EFFICIENCY VERSUS RESILIENCE IN CRITICAL INFRASTRUCTURE BEYOND THE TRADE-OFF

A Thesis

by

BENJAMIN CHUKWUMDINDU OZUMBA

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Chair of Committee,	David N. Ford
Co-Chair of Committee,	Charles M. Wolf
Committee Members,	Phil Lewis
	Patrick Suermann
Head of Department,	Robin Autenrieth

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ABSTRACT

Critical Infrastructure assets and systems enable the functioning of society, including commerce, governance, and public health. These systems vital to our way of life as humans are vulnerable to natural disasters, and their loss of functionality during and after the natural disasters hamper recovery efforts in other sectors. Improved resilience of these infrastructures is necessary but often leads to a loss of efficiency due to the associated costs. While important due to increasing demand for limited resources, improved efficiency in these infrastructures' operations adversely affects resilience due to associated cost-cutting and operational capacity stretching. A system dynamics model previously used to investigate a hospital's resilience to natural hazards is expanded to include variables to indicate its efficiency. Hypothetical scenarios with efficiency and resilience improvement strategies are simulated on the model to determine their impact on the hospital's overall performance (efficiency and resilience). The model was used to demonstrate the trade-off and identify the system drivers of performance. An understanding of these drivers influenced the design of strategies to improve overall performance when faced with the efficiency: resilience trade-off. These simulations show that greater benefit can be derived when investments are made towards efficiency and resilience compared to focusing on one of them. The results also show that a combination of innovative managerial strategies that improve resource allocation and incorporate managerial flexibility to manage uncertainty effectively mitigates the trade-off impacts. This investigation provides a framework for a performance-based measurement of

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resilience and efficiency in a hospital system and lays the groundwork for case study-based research

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DEDICATION

To my parents and Aunty Adaora for all their prayers.

To the Family Fraternity of Nigeria, may the sticks forever guide us.

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NOMENCLATURE

DRA	Dynamic Resource Allocation
BOTG	Behavior Over Time Graph
NIAC	National Infrastructure Advisory Commission
PPD-21	Presidential Policy Directive 2012
ROA	Real Options Analysis

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CHAPTER II

INTRODUCTION

Critical infrastructures are those assets which if lost or damaged, would result in significant harm to a nation’s security, economy, public health, and safety. Over the last 20 years, natural disasters have caused considerable damage to property, loss of human life, and massive interruptions in large infrastructure systems’ operations (Alderson et al., 2014). A study by the U.S. Department of Homeland Security estimates that the economic and insured losses from catastrophic events, particularly natural disasters such as hurricanes, earthquakes, and others, have increased significantly in the past decades (Kunreuther, 2016). Damages and losses sustained by Critical infrastructure systems and assets during and after natural disasters can be avoided or mitigated by improving resilience to these occurrences. Resilience is the capacity to experience an interruption in the supply of required input without suffering severe permanent damage Moteff, (2012). The National Infrastructure Advisory Committee NIAC (2010) defines Infrastructure resilience as an asset’s ability to reduce disruptive events’ magnitude and duration. It means the ability to prepare and adapt to changing conditions and withstand and recover rapidly from disruptions due to different factors such as naturally occurring threats and accidents (PPD-21, 2013). Resilience can be improved or enhanced by adding redundancies enabling the asset or system to switch operations through one or more subsystems or parallel components. It can also be improved by providing backup systems to replace a component or asset whose function is disrupted (Moteff, 2012). Critically, these methods of improving resilience reduce efficiency (described next).

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A stumbling block to the improvement of resilience is the concept of efficiency. Efficiency is the ratio of output to input (Meadows, 2020). According to Rutgers & Van der Meer (2010), Slichter (1950) describes efficiency as a ratio between input and outputs, investments and income, efforts and results, costs, and the resulting utility. When considering privately-owned infrastructure, efficiency represents the ratio of income to expenditure, given that private enterprises usually seek to maximize investment profit (Mihaiu et al., 2010). The output cannot always be measured monetarily for publicly funded infrastructure (Rutgers & van der Meer, 2010). Public administration efficiency is usually related to comparing the number of policy objectives achieved and the number of resources allocated or cost of policy implementation (Mandl et al., 2008). Therefore, for a publicly funded infrastructure system, e.g., school district, the inputs are the costs of running the school district and output, attainment rates of a specific age range of pupils. Efficiency can be improved by reducing redundancy (shedding excess capacity) and lowering diversity (e.g., reducing parallel operations and sticking with one or a few modes of operation) (Meadows, 2020). Critically, these methods of improving efficiency reduce resilience.

The study's importance and improvement of efficiency and resilience as regards Critical Infrastructure cannot be overstated. Given the substantial economic disruptions and fatalities experienced due to natural disasters, resilience building in infrastructure is unavoidable (Tonn et al., 2020). An increasing global population leads to a greater demand

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for the limited resource inputs in these infrastructure systems and underlines the need for greater efficiency in these systems (Rumbold et al., 2014), (Marshall et al., 2020). However, there are conflicts inherent in improving resilience through redundancy and increased efficiency through capacity shedding, cost-cutting, and just-in-time operational systems. The same features typically characterize resilient systems, redundancy, and diversity absent in many efficient systems (Galston, 2020). The Trade-off between efficiency and resilience is present in every sector of society (Meadows, 2020). Limits to amounts that can be raised through taxation and borrowing by governments and an aversion to losses by private businesses place constraints on resources that are available to be allocated. Decision-makers often have to choose between mutually exclusive investments to efficiency or resilience. For example, a hospital's management might decide to invest in an air ambulance system as a backup for periods after flooding or earthquakes when the roads may be impassable for motor ambulances. By doing so, the hospital's resilience to such disruptions improves. In contrast, its efficiency decreases as output measures such as the number of patients during normal times may not change, and input costs increases due to the added cost of maintaining an air fleet. On the other hand, the resources that may be channeled to improve resilience could be invested in teleconferencing equipment, reducing the number of patients that have to be seen in person, increasing the number of patients treated without increasing the costs of handling in-person traffic. A system dynamics model of a critical infrastructure asset is developed from the available literature for this work. Hypothetical scenarios are simulated where investments are made towards resilience and efficiency.

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Problem Description

Managers, public office holders, and policymakers have to plan for and improve critical infrastructure resilience. The PPD-21 states that "The Federal Government also has a responsibility to strengthen the security and resilience of its critical infrastructure, for the continuity of essential national functions, and to organize itself to partner effectively with and add value to the security and resilience efforts of critical infrastructure owners and operators." Such declarations signal the investment of large sums into resilience improvement efforts. Resilience improvement limits the loss of an asset's performance after a disruption and aids in a faster recovery process. This reduces the strain on public finances, freeing up funds for other investments. The Federal Emergency Management Agency within DHS provides grants, primarily to state and local governments or public authorities, that broadly support resilience by improving the ability to respond to and recover from incidents, Moteff (2012).

Managers are also obligated to be efficient in allocating private and taxpayer resources to develop critical infrastructure. Cost savings and increased revenue actualized from greater productivity can be channeled towards other investments. Public policy design and implementation are grounded in achieving efficiency in delivering public goods and services, Manzoor (2014). Woodrow Wilson (1887), in the last paragraph of his essay, Democracy and efficiency, argued that good governance and efficiency go hand in hand. In a study commissioned by the United Arab Emirates on Government efficiency, Deloitte (2013) opined that governments need to ensure that existing programs are efficient and

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future investments represent good value for money. This calls for efficiency to be borne in mind when making investments in critical infrastructure. Faced with numerous projects to actualize and limited resources, public officials must be careful to allocate resources to areas where they will most impact or be most effective. However, deciding how much to allocate and where it is to be directed is never easy. Public officials frequently have to defend their decisions on allocating funds in a plethora of budgetary and legislative hearings. The distribution of resources to plan for several extreme events that may never happen is never an easy sell (Boin et al., 2007). On the other hand, if such an event were to occur and any of the critical infrastructure systems and assets that support our everyday lives fails or does not recover quickly enough, lives would be lost, property damaged, heads would roll, and fingers pointed in blame at those responsible for planning for such an event.

Uncertainty regarding the location, time, and frequency of natural disasters make estimations of the severity of damages, resilience, and vulnerability of the asset more difficult, according to Sword-Daniels et al. (2016). This, in turn, complicates decisions regarding resource allocation for resilience improvement. Allocating resources to address the challenges of a natural disaster could draw public ire if one were to occur and the resilience improvement efforts are futile or if it were discovered that individual costs associated with the endeavor were unnecessary and avoidable. If the decision to undertake such efforts is made, the degree of losses associated with different magnitudes of disruptions would have to be estimated before designing strategies to manage them.

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However, strategies to address these critical uncertainties are difficult to identify in the pre-planning stage. In a real options analysis of a taxpayer-funded project, Ceylan et al. (2002) noted that critical uncertainties are difficult to identify and describe during preplanning efforts, leading to the development of strategies based on likely outcomes in suboptimal performance.

Consider a publicly funded Health Centre that provides services to those who cannot afford insurance in a region prone to earthquakes. In the event of an earthquake, the operations of this facility would be disrupted. Its ability to cater to the community's health needs, which it serves, would be affected. Disruptions in public health services can lead to economic damage (see background); therefore, the loss of functionality of the facility for the period during and after the earthquake would also affect the economy in the short and long-term in terms of lives lost and the population unable to work due to untreated ailments. Public officials in the allocation of resources should take the possibility of such an occurrence into their planning. Questions like "how much should we pay to improve the resilience of the facility?", "How much could we lose over time by investing in resilience?" "If such an event does occur, how much would have been lost?" would be asked. If these improvements are made, and the feared natural disaster does not occur, funds that could have been channeled into other things like education and transportation would have been lost. Inefficient use of resources may sacrifice loss of consumption opportunities elsewhere in the economy. Spending resources on inefficient care may

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reduce society’s willingness to contribute to health services’ funding, thereby harming health system performance, European Observatory on Health Systems and Policies (2016).

From our understanding, in tackling the problem presented, the manager would primarily like to know “How can built infrastructure planners and designers improve the total performance (Efficiency and resilience) of critical Infrastructure when subject to resource limits?” The following questions can help address this question.

- How can the actions and resources be applied to improve critical infrastructure’s resilience affect the non-hazard efficiency of its operations?
- How can a balance be struck in the relationship between efficiency and resilience by implementing innovative resilience and efficiency improvement policies?

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CHAPTER III

BACKGROUND

Resilience

Critical to resilience building is the ability to measure an asset's resilience. Heng Cai et al. (2018) reviewed over 100 articles on disaster resilience, focusing on infrastructure and other sectors. They noted that over 40% of the papers used quantitative measures, some of which were empirically valued. Narrowing it down to this study's focus, hospital disaster resilience, a review of existing literature shows that its resilience assessment has been approached on two fronts: indicator-based assessment and functionality-based assessment (Li et al., 2020). In an indicator-based evaluation, a series of indicators are set up and evaluated (WHO, 2015) identified the following indicators: Hazard identification, structural safety, non-structural safety, emergency, and disaster management. Indicatorbased assessments can be comprehensive as it allows for introducing different evaluation indicators to cover various dimensions dependent on the investigating party's objectives. A drawback to this approach is that these indicators are qualitatively described and open to different interpretations depending on the investigating party's metrics. Cimellaro (2010) proposed that the functionality Q(t) of a system is measured by the expected capacity or service that a system can deliver. It is measured in a range of 0-100% with 0%, meaning that the system provides zero services and 100%, meaning that the system can fully deliver the required service or is fully functional. Functionality-based assessment depends on two factors. Recovery time is the amount of time it takes for an asset to return to the full or desired functionality and Robustness is the difference between

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the total loss of performance and the system's actual performance levels immediately after a disruption. The use of recovery time and robustness in the assessment of resilience is supported by Fisher & Norman (2010) in a review of the PMI (Protection measurement index), a tool developed by the DHS to measure Critical Infrastructure protection from disruptions.

Researchers have advocated for the use of models to study resilience. Alderson et al. (2015) notes the need for models that (1) reflect the operation of infrastructure as a system and evaluate its continuity of function in the presence of a disruptive event, (2) incorporate the inherent ability of existing infrastructure systems to adapt to disruptions or changes to their operating environment, and (3) facilitate the systematic exploration of disruptive events and their potential consequences. System dynamics models have been successfully used to investigate hospital resilience to seismic disruptions by Li et al. (2020) and Khanmohammadi et al. (2018). These models were designed to measure hospital resilience by giving functionality as the current capacity ratio to the target capacity. Resilience was measured as the integral of hospital functionality during the recovery period. This modeling approach was initially proposed by Khanmohammadi et al. (2018). Li et al.(2020) improved on it by disaggregating utilities such as power, water. Variables were included to model the state of these utilities, transportation, and communications networks. They demonstrated the impacts of an earthquake on these utilities and the hospital system, and the recovery process. A limitation identified by the authors on the

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use of functionality for resilience assessment is that it requires many complex formulations that may be difficult for the practicing manager to understand.

Efficiency

In the study of hospital efficiency measurement/assessment, there are two main approaches: Stochastic Frontier Analysis and Data Envelopment Analysis (Dong et al.,2017) and (Hussey et al., 2009). SFA is a method of economic modeling that has been applied in the examination of cost and profit efficiency. The “Cost frontier” approach attempts to measure how far from full-cost minimization (i.e., cost-efficiency) the firm is (Kumbhakar et al., 2003). SFA has been applied successfully in the analysis of hospital efficiency. However, drawbacks to this approach include the necessity to estimate production functions and restriction to a single output. DEA is similar to the SFA as both identify a frontier defined as an extreme point. This method assumes that if a firm can produce a certain level of output utilizing specific input levels, another firm of equal size and scale of operations should be capable of doing the same (Berg, 2010). The difference is that the DEA approach has its roots in mathematical programming, whereas the SFA approach has more links to econometric theory (Bogetoft et al., 2011). DEA is a more flexible approach as it allows for multiple inputs and outputs. In contrast to SFA, DEA is a linear programming methodology to measure the efficiency of numerous decision-making units (DMUs) when the production process presents a structure of multiple inputs and outputs (Zhang et al., 2014). A DMU is a system or entity evaluated on its ability to

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turn inputs into outputs (Cooper et al., 2000). According to Allen et al. (2013), the efficiency score in the presence of various inputs and output factors is:

Equation 1: Efficiency score for Multiple decision-making units

$$Efficiency = \frac{Weighted\ sum\ of\ Outputs}{Weighted\ sum\ of\ Inputs}$$

Data envelope analysis has been applied across various systems, including health, education, commercial, financial, and defense. A DEA model compares the relative operational efficiency of different DMUs on a uniform set of production metrics. Fig 2 below shows five hospitals' performance with outputs as the number of patients treated and average patient treatment period while input is the operating costs. The most efficient samples, Hospitals E, C, and B, are chosen to form a frontier, as shown in Fig 2 below, enveloping all other DMUs. DEA aims to measure the efficiency of the DMUs by measuring their distance from the efficiency frontier. All DMUs on the efficiency frontier are regarded as efficient, while those within the envelope are the opposite. An inefficient DMU can be made more efficient by projection onto the frontier; for example, hospital D can become more efficient by reducing its treatment period, pushing it towards Hospital E, or increasing the number of patients treated, pushing it towards Hospital B on the efficiency frontier. the relative efficiency of a DMU_p can be calculated using the model proposed by Charnes et al.(1978) in equation 3

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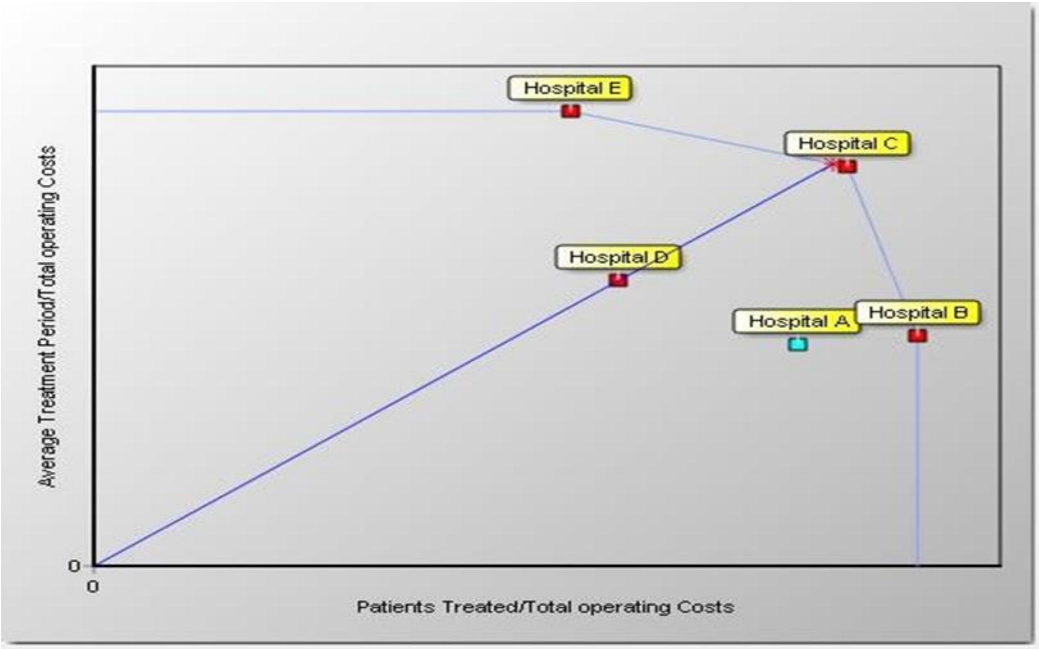

Figure 1: Diagram of Data Envelope Analysis for different Decision-making units

$$Max\ \frac{\sum_{k=1}^{s} \vartheta_k y_{kp}}{\sum_{j=1}^{m} u_j x_{jp}}$$

$$st:.\frac{\sum_{k=1}^{s} \vartheta_k y_{kp}}{\sum_{j=1}^{m} u_j x_{jp}} \leq \forall i$$

$$uk, uj \geq 0 \forall k, j$$

Where,
k = 1, …, s,
j = 1, …, m,
i = 1, …, n,
yki= amount of output k produced by DMU i,
xji= amount of input j utilized by DMU i,
ϑk= weight given to output k,
uj= weight given to input j

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As previously established in this work, output measures for public infrastructure such as hospitals cannot always be measured monetarily (see Introduction). Hussey et al. (2019) analyzed over 170 articles on hospital efficiency measures identified 265. These measures were divided into input and output measures. Input measures include physical measures like the number of beds and staff and output measures focused on the health services delivered, such as patient discharges. However, an average monetary value known as the VSL (Value of Statistical Life) can be used to quantify each life saved monetarily. The VSL estimates how much people are willing to pay for a reduction in mortality risks. Agencies use estimates of values of risk reductions when conducting a benefit-cost analysis of a new policy or regulation that may affect public health (EPA, 2017). Shih et al. (2014) applied system dynamics in a cost-benefit analysis of investments in renewable energy and energy improvement investments. The health benefits of the investments were measured monetarily using VSL. System dynamics has also been applied to investigate efficiency improvement policies in a medium-sized Italian hospital (Bendato et al., 2015) and publicly funded hospitals (Wong et al., 2017). In both cases, the models were used to simulate strategies to reduce patient wait times and treatment periods in emergency departments. Although DEA analysis can be carried out using Microsoft Excel and Frontier Analyst applications, a system dynamics model can be designed with variables to assess a hospital system's resilience and efficiency. This provides a simplified means of carrying out the policy/strategy analysis and eliminates the need to use multiple programs that may prove cumbersome for the practicing manager.

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There are studies on the relationship between efficiency and resilience of critical infrastructure. Marshall et al. (2020) proposed that automation could mitigate disruptions' impacts due to resource constraints, failure of aging systems, or socio-economic conditions--that addressing both system resilience and efficiency achieves this. They added stakeholder equity (fairness in the allocation of resources among stakeholders) as a factor that deserves consideration in addition to both previously mentioned. Essuman et al. (2020) studied the effects of a supply chain disruption on over 250 sub-Saharan firms and concluded that: improving resilience by increasing system robustness and recovery time can improve operational efficiency for disruptions of high and low magnitudes, respectively. These studies are limited in that they do not explicitly investigate the relationship between both concepts. Where the relationship is investigated, uncertainty regarding the occurrence and magnitude of disruption, coupled with the effect of the potential system response on efficiency, is not fully addressed or investigated. The current research partially fills this gap by focusing on the impacts of efficiency improvements on a system's resilience and the impacts of resilience improvement efforts on its normal operational efficiency, i.e., its efficiency if a disaster does not occur.

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CHAPTER IV

RESEARCH APPROACH AND METHODOLOGY

Hypothesis Development

As described above, owners of critical infrastructures that are vulnerable to hazards and seek to improve overall performance face a trade-off between improving efficiency and improving resilience. Resources can be used to improve either, but typically not both. Resilience in critical infrastructure systems can be improved by increasing redundancy and diversity (Johnsen, 2010); (Moteff, 2010); (Labaka et al., 2015). Redundancy in engineered systems includes extra components that are not strictly necessary to the system's functioning in case of failure of other components. Another redundancy description is duplicating critical components or functions of a system, usually as a backup or failsafe. For example, the publicly managed hospital modeled in this research. To improve the hospital's resilience, the officials in that region or the hospital management may employ more staff to deal with the expected loss of capacity if the earthquake occurs. These extra staff act as a backup and the extra-capacity they bring only comes into play if there is a disruption. Diversity is the condition of being composed of different elements. Diversity in engineering, infrastructure means the availability of other parts or components of a system that performs the same functions. Using the same example of the hospital, a strategy to improve diversity may entail adding a backup generator to buffer the hospital's power supply and reduce the risk of the hospital losing power if an earthquake occurs and the local grid's power supply is lost. The mix of the power supply from the local grid and the generator makes the hospital's power supply system diverse as two different

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components serve the same purpose. Note: If the generator adds more capacity than needed during normal operations, it also counts as a redundancy in the power supply system. The implementation of these resilience improvement costs will increase operating costs. These increases are due to the initial investment costs and maintenance costs, e.g., wages and extra staff benefits. The number of patients treated may not increase as the additional staff does not guarantee increased patient inflow and only add excess capacity. If the efficiency were to be measured by the unit cost of patient treatment, the hospital would have been made less efficient by these strategies.

