A Socio-Physical Approach to Systemic Risk Reduction in Emergency Response and Preparedness

William Ross, *Student Member, IEEE,* Alex Gorod, *Member, IEEE,* and Mihaela Ulieru, *Member, IEEE*

***Abstract*—This paper proposes a socio-physical approach that considers jointly the interaction and integration of the social and physical views of a system to improve emergency response and preparedness. Using network analysis, it is shown that the explicit socio-physical approach yields meaningful qualitative and quantitative differences when compared with approaches that focus on the social and physical views in isolation. The benefits of this proposed approach are illustrated on a case study using clustering analysis and a proof-of-concept simulation. This new approach leads to risk reduction by enabling a more informed and coordinated response strategy following an incident and a better identification of possible consequences and preparation strategies prior to an incident.**

***Index Terms*—risk reduction, socio-physical view, clustering coefficient, emergency response and preparedness, systemic risk, situational awareness.**

I. Introduction

Emergency-response efforts in major recent disasters such as Hurricane Katrina (2005), Deepwater Horizon (2010), and the Japanese earthquake and tsunami (2011) have revealed that the current uni-dimensional risk-reduction strategies are insufficient and that there is a need for a holistic systemic approach [1]–[4]. Traditionally, emergency-response activities, both nationally and internationally, have focused on managing consequences during the aftermath of disasters with insufficient emphasis placed on developing strategies a priori to reduce risk and minimize damage. Globally, the number of disasters has been growing, particularly in the least-equipped areas, where emergency preparedness efforts are constrained by existing financial resources, among other factors [5], [6].

Besides the large-scale crises caused by natural disasters, "normal" accidents can also lead to widespread devastation—in particular circumstances that can trigger chain reactions, as observed in [7]. Crises may also stem from social, economic, and political consequences [6]. Regardless of cause, it is imperative that emergency responders take into consideration both the social and physical implications resulting from their actions, allowing important interdependencies to be accounted for before and after a disaster [2], [8].

Considering the social and physical dimensions in isolation leads to a partial view of the problem space and, subsequently, to a marginal assessment of systemic risk [9]–[14]. Since risk-reduction strategies are based implicitly on the view taken of an emergency situation [15], [16], this paper proposes an encompassing socio-physical view, which considers jointly the interaction and integration of the social and physical views of a system. This combined view leads to enhanced awareness of how the system operates, increasing the potential for improved emergency response and preparedness in the face of systemic risk.

There have been several attempts to define and measure systemic risk [2], [9], [17]–[20]. In fact, the term finds its origin in financial systems, where it refers to "the risk that the failure of one financial institution (as a bank) could cause other interconnected institutions to fail and harm the economy as a whole" (Merriam-Webster). The term has also gained in popularity following the financial crisis of 2008, and numerous quantitative and qualitative analyses, metrics, best practices, and lessons learned can be extracted from the financial domain [21]–[24]. In emergency response, a parallel is to consider different system components, where a failure in one component could result in a failure that impacts not only other components, but the whole system, as well (e.g., electrical power failure). Using an integrative view of the system, such as the socio-physical view, is instrumental in improving responders' awareness of systemic risk and in allowing them to consider appropriate risk-reduction strategies that can leverage resources effectively to protect critical infrastructure and services.

Networks and their interactions are frequently the cause of the cascading failures that "are the most common mechanism by which local risks can become systemic" [1], [2], [25]–[28]. For example, scale-free-type networks are in the power-law form and, independent of network scale, are considered to be resilient to random attacks, yet are very vulnerable to deliberate attacks [29], [30]. This is just one example of how the underlying properties inherent within network structures can result in different failures and underscores the importance of network measures in increasing responder awareness. Other measures can be used, as well. In emergency response, for instance, the clustering coefficient, together with connectivity, can inform responders of the structural type of a network being examined, its distribution patterns, and underlying behaviour [30]–[33]—all of which can prove invaluable when facing the need to make difficult decisions (e.g., limited resources). These measures can provide insight into how to influence the network to reduce possible risks, making the entire system more resilient.

In order to objectively demonstrate the extensiveness of the explicit, combined socio-physical view in comparison to the social and physical views in isolation, the clustering coefficient is used as a "measure of local connections, or 'cliquishness'" [31], [34], and it is hypothesized that the different nodes

W. Ross and M. Ulieru are with the Adaptive Risk Management Lab, University of New Brunswick, Fredericton, NB, Canada e-mail: (william.ross@unb.ca, ulieru@unb.ca).

Alex Gorod is with SystemicNet, LLC in New York, NY, USA e-mail: (alex_gorod@yahoo.com).

Manuscript received ; revised.

that emerge as being critical in this combined view will more accurately represent the critical nodes in the system. Subsequently, this new holistic viewpoint allows for a more expanded representation and understanding of the system, particularly with respect to interdependencies considered in the context of emergency response and preparedness.

In this paper, a real-life case study involving an incident at a university steam plant is analyzed using the proposed approach. The clustering coefficient is calculated for different perspectives of the system to illustrate the role of the socio-physical view in increasing situational awareness and reducing systemic risk in emergency response and preparedness. Lastly, these results are incorporated into a simulation to gain further situational insight into an important subsystem related to the case study.

II. Risk Reduction in Emergency Response and Preparedness

There are many formal and informal definitions of risk related to emergency response, such as $risk = probability \times consequence$, $risk = threat \times vulnerability \times consequence$, and risk being, according to the World Health Organization, “the probability of harmful consequences resulting from interactions between natural or human-induced hazards and vulnerabilities” [1], [6], [35]–[37]. In spite of the variation in definitions, risk can be viewed in general as a function of hazards to which a system is exposed and system vulnerabilities, and is modified by the level of preparedness, as shown in the relation below [6]:

$$Risk \propto \frac{Hazard \times Vulnerability}{Level\ of\ Preparedness} \quad (1)$$

where $Hazard$ includes “any phenomenon that has the potential to cause disruption or damage to people and the environment” and $Vulnerability$ refers to “the conditions determined by physical, social, economic and environmental factors or processes, which increase the susceptibility of a community to the impact of hazards” [6].

The denominator, $Level of Preparedness$, reflects actions taken to increase emergency preparedness, including raising awareness, investing in critical infrastructure and training programs, and developing emergency-response plans. Thus, it also relates to the response phase. Emergency response and preparedness can be approached reactively and proactively [38]. A reactive phase seeks to combat the effects of a hazard after it has occurred, whereas a proactive phase strives to prepare for a hazard (or emergency) a priori. As an example, a proactive approach might seek to install a new power generator at a critical hub in the system to provide more time for electricity to be restored in the event of an emergency, while a reactive approach, following an emergency, seeks to restore the system to a point of stability. According to the relation in Eq. (1), any increase in the level of (response and) preparedness will reduce the level of risk.

