Meta-Theory and Machine-Intelligent Modeling of Systemic Changes for the Resilience of a Complex System

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***Abstract*— Resilience is the ability of a complex system to persist in, adapt to, or transform from dramatically changing circumstances. Our objective is to characterize the resilience of a complex system in depth by looking at what fundamentally constitutes and leads to system changes and how the system can be resilient to these changes. Our characterization is by a two-fold framework, 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 models, to realize our meta-theory. By starting with a meta-theory as background knowledge to guide our modeling, we avoid irrelevant, scattered and loosely knitted paradigms. Complementary, any truth presented by the inferred models that are not accommodated in the meta-theory may correct flaws in the meta-theory. To our knowledge, our framework that uses this linking of meta-theory and machine-intelligent modeling to characterize resilience is novel. The results we obtained from our simulations show that our framework is a systematic and pragmatic way of inferring predictive models of the contextual interaction behaviors of a resilient system.**

Keywords-dynamic system theories; resilience theories; system evolution theories; intelligent systems.

I. INTRODUCTION

We have witnessed in the past 10 years unprecedented massive devastations in terms of human lives, livelihoods and infrastructures brought about by strong natural hazards, such as Hurricane Katrina in 2005 that is considered to be one of the deadliest hurricanes in U.S. history, the Haiti earthquake of 2010 with its catastrophic magnitude of $7.0M_w$, the $9.0M_w$ undersea megathrust earthquake off the Pacific coast of Tōhoku Japan and the Fukushima nuclear power plant disaster that happened in its wake, and Haiyan in 2013 that is one of the strongest trophical cyclones ever recorded. To say, however, that our reality is mostly a series of mild and insignificant events punctuated by only a handful of massive devastations is inaccurate. The reality is that the occurrences of car, train and airplane crashes, sinking ships, oil, chemical and radiation spills and leaks, terrorist attacks, and spread of viruses, among others, are more frequent than we think. These so-called *normal accidents* [42] dictate the quick, frequent and incremental critical adaptations of our systems [27]. Then we can add to these the catastrophic events that are difficult to model and predict given their ill-defined and non-computable nature, or the so-called *Black Swans* and *X-events* (citations in [26][32]), which compel our systems to carry out dramatic and novel adaptations in order to survive and sustain their existence.

In other words, accidents and disasters are actually common and inevitable [27][47], hence, our systems that keep us, our way of life, and our world existing and flourishing must be *resilient*, i.e., able to withstand even large perturbations and dramatically changing circumstances and preserve its core purpose and integrity [53], and achieve generalized recovery once failure due to perturbation is inevitable [32]. While resilience theory has been adopted in various fields including ecology, biology, economics, finance, engineering, social science, and of course, human development (noteworthy surveys can be found in [31][32]), we argue for deepening further the analysis of what makes a system resilient through a deeper understanding of what *fundamentally* (foundational) constitutes and leads to systemic changes and how the system can be resilient through undesirable changes. To be resilient also means to embrace change [31]. We position our argument with the long-standing theories of system complexity, chaos, self-organization, and criticality, all of which are interesting emergent properties shared by complex systems and have been used to explain biological evolution [23][24], capacity for computation in physical systems [39][25][36], evolution of natural and socio-ecological systems [2][21][40][41], and the collapse of social systems [46][35][13][9]. We integrate essential concepts of these theories in varying grains of analyses and view this integration as a *meta-theory*.

We also argue for the use of a two-part machine-intelligent modeling, specifically, using network analysis and machine learning approaches, to automatically discover the hidden rules of contextual interaction behaviors of a complex system. 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 flaws in the meta-theory. Our meta-theory and machine-intelligent models can evolve together with increasing predictive isomorphism [34] to accurately represent the phenomena present *in*, i.e., endogenous (e.g., emergent properties, complexity, chaos, adaptation, and transformation, among others) and *with*, i.e, exogenous (e.g., disturbances, stress, and shocks), a complex system. To our knowledge, this linking of a meta-theory and two-part intelligent modeling to automatically characterize the contextual interaction behaviors of a resilient system is novel.

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Our paper is structured as follows. We elucidate in detail our meta-theory in Section II and discuss in length our machine-intelligent modeling approaches and simulation results in Section III. We make a final defense of our framework in Section IV and then conclude in Section V.

II. Our Meta-Theory

Figure 1 shows our meta-theory that cohesively puts together theories on complexity, chaos, self-organization, critical transition and resilience. The complex system evolution cycle in our meta-theory involves three regimes, namely, order, critical, and chaos. The second ordered regime, however, may 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 indicates system "fitness", i.e., the changing state of the system in terms of its capacity to satisfy constraints, its efficiency and effectiveness in performing tasks, its response rate (time to respond after experiencing the stimuli), returns on its invested resources or capital, and/or its level of control.

