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

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***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. This is accomplished through a reduction of systemic risk, which refers to a risk that could be greater than the sum of the risks of the individual system constituents. 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 systemic 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*—Clustering coefficient, emergency response and preparedness, risk reduction, situational awareness, socio-physical view, systemic risk.**

I. Introduction

USING an integrative view of the system is instrumental in improving emergency managers' 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. Since risk-reduction strategies are based implicitly on the view taken of an emergency situation [1], [2], 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 (e.g., consider a system where specific failures in one or more of its constituents, such as a sustained electrical power failure [3], could result not only in local impacts, but in system-wide impacts as well).

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 [4]–[6]. 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 [7], [8].

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 [9]. Crises may also stem from social, economic, and political consequences [8]. Regardless of cause, it is imperative that emergency managers take into consideration both the social and physical implications resulting from their actions, allowing important interdependencies to be accounted for prior to and following a disaster [10], [11]. Current approaches typically focus on either the physical view [12]–[15] or the social view [16]–[19]. However, considering the social and physical dimensions in isolation leads not only to a partial view of the problem space, but also to a marginal assessment of systemic risk [20]–[22], which can have severe implications to emergency management.

There have been several attempts to define and measure systemic risk [20], [21], [23]. 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, as evidenced by continued research in the area [24], and numerous quantitative and qualitative analyses, metrics, best practices, and lessons learned can be extracted from the financial domain [25]–[27]. Despite no single, agreed-upon definition, systemic risk has been characterized as follows: a risk originating from multiple sources that affects multiple agents and propogates quickly among individual parts or constituents of the network [20]; a risk or probability of breakdowns affecting an entire system and not just a breakdown in individual parts or constituents, as evidenced by correlations among most or all of the parts [28]; and, in its most general usage, a risk that shocks the system, impairing its crucial functions [29]. In this paper, systemic risk is described as a risk that could be greater than the sum of the risks of the individual system constituents [20].

Networks and their interactions are frequently the cause of the cascading failures which many attribute as "the most common mechanism by which local risks can become systemic" [10], [30], and knowledge of the underlying properties inherent within different network structures can reveal different vulnerabilities. Scale-free networks, for example, exhibit the power-law distribution and, independent of network scale, are

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considered resilient to random attacks, yet are highly susceptible to deliberate attacks [31], [32]. Such examples serve to underscore the importance of network measures in increasing awareness. In emergency response, for instance, the clustering coefficient, together with connectivity, can inform emergency managers of the structure of the network being examined, along with its distribution patterns and underlying behaviour [33]–[35]—all of which can prove invaluable when facing the need to make difficult decisions (e.g., under situations with limited resources). These measures can provide insight into how to influence the network to reduce possible risks, making the entire system more resilient.

In this paper, in order to objectively demonstrate the extensiveness of the explicit, combined socio-physical view in comparison to the social and physical views in isolation, we will use the clustering coefficient as a "measure of local connections, or 'cliquishness"' [36], [37]. It is hypothesized that the different nodes that emerge as being critical in this combined view will more accurately represent the critical nodes in the system, as failure of any of these nodes will more likely affect a larger portion of the system, potentially resulting in systemic failure. Subsequently, it will be argued that 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.

The remainder of the paper is structured as follows. Section II considers risk in emergency response and ways in which it can be reduced in general. Section III presents the socio-physical approach to risk reduction, in which the explicit use of both the social and physical views (and their interconnections) to describe and analyze a system is described. Section IV presents the figure of merit, clustering, as a means of analyzing the interconnections and dependencies within a system. Section V analyzes a real-life case study involving an incident at a university steam plant using the proposed approach. Specifically, 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. Section VI proposes an extension to existing clustering coefficients based on limitations identified during the case study in order to determine the contribution of a single node on the entire network. Section VII then shows how the socio-physical view can be used to improve simulation by focusing on an important subsystem identified in the case study. Lastly, Section VIII concludes the paper and outlines possible direction for future work.

II. Risk Reduction in Emergency Response and Preparedness

There are many formal and informal definitions of risk related to emergency response, such as $risk = probability \times consequence$ [38], [39], $risk = threat \times vulnerability \times consequence$ [40], 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" [8]. Despite definitional variation, *local risk* can be viewed, in general, as a function of hazards to which a portion of the system is exposed and the known and unknown system vulnerabilities related to it. Here $hazard$ refers to "any phenomenon that has the potential to cause disruption or damage" to a system constituent, while $vulnerability$ refers to "the conditions determined by physical, social, economic and environmental factors or processes, which increase the susceptibility" of a constituent [8].

