

ROBUST OPTIMIZATION OF COMPLEX CYBER-PHYSICAL SYSTEMS

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Abstract

The incorporation of robust design strategies to increase the insensitivity of system performance in the presence of uncertainty from both internal and external sources into complex system infrastructures can increase system reliability. This paper presents a novel approach to the robust design of complex cyber-physical systems by incorporating a high-level topological optimization strategy for network resilience to reduce the effect of cascading failures. This approach focuses on system robustness after cascading has occurred, and examines performance trade-offs of the resultant (or degraded) system state. In this research, robustness is defined as the resilience to initiating faults, where a robust network has the ability to meet system generation requirements despite propagating network failures. A mathematical model was developed representing a typical power grid network consisting of generation and demand nodes, as well as node connections based on actual topological transmission line relationships. Each node possesses either unique power generation or demand attributes, and various network connection configurations are examined based on system demand requirements. In this model, failure events are initiated by the removal of a single network connection, and remaining loads are redistributed throughout the system. Cascading failure effects are captured when the existing network configuration cannot support the resulting demand load, and transmission line failures propagate until the system reaches a steady state, based on remaining nodes and connections. By understanding network reactions due to cascading failures, as well as performance trade-offs required to mitigate these failures, reliability in power grid systems can be increased.

Keywords

Cascading failures, power grid, robust optimization.

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 (Ash & Newth, 2007; Hines, Cotilla-Sanchez, & Blumsack, 2010; S.Pahwa, A.Hodges, C.Scoglio, & S.Wood, 2010). Since complex infrastructure systems operate in highly stochastic environments, it is not cost-effective (or even possible) to design for total failure *resistance* from cascading failures. This research asserts that systems must be designed for failure *resilience* 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, as an alternative to complete system failure, is applicable for 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 reliably and consistently support this increased commuter volume, without exceeding the intended capacity for these routes. Alternatively, designing for failure resilience is equally important in complex 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 (Agogino, HolmesParker, & Tumer, 2012). Power grids are especially susceptible to unintended failure, as their components are primarily exposed to the environment. If a single transmission line is broken due to a falling tree, the power is immediately redistributed, potentially triggering a cascading failure effect. This paper introduces a system-level topological approach to the robust optimization of complex infrastructure networks, as a strategy for mitigating the effects of cascading system failure. The primary goal is to facilitate an understanding between design trade-offs in system performance and robustness. For example, if system optimization objectives (e.g., cost, ability to meet demand) were purely deterministic, a traditional optimization approach would suffice. This would provide the most desirable (e.g., cost) option, assuming negligible vulnerabilities to system failure. Conversely, if a system required invariant performance with respect to all potential failure scenarios, a purely robust strategy would be implemented, which would be the most reliable, highest cost option. Robust optimization examines trade-offs between performance and robustness, considering the effects of both external and internal system uncertainties.

This paper presents a methodology for modeling complex infrastructure systems using this strategy, accounting for both network attributes and system topology. An adjacency matrix is used to represent the system, where nodes represent specific network components, and node connectivity represents the physical connections. Optimization tradeoffs are between performance objectives and performance variability.

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 (Clausing, 1998; Phadke, 1989). 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 deterministically optimized for performance (e.g., cost) are particularly susceptible to failures due to uncertainty as they are finely tuned to meet a specific objective (or set of objectives) without consideration of failure events. In complex infrastructure systems, a single initiating fault can propagate throughout the network uncontrollably, resulting in severely degraded performance or complete failure. To understand these cascading issues, current methods have employed social network analysis for predicting emergent behavior (S.Pahwa et al., 2010; Wasserman & Faust, 1994). However, network theory performance metrics (e.g., node degree, centrality) are too far abstracted from actual complex system behavior and interactions to accurately assess the probability of cascading failures when creating reliable designs. *Specifically, there is no provision to incorporate robustness into complex infrastructure system design to mitigate the effects of cascading failures from uncertain environmental events.*