It is through our meta-theory that 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 [48]. Both characteristics are vital for the complex system to be resilient.

Our succeeding elucidation of our meta-theory, and the references that accompany our elucidation, would attest to the fact that the individual components, i.e., theories, which comprise our meta-theory are neither from a vacuum nor just mere speculations as they are evident in physics, ecology, biology, and system dynamics. What we are presenting here, however, is a plausible integration of these theories.

While complexity theory focuses on how systems consisting of many diverse elements give rise to well-organized, predictable behavior, chaos theory concerns itself with how simple systems pave the way for complicated nonlinear unpredictable behavior. Self-organization holds that structures, functions, and associations emerge from the interactions between system components and their contexts.

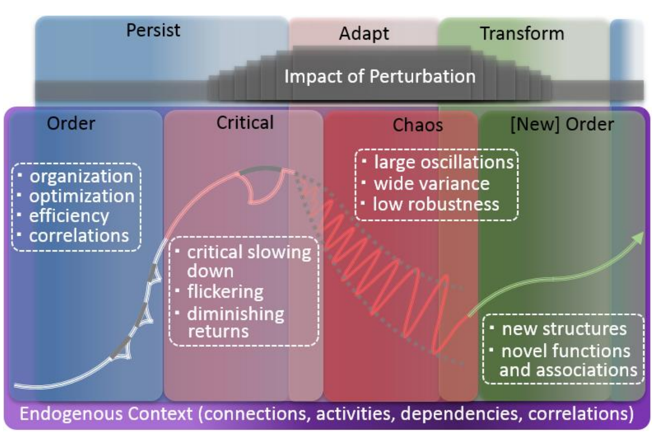

Figure 1. We integrate in varying grains of analyses how the different theories are plausibly related – hence, a *meta-theory*.

The critical regime, which we pay special attention to due to its importance, holds significant paradoxes – it may herald an unwanted collapse or become a harbinger of positive change [44], and while it may signal hidden fragilities [12], 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 [25][23][36]. While we adopt the terms order, critical, and chaos from dynamical systems theory [49], to persist, adapt, and transform is resilience thinking [14][8][10].

In the ordered regime, connections, interdependencies, and correlations begin to emerge. In this stage, the system will control and manage change. It will always attempt to re-establish equilibrium in order to persist in its ordered state each time it is perturbed (indicated by the dents in fitness). When it encounters a perturbation, it should readily bounce back and recover. System adaptations, however, will only be small, moderate, segmented and gradual, which are sufficient to handle only the manageable perturbations. The system changing or becoming permanently damaged from shock is not a major concern in this phase. To resume normal operations immediately and distort less in the face of minor perturbations is an increasing trait.

The ordered regime is a slow process characterized by increasing system efficiency and optimization of processes. What is also increasing, however, is the connectedness or tight coupling of the system components. Furthermore, the system's self-regulation becomes more finely tuned to the set of perturbations and responses it became familiar with. These tight coupling and rigidity only make the impact of any perturbation, regardless of its magnitude, to also increase. All this build-up is like an accident in the wings waiting to happen. Eventually, the system shall converge to a state that makes itself less adaptive to perturbations and therefore brings itself to the critical regime, which is at times also called the "edge of chaos" [25][23][36].

Scheffer et al. [44] elucidate the behaviors displayed by the system in the critical regime. One is a critical slowing down, i.e., the rate at which a system recovers from small perturbations becomes slow. Flickering may also be observed wherein a highly stochastic system flips to an alternative basin of attraction when exposed to strong perturbations. Page [40] added diminishing returns, which is the decrease in some system performance measure such as efficiency, robustness, or accuracy.

Comes a point when complexity can no longer be sustained and persistence and small adaptations are no longer possible, and so the system enters the chaotic regime. The building up of complexity becomes a constraint to adaptation and eventually leads to chaos. In the chaotic phase, the system will need larger adaptations, otherwise, it will need to transform to a new ordered regime to survive – one that will require dramatic change of structure and function.

Systems that demonstrate a transformative capacity can generate novel ways of operating or novel systemic associations and can recover from extreme perturbations [31]. Such systems learn to embrace change [31], and instead of bouncing back to specification, which is proved vulnerable and led to chaos, they bounce *forward* to a new form [29].

