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Modeling the Functional Forms of Grid Disturbances

October 2020

Sarmad Hanif
Vishvas Chalishazar
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U.S. DEPARTMENT OF ENERGY

Prepared for the U.S. Department of Energy
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Abstract

This report introduces a functional form that may be used to quantitatively predict the impacts of new grid tools and changing system qualities on the likelihoods, durations, and depths of various grid disturbances. Each disturbance scenario is modeled to have three component stages—avoidance, reactance and recovery, which together parametrically estimate one disturbance's impacts. The modeled scenario is then placed and replicated within an analysis period to represent the likelihood or frequency of the scenario and its consequent impacts. Whereas analysts have struggled to define and apply metrics for grid resilience, the functional form introduced by this report shares units of measurement with accepted grid-status measures (e.g., numbers of customers currently experiencing a service outage). Furthermore, the integrated and averaged functional form over an analysis period provides a meaningful normalized performance metric (e.g., customer outage minutes per year) that is ultimately independent of the duration of the period. The approach may be applied similarly regardless of the severity or frequency of the disturbances that are being analyzed. Because metrics can be chosen to be identical in both the hypothetical future and the actual historical past, the historical past eventually becomes the test of the future predictions, at least in a statistical sense.

The authors originally developed this approach to facilitate analysis of the effects of transactive energy (TE) systems' effects on electric power grid resilience. TE systems invite energy suppliers and consumers to actively collaborate toward the discovery of, and their responses to, the locational value of energy. The findings from this process are often embodied as energy prices, the dynamics of which indicate the locational value of energy and can further represent important grid service needs. While some academic papers claim to quantify the value of a specific TE system design toward grid resilience, the answer, in general, has been elusive. Not only do multiple and conflicting definitions of *resilience* and *reliability* exist, but countless TE systems are being invented. We conclude the following: (1) The ideal analysis should harmonize rather than differentiate *resilience* and *reliability.* Therefore, this report uses the more general term *disturbance* whenever the overloaded terms *resilience* and *reliability* can be avoided. (2) The effectiveness of TE systems must be mapped to underlying qualities of a TE system, thereby avoiding presumptions that every TE design offers similar advantages. The authors seek to evaluate the parametric effects of TE system qualities (e.g., spatial granularity, granularity of time steps, length of future prediction horizon) on avoiding, reacting to, and recovering from grid disturbances. Furthermore, any advantages (or disadvantages) must be fairly compared with the many alternative tools, systems, and strategies that might offer comparable benefits.

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1.0 Introduction

The electric power grid, including the generation, transmission, and distribution of electric power, represents critical infrastructure whose operation directly affects the economy and social wellbeing. With the ever-increasing reliance on the power grid, the need to have it always be operational is higher than ever. Recent blackouts in New York City (Manhattan power outage 2019) and Argentina (Argentina Blackout 2019) are two examples of busy regions coming to a standstill because of power outages. Many recent hurricanes like Irma, Maria, and Harvey have caused large-scale equipment damage and loss of power to hundreds of thousands of customers.

The objective of this report is to introduce a parametric functional form for quantifying the expected impacts of existing and new mitigative actions and tools on both large and small grid disturbances. It is our hope that this theory will facilitate meaningful analysis of transactive energy systems with respect to grid health and in a way that supports fair comparisons among alternative mitigative tools and practices. We further hope that this theory harmonizes the concepts of power system reliability and resilience.

1.1 Concepts of Resilience and Reliability

This section reviews the current usage of terms *resilience* and *reliability* and articulates why these terms hinder theoretical analysis. The model of grid disturbances introduced in this report is arguably applicable to many disturbance types and severities and thereby helps harmonize the usage of the terms.

1.1.1 Power System Resilience

Resilience has become an area of great interest for researchers. A large body of research focusing on the definition of and metrics for grid resilience. The U.S. Presidential Policy Directive (PPD) 21 defines *resilience* as "the ability to prepare for and adapt to changing conditions and withstand and recover rapidly from disruptions." In its definition of resilience, PPD 21 further clarifies that resilience includes a system's "ability to withstand and recover from deliberate attacks, accidents, or naturally occurring threats or incidents" (Directive, Presidential Policy 2013). Numerous other studies that define resilience using different phases or terms. For example, Rieger (2014) and Phillips (2020) uses 5 Rs of resilience—recon, resist, respond, recover, and restore.

Almost all resilience-oriented studies use different metrics to quantify system resilience and analyze different aspects of resilience. Some commonly used metrics are demand/energy not served (Johnson et al. 2020), time and cost of recovery, load recovery factor, and lost revenue (Chalishazar 2019; Chalishazar et al. 2020). Still other metrics are restoration efficiency index, vulnerability index, degradation index, microgrid resilience index (Amirioun et al. 2019), and maximum number of customers out of service (Kazama and Noda 2012). (Panteli et al. 2017a, 2017b) propose resilience evaluation of the grid as a four-stage procedure. Stage 1 and 2 evaluate how fast and how low system degrades. Stage 3 and 4 respectively describe how extensive and how extensive the post-event degradation is and how quickly the system recovers as compared to the pre-event resilience state. Almost all resilience-oriented frameworks are designed for specific applications and apply only to high-impact, low-probability (HILP) grid disturbances.

Efforts to analyze and measure system resilience through “resilience events”, which are infrequent hazard conditions, usually lead to difficulties in truly testing system resilience. First, with this approach, there is no true baseline by with which an entity can measure its improvement or slippage of system resilience. Second, a system is deemed resilient by that which does not occur. For example, can system resilience be claimed to have been doubled because twice as many events did not occur? This is difficult to assess, given that resilience never happens in the past, and in the future, it is only a theoretical ideal, meaningful only in a statistical sense.

1.1.2 Power System Reliability

The North American Electricity Reliability Corporation (NERC) recognizes power grid reliability as an attribute of (1 the adequacy of the supply to meet energy demands for scheduled and reasonably unscheduled outages, and (2 withstanding sudden disturbances such as electric short circuits or unanticipated loss of system components (NERC 2007). Numerous reliability metrics that have been widely accepted and used across power industry partners and regulators. Some of them are (1 System Average Interruption Duration Index (SAIDI), (2 Customer Average Interruption Duration Index (CAIDI), (3 Loss Of Load Probability (LOLP), (4 System Average Interruption Frequency Index (SAIFI), (5 Momentary Average Interruption Frequency Index (MAIFI), etc. These reliability metrics are often used by utilities to make sure that the number and extent of grid disturbances are kept as low as possible. An example of how reliability metrics are used is one of LOLP where the power system requires LOLP to be < 0.1, which dictates the system’s reserve requirements so that the power supply reliability level is maintained, and no system disturbance is caused. To summarize reliability metrics encapsulates all grid disturbances, small scale and large scale whereas resilience has traditionally only been capturing the HILP disturbances.

