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Understanding the Impact of Decision Making on Robustness During Complex System Design: More Resilient Power Systems

Robust design strategies continue to be relevant during concept-stage complex system design to minimize the impact of uncertainty in system performance due to uncontrollable external failure events. Historical system failures such as the 2003 North American blackout and the 2011 Arizona-Southern California Outages show that decision making, during a cascading failure, can significantly contribute to a failure's magnitude. In this paper, a scalable, model-based design approach is presented to optimize the quantity and location of decision-making agents in a complex system, to minimize performance loss variability after a cascading failure, regardless of where the fault originated in the system. The result is a computational model that enables designers to explore concept-stage design tradeoffs based on individual risk attitudes (RA) for system performance and performance variability, after a failure. The IEEE RTS-96 power system test case is used to evaluate this method, and the results reveal key topological locations vulnerable to cascading failures, that should not be associated with critical operations. This work illustrates the importance of considering decision making when evaluating system level tradeoffs, supporting robust design. [DOI: 10.1115/1.4044471]

Introduction and Motivation

As the demand for reliable complex infrastructure systems (e.g., microgrids, satellite networks, etc.) becomes increasingly critical, designers are looking for computational approaches to evaluate concept-stage designs. An advantage of computational design strategies is the ability for designers to explore key performance tradeoffs early in the design phase when design modifications are less costly [1]. 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 relatively small sets of initiating events [2–8]. 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 [9]. 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.

Significant barriers exist to creating accurate system models for relevant time-scales of complex infrastructure systems. These barriers include subsystem interactions (e.g., mechanical, electrical), environmental uncertainty, changing topology, emergent behavior, and decision making during a failure event [10–12]. While each of these detriments to system performance has been explored extensively independent of domain, addressing them concurrently within a highly nonlinear and heterogeneous complex system creates a challenge during concept-stage design. For example, the Blackout of 2003 and the 2011 Arizona-Southern California Outages highlight the vulnerability of existing infrastructure systems such as the North American power grid (NAPG) [13–15]. Beyond hardware and software failures, system operator decision making contributed to the magnitude of the Blackout [16,17]. Although the cascading failure occurred over approximately 7 h, independent regions struggled to obtain operational information from adjacent utilities, forcing system operators to make uninformed decisions to protect their local network. This lack of a comprehensive, wide-area communication mechanism for system level

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decision making throughout the NAPG interconnections is primarily a function of federal deregulation policies [18–21].

While control strategies can be implemented into the design of these systems (e.g., protective relays, intelligent electronic devices) to mitigate critical component failures, 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 can exert free will during an *emergency* decision-making scenario, their range of control and position within the system must be constrained.

This paper examines the system level impact of decision-making during a failure event and suggests that designers can incorporate decision making into concept-stage models to evaluate system robustness. Robustness is modeled as the invariability of the resultant steady-state system performance after a cascading failure has occurred.

Contributions

Current literature formally addressing robustness during concept-stage complex infrastructure system design presents an opportunity for capturing the impact of decision making during a cascading failure event. This is primarily because many robust design methods focus on minimizing performance variability of the system during fully functional operation, and do not examine the uncertainties due to decision making contributing to cascading failure. This distinction is highly significant as complex systems are often designed and operated at a low factor of safety. This work directly addresses this concern, postulating that robust design strategies can be used to optimize decision making during failure events, subsequently minimizing the resultant performance variability and increasing robustness.

Key Improvements and Benefits to Complex System Design. In previous work, Piacenza et al. [22,23] consider the problem of designing an optimal network topology that is robust to uncertain failure events. That approach enabled a concept-stage model that allowed designers to create a system topology which predictably met minimum desired performance requirements.

In this research, a model-based design approach is presented to optimize the quantity and location of decision-making agents in a complex system, to minimize performance loss variability after a cascading failure, regardless of where the fault originated in the system. The result is a computational model that enables designers to explore concept-stage design tradeoffs based on individual risk attitudes (RA) for system performance and performance variability, after a failure.

Background

There is an abundance of methods aimed at analyzing failure propagation and reliability in complex systems [24–34]. A key challenge, however, is creating designs that are robust to the various types of failures and uncertainties present in complex and often largely distributed infrastructure systems.

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 [35,36]. 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., control factors) can include performance variations often resulting from system level decision making during a failure event (Fig. 1).

To understand failure propagation in complex infrastructure systems, current methods have employed both agent-based and social network analysis for predicting emergent system behavior [5,37–39]. However, agent-based and network theory performance metrics (e.g., agent evaluation functions, node degree, centrality) are abstractions of actual complex systems, which may limit their ability to accurately assess the impact of cascading failures when creating reliable designs.

Currently, there is an opportunity to further increase robustness during concept-stage complex system design by examining the impact of decision-making on system robustness. This work builds on current complex system design methods, discussed next.

Robust Design Using 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 during system optimization, often drawing from network theory where networks are represented mathematically, often with an adjacency matrix [3,4,37,40–43]. Piacenza et al. explore the idea of increasing system robustness in a complex infrastructure system using topology optimization [22]. In this work, robustness was quantified by minimizing the variation in degraded system performance after a failure event occurred. Other key network performance indices studied in the literature can be primarily categorized by three major properties: average distance between nodes, the tendency of vertices to be locally interconnected, and distribution of degrees of vertices [6,44–47].

Topological graph models are flexible and can apply to different domains. For example, Kinney et al. modeled a power system case study with an adjacency matrix, where each node represented either a generation or demand component in a network and arcs connecting the nodes represented connectivity [40]. In that work, failures were examined by removal of a single node, which triggered an overload cascade in the network. Similar methods are used by Duenas-Osorio and Vemuru, where total connectivity loss measured network performance [48]. Ash and Newth examine the optimization of complex networks with respect to the average efficiency of the network, which was first introduced by Ash and Newth [2] and Crucitti et al. [12]. 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 and electrical metrics within the same system to predict failure magnitudes in standard test cases and real utility models [4]. 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. used 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 asserted that some methods of suppressing subsystem failures could ultimately increase the risk of uncontrollable system-level failures [49].

Recent work by the IEEE working group on cascading failure emphasized the wide variety of mechanisms involved in the

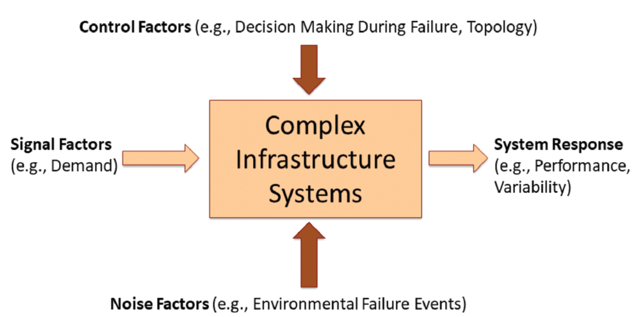

Fig. 1 Parameter diagram for complex infrastructure systems

propagation of cascades as well as the challenges to find agreement on the principal assumptions of quasi-steady-state modeling tools [50].

