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THE DEPENDENCE OF INFRASTRUCTURE RESTORATION ON TRANSPORTATION NETWORK

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16. ABSTRACT

The increased number of extreme events and the management of complex interdependent infrastructure systems produce a need for better post-disaster recovery plans. Researchers have presented important approaches in restoring components of interdependent infrastructure systems after an extreme event. These approaches include the selection of components that should be restored, the scheduling, and the assignment of these components to the restoration work crews or machines. However, the accessibility of the transportation network is ignored in previous analyses, assuming work crews can move instantaneously along the transportation network to perform restoration tasks. The availability of the transportation network is the key component that will help the restoration of other infrastructure. With this new approach, we present an interdependent network model that considers the movement of work crews based on the availability and restoration of the transportation network. We provide results from computational experiments for a set of realistic interdependent networks from Panama.

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SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
°F	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	°C
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS FROM SI UNITS

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
°C	Celsius	1.8C+32	Fahrenheit	°F
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

*SI is the symbol for the International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380.
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I. Executive Summary

In this report, we describe the success of the research project examining the dependence of infrastructure restoration following an extreme event on the transportation network. Specifically, existing optimization models that determine which damaged infrastructure components are repair by which work crew and when are deficient because they assume that any two consecutive tasks can be completed by any work crew. This assumption is unrealistic because the transportation network is often obstructed due to debris from the extreme event, flooded, or structurally damaged.

This work removed the common assumption that the transportation network is never damaged and always accessible. Instead, we created and tested an optimization models that explicitly models the damage to the transportation network, restoration of the transportation network over time, and impact of the accessibility of the transportation on the restoration efforts for other infrastructure networks. Specifically, we modeled how the damage and restoration to the transportation network impacted the restoration and accessibility to restoration tasks by the power network.

We cultivated and refined infrastructure data sets representing the realistic transportation and power networks in Juan Diaz, Panama. We performed computational experiments to validate the performance of the new model. With the computational tests, we examined how the number of work crews, magnitude of damage to the transportation and power networks, and pre-positioning of the work crews impacted restoration efforts.

II. Introduction

This research project develops an approach for deriving post-disaster plans to restore components within a set of interdependent infrastructure networks. We develop a mixed-integer programming model that determines *which* work crews restore *selected* network components at *what times* after an extreme event. We denote this problem an Interdependent Integrated Network Design and Scheduling problem with movement of machines (IINDS-MM).

The main contribution of The IINDS-MM is that we explicitly restrict restoration decisions based on the ability of the work crews to access consecutive restoration tasks by traversing an under repair transportation network. Thus, the IINDS-MM is developed in order to realistically model restoration by incorporating:

(i) movement of work crews throughout a transportation network; (ii) interdependence of 2 or more infrastructures on the status of the transportation network; and (iii) restoration activities over time for the interdependent infrastructures based on the ability to reach the tasks via the transportation network. Hence, we remove the common assumption that work crews can instantaneously move along any transportation arc.

Managers of infrastructure systems require tools that dictate the best system-wide restoration on a set of interdependent infrastructures. Infrastructure systems are critical to the function of society as they provide basic services including transportation, telecommunication, water, and electrical power systems [29]. Infrastructures are dependent or interdependent when there exists a directional or bidirectional relationship which the state of each is correlated [32]. Interdependencies cause infrastructures to be vulnerable to cascading failures following extreme events. Moreover, restoration tasks of one infrastructure could contribute to or impact the restoration efforts of other infrastructures [34]. As a results, decision makers need to consider interdependencies when coordinating restoration efforts to lead to a more resilient system.

Countries vulnerable to natural disasters need effective disaster preparedness and response plans. In a 2010 study examining over 60 countries, Panama was ranked 14^{th} based on land area for high exposure to multiple hazards [12, 15]. Similarly, the United Nations Office for Disaster Risk [16] indicates that Panama has high indicator levels for hazard and exposure (2.9% of the population) and lacks coping capacity (4.8 out of 10). Since 2000, 42 events have occurred in Panama affecting many people. From 1995 to 2006 in Panama, 82,514 people were impacted by disasters resulting in 15,850,000 USD of damage. In the last 10 years (2007-2016), the number of affected people increased to 172,097 people resulting in 210,000,000 USD of damage [10].

Given the importance of Panama, we perform a case study using the developed IINDS-MM model for Juan Diaz, Panama. For this case study, we consider flood scenarios using the the transportation and electrical power networks. We quantitatively determine the best restoration activities to conduct in both networks in order to maximize the amount of demand satisfied in the electrical power network over time. We assume that restoration efforts are coordinated for both networks and analyze how the placement of work crews, capabilities of work crews, and amount of damage impact the restoration insights learned.

There are several factors that motivate this research. Extreme events can be manmade disasters or natural disasters [14]. Historically, natural disasters, such as hurricanes, can cause large-scale damages. Floods comprise the third highest percentage (8.8%) of major natural hazards that impact land area in the world [12]. In total, floods have affected around 38% of the population from 1985 to 2003 causing $\$14,670 \times 10^9$ in damages [12]. The transportation systems is impacted greatly by floods wherein $1,191 \times 10^3$ km of road and rail from 1985 to 2003. Given these values, current infrastructure restoration models that assume the transportation network is always available for traversing from one restoration task to the next are not realistic.

III. Literature Review

There are many areas of study related to the outlined work on Interdependent Integrated Network Design and Scheduling Problems with Movement of Machines. A collection of literature is reviewed in this chapter. The literature review is divided into three subsections: disasters and disaster management, restoration interdependence, and mathematical models related to disasters.

A. Disasters and Disaster Management

According to Ergun et al. [14] there are two categories of disasters: man-made disasters and natural-disasters. Some disasters can be slow to start such as political crisis and famine, but others begin in an abrupt way, such as terrorist attacks and floods. The process of the management of any disaster is divided into three different phases: pre-disaster, disaster and post-disaster. In pre-disaster (phase I), organizations conduct mitigation and preparedness activities. In this phase I, the risk factor and vulnerability assessments contribute to better planning in infrastructure, policy, capacity and availability of resources.

Phase II of the disaster management process includes response management which includes relief and logistics operations. Larson et al. [21] outline how applying operation research techniques can facilitate decision makers when in planning emergency responses. The authors indicate how location theory can be used to determine placement for supplies and equipment, and new theories can be addressed in order to plan emergency response possibly incorporating the inaccessibility of transportation pathways. Dispatching and deployment algorithms can be used when including second- and third-tier responders such as resident volunteers and off-duty personnel. These decisions should include where to allocate these new workers, how to coordinate them, and how these changes can improve the response times.

The last stage presented by Ergun et al. [14] is the post-disaster phase or phase III, actions are concentrated on recovery plans. Resilience is closely related to the post disaster phase. O'Rourke [30] defines resilience in the context of extreme events, which is infrastructure recovering after an extreme event. Hosseini, and Ramirez-Marquez [19] define resilience using four sub-areas: organizational, social, economic and engineering. Tierney and Bruneau [35] remark on the importance of measuring resilience in order to reduce the effects of disaster. After a disaster, resilience is measured based on the quality of infrastructure, and the recovery time of the system.

Analysis of some disasters has been done. Abramson and Redlener [1] provide a short insight of systems' failures after an extreme event occurs. The authors mention some of the issues that occur during and after Hurricane Sandy, such as the disruption of the energy supply and fuel distribution network. For instance, gas shortages affected medical and public populations. All levels of communication were also affected due to the lack of coordination. The authors encourage that decision makers build an integrated system with redundancy so that the impact of disasters is mitigated. In similar studies, Larson et al. [21] investigate and analyze the management of emergency response. The authors present strengths and weaknesses for the Oklahoma City bombing (1995), the United Airlines Flight 232 crash (1989), the Tokyo subway sari attack (1995), Hurricane Floyd (1999), and Hurricane Charlie (2004). These analyzed events are denominated as high-consequence, low-probability. The recommendations from the findings on using operations research improve the decision making processes, specifically in preparedness and response. For example, in the Oklahoma City bombing, Larson et al. [21] identify eight problems which influenced the response effort. These problems are: intake and storage of donated and requested goods, telephone and radio communications, identification of workers and volunteers, operation of triage center, accountability of backup personnel and volunteers, importance of compatible medical records and problem with the media.

The wide range of post analysis woks in disasters demonstrates the importance of disaster preparedness and response plans. Devise effective methods will improve post-disaster managment. We proceed by reviewing the literature focused on interdependence of infrastructure systems.

B. Restoration Interdependence

The concepts of interdependence, infrastructure and any combination of them have been reinforced through the years. According to Rinaldi et al. [32] infrastructure is defined as the primary structure connecting different levels of systems and processes in order to facilitate the exchange of needed goods and services. The Department of Homeland Security in the United States [29] has identified 16 critical infrastructures by sectors as follow: chemical, commercial facilities, communication, critical manufacturing, dams, defense industrial base, emergency services, energy, financial services food and agriculture, government facilities, healthcare and public health, information technology, nuclear reactors, materials and waste, transportation system, water and wastewater systems. Rinaldi et al. [32] define interdependency as the relationship between each infrastructure ensuring the connection in both directions. From this, there are six dimensions for the conceptual model of critical interdependence infrastructure which are: type of interdependence, environment, coupling and response behavior, type of failure, infrastructure characteristics, and state of operation. In addition, Rinaldi et al. [32] categorize of interdependence into physical, cyber, geographical and logical.

Restoration interdependencies are a new type of interdependence introduced by Sharkey et al. [34]. Restoration interdependence occurs when a restoration task, process or activity in an infrastructure is impacted by a restoration task, process, or activity in a different infrastructure. Focusing on restoration efforts after extreme events, Sharkey et al. [34] provides an overview taking in consideration the frequency, infrastructure involvement and potential impact. They introduce five classes of restoration interdependence: traditional precedence, effectiveness precedence, options precedence, time-sensitive options, and competition for resources.

In new approaches related to interdependence, Chang, et al. [9] present the impact of interdependent failures of critical infrastructures in disasters while Mendoça and Wallace [25] present the behavior of disrupted interdependent critical infrastructure system. Chang, et al. [9] introduce a systematic framework called infrastructure failure interdependencies (IFIs) which can be used as a tool to post disaster impacts. Conceptual definitions of IFIs focus on finding experimental data patterns after one of the main electrical power outage events, 1998 Ice Storm in Canada. In order to identify infrastructure interdependence on infrastructure systems, Mendoça and Wallace [25] consider four classifications: input, shared, exclusive-or, and colocation.

