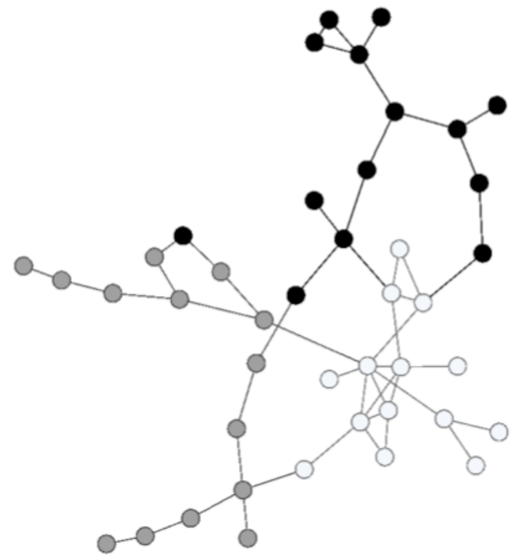

Figure 5.13d: High risk aversion robust optimization of the 3-IEEE 14 network using SA algorithm

5.8 Conclusions and Future Work

This paper presents a novel approach for the robust optimization of complex infrastructure systems by capturing the impact of cascading failure when evaluating system performance. As infrastructure systems operate in highly stochastic environments, they must be designed for robustness by minimizing performance variability in the resultant degraded system state. A mathematical model was created that integrates physics-based modeling and network analysis to iteratively test various network topology designs against uncertain failure events. Quantifying the behavior of cascading failures in complex infrastructure systems is a key contribution, as well as identifying important design tradeoffs between performance and robustness for early design.

Both the single IEEE 14 test bus and the 3-IEEE 14 test bus case studies demonstrated the effectiveness of the approach presented, comparing objective values between the original network, the performance-based optimized network, and the robust optimized network. These case studies highlight the significance of considering subsystem/system topology when optimizing complex infrastructure systems, and examine the influence of cascading failures from one subsystem to another.

One challenge in this research is the ability to validate the method as an accurate abstraction for modern complex infrastructure systems. While the case studies presented show merit, scaling the method to a larger network will assist in determining the solution accuracy. Future work will include modeling of synthetic (e.g., IEEE RTS-96) and real size (e.g., Poland) power grid networks, and comparing the results of this approach to other solutions in the literature.

Despite these concerns, this research contributes measurably to the field of complex infrastructure system design by directly addressing the fundamental issue of uncontrollable cascading failures due to existing topological configurations. Designing for robustness increases the predictability of failure effects by incorporating uncertainty into a system model, and optimizing for degraded performance variability. In addition, the hybrid approach presented captures important topological performance metrics from network analysis, while maintaining critical physical relationships necessary to accurately model a system. Incorporating key system characteristics from each of these design strategies will provide higher fidelity system abstractions than existing network analysis approaches, and alternatively allow higher computational efficiency and scalability over exclusively physics based simulations. Future work will focus on the continued validation of the approach presented by comparatively analyzing case study results between this and other methods for complex infrastructure system design. Specifically, there is additional research required to formulate increasingly accurate system model abstractions, capturing optimal trade offs between physical properties, simulation assumptions, and topological relationships. By understanding the effects of these trade offs, designers can create context specific simulations that balance accuracy, efficiency, and scalability.

5.9 Acknowledgements

The authors would like to acknowledge the support of the University of Alabama in Huntsville Systems Engineering Consortium through NASA Marshall funding under grant SUB2012-052.

CHAPTER 6: EVALUATING THE IMPACT OF HUMAN IN-THE-LOOP DECISION MAKING IN ROBUST DESIGN

Joseph R. Piacenza, Mir Abbas Bozorgirad, Eduardo Cotilla-Sanchez, Christopher Hoyle, Irem Y. Tumer

Conference: Hawaii International Conference on System Sciences

Address: http://www.hicss.hawaii.edu

Submitted: June 2014

Journal: IEEE Transactions on Power Systems

Address: https://ieeexplore.ieee.org/xpl/RecentIssue.jsp?punumber=59

Submitted: June 2014

6.1 Abstract

Robust design strategies are becoming increasingly relevant in complex system design to minimize the impact of uncertainty in system performance due to uncontrollable external failure events. This paper presents a novel approach for the robust design of complex infrastructure systems by capturing the impact of human decision-making during a cascading failure. System performance and performance variability are evaluated based on the resulting (i.e., degraded) system state. This work is motivated by historical system failures such as the 2003 North American blackout and the 2010 Deepwater Horizon disaster, where human in-the-loop decision making significantly contributed to uncontrollable failure propagation. A simulation is presented using the IEEE-118 test case to provide an understanding of how this approach can be used to model the impact of human decisions on system reliability. The results of this study illustrate the importance of capturing these decisions when evaluating system level trade offs, supporting robust design.

6.2 Introduction and Motivation

As the demand for reliable complex infrastructure systems (e.g., power grids, satellite networks) becomes increasingly critical, designers are looking for computational approaches to evaluate designs. An advantage of computational design strategies is the ability for designers to explore key performance trade offs early in the design phase, when design modifications are less costly [123]. This is of particular interest in complex infrastructure systems, as the network topology is typically heterogeneous and distributed in nature, resulting in a system that is vulnerable to cascading failure due to a single initiating event.

Significant barriers exist to creating accurate models of complex infrastructure systems including subsystem interactions (e.g., mechanical, electrical), environmental uncertainty, distributed topology, emergent behavior, and human interactions [60, 106, 124]. While each of these detriments to system performance has been explored extensively independent of domain, addressing them concurrently within a highly non-linear and heterogeneous complex system creates a challenge for system designers.

Control strategies can be implemented into the design of these systems (e.g., circuit breaker, relay) to mitigate critical component failures, although the inherent system complexity provides a barrier for designers to identify (and account for) predominant failure scenarios. Leveraging the input of human agents (i.e., system operators) is also a solution for failure resolution; however, it is difficult to identify and evaluate the impact of their role in the system. For example, key considerations include agent location, number of agents, and agent control variables. Since agents also have the ability to exert free will during an "emergency" decision making scenario, their range of control and position within the system must be constrained.

Minimizing the impact of cascading failure within a system is of particular interest, as the distributed topology makes these systems highly vulnerable to propagating failures stemming from a single initiating event. The Blackout of 2003 highlights the vulnerability of existing infrastructure systems such as the North American Power Grid (NAPG), where over 45 million people in the Northeast U.S. and Canada lost power due to uncontrollable cascading outages [4, 61]. Beyond hardware and software failures, communication deficiencies between regions were a contributing factor to the Blackout [1, 62]. Since the cascading outage took place over approximately 7 hours, independent regions struggled to obtain operational information from adjacent utilities, forcing system operators to make poor, uninformed decisions to protect their local network. This lack of a comprehensive communication system throughout the NAPG interconnections is primarily a function of federal deregulation policies [64]. From an engineering design perspective, considering the impact of "human in-the-loop" decision making within an existing network could potentially mitigate the system level impact of cascading failures.

The Deepwater Horizon disaster of 2010 also illustrates the consequences of cascading failures due to operator decisions made during an emergency failure event [3]. The National Commission on the BP Deepwater Horizon Oil Spill and Offshore Drilling report acknowledges a combination of cascading mechanical, electrical, and decision based failures ultimately leading to the oil rig explosion [5]. Venkatasubramanian examines the Deepwater Horizon incident, and addresses the broader perspective of the potential fragility of all complex engineered systems, empathizing the need to understand the commonalities and differences in these types of failures, in order to better design and control such systems in the future [65].

This paper presents a novel approach for the robust design of complex infrastructure systems by examining the system level impact of human decision-making during a failure event. Robustness is modeled as the invariability of the resultant steady state system performance, after a cascading failure has occurred. This approach suggests that designers can capture and analyze the impact of human in-the-loop interactions within complex systems to evaluate system robustness.

6.3 Background

Robustness is defined in complex systems literature as the ability of a system to behave as intended, despite the effects of uncertainty from both internal and external sources [53, 98]. External sources of uncertainty (i.e., noise factors) are typically represented as variations in the environment that influence intended system performance, while internal sources (i.e., noise factors) can include subsystem performance variations and human decisions (Figure 6.1). For this work, human decision making is represented as a control factor (as opposed to a noise factor), since operators are strategically placed during system design. Therefore, human decisions can be optimized to improve system robustness. In complex infrastructure systems, a single initiating fault (e.g., mechanical, electrical, communication) can propagate throughout the network uncontrollably, resulting in severely degraded performance or complete failure. This is of particular interest, as complex infrastructure systems are often designed with a low factor of safety.

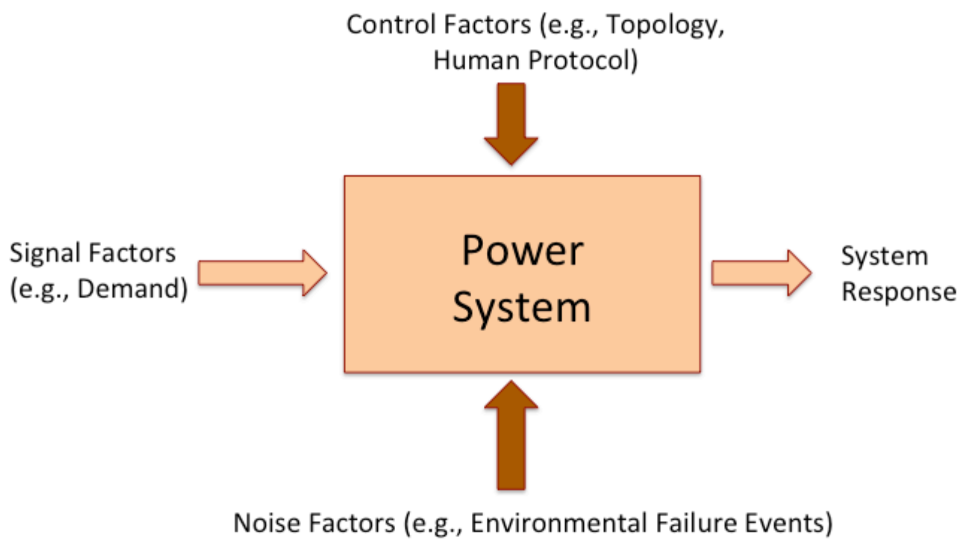

Figure 6.1: Parameter diagram for complex infrastructure systems

To understand cascading, current methods have employed both agent-based and social network analysis for predicting emergent system behavior [55, 96, 97, 125]. However, agent-based and network theory performance metrics (e.g., agent evaluation functions, node degree, centrality) focus heavily on system scalability and are too far abstracted from actual complex system behavior to accurately assess the impact of cascading failures when creating reliable designs.