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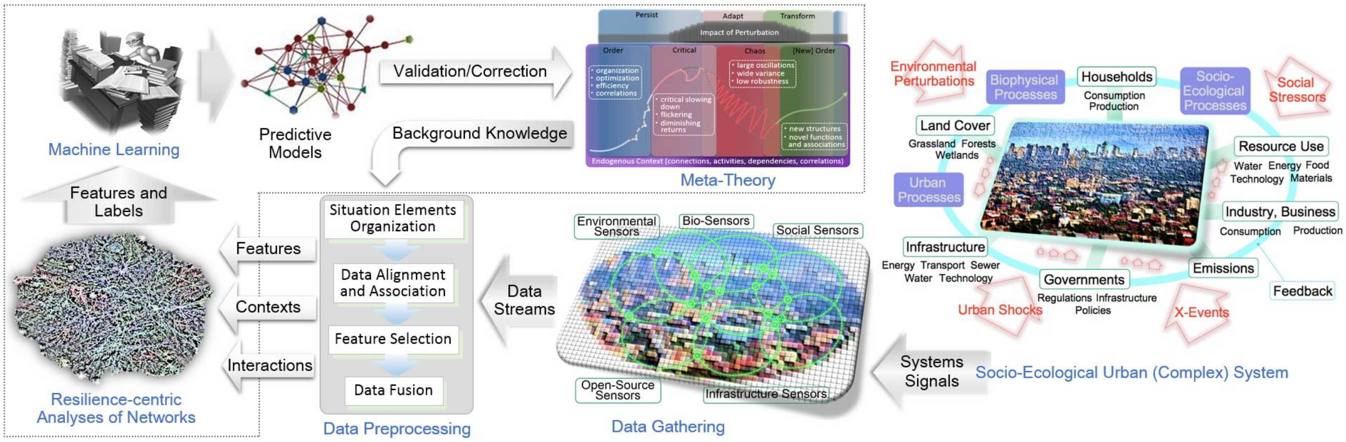

Figure 2. Our entire complex systems resilience modeling architecture, which includes our two-fold framework (enclosed in dotted lines).

III. MACHINE-INTELLIGENT MODELING OF THE RESILIENCE OF A COMPLEX SYSTEM

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 a *socio-ecological urban system* (SEUS), as shown at the right side of Figure 2, where diverse components, which can be systems in themselves [5][50], are intricately connected and may at times display rather extreme interdependencies. This SEUS contains continuous flow of resources, information, energy, capital, commerce, and people. The sustainability of a component will critically depend on its place in the system and how it, and the entire SEUS, can withstand perturbations.

The meta-theory shall be the by-product of integrated transdisciplinary perceptions of what characterizes systems resilience. We can develop social computing platforms for the collaboration and integration of expert and experiential knowledge (e.g., of aborigines and natives whose breadth and depth of experiential knowledge make their lack of formal education insignificant) [26]. We can also develop knowledge extraction 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 situation (e.g., disaster prevention, mitigation and management).

To gather large amount of data to model the SEUS, ubiquitous smart and interacting daily-living objects can offer a wide range of possibilities [6][43]. Urban services, such as vehicular traffic, banking, purchasing, personal security for citizens, social services, and tourism support, among others, have been recently enhanced by digital networks and mobile technology. Digital networks may also control sanitation and waste, water, traffic, communication, and energy. Tiny interacting embedded systems could also play a valuable role in protecting the environment from perturbations, e.g., sensors so minute, as the size of dust particles, but can detect the dispersion of oil spills or forest fires [6]. Furthermore, signals can come from volunteered data of people's use of mobile devices, social media, web searches, and online transactions, among others, which reflect human cognitive, affective and social behavior patterns. Using distributed multisensing capabilities and information processing, it is possible for the machine intelligence in the SEUS to infer accurate and informative models for situation analysis, situation awareness, decision-making and response, and component feedback in order for the SEUS to sense and shape the contexts that embed it.

Heterogeneous data related to humans, 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. Data pre-processing techniques can be employed to organize, align, and associate input data with context elements. With feature selction, it can also reveal which features can help improve concept recognition, generalization and analysis. Lastly, data fusion can address data and algorithmic complexities and the associated challenges that arise when independent data sources are combined to improve the quality of information.

All the pertinent features, contexts and interactions inferred in the preprocessing stage will be used in our two-part machine intelligent modeling. First, these information will be organized, represented and analyzed as a network. Paperin et al. [41] 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. 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 the disturbances (exogenous feature) that perturb it, will dictate its resilience.

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A. Simulation of a Complex System and its Properties

Although our aim is to model a socio-ecological urban system and its intricate properties, our major concern at this time, however, is that we have yet to embark on this endeavor. However, as a more than plausible work-around to this lack of complex system to analyze the viability of our framework, we used random Boolean networks (RBNs) to simulate the behavior of a complex system. The question, however, is whether the use of a RBN in lieu of an actual complex system plausible in demonstrating our concepts?