Considering systemic risk, where the failure of one system component may lead to the failure of the entire system, results in the following relation:

$$Risk_{Sys} \propto \sum_{i=1}^{n}\sum_{j=1}^{m} \frac{Hazard_i \times Vulnerability_{ij}}{Level\ of\ Preparedness_{ij}} \quad (2)$$

where $Risk_{Sys}$ includes risks associated with all hazards (1 to n) and system components (1 to m), $Hazard_i$ is the hazard being considered, and $Vulnerability_{ij}$ is the current system component (e.g., structure or organization) whose vulnerability is being assessed according to $Hazard_i$. $Level\ of\ Preparedness_{ij}$, then, is the associated preparedness of system component j with respect to $Hazard_i$.

It should be noted that the vulnerability of a specific component is not considered in isolation. Instead, the vulnerability will depend on the view under which it is assessed. If viewed from only a physical (or social) perspective, for instance, a different vulnerability might be assessed than if considered from a socio-physical perspective. In this way, the vulnerability of component j may involve the synergistic effect of vulnerabilities across all components in the entire system, if viewed from a holistic perspective.

Based on the relation in Eq. (2), an investment in a system component during the proactive phase that increases the level of preparedness (e.g., infrastructure and training) will lead to a decrease of the overall systemic risk. Likewise, following a hazard or emergency, improved understanding of how the hazard impacts system components during the reactive phase will also diminish the overall systemic risk, as critical components can be secured first before moving onto secondary components.

While we currently have no control over natural disasters, work has been done to reduce the likelihood of human-induced hazards, particularly those resulting from accidents [7], [39]–[41]. Reason, for example, posits that accidents can be traced to one or more of the following areas—organizational influences, unsafe supervision, preconditions for unsafe acts, and unsafe acts themselves—and offers the Swiss Cheese Model for analogy, noting that holes exist in each of these areas (like in different slices of the cheese), but that accidents occur when the holes momentarily align [39], [40]. Reason further suggests that these holes are the result of two types of failures: active failures, which are humans performing unsafe actions; and latent failures, which are actions stemming from organizational and technical decisions that permit active failures to occur (e.g., poor safety culture [39], [40]). STAMP (Systems-Theoretic Accident Model and Processes) similarly seeks to improve safety through embedded control structures that enforce system constraints, as it views accidents as resulting from either a failure to enforce a system constraint or a failure to identify a constraint during system design [41]. Even so, others contend that some safety interventions are not always beneficial. Perrow’s Normal Accident Theory, for instance, among other things considers the interaction of safety devices and complexity, and argues that in systems with high complexity and tight coupling, the addition of safety measures may actually increase the risk of human-induced hazards [7]. Nevertheless, these all point to the importance of considering hazards from a holistic perspective that includes the human factor, and the current paper builds off this work by proposing the explicit use of the socio-physical approach in better equipping responders to prepare for and respond to hazards.

III. Socio-Physical Approach to Risk Reduction

In emergency response, systems have generally been viewed fragmentally [38], thus lessening the overall understanding of the system and therein contributing to systemic risk. These views typically capture either the physical (e.g., critical infrastructure) [42]–[45] or the social (e.g., organizations, individuals, and policies) [46]–[48] system dimensions. The proposed approach, however, takes into consideration an integrated socio-physical perspective, where both the physical and social system components and their interactions are explicitly captured. By being aware of this broader perspective, each stakeholder in the system increases their awareness of how their service(s) affect others and how others' services affect them.

Generally, stakeholders, depending on their interests and responsibilities, have different views of what constitutes "the system." For example, municipal technicians might be directly involved only in the maintenance of the physical structures of a city (e.g., electricity and water), police and ambulance in the safety of the citizens and the condition of the roads, and businesses might be concerned primarily about reducing the down-time resulting from the emergency. These partial views, if kept in isolation, result in an incomplete picture of the system. This is why an explicit, combined, socio-physical view of the system that takes into account these partial views is imperative for increasing awareness during an emergency. This would be particularly relevant to an incident commander in charge of responding to the incident and, for preparedness, to stakeholders in charge of maintenance and upgrades.

Having an expanded representation of the system enables its components to be enumerated and the interrelationships within and across views to be clearly identified. This makes it possible for the effect of a hazard on the entire system to be more readily assessed. Furthermore, critical components, which may affect the system more than others, can be recognized in advance without considering a specific hazard. This can be used in the proactive phase to determine an appropriate preparedness strategy for a host of possible hazards, and similarly, the same information can be employed in the reactive phase to strategically prioritize resource allocation during response.

When constructing the socio-physical view, which components and interactions are added to "the system" is more often a matter of art than of science. However, the following are some rules of thumb which we have found useful. (Note that several tools exist that can be used to assist in the creation of the socio-physical diagram, including UML diagramming tools, Python's NetworkX package, and Systemigrams [49].) For the physical view, start by considering those components that provide vital services, such as electricity, before moving onto secondary components like office buildings. Also, consider grouping similar components together; for example, if considering a university, several residence buildings could be grouped into a single component: on-campus housing. The

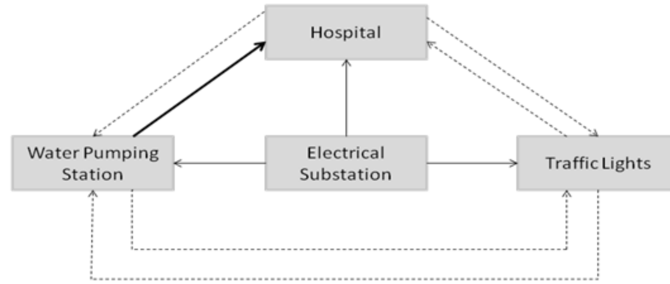

Fig. 1. Clustering coefficient example (actual service provision is shown using solid lines, while potential service provision is shown using dashed lines)

interactions between the components should be directional and take the form **component X** *provides [some service]* to **component Y**. Once again, begin by focusing on the vital services, as the diagram can quickly become cluttered. For the social view, consider the human components that make the system what it is. Continuing with the university example, we can consider students and teaching and operations staff immediately. We can then add the interactions between the components in the same way as we would physical components. Lastly, to link the physical and social views, consider which services components in the physical view provide to components in the social view, and vice versa, and add these to the diagram (see [38] for detailed diagrams).

IV. Clustering as a Metric for Emergency Response and Preparedness

The socio-physical approach presents the system as a set of components (i.e., nodes) and relationships (i.e., links). Therefore, when identifying critical system components, various measures from network theory can be applied. In [38], for instance, measures of centrality were used to identify key system components according to their consumption and production of services.

The clustering coefficient can be used as a measure of systemic risk [21], [50]. In this paper, the clustering coefficient is adopted to identify critical nodes [51] using a combined socio-physical perspective, which provides a more complete and accurate picture of the system. This is crucial, as emergencies often impact only a few components of the system directly, but, indirectly, because of the interrelationships that exist among components, have a much broader systemic effect.

As an example of the use of clustering in emergency response, consider the situation shown in Fig. 1. The electrical substation supplies power to the hospital, traffic lights, as well as to the water pumping station (solid, non-bolded directed edges). The traffic lights and hospital do not provide services to each other or to the water pumping station. However, the water pumping station, supported by the electrical substation, provides water to the hospital (bolded directed edge).

