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ABSTRACT

In early 2014, a number of large scale adverse weather events in the United States (and elsewhere) have renewed discussions of event response and resilience. Unlike events *caused* by human error or malicious intent, adverse natural events can be seen as uncontrolled and unpreventable; the measure of response success is the mitigation of adverse and disastrous *effects*. However, significant cognitive limitations interfere with human decision makers' ability to effectively estimate likelihood, magnitude, and effective response of large scale events in the face of multiple forms of uncertainty and system dependencies. Some authors highlight stability and maintenance of original design capability as the fundamental goal of robust and resilient response. Long-standing traditions from systems dynamics, population ecology, and process control suggest that improved understanding of system response ranges and dynamic equilibria provide a better description of effective event response. Challenges due to cognitive framing and deep uncertainty influence critical interplays of event characteristics, decision maker expertise, and resource availability. The concept of *resilience boundary framing* is introduced as a desirable, but difficult to achieve, goal for decision makers to respond gracefully to large scale natural events. Examples from January and February 2014 are used to highlight these issues.

1. INTRODUCTION

As of January 2014, the term "Polar Vortex" has come to represent the most recent examples of social and economic disruption due to large scale, severe weather events. Between January 4 and 7, a large zone of extreme cold air followed a substantial snowstorm and resulted in temperatures and wind chill conditions that affected 200 million people in the United States (James, 2014) over a period of 2-3 days. One example of the effects of the weather event occurred in northern Indiana where temperatures reached -22F (-30C), a temperature not seen since the 1990s. After approximately 10 inches (25 cm) of snow, high winds combined with these temperatures made snow plowing, snow removal or salting of highways infeasible. Over 60 miles (100 km) of major north-south (I-65) and east-west (I-80/94) interstate highways were closed for two days. As a result of both airport and highway closures, mail and package deliveries were largely suspended for most of the week; most of the state of Indiana was under a travel warning (no travel other than essential / emergency personnel).

Relatively few casualties and little long-term damage are attributed to the Polar Vortex event. Nonetheless, the Polar Vortex has served as another example of the cascading effects of large-scale events, and the challenges of maintaining "normal" societal patterns in the face of those events. Other types of severe weather, such as hurricanes and tornadoes, can have more severe damage effects due to flooding and/or winds that cause large-scale destruction over many square miles/kilometers. Although not as clearly visible, pandemic events can also result in substantial loss of life and economic disruption. All of these events represent concerns for policy makers, scientists, and engineers attempting to develop and maintain economic and societal "resilience," including developing principles and practices of "resilience engineering" (Hollnagel, Woods, and Leveson, 2006).

Westrum (2006) and Caldwell (2013) emphasize that elements of a discussion of resilience must address questions including resilience with respect to what features, and to what extent? (In other words, we cannot be infinitely resilient to all possible threats.) Unlike a discussion of accidents in engineered systems, or threats to those systems by external (intentional) agents, an analysis of resilience to severe weather and other large-scale events is not whether the event can be prevented. The issue, instead, becomes how effective can we be in minimizing the consequences and adverse outcomes of the event, and how soon / how well can we re-establish effective functioning of affected social, technical, or economic systems after an event has occurred.

At least since Weiner (1961) and Forrester (1961), there have been attempts to describe and analyze social systems and their dynamics according to systems engineering principles. Whether these attempts are described as cybernetics, system dynamics, or other terms, the emphasis should not be seen as attempts of exerting complete control over social and natural events (as the term "command and control" might suggest). What may in fact be a more important issue is why, with the large quantities of dollars, person-years, and planning efforts devoted to disaster and event response *planning*, there are still frequent cases of breakdowns and failures in effective response and recovery *execution*. In prior work (Caldwell 2006; 2013; Caldwell & Garrett, 2011; Onken & Caldwell, 2011), this author has addressed components of event detection, response and management in both focused complex engineering systems (e.g. healthcare facilities; space flight operations) and large scale events (e.g., earthquakes, hurricanes, pandemics). For the purposes of illustration in this paper, the main focus will be on large scale events, particularly to enable a focus on the following event characteristics:

- Effects are felt over wide geographic areas not defined by political boundaries;
- Event characteristics develop, occur, and sustain over relatively long time periods (minutes to hours to days) rather than "impulse" effects (seconds);
- Event magnitudes, durations, and frequencies are not limited to human-scale energy or technology production capabilities.