From the utilities’ perspectives, *reliability* is today discussed in terms of business-as-usual conditions and explicitly excludes major disturbances. This practice has emerged to prevent prolonged major events from skewing utilities performance measures, but the discontinuity between two corresponding event types is not at all conducive to theoretical analysis of the type needed to assess new and alternative mitigative tools. System resilience is prone to these business-as-usual stresses and conditions, which may lead to grid outages and failures. *Reliability,* in fact, can be a great metric for actual and historical device and system failures and can be used as a metric or baseline into the future, but only in a statistical sense (i.e., likelihood of failure). Hence, we assert that reliability is, in fact, the metric for resilience. All we can say with confidence is that a resilient system will, on average, have better reliability than one that is less resilient.

For these reasons, this report avoids using the overloaded terms *resilience* and *reliability* whenever possible and instead uses the softer, inclusive term *grid disturbance*.

1.2 Transactive Energy Systems

Transactive energy (TE) systems are gaining wide interest, and associated research has been transitioning from theory to application (Hammerstrom et al. 2016; Widergren et al. 2017, 2018). TE systems are a collection of economics and controls technique that uses market-based constructs to manage the supply and demand of electricity within a power system. Because of the ability to introduce distributed intelligence in power systems, TE systems have been widely discussed as a means of managing the increasing need for flexibility in grid operations (Kok and Widergren 2016). This report highlights potential TE qualities and how they may help in counteracting to disturbances experienced by the grid. For example, if the transmission or distribution system can be isolated, the operation of the rest of the grid with TE system implementation can help minimize further outages and associated loss of power to customers. If the safe coordination of distributed energy resources (DERs), especially battery systems, is possible, TE systems may help further minimize customer outages with limited additional generation source deployment.

1.3 Report Organization

The rest of this report is organized as follows: Chapter 2 introduces the functional forms for the system performance measure in different phases of the outage modeling, which are avoid, react and recover. Chapter 3 details system performance derivation using the functional forms developed in Chapter 2. Chapter 4 discusses different system attributes/qualities for both conventional and transactive-energy power and qualitatively analyzes their contribution towards the proposed outage modeling theory. The final chapters present conclusions, future work, and the reference list.

2.0 Functional Form Modeling for All Grid Disturbances

The proposed theory of functional form modeling for all grid disturbances considers three main features:

1. Avoid a grid disturbance.
2. React during a disturbance to lessen the extent of system degradation.
3. Recover rapidly after a disturbance has occurred.

Figure 1 shows these three features of the system. Following the practice described by the Gridwise Architecture Council (2020), the system performance measure in Figure 1 is taken to be the number of customers online. The three features are intended to be independent, to the degree that independence can be achieved. In this way, each feature can have its pre-assigned role and characteristics, while allowing for its planning and activation with respect to the grid disturbances.

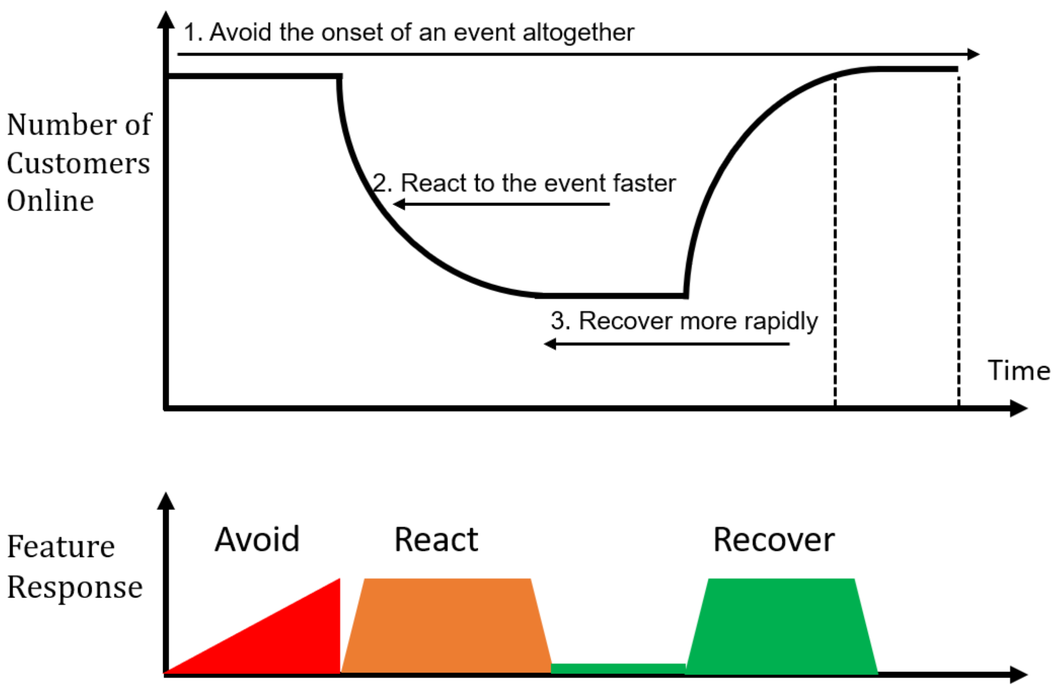

Figure 1. Typical grid disturbance system response and its features (GridWise Architecture Council 2020).

2.1 Functional Forms Prerequisites

Throughout this report, the term *grid disturbance* is used to refer to outages. The softer *scenario* is introduced to refer to stressful conditions that could, but do not necessarily, turn into a grid disturbance that causes the system performance measure to deteriorate. The careful terminology is needed to value mitigative actions by their likely future benefits, which may entirely avoid outages. Similarly, the functional form has two time periods of interest: (1) an analysis time period and (2) a scenario time period. The analysis time period is the period of interest during which numbers of scenarios (for relatively frequent scenarios) or fractions of likely scenarios for very infrequent types are expected to exist. The scenario time period is the time frame of a single scenario that could turn into a grid disturbance if a reduction in the system performance measure occurs. The scenario time is always referenced relative to the analysis period. Multiple scenario time frames can exist within the analysis time frame.

