User Study Analysis of a Geovisualization Decision Support Environment for Critical Infrastructure Recovery

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Abstract

Critical Infrastructures (CI) are vulnerable to potentially catastrophic failures on many levels, especially when cascading disablements have escalating impacts across multiple connected infrastructures. In responding to outages, such cross-infrastructure effects can make analysis for decision makers and responders far more complex. To facilitate recovery in the dynamic context of such scenarios, decision makers need to utilize specialized decision support tools to assist in prioritizing alternatives. We have developed a recommender system based framework for CI decision support, focused on CI recovery. It models impacts of infrastructure elements, both within and across infrastructures, in order to recommend focus areas for reconstitution resources. Our system utilizes an interactive geovisualization interface to provide a natural context for infrastructure analysis support. This paper presents a user study evaluation of our approach, comparing its effectiveness to standard GIS tools that are used for CI analysis. Results show that our approach improves interaction quality and efficiency, as well as reducing cognitive load.

Keywords: Critical Infrastructure, Recommender System, Geovisualization, User Study, Cross Infrastructure, Mental Demand

1 Introduction

Protection of critical infrastructures (e.g., electrical power grids, communication networks) has become an increasingly significant concern in the public and private sectors. Critical infrastructures involve multi-dimensional, highly complex collections of technologies, processes, and people, and as such, are vulnerable to catastrophic failures (intentional or unintentional) on many levels. A well-documented example can be seen in the August 2003 blackout in the north-eastern U.S. and eastern Canada [13]. A series of unintentional events led to cascading failures across 263 power plants. Moreover, failure in the electrical power infrastructure had serious impacts on other critical infrastructures.

In order both to guard against and respond to critical infrastructure failures, multi-dimensional infrastructure modelling and simulation has been proposed as a way to support analysis and decision-making [2, 3, 4, 7, 11]. In this context geographic relationships provide a coherent foundation for the integration and visualization of multiple infrastructures, as well as for scenario scoping and impact analysis. As part of spatial decision support in GIScience, Andrienko et al. [1] have noted the need for cross-disciplinary research, and this is especially true for CI analytics. In our research, we focus on CI planning and decision-making efforts in the aftermath of a disaster from a recommender systems perspective.

We have developed an innovative approach to modelling critical infrastructures for decision-making support during reconstitution efforts in response to infrastructure disruptions [14]. By modelling the impact of infrastructure elements, both within and across infrastructures, we can recommend focus areas for reconstitution resources across different stakeholders in the context of their current goals. Our framework has been implemented in a prototype Decision Recommendation Tool (DRT) called the "Critical Infrastructure Explorer" (CIE) that utilizes an interactive geovisualization interface to provide a natural context for infrastructure analysis support.

In order to evaluate our approach, we conducted a user study with system experts and GIS analysts. This helped us determine the advantages and disadvantages of such a system in order to understand the validity of our approach. The user study collected performance data as users ran through several disablement analysis scenarios separately with the CIE and commonly used GIS tools. ArcGIS with the Utility Network Analyst extension was selected as the comparison point based on feedback from our system experts about tools they employed for CI analysis. For this paper we will refer to out of the box ArcGIS tools as Standard GIS (STDGIS). We then performed quantitative analyses comparing results for the two platforms in terms of effectiveness measures for end users. This paper begins with an overview of our CI decision support approach, describes our user study, and presents our study results, discussion and conclusions.

2 CI Decision Support Approach

Our approach for CI decision support is grounded in a framework for prioritizing infrastructure elements based on potential impacts – recommending high-impact infrastructure elements to consider in planning resource allocation to CI recovery efforts. As illustrated in Figure 1, this framework is comprised of four primary components:

• **Target model** defines individual infrastructure knowledge, cross-infrastructure dependency knowledge, and the knowledge necessary to enable the metric assessment of desired outcomes;
• **Simulation engine** calculates effects within and across infrastructures based on initial conditions and perturbations;
• **User model** defines general task goal categories for individual users, their specific category weightings and geographic scope of interest;
• **Recommender engine** maps user goals to metric assessment in the context of modelling and simulation to prioritize the impact of infrastructure elements.