Currently, there is no approach to incorporate robustness into complex infrastructure system design to minimize the impact of cascading failures due both to internal and external sources of uncertainty. Examining the impact of human in-the-loop decision-making as a means of increasing design robustness builds on existing approaches, expanding current methods into complex infrastructure systems, discussed next.

6.3.1 Robust Design in Complex Networks

While there are many methods to analyze failure propagation and reliability in complex systems, these approaches are typically hardware driven. Also, they do not address the formalized concept of robustness, and how infrastructure systems can be designed to minimize system failures [43-51, 54, 69]. The primary issue, however, is creating designs that are robust to the various types of failures and uncertainties present in complex and largely distributed infrastructures. Examining the network topology can help minimize the impact of cascading failures, especially in heterogeneous systems.

Current literature addresses the importance of considering topology in network optimization, often drawing from network theory where networks are represented mathematically [55-57]. For example, Kinney et al. model a power system case study with an adjacency matrix, where each node represents either a generation or demand component in a network, and arcs connecting the nodes represent connectivity [57]. In that work, failures are examined by removal of a single node, which triggers an overload cascade in the network. Similar methods are used by Leonardo and Vemuru, where total connectivity loss measures network performance [58]. Ash and Newth examine the optimization of complex networks with respect to the average efficiency of the network, which was first introduced by Crucitti et al. [59, 60]. While these types of topological measures provide valuable information about a specific network, it is important to recognize that these mathematical models are abstractions of complex systems. Hines et al. have addressed this concern directly, comparatively evaluating topological metrics within the same system to predict failure magnitudes in standard test cases [56]. Their work concluded that while exclusively using topological measures can provide general information about a system's reliability, they can be misleading due to the level of abstraction and should be used in conjunction with a physics-based model. Dobson et al. use a probabilistic analysis based on past power system performance to suggest that the frequency of large blackouts is governed by a power law. In this work, the author's assert that some methods of suppressing subsystem failures could ultimately increase the risk of uncontrollable system level failures [126].

6.3.2 Human In-the-Loop Considerations in Complex System Design

While many cascading system failures begin as a result of external occurrences such as extreme environmental conditions (e.g., excessive well bore pressure on the Deepwater

Horizon, above normal summer temperature in the Northeast U.S. during the Blackout), case studies show that human in-the-loop decision-making has the potential to affect the resultant system outcome [66]. The overarching challenge of complex infrastructure design is to understand system level interactions, and how an agent (or set of agents) can impact the subsequent emergent system behavior, during early design.

Watts examines this concept from a sociology perspective, citing parallels to engineered systems [67]. In this work, he postulates that individuals in a population exhibit herd-like behavior because they are making decisions based on the actions of other individuals rather than relying on their own information about the problem. This is a concern in agent-based control strategies for complex systems, as agents must make decisions based on information about both their local and global network. Hines and Talukdar examine this relationship by developing a method to create a social network of autonomous agents to solve a global control problem with limited communication abilities [68]. This approach uses distributed model predictive control and cooperation to minimize cascading failure in an IEEE test bus. However, it requires an agent to be present at each location (i.e., node) of the system. This solution is not economically efficient, or even possible in many complex systems. Other approaches also draw from social network analysis, where reliability indicators rely heavily on high-level system abstractions [45, 55, 69].

Alternatively, decision-based design strategies have also been examined for estimating agent decision-making behavior in complex systems. Sha and Panchal have explored this concept comparing the benefits between generalized preferential attachment, a statistical regression-based approach, and multinomial logit choice modeling [70]. Both multinomial and nested logit models have been used extensively to predict individuals' decisions in a variety of domains including sociology, economics, and civil engineering (e.g., traffic networks) [71]. The barrier to using these methods in early design is the reliance on historical behavior required to generate a utility function capable of predicting behavior.

6.4 Contributions

Current literature formally addressing robustness in complex infrastructure system design displays a deficiency in strategies for capturing the impact of operator decision-making. This is primarily due to the fact that most robust design methods focus on minimizing performance variability of the system during fully functional operation, and do not examine the uncertainties contributing to cascading failure. This distinction is highly significant as complex systems are often designed and operated at a low factor of safety, For example, uncertain failure events (e.g., environmental effects, agent decisions, hostile attacks) can result in cascading failure, and must be accounted for when designing predictable and robust systems. The 2003 Blackout and the 2010 Deepwater Horizon incidents further illustrate the need to consider various sources of uncertainty, specifically the impact of human decision-making during a failure scenario. The research presented in this paper directly addresses this concern, postulating that robust design strategies can be used to optimize agent interaction within a complex system, minimizing performance variability after an initiating failure event.

A novel approach has been developed to optimize the number and location of control agents present in a complex system during conceptual design, to minimize performance loss during an uncontrollable failure propagation scenario. In this method, robustness is represented as the ability of a system to satisfy minimum performance requirements, after a cascading failure event. This research captures system specific stochastic failure effects, and accounts for the ability to meet specified design objectives. A two-stage optimization approach is utilized, where instantaneous system performance is calculated within the outer-loop objective function to capture continuous performance degradation during cascading. This optimization is performed using a multi-objective simulated annealing algorithm, based on its ability to efficiently handle discrete solutions [109].

The inner-loop simulation is based on the IEEE 118 test bus. The network is created using a series of adjacency matrices, where system attributes for power generation, regional demand, system topology, and agent interactions are included [99]. MatPower, an analysis toolbox designed to operate within the MatLab, is used to calculate the quasi-steady state decoupled optimal power flow (DCOPF) [108, 127]. The result is a computer Model identifying Pareto optimal design trade-offs between performance and performance variability of a degraded system, based on the quantity and location of system agents.

6.5 Methodology

The research presented in this paper aims to capture the impact of human in-the-loop decision making during an uncontrollable cascading failure. A two-stage optimization framework has been developed that identifies design trade offs in an outer-loop optimization that identifies quasi-steady state system conditions during a cascading failure scenario (Figure 6.2). Design trade offs include performance, performance variability, and number of agents.

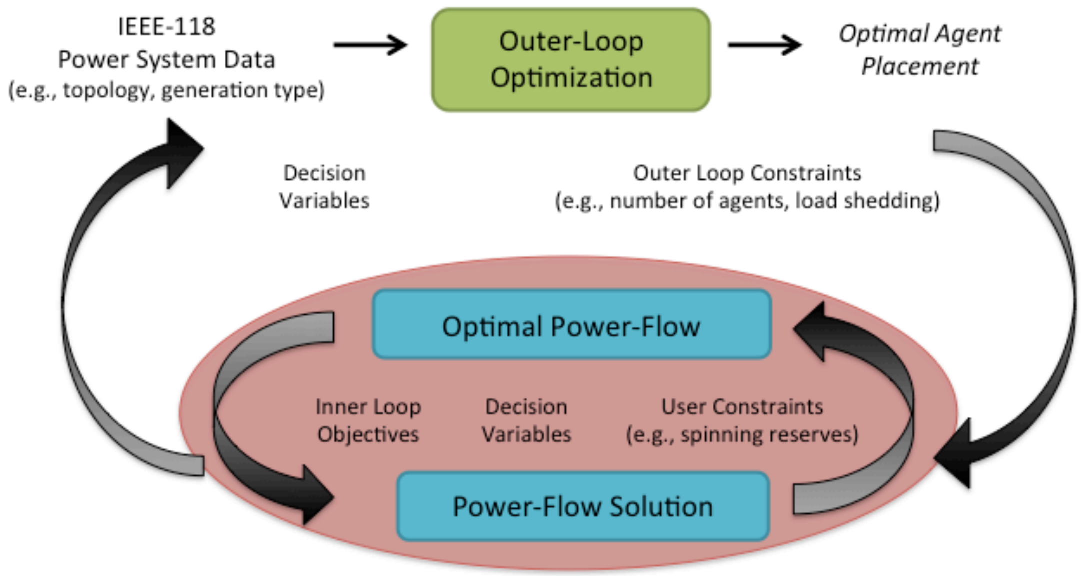

Figure 6.2: Two-stage optimization framework

MatPower performs the inner-loop optimization, calculating instantaneous power flow based on physical relationships such as generation, demand, and existing topology. The simulation consequently outputs decision variables for the number and location of agents to the outer-loop optimization. This allows a designer to explore Pareto solutions, based on their requirements and preferences.

6.5.1 Solving Quasi-Steady State System Performance in MatPower

MatPower is a package designed for solving both power flow (PF) and optimal power flow (OPF) problems [108, 127, 128]. The power flow problem is a numerical analysis of a power system in steady-state conditions using voltage magnitudes and phase angles at each bus (i.e., node). The input data is provided using standard test cases, and consists of system elements such as topology, generator limits, and transmission line specifications. The outputs of these calculations are the active and reactive power injections at each bus required to keep the system within operating specifications. Linear programming is used to optimize generation ramping while enforcing transmission line limits required to avoid an overload. This is known as the optimal power flow [128]. The simulation fidelity can be increased by adding additional details such as generation costs (at each source), and will provide the user with the lowest cost per kilowatt-hour delivered option.