C. Mathematical models in disasters

There are different mathematical models in the area of operations research and management science (OR/MS) that have been developed in disasters. A comprehensive review of this mathematical models is presented as a framework of this project research. We identify analytical methods that contribute to different disaster stages.

McLay [24] presents an introductory tutorial providing an overview of the discrete optimization models that have been applied to different types of disasters and homeland security problems. She provides an overview of the techniques and problems that occur during mitigation, preparedness, response and recovery stages. Further, she indicates that often disaster management efforts require the ability to handle lack of resources and address multiple criteria. Altay and Green [3] examine operations management techniques to devise restoration plans after an extreme event. According to Altay and Green [3] the objectives of OR/MS in disasters are: reduce the impact when an extreme event happens, improve the response capacity by reducing the time, and facilitate easy recovery. In other words, the effectiveness and management efficiency in disaster is seeking. Altay and Green [3] emphasize the need of OR/MS in Humanitarian Logistics and Humanitarian Security by considering all type of disasters that are of interest of the International Federation of Red Cross and Red Crescent Societies. Contributing to recovering plan, Bryson et al. [7] present a prescriptive mathematical programming model used to support disaster recovery plans (DRP) while ensuring the effectiveness of infrastructure operability during and after an extreme event. The goal of the DRP is to minimize the impact in loss and identify and prioritize the organizational importance for recovery. The features mixed-integer mathematical decision model are the sub–plan selection, the DRP implementation, and the risk of lock out.

There are other mathematical model approaches that contribute the restoration of infrastructures, such as stochastic models, simulation and economic techniques. A stochastic approach for two interdependent networks is developed by Dueñas-Osorio et al. [13]. The authors establish network interdependencies between elements of a network according to the geographical proximity. The model use graph to represent infrastructure systems and incorporate the conditional probability of failure between two elements of the electric power and potable water networks. Matisziw et al. [23] present an alternative method to mathematical programming models using simulation for assesing critical network infrastructure risk and vulnerability after a disruption. The impact of the disruption in node and arcs is analyzed using risk ranges which contribute to system protection, mitigation and recovery plan. In other studies, a discussion about the theory and methodology behind in the input-output model (IIM) applied to attacks on electric power and telecommunications systems is presented by Haimes et al. [18]. Based on Leontiefs input-output model, the IIM provides a characterization of interdependency among sectors in the economy. A breakdown of initial disruptions to a set of sectors and the resulting ripple effects is also presented. In the characterization of interdependency, IIM shows the level of interconnections among different economic sectors. IIM can be useful for modeling workforce recovery and for model different temporal aspects of recovery. Considering a number of critical interconnected sectors, output is the inoperability and input refers to one or multiple failures, accidents or act of terrorism. In this model inoperability which is also a measure of quality of the system is describes as a numerical factor between 0 and 1, where 0 is no flaw in the operable system state and 1 when the system is inoperable.

Network models have been developed in post disaster efforts. Guha et al. [17] address the effects and the efficient recovery after a disaster impacts a power system. They present two mathematical options for analyzing the effects and the efficient recovery: the budgeted problem and the minimum weighted latency problem. They examine both options for a general network, tree network, and bipartite network. In evacuation plan, Kalafatas and Peetas [20] present experiments and sensitivity analysis focused on computational efficiency of a proposed mathematical programming model. The experiments include the description of the test network, and the selected scenario sets. There are three scenarios applied: the first one examines the impact of the available budget resources amount. The second scenario set is focused on the breakdown of the population size evacuation, while the third scenario analyzes quantity and spatial distribution of evacuation considering the origin–destination of the demand. Nagurney and Qiang [26] introduce a network model, which considers demand, flows, costs, and behavior on network in order to measure the performance or network efficiency. Transportation and internet networks are analyzed by applying Nagurney-Qiang measure (N-Q measure) which gives an insight of the major impact of removing particular nodes and links, directly affecting vulnerability and security. Averbakh and Pereira [5] consider a complex network problem which is strongly NP-hard, develop a mixed-integer linear programming formulations, propose fast and simple heuristics, and present a branch-and-bound algorithm. They consider two types of problems: the first one is the Flowtime Network Construction Problem (FNCP) with an objective to minimize the sum of the recovery times by choosing a schedule of construction activities for server (e.g., a construction crew). The second type of problem is a modified FNCP called FNCP-W where the objective is to minimize the weighted recovery times of all nodes.

In interdependent network approach, Lee et al. [22] examine a network flow model for restoring interdependent infrastructures after an extreme event. The authors identify five types of interrelationships between infrastructure systems in the framework of their study. They build a network model as an interdependent layer network, ILN, by considering multiple commodities in which they seek to minimize the cost and weighted flow. In order to model a realistic scenario of this INL, the authors use data from interdependent infrastructure systems of power, telecommunications and subways after the September 11 attacks on the World Trade Center. In an extension of this first approach by Lee et al. [22], Cavdaroglu et al. [8] present a mathematical model for restoration and scheduling model in disrupted interdependent infrastructure systems. Capturing different type of interdependence, Cavdaroglu et al. [8] concentrate on modeling the power and telecommunications infrastructure of lower Manhattan, New York. The objective function consists of three type of weighted costs: the infrastructure operating cost, the unmet demand cost and the restoration costs. The authors propose a three–phase heuristic solution method when restoring a portion of the network that is completely damaged. The three phases are three different phases which calculate the network operation over time, network design which select which arc to repair or install, and scheduling which take the selected set of new arcs and assigns them to a work group.

Significant effort has been given to integrating network design and scheduling decisions. Boland et al. [6] examine the problem of selecting and scheduling maintenance on a network over time. They prove the problem is NP-hard and propose four different heuristics which integrate maximum flow solutions, explore the maximum flow objective function structure, the availability of primal and dual solvers, and dual information. They seek to maximize the flow through the network over time while maintenance is conducted using an integer programming formulation. In restoration efforts on the network, Averbakh [4] schedules the restoration of work crew in a disrupted transportation network after extreme events. The proposed polynomial time algorithms look to restore different network paths when workers are at both, fixed and flexible initial locations. They also consider a variation with speeds. When there are different restoration speeds of workers, the problems are strongly NP-hard. The proposed algorithm considers workers such as the construction crew, nodes of the networks called depots, recovery time when a node is reached at the first time, and additive property is applied for servers working at the same time. In other restoration effort approach, Nurre et al. [27] consider selecting and scheduling the restoration of damaged arcs in a network over time. They use an integrated network design and scheduling problem for a network that has operational and non-operational arcs. Using a parallel machine scheduling environment, they select the set of arcs to install into the network, assign this selected set specific work groups for restoration/installation, and schedule this set of arcs on the work groups over time. They seek to maximize the cumulative weighted maximum flow over time. The authors present a heuristic dispatching rule which selects the next set of tasks. They test a mixed integer programming formulation and the heuristic on data representing different infrastructure systems in lower Manhattan New York, United States. Sharkey et al. [33] incorporate mathematical formulations related to interdependence infrastructure restoration on the interdependent integrated network design and scheduling problem developed by Nurre et al. [27]. The authors proposed a centralized environment for decision-making process in order to reduce the loss when the systems among interdependent infrastructures are decentralized. Furthermore, Nurre and Sharkey [28] examine a variation of the interdependent integrated network design and scheduling problem by using parallel identical machines. With this new approach, the performance of the network is evaluated.

From this review, this research aims to contribute in the recovery planning phase helping the decision-making process of the infrastructure system managers. The INDS model presented by Nurre et al. [27] is the base model of this research project extending the restoration activities of the model on a set of two interdependent infrastructure networks. The model is unique from others interdependent infrastructure work because integrate interdependence by using the transportation network to support restoration efforts on other infrastructures and by modeling the movement of work crews on the transportation network.

IV. Problem Statement

In this section, we formally define the interdependent integrated network design and scheduling problem with movement of machines (IINDS-MM). In the formal definition, we explicitly define the layered networks, scheduling and machine environment, and interdependence between the status of the transportation network and ability for scheduling machines to move from job to job.

Given a set of networks layers $\ell \in L$ and time $t \in T$, let $G_{\ell t} = (N_\ell, A_{\ell t}, A'_{\ell t})$ represent the network of layer ℓ at time t, where N_ℓ represents the set of nodes, $A_{\ell t} \cup A'_{\ell t}$ represents the set of directed arcs comprised of operational arcs $A_{\ell t}$ and non-operational arcs $A'_{\ell t}$ at time t. Without loss of generality, we assume nodes are always operational. This is not a simplifying assumption as non-operational nodes can be equivalently represented as non-operational arcs in a network through the use of a standard network transformation technique [2]. For the set of all network layers L, we denote $G_t = (\bigcup_{\ell \in L} N_\ell, \bigcup_{\ell \in L} A_{\ell t}, \bigcup_{\ell \in L} A'_{\ell t})$ as the entire multilayered network at time t, where G_0 is the initial multilayered network.

Machines must complete processing on a non-operational arc $(i, j) \in A'_{\ell t}$ for it to transition to the operational set $A_{\ell \bar{t}}$ for some time period $\bar{t} > t$. In order for any machine m to start processing arc $(i, j) \in A'_{\ell t}$, machine m must be able to feasibly reach the location associated with node i. Machines use layer 0, which we denote as the *transportation network layer*, to move from node to node throughout the network. Thus, we assume that each node $i \in N_\ell$ for $\ell \neq 0$ such that $(i, j) \in A'_{\ell 0}$ is present in the transportation network layer. Further, we assume that *when* the transportation network is not damaged (i.e., $A'_{0t} = \emptyset$) that G_{0t} is a connected network, i.e., there exists a directed path from any node k to node k' for $k, k' \in N_0$ using arcs in A_{0t}.