Decision-Making Considerations in Complex System Design. While many cascading system failures begin as a result of external occurrences such as extreme environmental conditions (e.g., 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 [51]. 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 examined this concept from a sociology perspective, citing parallels to engineered systems [52]. In this work, he postulated 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 examined this relationship by developing a method to create a social network of autonomous agents to solve a global control problem with limited communication abilities [53]. This approach used distributed model predictive control and cooperation to minimize cascading failure in the IEEE reliability test system. Where nodes represented substations, and lines represented either transmission lines or transformers. However, the approach requires an agent to be present at each location (i.e., node) of the system and, hence, is not an economically efficient solution 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 [26,34,37].

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 by comparing the benefits of generalized preferential attachment, a statistical regression-based approach, and multinomial logit choice modeling [54]. 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) [55]. 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.

Methodology

The research aims to capture the impact of decision making during a cascading failure event. For this work, decision making is represented as a control factor (as opposed to a noise factor), since decision-making agents are strategically placed during system design. A nested optimization framework is presented that identifies design tradeoffs for performance, performance variability, and the number of agents in the system. The *outer-loop* optimization identifies quasi-steady-state system conditions during cascading failure (Fig. 2).

MATPOWER performs the *inner-loop* quasi-steady-state simulation, calculating instantaneous power flow based on physical relationships, such as generation, demand, and fundamental electrical laws. The inner-loop consequently outputs system performance values based on decision variables for the quantity and location of agents to the outer-loop optimization objectives. This allows a designer to explore Pareto solutions, based on their requirements and preferences.

Nested Optimization Framework. The framework presented here is composed of an inner-loop model (i.e., quasi-steady state decoupled power flow (DC-PF) simulation) nested within an outer-loop model (i.e., heuristic optimization) to estimate system performance as illustrated in Fig. 2. The outer-loop optimization objective 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. (1)).

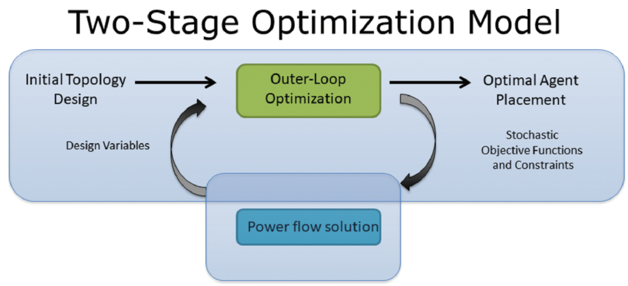

Fig. 2 Nested optimization framework

$$
\begin{aligned}
&\text{find } A_{ij}\\
&\text{minimize}\\
&\qquad f_1 = a_g(A_{ij})\\
&\qquad f_2 = -D_E(A_{ij})\\
&\qquad f_3 = \sigma^2_{D_E}(A_{ij})\\
&\text{subject to}\\
&\qquad g_1:\ \sum a_g - N_{\text{total}} \le 0\\
&\qquad h_1:\ \text{Agents per Node} = 1\\
&\qquad h_2:\ A_s - P(m, \sum a_g) = 0
\end{aligned} \tag{1}
$$

where the decision variable (A_{ij}) is an adjacency matrix representing the number and location of agents (a_g) in the system, a_g is a vector that represents the number of agents at each location, $\sigma^2_{D_E}$ is the expected demand variance, and $P(m, \sum a_g)$ is $\sum a_g$ permutations of m, where $\sum a_g$ is the number of agents taken from a set of agents $m = [a_1, a_2, a_3 \ldots a_m]$. In this formulation, no weights are assigned to the objectives, so all Pareto optimal solutions can be evaluated. N_{total} is the number of nodes in the system, limiting the overall quantity of possible agents $\sum a_g$. A_s represents the set of discrete load shedding percentage possibilities each agent may select during a cascading failure scenario. Constraint h_1 indicates that only one agent may exist at a particular node.

The inner-loop simulation is the DC-PF analysis, is nested within the outer-loop optimization to evaluate the steady-state conditions of the system during cascading. This simplified power flow is performed by solving a set of linear equations to find the system voltage angles $x = \theta_i$ for each bus (with the exception of the reference bus):

$$B_{\text{dc}}x - P_{\text{dc}} = 0 \tag{2}$$

where P_{dc} is the vector consisting of active power injections, and B_{dc} the DC connectivity matrix (derived from system admittances). Complete details for this formulation can be found in the MATPOWER user's manual [56].

By nesting the DC-PF 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.

Modeling Decision Making in Complex Systems. During the 2003 Blackout, decisions made by system operators contributed to the magnitude of this historic failure event and influenced the system's emergent behavior. This observation provides insight when attempting to model decision making during concept-stage system design. Drawing from existing physical design elements of the NAPG, Fig. 3 represents a highly simplified visual abstraction of a power system. This system consists of three connected subsystems, each containing a generator, and multiple demand and interconnection nodes. In addition, a decision-making agent (e.g., human, computer) is located within each subsystem.

During normal operation, subsystem generators dynamically adjust power output to match demand fluctuations. However, in the case of an unexpected line failure, this subsystem level of control can be inadequate to prevent line overloading elsewhere in the subsystem and can subsequently lead to uncontrollable cascading failures. Alternatively, controlled failure mitigation strategies such as strategic load shedding can minimize line overloading. This is achieved by an agent strategically reducing the demand normally required by the nodes in a subsystem or region. However, the design trade-off is that load shedding reduces the power being transferred through a subsystem. Load shedding is achieved in practice by exercising a load shedding agreement, where a commercial customer voluntarily curtails power demand.

As a strategy for increasing system robustness during concept stage design, this research explores the benefits of strategically placing agents within a given network. In the event of a line failure, each agent has the ability to shed a fixed percentage of demand load for their local region, potentially reducing the magnitude of system failure during cascading.

System Level Optimization. The outer-loop optimization is performed using a multi-objective simulated annealing (SA) algorithm to evaluate the system level objectives [57]. The SA algorithm was selected as it avoids getting trapped in local optima by accepting deteriorated solutions. Czyżak and Jaszkiewicz developed pareto simulated annealing to adopt this search for multi-objective optimization problems [58]. This search is conceptually identical to the single-objective SA but, instead of using one candidate to represent the final solution, pareto simulated annealing uses a set of interacting solutions at each iteration [59].

In this research, an 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 nondominated 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:

$$P(A_x, A_y, T) = \min\left\{1,\ \exp\left(\frac{\sum_{j=1}^{N_{SA}}(A_x - A_y)}{T}\right)\right\} \tag{3}$$

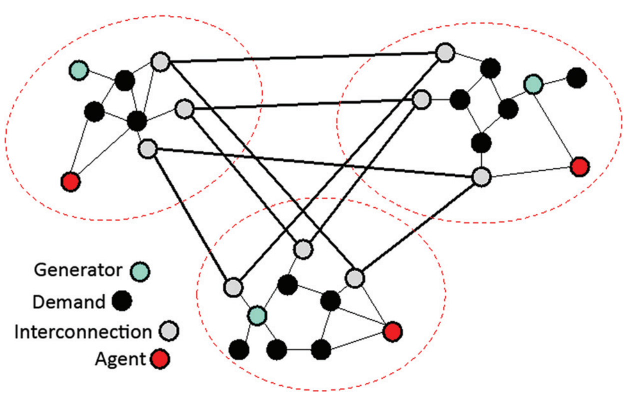

Fig. 3 Simplified power system model visualization

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 the SA algorithm are as follows:

- Initial temperature = 100
- Stop temperature = 1×10^{-3}
- Cooling rate = 0.95

Optimization Framework Process Flow. To clearly illustrate the steps performed during the nested optimization model, a process flow diagram is presented (Fig. 4).