Importantly, in emergency response, risk may be mitigated by the level of preparedness which seeks to reduce vulnerabilities. This includes such actions as raising awareness, which lessens the effect of the hazard on identified vulnerabilities, investing in critical infrastructure and training programs, and developing emergency-response plans. Thus, risk reduction also relates to the response phase: the more prepared one is to respond to a particular vulnerability-inducing hazard, the less impact this vulnerability will have on the constituent and the system as a whole. Furthermore, emergency response and preparedness can be approached reactively and proactively. 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 description above, any increase in the level of (response and) preparedness will reduce the level of risk.

Considering now *systemic risk*, where the failure of one system constituent may lead to the failure of the entire system, necessitates assessing not only the various local risks, but also the interactions among system constituents. This interconnected vulnerability, if examined comprehensively, implies that there are many unique combinations of hazards and vulnerabilities which can negatively impact the system [41]. In this case, the vulnerability of a specific constituent is not considered in isolation; instead, vulnerability depends on the view under which it is assessed. If viewed from only a physical (or social) perspective, for instance, different vulnerabilities might be assessed than if considered from a socio-physical perspective. The vulnerability of one constituent, if viewed from a holistic perspective, may involve the synergistic effect of vulnerabilities across all constituents in the entire system. In this way, the more interconnections and vulnerability the system constituents have, proportionately the greater the risk for system failure.

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

While we have no control over natural disasters, work has been done to reduce the likelihood of human-induced hazards, particularly those resulting from accidents [9], [42]–[44]. 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 [42], [43]. 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 [42], [43]). 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 [44]. 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 [9]. 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 emergency managers to prepare for and respond to hazards.

III. Socio-Physical Approach to Risk Reduction

In emergency response, systems have generally been viewed fragmentally [2], [41], 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) or the social (e.g., organizations, individuals, and policies) system dimensions. The proposed approach, however, takes into consideration an integrated socio-physical perspective, where both the physical and social system constituents 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 emergency manager in charge of responding to the incident and to stakeholders in charge of maintenance and upgrades for preparedness.

Having an expanded representation of the system enables its constituents 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 constituents, 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—both of which would assist in reducing risk. This can be supported by using existing, well-known risk analysis techniques, such as those presented in [45]. In the failure mode and effects analysis (FMEA) approach, for example, different failure modes, effects, and probabilities can be associated with system constituents in a collaborative fashion to improve the overall understanding of the system-of-interest [46], [47].

When constructing the socio-physical view, which constituents 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 [48].) For the physical view, start by considering those constituents that provide vital services, such as electricity, before moving onto secondary constituents like office buildings. Also, consider grouping similar constituents together; for example, if considering a university, several residence buildings could be grouped into a single constituent: on-campus housing. The interactions between the constituents should be directional and take the form **constituent X** *provides [some service]* to **constituent Y**. Once again, begin by focusing on the vital services, as the diagram can quickly become cluttered. For the social view, consider the human constituents 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 constituents in the same way as we would physical constituents. Lastly, to link the physical and social views, consider which services constituents in the physical view provide to constituents in the social view, and vice versa, and add these to the diagram.

In this paper, the Python NetworkX package was used to capture the networks, facilitating graphical presentation and mathematical computation. This is particularly beneficial for large networks where software automation facilitates the application of the proposed approach. However, for improved visualization, larger systems can also be captured using Systemigrams, which may span multiple pages.

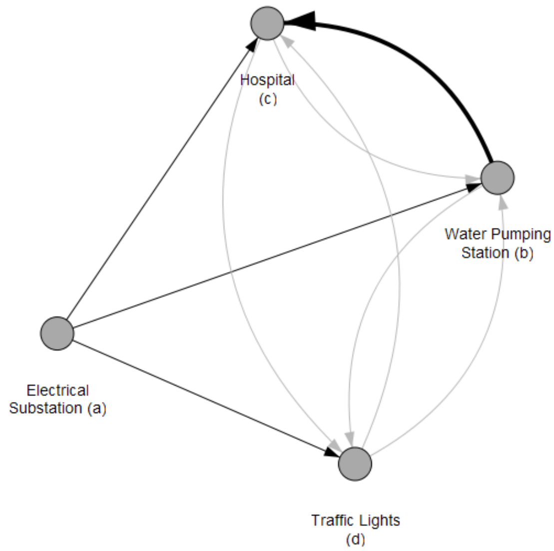

Fig. 1. Clustering coefficient example (actual service provision is shown using black edges, while potential service provision is shown using grey edges)