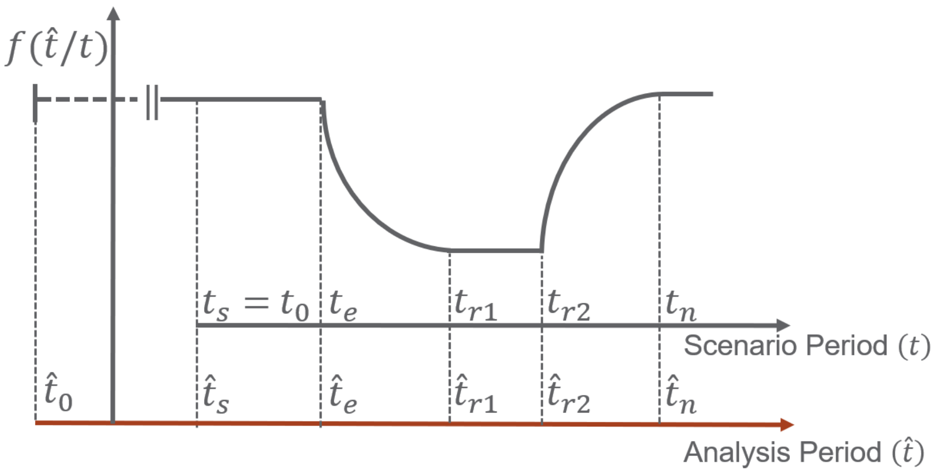

Figure 2   A generalized grid disturbance scenario.

Table 1.   Notations for describing a generalized grid disturbance.

$f(\cdot)$	Performance measure (e.g., customers being served, etc.) in an analysis or scenario time frame
$\hat{t}$	Time in an analysis time frame
t	Time in a scenario time frame
$\hat{t}_s$, $t_s = t_0$	Scenario start time
$\hat{t}_e, t_e$	Disturbance event start time
$\hat{t}_{r1}$, t_{r1}	React stage end time and recover stage start time.
$\hat{t}_{r2}, t_{r2}$	Effective recovery stage start time
$\hat{t}_n$, t_n	Effective recovery stage end time. Return to normalcy.
$u(t)$	Unit step input
Γ	Indicator function
$t_{\rightarrow}$	Transition times between responses within a stage

The anticipated function forms needed for such a model include time delays, exponential decays over time, exponential recoveries over time, and general functional relationship of system states (i.e., stressors) and control actions.

2.1.1 Modeling Delays

It will be necessary to model time delays. Important time translation rules are derived from those in both the time and Laplace transform domains. A delay can be modeled in time by a step function and by an exponential term in the Laplace domain (Miller and Orloff n.d.).

$$\boldsymbol{\mathcal{L}}\big(u(t-a)\,f(t-a)\big) = e^{-as}\,F(s) \tag{1a}$$

$$\boldsymbol{\mathcal{L}}\big(u(t-a)\,f(t)\big) = e^{-as}\,\boldsymbol{\mathcal{L}}\big(f(t+a)\big) \tag{1a}$$

$$\boldsymbol{\mathcal{L}}\big(u(t-a)\big) = {e^{-as}}/{s} \tag{1a}$$

$$\boldsymbol{\mathcal{L}}\big(\delta(t-a)\big) = e^{-as} \tag{1a}$$

Of these, (1a) may be most useful because it describes how to translate a function that is specified with respect to its own time frame to another relative or absolute time frame.

2.1.2 Modeling Exponential Delay and Recovery

The generalized exponential growth and decay functions have the following form in the time and Laplace domain:

$$f(t) = 1 \cdot e^{-at} \;\triangleq\; F(s) = \;\boldsymbol{\mathcal{L}}(e^{-at}\,) = \frac{1}{s+a} \tag{2}$$

Similarly, a factor other than 1 will scale the Laplace domain solution above.

2.1.3 Modeling General Functions of System States and Control Actions

The function $f(t)$ exhibiting a combination of two trajectories $f_1(t)/f_2(t)$ is modeled through a binary indicator function Γ as

$$f(t) = \Gamma \cdot f_1(t) + (1-\Gamma) \cdot f_2(t), \tag{3}$$

which is a condensed version of

$$f(t) = \begin{cases} f_1(t), \;\forall t \text{ for } \Gamma = 1 \\ f_2(t), \;\forall t \text{ for } \Gamma = 0 \end{cases}. \tag{4}$$

2.2 Avoid Stage

The avoid stage begins during the normal pre-contingency state and ends when the value of the performance metric actually degrades. During the avoid stage, the system may take actions to defer and reduce the likelihood of a grid disturbance. Certain mitigative actions delay and perhaps entirely prevent the adverse consequences, i.e., avoid a grid disturbance. The scenario starting time $\hat{t}_s$ must be determined within the analysis time frame

$$\hat{t}_s \triangleq t_0 - \hat{t}_0, \tag{5}$$

where t_0 is the absolute start time in the scenario time frame and $\hat{t}_0$ is the analysis time frame start time. From the onset of the scenario, the avoidance of the grid disturbance is then to prevent any disturbance in a time window

$$f(\hat{t}_s + t)\;\;\forall\, t \in [0,\, t_e]. \tag{6}$$

The avoid stage maintains the nominal performance of the system until the scenario turns into a major disturbance event, i.e., identification of a grid disturbance's onset t_e. The functional form of a scenario's performance may therefore be treated as a delay within the analysis time frame. The translations of the scenario function within the analysis window may be formalized using the delay translations introduced by Equation (1a).

$$\boldsymbol{\mathcal{L}}(u(\hat{t} - \hat{t}_s)\, f(\hat{t} - \hat{t}_s);\, s) = e^{-\hat{t}_s s}\, F(s) \tag{7a}$$

$$\boldsymbol{\mathcal{L}}\big(u(\hat{t} - \hat{t}_s)\, f(\hat{t})\big) = e^{-\hat{t}_s s}\ \boldsymbol{\mathcal{L}}\big(f(\hat{t} + \hat{t}_s)\big) \tag{7b}$$

$$\boldsymbol{\mathcal{L}}\big(u(\hat{t} - \hat{t}_s)\big) = {e^{-\hat{t}_s s}}/{s} \tag{7c}$$

$$\boldsymbol{\mathcal{L}}\big(\delta(\hat{t} - \hat{t}_s)\big) = e^{-\hat{t}_s s} \tag{7d}$$

Three conditions can lead to the onset of a disturbance scenario, and hence need to be captured in the avoid stage:

- Disturbance scenarios often have a purely probabilistic frequency and likelihood that must be captured by estimating the numbers of scenarios that will occur within an analysis period.
- When the start of a scenario is not purely statistical, the scenario's starting time (and consequent delay in the analysis period) might be functionally determined. This is a more general case than that of the purely probabilistic scenario starting time. In this case, scenarios are initiated by the observation of stressors that could, but do not necessarily, result in a measurable disturbance.
- Still other scenarios may have undefinable starting times. In this still-more-general case, the condition of a stressor variable must be functionally tracked throughout an analysis period.