Whenever a particular node (e.g., water pumping station) is supported in its task to deliver a service to another node (e.g., hospital), which is itself sustained through a service by the helping node (e.g., electrical substation), the "triple" that is formed by these three nodes becomes connected and is termed a "triangle." The example shown in Fig. 1 contains one "triangle" (bolded line) and six possible "triples" (dashed lines and bolded line). It is the ratio of triangles to triples that is being measured by the clustering coefficient.

By being aware of the dependency triangle, response efforts could focus first on the electrical substation, rather than the water pumping station, under limited resources, as electricity is a necessary prerequisite to pump water to the hospital. In this way, the clustering coefficient can be used to identify critical interdependencies and help prioritize response efforts.

More importantly, this figure of merit allows us to objectively compare different approaches and determine which is better for emergency-response: social and physical (in isolation) or a combined socio-physical approach. It will be shown quantitatively that the combined perspective provides increased information to emergency responders. In addition, it will be shown that this metric can also be used to say something (qualitative) about the criticality of nodes.

A. Clustering Equations

Clustering can be measured using a directed or undirected network, which in turn impacts what equation is used; and it can also be measured locally, from the perspective of each system component, or globally, from the perspective of the entire system [33]. In this paper, because the networks we consider are directed based on service provision, we focus on the directed network equations using both local (i.e., local clustering coefficient) and global (i.e., average local clustering coefficient and global clustering coefficient) measures.

1) Local Clustering Coefficient: The local clustering coefficient is a measure from the perspective of each node regarding the number of triangles it forms versus the total number of possible triangles (i.e., triples) it could form in its local neighbourhood, which includes all nodes to which the current node connects. In other words, it is the ratio of how many of the nodes in the local neighbourhood receive a service from the current node and provide a service to another node in the neighbourhood. The equation for the local clustering coefficient is as follows (adapted from [52]):

$$C_i = \frac{number\ of\ triangles\ connected\ to\ node_i}{number\ of\ triples\ centered\ on\ node_i} \tag{3}$$

where C_i is the local clustering coefficient of $node_i$; the numerator is the number of triangles connected to $node_i$, i.e., the number of neighbours $node_i$ has in common with its connected neighbours; and the denominator is the total number of triples centered on $node_i$, i.e., the total number of possible common neighbours defined by the following equation:

$$triples_i = neighbours_i \times (neighbours_i - 1). \tag{4}$$

2) Average Local Clustering Coefficient: The average local clustering coefficient is a measure from the perspective of the entire network. It tells the average ratio of support to service-providing nodes compared to support to non-service providing nodes, considering a set of localized neighbourhoods. It takes the local clustering coefficients for each network node and averages them to achieve a global measure, according to the following equation [52]:

$$\bar{C} = \frac{1}{n}\sum_i C_i \tag{5}$$

where $\bar{C}$ is the average local clustering coefficient of the network, n is the total number of nodes, and C_i is the local clustering coefficient of $node_i$.

3) Global Clustering Coefficient: The global clustering coefficient considers the entire network, as well, but rather than averaging local clustering coefficients, it computes a single ratio for the entire network. In doing so, it characterizes the network according to a global ratio of interdependence, as the entire network and not patches of local neighbourhoods is taken into account. The equation for the global clustering coefficient is as follows (adapted from [52]):

$$C = \frac{number\ of\ triangles\ in\ the\ network}{number\ of\ triples\ of\ nodes} \tag{6}$$

where C is the global clustering coefficient of the network, the numerator is the total number of connected triangles in the network, and the denominator is the total number of triples in the network.

These three measures will be used to analyze the university case study presented in the next section and, in particular, the merit of the socio-physical view in relation to the social and physical views in isolation.

V. University Case Study

In early December 2006, an incident in the steam plant at a university in south-western Ontario, Canada, resulted in the closure of the university for half-a-day. The incident stemmed from a combination of factors, including routine boiler maintenance and an unexpected drop in water pressure supplied to the steam plant by the city, which caused water to collect in the steam pipes and resulted in a water-hammer explosion when the boiler was brought back online.

Although steam was restored by early evening, this seemingly innocuous incident revealed several critical interdependencies within the university system. For example, the lack of steam production affected student residences on campus and nearly resulted in the cancellation of student examinations the following day. More crucially, however, it also affected the university hospital, where steam is used to sterilize equipment and bedding. In fact, as a result of the incident, hospital evacuation procedures were begun, wherein many surgeries needed to be rescheduled and non-essential hospital services temporarily suspended. These procedures also involved the nearby network of city hospitals, which had to prepare for the potential receiving of evacuated patients.

On the day of the incident, the EOC did not have a clear understanding of what caused the explosion, but they were expected to respond to the immediate needs of the university community: protecting critical research labs and restoring heat to residences and classrooms. Of importance, the EOC did not have a social understanding of what role steam played in the university hospital, and were only informed about the

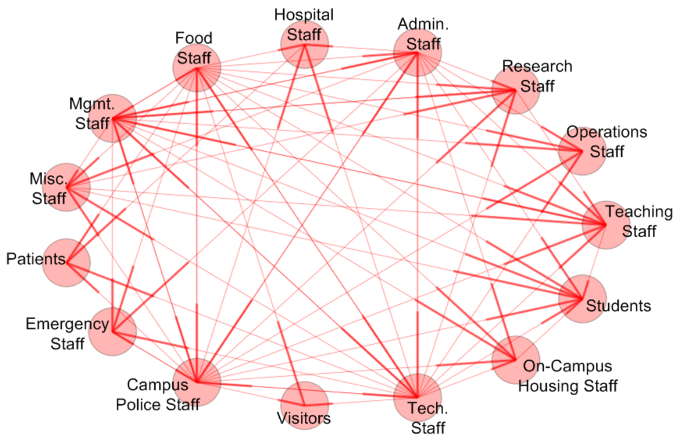

Fig. 2. Social view of the university system (directed edges represent services provided from one node to another)

issue once it began affecting hospital staff. Such unawareness nearly resulted in a major cascading systemic effect that would have impacted the entire city, including bus services—as buses would have been used to assist in the evacuation.

In response to such partial views, we propose a combined socio-physical view for emergency response, and compare this approach using the above case against the social and physical views in isolation. Using clustering as a metric, three views of the university system will be presented, along with analysis, to objectively determine which view provides responders with the better understanding of the system-of-interest, all in an effort to reduce systemic risk. It should be noted that this type of oversight is easy to correct prior to an incident, but not during one, when other pressures and responsibilities take precedence and must be managed.

A. *University's Social View*

The social view of the university is shown in Fig. 2. It captures the social network components (i.e., nodes) and interrelationships (i.e., links) in the university system. Fifteen social nodes have been identified, including students, teachers, researchers, operations staff (e.g., maintenance), and management staff; university hospital staff and patients have also been included in the network. Interrelationships between these nodes, such as *provide instruction*, *provide administrative assistance*, and *provide care* have also been captured, but, to facilitate readability, do not appear in the figure. These represent the services, from the social perspective, that one node provides to other nodes in the network. This is depicted in the figure using thin and thick line endings. For each of the line endings in the figure touching a node, a thick end means that the node is receiving a service from another node, while a thin end means the node is providing a service to another node.

