Meta-Theorizing and Machine-Intelligent Modeling a Complex Adaptive System that is Poised for Resilience Using Architectural and Empirical Indicators

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Abstract—**With our world witnessing critical systemic changes, we argue for a deeper understanding of what fundamentally constitutes and leads to critical system changes, and how the system can be resilient, i.e., persist in, adapt to, or transform from dramatically changing circumstances. We position our argument with long-standing theories on complexity, self-organization, criticality, chaos, and transformation, which are emergent properties shared by natural and physical complex systems for evolution and collapse. We further argue that there are system regimes that, although normally denote impending peril or eventual collapse, could actually push the system positively to be poised for resilience. In light of resilient systems, criticality and chaos can actually be leveraged by the system to promote adaptation or transformation that can lead to sustainability. Furthermore, our extensive simulation of complex adaptive system behaviors suggests that advantageous and deleterious system regimes can be predicted through architectural and empirical indicators. We framed our arguments in a two-fold complex systems resilience framework, i.e., with a meta-theory that integrates theories on complex system changes, and a machine-intelligent modeling task to infer from data the contextual behaviors of a resilient system.**

Keywords- complex adaptive systems; intelligent systems; systems resilience.

I. INTRODUCTION

We argued in [1] that we need to deepen our analysis and understanding of what makes a system resilient through a deeper understanding of what constitutes and leads to systemic changes, and how the system can be resilient through changes that are undesirable. Our world has been experiencing both slow and fast critical systemic changes on multiple levels and scales. On a global scale, for instance, Rockström and his colleagues [2] have argued that there are significant shifts happening in extremely important earth biophysical processes (e.g., climate change, freshwater and land uses, ozone depletion, and biodiversity loss), but all towards criticality. Some environmental scientists have been pointing at human activities as expediting what are supposedly naturally slow processes; hence, the debate on whether we have arrived at the Anthropocene [3]. Systemic changes also happen in the social realm when the existence of communities is significantly altered due to unprecedented massive devastations in terms of human lives, livelihoods and infrastructures brought about by natural hazards, such as Katrina of 2005, the Haiti earthquake of 2010, the triple disaster of 2011 in Tōhoku, and Haiyan of 2013, all of which brought significant human and economic losses [1]. Communities are not only evacuated, even worse, uprooted permanently as the natural environment and physical infrastructures that once supported their existence are completely destroyed. But make no mistake; it is not that our reality consists mostly of forgettable events marked by only a handful of massive devastations, but rather we hear daily the occurrence of accidents in land, air or sea, oil, chemical and radiation spills and leaks, terrorist attacks, spread of viruses, and most recently, the migration of millions of escapees and refugees crossing international borders to avoid wars, but only to find themselves enclosed by humanitarian crises. Such events can only compel our systems to carry out dramatic and novel adaptations in order for humanity to survive and sustain its existence. In the midst of critical systemic changes, our world and life systems should be *resilient*, i.e., they are able to withstand even large perturbations and dramatically changing circumstances and preserve their core purpose and integrity [4], and embrace change once transformation due to extreme perturbation is inevitable [5]. Otherwise, our systems would fail to provide the expected conditions for life to persist.

In [1], we positioned our arguments to further understand systemic changes with long-standing theories on complexity, self-organization, criticality, chaos, and transformation, all of which are interesting emergent properties shared by complex systems, and have been used to explain the evolution of complex adaptive systems (e.g., biological, natural, and socio-ecological [6]-[11]), computation by physical systems [12]-[14], and the collapse of social systems [15]-[18]. We discussed in detail our framework, supporting concepts, simulation results, and analyses. What is significantly missing, however, is further elucidation as to which aspects of systemic changes can actually push the system positively to be poised for resilience. We also need to explain further how these advantageous systemic changes can manifest themselves through architectural and empirical indicators. We extend our discussions in [1] to address these two issues.

Our paper is structured as follows. We discuss in Section II the Campbellian realistic basis, as well as the real-world application, of our complex systems resilience framework. Our framework is two-fold, i.e., with a meta-theory that integrates long-standing foundational theories of systemic change, and a two-part machine-intelligent computational modeling, specifically, using network analysis and machine learning algorithms, to realize our meta-theory. We detail our meta-theory in Section III and highlight in Section IV how the different aspects of the meta-theory relate to how the system is poised for resilience. We then discuss in length our machine-intelligent modeling approach and simulation results in Section V, and end that section with the seemingly insurmountable challenges that our approach would face in the future. We then conclude in Section VI.

II. Our Complex Systems Resilience Framework

A. Campbellian Realism – Theoretical Basis

Donald Campbell, together with scientific realists, allied with the semantic conception theorists to replace the syntactic or axiomatic basis of theory, in Figure 1a, with its semantic conception using a *theory-model* link, in Figure 1b, wherein the axiom may or may not be necessary (indicated by the broken arrow from the axiomatic base in Figure 1b) [19]. This important aspect of Campbellian realism (other aspects are elucidated in [20]) urges scientists to coevolve the development of theory and model (as indicated by the blue bidirectional arrows in Figure 1b). Figure 1c shows our framework that conforms to Campbellian realism and the thrust of the semantic conception.

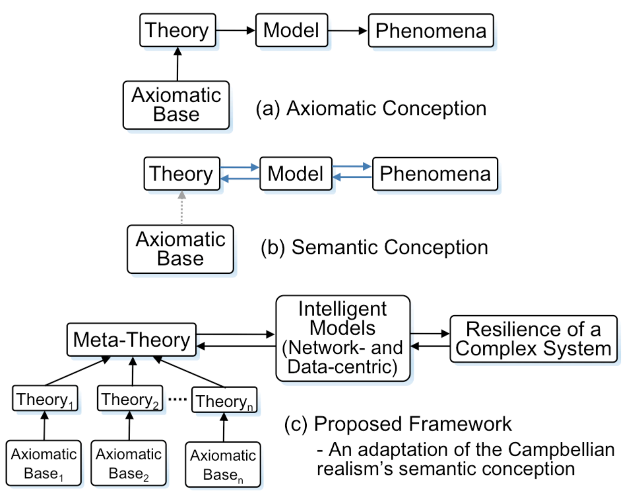


Figure 1. Conceptions of Axiom-Theory-Model-Phenomena relationship from the (a) axiomatic and (b) semantic bases [19], and (c) our linking that conforms to the thrust of the semantic conception.

We started with the Campbellian realism concept to point out that, following Campbellian realism, although the component theories of our meta-theory may have axiomatic bases, our meta-theory has no accompanying axiom. What will propel our meta-theory to becoming realistically grounded, however, is the intelligent modeling constantly updating it. Secondly, we also point out that our elucidation in Section III of the meta-theory, and the references that accompany our elucidation, would attest to the fact that the individual theories that comprise our meta-theory are neither from a vacuum nor just mere speculations as they are evident in physics, ecology, biology, or system dynamics. What we are putting for consideration, however, is a theory of how these theories are related that characterizes the resilience of a complex system. We integrated essential concepts of these theories in varying grains of analyses and view this integration as a *meta-theory*. Lastly, while the idea of Campbellian realism is to derive models manually, our modeling hinges on automatic and incremental knowledge inference using machine learning, hence the *machine-intelligent modeling*.

By starting with a meta-theory as background knowledge to guide our modeling, we avoid scattered and loosely knitted paradigms. Complementary, any truth present in the inferred models that is not accommodated in the meta-theory shall correct the flaw in the meta-theory. Our meta-theory and machine-intelligent models can therefore evolve together with increasing "predictive isomorphism" [19, p.7] to accurately represent the phenomena that are endogenous and exogenous to the system. We believe that this mutual reinforcing of meta-theory and intelligent modeling to automatically characterize the contextual interaction behaviors of a resilient system is novel and is not found in the more established frameworks, such as the Adaptive Cycle [9], Self-organized Criticality [8], and Dual-Phase Evolution [11].

Our machine-intelligent modeling consists of two parts, namely, network analysis and machine learning. Network theory concerns itself with the order and patterns that emerge from the self-organization of complex systems than with elucidating the underlying mechanisms by finding simplified mathematical engines [21]. The intractable nature of complex adaptive system behavior significantly prohibits the application of mathematical formulation since it would only result to futility, e.g., several researchers have addressed the fact that the formal models used to study the resilience of socio-ecological systems do not explicitly include the internal structural characteristics of these systems that are in constant interaction [22]-[24]. The tendency of formal models is to abstract many of the system's internal workings [25]. Furthermore, network theory concerns itself with system phase transitions wherein the processes of adaptation and transformation are possible [21].

We employ machine learning to automatically discover hidden relational rules that can describe the emergent system behaviors that are indicative of resilience. Machine learning algorithms can detect hidden behavior patterns in the data, which the system can use to understand its resilience capability and adjust its behavior accordingly. Our framework is data-centric as opposed to using formal verifications. Again, we can argue that formal or mathematical verification does not always guarantee reality and is not absolutely reliable. It can even fall short given the computational intractability of complex systems. The intractability of a complex system state space leads to issues of big data, which is where machine-learning inference becomes viable. Furthermore, and again as above, formal models tend to abstract much of the realistic nonlinear and stochastic intricacies of the system's internal workings [25].

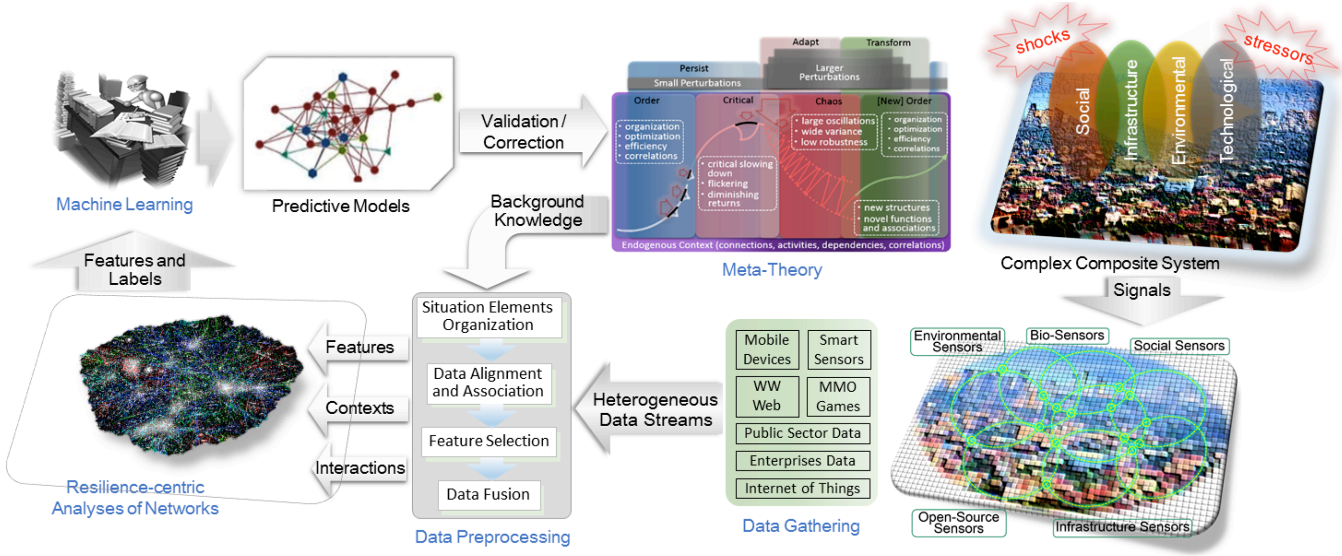


Figure 2. Our entire complex systems resilience modeling architecture, which includes our two-fold framework.

B. *Application of the Framework*

When we speak of complex system properties, we speak of system-wide behaviors emerging from the interaction and interdependencies of diverse system components. To be more concrete, our long-term objective is to model the complex hyper-connections of our social, infrastructure, environmental and technological systems, as shown at the right side of Figure 2, where system components, which can be composite systems in themselves [26][27], are intricately connected and may display extreme dependencies. This complex system-of-systems contains continuous flow of information, energy, capital, and people, among other resources. The resilience of any component will critically depend on its place in the system and how it, and the entire complex system, can withstand perturbations.

The meta-theory can be viewed as by-product of integrated transdisciplinary perceptions of what characterizes complex systems resilience. Carpenter et al. [28] suggest that to account for uncertainties in complex systems, we must consider a wide variety of sources of knowledge and stimulate a diversity of models. They also suggest that the tendency to ignore the non-computable aspects of complex systems can be countered by considering a wide range of viewpoints and encouraging transparency with regard to conflicting perspectives. They emphasized that there are instances where expert knowledge may not suffice since they can demonstrate narrow and domain-dependent practices. They went on to provide evidences where the perceptions of local people, who are experience-filled individuals, led to breakthroughs. Knowledge engineering approaches can be used to build and maintain knowledge-based systems that capture relevant contributions based on expertise and experience. We can also develop knowledge representation, extraction, inference and integration technologies that can infer relationships that exist among knowledge from largely varying domains and can synthesize individualized, micro-level, and domain-dependent knowledge towards contextual systemic knowledge that can lead to actionable information for resilience. Such actionable information, for example, can be in the form of a repository of evidences of what works (predictive) and may work (innovative) in a given situation (e.g., disaster management).