One feature of MatPower is the ability to analyze the decoupled (DC) power flow, which is a linear and simplified version of an alternating current (AC) power flow. The DC power flow purely looks at active (i.e., real) power, neglecting transmission losses, voltage support, and reactive power management. For this research, only DC power flow will be considered, since the concept of a supporting performance flow (i.e., reactive power) is inherent only to power systems, and not other complex infrastructure cases such as communication and traffic networks. In the DC-OPF solver, the voltage magnitude and reactive power is eliminated from the problem completely, and active power flow is modeled as a linear function of the voltage angles [127]. MatPower then outputs active power limits and topology changes due to line overloading.

6.5.2 Two-Stage Optimization Framework

The framework presented here is composed of both an outer-loop (i.e., system-level) and inner-loop (i.e., power flow) optimization to estimate system performance as illustrated in

Figure 6.2. The outer-loop optimization contains objectives directly relating to increasing system robustness, or insensitivity to uncertainty (Equation 6.1). These are defined broadly as design trade offs for performance, performance variability, and cost (i.e., number of agents).

find A_n (6.1)

minimize

$f_1 = -\mu_{D_E}$

$f_2 = \sigma^2_{D_E}$

$\mathrm{f}_3 = A_n$

subject to

$g_1: A_n - N_{total} \leq 0$

$h_1: AL_{shedding} - 10\% = 0$

where the decision variable (A_n) is an adjacency matrix representing the number and location of agents in the system. D_i is the demand satisfied for a single cascading scenario, and D_E is the total average demand satisfied for a given number of discrete failures, shown in Equation 6.2.

$$D_E = \frac{\sum D_{i \dots n}}{n} \tag{6.2}$$

μ_{D_E} is the mean of the resultant demand values, and $\sigma^2_{D_E}$ is the variance of these values. N_{total} is the number of nodes in the system (i.e., 118 for the IEEE 118 case), limiting the overall quantity of possible agents ($\mathrm{A_n}$). $\mathrm{AL_{shedding}}$ represents the discrete shedding percentage each agent may utilize during a cascading failure.

The inner-loop simulation is the optimal power flow (OPF) analysis which is embedded within the outer-loop (i.e., system level) optimization to evaluate the steady state conditions of the system during cascading. This simulation contains its own set of subsystem objectives, constraints, and decision variables. The objective of the OPF is to minimize the cost of the active power injections (i.e., generator ramping) required to maintain system stability based on a single loading scenario (Equation 6.3). The inner-loop optimization objective is defined as:

find P_g, θ (6.3)

minimize

$$f_1 = \sum_{i=1}^{n_g} f_P^i \,(p)_g^i$$

where p is the vector consisting of P_g, the active power injection, and θ, the voltage angle (Equation 6.4). Complete details for this formulation can be found in the MatPower User's Manual [129].

$$p = \begin{bmatrix} \theta \\ P_g \end{bmatrix} \tag{6.4}$$

By nesting the DCOPF of the test case within the system level optimization, each instantaneous power flow analysis can be performed as the network topology changes during a cascading failure.

6.5.3 Modeling Decision Making in Complex Systems

In both the 2003 Blackout and the Deepwater Horizon incident, decisions made by system operators after an unexpected initiating failure event influenced the system's emergent behavior. This observation provides insight into how human in-the-loop interactions could be modeled during concept-stage system design. Drawing from existing physical design elements of the NAPG, Figure 6.4 represents a highly simplified abstraction of a power system. This system consists of three connected subnetworks, each containing a generator and multiple demand nodes. In addition, a subsystem operator, or agent, is located adjacent to the generator. The task of the subsystem agent is to dynamically adjust the power output of the generator to match demand fluctuations, known as demand response. However, in the case of an unexpected line failure, this level of control can be inadequate to prevent subsequent line overloading. Line overloading occurs when the power delivered to a line exceeds its rated capacity. Performing intentional islanding or strategic load shedding can prevent this overload. By ramping down power generation, load shedding reduces the power being transferred through a subnetwork. As an alternative strategy for reducing line loss, this research explores the benefits of strategically placing agents within a given network. In the event of a line overload, each agent has the ability to shed a fixed percentage of demand load for their local region. This practice allows the agents to make discrete control decisions, potentially reducing the magnitude of system failure during cascading.

When formulating this approach, the following agent responses to a cascading event were identified and evaluated:

- *Response 1*: Let failure happen
- *Response 2*: Isolate failure (i.e., engage circuit breaker)
- *Response 3*: Reduce load (i.e., load shed)

Response 1 occurs when the agent chooses not to take action, and Response 2 is the act of selfish agent (or circuit breaker). We will focus on Response 3, in which an agent can shed demand load for their location. This will allow the exploration of an intermediate failure mitigation solution at a node, increasing the total set of Pareto designs in the system-level optimization. This is achieved in practice by exercising a Load Shedding Agreement, where a commercial customer voluntarily curtails power demand. Strategically placing load-shedding agents in power system subnetworks could reduce local line failure, consequently minimizing system level performance degradation.

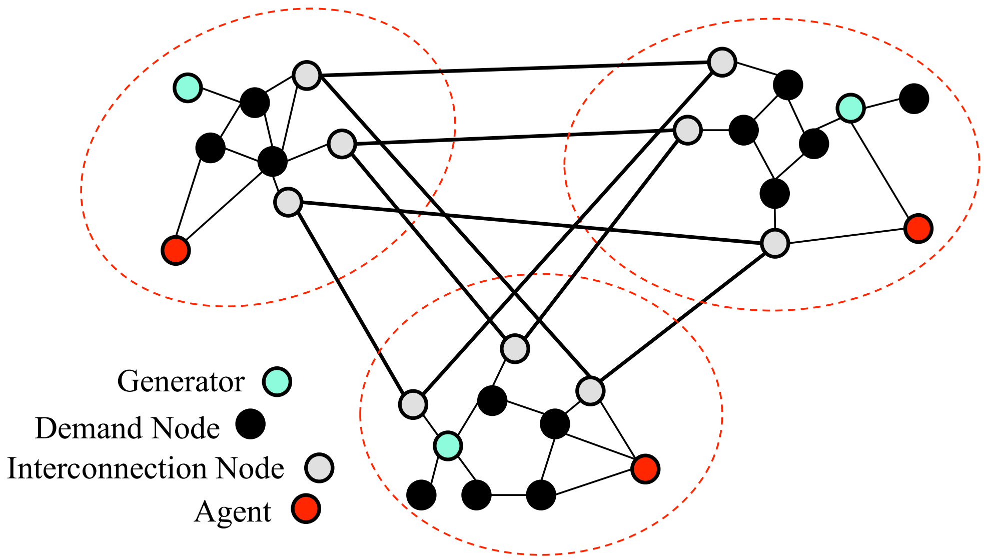

Figure 6.3: Power system visualization with agent decision locations

6.5.4 System Level Optimization

The outer-loop optimization is performed using a multi-objective simulated annealing (SA) algorithm to evaluate the system level objectives [109]. The SA algorithm was selected as it avoids getting trapped in local optima by accepting deteriorated solutions. Czyżak and Jaszkiewicz developed Pareto simulated annealing (PSA) to adopt this search for multi-objective optimization problems [110]. This search is conceptually identical to the single-objective SA but, instead of using one candidate to represent the final solution, PSA uses a set of interacting solutions at each iteration [111].

In this research, a SA strategy is performed that perturbs an individual solution at each iteration. If the perturbed solution is not dominated by its preceding solutions, it enters the non-dominated set of Pareto fronts and this set gets updated accordingly. The next seed of SA is selected randomly from the updated set of Pareto fronts. If the perturbed solution is dominated by at least one of its preceding solutions, it will not enter the Pareto front set, however it will still be selected for the continuation of the algorithm with the following probability (Equation 6.5):

$$P(A_x, A_n, T) = min\ \{1, exp\left(\frac{\sum_{j=1}^{N_{SA}}\left(f_j(A_x) - f_j(A_n)\right)}{T}\right)\} \tag{6.5}$$

where the adjacency matrix A_n is the solution obtained by perturbing the adjacency matrix A_x, N_{SA} is the total number of objective functions, and T is the temperature at each iteration. Details of SA algorithm are as follows:

- Population = 400
- Initial temperature = 1000
- Stop Temperature = 1e^{-6}
- Cooling Rate = 0.95

6.5.5 Optimization Framework Process Flow

To clearly illustrate the steps performed during the two-stage optimization model, a process flow diagram is presented (Figure 6.4). First, the IEEE 118 test case is imported. Next, a random number and location of agents is generated using an adjacency matrix. This initial agent placement uses the fixed topology of the IEEE 118 test case. A random line is then removed from the system, and the DCOPF is calculated using MatPower. The redistribution of power in the test case may cause additional lines to overload, initiating a cascading failure. To mitigate this failure, the agents placed at a line location where demand exceeds capacity will shed 10% of the demand at that node. The DCOPF and load distribution loop is repeated until the system reaches a steady state, where demand load does not exceed capacity at any point. Although load shedding may prevent an overload, it will also reduce the total demand satisfied. This trade off is incorporated into the system level optimization objective (Equation 6.1).

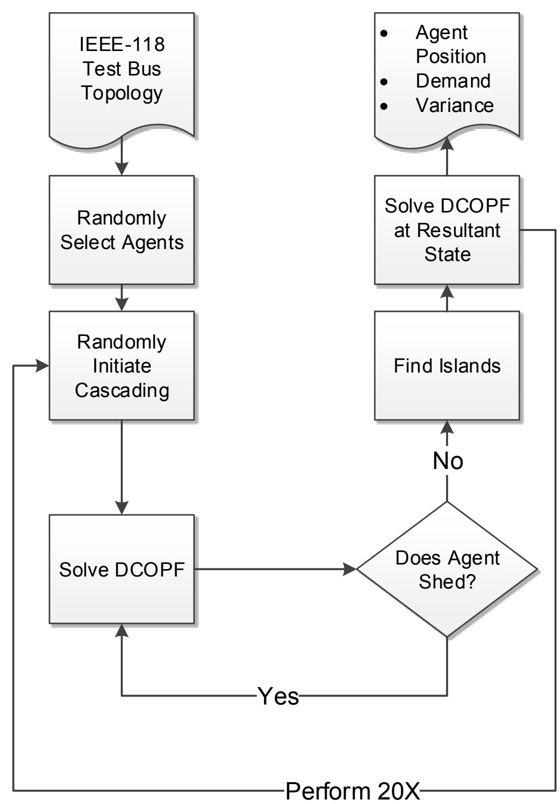

Figure 6.4: Two-stage optimization model process flow

In practice, it is typical for a power system network to become partially disconnected after a cascading failure, resulting in multiple independent subsystems, or islands [63]. This action is captured during the simulation, and the DCOPF is performed for each disconnected subnetwork. The resultant system level demand satisfied (D_i) for each line failure scenario is calculated by summing the demand satisfied for each island (Equation 6.6). It should be noted that an island might not include a generator, subsequently resulting in a total subnetwork failure.

$$D_i = \sum_{i=1}^{n} D_{i_n} \tag{6.6}$$

For each agent placement design (A_n), 20 unique line removal scenarios are performed. This quantity is selected as a function of network size, building on random removal techniques from existing literature [59]. These solutions are used to evaluate the mean of the resultant demand served values (μ_{D_E}), and the variance of demand served ($\sigma_{D_E}^2$).

