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MODEL FOR MITIGATING ECONOMIC AND SOCIAL DISASTER DAMAGE
THROUGH STRUCTURAL REINFORCEMENT

A THESIS APPROVED FOR THE
SCHOOL OF INDUSTRIAL AND SYSTEMS ENGINEERING

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To my family,
Who encourages me to dream bigger, through every season of life.

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Abstract

Natural disasters have both severe negative short-term consequences on community structures, inhabitants, and long-term impacts on economic growth. In response to the rising costs and magnitude of such disasters to communities, a characteristic of modern community development is the aspiration towards resilience. An effective and well-studied mitigation measure, structural interventions reduce the value lost in buildings in earthquake scenarios. Both structural loss and socioeconomic characteristics are indicators for whether a household will dislocate from their residence. Therefore, this social vulnerability can be mitigated by structural interventions and should be minimized as it is also indicator of indirect economic loss. This research presents a model for mitigating direct economic loss and population dislocation through decisions regarding the selection of community structures to retrofit to higher code levels. In particular, the model allows for detailed analysis of the tradeoffs between budget, direct economic loss, population dislocation, and the disparity of dislocation across socioeconomic classes given a heterogeneous residential and commercial structure set. The mathematical model is informed by extensive earthquake simulation and as well as recent dislocation modeling from the field of social science. The non-dominated sorting genetic algorithm II (NSGA-II) is adapted to solve to model, as the dislocation model component is non-linear. Use of the mitigation model is demonstrated through a case study using Centerville, a test bed community designed by a multidisciplinary team of experts. Details of the retrofit strategies are interpreted from the estimated Pareto front.

Chapter 1.0 Introduction

Natural disasters have both severe negative short-term consequences on a communities and long-term impacts on economic growth. In 2016, 15 different United States communities were affected by natural disasters resulting in losses exceeding $1 billion each. Further, both the magnitude and effect of natural disasters on communities have increased in the last few decades (NOAA, 2017). In response to the outlook urgency, a characteristic of modern community development is the aspiration towards resilience. Community resilience is the ability of a community to return its physical, social institutions, and its people to return to a level of normalcy in a reasonable amount of time (Ellingwood, 2016) (Mileti,1999) (Bruneau,2003) (Godschalk,2003). The timeframe in which a community resumes normal function impacts the loss, economic or otherwise, experienced. Communities with low resilience experience limited capacities to function which results in prolonged recovery. In addition to economic loss, the individuals in the affected community are more at risk for dislocating from their home, health and mental problems, and loss of property (Sherrieb, Norris, Galea, 2010). Due to the increasingly interdependent nature of communities, resilience is not only critical to the sustainability of individual communities, but to nations as well. To reduce the nation's vulnerability, the resilience of its communities must increase as to limit economic disruption and its impact on inhabitants. For this reason, resilience improvement tools that may be adapted to any modern community are needed.

International governments and organizations have recognized the importance of community resilience through their investment in sustainable development (Benson & Clay, 2003). The United Nations background paper on natural disasters clearly states that building resilience into communities is the only way to sustain development efforts in light of increasing cost and threats of natural disasters (United Nations, 2017). Because of the fairly unpredictable and unchangeable nature of natural disasters, the cornerstone of the nation's emergency management's approach is limiting community vulnerability through mitigation (FEMA 2000b). Disaster mitigation is action taken prior to the onset of a disaster to reduce or limit the long-term damage felt by inhabitants and physical infrastructure from natural hazards (Godschalk,2003). Mitigation is different from other activities enveloped in disaster preparedness, response, and recovery due to its long planning horizon and proactive nature. One of the most successful mitigation approaches has been of strengthening buildings and public facilities against the effects of earthquake damage. A study on the Northridge Earthquake of 1994 showed the greatest physical loss was sustained by buildings built prior to 1976, demonstrating the potential improvement to resiliency by improving the structural integrity of physical structures (FEMA 2002). In addition to being a proven method, the predicted improvements of structural reinforcement can be estimated for any range of earthquake severity (Lin & Wang, 2016). Supported by this capability, this research addresses the problem of disaster mitigation for earthquake disasters through the investment in structural reinforcements.

Certainly, the more immediate and visible effects of earthquakes have been well established and recorded. In 2002, FEMA estimated annual earthquake loss for the United States to be $4.4 billion, with by far the most serious damage being structural (FEMA 2002). Building collapse from structural damage is the leading cause of human death from earthquakes (Ara, 2013). However, disasters have other impacts on social components of communities that have proven more difficult to predict. One such impact is the tendency of households to leave their homes following a disaster. Population dislocation is considered a significant indicator of the indirect loss experienced by an economy (Lin, 2009). This is because dislocation results in a disruption of money flow due to the sudden loss of people, reducing the overall financial resources available to local governments from loss in sales, tax, property and personal income (Lindell & Prater, 2003; Lindell et al., 2006). While there are many factors that influence this human behavior, it is known that the extent of housing damage is a significant indictor of whether or not a family leaves their home (MAEviz, 2008). Therefore, one way to mitigate the effects of any disaster on population dislocation is to reduce the damage to residential structures. In this research, resilience is measured not only by overall direct economic loss, but also through population dislocation in order to also capture the impact on inhabitants of the community.

While resilience is usually used to characterize a community as a whole, particular households and zones experience different levels of vulnerability to disasters. Structures at lower building code levels, for example, are inherently more susceptible to damage and will reach a "not livable" state at lower levels of seismic exposure than those at higher code levels. A characteristic of the physical infrastructure, dislocation behavior differs depending on building code (Higheld et al., 2014). Using population dislocation as an indicator of household vulnerability, other factors besides code level have been shown to affect dislocation behavior. These factors include race of the household and whether the residence houses multiple families, such as an apartment complex (Lin, 2009). Vulnerability inequality between households may be exacerbated by a disaster. According to the United Nations Commission on Sustainable Development, resiliency development efforts must not increase vulnerability of a society (Godschalk, 2003). While structural intervention efforts would logically not increase the vulnerability of a community, it will likely increase the vulnerability disparity between subsets of the community. Following this principle, population dislocation disparity must not exceed its current level across income levels in this research.

The goal of this research is to identify near-Pareto optimal solutions for building retrofit strategies to study the tradeoffs of direct economic loss and population dislocation in an earthquake scenario. Simultaneously, all retrofit strategies considered must have a limited effect on dislocation disparity. This work extends the work by Zhang and Nicholson (2016) with a refined dislocation model, modified problem formulation, and an extensive analysis of the results. As previously discussed, structural reinforcement can reduce both economic loss and population dislocation. However, retrofit interventions for commercial structures have different effects on economic loss than those on residential structures. Due to their size and role in the local economy, commercial structure damage results in significantly greater economic loss than residential structure damage. Thus, by the criteria of economic loss, the best policy would include reinforcing mainly commercial structures. But reinforcing commercial structures offers no improvement to population dislocation, thus the two objectives for the policy are competing. Beyond the policy objectives, there is much more complexity in the mitigation resource allocation model; a portion of which will be introduced in the exploration of previous approaches the problem.

Chapter 2.0 Literature Review

While much research has been done in resilience based community planning in the last several years, many gaps exist between works due not only to the large-scale of the topic, but also because of the complex nature of the factors and components existing in the problem space. An example of such work is the model developed by Cimellaro et al. (2010). In this work, a model is proposed for determining a retrofit strategy specifically for a set of six hospitals within a city in light of four potential hazard levels. Four retrofit actions were considered: "no action", retrofit to life safety level, retrofit to immediate occupancy level, and rebuild. Used to evaluate the impact of such decisions were four primary metrics that both capture both direct and indirect costs. The metrics used were content loss, casualties directly resultant from the event, casualties resultant from structure dysfunction or inaccessibility, and direct economic loss from relocation or business interruption. The scope of the model, including six structures of a specific type with similar construction, represents the aspiration towards resiliency driven decision making but is lacking the critical ability to represent any community as a complete set of structures. The scope and robustness of mitigation resource allocation models must allow for the capturing of the community as a whole, diverse, set of structures such that damage estimates that occur at the community level, such as dislocation disparity, are accounted for.

Few approaches to the this mitigation problem have exhibited the community-based perspective required to evaluate decisions using community-wide social vulnerability metrics. Jennings et al. (2015) developed a model for community-wide retrofit decisions for wood-framed structures that minimized cost, economic loss, casualties, as well as recovery time. So, while the scope is appropriate for the damage perspective addressed in this research, it does not include the diversity of structures that any community could have.

Meaning, this model does not fit the need for a retrofit decision framework that has nation-wide applicability. In response, the research presented in this paper is robust to building diversity in its ability to model based on structural characteristics (type, age, value, etc.) and purpose (e.g., residential, commercial, government). An interesting characteristic of the work by Jennings et al. (2015), though, was its investigation of how retrofit policy can reduce the probability of an individual to develop post traumatic stress disorder (PTSD). This work acknowledged the complexity of human nature, which provides challenges for incorporating what is known from social science in the decision frameworks being developed for community resilience. To further develop the existing capability of planning communities in light of social vulnerability, the research presented in this paper accounts for population impacts by minimizing the probability that a household will dislocate.