To gather large amount of data to model the complex system-of-systems, ubiquitous smart and interacting daily-living objects can offer a wide range of possibilities [26][29]. The World Wide Web is an open world and quintessential platform for us to share and receive information of various kinds. Web contents are created and duplicated rapidly and continuously. Crawlers or scrapers can be written to extract data stored deep in the Web. Our mobile devices have become ubiquitous in our lives that we rely on them for communication and information, keeping them within reach so that we can check them, at times unconsciously, every few minutes. But our mobile devices also have powerful sensing, computing and communication capabilities that allow us to log our daily activities, do web searches and online transactions, and interact on social media platforms and micro-blogging sites, among others. Ubiquitous and interacting ambient sensors [26][29] can gather large volumes of human- (e.g., individual mobility, physiology and emotion signals, crowd or mass movements, traffic patterns) and environment-related (e.g., climate and weather changes, changing landscapes and topographies, light and CO_2 emissions) data. Tiny interacting embedded systems could also play a valuable role in protecting the environment from hazards, e.g., sensors so minute, as the size of dust particles, but can detect the dispersion of oil spills or forest fires [26]. There are also the massively multiplayer online games (MMOGs) that have become unprecedented tools to create theories and models of individual and group social and behavioral dynamics [30], which might shed some light on human resilience behavior. There are data that the public sector produces, which include geographical information, statistics, environmental data, power and energy grids, health and education, water and sanitation, and transport. There are the systematically acquired and recorded census data about households and the services made available to them (e.g., health and medical, education, water, garbage or waste disposal, electricity, evacuation, and daily living-related programs). Enterprises (corporations, small businesses, non-profit institutions, government bodies, and possibly all kinds of organizations) may collect billions of real-time data points about products, resources, services, and their stakeholders, which can provide insights on collective perceptions and behaviors, as well as resource and service utilizations. And lastly, there is the Internet of Things (IoT) that extends the reach of the Internet beyond our desktops, mobile phones and tablets to a plethora of devices and everyday things (e.g., wearable and ambient sensors, CCTVs, thermostats, electric power and water usage monitors, etc.). Data can be made available online and publicly through the IoT, and therefore democratized, i.e., accessed freely for the common good. Hence, our digital universe is ever expanding as millions of data points are continuously created by and acquired from heterogeneous sources. Machine intelligence can be used to infer from these massive data points accurate informative models for situation analysis and awareness, decision-making and response, and component feedback. All these to aid the complex system sense and shape the contexts in which it is embedded.

Heterogeneous data related to humans, infrastructures, environments, and technologies, and their interactions will often be reported or obtained from a multiplicity of sources, each varying in representation, granularity, objective, and scope. Preprocessing techniques can be used to organize, align, and associate input data with context elements. With feature selection, it can also reveal which features can improve concept recognition, generalization and analysis. Lastly, data fusion can address the challenges that arise when heterogeneous data from independent sources are combined.

All the pertinent features, contexts and interactions inferred in the preprocessing stage will be used in our two-part machine-intelligent modeling. First, information will be organized, represented and analyzed as a network. Paperin et al. [11] provide an excellent survey of previous works that demonstrated how complex systems are isomorphic to networks and how many complex properties emerge from network structure rather than from individual constituents. One may think of the human body and brain, local community, virtual community of socially related digital natives, banking systems, electric power grid, and cyber-physical systems as networks. Furthermore, the science of complexity is concerned with the dynamical properties of composite, nonlinear and network feedback systems (citations in [31]). Second, using as inputs the network and resilience properties of the system, machine learning will be used to infer the relational rules of system contextual interaction behaviors that define its adaptive and transformative walks and therefore define its resilience. Our modeling will capture how the complex system's ability to vary, adjust or modify the connectivity, dynamism, topology, and linkage of its components (endogenous features), and its capacity to withstand perturbations (exogenous feature), can dictate its resilience.

III. Our Meta-Theory

Figure 3 shows our meta-theory that cohesively puts together complexity, self-organization, critical transition, chaos, resilience, and network theories. While we adopt the terms order, critical, and chaos from dynamical systems theory [32], to persist, adapt, and transform is resilience thinking [33]-[35]. Scheffer et al. [36] proposed integrating the architectural, i.e., the underlying network configuration, and empirical indicators of system phase transition. They suggested that since these two approaches have been largely segregated, a framework that can smartly unify them could greatly enhance the capacity to anticipate critical transitions. Although Scheffer's primary concern in [36] is the critical transition, we adapt these two approaches to observe complex system behaviors. While the top layer of our meta-theory specifies the empirical indicators, the bottom layer specifies the network configuration-based indicators.

A complex system can be highly composite, i.e., it can consist of very large numbers of diverse components, which can also be composites in themselves, and these components are mutually interacting with each other. Their repeated interactions over time eventually leads to a rich, collective behavior, which in turn, becomes a feedback to the individual components [37]. Self-organization holds that structures, functions, and associations emerge from the interactions between system components and their contexts. For Levy [21], the most appealing and persuading aspect of complexity theory is its promise to elucidate how a system can learn more effectively and spontaneously to self-organize into well structured, sophisticated forms to better fit the constraints of its environment.

The complex system evolution cycle in our meta-theory involves three regimes, namely, order, critical, and chaos. The second ordered regime, however, could be novel in the sense that it required the system to transform when adaptation back to the previous state was no longer attainable. The moving line at the top layer indicates system "fitness", i.e., the changing state of the system in terms of its capacity to satisfy constraints, efficiency and effectiveness in performing tasks, response rate (time to respond after experiencing the stimuli), returns on its invested resources or capital, and/or its level of control. The fitness curve may indicate growth (e.g., exponential, i.e., an initial quantity of something starts to grow and the rate of growth increases, or *s*-shaped, i.e., an initial exponential growth is followed by a leveling off), degression (gradual) or quick descent, or oscillation where the fitness fluctuates around some level.

This section discusses in detail the various aspects of our meta-theory. We want to believe that through our meta-theory we can view a complex system as *open*, i.e., always in the process of change and actively integrating from, and disseminating new information to, changing contexts, as well as *open-ended*, i.e., it has the potential to continuously evolve, and evolve ways of understanding and manipulating the contexts (endogenous and exogenous) that embed it [38]. Both characteristics are vital for the resilience of the complex system.

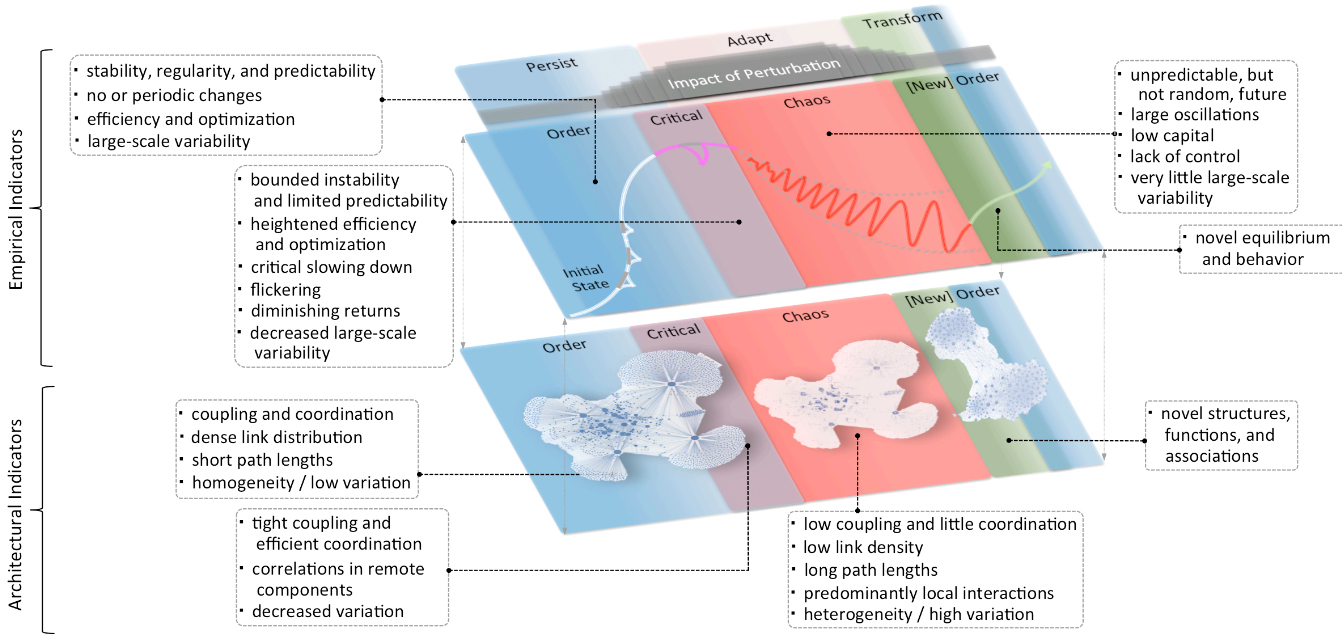


Figure 3. We integrate in varying grains of analyses how the different theories are plausibly related – hence, a *meta-theory*.

A. Order

It is in the ordered regime that dependencies and correlations begin to emerge in the structural and logical connections of the system components. The components become coupled and coordinated. Eventually, the system will settle into a regular behavior, i.e., a state of equilibrium. It is also possible for a system to have multiple feasible equilibriums wherein it shifts between equilibriums. Its components have high degrees of freedom to interact with each other that it can have many possible trajectories [39].

The system will always attempt to establish equilibrium each time it is perturbed (as illustrated by the dents along the fitness line at the top layer) in order to persist in its ordered state. Perturbations are assumed to be largely, albeit not totally, identifiable and unambiguous. When it encounters a perturbation, it will aim to resume normal operations as soon as possible. The system will always control and manage change, with its agent components acting in accordance to an accepted set of rules. The system will act in predictable ways, either executing once again previous behaviors or selecting from its known limited range of behaviors with anticipated or foreseeable results [31]. The system will operate in a negative feedback manner, with the appropriate rules, to reduce fluctuations and maintain its regular predictable behaviors [31]. Hence, its success is measured in terms of stability, regularity and predictability [40].

The ordered regime is also characterized by increasing system efficiency and optimization of processes. The system will carry out its tasks efficiently as possible according to the well-defined structural and logical connections of its components and policies and procedures it strictly adheres to. The system's self-regulation becomes optimized specifically to the set of perturbations and responses it already became familiar with.

B. Critical

In highly coupled systems, the iterative recovery from small-scale perturbations give the illusion of resilience when in fact the system is transitioning to a critical change and setting itself up for an unwanted collapse [36]. The coupling among components has become tight to the point where the order of the system becomes highly dependent to the strong coordination of its parts. All this build-up, however, is like an accident in the wings waiting to happen. This rigid tight coupling makes the impact of any perturbation to also increase, regardless of whether its magnitude is small or large. One situation, even though stirred by a small perturbation, can easily become critical and can trigger other events in a cascading fashion such that the different situations within the propagation enhance themselves to criticality. As one of the bedrocks of complexity science, complex adaptive systems have the tendency to move towards criticality when provoked with complexity [40].

As a real world example, Lewis [41] cited several reasons why the electrical power grid can self-organize to criticality due to heightened complexity. These include the increase of components' reliability that consequently increases the cascade of failures and its consequences, optimization of the grid by power stations and centralizing substations, tight coupling of hubs in telecommunications networks, and the simultaneous occurrence of stable load increase as more people consume more electricity, electricity providers maximize profit, and maintenance procedures become more efficient. Also, when Levinthal [42] applied random Boolean networks to simulate the adaptation of business organizations to their environment, he found that tightly coupled firms find it hard to adjust to changes.

It is also the case, however, that one of the profound insights from the science of complexity is that this regime – that is poised between stasis, where there is no or regular changes, and chaos, where changes are irregular – holds significant paradoxes. It is neither stable nor unstable, but both at the same time [31]. It is both optimal and fragile [39]. It may herald an unwanted collapse and become a harbinger of positive change [36]. Furthermore, while it may signal hidden fragilities [43], it is also theorized to facilitate complex computations, maximize information storage and flow, and be a natural target for selection because of its hidden characteristics to adapt [13][6][14].

C. Chaos

Comes a point when complexity can no longer be sustained, persistence is no longer possible, and predictive adaptations are not anymore sufficient. Eventually, the system converges to a state that makes itself less adaptive to perturbations and moves to chaos. The building up of complexity becomes a constraint to adaptation and eventually leads to chaos.

Chaos denotes a state of non-equilibrium, thus, instability, and turbulent, aperiodic changes that lead to crisis, disorder, unpredictable outcomes, or, if on a large scale, to collapse. The notion of chaos has been used interchangeably, or in association with, several other concepts, such as non-linear systems models and theories on disorder, dynamical complexity, catastrophe, bifurcation, discontinuity, and dialectical dynamic, among others (refer to [44]).

When in chaos, the system would need larger adaptations if only to survive. The system must learn how to minimize the negative effect of chaos and maximize its positive properties, which is a compelling and yet to be fully addressed key problem of social and natural scientists [44].

D. New Ordered Regime through Transformation

When chaos happens, the once tight connections and rigid coordination are broken. This then becomes an opportunity for the system to try other, perhaps novel, connections that can lead to positive transformation. Systems may undergo a transformational process, as it is provoked by instabilities, potentially leading to an emergent order that is different from its previous ordered state [31]. Systems that demonstrate a transformative capacity can generate novel ways of operating or novel systemic associations and can recover from extreme perturbations [5]. Such systems learn to embrace change [5], and instead of bouncing back to specification that has been proved vulnerable and led to chaos, they bounce *forward* to a new form [45].

IV. META-THEORIZING A COMPLEX SYSTEM THAT IS POISED FOR RESILIENCE

We posit in this section that in the critical and chaotic regimes the system can be poised for resilience. We also discuss here the different architectural and empirical indicators of system changes.

A. Critical Transition that is Poised for Resilience

1) Intituition Behind the Concept

The intuition is both appealing and intriguing: systems that are highly stable are static and those that are chaotic are too unstable to coalesce, and thus it is only at the border between these two behaviors that the system can perform productive activities [46][40]. Another bedrock principle of complexity science is that complex adaptive systems are at risk when in equilibrium, and that this stasis is a precursor to the system's death [40]. In cybernetics lingua, competing pressures must perturb the system far away from its normal arrangements before it can significantly evolve to a new form. This state of being far away from equilibrium but not in chaos has been called by several names, including the edge of chaos [46] or instability [31]. This edge is not sharp and unambiguous, but rather, it is like overlapped coatings with bidirectional gradation between order and chaos.

According to Miller and Page, "In its most grand incarnation, the edge of chaos captures the essence of all interesting adaptive systems as they evolve to this boundary between stable order and unstable chaos." [46, p. 129] The proponents of this condition think of it as holding "the secret of everything from learning in the brain to the evolution of life" [21, p. 73]. Similarly, Pascale stated that as systems continue to self-organize, they "all flourish in a boundary between rigidity and randomness and all occasionally forming large structures through the clash of natural accommodation and competition." [40, p. 3] For instance, Krotov et al. [47] hold evidence to suggest morphogenesis at criticality in the genetic network of early Drosophila embryo.