The literature is rich with RBNs being models of large scale complex systems [1][20]. RBNs are idealizations of complex systems where its systemic elements evolve [11]. They are general models that can be used to explore theories of evolution or even alter rugged adaptive landscapes [16]. Furthermore, although RBNs were originally introduced as simplified models of gene regulation networks [22][23][24], they gained multidisciplinary interests since they could contribute to the understanding of underlying mechanisms of complex systems, albeit their dynamic rules are simple [52], and because their generality surpassed the purpose for which they were originally designed [34][52][30][17].

A RBN consists of N Boolean nodes, each linked randomly by K connections. The state of a node at time t+1 depends on the states of its K inputs at time t by means of a Boolean function. The randomly generated Boolean functions can be represented as lookup tables that represent all possible 2^K combinations of input states. N represents the number of significant components comprising an adapting entity, such as gene, chromosome, trait, species, process, business unit, firm, traders, bankers, or workers – generally the number of agents attempting to achieve higher fitness [34]. The Boolean values may represent, for example, contrasting views, beliefs and opinions, or alternatives in decision-making (e.g., buying or selling a stock [24], cooperating with community or not). We can view K conceptually as affecting the mutual influence among nodes in an information network [52] 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 [52].

How complex can a RBN be? Given N and K, there can be $(N!/(N\text{-}K)!)^N$ possible connectivity arrangements, $(2^{2^K})^N$ possible N Boolean function combinations, and $((2^{2^K} N!)/(N\text{-}K)!)^N$ RBNs [19]! This is not counting the many possible updating schemes [16], and possibly extending to have nodes with multiple states [45]. With these 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 [20].

Inherent to RBNs are certain parameters that we found having accounted for by our meta-theory. At the same time, these parameters can be the controlling variables that the system can modify or adjust to demonstrate its resilient capabilities. In a plausible sense, these parameters can be viewed as *simulated* (but possible) outputs of the pre-processing stage of our architecture (in Figure 2) that led to the construct 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 becomes 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 in the last column of the lookup table. 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 high adynamical ctivity since there is no bias as to how the outputs should be [17]. High dynamical activity means high variability.
- *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 [52], hence, there is more variation in the network. Following [38], the number of inputs for the scale-free topology is drawn from a Zeta distibution 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 (set 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 neighbourhood $(i\text{-}lattice_i * k_i):(i+lattice_i * k_i)$ 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.

B. Simulation Models, Results, and Analyses

We now discuss our various simulation models starting with the base case. Our *base case* is a “conventional” RBN wherein 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 (i.e., 20).

The simulations we conducted involved testing the RBN's *robustness* when faced with perturbations. We applied the program of Müssel et al. as outlined in their BoolNet vignette [38] as follows. A perturbation is achieved by randomly permutating the output values of the transition functions, which although preserved the numbers of 0s and 1s, may have completely altered the transition functions. For each simulation a total of 1,000 perturbed copies of the network were created, and the occurences of the original attractors in the perturbed copies were counted. Attactors are the stable states to which transitions from all states in a RBN eventually lead. The robustness, R, value is then computed as the percentage of occurrences of the original attractors.

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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 3. Base case: map of the different regimes based on the sensitivity of conventional RBNs to perturbations.

It is very important to realize that robustness here is *not* resilience per se, since resilience refers to *what* enables a system (such as change in connectivity, dynamism, topology, and linkage, among others) to preserve its core identity when faced with perturbations [53]. We used *R to quantify the amount of RBN core identity that was preserved*. Hence, R is an indicator or measure of systems resilience.

Figure 3 shows our base case R-matrix in a dynamism-connectivity space, where each component is a R value. We can observe that it is at K=1 that the RBNs were most robust. The RBNs losing robustness at K=2 is indicative of critical slowing down and the system may therefore be tipped more easily into an alternative state [44], i.e., from order to chaos, which therefore reflects criticality. Hence, the ordered phase is found when K<2, the chaotic phase occurs for K>2, while the critical regime lies at the phase transition, i.e., at K=2 [16]. We can therefore observe from the base case the regimes present in our meta-theory (blue is order, purple is critical, and red is chaos).