A model developed by Zhang and Nicholson (2016) addresses the same gaps in current models by mitigating economic loss as well as population dislocation using a community scale retrofit policy. Their model allows for a detailed analysis of the tradeoffs between economic loss, budget level, and population dislocation given a heterogeneous set of residential and commercial structures. Population dislocation was included as the linear regression model developed by the Mid-America Earthquake Center Seismic Loss Assessment System as proposed in MAEviz (2008). The work predicts dislocation at the zone level as a function of structural damage, non-structural damage, median household income, percentage of vacant housing, and percentage of the population that is Black. However, a study based on data collected following the 1992 Hurricane Andrew by Lin (2009) showed that dislocation is more accurately predicted by a model developed using logistic regression. Zhang and Nicholson (2016) acknowledged the limitations of the linear approach. In their work, the linear regression model predicted more dislocation in certain zones than the original population in the same zone. This problem was ameliorated by truncating dislocation percentages to a maximum of 100% per zone. This is obviously less than ideal. Not only did Lin (2009) show that the probability of dislocation is not linear with respect to the predictors, but the significant predictors also differ between the two models as well.

The improved population dislocation model developed by Lin (2009) was found using an empirical approach supported by several data sources describing the damage incurred from Hurricane Andrew in Miami-Dade County, Florida. The first data source, the South Dade Population Impact Survey, documented the dislocation decision and ethnic/racial information for the nearly 3,000 households sampled. In all, 17 remaining potential predictors, including loss, were compiled from the 1990 Census and the Housing Tax Appraisal Database for 1992. The result of testing various logit models, the final prediction tool with a Nagelkerke R-square of 0.205 is a logistic function of a particular structure's percent value loss, whether or not the residence is a single-family detached home, the percentage of population in the surrounding block group that are Black, and then the percentage that are Hispanic. As two of the variables exist at the structure level, it follows that the model predicts dislocation at the household level, which may be aggregated to suite various planning needs. Because the model indicates the predictive power of loss in determining dislocation, the influence of retrofit policy in mitigating the behavior remains.

Despite the valuable contribution to knowledge of population dislocation, there are two limitations already seen with the model developed by Lin (2009). It is important to present that being located along the coastline appears in one study as a significant indicator of population dislocation, a factor that could not be studied when sampling from only one county (Esnard, Sapat, & Mitsoca, 2011). Miami-Dade being a coastline county, an implication of using the logit model in Lin (2009) is that dislocation is likely overestimated for inland communities. An additional concern with nation-wide model applicability is the severity of the disaster from which behavior was observed. The defense of using this model, in light of stated limitations, is that both the coastline and severity factors would most likely influence coefficients of the logistic regression coefficients and perhaps change the selection of significant factors. It is highly unlikely that further expansions of dislocation studies would find it to exhibit something other than logistic behavior. Further, is it even more unlikely that the true dislocation model is linear. Thus, the mitigation model and non-linear solution tool developed in this research will remain applicable in light of new discoveries in dislocation behavior.

By integrating the new predictor function for population dislocation into the model as an objective, the entire problem then becomes non-linear. Where Zhang and Nicholson (2016) were able to use linear optimization to efficiently and thoroughly determine exact solutions, the model in this research is too complex to be solved through an exhaustive method. As such, a heuristic method is used to estimate the Pareto front through an archive of all non-dominated solutions closely resembling the decision trade-off tool in the previous model. There exists a range of heuristic approaches that could be applied to the multi-objective problem, one of which being the non-dominated sorting genetic algorithm II (NSGA-II) developed in Deb et al. (2002). The specific motivation to adapt NSGA-II in this research was its intuitive behavior, existing documentation through existing research applications, and existing packages available for adaptation to reduce implementation time and ease in customization. One implication of this approach is the significant adaptation of both the problem model and algorithm required to make computation relatively efficient. A thorough explanation of these adaptations are provided in later sections to uphold the validity of the solver development.

In summary, the research community recognizes the need for robust community-wide development plans, but still, barriers limit the ability of policy models to meet the requirements of corresponding decision tools. The large scale and number of factors that influence and measure resilience provide a challenge to defining research questions. Human nature, as exhibited by population dislocation, is difficult to predict and lack of data with earthquakes specifically requires that new models be readily developed in light of new findings. By not only building a model to address the current gap between the mitigation model and dislocation findings, but also the adapted solver, this research anticipates new developments in the research area and will shorten their implementation time. Because the solver can be used regardless of problem complexity and can be quickly adapted to include additional objectives, its value spans beyond the application presented in this particular variation.

Chapter 3.0 Problem Formulation

This work integrates what is now known about dislocation behavior into the existing resource allocation model as an objective. The resulting decision variables are affected by altering the behavior of one of the two model objectives, the measures of solution quality. This change not only affects the results of the model, but also the method by which it is solved. In the original model (Zhang & Nicholson, 2016), population dislocation, in addition to all other components, are expressed by linear functions and relations. Because the model outlined in this research incorporates a logistic regression model for dislocation, a non-linear solution approach was implemented to replace the previously used linear programming solver. The development of the updated model and approach is outlined first by a description of the data, then through the formulation of the model, and finally by the development of the evaluation algorithm.

3.1 Mitigation Based Resource Allocation Model

The scope of the mitigation based resource allocation model can be described through the data that support it. The community referred to in this model has one or more distinct zones, group of structures associated by geographic region, type (e.g., residential, non-residential, government) and a subset socioeconomic demographics for the residential zones (e.g., median income, housing age and value, etc.) For the purpose of this analysis, the zones of a community are based on relative homogeneity of structure types or purposes. Zones may be categorized, for example, as commercial zones for their density of consumer retail outlets or high income residential zones as characterized by the demographics of inhabitants. Additionally, information associated with each structure in the community is required. Information denoting structure types, building code level, occupancy type, and estimated value must be available for every structure in each zone.

Using the aforementioned information, loss mitigation estimates can be generated using a functional relationship between retrofit strategies and experienced loss (Lin & Wang, 2016). It should be noted that this estimation process is unique for earthquake scenarios.

To structure the data for the optimization problem, let Z denote the set of community zones, S denote the set of structure types, and K denote the set of ordered code levels. The current number of buildings before retrofit interventions in zone $i \in Z$ of structural type $j \in S$ at building code level $k \in K$ is represented as parameter b_{ijk}. The estimated direct economic loss experienced in zone $i \in Z$ by structure type $j \in S$ at code level $k \in K$ is denoted as parameter l_{ijk}. Direct economic loss estimation is a function of the appraised value of the structure and its sustained damage. The damage sustained by a structure is split into four distinct categories: structural damage (SD), nonstructural drift-sensitive damage (ND), nonstructural acceleration-sensitive damage (NA), and content loss (CL). The economic loss function is adapted from analysis completed by the Mid-America Earthquake Center (Steelman et al. 2007).

$$\boldsymbol{l_{ijk} = M_{ijk}(\alpha_{ijk}^{SD}\mu_{ijk}^{SD} + \alpha_{ijk}^{ND}\mu_{ijk}^{ND} + \alpha_{ijk}^{NA}\mu_{ijk}^{NA} + \alpha_{ijk}^{CL}\mu_{ijk}^{CL})} \tag{1}$$

In the economic loss function, parameter M_{ijk} denotes the total appraised value of the associated building. The parameters $\alpha_{ijk}^{SD}, \alpha_{ijk}^{ND}, \alpha_{ijk}^{NA}$ represent the proportion of value associated with the respective category of damage. The parameter α_{ijk}^{Cl} reflects the value ratio of a buildings' contents to its appraised value. The final values in the loss function represent the mean damage ratio associated with each type of damage for each building. The mean damage ratios are shown as μ_{ijk}^{SD} , μ_{ijk}^{ND} , μ_{ijk}^{NA} , and μ_{ijk}^{CL}. More specifically, mean damage ratio is the proportion of repair cost to the total replacement cost as estimated by simulation.

If b_{ijk} represents the baseline building set prior to retrofit interventions, let the decision variable x_{ijk} represent the building set after structural improvements have been made. With this formulation, the difference between x_{ijk} and b_{ijk} may be interpreted as the interventions made by the resultant mitigation policy. With the decision variable defined, the first objective of the model, to minimize direct economic loss, is provided in Eq(2).

$$\min \sum_{i \in Z} \sum_{j \in S} \sum_{k \in K} l_{ijk} x_{ijk} \tag{2}$$

Direct economic loss is determined as the sum of the loss experienced by every structure category multiplied by the number of structures in the associated category.