2.2.1 Treatment of a Fully Probabilistic Scenario Starting Point

The beginning of a disturbance scenario must be referenced from a specific absolute time $\hat{t} = \hat{t}_s$ within the analysis time frame. A scenario start time can be easily determined, at least in the statistical sense, if the scenario is initiated by a major external event like a lightning strike or storm. The major event's occurrence may be purely probabilistic. Major storm surges, for example, are uncontrollable, even though the frequency of the events may be changing recently for largely uncontrolled environmental reasons. On the other hand, active controls or design decisions may directly affect the rates of some lesser events. For example, elevating a flood dike might decrease the statistical likelihood of a substation flood. The analyst may find it easier to directly model changes in the likelihood of substation flood occurrences than to model the detailed physics of rainwater as a stressor after a storm. A better example might be the replacement of equipment with an alternative device that has a shorter mean time between failures.

The statistics of uncertain and especially infrequent events should be treated over long integration analysis periods to capture their statistical outcomes. Scenario start times should be stated with respect to the beginning of an analysis period $\hat{t}_0$. The analysis period then may be assigned numbers of scenarios (for relatively frequent scenarios) or fractions of scenarios (for very infrequent types).

A decrease in the number of likely disturbance scenarios within an analysis represents effective deferral of such scenarios. The deferral of scenarios, if achieved, consequently reduces the average impacts of the scenarios. In many cases, further actions may be taken after the start of a scenario to avoid the scenario's adverse consequences, and these are discussed later.

Example 1: A scenario is expected to occur on average every interval $\hat{t}_s$. If a mitigative treatment is calculated to decrease the likelihood of the scenario by fraction $1/\gamma < 1$, then the expected start time delay would be γ times greater, namely $u(\hat{t} - \gamma k \hat{t}_s)$, where iteration index k has been introduced. An integrated outage metric would be reduced accordingly and could be reported on a per year (or other analysis period) basis. This approach should work even for very unlikely scenarios if at least one complete event cycle is integrated and divided by the expected interval between its occurrences. That is, for analysis period Γ (e.g., a year), the average impact expected during the analysis period would be

$$\frac{\overbrace{\Gamma}^{\text{scenarios per analysis period}}}{\gamma \hat{t}_s} \cdot \overbrace{\int_{\hat{t}=k\gamma\hat{t}_s}^{(k+1)\gamma\hat{t}_s} f(\hat{t})\,d\hat{t}}^{\text{impact per scenario}}. \tag{8}$$

2.2.2 Disturbance Scenarios that Are Initiated by a Stressor Condition

Some scenarios will be initiated not by major events, but instead by gradual accumulation of stressors. The stressor (i.e., temperature) often exists within a continuum. A scenario's starting time might be based on a stressor threshold, but the threshold criterion may be somewhat arbitrary. The arbitrary nature of the threshold is not problematic as long as a scenario's starting time can be located prior to significant decay of the performance measure that is being used.

Example 2: Consider a disturbance scenario built upon a continuous stress variable, not induced by a precipitous external disturbance. Due to various sources of uncertainty in electric power systems, resources (e.g., power generators, transport capacity, etc.) are held unused in reserve. The system is prepared and would not likely see any degradation in a performance measure while the system possesses strong reserves that can be applied. Risks of outages or other consequences may be small most of the time.

This scenario's starting time may be defined as the instance when reserves fall below some threshold. We could assert that the disturbance scenario's starting time $\hat{t}_s$ is triggered when reserve r becomes less than reserve threshold $r_{\text{threshold}}$. The disturbance scenario does not exist otherwise.

$$\hat{t}_s \triangleq \begin{cases} \hat{t}, r \geq r_{\text{threshold}} \xRightarrow{\text{transition}} r < r_{\text{threshold}} \\ \emptyset, \text{otherwise} \end{cases}. \tag{9}$$

Given that many types of reserves are maintained and monitored using communications, there may be still another delay from the time the scenario begins until system operators recognize and begin reacting to the threat. The delay would be like that used above for the statistical likelihood of delays prior to major events.

Natural and existing emergency reserves might be activated to return the system to a safe state in this scenario. Existing active controllers may do so as well. Still further mitigative actions may be considered and valued for their abilities to catch the diminishing reserves and help defer or entirely avoid consequences that occur once reserves become fully depleted. This general function describes the effect of such avoidance actions on the reserve after a disturbance scenario has begun. That is, the trajectory of reserve r may be modeled as a function of existing and new mitigative strategies, which are themselves functions of current reserves and time:

$$\mathrm{r} = f\left(p_{\text{existing}}(\mathrm{r}, t), p_{\text{new}}(\mathrm{r}, t), t\right) \geq 0, \tag{10}$$

where p_{existing} and p_{new} are existing and proposed new control strategies to be applied over time when reserves become limited. The exact functional form of the reserve is difficult to anticipate over time, especially if cascading outages must be anticipated. The avoid stage ends when the reserve become depleted, i.e., $\mathrm{r} < 0$.

2.2.3 Scenarios that Have Indeterminate Starting Times

Some scenarios effectively begin at the start of the analysis period. For example, a device's lifetime may be functionally determined by temperature over time. In this case, defining the starting time of a grid disturbance scenario may be elusive. Nonetheless, this treatment is important to system performance because avoidance actions may be taken to reduce the stressor, reduce the likelihood of outages, and thereby improve expected system performance.

<u>Example 3</u>: Consider the expected lifetime of a distribution transformer. Assume the rate of transformer damage doubles with each 10°C of increased temperature. A mitigative action could be taken to control the temperature, which is further a function of electrical loading and other environmental conditions, and thus avoid or defer the failure of the transformer. A transformer device would still be operational and would not lose functionality if this integral remains well below the threshold, so the performance measure, in this case, might be

$$30 \text{ years - } T_{\text{initial}} - \int 2^{\frac{30-T}{10}}\, dt, \tag{11}$$

where T_{initial} is the existing lifetime that is estimated to have expired.