For each network layer ℓ, node $i \in N_\ell$ is either a supply, transshipment, or demand node, where S_ℓ and D_ℓ denote the supply and demand nodes of network layer ℓ, respectively. We denote the supply of node $i \in S_\ell$ as $s_{i\ell}$ and demand of node $i \in D_\ell$ as $d_{i\ell}$. At the start of the time horizon T, nodes $i \in I_m$ are the set of source nodes for machines m. In other words, $i \in I_m$ are the set of nodes of starting locations for machines m. At the end of the time horizon T, nodes $i \in F_m$ for m is the set of sink nodes for machines m. This is where machines need to be positioned after planning horizon is completed. Consistent with network flow notation, we assume that $s_{i\ell} < 0$ and $d_{i\ell} > 0$. The set of arcs for each network layer ℓ remains constant over time, however non-operational arc $(i, j) \in A'_{\ell t}$ becomes operational after p^ℓ_{ij} units of processing. An operational arc $(i, j) \in A_{\ell t}$ can carry up to u^ℓ_{ij} units of flow at a cost of c^ℓ_{ij} per unit. The flow for all network layers $\ell \in L \setminus \{0\}$ is assumed to be instantaneous, however one unit of flow across arc (i, j) in the transportation network layer takes t_{ij} time periods to go from node i to node j.

Flow may only traverse (or start to traverse) arc (i, j) in network ℓ at time t if the arc is operational at time t. We a denote decision variable β^ℓ_{ijt} to indicate whether (equal to 1) or not (equal to 0) arc (i, j) in network ℓ is operational at time t. For all network layers $\ell \in L \setminus \{0\}$, excluding the transportation network, let decision variable x^ℓ_{ijt} denote the flow on arc (i, j) in network ℓ at time t. Let binary decision variable γ^0_{mijt} equalize if commodity m (e.g., machine m) leaves node i along arc (i, j) in the transportation network (network layer 0) at time t. Hence, if $\gamma^0_{kijt} = 1$ then commodity m arrives at node j at time $t + t_{ij}$.

Machines must be assigned to and process a non-operational arc to make the arc operational. As the different network's layers represent different physical entities, the set of machines who can perform processing on arcs in network layer ℓ may not be able to perform processing on arcs in network layer $\bar{\ell}$ for $\ell \neq \bar{\ell}$. As follows, let M^ℓ denote the set of machines who can perform processing on non-operational arcs within layer ℓ, where $M = \bigcup_{\ell \in L} M^\ell$. We assume that if machine $m \in M^\ell$, this machine is able to perform processing on all non-operational arcs within layer ℓ.

We assume a non-preemptive scheduling environment, where if machine m is assigned to arc (i, j) within layer ℓ once it starts processing it must continue processing for p^ℓ_{ij} time periods until processing is complete.

Let α^{ℓ}_{mijt} denote the binary decision variable which equals 1 if machine m completes processing of arc (i,j) in network ℓ at time t. For machine m to be assigned consecutive jobs (i,j) and (k,ℓ), the machine must move (flow) using the transportation network between nodes j and k during some time period after processing is complete on (i,j). If needed, the machine may sit idle or wait at a node in the transportation network between processing of jobs. Let w_{mit} denote the binary decision variable which equals 1 if machine m is idle (i.e., waiting) at node $i \in N^{\ell}$ from time t to time $t+1$.

The combination of machines moving (γ^{0}_{mijt} – variable) and idling (w_{mit} – variable) between consecutive jobs can be viewed as the general idea of sequence dependent set-up times [31]. However, in contrast to traditional scheduling problems, the value of the sequence dependent set-up time depends on the shortest traversal time path in the operational transportation network between the consecutive sets of jobs. The complicating factor is that the shortest path value changes over time as the operational status of the transportation network changes over time.

A. Mixed Integer Programming Formulation

In this section, we present the mixed integer programming (MIP) formulations of the IINDS-MM problem.

Decision Variables: Let x^{ℓ}_{ijt} represent the flow on arc (i,j) in network ℓ at time t; β^{ℓ}_{ijt} represents whether (equal to 1) or not (equal to 0) arc (i,j) in network ℓ is operational at time t; α^{ℓ}_{mijt} equals 1 when machine m completes processing of arc (i,j) in network ℓ at time t; w_{mit} equals 1 if machine m is idle at node $i \in N^{0}$ from time t to time $t+1$; v^{ℓ}_{it} represent the flow consumed by demand node $i \in D^{\ell}$ in network ℓ at time t; and γ^{0}_{mijt} represent that commodity m (e.g., machine m) leaves node i along arc (i,j) in the transportation network (network layer 0) at time t.

Parameters: g_t is the weight associated with the performance of the network at time t; $s_{i\ell}$ is the supply generated at node i on network ℓ; $d_{i\ell}$ is the demand generated at node i on network ℓ; and u^{l}_{ij} is the capacity associated to the network ℓ on arc (i,j). The full MIP formulation is as follows.

$$\max \sum_{t=1}^{T} \sum_{\ell \in L} \sum_{i \in D_{\ell}} g_t v^{\ell}_{it}$$

subject to: (IINDS-MM)

$$\sum_{j:(i,j)\in A_{00}\cup A'_{00}} \gamma_{mijt} + w_{mit} + \sum_{\ell\in L} \sum_{\substack{j:(i,j)\in A'_{\ell 0},\\ t+p^{\ell}_{ij} \le T-1}} \alpha^{\ell}_{mijt+p^{\ell}_{ij}} - w_{mit-1}$$

$$- \sum_{j:(j,i)\in A_{00}\cup A'_{00},\ t-t_{ij} \ge 1} \gamma_{mjit-t_{ij}} - \sum_{\ell\in L} \sum_{j:(j,i)\in A'_{\ell 0}} \alpha^{\ell}_{mjit} = 0 \qquad \text{for } m\in M, i\in N_0,\ t=1,\dots,T-2, \tag{1}$$

$$\sum_{j:(i,j)\in A_{00}\cup A'_{00}} \gamma_{mijt} + w_{mit} + \sum_{\ell\in L} \sum_{\substack{j:(i,j)\in A'_{\ell 0},\\ t+p^{\ell}_{ij} \le T-1}} \alpha^{\ell}_{mijt+p^{\ell}_{ij}} = 1 \qquad \text{for } m\in M, i=I_m,\ t=0, \tag{2}$$

$$-w_{mit-1} - \sum_{j:(j,i)\in A_{00}\cup A'_{00},\ t+t_{ij} \ge 1} \gamma_{mjit-t_{ij}} - \sum_{\ell\in L} \sum_{j:(j,i)\in A'_{\ell 0}} \alpha^{\ell}_{mjit} = -1 \qquad \text{for } m\in M, i=F_m,\ t=T, \tag{3}$$

$$\sum_{j:(i,j)\in A_{\ell 0}\cup A'_{\ell 0}} x^{\ell}_{ijt} - \sum_{j:(j,i)\in A^{\ell}\cup A'_{\ell 0}} x^{\ell}_{jit} \le s_{i\ell} \qquad \text{for } \ell\in L\setminus\{0\},\ i\in S_{\ell},\ t=0,\dots,T-1, \tag{4}$$

$$\sum_{j:(i,j)\in A_{\ell 0}\cup A'_{\ell 0}} x^{\ell}_{ijt} - \sum_{j:(j,i)\in A_{\ell 0}\cup A'_{\ell 0}} x^{\ell}_{jit} = 0 \qquad \text{for } \ell\in L\setminus\{0\},\ i\in N_{\ell}\setminus\{S_{\ell}\cup D_{\ell}\},\ t=0,\dots,T-1, \tag{5}$$

$$\sum_{j:(i,j)\in A_{\ell 0}\cup A'_{\ell 0}} x^{\ell}_{ijt} - \sum_{j:(j,i)\in A_{\ell 0}\cup A'_{\ell 0}} x^{\ell}_{jit} \ge -d_{i\ell} \qquad \text{for } \ell\in L\setminus\{0\},\ i\in D_{\ell},\ t=0,\dots,T-1, \tag{6}$$

$$0 \le \sum_{m\in M} \gamma_{mijt} \le u^0_{ij} \qquad \text{for } (i,j)\in A_{00},\ t=0,\dots,T-1, \tag{7}$$

$$0 \le \sum_{m\in M} \gamma_{mijt} \le u^0_{ij}\beta^0_{ijt} \qquad \text{for } (i,j)\in A'_{00},\ t=0,\dots,T-1, \tag{8}$$

$$0 \le v^{\ell}_{it} \le d_{i\ell} \qquad \text{for } \ell\in L\setminus\{0\},\ i\in D_{\ell},\ t=0,\dots,T-1, \tag{9}$$

$$0 \le x^{\ell}_{ijt} \le u^{\ell}_{ij} \qquad \text{for } \ell\in L\setminus\{0\},\ (i,j)\in A_{\ell 0},$$

$$t = 0,\dots,T-1, \tag{10}$$

$$0 \le x^{\ell}_{ijt} \le u^{\ell}_{ij}\beta^{\ell}_{ijt} \qquad \text{for } \ell \in L \setminus \{0\},\ (i,j) \in A'_{\ell 0},\quad t = 0,\dots,T-1, \tag{11}$$

$$\beta^{\ell}_{ijt} - \sum_{s=0}^{t}\sum_{m=1}^{M} \alpha^{\ell}_{mijs} \le 0 \qquad \text{for } \ell \in L, (i,j) \in A'_{\ell 0},\quad t = 0,\dots,T-1, \tag{12}$$

$$\sum_{i \in N_0} w_{mit} + \sum_{j:(i,j)\in A_{00}\cup A'_{00}} \sum_{s=max\{0,\ t-t_{ij}+1\}}^{t} \gamma_{mijs} + \sum_{(i,j)\in A'_{\ell 0}} \sum_{s=t}^{min\{T,\ t+p_{ij}-1\}} \alpha^{\ell}_{mijs} = 1 \qquad \text{for } \ell \in L,,\ m \in M^{\ell},\quad t = 0,\dots,T-1, \tag{13}$$

$$\sum_{t=0}^{p^{\ell}_{ij}-1} \beta^{\ell}_{ijt} = 0 \qquad \text{for } \ell \in L, (i,j) \in A'_{\ell 0}\ , \tag{14}$$

$$\sum_{m \in M^{\ell}} \sum_{t=0}^{p^{\ell}_{ij}-1} \alpha^{\ell}_{mijt} = 0 \qquad \text{for } \ell \in L,\ (i,j) \in A'_{\ell 0}, \tag{15}$$

$$\alpha^{\ell}_{mijt} - \alpha^{\ell}_{mijt-1} \le \sum_{m=1}^{M} \sum_{s=1}^{max\{0,\ t+p_{ij}\}} \alpha^{0}_{mijs} \qquad \text{for } \ell \in L, (i,j) \in A'_{\ell 0}\quad t = 0,\dots,T-1, \tag{16}$$

$$\alpha^{\ell}_{mijt} \in \{0,1\} \qquad \text{for } \ell \in L, m \in M^{\ell},\ (i,j) \in A'_{\ell 0},\quad t = 0,\dots,T-1, \tag{17}$$

$$\beta^{\ell}_{ijt} \in \{0,1\} \qquad \text{for } \ell \in L,\ (i,j) \in A'_{\ell 0},\quad t = 0,\dots,T-1, \tag{18}$$

$$\gamma_{mijt} \in \{0,1\} \qquad \text{for } m \in M,\ (i,j) \in A_{00} \cup A'_{00},\quad t = 0,\dots,T-1, \tag{19}$$

$$w_{mit} \in \{0,1\} \qquad \text{for } m \in M,\ i \in N_0,\quad t = 0,\dots,T-1, \tag{20}$$