IV. Clustering as a Metric for Emergency Response and Preparedness

The socio-physical approach presents the system as a set of constituents (i.e., nodes) and interrelationships (i.e., edges). Therefore, when identifying critical system constituents, various measures from network theory can be applied. The clustering coefficient, for instance, can be used as a measure of systemic risk [34], [49], and, in this paper, the clustering coefficient is adopted to identify critical nodes [50] 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 constituents of the system directly, but, indirectly, because of the interrelationships that exist among constituents, 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 and traffic lights, as well as to the water pumping station (black, non-bolded, directed edges). The traffic lights and hospital do not provide services to each other or to the water pumping station, but could possibly in an alternate situation (grey, directed edges), while the water pumping station, supported by the electrical substation, does provide 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) by a third node which provides a service to both nodes (e.g., electrical substation), the "triple" formed by considering these three nodes becomes connected in a special relationship termed a "triangle." In graph theoretic notation, if the directed edges (a,b), (a,c), and (b,c) exist among three nodes, a, b, and c, then these nodes are said to form a "triangle." By considering the support provided from the perspective of node a, it is seen in Fig. 1 that each of its neighbours could potentially provide facilitated support to the other two remaining neighbours; thus, there are six "triples" (five grey edges plus the bolded edge). However, in this example, only one of these edges actually exists (bolded edge), so there is one "triangle". It is the ratio of triangles to triples that is being measured by the clustering coefficient.

By being aware of this 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, thereby reducing risk.

More importantly, this figure of merit allows one 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 managers. 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 in a variety of ways: it can be measured using a directed or undirected network, which in turn impacts which equations are used; and it can be measured locally, from the perspective of each system constituent, or globally, from the perspective of the entire system [51]. In this paper, because the networks we consider are directed based on service provision, as shown in Fig. 1, 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. These measures have been selected based on their widespread use in the literature and their ability to compare different networks. Specifically, the local measure will be used to help determine node criticality, while the global measures will be used to compare views.

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]):

$$C_i = \frac{number\ of\ triangles\ connected\ to\ node_i}{number\ of\ triples\ centered\ on\ node_i} \tag{1}$$

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:

$$triples_i = neighbours_i \times (neighbours_i - 1). \tag{2}$$

With each of its neighbours (i.e., $neighbours_i$), $node_i$ could share (or have in common) a maximum of all other of its neighbours (i.e., $(neighbours_i - 1)$); thus, the number of triples, which represents the maximum number of possible triangles, is the product of these two numbers.

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]:

$$\bar{C} = \frac{1}{n}\sum_i C_i \tag{3}$$

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]):

$$C = \frac{number\ of\ triangles\ in\ the\ network}{number\ of\ triples\ of\ nodes} \tag{4}$$

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 Emergency Operations Center (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 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 traditional social and physical views in isolation (i.e., without any interconnections between them). Using clustering as a metric, different views of the university system will be presented, along with analysis, to objectively determine which view provides emergency managers 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, stemming from the use of partial views, is easy to correct prior to an incident, but not during one, when other pressures and responsibilities take precedence and must be managed.

A. Three Different Views of the University System

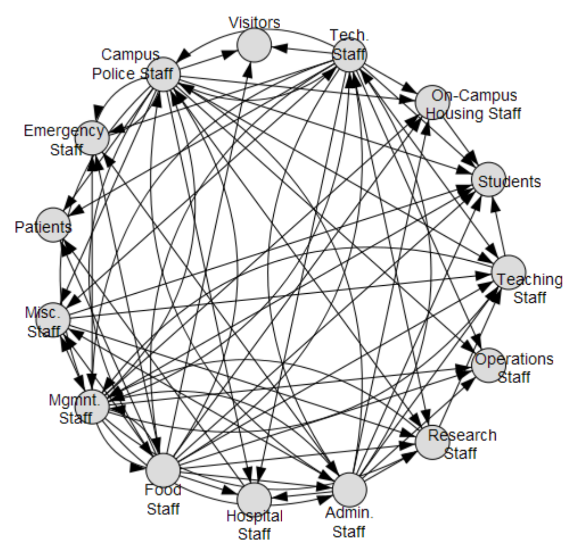

Fig. 2. Social view of the university system (directed edges represent services provided from one node to another)

1) University's Social View: The social view of the university is shown in Fig. 2. It captures the social network constituents (i.e., nodes) and interrelationships (i.e., edges) in the university system. Fifteen social nodes have been identified, including students, teachers, researchers, operations