First, a test case including key system information (e.g., topology, line capacities) is imported, and the lines with the top 10% largest capacities are identified. Next, an initial random quantity of agents are generated and randomly assigned to a position using an adjacency matrix. This initial agent placement uses the fixed topology of the imported test case. Agents are then randomly assigned a discrete load shedding percentage. Line removal is performed either iteratively or randomly based on user preference, and the DC-PF is calculated using MATPOWER. The redistribution of power in the test case may cause some lines to exceed their capacity based on the fixed parameter factor of safety, potentially initiating a cascading failure. To mitigate this failure, the agents placed at a node location (requiring a fixed demand) intersecting a line at risk of exceeding its capacity will shed their load based on the previously assigned percentage. This shedding may or may not prevent a line failure. The DC-PF and load redistribution loop are repeated until all opportunities for agent load shedding have been exhausted, and the system reaches a steady-state where demand load does not exceed capacity at any line. Although agent 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 (Eq. (1)).

In practice, it is possible for a power system network to become partially disconnected during a cascading failure, resulting in multiple independent subsystems, or islands [60]. This action is captured during the simulation, and the DC-PF is performed for each disconnected subnetwork.

Since the remaining lines must support the load from the failure, the new distribution of power flows may cause other lines to exceed line limits and trip their associated relays, 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. *Expected demand* (D_E) is calculated based on the average of resultant demand for each of the failure scenarios (Eq. (2)), where n is the total number of lines removed.

The resultant system level demand satisfied (D_i) for each line failure scenario is calculated by summing the demand satisfied for each island (Eq. (4)). It should be noted that an island might not include a generator, subsequently resulting in a total subnetwork failure.

$$D_i = \sum_{i=1}^{n} D_{i_n} \tag{4}$$

Line removal is performed until the SA algorithm converges, building on random removal methods from existing literature [2]. These solutions are then used to evaluate the mean of expected demand (μ_{D_E}) and the variance of Expected Demand $(\sigma^2_{D_E})$. Based on the system level objectives of Eq. (1), the SA algorithm outputs a set of Pareto optimal solutions. These solutions allow the designer to explore the tradeoffs 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.

Test Case Implementation and Results

RTS-96 Case Study: Physical System Properties. The RTS-96 is a 73 node test case that illustrates the method described earlier [61]. In this case, demand nodes have an associated load (in MW) that must be satisfied by the generation portfolio 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. Quasi-steady-state simulation assumes no transients; thus, if all elements are connected, three-phase balanced, and if machines are operating near nominal frequency, power can flow unaffected between both types of nodes.

In this model, each line has a maximum available capacity for power transmission, and an associated line load based on the number of nodes that are injecting power. Line load (L_{Load}) is the amount of active power flowing through a line. Line capacity (L_{Cap}) is defined as the maximum active power (in MW) that can flow through an individual line before a failure may occur (or a relay takes the line out of service), based on a fixed parameter factor of safety (γ) (Eq. (5))

$$L_{\text{Cap}} = (1+\gamma) * L_{\text{Load}} \tag{5}$$

To initiate failure in the model, a single line is removed from the test case topology. While many power system topologies are designed to handle a single element fault (i.e., $n-1$), this approach is intended to extend to different domains, where a single fault can result in uncontrollable cascading failure [62]. In this work, line removal is conducted in either one of two ways. First, line removal could be performed randomly, where each line has an equal probability of being removed. Future work in both power systems and other domains will consider incorporating failure distributions based on historical component reliability data. Next, line removal could be performed iteratively for each of the lines with the 10% highest capacity lines in the test case. This 10% highest capacity method is chosen as an alternative to a random search in an effort to test the hypothesis that removing the highest capacity lines will have the greatest impact on system performance.

Line removal is performed where $L_{\text{Load}}(t)$ is the initial line load at time t, and its value is based on the demand node values associated with it. In this model, multiple generators can satisfy a single node demand. Since the remaining lines must support the load from the failure, the new distribution of power flows may cause other lines to exceed line limits and trip their associated relays, 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. Expected demand (D_E) is calculated based on the average of resultant demand for each of the failure scenarios (Eq. (2))

$$D_E = \frac{\sum D_{f_{1\ldots n}}}{n} \tag{6}$$

where n is the number of failure iterations.

Test Case Experiments. For the RTS-96 test case, five key experiments are presented that highlight the method of this paper (Table 1). In *experiment 1*, the 10% highest capacity lines are selected for iterative line removal, and discrete agent load shedding values are either 1%, 10%, 25%, 40%, 50%, or 75%. *Experiment 2* considers all lines for random removal (not just the ones with the 10% highest capacity), and possible agent load shedding can be 10% only. *Experiment 3* also considers all lines for random removal but uses discrete load shedding values of 1%, 10%, 25%, 40%, 50%, or 75%. *Experiment*s *4* and *5* mirror experiments 1 and 3, respectively, however, there is no load shedding, so the RTS-96 test case responds to line failure as it would without any decision-based changes to the system design. Subsequently, experiments 4 and 5 were performed to provide baseline values for expected demand and expected demand variance, when no load shedding was performed.

Results Interpretation. To explore the hypothesis that system robustness is represented as a function of performance