The device (or fleet of devices) has no definitive start to this disturbance scenario that plays out over many years. At some hopefully distant future time, the transformer may indeed fail. However, the given performance measure might also be used to decide when to replace the device—another mitigative action.

2.3 React Stage

Upon failure of avoidance efforts, system damage begins to occur and the system enters the react stage. As discussed in the previous section, the location of a disturbance scenario within the analysis time frame has already been addressed, so the remaining disturbance scenario stages, including the react stage, may be defined within the disturbance scenario's reference time frame:

$$t_{\text{react}} \in (t_e,\ t_{r1}] \tag{12}$$

Measurable degradation of system performance is observable from the beginning of the react stage at t_e, and the react stage continues until the system degradation ends at t_{r1}. The stage ends when the rate of change of system degradation becomes zero.

2.4 React Stage Functional Form Model

The react stage functional form $f_{\text{react}}(\cdot)$ is defined to have two substages—an instantaneous degradation $f_i(\cdot)$ and a mitigative degradation $f_m(\cdot)$:

$$f_{\text{react}}(t_e + t) = u(t - t_e) \cdot \Big(\Gamma \cdot f_i(t) + (1 - \Gamma) \cdot \Big(f_m(t) + \big(f_{\text{m}}(t_{\rightarrow}) - f_i(t_{\rightarrow})\big)\Big)\Big) \tag{13}$$

2.4.1 Initial Degradation

The initial degradation of the system represents initial system decay during the grid disturbance following the unsuccessful avoid stage:

$$f_i(t) = f(t_e) \cdot (1 - (1 - a_{ss}) \cdot (1 - e^{-at})) \tag{14}$$

In Equation (14), parameter $a_{ss} \in (0, f(t_s))$, represents the final trajectory value if the initial damage trajectory were to continue unchecked. Initial degradation $f_i(t \rightarrow \infty)$ with exponential factor $a > 0$ defines the rate at which initial system degradation happens. As an example, consider $f_i(t)$ to capture the system response as several tie-lines become damaged. Detection of the initial damages could trigger outage management services of an islanded portion of the grid to salvage whatever portion of the grid can still be kept up and running, which mitigation alters the disturbance trajectory, as described next.

2.4.2 Mitigative Degradation

Mitigative strategies slow the system degradation(s) and may be modeled as follows:

$$f_m(t) = f(t_e) \cdot \big(1 - (1 - a_{ss}) \cdot (1 - e^{-a(t+\alpha)})\big). \tag{15}$$

In Equation (15), parameter $\alpha > 0$ is introduced and represents acceleration in time from the initial degradation rate and the initial degradation trajectory. Intuitively, it can be imagined that $f_m(t)$ is composed of continuous measurements of the system state, coordinating with emergency handling agencies and public advisory services.

The overall react response (Equation (13)) also contains the term $\big(f_m(t_{\rightarrow}) - f_i(t_{\rightarrow})\big)$, which is the difference between initial and mitigative trajectories at the time of transition $t_{\rightarrow}$ between the two, when mitigative actions are first applied. This transition is affected by changing Γ from 0 to 1 as the mitigative strategy is applied. With this, the overall react trajectory could be explained as follows: Following the unsuccessful avoid stage, the initial system degradation $f_i(t)$ follows Equation (14), capturing the initial failure of vulnerable equipment. These vulnerable equipment failures continue, and if left unmitigated, the performance measure keeps getting degraded at an exponential rate until settling at the steady-state value a_{ss}. The goal of the mitigative strategy $f_m(t)$ is to safeguard the vulnerable equipment, reducing the set of failing equipment such that the overall trajectory in the react stage is shallower than and less steep than the initial degradation trajectory. This mitigation is captured through the functional form of $f_m(t)$, which translates the initial trajectory forward in time by α, i.e., it reduces the set of vulnerable equipment failures. The difference between the two trajectories (initial and mitigative degradation) is then made a seamless transition at the point where the trajectory has been mitigated.

Initial Degradation Example: Consider a hurricane scenario in which high winds cause multiple transmission lines to be lost over time. Initially, the system would be in avoid stage and would be able to absorb some losses by rerouting the power using other online transmission lines. But upon experiencing further losses, the avoid stage would be rendered unsuccessful, and the system would enter the react stage. As the react stage begins, the system would begin a precipitous initial degradation trajectory. The performance measure (e.g., percent of customers connected to the grid) would degrade sharply. The instantaneous loss of transmission lines would put extra burden on the grid which would cause cascading failures of vulnerable equipment and reduce the numbers of customers connected to the grid at an exponential rate of 8% of the total number of customers every hour. If not checked, the event would leave only 50% of customers with service. A pictorial representation of this example is shown in Figure 3.

Mitigative Degradation Example: After the initial brunt of the degradation in the performance measure, the system would react with some remedial action schemes that are specifically designed to protect the system from cascading losses and complete blackout. Consider that these mitigative actions would start modifying the initial react stage trajectory after 5 hours. Assume that the mitigative actions would reduce the set of vulnerable equipment such that the mitigative degradation trajectory appears to be 10 hours ahead of the initial trajectory. The mitigated trajectory would relax to degraded state service with 68% customers online, i.e., fewer outages than 50% that were projected by the initial trajectory. The effectiveness of the mitigative strategy is shown in Figure 3.