The population dislocation behavior evaluated by the second objective is more complex, depending on both the loss experienced, structure characteristics, and select population demographic data. Logically, population dislocation is only experienced in residential zones. Thus, let $R \subset Z$ denote the set of residential zones in the community. For each residential zone $i \in R$, the number of households dislocated as a result of earthquake damage is estimated by a model adapted from work by Lin (2009). The logistic regression model predicts dislocation as a function of experienced loss, structure type, the proportion of Black residents in each zone, and the proportion of Hispanic residents in each zone. Let the parameter $loss_{ijk}$ represent the ratio of damage experienced, discounting content loss, to total appraised value of the structures in zone $i \in R$ for structure type $j \in S$ of code level $k \in K$. This parameter, as calculated in Eq. (2), represents the percent of structural value lost from a residential structure. The parameter M_{ijk} denotes the appraised value of the structure while l_{ijk}^{-c}represents the value loss not including contents.

$$loss_{ijk} = \frac{l_{ijk}^{-c}}{M_{ijk}} * 100 \tag{3}$$

Let d_i denote the number of households dislocated in each zone $i \in R$, recognizing this as an aggregated result of the dislocation behavior computed for each structure type $j \in S$ at each code level $k \in K$. Eq. (4) yields the estimated probability of dislocation dependent on the damage level, the loss parameter exhibiting the variation resulting from decision variable manipulation.

$$p(d_{ijk}) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 loss_{ijk} + \beta_2 s_i + \beta_3 B_i + \beta_4 H_i)}} \tag{4}$$

After loss, the next parameter in the probability dislocation function, s_i represents the proportion of structures in zone $i \in R$ that are single-family detached structures, a subset of structure types $j \in S$. The last two parameters, B_i and H_i represent the percentage of the population that is Black and Hispanic, respectively. The regression coefficients $\beta_0, \dots, \beta_4$ provided by Lin (2009) are -0.42523, 0.02480,-0.50166,-.01826, and -0.01198, respectively.

The probability of dislocation for each zone $i \in R$ for each structure type $j \in S$ is then used to determine the total dislocation for each zone as shown in Eq. (5). Let the parameter H_{ij} denote the number of households in each structure type $j \in S$ in each zone $i \in R$. Thus, multiplying the probability of dislocation by the number of potential households dislocated yields the dislocation associated with a certain set of decision variables.

$$d_i = \sum_j \sum_k H_{ij} * x_{ijk} * p(d_{ijk}) \tag{5}$$

Thus, the second objective, in competition with the first, is represented by Eq. (6) as the total dislocation in the community as influenced by the retrofit strategy.

$$\min \sum_{i} d_i \tag{6}$$

To limit the solutions such that the dislocation disparity among income levels must not exceed the baseline values, the following constraint is formulated. To denote residential zones of different income level, let R_l, R_m, R_h with $R = R_l \cup R_m \cup R_h$ define the zones of low, medium, and high income. The baseline dislocation disparity $\bar{D}$ is thus calculated as the sum of the differences among the baseline dislocation in each income level, denoted by $\bar{d}_\iota$.

$$\boldsymbol{\bar{D}} = \left|\sum_{i\in R_l} \boldsymbol{\bar{d}_\iota} - \sum_{i\in R_h} \boldsymbol{\bar{d}_\iota}\right| + \left|\sum_{i\in R_l} \boldsymbol{\bar{d}_\iota} - \sum_{i\in R_m} \boldsymbol{\bar{d}_\iota}\right| + \left|\sum_{i\in R_m} \boldsymbol{\bar{d}_\iota} - \sum_{i\in R_h} \boldsymbol{\bar{d}_\iota}\right| \tag{7}$$

After the retrofit actions are implemented, the constraint on inequity limits the resultant disparity to be less than or equal to the baseline.

$$\left|\sum_{i\in R_l} d_i - \sum_{i\in R_h} d_i\right| + \left|\sum_{i\in R_l} d_i - \sum_{i\in R_m} d_i\right| + \left|\sum_{i\in R_m} d_i - \sum_{i\in R_h} d_i\right| \le \bar{D} \tag{8}$$

The retrofit policy is also subject to limited financial resources. Let B denote the maximum allowable budget for the policy. The cost of retrofitting a structure to a higher code level is estimated as the difference in assessed structural value between the two levels. Specifically, if a particular structure assessed at a value of M_{ijk} and is of type j in zone i is raised to code level $k' > k$, then the cost of the intervention is calculated as $M'_{ijk} - M_{ijk}$. As shown in Eq. (9), the cost of a candidate policy is given as the difference between the decision x_{ijk} and the current state before retrofits are applied.

$$\sum_{i\in Z}\sum_{j\in S}\sum_{k\in K} M_{ijk}\left(x_{ijk} - b_{ijk}\right) \le B \tag{9}$$

In addition to the social vulnerability and budget constraints, there are several other logical constraints in the model. Given that the only change to the community structures is code level, the quantity of buildings in every zone i of type j must remain the same. This is formulated in Eq. (10) and is referred to from this point on as the building count constraint.

$$\sum_{k \in K} x_{ijk} = \sum_{k \in K} b_{ijk} \tag{10}$$

The next set of constraints force the model to only consider retrofit policies that represent an improvement in code level for each structure. Beginning with code level one, the resultant policy must not add structures to this level as it would imply bringing buildings from other levels down. Expanding on that, the quantity of structures at code one and two together must not increase. Constraining code level two independently of level one would improperly and overly constrain the problem, as the number of structures at code level two must be allowed to increase. Also as not to overly constrain the problem, the only constraint on the decision with code level three is non-negativity. Because all other code levels are constrained, the building count constraint bounds this decision already. The last code level, four, must contain at least the same quantity of structures than the baseline. Together, these constraints define the solution space with respect to the improvement constraint and simultaneously represent non-negativity requirements.

$$\mathbf{0 \leq x_{ij1} \leq b_{ij1} \quad \forall i \in Z, \forall j \in S} \tag{11}$$

$$\mathbf{0 \leq x_{ij1} + x_{ij2} \leq b_{ij1} + b_{ij2} \quad \forall i \in Z, \forall j \in S} \tag{12}$$

$$\mathbf{x_{ij3} \geq 0 \quad \forall i \in Z, \forall j \in S} \tag{13}$$

$$\mathbf{0 \leq b_{ij4} \leq x_{ij4} \quad \forall i \in Z, \forall j \in S} \tag{14}$$

As a summary, the allocation model describes the outcome of the community in the event of the earthquake. The damage from the event is measured by three attributes.

Total economic loss is the result of structural loss in addition to the loss experienced by surrounding businesses as a result of the damage. Also, population dislocation is defined as the total number of households in the community that leave their home after the disaster. In the model, total economic loss and total population dislocation are minimized as competing objectives. As such, multiple Pareto solutions will be identified that satisfy the budget, disparity, and logical constraints.

3.2 Model Verification

After defining the mathematical model, it was verified by analyzing preliminary objective behavior. This was done by supporting the non-linear model with the optimal solutions from the previous, linear model to compare the resultant economic loss for each policy. By ensuring economic loss values, whose calculations in this model are the same as in Zhang and Nicholson (2016), the behavior of that objective was verified. Next, the behavior for dislocation was analyzed. This was done by plotting the dislocation probability distribution for two structure categories to look specifically for sensitivity to value loss, which implies relation to the decision variables, and also for the range between distributions. From the model, the structure category with the highest probability of dislocation is one comprised of 0% single-family detached homes, and no proportion of either Black or Hispanic residents. The lowest probability category contains no single-family structures and Black residents account for 100% of the population. These are not intended to describe the most probable building zone, but instead show the extremes of the dislocation behavior model developed in Lin (2009). Though these extremes can be computed with the model, it does not guarantee accurate prediction outside the bounds of the data the model was developed with. Figure 1 shows this probability distribution range.