Another aspect of large scale natural events such as earthquakes, floods or storms is that of "deep uncertainty" (Walker, Lempert, and Kwakkel, 2012). Because the event itself is outside of and beyond the scope of human control, the focus here is on event recognition, response and recovery dynamics. Because of the focus of *JCEDM*, the focus of this paper is also directed at elements of human cognitive performance (rather than policy, sociological, or technological factors) that limit our ability to maintain resilience in the face of large-scale events.

The more specific aim of this paper is to consider, using concepts developed to study complex systems dynamics (Forrester, 1971/1990; Meadows, 2008), the interplay between event dynamics, human decision making under uncertainty and information delay, and feedback control engineering in the context of disaster response management. Multiple components of event response (mathematical descriptions of system stability; system response to disturbances; uncertainty of event prediction combined with limited capability for event prevention), combined with the global impact of large-scale natural events (nearly US$200 billion in 2013, and over US$2.5 trillion since 2000: see Caulderwood, 2014; "Natural Disasters," 2013). However, the concept of "disaster" is related to the impact of the event due to event *consequences*. As described in the United Nations Office for Disaster Risk Reduction,

> "A disaster's severity depends on how much impact a hazard has on society and the environment. The scale of the impact in turn depends on the choices we make… Each decision and action makes us more vulnerable to disasters – or more resilient to them. Disaster risk reduction is the concept and practice of reducing disaster risks through systematic efforts to analyse and reduce the causal factors of disasters" (http://www.unisdr.org/who-we-are/what-is-drr).

This paper seeks to identify and examine how cognitive engineering factors interact with other event progression and information availability factors to affect disaster risk.

2. FEEDBACK CONTROL AND COMPLEX HUMAN SYSTEMS

In the case of analyzing (and potentially improving) human responses to natural (exogenous) events, there is a desire to understand both the characteristics of the event, the characteristics of the human response, and the interplay between them. A general approach to system dynamics and feedback control has been a quantitatively powerful technique with applications across a very wide range of biological, psychological, social, and technological systems types (D'Azzo and Houpis, 1966; Forrester, 1961; Holling, 1973; Lewin, 1951; von Bertalanffy, 1968). Feedback control approaches to human interactions with complex systems, and in response to external events, have been discussed by authors such as McRuer (1980) in the context of direct (perceptual-motor) machine interactions, and Sheridan (2006) in the broader sense of human supervisory control. This approach to supervisory control has the additional power of distributing human intention and action capabilities over a wide area through communication, delegation, and dissemination of inputs and control outputs (see also Hancock, 2009). Trying to coordinate responses over larger, interconnected systems increases system complexity and uncertainty, and adds interacting feedback loops. Such system complexity challenges human cognitive, information processing, and training capabilities (Reason, 2008).

Forrester discusses these issues of information regarding external events and operator responses in terms of feedback control system dynamics. The term "rate equation" refers to the perceived characteristics of an event (including its magnitude, timing, potential impact, and need for a goal-directed task response); a "control decision" represents the analysis-based intentions of the operator to attempt a particular type of response to the event (Forrester, 1971/1990). Forrester describes how "the rate equations state our perception of how the real-system decisions respond to the circumstances surrounding the decision point." (Forrester,1971/1990, pg 10). The characteristics of the control decision are made more complex based on the lags of obtaining suitable information from all elements of the affected system potentially affected by the event (request configuration and transmission delays), and the execution of decisions once they have been made (action delays) (Caldwell, 2000). The characteristics of the human operator as a feedback controller has been suggested as a fundamental set of limits to our ability to effectively respond to very complex rules regarding rate equations, or significant lags in either input information or output control dynamics (Forrester, 1971/1990; Hoffmann, 1992; Sheridan, 2006; Sterman, 1989).

3. STABILITY AND RESILIENCE: OPERATIONS AT THE CENTER AND BOUNDARY

Three major conceptual challenges face decision makers when attempting to develop effective responses to large-scale natural events:

1) Over what range of conditions can we still manage "reasonable" operations?
2) What level of operations can be managed now, given the current event conditions?
3) How quickly and completely can we recover after the event prevents reasonable operations?

Note that, as mentioned above, the focus on large-scale natural events precludes a discussion of *prevention* of the event. Unlike accidents or human-scale activities (such as attacks), natural events are not seen as preventable—at best, *adverse outcomes* due to the event might be.