The IIMDS-MM is characterized by integrating the movement of machines along the transportation network and the coupled with all the network layers related to the entire independent system. The IIMDS-MM objective function depends on the flow that arrives at demand nodes, maximizing the cumulative weighted flow at each node over all time periods. Constraint (1) - (3) ensures flow balance for the movement of machines (work crews) along the transportation network. There are three activities performed by the machines along the transportation network: (i) Machines can be working (α) on any non-operational arc $(i, j) \in A'_{\ell 0}$, or (ii) machines can be moving along any transportation arc (γ) or (iii) machines can be waiting (w) at a specific node $i \in N_0$. Constraint (2) forces each machine conduct one of these activities at the source node of the machine (I_m) during the first time period t. Constraint (3) ensures that each machine must finish an activity that allows it to arrive at the sink node (F_m) at time T.

Each work group must do one task at time which is guaranteed in constraint (13), in other words, any machine must be executing a job, moving along arcs without executing a job, or waiting until the next activity is assigned.

Flow conservation constraints of commodities in non-transportation networks are represented in Constraints (4) - (6). Constraint (4) ensures that the flow leaving a supply node is less or equal to the supply capacity. Constraint (6) ensures that the demand is not exceeded at each demand node. For those nodes which are neither supply nor demand nodes, Constraints (5) guarantee the flow in equals the flow out.

Constraints (7) to (11) are capacity constraints. For the transportation layer, Constraints (7) and (8) limit the flow of work machines on each starting operational and starting non operational arc respectivly. Likewise, Constraints (10) and (11) are capacity constraints for networks $\ell \in L \setminus \{0\}$ that limit the flow on operational arcs at each time and non-operational arcs over time based on restoration status.

Constraints (12) relates the operability of an arc (i, j), and the completion this job for all time periods t. For instance, the operability of any arc cannot become online if restoration tasks are not completed at first. Constraints (14) ensure that arc (i, j) will not become operational before the processing time. Similarly, Constraints (15) forces that a machine will not complete a job before the completion or processing time. For those non-operational arcs $(i, j) \in A'_{\ell 0}$ that are in the transportation network and in other networks $\ell \in L$, constraint 16 ensures that the restoration on the non-operational arc in the transportation network happens first. Constraints (17) to (19) force variables to be 0 or 1.

V. Experimental Plan

To test the developed IINDS-MM model, we perform a series of computational experiments. We use the transportation and electrical power data sets for Juan Diaz, Panama. For this case study, we assume that the electrical power network has the same topology as the transportation network. We insert 1962 nodes into the transportation and electrical power networks that represent population demand points. We gathered population data from Juan Diaz, Panama [11] that represents 128 neighborhoods in the network. To connect these nodes, we add arcs which connect the population nodes to the nearest existing transportation and power nodes. Overall, the transportation network has 1962 nodes and 4760 directed arcs and the electrical power network 1962 nodes and 2380 directed arcs resulting in an interdependent network with 1962 nodes and 7140 arcs total. We note, for this case study that the transportation network has double the amount of arcs at the electrical power network to allow for flow in both directions in this directed network.

On these networks, we simulate the damage incurred from different levels of storm surge. We assume that damage occurs in both the transportation and electrical power networks equally (i.e., if arc (i, j) in the transportation network is damaged then (i, j) in the power network is also damaged). When work crews repair the damaged networks, we assume it takes one time unit to traverse an arc in the transportation network. In the following subsections, we describe in detail all of the data used to create scenarios for our computational results. For each scenario, we discuss the storm surge, machine capability and location, and restoration processing time. In total, we generate and examine 84 scenarios. For each scenario, we consider a time horizon of $T = 50$.

A. Storm Surge Simulation

We generate using GIS three levels of storm surge for Juan Diaz, Panama. In Figures 1, 2, and 3 we present the visualization for storm surges equal to 10, 15, and 20 feet. In the figures, we identify the population areas via circles where the size of the circle corresponds to the population amount. Further, we see that as the storm surge increases the population that is impacted by flooding dramatically increases. We present a summary of the damaged caused as a result of storm surge in Table 1.

Table 1: Storm surge scenarios

Scenario	Storm Surge	Description
1	10 feet	This generates 74 damaged power arcs and 148 damaged transportation arcs for a total of 222 damaged arcs. We present a geographical representation of this scenario in Figure 1.
2	15 feet	This generates 190 damaged power arcs and 380 damaged transportation arcs for a total of 570 damaged arcs. We present a geographical representation of this scenario in Figure 2.
3	20 feet	This generates 552 damaged power arcs and 1104 damaged transportation arcs for a total of 1656 damaged arcs. We present a geographical representation of this scenario in Figure 3.

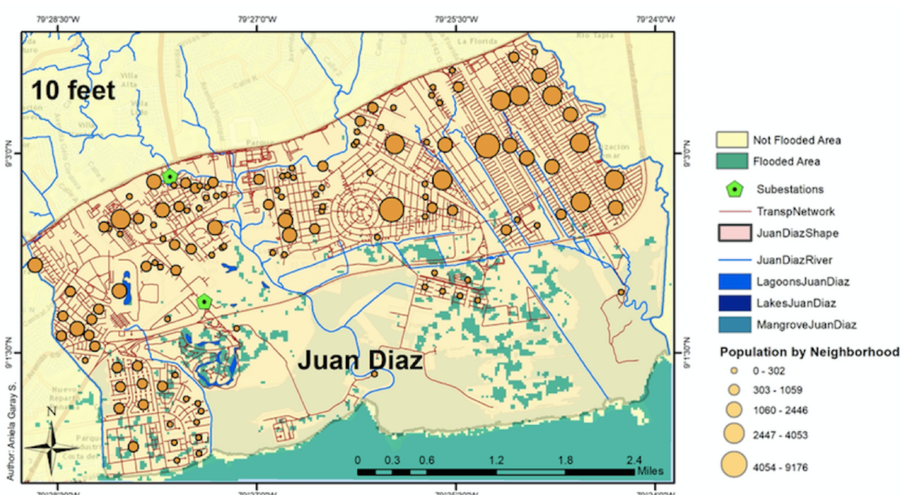


Figure 1: 10-foot storm surge impacting the transportation and power networks in Juan Diaz, Panama. Refer to storm surge description in Table 1 for description.

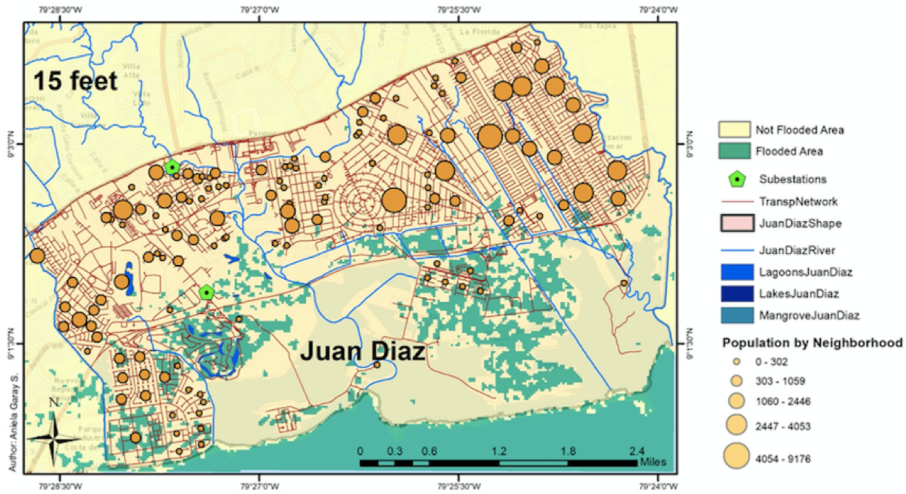


Figure 2: 15-foot storm surge impacting the transportation and power networks in Juan Diaz, Panama. Refer to storm surge description in Table 1 for description.

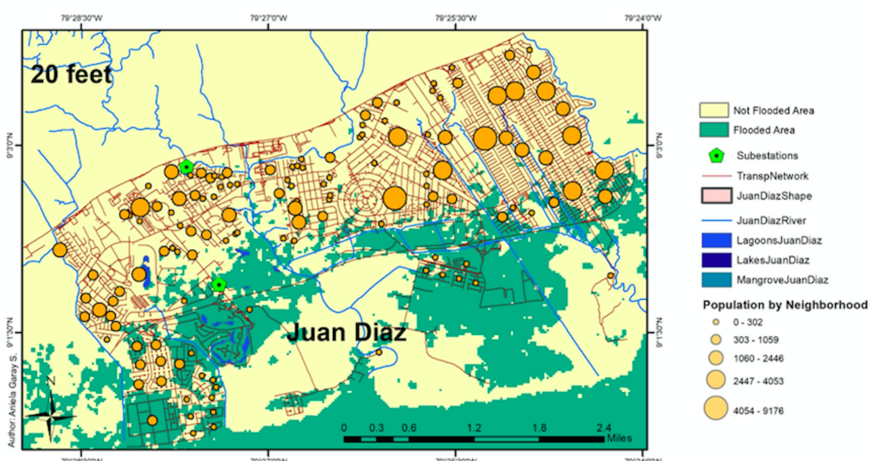


Figure 3: 20-foot storm surge impacting the transportation and power networks in Juan Diaz, Panama. Refer to storm surge description in Table 1 for description.

