Complexity-based Thinking in Systems Intelligence for Systems Resilience

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***Abstract*— We posit that our models and approaches in systems resilience persistently demonstrate fragmented and dispersed knowledge because we fail to fully perceive the complexities of our systems and the situations that daunt them. We argue for a systems intelligence that has complexity-based thinking at its foundation. Complexity-based thinking involves methodological pluralism, law of requisite knowledge, and complexity absorption. The system integrates knowledge from heterogeneous sources, namely, massive information data points, expert and experiential knowledge, and perceptions of human sensors. As new facts are continuously derived with incoming evidence, the intelligent system self-improves its knowledge. With the synergism of heterogeneous knowledge, the emergence of new intelligence is possible. The integrated knowledge may expose unstated assumptions, reconcile inconsistencies and conflicts, and elucidate ambiguities in complex system behavior. The integrated knowledge is also aimed to influence the course of system vulnerabilities, destructive perturbations, and critical systemic changes.**

Keywords-complex systems; intelligent systems; complexity-based thinking; systems resilience.

I. INTRODUCTION

Although we have achieved significant advances in science and technology, human and economic losses due to disasters, accidents, social upheavals, and humanitarian crises remain significant. We believe that the reason for this is that we have yet to fully perceive the complexities of our world and life systems. Their nature is indeed complex, i.e., nonlinear, spanning multiple simultaneous temporal and spatial scales, and with large interdependencies among parts, which make it almost impossible to decompose them into independent processes [1]. Such behaviors may cause one situation, albeit due to a small stress or shock, to become critical and trigger other events in a cascading fashion such that the different situations within the propagation enhance themselves to criticality. Their heightened complexity can also pave the way for hazards that are extreme, unknown, unforeseen, or ill defined to impact the social, physical, environmental and technological dimensions simultaneously.

Consider for example the tortilla riots in Mexico in 2007 that was indirectly caused by a seemingly disconnected event – Hurricane Katrina in 2005. Zolli and Healey [2] recounted the events: Katrina disrupted 95% of oil production in the Gulf for several months that led to the price surge of American gasoline. This surge spurred investments in the alternative ethanol, which has corn as primary ingredient. Mexican farmers found themselves competing with the euphoria of ethanol investment bubble and with the US corn being dumped on Mexican markets at almost 20% less production cost. These interrelations and interdependencies between systems, namely, the oil rigs in the energy system, Katrina of the ecosystem, corn of the agricultural system, global trade system, and the social and political systems of US and Mexico, resulted to a rich world-energy (barrel of oil of nearly $140) being in direct competition with poor-world food (skyrocketed cost of corn). Each individual shock might have been felt by some sectors individually, but no one would have predicted the coincident crises in energy, finance, and food, as well as the confluence of shocks [3].

Another example, as recounted by McCracken [4], is the fragmented knowledge that if were connected could have helped predict the events of 9/11: At the time of 9/11, any clear predictive knowledge of an attack was absent – vital indicative information that in combination could have served as a warning were scattered in isolated stovepipes in the CIA, NSA, FBI, and State Department. Hence, analysts across these agencies had only fragments that did not help prevent the loss of nearly 3,000 lives and 6,000 more injured, tons of rubble and steel that obscured eight city blocks for almost nine months, and a shock to pertinent US financial markets. Only after did the intelligence community piece together the indicators of the large-scale attack on US soil.

In the presence of daunting complexities, our systems need to be resilient. *Resilience* is the ability of a system to persist, adapt, or transform in structure and function in the midst of even large shocks and stresses that come from a range of hazards [1]. With looming world crises, resilience has rapidly found itself at the top of the global development agenda [5]. It is the case, however, that our shortcoming to comprehend the complexities of our systems leads to our models of, and approaches to, systems resilience to persistently demonstrate linear, fragmented and dispersed knowledge. Such limited knowledge prohibits the acquisition of a complete and coherent view, which only adds to the uncertainty problem. Our models do not demonstrate the critical links and interdependencies that mesh our world and life systems. Our approaches are intimidated by the task of elucidating our hyper-connected systems. These lead to our shallow understanding of the nature of systems complexity.

Hence, we argue in this paper for a systems intelligence that has complexity-based thinking at its foundation.