Based on the system level objectives from Equation 6.1, the SA algorithm outputs a set of Pareto optimal solutions. These solutions allow the designer to explore trade offs between performance, performance variability, and number of agents. In this method, the number of agents is captured by a cost variable, since there would be implementation and operations cost associated with their placement.

6.6 Implementation and Results

6.6.1 IEEE-118 Test Bus Case Study

Based on the system optimization objectives (Equation 6.1), the set of Pareto optimal solutions are displayed in Figure 6.5.

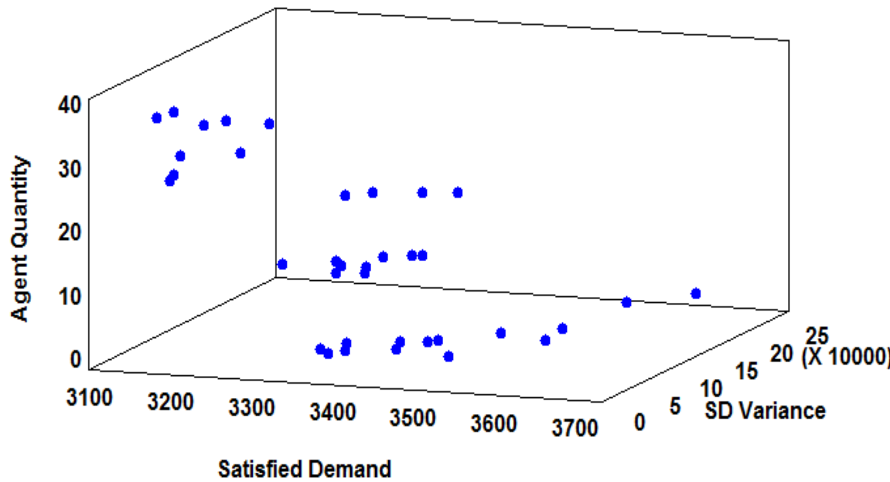

Figure 6.5: Pareto optimal solution for the outer-loop optimization

Since system robustness is represented as a function of performance invariability, the trade offs are explored between the performance variance ($\sigma^2_{D_E}$), mean performance (μ_{D_E}) and the number of agents (A_n). For example, if the degraded system performance requirements increase, the quantity of agents must be increased to minimize the performance variability. Table 6.1 displays a set of extreme solutions from the Pareto frontier, to establish a contextual range of solutions.

Table 6.1: Extreme design objective solutions

Solution Type		**Variance** $\sigma^2_{D_E}$	**Demand** μ_{D_E}	**Agents** A_n
Variance	**Low**	4329	2172	32
	High	692233	2467	0
Demand	**Low**	23265	1817	0
	High	637970	2502	1
Agents	**Low**	28408	1894	0
	High	4662	2298	41

In these selected results, the most risk averse (i.e., low variance) design is achieved using 32 agents in select locations. In comparison, the solution with the largest number of agents (41) has a higher variance. This relationship infers that increasing robustness is achieved through implementing a specific design strategy, instead of attempting to control system behavior with agents. Both high and low demand values are achieved with little or no agent control, emphasizing the broad range of potential performance scenarios after a cascading failure. The largest demand value has a high associated variability, indicating a risk taking solution. The relevance of risk attitudes in engineering design trades is discussed next.

6.6.2 Risk Attitudes in Engineering Design

Throughout a design process, engineers will often make decisions based on their individual risk attitude, or the risk attitude of their organization [118-121]. In the context of this research, a risk tolerant individual may be willing to accept a higher level of performance variability, in exchange for a less costly design. However, a risk adverse individual may be willing to significantly increase design cost in order to minimize performance variability. Table 6.2 presents an alternative selection of less extreme design solutions potentially aligning with different risk attitudes. Three designs are presented corresponding with an individual's tolerance for risk aversion (i.e., low, moderate, high). In these results, the average node degree of an agent's position is presented. The low risk solution has the highest node degree, indicating that limited agents should be placed in critical, highly connected areas of the network. As the risk aversion is increased (along with the number of agents), average agent node degree decreases. This is expected since the IEEE 118 network has overall average node degree of 3.03.

Table 6.2: Comparison of risk based design solutions

Risk Attitude	Variance	Demand	Agents	Avg. Agent Node Degree
Low Risk Aversion	40606	3420	2	7
Moderate Risk Aversion	14388	3369	17	6
High Risk Aversion	8711	3153	38	1.34

In terms of network topology, Figure 6.6 provides a network map for the IEEE-118 test case with agent locations indicated for the moderate risk aversion robust design.

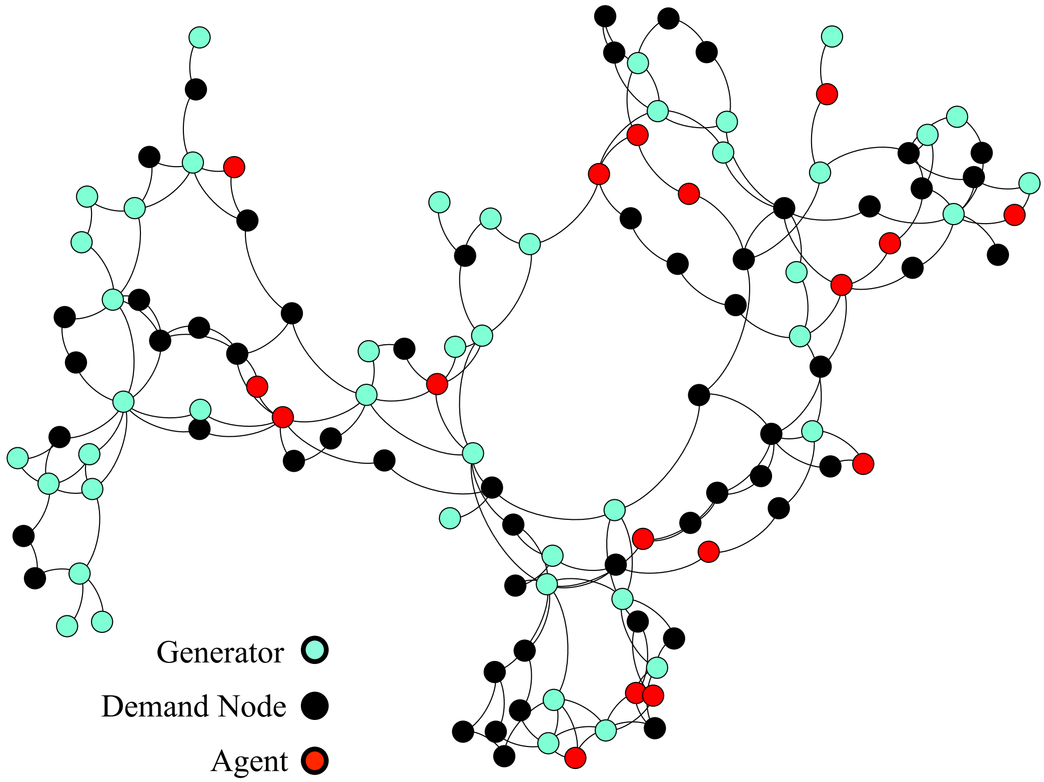

Figure 6.6: Network topology for the moderate risk aversion robust design

6.7 Conclusions and Future Work

The 2003 Blackout and the 2010 Deepwater Horizon incident both illustrate how human decisions made during a cascading fault event inadvertently contributed to system failure. As complex systems operate in highly stochastic environments, systems must be designed for robustness by incorporating the effects of failure propagation into optimization objectives, evaluating the performance of the resultant degraded system state. This paper presents a novel approach for incorporating robustness into complex infrastructure system design by leveraging the impact of human in-the-loop decision making to minimize performance variability during a cascading failure event. Robustness is represented as the invariability of system performance despite the impact of failures due to uncertain environmental events. This allows the system to meet minimum performance requirements, even during degraded operation. The formulated approach captures the impact of human in-the-loop decision-making on system reliability, consequently providing a set of design alternatives based on user requirements.

The design framework presented shows promise, and there are several opportunities for expansion. The first path forward is applying the author's approach to other domains outside of power systems. For example, the cascading failure timeline of the Deepwater Horizon incident has been extensively documented in literature. Application of this approach could help to identify optimum placement of human controlled access points in the system. The range of system operator control (at each location) could also be optimized. In addition, larger scale domains include regional communication systems or traffic networks, which could benefit by strategically placed operators with limited control.

Another direction for future work is addressing scalability. The results from the IEEE-118 test case do provide insight into emergent system behavior due to agent interaction, however the relationships identified may not remain consistent in larger networks. The Poland power grid, often cited in the power systems community, will be used for this purpose.

Finally, expanding the range of agent control and decision making ability will significantly increase the simulation fidelity. The current load shedding strategy in the model is based on existing power system best practices of blanket load shedding in a specific region. For example, a reinforcement learning strategy that offers an agent multiple discrete choices could increase the number of solutions in the Pareto frontier.