Figure 1 - Recommendation Framework
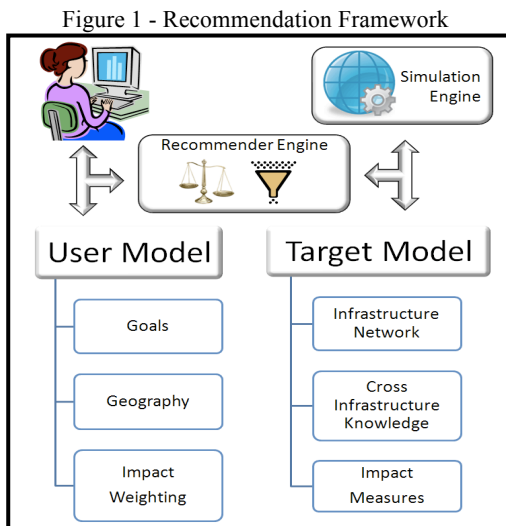
Source: [14]

2.1 Decision Recommendation Tool: CIE

At the start of a simulation, the user sets the initial state of the system to represent the failed infrastructure elements in the current scenario. The CIE models resulting disablements through the initial CI network and linked CI networks that depend on service from the initial network. It also relates each network node to target layer components in order to determine the effect of disablement of each network node (e.g., population affected). Coupling this with cascading disablement simulation provides an indication of the overall effect of each initial disabled point's effect on the ground.

The CIE affords an interactive interface enabling the user to explore various cross-infrastructure scenarios, visualize the effects of disablements, and thereby explore the best options for CI reconstitution. This includes simulation animations, tabular data, network table of contents, and three information tabs (Figure 2):

"Disablements" shows network disablements in a tree-view structure,

"Options" shows disablements and details in tabular form. Details can be clicked to initiate related animations on the map (see Figure 3). A summary is also provided for each initial disabled network element, showing the effect of its enablement on target service layers. For example, if node #15 is enabled then electrical service would be restored for approximately 15,000 people and communications (dependent on electric service) for approximately 39,000 people.

"Network Detail" enables the user to click for detailed information on individual nodes in the networks.
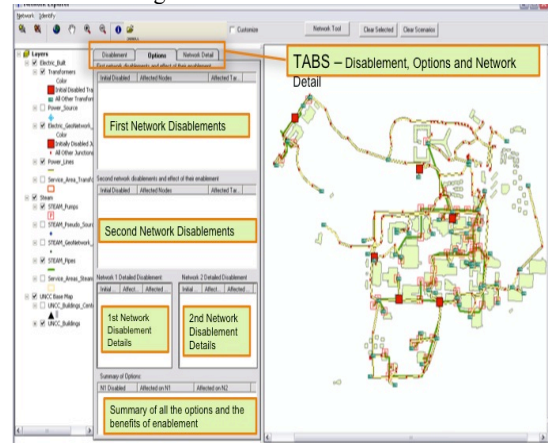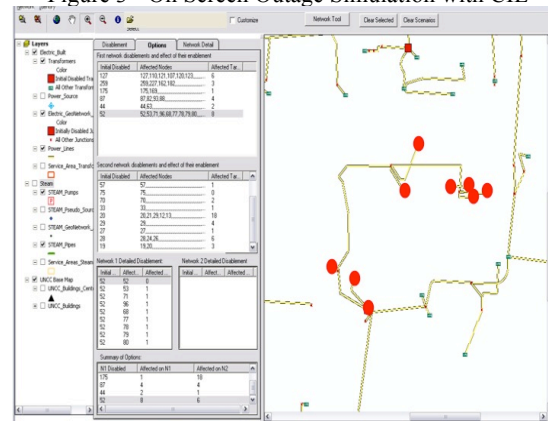
Figure 2 – CIE Interface Details

Figure 3 - On Screen Outage Simulation with CIE

3 Study Design

To evaluate our approach we have conducted a user study with system experts and GIS analysts. The study compares our implemented DRT approach (CIE) with out-of-the-box industry standard GIS tools (STDGIS), which are often employed by analysts for CI support, as

indicated by our study experts. Such controlled studies typically compare novel tools or techniques to state of the art [8, 9]. For example [10] compared three tree visualization tools, space tree, hyperbolic and window explorer. For this study we selected ESRI ArcGIS Desktop software products including Utility Network Analyst as the baseline for comparison (STDGIS).

Our hypothesis is that a DRT for CI recovery based on our framework (CIE) is more efficient and effective for multi-infrastructure reconstitution analysis than using standard GIS tools (STDGIS). More specifically, given the same scenario, decision makers can make decisions with less time and less cognitive load using CIE.