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Primarily, complexity-based thinking accepts the notion that our knowledge can only be limited and bounded. But instead of surrendering to this shortcoming, complexity-based thinking seeks new ways to redefine the limitation threshold and further enlarge the boundary of knowledge. Complexity-based thinking involves methodological pluralism, law of requisite knowledge, and complexity absorption. To embody this thinking, our system acquires (i.e., represents and infers) and integrates knowledge from heterogeneous sources, namely, massive information data points, expert and experiential knowledge, and perceptions of human sensors. With the synergism of diverse knowledge, the system opens itself for the emergence of new intelligence in the face of daunting complexities. The integrated knowledge is aimed to expose hidden assumptions, reconcile conflicts and inconsistencies, and elucidate ambiguities in complex system behavior. More importantly, the integrated knowledge may be used to sense, make sense of, and shape the course of impending, on-going or ensuing system vulnerabilities, destructive perturbations, and critical systemic changes.

Our paper is structured as follows. In Section II, we argue for resilience thinking to be complexity-based thinking, and elucidate in Section III the framework of our multi-dimensional intelligent system that embodies complexity-based thinking. We then discuss in Section IV the broad impact of the system's integrated knowledge. Finally, we conclude in Section V.

II. Resilience Should Be Complexity-Based

Gilpin and Murphy [6], while citing Richardson and Cilliers [7], explained that in the midst of numerous schools of thought within the complexity sciences, three broad approaches have emerged, namely, reductionist, soft, and complexity-based. They differentiated these three as follows. Reductionist complexity science uses a limited number of universal laws to characterize natural reality. Its problem, however, is that in emphasizing universal commonalities, it hides in the abstraction the individual system idiosyncrasies. Second, soft complexity science distinguishes between social reality and the natural world, and therefore rejects the application of complexity, which is a theory that originated in nature, to the social realm unless done metaphorically. However, it has been known that society exhibits complexity [8]-[10], and that the social and the natural are linked [11][13]. Complexity-based thinking, however, distances itself from any pursuit of exact knowledge or universal absolutes and deals with the fact that our knowledge is bounded, and we can only seek this boundary in whatever way possible and suitable [6].

We believe that resilience thinking should be complexity-based thinking. Complexity-based thinking, as pointed out by Gilpin and Murphy [6], adheres to the notion that "complex matters demand a methodological pluralism" [9, p.12]. Because knowledge can only be partial and bounded, pluralism provides several elucidations of a phenomenon. This roots back to Ashby's law of requisite variety, which states that by having diverse response mechanisms available to the system, the system is able to compensate a larger variety of perturbations [13]. Gilpin and Murphy also echoed Cooksey's compelling point, i.e., complexity-based thinking seeks "diverse avenues for discovering what may end up being a multiplicity of answers that are differentially sensitive to and grounded in specific circumstances, conditions, people, times, and places" [14, p.84]. Similarly, in resilience thinking, by making available to the system a diversity of mechanisms to sense, make sense of, and respond to situations, the system is able to be resilient to a larger variety of shocks and stresses.

We believe that complexity-based thinking also includes the law of requisite knowledge, which states that a system must not only be dependent on a variety of available response mechanisms but must also know which one to select and how [15]. Otherwise, the system would have to try out actions blindly, which would consequently compromise its resilience. Therefore, in managing the resilience of a system against shocks and stresses, increasing the variety of its actions must be accompanied by the increase in the capacity to choose the best action.

Lastly, complexity-based thinking involves complexity absorption. As explained by Gilpin and Murphy [6], complexity-based thinking not only prefers the diversity of options, as well as tolerance for their possibly conflicting representations, there is also the ability to adapt, as well as self-organize, as fresh knowledge is captured, generated or re-created in order to modify an existing goal or drop it for a new goal. In other words, there is a paradigm shift from fragmented, individual and controlling views to a complex adaptive system view that enables capture, creation and refinement of knowledge.

III. Systems Intelligence Framework

We detail in this section the various aspects of our intelligent system, as shown in Figure 1, with complexity-based thinking at its foundation. We then relate these aspects in the succeeding section to the processes of sensing, making sense, and shaping system-related complexities.

First, we need to distinguish between data, information, knowledge, and intelligence (which in our case refers to artificial intelligence) [6][16][17]. Data is a stream of facts about entities and events that are situated in a sequence. We can imagine everything in the world as represented by data points. We are surrounded by a massive amount of data that is "getting ever vaster ever more rapidly" [18, p.1]. What we have is a digital universe that is huge, and continuously increasing exponentially [19]. Information consists of data related to a given context [20]. It is descriptive as it demonstrates patterns that have sense [21]. Knowledge is the collection of information that has been proven useful in a given context [21]. Knowledge involves the appraisal of the information of its relative significance [20] using one's experience, values, insights and expertise [22][6]. Data, information, and knowledge lie along this continuum [20][6].

