Observations on the Effects of a Global Pandemic on the Time to Recovery (TTR) from Natural Disasters

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Abstract

Until the global outbreak of Coronavirus 2019 (COVID-19), little attention had been paid to the possibility that a significant number of critical personnel in both the infrastructure and disaster response and recovery supply chains could be incapacitated or otherwise unavailable due to an on-going pandemic. The purpose of this paper is to use CRISIS, an existing decision-support optimization tool for the restoration of civil infrastructure damaged by a hurricane, to investigate how a community's Time To Recovery (TTR) following a hurricane could be extended due to an on-going pandemic and what the consequences could be. The results of preliminary modeling presented here suggests that the impacts could be significant and that our current understanding of such compound extreme events is inadequate to the potential threat.

1. Introduction

Throughout the Spring and Summer of 2020, the United States was in the midst of a public health crisis unprecedented in over a century. During this time, most of the country was in some stage of self-imposed quarantine, the economy suffered as 2nd Quarter GDP fell at an annual rate of 32.9% [1] and unemployment reached levels not seen since the Great Depression [2], and by the end of September the death toll exceeded 200,000 Although the impacts of COVID-19 were devastating, on-going pandemics do not preclude the occurrence of hurricanes or other extreme events. In order to assess how a nation struggling with an infectious disease crisis might cope with a concurrent natural or human-caused disaster, the authors used CRISIS, an existing decision-support optimization tool for the restoration of civil infrastructure damaged by a hurricane, and CLARC, an artificial community data set, to investigate how a community's Time to Recovery (TTR) following a hurricane could be extended due to an on-going pandemic. The purpose of this paper is to describe the preliminary results from that exercise, suggest some policy steps that could be taken at the national level, and identify future research directions.

2. Background

By the end of September 2020, the total number of COVID-19 cases in the United States exceeded 7 million with more than 200,000 virus-related deaths reported [3]. To prevent the spread of the virus, communities practiced social distancing, wearing face masks, and other practices recommended by the Centers for Disease Control (CDC). Self-quarantining for 14 days was also recommended if there was reason to believe that a person had been in contact with someone carrying the virus. Demographic factors played a role in vulnerability to the virus with people in poverty, those over 65 years of age, and those with pre-existing medical conditions particularly vulnerable [4]. Coincidentally, this is the same demographic mix that has been found to be particularly vulnerable during a hurricane [5].

Coastal cities are most exposed to hurricanes whose impacts include heavy rain, high winds, and storm surge that damage buildings and infrastructure. Power and water outages are typical and vary due to the intensity of the storm. Hurricanes also damage roads which are critical during evacuations, response, and restoration. Although powerful hurricanes are often considered rare and unpredictable events, they are likely to become more intense and more frequent in the future. Freedman [6] explains that there has been a significant increase in a measure of hurricane intensity called the power dissipation index since at least 1970. This index includes wind speed and the total lifetime of the storm and model simulations of the 21st century shows the index increasing by 45% along with a 40%

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global increase in major hurricanes (Category 3 and greater) during the same period. Other sources such as the National Environmental Education Foundation [7] and National Geographic [8] support this finding. The prediction of an increasing number of more powerful hurricanes in conjunction with the current pandemic raises new concerns. To put an exclamation point on these predictions, as of the end of September 2020, there were 23 named storms in the Atlantic and Gulf of Mexico, including 8 hurricanes, two of which were considered major.

Thinking about preparing for and responding to a natural hazard while in the middle of a public health emergency is not a typical planning exercise. During a recent webinar on extreme events and the COVID-19 pandemic sponsored by the National Academies, Jane W. Baldwin of the Lamont-Doherty Earth Observatory observed that an extreme weather event occurring during the COVID-19 outbreak would create what she termed a "compound extreme event," which is "a series of events that are worse than the sum of their parts" [9]. Typically, in preparation for a hurricane's landfall, people living in vulnerable locations are encouraged to evacuate; out of the area if they have the resources to do so or to shelters if they do not. Sheltering hundreds of people in close proximity in, for example, a high school gymnasium with limited restroom capacity is precisely what social distancing seeks to avoid and it remains unclear whether people will voluntarily subject themselves to the perceived risk this entails. Contemporary experience with a cyclone in Bangladesh and a dam collapse and flooding in Michigan suggests that they may not [10]. Although there are many questions raised by the prospect of a hurricane intersecting with an-ongoing pandemic, this paper focuses on the role played by the availability of critical personnel in a community's post-event Time to Recovery (TTR).