Alternatively, resources can be used to improve efficiency, such as reducing slack. Slack reduction involves the reduction of excess capacity. This slack reduction/elimination can be achieved by reducing an input without affecting output or increasing output without affecting input (Harrison et al., 2001; Harrison et al., 2006). Either way, the increase in efficiency is achieved by a greater ratio of outputs to inputs. In reducing slack, the system would have to increase its capacity or shed excess capacity. Silo-Carroll et al. (2012) shows that implementing an Electronic Health Record (HER) system in hospitals promotes faster and more accurate communications and streamlined processes that increase patient flow. Such increases in the patient-discharge rate signal staff ability to treat higher numbers of patients or increase in patient-treatment capacity/staff. Implementation of efficiency improvement strategies will stretch the capacity of the system components. If EHR investments are made, loss of power supply during or after a

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natural disaster will limit the staff's ability to function, reducing patients' discharge rate and Hospital resilience.

Potential Strategies for Improvement

Infrastructure systems/assets are composed of many different component sections. Resources are allocated to these sections or departments to ensure smooth operation. These resources include staff, equipment, and supplies. Li et al. (2020) demonstrated that proper resource allocation could improve resilience. Patient inflow rates to different sections of a hospital are not equal. After a disaster, it is expected that the backlog of patients awaiting treatments in the different sections will not be equal. Allocation of resources during the recovery period according to the different departments' needs may limit performance losses by reducing the number of untreated patients. The different hospital sections' have different requirements. Factors such as patient inflow rates and death rates can be considered in designing these strategies. **Dynamic resource allocation based on demand may prove useful in improving total infrastructure performance (Resilience and efficiency).**

Real options analysis can also prove useful in improving total infrastructure performance compared to focusing on either efficiency or resilience. Identifying the drivers of the uncertainties that affect their performance can lead to the discovery of common performance drivers. This will then facilitate the design and analysis to understand how best to manage the uncertainties. Real options can be divided into two parts, focusing on

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monetary valuation and the other on the design and impacts of decision-making in practice. Managerial real options attempt to improve the decision-making process by structuring scenarios or circumstances beset by uncertainty as real options. This enables the manager/owner to design and implement effective alternative strategies. A simple tool developed by Ford & Garvin (2012) facilitates the structuring of flexible management strategies as options. The design and evaluation of the non-monetary aspects of an alternative strategy is the domain of a managerial real options approach. Whereas the evaluation of the performance of critical infrastructure on financial metrics can be approached by monetary valuation, its performance on other indices, such as reducing preventable deaths, can be evaluated by a managerial real options approach. For example, Hovmand & Ford (2009) applied Managerial real options to analyze the effectiveness of a U.S city's community intervention strategies. The managerial real options approach is used to structure the resilience improvement strategies as options. **Real options-based resource allocation strategies may help in mitigating the effects of resilience improvement on system efficiency.**

The current work develops and tests resource allocation strategies that may successfully address the efficiency: resilience trade-off challenge and improved critical infrastructure performance.

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System Dynamics

The system dynamics methodology applies a control theory perspective to the design and management of complex human systems. System dynamics combines servo-mechanism thinking with computer simulation to analyze systems. It is one of several established and successful approaches to systems analysis and design (Flood & Jackson, 1991; Jackson, 2003; Lane & Jackson, 1995). Forrester (1961) developed the methodology's philosophy, and Sterman (2000) specified the modeling process with examples and described numerous applications. The methodology has been extensively used for this purpose, including studying development projects. The system dynamics perspective focuses on how the internal structure impacts system and managerial behavior and, thereby, performance over time. The approach is unique in its integrated use of stocks and flows, causal feedback, and time delays to model and explains processes, resources, information, and management policies. Stocks represent accumulations or backlogs of work, people, information, or other system portions that change over time. Flows represent the movement of those commodities into, between, and out of stocks. The methodology's ability to model many diverse system components (e.g., work, people, money, value), processes (e.g., design, technology development, production, operations, quality assurance), and managerial decision-making and actions (e.g., forecasting and resource allocation) makes system dynamics useful for modeling and investigating military operations, the design of materiel, and acquisition.

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When applied to resilience, system dynamics has focused on how performance evolves in response to interactions among resources, the supply of utilities, and structural redundancies in facilities. System dynamics is appropriate for modeling the trade-off in investments between resilience and efficiency because of its ability to explicitly model critical aspects of development projects. System dynamics models of development projects are purposefully simple relative to actual practice to expose the relationships between causal structures and the behavior and performance they create. Therefore, although many processes and features of system design and participants interact to determine performance, only those that describe features related to the study topic are included. The importance of deleted features can be tested when system dynamics are used to test the model structure's ability to explain system behavior and performance. System dynamics has been successfully applied to a variety of issues, including real options analysis. Previous research has been done on the application of system dynamics for a real options analysis of real-life case studies Johnson, Taylor & Ford (2006); Ford & Sobek (2005) and hypothetical scenarios Bhargav & Ford (2006). A system dynamics model can be created and calibrated to reflect a CRI asset's operations, response, and recovery after a natural disaster. Variables reflecting and measuring the asset's resilience to the disruption and efficiency are developed and added to the model. The impacts of strategies developed to improve the asset's resilience will be measured and analyzed by changing the model variables to reflect the strategies and running multiple simulations. The results of the simulations will provide the insight necessary to facilitate improved strategy design and implementation.

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The Model

The model used in this work was developed from a previously existing model. Li et al. (2020) modeled a hospital's operations and its reactions to disruptions like earthquakes. This model was recreated from published model equations provided by the authors to create a base model and then modified to include variables to model efficiency and a performance-based approach to estimating resilience. The original model is described first, followed by a description of the modifications made for its use in the current research. A diagram of the aggregate and expanded model structure is seen below in Fig 3 with a brief description; a detailed description is found in Appendix 1

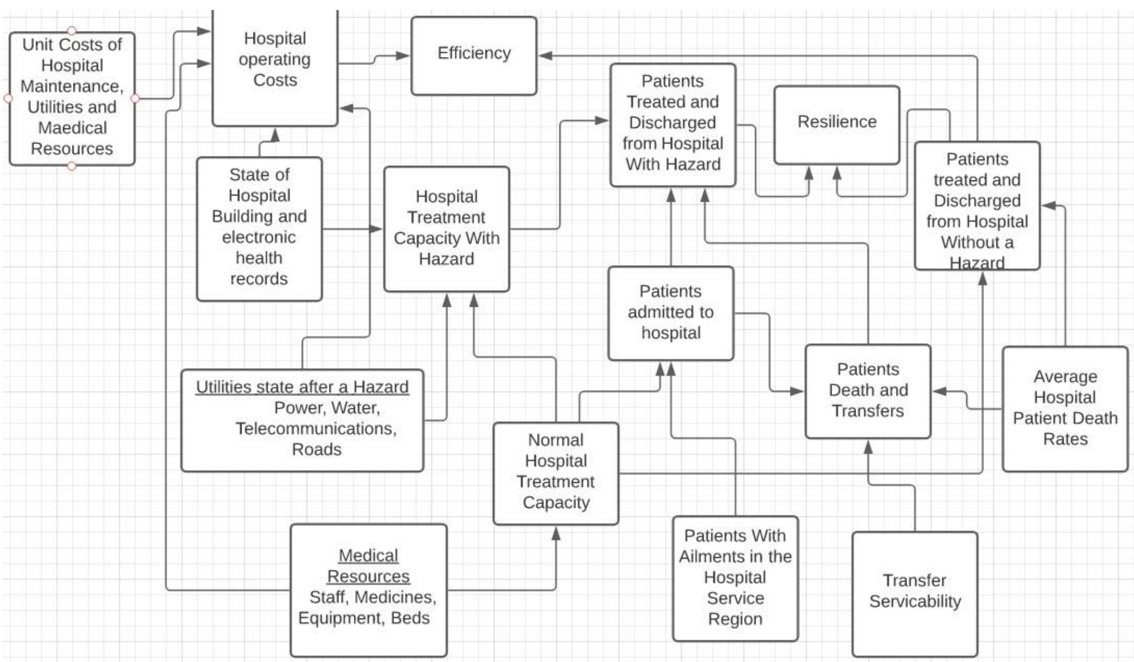

Figure 2:Aggregate model diagram of different model sections in the improved model

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Patients arrive from the hospital's service region and are admitted into the hospital depending on the hospital's treatment capacity. Some die during treatment, and the death rate is determined by the number of patients awaiting treatment and a fractional death rate. The rest are discharged. Utilities such as light, water, and transportation are needed for hospital operations. The hospital treatment capacity with a hazard is the daily number of treatments that can be carried out, considering constraints such as utilities, medical resources, etc. A hospital building and HIS(Health Information System) are needed to house patients and medical records. The non-hazard performance is the total of the expected treatment rates without disruption or resource constraints. The hospital operating costs are the utility charges, facility maintenance, and resource costs like staff wages and equipment maintenance. Resilience is the difference between the number of patient discharges without disruption and the number of patient discharges with one. Efficiency is the ratio of operating costs to the number of patients treated without a disruption.

The Original Model Structure

The original model starts with the inflow of patients after a disaster. Patients arrive at the hospital and wait before they are triaged into different sections according to their needs. The sections are divided into minor injuries, severe injuries, respiratory infections, and other diseases. The patients are either treated depending on the hospital capacity, transferred to other hospitals, or die. Fig 4 shows the flow of patients through a section of the hospital. Patient treatment, transfer, or death is determined by various resources, hospital buildings, and utilities. Resources include staff, beds, medical equipment, and

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consumables. The utilities include water, power, communications, roads, a backup power generator, and a water storage facility. The hospital building houses equipment and an electronic health records system. Damage to the hospital building limits the ability of these systems to work.

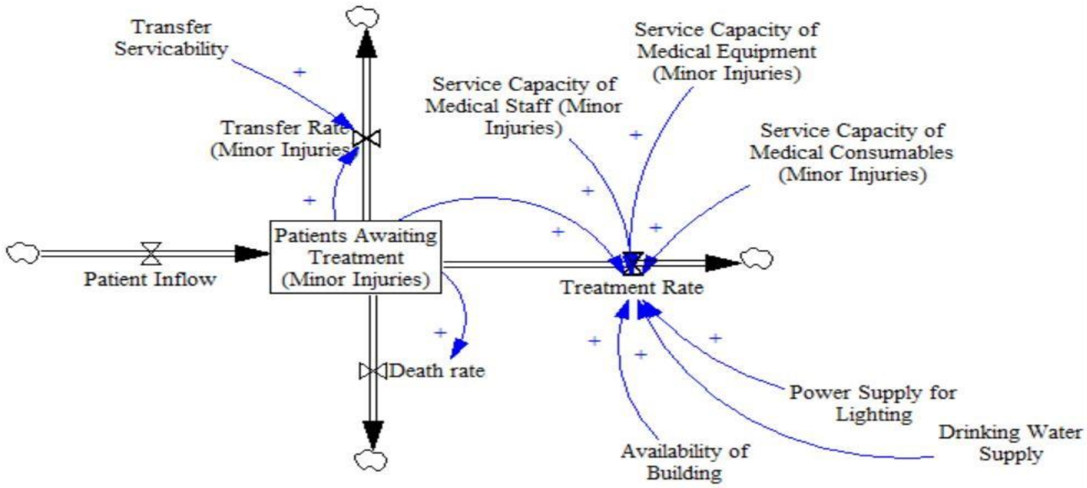

Figure 3:Dynamics of Patient Treatment

The aggregated model and variable relationships are described in the series of causal loop diagrams shown in Fig 5&6. A detailed stock and flow diagram can be found in the appendix. The model simulation starts with a drop in utilities, roads, and buildings' state to represent a natural disaster (earthquake). This drop reduces their availability, which reduces the hospital's service capacity and constrains the treatment rate. The reduction in service capacity also affects the treatment rate and the hospital's functionality. The hospital functionality is described as the hospital's actual service capacity ratio to its normal or standard service capacity. The normal capacity is the number of patients the

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hospital should treat if all resources were available and no constraints placed on the system due to lack of utilities and transportation. The actual treatment capacity is the number of patients the hospital can treat, given the resources at hand and the system's constraints. Functionality gradually recovers as the actual service capacity improves due to the recovery of the utility state and more parts of the hospital becoming available.

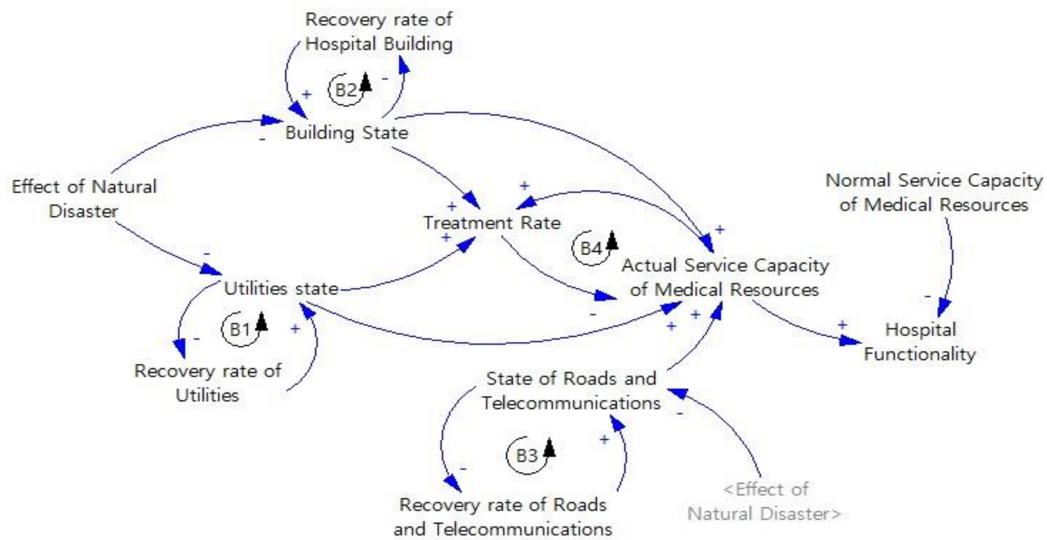

Figure 4:Causal loop diagram of model dynamics

Loops B1, B2, and B3 in *Fig 4* show the relationship between utilities, building state, and recovery efforts. Faster recovery rates lead to better building and utility states, reducing the need for recovery efforts. Loop B4 shows the relationship between the treatment rate and the service capacity of medical resources. Increases in treatment rate put a strain on the hospital's medical resources, limiting actual capacity and balancing its treatment rate. The actual capacity is limited as patients occupy beds and use medical consumables. The relationship in loop B4 is dis-aggregated and explained further in the next paragraph.

The treatment rate forms two balancing loops with the Service Capacity of Medical consumables and the Number of Available beds, as shown in fig 6 *below*. A sufficient number of unoccupied hospital beds enable the hospital to admit and treat more patients. As more patients are admitted and treated in the hospital, the number of available beds decreases, reducing the number of patients the hospital can treat. The second balancing loop describes the relationship between the service capacity of medical consumables and the treatment rate. The hospital staff needs medical consumables like medicines to be able to treat a patient. When the hospital runs out of medical consumables, the staff cannot treat patients, and as patient treatment deplete the number of medical consumables. The relationship between the utilities, building state, and the treatment rate is also shown in Fig 6. Power supply, drinking water supply, and a hospital building are needed for patient treatment. Limited availability of utilities mentioned above or the building reduces the number of patients treated in the hospital.

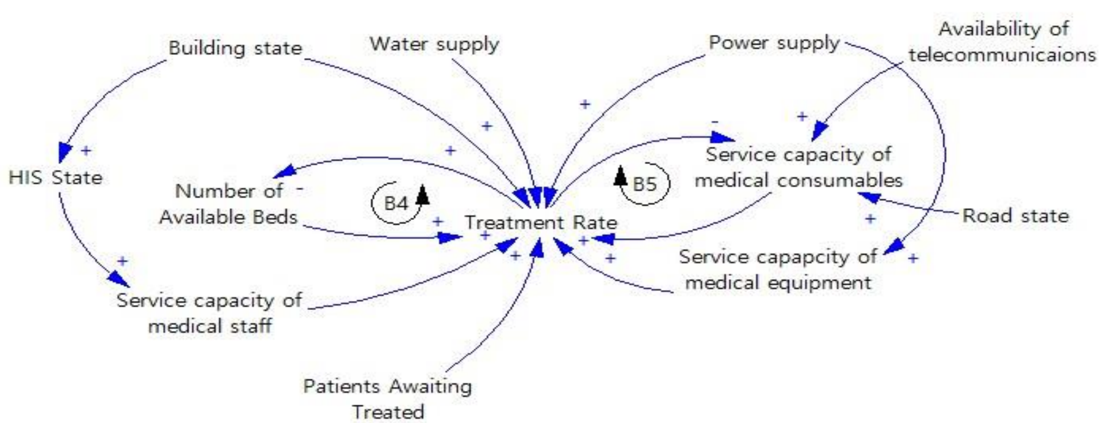

Figure 5: Causal loop diagram of medical resources, treatment rate, and utilities

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Original Model Validation

The base model was validated to verify that it was an accurate copy of the original (published) model and was potentially useful for the current work using standard model tests for system dynamics models, Sterman (2000). After recreating the model, simulations to replicate the behaviors generated by Li et al. (2020) are carried out. Six simulations in total were run. The first two simulations were the extreme conditions tests. Extreme condition 1 assumed that the municipal road network was destroyed after the earthquake and its recovery rate was 0, preventing the hospital from supplementing their stock of medical consumables and transferring patients. Extreme condition 2 assumed that the municipal power supply had a recovery rate of 0. The behaviors generated for these tests are seen in figures 7&8 below

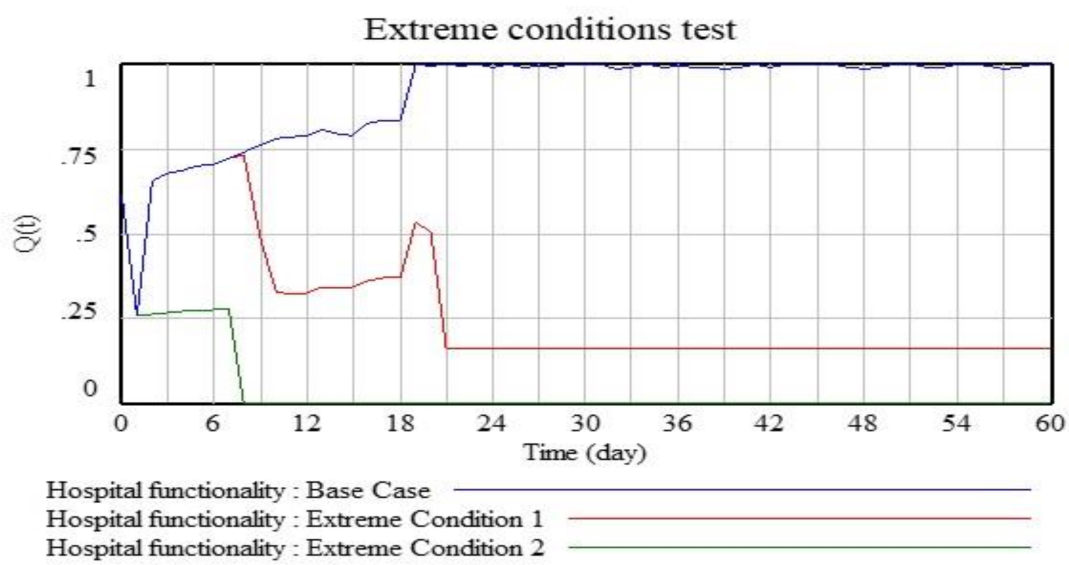

Figure 6: BOTG of Extreme conditions test carried out on a recreated model

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After generating expected behavior during the extreme condition tests, policies described by Li et al. (2020) simulated. Policy1- represents a scenario where the hospital reserves twice as much fuel, Policy2 represents a scenario where the hospital shifts 40 beds from Treatment of Disease C to Disease D, Policy3 represents a scenario where the hospital hires extra workers and reduces the number of days for full building recovery from 19 to 10 days and policy) represents the model, a situation where the hospital operates without a change. After the simulations, the model's behavior to all the above-described scenarios matched those generated by Li et al. (2020) for the same scenarios. This partially validated the base model. The behaviors generated for the policy simulations can be seen in *Fig 8* below. A table explaining which variables were changed and the degree of the changes to simulate the policies is found in Appendix 5.