B. Machines Capability and Location Selected

We consider up to 10 work crews that can repair the transportation network, power network, or both networks. We examine how the configuration of the number of transportation work crews and number of power work crews impact restoration efforts. Further, we examine how the initial geographic location of the work crews when restoration begins impacts the restoration of different regions in Juan Diaz. In Figure 4, we present the possible 10 locations where the work crews are prepositioned and ready for when restoration begins. We consider 3 positions in the western region, 4 positions in the middle region, and 3 positions in the eastern region of Juan Diaz. In Table 2, we outline the 7 scenarios we consider comprised of different work crew capabilities and locations. We synonymously use machines and work crews to represent the entity performing restoration activities on the damaged arcs. We denote work crews that can work in both the transportation and electrical power networks at multi-function machines (work crews).

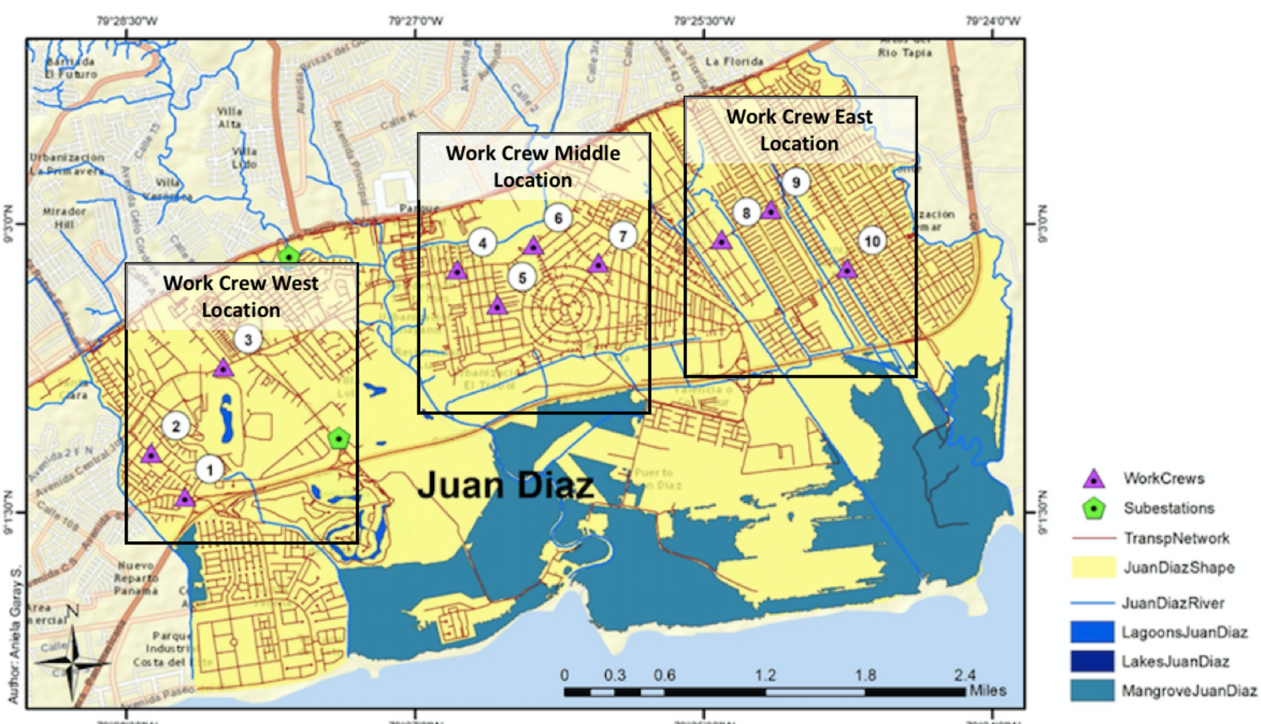


Figure 4: Regions and possible starting locations (source nodes) for restoration work crews in the town of Juan Diaz, Panama. Three possible locations are identified in the West region, 4 in the central region, and 3 in the East.

Table 2: Machines capabilities and locations

Scenario	Machine Number and Type	Location
1	10 multi-function machines	Each machine is located as shown in Figure 4.
2	10 multi-function machines	Machines are only location in the west and east regions. 2 work crews are at locations 1, 2, 8 and 9. There is 1 work crew at locations 3, and 10 (Figure 4)
3	10 multi-function machines	All 10 machines are located in the middle region. There are two work crews at locations 4 and 6. 3 works crews are at locations 5 and locations 7. (Figure 4)
4	4 power machines 6 transp. machines	All power machines are located in the middle position at nodes 4, 5, 6, and 7. 3 transportation machines are location in the east region at nodes 1, 2, and 3. 3 transportation machines are located at the west region at nodes 8, 9, and 10.
5	6 power machines 4 transp. machines	3 power machines are located in the east region at node 8, 9, and 10 and 3 power machines are location in the west region at node 1,2, and 3. All transportation machines are located in the middle position at node 4, 5, 6, and 7.
6	5 power machines 5 transp. machines	At location 2 in the west there are 2 power and 1 transportation machines. At location 6 in the middle there are 2 transportation and 2 power machines. At location 9 in the east there are 1 power and 2 transportation machines.
7	5 power machines 5 transp. machines	In the west, there is 1 transportation machine at location 2 and 2 power machines at location 1. In the middle, there are 2 power machines at location 7 and 2 transportation machines at location 6. In the east, there is 1 power machine at location 10 and 2 transportation machines at location 9.

C. Processing Time Estimation

For our computational experiments, we consider two options for the processing time needed to restore each damaged arc. For each option we convert simulated restoration times to time units for the IINDS-MM model. In Table 3, we present the values for Option A where the restoration processing times range from 2 to 4 hours as indicated by 8 to 15 values for the time units in our model. In Table 4, we present the values for Option B where the restoration processing times range from 30 minutes to 1.5 hours as indicated by 2 to 6 values for the time units in our model.

In the IINDS-MM model, we consider both the transportation and electrical power network in Juan Diaz, Panama. We examine all combinations of processing times using Option A and B: (1) the transportation network has option A processing times, the power network has option A processing times; (2) the transportation network has option A processing times, the power network has option B processing times; (3) the transportation network has option B processing times, the power network has option A processing times; and (4) the transportation network has option B processing times, the power network has option B processing times. With these combinations, we consider different magnitudes of damage which require different time units of effort in both networks.

In order to assign arc values from the real processing time, a factor is chosen. The real times are divided by this factor and the results are the time units used in the model. For this experimental plan, we chose the factor of 16.

Table 3: Processing time option A with values that range from 2 to 4 hours.

Real Time (min)	Time Unit
120 (2 hours)	8
150 (2.5 hours)	9
180 (3 hours)	11
210 (3.5 hours)	13
240 (4 hours)	15

Table 4: Processing time option B with values that range from 30 minutes to 1.5 hours

Real Time (min)	Time Unit
30 (0.5 hours)	2
45 (0.75 hours)	3
60 (1 hours)	4
75 (1.25 hours)	5
90 (1.5 hours)	6

D. Scenario Summary

In this section, we summarize the experimental plan that we utilize to conduct our computational experiments. In Table 5, we indicate the number of possible scenarios specific to each changing aspect (e.g., storm surge, work crew capability and location, and processing time). We note, that the work crew capability scenario number and location number will always be the same. For each storm surge level, there are 28 possible scenarios (see Table 6) thereby generating a total of 84 scenarios.These 84 settings are obtained from all combination of (i) 3 possible storm surge levels; (ii) 7 possible work crew capability and starting location scenarios; and (iii) 4 possible processing time scenarios.

Table 5: Summary of experimental plan

Storm Surge	Work Crew		Processing Time
	Capability	Location	
1	1	1	1
2	2	2	2
3	3	3	3
	4	4	4
	5	5	
	6	6	
	7	7	

Table 6: Total number of scenarios by storm surge.

Storm Surge	Total Number of Scenarios by Storm Surge
10	1–28
15	1–28
20	1–28
Grand Total	**84**

For ease of presenting the results, we assign an identification (ID) for each scenario used for each storm surge using the schematic outlined in Figure 5. The first number of the ID indicates the scenario number from 1 to 28. The second and third numbers must equal and represents the work crew capability and location information, respectively using a number from 1 to 7. The final number represents the processing time scenario using a number from 1 to 4.

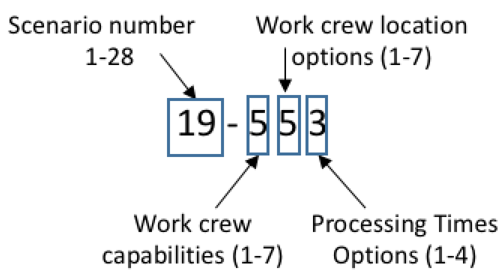


Figure 5: Scenario Indentification

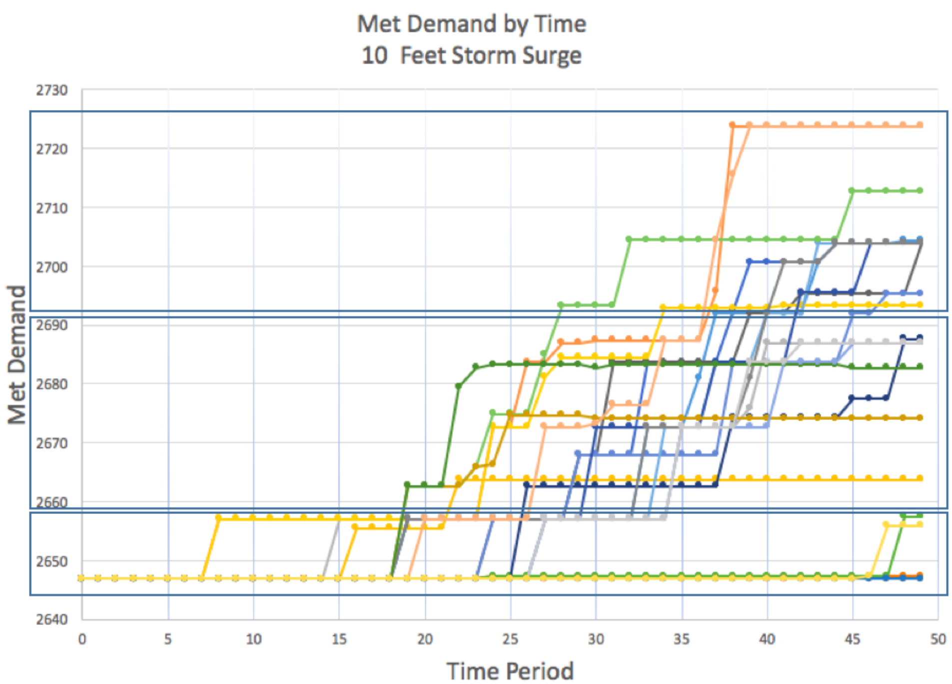
VI. Computational Results and Analysis

Using the data outlined in Section V., we perform a series of computational experiments to deduce policy insights about restoration infrastructure in Juan Diaz, Panama. We proceed by discussing the total amount of met demand over time, the insights gained by analyzing the high, middle, and low performing scenarios, and model effectivity. We solve the IINDS-MM using the optimization software package CPLEX 12.6.3. With a time limit of 2 hour was set up in the program. If the time limit is reached, we report the best known solution upon termination.