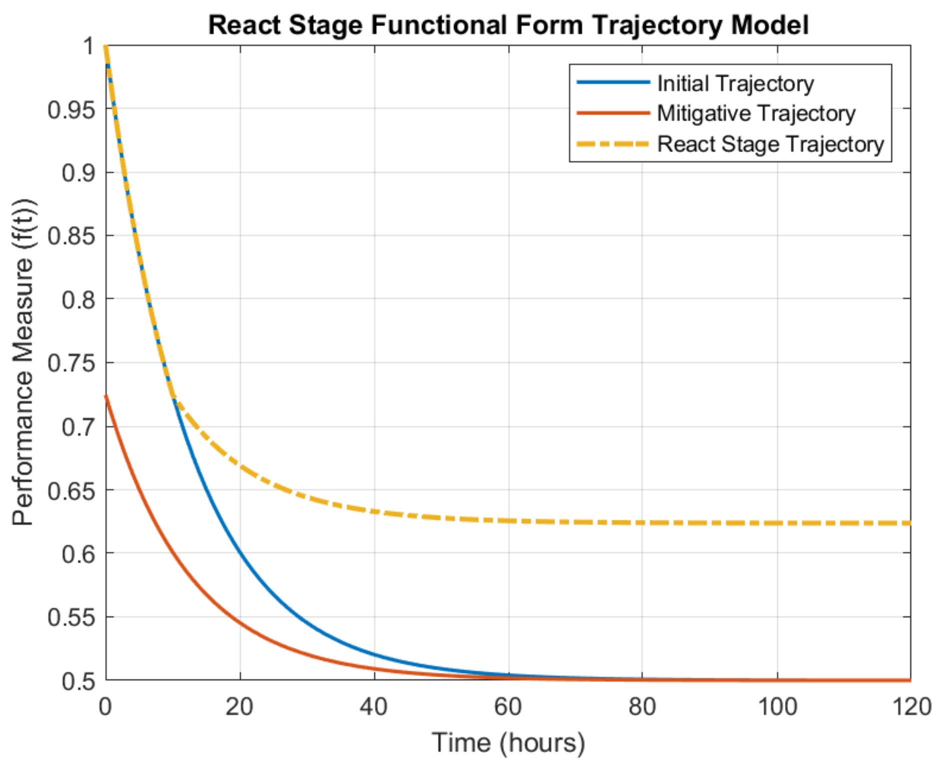

Figure 3 Demonstration of react stage functional form. The above trajectories are produced using parameters $f(\hat{t}_s) = 1.0,\ a_{ss} = 0.5,\ a = 0.08,\ \alpha = 10,\ \Gamma = 0\ \forall\ t \in [0,5]$ when the initial degradation is active and then $\Gamma = 1$ once the mitigative trajectory becomes activated.

2.5 Recover Stage

At the end of the react stage, the system has degraded to the disturbance scenario's worst performance measure and the recover stage begins. The recover stage time period extends from the beginning of the recover stage t_{r1} until the end $t_{\,n}$ when normalcy has returned, and the scenario's functional form has returned to its nominal value:

$$t_{\text{recover}} \in (t_{r1},\ t_{\,n}] \tag{16}$$

2.5.1 Recover Stage Function Model

The recover stage functional form $f_{\text{recover}}(.)$ consists of three substages—a delay $u(\cdot)$ while responses are staged but result in little system improvement, a short-term recovery $f_{st}(\cdot)$, and a long-term recovery $f_{lt}(\cdot)$. The substages comprise the recover stage functional form $f_{\text{recover}}(\cdot)$ as follows:

$$f_{\text{recover}}(t_{r1}+t) = f(t_{r1}) + u(t-\Delta t)\cdot\left(\Gamma\cdot f_{st}(t-\Delta t) + (1-\ \Gamma\ )\cdot f_{lt}(t-\Delta t)\right) \tag{17}$$

Delay ($\Delta t \coloneqq t_{r2}-t_{r1}$): The delay term captures the time delay it takes before the event consequences are recognized and while recovery efforts are staged. The system status remains in a static, degraded state during this delay. During this recovery delay, work crews must be safely staged and interdependent infrastructures such as roads and gas lines must be accessed and fixed.

Short-Term Response: The initial system capabilities to bring power back is represented in the short-term response of the recover stage:

$$f_{st}(t_{r2}+t) = f(t_{r2}) + \left(f(t_n) - f(t_{r2})\right)\cdot(1-e^{-b_1 t}) \tag{18}$$

The term $b_1 > 0$ is the initial rate at which the infrastructure can be brought online in the short-term response. Theoretically, the short-term responses may bring the performance measure back to its nominal stage, i.e., $f_{st}(t\to\infty) = f(t_n)$.

Long-Term Response: The long-term response of the recover stage captures the coordinated response to heal the system from the damages that were not restored during the short-term response. Such long-term response may consist of coordination among different infrastructure maintenance and construction crews and neighboring grids, which may take some time before their resources can be mobilized. We capture this response as follows:

$$f_{lt}(t_{r2}+t) = f(t_{r2}) + \left(f(t_n) - f(t_{r2})\right).\left(1-e^{-b_1\left(1-\frac{b_2}{b_1}\right)(t+\beta)}\right). \tag{19}$$

In Equation (19), two characteristics make the long-term response different from the short-term response. First, the rate at which infrastructure is restored is *decelerated* compared to that of the short-term response, i.e., $b_2 < b_1$. Second, the time $\beta > 0$ at which the long-term response is to succeed the short-term response is introduced and further improves the performance measure until the grid is fully restored. The long-term response is slower than the short-term response and it follows the short-term response after some time interval β.

From Equations (17)–(19), it can be seen that a seamless transition from short-term to long-term strategies may not exist, depending on the two exponents alone. However, parameter β

can be derived to make the transition seamless. For seamless transition between the short- and long-term trajectories, define

$$t_{\rightarrow} = \left(\frac{b_2}{b_1} - 1\right)\beta \, , \tag{20}$$

found by solving Equations (18) and (19) simultaneously and substitute t with $t_{\rightarrow}$. Hence, we can use $\beta = t_{\rightarrow}$ in Equation (19) to define the seamless shift from the short-term to long-term trajectories. Figure 4 demonstrates the case when $\beta = t_{\rightarrow}$.