3. Method and Materials

To assist in better understanding these and related questions, the performance of critical civil infrastructures, defined as the ability of a system to meet the demand for services, during a hurricane was modeled using CRISIS, a computer-aided decision-support model developed at Rensselaer Polytechnic Institute to optimize the scheduled repair of damaged civil infrastructures based on stakeholder-determined priorities for the restoration of social infrastructure services that depend on the damaged civil systems. [11]. CRISIS is composed of two principal parts, a damage/disruption simulation model for civil and social infrastructure systems and a restoration optimization model that is guided by community-determined priorities for the recovery of social infrastructure services and the disrupted state of the civil infrastructure systems on which the social infrastructures depend. The underlying premise of CRISIS is that because of interdependencies, disruptions to civil infrastructure services such as power, transportation, communications, and water and sewer service will impact the delivery of social infrastructure services as surely as collapsed or flooded buildings. For example, it does not identify police stations or medical facilities damaged by a hurricane that need to be rebuilt; rather, it identifies and schedules repairs to the flooded roadways and damaged bridges on which emergency vehicles, repair crews, and people requiring treatment must travel, and the power lines, water, sewer, and communication facilities that enable the disrupted facilities to function. It does so by determining the optimal strategy for repairing the damaged civil systems so that critical social infrastructure services will be restored as rapidly as possible. The logic flow of the model is shown in Figure 1. As a result, minimizing the Time to Recovery (TTR) of these systems following a hurricane is a high priority [9] and TTR with and without an on-going pandemic was selected as a surrogate measure of COVID-19 impact. Figure 2 illustrates the interdependencies between civil and social infrastructures and the critical role of people both in the provision and consumption of social infrastructure services and in response and recovery operations that CRISIS models.

Despite a long and well chronicled history of global disasters, the meaning of "recovery," particularly at the community level, remains difficult to define quantitatively. Quarantelli [12] called it " an attempt to bring a post-disaster situation to a level of acceptability" which Alesch expanded to encompass " the rectification of damage and disruption that has been inflicted upon an urban system's built environment, people and institutions" [13]. More recently, the United Nations Office for Disaster Risk Reduction [14] has defined disaster recovery as "The restoring or improving of livelihoods and health, as well as economic, physical, social, cultural and environmental assets, systems and activities, of a disaster-affected community or society, aligning with the principles of sustainable development and "build back better", to avoid or reduce future disaster risk." This has led to many efforts to develop metrics to measure and monitor recovery efforts. For example, Horney, et. al. [15] found over 500 possible recovery indicators in a literature review. However, regardless of how we define it, full community recovery from an extreme event typically takes many years and is probably better conceptualized as an on-going journey rather than one

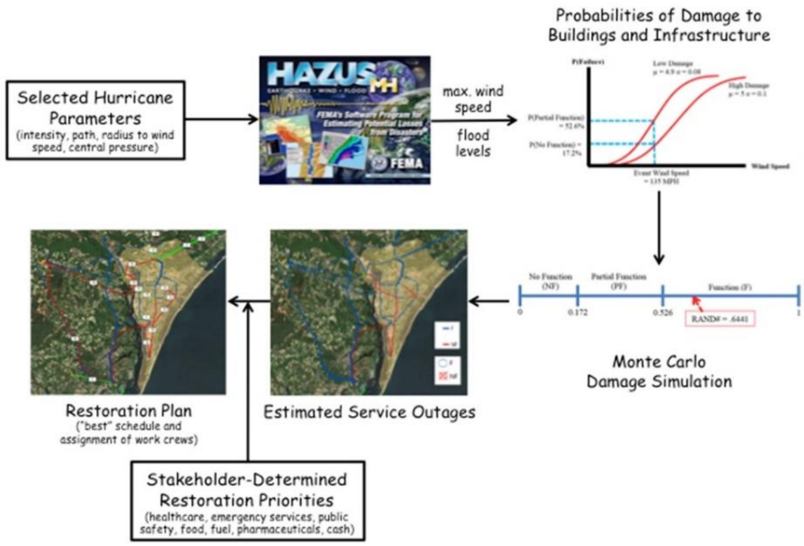

Figure 1. Logic flow of the CRISIS infrastructure damage-disruption-restoration model.