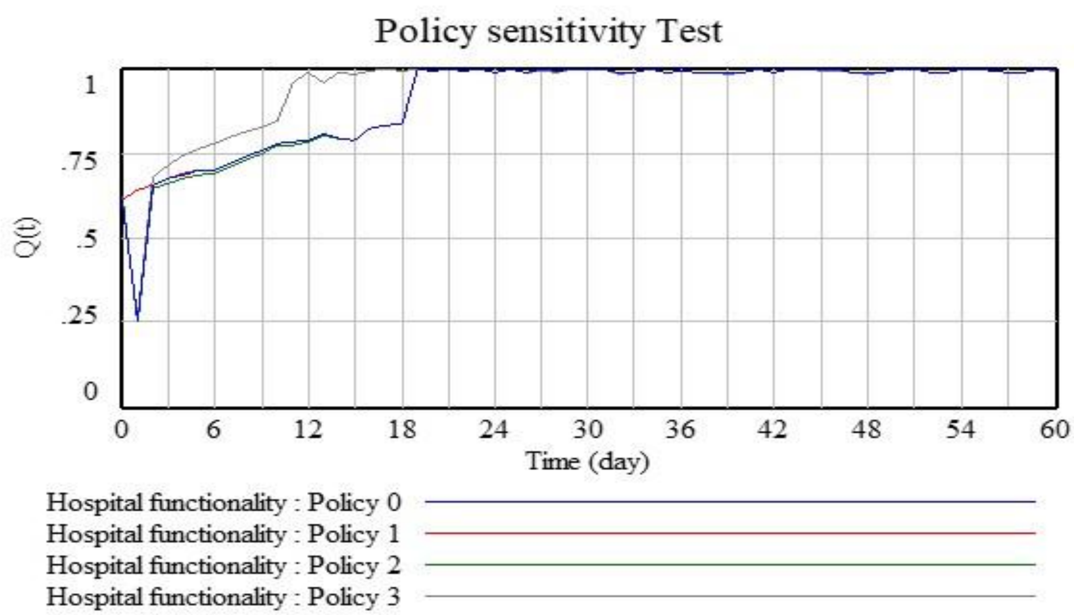

Figure 7: BOTG of Policy sensitivity tests carried out in recreated model

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For this study, changes were made to the base model to reflect the real system better and enable the owner to compare the total hospital performance, efficiency, and resilience with similar metrics. The model was calibrated to run on an equilibrium to understand the impacts of disruptions and performance improvement strategies fully. To do this, the modeler assumed that the inflow of patients is equal to the sum of outflows due to patient treatment, deaths, and transfers. Therefore, the hospital is always assumed to have as much or more demand for services than there is a supply of those services by the hospital. Patients applying for treatment at the hospital above the hospital capacity are assumed to be not accepted or treated. This assumption reflects a hospital situated in an underserved community such as in a rural or inner-city setting, with an infinite number of patients needing treatment. The hospital's patient inflow is the sum of the various hospital sections' expected treatment capacity. A new variable, "Expected treatment capacity," was created for each hospital section. The expected treatment capacity is the hospital's treatment capacity without the constraints placed on it because of disruption. This variable drives the hospital's equilibrium capacity.

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Modeling Hospital Performance

For this study, total hospital performance is the number of patients the hospital can treat over a period of time. A stock "No-Hazard Performance was created to measure expected total hospital performance. The inflow to no-hazard performance is the sum of the difference between the expected treatment capacities and the expected death rates for all hospital sections. This is the cumulative number of patients the hospital should be able to treat and discharge in the absence of disruption after accounting for patient deaths. The benefits of these changes are two-fold; improvements in hospital capacity to improve performance are immediately reflected in increased inflows, and the occurrence of disruptions leads to a backlog in the stock of patients awaiting treatment. This backlog occurs because the expected treatment capacity, which is the treatment capacity before a disruption occurs, regulates the patient inflow while the actual treatment capacity regulates patient treatment. The system's ability to limit and reduce the size of this backlog determines Actual system/hazard performance. The actual system performance is the cumulative number of patients the hospital can treat given the constraints placed on its treatment capacity by the disruption's effects. Fig 9 shows the model diagrams for patient inflows and outflows from the hospital.

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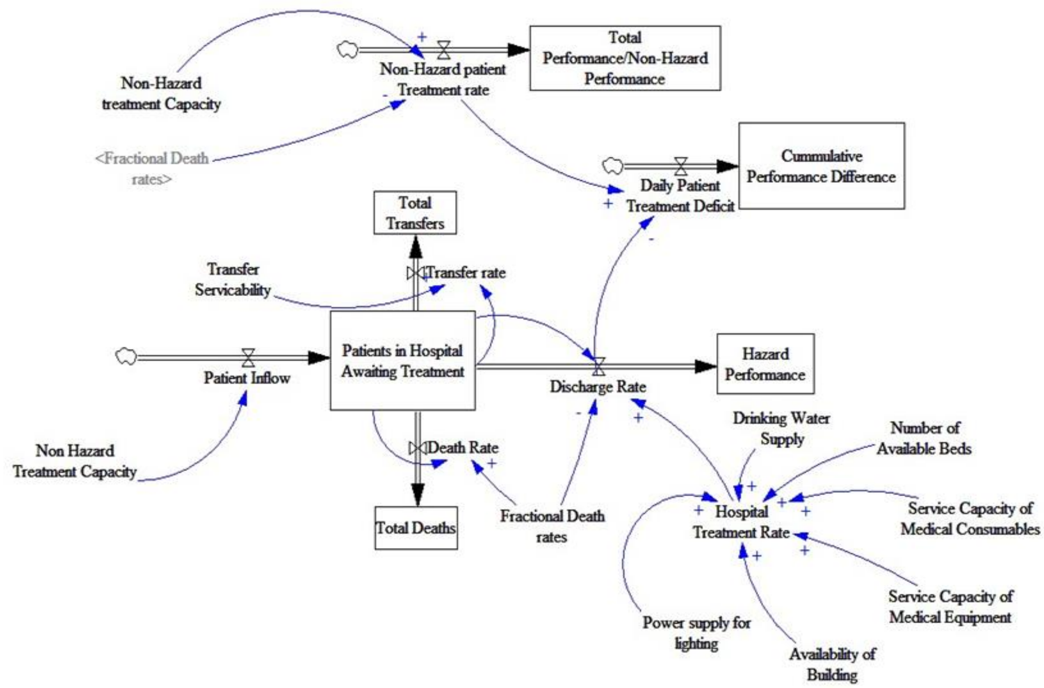

Figure 8: Expanded model diagram allowing for resilience to be measured by Cumulative Patient deficit

This study proposes a performance-based metric for resilience. Given that resilience is the ability of a system to withstand and recover from disruptions, resilience is measured by the difference between the expected (baseline) treatment performance, i.e., performance without disruption, and its actual performance with a disruption. Therefore, in this study, the hospital system's resilience is the number of patients left untreated over the planning period when a hazard occurs. The higher the number of patients left untreated, the lower the resilience. Therefore, a resilience improvement strategy would reduce the number of patients left untreated due to a disruption. Fig 9 above shows the interaction of the expected and actual patients treatment stocks to give the new variable "Cumulative Patient

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Treatment deficit." This stock was created to measure resilience. The inflow of this stock is the difference between the expected treatment rate and the actual treatment rate.

Conceptually efficiency is the ratio of output to input. In this work, efficiency is given as the patients' treated ratio (output) to the hospital's total operating costs (Input). The hospital's efficiency is then the number of patients it can treat over a period given a certain sum. This is equivalent to the inverse of the average cost to treat a patient. Therefore, an efficiency improvement strategy would reduce the cost/patient treated or increase the patients treated/ unit cost. Estimating the operating costs of the hospital required the addition of new model variables. The new variables include the "Total operating costs," reflecting the amount spent on resources, facility management, and utilities throughout the simulation. The total salary and equipment maintenance costs reflect the staff wages/benefits costs and the maintenance costs of medical equipment. Factors contributing to Hospital operating costs include staff wages, salaries, and benefits, building maintenance and support, equipment maintenance, utilities (Robert et al. 1999); (Gomez-Chaparro et al., 2020); (Sliteen & Catarina 2010). Fig 10 below shows the operating costs model diagram. Daily Unit costs were estimated and attached to the different model variables representing the previously mentioned factors. The estimation of the unit costs in the model was influenced by the percentage contributions of these factors to hospital operating costs identified in Sliteen & Catarina (2010); Bai & Zare (2020). The products of the unit costs and the number of units over the simulation period give the total operating expenses. Another variable, "Unit cost/ patient," was created. This

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variable measures the hospital efficiency, which goes up as unit cost/patient goes down. *The Non-hazard performance is used to calculate the treatment cost per patient. As previously mentioned (see background), resilience improvement can increase efficiency after a disruption. Given that this work focuses on how improvements to efficiency in normal times affect the systems' resilience and vice-versa, the hospital efficiency performance after a disruption is excluded from the analysis.*

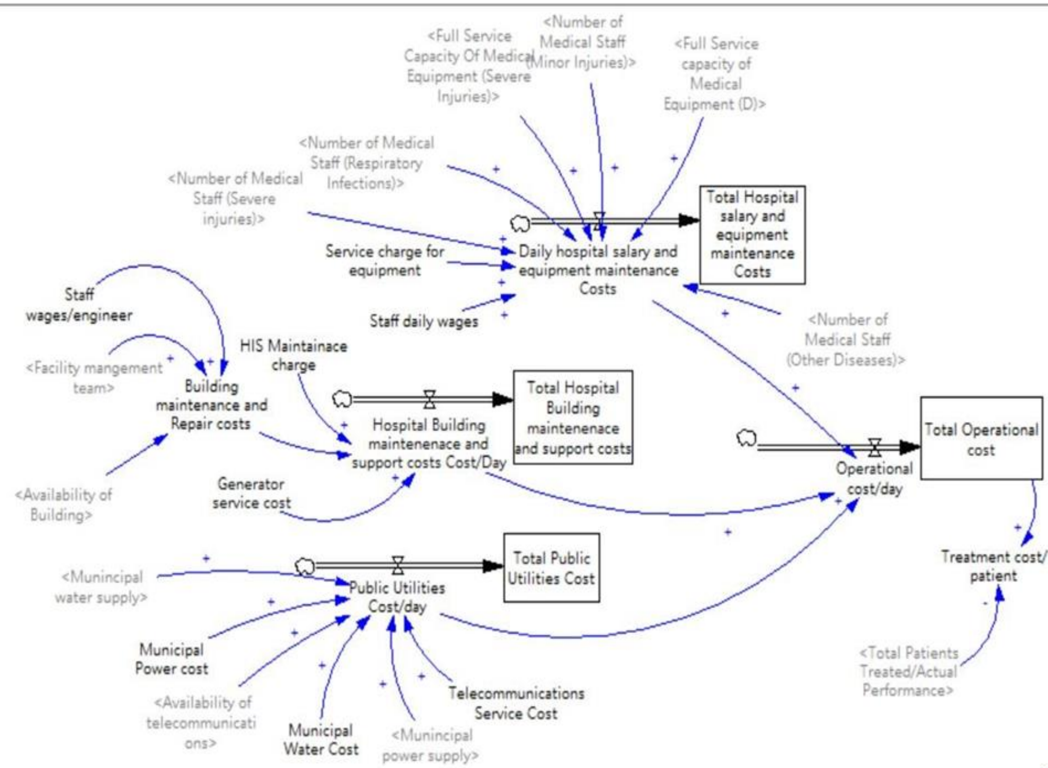

Figure 9: A model diagram showing the dynamics of operating costs and efficiency

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Revised Model Validation

The revised model was validated using standard model tests for system dynamics models Sterman,(2000). Boundary adequacy tests, parameter assessment, structural assessment, extreme conditions test, and dimensional consistency tests were carried out. A comprehensive table of the structural analysis is included in the appendix. Based on those tests, the revised model is assessed to be useful for the current work.

Typical Model Behavior and Model Analysis

To test the model's sensitivity to policies, simulations were run to reflect situations expected to induce behavioral changes in efficiency or resilience metrics. Patient backlogs and treatment rates are expected to remain steady, with a steady increase in the total number of patients treated. "EARTHQUAKE" reflects a situation where the earthquake happens on Day 50. In the following policy simulated, the hospital building is reconstructed and rehabilitated after an earthquake in 31 days instead of the baseline case of 42 days. This policy was designed to observe hospital performance with increased resilience due to a shorter recovery period.

The following summarizes the equations and metrics used in this study for measuring efficiency and resilience.

Resilience

Cumulative performance difference $= Non\ Hazard\ Performance - Hazard\ Performance \ldots\ldots$ **Equation 4**

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Non-Hazard Performance/ Total Performance =

$\sum Expected\ Discharge\ Rate \ldots\ldots$ **Equation 5**

Expected Discharge rate = $\sum Expected\ Treatment\ Rate -$

$\sum Expected\ death\ rate \ldots\ldots$ **Equation 6**

Where Expected Treatment rate is the treatment rate of the hospital without a disaster.

The expected Death rate is the death rate of the patients in the hospital without a disaster

Hazard Performance/ Total patients Treated = $\sum Total\ hospital\ Discharge\ rate$

$\ldots.$ **Equation 7**

Total Hospital Discharge rate =$\sum Sectional\ Discharge\ rates$ …. **Equation 8**

Average Waiting time = $\frac{\text{Patients in Hospital Awaiting Treatment}}{Total\ discharge\ rate + Total\ Transfer\ rate + Total\ Death\ rate}$

…………………………………………………………………………..**Equation 9**

Average waiting time is the amount of time a patient spends awaiting treatment before they die, are transferred, or are treated and discharged.

Efficiency

Treatment Cost/patient = $\sum \frac{\text{Total operational cost}}{\text{NonHazard performance}}$

Total operational cost is the hospital's cost accrued by the hospital over the simulation due to investments for performance improvement, costs due to resources, hospital maintenance, and utilities.

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Cumulative losses due to disruption = $Cummlative\ Performance\ difference * Treatment\ Cost/Patient$

"Cumulative losses due to disruption" measures the financial losses to the hospital as a result of the disruption. However, it is generallyency and vice versa, two variables, "Resilience as a ratio of the Base case" and "Efficiency as a ratio of the Base case," are introduced.

Resilience as a ratio of Base case = $\left(\frac{Cumulative\ Performance\ differnce\ of\ b}{Cumulative\ Performance\ Difference\ of\ a}\right)^{-1}$

Efficiency as a ratio of Base case = $\left(\frac{Treatment\ cost/patient\ of\ b}{Treatment\ cost/patient\ of\ a}\right)^{-1}$

Where

a = Base case value

b = Final value of the variable for investment strategy.

Fig 11 below show hospital resilience for different policies as a fraction of the base case value. Fig 12 shows the behavior of the patient backlog. The Base Case is simulated with no earthquake. The patient Backlog remains steady throughout the simulation period. In earthquake policy, the backlog sharply increases as patients are left untreated due to the hospital's functionality loss. This backlog tries to return to equilibrium as the system recovers. In the reduced recovery time policy, the patient backlog is lower than that of the previous policy as the hospital's faster recovery rate limits its growth. The resilience ratio, which is normally at zero in the base case when supply can meet demand as there is no

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disruption, increases rapidly from the earthquake occurrence time as the backlog overtakes the base case value and drops as capacity is restored till it reaches equilibrium. The equilibrium value is the correct value of the fractional change in resilience. This equilibrium value is at 1 in the earthquake policy, reflecting that no resilience improvements have been made. Increasing resilience by reducing hospital recovery time led to a smaller patient backlog and higher resilience ratio. From Fig 12, we can see that the resilience fraction only registers if there is an earthquake.

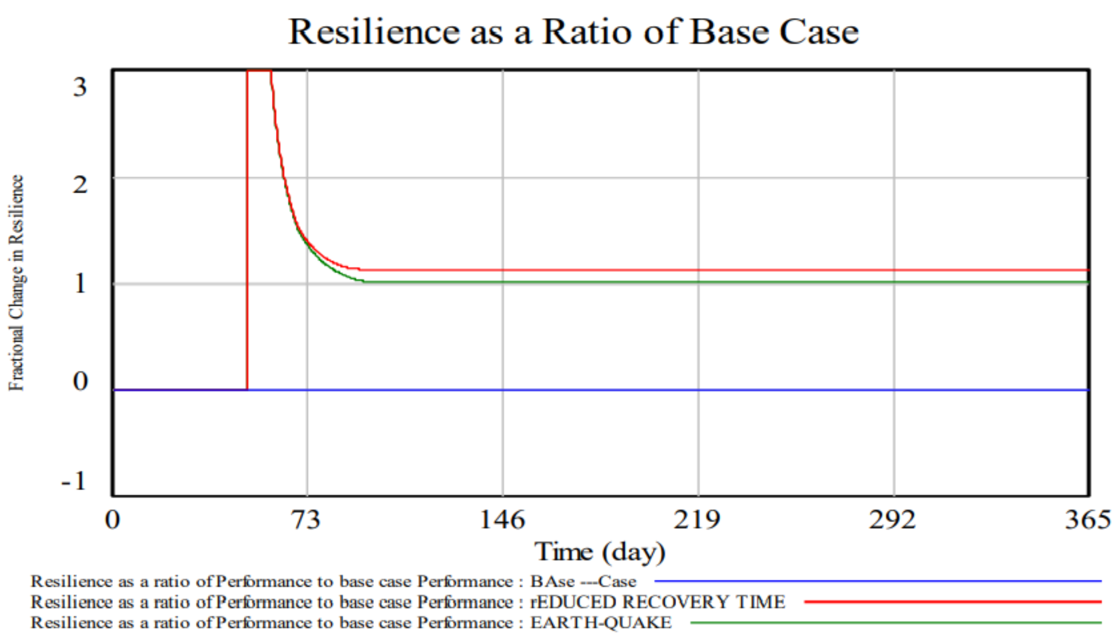

Figure 10: BOTG Of Resilience as a fraction of the base case value

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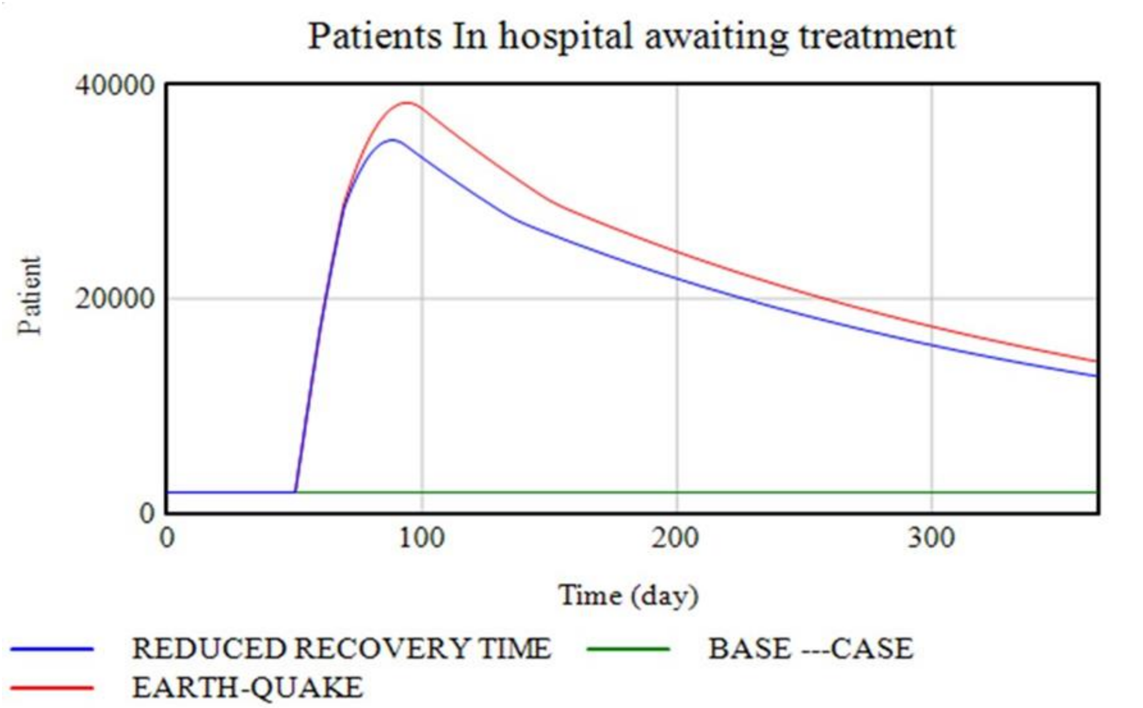

Figure 11: BOTG of Patient backlogs

Fig 13 below show the effects of the different policies designed to influence treatment cost/patient. The Base case shows the hospital efficiency's initial value without an earthquake (i.e., base case). The efficiency ratio remains at one as no efficiency improvement or reduction policies have been simulated. For the next policy, the hospital procures extra medical equipment to add excess capacity. The number of equipment is doubled in the hospital section for severe injuries. For the final policy, the hospital employs extra staff in the minor injuries section. When extra equipment is procured, the ratio of total expenditure to patients treated increases. This increase occurs as the daily operating costs are fixed costs and tied to the equipment number. This policy shows that increasing excess capacity leads to increased patient treatment costs and lower efficiency.

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The added staff policy led to greater patient inflow and treatment rates, countering the extra costs due to an increased salary budget. The policy to procure extra equipment was inefficient because it did not lead to higher treatment rates. The treatment rate is driven by the minimum service capacity of medical resources. For example, if the hospital staff can treat fifty patients, its equipment is enough for sixty patients but has supplies for only thirty patients, the hospital can only treat the thirty for which it has supplies. The hospital initially keeps more equipment than necessary in case of breakdowns. Adding extra equipment increases already excess capacity. Extra staff eliminated the difference/slack between medical staff and equipment's service capacities.