1) University Social View's Clustering Coefficient: As described in the previous section, the clustering coefficient can be used to help identify critical system nodes. The local clustering coefficient values for each social node are shown in Table I and have been computed based on the network depicted in Fig. 2. (Note that Table 1 contains values for the physical and socio-physical views, as well, to help simplify comparisons.)

The values for the social view are found under the "Social or Physical" column in Table I. For this view, eight social nodes participate in a clustering relationship, while the remaining seven nodes have a clustering coefficient of 0.0, which means that for each of these nodes none of its neighbours is connected to any other of its neighbours. The table also lists the number of triangles and triples (i.e., the total number of possible triangles) for each node.

The number of triangles indicates the density of the clustering. Two nodes may share the same local clustering coefficient value, but one node may participate in significantly more clustering relationships than the other node (i.e., its clustering is more *dense*). For example, node S1 has a local clustering coefficient of 0.5, while node S6 has a coefficient of approximately 0.32. Considering only the clustering coefficients would result in node S1 being assessed as the more clustered node. However, investigating the number of triangles (1 for S1 and 58 for S6) suggests that node S6 is actually the more clustered node. This type of a node supports more nodes in being fully operational (e.g., the electrical substation helping the water pumping station to operate) and can, therefore, be considered a more critical node. Subsequently, clustering density, expressed as the number of triangles, needs to be considered along with the clustering coefficient, which indicates the existence of at least one triangle. Both data are recorded for each node in Table I and depicted visually in Fig. 3 and Fig. 4.

For the social view, the most critical nodes are *Administrative Staff* (S4), *Food Staff* (S6), *Management Staff* (S7), *Campus Police Staff* (S11), and *Technology Staff* (S13). Evidently, these nodes do not represent the main functions of the university, which include teaching, learning, and research. Instead, they correspond to those supporting components that are needed by the university to maintain operational continuity.

In Fig. 3, the local clustering coefficients for each node in the university system are shown. The line on the bottom represents either the social or the physical view, while the line on top represents the combined socio-physical view, including the interrelationships across views. This information is taken from Table I and appears as stacked lines. As seen, in the majority of cases, the local clustering coefficient of a node increases when the more holistic socio-physical view is considered (the larger gaps between the two lines), and any non-zero value indicates the presence of at least one triangle.

By comparison, the number of triangles for each node in the university system is shown in Fig. 4. The information is extracted from Table I and includes node data from the social-or-physical column (bottom line) and the socio-physical column (top line). In all cases, the number of triangles in the socio-physical view is at least as large as the number of triangles when considering the social and physical views independently. As these represent non-averaged values, triangles are better in identifying the most critical supporting nodes in the system.

TABLE I
LOCAL CLUSTERING ANALYSIS, INCLUDING TRIANGLES AND LOCAL CLUSTERING COEFFICIENTS, FOR EACH OF THE THREE VIEWS: SOCIAL, PHYSICAL, AND SOCIO-PHYSICAL (UNDERLINED TRIANGLE VALUES IDENTIFY THE MOST CRITICAL NODES IN EACH VIEW)

View	Label (ID)	Social or Physical			Socio-Physical		
		Number of Triangles	Number of Triples	Local Clustering Coefficient	Number of Triangles	Number of Triples	Local Clustering Coefficient
Social Nodes	Teaching Staff (S1)	1	2	0.5	1	2	0.5
	Operations Staff (S2)	0	0	0.0	44	132	0.333333
	Research Staff (S3)	2	2	1.0	2	2	1.0
	Admin. Staff (S4)	53	132	0.401515	53	132	0.401515
	Hospital Staff (S5)	0	0	0.0	1	2	0.5
	Food Staff (S6)	58	182	0.318681	74	210	0.352381
	Mgmt. Staff (S7)	47	110	0.427273	47	110	0.427273
	Misc. Staff (S8)	2	6	0.333333	2	6	0.333333
	Patients (S9)	0	0	0.0	0	0	0.0
	Fire Safety & Emergency Mgmt. Staff (S10)	0	0	0.0	69	182	0.379121
	Campus Police Staff (S11)	56	182	0.307692	235	702	0.334758
	Visitors (S12)	0	0	0.0	0	0	0.0
	Tech. Staff (S13)	57	182	0.313187	74	210	0.352381
	On-Campus Housing Staff (S14)	0	0	0.0	0	0	0.0
	Students (S15)	0	0	0.0	0	0	0.0
Physical Nodes	Teaching System (P1)	0	0	0.0	1	6	0.166667
	Campus Police (P2)	0	0	0.0	3	6	0.5
	Operations (P3)	0	0	0.0	7	20	0.35
	On-Campus Housing (P4)	0	0	0.0	1	6	0.166667
	Food (P5)	0	0	0.0	72	182	0.395604
	Transportation (P6)	36	132	0.272727	243	702	0.346154
	Water & Sewage (P7)	7	56	0.125	156	506	0.308300
	Research System (P8)	0	0	0.0	0	6	0.0
	Hospital (P9)	0	0	0.0	1	6	0.166667
	Comm. & IT (P10)	0	42	0.0	131	462	0.283550
	Oil & Gas Inventory (P11)	1	2	0.5	1	2	0.5
	Steam (P12)	7	56	0.125	156	506	0.308300
	Electricity (P13)	35	132	0.265152	242	702	0.344729

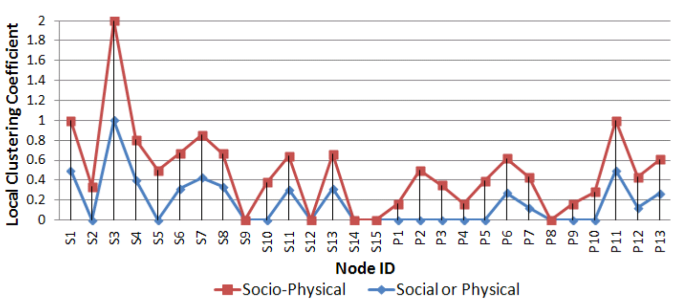

Fig. 3. Local clustering coefficients for all nodes considered from three views: social, physical, and socio-physical

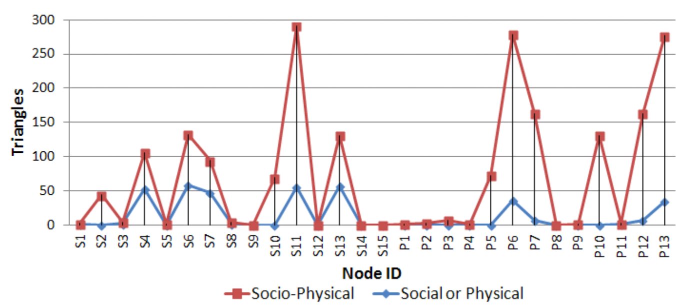

Fig. 4. Local triangles for all nodes considered from three views: social, physical, and socio-physical

B. *University's Physical View*

The 13 university physical nodes and their interrelationships are shown in Fig. 5. These include buildings (e.g., on-campus housing; university hospital; the teaching system, i.e., classrooms; and the research system, i.e., research labs) and critical infrastructure (e.g., steam; electricity; communication and IT, i.e., telecommunications; and transportation, i.e., roads). Interrelationships between these nodes, such as *provides electricity*, *provides steam*, and *connects* (for roads), have also been captured, but do not appear in the figure.