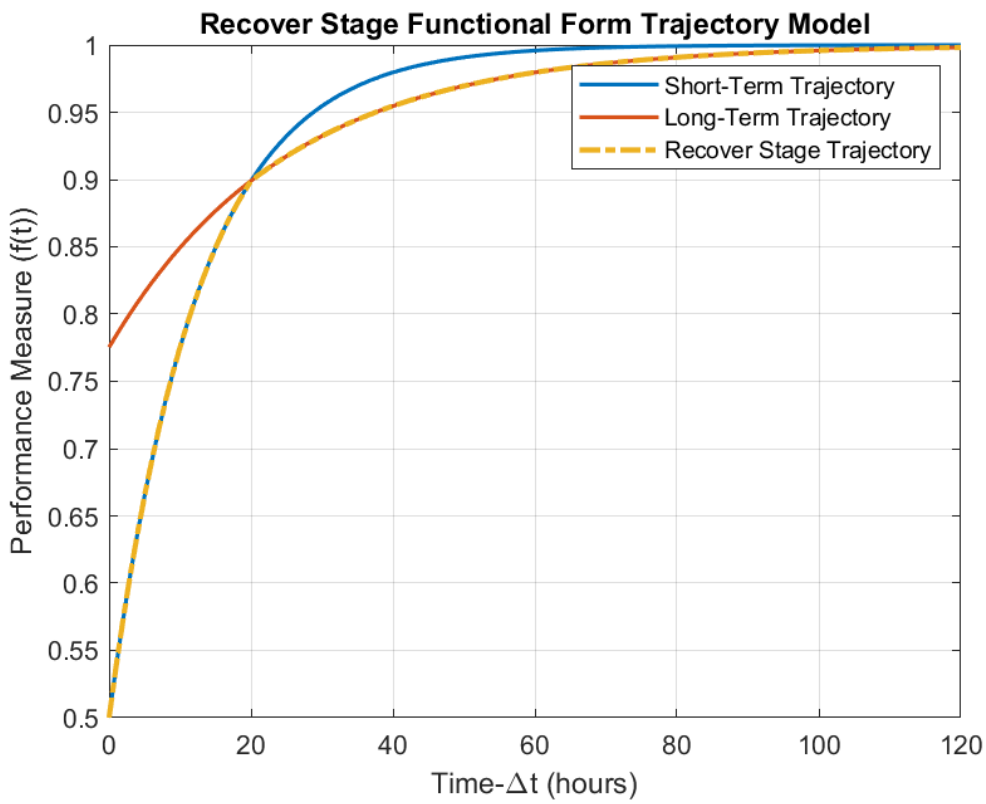

Figure 4 Demonstration of recover stage functional form, applied once the delay experienced in gathering the resources has been experienced at Δt. The above trajectories are produced using parameters $f(t_{r2}) = 0.5, f(t_0) = 1, b_1 = 0.08$, $b_2 = 0.04$, $\beta = 20$, $\Gamma = 1 \; \forall \; t \in [0{,}20]$ when the short-term response is active and then $\Gamma = 0$ once the long-term trajectory becomes activated.

<u>Example of Short-Term Response</u>: Using the hurricane example from the recovery section, after the hurricane occurs, recovery may begin. As soon as the hurricane has passed, a short recovery delay would occur before it becomes safe for crews to venture outdoors and while resources are staged prior to the short-term response. Initial short-term recovery would begin as automatic switching brings spares online and crews begin to manually return the damaged tie-lines to service. Figure 4 shows the short-term recovery, during which the initial system efforts would bring the offline customers back to the grid at an exponential rate of 8% of the remaining offline customers in the grid.

<u>Example of Long-Term Response</u>: Usually, the short-term response is not enough, and a long-term response is needed to completely bring back the power to the entire grid. For example, a

new high-voltage transformer has a lead time from when it was ordered to when it is installed in the field. With such actions being required for major restoration, the long-term recovery response would take a longer than the short-term response's initial trajectory before the system performance measure recovers to the pre-hurricane (pre-event) levels. Similar long-term efforts can be explained using the hurricane example: If the damaged equipment was installed and constructed in accordance with the long-term trajectory, power could be brought back at half the rate ($b_2 = 0.5. b_1$). At this rate, the long-term response would seamlessly follow the short-term trajectory if it were used from hour 20 onward. The long-term trajectory can be seen in Figure 4.

3.0 Deriving System Performance from Functional Forms

This section proposes how the functional forms presented in Section 2.0 may be used eventually to quantify system performance considering potential grid disturbances. Aggregate system performance is most meaningful, but performance can be considered more narrowly for the individual react and recovery stages, as well.

Because method presented in this report has used conventional system measures, any predicted performance is argued to be testable over time, at least in a statistical sense. Future system performance should ideally use the same measures as those used to monitor actual historical system performance. It is always important, of course, to conduct baseline evaluations to distinguish the predicted changes that are attributable to new, mitigative strategies and tools from natural system responses and existing mitigative strategies and tools.

3.1 Aggregate System Performance

The functional forms introduced in Section 2.0 should adopt and use conventional system measures like the number of customers being served (or equivalently, not being served). If this practice is adopted, the functional forms will also be meaningful in their integrated forms. The integrated functional form of each disturbance scenario defines a region on a figure like Figure 2, the area of which represents the severity of the disturbance. As described in Section 2.2, the likelihood of a disturbance scenario further weights the severity of the disturbance type within the analysis window.

If further normalized, the integrated performance measured becomes still more useful. For example, the analyst should report customer-outage-minutes per customer or customer-outage-minutes per year by dividing by total customers and by analysis window duration. Such normalized predictions facilitate meaningful comparisons between customer groups and between time periods.

3.2 React Stage Performance Measure

The focus of this report has been to facilitate useful aggregate performance measures for grid systems as they are affected by grid disturbances, but performance measure (21) may be used to characterize system performance during the react stage alone. We define a react state performance index R_eI as

$$R_eI = \frac{\int_{t_e}^{t_{r1}} f(t)dt}{f(t_s)\int_{t_e}^{t_{r1}} dt}, \tag{21}$$

which indicates how quickly the system reacts to the grid disturbance and how successfully it minimizes the disturbance's depth $R_eI \in [0, 1)$, with a small valuation in this range indicating a sustained, deep disturbance; an evaluation near unity indicates that the system reacted rapidly and limited system damages. However, R_eI can never equal unity, because that would mean that the react stage had been completely avoided.

3.3 Recover Stage Performance Measure

As for the react stage, system performance during a recover stage can be expressed using Equation (22). We denote system recovery index R_cI as

$$R_c I = \frac{\int_{t_{r1}}^{t_n} f(t)\,dt - f(t_{r1})}{\left(f(t_n) - f(t_{r1})\right)\int_{t_{r1}}^{t_n} dt}, \tag{22}$$

with $R_c I \in (0, 1]$. A small evaluation within this range indicates that recovery was slow to occur, and an evaluation near unity indicates that the system recovered nearly instantaneously.

4.0 On Mapping Transactive Energy System Qualities to Grid Disturbance Severity

Now that a parametric model of grid disturbances has been posed, we must address how various system qualities may affect the frequencies, depths, and durations of grid disturbances. At this time, we can do so only qualitatively, but we anticipate that severities of future grid disturbances can be quantified, as well, by calibrating basic qualities to historical grid disturbances. These are some examples of underlying qualities the specific status of which might be mapped to disturbance severity. The list is not intended to be comprehensive.

1. Actor Motivation – A generalized abstraction of an actor's disturbance consequence. Generally, actors will be more motivated to reduce event consequences if high costs are incurred during outages.

2. Contracted Response – The means by which useful controls, once negotiated, are expected to be managed. A good example is in contracted (Area Control Error) ACE responses, which, once contracted, follow another system signal.