Various definitions and discussions of "resilience" may refer to any of the three conceptual elements above. As Westrum (2006) notes, "Resilience is the ability to prevent something bad from happening, / Or the ability to prevent something bad from becoming worse, / Or the ability to recover from something bad once it has happened" (pg 59). In the same volume, Woods and Cook (2006) describe, in an examination of resilience and brittleness when examining averse events (incidents), "Resilience in particular is concerned with understanding how well the system adapts and to what range or sources of variation" (pg 69). In the context of the challenges above, such a definition is most compatible with 1). However, Holling (1973), when discussing stability of ecological populations in terms of systems dynamics, considers that,

> "resilience is concerned with probabilities of extinction…" and "how much the forces have to be changed before all trajectories move to extinction of one or more of the state variables… The measures of stability would be designed in just the opposite way from those that measure resilience. They would be centerd on the equilibrium, rather than on the boundary of the domain… The stability view emphasizes the equilibrium, the maintenance of a predictable world… A management approach based on resiliance, on the

other hand, would emphasize the need to keep options open…" (Holling, 1973, pp 20-21)

Holling's considerations, based on mathematical definitions of stability and state space dynamics, more closely represents 2) or 3) rather than 1) above. For the purposes of this discussion, I will consider *range of stability* as the consideration of 1), *response capability* as the consideration of 2), and *resilience* as the consideration of 3). This terminology will permit more consistent application of other feedback-based statistical and process control discussions later.

Dekker (2006) examines resilience in terms of organizational management of risk, and how these organizations "better manage the processes by which they decide how to control such risk" and "become sensitive about the models of risk that they apply to their search and control of pathways to failure" (pg 82). Here, and elsewhere (Dekker, 2011), Dekker describes "drift into failure" as a process by which operations move from a central or nominal concept of risk, to an untenable level of risk (and consequent failures). However, he suggests that drifting into failure as a discussion of system breakdown might only be that of "a *simile* (like 'drift into failure') rather than through a model" (pg 84, emphasis in the original).

However, the statistical tracking of process variation and risk of "drift into failure" is more than just a simile-based discussion—the techniques of statistical process control (SPC) or statistical quality control were initially developed by Shewhart in the 1920s to address production quality and reliability in component production (Shewhart, 1926). Shewhart's goal was to be able to determine when "the observed differences between the product for one period and that for another indicate lack of control for assignable causes, and when on the other hand, do the differences… indicate only fortuitous, chance or random effects which we cannot reasonably hope to control without radically changing the whole manufacturing process?" (Shewhart, 1926, pg 594). His goal was to use measurement of multiple attributes to address four quality control and SPC stability problems:

- Specification (identifying the form of the distribution of the measured quality);
- Estimation (determining estimates of process parameters based on the data collected);
- Distribution (determining how parameter estimates vary in samples, to determine error);
- Fit (calculating how well the theoretical distributions match observed data).

(In Figure 1, Specification and Estimation are shown by calculations of percent defective, arithmetic mean, and standard deviation; violations of normal distributions are shown in charts of skewness and kurtosis; Fit is measured by the Chi Square chart.) Unfortunately, without clearly identified agreement on what goals decision makers are trying to achieve (return to center, return to control range, maintenance of functional level, or recovery of functional level), or which attributes to measure, Shewhart's techniques are difficult to implement—not due to inherent lack of technical capability, but poor definition of appropriate attributes and time scales for measurement.