1) University Physical View's Clustering Coefficient: The critical nodes in the system from the physical point-of-view are shown in Table I under the "Social or Physical" column. These nodes include *Transportation* (P6), *Water & Sewage* (P7), *Steam* (P12), and *Electricity* (P13). The nodes signify traditional critical infrastructure, with *Communication & IT* (P10) notably missing since it participates in relationships external to the physical view and is useful insofar as it helps components in the social view.

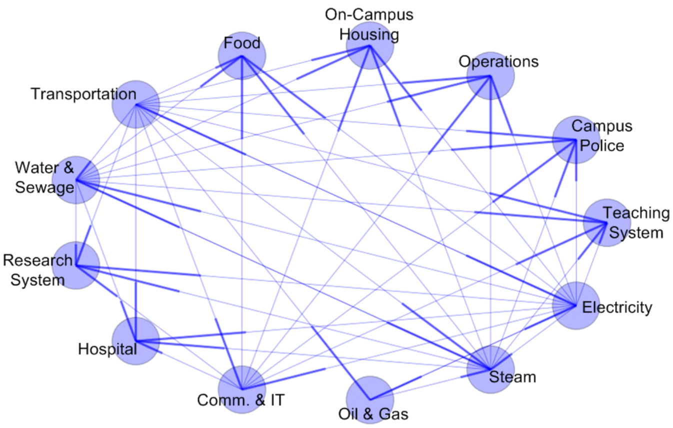

Fig. 5. Physical view of the university system (directed edges represent services provided from one node to another)

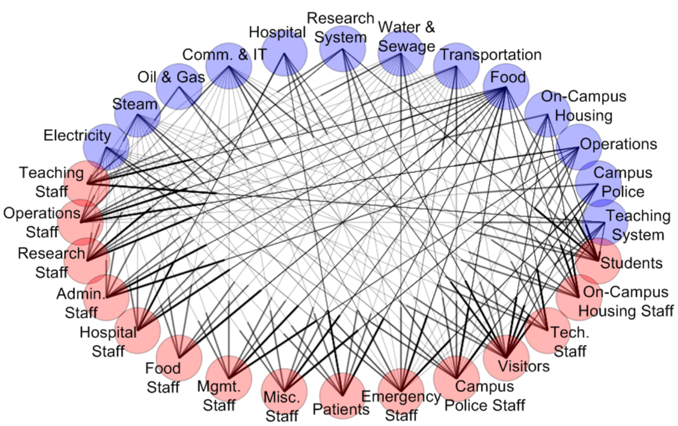

Fig. 6. Socio-Physical view of the university system (only links between the social and physical views are shown, and directed edges represent services provided from one node to another)

C. University's Socio-Physical View

Lastly, the combined socio-physical view is shown in Fig. 6 and incorporates the information from both social and physical views, including the nodes and their interactions (though for clarity these have been omitted from the figure). It further includes the interrelationships across views; that is, those interrelationships that exist from a physical node to a social node (e.g., a building *provides facilities* to students) and from a social node to a physical node (e.g., operations workers *monitor* critical infrastructure).

1) University Socio-Physical View's Clustering Coefficient: In the socio-physical view, all nodes are included, both social and physical. The local clustering coefficients are found under the "Socio-Physical" column in Table I. These calculations take into account the interrelationships within the social and physical views (i.e., the "Social or Physical" values in Table I) along with the interconnections that exist across these views. The most critical nodes in this combined view are as follows: *Food Staff* (S6), *Campus Police Staff* (S11), *Technology Staff* (S13), *Transportation* (P6), *Water & Sewage* (P7), *Communication & IT* (P10), *Steam* (P12), and *Electricity* (P13).

Table II shows the average local clustering coefficient from the social-or-physical and socio-physical perspectives, and clearly suggests the increased presence of clustering in the latter. However, the clustering coefficient alone, as argued above, does not reveal the full story. This is seen in the global clustering coefficient (also shown in Table II), where the values for both perspectives are similar. Investigating further, we see that the number of triangles in the socio-physical perspective is more than four-times that of the social-or-physical perspective. This underscores the importance of explicitly accounting for the interface between the two views.

In this section, the clustering coefficient of each node was considered independently of a specific emergency. If a specific emergency presented itself and affected a particular node, for example, the steam plant (P12), the clustering information could help provide a more complete representation of the nodes in the system that would be affected. Examining Table I, using P12 as the affected node, from the social or physical perspective, we see that 7 service-provision links would be impacted (as the number of triangles is 7). This same perspective, which was used on the day of the incident, does not include the hospital staff or patients. However, from the socio-physical perspective, we see a fuller picture: 156 service-provision links would be affected, including those to the students, patients, teaching staff, and hospital staff nodes that were affected on the day of the incident. Thus, the proposed explicit, combined socio-physical approach does, in fact, provide quantitatively and qualitatively more in-depth information about systemic interdependencies, which in turn can be used to help reduce systemic risk.

Although the system in this case study may initially appear small, the university community under consideration is in fact quite large—in excess of 15,000 individuals, including students, faculty, and staff, making it larger than several small communities in North America. It also has its own separate hospital, power and steam plants, and food and police services, making it sufficiently complex. The proposed approach to describe and analyze the network is very scalable, particularly with the aid of software tools, and can be used to investigate large cities and even networks of cities.

VI. Discussion

While the socio-physical approach is beneficial, we acknowledge that there are limitations to the present work. First, the clustering analysis as presented is currently based on static networks, and even though it was useful in showing the quantitative differences between the purely physical or social and combined socio-physical views, its direct application to emergency response appears limited. For example, it does not take into account specific subsets of the network that may be of most importance during an emergency (e.g., isolating only those nodes affected by the steam plant and performing a dynamic analysis), nor is the clustering coefficient able to identify indirect dependencies affecting nodes outside the immediate neighbourhood under consideration, which raises concern when qualitatively defining "critical" nodes. For instance, are nodes that provide service(s) to the currently marked critical node in fact more critical? It is true that clusters by themselves will not provide the entire picture, but they can

TABLE II
GLOBAL CLUSTERING ANALYSIS FOR THE SOCIAL AND PHYSICAL VIEWS IN ISOLATION (SOCIAL OR PHYSICAL) AND WHEN COMBINED (SOCIO-PHYSICAL)

	Average Local Clustering Coefficient	Global Clustering Coefficient	Number of Triangles	Number of Triples
Social or Physical	0.174627158556	0.297208538588	362	1218
Socio-Physical	0.312526190166	0.336526447314	1616	4802

provide some insight and certainly more than if no analysis were performed.