Stacey proposed that at the critical transition the outcomes can be indeterminate, or what he calls bounded instability [31]. His notion is that although the system behavior cannot be predicted over the long-term, hence the presence of instability, there is qualitative structure in the system's behavior that is recognizable and that short-term outcomes can be predicted, hence bounded. He stated that it is in the bounded instability that the complex system becomes changeable and its behavior patterns are in unpredictable variety. Stacey also stated that the agents are not constrained by their rules, schemas and scripts, but by the freedom they have to choose their actions within these constraints that will have major consequences for the system. Similar to the edge of chaos, in bounded instability, a system is far easier to adapt because small actions by any of the agents can escalate into major system outcomes [31].

2) Indicators of Critical Transition

A broad range of research has looked at connectivity and variation (from homogeneous to heterogeneous) of network components as what constitute the architecture of fragility [36]. Variation refers to the actually existing differences among individual system components in terms of type, structure or function [48]. According to Rickels et al. [37], a system is at critical point when the degree of connectivity and dependence among the components is extremely high. For instance, in the investigation of Krotov and his colleagues, criticality manifested itself as patterns of correlations in gene activity in remote locations [47][49].

The system enters criticality as its components become more and more coupled. As a consequence, a small perturbation in the system can lead to massive systemic changes. Scheffer et al. [36] stated that a network with low connectivity and heterogeneous components has greater adaptive capacity that enables it to change gradually, as opposed to abruptly, in response to perturbations. At the same time, a network with tightening couplings and heightening homogeneity of its components can only manage to resist change up until a certain threshold where critical transition is reached. According to Page [10], the amount of variation is low at stasis and high when the system is in flux. Page pointed out both the obvious and deep insight to this: it is obvious that there is more variation when the system has yet to settle down; however, it also means that there is more variation in a system that is about to transition since the used to be stable configurations found difficulty holding together.

Scheffer et al. [36] explained the various empirical indicators of critical transition. One is critical slowing down, i.e., the rate at which the system bounces back from small perturbations becomes very slow, which makes it more vulnerable to be tipped more easily to another state. Critical slowing down can be inferred indirectly from rising variance and correlation (e.g., higher lag-1 autocorrelation). Another is flickering wherein a highly stochastic system flips to an alternative basin of attraction when exposed to strong perturbations. Rising variance is also indicative of such a change, as well as the multimodality of system state frequency distribution over a parameter range. Scheffer et al. also stated that while critical slowing down may point to an increased probability of an abrupt transition to a new unknown state, flickering suggests an opposite regime to which the system may transition into if conditions change.

Page [10] elaborated in his book why diminishing return is an empirical indicator of criticality. He described diminishing returns as the decrease in some system performance measure such as efficiency, accuracy or robustness. For example, as Lewis pointed out, lessening of reactive power, transmission capacity, and information in the grid indicates that the grid is in a critical phase [41]. Furthermore, according to Dixit, the tension between increasing and diminishing returns would likely result to the self-organized criticality of economic systems [78].

Lastly, there is also variability as empirical indicator. Variability describes the potential or propensity to change (e.g., variability of a phenotypic trait in response to environmental and genetic influences) [48]. It implies rules that can lead to periodic or aperiodic dynamics. While connectivity and variation can be directly observed, according to Wagner and Altenberg, variability is harder to measure due to its "dispositional nature" [48]. They used the concept of solubility as akin to variability being dispositional, i.e., it does not describe the current state the substance is in, but rather the behavior that results when a substance gets in contact with enough solvent. In Paperin et al.'s Dual-Phase Evolution [11], order is described as a well-connected phase that is characterized by highly dense link distributions, short path lengths and wide-scale interactions between most system components – hence tight coupling, with little local variation and high large-scale variability. The poorly connected phase that is akin to chaos is quite the opposite, i.e., the link density is low, path lengths are long, with mostly within sub-network (local) interactions, and strong local variation but little large-scale variability.

3) Critical Transition To Resilience

Although there is still a lot to be done in terms of anticipating critical transitions, even though methods and approaches are already emerging, there are works that suggest leveraging critical transitions for the resilient walks of the system. For one, critical systems by nature will move toward, rather than away from, the precipice of collapse [41]. Bak et al. [8] asserted that a system collapse is inevitable mainly because of the internal dynamics rather than from any exerted exogenous force. This is in line with the classical approaches within evolutionary biology that view organisms as simply passive objects that can be controlled by internal or external forces, and that these forces are beyond the ability of the organisms to influence, let alone surmount [50]. Dialectics argue, however, that organisms can also be subjects of their own evolution [50]. Page [10] posited that this critical transition is not a system state, but rather, this border is in the space of system behaviors, i.e., the set of the agent's decision rules and interaction scripts [46]. Hence, at the critical transition, a complex adaptive system can have the ability to tune its rules and scripts towards resilience (or vulnerability). The notion of "edge" of chaos or instability can be that narrow but sufficient space where the adaptive system has the ability to see qualitative structures and relations, and can predict sufficiently, even if for a bounded distance, and change its course for the better. The system can utilize both amplifying and dampening feedbacks to flip itself autonomously from one equilibrium to the next and not be pinned down to just one.

In [36], Scheffer et al. discussed how the different architectural features and empirical indicators that enhance criticality could actually offer provisions for diagnosis and potential intervention. For instance, since it can be predicted that a network with low diversity and high connectivity is positioned for critical transition, the potential response could be to redesign the system for more gradual adaptive response or further strengthen the preferred state. Furthermore, as it can be predicted that critical slowing down can elevate chances of critical transition and that flickering can increase the probability of tipping to alternative states, in both cases, the system can get ready for the anticipated change, lessen the risk of unwanted transition, or leverage the opportunity to promote the desired transition since the system is more open to change. Again, on the upside, a tightly coupled system makes it possible for tiny interventions, perhaps undetectable and hard to quantify, to escalate into major qualitative interventions that can alter the course of the system's life [31]. For instance, in a biological perspective, this is akin to a protein or a neuron firing so as not to self-organize to criticality [49].

Lewis [41] provided real-world suggestions on how the system can "un-SOC" itself – since self-organizing criticality (SOC) will eventually lead to collapse, the system can extend its life by *un*doing the SOC process. In other words, allow the system to loosen the connections and modularized or decentralized its components, and make its processes less efficient and suboptimal. He suggested the policy of link depercolation to keep SOC under control, i.e., prevent a node from having too many connections or thin out current links, or reduce the links of hubs. As Casti [18] also pointed out, the only realistic alternative is to loosen up the tight coupling of the components. Since the decoupled dynamics constrain stimuli locally, the entire system becomes more robust in the face of perturbations [11]. In the wake of a pandemic, for example, if a vaccine has been proved to kill the virus, high connectivity and interdependencies among agents will greatly aid the inoculation process. However, if the population is too massive to inoculate, or no vaccine has yet been discovered to cure the population, depercolation, e.g., by quarantine or limiting the contact of people, will be the next best solution [41]. Lewis also suggested reducing operational efficiency in different sectors, e.g., energy, transportation, and telecommunication, since these work better when they are less efficient and more decentralized.

To end this section, we echo what Casti stated in his book, specifically, "sustainability is a delicate balancing act calling upon us to remain on the narrow path between organization and chaos" [18, p. 46]. The idea, therefore, is for the system to stay away from the steady state to remain flexible [21] and be close to chaos while retaining some degree of order.

B. *Creative Chaos that is Poised for Resilience*

1) *Intituition Behind the Concept*

In an article written by M. Fisher for The Atlantic [51] is an articulate description of how the pre-war Japanese ideology transited from rigidity, to collapse, and to the emergence of a totally new ideology that brought about the reorganization of a country – a transformation that has affected the world even today: For many years prior to the end of the World War II, the then Japanese citizenry had been embedded in an ideology of imperialism, ultra-nationalism, radical militarism, and international primacy. Such rigid ideology drove the country to a quest of imperial expansion, which at the beginning marked Japan's military strength and dominance in the region. Towards the end, however, when Japan's defeat in the international scene became inevitable and the devastation brought upon it was immeasurable, the people feared that with the rigid ideology, where surrender was not an option, they would be forced to choose death over imperial ideology. What the Emperor spoke in those critical moments when their survival as a nation hanged in the balance, however, was different. They were asked instead to choose the radical alternative – embrace the surrender towards a noble change, i.e., one of moral integrity, nobility of spirit, peace and international progress. This marked the collapse of the ideology that was once held unbreakable. The accompanying suffering was indeed enormous (in [79]), but the result after a generation was a nation of renewed identity that emerged to become one of the great leaders of our modern economic and technological progress.

When allowed to progress in complexity and rigidity, a system would eventually collapse. However, in an inevitable collapse, the system can open itself up to possibilities to become a new and better system, if only adaptive and not to maladapt in the midst of chaos. Holling describes the chaotic phase in ecological systems, which he refers to as the backloop of his Adaptive Cycle [52][9], as the sudden release of complexity, characterized by significant decrease in capital and loss of connection among parts. When this happens, however, the system begins to open itself up to novel forms, functionalities, and systemic associations [56]. For example, an essential part of the forest ecosystem is the occurrence of natural fire since it replenishes soil nutrients, allows new plant species to grow, and reduce pathogens and infestations, among others [56]. In evolution, although deleterious mutation is assumed to inject harm and impede adaptive evolution, it also has the potential to evolve complex new functions (refer to [53]). One example in the technology sector, albeit not with a happy ending, is Kodak, as recounted in [54]: From being a worldwide market leader in film photography in the 80s, Kodak collapsed to bankruptcy in 2012. The notion that Kodak collapsed because it missed the rise of digital technology is untrue – the engineers at Kodak have already developed the technology in the 70s. Rather, the management was deceived by its very comfortable position and large profit margins in the film market that it did not want to take the risk of investing in the new products despite the various internal red flags. When Kodak eventually turned to digital photography, it was not anymore an open space for innovation since competitors had already filled the space. Hence, when chaos ensued, there was no room for Kodak to transform; consequently, its total collapse. Kodak failed to rise beyond the innovator's dilemma [41][80] – it stubbornly followed its star technology to its peak (and eventual demise) instead of risking everything for the next big thing.

2) *From Chaos to Resilience*

Schumpeter's creative destruction theory [55] states that a continuous uninterrupted unpleasant transformation from within that destroys the old one also incessantly creates a new one. If progress means turmoil, then why not accelerate the turmoil if only to also accelerate getting to the new and better progress. Similarly, in [56] we suggested the strategy of deliberately injecting or inducing regulated and controlled shocks into the system as complexity and rigidity among its components begin to build up: This is in a way forcing the system to transition itself to chaos in order for novelty to emerge. The motivating principle behind this strategy is to let the system embrace the fact of an inevitable failure and learn how to deal with it swiftly once it happens. It is more effective to create situations that can force latent systemic problems to surface and become visible, rather than design the system not to fail, which, paradoxically, only makes it less resilient. This strategy will certainly cause disorder and crisis in the system, to say the least, but such will last relatively shorter than if chaos was actually not staged.

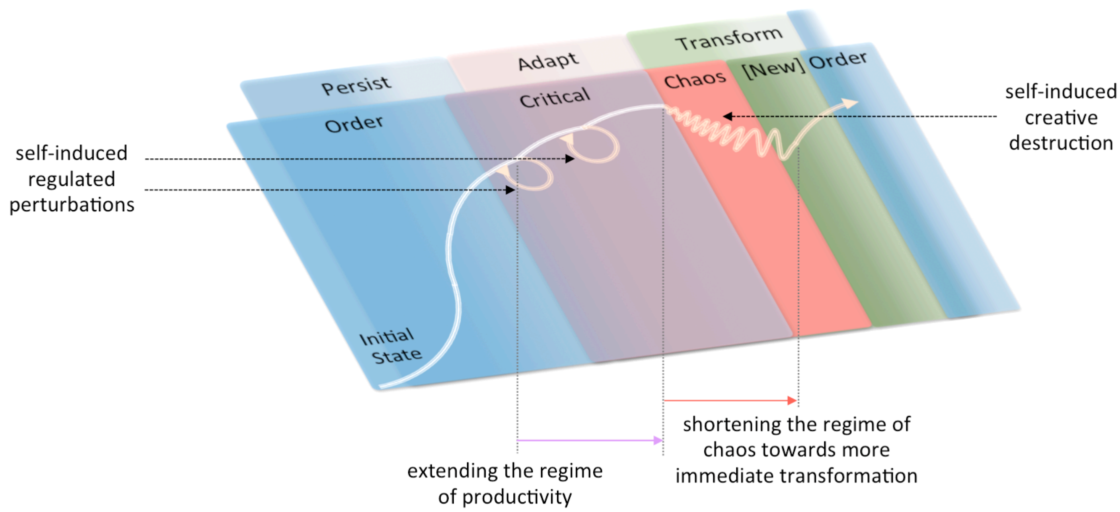


Figure 4. For a complex system to be poised for resilience, it must be able to promote its own desired transition.

C. System Being Self-Poised for Resilience

Merriam-Webster dictionary defines "poised" as "in a state, place, or situation that is between two different or opposite things", as well as being "ready or prepared for something". The critical regime is poised between order and chaos marked with complexity and decreased fitness. And yet, this complexity does not destroy the ability of the system to self-organize. With optimal connectivity and coordination they have enough stability to store and propagate information, as well as the fluidity to productively adapt based on the received information. At the same time, a system in the state of chaos has lost most much of its stored information and connectivity, and yet, has become ready to create new associations and transmit improvised information.

Given the above, a system that has the ability to detect through architectural and empirical indicators the critical state can promote the desired transition by (*a*) extending the edge of productivity through necessary adaptations that involve regulated self-induced perturbations (e.g., manageable reorganization or reconfigurations), or (*b*) reducing the risk of unwanted transition by imposing upon itself the self-induced creative destruction that can lead to shorter chaos and groundbreaking innovation. Figure 4 shows our meta-theory for a complex adaptive system's self-imposed transitions to achieve resilience. Notice how criticality is extended while chaos is shortened.