A. Total Met Demand Over Time

In this section, we examine the total amount of demand met over time for the 84 scenarios. In Figures 6, 7, and 8, we display the amount of met demand over time for the scenarios after experiencing 10, 15, and 20 feet storm surges, respectively. When comparing the different storm surge levels, we note that the maximum amount of demand met at the end of the time horizon ($T = 50$) varies dramatically. Further, we see that the amount of met demand that is restored can be done more quickly when the storm surge is lower.

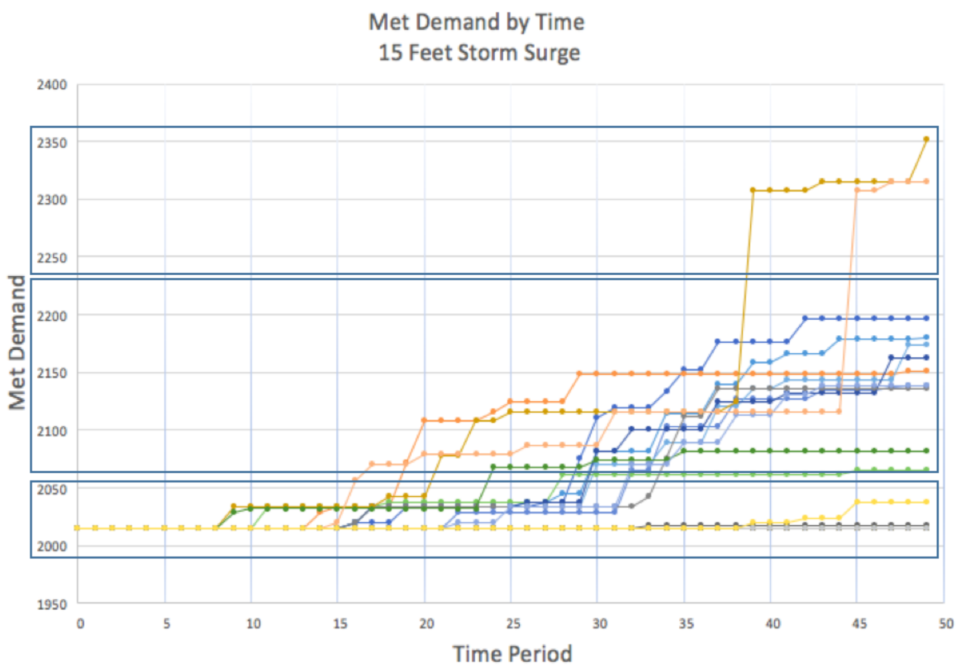
When comparing the 28 scenarios examined within each individual graph, we see groups of scenarios that perform similarly. In Figures 6, 7, and 8 we group similar performing scenarios together into high, middle, and low performing groups. We proceed in Section A. and explain the characteristics of the scenarios that are grouped into high, middle, and low and the additional annotations we indicate on Figures 6, 7, and 8.



Performance

Performance	Scenario Number	Final Met Demand
High	1	2703.872
	5	2704.351
	9	2703.872
	13	2695.278
	14	2723.72692
	16	2693.341
	17	2703.872
	18	2712.717
	19	2703.872
	21	2703.872
	26	2723.72693
Middle	4	2663.82
	7	2687.619
	15	2686.98
	22	2674.169
	24	2682.763
	25	2686.98
	27	2686.98
Low	2	2647.407
	3	2646.928
	6	2657.506
	8	2646.928
	10	2646.928
	11	2646.928
	12	2646.928
	20	2646.928
	23	2646.928
	28	2656.001

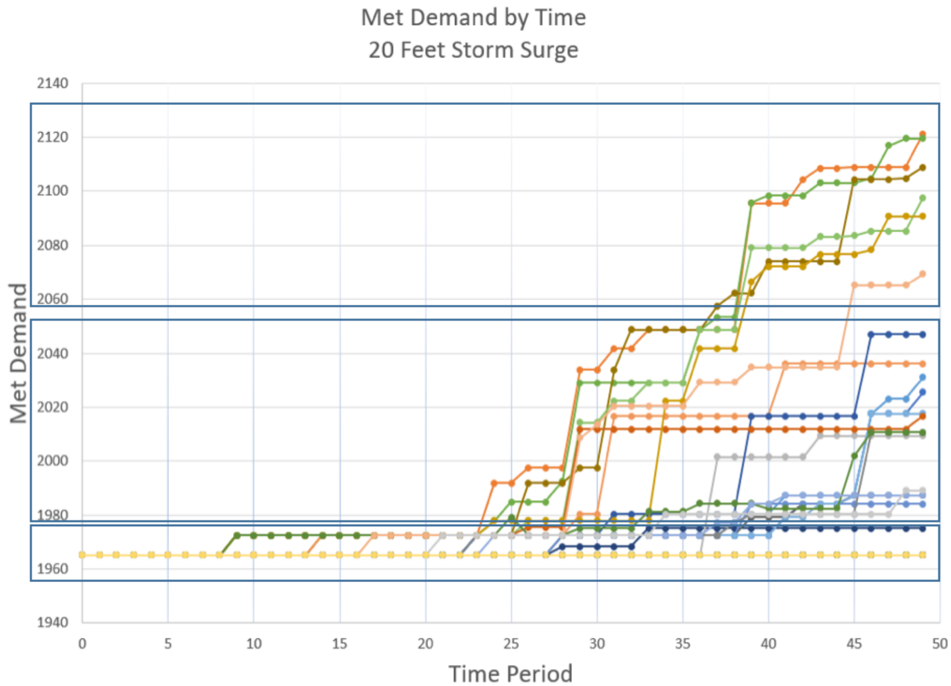
Figure 6: Total met demand over time periods for the 28 scenarios experiencing 10 foot storm surge. The color of the lines have no significance other than to distinguish each of the scenarios. On the right of the figure, we list the 28 scenarios and group them into high, medium, and low performing scenarios.



Performance

Performance	Scenario Number	Final Met Demand
High	22	2350.968
High	26	2315.498
Middle	1	2195.774
Middle	5	2179.909
Middle	13	2137.8958
Middle	14	2150.867
Middle	17	2173.092
Middle	18	2065.655
Middle	19	2161.899
Middle	21	2135.616
Middle	24	2081.522
Middle	25	2138.716
Low	2	2014.456
Low	3	2014.456
Low	4	2014.456
Low	6	2014.456
Low	7	2014.456
Low	8	2014.456
Low	9	2017.556
Low	10	2014.456
Low	11	2014.456
Low	12	2014.456
Low	15	2014.456
Low	16	2014.456
Low	20	2014.456
Low	23	2014.456
Low	27	2014.456
Low	28	2037.252

Figure 7: Total met demand over time periods for the 28 scenarios experiencing 15 foot storm surge. The color of the lines have no significance other than to distinguish each of the scenarios. On the right of the figure, we list the 28 scenarios and group them into high, medium, and low performing scenarios.



Performance

Performance	Scenario Number	Final Met Demand
High	2	2121.255
	6	2119.637
	10	2108.945
	18	2097.593
	22	2090.709
	26	2069.303
Middle	1	2025.489
	5	2031.074
	9	1987.215
	13	1984.115
	14	2036.204
	15	2009.442
	17	2017.556
	19	2047.009
	20	2016.668
	21	2010.672
	24	2001.918
	25	1987.215
	27	1989.13
Low	3	1965.172
	4	1965.172
	7	1975.156
	8	1965.172
	11	1965.172
	12	1965.172
	16	1965.172
	23	1965.172
	28	1965.172

Figure 8: Total met demand over time periods for the 28 scenarios experiencing 20 foot storm surge. The color of the lines has no significance other than to distinguish each of the scenarios. On the right of the figure, we list the 28 scenarios and group them into high, medium, and low performing scenarios.

Insights for High, Middle, and Low Performing Scenarios

To interpret the characteristics of the scenarios present in the high, middle, and low performing groups, we present Table 7 which lists the scenario IDs by performance group and storm surge amount. We reiterate the scenario ID information from Section V.: the first number indicates the scenario number, the second and third numbers indicate the work crew capabilities and location, and the fourth number indicates the processing time configuration.

In Table 7 and Figures 6, 7, and 8, we highlight the scenarios that appear in the same group (high, middle, low) for each of the storm surge values. Scenario 26 appears in the high performing group for all 3 storm surge levels. In scenario 26, we have 5 power work crews and 5 transportation work crews spread throughout the region relatively evenly (see Table 2 in Section V.). It is interesting to note that scenario 26 using processing time scenario 2 which has Option A for the transportation network and Option B for the power network. If you recall, Option A has longer average processing times and Option B has shorter average processing times. The result that scenario is high performing is counter to our intuition. We would expect that because portions of the transportation network much be repaired to enable access to power restoration tasks, we would hypothesize that when the transportation network has Option B processing times, we would see better performance in terms of the total met demand over time. Further, we would hypothesize that scenarios with processing time scenario 24 would perform best due to the reduced overall processing times. In high performance groups, most part of the scenarios have Option A in processing time for both the transportation and power networks, and processing time Option B on power network. Work capability and location seems to not have any influence on the high performance scenarios since combinatorial factors from 1-7 appears for machine capability and location.