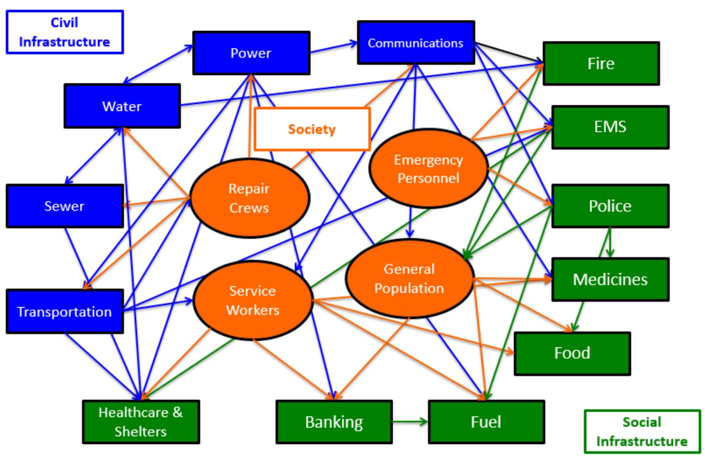

Figure 2. The interdependencies between civil and social infrastructures and the people who operate, repair, and consume their services.

with a fixed destination. In light of this, the current effort focuses on a single but essential element in the recovery process; the restoration of civil infrastructure disrupted by an extreme event. Using civil infrastructure as a surrogate for recovery is considered reasonable because all other sectors, public and private, require civil infrastructure to function. If infrastructure recovery lags, community recovery cannot proceed effectively. In the absence of reliable quantitative data for system performance during an actual hurricane/pandemic event, the modeling on which this analysis is based was conducted in CLARC, an artificial community that was developed concurrently with CRISIS to serve as a test bed for the model [16]. CLARC is structured as a hurricane-prone coastal county of approximately 1,065 square miles with a population of 500,000. The CLARC data set includes civil and social infrastructures as well as selected demographic and geographic data such as population, average income, terrain type, and Social Vulnerability Index (SoVI) [17]. Selected characteristics of the civil and social infrastructures contained in the CLARC data set are summarized in Table 1.

Table 1. CLARC Infrastructure Classification Scheme

Classification	Operational Characteristic for Modeling	Examples
Civil Infrastructure Systems	A system in which goods or services flow instantaneously in an autonomous network from supply sources to fixed demand points	Power, Water, Wastewater, Transportation, Communications
Public Safety	A system in which services flow through the transportation network from discrete supply points to randomly located demand points	Emergency Management Services (EMS), Police, Firefighters
Critical Commercial Services	A system in which goods or services flow through the transportation network from production sites, to distribution centers, to supply points where they are obtained by customers who must also travel to the supply points	Fuel Distribution, Personal Banking Services, Food Distribution, Pharmaceuticals
Community Services	A system in which people move through the transportation network to fixed supply points to obtain services.	Healthcare, Shelters, Government Facilities

To model a theoretical hurricane, CRISIS uses the storm parameters typically provided by the National Oceanic and Atmospheric Administration (NOAA) (e.g., intensity, path, radius to a given wind speed, translation speed, and central pressure) as inputs to HAZUS-MH® to calculate the maximum wind speeds and flood levels expected in a given region. Once the wind speeds and flood levels are estimated, the probability that buildings and infrastructure would be damaged as a result can be determined. The probabilities corresponding to full, partial, and no function are determined and plotted to 3 decimal places, i.e., 0.xxx. The estimated level of damage sustained is then simulated using Monte Carlo techniques to generate a 3-decimal random number and the combined results of many simulations performed for each infrastructure component in the affected area produce a damage scenario which is then translated into service outages. The effects of these outages are determined both for operational issues, i.e., does a social infrastructure such as a dialysis center have electric power and water to deliver services to customers; and supply chain issues, i.e., is the infrastructure necessary for patients and healthcare workers to access the dialysis center functioning [18]. Based on a set of stakeholder-determined priorities, CRISIS's restoration solver then develops an optimal restoration plan for that scenario by solving for the best schedule and assignment of work crews that will restore each damaged infrastructure component in the shortest amount of time to maximize, in terms of met demand, the following objective function for the three sets of social infrastructures summarized in Table 1.