V. MACHINE-INTELLIGENT MODELING

A. Simulation of a Complex System and its Properties

Although our aim is to model a real-world complex adaptive system and its intricate properties, as per Figure 2, our major concern at this time, however, is that we have yet to embark on this endeavor. In order to demonstrate our concepts, we used random Boolean networks (RBNs) to simulate the properties of a complex adaptive system. RBNs have been used as models of large-scale complex systems [57][58]. These are idealizations of complex systems where systemic elements evolve [59]. RBNs are general models that can be used to explore theories of evolution or even alter rugged adaptive landscapes [60]. Furthermore, although RBNs were originally introduced as simplified models of gene regulation networks [61][6][7], they gained multidisciplinary interests since they contribute to the understanding of underlying mechanisms of complex systems even though their dynamic rules are simple [62], and because their generality surpassed the purpose for which they were originally designed [20][62]-[64]. By using RBNs, we were able to analyze complex system behaviors and describe the viability of our framework.

A RBN consists of N Boolean (1 being on/active and 0 as off/inactive) nodes, each linked randomly by K connections. A RBN can be viewed as consisting of N automata with only two states available per automaton [65]. N represents the number of significant components comprising an adapting entity, generally, the number of agents attempting to achieve higher fitness [20]. We can view K conceptually as affecting the mutual influence among nodes in an information network [62] since a directed edge $<x, y>$ means that agent y can obtain information from, and can be influenced by, agent x. In this way, K is proportional to the quantity of information available to the agent [62]. The Boolean values may represent, for example, contrasting views, beliefs and opinions, or alternatives in decision-making (e.g., buying or selling a stock [7], cooperating with the community or not). The state of any node at time t+1 depends on the states of its K inputs at time t by means of a Boolean function that maps each of the 2^K possible input combinations to binary output states. The randomly generated Boolean functions can be represented as lookup tables that represent all possible 2^K combinations of input states.

Given N and K, there can be 2^N network states, $(N!/(N-K)!)^N$ possible connectivity arrangements, $(2^{2^K})^N$ possible N Boolean function combinations, and $((2^{2^K}N!)/(N-K)!)^N$ RBNs [66]. This is not counting the many possible updating schemes [60], and possibly extending to have nodes with multiple states [67]. With this huge number of possibilities, it is therefore possible to explore with RBNs the various properties of even large-scale complex systems and their many possible contexts [58].

As RBNs are systems with information flowing across parts, network theory can be used to define the properties that characterize the configuration of a RBN. These properties can be viewed as the controlling variables that the system can modify or adjust to demonstrate its resilient capabilities. In a plausible sense, these can also be viewed as the *simulated* outputs of the pre-processing stage of our framework (as per Figure 2) that led to the configuration of the network. The parameters are as follows:

- *Connectivity* (K). This refers to the maximum or average number of nodes in the input transition function of a network component. As we increase K, nodes in the network become more connected or tightly coupled, and more inputs affect the transition of a node.
- *Dynamism* (p). A Boolean function computes the next state of a node depending on the current state of its K inputs subject to a probability p of producing 1, and a probability of 1-p of producing 0, in the last column of the lookup table [81][60]. If p=1 or p=0, then there is no actual dynamics, hence low activity, in the network. However, p close to 0.5 gives a high dynamical activity since there is no bias as to how the outputs should be [60].
- *Topology* (or *link distribution*). A RBN may have a fixed topology, i.e., all transition functions of the network depend on exactly K inputs, or a homogeneous topology, i.e., there is an average K inputs per node. Another type of topology is scale-free, where the probability distribution of node degree obeys a power law. In an information network, a scale-free property means that there is a huge heterogeneity of information existing [62], hence, there is more variation in the network. Following [68], the number of inputs for the scale-free topology is drawn from a Zeta distribution where most nodes will have few inputs, while few nodes will have high number of inputs. The shape of the distribution can be adjusted using the parameter γ (we set initially to 2.5) – when γ is small/large, the number of inputs potentially increases/decreases.
- *Linkage* (or *link regularity*). The linkage of a RBN can be uniform or lattice. If the linkage is uniform, then the actual input nodes are drawn uniformly at random from the total input nodes. Following [38], if the linkage is lattice, only input nodes from the neighborhood (i-$lattice_i$*k_i):(i+$lattice_i$*k_i) are taken, where i is the position of the node in the RBN and $lattice_i$ is its lattice dimension whereby nodes are dependent to those in the direct neighborhood. A wider lattice dimension can lead to a RBN with highly interdependent nodes.

While the above properties indicate the architecture that underlies system regimes, we add another property that serves as empirical indicator of upcoming transition. We measured the *robustness* of the system when faced with perturbations. Note as well that the difference in the number of Boolean functions not only contributes to the variation in variable transitions, but also influences the variability of information flow in the network. Hence, we *combined both architectural and empirical indicators of system regimes*.

Using the BoolNet package [82] for the R programming language for statistical computing, we applied the program of Müssel et al. as outlined in their BoolNet vignette [68] as follows. A perturbation is achieved through random permutation of the output values of the transition functions, which although preserved the numbers of 0s and 1s, might have completely altered the transition functions. For each simulation, a total of 1,000 perturbed copies of the network were created, and the occurrences of the original attractors in the perturbed copies were counted. Attractors are the stable states to which transitions from all states in a RBN eventually lead. The robustness, R, is then computed as the percentage of occurrences of the original attractors.

It is very important to realize that robustness here is *not* resilience per se, since resilience refers to *what* enables a system, i.e., change in connectivity, dynamism, topology, and linkage, to preserve its core identity when faced with perturbations [4]. We used *R to quantify the amount of RBN core identity that was preserved*. Hence, R is an indicator or measure of systems resilience.

B. Identifying the System Regimes

We started by identifying the system regimes given the RBN properties we specified above. To achieve this, we began our simulations with a base case. Our *base case* is a "conventional" RBN, i.e., the topology is fixed and the nodes are updated at the same time by the individual transition functions assigned to each, i.e., synchronous update. With several conditions to check, we used for now a single value for N, which is 20. We computed for the robustness of various RBNs in a dynamism-connectivity plane, i.e., how a RBN with specific dynamism and connectivity values is robust after 1,000 different perturbations. Figure 5 shows our base case R-matrix in a dynamism-connectivity space where each component is R-value.

R (robustness) matrix

dynamism (p) \ connectivity (K)	1	2	3	4	5	6	7	8	9	10
0.9	48.700	34.067	31.300	55.300	2.050	0.000	1.900	1.680	0.000	6.267
0.85	49.000	29.075	15.560	4.033	0.000	0.000	1.289	0.000	0.000	6.150
0.8	48.900	26.500	17.180	3.567	0.000	0.000	1.800	0.000	0.000	6.138
0.75	48.200	26.400	14.460	5.033	0.000	0.000	1.444	0.000	0.000	6.288
0.7	49.600	26.875	15.360	3.433	0.000	0.033	1.389	0.000	0.000	6.113
0.65	49.600	24.425	12.340	4.033	0.100	0.000	1.767	0.000	0.000	5.913
0.6	53.800	27.050	13.900	3.933	0.000	0.033	1.611	0.000	0.000	5.813
0.55	49.100	26.100	15.780	4.533	0.000	0.000	1.456	0.000	0.000	5.913
0.5	48.000	26.050	13.280	4.667	0.100	0.000	1.367	0.000	0.000	6.088
0.45	49.400	30.100	16.160	4.267	0.000	0.033	1.689	0.000	0.000	6.275
0.4	49.100	22.575	15.380	3.467	0.100	0.033	1.289	0.000	0.000	5.913
0.35	50.900	26.775	15.820	4.600	0.000	0.000	1.489	0.000	0.000	6.288
0.3	50.700	26.625	15.720	3.900	0.000	0.033	1.478	0.000	0.000	6.013
0.25	49.600	26.675	13.920	4.467	0.000	0.033	1.600	0.000	0.000	5.875
0.2	51.300	27.475	14.680	4.333	0.100	0.000	1.533	0.000	0.000	6.338
0.15	49.600	26.925	14.340	3.700	0.000	0.000	1.478	0.000	0.000	6.275
0.1	49.400	26.100	14.720	4.433	0.000	0.000	1.756	0.000	0.000	6.250

Figure 5. R-matrix that summarizes the sensitivity of various conventional RBNs in a dynamism-connectivity space to different perturbations.

However, the question is where are the system regimes located? It is fundamental for us to know where and when the system is poised for resilience. To determine the separation of regimes, we applied two methods that are known for this purpose, namely, state space trajectories and sensitivity to initial conditions. To implement these two approaches, we used the RBNLab software [83].

Figure 6a shows the matrix of trajectories through space of RBNs with different dynamism-connectivity values. Each cell in the matrix represents the state transitions of network nodes, as shown in Figure 6b, with oscillating (enclosed in red rectangle) and stable states. Oscillation indicates change in system behavior with the stable condition yet to be reached. A column in the cell represents the states of the network nodes at time *t*. Initial states are at the left and time (until 60 steps) flows to the right. Some nodes exhibit oscillations that quickly died out after a few steps, at times after only a single step, e.g., in Figure 6c, and were immediately followed by stable states. While other nodes continued to oscillate longer before reaching a stable state, others never reached stability, e.g., in Figure 6d, even as we continued the simulation for 4,500 time steps.

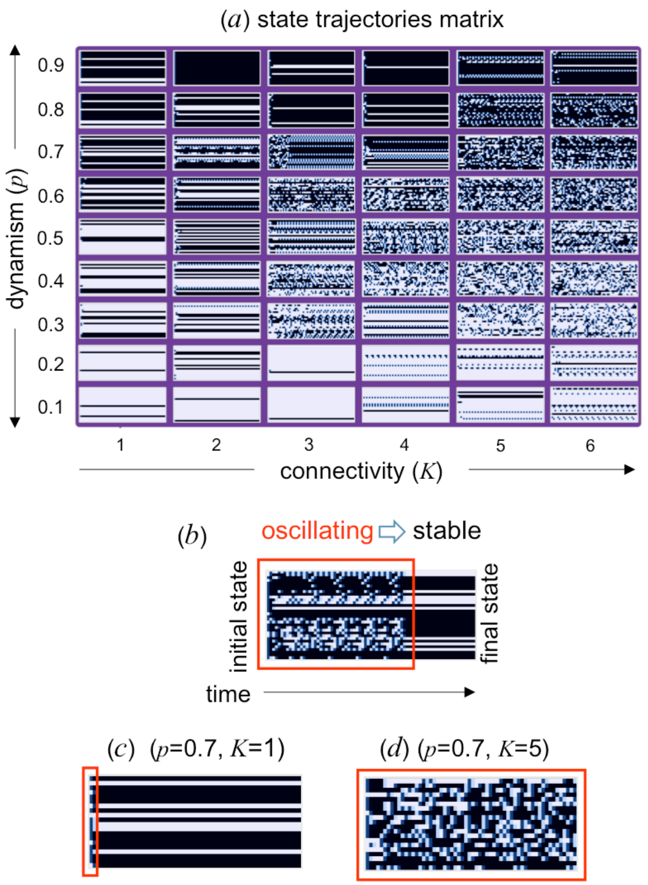


Figure 6. Trajectories of RBNs through the dynamism-connectivity space. Black and white colors indicate active and inactive states, respectively, while light blue colors indicate changing states.

It can be observed from Figure 6a that networks can become overly stable at lower K values and p close to 0 or 1. These sparsely connected networks had very short state cycles and the system froze up (stable to 0 or 1) very quickly. It can be said that they are rigid and uninteresting [21]. At K=2, however, we can see that not all nodes were frozen, unlike those at K=1. At (p=0.7, K=2), for example, the network nodes continued to fluctuate between 0 and 1 and never reached a stable state.

To further define this separation between regimes, we applied sensitivity to initial conditions as a measure of chaos [60][10] – if we change the initial point even by a little bit, the network ends up on a different path. We followed the approach of Gershenson [60] to measure this condition. Using again the RBNLab, we created an initial state I_1, and flipped one node (changed the bit value) to have another state I_2. We ran each initial state in the network for 4,500 time steps to obtain the final states F_1 and F_2, respectively. We then computed separately the normalized Hamming distance of the initial states, as in (1), and the final states to obtain parameter λ, as in (2):

$$H\left(I_1,I_2\right)=\frac{1}{N}\sum_{j=1}^{N}\left|i_{1j}-i_{2j}\right| \tag{1}$$

$$\lambda = H\left(F_1,F_2\right)-H\left(I_1,I_2\right) \tag{2}$$

While a negative λ means that both initial states moved to the same attractor, which is indicative of a stable or ordered state, a positive λ, on the other hand, indicates that the dynamics of similar initial states diverge, which is common to chaotic regimes.

Figure 7 shows the different λ values we obtained for the dynamism-connectivity matrix, and we can observe where order (in blue) and chaos (in red) are. We can also observe from the table of average λ per K where the critical regime is – the positive average λ started at K=2 (in purple), where there is a balanced mix of order and chaos.

λ values

dynamism (p) \ connectivity (K)	1	2	3	4	5	6
0.9	-0.05	-0.05	-0.05	-0.05	-0.05	0.05
0.8	-0.05	-0.05	0.10	0.15	0.25	0.45
0.7	-0.05	0.05	0.20	0.10	0.30	0.30
0.6	-0.05	0.15	0.10	0.30	0.20	0.55
0.5	-0.05	0.25	0.10	0.35	0.25	0.60
0.4	-0.05	0.20	0.15	0.45	0.20	0.25
0.3	-0.05	0.20	0.15	0.25	0.45	0.40
0.2	-0.05	-0.05	0.05	0.10	0.20	0.30
0.1	-0.05	-0.05	-0.05	-0.05	0.05	0.30
Average λ	-0.1	0.1	0.1	0.2	0.2	0.4

Figure 7. Map of the different regimes based on the sensitivity of conventional RBNs to initial conditions.

