Journal of Human Performance in Extreme Environments

Volume 11 | Issue 1 Article 2

Published online: 12-9-2013

Robust Resilience: Metaphor and Meaning in Assessing System Performance Ranges

Barrett S. Caldwell
School of Industrial Engineering, Purdue University, West Lafayette, IN, USA

Recommended Citation
Caldwell, Barrett S. (2013) "Robust Resilience: Metaphor and Meaning in Assessing System Performance Ranges," *Journal of Human Performance in Extreme Environments*: Vol. 11 : Iss. 1, Article 2.
DOI: 10.7771/2327-2937.1057
Available at: https://docs.lib.purdue.edu/jhpee/vol11/iss1/2

Robust Resilience: Metaphor and Meaning in Assessing System Performance Ranges

Barrett S. Caldwell, PhD

School of Industrial Engineering, Purdue University, West Lafayette, IN, USA

Abstract

The current emphasis on Resilience Week and the International Symposium on Resilient Cognitive Systems highlights a growing awareness of the importance of designing and operating engineering systems under a variety of environmental conditions and in response to dynamic events. Although there has been considerable confusion and drift in the use of the term, "resilience" as a concept dates back to dynamic systems study of complex ecological systems in the 1970s. This original definition relates clearly to quantitative metrics that link also to statistical process control techniques describing system performance as affected by external, "assignable" causes. This paper discusses important elements in the consideration of resilience as a quantitative metric to improve consistency and clarity of evaluation in engineering systems. Rather than simply a binary attribute of systems, resilience should be considered in terms of system performance measures as affected by environmental conditions or events, energy flow couplings, and statistical process control limits. Our estimations of system resilience are seriously compromised when process control estimates are extrapolated beyond linear ranges of environmental conditions or when including discontinuous performance/event outliers exceeding appropriate forecasting estimates.

Introduction

The concepts of resilience in systems engineering, and the requirements for designing and operating resilient systems, have taken on increased importance in recent years. Images of flooded Manhattan buildings and snowdrifts engulfing cars on Chicago highways help to remind us that large fractions of the public can be at risk when environmental, situational, or other system dynamic factors prevent our infrastructures and normal operating processes from functioning as designed.

As communities as diverse as human factors and cognitive engineering; electrical and control systems engineering; and civil and infrastructure management attempt to work together on improving resilience of critical engineering and societal resources, there are inevitable needs for effective communication and coordination of tasks across research domains.

However, if resilience is to move from simply an area of concern and societal awareness to an implementation criterion for improving engineering design and operations, considerations of additional systematic detail and technical definitions are required. One of the most fundamental of these considerations is that of operationalization—what is the current state? How do we know whether we have made something better, and if so, by how much? How do we compare one system to another on some parameter of general interest?

By addressing these operationalization questions, it will be easier for us to determine answers to questions such as "How much resilience can we expect?" "Resilience with respect to which disturbances, and to what extent?" "What price and risk are we willing to accept to obtain a particular level of resilience?" The purpose of this paper is to examine some of the issues associated with developing, utilizing, integrating, and sharing common language and understanding.

Finding and Losing Resilience

One significant challenge is that a large number of definitions and applications of the resilience concept have been developed since the term was originally suggested by Holling in the 1970s (Bhamra, Dani, & Burnard, 2011; Holling, 1973; Walker, Holling, Carpenter, & Kinzig, 2004). More importantly, the original Holling definition draws quite directly from a set of established mathematical definitions of stability and system performance. These references to the mathematical descriptions of dynamic systems are in common with other cybernetic and "systems thinking" concepts applied to biological and ecological systems (Caldwell, 2009; von Bertalanffy, 1968; Wiener, 1961). Unfortunately, many of the subsequent uses of the term "resilience" did not maintain consistency with the original, systems-level definition. Multiple disciplines have tried to utilize the concept of resilience ranging from individuals (reflecting their ability to continue in the face of perceived or real

https://doi.org/10.7771/2327-2937.1057

adversity) to organizations, and examining both engineered and naturally occurring systems. In addition, it appears that most authors capitalized on the conceptual aspects of the term, while keeping little or no definitional, operational, or quantitative consistency with the original technical definitions (Bhamra et al., 2011). This trend is in line with other descriptions of the use of originally technical, quantitative mathematical or engineering descriptions in metaphoric, rather than quantitatively consistent, terms (Caldwell, 1994).