It must be emphasized that the socio-physical approach advocated does not claim to present a single metric capable of identifying the most critical node in every situation. Instead, it focuses on the benefits of the combined socio-physical view and presents a heuristic for comparison purposes. Still, this heuristic can be used to allocate resources if no labels are associated with the nodes (i.e., if every node is considered to be of equal importance): meaning that if the only information an incident commander were presented with was a list of node ids and associated clustering coefficients (and triangles), the incident commander could make an allocation decision better than random chance simply by focusing on the hubs. The logic being that hubs, by virtue of their increased interconnectedness, have a farther-reaching impact than do relatively isolated nodes.

Importantly, this simplistic prioritization mechanism can be improved by associating weights with different nodes based on the context of the response (e.g., if lives are at risk, nodes related to the process of saving lives would be given higher weights than nodes associated with day-to-day business operations). Clustering can further be used as a benchmark when comparing alternative measures of what constitutes the most critical node, and can also be combined with other metrics, such as those outlined in [38], to participate in more sophisticated analysis. Finally, these static measures can be combined with simulation to perform dynamic analysis. For example, they can be used as initial conditions in the simulation and depending on how external factors (e.g., hazards) affect the system, highlight the criticality of different nodes based on weighting. This would facilitate stress-testing the system based on different hazards.

These various improvements the authors leave for future work. However, in the next section, a proof-of-concept simulation is discussed, which combines those components of the socio-physical view from the university case study which proved most relevant during the incident.

VII. Socio-Physical Modelling & Simulation

In this section, we will explore how simulation can be used to reactively and proactively reduce systemic risk. We will consider specifically the university case study. Rather than using network metrics, the applicability of the socio-physical approach to modelling and simulation is being investigated. For the implementation of the proof-of-concept simulation, a combination of discrete-event and agent-based models were used.

Fig. 7 shows a screenshot of the running simulation. Considering the university case study, those components which proved most relevant were, for the physical view, the steam plant, water system, university hospital, (critical) research labs, on-campus housing (i.e., residences), and classrooms, and, for the social view, the patients (and specifically the impact of the steam on patient care). These key components are shown in the simulation screenshot, along with a dashboard showing hospital steam demand and supply over time, as well as steam distribution across the various physical components.

In the screenshot, only two buildings are receiving steam (grey input lines)—the university hospital and research labs—while every building is being supplied with water (blue input lines). Both steam and water distribution throughout campus can be modified within the simulation in real-time to simulate the consequences of specific response decisions on the system. Furthermore, the water being supplied by the city can be modified to account for different external factors impacting the system-of-interest (i.e., the campus). Lastly, the various patients in the hospital awaiting/receiving treating are shown. These patients are impacted by the lack of steam to the hospital and may need to be evacuated to city hospitals (external to the system-of-interest). Patients appear in two groups: yellow patients, who can be transported via bus; and red patients, who will need to be transported via ambulance.

The simulation, moreover, can be used both reactively, to anticipate the consequence of specific response decisions, and proactively, to explore the benefit of modifying the system prior to an emergency. In the simulation run shown in Fig. 7, for example, an additional piece of infrastructure was added to the system: an on-campus water storage facility. This is used to help mitigate the effect a reduction in water supply from the city may have on steam production. Its benefit to the risk resilience of the system can then be tested, by exploring for example the maximum level of water-supply variability from the city that can be compensated for.

At a glance, using such a simulation, the added benefit of combining both the social and physical views for emergency response is shown. For instance, without modelling physical constraints like water transmission, water's impact on the social level (i.e., patients) is not explicitly captured. Among other things, this makes it more challenging to explore the effect of certain external factors on patient care, such as the water supplied from the city, as the model is limited in its representation of the real-world. Similarly, without explicitly considering the social level, its impact on the physical level remains implicit and outside the exploration of the simulation.

A subset of the socio-physical view was considered in this proof-of-concept simulation and the impact of components across the system was modelled. Having a combined physical and social simulation allows risk-mitigation strategies to be

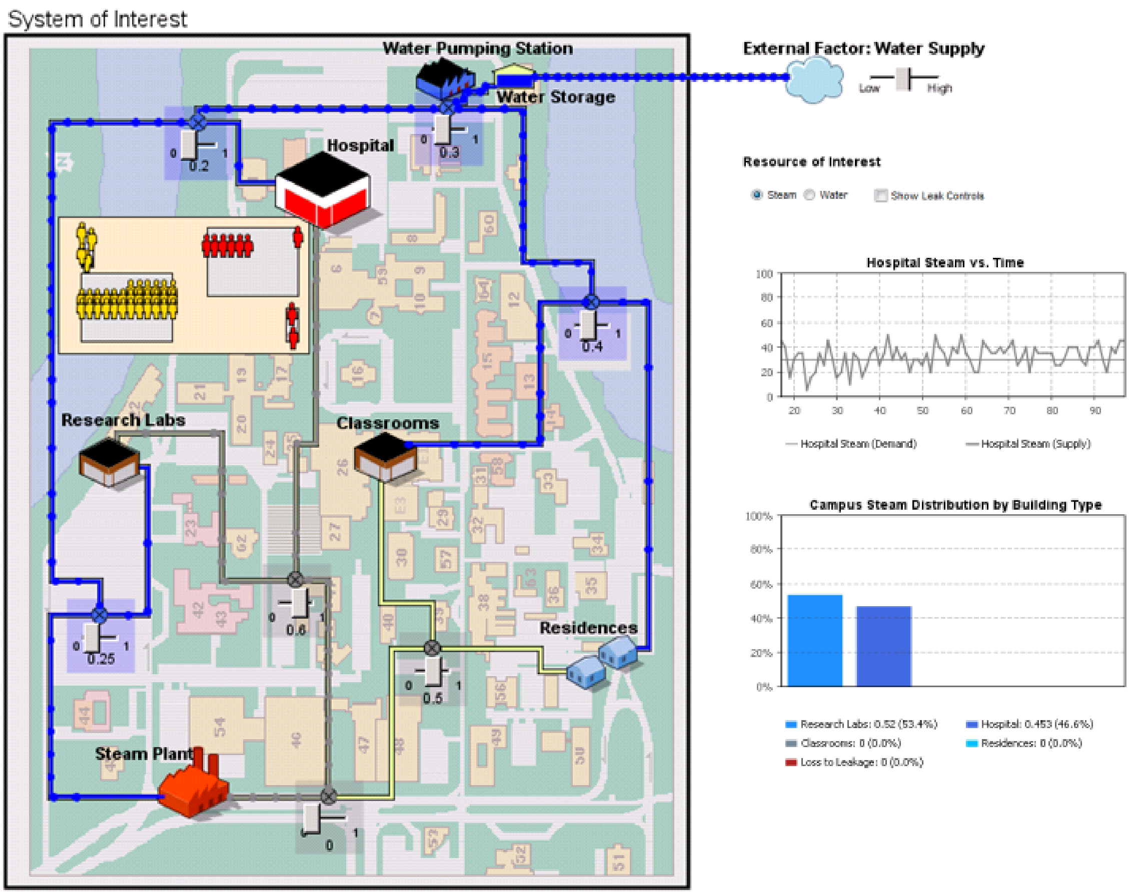

Fig. 7. Screenshot showing an execution run of the combined socio-physical simulation, in which key physical and social components are included in a single model

explored prior to an incident (via what-if scenarios) and the consequences of response actions to be considered following an incident (using real-time data via the dashboard). In both cases, systemic risk can be reduced through increased awareness, resulting in improved emergency response and preparedness: the more information an incident commander has to make a decision and to know about the potential consequences, the more assurance that the desired effect will result.