Intelligence, however, is a process. It involves learning and applying knowledge in order to respond to changing contexts. Our system is intelligent since it performs the acquisition, integration, and application of knowledge. Furthermore, as new data and information come in, the system's knowledge should improve based on new evidence,

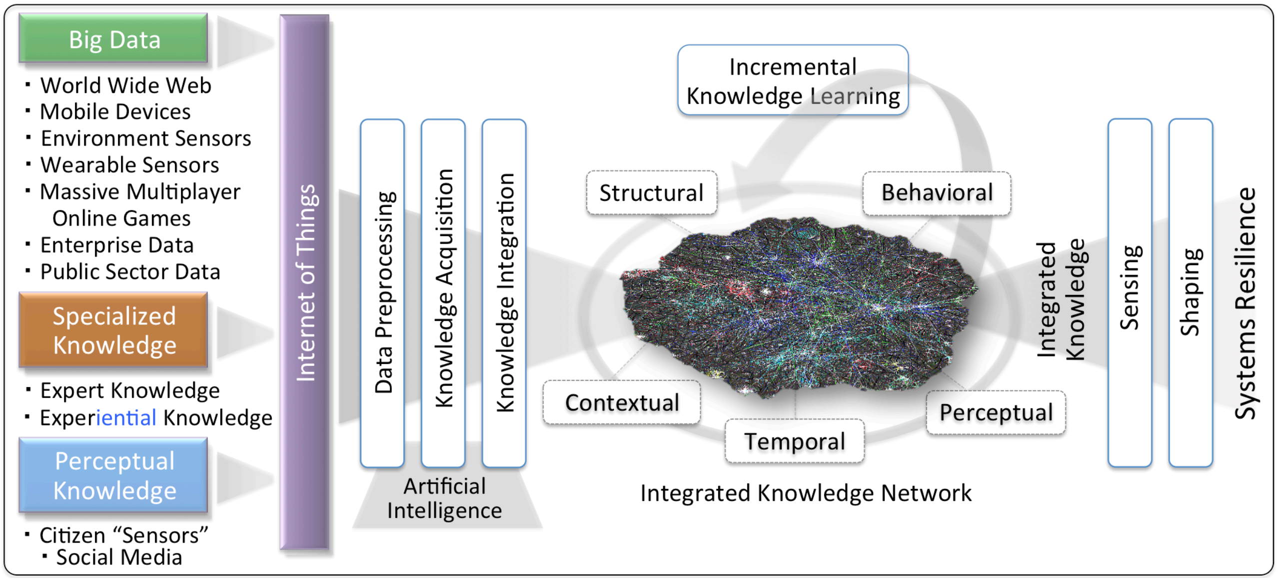

Figure 1. Complexity-based systems intelligence framework for systems resilience

hence, it learns new knowledge and does it incrementally. This makes our system suited for complexity – as Friedrich Engels wrote, "that the world is not to be comprehended as a complex of ready-made *things*, but as a complex of *processes* in which the things… go through an uninterrupted change of coming into being and passing away." [23, p. 44, italics in source]. Our system is also intelligent since it involves sensing (acquiring), making sense (integrating) of, and shaping (applying knowledge) itself or its situation. Sensing involves physical and social sensors obtaining data and information. The process of making sense involves predictive modeling, situation analysis and awareness, anticipation, as well as providing actionable information. Shaping is influencing and changing the course of the situation and the way the system adapts to its environment.

A. *Complexity Thinking Is Methodological Pluralism*

In light of the above, our goal is to realize an intelligent system that can infer and integrate heterogeneous knowledge from three varied sources, namely, massive mostly non-structured data or Big Data, expert and experiential knowledge, and public perceptual knowledge sourced by citizen sensors. While the last two are contextualized knowledge, the intended knowledge has yet to be derived from the first. The intelligent system must cull through massive data points, theoretical and empirical evidences, and human perceptions that are made available through the Internet of Things (IoT) where data and technology are democratized, i.e., available to as many people as possible.