After applying the above two methods, we observed that it is at K=2 that the networks began to show signs of criticality. In other words, the critical regime lies mostly, although not entirely, at K=2. This gave us a hint as to where the regimes could be in our base case R-matrix in Figure 5.

We need to emphasize that the fundamental difference of the method by which we derived the R-matrix in Figure 5, as compared to the previous two, is that each R-value is a synthesis of 1,000 network perturbations, which statistically tells more than the cells in the previous two matrices (in Figures 6a and 7) that were derived using at most only two network variations and a single-bit perturbation. This implies that the separation between regimes in the *R*-matrix in Figure 5 may be more pronounced. Looking at the *R*-matrix once again, we can observe how the range of *R*-values differed significantly per column, i.e., [48.0, 53.8], [24.4, 34.1], [12.3, 17.2], and [0.0, 6.3] for *K* equals to 1, 2, 3, and >3, respectively. Also, when we computed the average *R* per *K*, as shown in Figure 8, we can see how the average *R* significantly deteriorated by almost half per increase in connectivity starting with *K*=2 until *K*=6, and then stayed low until *K*=10. It is at *K*=1 that the RBNs were most robust. The RBNs losing robustness at *K*=2 may be indicative of critical slowing down or diminishing returns, and the system may therefore be tipped more easily into an alternative state, i.e., from order to chaos, which therefore reflects criticality. With these analyses, we hypothesize that the separation of regimes in our base case matrix is the one shown in Figure 9. We can therefore observe from the *R*-matrix the regimes that are present in our meta-theory.

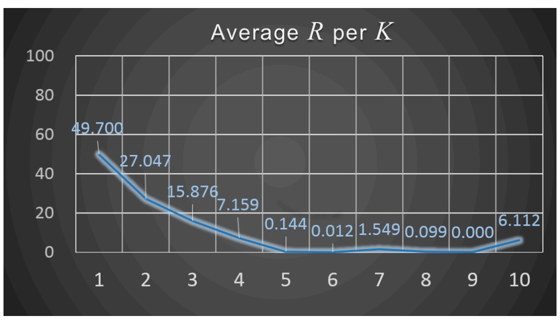
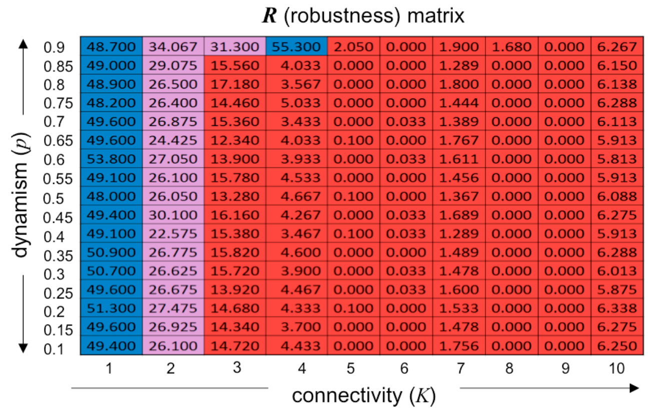


Figure 8. Each value corresponds to the averaged *R*-values across all *p*-values per *K*.

With the base case, we were able to empirically identify the initial range of values that would separate the regimes. After performing and analyzing all our simulations, we further observed that the range of values for each regime could be refined as follows – order: [43,100] (in blue), critical: [22, 43) (in purple), and chaos: [0, 22) (in red).



R (robustness) matrix

dynamism (p) \ connectivity (K)	1	2	3	4	5	6	7	8	9	10
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0.5	48.000	26.050	13.280	4.667	0.100	0.000	1.367	0.000	0.000	6.088
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0.25	49.600	26.675	13.920	4.467	0.000	0.033	1.600	0.000	0.000	5.875
0.2	51.300	27.475	14.680	4.333	0.100	0.000	1.533	0.000	0.000	6.338
0.15	49.600	26.925	14.340	3.700	0.000	0.000	1.478	0.000	0.000	6.275
0.1	49.400	26.100	14.720	4.433	0.000	0.000	1.756	0.000	0.000	6.250

Figure 9. Map of the different regimes based on the sensitivity of conventional RBNs to perturbations. The colors of the cells correspond to that of our meta-theory: blue is order, purple is critical, and red is chaos.

C. Tracking System Regimes and Transitions

We now discuss the results of the different simulation models we ran while we varied the network and perturbation configurations. We begin with the one in Figure 10. Each rectangle in the 3×5 *topology-linkage* space is a *R*-matrix with *p*-*K* dimensions. For example, $R_{2,3}$ matrix corresponds to the robustness matrix of the RBNs with homogeneous topology and lattice linkage of size 2.5. The $R_{1,1}$ matrix is the same *R*-matrix in Figure 9.

We can see from the different *R*-matrices the interesting properties that emerged. We can observe the critical regime broadening to *K*=3 (in $R_{1,2}$, $R_{2,2}$, $R_{2,3}$, $R_{2,4}$, and $R_{2,5}$) or re-occurring at *K*>2 (in $R_{1,3}$ and $R_{1,5}$) between chaotic regimes in the fixed and homogeneous RBNs with wider lattice. These extensions and re-occurrences of the critical regime mean alternative opportunities for the system to take advantage of the benefits of the critical regime and the balance of stability and chaos [64]. The wider lattice led to more interdependencies among nearest neighbors, which formed small world networks that brought about such behaviors of the critical regime. This is consistent with the findings of Lizier et al. [69] that a small world topology leads to critical regime dynamics.

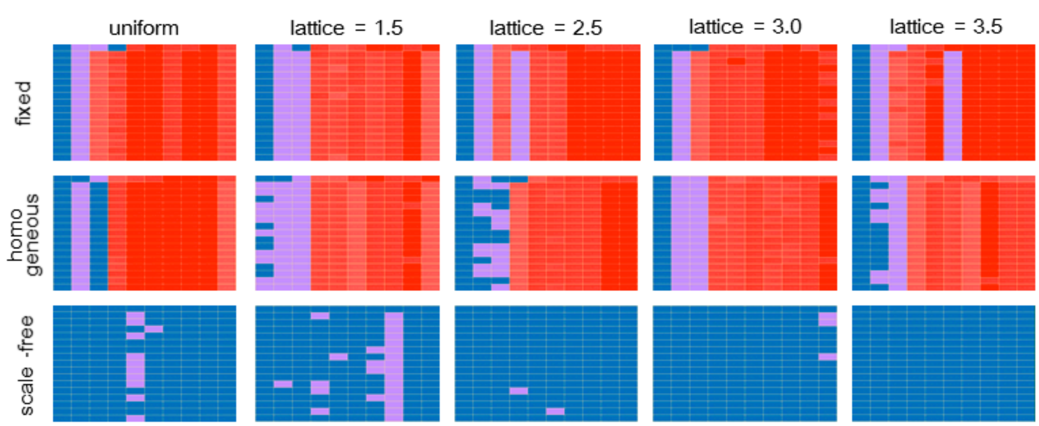
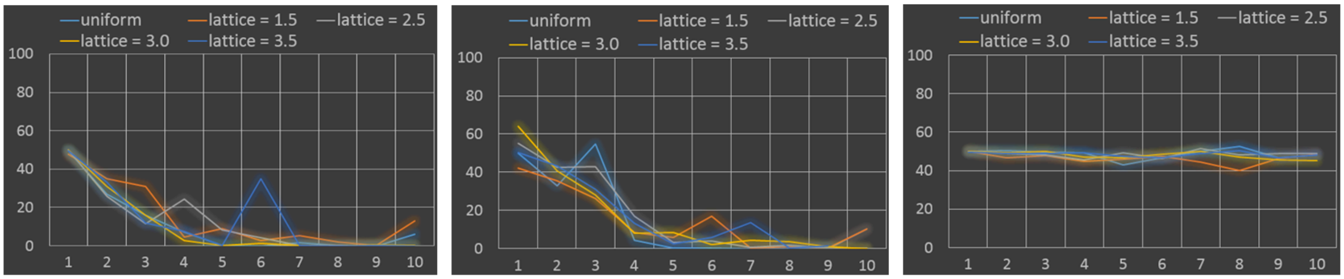


Figure 10. Map of the different regimes based on the sensitivity of RBNs to perturbations when dynamism, connectivity, topology, and linkage were varied



(a) fixed (b) homogeneous (c) scale-free

Figure 11. Mean robustness behaviors of the different RBNs in Figure 10

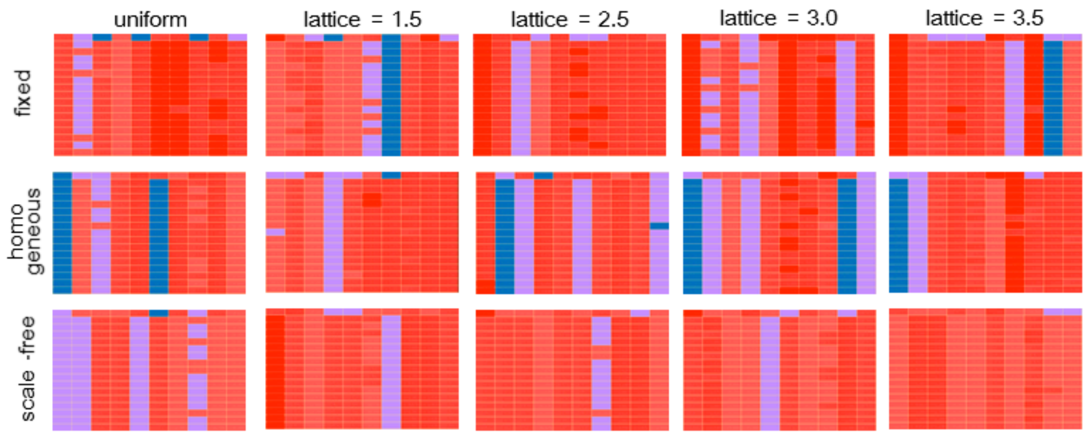


Figure 12. Map of the different regimes based on the sensitivity of RBNs to greater perturbations

Furthermore, the ordered regime expands with homogeneous RBNs. Since the number of input nodes is drawn independently at random, there is more variation in the way components influence each other. This also means that with less tighter connections among components (i.e., as the couplings in the network are loosened), the system becomes less vulnerable to perturbations. $R_{2,1}$, for example, shows how the system could transform to the next ordered state from a critical phase instead of deteriorating to a chaotic regime. With the scale-free topology, however, we can see highly robust RBNs. Since few nodes have more connections, and most nodes have few connections, changes can propagate through the RBN only in a constrained fashion.

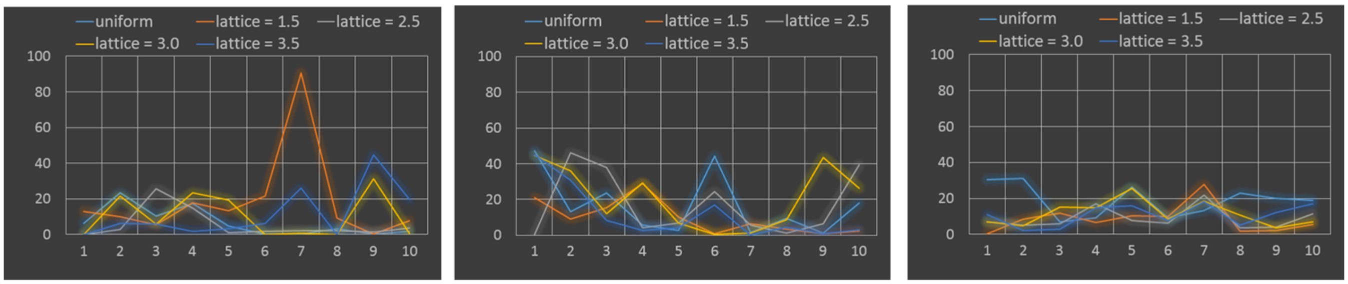
Figure 11 shows the mean (μ) R-values (the colored lines indicate the linkage type), with each value computed as:

$$\mu R_i = \frac{\sum_{p=0.1}^{p=0.9} R_{topology,linkage}\left[p, K_i\right]}{p\ steps} \quad (3)$$

We can see the different μR-values continuously decreasing towards zero for the fixed and homogeneous topology. We interpret this as critical slowing down or diminishing returns that began at K=2 before transitioning to the chaotic regime. The μR-values for the scale-free RBNs, however, remained satisfactory throughout. Hence, a complex adaptive system may demonstrate [self-imposed] resilience by *broadening* (*extending*) *the critical regim*e, *making the critical regime reoccur*, or *transforming to a scale-free topology*.

Lastly, by applying again the method of Müssel et al. [68], we tested next the sensitivity of the RBNs to greater perturbations. To simulate greater perturbation impacts, for each network transition, the transition function of one of the components is randomly selected, and then five bits of that function is flipped. Figure 12 shows the results we obtained. The first interesting phenomenon is the multiple occurrences of the ordered (in $R_{2,1}$ and $R_{2,4}$) and critical regimes (e.g., in $R_{1,4}$, $R_{2,3}$, $R_{2,4}$, $R_{3,1}$, etc.), even after the chaotic regimes, which are all indicative of resilience. The second is that we can obviously see how the behavior of the scale-free RBNs changed drastically, i.e., we could not find any ordered regime and their μR-values, as shown in Figure 13, dropped significantly. This is consistent with the findings of Barabási and Bonabeau [70] that scale-free networks are very robust against random failures but vulnerable to elaborate attacks. In our case, five flipping bits in every transition of the network was too much perturbation for the scale-free RBN.

This does not mean, however, that the resilience of the scale-free network is entirely lost. When we varied the parameter γ of the Zeta distribution from γ=2.5 to other values, another interesting phenomenon emerged, as shown in Figure 14 – we see more expansions and reoccurrences of the critical regime given other γ values. This means that *varying the scale-free network configuration* is another alternative to *prolong or increase the number of critical regime occurrences*, which is indicative of resilience.



(a) fixed (b) homogeneous (c) scale-free

Figure 13. Mean robustness behaviors of the different RBNs in Figure 12.