Some examples presented in Bharma et al.'s (2011) literature review do seem to define resilience in terms of other system dynamics and differential equations measures of system performance. For instance, an example presented on p. 5388 shows three images of a ball within a bounded trajectory of "V", "U", or "W" shapes. The width of the trajectory shape is described in these examples as "resilience" due to the range of values for which the ball will return to the bottom of the trajectory shape. While this is a conceptually compelling idea, the mathematical principles described are actually defined as *stability* and *equilibrium*: the sizes of perturbation that will allow the system to return to an initial state without additional input energy (Boyce & DiPrima, 1969; Kolmanovskii & Nosov, 1986).

Another critical issue is that stability and equilibrium are defined in terms of a context, and are not binary (yes/no) considerations. In the example presented in Bharma et al. (2011), "resilience" is defined as the ability to withstand a disturbance of a particular size or energy level, over an operating condition or trajectory of a particular range, and return to a particular local minimum energy equilibrium state. Resilience thus must be measured with respect to a set of dynamic environmental conditions or events. Systems that are capable of performing adequately in some ranges of situational conditions (and thus would be resilient to events of some energy disturbance "magnitude") are unable to respond to more extreme conditions (and thus would not be resilient to disturbances beyond that magnitude) (Caldwell & Garrett, 2011).

Thus, it does appear that while the concept of resilience does have its origins in a quantitative system dynamics framework, the use of the term has been subject to conceptual slippage—in essence (and ironically), the resilience concept has not been resilient to changes in definition by scholars across disciplines. *How do we apply additional control to increase the stability of the quantitative measures of resilience?* While this question could seem like a sarcastic meta-question about resilience, it does suggest that additional focus on statistical analysis and measures of process variability will help place an emphasis on what is required to define and evaluate resilience in an organizational or sociotechnical context.

Resilience and Statistical Control

Relatively independently of this systems dynamics history, there also exists a statistical approach to defining process stability and effective process control of ongoing production systems. Statistical process control (SPC), such as control charts and run charts, has been in existence for nearly 100 years, dating back to the "efficiency management" roots of the industrial engineering discipline in the 1920s and 1930s (Shewhart, 1925, 1926). First developed in the 1980s, "robust process control" (RPC) represents a breakthrough method in the definition, measurement, and improvement of the ability to efficiently improve the quality of process outcomes (Devore, 2012; Rocke, 1989).

Dating from Shewhart's original configurations, the goal of statistical process analysis is to determine systematic ("assignable") causes for variation, and to distinguish them from random ("unassignable") causes. SPC, as well as the later RPC, is used to determine when a process is "in control" (i.e., whether observed variance in a performance parameter is due solely or primarily to unassignable causes) or "out of control" (subject to systematic causes affecting output). The normal variation in process outputs, as indicated by the range between expected upper and lower limits of the variance due to unassignable causes, would generate the "resilience" of the process (where an assignable cause does not create a systematic decrement to process quality and reliability).

There are four required steps important in determining whether a process is in control (Shewhart, 1926). The first is to collect appropriate data from a variety of observations with variations based on the parameter of interest. After that step, issues of estimation, distribution, and fit of the observations compared to some estimated distribution of "acceptable" random variation are based on the comparison of statistical theory to the observed variability. Shewhart points out that this task is infeasible based on a single observation—there must be some sequence of observations upon which our estimations of control (and subsequently resilience) must be based. As Shewhart (1926) indicates, such statistical "[e]vidence of lack of control calls for immediate attention," but the search for process variation is unwarranted if the "variations are not large enough to indicate lack of control" (p. 603).

Both the original SPC and later RPC tools recognize that maintaining a process within control limits is an important production systems and organizational goal, but it cannot be achieved in the absence of other considerations such as cost, magnitude of exogenous inputs, or speed of desired recovery response. Conversely, as our analysis and process management capabilities improve, RPC suggests that we can determine smaller levels of variance that we are willing to tolerate. This statistical approach suggests that resilience is not simply the range of acceptable conditions, but the ability to maintain productivity within those conditions over time, and the ability to return to acceptable conditions once the process control has been exceeded.