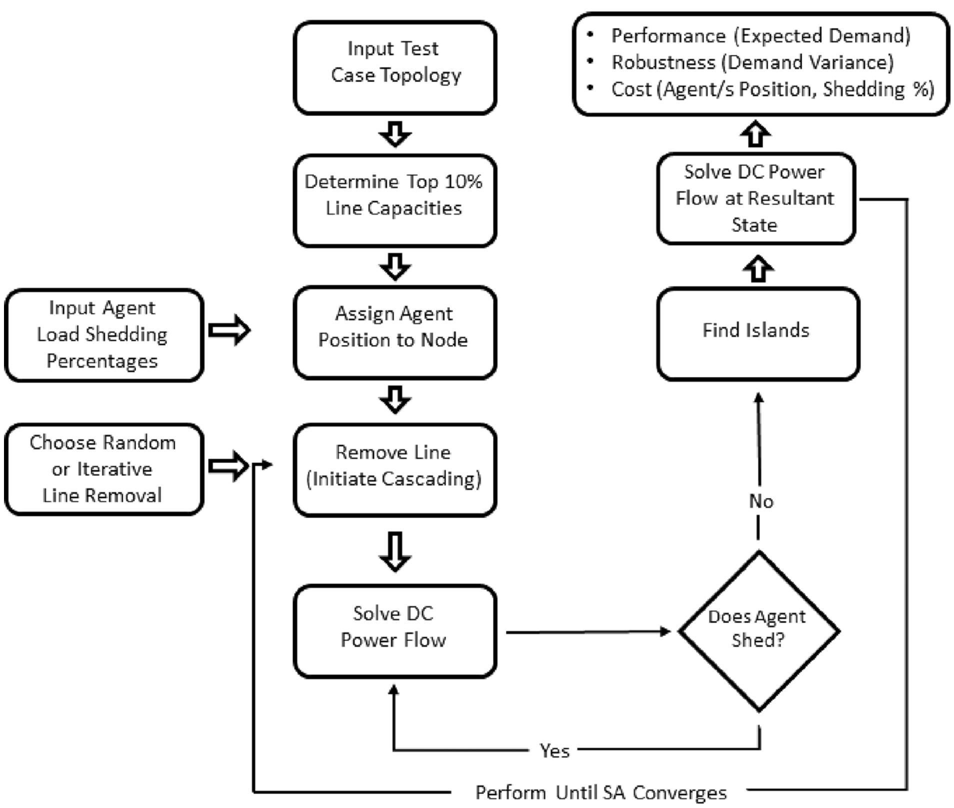

Fig. 4 Nested optimization framework process flow

Table 1 RTS-96 test case experiment matrix

Experiment number	Random line failure	Iterative line failure	10% highest capacity lines	Shedding percentage (10% Only)	Shedding percentage (1%, 10%, 25%, 40%, 50%, 75%)
1		X	X		X
2	X			X	
3	X				X
4		X	X	NA	NA
5	X			NA	NA

invariability, the design solution tradeoffs for experiments 1–3 are presented in Figs. 5–7, which aids to visualize the relationship between the quantity of agents (a_g) placed in the system, the expected demand (μ_{D_E}), and the expected demand variance ($\sigma^2_{D_E}$). In Figs. 5(*a*), 6(*a*), and 7(*a*), there is a clear trade-off, showing that as the quantity of Agents increases, Variance decreases. However, since adding Agents to the system's design adds opportunities for load shedding during a cascading failure, a greater quantity of agents also reduces expected demand (Figs. 5(*b*), 6(*b*), and 7(*b*)). So, a designer could use these results to assist in deciding how much minimum system performance is required to support critical operations, and how much performance variation they are able to tolerate in the event of a failure.

To examine the above conclusion numerically, the lowest expected demand variance (i.e., robust) designs from experiments 1–5 are presented in Table 2. For reference, the demand value of the standard RTS-96 DC-PF (8550 MW) is also provided in Table 2 [61]. In these selected results, the most robust (i.e., low variance) design is achieved during experiment 2, where 26 individual agents are utilized, and load shedding is discretely set to 10%. However, this design is not only the most expensive in terms of agents, but it also has the lowest value for expected demand. In comparison, experiment 1 has the highest variance (over eight times experiment 2) and the lowest number of individual agents (6). Experiment 1 also has a slightly higher expected demand value (3.3% higher than experiment 2). Experiment 3 presents an alternative solution that could be considered a compromise