Robust Design

While there are many methods contributing to failure propagation in complex systems, these approaches are typically hardware driven and do not address the formalized concept of robustness, and how complex systems can be designed to be resilient to failures (Carreras, Lynch, Dobson, & Newman, 2002; Faza, Sedigh, & McMillin, 2009; Kurtoglu, Jensen, & Tumer, 2010; Kurtoglu & Tumer, 2008; Lininger, McMillin, Crow, & Chowdhury, 2007; North et al., 2002; Papakonstantinou, Sierla, Tumer, & Jensen, 2012; Pottonen & Oyj, 2005; Tumer & Smidts, 2011). In addition, it is difficult to scale component level failure propagation methods to represent large and distributed networks in terms of computational efficiency. In this context, robust design is defined as the insensitivity to noise (or uncertainty) on system performance from both internal and external sources (Chen, 2012).

Historically, robust design has been used in manufacturing to minimize unintended consequences (variability) from uncontrollable environmental effects (Phadke, 1989). One drawback of robust design in manufacturing is the focus on optimizing a single variable (e.g., size, weight). Expanding on Taguchi's fundamental methods (Phadke, 1989), 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 (Chang, Ward, Lee, & Jacox, 1994). 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 methodology to design systems robust to sources of uncertainty, such as failures in the power grid, without the need to understand or reduce these sources of uncertainty.

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 unpredicted 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 complex infrastructure systems, discussed next.

Network Theory and Topological Graph Models

Based on the distributed nature of many complex infrastructure systems, understanding topological effects is important when designing for failure resilience. 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 (Hines et al., 2010; Kinney, Crucitti, Albert, & Latora, 2005; Wasserman & Faust, 1994). 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 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 (Kinney et al., 2005). In their 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 (Dueñas-Osorio & Vemuru, 2009).

Another method by Ash and Newth examines the optimization of complex networks with respect to the average efficiency of the network (Ash & Newth, 2007). Average efficiency (E) was first introduced by Crucitti et al. and is among the vitality measures (Crucitti, Latora, & Marchiori, 2004). 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, 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 (Hines et al., 2010). 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.

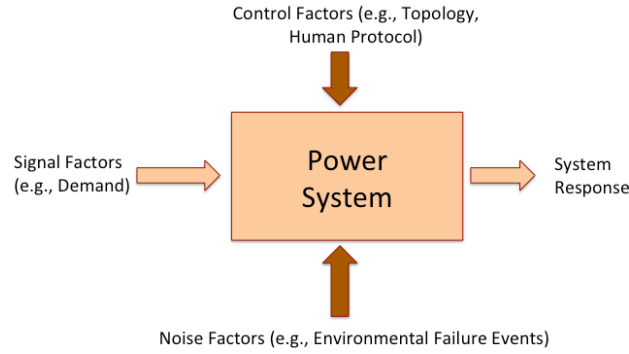
Methodology

The research presented in this paper integrates robust optimization techniques with system specific network topology analysis. In this approach, the system network (NAPG case study) is created in MatLab, represented by an $N \times N$ adjacency matrix, where $N = N_g + N_d$, N_g representing the number of generation nodes and N_d representing the number of demand populations. An initial matrix is created randomly, based on user inputs for the desired number of generation and demand nodes. The generated network is then tested for connectivity, as each demand population must be serviced (connected) to a generation node to meet expected demand.