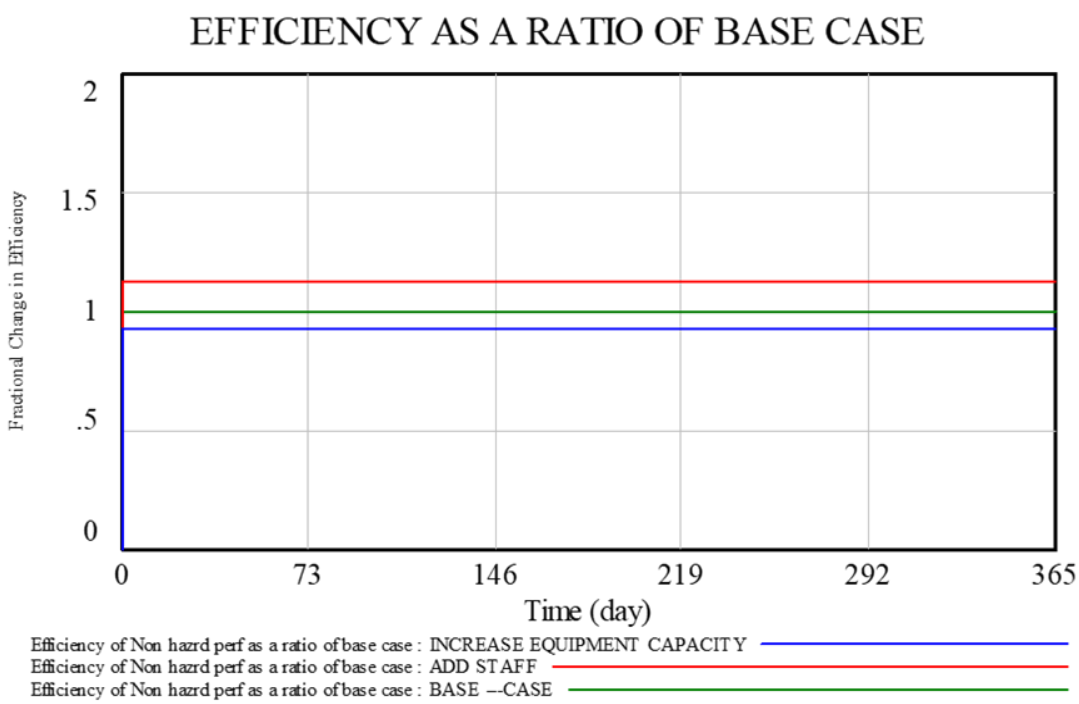

Figure 12: BOTG of Efficiency as a fraction of its Base Case value

The results of the policy simulations indicate that the model can measure resilience and efficiency

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CHAPTER V

RESULTS AND ANALYSIS

Mutually Exclusive Investments

In this set of strategy simulations, investments are made towards either resilience or efficiency but not to both at the same time. The results of these simulations are seen below. Figs 14&15 show the behavior of non-hazard performance metric. When investments are made toward efficiency, patient inflow and treatment capacity increase to give a greater cumulative value of patients treated during the simulation period. On the other hand, investments toward resilience do not increase treatment capacity; therefore, the cumulative of patients treated remain the same as the base case for all levels of investments toward resilience.

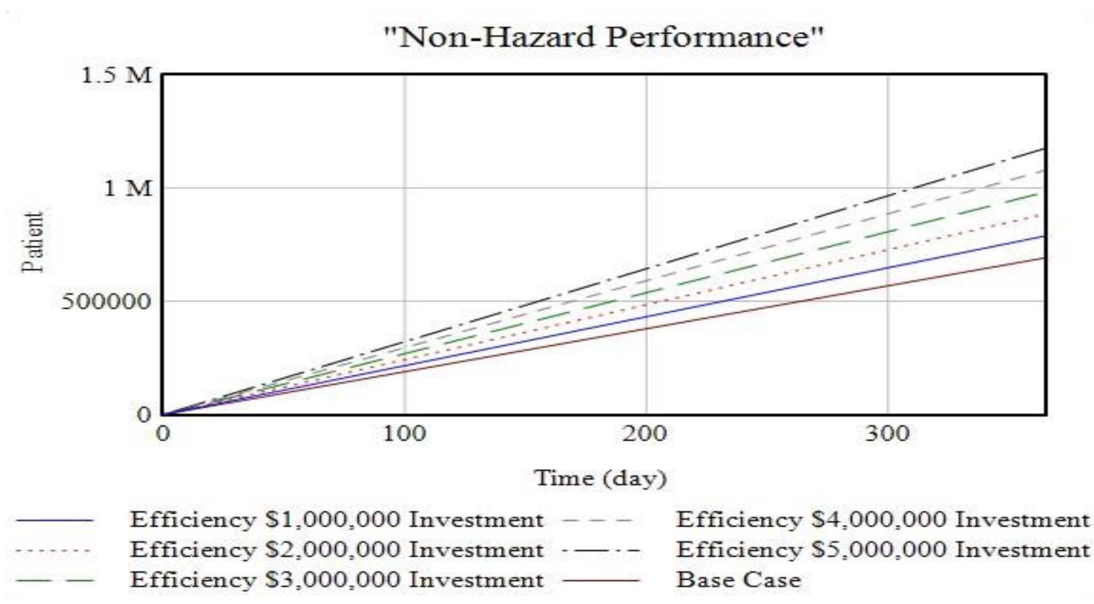

Figure 13: Non-Hazard Performance for Efficiency Investments

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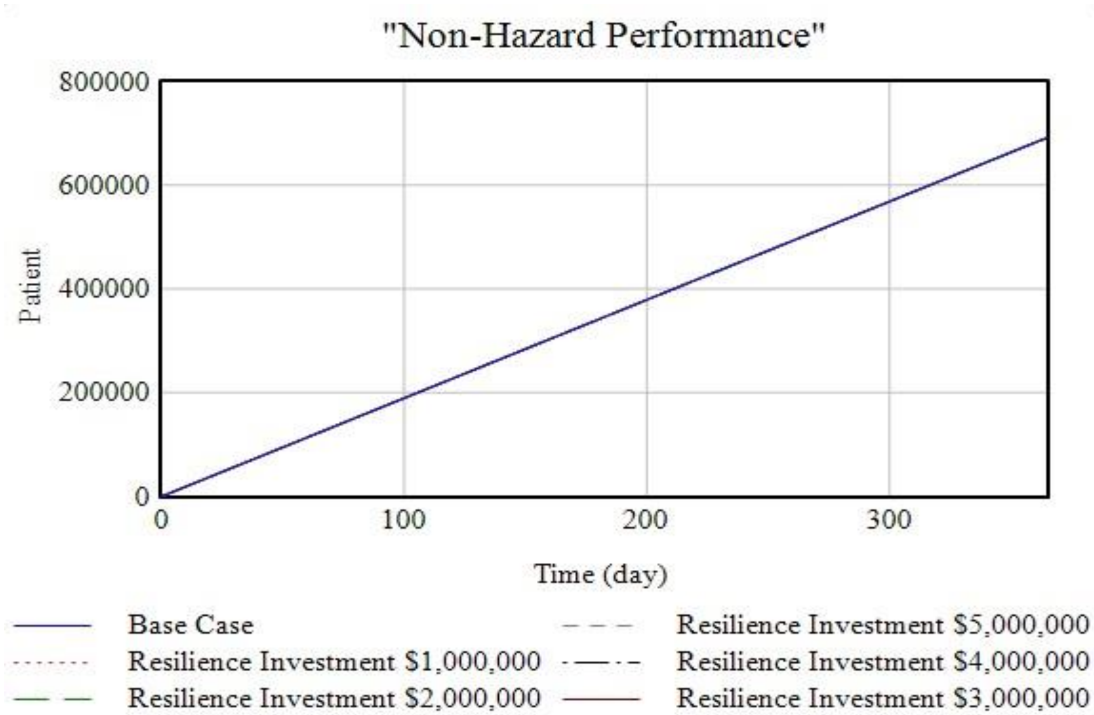

Figure 14: Non-Hazard Performance for resilience Investment

Figs 16&17 below show the behavior of the treatment cost per patient for hospital operations in the absence of disruption. *A "minimum" function restricts the metric for reasons of scale and audience clarity. The investment is made at the beginning of the simulation as an initial value of the stock of total operational costs. On day two, when the hospital has treated and discharged around five thousand patients with an expenditure of fifty thousand dollars plus an investment sum of say five million, the value of the treatment cost per patient would shoot up to around a thousand dollars before returning to normal as the cumulative of the patients treated increase. This, however, leaves the final values indiscernible to the naked eye due to the scale. The more patients the hospital treats and discharges relative to the investment's size, the faster the metric returns to the maximum*

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allowable value. This is seen in figs 3&4 as the simulations with the lowest investment sums return to the $50 line earlier. When investments are made toward resilience, the cost of patient treatment increases, signaling a loss in efficiency, as seen in Fig 17. On the other hand, as investments are made toward efficiency, the cost per patient treated reduces, signaling an increase in efficiency. In Fig 16, with increasing investments, the patient treatment costs are initially higher but recover faster with a much steeper slope leading to an intersection at the base case value before ending at a lower value of treatment cost per patient.

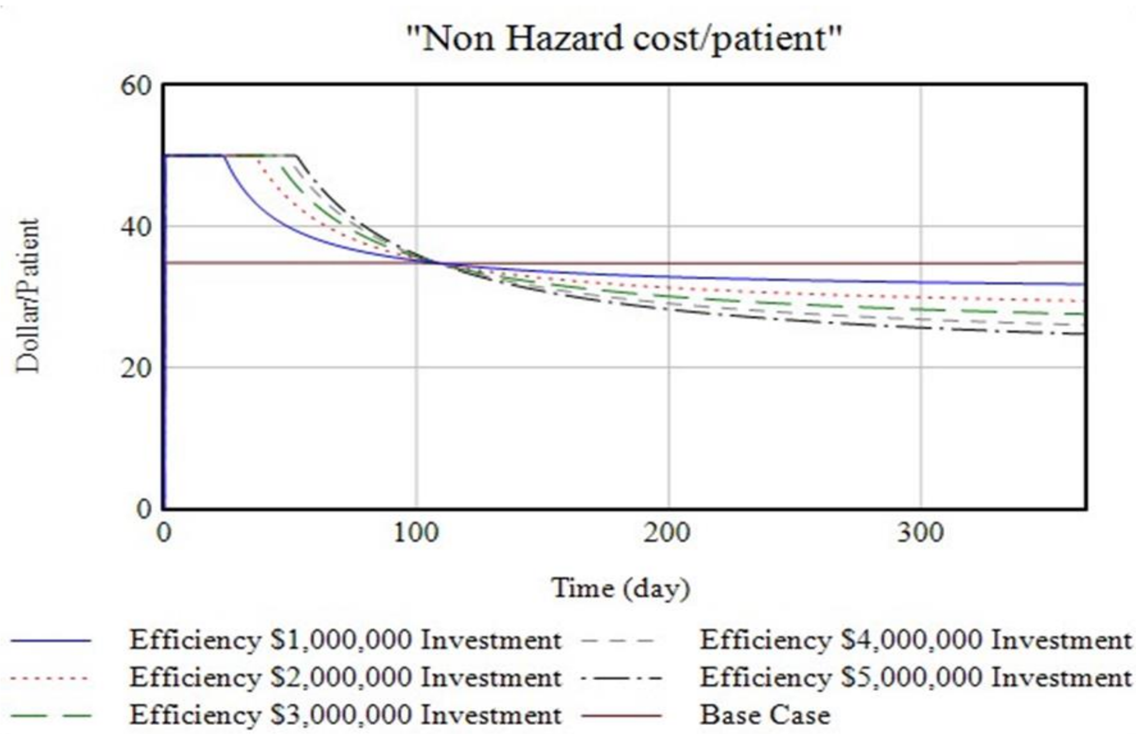

Figure 15:Treatment cost per patient for investments towards efficiency

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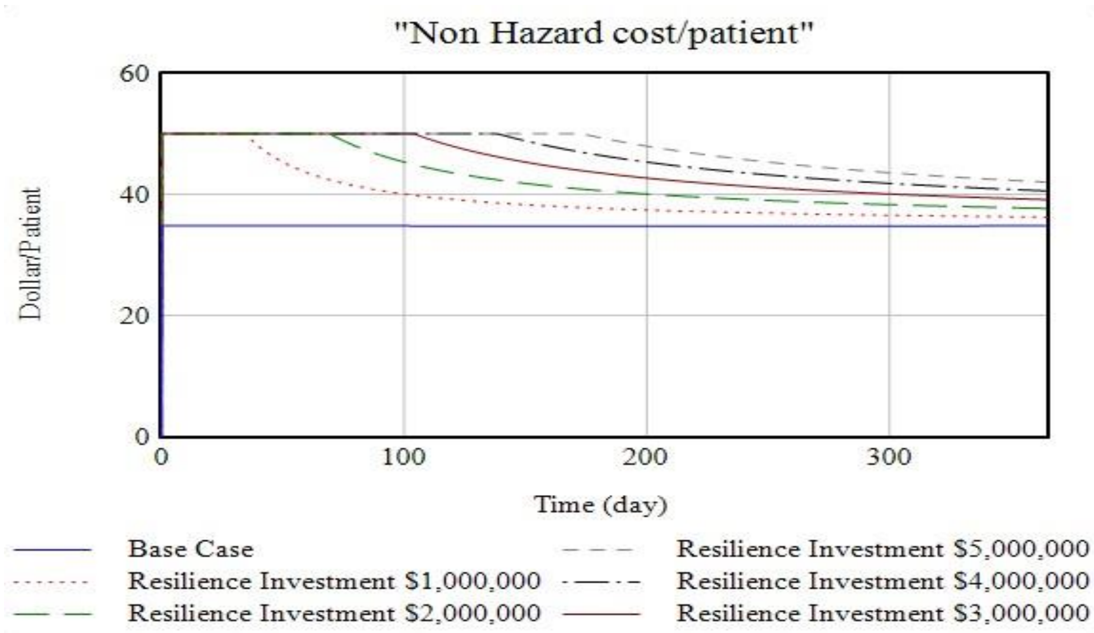

Figure 16:Treatment cost per patient for investments in resilience

Figs 18&19 below shows the average waiting of patients awaiting treatment in the hospital. This is the ratio of the patient backlog to its outflows. Without a disaster, the metric remains constant. When the disaster occurs on day 100, Patient backlog drastically increases, pushing patients' average waiting time to forty days in the base case. The hospital regains some of the lost treatment capacity ten days later, initially reducing waiting time as the medical equipment regains full capacity when the power supply is restored. However, the waiting time increases again as patient inflow remains steady, and treatment capacity is not fully recovered due to limited hospital building availability. The waiting time peaks and resumes a downward trend as the hospital building reconstruction provides room for increased treatment capacity. A slight increase in waiting time is seen before it drops with full building recovery. This is due to the recovery rate of the HIS state. The availability of the HIS impacts staff treatment capacity (see appendix). The HIS

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state lags building recovery by two days, as the computer technicians can only carry out repairs on systems in parts of the hospital that are fully rehabilitated. Increased investments in resilience reduce the average waiting time at the end of the simulation and reduce the peak value of waiting time. There is no relapse in the system due to a loss of power supply for the highest resilience investment, as seen in Fig 20. This occurs because the generator fuel storage capacity allows uninterrupted power supply for ten days which is the amount of time it takes for municipal power supply to be restored. In Fig 19, increased efficiency leads to higher peaks of waiting time and higher values for the Average waiting time at the end of the simulation.

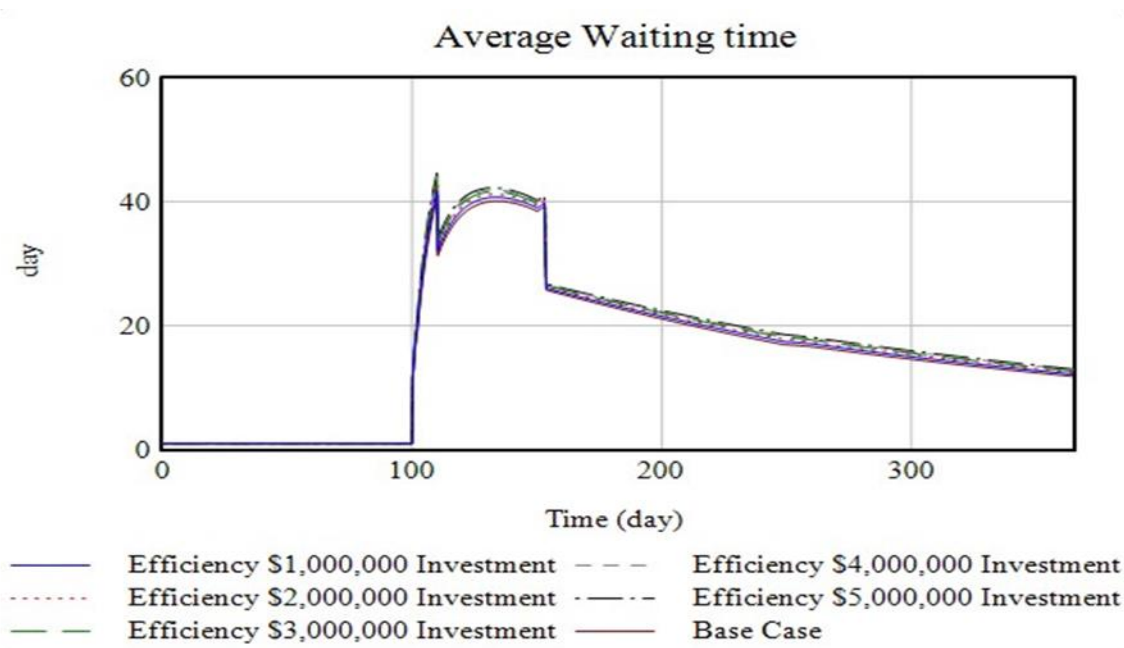

Figure 17: Average Patient wait time for investments to efficiency.

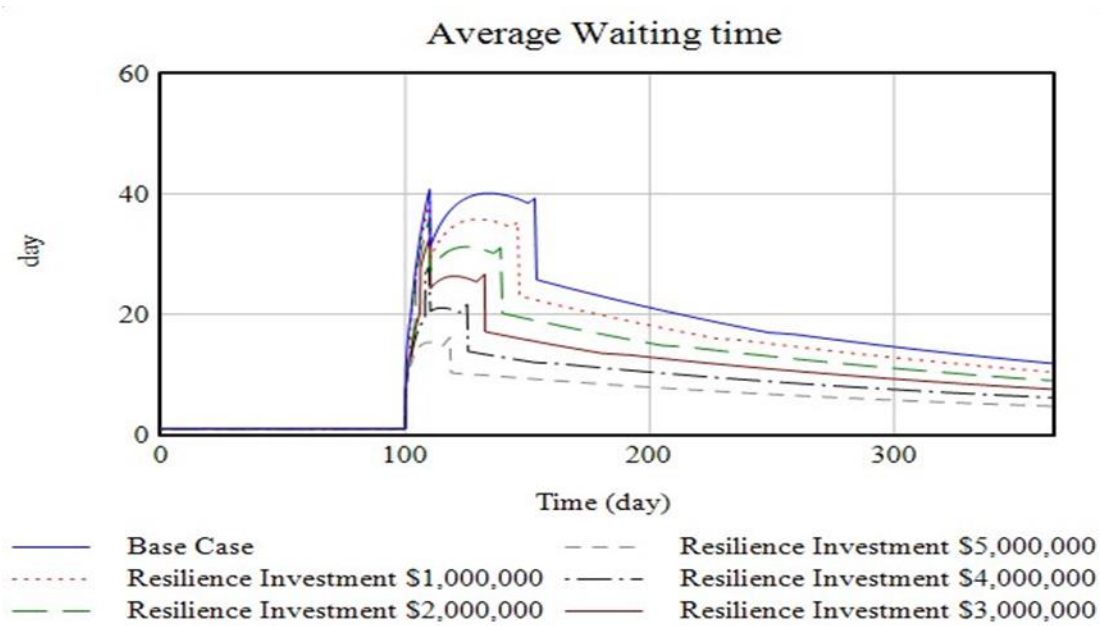

Figure 18: Average patient wait time for investments in resilience.

Figs 20&21 below show the total patient discharge rates for the hospital. In *Figure 21, the discharge rate starts higher for each increment in the investment towards efficiency to reflect the hospital staff's increased service capacity*. It mimics the behavior of the base case. After the occurrence of the disaster on day 100, the patient discharge rate drops by 80%. The discharge rate recovery receives a jump as power from the municipality is restored on day 10. The recovery continues as more parts of the hospital become available. The final pause before full recovery occurs during the wait for full recovery of the HIS state. With the recovery of the HIS state, the discharge rate returns to pre-disaster levels. In Fig 21, Investments in resilience limit the drop in the discharge rate. This occurs because the hospital does not lose the power supply. When the amount of fuel stored by the hospital runs out, the discharge rate drops to the base case level at that point in time. In the highest level of investment to resilience, the rate never drops because stored fuel

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never runs out, and the power supply remains steady. The reduced recovery time effect is seen as the discharge rate returns to pre-disaster levels earlier with increased resilience investments.