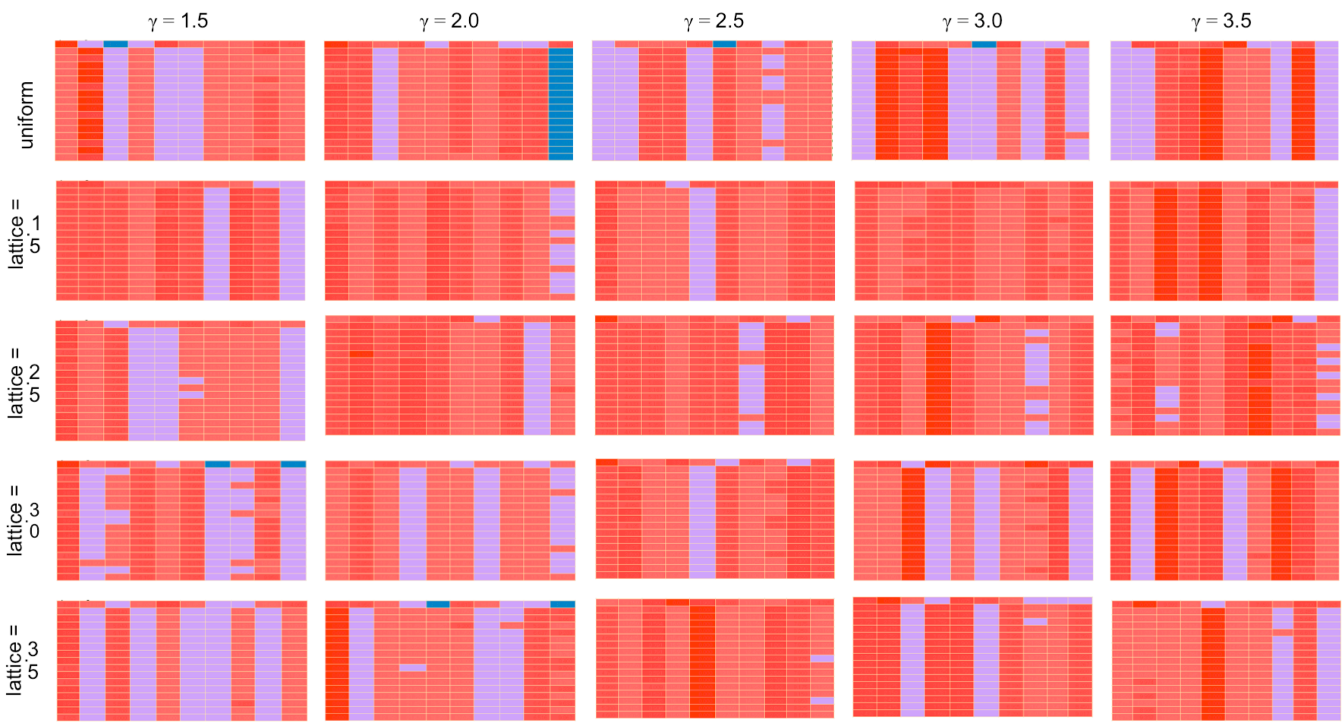


Figure 14. We simulated what will happen with changing γ values. The tables show that with other γ comes more expansions of the critical regime.

D. Machine-Intelligent Modeling

It is clear from our simulations that the combinations of the parameter values can characterize system states and regimes. The question now is how to infer these parameter relations as rules of contextual interaction behaviors that can define the complex system's adaptive and transformative walks and therefore define its resilience. Our solution is to use machine learning (ML) to discover the hidden relations.

The ML algorithm should infer a model that is predictive – given the states of the system and the perturbation, which regime in the space of possible regimes is the system in? We illustrate this viability of the predictive model in Figure 15. More importantly, the predictive model should help steer the system to a desirable regime – from the current states of the system and the perturbation, wherein the regime may be undesirable, which system parameters can or should be modified to achieve a desirable regime? *This capacity to modify the system parameters and predict the resulting regime can make the system resilient*.

We represent together the endogenous parameters of the system and the impact of the exogenous perturbation in a feature vector, which is a tuple of attribute values, i.e., <*connectivity*, *dynamism*, *topology*, *linkage*, *lattice*, *gamma*, *perturbation*>, where the possible values are as follows:

- connectivity = [1..10]
- dynamism = (0.10, 0.15, 0.20, ..., 0.80, 0.85, 0.90)
- topology = (fixed, homogenous, scale-free)
- linkage = (uniform, lattice)
- lattice = (1.5, 2.5, 3.0, 3.5)
- gamma = (1.5, 2.0, 2.5, 3.0, 3.5)
- perturbation = (minor, major)

We labeled each feature vector with the corresponding *R*-value that is indicative of the system regime.

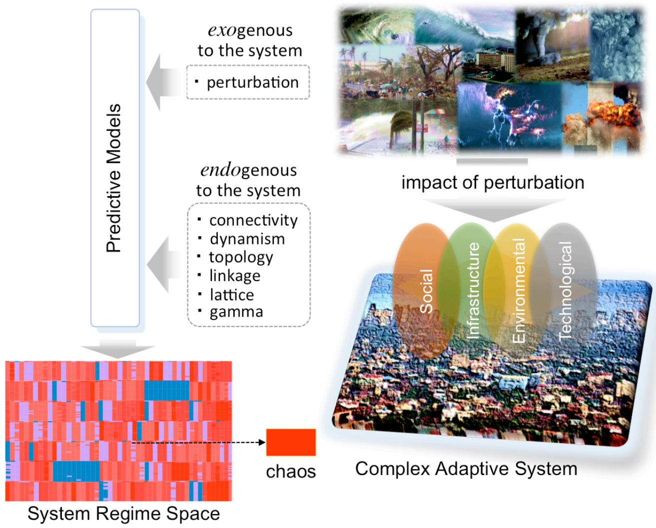


Figure 15. Viability of the predictive model

Our dataset consisted of 7,120 feature vectors, which corresponds to the various simulation scenarios we ran using our different RBN models. It is important to note that even though our data can still be considered minimal (considering for example that we only used one value for *N*, limited value ranges for the parameters, and only synchronous updates), the advantage of using a data-centric approach is that as the volume and dimensions of the data further increases, ML can be used to automatically handle the growing intricacies and complexities, as well as automatically infer the new relations emerging in the data.

To obtain the model with the best predictive capacity, we ran several well-known ML algorithms using the WEKA open-source software. Due to space constraints, it is best that we refer the reader to the documentation [71] of these algorithms. The ML algorithms are (*a*) function-based: linear regression models (LRM), multi-layer perceptrons (MLP), radial basis function networks (RBFN), and support vector machines for regression (SMOR), (*b*) instance-based or lazy: *K** and *k*-nearest neighbor (Ibk), and (*c*) tree-based: fast decision tree (REPTree) and MP5 model tree (MP5Tree). We used *%-split* validation where *x*% of the data was used for training and the rest for testing the accuracy of the model. We measured the performance of the regression analysis in terms of correlation coefficient and root mean squared error to show the strength of prediction or forecast of future outcomes through a model or an estimator on the basis of observed related information. The correlation coefficient is also indicative of how good the approximation function might be constructed from the target model. We constructed several models by increasing the size of the training set from 10% to 90% of the total data, with increments of 10% (horizontal axis of the graphs in Figure 16), which allowed us to see the performance of the inferred models with few or even large amount of data, and also gave us the feel of an incremental learning capacity.

Figure 16 shows the accuracy of the predictive models. We can see that the models inferred by the decision tree-based (REPTree and MP5Tree) and instance-based *k*-nearest neighbor (Ibk) algorithms outperformed the others. These models can accurately predict in more than satisfactory levels the contextual interaction behaviors of the system even with only 10% of the data. We note that our goal at this time is not to improve the algorithms or discover a new one, but to prove the viability of our framework. We anticipate, however, that as the complexity of the system and the data grows, our algorithms would need to significantly improve.

The other advantage of the tree-based models is that the relation rules can be explicitly observed from the tree. Model trees are structured trees that depict graphical if-then-else rules of the hidden or implicit knowledge inferred from the dataset [72][73]. Model trees used for numeric prediction are similar to the conventional decision trees except that at the leaf is a linear regression model that predicts the numeric class value of the instances reaching it [73]. Figure 17 shows the upper portion (we could not show the entire tree of size 807 due to space constraints) of the REPTree we obtained using 10%-split validation with the elliptical nodes representing the features (colored so as to distinguish each feature), the edges specifying the path of the if-then-else rules, and the square leaf nodes specifying the corresponding *R*-values depending on which paths along the tree were selected. We can see how the rules delineated in a fine-grained manner the attribute values that eventually led to satisfactory predictions. We can also see how certain features are more significant to the classification task even early in the tree. The connectivity feature, for example, is prominent in both sides of the tree, and that the dynamism feature is not as significant in the upper levels compared to the lattice.

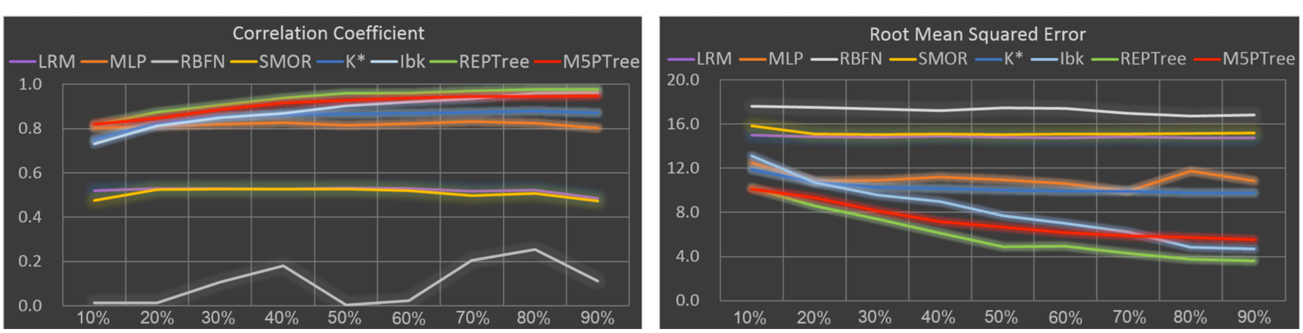


Figure 16. Prediction accuracy of the various models using %-split validation with increasing *x*% values

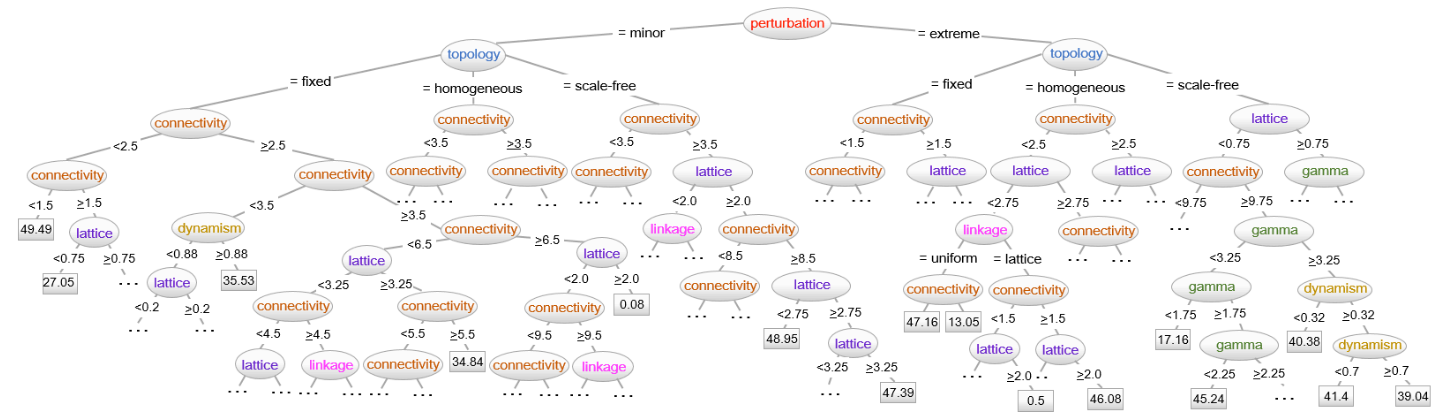


Figure 17. REPTree generated using Weka with a 10%-split validation. The size of the tree is 807, but only parts of it can be shown here due to space constraints. The nodes specify the features (colored so as to distinguish each) with the edges as attribute values, and the leaf nodes as R-values.