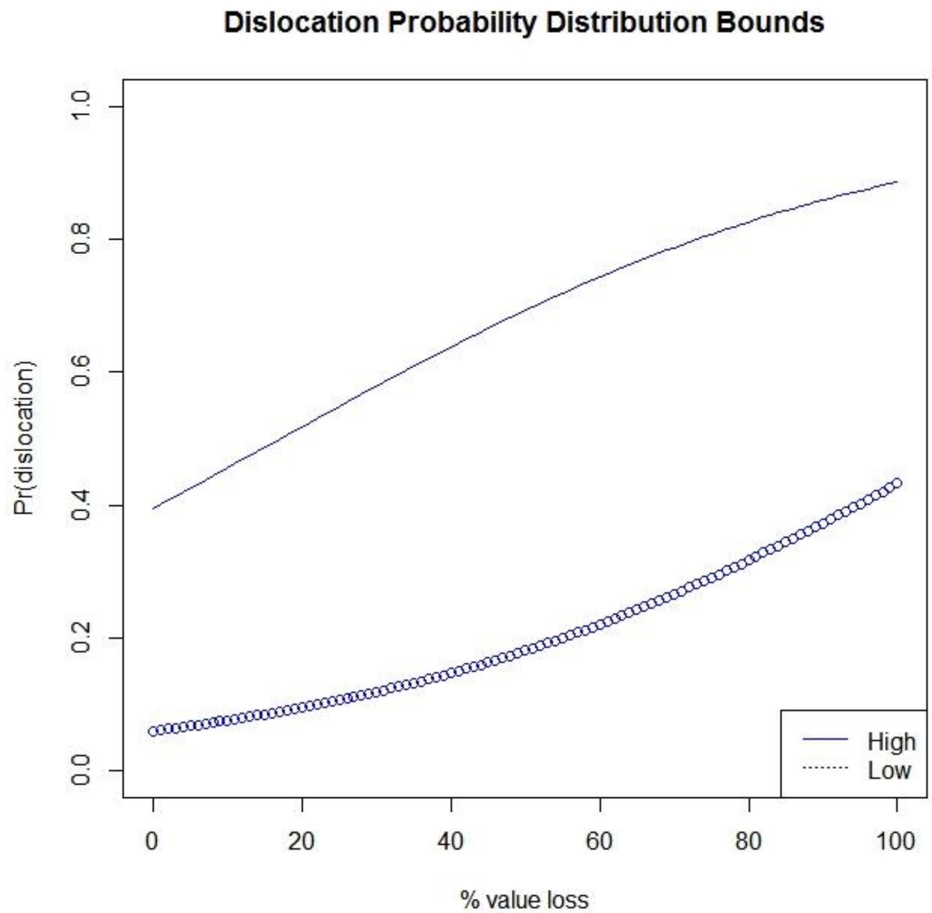

Figure 1: Sensitivity range of dislocation behavior

A few characteristics of the probability distributions are worth noting. The first being that even at a 0% loss in value, 40% of the highest, or "most mobile" residents will dislocate. This implies that regardless of what structural interventions are made for these residences, there is a limit to the dislocation that can be prevented. Alternatively, even when those same residences are 100% damaged, roughly 10% of the population is modeled as remaining in the structure, which intuitively seems like an underestimate. Looking at the "least mobile" structure category, the positive slope of the distribution between losses of 0 to 50% is lower than that of the curve about it. This means that it requires a greater reduction in loss to prevent a household from leaving if they are on the lower curve than if they were closer to the higher. In determining which residential structures are the best investment, the model will select the higher curve given that the costs are the same. While no function is expected to exactly describe human behavior, the limitations of such functions are critical to the interpretation and implementation of models driven by them.

Chapter 4.0 Algorithm Development

The ECsPy package was used to implement NSGA-II for the allocation problem. ECsPy is a free open-source Python package for evolutionary computation. To adapt the solver for the allocation problem, significant changes were made to the formulation of the problem as well as to the NSGA-II algorithm in the solution approach. One of which was changing the encoding of the decision variable and constraints to meet the evolutionary requirements of the solver design. Additionally, the generator, variator, mutator, and evaluator of NSGA-II were customized to fit the problem model. In the presentation of each modeling adaptation, the corresponding algorithm design change will be presented alongside.

4.1 Candidate Solutions

The final state of a retrofit intervention strategy is represented in the problem model as the decision variable X_{ijk} , a quantity of structures . However, candidate solutions are coded for each structure type j in each zone i as the proportion of structures at each code level such that through generation, crossover, and mutation, the candidate remains independent of the structure volume in any given zone $i \in Z$ of type $j \in S$. This maximizes computational efficiency with respect to candidate manipulation. Candidate solutions are encoded as a list whose length is dependent on the number of zones (Z) and the number of structure types (S), the code levels remaining at a length of 4. In the candidate list, each proportion of structures from zone i of type j at code level k is represented as its own element. The advantages of this encoding are apparent through the discussion of the model constraints.

The building count constraint dictates that the count of structures of type j in zone i in a feasible solution must remain the same as the baseline count. Thus, an efficient way to ensure that this constraint is met in the generation and evolution of candidates is by making the solution independent of building count. This is the main motivation for the encoding method. In order to satisfy the improvement constraint, stating buildings must only remain at the current or improve in level, the candidate solution generator was customized in the following way. For each set of buildings in zone i of structure j ,the proportion in each code level is generated through a uniform random distribution, each level having specific minimum and maximum potential values.

The specific generation of the proportions guarantees each candidate is feasible, while allowing the entire solution region to be searched. Specifically, the proportion of structures in code level one must be less than or equal to the baseline proportion in level one. The proportion in code level two must be less than or equal to the minimum between the remaining buildings and the baseline count and the baseline proportion at and below level two. Then, the remaining proportion is split among levels three and four, beginning with level four to ensure a feasible candidate. The proportion in level four is then set between the level four base and the proportion that has been allocated. The remaining proportion is allocated to code level 3. While retaining an exploratory property, this generation technique limits the solution space to only feasible candidates.

4.2 NSGA-II Parameters

The parameters used in NSGA-II impact how candidate solutions are manipulated in the search for non-dominated solutions. Population size, number of generations, and mutation rate can, thus, influence the solution quality and the computation time. This was observed in the tuning of such parameters in the case study. It was seen that the most important parameter for determining the number of solutions in the Pareto front was number of generations, which is set to 1,000. While having a high population size is preferred in terms of exploration, population size was set to 50 in order to balance problem size and computation time. The final parameter, mutation rate, is set to the algorithm default to introduce a mutated element at a probability of 0.1. Once the maximum number of generations is reached, the current Pareto front is archived and used as the decision curve.

5.0 Case Study: Centerville

5.1 Baseline Scenario

In order to demonstrate the application an interpretation of the allocation model, an earthquake disaster was simulated in the virtual city of Centerville. Centerville is a virtual city that was created as a testbed for collaborators to the Center of Risk-based Community Resilience Planning. It exists to provide a fundamental problem with which to initiate and develop assessment algorithms, such as the allocation model, in preliminary form. As the Centerville Virtual Community Testbed was developed by a team of engineering, social science, and economic professionals, it has both diverse infrastructure and population demographics necessary to asses potential post-disaster impacts on the local economy, the inhabitants, and public services (Ellingwood, 2016). The layout of Centerville is depicted in Figure 2.

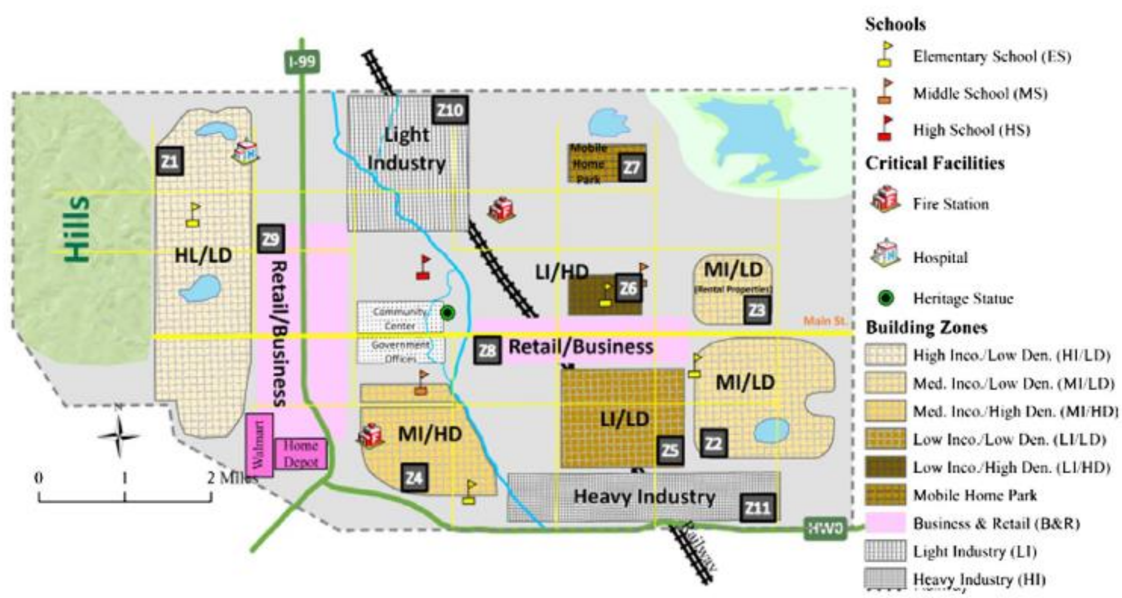

Figure 2: Centerville zoning map

Centerville contains roughly 20,000 households spread among a diverse building set of over 15,000 structures. The residential structures include single family units, apartment complexes, and mobile home units. Of the 21 total zones, 7 are residential ($Z1$-$Z7$), 2 are commercial ($Z8$, $Z9$), and 2 are industrial ($Z10, Z11$). There is 1 hospital (HC), 2 fire stations ($Fire1, Fire2$), and 7 schools ($ES1$-$ES4, MS1, MS2,\ HS$). The residents of Centerville have a median income reflective of the US population, however, income level ranges from low to high across the residential zones. There are 16 different structure types to classify buildings which can be seen in Table 1.

Table 1: Description of Centerville structure types

Structure Type	Description
W1 -W6	Wood
S1 - S4	steel braced frame
RC1 - RC3	Concrete
RM1 - RM3	reinforced masonry

Using the building code levels defined in HAZUS (1997), each structure type is assigned a code level. Table 2 summarizes the number of buildings of each structure type, in which zones they exist, and the corresponding appraised structure value for Centerville. Table 3 contains the demographic parameters used in the logistic dislocation prediction model.