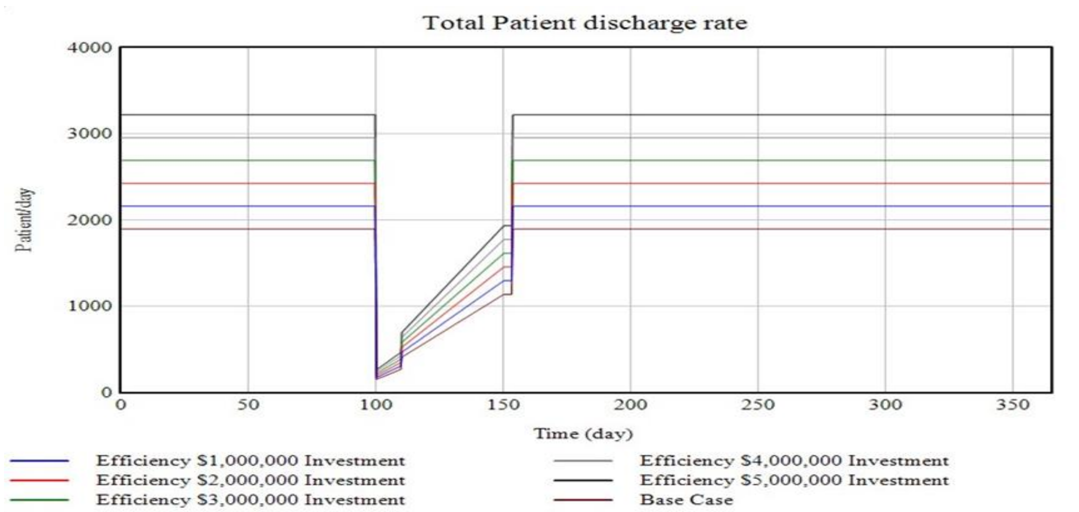

Figure 19: Total patient discharge rate for investments in efficiency

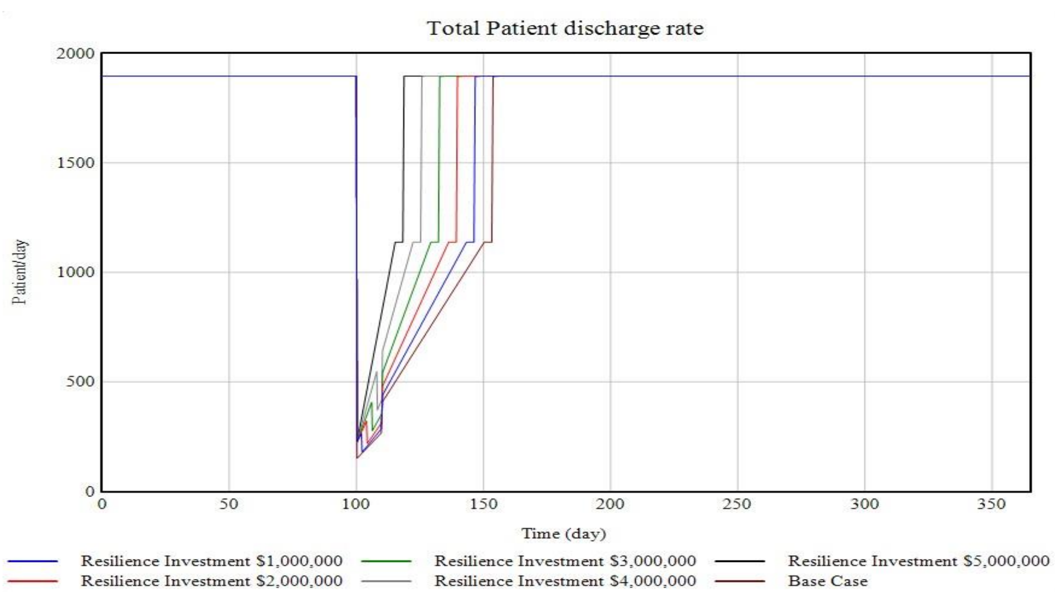

Figure 20: Total Patient discharge rates for investments in resilience.

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Figs 22&23 show the cumulative number of patients left untreated due to the disruption. This is the difference between the hazard and non-hazard performances. In Fig 22, increasing efficiency investments increase the cumulative difference from the base case, reflecting decreased resilience. On the other hand, increases in the investments towards resilience lead to a decrease in the cumulative difference to reflect increasing resilience. The metric remains zero before the disruption in both graphs, indicating that the hospital functions at the standard capacity. The difference is seen at day 100 after the disaster as the hospital is no longer able to maintain its standard treatment rate. The growth in the cumulative difference stops and plateaus with full hospital recovery.

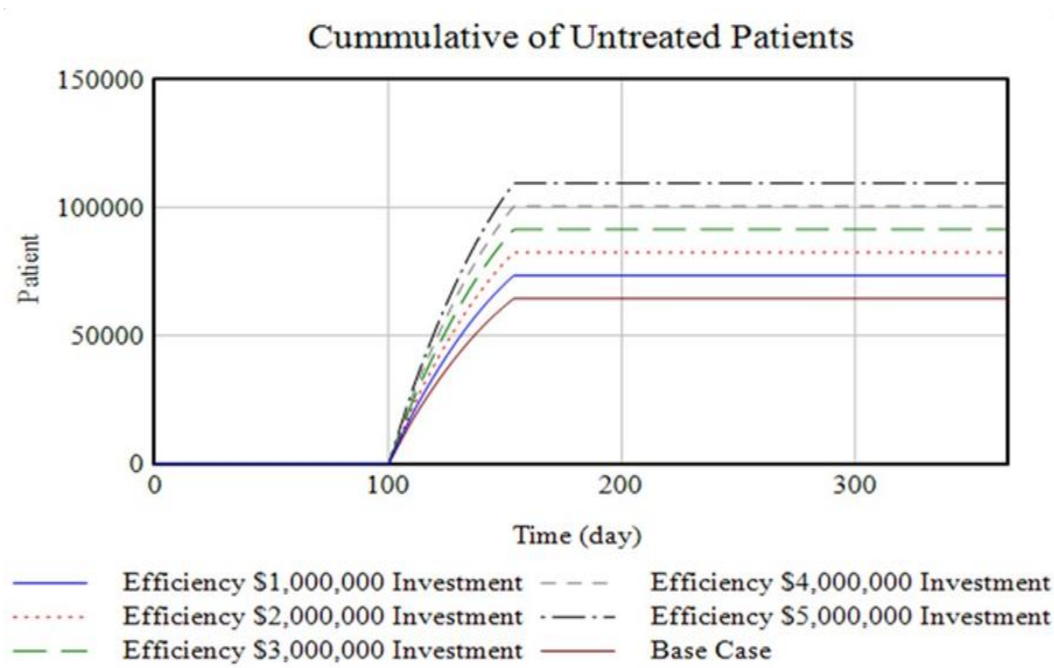

Figure 21: Cumulative of untreated Patients showing increasing performance

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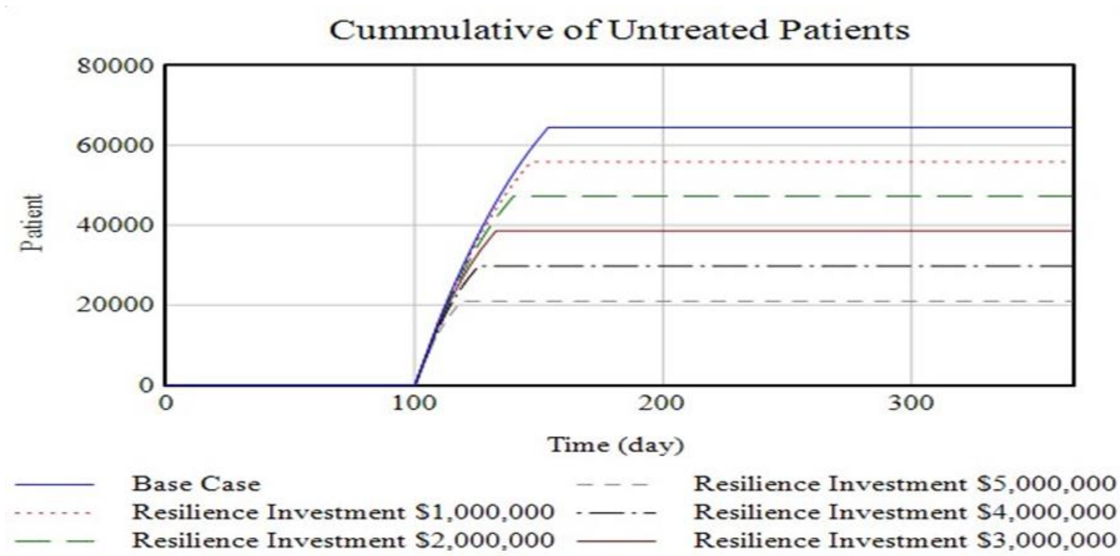

Figure 22: Cumulative of untreated patients showing reducing performance difference (improving resilience) as investments are made towards resilience.

Figs 24&25 show the cumulative losses due to the disaster. This is the product of cumulative of untreated patients and the treatment cost per patient without a disruption. It reflects the amount of money lost by the hospital due to the disruption. The losses start counting with the occurrence of a hazard and stop with the recovery of full treatment capacity. With investments in either resilience or efficiency, after the recovery of treatment capacity, the losses slightly adjust to a goal as the treatment cost per patient also adjusts, as seen in Figs 24&25. Investments in resilience lead to lower-cost losses as compared to the base case. In comparison, investments in efficiency lead to higher losses. When comparing the total operational cost to the hazard performance, the increase in investments leads to increases and reductions in the cost per patient treated after a hazard for resilience and efficiency investments, respectively, and therefore do not reflect the financial losses due to the disruption. The "cumulative losses due to disruption" serve as

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a useful metric of hospital efficiency when the disruption is considered. The graphs below support the claim by Essuman et al. (2020) that increased resilience leads to greater efficiency when the effects of disruption are considered (see background).

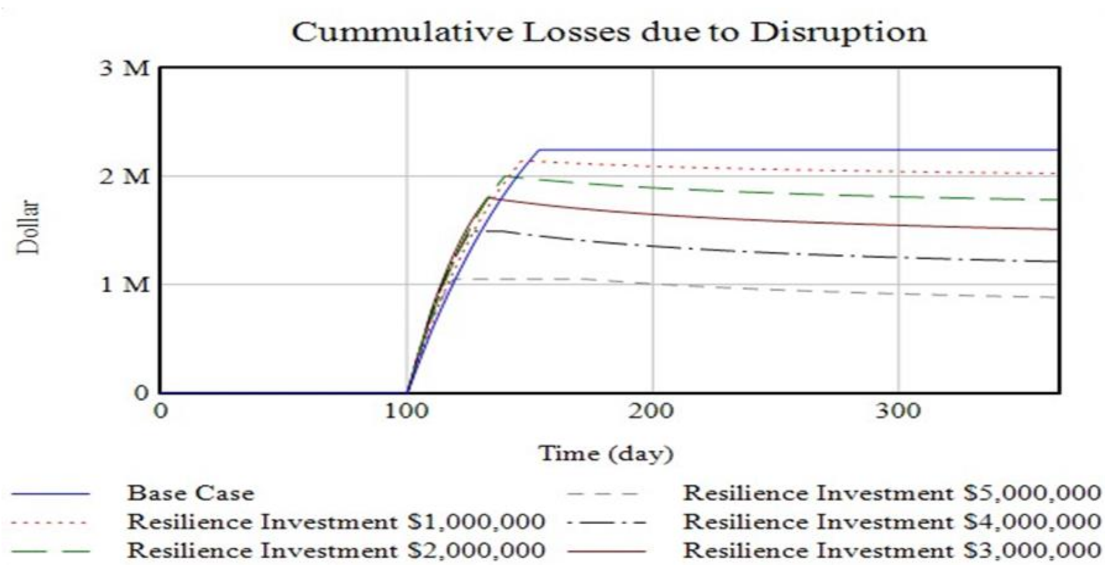

Figure 23: BOTG showing Cumulative losses due to disruption for investments in resilience

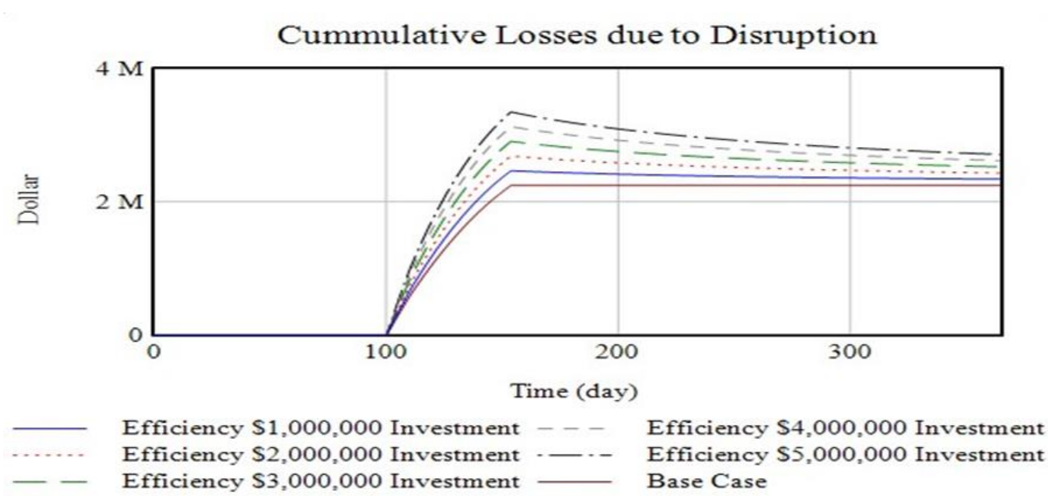

Figure 24:BOTG showing increasing Cumulative losses due to disruption for

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In Table 1 below, the final values of essential variables for the mutually-exclusive-funding simulations are given. These are the values of the variables at the end of the simulation period. Investments in efficiency lead to increases in total/non-hazard performance as the hospital's patient flow increases correspondingly with the medical staff's service capacity. However, these increases lead to a more significant number of patients left without treatment after a disruption, which measures hospital resilience. As investments are made toward efficiency, the treatment cost per patient reduces and is reflected in the increased efficiency ratio as expected with increased efficiency. Investments in resilience do not lead to improved non-hazard/total performance as they do not increase treatment capacity. However, the performance loss or cumulative performance difference reduces, and the resilience ratio increases as increments are made in the amount invested in resilience. Treatment cost per patient increases leading to a reduction in the efficiency ratio as investments toward resilience are made due to the static nature of the hospital's performance. A graph of cumulative performance difference plotted against treatment cost per patient is found in Appendix D

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Table 1: Table of final values of important variables (Mutually exclusive

	Total/No hazard Performance * 1000(Patients)	**Hazard Performance *1,000 (Patients)**	**Resilience as a ratio of the Base case Value**	**Operational Cost *1000 ($)**	**Efficiency as a Ratio of the Base case value**
Efficiency $1,000,000 Investment	788.90	738.781	0.59	29094.4	1.41
Efficiency $2,000,000 Investment	885.64	829.384	0.64	28094.4	1.34
Efficiency $3,000,000 Investment	982.38	919.987	0.71	27094.4	1.26
Efficiency $4,000,000 Investment	1,079.11	1010.59	0.78	26094.4	1.18
Efficiency $5,000,000 Investment	1,175.85	1101.19	0.89	25094.4	1.09
Base Case	692.17	648.178	1	24094.4	1.
Resilience $5,000,000 Investment	692.17	670.135	1.13	25094.4	0.96
Resilience $4,000,000 Investment	692.17	666.344	1.28	26094.4	0.93
Resilience $3,000,000 Investment	692.17	662.367	1.48	27094.4	0.91
Resilience $2,000,000 Investment	692.17	657.867	1.70	28094.4	0.88
Resilience $1,000,000 Investment	692.17	653.1	1.90	29094.4	0.84

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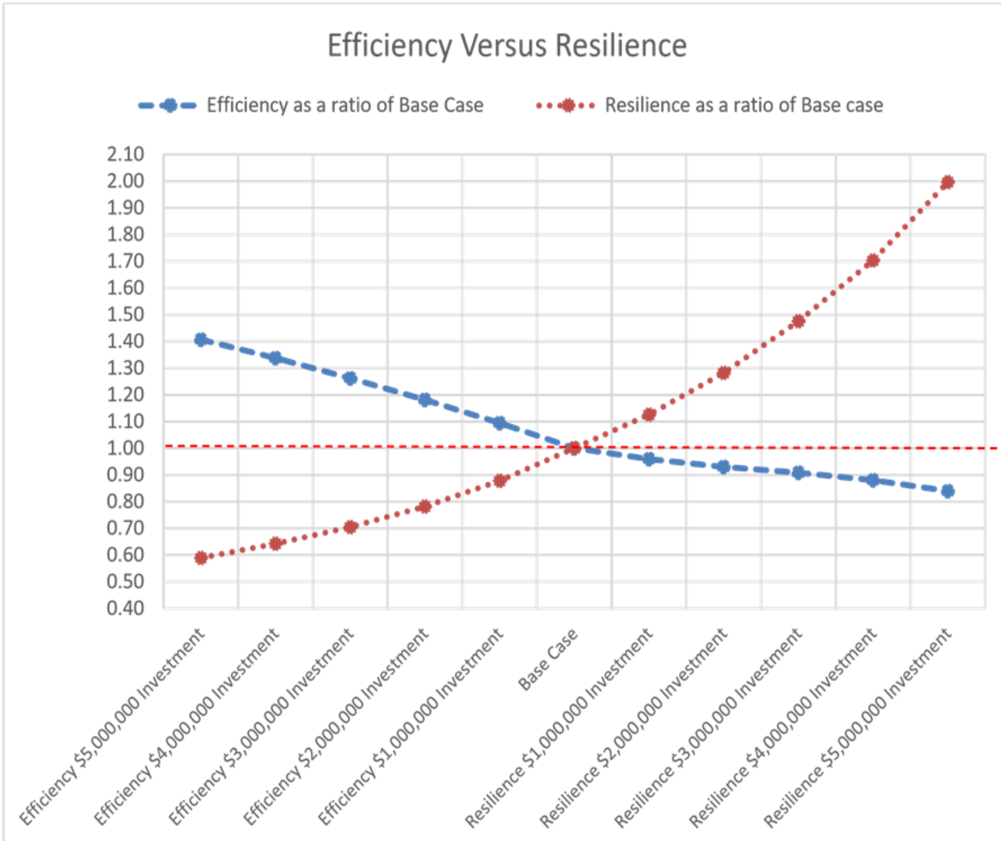

Figure 25: Graph of Efficiency VS Resilience as a ratio of their base case values

The graphs of efficiency and resilience as ratios of their base cases metrics are plotted in fig 26 above. With each investment towards efficiency, an increase in the efficiency ratio to the base case brings about a corresponding decrease in the resilience ratio. This behavior is also observed in the reverse as investments are made towards resilience. **Figure 26 demonstrates one aspect of the problem: the hospital owner faces a tradeoff between efficiency and resilience if forced to fund one or the other but not both.**

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Total investment with Split Allocation of Funds

These simulations represent a scenario where the owners invest the entire fund divided between efficiency and resilience in varying percentages. The model changes for different investment sums remain the same. In Fig 27, the Non-Hazard performance improves as the balance of investments shifts to efficiency. The base case value and the strategy with the highest investment in resilience share the same line. In Fig 28, average waiting time improves as the balance of investment shifts to resilience and worsens as the balance of investments shift to efficiency. However, due to the split nature of the investments, the average waiting time improves across all simulations compared to the base case. The only exception is the strategy with the total fund going to efficiency. In Fig 29, the patient discharge rates' initial values decrease as the balance of investments shift to resilience. Simultaneously, the recovery time to pre-disaster levels reduces as the balance of investments shifts to resilience. The Base case and the strategy with the total fund invested in resilience start at the same point but diverge after the disaster occurs with a lower loss and faster recovery for the resilience investment.

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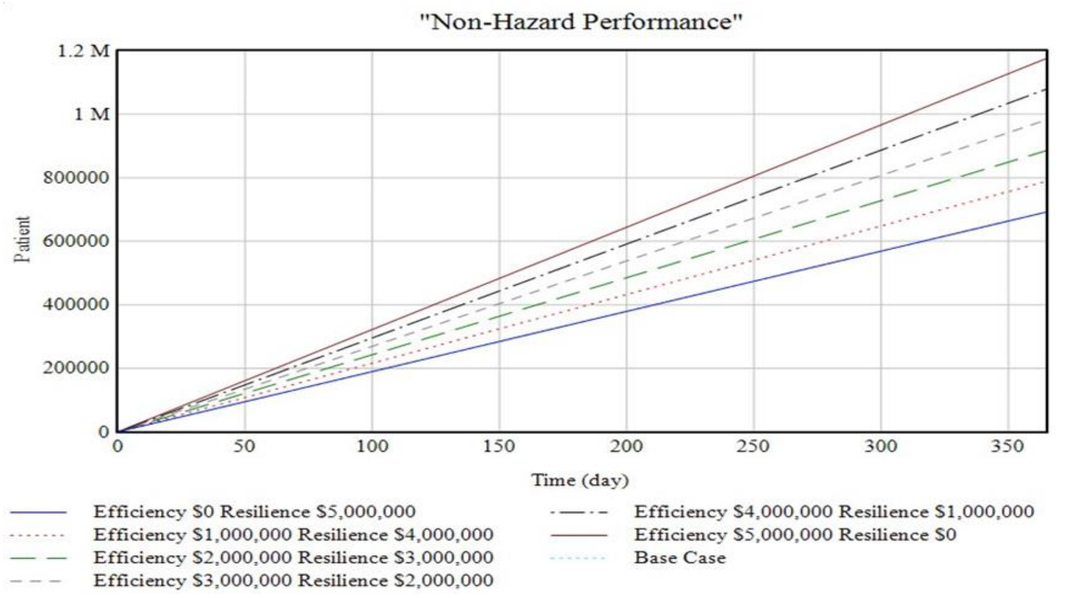

Figure 26: BOTG of Non-Hazard Performance for Split investments.