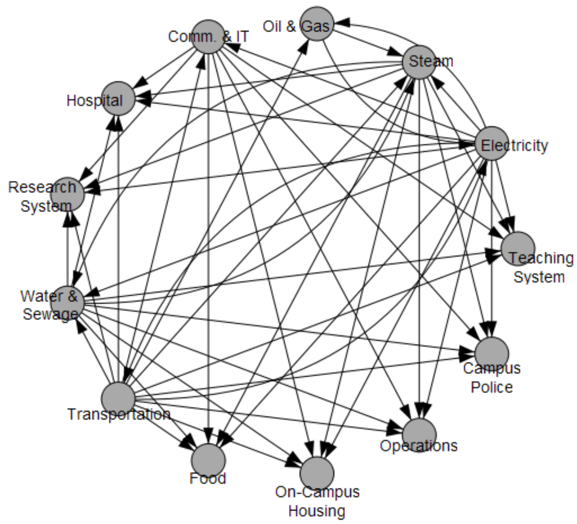

Fig. 3. Physical view of the university system (directed edges represent services provided from one node to another)

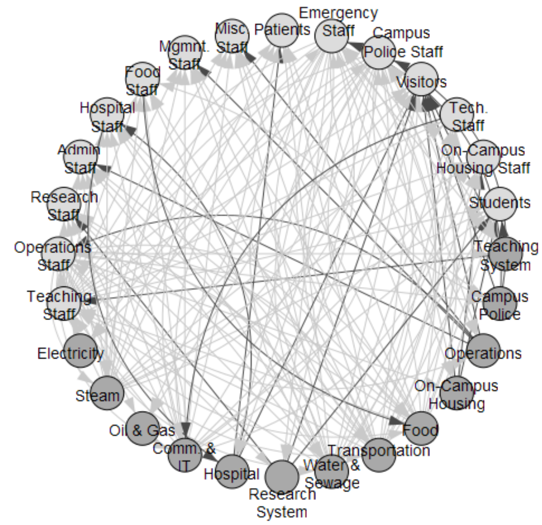

Fig. 4. Socio-Physical view of the university system (only edges between the social and physical views are shown, and directed edges represent services provided from one node to another)

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, the edge labels do not appear in the figure. These represent the services, from the social perspective, that one node provides to other nodes in the network, and this is depicted in the figure using directed edges: the arrow points to the node receiving a service from another node.

2) University's Physical View: The 13 university physical nodes and their interrelationships are shown in Fig. 3. 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 the labels have been omitted from the figure to improve readability.

3) University's Socio-Physical View: Lastly, the combined socio-physical view is shown in Fig. 4 and 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). To assist in understanding the figure, two different coloured edges have been used. The lighter edges represent the case when a node of one type (either social or physical) provides a service to the majority of the nodes of the opposite type. This is seen, for example, with the *Transportation* node: directed edges starting from this node are lighter than edges starting from some other nodes, indicating that this physical node provides a service to most of the social nodes. By contrast, darker edges represent the case when a service is provided to only a minority of nodes of the opposite type. This is seen with the *Hospital* node, which *provides facilities* only to *Hospital Staff*, *Patients*, and *Visitors*. The socio-physical view further incorporates the interrelationships from both the social and physical views, as appear in Fig. 2 and Fig. 3, respectively, though for readability these interrelationships have been omitted from the figure, along with edge labels.

B. View-Specific Clustering Coefficients

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 social or physical and socio-physical views to help simplify comparisons. Importantly, the "social or physical view" can be thought to contain all nodes in the system, only without any interrelationships across views. Thus, what is being compared is the same system, only with the traditional segmented view versus systemic view.

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. 5 and Fig. 6.

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). These nodes do not represent the main functions of the university, which include teaching, learning, and research. Instead, they correspond to those supporting constituents that are needed by the university to maintain operational continuity.