$$\sum_{s \in S^{PS}} W^s \text{x } \Pi^s + \sum_{s \in S^{CC}} W^s \text{x } \Pi^s + \sum_{s \in S^{CS}} W^s \text{x } \Pi^s \qquad (1)$$

where Π^S = the overall performance of a social infrastructure system; S^{PS} = set of systems within the public safety category; S^{CC} = set of systems within the critical commercial services category; and S^{CS} = set of systems within the community services category. For all three categories, each system is weighted independently by a factor, W^S. Weighting each system serves two purposes. First, it allows the decision maker to prioritize one system's performance over the others based on community preferences. For example, to determine the optimal restoration plan to maximize just the performance of the emergency management system (EMS), the public safety system would be given a weight of 1, whereas the other two systems are given a weight of 0. In this example, CRISIS seeks to maximize Π^S, the performance, in terms of met demand, of the Public Safety component of social infrastructure (Equation 2).

$$\Pi^s = \sum_{t=1,\dots,T} (\text{HW} \times \sum_{i \in V^{s-}} w_i^s \times (v_{it}^s - D_{it}^s) - \sum_{(i,j)\in E^s \cup \bar{E}^s} \sum_{z=\{1,2\}} c_{ijz} x_{ijtz}^s) \ \forall \in S^N \quad (2)$$

The first term in this equation is the penalty for not meeting the demand for emergency services; the second term is the sum of the amount of time that the emergency services uses in responding to the demand; D_{it}^s= adjusted demand level for service *s* at node *i* in time period *t*; and v_{it}^s = amount of demand met at node *i* in time period *t*. Each demand node is weighted independently by w_i^s. For the second term, x_{ijtz}^s = flow of service *s* on arc *i*,*j*,*z* in time period *t* and c_{ijz} = time traversing arc *i*,*j*,*z*. In order to balance the two terms and because it is important that the demand for public safety is met even at a high cost, a moderately heavy weight HW is put on the term for unmet demand. This weight should be just large enough to ensure that meeting demand is always the priority over the cost of meeting the demand.

Because roads are used by utility workers to restore other damaged infrastructure, public safety and EMS vehicles, households to obtain food and other essential items such as medicine, and government officials and volunteers to begin recovery operations, roads and intersections are some of the most important restoration priorities. In the examples described herein, CRISIS models the varying effects that COVID-19 could have on community recovery by alternately increasing the demand for public safety and EMS workers and decreasing the supply of these workers due to isolation and illness during hurricanes of varying intensities.

The performance of several commercial supply chains during the COVID-19 pandemic prove illustrative for the critical role played by people in the production and delivery of vital goods and services [17,18,19]. At the most basic level, supply chains are nothing more than networks of public and private infrastructures arrayed to deliver everything from raw materials to finished products to demand points along the chain. During extreme natural events such as hurricanes or earthquakes, links in the supply chain usually breakdown due to damage to supporting civil infrastructure such as power, water, or transportation or to direct damage to processing or production facilities. During the COVID-19 pandemic, however, physical damage was not the issue. Instead, it was the unavailability of workers, either through isolation, incapacitation, or travel restrictions that was the source of disruption.

Because of the exploratory nature of this work, a range of scenarios were selected to determine the sensitivity of the model to bounding conditions. Two baseline scenarios determined the damage and disruption a hypothetical hurricane would cause when there is no pandemic and when there is a pandemic but no hurricane. The second scenario examines the difference in impacts between a Category 2 and a Category 3 hurricane and which infrastructures are damaged and disrupted when there is no pandemic. These categories were selected based on prior experience with the model wherein Category 1 storms produced little significant damage and the damage from Category 4 and 5 storms was so severe that the model could not generate a restoration solution within the time frames allotted. The third scenario models Category 2 and Category 3 hurricanes occurring during an on-going pandemic with only 50% and 75% of the normal workforce available coupled with the increased demand for these workers that would be expected during a hurricane. Again, these levels of workforce participation were chosen to determine boundary conditions rather than anticipating a specific event.