Table 2: Summary of Centerville building inventory

Type	Building Quantity	Zones	Code	Appraised Value ($)
W1	6190	Z2,Z3,Z4,Z5,Z6	pre-code W2	139,426
W2	4000	Z1,Z2,Z3,Z4	low-code W1	239,016
W3	50	Z1	moderate-code W1	318,816
W4	3196	Z1,Z2,Z3	pre-code W1	239,016
W5	102	Z4,Z6	low-code W2	3,918,960
W6	1352	Z7	low-code MH	61,800
S1	45	Z8,Z9	low-code S2L	5,134,500
RC1	32	Z8,Govt	low-code CIL	4,948,000
RM1	76	Z8,Z10	pre-code RMIL	2,205,250
S2	6	Z9	low-code S3	7,738,750
S3	25	Z10	pre-code S2L	7,382,000
S4	45	Z11	moderate-code S2L	39,305,000
RC2	1	HC	low-code CIM	17,352,000
RM2	2	Fire1,Fire2	low-code RMIL	1,103,400
RC3	4	MS1,MS2mHS	moderate-code CIL	9,022,000
RM3	4	ES1,ES2,ES3,ES4	moderate-code RMIL	9,521,000

Table 3: Logistic regression parameters

Zone	% Black	% Hispanic	%Single-family Detached	Income Level
Z1	1	1	100	High
Z2	16	10	100	Medium
Z3	10	12	100	Medium
Z4	15	20	75	Medium
Z5	19	14	100	Low
Z6	37	25	16	Low
Z7	20	15	0	Low

The final key information needed from Centerville is a set of loss estimates for every structure in inventory. Rather than being a characteristic of the community itself, loss estimates require the study of the interaction between the infrastructure and seismic activity exposure. A scenario of a 7.8 magnitude earthquake was simulated distance 35 kilometers southwest from the center of Centerville. The detailed calculation of structural loss and direct economic loss is found in Lin and Wang (2016). In the baseline scenario, the direct economic loss is $856M. It should be noted that losses from commercial and industrial stock, comprising just 2% of the inventory, account for over half of the overall loss ($434M). Further, following the discussion of the dislocation-loss tradeoff between commercial and residential buildings, it is clear that the model would favor investment in commercial structures to minimize economic loss. Introducing the competing objective, a summary of households that dislocate by zone before any retrofits are applied is shown in Table 4.

Table 4: Baseline dislocation summary

Zone	Income Level	% Loss	Households	Dislocated	% Dislocated
Z1	High	9.29	4,246	1,384	32.6
Z2	Medium	8.38	2,267	557	24.6
Z3	Medium	7.8	800	207	25.9
Z4	Medium	12.42	4,767	1,673	35.1
Z5	Low	12.05	1,856	449	24.2
Z6	Low	10.81	4,396	1,067	24.3
Z7	Low	12.43	1,352	460	34.0

It is interesting that zone 1 has the third highest proportion dislocated though it experienced the third lowest damage losses. This is attributed to the demographic parameters and structure type, but not the code level, as all are code level 1. Additionally, the distinction between voluntary and involuntary dislocation is not made. Thus, dislocation from zone 1 has the same priority as zones with more damage, whose structures may not be livable. The implication of this will be discussed in a later section. While dislocation behavior is summarized by zone level, the dislocation model is actually dependent on loss at the zone, structure type, and building code level. The significance of this is that there exists more variability in dislocation distribution than what may be represented at the aggregate zone level. This is visualized in Figure 2 which shows how dislocation increases with loss for the two Centerville zones representing the highest and lowest dislocation.

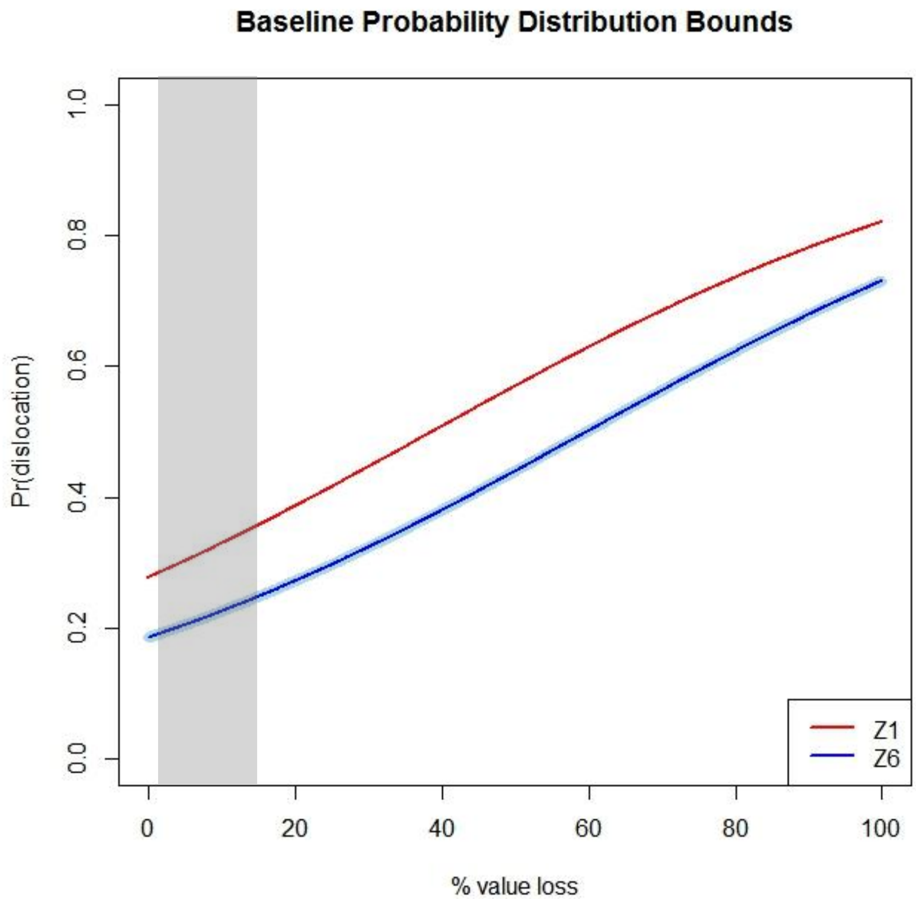

Figure 3: Baseline dislocation sensitivity bounds

At the functional level, the lowest dislocation (20.5%) occurs in the zone 5 structures of type W1 at code level 4. It is expected that the lowest dislocation occur at structures at code level 4, the most structurally sound. The highest (35.7%) is found in the zone 4 structures of type W1 at code level 1. Similarly, the highest dislocation is associated with a structure category describing code level 1. Integrating these findings on Figure 2, the shaded area represents the earthquake scenario in this case study. As there are several other factors that influence dislocation and their behavior is complex, this level of detail will not be discussed further. Rather, understanding how the model behavior functions is more valuable than discrete values for a specific scenario.

The highest number of households dislocated is 1,384 in zones with high income level, compared to 1,673 for medium income, and 1,067 for low level zones. Thus, the absolute difference of dislocated households between different income levels should be less than or equal to 606 for any candidate mitigation policy.

5.2 Retrofit Decisions

It would cost $347M to retrofit all structures in Centerville to code level 4, representing the strategy that would not only minimize economic loss, but dislocation as well. Without any competition of resources, the Pareto front for a budget level of 100% consists of one single point. In this case, direct economic loss is reduced from $865M to $365M and dislocation is reduced from 5,797 to 5,152. Interestingly, the estimated loss avoidance for just one earthquake is greater than the cost of the mitigation policy itself, which could partially withstand the event. The purpose of this model, however is to provide a decision tool for investigating the tradeoff between the two objectives given limited resources. Given a budget set at 60%, the decision becomes where to use the available $208M to minimize both loss and dislocation. The estimated Pareto front is shown in Figure 4.