3. Forecast Time Horizon – The distance into the time future into which prediction is supported or expected by the system. A day-ahead market has a horizon of at least 24 hours, for example.

4. Locational Granularity – The degree to which a system is fractionated into distributed control or decision-making regions. Equivalently, *locational granularity* is the size of a typical agent's domain in the system. Today, wholesale electricity markets might discover marginal prices for transmission zones or nodes. Price could be discovered, however, for every substation, every feeder, every building, etc. with much finer granularity.

5. Nature of DER Control – Probably separable into multiple qualities that are attributable to a system's controllable asset(s). For example, the exact same device might be provided continuous control by one vendor and discrete on/off control by another. Minimum run-time might be another such quality. Black-start capability still another.

6. Prosumer Incentive – Typically, this refers to monetary rewards to engage prosumers to offer their devices toward needed services. These incentives may differ by device type.

7. Supplier Incentive – The specific motivations of electricity suppliers to avoid costs and maximize revenues.

8. Time Interval Granularity – This refers to the duration of forecast time intervals during which system actions are defined and may be the same as an energy market period.

9. Transacted Commodity – A commodity to which market quantity and price refer. Many services can be procured as derivatives of electricity. Choice of commodity may limit the directness and efficiency with which certain services or outcomes can be procured. An interesting example today is the ramping product, which in fact may be equivalently achieved via more granular treatment of energy in time.

We are particularly interested in applying this theory to TE systems because, as discussed in the report's introduction, the roles of TE systems in making electric grids resilient is nascent. Table 2 lists various example qualities of TE systems in the left column and suggests the parametric effect of the quality during the *avoid*, *react*, and *recover* stages of a disturbance. Some, but not all, of the qualities were listed above.

Table 2: Transactive Energy System Qualities' Expected Effects on Disturbance Stage Depths and Durations

	Avoid	React	Recover
Actor motivation	Own self-interest to avoid disturbances. Costs incurred during an electricity outage.	Own self-interest to lessen disturbance severity. Costs incurred during an electricity outage.	Own self-interest to recover from disturbance. Costs incurred during an electricity outage.
Contracted response	Economic scheduling	Contracted autonomous	Various
Forecast time horizon	Medium to long	Irrelevant	Short to medium
Locational granularity	Fine, on order of possible event causation	Fine, on order of possible event causation	Medium, on order of event impact
Nature of DER control	Economically steerable, continuously variable preferred	Responsive, aggregated asset on standby. On/off control is fine.	Safely black-start-able, locationally responsive. On/off control is fine
Prosumer incentive	Favorable incentives keep prosumer devices constantly engaged.	Standby payments keep prosumer devices ready to respond.	Prosumer is rewarded for supply in islanded state.
Supplier incentive	Prevent incurring generation startup costs.	Avoid damages to generators. Prevent damage during off-nominal conditions.	Recover sales profits. A supplier is incentivized if production is profitable.
Time interval granularity	As short as is needed to avoid risky system states	Very short, possibly even event-driven	Short
Transacted commodity	Commitment of spinning and non-spinning reserves, both up- and down-regulating	Coordinated dispatch of spinning reserves	Coordinated dispatch of non-spinning reserves. Sensing and facilitation of information flow.

Example: Continuing the same example scenario from the previous section, we give an example of how the TE quality *Nature of DER Control* may be used for a hurricane.

To *avoid* hurricane impacts, a TE platform can use the forecasted vulnerability of transmission lines and formulate price signals that will incentivize DER procurement. The DER offers may be prioritized by the flexibility each offers.

At the onset of disturbance, the grid enters the *react* stage, during which the DERs become responsive and proactively support local energy requirements. A TE system platform can aggregate DERs based on their nature of control and maximize the support from them based on their local conditions. For example, energy storage can be discharged to provide power to areas where transmission line outages have happened, whereas aggregated thermostatically controlled devices may be used to defer extra load still served by energized transmission lines, due to neighboring areas outages.

In the *recover* stage, once the grid has settled to a degraded state, a TE system platform can enable various DER controls to bring the grid back to its nominal state. As a TE system values the cost of operating the underlying system and reenergizing customers not being served, the TE system can generate locational signals to group various DER for economic-based recovery of the system (Bishnu et al. 2019). These locational signals can aid DERs by offering capacity for providing black-start capabilities so that they can compete with conventional resources. In this way DERs can be prioritized for the most effective system recovery.

As we explained the impact of the *nature of DER control* on the grid disturbance above, other TE qualities listed in Table 2 may also be envisioned in a similar thought experiment.

5.0 Conclusion

This report introduces a functional form for model grid disturbances. The model considers a continuum of disturbances from infrequent, catastrophic events to less severe outages like those caused by ever-present grid stresses. In this way, this work harmonizes the terms reliability and resilience in a way that is useful for analysts and innovators who must justify investments in, or faithfully compare, alternative mitigative tools and strategies.

To the degree possible, each component of the functional form was made functionally independent, so a cumulative metric can predict the costs of disturbances based on the parametric effects of system qualities on each component of the functional form. We introduce three features to explain grid response to a disturbance: (1) avoid – identifies the scenario onset that could turn into measurable grid disturbances and tracks the effectiveness of strategies to defer or fully avoid any measurable grid disturbance, (2) react – provides strategies to mitigate the degradation experienced by the grid and lessen the disturbance's depth, and (3) recover – provides strategies to bring the system back to the nominal operations.

We hypothesize that the functional forms are parametrically dependent on various system characteristics. This possibility was exemplified using TE system qualities that were mapped, qualitatively for now, to their impacts on grid disturbance likelihoods, depths, and durations.

6.0 Future Work

This work introduced a parametric model for predicting grid performance for future grid disturbances that occur in the system. Because of the modular nature of the functional forms, i.e., their operational independence, this model paves the way for analyzing many anticipated grid disturbances in detail.

Three near-term modeling efforts are needed:

- Address individual and system-level design and planning components for further refinement of the parameters of the proposed grid disturbance model.
- Compare the characteristics of grid disturbances with and without TE systems.
- Use known historical grid disturbances to calibrate event scenario models. If multiple similar disturbances are available, explore how the model may be extended to estimate the uncertainties of its modeled outcomes.

The ultimate future work goal related to this work should be to embed functional form modeling and analysis in utilities' planning processes and outage management systems. In this way, the functional form modeling can pave the way to developing new tools and methods, which can make power grids more robust relative to frequent and infrequent threats.

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