The existence of outliers, and forecasting of future assignable causes, creates both statistical and conceptual challenges to RPC. The existence of outliers in the data due to assignable causes expands the control range of the process, and thus reduces the sensitivity of the statistical analysis (Rocke, 1992). It is unlikely that previously unacceptable outputs will become *more* acceptable as our ability to exercise robust control increases. Owing to either one-time causes or systematic drift, outliers beyond the desired performance control range cause a continued degrading effect on control. Further, the use of historical data of new or only poorly understood control systems is of limited effect in generating forecasts of large or discontinuous changes (Armstrong, 2001). Forecasts that rely on extrapolations well beyond the existing range of data are especially subject to substantial qualitative errors in state estimation, and not simply quantitative errors in control limit estimation (Nelson & Savin, 1990). In fact, some authors treat the cases of outliers as problems to be eliminated from forecast models, due to the effects of such outliers on forecasting accuracy (Armstrong, 2001). Thus, SPC and RPC tools that suggest future situational conditions and resilience capability based on extended forecasts through discontinuous or nonlinear extrapolations of current conditions must be considered carefully.

Describing Resilience as a Performance Measure

Humans live in a contextualized, dynamic, situationally variable, and uncertain world. While our hope may be to create systems and sociotechnical entities that are infinitely robust (can operate in *all* environmental conditions) or infinitely resilient (can recover from *all* environmental disturbances), this is neither thermodynamically nor economically possible. A truism of SPC is that it is infinitely expensive to keep a process in perfect control (zero variance), or maintain control against all possible assignable causes. Thus, a perfectly robust system is not achievable. Further, system recovery from any out-of-range environmental conditions would require energy to return to the original process design. Major and irreparable catastrophic system failures would require an extreme (if not infinite) energy requirement to recover previously achieved system performance. A perfectly resilient system (one capable of recovery from all disruptions) is therefore also impossible.

Nonetheless, it is reasonable to consider design resilience and operational resilience as performance measures that can be explicitly quantified. In order to do so, engineers must be able to specify which performance measure(s) will be of interest to designers, users, and other stakeholders; the type and magnitude of environmental change or system dynamics events that are tolerable as control limits for system performance; and which operational conditions/trajectories are considered achievable and reasonably reachable for a particular system. (This third condition is important in the sense that, while global response to an event may result in a distinct "local minimum" system state, the processes of achieving that state may be considered unacceptable. As an example, new U.S. Atlantic coast beaches may be considered an environmentally and aesthetically positive condition. However, creating those beaches out of previously inhabited towns, such as what has occurred in the aftermath of Superstorm Sandy and the resulting winter season storms, would be seen as an undesirable trajectory to that new condition.)

Statistical control examples of resilience analyses

If the search for effective quantification of resilience is to be successful, there should be available examples of how these quantification processes would be applied in both prospective and retrospective statistical control analyses. Our goals, for the purposes of this discussion, would be to look at a system that demonstrates limited resilience, and then identify the appropriate control range beyond which standard RPC or SPC tools might be suspect.

Three examples will be addressed in this paper: the fatal accidents of the Space Shuttles *Challenger* (in 1986) and *Columbia* (in 2003), and effects of the Fukushima earthquake (in 2011) affecting the local nuclear plant. Woods (2004) has commented in some detail regarding resilience in both Shuttle accidents. Woods' discussion of "drift into failure" (Dekker, 2011) addresses (although conceptually and qualitatively) various types of dangerous shifts of process control analysis and extrapolation. Thus, this appears to be a reasonable starting point for this discussion.

It is important to recognize that it is difficult to define the resilience of a space vehicle, or a nuclear power plant, in the absence of three distinct considerations: the performance measure of system components or the system as a whole; the effects of various environmental conditions on that system performance measure; and the role of prior analyses and forecasts in the understanding of particular assignable causes. Interestingly, all three of these cases include a considerable flaw in statistical extrapolation of condition/event effects on system performance, as well as coupling between system components (indicating extrapolation of acceptable SPC limits and coupling as fourth and fifth issues of note).

In the case of the *Challenger* explosion, the primary engineering cause was the failure of multiple O-rings after launch causing rocket degradation and explosion (Lavine, 1991). The launch decision had been made based on a review of O-ring deterioration (the performance measure) as a function of pre-launch temperature (the environmental condition). However, as shown in subsequent analysis, the elastic behavior of the O-rings demonstrated a significant, distinct, and previously known discontinuity in performance as O-ring temperatures fall from the linear SPC range of 53 ℉ (12 ℃) to a nonlinear range of 31 ℉ (0 ℃). From an SPC perspective, extrapolating system resilience from the linear control range through the region of discontinuity invalidates the previously developed (and historically based) concept of the control limits. The failure of the solid rocket booster then created an explosion that cascaded through to the liquid tank—system components that are highly coupled in physical, aerodynamic, and thermodynamic senses, with energy flows too fast to permit any response by crew or ground control. (Had the solid rocket booster failure occurred after separation, of course, no coupling would have existed, and thus the explosive cascade would not have occurred.)