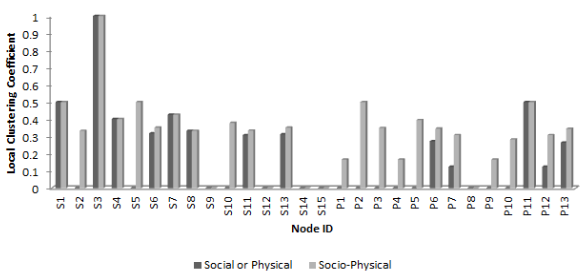

Fig. 5. Local clustering coefficients for all nodes considered in the social or physical and socio-physical views

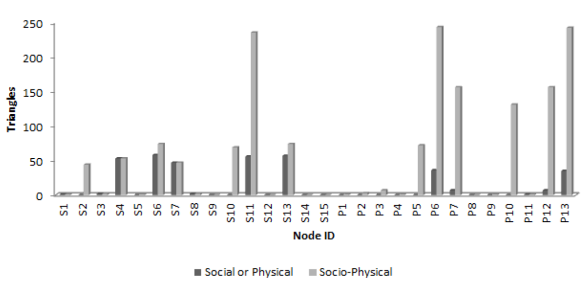

Fig. 6. Local triangles for all nodes considered in the social or physical and socio-physical views

In Fig. 5, the local clustering coefficients for each node in the university system are shown. The darker bars represent the social or physical view, while the lighter bars represent the combined socio-physical view, including the interrelationships across views. This information is taken from Table I and appears as bar charts. As seen, in the majority of cases, the local clustering coefficient of a node increases when the more holistic socio-physical view is considered, 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. 6. The information is extracted from Table I and includes node data from the social-or-physical column (darker bars) and the socio-physical column (lighter bars). 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, rather than using the clustering coefficient alone.

2) 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. However, *Communication & IT* (P10) is notably missing from this list, since in the physical view for this case study, the nodes to which it provides a service do not provide any service to one another, as seen in Fig. 3 (i.e., there are no triangles).

3) University Socio-Physical View's Clustering Coefficient: The local clustering coefficients for the socio-physical view 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 view are as follows and relate to the criticality across both the social and physical views combined: *Food Staff* (S6), *Campus Police Staff* (S11), *Technology Staff* (S13), *Transportation* (P6), *Water & Sewage* (P7), *Communication & IT* (P10), *Steam* (P12), and *Electricity* (P13).

4) University Global Clustering Coefficients: Lastly, two global clustering cofficients have also been considered in this case study to demonstrate the additional network-level information available from the socio-physical view. 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, it is seen that the number of triangles in the socio-physical perspective is more than four-times that of the social or physical perspective.

C. Discussion

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 edges 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 edges would be affected, including those to the students, patients, teaching staff, and hospital staff

TABLE I
LOCAL CLUSTERING ANALYSIS, INCLUDING TRIANGLES AND LOCAL CLUSTERING COEFFICIENTS, FOR THE SOCIAL OR PHYSICAL AND SOCIO-PHYSICAL VIEWS (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)	<u>53</u>	132	0.401515	53	132	0.401515
	Hospital Staff (S5)	0	0	0.0	1	2	0.5
	Food Staff (S6)	<u>58</u>	182	0.318681	<u>74</u>	210	0.352381
	Mgmt. Staff (S7)	<u>47</u>	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)	<u>56</u>	182	0.307692	<u>235</u>	702	0.334758
	Visitors (S12)	0	0	0.0	0	0	0.0
	Tech. Staff (S13)	<u>57</u>	182	0.313187	<u>74</u>	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)	<u>36</u>	132	0.272727	<u>243</u>	702	0.346154
	Water & Sewage (P7)	<u>7</u>	56	0.125	<u>156</u>	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	<u>131</u>	462	0.283550
	Oil & Gas Inventory (P11)	1	2	0.5	1	2	0.5
	Steam (P12)	<u>7</u>	56	0.125	<u>156</u>	506	0.308300
	Electricity (P13)	<u>35</u>	132	0.265152	<u>242</u>	702	0.344729

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 as shown in Tables I and II, which in turn can be used to help reduce systemic risk.

Although the system in this case study may initially appear to be 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 scalable, particularly with the aid of software tools, and can be used to investigate large cities and even networks of cities.

It must be emphasized, however, 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. Nevertheless, 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 emergency manager were presented with was a list of node IDs and associated local clustering coefficients (and triangles), the emergency manager 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 could be given higher weights than nodes associated with day-to-day business operations). This weighting can also be based on the resource requirements associated with particular response actions needed to restore a node's operational capability [53]. 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 node centrality, to participate in more sophisticated analysis. Finally, these static measures can be combined with simulation to perform dynamic analysis [19]. 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

TABLE II
GLOBAL CLUSTERING ANALYSIS FOR THE SOCIAL OR PHYSICAL AND SOCIO-PHYSICAL VIEWS

	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

would facilitate stress-testing the system based on different hazards, as well as in applying complementary risk analysis techniques, such as FMEA.