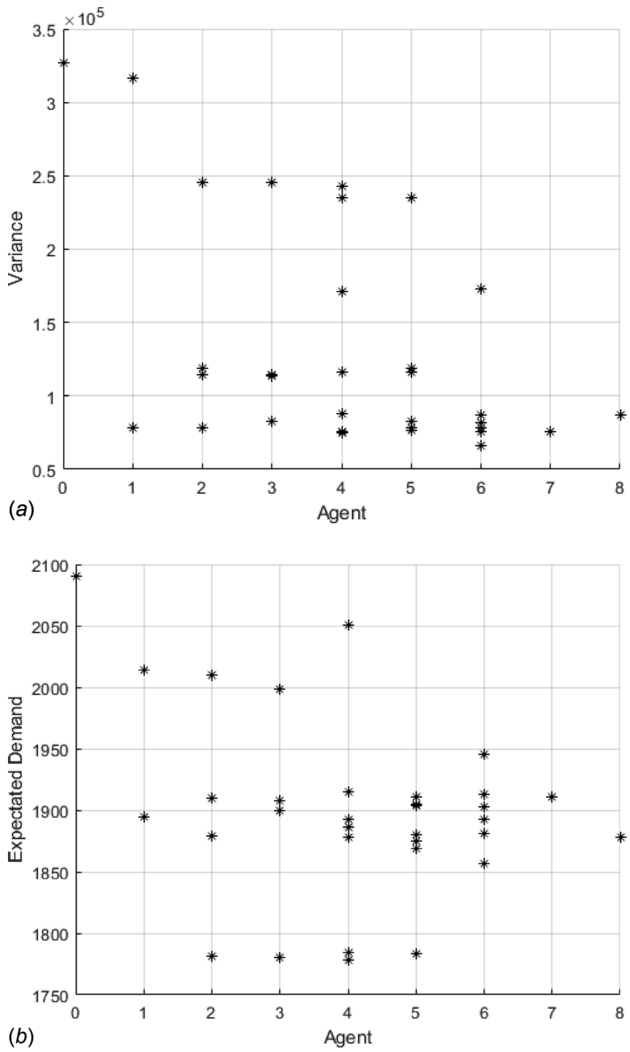

Fig. 5 Pareto optimal solutions for the outer-loop optimization of experiment 1

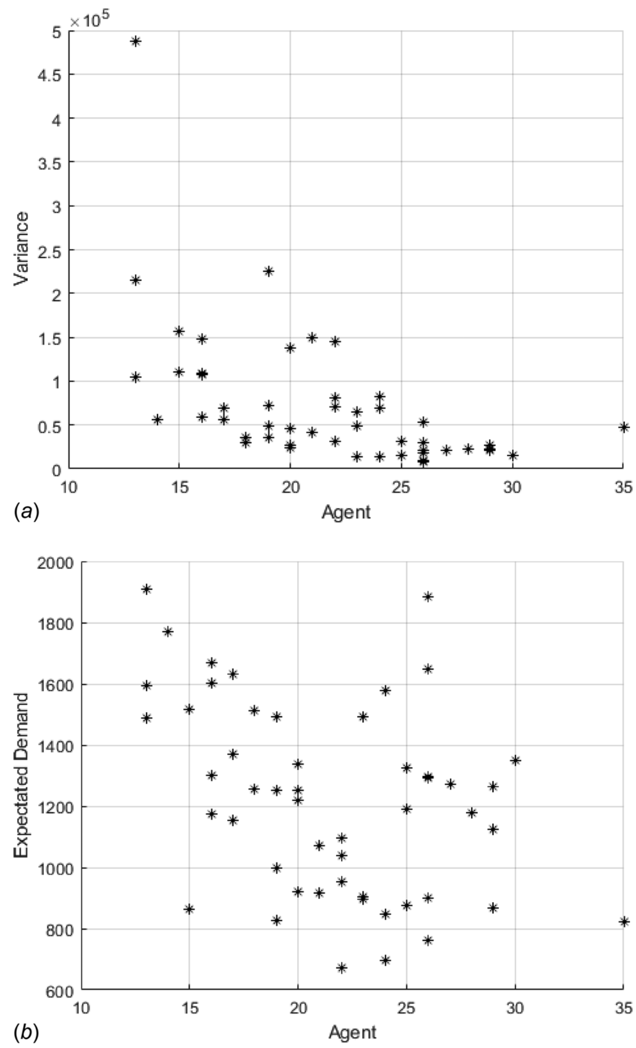

Fig. 6 Pareto optimal solutions for the outer-loop optimization of experiment 2

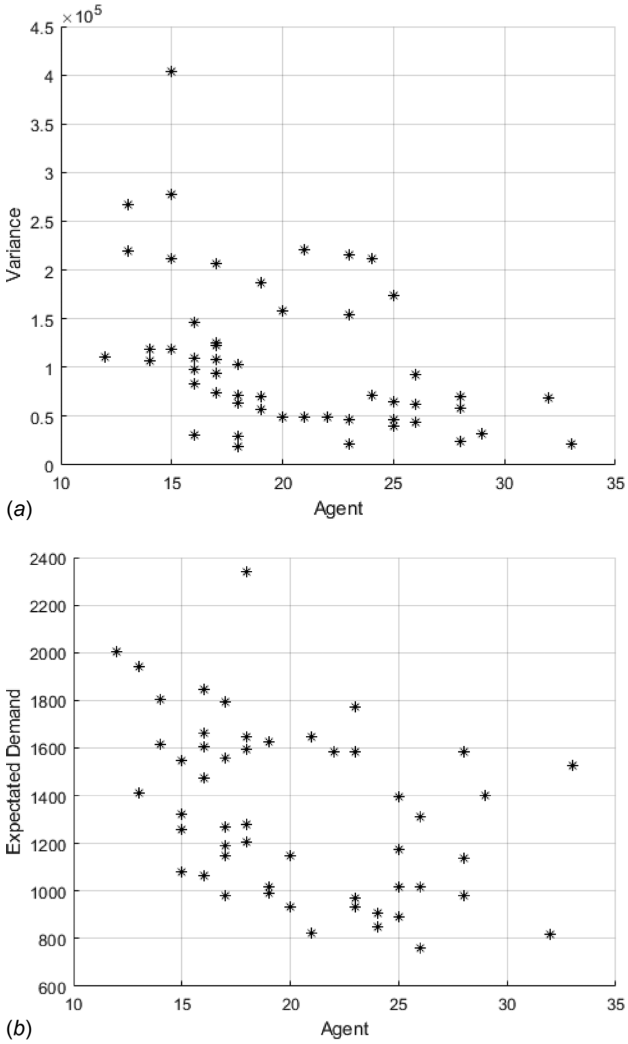

Fig. 7 Pareto optimal solutions for the outer-loop optimization of experiment 3

Table 2 Robust design solutions and RAs for experiments 1–5

Experiment number	Expected demand variance ($\sigma^2_{D_E}$)	Expected demand (μ_{D_E}) (MW)	Number of agents (a_g)	RA
1	66,327	1945	6	Low RA
2	8238	1883	26	High RA
3	19,215	2339	18	Moderate RA
4	394,142	1832	0	NA
5	92,318	2086	0	NA
RTS-96 DC-PF	NA	8550	NA	NA

between experiments 1 and 2, trading off between the number of agents and variance.

To highlight the merits of this method, experiments 4 and 5 display values for expected demand variance when no agents are placed in the system, and these values are significantly larger than experiments 1–3. These results suggest that strategically placing decision making agents throughout an infrastructure system (e.g., microgrid) during the concept design stage may decrease the uncertainty associated with failure magnitude, potentially increasing robustness. Although, concept-stage design decisions are often based on individual/organizational risk attitudes, discussed next.

Risk Attitudes in Engineering Design. Throughout the design process, engineers will often make decisions based on their individual RA, or the risk attitude of their organization [62–65]. 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-averse individual may be willing to significantly increase design cost in order to minimize performance variability. Table 2 displays the likely risk attitudes associated with each solution. The three designs presented correspond with an individual's tolerance for risk aversion (i.e., low, moderate, high). Further exploration of this trend will be explored when investigating larger networks in future work.

Agent Placement Within the RTS-96 Test Case Topology. In terms of network topology, Figs. 8–10 help to illustrate how the low-variance solutions from experiments 1–3 are implemented within the RTS-96 test case. Also, the RTS-96 test case is comprised of three similar subtopologies linked together (i.e., nodes

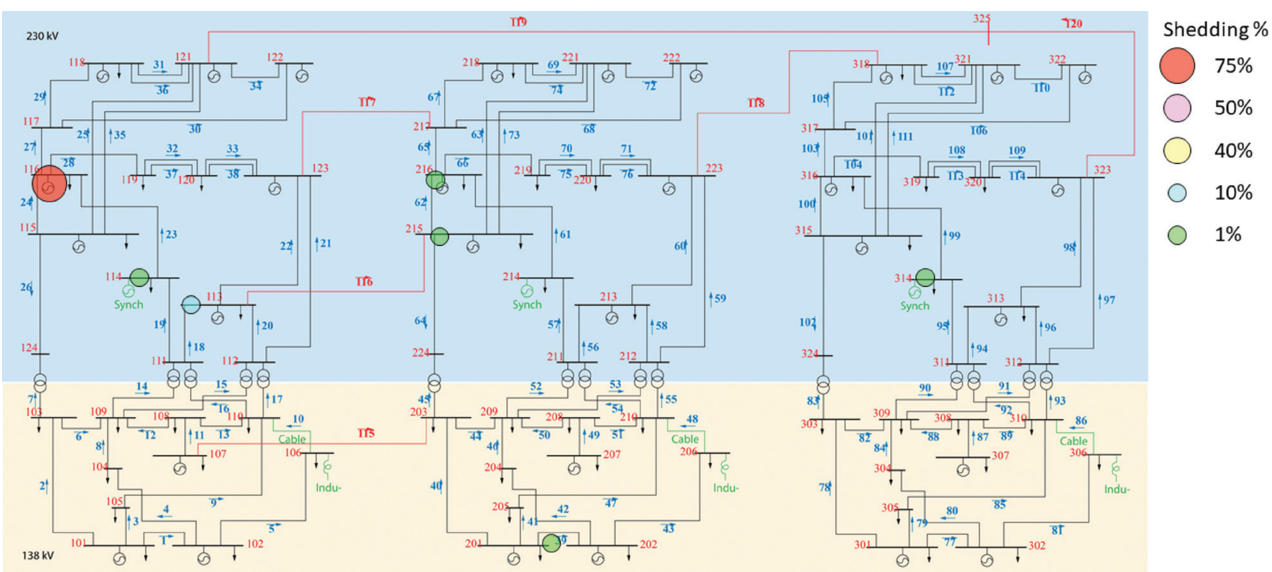

Fig. 8 RTS-96 topology displaying agent locations and load shedding percentages for experiment 1 (iterative line removal of the 10% highest capacity lines)