Similar statistical extrapolations have been described in the analysis of erroneous SPC analyses prior to the *Columbia* accident. The primary engineering cause in this case was a loss of a large piece of insulating foam that struck the leading edge of the orbiter wing, where re-entry temperatures are highest (CAIB, 2003). Although multiple prior cases of foam damage had been observed throughout the entire Shuttle program, smaller areas of damage had been due to smaller foam pieces (the environmental condition) in areas where re-entry temperatures were lower (the performance measure). The foam debris affecting *Columbia*'s leading edge was perhaps two to three *orders of magnitude* larger than the pieces used to model the SPC range of acceptable foam damage. Finally, the leading edge damage resulted in extremely rapid heating and destruction of critical vehicle subsystems in a vehicle without the aerodynamic flexibility to limit exposure of leading edges to additional heating (physical, aerodynamic, and thermodynamic coupling preventing any possible response by the crew).

In the case of the Fukushima nuclear power plant, the response of the plant to the original magnitude 9.0 earthquake (environmental condition) was acceptable, and the cooling systems and plant power continued to operate (performance measure). However, due to the resulting tsunami, seawater flooded the plant and damaged the operating systems, backup generators, and containment vessels. Earthquakes near shore do generate significant tsunamis, and so these should be certainly considered coupled energy flows. While plant designers had accurately modeled effects on the plant by ground movement, they did not estimate the potential size of the tsunami wave. The statistical extrapolation in this case can be identified by an examination of expected sizes of fault ruptures as a function of earthquake magnitude (Darragh & Bolt, 1987). This analysis indicated that source fault rupture lengths can be considerably longer than surface fault lengths, and that these effects can have a nonlinear growth with earthquake magnitude size. Physical and statistical limits in those authors' study limited the ability to project fault rupture lengths for earthquakes above magnitude 6.7. Extrapolations through two more orders of magnitude, with resulting projections of seafloor rather than sea level movement, further call into question the understanding of possible SPC resilience designs.

In retrospect, the power plant designers may not have known the limitations of the seafloor movement and resulting tsunami height model projections. An important consideration in such complex systems designs is that modelers should specifically indicate the range of environmental conditions their models have assumed, and the risks of extrapolating beyond those ranges. While ignoring or downplaying the role of outliers may be a reasonable statistical technique in some cases, it is an unacceptable violation of our ability to understand system performance due to exceptional assignable causes.

Extending an assumed linear control relationship beyond the range of linear system performance potentially invalidates the control model, and compromises the assumptions of the system's capability to recover system function. Errors of this type are not simply limited to the original model, but propagate to all models using the original assumption (perhaps unknowingly) to design system behavior outside of its range of environmental responsiveness.

In summary, each of the above examples demonstrates the role of system performance and response to ranges of environmental demand. Resilience can be described with respect to environmental shifts or events. SPC techniques have been used to estimate system behavior in all of these examples. Invalid extrapolations of resilient and recoverable system performance can be an outcome of poor communication of assumptions regarding the range of model validity. Design or operation decisions based on poor use of SPC or RPC projections may be addressed by the following question: *Do designers and operators understand the available behavior of the system throughout the range of conditions where such performance is expected and required?*

System Models for Resilience Estimates

When addressing the range of conditions for which a system may be considered resilient (capable of ongoing functioning), designers and modelers must recognize that system performance is not identical to that of their models. Models of environmental conditions and changes are distinct from models of system behavior. How these models of environments and system behavior differ from actual environmental dynamics and the performance of the system-in-environment are critical, especially if linear models are projected into nonlinear ranges of real-world behavior.

Caldwell and Onken (2011), in their discussion of real-time adjustment of "dynamic functional autonomy," discuss how designers and operators need to respond to both initial system designs of task requirements and environmental ranges, and how prior events or current operational plans may require adjustments of achievable levels of autonomy and function allocation. As discussed above, engineering system designs include implicit models of what levels of system performance are achievable over what range of environmental conditions. Thus, environmental conditions represent a potential SPC parameter to estimate, forecast, or at least communicate between designers.