VIII. Conclusion and Future Research

This paper proposes using a socio-physical view of a system, for emergency response and preparedness, to increase situational awareness and thereby reduce systemic risk. This explicit, combined and integrated socio-physical approach allows the situation to be viewed holistically and reveals a more complete representation of the network under consideration. The application of the proposed approach was illustrated on a case study, where clustering analysis was used to extract network data for the social, physical, and socio-physical views of the university system. An examination of the case shows that clustering coefficients vary depending on the view taken. It also highlighted the importance of clustering density, based on triangles, in identifying critical nodes.

The clustering analysis demonstrated objectively that the information garnered from the proposed approach is broader and more relevant than using either the social or physical views. A proof-of-concept simulation was also presented to further underscore the benefit of the approach. In conclusion, having this expanded perspective provides much needed, critical information for raising the level of emergency preparedness (for stakeholders) and for responding more effectively and efficiently to a hazard (for the incident commander).

The introduced socio-physical approach has diverse application to many different areas of emergency response and preparedness, including:

- Education and training,
- Modelling and simulation of what-if scenarios,
- Stress-testing the system prior to an emergency,
- Building the system's capacity to cope with disruptions more effectively and efficiently,
- Improving communication between stakeholders, and
- Creating a more collaborative and coordinated environment for response.

Triangulation would be beneficial to help further support the proposed approach, and the authors are working toward applying the approach to other case studies as part of future research, including larger disasters. Modelling and simulation of what-if scenarios based on these case studies will also be examined and can further serve as a foundation for designing and developing safer and more resilient systems. Finally, the current work considers only static snapshots of the network, but changes to the system (e.g., from hazards or accidents) will impact the network topology. As such, we also plan to capture network measurements resulting from the real-time dynamics of the network "in time" through simulation as outlined in the discussion.

REFERENCES

[1] B. Wisner, "Are we there yet? reflections on integrated disaster risk management after ten years," *Journal of Integrated Disaster Risk Management*, vol. 1, no. 1, 2011.

[2] D. Helbing, "Systemic risks in society and economics," *International Risk Governance Council*, 2010.

[3] S. Lowe, J. Lebens, and M. Pummell, "Deepwater horizon disaster: Insurance industry implications," *Emphasis*, vol. 2, pp. 2–6, 2010.

[4] F. Diaz Maurin, "Fukushima: Consequences of systemic problems in nuclear plant design," *Econ Polit Wkly*, vol. 46, pp. 10–2, 2011.

[5] EMDAT, "The international disaster database, www.emdat.be," 2011.

[6] WHO, "Risk reduction and emergency preparedness: Who six-year strategy for the health sector and community capacity development," 2007.

[7] C. Perrow, *Normal accidents: Living with high risk technologies*. Princeton University Press, 1999.

[8] M. Dore and D. Etkin, "The importance of measuring the social costs of natural disasters at a time of climate change," *Australian Journal of Emergency Management*, vol. 15, no. 3, pp. 46–51, 2000.

[9] K. Giesecke and B. Kim, "Systemic risk: What defaults are telling us," *Management Science*, pp. 1387–1405, 2011.

[10] X. Huang, H. Zhou, and H. Zhu, "A framework for assessing the systemic risk of major financial institutions," *Journal of Banking & Finance*, vol. 33, no. 11, pp. 2036–2049, 2009.

[11] V. Acharya, L. Pedersen, T. Philippon, and M. Richardson, "Measuring systemic risk," *FRB of Cleveland Working Paper No. 10-02*, 2010.

[12] S. J. Gandhi, A. Gorod, and B. Sauser, "Systemic risk of outsourcing," in *30th Annual American Society of Engineering Management Conference Springfield, MO*, 2009.

[13] C. Brownlees and R. Engle, "Volatility, correlation and tails for systemic risk measurement," *New York University Working Paper*, 2010.

[14] S. Gandhi, A. Gorod, V. Ireland, and B. Sauser, "Systemic risk management framework for system of systems (sos)," *Engineering Management Journal (EMJ)*, 2011, under review.

[15] M. Ulieru and P. Worthington, "Adaptive risk management system (arms) for critical infrastructure protection," *Integrated Computer-Aided Engineering, Special Issue on Autonomic Computing*, vol. 2, no. 2, pp. 63–80, 2006.

[16] O. Cardona, "The need for rethinking the concepts of vulnerability and risk from a holistic perspective: a necessary review and criticism for effective risk management," *Mapping Vulnerability: Disasters, Development and People*, p. 17, 2003.

[17] ECB, "Analytical models and tools for the identification and assessment of systemic risks," 2010.

[18] ——, "New quantitative measures of systemic risk."

[19] S. Gandhi, A. Gorod, and B. Sauser, "A systemic approach to managing risks of sos," in *Systems Conference (SysCon), 2011 IEEE International*. IEEE, 2011, pp. 412–416.

[20] R. Cont, A. Moussa, and E. B. e. Santos, "Network structure and systemic risk in banking systems," *Columbia University Working Paper*, 2010.

[21] B. Tabak, M. Takami, J. Rocha, and D. Cajueiro, "Directed clustering coefficient as a measure of systemic risk in complex banking networks," *Working Papers Series No. 249*, 2011.

[22] J. Marczyk, *A new theory of risk and rating: New tools for surviving in a complex and turbulent economy*. Editrice UNI Service, 2011.

[23] D. Bisias, M. Flood, A. Lo, and S. Valavanis, "A survey of systemic risk analytics," *Annual Review of Financial Economics*, 2012.

[24] World Economic Forum, "Rethinking risk management in financial services: Practices from other domains," 2010.

[25] J. Lorenz, S. Battiston, and F. Schweitzer, "Systemic risk in a unifying framework for cascading processes on networks," *The European Physical Journal B-Condensed Matter and Complex Systems*, vol. 71, no. 4, pp. 441–460, 2009.

[26] D. Helbing and C. Kühnert, "Assessing interaction networks with applications to catastrophe dynamics and disaster management," *Physica A: Statistical Mechanics and its Applications*, vol. 328, no. 3, pp. 584–606, 2003.

[27] L. Buzna, K. Peters, and D. Helbing, "Modelling the dynamics of disaster spreading in networks," *Physica A: Statistical Mechanics and its Applications*, vol. 363, no. 1, pp. 132–140, 2006.

[28] L. Buzna, K. Peters, H. Ammoser, C. Kühnert, and D. Helbing, "Efficient response to cascading disaster spreading," *Physical Review E*, vol. 75, no. 5, p. 056107, 2007.

[29] R. Albert, H. Jeong, and A.-L. Barabási, "Error and attack tolerance of comlex networks," *Nature*, vol. 406, no. 27, 2000.