This would allow a more appropriate design choice based on system requirements, and potentially further reduce performance variability.

6.8 Acknowledgments

The authors would like to acknowledge the support of the University of Alabama in Huntsville Systems Engineering Consortium through NASA Marshall funding under grant SUB2012-052.

CHAPTER 7: GENERAL CONCLUSIONS AND FUTURE WORK

7.1 Research Overview and Summary

This research presents a comprehensive engineering framework for the robust design of infrastructure systems. Each element of the framework identifies a key strategy for increasing system robustness, and contains its own stand-alone design method, simulation, and design analysis. However, the combination of each method produces an inclusive approach that addresses a range of critical issues during robust design. The overarching theory behind the three manuscripts in this dissertation is to create a flexible design framework that broadly aims to minimize performance variability, even when uncertainty in present. This goal is addressed at the concept-stage design level by examining system robustness in terms of cascading failures, network topology optimization, and the impact of human in-the-loop interactions. Several power system domain case studies are presented that illustrate the benefit of robust design strategies at both the system and subsystem level. At the system level, network topologies and human behaviors are explored to determine their influence on design robustness. The subsystem level also investigates human behavior, but from a low-level energy conservation standpoint that will ultimately influence high-level system performance. However, the end goal of this research is to provide an approach that is applicable across various infrastructure domains (e.g., satellite and traffic networks).

To demonstrate the importance of examining both high (i.e., system) and low level (i.e. subsystem) design strategies for infrastructure systems, a case study of the North American Power Grid (NAPG) is considered. Chapter 4 first outlines the projected energy requirements of the United States, and addresses the need to implement standardized energy conservation initiatives, specifically in commercial buildings. Sustainable building mandates (e.g., LEED, Living Building Challenge) are explored as potential alternatives to increasing energy production. One concern however, is that designers cannot quantify every aspect of sustainable building mandates, the most subjective being the influence of human behavior. The strategy developed in this chapter for quantifying LEED's Indoor Environmental Quality (IEQ) estimates causal relations between design attributes, and both the stated and revealed user preferences for sustainable buildings. Structural equation modeling (SEM) is used to evaluate postulated significant correlations between the fixed design attributes, observed variables, and latent variables. Within this model, latent variables uncovered through statistical analysis represent emergent user preferences resultant of a building's indoor environment. This method enables designers to explore tradeoffs between fixed costs, operational costs, and cost savings due to sustainable building mandates. Understanding an individual's preferences for sustainable design characteristics could offset additional costs required to support energy conservation strategies. In addition, reducing demand load (i.e., conservation) within multiple subsystems will increase high-level power system robustness.

Chapter 5 illustrates the second thrust of the framework by examining the impact of topology optimization as an approach for minimizing performance reduction due to cascading failures. Since infrastructure systems operate in highly stochastic environments, they must be designed for robustness by incorporating the effects of failure propagation into the design optimization objective. System performance is then evaluated based on the resultant degraded state. Throughout this dissertation, robustness is represented as the invariability of performance due to uncertain effects (both internal and external) on the system. The power system case studies presented are modeled mathematically using a combination of physics-based modeling and network analysis, iteratively testing multiple network topology configurations against an initiating failure event. These events are simulated by randomly removing a single network arc in each design, and examining the resulting steady state system performance after cascading has occurred. Design trade-offs are examined between performance and performance variability (i.e., robustness) of the degraded system. Using this method, network designs can be created that account for, and are robust to, uncertainty from external events (e.g., natural disasters) often affecting highly distributed infrastructures. Specifically, this research captures system specific stochastic failure effects, and accounts for the ability to meet specified requirements, as well as considering cost. Quantifying the behavior of cascading failures in infrastructure systems is a key contribution, as well as identifying important design tradeoffs between performance and robustness for early design.

The final component of this framework again focuses on system level robustness, and captures the impact of human decision-making on performance. Chapter 6 ties these elements together by first citing two historical case studies: the 2003 Blackout and the 2010 Deepwater Horizon incident. Both of these historical examples illustrate how human behavior during a cascading failure inadvertently contributed to critical performance reduction, and ultimately complete system loss. The method developed in Chapter 6 addresses these case studies directly by incorporating robustness into the infrastructure design. This is achieved by leveraging the impact of human in-the-loop decision making within a given network topology to minimize performance variability during cascading failure. To understand the influence of human behavior on emergent system performance, a two-stage optimization approach is utilized. Instantaneous system performance is calculated within the outer-loop objective function to capture continuous performance degradation during cascading. The inner-loop objective function focuses on minimizing control costs associated with maintaining performance stability. A mathematical abstraction the system is represented with a series of adjacency matrices, consisting of system attributes for power generation, regional demand, system topology, and agent placement.

The holistic theory behind this research framework will allow for the design space exploration of infrastructure systems. These Pareto solutions will provide a wide breadth of potential system designs based on domain specific failure characteristics, topology constraints, and human interactions. The resultant methods from this theory will provide concept-stage insight to designers by helping to identify key trade offs, without the need to explicitly model all component level interactions. This work has focused on fundamental research objectives toward quantifying high-level emergent system behavior, which can be leveraged to design robust infrastructure systems.

7.2 Expanding the Research Framework

This section of the dissertation outlines specific opportunities and strategies for expanding both the fidelity and applicability of the individual methods presented. Section 7.3 will address future work pertaining to the collective integration of each method into a single, generalizable approach for the robust design of infrastructure systems.

7.2.1 Ongoing Research Toward Quantifying Indoor Environmental Quality for Sustainable Building Design

While the approach developed in Chapter 4 for quantifying Indoor Environmental Quality (IEQ) shows merit, there is an opportunity for continuing research. In the LEED building case study presented, additional empirical measurements could be implemented such as indoor temperature, humidity, and air quality. Incorporating a broad range of environmental factors into the Structural Equation Model will provide designers with additional insights for specific building attributes that drive user behavior. In addition, the empirical data could be collected from additional LEED buildings to verify consistency. Examining other LEED buildings and user preferences outside of a university campus will address any biases present in an academic institution. On a larger scale, the next big step is incorporating projected energy savings from sustainable buildings into the high-level power system model utilized in Chapters 5 and 6. This will identify cost trade offs between sustainable building strategies, and increasing energy generation when determining how to meet predicted energy needs.

7.2.2 Topology Optimization for Robust Infrastructure Systems

The primary challenge of exploring robust designs for infrastructure topologies is the ability to validate the model as an accurate abstraction the system it represents. There is room for additional research to increase model accuracy, capturing optimal trade offs between physical properties, assumptions, and topological relationships. In particular, there is a concern when issue developing a method that is scalable to real life networks, which are larger and more complex than cases presented. Future work will include the modeling of other synthetic (e.g., IEEE RTS-96) and real size (e.g., Poland) power grid networks. These results will then be compared to the solutions from other robust design approaches in the literature.

The strategy developed for initiating cascading failure is another area of exploration when evaluating system robustness. Currently, a single failure event initiates failure propagation, however it is possible multiple arcs could fail simultaneously. Future work will included the random removal of multiple, which is representative of how natural disasters (e.g., hurricane, earthquake) often impact a region.

7.2.3 Human In-the-Loop Considerations for System Robustness

The work presented in Chapter 6 has addressed some fundamental concerns for the concept-stage design of infrastructure systems, however there is considerable room for development. First, expanding the range of agent control and decision making ability will significantly increase the simulation fidelity. The current load shedding strategy in the model is based on existing power system best practices of blanket load shedding in a specific region. Instead, offering the agent multiple discrete choices could increase the number of solutions in the Pareto frontier. This would allow a more appropriate design choice based on system requirements, and potentially further reduce performance variability.

The next direction for future work is again addressing scalability issues as in Chapter 5. The results from the test cases presented do provide insight into emergent system behavior due to agent interaction, however the relationships identified may not remain consistent in larger networks. The Poland power grid, often cited in the power systems community, will be used for this purpose.

Finally, last path forward is applying the author's approach to other domains outside of power systems. For example, the cascading failure timeline of the Deepwater Horizon incident has been extensively documented in literature. Application of this approach could help to identify the optimum placement of human operation points in the system. The range of system operator control (at each location) could also be optimized. In addition, larger scale domains including regional communication systems or traffic networks could benefit by strategically placed operators with limited control.

7.3 Generalizable Robust Design Approach

The framework presented in this dissertation directly addresses three unique challenges for designing robust, concept-stage infrastructure systems. While each method aims to overcome various robust design deficiencies identified in the literature, there is still a need to develop a generalizable approach, applicable across various system domains. An opportunity exists to create an integrated robust design approach that contains key elements of the current framework, enabling a more comprehensive infrastructure design solution.

This approach will utilize the existing two-stage optimization method, allowing designers to incorporate their desired optimization objectives (i.e. outer loop optimization), as well as relevant physics based system relationships and engineering risk attitude (Figure 7.1).