Among the scenarios that are in the middle performing group, Scenarios 24 and 25 appear for all three storm surge levels. Scenario 24 has 5 transportation work crews and 5 power work crews wherein both transportation and power work crews and location in the east, middle, and west regions of Juan Diaz. Scenario 24 has processing time scenario 4 which using Option B for both the transportation and power networks. Scenario 25 has 5 transportation work crews and 5 power work crews spread throughout the region relatively evenly. Scenario 25 has processing time scenario 1 which uses Option A for the transportation and power network. We note that all of the scenarios that consistently occur in the high and middle performing groups all used the same number of transportation and power work crews spread throughout the region. This leads us to the policy insight that to obtain the best results for this case study, we recommend evenly splitting the number of work crews between the infrastructure networks and locating all types of work crews throughout the network. This insight is counterintuitive as we would have expected that the multi-function work crews would result in the highest performance.

There are many scenarios which consistently perform in the low group including scenarios 3, 8, 11, 12, 23, and 28. Similar among all of these scenarios is processing time scenarios 3 and 4 combined with not convinient capability/location makes the scenario to have low performance. Also, we see that work crew capability 3 appears in both scenarios 11 and 12 which locations all work crews in the middle region of Juan Diaz.

Table 7: Summary of scenarios by storm surge and performance.

	Storm Surge		
Performance	10 feet	15 feet	20 feet
High	1 - 1 1 1	22 - 6 6 2	2 - 1 1 2
	5 - 2 2 1	26 - 7 7 2	6 - 2 2 2
	9 - 3 3 1		10 - 3 3 2
	13 - 4 4 1		18 - 5 5 2
	14 - 4 4 2		22 - 6 6 2
	16 - 4 4 4		26 - 7 7 2
	17 - 5 5 1		
	18 - 5 5 2		
	19 - 5 5 3		
	21 - 6 6 1		
	26 - 7 7 2		
Middle	4 - 1 1 4	1 - 1 1 1	1 - 1 1 1
	7 - 2 2 3	5 - 2 2 1	5 - 2 2 1
	15 - 4 4 3	13 - 4 4 1	9 - 3 3 1
	22 - 6 6 2	14 - 4 4 2	13 - 4 4 1
	24 - 6 6 4	17 - 5 5 1	14 - 4 4 2
	25 - 7 7 1	18 - 5 5 2	15 - 4 4 3
	27 - 7 7 3	19 - 5 5 3	17 - 5 5 1
		21 - 6 6 1	19 - 5 5 3
		24 - 6 6 4	20 - 5 5 4
		25 - 7 7 1	21 - 6 6 1
			24 - 6 6 4
			25 - 7 7 1
			27 - 7 7 3
Low	2 - 1 1 2	2 - 1 1 2	3 - 1 1 3
	3 - 1 1 3	3 - 1 1 3	4 - 1 1 4
	6 - 2 2 2	4 - 1 1 4	7 - 2 2 3
	8 - 2 2 4	6 - 2 2 2	8 - 2 2 4
	10 - 3 3 2	7 - 2 2 3	11 - 3 3 3
	11 - 3 3 3	8 - 2 2 4	12 - 3 3 4
	12 - 3 3 4	9 - 3 3 1	16 - 4 4 4
	20 - 5 5 4	10 - 3 3 2	23 - 6 6 3
	23 - 6 6 3	11 - 3 3 3	28 - 7 7 4
	28 - 7 7 4	12 - 3 3 4	
		15 - 4 4 3	
		16 - 4 4 4	
		20 - 5 5 4	
		23 - 6 6 3	
		27 - 7 7 3	
		28 - 7 7 4	

From this analysis, we deduce some key insights. We observed that when the power network has Option B with smaller processing time the networks come back online faster and meet more demand. This insight occurs even when the transportation network has longer processing times. Additionally, we observe that when all work crews are located in the middle of Juan Diaz, the amount of met demand is less. The most amount of met demand occurs when there are an even number of transportation and power crews spread relatively evenly throughout the region or closer to damaged areas. Finally, if we observe Figures 1, 2, and 3, the west area has more damaged arcs than any of other area. This means that if we allocate more power machines on the west area, the met demand will increase faster. Scenarios that provide closer power machines to the west area are: 6 and 7 from machine capability and location.

B. Machine Movement and Optimality Gaps

In the last set of analysis, we examine the performance of the IINDS-MM model using the solver CPLEX 12.6.3. We first examine the movement of work crews for a selected scenario. Next, we report on the optimality gaps for all 84 scenarios upon termination at the 2 hour time limit. The computer specification is: MacOS Sierra version 10.12.5, Intel Core i7 processor with 2.2 GHz speed, and RAM memory of 8 GB 1600 MHz DDR3.

First, we examine the movement of the machines for scenario 1 (1-1 1 1 from Table 7) and 15 feet storm surge. In scenario 1, there are 10 multi-function work crews that can perform tasks on both the transportation and power networks. Each work crew is pre-positioned at the locations indicated in Figure 4. In Figure 9, we present the movement and sequence of tasks conducted in Juan Diaz for 3 selected work crews: (i) Work crew 1 located in the west region of Juan Diaz town; (ii) Work crew 7 located at the middle region of Juan Diaz town; and (iii) Work crew 10 located at the east region of Juan Diaz town.

In Figure 9, a blue highlight on an arrow with a continue line means that a work crew is restoring a transportation arc. If the highlight is orange a work crew is restoring an electrical power arc. If the work crew wait in a node, this is indicated by a red circle. In Figure 9 part (a), we show that work crew 1 starts at location 1 and moves (dashed lines) on 3 different operational transportation arcs before reaching the first transportation restoration task. Next, work crew 1 completes the second restoration task in the power network, and lastly work crew completed restoration of a transportation arc. Until the end of the time horizon, work crew 1 waits at the red in Figure 9 part (a) until to the end of the time horizon. In part (b) of Figure

9, the movement of work crew 7 is very different from work crew 1. Work crew 7 is farther away from the damage and thus, must spend more time moving through the network in order to reach a restoration task. Thus, work crew 7 is only able to complete one restoration task before the end of the time horizon. We note, a current limitation of our model is the difference in time scales between traversing arcs and completing restoration tasks. Future work, should consider different magnitude between traversing an arc and performing processing. Work crew 10 uses the operational portion of the transportation network to reach a location with 3 damaged arcs (see part (c) Figure 9). Work crew 10 performs restoration of two power arcs and then performs restoration of 1 transportation arc.

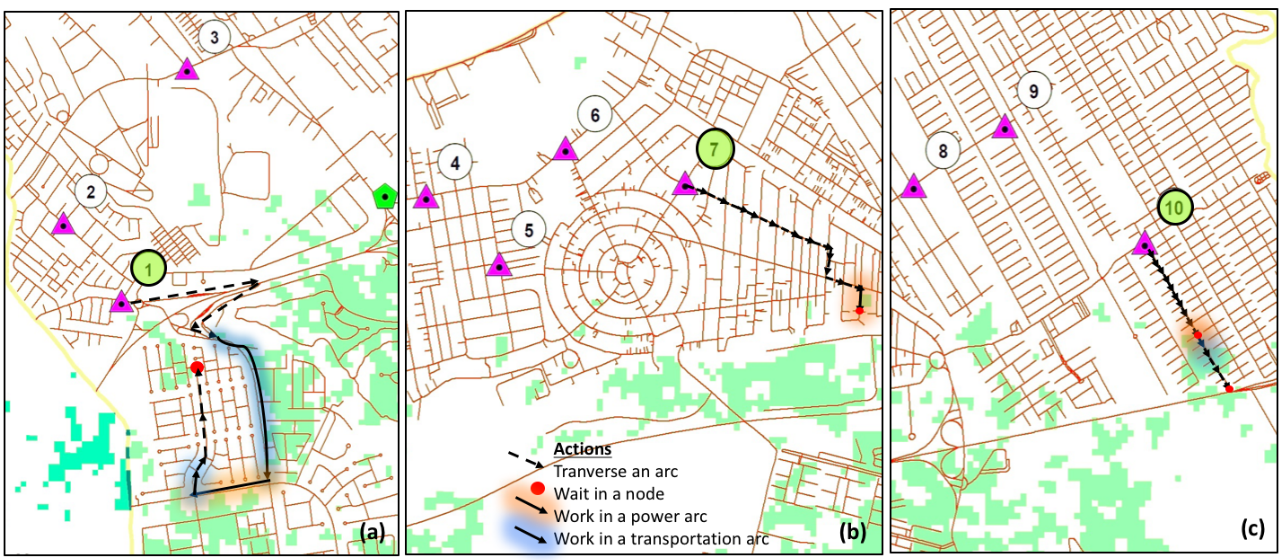


Figure 9: Scenario 1 from 15-foot storm surge. In part (a), the movement of machine 1 is presented starts at location 1 in the Western region then moves South, West, and North. In Part (b), the machine starts at location 7 in the central region and moves Southeast. In (c), the machine starts at location 10 in the Eastern region, and moves along one road to the Southeast.

From these 3 contrasting movement patterns, we observe that the position of the work crew can dramatically aid in being able to quickly reach restoration tasks. Further, we observe that when a work crew is capable of performing restoration in both the transportation and power, then the work crew can easily alternate between these tasks in order to restore many damaged arcs within a geographic region.