System Parameter Design

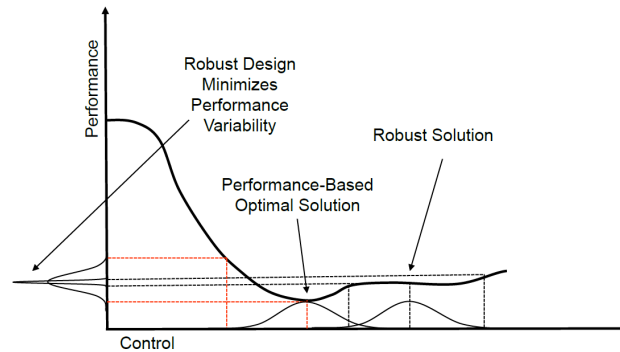
The research methodology requires one to apply Taguchi's Parameter Design approach to the system, displaying how different sources of uncertainty effect system response (Exhibit 1) (Chen, 2012; Phadke, 1989). In this approach, the system control factors are elements that can be varied within the system, and noise factors are environmental elements that cannot be controlled. When addressing potential initiating events for fault propagation, both types of factors must be considered. Failures from external events are addressed in the context of Type I (Parameter) robust design, or design intended to minimize performance loss from external noise. To address internal noise, Type II (Tolerance) robust optimization can be applied to a design. This method reduces performance losses due to uncertainty from internal control variables within the system. In the context of the NAPG, this would include uncertainty due to fluctuations in energy generation from variable sources such as wind generation or demand fluctuation.

Exhibit 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 (Lewis, Kalsi, & Hacker, 2001). The goal of Lewis' formulation is to meet performance requirements, while minimizing the variation about the mean. Exhibit 2 outlines this relationship, displaying how the optimized solution may exist at the boundary of an objective, where variability is greatest (Chen, 2012; Lewis et al., 2001). 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, including external noise factors (e.g., natural disasters) and internal noise variables (e.g., expected demand); however, research is needed to understand how robust design can be applied to distributed complex system design.

Exhibit 2. Visual Relationship Between The Deterministic And Robust Solution.



In this work, the IEEE 14 Test Bus system is used to demonstrate and validate the research methodology (University of Washington, 1999). This network consists of 2 power generation stations, and 12 additional demand connections. Since cascading failure is being evaluated in terms of transmission line loading, the physical topology of lines was considered, based on IEEE 14 transmission line lengths calculated by the Power Systems Engineering Research Center. A geographical power grid map is constructed (Power Systems Engineering Research Center, 2007); this is an important system attribute as line lengths directly drive connectivity costs. In order to accurately represent system demand, nominal demand node power requirement values are used from the IEEE 14 system.

Optimization Objective

The robust design of a power grid is addressed using a non-linear optimization formulation. To understand important power grid interactions and design for failure resilience, an objective function is formulated based on the ability of a network to satisfy population demand (D_E) after a cascading failure occurs, for the lowest cost (C_{Tot}). Both D_E and C_{Tot} are functions of the physics of the network after the occurrence of a fault initiating event in the power grid. *Robustness* is incorporated into the objective by minimizing the variation of satisfied demand ($\sigma_{D_E}^2$) in the solution (Eq. 1).

find **A**

to minimize

$$f_1 = C_{Tot}(A)$$

$$f_2 = -D_E(A)$$

$$f_3 = \sigma_{D_E}^2(A)$$

(1)

subject to

$$h_1: N_{\text{Comp}} - 1 = 0$$

$$h_2: A = [0,1]_{N \times N}$$

where A and N_{Comp} respectively represent the adjacency matrix and the number of disconnected components of the network. Two constraints are provided to ensure the network is always connected (i.e., there are no separate islands), and to ensure the elements of the adjacency matrix are either 0 or 1.

Optimization Algorithm

A genetic algorithm (GA) was used within the MatLab Optimization Toolbox (The MathWorks Inc., 2011). Since Satisfied 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 Satisfied Demand*, and *Satisfied Demand Variance* from the original IEEE 14 transmission line configuration. These nominal values were included in the fitness function for each objective (Eq. 2). 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:

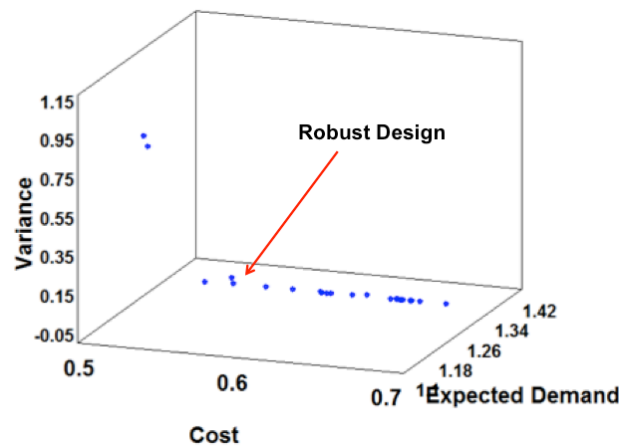
$$f(x) = \frac{\text{Obj}_n}{\text{IEEE14}_n} + \text{PF}_{\text{Conn}} \quad (2)$$

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.

Optimization Results

The simulation was run for approximately 600 iterations. The resulting plot of Pareto optimal solutions is displayed in Exhibit 3. In this plot, design values are normalized with respect to the performance of the original IEEE 14 network configuration. 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 Demand Variability increases.

Exhibit 3. Normalized Pareto Solutions for The IEEE 14 Test Bus Network Using The GA.



To verify this method is producing an optimized robust solution, the simulation was tested with the removal of *demand variance* objective. In this version of the solution, only *cost* and *expected demand* are considered as objectives, and *variance* is ignored (i.e., a conventional optimization). All existing constraints remained, and the normalized fitness function values are also based on the original IEEE 14 solution. A summary of the simulation performance metrics is shown in Exhibit 4. Information on the original IEEE 14 network was also provided to provide a baseline comparison. Based on the results, the Conventional GA solution for *cost* is slightly lower than the robust solution. In addition, *expected demand* satisfied is also lower, since a low *cost* (smaller number of network connections) solution is more affected by failure events. The most significant difference between the

solutions is in the *demand variance*: the variance in demand satisfied is much lower in the robust solution. The Conventional GA optimal solution represents a power grid design that is low cost, but less resistant to cascading failure than the robust solution since the ability to satisfy demand is lower and the variance in demand satisfied is much higher. The Original network *cost* is the highest, and these results are expected as the IEEE 14 network was physically constructed based on both population demand and geography.

Exhibit 4. Objective Values For The Original, Deterministic, and Robust Design of the IEEE 14 Test Bus.

IEEE 14 Network (GA)	Network Cost	Expected Demand	Demand Variance	Network Connections	Average Node Degree	Maximum Node Degree
Original	1212	182	5738	18	2.6	4
Conventional GA	660	224	769	17	2.4	6
Robust Design GA	666	235	235	18	2.6	5

Conclusions and Future Work

This paper presents a novel methodology for the robust optimization of complex infrastructure systems by incorporating the effects of cascading failure due to variations in system topology. As these systems operate in highly stochastic environments, systems must be designed for failure resilience by incorporating the effects of fault propagation into optimization objectives, evaluating the performance of the resultant degraded system state.

Modeling this system mathematically using an integrated physics-based modeling and network analysis approach provides the opportunity to iteratively test various network connection strategies against an initiating failure event, and address subsequent cascading failure effects. In this research robustness is represented as the variability of system performance as a result of uncertain effects (both internal and external) on the system. This is represented as the removal of a network connection arc in the North American Power Grid case study used in the paper. This approach characterizes system robustness as the ability of a network to successfully operate in a degraded state based on designer requirements, minimizing performance variability due to cascading failure effects. 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.

The IEEE 14 test bus case study demonstrated the effectiveness of the approach presented, comparing objective values between the original network, the deterministically optimized network, and the robust design network. This proof-of-concept simulation highlights the significance of topology configurations within a complex infrastructure system, and examines the influence of cascading failures from one subnetwork to another. It also validates the use of a mathematical model as a tool in early complex infrastructure system design, drawing from several existing approaches in design theory.

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 theory, while maintaining critical physical relationships necessary to accurately model a system. Incorporating key system characteristics from each of these design strategies (i.e., network analysis, model based design) 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.

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