We now move on to the results of the various simulation models we ran, beginning with the one in Figure 4. Each rectangle in the 3×5 *topology-linkage* space is a R-matrix with p-K dimensions. For example, $R_{2\times3}$ corresponds to the robustness matrix of RBNs with homogeneous topology and lattice linkage of size 2.5. $R_{1\times1}$ is the same R-matrix in Figure 3. We can see from the R-matrices the interesting properties that emerged. We can observe the critical regime broadening to K=3 (e.g., $R_{1\times2}$, $R_{2\times2}$, $R_{2\times3}$, etc.), or reoccurring at K>2 (e.g., $R_{1\times3}$ and $R_{1\times5}$) in between chaotic regimes, in the fixed and homogeneous RBNs with wider lattice. These extensions and reoccurrences 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 [17]. 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. [28] that a small world topology leads to critical regime dynamics.

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. $R_{2\times1}$, 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. We also have evidence wherein the *over-all mean* robustness began to continuously decrease towards zero for the fixed and homegeneous topology at K=2, which we interpret as a form of diminishing returns before transitioning to the chaotic regime. The over-all mean robustness values for the scale-free RBNs, however, remained satisfactory throughout. A complex system may therefore demonstrate resilience by *broadening* (*extending*) *the critical regim*e, *making the critical regime reoccur*, or *changing to a scale-free topology*.

Lastly, by applying again the methods of Müssel et al. [38], we tested for the sensitivity of the RBNs to greater perturbations. In each network transition, the transition function of one of the components is randomly selected, and then five bits of that function is flipped. Figure 5 shows the results we obtained. The first interesting phenomenon is the multiple occurrences of the ordered (e.g., in $R_{2\times1}$ and $R_{2\times4}$) and critical regimes (e.g., in $R_{1\times4}$, $R_{2\times3}$, $R_{2\times4}$, and $R_{3\times1}$), even after the chaotic regimes, which can point to resilience. The

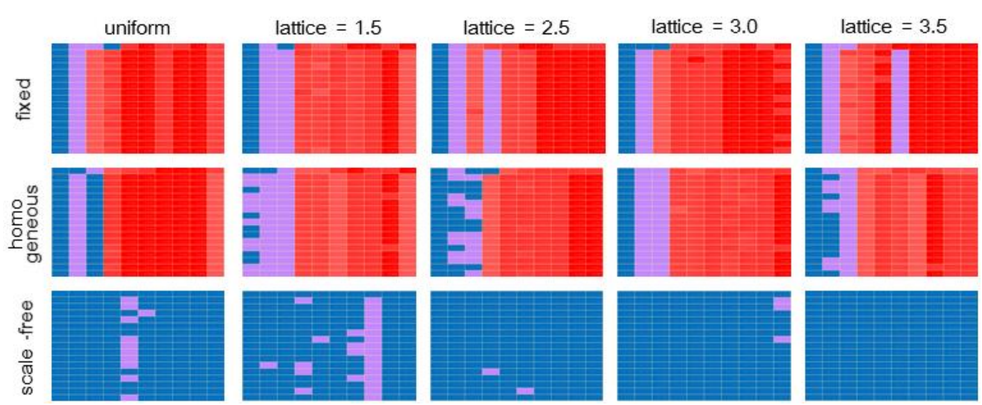

Figure 4. Map of the different regimes based on the sensitivity of RBNs to perturbations when activity, connectivity, topology, and linkage values were varied. The R-value ranges for each regime are as follows – order: [43,100] (in blue), critical: [22, 43) (in purple), and chaos: [0, 22) (in red).

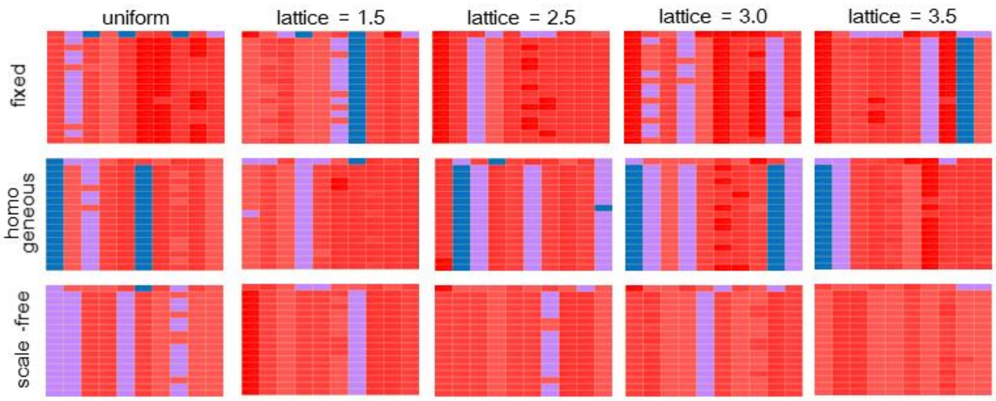

Figure 5. Map of the different regimes based on the sensitivity of RBNs to greater perturbations.