IoT extends Internet connectivity beyond desktop and mobile computers to a diverse range of sensors (e.g., physical ambient sensors that include UAVs and satellites), machines (e.g., from coffee makers and washing machines to jet engine components), and devices (e.g., mobile and wearable devices) that we can think of that communicate and interact with the external environment and to each other. According to Intel, the IoT world is growing in a very fast pace, i.e., from two billion in 2006, 15 billion in 2015, to a projected 200 billion by 2020! [24].

1) Big Data

The digital universe is ever expanding as millions of data points from diverse sources are created every second from heterogeneous sources. The World Wide Web is basically an open world where information of various kinds are sent, uploaded, downloaded, and received. 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 powerful computing sensors and software that allow us to collect data about our physiology and mobility. It also allows us to log our daily activities that include fitness routines, web searches, online transactions, and interactions in social media platforms and micro-blogging sites, among others. Furthermore, ubiquitous ambient sensors [25] can also offer a wide range of possibilities for gathering large volumes of data that are human-related (e.g., displacements of millions of refugees), environmental (e.g., earthquakes, tsunamis, climate and weather changes, and changing landscapes). There are also the massive multiplayer online games that have become unprecedented tools to create and validate theories and models of social and behavioral dynamics of individuals, groups, and networks within large communities [26]. Enterprises may collect billions of real-time data points on products, resources, services, and stakeholders, which can provide insights on collective perceptions and behaviors, as well as resource and service utilizations. There are also data that public bodies produce or collect, 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 (e.g., health and medical, education, water, waste disposal, electricity, evacuation, and daily living-related programs) made available to them.

2) Specialized Knowledge

Carpenter et al. [3] stated that we have the tendency to wrap our minds around the computable and ignore the non-computable aspects of systems complexity. To account for the non-computable, they admonished considering a wide range of perspectives. They clarified why our society should put value not only on expert models, since they also emphasize narrow, segregated and domain-dependent views, but also look at instances where perceptions of experience-filled individuals, although lacked in formal education, led to breakthroughs. They cited several cases: crucial information from hunters and loggers prompted new approaches that saved the giant jumping rat in Madagascar from their sudden demise, and information from indigenous fishermen saved endangered bumphead parrotfish.

Complex problems may have many solutions that may differ in the required execution to obtain the quality of the desired outcome [3]. Hence, a diverse team of experienced individuals is more suited than a team of expert solvers [27].

3) Perceptual Knowledge of Human Sensors

We adopt the definition of perception as the process in which we actively and purposefully [28] acquire, organize, recognize, and interpret the sensory information we receive in order to make sense of what we perceive [29][30]. Perception therefore allows us to take in all, or part of, the sensory information presented to us and transform them into something meaningful [31]. Perception also includes how we respond to the information we receive [31]. An input to our perception triggers in us a psychological (i.e., cognitive and affective) response, and on the basis of this response, we perform an action [32]. Our individual differences dictate the difference in our perceptions, which can explain why individuals and communities respond differently despite being presented with the same facts, conditions, support, assurance, resources, and other forms of stimuli [33].

Perceptual knowledge on resilience can be provided by, or obtained from, individuals who are physically on the ground, i.e., those who are directly experiencing the situation (e.g., war, refugee migration, pandemic, radiation leaks, etc.) such as the members of the affected community, local government, law enforcers, first responders, and disaster managers, and from those who are virtually on it, i.e., those who are not in the affected area but have a good view of the situation as seen on TV, Internet, and social media. Armed with their mobile devices and sensors, these individuals will relay all information they perceive, as well as add their own analyses, sentiments, and judgments as they deem necessary.

B. Law of Requisite Knowledge

1) Knowledge Acquisition

Our focus is on data that are made available publicly and online through the IoT, and accessed freely for the common good. For example, if satellite imagery credibly shows troops massing outside a village, the people of that village can be informed so as to flee, or if necessary, respond with violence to save their lives [34]. There have been advocacies for data and technology to be *democratized*, i.e., to be made available to as many people as possible, including the grassroots population, and not just to those who are inherently, or were made to assume, to be in a position to use them (e.g., governments, international organizations, multi-national companies, and Internet giants, among others) [34]. History has demonstrated how ordinary people achieved resilience when empowered by technology and big data [4][35]. Furthermore, having more data openly available will encourage public participation to achieve novel and innovative solutions to societal challenges.