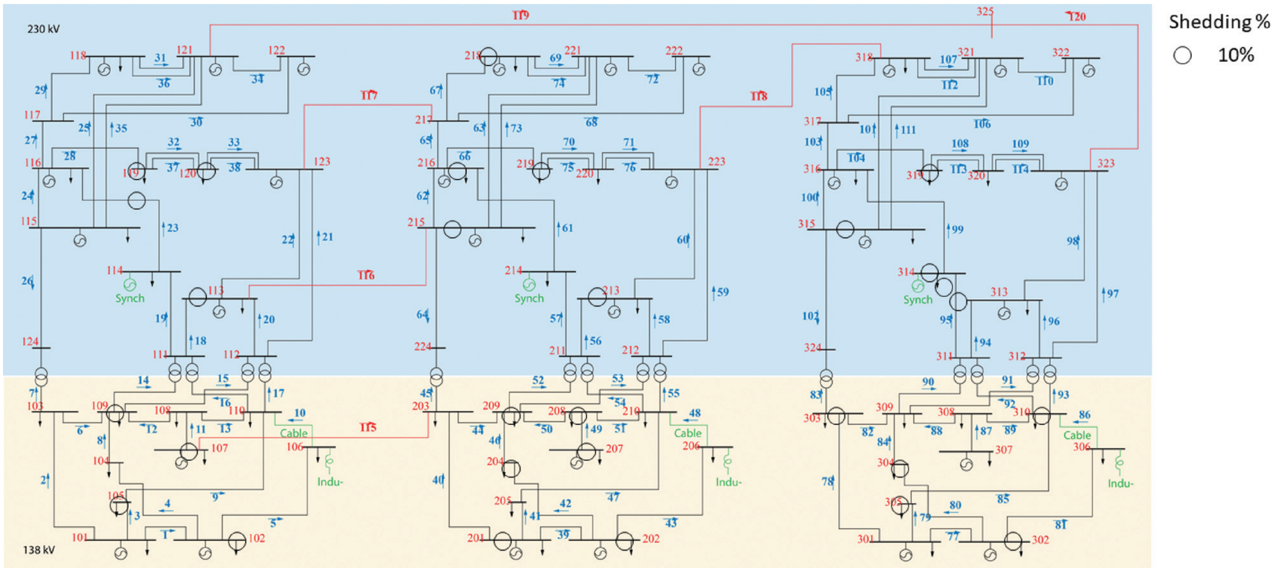

Fig. 9 RTS-96 topology displaying agent locations and load shedding percentages for experiment 2

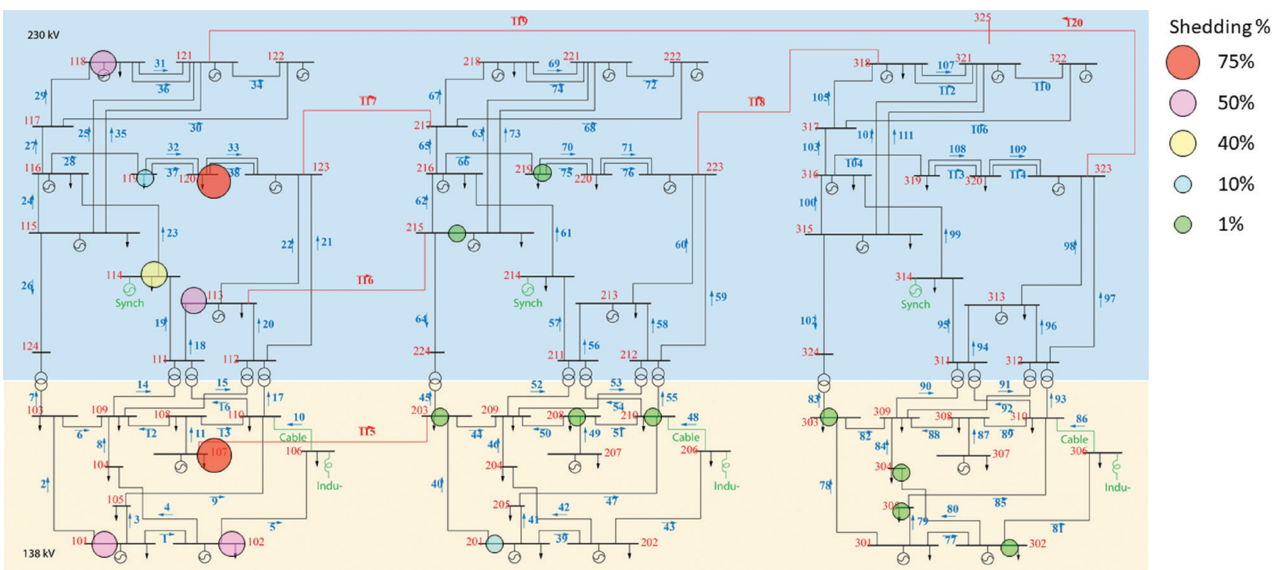

Fig. 10 RTS-96 topology displaying agent locations and load shedding percentages for experiment 3

116, 216, and 316 have common attributes), which helps to identify critical locations/nodes in the system. For example, shedding occurs in two of the three experiments in nodes 102, 107, 114, 119, 120, 201, 208, 216, 219, 302, 303, 304, 305, and 314. And, shedding occurs at nodes 113 and 215 in all three experiments. These topological shedding locations reveal key locations in the network subject to capacity overload stemming from cascading failures that originate elsewhere in the system. From a system vulnerability standpoint, these locations (especially 113 and 215) should not be associated with critical system operations.

Besides guiding the decisions on investments and upgrades to mitigate the cascading, this research also informs how to implement load shedding in practice. Current power system substation technologies (for example, a real-time automation controller) are able to implement load shedding schemes, however, there are still open questions about the level and location of these devices and how they can coordinate their protective actions.

Conclusions and Future Work

The 2003 Blackout illustrates how system-level decision making during a cascading fault event can inadvertently contribute to significant system failure. As complex systems operate in highly stochastic environments, systems must be designed for robustness by incorporating the effects of fault propagation into optimization objectives, evaluating the performance of the resultant degraded system state. This paper presents a model-based design approach for the concept-stage robust design of complex infrastructure systems that captures the impact of decision making 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 approach enables a system design that meets minimum desired performance requirements, even during degraded operation. The formulated approach considers decision making when designing for system robustness, consequently providing a set of design alternatives based on individual risk attitudes.

The design framework presented shows promise, and there are several opportunities for future work. The first step will be addressing scalability. The results from the RTS-96 test case do provide insight into emergent system behavior due to agent interaction. However, the relationships identified may not remain consistent in larger networks. A representation of the Poland power grid often studied in the power systems community will be used for this purpose.

Next, 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. Using machine learning algorithms, a more appropriate design choice based on system requirements, and potentially further reduced performance variability, can be selected. This can be achieved by generalizing a learned model from the available discrete choices.

Finally, the authors plan to apply this approach to other complex infrastructure systems. For example, other domains such as regional communication systems, traffic networks, and satellite networks may benefit in terms of robustness from strategically placed decision-making agents.