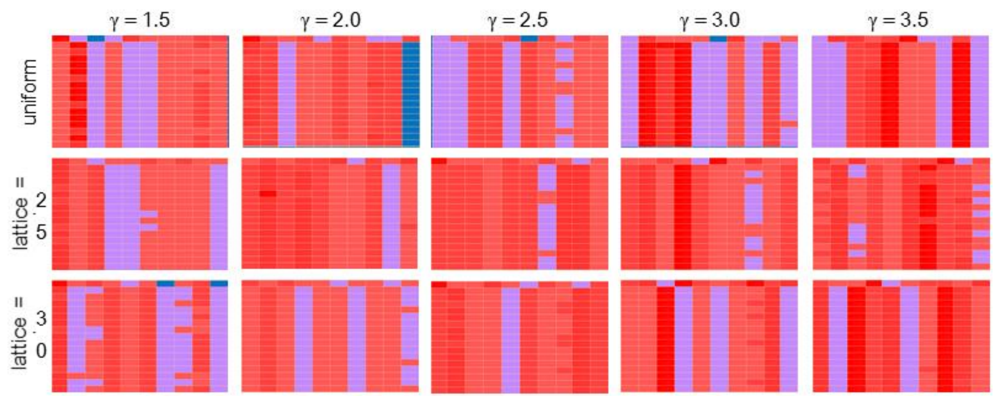

Figure 6. We simulated what will happen with changing γ values. The tables show that with other γ comes more expansions of the critical regime.

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. This is consistent with the findings of Barabási and Bonabeau [3] that scale-free networks are very robust against random failures but vulnerable to elaborate attacks. In our case, flipping bits in each transition of the network was too much perturbation for the scale-free RBN. But this does not mean, however, that its resilience is entirely lost. When we varied the parameter γ of the Zeta distribution, another interesting phenomenon emerged as shown in Figure 6 – we see more expansions and reoccurrences of the critical regime given other γ values. Again, to be capable of *prolonging or increasing the number of critical regime occurrences is indicative of a system being resilient*.

C. Machine-Intelligent Modeling

We can see from our simulation results that the various parameters we used can quantitatively explain our meta-theory. It is clear that the combinations of their specific values can be used to predict system states and changes and steer the system to desirable regimes, i.e., resilient states. The question now is how to infer these parameter relations that can be used as rules of contextual interaction behaviors that define the complex system's adaptive and transformative walks and therefore define its resilience.

Our solution is to use machine learning (ML) to automatically discover the hidden relations from the data we obtained about the complex system. We represent system contextual interaction behaviors as sets of feature vector and label pairs. Each feature vector is represented as a tuple of attribute values, i.e., <*topology*, *linkage*, *lattice*, *gamma*, *connectivity*, *activity*, *perturbation*>, and labeled with the corresponding *R* value that is indicative of system regime.

The ML algorithm should infer a model that is predictive – given the feature vector, what is the system regime (and its robustness)? Furthermore, the predictive model is one that can be used to help steer the system to a desirable regime – from the current feature vector that indicates the contextual situation of the system, which may be undesirable given *R*, which features can or should be modified to achieve a desirable regime. *This capacity to modify the contexts and predict the resulting behavior can make the system resilient*.

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 data further increases, ML can be used to automatically handle growing intricacies and complexities, as well as automatically infer the new relations emerging from the data.

To obtain the model with the best predictive capacity, we ran several well-known ML algorithms that are (*a*) function-based: linear regression models (LRM), multi-layer perceptrons (MLP), radial basis function networks (RBFN),

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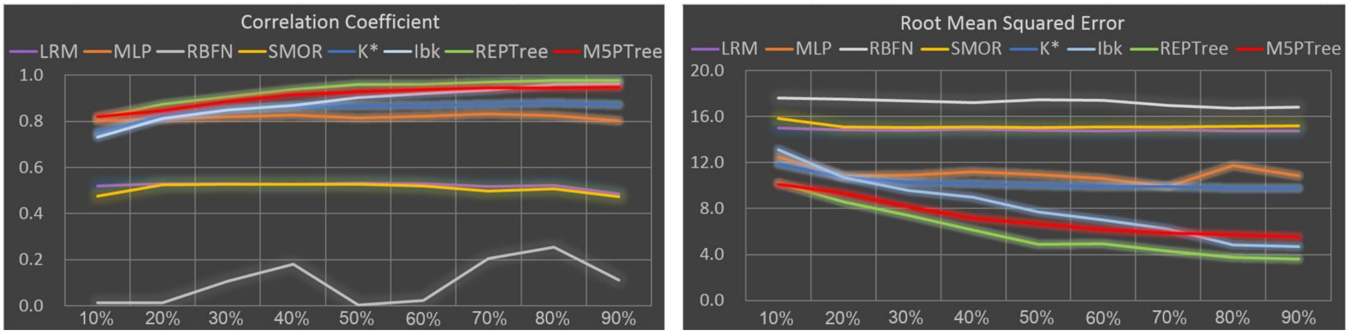