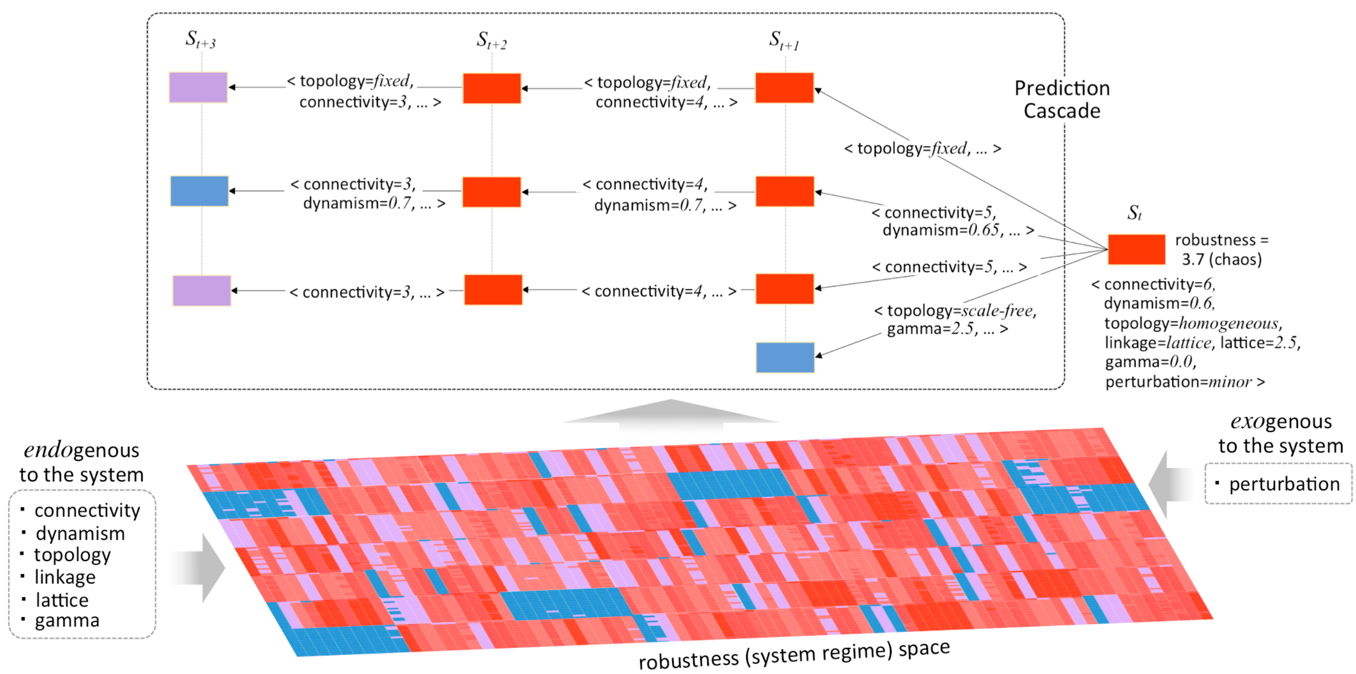


Figure 18. Illustration of how the strength of the predicitve models can be used to find the desirable regime states. For the top illustration, the regime states (colored blocks) and their contextual features (in angle brackets) were taken from the robustness maps, i.e., $R_{2,3}$, $R_{1,3}$, and $R_{3,3}$, in Figure 10.

All these mean that by observing the tree, we can determine which features are significant not only to the classification task, but more importantly to a more relevant sense, which features are actually influential to the resilient (as well as vulnerable) walks of the system.

Lastly, we illustrate in Figure 18 how our predictive model can be used to help steer the system to a desirable regime. The regime states shown in the figure, which were taken from the regime maps in Figure 10 (specifically, from $R_{2,3}$, $R_{1,3}$, and $R_{3,3}$), are obviously only a tiny portion of the possible entire regime space since each cell in every R-matrix in Figures 10, 12 and 14 is a regime state. Let us say that the system landed in the chaotic regime S_t, hence undesirable, as a result of the situational context (indicated by the feature vector shown below) it found itself into. The predictive model can be used to predict the resulting regime when one or more of the S_t contextual features are changed. Hence, from the current regime S_t, depending on which features the system change, the system may enter in one of the many possible S_{t+1} regime states. Although it seems elementary for the system to follow the prediction that suggests changing to scale-free topology with γ=2.5 in order to immediately reach a new ordered state, what should be considered is the high cost of changing to a topology that will necessitate breaking many of the current ties (e.g., geophysical, relational, monetary, etc.). Hence, it may be more advantageous for the system for the long haul to seek alternative paths with longer chaos, but less painful and costly. Again, this capacity to modify contextual features and predict the resulting regime demonstrates systems resilience.

E. Challenges Ahead for the Machine-Intelligent Modeling

We touched briefly in [1] the huge challenges we may need to address in our future work for a truly strong machine-intelligent predictive modeling capacity. We see the need to further elaborate here our points.

1) Finding the Optimal Path to the Desirable Regime

One formidable challenge in determining the optimal path to the desirable regime is the possibly huge number of potential paths, each with its own set of multiple candidate divergence. This is depicted in Figure 19, which is only a small portion of what could possibly be a huge set of system trajectories. Without special algorithms to find the correct paths efficiently, the required computing resources might be prohibitive. Equally challenging is the notion that the shortest path is not necessarily the optimal one. A myopic behavior by the system may find the immediate next step as optimal only to realize that the few poor or sub-optimal steps forward can eventually lead to better long-term outcomes. This also begs the question of how we can make our system's foresight to be as far reaching as possible.

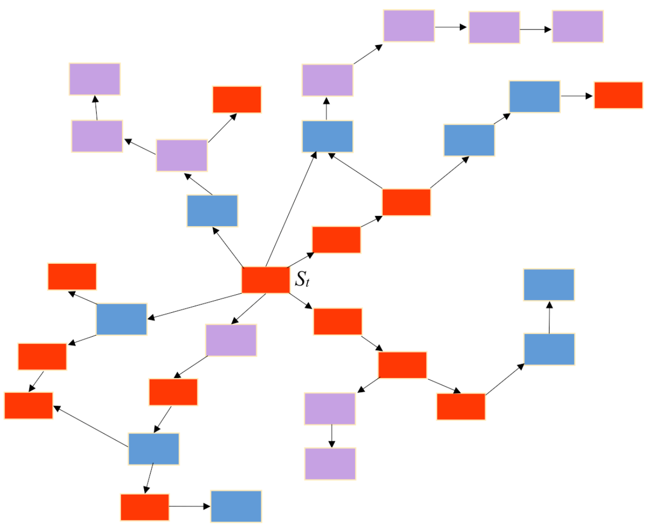


Figure 19. Depiction of possible trajectories of the model's prediction

2) Cost of Being Resilient

What is significantly missing in our modeling is the cost associated to every adaptation and transformation. Although we can account for the actual cost accurately only in retrospect, the challenge is for us to find the function that can meaningfully approximate the cost of system adaptation and transformation. Again is the notion that the shortest path is not necessarily the optimal one. The longer path may in fact possess the more bearable cost compared to that of an immediate, but extreme and radical, change. A similar but real-world insight was drawn after Katrina and Sandy that was shared by Goodman [74], which is "looking not at current losses and rebuilding what was destroyed, but rather at the costs – over time… in the long aftermath of the event." She further stated that it is "looking at any current destruction less as loss but rather as opportunity to create something completely different, perhaps elsewhere, with more wisdom, foresight and technological know-how."

3) Unknown-unknowns in Complexity

As pointed out in the report of the International Risk Governance Council, it is not always that we have knowledge of the multiple plausible alternate futures of our system's behavior [54]. Indeed, the nature of our systems is complex – nonlinear, spanning multiple simultaneous temporal and spatial scales, and with large interrelations and interdependencies among parts. Their evolving nature can affect physical, ecological, economic, and social dimensions simultaneously [28]. Our models can continue to exhibit incomplete and segregated knowledge for several reasons.

First, our predictions will be inaccurate or uncertain since our statistical extrapolations are based on a handful of analogous past experiences or mechanistic models that mislead to dire situations [28]. What we may have is dearth of historical data for predictive analysis [75]. We are therefore made to erroneously believe that certain situations are outside our expected possibilities and will never happen.

Second, our models may not demonstrate the critical links and interdependencies that mesh our systems into a cohesive and coherent whole. Our approaches are intimidated by the task of disentangling and elucidating a messy linked system-of-systems. This leads to a shallow and fragmented understanding of the evolving nature of our complex systems.

Lastly, even if perfect knowledge of costs and probabilities could be assigned to each and every alternative junction in the system phase trajectories, it is still highly possible that our calculations of the aggregate of all costs and probabilities over several junctions are inaccurate.

VI. Conclusion

With our world witnessing critical systemic changes [76], we are concerned with how our systems can be resilient, i.e., able to persist in, adapt to, or transform from dramatically changing circumstances. We believe that a deeper understanding of what fundamentally constitutes and leads to critical system changes sheds light to our understanding of the resilience of our systems. We discussed in length in this paper our contribution towards this understanding of resilience, which is a two-fold complex systems resilience framework that consists of a meta-theory that integrates long-standing theories on system-level changes and a machine-intelligent modeling task to infer from data the contextual behaviors of a resilient system.

Our framework of mutual reinforcing between theoretic and data-centric models allows for less perfect theory and inferred models to begin with, but with both components learning mutually and incrementally towards improved accuracy. Through our meta-theory we are able to have a strong basis of what will constitute our machine intelligent modeling. What the meta-theory can take from the inferred models, however, is to improve its knowledge by incorporating the fine-grained features, e.g., changing lattice and γ values, as well as the magnitude of the perturbations, which can have specific influences towards specific regimes. The knowledge exhibited by the meta-theory has to incrementally improve based on what has been inferred by the intelligent modeling component. Our theoretic and data-centric models will surely need to co-evolve as we collect more data with increased range of network parameter values, other ways of introducing perturbations, using different transition schemes [60], and with agents having multiple states [67], among others. Furthermore, as nonlinear and unpredictable system intricacies become more detailed and pronounced, our machine-intelligent modeling should account for emerging algorithmic and data complexities.

Due to the absence of our intended real-world complex system data, we simulated the viability of our framework using random Boolean networks (RBNs). If RBNs were in fact sound models of complex systems, then our simulations would have sound basis – which is actually the case. RBNs are models of self-organization in which both structure and function emerge without explicit instructions [77]. Secondly, it is by the random nature of RBNs, albeit the transition functions are fixed, that systemic behaviors that emerge from known individual component behaviors cannot be determined a priori (e.g., exact number and characteristics of possible basins of attractions). All these and that a RBN's "infusion of historical happenstance is to simulate reality" [59, p.88] may attest to the fact that our meta-theory being demonstrated by RBNs is not at all forced. Our network-centric analyses show that the ability by which the system can vary, adjust or modify its controlling variables, specifically those that pertain to the connectivity, dynamism, topology, and sphere of influence of its components (all endogenous), and its capacity to withstand the disturbances (exogenous) that perturb it, will dictate the rules of its adaptation and transformation.

It would be a mistake, however, for us to conclude that since we find evidence of our meta-theory in RBNs, our meta-theory shall hold true for all kinds of complex adaptive systems. First, since we claim that our meta-theory should evolve together with the machine-intelligent modeling task to genuinely represent real phenomena that are endogenous and exogenous to the system means that our meta-theory (as well as our machine-intelligent modeling) is not one size fits all. However, as per the Campbellian realism, the meta-theory may be updated according to the specific contextual realities of the environment in which the system is embedded. Second, although it would also be inaccurate to say that "all" complex system realities can be approximated with RBNs, RBNs can indeed mimic certain complex system behaviors. However, by the fact that we intend to use real word data means that we believe that there are more realities to be discovered beyond what RBNs present. However, our conclusion is that the positive results we obtained with RBNs (which are sound models of complex systems) only demonstrate (proof of concept) the viability of our entire framework. If there is any added knowledge we may have derived regarding RBNs, this is only consequential to our primary objective of further elucidating the concept of complex systems resilience through our framework.

The major addition of this paper to our earlier work [1], which one would be remiss to overlook, is that we expanded our notion of systemic changes to what can actually push the system positively and be poised for resilience. The terms critical and chaos normally denote negative outcomes or impending perils. However, in light of resilient systems, such regimes may even be leveraged by the system to promote novel adaptations that can lead to desired sustainability. We also emphasized in this paper how architectural and empirical indicators of systemic changes, in combination, can help steer the system to desirable regimes. We have expanded our experiment results and analyses to further demonstrate this.

We believe that we have barely scratched the surface of our research problem. Our immediate next concern is to find and collect real world data on hyper-connected composite systems in order for us to further ground our meta-theory and machine-intelligent modeling approaches.

REFERENCES

[1] R. Legaspi and H. Maruyama, "Meta-theory and machine-intelligent modeling of systemic changes for the resilience of a complex system," Proc. Tenth International Conference on Systems (ICONS 2015), IARIA, L. Koszalka and P. Lorenz, Eds. ThinkMind Digital Library, 2015, pp. 102-111.

[2] J. Rockström et al., "A safe operating space for humanity," Nature, vol. 461, Feature, September 2009.

[3] W.F. Ruddiman, "The Anthropocene," Annual Review of Earth and Planetary Sciences, vol. 41, pp. 45-68, May 2013.

[4] A. Zolli and A.M. Healy, Resilience: Why Things Bounce Back. New York, NY: Free Press, July 2012.

[5] P. Martin-Breen and J.M. Anderies, "Resilience: A literature review," The Rockefeller Foundation, September 18, 2011.

[6] S.A. Kauffman, "Antichaos and adaptation," Scientific American, vol. 265, no. 2, pp. 78-84, August 1991.

[7] S.A. Kauffman, The Origins of Order: Self-Organization and Selection in Evolution. New York, NY: Oxford University Press, 1993.

[8] P. Bak, How Nature Works: The Science of Self-Organised Criticality. New York, NY: Copernicus Press, 1996.

[9] C.S. Holling, "Understanding the complexity of economic, ecological, and social systems," Ecosystems, vol. 4, no. 5, pp. 390-405, 2001.

[10] S.E. Page, Diversity and Complexity. Princeton, NJ: Princeton University Press, 2011.

[11] G. Paperin, D.G. Green, and S. Sadedin, "Dual-phase evolution in complex adaptive systems," Journal of The Royal Society Interface, vol. 8, no. 58, pp. 609-629, 2011.

[12] N.H. Packard, "Adaptation toward the edge of chaos," in Dynamic Patterns in Complex Systems, J.A.S. Kelso, A.J. Mandell, and M.F. Shlesinger, Eds. Singapore: World Scientific, pp. 293-301, 1988.

[13] C.G. Langton, "Computation at the edge of chaos: Phase transitions and emergent computation," Physica D, vol. 42, pp. 12-37, 1990.

[14] M. Mitchell, P.T. Hraber, P.T., and J.P. Crutchfield, "Revisiting the edge of chaos: Evolving cellular automata to perform computations," Complex Systems, vol. 7, no. 2, pp. 89-130, 1993.

[15] J.A. Tainter, The Collapse of Complex Societies. Cambridge, UK: Cambridge University Press, 1988.

[16] D. Meadows, J. Randers, and D. Meadows, Limits to Growth: The 30-Year Update. White River Junction, VT: Chelsea Green Publishing Company, 2004.

[17] J. Diamond, Collapse: How Societies Choose to Fail or Survive. England: Penguin Publishing Group, 2011.

[18] J. Casti, X-Events: The Collapse of Everything. New York, NY: HarperCollins Publishers, 2012.