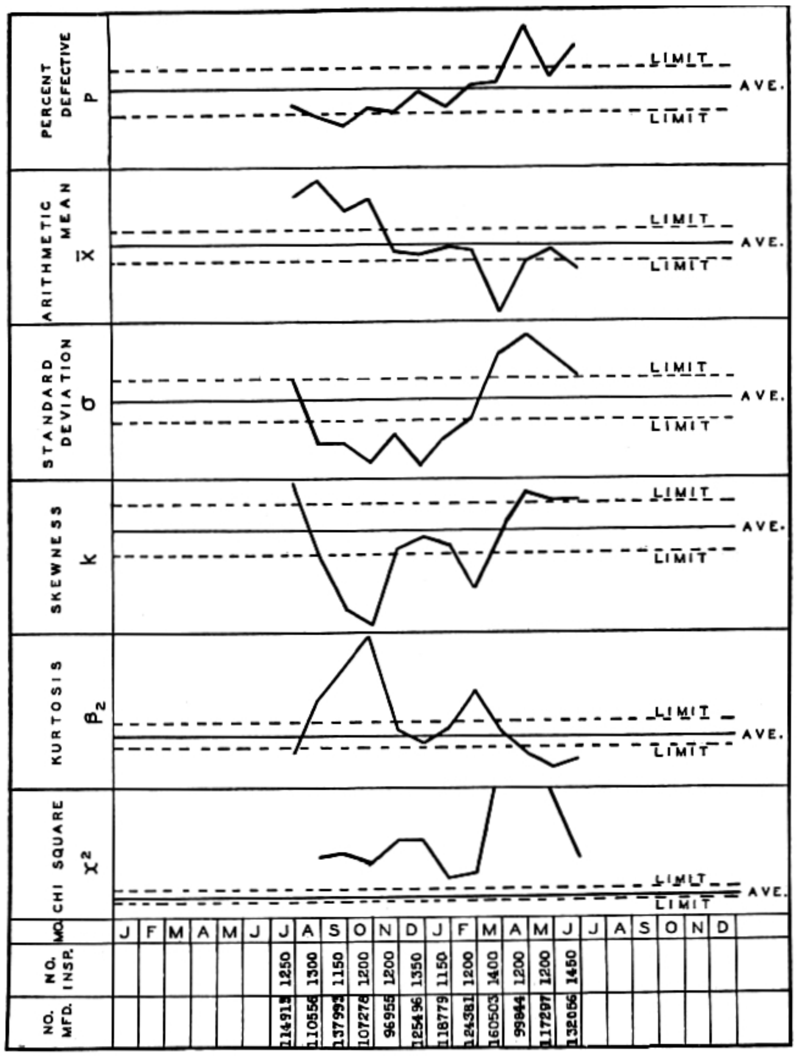

Figure 1: Process and Quality Control charts of production system attributes. From Shewhart, 1926, pg 602

The problems of specification, estimation, and distribution are cognitively difficult for decision makers who must operate in the absence of long-term historical data, and with lagged estimates of critical parameters. (From a climatological perspective, 50-100 years of weather records, with perhaps a few major events, does not represent "long-term" data: this point strongly echoes those emphasized by Dekker, Woods and Cook, and others.) Estimation, distribution and fit parameters can be subject to decades-long delays in calculation, such as flood height and insurance risk estimates for coastal Louisiana flood models based on parameters calculated in the 1970s through 1990s (D. Johnson, personal communication, Jan 16-17, 2014).

Using SPC tools with a long history in managing process stability and quality control can be seen as an approach consistent with our understanding of managing system behavior under a range of input conditions. More recent "robust process control" tools (see, for example, Rocke, 1989) have been developed to further enhance the ability of decision makers to effectively manage adequate performance in the face of process variability (without assuming that a single fixed outcome is either feasible or necessary). An important issue in SPC and robust control techniques is that no system can be robust to all possible events. Thus, there are important tradeoffs between characteristics of the system and its expected performance within the stable operation range; expertise in determining and applying control inputs based on event dynamics; and ability to recover capability and return operations to within control range performance expectations. In accordance with the discussion above, **robust** performance is characterized by the range of conditions for which a high level of system performance can be maintained; **resilient** performance is characterized by processes of returning to that level of performance after the system has been compromised or degraded. The next section addresses some of the cognitive challenges associated with the prediction, estimation, and response to uncertain large-scale natural events.

4. EVENT DYNAMICS AND COGNITIVE RESPONSE

The concepts of resilience or robustness in system performance, must be defined in the context of the types and ranges of events for which the system is designed to respond effectively. For example, a house without a heating system would be considered intolerable in the Indiana environment described above, but reasonable in an equatorial environment where temperatures never drop below 59F (15C). Although different groups of people may use the same term, “cold” to describe temperatures that are unusually low ***for them***, a more systematic comparison of resilience must address, whenever possible, quantitative measures of event characteristics on dimensions of interest.

Planning and response to large-scale natural events represent a form of naturalistic decision making (Klein, 2008) with multiple sources of complexity in the dynamics of the event. As colleagues and I have discussed previously (Caldwell and Garrett, 2010; Onken and Caldwell, 2011), the ability to effectively recognize and plan for the (human, social) response demands to an impending (natural) event in advance of the event helps improve the quality and timeliness of resource “foraging” / allocation to mitigate the potential negative effects of that event. With additional advance information regarding the event, actors and decision makers have additional capability to identify the types and amounts of necessary resources, and reallocate them to where they are most needed. In the case of allocating physical resources (e.g., repair crews, equipment, emergency response materials) for large-scale event response, advance information is especially important because of the time required to physically reposition the resource. Advance information can also identify *how many* resources are required to respond to an event of a particular magnitude.