From structured data stored in spreadsheets and relational databases, Internet-based technologies have allowed the collection of unstructured data. For example, the company Digital Reasoning (www.digitalreasoning.com) estimates the unstructured data created per day to be 2.5 quintillion. Unstructured data does not follow the traditional database field formats nor adheres to a formal data model. This includes video, audio, images, graphics, and sensor signals, as well as partially formatted or semi-structured data, including text-based documents (e.g., word processing, PDFs, emails, blogs, wikis, tweets, web pages, and web components) and documents with self-describing elements such as tags and markers (e.g., XML and HTML). While structured data is organized in a database format and are readily accessible by search algorithms, the irregularities and ambiguities in unstructured data make its representation, let alone its comprehension by the machine, difficult.

Expert knowledge, which is organized and scientifically validated, mostly appears in scholarly publications. Experiential knowledge, however, is commonly unpublished in the literature since they are hard to express, specify, and scientifically validate. Consider tacit knowledge, for example, which highly depends on personal character traits that it cannot be subject to accurate communication [6]. Social computing, however, can help design platforms for diverse problem solvers to articulate and collaborate their perceptions, and incorporate them in a repository of evidences of what may or may not work in a situation [33]. Similarly, perceptions of citizen sensors are unstructured knowledge that populates traditional and social media in the form of meaningful texts, videos, photos, and audio.

The difficulty with data acquired from various sources is that they tend to be heterogeneous in terms of their spatial and temporal aspects, data collection modalities, structure type (structured, semi-structured or unstructured), data type (hard physical data vs. soft data), and in sensor outputs with different resolutions and sampling rates. Data preprocessing should therefore be carried out, the result of which will be a set of features that can characterize the various entities of interest. This is certainly a non-trivial task. If the varied data are commensurate, then raw signal data can be easily combined (e.g., using Kalman filtering) [36]. If not, extracting the common features may involve further data transformation, such as filtering out noises and outliers, data alignment (remove any positional or sensing geometry and timing effects from the various data), common spatio-temporal referencing, and data association (determine which object is associated to which event) [37]. Metadata may also be generated to describe the heterogeneous data [36].

Artificial intelligence is needed to transform data to knowledge. The first step is knowledge acquisition (and not information acquisition as it is only a means to this end), which involves a lot of processes to transition from bytes to usable patterns and meanings. We use the term "acquisition" to refer to various approaches to obtain knowledge from data. Knowledge representation [38] is one of the central and most important concepts in artificial intelligence that constructs formalisms (e.g., semantic nets, ontologies, systems architecture, logic rules) that will make complex systems easier to design and implement. It represents information about the world in a machine-understandable form that a computer system can utilize for complex problem-solving tasks. Knowledge inference [38] refers to acquiring new knowledge from existing facts based on certain rules and constraints that are made understandable through knowledge representation. Automated reasoning (e.g., inference engines, theorem provers, and classifiers) is the mechanism behind inferring new knowledge by applying existing facts and logic rules [39]. A similar concept is knowledge discovery, which was borne out of data mining and describes the process of automatically searching through large volumes of data for patterns that can be considered knowledge.

2) Knowledge Integration

Once knowledge is inferred from these varied sources, the next step is to weave them together. *Knowledge integration* will involve inferring knowledge relationships among hugely varying domains into a coherent structure while revealing hidden assumptions and reconciling areas of conflicts, inconsistencies, and uncertainties. It should describe how domain-specific concepts are interrelated for transdisciplinary problem and solution formulation. It must be able to synthesize micro-level, individualized and domain-dependent knowledge to contextual systemic knowledge. The integration of knowledge from diverse sources should not lead to vague generalities, but rather to become effective in enhancing knowledge. This task is difficult and remains an open research area.

Knowledge integration involves weaving the diverse knowledge into coherent networks, hence, a *knowledge network*. Paperin et al. [40] 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. Representing the integrated knowledge into coherent networks can be accomplished by using network and dynamic graphs theories and models.

Another aspect of knowledge integration is to incorporate new incoming knowledge into existing prior knowledge [41]. This allows the body of knowledge to grow incrementally. This is also a non-trivial task as new and existing knowledge may interact in unanticipated ways that may demand significant changes to the developing knowledge [41].

3) What Kind of Knowledge?

We aim for our system to infer knowledge that can be used to describe the complexity of our hyper-connected systems, the endogenous and exogenous forces that influence them, and their interactions. We believe that the Five Aspects Taxonomy [42] provides a good coverage of the essential aspects of the complexity, which our intelligent system needs to be knowledgeable of.