VI. DETERMINING A SINGLE NODE'S IMPACT ON THE NETWORK

In the previous section, the benefit of considering a comprehensive view of the system was shown quantitatively, using the metrics described in Section IV. However, these established approaches for measuring clustering and comparing the results from different networks appear to have some limitations when applied to emergency response, even though they were useful in showing the quantitative difference between the isolated physical or social and the combined socio-physical views. Specifically, the local clustering coefficient, while beneficial for measuring the clustering within a local neighbourhood, cannot identify indirect dependencies affecting nodes outside the immediate neighbourhood under consideration, which raises concern when qualitatively defining "critical" nodes. Moreover, the global clustering metrics, while beneficial for comparing general trends across different networks, cannot quantify the impact of a single node on the network. These existing limitations necessitate an alternative method for such a quantification, which can assist in identifying node criticality, thereby improving system awareness and, in turn, facilitating proactive and reactive risk-reduction strategies.

Different extensions to the local clustering coefficient have been proposed, including [54] and [55]. The latter considers nodes beyond the immediate neighbourhood, allowing for the specification of the reach (or depth) of the neighbourhood. Where typically a neighbourhood would only include the immediate neighbours (depth = 1), different depth levels can be specified, including neighbours of the immediate neighbours (depth = 2), neighbours of the neighbours of the immediate neighbours (depth = 3), and so on. This permits an analysis of a larger subset of the network.

In this section, because we are interested in the impact of a single node on the entire network, the neighbourhood of interest is that which includes all nodes that can be reached from the origin node (i.e., that node whose impact is being assessed). This set of nodes will be called the *reachability set*. Furthermore, because cycles containing the origin node are also of interest, the origin node will be considered when computing the number of triangles and triples. This is in contrast to existing clustering coefficient methods, which consider only open neighbourhoods (i.e., ones not including the origin node), rather than a closed ones [37], [54], [55]. The combination of the reachability set with the origin node will be called the *closed reachable neighbourhood*.

This neighbourhood is then used in the determination of the clustering impact of the origin node. It is the ratio of triangles in this neighbourhood to the total number of possible triangles (i.e., triples) within the network that determines the connection density (i.e., clustering) of the origin node across the network. The equation for the *reachable clustering coefficient* is as follows, and combines features from both the local and global clustering coefficients to determine the impact of a single node on the network:

$$rC_i = \frac{triangles\ in\ closed\ reachable\ neighbourhood_i}{triples\ in\ network} \tag{5}$$

where the numerator is defined in Algorithm 1, below, and the denominator, the total number of triples in the network, is defined by the following equation:

$$triples\ in\ network = n \times (n-1). \tag{6}$$

Here n refers to the total number of nodes in the network, and this equation says that every node can potentially connect to every other node in the directed network. As is the case with the other clustering coefficients referenced, there are no self-loops permitted (i.e., a node cannot connect to itself); conceptually, in the context of emergency response, this would imply that a constituent helps itself, which is redundant.

Algorithm 1 An algorithm for determining a single node's clustering impact on the network

```
function ReachableClusteringCoefficient(g, n, s, o)
    triangles ← 0
    n.visited ← true
    nSet ← s ∪ g.neighbours(n)
    for node in g.neighbours(n) do
        if node.visited is false then
            val ← Reachable...Coefficient(g, node, nSet, o)
            triangles ← triangles + val
        end if
    end for
    if n ≠ o then
        triangles ← triangles + size(s ∩ n.neighbours)
        return triangles
    else
        rC ← triangles/g.nodeCount × (g.nodeCount − 1)
        return rC
    end if
end function
```

Algorithm 1 shows the steps used to determine a single node's clustering impact on the network, i.e., the reachable clustering coefficient. Four parameters are passed to the recursive function: the graph, g; the current node, n; the set of reachable neighbours discovered so far, s; and the origin node, o. In the initial call, the current node and origin node are identical and the neighbour set includes only the origin node. As the function is executed, the number of triangles, $triangles$, is initialized to zero; the current node's $visited$ attribute is set to true; and a new neighbour set, $nSet$, which includes s and the immediate neighbours of n is created. (Eventually, this set will include all nodes in the closed reachable neighbourhood.) For each neighbour, $node$, of the current node, n, a logical condition is evaluated to determine whether or not this node has previously been visited. If it has not yet been visited, a recursive call to the same function is made in which the graph, unvisited node, increased neighbour set, and origin node are passed. This process is used to discover every node reachable from the origin node. For every node discovered (i.e., for every node that is not the origin node), the number of triangles contributed by this node is equal to the size of the intersection of this node's neighbours with the set of all neighbours found within the reachable neighbourhood so far (i.e., s). These values are tallied as the recursive calls return until all triangles have been accounted for, i.e., until the final recursive call is returned to the node which originally began the recursive process. In this case, n will equal o and the else condition is executed. The reachable clustering coefficient is then computed based on Eq. 5 and returned to the original caller of the function.