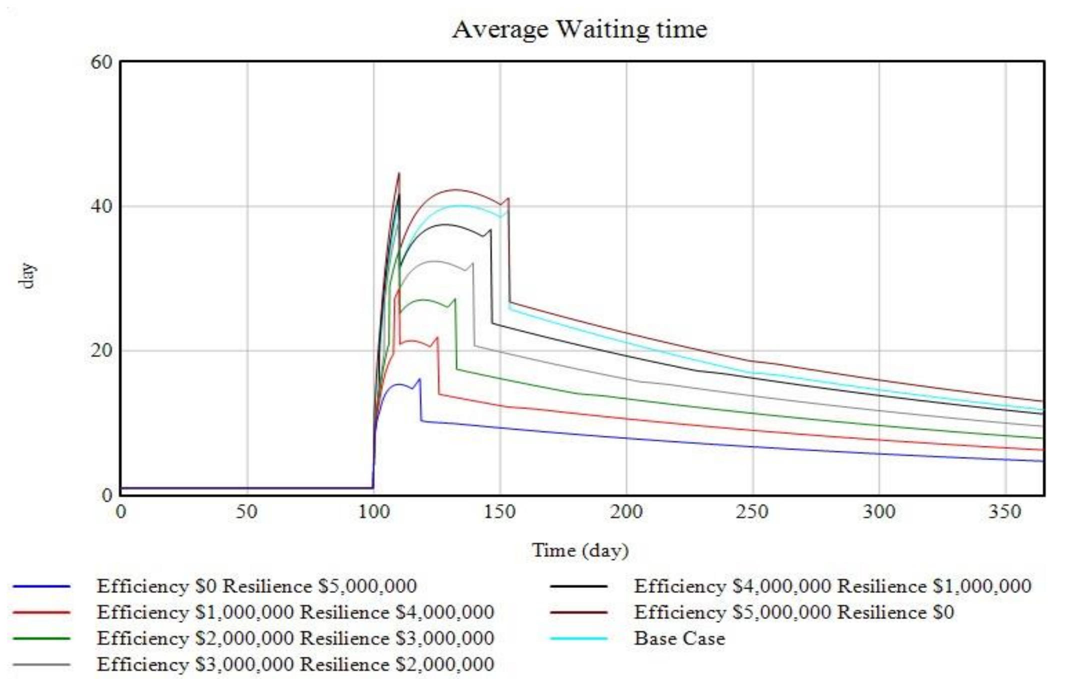

Figure 27: BOTG of Average Patient wait time for split investments.

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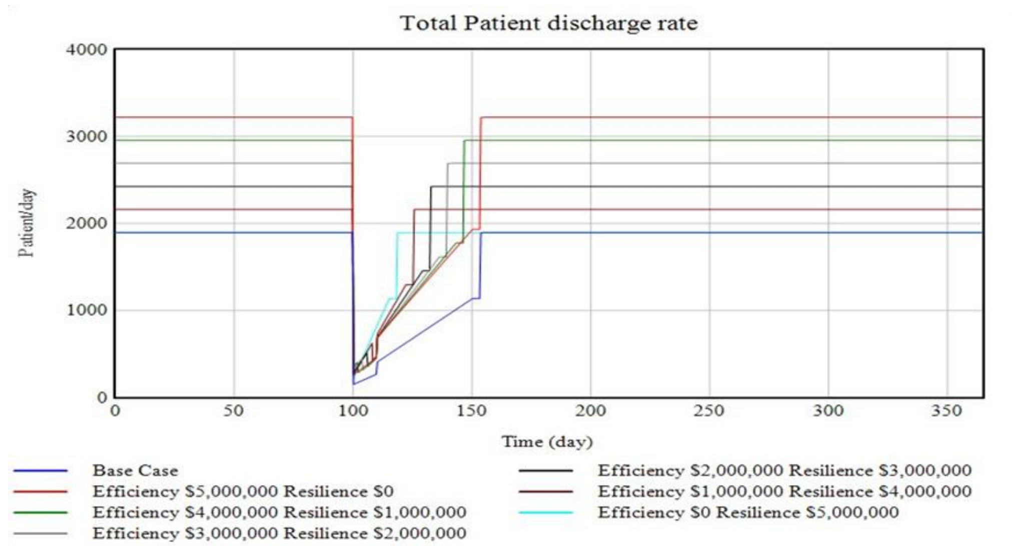

Figure 28: BOTG of Total Patient Discharge rate for split investments

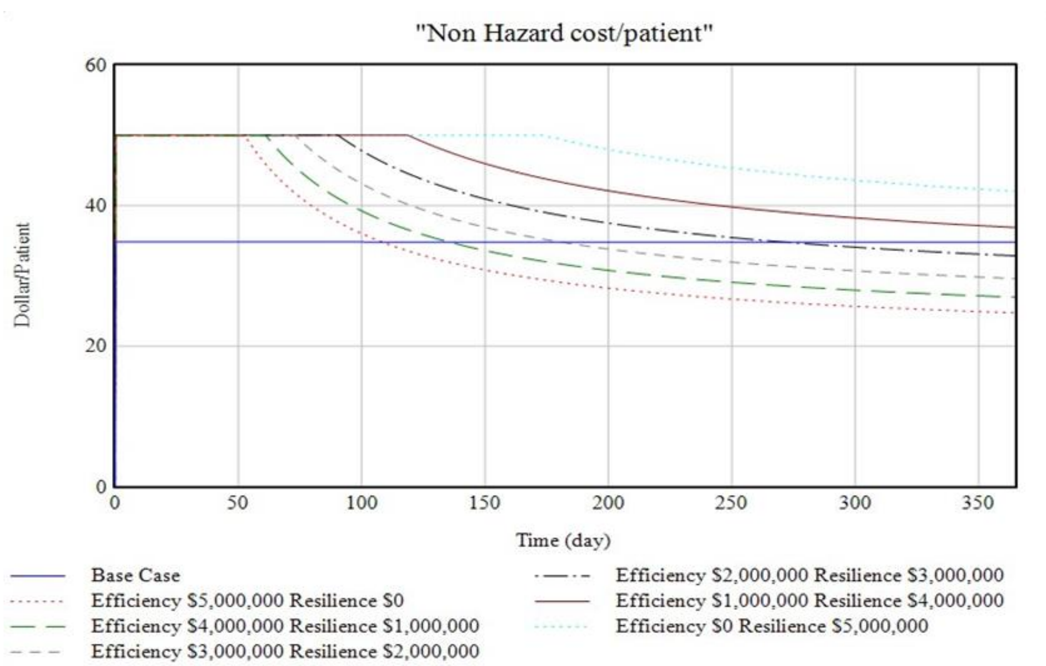

Figure 29: BOTG of treatment cost per patient for split investments.

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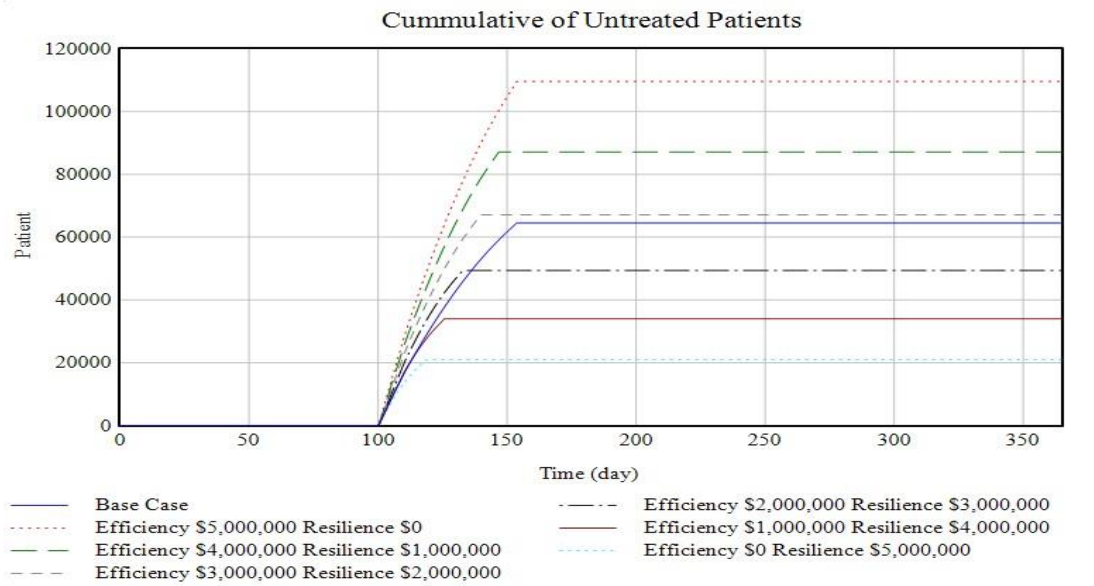

Figure 30: BOTG of Cumulative of untreated patients for split investments

In Fig 30 & 31 above, the behaviors for the treatment cost per patient and the cumulative performance difference are shown, respectively. As previously seen in the mutually exclusive investment strategies, the cumulative performance difference increases and decreases as investments are made towards efficiency and resilience, respectively. In this case, however, the strategy with three-fifths of the fund going to efficiency is very close to the base case. In Fig 30, also mimicking the behavior of the mutually exclusive investments, the treatment cost per patient increases and decreases as investments are made towards resilience and efficiency, respectively. Figs 30 & 31 show that by increasing resilience, a delicate balance can be struck by investing in both resilience and efficiency. Fig 32 below shows the behavior of the hospital patient backlog to a split investment. The backlog size increases as the amount invested in efficiency increases and drops when the balance tilts toward resilience. This behavior replicates that of the patient backlog in the

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simulations with mutually exclusive investments. Table 2 below shows the values of important model variables at the end of the simulation. As the percentage of the investment sum going towards efficiency increases, the total performance and cumulative performance difference increases, while the patient's treatment cost decreases. The reverse is the case as the balance of the investments moves towards resilience. *Fig 34* shows these variables' performance measured in resilience and efficiency as their base case ratio. Moving from right to left, the ratios of efficiency reduce, and resilience increases as investments in efficiency are reduced, favoring resilience. *The results of these different types of investment strategies show that greater benefit can be derived by investing in both resilience and efficiency than investing solely in resilience or efficiency. An investment ratio of 2:3 with the greater investment sum to resilience, as seen in Figure 34 and Table 4, increases total performance value while gaining resilience and efficiency*. A focus is then placed on investments of varied sums. Results of simulations with mutually exclusive invests are seen in Appendix D

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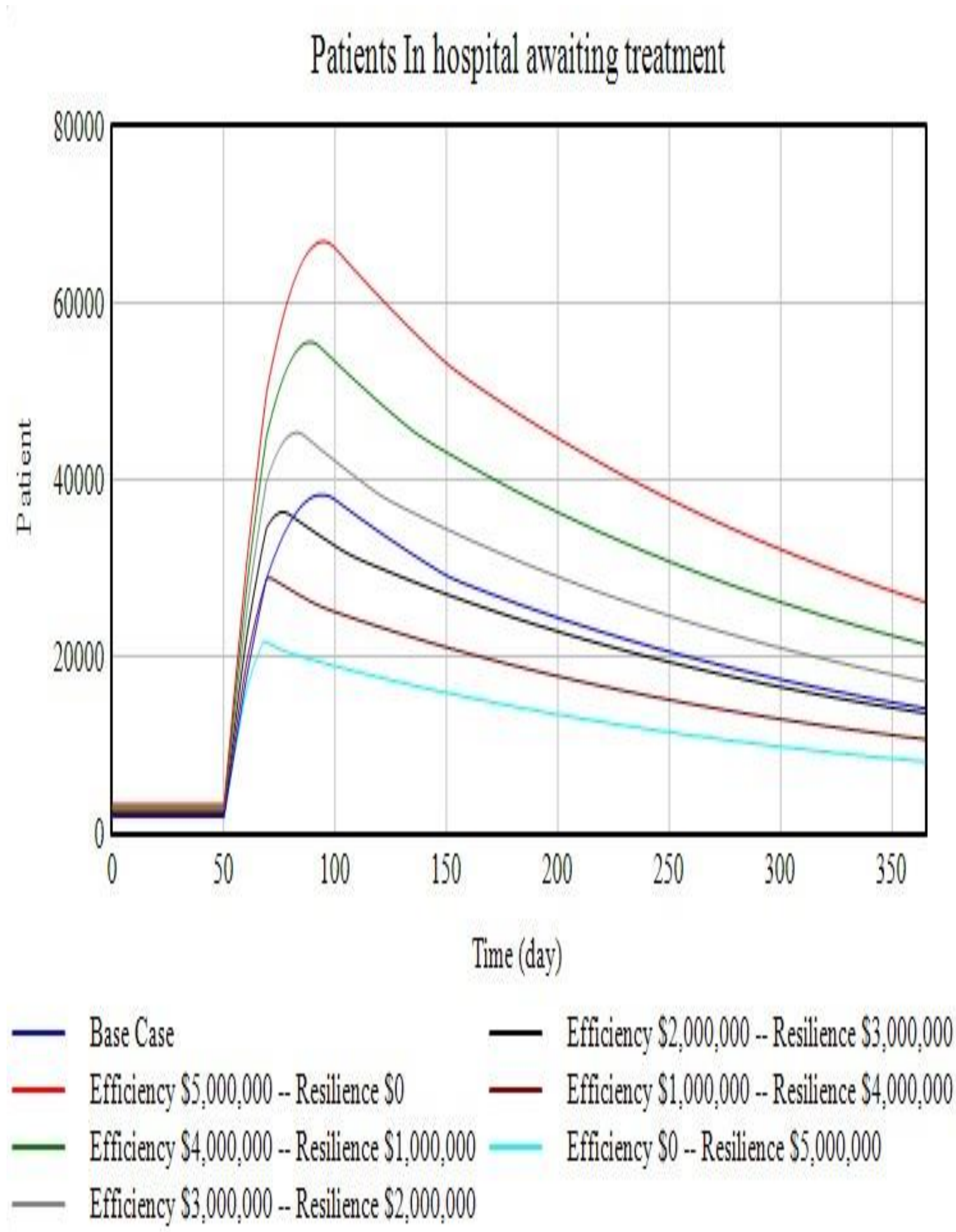

Figure 31: BOTG of Patient backlog for Varied investment sums in both Resilience and Efficiency

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Table 2: Table of final values for important model variables (Varied amounts of investments)

	Total/No hazard Performance * 1000 (Patient)	Hazard Performance * 1000 (Patients)	Resilience as a Ratio of the base case value	Operational Costs	Efficiency as a ratio of the Base case value
Base Case	692	648	1	24,094.40	1
Efficiency $5,000,000 Resilience $0	1,176	1101	0.59	29,094.40	1.41
Efficiency $4,000,000 Resilience$1,000,000	1,079	1018	0.72	29,094.40	1.29
Efficiency $3,000,000 Resilience$2,000,000	982	934	0.9	29,094.40	1.18
Effficiency$2,000,000 Resilience$3,000,000	886	848	1.16	29,094.40	1.06
Efficiency$1,000,000 Resilience$4,000,000	789	759	1.49	29,094.40	0.94
Efficiency$0 Resilience $5,000,000	692	670	1.99	29,094.40	0.83

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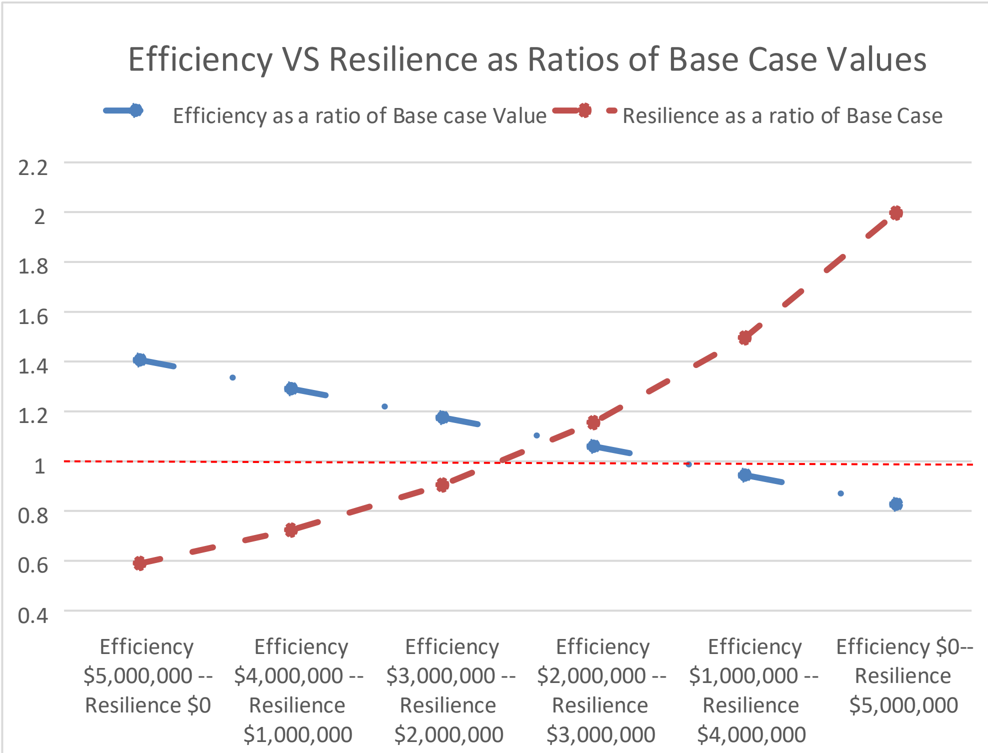

Figure 32:Graph of Resilience VS Efficiency as a Ratio of their Base Case Values

These simulation results support the problem description; investments made toward efficiency negatively impact an asset's resilience to disruptions, while investments made toward resilience affect a system's efficiency of operations. **Figure 33 demonstrates a second aspect of the problem: the hospital owner faces a trade-off between efficiency and resilience if allowed to allocate a total investment between efficiency and resilience.**

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Strategies To Improve the Trade-off

Dynamic Resource Allocation

As seen in Fig 32, the disruption causes the hospital departments to depart from equilibrium conditions and develop backlogs of patients awaiting treatment. The system, on its own, struggles to return to equilibrium despite the reduced recovery period due to resilience investments. The simulations above assume that resource levels remain static. To facilitate system return to equilibrium conditions, a dynamic resource allocation strategy is proposed. This strategy aims to reduce the backlogs' size by allocating the staff to different departments based on the size of the backlogs and medical staff's treatment capacity. The aim of this strategy is backlog reduction and equilibrium recovery. In practice, various hospital resources differ in the extent to which they can be dynamically allocated to specific needs. For example, custodial staff can change what part of the hospital they serve easily, and nurses and administrative staff have some flexibility in where they can serve. However, specialists such as emergency room doctors or single-use equipment cannot be reallocated to other uses. For this study, it is assumed that various hospital staff skills can be transferred across sections of the hospital with the exclusion of the facility management department. However, "full-service capacity," which is the number of patients each staff can treat per day, is static. Therefore, the medical staff's capacity to treat a patient depends on the type of ailment and not the staff's skill set. A dynamic resource allocation strategy such as this tracks the sectional backlogs and moves staff around different hospital sections as the backlogs increase and reduce. A new model section, "Dynamics of Resource allocation", is developed to implement this strategy, as

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shown in Appendix 2. The management calculates the number of staff required per section based on the number of patients awaiting treatment and the hospital section's treatment capacity. The total number of staff in the hospital and the sectional staff's ratio to the total required staff gives the number of staff to be allocated to a hospital section— the staff move in and out of the sections through a network of perception delays. The staff move across the various departments as the system continuously adapts to the differences between the actual number of staff in the section and the number of staff allocated. Although the resource allocation strategy is present throughout the simulation, its effects are observed when the patient backlog exceeds the hospital treatment capacity, given the average treatment time.