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Nomenclature

a_g = vector representing the number of agents in the system
A_s = represents the set of discrete load shedding percentage possibilities
A_x = initial adjacency matrix in simulated annealing algorithm
A_y = solution obtained by perturbing the adjacency matrix A_x
A_{ij} = adjacency matrix representing the number and location of agents (a_g)
B_{dc} = imaginary portion of the nodal admittance matrix
D_E = expected demand: average of resultant demand values that are satisfied after a failure has occurred
D_f = resultant demand that is satisfied after a failure has occurred
D_i = system level demand satisfied
g_1 = optimization inequality constraint
h_1 = optimization equality constraint
i = bus index
L_{Cap} = maximum power that can flow through an individual line
L_{Load} = amount of active power flowing through a line
$L_{\mathrm{Load}}(t)$ = initial line load at a given time t
$m = [a_1, a_2, a_3 \ldots a_m]$
m = number of agents in a set
n = number of failure iterations
N_{SA} = number of objective functions in simulated annealing algorithm
N_{Total} = number of nodes in the system
$P(m, \sum a_g)$ = permutations of m where $\sum a_g$ is the number of agents taken from a set of agents
P_{dc} = vector of active power injections for each bus
t = instantaneous time associated with a line load
T = temperature at each iteration of the simulated annealing algorithm
x = unknown voltage angles $x = \theta_i$ for each bus
γ = parameter for line factor of safety
θ = voltage angle
μ_{D_E} = mean of expected demand
$\sigma^2_{D_E}$ = expected demand variance

References

[1] Silver, M. R., and de Weck, O. L., 2007, "Time-Expanded Decision Networks: A Framework for Designing Evolvable Complex Systems," Syst. Eng., **10**(2), pp. 167–186.

[2] Ash, J., and Newth, D., 2007, "Optimizing Complex Networks for Resilience Against Cascading Failure," Phys. A, **380**, pp. 673–683.

[3] Braha, D., 2007, "The Topology and Dynamics of Complex Man-Made Systems," IEEE International Conference on Systems, Man and Cybernetics, Montreal, QC, Canada, Oct. 7–10, pp. 4062–4068.

[4] Hines, P., Cotilla-Sanchez, E., and Blumsack, S., 2010, "Do Topological Models Provide Good Information About Electricity Infrastructure Vulnerability?," Chaos, **20**(3), p. 033122.

[5] Pahwa, S., Hodges, A., Scoglio, C., and Wood, S., 2010, "Topological Analysis of the Power Grid and Mitigation Strategies Against Cascading Failures," Stat. Mech. Appl., **338**(1–2), pp. 92–97.

[6] Chinellato, D. D., Epstein, I. R., Braha, D., Bar-Yam, Y., and Aguiar, M. A. M. D., 2015, "Dynamical Response of Networks Under External Perturbations: Exact Results," J. Stat. Phys., **159**(2), p. 221.

[7] Golbayani, H., and Kazerounian, K., 2015, "On Risk-Based Design of Complex Engineering Systems: An Analytical Extreme Event Framework," ASCE-ASME J. Risk Uncertainty Eng. Syst., Part B: Mech. Eng., **1**(1), p. 011002.

[8] Haley, B. M., Dong, A., and Tumer, I. Y., 2016, "A Comparison of Network-Based Metrics of Behavioral Degradation in Complex Engineered Systems," ASME J. Mech. Des., **138**(12), p. 121405.

[9] Ye, Y., Jankovic, M., and Kremer, G. E., 2015, "Understanding the Impact of Subjective Uncertainty on Architecture and Supplier Identification in Early Complex Systems Design," ASCE-ASME J. Risk Uncertainty Eng. Syst., Part B: Mech. Eng., **1**(3), p. 031005.

[10] Thunnissen, D. P., 2005, "Propagating and Mitigating Uncertainty in the Design of Complex Multidisciplinary Systems," Ph.D. thesis, California Institute of Technology, Pasadena, CA.

[11] Lewis, K., Kalsi, M., and Hacker, K., 2001, "A Comprehensive Robust Design Approach for Decision Trade-Offs in Complex Systems Design," ASME J. Mech. Des., **123**(1), pp. 1–10.

[12] Crucitti, P., Latora, V., and Marchiori, M., 2004, "A Model for Cascading Failures in Complex Networks," Phys. Rev. E, **69**, p. 045104.

[13] 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, Report.

[14] Federal Energy Regulatory Commission, and North American Electric Reliability Corporation, 2012, "Arizona-Southern California Outages on September 8, 2011 Causes and Recommendations," Federal Energy Regulatory Commission, Washington, DC.

[15] Fairley, P., 2004, "The Unruly Power Grid," IEEE Spectrum, **41**(8), pp. 22–27.

[16] 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.

[17] White, D., Roschelle, A., Peterson, P., Schlissel, D., Biewald, B., and Steinhurst, W., 2003, "The 2003 Blackout: Solutions That Won't Cost a Fortune," Electr. J., **16**(9), pp. 43–53.

[18] Electrical Power Research Institute, 2000, "RX for Stress: Power Delivery Reliability Initiative," Electrical Power Research Institute, Palo Alto, CA.

[19] Bourne, K. J., 2010, "The Deep Dilemma National Geographic," National Geographic, **218**(4), p. 40.

[20] 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*," National Commission on the BP Deepwater Horizon Oil Spill and Offshore Drilling (U.S.), Washington, DC.

[21] Venkatasubramanian, V., 2011, "Systemic Failures: Challenges and Opportunities in Risk Management in Complex Systems," Am. Inst. Chem. Eng., **57**(1), pp. 2–9.

[22] Piacenza, J. R., Proper, S., Bozorgirad, M. A., Hoyle, C., and Tumer, I. Y., 2017, "Robust Topology Design of Complex Infrastructure Systems," ASCE-ASME J. Risk Uncertainty Eng. Syst., Part B: Mech. Eng., **3**(2), pp. 021006–021006-021010.

[23] Piacenza, J. R., Proper, S., Bozorgirad, M. A., and Hoyle, C., 2015, "Robust Topology Design of Complex Infrastructure Systems," ASME Paper No. DETC2015-46560.

[24] Faza, A. Z., Sedigh, S., and McMillin, B. M., 2009, "Reliability Analysis for the Advanced Electric Power Grid: From Cyber Control and Communication to Physical Manifestations of Failure," *Computer Safety, Reliability, and Security. SAFECOMP 2009* (Lecture Notes in Computer Science, Vol. 5775), B. Buth, G. Rabe, and T. Seyfarth, eds., Springer, Berlin.

[25] North, M., Conzelmann, G., Koritarov, V.,Macal, C., Thimmapuram, P., and Veselka, T., 2002, "E-Laboratories: Agent-Based Modeling of Electricity Markets," American Power Conference, Chicago, IL, May 3, Paper No. ANL/DIS/CP-107570.

[26] Carreras, B. A., Lynch, V. E., Dobson, I., and Newman, D. E., 2002, "Dynamics, Criticality and Self-Organization in a Model for Blackouts in Power Transmission Systems," International Conference on System Sciences, Big Island, HI, Jan. 10.

[27] Pottonen, L., and Oyj, F., 2005, "A Method for Analysing the Effect of Substation Failures on Power System Reliability," 15th Power Systems Computation Conference (PSCC), Liege, Belgium, Aug. 22–26, Paper No. 3.

[28] Lininger, A., McMillin, B., Crow, M., and Chowdhury, B., 2007, "Use of Max-Flow on FACTS Devices," 39th North American Power Symposium, Las Cruces, NM, pp. 288–294.