An additional complexity in managing large-scale event response is that of *coupling*, or the influence of one aspect of system behavior on another. For example, large-scale flooding affects communications, electrical systems, and physical transportation, even though telephone communications and power transmission lines are not limited to physical wires strung near roadways. Flooding sufficient to make road impassible (and even make it difficult to determine where roads and street addresses were) can also serve to short out communications towers and cause widespread blackouts. Without power to support cellular telephones and GPS-based signal processing, first responders cannot effectively communicate to each other which roads are impassible at a given time, or what alternatives are acceptable. Without doubt, such "hidden dependencies" are due to other factors in infrastructure construction and operation, not due to decisions by the event response managers. Expert managers are more likely to recognize and even take advantage of dependencies in devising creative solutions to maintain and restore operations. The goal of this discussion is to highlight that design of safety-critical processes, integration of system controls, and leveraging of human expertise are linked factors in managing event response.

While authors such as Perrow (1984) decry "tight coupling" in complex systems, increasing complexity and span of operations can only be managed by more efficient and accurate information flow between system components. However, there is an interaction between event conditions, operator expertise, and the coupling of control systems. For example, "loose coupling" in automobile driving would mean that inputs to the steering wheel, gas and brake pedals would only be slowly and partially communicated from the driver to the car. This type of "loose coupling" is mildly problematic during benign driving situations (driving on straight highways in good weather at constant speeds). In more challenging situations closer to the boundary of safe driving (such as icy roads with blowing snow), loose coupling of automotive controls is more likely to lead to accidents than tight coupling, or efficient flow of information from driver to vehicle. It is also true that the fastest possible safe speed is higher in benign than boundary conditions; given a particular set of conditions, the fastest possible safe speed is higher for a skilled driver driving a tightly rather than loosely coupled car. For a driver who is prone to overcorrections and panic responses, loosely coupled controls may provide advantages if they smooth out the more extreme or sudden driving controls.

Forecasting event probabilities and allocating resources in response to those events are critical tasks in cognitive assessment and decision making. However, the ways that information is presented in support of these assessment tasks can have a tremendous (and often transformative) influence on how decision makers interpret event likelihood, magnitude, or impact. Seminal research in this area, known as "cognitive framing," highlights that presentation of event probabilities, especially in terms of non-rational choice criteria or socially (un)desirable presentations of outcomes, substantially influences choice behavior (Tversky and Kahneman, 1981, 1986). This paper is not intended to suggest that all forms of cognitive framing are negative, or even that cognitive framing can be avoided when decision makers are presented with complex decisions and limited information. In this paper, I address the concern that arises when decision makers select a particular framing bias without recognizing that bias or considering other options.

Presentation of resilience boundary information and probabilities is, in essence, a statement about the likelihood that the system will experience severely degraded outcomes (*resilience boundary framing*), rather than the likelihood that the system will behave as originally designed / desired (*stability control framing*). In the context of points 1) – 3) in section 3 above, identifying the range of conditions under which "normal" operations can continue (challenge 1) is a process of stability control framing; determining processes of recovery after assumed degradation of performance (challenge 3) is a process of resilience boundary framing. The decision maker's assumptions of what level of operations can be achieved at a given time, under "current" conditions (challenge 2) involves both control and boundary framing processes.

As Tversky and Kahneman indicate, even if the probabilities are rationally equivalent, decision makers may choose, create, and confirm biases based on their preferred framing structure. With fewer empirical examples to draw upon, or greater social pressure to present a particular framing stance, decision makers may further vary from a boundary framing perspective, even if such a perspective allows for greater flexibility of robust and resilient operations in response to current event conditions (challenge 2).

The interplay of event dynamics, expertise distribution, and flows of resources (both information and physical resources) during and after a large scale event highlight the concerns of "deep uncertainty," which are further described in the next section. Effective decision making under uncertainty is a long-standing concern from economic, modeling and psychological perspectives (see, for example, Clemens and Riley, 2001; Kwakkel, Walker and Marchau, 2010; Wickens and Hollands, 2000). However, as will be discussed, even the *nature and level of uncertainty* becomes a challenge in decision-makers' access, sharing and use of information in their response to large-scale natural events and other adverse conditions.