Turning now to the application of this approach, when applied to the case study, the results reveal that most nodes have nearly identical reachable clustering coefficients as the network is highly interconnected. Therefore, in place of displaying the results in a table, the results of two exemplar nodes—the *Hospital* and the *Steam* constituents—will be analyzed, while a possible extension will be discussed further in the section which could enable more discriminating results.

The *Hospital* constituent is an example of a node with a small number of outgoing edges. Its immediate neighbours are *Hospital Staff*, *Patients*, and *Visitors*. Because the $Hospital$ constituent is a physical node and its neighbours are social nodes, the reachable clustering coefficient is 0.0 when the social or physical view is considered (i.e., there are no triangles). When the socio-physical view is considered, on the other hand, two triangles are found in its closed reachable neighbourhood, yielding a reachable clustering coefficient of 0.002646 (i.e., $2\ triangles\ /\ 28 \times 27\ triples$). This is in contrast to the one triangle found using the local clustering coefficient (see Table I), which resulted in a value of 0.166667, as only the six triples in the immediate neighbourhood were considered.

By comparison, the *Steam* constituent is an example of a node with a large number of outgoing edges. It includes eight immediate neighbours in the social or physical view and 23 in the socio-physical view. Considering the segmented view first, the algorithm identifies eight triangles, resulting in a reachable clustering coefficient of 0.010582 over the network, while, for the combined view, it identifies 247 triangles, which equates to a reachable clustering coefficient of 0.326720. This represents a significant increase between views in the amount of network clustering. To contrast, the local clustering coefficient in Table I yields a value of 0.125 (i.e., $7/56$) and 0.308300 (i.e., $156/506$), respectively, for the different views. As can be seen, using the reachable clustering coefficient facilitates comparisons across and within networks by combining local and global aspects. For example, the coefficient of *Steam* for the social or physical view is nearly four times as large as that of *Hospital* for the combined view, and *Steam*'s clustering coefficient for the combined view is close to thirty times as large as its coefficient for the segmented view. Such comparisons, using only the local clustering coefficient without considering the number of triangles, are more difficult.

In addition to the clustering results, seven cycles were identified in the *Steam* constituent's closed reachable neighbourhood (this logic was omitted in Algorithm 1 to improve readability). The constituents connecting back to *Steam* include *Water & Sewage*, *Electricity*, *Oil & Gas*, *Transportation*, and *Operations Staff*. However, with the exception of the first two constituents, the remainder only become critical to the production of steam under specific situations. For example, *Oil & Gas* becomes critical when *Electricity* fails and *Operations Staff* becomes critical if there is a failure in the *Steam* constituent.

These concrete examples offer opportunity to refine the approach in its application to risk reduction. Specifically, in addition to the present formulation for determining the reachable clustering coefficient of a node, various extensions can be applied, including adding weights to the nodes and to the triangle edges to further discriminate results. Nodes can be weighted based on the importance of the node to the functioning of the entire system—for example, *Patients* could receive a lower weighting than *Steam*, as it provides a relatively less operationally vital service—, while edges can be weighted based on the distance of the nodes they connect from the origin node—the idea being that the origin node has reduced contribution to the operation of another node the further away that node is from the origin. Such extensions could also include weighting rules based on situational context. For example, the weight of the *Steam* node might increase when temperatures fall below a certain threshold or the weight of the *Comm. & IT Staff* node could be increased if the *Comm. & IT* node experiences a reduction in service. This is because the former is responsible for maintaining the latter and is needed to restore normal service levels; however, when there are no service issues, *Comm. & IT Staff* is less critical.

These extensions are particularly relevant when applying this metric to a broader set of cases, and these various improvements the authors leave for future work. However, in the next section, a proof-of-concept simulation is discussed, which combines those constituents of the socio-physical view from the university case study which proved most relevant during the incident. It is envisioned that such a simulation could be extended with network analysis capabilities to facilitate the application of the proposed metric.