[19] B. McKelvey, "Self-Organization, complexity catastrophe, and microstate models at the edge of chaos," in Variations in Organization Science: In Honor of Donald T. Campbell, J.A.C. Baum and B. McKelvey, Eds. Thousand Oaks, Calif: SAGE Publications, pp. 279-307, 1999.

[20] B. McKelvey, "Towards a Campbellian realist organization science," in Variations in Organization Science: In Honor of Donald T. Campbell, J.A.C. Baum and B. McKelvey, Eds. Thousand Oaks, Calif: SAGE Publications, pp. 279-307, 1999.

[21] D.L. Levy, "Applications and limitations of complexity theory in organizational theory and strategy," in Handbook of Strategic Management, J. Rabin, G.J. Miller, and W.B. Hildreth, Eds. New York: Marcel Dekker, pp. 67-87, 2000.

[22] J.M. Anderies, B.H. Walker, and A.P. Kinzig, "Fifteen weddings and a funeral: Case studies and resilience-based management," Ecology and Society, vol. 11, no. 1, article 21, 2006.

[23] J.C. Rocha, "The domino effect: A network analysis of regime shifts drivers and causal pathways," Master's Thesis, Ecosystems, Governance and Globalization Program, Stockholm University, May 2010. Available online: http://www.diva-portal.org/smash/get/diva2:369772/FULLTEXT02. Accessed on 2015.11.24.

[24] Ö. Bodin and M. Tengö, "Disentangling intangible social-ecological systems," Global Environmental Change, vol. 22, no. 2, pp. 430-439, May 2012.

[25] F. Morrison, The Art of Modeling Dynamic Systems: Forecasting for Chaos, Randomness and Determinism. Mineola, NY: Dover Publications, 2008.

[26] J. Bohn, V. Coroamă, M. Langheinrich, F. Mattern, and M. Rohs, "Social, economic, and ethical implications of ambient intelligence and ubiquitous computing," in Ambient Intelligence, W. Weber, J.M. Rabaey, and E. Aarts, Eds. Springer Berlin Heidelberg, pp. 5-29, 2005.

[27] R. Valerdi et al., "A research agenda for systems of systems architecting," International Journal of System of Systems Engineering, vol. 1, no. 1/2, pp. 171-188, 2008.

[28] S.R. Carpenter, C. Folke, M. Scheffer, and F. Westley, "Resilience: Accounting for the noncomputable," Ecology and Society, vol. 14, no. 1, article 13, 2009.

[29] S. Poslad, Ubiquitous Computing: Smart Devices, Environments and Interactions. Wiley, 2009.

[30] K.J. Shim, N. Pathak, M.A. Ahmad, C. DeLong, Z. Borbora, A. Mahapatra, and J. Srivastava, "Analyzing human behaviour from multiplayer online game logs: A knowledge discovery approach," Trends and Discoveries, vol. 26, no. 1, pp. 85-89, 2011.

[31] R.D. Stacey, "The science of complexity: An alternative perspective for strategic change processes," Strategic Management Journal, vol. 16, no. 6, pp. 477-495, September 1995.

[32] E. Thelen, "Dynamic systems theory and the complexity of change," Psychoanalytic Dialogues vol. 15, no. 2, pp. 225-283, 2005.

[33] C. Folke et al., "Resilience thinking: Integrating resilience, adaptability, and transformability," Ecology and Society, vol. 15, no. 4, article 20, 2010.

[34] S.R. Carpenter et al., "General resilience to cope with extreme events," Sustainability, vol. 4, pp. 3248-3259, 2012.

[35] L. Chelleri, J.J. Waters, M. Olazabal, and G. Minucci, "Resilience trade-offs: addressing multiple scales and temporal aspects of urban resilience," Environment & Urbanization, pp. 1-18, 2015.

[36] M. Scheffer et al., "Anticipating critical transitions," Science, vol. 338, no. 6105, pp. 334-348, 19 October 2012.

[37] D. Rickles, P. Hawe, and A. Shiell, "A simple guide to chaos and complexity," Journal of Epidemiology and Community Health, vol. 61, no. 11, pp. 933-937, November 2007.

[38] T. Taylor, "Exploring the concept of open-ended evolution," Proc. Thirteenth International Conference on the Simulation and Synthesis of Living Systems (Artificial Life 13), C. Adami, D.M. Bryson, C. Ofria, and R.T. Pennock, Eds. MIT Press, 2012, pp. 540-541.

[39] D.R. Gilpin and P.J. Murphy, Crisis Management in a Complex World. Oxford, NY: Oxford University Press, 2008.

[40] R.T. Pascale, "Surfing the edge of chaos," MIT Sloan Management Review, Spring 1999. Available online: http://sloanreview.mit.edu/article/surfing-the-edge-of-chaos/, accessed 2015.11.25.

[41] T.G. Lewis, Bak's Sand Pile: Strategies for a Catastrophic World. Williams, CA: Agile Press, 2011.

[42] D. Levinthal, "Adaptation on rugged landscapes," Management Science, vol. 43, no. 7, pp. 934-950, 1997.

[43] J.P. Crutchfield, "The hidden fragility of complex systems – Consequences of change, changing consequences," in Cultures of Change: Social Atoms and Electroniuc Lives, G. Ascione, C. Massip, J. Perello, Eds. Barcelona, Spain: ACTAR D Publishers, pp. 98-111, 2009.

[44] A. Farazmand, "Chaos and transformation theories: A theoretical analysis with implications for organization theory and public management," Public Organization Review: A Global Journal, vol. 3, Kluwer Academic Publishers, pp. 339-372, 2003.

[45] P.H. Longstaff, T.G. Koslowski, and W. Geoghegan, "Translating resilience: A framework to enhance communication and implementation," Proc. 5th International Symposium on Resilience Engineering, June 2013.

[46] J.H. Miller and S.E. Page, Complex Adaptive Systems. Princeton, NJ: Princeton University Press, 2007.

[47] D. Krotov, J.O. Dubuis, T. Gregor, and W. Bialek, "Morphogenesis at criticality," Proceedings of the National Academy of Sciences of the United States of America (PNAS), vol. 111, no. 10, pp. 3683-3688, March 2014.

[48] G.P. Wagner and L. Altenberg, "Perspective: Complex adaptations and evolution of evolvability," Evolution, vol. 50, no. 3, pp. 967-976, June 1996.

[49] B. Keim, "Biologists find new rules for life at the edge of chaos," WIRED, Science, May 2014. Available online: http://www.wired.com/2014/05/criticality-in-biology/, accessed 2015.11.25.

[50] C. Royle, "Dialectics, nature and the dialectics of nature," International Socialism, vol. 141, pp. 97-118, 2014.

[51] M. Fisher, "The Emperor's speech: 67 years ago, Hirohito transformed Japan forever," The Atlantic, Aug 15, 2012. Available online: http://www.theatlantic.com/international/archive/2012/08/the-emperors-speech-67-years-ago-hirohito-transformed-japan-forever/261166/, accessed 2015.11.30.

[52] C.S. Holling, "Resilience and stability of ecological systems," Annual Review of Ecology and Systematics, vol. 4, pp. 1-23, 1973.

[53] A.W. Covert III, R.E. Lenski, C.O. Wilke, and C. Ofria, "Experiments on the role of deleterious mutations as stepping stones in adaptive evolution," Proceedings of the National Academy of Sciences of the United States of America (PNAS), vol. 110, no. 34, August 20, 2013.

[54] IRGC, Guidelines for Emerging Risk Governance. Lusanne: International Risk Governance Council (IRGC), 2015. Available from: http://www.irgc.org. Available online: http://www.mercerfinancialservices.com/content/dam/mmc-

web/Global%20Risk%20Center/Files/IRGC-Emerging-Risk-WEB-31Mar.pdf, accessed 2015.11.30.

[55] J.A. Schumpeter, Capitalism, Socialism and Democracy. New York: Harper & Brothers Publisher, 1942.

[56] H. Maruyama, R. Legaspi, K. Minami, and Y. Yamagata, "General resilience: taxonomy and strategies," Proc. IEEE 2014 International Conference and Utility Exhibition on Green Energy for Sustainable Development (ICUE), IEEE Press, March 19-21, 2014, pp. 1-8.

[57] R. Albert and A.-L. Barabási, "Dynamics of complex systems: Scaling laws for the period of boolean networks," Physical Review Letters, vol. 84, no. 24, pp. 5660-5663, June 2000.

[58] K.A. Hawick, H.A. James, and C.J. Scogings, "Simulating large random Boolean networks," Research Letters in the Information and Mathematical Sciences, vol. 11, pp. 33-43, 2007.

[59] R.S. Cohen, "How useful is the complexity paradigm without quantifiable data? A test case: The patronage of 5th-6th century Buddhist caves in India," in Chaos and Society (Frontiers in Artificial Intelligence and Applications), A. Albert, Ed. Amsterdam, The Netherlands: IOS Press, pp. 83-99, 1995.

[60] C. Gershenson, "Updating schemes in random Boolean networks: Do they really matter?" Proc. Ninth International Conference on Simulation and Synthesis of Living Systems (Artificial Life IX). MIT Press, 2004, pp. 238-243.

[61] S.A. Kauffman, "Metabolic stability and epigenesis in randomly constructed genetic nets," Journal of Theoretical Biology, vol. 22, no. 3, pp. 437-467, March 1969.

[62] T. Zhou, B.-H. Wang, P.-L. Zhou, C.-X. Yang, and J. Liu, "Self-organized Boolean game on networks," Physical Review E, vol. 72, no. 046139, pp. 1–6, October 28, 2005.

[63] A.M. Machado and A.L.C. Bazzan, "Self-adaptation in a network of social drivers: Using random Boolean networks," Proc. Workshop on Organic Computing, held in conjunction with the 8th International Conference on Autonomic Computing (ICAC '11), 2011, pp. 33-40.

[64] C. Gershenson, "Guiding the self-organization of random Boolean networks," Theory in Biosciences, vol. 131, no. 3, pp. 181-191, November 30, 2011.

[65] B. Luque, F.J. Ballesteros, and M. Fernandez, "Variances as order parameter and complexity measure for random Boolean networks," Journal of Physics A: Mathematical and General, vol. 38, pp. 1031-1038, 2005.

[66] I. Harvey and T. Bossomaier, "Time out of joint: Attractors in asynchronous random Boolean networks," Proc. Fourth European Conference on Artificial Life, July 1997, pp. 67-75.

[67] R.V. Solé, B. Luque, and S. Kauffman, Phase Transitions in Random Networks with Multiple States," Santa Fe Institute Working Paper 2000-02-011, 2000. Available online: http://www.santafe.edu/media/workingpapers/00-02-011.pdf, accessed 2015.11.30.

[68] C. Müssel, M. Hopfensitz, and H.A. Kestler, BoolNet Package Vignette, February 25, 2015. Available online: http://cran.r-project.org/web/packages/BoolNet/vignettes/BoolNet_package_vignette.pdf, accessed 2015.11.30

[69] J.T. Lizier, S. Pritam, and M. Prokopenko, "Information dynamics in small-world Boolean networks," Artificial Life, vol. 17, no. 4, pp. 293-314, Fall 2011.

[70] A.-L. Barabási and E. Bonabeau, "Scale-free networks," Scientific American, vol. 288, no. 5, pp. 60-69, May 2003.

[71] Weka 3: Data Mining Software in Java. Available online: http://www.cs.waikato.ac.nz/ml/weka/index.html, accessed 2015.09.15.

[72] R.C. Barros, M.P. Basgalupp, D.D. Ruiz, A.C.P.L.F. de Carvalho, and A.A Freitas, "Evolutionary model tree induction," Proc. ACM Symposium on Applied Computing (SAC '10), 2010, pp. 1131-1137.

[73] M. Göndör and V.P. Bresfelean, "REPTree and M5P for measuring fiscal policy influences on the Romanian capital market during 2003-2010," International Journal of Mathematics and Computers in Simulation, vol. 6, no. 4, pp. 378-386, 2012.

[74] A. Goodman, "Calculating the cost of disaster vs. the price of resilience," GreenBiz, December 7, 2012. Available online: http://www.greenbiz.com/blog/2012/12/07/Calculating-cost-disaster, accessed 2015.12.01.

[75] T.B. Fowler and M.J. Fischer, Eds., Rare Events: Can We Model the Unforeseen? Sigma, vol. 10, no. 1. Noblis, September 2010. Available online: http://www.noblis.org/noblis-media/20f758e0-b3b9-4b76-8b81-4cde0d7341f9, accessed 2015.12.01.

[76] R. Legaspi, H. Maruyama, R. Nararatwong, and H. Okada, "Perception-based Resilience: Accounting for the impact of human perception on resilience thinking," Proc. 2014 IEEE Fourth International Conference on Big Data and Cloud Computing, December 2014, pp. 547-554.

[77] H. Atlan, F. Fogelman-Soulie, J. Salomon, and G. Weisbuch, "Random Boolean Networks," Cybernetics and Systems: An International Journal, vol. 12, nos. 1-2, pp. 103-121, 1981.

[78] A. Dixit, "Comments on conference version of paper," in New Directions in Trade and Theory, A.V. Deardoff, J.A. Levinsohn, and R.M. Stern, Eds. University of Michigan Press, pp. 47-52, 1995.

[79] J.W. Dower, Embracing Defeat: Japan in the Wake of World War II. W.W. Norton & Co./ The New Press, 1999.

[80] C.M. Christensen, The Innovator's Dilemma: When New Technologies Cause Great Firms to Fail. Harvard Business School Press, 1997.

[81] B. Derrida and Y. Pomeau, "Random networks of automata: A simple annealed approximation," Europhysics Letters, vol. 1, no. 2, pp. 45-49, 1986.

[82] C. Müssel, M. Hopfensitz, and H.A. Kestler, "BoolNet – An R package for generation, reconstruction and analysis of Boolean networks," Bioinformatics, vol. 26, no. 10, pp. 1378-1380, 2010. Package available online: http://cran.r-project.org/web/packages/BoolNet/index.html, accessed 2015.11.30.

[83] C. Gershenson, RBNLab, 2003. Online software: http://rbn.sourceforge.net.