Simulation results

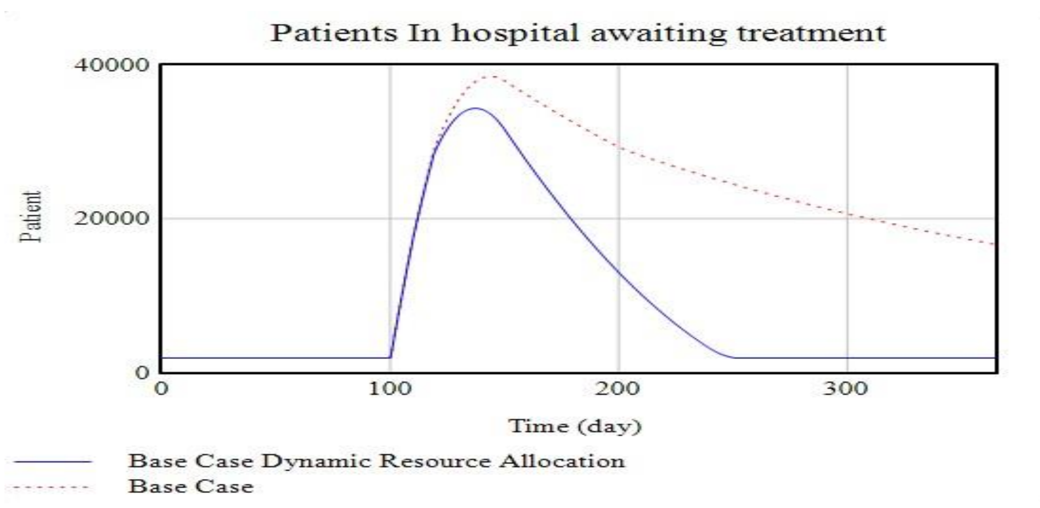

Figure 33: BOTG of Patient Backlogs for Simulations with and without Dynamic

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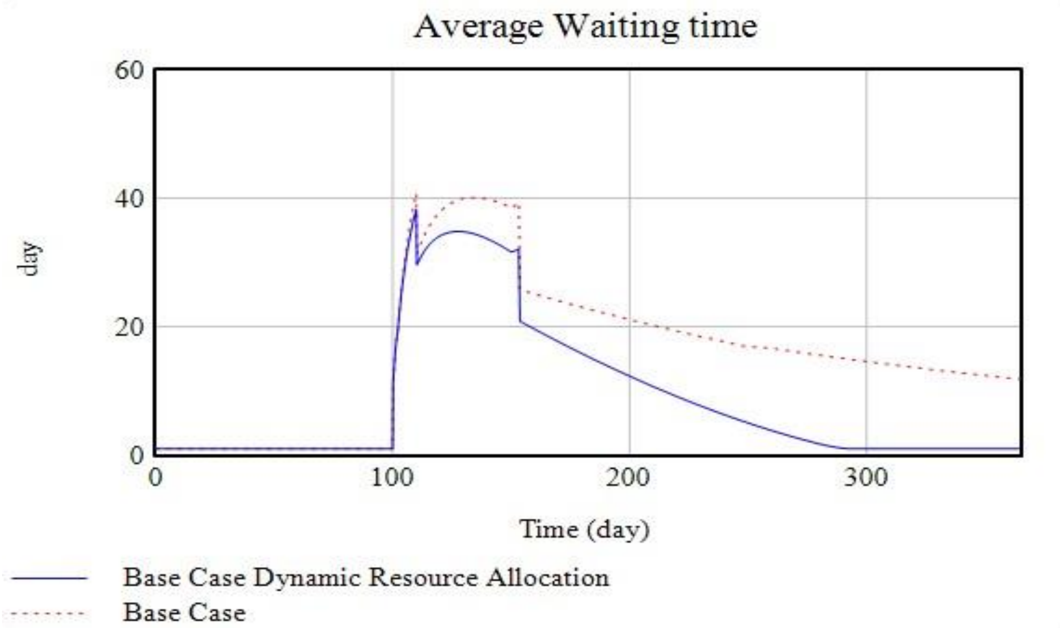

Figure 34: BOTG of Average waiting time for simulations with and without Dynamic Resource Allocation

Figure 34 & 35 above shows the patient backlogs' and the "Average waiting time" behavior when a dynamic resource allocation strategy is implemented. The backlogs' size increases and reduces as the investment sum tilts toward efficiency and resilience, respectively, as in the previous simulations. However, due to the executive actions taken regarding resource allocation, the system returns to equilibrium conditions, unlike the previous scenarios. The recovery speed increases as investments are made towards resilience and reduce as the fund invested towards resilience increases. The improved recovery speed and smaller backlog occur due to the transfer of medical staff from the severe injuries section to other parts of the hospital, as shown in Fig 36 below. After the disruption occurs and the patient backlog surpasses the hospital's treatment capacity, the management quickly moves to limit the backlog growth and transfer staff from the hospital

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section with minimum needs to others with more urgent needs. The staff are returned to their various departments as the system returns to equilibrium conditions.

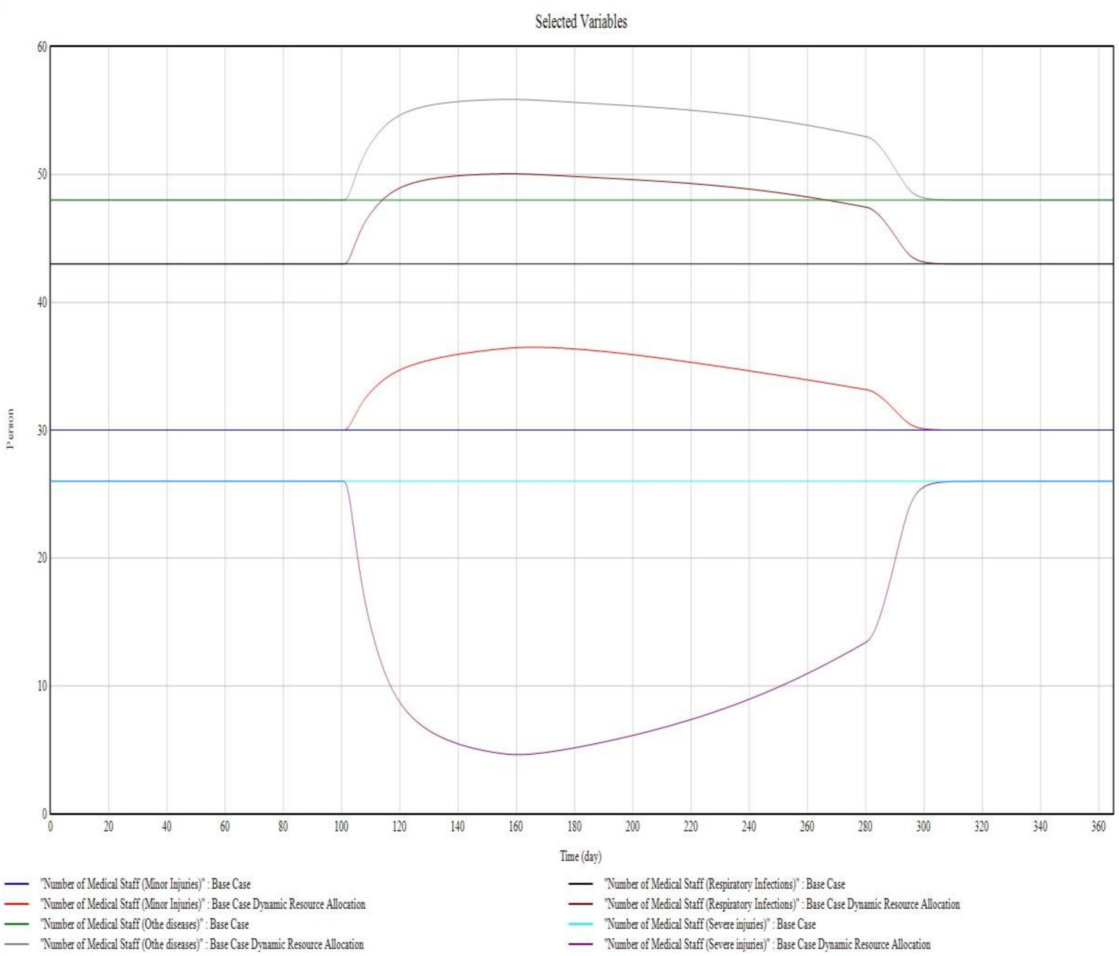

Figure 35 :BOTG of Staff numbers across various hospital sections (Dynamic Resource Allocation)

The impacts of dynamic resource allocation are also seen in the total discharge rate. The transfer of patients to other hospital sections pushes the treatment capacity past pre-disaster levels, as seen in Fig 37 below. This occurs due to the differences in the full-service capacity of medical staff across the hospital sections. For example, in the severe injuries section, one staff can treat four people per day, while in the minor injuries, one

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staff can attend to thirty patients per day. Moving staff to a department with a higher individual treatment capacity pushes increases the number of patients that the department can treat past pre-disaster levels. In the actual system, this represents a scenario where the hospital focuses on patients with easily treatable illnesses to increase the patient discharge rate.

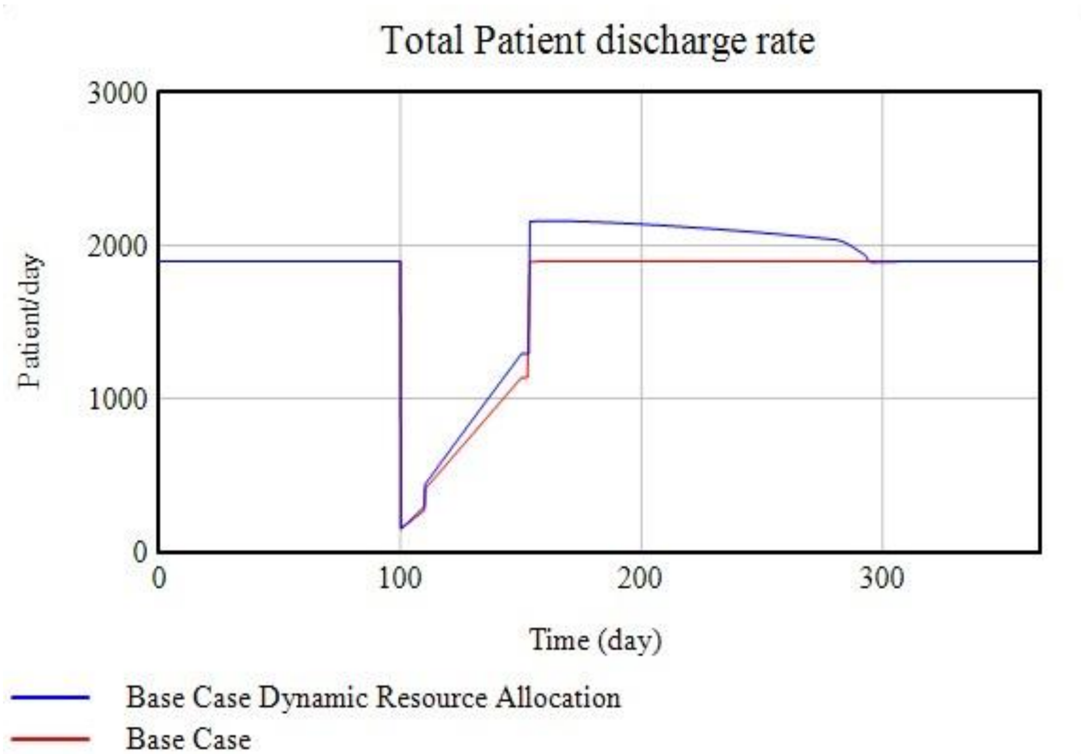

Figure 36: BOTG of Patient Discharge rate for Simulations With and Without Dynamic Resource Allocation

Table 3 shows the important model variable’s values at the end of the simulation for the scenarios where the management implements the resource allocation strategy after a disruption. As has been previously established, total performance increases when efficiency increases. The hazard performance improves with the resource allocation strategy as the management can better limit the backlog growth and reduce recovery time.

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Fig 38 below shows the values of resilience and efficiency as ratios of their base case values. The resilience loss with increasing efficiency diminishes with the resource allocation strategy, supporting this resilience improvement strategy. The results mirror the scenarios without the resource allocation strategy, showing that an investment in both resilience and efficiency gives greater benefit than investing solely in either. With the implementation of a dynamic resource allocation strategy, the owners can increase efficiency, increasing total performance and resilience. Fig 38 suggests that an investment ratio of 3:2 with the greater sum towards efficiency is the optimal investment ratio (highlighted), leading to increased resilience and efficiency.

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Table 3: Table of final values for important model variables in strategies with varied investment sums (Dynamic Resource Allocation)

	Total/No hazard Performance * 1000(Patients)	Hazard Performance *1000 (Patients)	Resilience as a Ratio of base Case values (DRA)	Operational Costs *1000 ($)	Efficiency as a Ratio of base case values
Base Case without DRA	692	648	1	24,094.40	1
Base Case (DRA)	692	673	1.00	24,094.40	1
Efficiency$5,000,000 Resilience $0 (DRA)	1,176	1150	0.75	29,094.40	1.41
Efficiency $4,000,00 Resilience$1,000,000 (DRA)	1,079	1058	0.92	29,094.40	1.29
Efficiency $3,000,00 Resilience$2,000,000 (DRA)	982	965	1.14	29,094.40	1.18
Effficiency$2,000,00 0 Resilience$3,000,000 (DRA)	886	872	1.42	29,094.40	1.06
Efficiency$1,000,00 Resilience$4,000,000 (DRA)	789	778	1.78	29,094.40	0.94
Efficiency$0 Resilience$5,000,000 (DRA)	692	683	2.26	29,094.40	0.83

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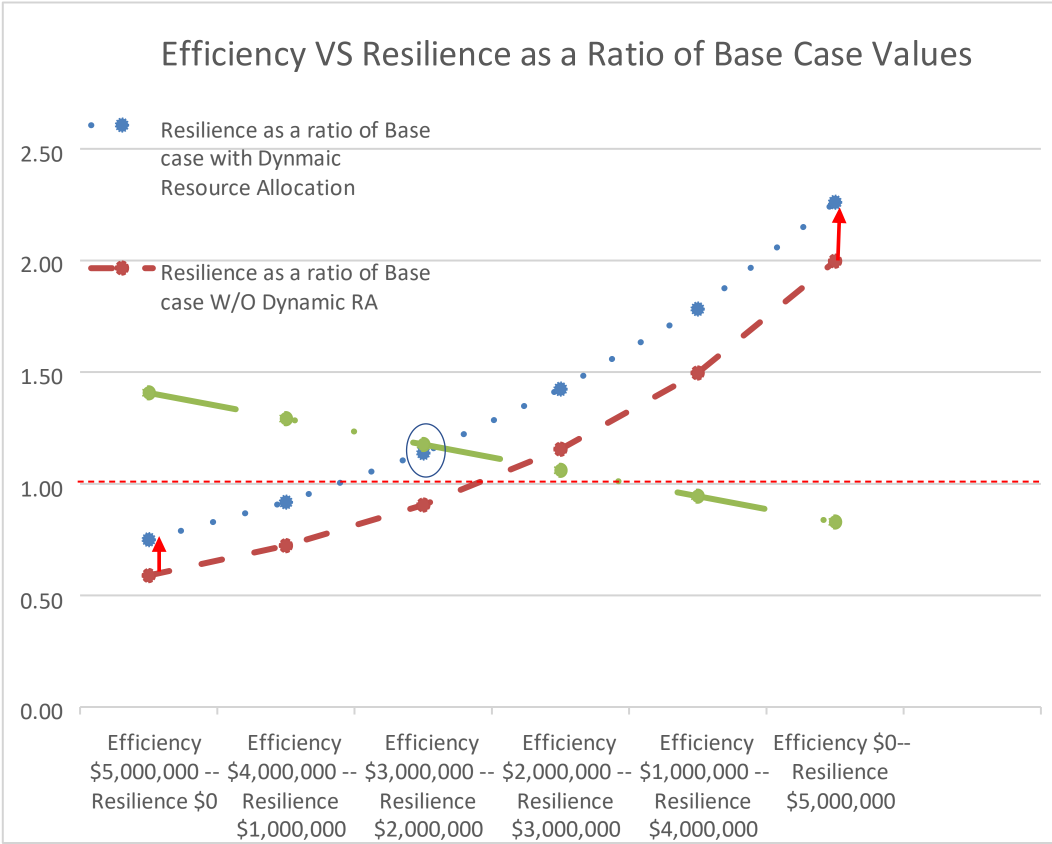

Figure 37: Graph of Efficiency VS Resilience as Ratios of the base case values (split Investment sums--- Dynamic resource Allocation)

As a sidebar, Fig 39 below shows the "Hospital's cumulative losses" values for investments with and without dynamic resource allocation. Compared with the base case values, dynamic resource allocation leads to greater hospital efficiency due to reduced losses after a disruption. The flexibility required to implement dynamic resource allocation is more likely to occur in hazard-induced circumstances which are extreme but temporary, such as non-expert professionals (doctors, nurses, etc.) supplementing experts in specific areas such as emergency rooms.

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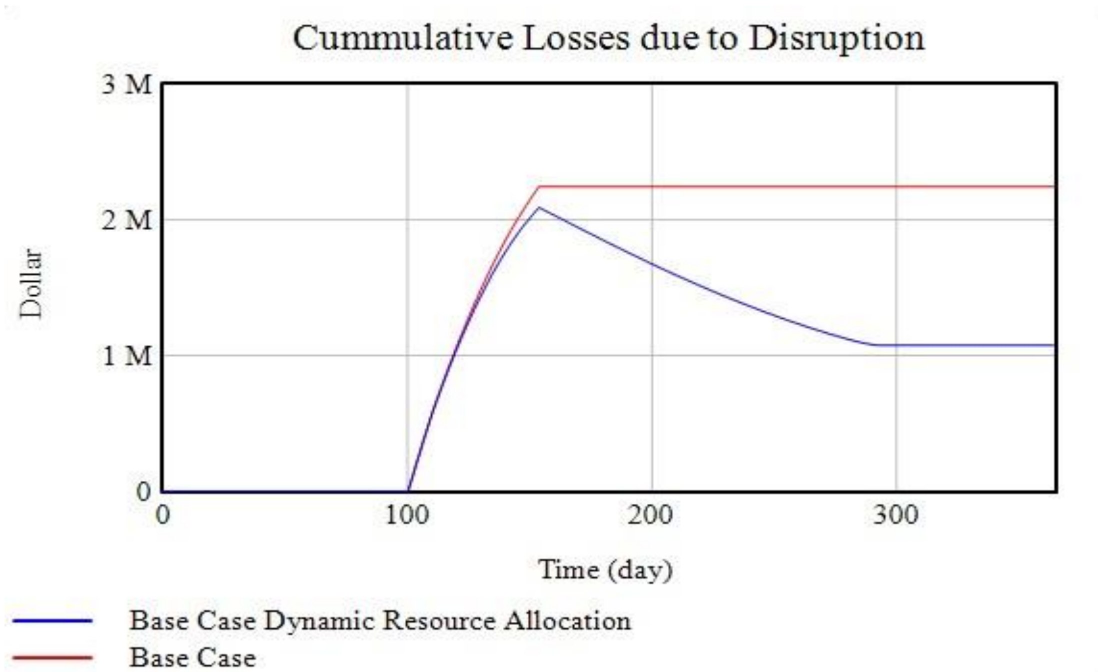

Figure 38: BOTG cumulative losses due to disruption of simulations with and without Dynamic Resource Allocation

Real options Inspired Resilience Improvement Strategy

An analysis of the model structure points to resilience improvement costs as the driver of efficiency losses. Investments in resilience lead to higher operating costs that do not translate into increased productivity, reducing the ratio of outputs to inputs. These investments only serve as a safeguard against disruptions that may or may not occur. As these investments are made at the beginning of the simulations, their benefits are lost if the disruption does not occur. A strategy that incorporates a delayed decision-making process, allowing the management to implement the previously mentioned strategies and investments at the time of the disruption, may limit the accompanying efficiency losses.

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Such delayed-decision strategies can take many forms. For example, the owner may decide to maintain a contract with a local construction company to provide workforce, equipment, and technology for reconstruction efforts after a disruption. To do this, they may incur a premium, as demand for construction capacity in the region may be higher after a disruption as other facilities try to rebuild. The contractor's reconstruction speed and productivity would determine the cost of the premium, mobilization, and final contract sum. This strategy allows the management to save on costs resulting from developing inhouse capacity, primarily if the disruption does not occur. It also allows the owner flexibility to invest in a better alternative resilience improvement strategy in the future, which may not have been possible if the entire resilience investment budget had was sunk in improving in-house capacity. As it is, the owner can choose between three alternatives to reduce the amount of time spent on reconstruction. The first option is investing in the development of in-house capacity and wait for a disaster to occur before reaping the benefit. If a disaster does not occur, the sum invested is lost. The second option is the previously described where the owner enters into a contract regarding reconstruction efforts. This strategy allows the management to save on costs resulting from developing in-house capacity. If the disaster does not occur, the owner can keep the rest of the investment sum. Finally, the owner may forgo any of the above options and wait until a disaster occurs and rebuild with inhouse capacity, albeit slower or employing a contractor at inflated market prices. The second option gives the owner the benefit of increased resilience due to a shorter recovery period and limited investment loss if the disaster does not occur. It also allows the owner flexibility to invest in a better alternative resilience

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improvement strategy in the future, which may not have been possible if the entire resilience investment budget was sunk in improving in-house capacity.

To summarize the strategy structured above, the owners enter into a contract with a local contractor for reconstruction after a disaster. The contract stipulates the schedule for reconstruction. Here we assume that the contractor will always complete the workload on the stipulated time. The contract sum increases as the reconstruction period stipulated in the contract decreases, reflecting increasing resilience investments. After a disaster, a surge in demand for construction services in the hospital service region is expected. To guarantee the services of the contractor, the Hospital pays a premium. Adding to the premium cost are regular drills and training sessions for the facility management team and contractor to ensure cohesion between the two teams during reconstruction efforts. The premium is a quarter of the total investment sum. It is non-refundable and paid at the beginning. If the disaster occurs, the owners must pay the remaining of the total investment sum as fees to the contractor. If the disaster does not occur, the owners only pay the premium.

A tool proposed by Ford & Garvin (2012) facilitates the structuring of management strategies as options. This tool allows managers to articulately describe and structure management problems and their proposed solutions as real options. In tabular form, variables that define an option are listed on the left, while their counterparts in the

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system are listed accordingly on the left. The management strategy to address the uncertainty regarding the disruption is framed in Table 4 below

Table 4: Table of Resilience Improvement Strategy Framed as a Real Option

Uncertain Performance Measure	Loss of treatment capacity
Driver of Performance Uncertainty	Possibility of a Disruption
Reference Strategy	Maintain facility management capacity at normal/base case levels. Pay market price for the restoration of services in case of hazard
Alternative Strategy	Employ contractor for added capacity during building rehabilitation and repair at less than market prices in case of hazard
Signal for Changing Strategy	Occurrence of a disruption
Conditions for Strategy Change	Loss of building functionality
Actions required to obtain or retain flexibility	Enter an agreement with a contractor regarding repair efforts, conduct training between contractor and facility staff
Action Required to Change Strategy	Mobilize Contractor
Decision Rule for Changing Strategy	IF (Building loses functionality due to disruption) THEN (Mobilize Contractor) ELSE (Continue Operations with the in-house team)

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Two new variables were created for this set of simulations: “Resilience Fraction” and “Premium fraction”. The premium fraction is the fraction of the investment budget going to resilience, paid to the contractor as a retainer. It was assumed to be 0.25 for all simulations. The Resilience fraction is the fraction of the investment fund allocated to resilience improvement. The initial value of the “Total operational costs” was given as: The table below summarizes the expected cost implications for the different approaches to resilience improvement.