5. COGNITIVE CHALLENGES OF DEEP UNCERTAINTY

If I were to offer someone a standard (cubic) die, and asked them to predict the outcome of a particular roll, there would be some uncertainty, but that certainty is limited to the number of options available (six). Even if I asked the person to select one die from a large bag of standard dice, and predict the outcome, the answer is the same (one through six). Even with a large number of selections, the predicted distribution does not change. This is an example of what some authors call "shallow" (Kwakkel, et al., 2010) or "Level 1" (Walker, et al., 2011) uncertainty. Another level of uncertainty is added by mixing a number of dice from possible polyhedral "gamers" dice (including 4, 6, 8, 12, and 20-sided dice). Still more uncertainty results when the rule itself is shifted: if the *outcome of the first roll identifies the number of dice to select and / or the combination rule for determining* the total outcome of a second roll of multiple dice, the range and probability of individual outcomes becomes much more difficult for a person to quickly calculate or estimate.

A major concern for decision makers (and one that seems to be a consistent source of difficulty) is not just that dealing with uncertainty is difficult, but that decision makers are uncertain (or simply mistaken) about the depth of uncertainty about the event. Again, deep uncertainty is not simply a function of the decision maker's expertise, but the limits in predicting the exact magnitude, duration, and scope of the event. These limits in understanding can affect the perceptions of both the *current capability* of the system to respond to (one or more) events of a particular magnitude or event duration, and the *need* *for resources* to effectively respond (see Caldwell and Garrett, 2010). Researchers studying flood mitigation strategies for coastal Louisiana note that base scenarios for sea level rise and storm intensity incorporate some levels of uncertainty. However, decision makers and emergency response planners may still have trouble shifting from the estimates of *mean* level of projected impact to incorporate the *range* of possible impacts (D. Johnson, personal communication, 16 January 2014).

One of the perspectives emphasized in this paper is that system resilience is not a single global system characteristic, but a dynamic parameter that considers intended outcomes, ranges of impacting events, and the skilled decisions and actions of responders. It is only by providing clear and rapidly communicated information within and across system elements that enables proactive or rapidly reactive response to large-scale external events. However, responders who are more subject to strategic missteps or tactical overcorrections could experience more negative outcomes when system conditions are closer to the boundary of stable operations. Unfortunately, it is sometimes difficult to recognize that we are near or beyond the boundary of stable (or recoverable) operations until after it is too late, due in part to deep uncertainty about the current state of the world.

System dynamics researchers examining problems of state determination (in essence, asking the question, "What's happening right now, and what is our ability to function?") have long considered the cognitive limits of decision makers trying to determine state from non-constant lags in state information (see Forrester, 1961; 1971/1990; Sterman, 1989). When the problem moves from simply making a decision to actually executing the decision, the lag problem is intensified. Lags exist both in the "rate equation" (feedback control measure of system dynamics) for the availability of information regarding the state of the world, and for the execution of actions based on that information. Delays k_1 (lag times of when currently available information was generated, perhaps resulting in invalid or "stale" information) and k_2 (delays from the initiation of a response to outcome) both serve to increase the instability and uncertainty of a control action (Forrester, 1971/1990; Hoffmann, 1992; Sterman 1989). Both k_1 and k_2 are variables, and may in fact be affected unpredictably by the event itself (such as a power outage to a server room preventing email exchanges, or high winds and water limiting cellular tower signals).

Thus, the issues of time delay and lags affecting both information availability and decision-action execution represent another aspect of deep uncertainty. At a given time, particularly in a large-scale disaster or other natural event, it is difficult for a decision maker to know what resources are needed and available (right now) to match the current demands of the event (right now). If a decision is made to reallocate resources, and respond to particular event characteristics, it is unclear how long before the results of that decision are executed, and whether the response at that (future) place and time will be suited for the time course of the event up to that (future) point.

6. CAN WE SETTLE FOR RESILIENCE AS DYNAMIC EQUILIBRIUM FOR LONG-TERM SURVIVAL?

All dynamic processes, including civil infrastructure systems, are subject to multiple sources of variability in both operating conditions and outcomes. In the case of response to large-scale natural events, our strategy is often to mitigate adverse outcomes due to events, rather than preventing the events themselves.