For each participant we recorded the screen, user voice and user video with Morae usability software. Users were asked to complete an exit survey on tool use, cognitive load, user preference, and general feedback. Users were also asked to fill out the NASA TLX Mental Demand evaluation questionnaire twice, once for each tool in the same context.

3.1   Participants

Our user base consists of: employees of one of the US National Research Laboratories who have been working on CI related projects at least last five years, as well as UNC Charlotte staff and student GIS users who are proficient in GIS theory and usage of GIS tools. Participants were recruited to gain insight both into the decision makers' approach and the approach that GIS analysts would take to make recommendations to decision makers.

We recruited 5 system experts from national labs and 10 GIS users from UNC Charlotte. Out of 15 participants 13 had at least three or more years of GIS experience. More than half of all the users defined themselves as experts in GIS. For our study, domain experts are considered to be individuals who have been working professionally with critical infrastructure analysis (our national lab subjects). As employees of a federal national lab these individuals have been providing support to real decision makers throughout the U.S. in emergency situations involving critical infrastructures. GIS users are then the students and professionals who are proficient in GIS and therefore are qualified to play a "GIS Analyst" role with training in CI analysis that we provided.

We selected a within subject study design because we are comparing the performance and experience of the same group of users in different scenarios with two different tools, and because our targeted user population is small. We counter-balanced the presentation of the interfaces allowing half to be presented with STDGIS first (Group A, 8 participants) and the other half with CIE first (Group B, 7 participants). We have equally assigned system experts to our counter-balanced participant sample.

3.2   Evaluation

To evaluate system effectiveness, we considered task efficiency and outcome quality. We also considered cognitive load, which is important for improving decision quality for decision makers [12]. Quantitatively we measured: time spent on each task, rate of outcome correctness, and rate of analysis correctness. These were measured and validated through analysis of recorded participant sessions. To measure cognitive load we utilized the NASA Task Load Index (TLX) tool [5,6].

3.3   Experiment Setup

In order to familiarize users with the software tools in the study, each participant was provided an initial training session on a sample CI outage scenario covering cascades and cross infrastructure effects. We first drew an example scenario on paper – one network with two initial disabled points. Then we showed the participants how the service areas are utilized to determine the buildings that would be affected by these outages. Then we drew the second network elements overlaying the first outage and showed participants how to determine the second network outages based on the first network's service areas. Next we cascaded down the second network outage and showed how those would be related the number of buildings in the service areas of the disabled second network elements. Based on this we created a table that lists the first network disabled points and overall effect of each of those in the buildings with respect to type of service being disrupted. After the paper disablement scenario demonstration we ran through an outage scenario once with STDGIS and once with our CIE. These example scenarios had one initial disabled point on the first network and two interacting infrastructure networks.

Users were then asked to work through four outage scenarios at increasing levels of complexity. Complexity was set to be similar at each level but with different initial disablements. We applied four levels of complexities, so users worked through eight different scenarios. Users were instructed to act as the GIS analyst in an outage-emergency situation where they are required to provide a report to the Decision Maker (DM) on the priority of the initial disabled points in importance of their effect in each specific situation. This way the DM could allocate appropriate resources to the CI elements with greatest effect on target layer elements for optimum recovery. The network data employed is adapted from UNC Charlotte Critical Infrastructure network data. For this experiment we used CI network data, buildings and building center point layers (Figure 4).

The first scenario included one network (water) and two network elements disabled initially. The second scenario included one network (electric power) and six network elements disabled initially. The third scenario included two networks (water, gas) and two elements initially disabled on each network, with the water network interacting with gas in a source-sink relationship (e.g., pump cooling). The last scenario had the electrical power network interacting with the steam

network in a source-sink relationship with six initial disabled elements. Users were asked to determine which of the initial disabled network elements should be restored first to provide most benefit. All the initial disablements were on the first network, which was presumed to be providing services essential for elements of the second network to function. For purposes of this study, we presumed a one-way source sink relationship between networks.