A traditional view of system optimization may suggest defining a region of "best achievable" system performance, assuming a particular value of environmental conditions (e.g., temperature, external winds, relative humidity). However, this "optimal" performance may be quite brittle to changes in conditions. While uniformity may be a primary *output goal* in controlled engineering systems, such uniformity of *input conditions* cannot be safely assumed. Thus, environmental range conditions as estimated from prior data or expert estimates can also be described in terms of process control charting. Robust control statistics such as interquartile range (Rocke, 1992) can be used to more sensitively identify "out of control" range statistics (in this case, environmental conditions that may violate assumed system performance models of environmental range). Delphi methods of aggregating forecasts among experts and extrapolations from prior data are well known in the forecasting area (Caldwell, Wang, Ghosh, Kim, & Rayalu, 2005), and may be used to generate environmental conditions estimates for interquartile range estimators.

Once the set of range data have been acquired, Rocke suggests that upper and lower control limits be calculated based on estimated interquartile range statistics

$$\mathrm{UCL} = D_4^{\mathrm{Q}}\mathrm{Mean}(\mathrm{IQR}); \quad \mathrm{LCL} = D_3^{\mathrm{Q}}\mathrm{Mean}(\mathrm{IQR}) \qquad (1)$$

where D_3^{Q} and D_4^{Q} are calculated from standard statistical constants d_2 and d_3 found in SPC tables (Montgomery & Runger, 2011; Rocke, 1992).

Even if we determine that our range of reasonable or achieved environmental conditions does not exceed our system models' assumptions, there are still "cognitive" factors that affect our risk of moving systems into extinction (rather than persistence, in Holling's (1973) terminology). Our control actions are subject to delays in information availability about the current state of the system being controlled, and delays in the delivery of a control action command once it has been made. If those parameters are described as k_1 and k_2, these delays (and designers' and operators' correct modeling of them) will significantly affect the effectiveness of any control actions attempted.

As described above, there are multiple sources of deviation between system designers' models of the system-in-environment performance, as well as system operators' models of system-in-environment performance. When the system is performing in a well-understood, appropriately modeled linear input–output range, control actions are likely to have clearly understood and well-managed effects on the system. However, the critical source of information about the potential "drift into failure" is the gap between the system behavior change for a given input, and the modelers' or operators' models for that behavior change. These two functions might be considered axes of a phase space description of system performance. When models and reality are highly coupled and correlated, such phase spaces would take the form of stable limit cycles (even if resulting system behavior is not static). Discontinuities in system response or underlying nonlinearities in input–output relations that are not appropriately modeled would result in diverging errors and thus unbounded limit cycles. This too is a potential metric to address in the search for impacts on system resilience originating from designers and operators of complex systems.

Of course, assumptions of independent, non-correlated events may also be invalid when considering system behavior over time. Caldwell and Garrett (2011) discuss issues of uncertainties regarding event magnitude and dynamics when responders are required to effectively coordinate resources, information, and tasks. Not only single, but multiple events need to be considered. Many recovery processes have, but do not explicitly address, a characteristic time required to recover fully from one event (t_r) to the system control limit. When multiple events affect the system, we must also consider time available between events (t_a). As the ratio t_r/t_a increases past 1.0, the likelihood that effective system response and continued resilience can be maintained decreases.

Conclusion

Despite an apparent lack of development or standardization of the concept of resilience, the term has been in use, with a firm and quantitative systems dynamics foundation, for 40 years. The widespread conceptual appeal of the concept has had the unexpected and negative result of the creation of multiple, less well specified, and sometimes inconsistent definitions that have served to increase confusion and reduce mathematical consistency of application.

Progress is limited if the field continues to describe resilience and robustness in purely qualitative terms, or as static binary attributes (a system is either resilient/robust, or it is not). Statistical tools in use for nearly 90 years, by contrast, provide a clear description of process control performance. SPC (and later RPC) tools describe system "control" in terms of a system performance measure; assignable causes due to environmental or other conditions; determinations of acceptable control ranges (as a tradeoff among cost, feasibility, and other performance criteria); ranges of acceptable statistical extrapolation; and energy flow couplings that link environmental conditions or events to system performance outcomes. Each of these properties can quantitatively describe a system that performs in an environmental context over time.

In the attempt to design safe, reliable, robust, and resilient systems, we as designers, operators, and users must take care to understand the limits of our control systems and performance capabilities. Additional efforts are needed to help move discussions beyond justifying the need for resilience to actual implementations. This is not an abstracted or context-free discussion of system resilience, but tied closely to our understanding of dynamic coupling between societal, sociotechnical, and systems engineering components.