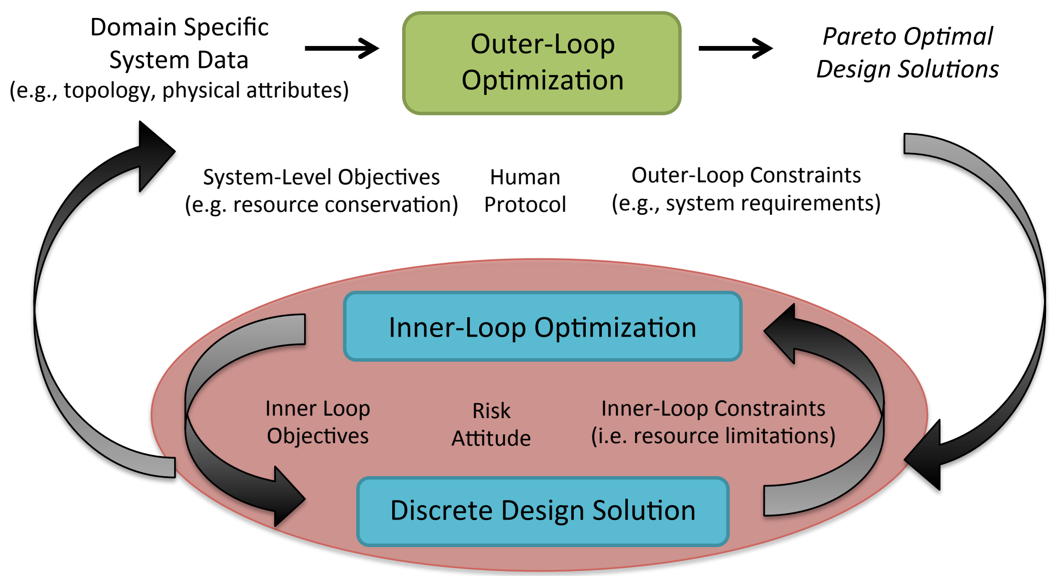

Figure 7.1: Generalizable two-stage robust design model

This integrated robust design approach incorporates each component of the dissertation framework, capturing resource conservation, system topology, and human protocol. In the case of the 2003 Blackout, cascading occurred because the demand load on the power transmission lines continued to exceed capacity after an initiating failure event. If energy resource conservation strategies (e.g., sustainable building design) were implemented during early design, this scenario may have been avoided due to an overall reduced grid load. In addition, regional power system operators did not correctly implement protection practices such as load shedding, which could have further minimized failure. Optimizing human protocol and control locations within the NAGP topology would have contributed to system robustness, reducing demand losses.

Applying an integrated robust design approach could also have mitigated the cascading failure scenario during the Deepwater Horizon disaster. In this case, a mechanical failure event cascaded through several mechanical and electrical subsystems, until a system operator was alerted to the failure. Designing for optimal operator location would have reduced the number of failures that occurred before operator notification. Additionally, the Deepwater Horizon operators ignored the required decision protocol, ultimately leading to catastrophic system failure. If decision protocol had been optimized for limited discrete control, total system failure may have been avoided. Examples of specific control locations for the offshore oil platform include the *blowout preventer*, *drill pipe*, and *engine room*. Corresponding control protocols are *shear ram actuation*, *well-bore pressure*, and *drill speed* respectively.

In both of these case studies, a robust design approach will provide a set of Pareto optimal solutions, where designers can trade off objectives based on their (or their system's) risk attitude. For the NAPG, risk attitude in analogous to a desired security constraint such as N-1, where the system must perform as intended despite the loss of a single transmission line [130]. The Deepwater Horizon case is similar, where risk attitude could relate to well-bore pressure conditions or drill speed. These design variables correspond directly with oil platform performance. Creating a comprehensive design approach, based on the framework presented in this research, will enable robust infrastructure system designs that capture resource conservation, topology optimization, and human protocol.

BIBLIOGRAPHY

[1] Hines, P., Apt, J., and Talukdar, S., 2009, "Large blackouts in North America: Historical trends and policy implications," Energy Policy, 37(12), pp. 5249-5259.

[2] Hines, P., Apt, J., and SaroshTalukdar, "Large blackouts in North America: Historical trends and policy implications," Energy Policy, 37, pp. 5249-5259.

[3] Bourne, K. J., 2010, "The Deep Dilemma," National Geographic.

[4] Fairley, P., 2004, "The Unruly Power Grid," IEEE Spectrum, pp. 23-27.

[5] National Commission on the BP Deepwater Horizon Oil Spill and Offshore Drilling, 2011, "Deep Water: The Gulf Oil Disaster and the Future of Offshore Drilling."

[6] International Living Building Institute, 2010, "Living Building Challenge 2.0," Cascadia Region Green building Council, International Living Building Institute, Seattle, WA, p. 48.

[7] Piacenza, J., Tumer, I. Y., Stone, R., Knighton, J., and Elzeyadi, I., "Towards a System Analysis and Integration Framework for Early Design Trades in Sustainable Building Design," Proc. International Mechanical Engineering Congress & Exposition.

[8] Hoyle, C., Tumer, I., Mehr, A., and Chen, W., 2009, "Health Management Allocation during Conceptual System Design," Journal of Computing & Information Science in Engineering, 9(2).

[9] Hazelrigg, G. A., 1996, Systems Engineering: An Approach to Information-based Design, Prentice Hall.

[10] Balling, R. J., and Sobieszczanski-Sobieski, J., 1996, "Optimization of coupled systems- A critical overview of approaches," AIAA, 34(1), pp. 6-17.

[11] Geyer, P., 2008, "Multidisciplinary Grammars Supporting Design Optimization of Buildings," Res Engineering Design, 18, pp. 197-216.

[12] Stiny, G., 1990, "What is Design," Environment and Planning B: Planning and Design, 17, pp. 97-103.

[13] Tuhus-Dubrow, D., and Krarti, M., 2010, "Genetic-Algorithm Based Approach to Optimize Building Envelope Design for Residential Buildings," Building and Environment, 45, pp. 1574-1584.

[14] Wang, W., Rivard, H., and Zmeureanu, R., 2006, "Floor Shape Optimization for Green Building Design," Advanced Engineering Informatics, 20, pp. 363-378.

[15] Craig Christensen, Blaise Stoltenberg, and Barker, G., "An Optimization Methodology for Zero Net Energy Buildings," Proc. Internation Solar Energy Conference, ASME.

[16] Diakaki, C., Grigoroudis, E., and Kolokotsa, D., 2008, "Towards a Multi-Objective Optimization Approach for Improving Energy Efficiency in Buildings," Energy and Buildings, 40, pp. 1747-1754.

[17] Heiselberg, P., Brohus, H., Hesselholt, A., Rasmussen, H., Seinre, E., and Thomas, S., 2009, "Application of sensitivity analysis in design of sustainable buildings," Renewable Energy, 34, pp. 2030-2036.

[18] Veitch, J. A., 2006, "Lighting for high-quality workplaces," National Research Council Canada, Ottawa.

[19] Oregon Sustainability Center, 2011, "http://www.oregonsustainabilitycenter.org/," http://www.oregonsustainabilitycenter.org/.

[20] Kamarulzaman, N., Saleh, A. A., Hashim, S. Z., Hashim, H., and Abdul-Ghani, A. A., 2011, "An Overview of the Influence of Physical Office Environments towards Employees," Procedia Engineering, 20, pp. 262-268.

[21] Dul, J., and Ceylan, C., 2011, "Work environments for employee creativity," Ergonomics, 54(1), pp. 12-20.

[22] Yi, L., 2011, "Empirical study of the impact of physical environment on the employees performance," 2nd IEEE International Conference on Emergency Management and Management Sciences (ICEMMS), IEEE, Beijing.

[23] Reinhart, C. F., Mardaljevic , J., and Rogers , Z., 2006, "Dynamic daylight performance metrics for sustainable building design," National Research Council Canada, Ottawa.

[24] Architectural Energy Corporation, 2006, "Daylighting Metric Development Using Daylight Autonomy Calculations In the Sensor Placement Optimization Tool," Boulder.

[25] Jensen, K. L., Toftum, J., and Friis-Hansen, P., 2009, "A BayesianNetwork Approach to the Evaluation of BuildingDdesign and its Consequences for Employee Performance and Operational Costs," Building and Environment, 44, pp. 456-462.

[26] Boyce, P., Hunter, C., and Howlett, O., 2003, "The Benefits of Daylight through Windows," U.S. Department of Energy.

[27] Juslén, H., 2007, "Lighting, Productivity and Preffered Illuminances - Field Studies in the Industrial Environment," Doctor of Science in Technology, Helsinki University, Espoo.

[28] Ruffer, W., 1927, "Licht und Leistung, Licht und Lampe," pp. 242-245.

[29] Hunter, J. E., and Schmidt, F. L., 1983, "Quantifying the Effects of Psychological Interventions on Employee Job Performance and Work-Force Productivity," American Psychologist, pp. 473-478.

[30] U.S. Green Building Council, 2009, "LEED 2009 for New Construction and Major Renovations," U.S. Green Building Council, Washington D.C.

[31] Abdou, O. A., 1997, "Effects of Luminous Environment on Worker Productivity in Building Spaces," Journal of Architectural Engineering, 3, pp. 124-132.

[32] Edwards, L., and Torcelleni, P., 2002, "A Literature Review of the Effect of Natural Light on Building Occupants," National Renewable Energy Laboratory, Golden.

[33] Romm, J. J., and Browning, W. D., 1994, "Greening the Building and the Bottom Line," Rocky Mountain Institute, Snowmass, CO.

[34] Day, J., Theodorson, J., and Wymelenberg, K. V. D., 2012, "Understanding Controls, Behaviors and Satisfaction in the Daylit Perimeter Office: A Daylight Design Case Study," Journal of Interior Design, 37(1), pp. 17-34.

[35] Hua, Y., Oswald, A., and Yang, X., 2011, "Effectiveness of daylighting design and occupant visual satisfaction in a LEED Gold laboratory building," Building and Environment, 46, pp. 54-64.

[36] Louviere, J. J., Hensher, D. A., and Swait, J. D., 2000, Stated choice methods: Analysis and application, Cambridge University Press, New York.

[37] Street, D. J., and Burgess, L., 2007, The construction of optimal stated choice experiments: Theory and methods, Wiley-Interscience, Hoboken, N.J.

[38] Chen, W., Hoyle, C., and Wassenarr, H. J., 2012, Decision-Based Design: Integrating Consumer Preferences into Engineering Design, Springer.

[39] Hoyle, C., Ankenman, B., Chen, W., and Wang, N., "Optimal Experimental Design of Human Appraisals For Modeling Consumer Preferences In Engineering Design," Proc. ASME 2008 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference, ASME.

[40] Jones, B., and Nachtsheim, C. J., 2009, "Split-Plot Designs: What, Why, and How," Quality Technology, 41(4), pp. 340-361.

[41] Everitt, B. S., 1984, An Introduction to Latent Variable Models, University Press, Cambridge.

[42] Loehlin, J. C., 1998, Latent variable models, an introduction to factor, path, and structural analysis, L. Erlbaum Associates, Mahwah, NJ.