Figure 4 – Scenario Critical Infrastructure Overview
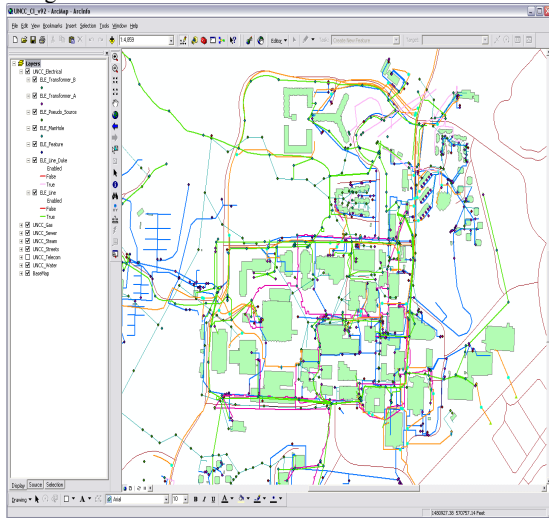
4   Results

Results for successful task completion and correctness of supporting analysis are shown in Figure 5a and Figure 5b. As shown in Figure 5a, participants who worked through the scenarios in CIE completed the tasks with correct conclusions based on correct analysis almost in all cases. However, as shown in Figure 5b, participants working with STDGIS reached correct answers significantly less frequently. For Tasks 1 and 2, only 70% and 60% of participants completed successfully with correct analysis and only 30% in Tasks 3 and 4. For Tasks 2 and 4 in Figure 5b where the participants are prioritizing among six alternatives, 10% and 50% of the participants respectively did not reach the correct conclusion for various reasons. Some participants carried over the disablement to the second network, but neglected to cascade the disablement through the second network, whereas some simply lost track of details in the process. Even for straightforward tasks 1 and 3 (2 initial disablements), when using the STDGIS tools 30% of the participants on Task 1 and 70% of the participants on Task 3 did not have the correct numbers even though they reached the correct overall conclusion (Figure 5b).

Figure 5 - Distribution of successful task completion among participants using (a) CIE, (b) STDGIS

a-) Success Distribution by Task
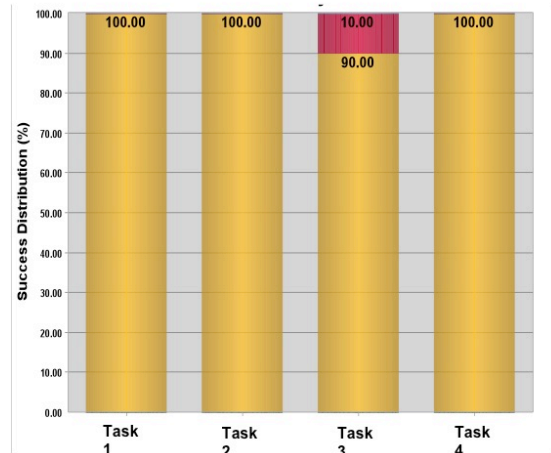
b-) Success Distribution by Task
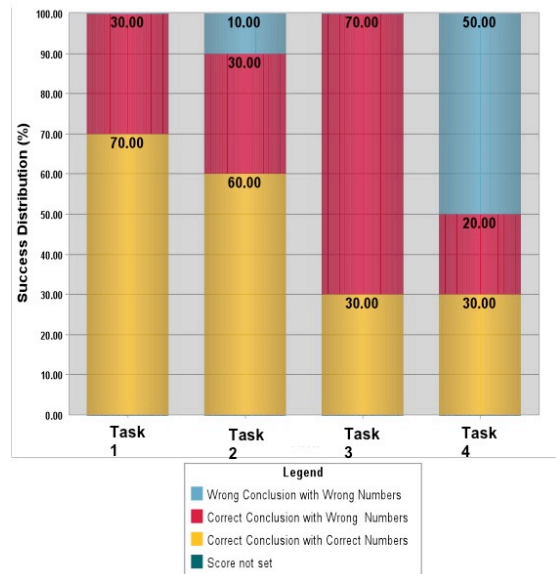
Results for average task completion time are shown in Figure 6 (overall) and Figure 7 (only correct conclusions with correct analysis). Tasks were set up with increasing complexity and therefore difficulty. Overall, as the participants progressed through the tasks it took them longer to make the connections and come up with a conclusion. Completion time in Task 2 is lower for CIE. Our observations indicate that users spent additional time exploring and familiarizing themselves with the CIE tool upon first use, accounting for additional time spent on a simpler task.

Task completion time increases in direct proportion to complexity for STDGIS tools, while completion time for CIE remains relatively flat. In the most complex scenario, STDGIS takes almost three times as long. This

is even more apparent if we use the data from only those who reached the correct conclusion with using correct numbers (Figure 7). Solutions with STDGIS remain a more manually driven process where the participants have to pay a lot of attention to the task at hand to produce the correct numbers so that they can base their prioritization decision on correct numbers.