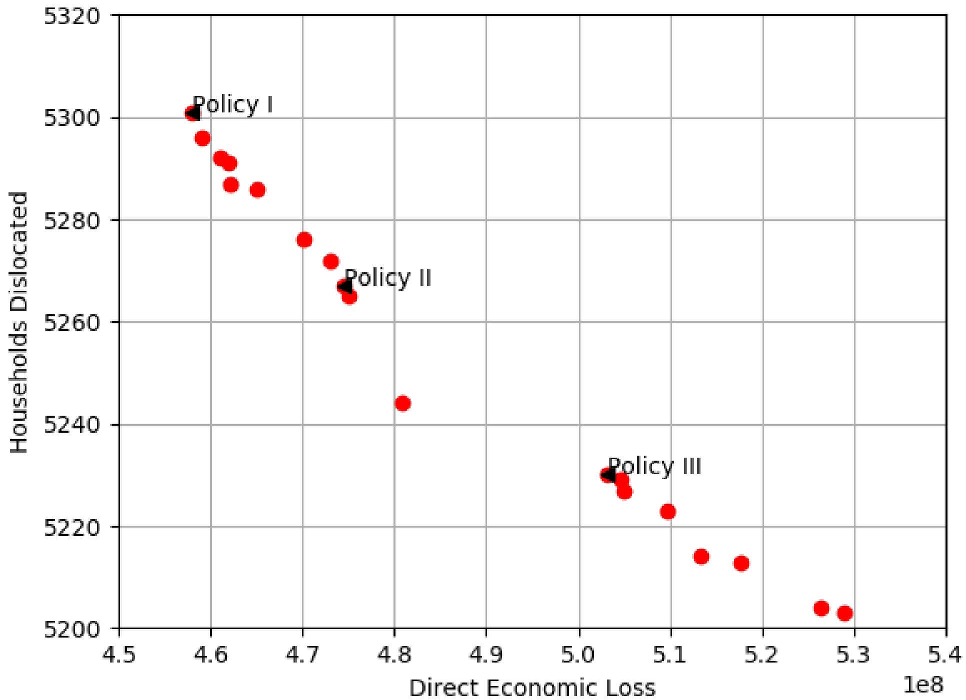

Figure 4: Pareto front: economic loss and dislocation (B=$208M)

Interpreting the results, the minimum direct economic loss that can be achieved with 60% of the maximum budget is $458M. The maximum economic loss, when more resources are spent retrofitting residential structures, is $540M. Similarly, the dislocation for this budget level drops from 5,301 to 5,193 as loss is sacrificed. Comparing the range of direct economic loss to dislocation, it takes a tradeoff of $82M to prevent 108 households from dislocating. For this particular scenario, there appears to be a large tradeoff for relatively small subset of the city. Intuitively, the tradeoff behavior is subject to differences in infrastructures, demographics, and earthquakes depending on the model community. To demonstrate use of the tradeoff surface, three policies were selected along the Pareto frontier to discuss in detail. The performance summary of these three policies is shown in relation to the baseline behavior in Table 5.

Table 5: Direct retrofit effects

Policy	Loss	Dislocation	Cost ($)
base	856M	5797	--
I	458M	5301	207.6M
II	474M	5267	207.9M
III	503M	5203	207.9M

Table 6: Residential retrofit summary

Residential	% Code 3	% Code 4	Quantity
Policy I	68%	32%	10,859
Policy II	53%	47%	11,365
Policy III	53%	47%	13,100

A summary of the residential retrofits is shown in Table 6 to demonstrate how the tradeoffs in Table 5 manifest through investments in the housing sector. Policy I, with low dislocation priority, has close to 500 less retrofits than policy II. Additionally, the quality of the retrofits is the lowest by 15%. Between policies I and II, the distribution between code levels 3 and 4 remained the same, however there is a significant change in the number of retrofits. Policy III calls for 1,735 retrofits more than policy II, preventing 64 predicted household from dislocating (Table 5).

Table 7: Detailed residential retrofit policy

Zone	Type	Policy I	Policy II	Policy III
Z1	W2	1241 (2 →3)	937 (2 →3)	706(2 →3)
		759 (2 →4)	1063 (2 →4)	1294 (2 →4)
Z1	W3	23 (3 →4)	23 (3 →4)	37 (3 →4)
Z1	W4	511 (1 →3)	574 (1 →3)	1795 (1 →3)
		10 (1 →4)	203 (1 →4)	86 (1 →4)
Z2	W1	572 (1 →3)	241 (1 →3)	716 (1 →3)
		129 (1 →4)	525 (1 →4)	44(1 →4)
Z2	W2	425 (2 →3)	672 (2 →3)	635 (2 →3)
		275 (2 →4)	28 (2 →4)	65 (2 →4)
Z2	W4	7 (1 →3)	159(1 →3)	526(1 →3)
		17 (1 →4)	7 (1 →4)	274(1 →4)
Z3	W1	219 (1 →3)	161 (1 →3)	101 (1 →3)
		2 (1 →4)	132 (1 →4)	154 (1 →4)
Z3	W2	137 (2 →3)	240 (2 →3)	58 (2 →3)
		163(2 →4)	60(2 →4)	242(2 →4)
Z3	W4	125 (1 →3)	95 (1 →3)	72 (1 →3)
		75 (1 →4)	105 (1 →4)	126 (1 →4)
Z4	W1	2118 (1 →3)	1080 (1 →3)	84 (1 →3)
		449(1 →4)	1487(1 →4)	2483(1 →4)
Z4	W2	294 (2 →3)	924 (2 →3)	680 (2 →3)
		706(2 →4)	76(2 →4)	320(2 →4)
Z4	W5	16(2 →3)	10(2 →3)	15(2 →3)
		9(2 →4)	15(2 →4)	10(2 →4)
Z5	W1	1433(1 →3)	416(1 →3)	1325(1 →3)
		423(1 →4)	1440(1 →4)	531(1 →4)
Z6	W1	274(1 →3)	456(1 →3)	274(1 →3)
		370(3 →4)	159(3 →4)	370(3 →4)
Z6	W5	41(2 →3)	18(2 →3)	16(2 →3)
		36(2 →4)	59(2 →4)	61(2 →4)

Table 8: Detailed non-residential retrofit policy comparison

Building Class	Zone	Type	Policy I	Policy II	Policy III
	Z8	S1	15(2 →3)	9(2 →3)	15(2 →3)
			1(2 →4)	7(2 →4)	1(2 →4)
Commercial	Z8	RC1	3(2 →3)	6(2 →3)	3(2 →3)
			8(2 →4)	5(2 →4)	8(2 →4)
	Z8	RM1	30(1 →3)	27(1 →3)	24(1 →3)
			6(2 →3)	3(2 →4)	6(2 →4)
	Z9	S1		16(2 →3)	
			23(2 →4)	13(2 →4)	29(2 →4)
	Z9	RC1	3(2 →3)	3(2 →3)	7(2 →3)
			10(2 →4)	10(2 →4)	6(2 →4)
	Z9	RM1	8(1 →3)	35(1 →3)	1(1 →3)
			38(1 →4)	11(1 →4)	45(1 →4)
	Z9	S2	6(2 →4)	6(2 →4)	3(2 →3)
					3(2 →4)
Industrial	Z10	S3	1(1 →3)	3(1 →3)	3(1 →3)
			24(1 →4)	22(1 →4)	22(1 →4)
	Z11	S4	41(3 →4)	30(3 →4)	7(3 →4)
	Fire1	RM2	1(2 →4)	1(2 →3)	1(2 →4)
Government	Fire2	RM2	1(2 →4)	1(2 →4)	1(2 →4)
	Govt	RC1	3(2 →3)	3(2 →3)	3(2 →3)
			5(2 →4)	5(2 →4)	5(2 →4)

Table 9: Non-residential retrofit policy summary

Non-residential	% Code 3	% Code 4	Quantity
Policy I	30%	70%	230
Policy II	48%	52%	216
Policy III	30%	70%	193

The detailed retrofit policies associated with each can be compared in Tables 7 and 8, showing where and how many structures are retrofitted. Noting that policies I through III progress through the tradeoff of economic loss for reducing dislocation, it is immediately apparent in Table 6 how that manifests in the investment decisions. In policy I, commercial, industrial, and government structures are raised to code level 4 while most residential decisions involve level 3. Progressing to policy III, there are significantly more investments in residential structures, with a great proportion raised to level 4 as well. As seen in the decrease of level 4 investments in the commercial and industrial structures, the investments in decreasing dislocation were at the cost of mitigating economic loss.

6.0 Conclusions

Threatened with the immense cost and damage of natural disasters, community policy makers need tools that facilitate the exploration of decision tradeoffs and consequences. The purpose of this research is to extend the mitigation resource allocation model of Zhang and Nicholson (2016), a solution tool for creating and examining exact optimal solutions for building retrofit strategies to study the tradeoffs of direct economic loss and population dislocation in an earthquake scenario. Specifically, the prediction of population dislocation is updated to reflect the empirical research of Lin (2009), making the model more realistic, but also non-linear. The updated model was then evaluated using the metaheuristic NSGA-II, which generates near Pareto-optimal solutions. The examination of the solution set through tradeoff analysis is demonstrated for the virtual city of Centerville. A key finding from the tradeoff analysis is that population dislocation is less sensitive to loss than previously modeled, illustrating the gap between what was modeled and current knowledge regarding the behavior. In addition to being more accurate, this non-linear solution tool is now significantly more adaptable to new modifications.

There are several limitations to the allocation model which should guide future extensions of it, the first pertaining to the diversity of the structures included. The solutions of the model dictate only the allocation of resources between residential and non-residential structures. The set of non-residential structures are limited to three categories: commercial, industrial, and government. In reality, communities exhibit a much broader range of non-residential structures, such as hospitals, schools, and sports stadiums. As it is difficult to quantify their contribution to resilience, applied research is needed to appropriately model such structures' performance measures and their relationship with intervention strategies. Future work should incorporate the differences among non-residential structures depending on how critical they are to community functionality. Additional objectives to the present multi-objective model may be necessary to incorporate such building classes.