Lastly, we examine the optimality gaps for all 84 scenarios. In Figures 10, 11, and 12, we present the gaps for 10, 15, and 20 feet storm surge values. We note, that we set a 2 hour time limit and upon termination capture the best known solution and optimality gap. Thus, scenarios that are solved to optimality are indicated by a 0.00% optimality gap. The largest observed optimality gap for the scenarios with a 10 foot storm surge is approximately 1.82%. We notice a pattern among the scenarios that repeats with every 4 scenarios. The similarity for each pair of scenarios: 1 and 5, 2 and 6 , 3 and 7, 4 and 8 is the same processing time. Scenarios 1 and 5 has processing time Option A for both networks. Scenarios 2 and 6 have processing time Option A for transportation network and Option B for power network. Scenarios 3 and 7 have Option B for tranportation network and Option A for power network. Scenarios 4 and 8 have processing time Option B in both networks. The scenarios with a larger optimality gap often have shorter processing times (Option B, see Table 4) in the power network. Smaller gaps have larger processing time (Option A, see Table 3). We notice a change in the trend for Scenarios 13 - 4 4 1. These scenarios have different work crew configurations: 4 power work crews and 6 tranportation work crews. All power machines are located at the middle position from Figure 4. Transportation work crew are located as follow: 3 at the east area and 3 at west area (Figure 4). From Figure 10, we notice that scenarios 2, 4, 6, 8, 10, 12, 14–16, 18, 20, 22, 24, and 26 –28 are harder than the others. Every 2 or 3 scenarios remains with the same scenario for capabiity and location. For example, scenarios 2 and 4 have same capability and location for work crew (scenario 1 from Table 2): all multi-function machines and each machine is located as Figure 4.4. Scenarios 6 and 8 also have same work crew capability and location (scenario 2 from Table 2): all multi-function machines and work crew are located at east and west area. Scenarios 1, 5, 9, 13, 17, 19, 21, 23, and 25 are easier than the others and we notice that most part of them have same processing time scenario 1 where Option A is for transportation and power networks.

In Figure 11, we present the optimality gaps for scenarios with a 15 foot storm surge. The pattern every 4 scenarios is also present for these scenarios, however, we note that the optimality gaps are much larger. The largest optimality gap observed is 13.33%. We notice that starting with scenario 14, the second scenario of each 4 grouping (scenario 15, scenario 18, scenario 22, scenario 26) becomes easier. 3 out of 4 have processing time Option A for tranportation network and Option B for power network.(Tables **??**tab:ProcTimeA, 4). The pattern among the scenarios from 1 to 13 repeats with every 4 scenarios. The processing time is the same for each pair of scenarios: 1 and 5, 2 and 6 , 3 and 7, 4 and 8. Scenarios 1 and 5 has processing time Option A for both networks. Scenarios 2 and 6 have processing time Option A for transportation network and Option B for power network. Scenarios 3 and 7 have Option B for tranportation network and Option A for power network. Scenarios 4 and 8 have processing time Option B in both networks. Same as 10 foot storm surge, scenarios with a larger optimality gap often have shorter processing times (see Table 4) in the power network.

Lastly, in Figure 12 we present the optimality gaps for scenarios experiencing a 20 foot storm surge. A trend is apparent again with every 4 scenarios. However, we note that the average optimality gap decreases to at most 4.6% and the second scenario of each set of 4 is easier to solve. The trend remains the same in all scenarios as follows:

- Scenarios 1, 5, 9, 13, 17, 21, 25 have processing time scenario 1 with Option A in both networks.
- Scenarios 2, 6, 10, 14, 18, 22, 26 have processing time scenario 2 with Option A in transportation network and Option B in power network.
- 3, 7, 11, 15, 19, 23, 27 have processing time scenario 3 with Option B in transportation network and Option A in power network.
- 4, 8, 12, 16, 20, 24, 28 have processing time scenario 3 with Option B in both networks.

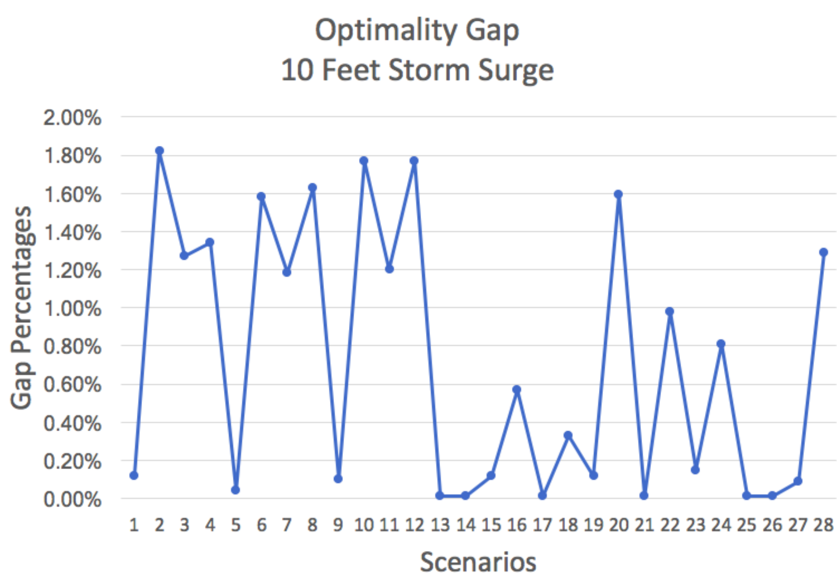


Figure 10: Average optimality gap for 10-foot storm surge where the maximum optimality gap is just over 1.8% and the minimum is 0%. We see a pattern with every 4 scenarios where, in general, the optimality gap starts low, increases, decreases, and increases.

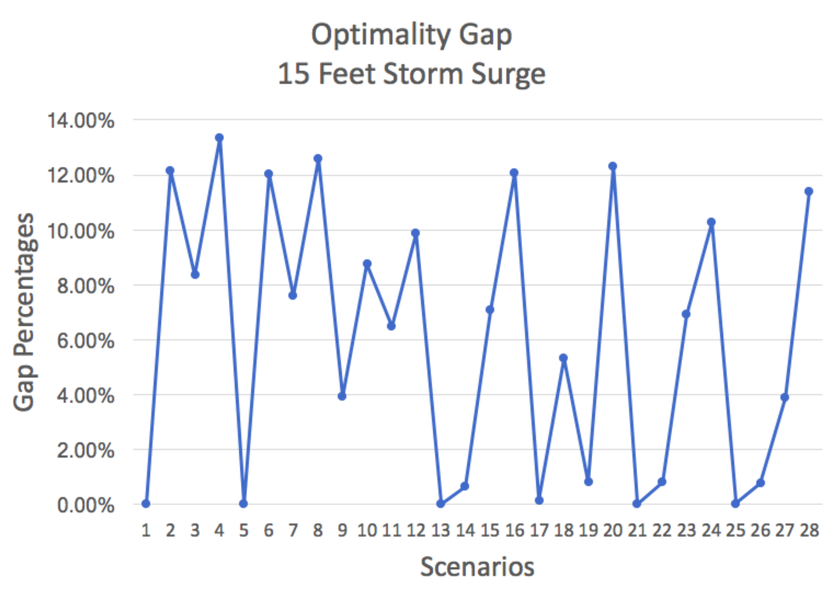


Figure 11: Average optimality gap for 15-foot storm surge where the maximum optimality gap is just over 13% and the minimum is 0%. We see a pattern with every 4 scenarios where, in general, the optimality gap starts low, increases, decreases, and increases.

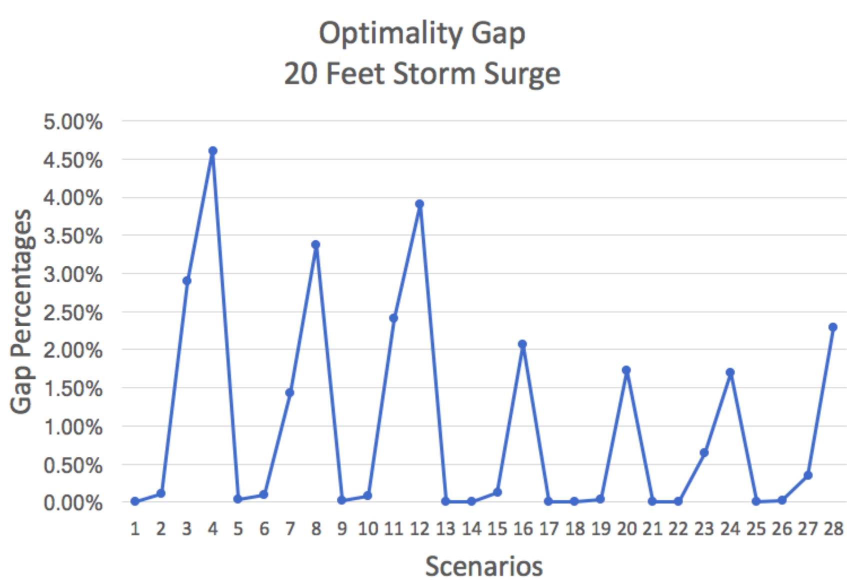


Figure 12: Average optimality gap for 20-foot storm surge where the maximum optimality gap is just over 4.5% and the minimum is 0%. We see a pattern with every 4 scenarios where, in general, the optimality gap starts low, increases slightly, increases again, and increases to the peak.

VII. Conclusions

This project introduced a mixed-integer programming model for an Interdependent Integrated Network Design and Scheduling problem with movement of machines (IINDS-MM) that determines (i) which tasks to select to be restored in a damaged interdependent network; (ii) which work crew performs the restoration tasks; (iii) at what time restoration is performed; and (iv) how work crews traverse through a network to move between restoration tasks. With an IINDS-MM model we link the restoration tasks on two or more interdependent infrastructure networks by explicitly requiring the transportation network to be operational for work crews to move throughout the network. With this, we shown how the availability of the transportation network impacts system-wide infrastructure restoration. A main contribution of this work is the removal of the common assumption that work crews can reach any restoration task at any time.

We performed a series of computational experiments using the transportation and electrical power networks of Juan Diaz, Panama. On these networks we simulated different storm surge damage, work crew capabilities and locations, and magnitude of damage requiring different processing times. From the results of our case study, we observed that scenarios with the same number of transportation and power work crews performed best when the work crews are evenly spread through the geographic region. We also observed a counter-intuitive trend that scenarios with small processing times for the power network and even large processing times for the transportation network performed well.

This model is a starting point for modeling complex interdependent infrastructure restoration. Future work should consider modeling the transportation network as an undirected network to reduce the number of variables in the model. Further work should consider the different time scales between traversing arcs in the network and performing restoration. Lastly, heuristic methods should be developed for this complex model that dramatically increases when considering larger geographic regions and time horizons for restoration.

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