[29] Kurtoglu, T., Jensen, D. C., and Tumer, I. Y., 2010, "A Functional Failure Reasoning Methodology for Evaluation of Conceptual System Architectures," Res. Eng. Des., **21**(4), p. 209.

[30] Kurtoglu, T., and Tumer, I. Y., 2008, "A Graph Based Fault Identification and Propagation Framework for Functional Design of Complex Systems," ASME J. Mech. Des., **30**(5), p. 051401.

[31] Tumer, I. Y., and Smidts, C. S., 2011, "Integrated Design-Stage Failure Analysis of Software-Driven Hardware Systems," IEEE Trans. Comput., **60**(8), pp. 1072–1084.

[32] 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 J. Comput. Inf. Sci. Eng., **12**(3), p. 031007.

[33] 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," Res. Eng. Des., **6**(4), pp. 211–222.

[34] 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**(2), p. 026103.

[35] Phadke, M. S., 1989, *Quality Engineering Using Robust Design*, Prentice Hall, Upper Saddle River, NJ.

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

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

[38] Agogino, A., HolmesParker, C., and Tumer, K., 2012, "Evolving Large Scale UAV Communication System," 14th International Conference on Genetic and Evolutionary Computation Companion, Philadelphia, PA, July 7–11, pp. 1023–1030.

[39] Haley, B. M., Dong, A., and Tumer, I. Y., 2014, "Creating Faultable Network Models of Complex Engineered Systems," ASME Paper No. DETC2014-34407.

[40] Kinney, R., Crucitti, P., Albert, R., and Latora, V., 2005, "Modeling Cascading Failures in the North American Power Grid," Eur. Phys. J. B, **46**(1), pp. 101–107.

[41] Wang, Z., Scaglione, A., and Thomas, R. J., 2010, "Generating Statistically Correct Random Topologies for Testing Smart Grid Communication and Control Networks," IEEE Trans. Smart Grid, **1**(1), pp. 28–39.

[42] Wang, Z., and Thomas, R. J., 2015, "On Bus Type Assignments in Random Topology Power Grid Models," 48th Hawaii International Conference on System Sciences, Kauai, HI, Jan. 5–8, pp. 2671–2679.

[43] Pagani, G. A., and Aiello, M., 2013, "The Power Grid as a Complex Network: A Survey," Phys. A, **392**(11), pp. 2688–2700.

[44] Buldyrev, S. V., Parshani, R., Paul, G., Stanley, H. E., and Havlin, S., 2010, "Catastrophic Cascade of Failures in Interdependent Networks," Nature, **464**(7291), pp. 1025–1028.

[45] Braha, D., and Bar-Yam, Y., 2007, "The Statistical Mechanics of Complex Product Development: Empirical and Analytical Results," Manage. Sci., **53**(7), pp. 1127–1145.

[46] Albert, R., and Barabási, A.-L., 2002, "Statistical Mechanics of Complex Networks," Rev. Mod. Phys., **74**(1), pp. 47–97.

[47] Braha, D., 2016, "The Complexity of Design Networks: Structure and Dynamics," *Experimental Design Research: Approaches, Perspectives, Applications*, P. Cash, T. Stanković, and M. Štorga, eds., Springer International Publishing, Cham, Switzerland, pp. 129–151.

[48] Dueñas-Osorio, L., and Vemuru, S. M., 2009, "Cascading Failures in Complex Infrastructure Systems," Struct. Saf., **31**(2), pp. 157–167.

[49] Dobson, I., Carreras, B. A., and Newman, D. E., 2005, "A Loading-Dependent Model of Probabilistic Cascading Failure," Probab. Eng. Inf. Sci., **19**(1), pp. 15–32.

[50] Henneaux, P., Ciapessoni, E., Cirio, D., Cotilla-Sanchez, E., Diao, R., Dobson, I., Gaikwad, A., Miller, S., Papic, M., Pitto, A., Qi, J., Samaan, N., Sansavini, G., Uppalapati, S., and Yao, R., 2018, "Benchmarking Quasi-Steady State Cascading Outage Analysis Methodologies," IEEE International Conference on Probabilistic Methods Applied to Power Systems (PMAPS), Boise, ID, June 24–28.

[51] Little, R. G., 2002, "Controlling Cascading Failure: Understanding the Vulnerabilities of Interconnected Infrastructures," J. Urban Technol., **9**(1), pp. 109–123.

[52] Watts, D. J., 2002, "A Simple Model of Global Cascades on Random Networks," Proc. Natl. Acad. Sci., **99**(9), p. 5766.

[53] Hines, P., and Talukdar, S., 2007, "Controlling Cascading Failures With Cooperative Autonomous Agents," Int. J. Crit. Infrastruct., **3**(1–2), pp. 192–220.

[54] Sha, Z., and Panchal, J. H., 2014, "Estimating Local Decision-Making Behavior in Complex Evolutionary Systems," ASME J. Mech. Des., **136**(6), p. 061003.

[55] 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, Washington, DC.

[56] Zimmerman, R. D., and Murillo-Sánchez, C. E., 2011, "Matpower 4.1User's Manual," Power Systems Engineering Research Center, Cornell University, Ithaca, NY.

[57] Metropolis, N., Rosenbluth, A. W., Rosenbluth, M. N., Teller, A. H., and Teller, E., 1953, "Equation of State Calculations by Fast Computing Machines," J. Chem. Phys., **21**(6), pp. 1087–1092.

[58] Czyżak, P., and Jaszkiewicz, A., 1998, "Pareto Simulated Annealing-a Metaheuristic Technique for Multiple-Objective Combinatorial Optimization," J. Multi-Criteria Decis. Anal., **7**(1), pp. 34–47.

[59] Duh, J.-D., and Brown, D. G., 2006, "Knowledge-Informed Pareto Simulated Annealing for Multi-Objective Spatial Allocation," Comput. Environ. Urban Syst., **31**(3), pp. 253–281.

[60] 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 Syst., **3**(1), pp. 77–93.

[61] Grigg, C., Wong, P., Albrecht, P., Allan, R., Bhavaraju, M., Billinton, R., Chen, Q., Fong, C., Haddad, S., Kuruganty, S., Li, W., Mukerji, R., Patton, D., Rau, N., Reppen, D., Schneider, A., Shahidehpour, M., and Singh, C., 1999, "The IEEE Reliability Test System-1996. A Report Prepared by the Reliability Test System Task Force of the Application of Probability Methods Subcommittee," IEEE Trans. Power Syst., **14**(3), pp. 1010–1020.

[62] Thurston, D. L., Lewis, K., Chen, W., and Schmidt, L., 2006, "Utility Function Fundamentals," Decis. Making Eng. Des., **4**(1), pp. 5–14.

[63] Holt, C. A., and Laury, S. K., 2002, "Risk Aversion and Incentive Effects," Am. Econ. Rev., **92**(5), pp. 1644–1655.

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

[65] Raffia, H., 1970, *Decision Analysis: Introductory Lectures on Choices Under Uncertainty*, Addison-Wesley, Reading, MA.