References

Armstrong, J. S. (2001). Extrapolation for time-series and cross-sectional data. In J. S. Armstrong (Ed.), *Principles of forecasting: A handbook for researchers and practitioners*. New York, NY: Springer. (Reprinted from: Scholarly Commons.)

Bhamra, R., Dani, S., & Burnard, K. (2011). Resilience: The concept, a literature review and future directions. *International Journal of Production Research*, *49*(18), 5375–5393. doi:10.1080/00207543.2011.563826.

Boyce, W. E., & DiPrima, R. C. (1969). *Elementary differential equations* (2nd ed.). New York, NY: John Wiley & Sons.

CAIB. (2003). *Columbia Accident Investigation Board report* (Vol. 1). Washington, DC: Columbia Accident Investigation Board/NASA.

Caldwell, B. S. (1994). Quantitative approaches to team communication and performance: A harmony of systems analysis tools. Paper presented at the Proceedings of the Human Factors and Ergonomics Society 38th Annual Meeting, Santa Monica, CA.

Caldwell, B. S. (2009). Perspectives on systems engineering and impacts on SE education. Paper presented at the Proceedings of the 2009 Industrial Engineering Research Conference, Miami, FL.

Caldwell, B. S., & Garrett, S. K. (2011). Coordination of event detection and task management in time-critical settings. In K. L. Mosier & U. M. Fischer (Eds.), *Informed by knowledge: Expert performance in complex situations*. New York, NY: Psychology Press.

Caldwell, B. S., & Onken, J. D. (2011). Modeling and analyzing distributed autonomy for spaceflight teams. Paper presented at the 41st International Conference on Environmental Systems, Portland, OR.

Caldwell, B. S., Wang, E., Ghosh, S., Kim, C., & Rayalu, R. (2005). Forecasting multiple generations of technology evolution: Challenges and possible solutions. *International Journal of Technology Intelligence and Planning*, *1*(2), 131-149.

Darragh, R. B., & Bolt, B. A. (1987). A comment on the statistical regression relation between earthquake magnitude and fault rupture length. *Bulletin of the Seismological Society of America*, *77*(4), 1479-1484.

Dekker, S. (2011). *Drift into failure: From hunting broken components to understanding complex systems*. London, UK: Ashgate.

Devore, J. L. (2012). *Probability and statistics for engineering and the sciences* (8th ed.). Boston, MA: Brooks/Cole.

Holling, C. S. (1973). Resilience and stability of ecological systems. *Annual Review of Ecology and Systematics*, *4*, 1-23.

Kolmanovskii, V. B., & Nosov, V. R. (1986). *Stability of functional differential equations* (Vol. 180). London, UK: Academic Press.

Lavine, M. (1991). Problems in extrapolation illustrated with Space Shuttle O-ring data. *Journal of the American Statistical Association*, *86*(416), 919-921.

Montgomery, D. C., & Runger, G. C. (2011). *Applied statistics and probability for engineers* (5th ed.). New York, NY: John Wiley & Sons.

Nelson, F. D., & Savin, N. E. (1990). The danger of extrapolating asymptotic local power. *Econometrica*, *58*(4), 977-981.

Rocke, D. M. (1989). Robust control charts. *Technometrics*, *31*(2), 173-184.

Rocke, D. M. (1992). X_Q and R_Q charts: Robust control charts. *Journal of the Royal Statistical Society, Series D (The Statistician)*, *41*(1), 97-104.

Shewhart, W. A. (1925). The application of statistics as an aid in maintaining quality of a manufactured product. *Journal of the American Statistical Association*, *20*(152), 546-548.

Shewhart, W. A. (1926). Quality control charts. *Bell System Technical Journal*, *5*, 593-603.

von Bertalanffy, L. (1968). *General system theory: Foundations, development, applications*. New York, NY: George Braziller.

Walker, B., Holling, C. S., Carpenter, S. R., & Kinzig, A. (2004). Resilience, adaptability and transformability in social–ecological systems. *Ecology and Society*, *9*(2), 5.

Wiener, N. (1961). *Cybernetics* (2nd ed.). Cambridge, MA: MIT Press.

Woods, D. D. (2004). *Creating foresight: Enhancing resilience from Columbia*. Retrieved from http://csel.eng.ohio-state.edu/woods/space/create/foresight col-draft.pdf