4. Findings

Together these scenarios demonstrate that there is a range of possible outcomes if no pre-event actions were taken to address workforce reductions if a hurricane occurred during an on-going pandemic.

For the purpose of this exercise, it was assumed that an increase in response time could be generated by two distinct events; physical damage to the roadway network caused by a hurricane that would delay response or a shortage of repair crews caused by the pandemic. The total amount of time that it takes to respond to and complete a repair demand generated by the model was chosen as the metric to compare pandemic to non-pandemic response situations.

Among the most significant findings are:

1. There are increased outages of civil infrastructure with pandemic-induced workforce reductions. A baseline scenario was run for Category 2 and 3 hurricanes with no pandemic and then a pandemic situation where workforce capacity was reduced by 25% and 50%. The model generated more infrastructure outages during a pandemic situation.
2. In analysis of the runs, a need to restore damaged infrastructure was generated 3 times more frequently in water and power systems than other civil infrastructures.
3. The greatest disruption of civil infrastructure occurs after the loss of the first 25% of workers. This is based on a comparison of multiple scenarios to determine the number of cases where

a decision to restore damaged infrastructure was generated. These comparisons included (a) Category 3 storm baseline vs 50% personnel reduction, (b) Category 3 storm baseline vs 25% personnel reduction, (c) Category 2 storm vs 50% personnel reduction, (d) Category 2 storm baseline vs 25% personnel reduction, (e) Category 2 storm with 25% personnel reduction vs 50% reduction, (f) Category 3 storm with 25% personnel reduction vs 50% reduction. In Category 2 hurricanes there were ~9 times more restoration decisions generated in the loss of the first 25% of workforce and a Category 3 storm produced similar results.

4. Modeling a pandemic scenario with the assumed personnel reductions of 25% and 50% delayed the start time and increased the time required to complete restoration by a factor of three when compared to a "no pandemic" situation.
5. When the demand for infrastructure services was increased to reflect more citizens needing service during a hurricane or pandemic and workforce availability was held constant, the model generated more outages that required restoration.

Three restoration scenarios are compared in Figure 3. The three runs represent a Category 3 hurricane with full, half, and three-quarters of a functioning workforce, respectively. During a hurricane where there is no pandemic and the workforce is assumed to be at full capacity (Run 4), Figure 3 shows that no restoration demands are generated within the allotted twelve 6-hour units of time (72 hours). When only half of the workforce is available (Run 5), the model generates four restoration demands that require up to three units of time (18 hours) to complete as shown in the "Finish" column. Where 25% of the workforce is unavailable (Run 6), there are two restoration actions needed. Both restoration actions can begin earlier than when the workforce is at half capacity. In one instance, one 6-hour time unit earlier, and in the other, five time units earlier.

As previously noted, if the workforce is decreased to 75% of normal capacity during a pandemic, the restoration of service after a hurricane would take three times longer which could result in larger economic impacts and more adverse healthcare outcomes. The initial 25% depletion of workers was also found to be the most critical. Over many runs of the model, when total outages of civil infrastructure increased during a pandemic situation, there were 501 instances when the workforce decreased to 75% capacity. As the workforce continued to decrease, there were only an additional 197 outages at 50% capacity. Additionally, the total number of outages were two and a half times larger after the first 25% of workers became unavailable to work than after workforce depletion reached 50%.

Based on this modeling, an inverse relationship appears to exist between workforce availability and infrastructure performance, i.e., when the workforce is decreased due to travel restrictions, isolation, or illness, the number of civil infrastructure outages during a hurricane increases as does response time to initiate and complete a repair and overall TTR. Power and water systems are three times more likely to be disrupted than other civil infrastructures which is significant because without functioning power and water, many facilities providing healthcare, public safety, and commercial services are not able to function. However, even if there is little or no physical damage, if the necessary workforce is not available to provide service to their clients or customers at the point of delivery, the result is the same; critical services will not be available. This suggests that keeping workers healthy and safe is just as important in preventing outages and keeping the population safe during disasters as is restoring facilities once damaged.