The efficiency of the model is another important area for improvement. Resultant from the non-linear nature and complexity of the model, the computation time of the model is significant compared to the previous, linear, version which completed in one millisecond. Depending on the budget restriction, the updated model requires 8 to greater than 72 hours to generate a set of non-dominated solutions on the same machine. A portion of this time is attributed to the nature of the NSGA-II evolution method, but it is highly suspected that most of this time can be reduced through more efficient coding. One example of this is the observation of the direct link between computation time and budget restriction. Because candidate solutions are generated independently of available budget, a decreasing proportion of generated candidates are feasible, prolonging computation time. An anticipated use of this tool is to lobby for available funds based on potential disaster outcomes. Therefore, it is critical to reduce computation time to allow policy makers to efficiently explore the decision atmosphere at various budget levels.

Adapting the MRA model to a non-linear solver creates the opportunity to account for more complex components. A more robust, sophisticated measure of economic performance is needed. Computable general equilibrium (CGE) models are based on actual economic data that estimate how an economy might react in the event of an external event, such as a natural disaster (Cardenete, 2012). The first objective in the allocation model, direct economic loss, is only one main component of a CGE model used to capture the broader, cascading impacts resultant from disasters. The value of this solution approach is its ability to be quickly modified as those complex factors and relationships are discovered.

The present research implicitly assumes that decision makers have an effective method for incentivizing the retrofits of privately owned buildings. However, the effectiveness of such incentives will require more investigation. Additionally, there is a need for population dislocation models to diverge based on more granular characteristics of the behavior. The ability to distinguish between households that leave voluntarily and involuntary is critical to monitoring and controlling the disparity as it indicates social vulnerability. Similarly, it is necessary for advancements in social science models to distinguish between permanent and short-term dislocation, as they have different impacts on economic performance.

Only one component of the MRA model, population dislocation, required the use of a non-linear solution method. However, the reality of all other model components, current or future, may be highly complex and non-linear. This research not only updates the dislocation model but also expands the ability of the solution approach to handle the anticipated level of complexity in future research. The CGE model, which is essentially a system of non-linear equations which are solved simultaneously, can possibly be integrated more directly in the existing mathematical model. The allocation model should be expanded in several ways. Independent from applied research from social science, the efficiency of the model should be improved and the decision variables should be made integers to reflect real world decisions. An understanding of the functional relationship between more diverse structures, economic impacts, and dislocation behavior is required from multiple disciplines in order to integrate perspectives of community performance. This research being just one step in the aspiration of community resilience, modeling post-disaster behavior is imperative to the modern world's ability to develop sustainable communities in light of urban development and the rising threat of natural disasters.

References

Cardenete, M. A, Guerra, A., and Sancho, F. (2012). An Introduction. *Applied General Equilibrium*. Verlag Berlin Heidelberg: Springer.

Cimellaro, P., Reinhorn A., and Bruneau, M. (2010). *Framework for analytical quantification of disaster resilience. Engineering Structures, 32(11)*, 3639-3649.

Bilham, R. (2009). The seismic future of cities. *Bulletin of Earthquake Engineering, 7*, 839–887.

Deb, K., Pratap, A., Agarwal, S., and Meyarivan, T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE *Transactions on Evolutionary Computation, 6(2)*, 182-197.

Earthquake Hazard Mitigation Handbook (2002). *Federal Emergency Management Agency*.

Lin, P., and Wang, N. (2016). Building portfolio fragility functions to support scalable community resilience assessment and effective risk communication. *Sustainable and Resilient Infrastructure. 1(3-4)*, 108-122.

Earthquake loss estimation methodology : HAZUS technical manual (1997). *National Institute of Building for the Federal Emergency Management Agency*.

Ellingwood, B. R., Cutler, H., Gardoni, P., Peacock, W. G., Lindt, J.W., and Wang, N. (2016). The Centerville Virtual Community: a fully integrated decision model of interacting physical and social infrastructure systems. *Sustainable and Resilient Infrastructure, 1(3-4)*, 95-107.

Esnard, A., Sapat, A., and Mitsova, D. (2011). An index of relative displacement risk to hurricanes. *Natural Hazards, 59*, 833–859.

Jennings, E., Lindt, J., and Peek, L. (2015). Multi-objective community-level seismic retrofit optimization for resiliency using engineering and socioeconomic variables. *Sustainable and Resilient Infrastructure, 1(3-4)*, 123-136.

Lindell, M. K., and Prater, C. S. (2003). Assessing community impacts of natural disasters. *Natural Hazards Review, 4*, 176-185.

Lindell, M. K., Prater, C. S., Perry, R. W., & Nicholson, W. C. (2006). Fundamentals of emergency management. *Federal Emergency Management Agency*.

Lin, P., and Wang, N.(2016). Building portfolio fragility functions to support scalability community resilience assessment and effective risk communication. *Sustainable and Resilient Infrastructure. 1(3-4),108-122*.

Lin, Y.S (2009). Development of algorithms to estimate post-disaster population dislocation - a research based approach (Doctoral dissertation). Texas A&M University.

Lin, Y.S., Peacock, W.G., Lu, J.C., and Zhang, Y.(2008). Household Dislocation Algorithm 3: A Logistic Regression Approach. *Hazard Reduction and Recovery Center, Texas A&M University. HRRC Reports*, 08-05.

Higheld, W., Peacock, W. , and Van Zandt, S. (2014). Mitigation planning: Why hazard exposure, structural vulnerability, and social vulnerability matter. Journal *of Planning Education and Research 34(3)*, 287-300.

Liu, J., Dietz T., Carpenter, S.R., Alberti, M., Folke, C.,Moran, E., Pell, A.N., Deadman, P., Kratz, T., Lubchenco, J., Ostrom, E., Ouyang, Z., Provencher, W., Redman, C.L., Schneider, S.H., and Taylor, W. (2007). Complexity of Coupled Human and Natural Systems. *Science, 317*, 1513–1516.

Steelman, J.,Song, J., and Hajjar, J. (2007). Integrated data flow and risk aggregation for consequence-based risk management of seismic regional losses. Tech. rep., Mid-America Earthquake Center, University of Illinois at Urbana-Champaign.

Sherrieb, K., Norris, F.H, and Galea, S. (2010). Measuring Capacities for Community Resilience. *Social Indicators Resilience, 99(2)*, 227–247.

Planning for a sustainable future: The link between hazard mitigation and livability (2000). *Federal Emergency Management Agency (FEMA),* Publication 364.

U.S. Billion-Dollar Weather and Climate Disasters (2017). *NOAA National Centers for Environmental Information (NCEI).* Retrieved from https://www.ncdc.noaa.gov/billions/

Zhang, W. and Nicholson, C. (2016). A multi-objective optimization model for retrofit strategies to mitigate direct economic loss and population dislocation. *Sustainable and Resilient Infrastructure*, *1(3-4)*, 123-136

Appendix A.1 ECsPy MRA Custom Modules

Appendix A.1.1 Generator

```
#-------------------------------------------------------------
#  Generate Code Level Distribution
#-------------------------------------------------------------
def distribution(base):

    x = [0,0,0,0]

    #between 0 and current proportion
    x[0] = random.uniform(0,base[0])

    #between 0 and the min(what's left & the max value it can be)
    x[1] = random.uniform(0,min(base[3],(base[0]+base[1])))

    x[3] = random.uniform(base[3],(1-x[0]-x[1]))

    x[2] = 1-x[0]-x[1]-x[3]

    total = sum(x)  #equal to 1

    return(x)

#---------------------------------------------------------------
#  Create an individual
#--------------------------------------------
    def __init__(self):
        x = {}
        IJK = data().dictionary
        base = data().base
        building_set = data().building_set

        for i,j,k in IJK:
            x[i,j,k] = 0

        multiplier = {}

        for i,j,k in IJK:
            multiplier[i,j] = 0

        for i,j,k in IJK:
            if k == 1:
                multiplier[i,j] = distribution(base[i,j])

        hold = []
        for i,j,k in IJK:
            if k == 1:
                hold.append(multiplier[i,j])

        dist_list = ([item for sublist in hold for item in sublist])
        #for i,j,k in IJK:
                #x[i,j,k] = building_set[i,j] * multiplier[i,j,k]

        self.x_dict = to_dict(dist_list,IJK)
        indv_list = dist_list
        self.indv_list = indv_list

    def return_individual(self):
        return(self.indv_list)

#----------------------------------------------------------
# Generate a pool of candidates
#----------------------------------------------------------
def generate_candidates(random, args):
   #argument for EcsPy
    candidate =  individual_2().indv_list
    return candidate
```

Appendix A.1.2 Mutator

```
@mutator
def custom_mutator1(random, candidate, args):

    candidate = perform.individual_2().indv_list

    candidate = [candidate[i:i+4] for i in range(0, len(candidate), 4)]

    base = perform.data().base
    base = dict.values(base)
    #base = [base[i:i+4] for i in range(0, len(base), 4)]

    mut_rate = 0.1

    for i in range(len(candidate)):
        if random.random() < mut_rate:

            candidate[i] = perform.distribution(base[i])

    candidate = ([item for sublist in candidate for item in sublist])

    candidate = bounder(candidate, args)
    return candidate
```