Deep uncertainty represents a very strong challenge to effective response. This challenge is exacerbated when the expectation for planners and responders to maintain a strict "back to normal" control policy. From a process control or system dynamics perspective, strict adherence to "normal" is perhaps the most brittle policy of all. Such a policy suggests on insistence on systems that experience no variation at all from an ideal performance value throughout the performance range, or that must be reconstructed exactly as they were prior to the adverse event. In such cases, of course, such strict maintenance of output conditions is very expensive, and is insensitive to differentiating "assignable" and "random" causal contributors to variance. Further, when boundary conditions are exceeded and system capabilities are overwhelmed, resources and expenses are devoted to restoring the system to exactly the characteristics that made it susceptible to catastrophic failure when boundary conditions were exceeded.

Unfortunately, the alternative perspective to resilience as dynamic equilibrium in the face of deep uncertainty suggests that losses in function or capacity may be necessary in order to avoid even more catastrophic breakdowns. One interesting outcome of recent droughts in the western US is the uncovering of "ghost towns," whose viability and continued existence could no longer be maintained (Carlton, 2014). Towns such as Bluffton, TX and Red Bank, CA had once been active but failed due to social, technological, or environmental changes that exceeded their capability to adapt and recover. (In the language of this paper, these towns had exceeded their stability region and resilience boundaries—they could no longer continue as functioning towns.) In the case of these towns, human artifacts (dams) rather than natural events submerged the towns after the last residents had departed. After decades of abandonment, a new large-scale natural event (catastrophic drought) reminds visitors of the prior existence of these towns and the circumstances of their downfall.

A sociological and ethical challenge is inherent in the decision to abandon specific neighborhoods or towns *during* an event when the dynamics of the event exceed human response capabilities. (This type of decision is an example of challenge 2) in section 3 above, and is subject to both control and boundary framing decision pressures.) However, different cognitive processes seem to be in place when deciding to restore a neighborhood or town *after* a large-scale natural event. (Post-event recovery is more consistent with challenge 3) in section 3 above, and considers boundary framing decision pressures.) These challenges force authorities, planning groups, or residents themselves to determine that it is no longer feasible to restore and maintain a reasonable or safe level of existence. Several factors of cognitive framing (Tversky and Kahneman, 1986) seem to characterize the cognitive challenges (and resistance to "rational" evaluations) associated with determining the boundaries of achievable resilience and the necessary conditions for choosing stable vs. unstable equilibrium responses to dynamic environmental conditions. Although beyond the scope of this paper, it may be relevant to consider the effect on groups and societies by their members' belief systems regarding the capability of science and technology (or deities) to protect and proof them from future environmental impacts.

The lessons of ghost towns suggest that it is better that resilience boundaries are recognized while it is still possible to develop an organized and structured response to create stable functioning elsewhere. A new dam reservoir is different than a flood in that the timing, magnitude, and impact of the event can be planned and foreseen; people and treasured objects can be resettled in an ordered manner. Even in these cases, reconfigurations of this type can be seen as resilience in the sense of Holling (1973), because it can ensures continued survival (or managed elimination) as an adaptive response to environmental conditions.

7. A TALE OF TWO STORMS

Additional examples of the devastating impacts of weather events overwhelming response capabilities, as well as problems in the failure to manage uncertainty and stability in the preparation and response to such events, have been seen in the experiences of the metropolitan Atlanta region in late January and early February, 2014. In the first of two winter storms, approximately 2.5 in (6 cm) of snow fell on Atlanta, which does not have civil infrastructure or snow removal equipment capable of restoring transportation network stability. Despite National Weather Service and local forecasts of the possibility of such a snowfall (one that would not be seen as a major snowfall in Indiana, where snow removal equipment is readily available), it is apparent that governmental decision makers were not able to proactively manage the city's response to the storm (Reeves, 2014). "Deep uncertainty errors" regarding the range of prediction models, the impact of simultaneous closing of schools and businesses without warning on traffic volumes, and the degradation of the traffic network due to the combination of volume and weather led to substantial degradation of both the local area and the national airspace system. (Delta Airlines, and the Atlanta Hartsfield-Jackson airport, were both heavily affected.)