Findings from Hurricane Maria in 2017 [22] and other recent storms [23] show a positive relationship between increased TTR and adverse health outcomes. This strongly suggests that delays in TTR caused by the pandemic could exacerbate the negative health impacts typically associated with hurricanes [5]. Thus, the population most vulnerable to the pandemic, i.e., those living in nursing homes and temporarily in shelters as well as those being treated in hospitals, are also most at risk during a hurricane when fewer emergency services are available. Reliable electricity and water service are critical to this population because many rely on medical devices to remain alive and air conditioning to reduce the risk of heat stroke; potable drinking water is required for hydration, medical treatments such as dialysis, surgery, and sanitation. This is an important consideration for decision makers who need to put their resources into the most vulnerable places first.

Although this modeling effort has confirmed some obvious relationships and illuminated some that are less so, it does have limitations. Its principal weakness is that it begins to break down during very powerful storms. At Category 3 and above, the hurricane becomes too strong and destructive for the

Run4			Run5			Run6		
Decision	Finish	Start	Decision	Finish	Start	Decision	Finish	Start
0	12	12	1	9	8	1	8	7
0	12	12	1	7	6	1	2	1
0	12	12	1	5	3	0	12	12
0	12	12	1	4	1	0	12	12
No Pandemic-induced Workforce Disruption			**50% Pandemic-induced Workforce Disruption**			**25% Pandemic-induced Workforce Disruption**		

Figure 3. The impact of pandemic-induced workforce reduction on restoration activities

model to determine the number of workers needed to keep the civil infrastructure intact. At this point, the model will cease computing and the number of outages predicted does not change regardless of workforce availability or system demands. It is still important to note, however, that this preliminary work does suggest that a Category 1 or Category 2 hurricane occurring during a pandemic might be manageable, for a Category 3 or larger storm, that is unlikely. This is supported, at least anecdotally, by the response to Hurricane Laura [24].

5. Conclusion and Next Steps

In the event that a hurricane occurs during an on-going pandemic, normal emergency response and recovery procedures will probably be disrupted to some degree. Using a virtual community to model realistic scenarios for a compound extreme event such as a hurricane and the ongoing COVID-19 pandemic, it shows that decreasing the workforce due to the pandemic and increasing the demands for emergency services due to the hurricane would increase the number of infrastructure service outages in a community as well as extending TTR to some extent.. Planning and preparedness exercises should be undertaken for a wide range of scenarios to inform public and private decision-makers of the effectiveness of alternative strategies for emergency response during a future pandemic. Using decision-support tools such as CRISIS and an artificial community such as CLARC would be less costly and time intensive than actual field exercises. There should also be efforts undertaken by these same decision makers to improve the personal protection of essential workers to reduce their likelihood of contracting the infectious disease.

Some of the questions that this exercise raises for decision makers and lawmakers to address include the following: How will a mass evacuation be possible if social distancing is a necessary precaution? Where will evacuated people be placed if they are infected or possibly infected? When power lines are damaged during a hurricane, will workers be willing and able to enter zones that have widespread outbreaks of coronavirus? If hospitals or shelters exceed capacity, will other states open their borders to people if they are infected with the virus? Will FEMA Urban Search and Rescue (USAR) teams and utility repair crews from out of the affected area be available and deployable? Will volunteers from NGOs such as the Red Cross and Salvation Army, many of whom are in a vulnerable age cohort, be available? Will workers providing critical commercial services be available and able to work?

Although the CRISIS model was able to produce some reasonable, broad-brush findings regarding a compound extreme event, the nature of the model required that infrastructure performance serve as a surrogate for impact on a community. However, COVID-19 has impacted people, directly if they were infected themselves or indirectly if they were exposed to an infected person or had to care for one, much more so than physical systems. We have been able to observe qualitative impacts of the coronavirus on supply chains, construction, and utility maintenance and repair for example, but are lacking quantitative data to develop the realistic algorithms necessary to predict how workforce availability, or lack thereof, could impact future performance. Going forward, simulation tools from the social sciences, such as agent-based modeling may provide better insight into these situations. What the present exercise has shown, however, is that there are fundamental questions that will need to be addressed regarding preparedness and response for extreme events in the era of global pandemics. COVID-19 will not be the last.

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