Appendix A.1.3 Evaluator

```
#---------------------------------------------------------
# Economic Loss Measure
#---------------------------------------------------------

def econ_loss(individual):

    #convert to #buildings from distribution
    individual = dis_convert(individual)
    dat = data()

    IJK , building_set , total_loss = dat.dictionary , dat.building_set ,
dat.total_loss


    #Convert individual list into dictionary for evaluation

    indiv = to_dict(individual, IJK)

    #number of residential strs * loss of each, aggregated by code level
    Loss = {}
    for i,j,k in IJK:
        Loss[i,j] = 0
    for i,j,k in IJK:
        Loss[i,j] = Loss[i,j] + total_loss[i,j,k] * indiv[i,j,k]
                #Expected loss for each str type and zone

    Total_DEL = sum(Loss.values())

    return Total_DEL
#--------------------------------------------------------
# Population Dislocation
#--------------------------------------------------------
class dislocation():
    def __init__(self,individual):
        dat = data()
        IJK = (dat.dictionary)

        residents_list = dat.residents_list
        B,V,H,s = dat.B, dat.V, dat.H, dat.s
        building_loss = dat.building_loss
        value = dat.value
```

```
        building_count = dat.building_count
        Count_HH = dat.Count_HH

        individual = dis_convert(individual)       #convert to buildings from
distribution

        #checking to see where bug is


        x = to_dict(individual, IJK)
        #print("X",x)
    #PARAMETERS____________________

    #Percent Value Loss
            #SUBSET TO ONLY RESIDENTIAL STRS


        value_loss = {}
        num = {}
        numb = {}
        deno = {}
        den = {}
        loss = {}


    #init dictionaries for numerator and denominator of value loss by zone and
building type
        numb = {}
        deno = {}

        for i,j,k in IJK:
            if i in residents_list:

                numb[i,j] = 0
                deno[i,j] = 0

    #calculation value loss by zone and building type
        for i,j,k in IJK:
            if i in residents_list:
                numb[i,j] = numb[i,j] + building_loss[i,j,k] * x[i,j,k]
#total building loss excluding content
                deno[i,j] = deno[i,j] + value[i,j,k] * x[i,j,k]
#total appraised value


        for i,j,k in IJK:
            if i in residents_list:

                loss[i,j] = ( numb[i,j] / deno[i,j] ) * 100




        #coefficients in LR from (Lin, 2009)
        coe = [-0.42523, 0.02480,-0.50166,-.01826,-0.01198]

        prob_dis = {}

        for i,j in loss:
            prob_dis[i,j] = 1/(1+exp(-
(coe[0]+coe[1]*loss[i,j]+coe[2]*s[i]+coe[3]*B[i]+coe[4]*H[i])))


    #Count the number of buildings in each zone
        buildings_of_zone = {}
        for zone in residents_list:
            buildings_of_zone[zone] = 0
            for i,j,k in IJK:
                if i==zone:
                    buildings_of_zone[zone] += x[i,j,k]

    #Calculate the number of households in the current building selection
```

```
    #aggregate by level
        HH_zone_str= {}

    #initialize
        for i,j,k in IJK:
            HH_zone_str[i,j] = 0

        for i,j,k in IJK:
            if i in residents_list:
                HH_zone_str[i,j] = HH_zone_str[i,j] + x[i,j,k] * Count_HH[i,j]


        self.HH_zone_str = HH_zone_str
        #print("households[i,j] :",self.HH_zone_str)


    #Calculate the number of dislocated households
    #aggregate by str type
        Dislocation_zone= {}

    #initialize
        for i,j,k in IJK:
            Dislocation_zone[i] = 0

        for i,j,k in IJK:
            if i in residents_list:
                Dislocation_zone[i] = Dislocation_zone[i] + (HH_zone_str[i,j]
* prob_dis[i,j])


        Total_Dislocation = 0
        for i,j,k in IJK:
            if i in residents_list:
                if k == 1:
                    Total_Dislocation = Total_Dislocation +
Dislocation_zone[i]


        self.Total_Dislocation = Total_Dislocation

        self.Dislocation_Zone = Dislocation_zone

    def return_values(self):
        x = self.Total_Dislocation
        return x
#--------------------------------------------------------
# Evaluate Fitness
#--------------------------------------------------------

def evaluate(candidates,args):
    IJK = data().dictionary


    fitness = []

    for cs in candidates:



        loss = econ_loss(cs)      #change econ_loss ftn when change is made
        dislo = dislocation(cs).Total_Dislocation
        fitness.append([loss,dislo])

    return fitness
```

Appendix A.1.4 Bounder

```
class Bounder(object):

        def __init__(self, lower_bound=None, upper_bound=None):
                self.lower_bound = lower_bound
                self.upper_bound = upper_bound
                if self.lower_bound is not None and self.upper_bound is not
None:
                        try:
                                iter(self.lower_bound)
                        except TypeError:
                                self.lower_bound =
itertools.repeat(self.lower_bound)
                        try:
                                iter(self.upper_bound)
                        except TypeError:
                                self.upper_bound =
itertools.repeat(self.upper_bound)


        def __call__(self, candidate, args):


                dat = perform.data()
                IJK = dat.dictionary

                p = 0
                while p == 0:
                        p = perform.feasible(candidate)
                        if p == 1:
                                bounded_candidate = candidate
                        else:
                                candidate = perform.individual_2().indv_list
                return bounded_candidate
```

Appendix A.2 ECsPy MRA Interface

```
from random import Random
from time import time
from ecspy import emo
from ecspy import observers
from ecspy import variators
from ecspy import terminators
from ecspy import benchmarks
from ecspy import ec
import EcspyClasses as perform
import bounder1



def main(do_plot=False, prng=None):
    if prng is None:
        prng = Random()
        prng.seed(time())


    problem = "MRA"
    ea = emo.NSGA2(prng)
    ea.variator = [variators.n_point_crossover,variators.gaussian_mutation]
    ea.observer = observers.default_observer
    ea.terminator = terminators.generation_termination
    final_pop = ea.evolve(generator=perform.generate_candidates,
                          evaluator=perform.evaluate,
                          pop_size=50,
                          maximize=False,
                          bounder= bounder1.Bounder(None,None),
                          max_generations=1000)


    final_arc = ea.archive


    if do_plot:
        final_arc = ea.archive
        print('%s MRA with logistic dislocation (%s) Best Solutions: \n' %
(ea.__class__.__name__, problem.__class__.__name__))
        for f in final_arc:
            print(f)
        import pylab
        x = []
        y = []
        for f in final_arc:
            x.append(f.fitness[0])
            y.append(f.fitness[1])
        pylab.scatter(x, y, color='b')
        pylab.savefig('%s Example (%s).pdf' % (ea.__class__.__name__,
problem.__class__.__name__), format='pdf')
        pylab.show()

        final_pop.sort(reverse=True)
        print(final_pop[0])


    return ea
```

Appendix A.3 Solution Interpreter

```
from random import Random
from time import time
from ecspy import emo
from ecspy import variators
from ecspy import terminators
from ecspy import benchmarks
import EcspyClasses as ec
import numpy as np, numpy.random
import random
import pandas as pd
import ast
from math import exp
import itertools

def expand(individual):
    dat = ec.data()
    IJK = (dat.dictionary)
    building_set = dat.building_set

    x = {}
    print("IN",individual)

    for i,j,k in IJK:
            x[i,j,k] = building_set[i,j] * individual[i,j,k]

    individual = x
    print("individual",individual)

    return(individual)


#input an individual resultant from Ecspyproblem_interface.py

list = list_input

budget = ec.indv_budget(list)
print("Budget",round(budget))

dislocation = ec.dislocation(list)
loss = dislocation.loss
hold = ec.data().building_set

count = {}
for i,j in hold:
    count[i] = 0
for i,j in hold:
    count[i] = count[i] + hold[i,j]


#Dislocation by zone
dis = ec.dislocation(list)
Zone_P = dis.Zone_P

print("Zone dislocation", Zone_P)

dict = ec.data().dictionary

base = ec.data().base_indv


individual = ec.to_dict(list,dict)


policy = {}
for i,j,k in dict:
    policy[i,j,k] = (individual[i,j,k]) - base[i,j,k]
```

```
policy = expand(policy)


Zones =
['Z1','Z2','Z3','Z4','Z5','Z6','Z8','Z9','Z10','Z11','Fire1','Fire2','Govt']

print("------------------------------------------------------")
print("Retrofit Policy")
print("------------------------------------------------------")

for zone in Zones:
    for i,j,k in dict:
        if i == zone:
            if policy[i,j,k] != 0.0:
                print(i,j,k, round(policy[i,j,k]))

individual = expand(individual)
#how many structures are at each zone level
dist = [0,0,0,0]
for i,j,k in policy:
    if k == 1:
        dist[0] = dist[0] + individual[i,j,k]
    if k ==2:
        dist[1] += individual[i,j,k]
    if k ==3:
        dist[2] += individual[i,j,k]
    if k ==4:
        dist[3] += individual[i,j,k]
print(dist)
```