Figure 7. Prediction accuracy of the various models using %-split validation with increasing % values

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), using the WEKA open-source software. Due to space constraints, it is best that we refer the reader to the documentation [51] of these algorithms. 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 7), 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 7 shows the accuracy of prediction of the 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 may also need to 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 [4][18]. 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 [18]. Figure 8 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 of the tree as compared to the lattice feature. 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.

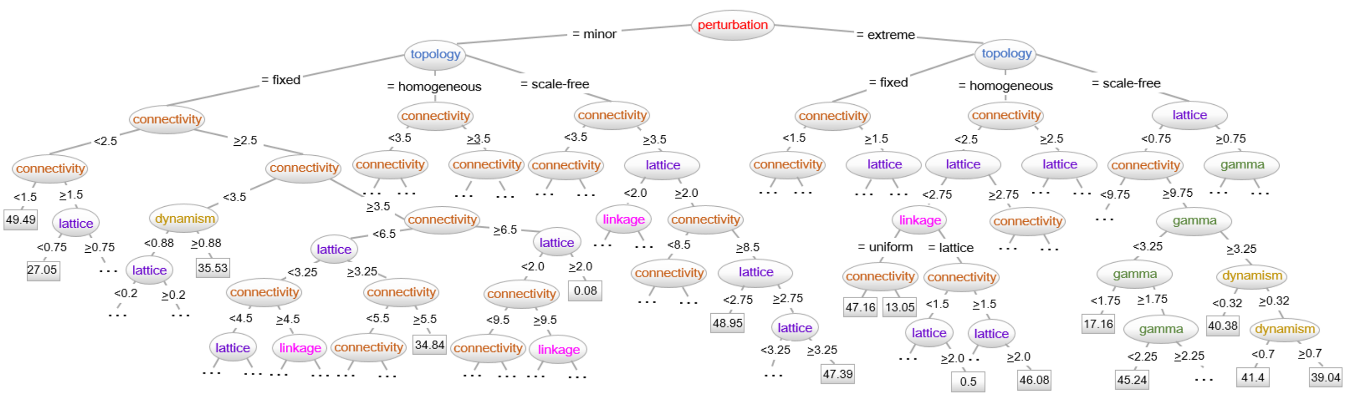

Figure 8. REPTree generated using Weka with a 10%-split validation. The size of the tree is 807, but only parts of it can be shown due to space constraints. The nodes specify the features (colored so as to distinguish each) with the edges as attribute values, and the leaf nodes as *R*-values.

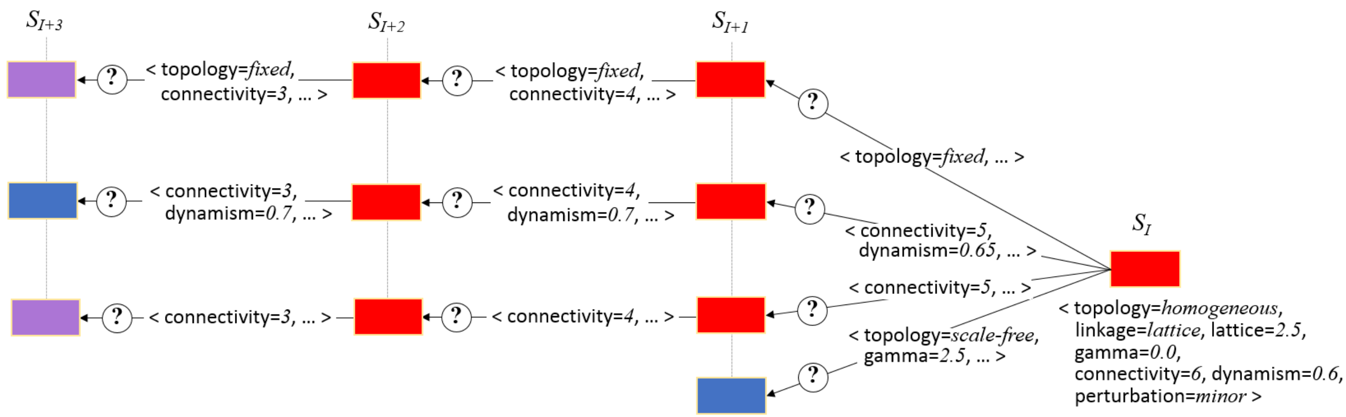

Figure 9. Illustration of how the strength of the predicitve models can be used to find the desirable regime states. The regime states (colored blocks) and their contextual features (in angle brackets) were taken from the robustness maps, i.e., $R_{2\times3}$, $R_{1\times3}$, and $R_{3\times3}$, in Figure 4.