Figure 6 – Average time spent on each task in minutes including data from all GIS user participants
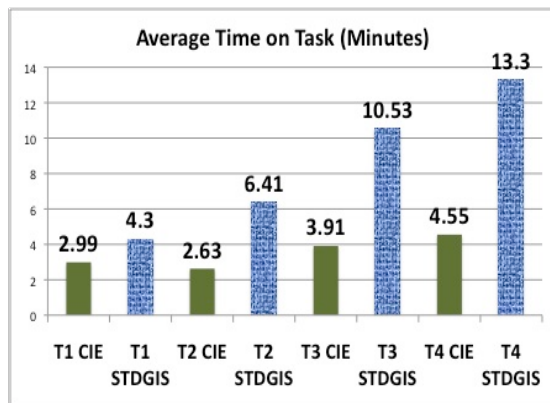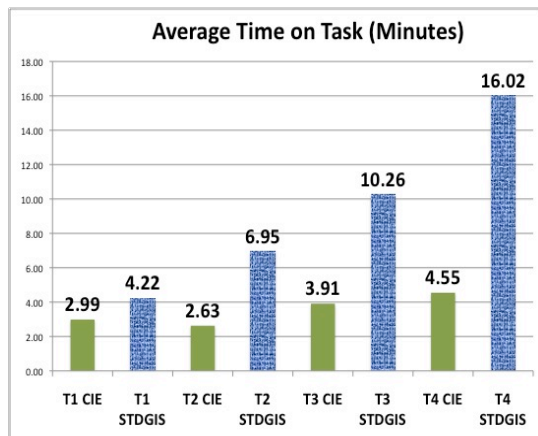

Figure 7 - Average time on task: Only the participants who reached the correct result using correct numbers

Results for cognitive load are shown in Table 1. We found a significant difference between the average TLX score using CIE (M=21.26; SD=12.22) and STDGIS (M=65.26; SD=13.21); t (14)= -9.032, p= 0.00. The TLX score of 21.26 for CIE is significantly smaller than the TLX score for STDGIS with a TLX score of 65.26 where they both have similar standard deviations. We can conclude that participants' mental demand was significantly lower with CIE than STDGIS tools. This interpretation is also supported by comments from users' exit interviews where they indicated that they had to concentrate much harder to get to a conclusion using STDGIS tools compared to CIE, and there was much

greater room for mistakes and confusion even if they keep their attention at highest level.

We also found a significant difference between the average TLX scores for STDGIS tools, based on experiment type. Group A has lower TLX score than Group B for STDGIS tools: Group A: M=58.54, SD=13.56, Group B: 72.95, SD=7.94; t(11.49)=-2.547, p=.026. In other words, while evaluating STDGIS tool for mental demand, participants didn't find performing the tasks as equally demanding if they performed the task with STDGIS tools first and than a similar one with CEI. We can interpret this as by performing the task first with CIE they experienced a tool that provides easier interaction and better visualization. And therefore doing a similar task with a tool that requires more manual interaction appeared to be taking a greater mental toll, hence higher TLX score. Moreover, if the participants first performed the tasks with STDGIS tools and than with CIE, they indicated higher mental demand required for CIE. Thus the users seem to be mentally fatigued upon starting to use CIE if they performed the task with STDGIS first.

Table 1 – Group TLX Statistics Based on Experiment Type

	Group	N	Mean	Standard Deviation	Standard Error Mean
TLX: CIE	A	8	23.08	14.69	5.19
	B	7	19.19	9.34	3.53
TLX: STDGIS	A	8	58.54	13.57	4.80
	B	7	72.95	7.94	3.00

5 Conclusion

Results for user task efficiency, task completion, and cognitive load consistently support our hypothesis: given the same scenario, decision makers can make better decisions with less time and less cognitive load using CIE. Applying our approach for CI reconstitution, users successfully completed more scenarios more accurately (Figure 5a and 5b), in less time (Figure 6, Figure 7), and with lower cognitive load (Table 1). Overall, we believe that such approaches are essential to address the information overload problem in complex, multi-dimensional analysis for CI in general and reconstitution efforts in particular. Results from this user study provide a baseline for our investigation of recommender based geovisualization tools for CI decision support. Future work will study how refinements on underlying decision support strategies, interface and interaction affordances, and individual user goal weighting impact the effectiveness of CI analysis.

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