The taxonomy is conceived for the engineering of socio-technical systems that exhibit complexities in multiple levels (i.e., components, subsystems, systems, and system of composite systems) and dimensions (aspects). The five aspects include: (a) *structural* – elaborate hierarchical or layered network arrangement of system components that demonstrate couplings and dependencies in multiple scales; (b) *behavioral* – variances in system responses to different stimuli; (c) *contextual* – environmental circumstances in which the system exists; (d) *temporal* – various system properties, dimensions and needs may change over time together with the dynamic environment in which it exists; and (e) *perceptual* – stakeholder perceptions of the system and the environment that embeds it, which may change with context shifts and cognitive constraints and biases.

We can imagine the knowledge network as consisting of nodes that represent entities, such as system components (and subcomponents), as well as endogenous and exogenous factors. The edges depict their interactions as per the Five Aspect Taxonomy.

C. Complexity Absorption

As per above, knowledge integration can be defined as the process of incorporating new information into existing knowledge, which may require modifying the existing knowledge to accommodate the new knowledge *and/or* modifying the new in light of the existing knowledge [41][43]. Integration of knowledge from various knowledge sources can result in novel knowledge on how to solve a problem. Knowledge integration can also help unmask the uncertainty created by the multiple sources of knowledge.

The argument for knowledge integration is also present in resilience as evidenced by Bohensky and Maru [43]. Complexity and uncertainty management in socio-ecological systems can benefit from integrating diverse types of knowledge. Also, collaborations that facilitate integration of diverse perceptions lead to socio-ecological resilience [3].

Our intelligent system is aimed to integrate and preserve heterogeneous knowledge for triangulating for the truth, continuously track incoming and on-going information as well as evolving circumstances and conditions, and aid the system to better self-organize as it acquires new knowledge, adapts with new functions, and transforms to new goals. New facts should be continuously derived, and incoming evidence should be used, to improve current knowledge repositories. Hence, knowledge will be learned incrementally by our system. Our system, with its synergistic integration of knowledge, may lead to the emergence of increasing intelligence in the midst of complexity.

IV. Sense, Make Sense Of, and Shape Complexity

With the network of connected and evolving knowledge about systems and their complexities in terms of structure, behavior and context, and how they are perceived, to be changing over time as derived from heterogeneous sources, what then can we use this knowledge for? Again, to sense, make sense of, and shape system behaviors when faced with complexities that can threaten the existence of the system.

Sensing involves detection, whereas making sense involves recognition and identification. Detection is similar to when an alarm goes off at home; we know that something has occurred but we may not recognize what it is. Recognition happens when the alarm is matched with a known reference, already known pattern, or learned category, e.g., the alarm matches either a gas leak or possible burglary. Identification is when we go down to the kitchen and finds out that the gas leak indicator is also blinking.

There were cases, however, that the alarm did not go off when it should. Indicators leading to 9/11 were pointing to an imminent large-scale attack on US soil [4]. The alarm did not go off because the consequence then of these indicators were not clear, the US intelligence community had only fragments, and there was no actionable information that was presented [4]. The increase of the price of tortilla by 400% easily set off the alarm of a food riot in the streets of Mexico, but no one could have predicted that Hurricane Katrina indirectly, but significantly, caused it [2]. Other examples are provided by Robertson and Olson [34]: When the social web during Iran's postelection crisis in 2009 was datamined, shifting perceptions in terms of awareness, advocacy, organization, mobilization, and eventual action and reaction were unmasked; the data visualization at that time of the Iranian blogosphere revealed a dramatic increase of user population with religious orientation; and the examination of microblogs related to Arab Spring revealed that socio-economic terms (e.g., housing, income and minimum salary) were most relevant in 2010, but in 2011, tweets were related to corruption, revolution, and freedom. The alarm did not go off in these instances because it was not set to detect the proxy indicators of upcoming dramatic system changes and there was no inter-related set of knowledge regarding a multiplicity of factors.