Lastly, we refer to Figure 9 to illustrate how our strong 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 4 (specifically, from $R_{2\times3}$, $R_{1\times3}$, and $R_{3\times3}$), are obviously only a tiny portion of the possible entire regime search space since each cell in every *R*-matrix in Figures 4 to 6 is a regime state. Let us say that the system landed in the chaotic regime S_I, hence undesirable, as a result of the situational context (indicated by the feature vector shown below it) it found itself into. The predictive model can be used to predict the resulting regime when one or more of the S_I contextual features are changed. Hence, from the current regime state S_I, depending on which features are changed, the system may enter in one of the many possible S_{I+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 long haul for the system to seek alternative paths with longer chaos, but less painful and costly. This capacity to modify contextual features and predict the resulting regime demonstrates systems resilience.

The next challenges we need to consider in our future work towards a truly strong predictive capacity is greater. One formidable challenge in determining the optimal path to the desirable regime is the possibly thousands, millions or even astronomical number of potential paths, each with its own set of multiple candidate divergence. Without special algorithms to find the correct paths efficiently, the required computing time might be prohibitive. Equally challenging is the notion that the shortest path is not necessarily the optimal one. Again, the longer path may in fact possess the more bearable pain, trauma and adjustment compared to the immediate, but extreme and radical, change. Hence, what is significantly missing in our modeling is the quantifiable cost associated to each change. 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.

IV. In Defense of Our Framework and Approach

With our world witnessing critical systemic changes [26], we are concerned with how our systems can be resilient, i.e., it is 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 on our understanding of the resilience of our systems.

Our solution 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 meta-theory has to incrementally improve its knowledge based on what is being discovered 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 [16], and with agents having multiple states [45], 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. This mutual reinforcing of theory and intelligent models is not found even in well-established frameworks, such as the Adaptive Cycle [21], Self-organized Criticality [2], and Dual-Phase Evolution [41].

Our framework is data-centric as opposed to using formal verifications. 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, formal models tend to abstract

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much of the realistic nonlinear and stochastic intricacies of the system's internal workings [37].

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 are in fact general 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 [54]. 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" [11, p.88] may attest to the fact that our meta-theory being demonstrated by RBNs is not at all forced.

Lastly, we also believe that our proposed framework's contribution is to help solve the problem of persistently having linear, fragmented and incomplete knowledge in our theories and models. This insufficiency of knowledge is because our system and the contexts that engulf it are complex, indeed chaotic, and their behaviors are nonlinear, spanning multiple simultaneous temporal and spatial scales, and with large interrelations and interdependencies among variables. And even though we are fully cognizant of their non-computable aspects [7][15], we continue to wrap our minds around what is only computable [7]. All these lead to shallow and disconnected understanding of the evolving nature of our systems and the phenomena that consist and embed them. We address this problem by having knowledge integration and incremental learning in our framework, i.e., (*i*) the integration of transdisciplinary knowledge via our meta-theory, (*ii*) the integration into data-centric models of low-level signals or features of various phenomena that are endogenous (e.g., interdependencies, dynamism, topology, connectivity, etc.) and exogenous (e.g., perturbations) to the complex system, and (*iii*) the mutual reinforcing and incremental knowledge learning of the meta-theory (theoretic) and intelligent models (data-centric) that shall lead to increased predictive isomorphism [33][34].

V. Conclusion

We argued for a framework that characterizes what fundamentally constitutes complex system change by cohesively integrating concepts in complexity, chaos, self-organization and critical transition theories into one meta-theory. The meta-theory states that what comprises system change are the changing contexts, the fitness of the system to continuously evolve, and the capacity of the system to evolve its understanding and manipulation of the context.

We then argued for the use of networks and machine learners to quantitatively explain what leads to system change and how the system can adapt to and transform through change. 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. We obtained these rules as relations of system controlling variables by mining the data using ML algorithms instead of the conventional abstract mathematical formulations.

The meta-theory and intelligent modeling link will need to evolve as we collect more data with increased range of system endogenous and exogenous parameter values and more ways of introducing perturbations.

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