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

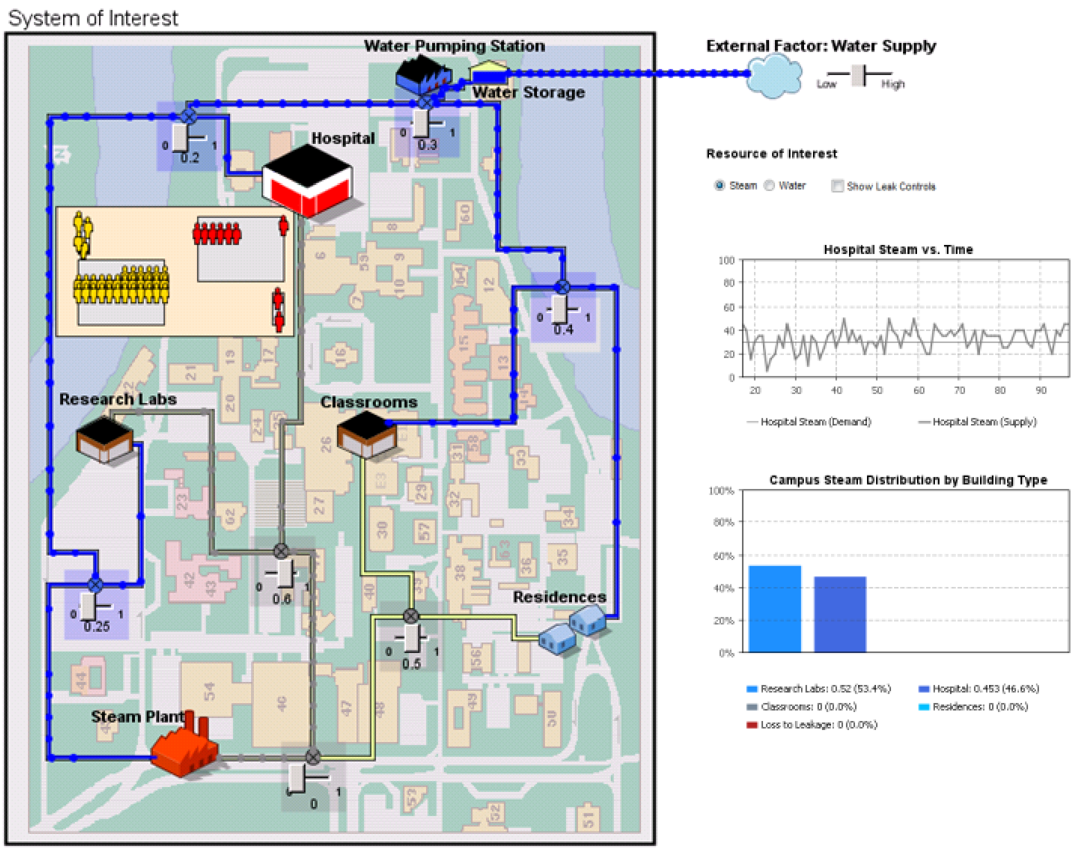

Fig. 7. Screenshot of the combined socio-physical simulation, in which key physical and social constituents are included in a single model

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 constituents which proved most relevant were, for the physical nodes, the steam plant, water system, university hospital, (critical) research labs, on-campus housing (i.e., residences), and classrooms, and, for the social nodes, the patients (and specifically the impact of steam on patient care); no other social node dominated the incident. These key constituents 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 constituents. The data used in the simulation can be specified by the user in order to facilitate the analysis of different scenarios; however, for the purposes of the proof-of-concept simulation, the data used in Fig. 7 were selected to assist with visualization and are not based on the case study.

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 university). 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) as discussed in the case study. 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, along with their interconnections, 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 constituents across the system was modelled. Having a combined socio-physical simulation allows risk-mitigation strategies to be 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 emergency manager has to make a decision and to know about the potential consequences, the more assurance that the desired effect will result. As part of future work and to assist researchers and practitioners in applying the approach proposed in this paper, we are continuing to improve the simulation capability with more constituents and the incorporation of network metrics.

VIII. Conclusion & 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 or physical and socio-physical views of the university system. An examination of the case showed that clustering coefficients vary depending on the view taken. It also highlighted the importance of clustering density, based on triangles, in identifying critical nodes. Moreover, it revealed the limitation of existing clustering approaches in describing the impact of a single node on the entire system and proposed a new metric, the reachable clustering coefficient, to address this limitation.

The clustering analysis demonstrated objectively that the information garnered from the proposed socio-physical approach is broader and more relevant than using the social or physical view. 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 emergency manager).

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 to show its scalability. 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.

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