[43] Faza, A. Z., Sedigh, S., and McMillin, B. M., "Reliability Analysis for the Advanced Electric Power Grid: From Cyber Control and Communication to Physical Manifestations of Failure," Proc. International Conference on Computer Safety, Reliability, and Security, pp. 257 - 269.

[44] North, M., Conzelmann, G., Koritarov, V., Charles Macal, Thimmapuram, P., and Veselka, T., 2002, "E-Laboratories: Agent-Based Modeling of Electricity Markets," American Power Conference, Argonne National Laboratory, Chicago, IL.

[45] Carreras, B. A., Lynch, V. E., Dobson, I., and Newman, D. E., "Dynamics, Criticality and Self-organization in a Model for Blackouts in Power Transmission Systems," Proc. International Conference on System Sciences, IEEE.

[46] Pottonen, L., and Oyj, F., "A Method for Analysing the Effect of Substation Failures on Power System Reliability," Proc. 15th Power Systems Computation Conference, PSCC.

[47] Lininger, A., McMillin, B., Crow, M., and Chowdhury, B., 2007, "Use of Max-Flow on FACTS devices," 39th North American Power Symposium, pp. 288-294.

[48] Kurtoglu, T., Jensen, D. C., and Tumer, I. Y., 2010, "A functional failure reasoning methodology for evaluation of conceptual system architectures," Research in Engineering Design, 21.

[49] Kurtoglu, T., and Tumer, I. Y., 2008, "A graph based fault identification and propagation framework for functional design of complex systems," ASME Journal of Mechanical Design, 30(5).

[50] Tumer, I. Y., and Smidts, C. S., 2011, "Integrated design-stage failure analysis of software-driven hardware systems," EEE Transactions on Computers. Special Issue on Science of Design for Safety Critical Systems, 60(8), pp. 1072-1084.

[51] Papakonstantinou, N., Sierla, S., Tumer, I. Y., and Jensen, D., 2012, "Multi-Scale Simulation on Interactions and Emergent Failure Behavior During Complex System Design," ASME Journal of Computing & Information Sciences in Engineering, 12(3).

[52] Chen, W., 2012, "Design Under Uncertainty," Design Under Uncertainty, Northwestern University, Evanston.

[53] Phadke, M. S., 1989, Quality Engineering Using Robust Design, Prentice Hall.

[54] Chang, T.-S., Ward, A. C., Lee, J., and Jacox, E. H., 1994, "Conceptual Robustness in Simultaneous Engineering: An Extension of Taguchi's Parameter Design," Research in Engineering Design, 6, pp. 211-222.

[55] Wasserman, S., and Faust, K., 1994, Social Network Analysis, Cambridge University Press, New York.

[56] Hines, P., Cotilla-Sanchez, E., and Blumsack, S., 2010, "Do topological models provide good information about electricity infrastructure vulnerability?," Chaos, 20.

[57] Kinney, R., Crucitti, P., Albert, R., and Latora, V., 2005, "Modeling cascading failures in the North American power grid," European Physics Journal B, 46, pp. 101-107.

[58] Dueñas-Osorio, L., and Vemuru, S. M., 2009, "Cascading failures in complex infrastructure systems," Structural Safety, 31, pp. 157-167.

[59] Ash, J., and Newth, D., 2007, "Optimizing complex networks for resilience against cascading failure," Physica A, 380, pp. 673–683.

[60] Crucitti, P., Latora, V., and Marchiori, M., 2004, "A model for cascading failures in complex networks," Physics Review E, 69.

[61] U.S.-Canada Power System Outage Task Force, 2003, "Interim Report: August 14th Blackout in the United States and Canada," U.S. Secretary of Energy Minister of Natural Resources Canada.

[62] White, D., Roschelle, A., Peterson, P., Schlissel, D., Biewald, B., and Steinhurst, W., 2003, "The 2003 Blackout: Solutions that Won't Cost a Fortune," The Electricity Journal, pp. 43-53.

[63] Fan, N., Izraelevitz, D., Pan, F., Pardalos, P. M., and Wang, J., 2012, "A mixed integer programming approach for optimal power grid intentional islanding," Energy Systems, 3, pp. 77-93.

[64] Electrical Power Research Institute, 2000, "Rx for Stress: Power Delivery Reliability Initiative," Electrical Power Research Institute, Palo Alto.

[65] Venkatasubramanian, V., 2011, "Systemic Failures: Challenges and Opportunities in Risk Management in Complex Systems," American Institute of Chemical Engineers, 57(1), pp. 2-9.

[66] Little, R. G., 2002, "Controlling Cascading Failure: Understanding the Vulnerabilities of Interconnected Infrastructures*," Journal of Urban Technology, 9(1), pp. 109-123.

[67] Watts, D. J., 2002, "A simple model of global cascades on random networks," Proceedings of the National Academy of Sciences, 99(9).

[68] Hines, P., and Talukdar, S., 2007, "Controlling Cascading Failures with Cooperative Autonomous Agents," Internation Journal of Critical Infrastructures, 3(1).

[69] Dobson, I., Carreras, B. A., Lynch, V. E., and Newman, D. E., 2007, "Complex systems analysis of series of blackouts: Cascading failure, critical points, and self-organization," CHAOS, 17.

[70] Sha, Z., and Panchal, J. H., 2014, "Estimating Local Decision-Making Behavior in Complex Evolutionary Systems," Journal of Mechanical Design.

[71] Koppelman, F. S., and Bhat, C., 2006, "A Self Instructing Course in Mode Choice Modeling: Multinomial and Nested Logit Models," U.S. Department of Transportation Federal Transit Administration.

[72] U.S. Green Building Council, 2011, "Leadership in Energy and Environmental Design," U.S. Green Building Council, Washington, DC.

[73] United States Energy Information Administration, 2010, "Annual Energy Outlook 2010 with Projections to 2035," United States Energy Information Administration,.

[74] Tatari, O., and Kucukvar, M., 2011, "Cost premium prediction of certified green buildings: A neural network approach," Building and Environment, 46, pp. 1081-1086.

[75] Brownstone, D., Bunch, D. S., and Train, K., 2000, "Joint mixed logit models of stated and revealed preferences for alternative-fuel vehicles," Transportation Research, 34, pp. 315-338.

[76] Piacenza, J. R., Tumer, I. Y., and Hoyle, C., "Lighting Optimization for Sustainable Building Design Considering User Productivity," Proc. International Design Engineering Technical Conferences & Computers and Information in Engineering Conference, ASME.

[77] Electrical Power Research Institute, 1991, "Statistical Abstract of the United States," EPRI, Washington D.C.

[78] Fisk, W. J., 2000, "Health and Productivity Gains from Better Indoor Environments and Their Relationships with Building Energy Efficiency," Annual Review Energy Environment, 25, pp. 537-566.

[79] Ouyang, J., and Hokao, K., 2009, "Energy-saving potential by improving occupants' behavior in urban residential sector in Hangzhou City, China," Energy and Buildings, 41, pp. 711-720.

[80] Song, X.-Y., and Lee, S.-Y., 2012, Basic and Advanced Bayesian Structural Equation Modeling, John Wiley & Sons Ltd.

[81] Wheaton, B., Muthén, B., Alwin, D. F., and Summers, G. F., 1977, "Assessing Reliability and Stability in Panel Models," Sociological Methodology, 8, pp. 84-136.

[82] Fox, J., 2006, "Structural Equation Modeling With the sem Package in R," Structural Equation Modeling, 13(3), pp. 465-486.

[83] Guy, R. F., and Morvell, M., 1977, "The Neutral Point on a Likert Scale," Journal of Psycology, 95, pp. 199-204.

[84] DeVellis, R. F., 2003, Scale Development Theory and Applications, Sage Publications, Thousand Oaks.

[85] Church, A. H., 1993, "Estimating the Effect of Incentives on Mail Survey Response Rates: A Meta-Analysis," Public Opinion Quarterly, 57, pp. 62-79.

[86] Institutional Review Board, 2012, "Institutional Review Board Services," http://www.irbservices.com.

[87] Johnson, R. A., and Wichern, D. W., 2002, Applied Multivariate Statistical Analysis, Prentice Hall, New Jersey.

[88] StataCorp, 2012, "STATA Data Analysis and Statistical Software," http://www.stata.com.

[89] Kaiser, H. F., 1958, "The Varimax Criterion for Analytic Rotation in Factor Analysis," Psychometrika, 23, pp. 187-200.

[90] Lewis-Beck, M., Bryman, A., and Futing, T., 2003, Encyclopedia of Social Sciences Research Methods, Sage, Thousand Oaks, CA.

[91] Tzempelikos, A., and Athienitis, A. K., 2007, "The Impact of Shading Design and Control of Building Cooling and Lighting Demand," Solar Energy, 81, pp. 369-383.

[92] Montgomery, D. C., 1991, Design and Analysis of Experiments, John Wiley & Sons, New York.

[93] StatPoint Technologies Inc., 2012, "Statgraphics Centurion," http://www.statgraphics.com.

[94] Team, R. D. C., 2011, "A language and environment for statistical computing," R Foundation for Statistical Computing, Vienna, Austria.

[95] Hooper, D., Coughlan, J., and Mullen, M. R., 2008, "Structural Equation Modelling: Guidelines for Determining Model Fit," Electronic Journal of Business Research Methods, 6(1).

[96] S.Pahwa, A.Hodges, C.Scoglio, and S.Wood, 2010, "Topological Analysis of the Power Grid and Mitigation Strategies Against Cascading Failures," Statistical Mechanics and its Applications, 338(1-2), pp. 92-97.

[97] Agogino, A., HolmesParker, C., and Tumer, K., "Evolving Large Scale UAV Communication System," Proc. 14th International Conference on Genetic and Evolutionary Computation Companion, Association for Computing Machinery.

[98] Clausing, D., 1998, "MIT Open Courseware," Massachusetts Institute of Technology, Cambridge.

[99] University of Washington, 1999, "Power Systems Test Case Archive," http://www.ee.washington.edu/research/pstca/pf14/pg_tca14bus.htm.