How then can the knowledge network be used for sensing and making sense? The following can only be possible with the connected multi-dimensional knowledge present in the integrated knowledge network:

- *Describe the emergence of system-wide properties*. In the sciences and arts, emergence is a process whereby systemic entities, patterns, and regularities arise through interactions among smaller or simpler entities that themselves do not exhibit such properties. Individual idiosyncrasies get lost as the components become tightly coupled and dependent. However, since our system will track the historical transitions of bytes to integrated knowledge, we theorize that it can also describe the evolution and emergence of system properties.
- *Perform anomaly detection*. After using intelligent algorithms to determine systemic "habitual" (i.e., normal, routinely behavior) patterns, anomaly detection techniques can then be used to detect what is out of the normal, which can include proxy indicators or digital alarms of upcoming changes [34].
- *Resolve conflicting information from same or different sources*. When platforms are made open for humans (and intelligent artifacts alike) to contribute information, it is possible that conflicting information are received due to cognitive biases, perceptual errors, or communication differences. For example, social media can generate a ton of interests in seconds, but can also warp and disperse the true information (at times intentional, e.g., tampering data, spreading rumors) into thousand fragmented pieces. With our methodological pluralism, it is possible to perform multi-dimensional corrections and validations to eliminate the false positives.
- *Perform "unsaid-knowledge" analytics*. We introduce this term to refer conceptually to mining for knowledge that cannot be explicitly stated since it depicts intuition, common sense, wisdom, and culture-based assumptions – those that are hard to quantify and measure but have proved essential to identifying anomalies. It also includes tacit knowledge that is abstracted by our understanding and difficult, if not impossible, to codify or transmit [6].
- *Perform descriptive and predictive analyses* [44]. Descriptive analysis is to mine past knowledge that are connected and related physically, semantically and conceptually to explain what has already happened and why it happened. Predictive analysis is forecasting future outcomes across various scenarios or situations.

Sensing technologies can provide support, but, unlike shaping, they do not necessarily change the system state. Early warning systems, for example, can help people get out of the way of an inevitable disaster, whether or not they change the course of events. The knowledge network is aimed to provide actionable strategies that will convert sensing to shaping, which can be achieved as follows:

- *Perform prescriptive analytics*. The aim of prescriptive analysis is to identify which decision and response will lead to the optimal or most effective result given a specific set of objectives and constraints [44]. The challenge for a truly strong prescriptive capacity is great. One that is formidable, for example, is determining the optimal path to the desirable regime where the potential paths are possibly thousands, each with its own set of multiple candidate divergences. Without the algorithms to find the optimal path efficiently, the required computing resources can become detrimental [1].
- *Guide the planning and implementation of a creative chaos* [45]. The idea is to use the knowledge network to simulate system shocks that can propel the system into the vortex of change. It is efficient and effective to scan for situations that can force latent problems to surface than design the system to not fail, which, paradoxically, only makes the system more vulnerable and less resilient. Furthermore, by introducing chaos into the system, not only do we prepare the system to be adaptive to failures, but also to bring out opportunities for innovation since

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chaos would break tight couplings only to give way to new and previously unknown effective connections. Incidentally, the Five Aspect Taxonomy is a frame to comprehend facets of innovation strategies and communicate emerging technologies [42].

- *Infer a theory of lever point* [46]. A lever point is known as that critical point within the system where applying a little change can make a big difference and a small shift a big change. At that point the behavior of the complex system changes fundamentally.
- *Infer theories of system openness and modularity and their trade-offs* [47]. Modularity can help contain ensuing disasters by compartmentalizing. However, too much compartmentalization can prevent aid from moving in and out of the system from various sources. Also, too much openness can transmit harmful shocks, as in financial collapse, pandemics, and invasive species migrating easily across similar and connected landscapes.
- *Perform complexity mapping*. Provide real-time mapping of the events and feedback loops occurring during complex situations. The ability to monitor the behaviors of social, physical, environmental and technological systems in real time make it possible to understand where models, plans, policies and programs are failing and to make necessary adaptations.

V. CONCLUSION

Resilience can be enhanced and sustained by integrating, rather than fragmenting and dispersing, knowledge about the complexities of our systems. Mastering a more holistic understanding of our systems will shed light on their couplings, temporal and spatial boundaries, interaction behaviours, and emerging irregularities or inaccuracies, as well as proven or plausible alternative resilient strategies.

We argued that the fundamental difficulty in managing resilience is the complexity that characterizes our systems. We then argued for managing resilience by realizing an intelligent system whose intelligence framework is based on complexity thinking. The result is an integrated knowledge of systems complexity, which is automatically inferred from heterogeneous data about the nature and contextual interaction behaviours of our systems. With this integrated knowledge realized, our systems can better meet head-on the so-called unknown unknowns or uncertain uncertainties.

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