Only two weeks later, a second (and potentially larger magnitude) storm combining snow, sleet, and ice was predicted for Atlanta. However, system degradation in this case was much more proactively managed. Airline cancellations were announced as much as 36 hours before the arrival of the storm, and city and state authorities declared states of emergency (and closures of schools and businesses) well before any precipitation had fallen. Of course, it is highly likely that the lessons of late January were both highly available and painfully fresh with another storm event response required so quickly after the first, admittedly disastrous, failure. In this second case, the expected intensity of the storm was not overestimated, and residents were affected by cold, ice, and power outages ("Winter Storm Kills At Least 12 Across the South", 2014). Had the second storm not materialized, or been of a smaller magnitude than the "catastrophic" warning (Cassidy, 2014), perhaps the willingness of local decision makers to make the more conservative choices to acknowledge and adapt to reduced activity and sociotechnical functioning would be reduced. Support for this perspective is gained by a review of a 2011 storm where the same governor had to respond to similar criticisms about poor response to another ice storm (Galloway and Hart, 2011). A specific evaluation of the poor boundary framing of the 2011 storm indicates "there was no evidence… of a coordinated, regional response to a transportation catastrophe" (Galloway and Hart, 2011, 1st paragraph).

The story of these two storms highlights that resilience may be a process of admitting limits, rather than attempting control or continued functioning at all costs. Acknowledging our limited capability of responding to large-scale events, and proactively working to mitigate the effects of the event that create damaging instabilities, may be the best possible response. This capacity, defined in terms of prior cognitive science and system dynamics language, might be described as appropriate boundary framing under deep uncertainty. However, both cognitive limitations and the deep uncertainty of such events serve as constraints on the functional stability of communities and populations in the face of environmental challenges. While there may be some advances to be made with respect to the prediction of such events, it is clear that greater performance gains and safety enhancements will result from our ability to overcome the cognitive deficits associated with decision making, planning, and response to events and our capacity for sociotechnical system behavior in their aftermath.

8. CONCLUSIONS

Large scale natural events, ranging from earthquakes and tsunamis to hurricanes and blizzards, represent significant global threats to safety, economic viability, and quality of life for much of the world's population. However, the pathway from event to disaster includes the impact of those events on society based on technology, decision making, and event response. As indicated by the United Nations Office for Disaster Risk Reduction, reducing that impact comes from effective analysis and understanding to interrupt that pathway.

This paper has addressed how engineering principles of feedback response and statistical process control can be used to quantitatively describe strengths and vulnerabilities of event response systems integrating human experts and other resources. Quantitative assessment of event conditions and responses are required to support effective technology design and engineering control capabilities; expert human decision making can substantially augment the quality and effectiveness of response. When attempting to reduce the impact of adverse events, event managers must integrate technological systems and information to assess the current situation and determine appropriate responses. My past research in this area has described characteristics of event identification and proactive / reactive response in an uncertain environment.

From past research as well as case studies of weather-related events of early 2014, I characterize event response managers as addressing challenges of resilience response: 1) understanding the range of conditions that will still permit "reasonable" operations with available resources; 2) what are the current conditions and impacts on operations; and 3) how can resources be used to return to reasonable operations once event conditions make those operations no longer possible. These challenges represent tradeoffs between different elements of decision making processes described in classic cognitive science research as cognitive framing. While framing is necessary for experts to make sense of complex information, one concern is that event conditions may shift a decision maker from a posture I describe as *stability control* framing (operating in challenges 1 and 2) to one I describe as *boundary resilience* framing (operating in challenges 2 and 3). Those conditions may not be recognized by the decision maker, and the effects of these different framing perspectives may not be evident, due to changes in information flow and event awareness affected by the event itself.

One consideration that affects decision makers in their shift from stability control to boundary resilience framing processes is the concept of deep uncertainty. Such uncertainty limits the validity of prediction or estimation of event dynamics. Both strategic and ethical questions are raised by decision makers' choices to maintain either a control or resilience framing posture, especially when conditions of deep uncertainty affect the potential impacts of those postures. The goal of this paper is not to suggest that either posture is necessarily wrong, but that further research is warranted to determine the effects and impacts of those postures, especially when considering resilience as long-term societal health and rapid event recovery. The successive response of decision makers to two snowstorms in Atlanta within a single month shows how recent expertise can be of tremendous value in finding an appropriate balance between control and resilience postures.

As the weather events of 2014 have demonstrated, the need for additional research, understanding, and system analysis is required to help limit the progression from event to disaster. Control systems engineering, systems modeling, and human decision making must be integrated to provide effective interventions to aid societal resilience and reduce disaster risk.

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