[100] Moslehi, K., and Kumar, R., 2010, "A Reliability Perspective of the Smart Grid," IEEE Transactions On Smart Grid, 1(1).

[101] Long Island Power Authority, 2009, "Project K014: Probabilistic Risk Assessment (PRA) User's Group," Long Island Power Authority.

[102] Hingorani, N. G., 1988, "High Power Electronics and Flexible AC Transmission System," IEEE Power Engineering Review.

[103] Asare, P., Diez, T., Galli, A., O'Neill-Carillo, E., and Robertson, J., 1994, "An Overview of Flexible AC Transmission Systems," Purdue University, West Lafayette.

[104] Pinar, A., Meza, J., Donde, V., and Lesieutre, B., 2010, "Optimization Strategies for the Vulnerability Analysis of the Electric Power Grid," Society for Industrial and Applied Mathematics, 20(4), pp. 1786-1810.

[105] Talukdar, S. N., Apt, J., Ilic, M., Lave, L. B., and Morgan, M. G., 2003, "Cascading Failures: Survival versus Prevention," The Electricity Journal, pp. 25-31.

[106] Lewis, K., Kalsi, M., and Hacker, K., 2001, "A Comprehensive Robust Design Approach for Decision Trade-Offs in Complex Systems Design," Journal of Mechanical Design, 123(1), pp. 3-10.

[107] Power Systems Engineering Research Center, 2007, "Uncertain Power Flows and Transmission Planning," Arizona State University, Tempe.

[108] The MathWorks Inc., 2011, "MATLAB version 7.13.0.564,"Natick, Massachusetts.

[109] Metropolis, N., Rosenbluth, A. W., Rosenbluth, M. N., Teller, A. H., and Teller, E., 1953, "Equation of State Calculations by Fast Computing Machines," The Journal of Chemical Physics, 21(6), pp. 1087–1092.

[110] Czyzżak, P., and Jaszkiewicz, A., 1998, "Pareto simulated annealing-a metaheuristic technique for multiple□objective combinatorial optimization," Journal of Multi□Criteria Decision Analysis, 7(1), pp. 34-47.

[111] Duh, J.-D., and Brown, D. G., 2006, "Knowledge-informed Pareto simulated annealing for multi-objective spatial allocation," Computers, Environment and Urban Systems, In Press.

[112] Goffe, W. L., Ferrier, G. D., and Rogers, J., 1994, "Global Optimization of Statistical Functions with Simulated Annealing," Journal of Econometrics, 60(1), pp. 65-99.

[113] Amazon Web Services, 2013, "Amazon Elastic Compute Cloud (Amazon EC2)," http://aws.amazon.com/ec2/.

[114] Braun, R. D., and Kroo, I. M., 1996, "Development and Application of the Collaborative Optimization Architecture in a Multidisciplinary Design Environment," NASA Langley Research Center, Langley.

[115] Chachrere, J., Levitt, R., and Kunz, J., 2003, "Can You Accelerate Your Project Using Extreme Collaboration? A Model Based Analysis," Stanford University, Stanford.

[116] Wagner, T. C., and Papalambros, P. Y., 1993, "A General Framework for Decomposition Analysis in Optimal Design," Advances in Design Automation, 2(65).

[117] Wagner, T. C., and Papalambros, P. Y., 1996, "Decomposition Analysis of an Automotive Powertrain Design Problem: Model Developmet, Partitioning, and Optimization," University of Michigan, Ann Arbor.

[118] Holt, C. A., and Laury, S. K., 2002, "Risk aversion and incentive effects," American Economic Review, 92(5), pp. 1644-1655.

[119] Thurston, D. L., Lewis, K., Chen, W., and Schmidt, L., 2006, "Utility Function Fundamentals," Decision Making in Engineering Design, pp. 5-14.

[120] Keeney, R. L., and Raiffa, H., 1993, Decisions with Multiple Objectives: Preferences and Value Tradeoffs, Cambridge University Press, New York.

[121] Raffia, H., 1970, "Decision Analysis: Introductory lectures on Choices under Uncertainty," Addison-Wesley, Reading, Massachusetts.

[122] Amin, M., 2008, "Challenges in Reliability, Security, Efficiency, and Resilience of Energy Infrastructure: Toward Smart Self-healing Electric Power Grid," IEEE Computer Applications in Power.

[123] Silver, M. R., and Weck, O. L. d., 2007, "Time-Expanded Decision Networks: A Framework for Designing Evolvable Complex Systems," Systems Engineering, 10, pp. 167-186.

[124] Thunnissen, D. P., 2005, "Propagating and Mitigating Uncertainty in the Design of Complex Multidisciplinary Systems," Doctor of Philosophy, California Institute of Technology, Pasadena.

[125] Haley, B., Dong, A., Technical, I. Y. T. I. A. I. D. E., and Conference, C. a. C. a. I. i. E., "Creating faultable network models of complex engineered systems," Proc. International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, ASME.

[126] Dobson, I., Carreras, B. A., and Newman, D. E., 2005, "A Loading-Dependent Model of Probabilistic Cascading Failure," Probability in the Engineering and Informational Sciences, 19, pp. 15-32.

[127] Zimmerman, R. D., Murillo-Sanchez, C. E., and Thomas, R. J., 2011, "Matpower: Steady-State Operations, Planning and Analysis Tools for Power Systems Research and Education
," Power Systems, IEEE Transactions, 26(1), pp. 12-19.

[128] Glover, J. D., Sarma, M. S., and Overbye, T. J., 2012, Power System Analysis & Design, Cengage Learning, Samford, CT.

[129] Zimmerman, R. D., and Murillo-Sanchez, C. E., 2011, "Matpower 4.1User's Manual," Power Systems Engineering Research Center.

[130] McCalley, J. D., Vittal, V., and Abi-Samra, N., "An overview of risk based security assessment," Proc. Power Engineering Society Summer Meeting, 1999. IEEE, pp. 173-178 vol.171.

APPENDIX

In this survey, you will be asked to give your feelings on one of three buildings on campus. Please select one of the following buildings on campus that you are familiar with, and base your evaluations on the building you select.

Kelly Engineering Center Kearney Hall Linus Pauling Building

Please take your time and answer all the following questions thoughtfully and carefully by circling the option that most accurately reflects your opinion. This should take about 15 minutes.

1. How often do you use your building of choice

Never Rarely Sometimes Frequently

2. When studying I prefer to use my building of choice over other buildings on campus.

Strongly Disagree	Disagree	Moderately Disagree	Have no Opinion	Moderately Agree	Agree	Strongly Agree

3. When socializing I prefer to use my building of choice over other buildings on campus.

Strongly Disagree	Disagree	Moderately Disagree	Have no Opinion	Moderately Agree	Agree	Strongly Agree

4. I prefer the lighting in my building of choice over other buildings on campus.

Strongly Disagree	Disagree	Moderately Disagree	Have no Opinion	Moderately Agree	Agree	Strongly Agree

5. I like the temperature of my building of choice more than other buildings on campus.

Strongly Disagree	Disagree	Moderately Disagree	Have no Opinion	Moderately Agree	Agree	Strongly Agree

6. I like the types of available seating at my building of choice more seating in other buildings on campus.

Strongly Disagree	Disagree	Moderately Disagree	Have no Opinion	Moderately Agree	Agree	Strongly Agree

7. The architecture of my building of choice is aesthetically pleasing.

Strongly Disagree	Disagree	Moderately Disagree	Have no Opinion	Moderately Agree	Agree	Strongly Agree

8. The availability of amenities (coffee shops, sofas, soda machines) in my building of choice influences my opinion of it.

Strongly Disagree	Disagree	Moderately Disagree	Have no Opinion	Moderately Agree	Agree	Strongly Agree

9. I like the use of windows in my building of choice.

Strongly Disagree	Disagree	Moderately Disagree	Have no Opinion	Moderately Agree	Agree	Strongly Agree

10. I complete work faster in my building of choice than at other building.

Strongly Disagree	Disagree	Moderately Disagree	Have no Opinion	Moderately Agree	Agree	Strongly Agree

11. I complete the majority of my homework in my building of choice.

Strongly Disagree	Disagree	Moderately Disagree	Have no Opinion	Moderately Agree	Agree	Strongly Agree

12. My building of choice's popularity encourages me to work there myself.

Strongly Disagree	Disagree	Moderately Disagree	Have no Opinion	Moderately Agree	Agree	Strongly Agree

13. When studying for a test, a well lit space is important to me.

Strongly Disagree	Disagree	Moderately Disagree	Have no Opinion	Moderately Agree	Agree	Strongly Agree

14. I feel I am more productive when I am surrounded by other people working.

Strongly Disagree	Disagree	Moderately Disagree	Have no Opinion	Moderately Agree	Agree	Strongly Agree

15. It's easier for me to work in an environment that I am familiar with.

Strongly Disagree	Disagree	Moderately Disagree	Have no Opinion	Moderately Agree	Agree	Strongly Agree

16. When choosing a location to study, temperature is important to me.

Strongly Disagree	Disagree	Moderately Disagree	Have no Opinion	Moderately Agree	Agree	Strongly Agree

17. When studying, I prefer a traditional workspace, such as a desk or table.

Strongly Disagree	Disagree	Moderately Disagree	Have no Opinion	Moderately Agree	Agree	Strongly Agree

18. A quiet work environment is important to me.

Strongly Disagree	Disagree	Moderately Disagree	Have no Opinion	Moderately Agree	Agree	Strongly Agree

19. Fresh air is important for a building.

Strongly Disagree	Disagree	Moderately Disagree	Have no Opinion	Moderately Agree	Agree	Strongly Agree

20. I feel better about myself when working in a building that has been constructed using sustainable building practices.

Strongly Disagree	Disagree	Moderately Disagree	Have no Opinion	Moderately Agree	Agree	Strongly Agree

21. The interior color of my building of choice is aesthetically pleasing.

Strongly Disagree	Disagree	Moderately Disagree	Have no Opinion	Moderately Agree	Agree	Strongly Agree