[30] X. Wang and G. Chen, "Complex networks: small-world, scale-free and beyond," *Circuits and Systems Magazine, IEEE*, vol. 3, no. 1, pp. 6–20, 2003.

[31] S. Horvath, *Weighted Network Analysis: Applications in Genomics and Systems Biology*. Springer Verlag, 2011.

[32] E. Ravasz, A. Somera, D. Mongru, Z. Oltvai, and A. Barabási, "Hierarchical organization of modularity in metabolic networks," *Science*, vol. 297, no. 5586, pp. 1551–1555, 2002.

[33] P.-N. Tan, M. Steinbach, and V. Kumar, "Chapter 8: Cluster analysis: Basic concepts and algorithms," in *Introduction to Data Mining*. Addison Wesley, 2005.

[34] D. Watts and S. Strogatz, "Collective dynamics of small-world networks," *Nature*, vol. 393, no. 6684, pp. 440–442, 1998.

[35] D. Brown and W. Dunn, "Application of a quantitative risk assessment method to emergency response planning," *Computers & Operations Research*, vol. 34, no. 5, pp. 1243–1265, 2007.

[36] S. Kaplan and B. Garrick, "On the quantitative definition of risk," *Risk Analysis*, vol. 1, no. 1, pp. 11–27, 1981.

[37] L. A. Cox, Jr., "Some limitations of "risk = threat x vulnerability x consequence" for risk analysis of terrorist attacks," *Risk Analysis*, vol. 28, no. 6, pp. 1749–1761, 2008.

[38] W. Ross, A. Gorod, and M. Ulieru, "A socio-physical governance framework for emergency response and preparedness," *IEEE Systems Journal*, 2011, under review.

[39] J. Reason, *Human error*. Cambridge university press, 1990.

[40] ——, "Human error: models and management," *BMJ*, vol. 320, no. 7237, pp. 768–770, 2000.

[41] N. Leveson, M. Daouk, N. Dulac, and K. Marais, "Applying stamp in accident analysis," in *NASA CONFERENCE PUBLICATION*. NASA; 1998, 2003, pp. 177–198.

[42] U. S. DHS, "National response framework," 2008.

[43] Government of Canada, "An emergency management framework for Canada: second edition," 2001.

[44] G. Barbarosogcaron and Y. Arda, "A two-stage stochastic programming framework for transportation planning in disaster response," *Journal of the Operational Research Society*, vol. 55, no. 1, pp. 43–53, 2004.

[45] D. Dudenhoeffer, M. Permann, and M. Manic, "CIMS: A framework for infrastructure interdependency modeling and analysis," in *Proceedings of the 38th conference on Winter simulation*. Winter Simulation Conference, 2006, pp. 478–485.

[46] N. Britton, "A new emergency management for the new millennium?" in *Second International Conference on Cities on Volcanoes*.

[47] D. Mendonca, G. Beroggi, and W. Wallace, "Decision support for improvisation during emergency response operations," *International Journal of Emergency Management*, vol. 1, no. 1, pp. 30–38, 2001.

[48] L. Comfort, K. Ko, and A. Zagorecki, "Coordination in rapidly evolving disaster response systems," *American Behavioral Scientist*, vol. 48, no. 3, pp. 295–313, 2004.

[49] J. Boardman and B. Sauser, *Systems thinking: Coping with 21st century problems*. CRC, 2008, vol. 4.

[50] C. Wang and R. Chen, "The structural variables of multi-layer networks and early warning mechanism for industrial cluster risks," in *Information Management, Innovation Management and Industrial Engineering (ICIII), 2012 International Conference on*, vol. 1. IEEE, 2012, pp. 313–317.

[51] P. Paymal, R. Patil, S. Bhowmick, and H. Siy, "Measuring disruption from software evolution activities using graph-based metrics," in *27th IEEE International Conference on Software Maintenance (ICSM)*. IEEE, 2011, pp. 532–535.

[52] M. Newman, "The structure and function of complex networks," *SIAM review*, vol. 45, no. 2, pp. 167–256, 2003.

William Ross received his BCS (2005) and MCS (2007) from the University of New Brunswick. Prior to returning to graduate studies, he worked in the e-learning industry as a software developer and instructor. Currently, he is a Ph.D. student under the supervision of Dr. Mihaela Ulieru. His research focuses on investigating and modelling interdependencies and emergence for the development of agile organizational practices.

Alex Gorod received his BS in Information Systems, MS in Telecommunications from Pace University and PhD in Engineering Management from Stevens Institute of Technology. Prior to his graduate studies, he held a research analyst position at Salomon Smith Barney. He is a former Robert Crooks Stanley doctoral fellow in Engineering Management at Stevens Institute of Technology, with research interests in the area of management of complex systems. He is a member of SystemicNet, LLC in New York and a visiting fellow at the University of Adelaide in Australia.

Mihaela Ulieru (S93M95SM02) received the Ph.D. degree in diagnostics and controls of dynamical systems from the Darmstadt University of Technology, Darmstadt, Germany, in 1995. She was a Postdoctoral Fellow in the Intelligent Robotics and Manufacturing Group led by Prof. William Gruver at Simon Fraser University, Burnaby, BC, Canada, from 1996 to 1998. She was a Member of the faculty with Brunel University, Uxbridge, U.K., and with the University of Calgary, Calgary, AB, Canada, where she held the Junior Nortel Chair in Intelligent Manufacturing and founded the Emergent Information Systems Laboratory. She has been holding the Canada Research Chair in Adaptive Information Infrastructures for the e-Society since 2005 when she also established (with the Canada Foundation for Innovation funding) and leads the Adaptive RiskManagement Laboratory (ARM Lab), researching complex networks as control paradigm for complex systems to develop evolvable architectures for resilient e-networked applications and holistic security ecosystems. In 2007, she was appointed to the Science, Technology and Innovation Council of Canada by the Minister of Industry to advise the government and provide foresight on innovation issues related to the information communication technology (ICT) impact on Canadas economic development and social well-being against international standards of excellence. She has held and holds appointments on several international science and technology advisory boards and review panels, among which are the Science and Engineering Research Council of Singapore, the Scientific Council of the EU Proactive Initiative on Pervasive Adaptation (PERADA), the EU Network of Excellence in Intelligent Manufacturing (IPROMS), and the Natural Science and Engineering Research Council of Canadas Advisory Panel on International Strategy, and as an expert on its ICT and security review panels, as well as the U.S. National Science Foundation Cyber-Systems and several EU FP7 expert panels. To capitalize on her achievements and expertise in distributed intelligent systems by making ICTs an integrated component of policy making targeting a safe, sustainable, and innovation-driven world, she recently founded the Innovation Management and Policy Accelerated by Communication Technologies (IMPACT) Institute for the Digital Economy, for which she currently acts as President. Dr. Ulieru, as a member of the Administrative Committee of the IEEE Industrial Electronics Society (IES), founded the international industrial informatics research community and its two major forums: the IEEE Industrial Informatics Conferences and the IEEE-IES Industrial Agents Technical Committee. She also founded the IT Revolutions Forum and was the General Chair of its first conference held in Venice, Italy, in December 2008.