Table 5: Table of Resilience Improvement Options

Strategy	**Non-Hazard cost**	**Hazard Cost**	**Losses due to Hazard**
Invest in in-house capacity	$5,000,000	$0	$0
Employ and Retain Contractor	$1,250,000	$0	$0
Wait for Hazard	$0	$7,500,000	$2,500,000

Simulation results

The implementation of resilience improvement strategies structured as real options led to improved performance for system efficiency. Non-hazard operational costs reduce with increasing resilience, leading to increased efficiency relative to previous scenarios for strategies where most of the investment fund went to resilience. The reduction of operational costs in the absence of a hazard is due to the nature of the resilience investment

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strategy, where only a premium (fraction of the resilience investment budget) is paid in the absence of a hazard. Although the system resilience ratios do not change relative to the initial simulations, the strategy led to increased efficiency for the percentage of investment sum that went to resilience and increased cost savings. At the optimal investment ratio- the ratio that gives the best values of resilience, efficiency, and total performance combined, the efficiency ratio is increased to 1.15, as shown in Table 6 & Fig 40. The highest value of resilience without a loss in efficiency was 1.4 compared to 1.14 in the original simulations. These results suggest that strategies structures as real options are useful in increasing system resilience without losing efficiency and mitigating the impacts of uncertainty regarding the occurrence of a disaster.

Table 6: Table of final Values for important model Variables (ROA Inspired strategy)

	Total/No hazard Performance *1000(Patients)	**Hazard Performance *1,000 (Patients)**	**Cumulative Performance difference (Patients)**	**Resilience as a ratio of the base case value**	**Efficiency as a ratio of the base case value**
Efficiency$5,000,000 Resilience $0	1,176	1,101	74654	0.75	1.41
Efficiency$4,000,000 Resilience$1,000,000	1,079	1,018	60851	0.92	1.33
Efficiency$3,000,000 Resilience$2,000,000	982	934	48640	1.14	1.24
Efficiency$2,000,000 Resilience$3,000,000	886	848	38101	1.42	1.15

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Efficiency$1,000,000 Resilience$4,000,000	789	759	29416	1.78	1.05
Efficiency$0 Resilience$5,000,000	692	648	43990	2.26	0.95

Table 7: Continued

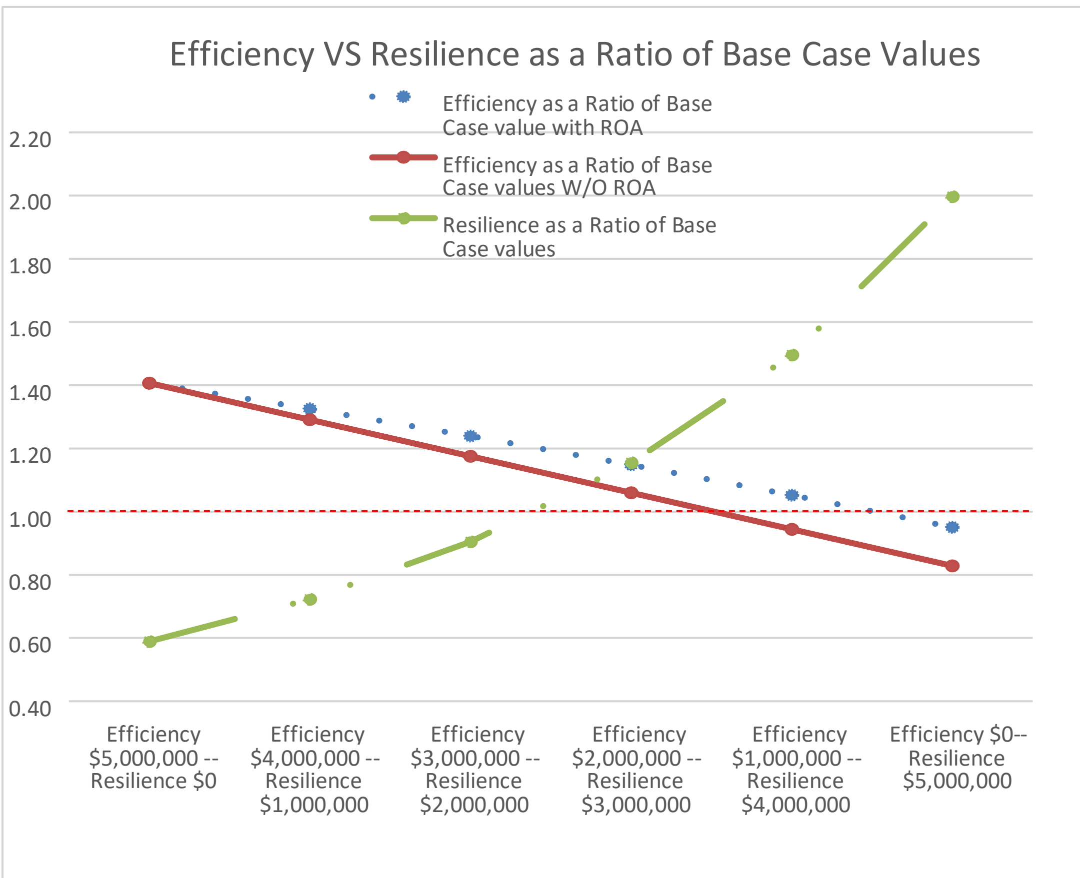

Figure 39: Graph of resilience VS Efficiency for Real Options Inspired strategy

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Analysis

In this work, the modeler does not seek to provide the best investment strategy or readymade solutions to the trade-off problems as defined in the problem description. Instead, this work can provide a model for designing and structuring innovative managerial strategies to address the problem. Incorporating managerial tools such as system dynamics to analyze managerial strategies, including real options and dynamic resource allocation, achieves this. The problem behavior, as described, is shown in the initial simulations. These first sets of simulations suggest a greater benefit for simultaneous investments in resilience and efficiency than mutually exclusive investments. These results can prove useful to the practicing manager as it shows how a focus on the improvement of only one metric can negatively affect the other. Investing solely in efficiency or resilience leads to a loss in the other that deepens as the investment increases. With an investment in both, an equilibrium is possible. Subsequent strategies to improve system performance focus on investment in both.

With the implementation of a dynamic resource allocation strategy, system resilience improves considerably. The optimal investment ratio, defined as the ratio with the highest values of total performance, resilience, and efficiency are attained- gives a greater performance metric for the previously listed metrics. The modeled system performance on implementation of this can be particularly useful in its real-life counterpart as it shows that in the absence of an investment, a managerial strategy like dynamic resource allocation that takes into consideration the evolving dynamics of the system such as

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changes and differences in patient backlogs and treatment capacity can improve system resilience. In the absence of finances for investments in immobile facilities and resources, such strategies can improve system resilience. However, this approach has complications that can lead to limitations in its implementation in the real system. Before the disaster occurs, the different hospital sections already function at maximum capacity, leading to a proportional increase in backlog sizes after the disruption. Removing resources from the department with the lowest capacity needs favoring those with higher leads to poorer performance in that section. As staff is allocated from other departments from the severe injuries section, the backlog increases and takes a longer time to return to equilibrium. This, in turn, leads to increased death rates in that section as patients spend a more extended period awaiting treatment due to a lack of medical staff, as seen in fig 42. Overall, the total system deaths are lower than previous scenarios see Fig 41, given that the increased deaths in that section are compensated for by reduced the reduced death rate in other sections. However, this could pose a moral dilemma for the real system owners as they are forced to choose who should live and die. Scenarios such as this could dampen the enthusiasm for the implementation of this strategy as is. This calls for further investigation and refinement of the dynamic resource allocation strategy to mitigate the identified policy resistance.

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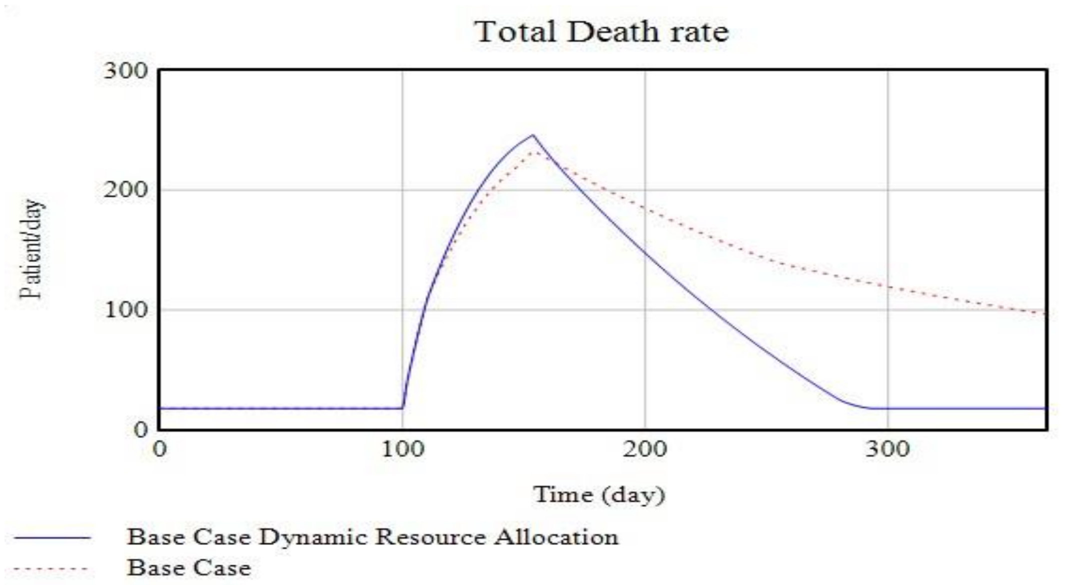

Figure 40: BOTG of total death rates for scenarios with and without Dynamic Resource Allocation

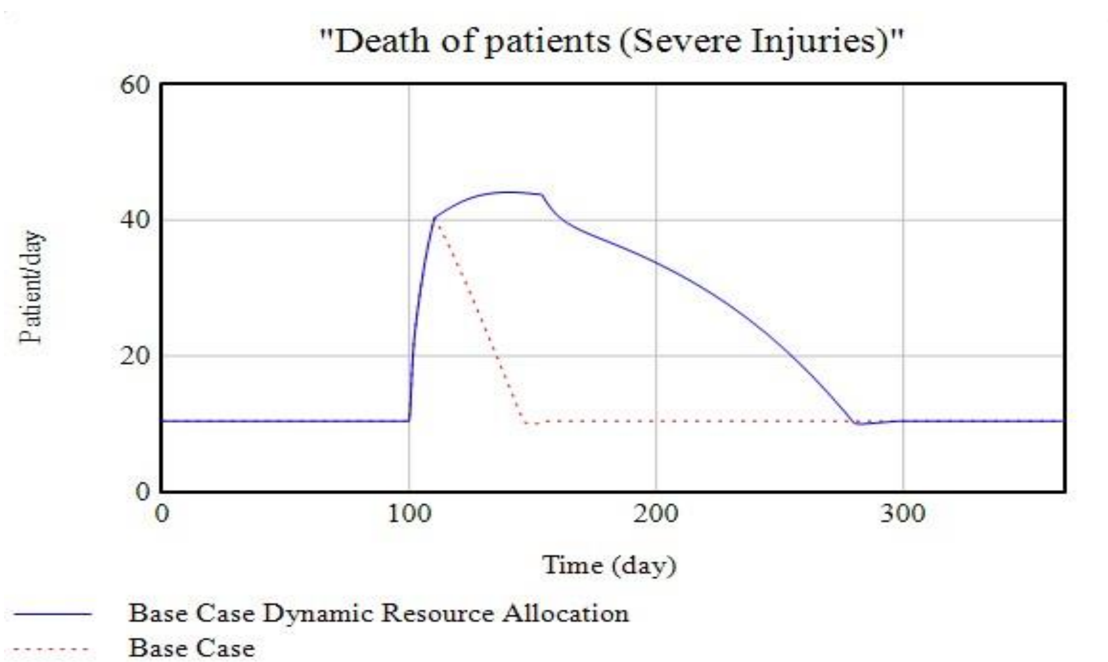

Figure 41: BOTG of Death rates for Patients With severe injuries in simulations with and without Dynamic Resource Allocation.

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Structuring resilience improvement strategies using a real options approach can lead to lower efficiency losses as the investments in resilience improves. This strategy allows the owners to improve system resilience, limiting the efficiency losses that occur if the investments toward resilience are made that may later prove unnecessary. This is observed as the owners only have to pay a premium to retain the added resilience while reducing total operational costs if a disaster does not occur. This investment strategy's delayed nature also provides the owners with the flexibility to change to more effective resilience improvement strategies in the future, especially as newer technology is developed. It addresses the uncertainty of the occurrence of the feared disruptions as the occurrence and severity of these disasters cannot always be adequately estimated and predicted. The drawbacks of adopting real options-inspired strategies include the premiums' pricing to retain the option. Estimating the most efficient premium cost calls for applying valuation models that may further complicate the design of the practicing manager's strategy.

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Discussion

The initial simulation results indicate that investing in both resilience and efficiency can improve overall system performance compared to mutually exclusive ones. These results underlined the trade-off between resilience and efficiency that should be considered in designing policies to improve either in the actual system. From subsequent simulations, these initial results were improved upon by implementing innovative managerial strategies. Total performance increased by a hundred thousand patients, an 11% increase from the base case, while efficiency increased by six percentage points while implementing a dynamic resource allocation strategy, as shown in Table 7 & Fig 43 below. Incorporating a strategy that allows managerial flexibility in resilience investment reduces total operating costs in the absence of a disaster, reducing efficiency losses while retaining improved resilience. A combination of dynamic resource allocation and flexible resilience investment strategy gives the most significant benefit for total performance and efficiency while also retaining increased resilience. These results suggest that practicing managers should incorporate multiple managerial strategies and approaches in resilience and efficiency improvement efforts for optimal performance and trade-off mitigation in critical infrastructure. This work identified potential roadblocks to implementing such managerial strategies, such as the complexity of valuation with managerial flexibility and the moral dilemma accompanying performance measurement based solely on numbers. In designing such strategies, the author proposes that the owners initially develop a profound understanding of the system to better understand the implications of such strategies'

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implementations. Social implications and complexities arising from their design and implementation also require consideration.

Table 8: Table of optimal performance values for different strategies

Strategy	Total System Performance (Patients) * 1000	Resilience as a Ratio of Base case values	Efficiency as a Ratio of Base case values	Total operational Costs	Investment Allocations as a percentage of total investment fund
Investments in both Resilience and Efficiency	886	1.15	1.06	$29,094	Efficiency 40%- Resilience 60%
Dynamic Resource Allocation	982	1.14	1.18	$29,094	Efficiency 60%- Resilience 40%
Real Options Strategy	886	1.15	1.15	$26,844	Efficiency 40%- Resilience 60%
Dynamic Resource Allocation and Real Options	982	1.14	1.25	$27,594	Efficiency 60%- Resilience 40%

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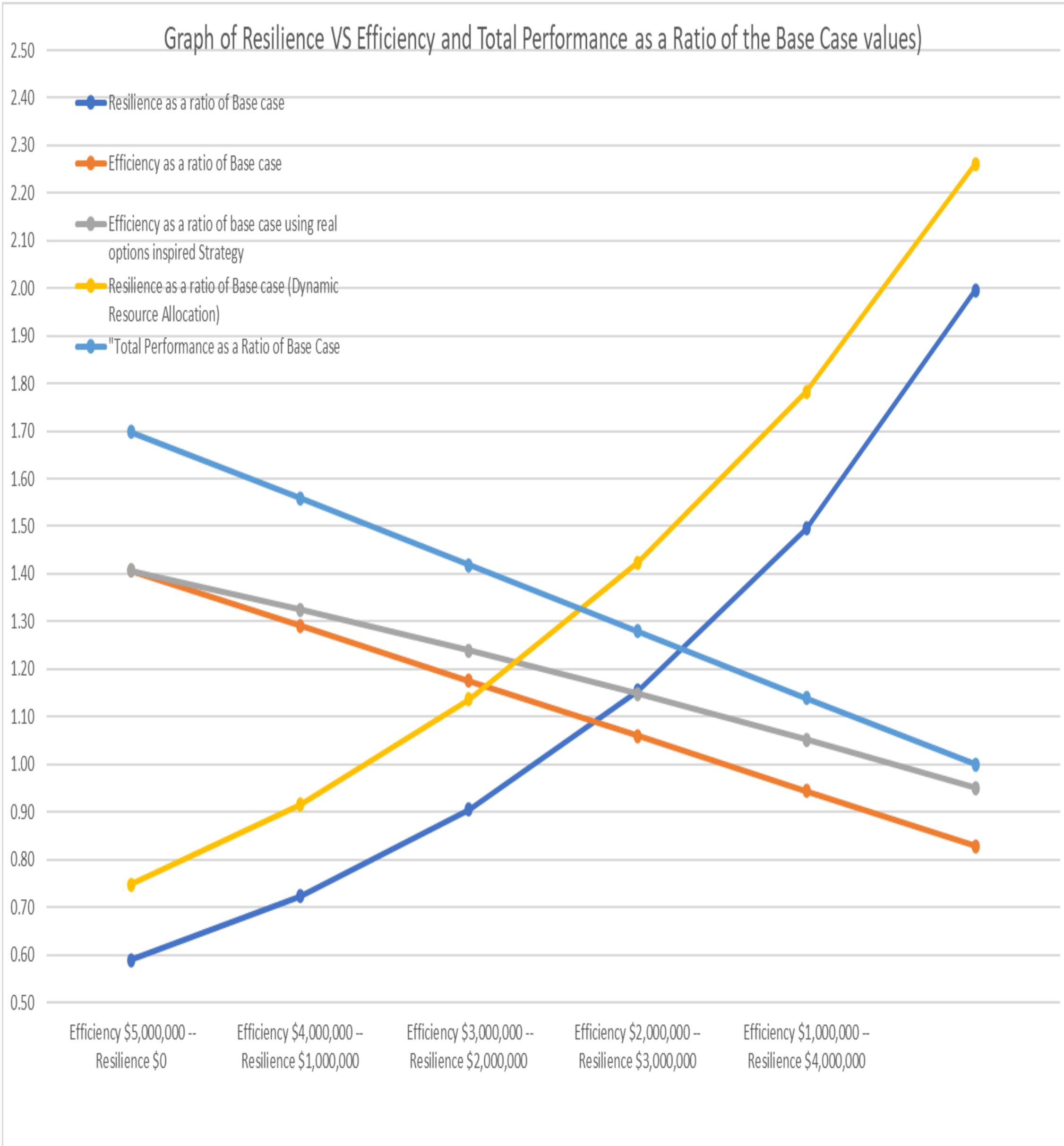

Figure 42:Graph of Efficiency VS Resilience and Total Performance for all strategies

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The investigation of the efficiency resilience tradeoff in other systems and industries would require a model with variables that reflect peculiar system characteristics. This sort of research entails establishing performance metrics that reflect the services that the system is designed to provide; for example, a power production plant would measure performance in mega or gigawatt-hours while an education system could measure performance in graduation rates or test scores of students. Some approaches, such as the performance-based measurement of resilience used in this work, could be applied in other systems. However, depending on the structure and level of aggregation of the modeled system and the depth of the modeler's system understanding, approaches such as DEA can be applied to set up an efficiency frontier. The use of single variables for input and output metrics for efficiency estimation eliminated the need for a data envelope analysis in this work. The static nature of non-hazard performance drivers such as fractional death rates and patient arrival rates leads to a positive correlation between the non-hazard performance and potential output metrics, including total deaths and average treatment delay. The disaggregation of the fractional death rate and patient inflow from constants to dynamic auxiliaries could lead to less correlation between the previously mentioned variables and promote the need for an efficiency frontier for improved efficiency estimation. The use of an efficiency frontier can also be applied to other critical infrastructure systems. For example, in a city metro system with multiple inputs such as the number of trains, operators- and outputs such as the number of passengers ferried, average waiting times, and revenue.

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Although this study's results recommend a focus on both resilience and efficiency, investment decisions can be skewed in favor of one depending on factors like the type of service the infrastructure system provides and the importance of the system in its service region. For example, a hospital's owners may prioritize resilience to ensure continuous service after a disaster and cater for an expected increase in population injury rates due to the disaster. On the other hand, a power generating plant that provides irregular but much needed power supply in a developing region may prioritize efficiency as the impacts as other dependent infrastructure systems may already have a backup power generation capacity to mitigate the irregularities in supply. In such situations, however, the extra costs of resilience improvements may be overlooked as the consumers of these services may be willing to pay extra for the added resilience to eliminate the backup systems' costs.

The approaches to designing investment strategies for efficiency and resilience performance improvement used in this work can be applied across other types of systems with a few modifications. Resilience improvement in most systems requires an investment in diversity and redundancy, while efficiency improvements require investments in slack reduction to reduce operational costs and improve productivity. Strategies such as dynamic resource allocation can also be applied to mitigate performance losses due to hazards. However, the rationale behind the resource allocation strategies may not always be based on need or backlogs but rather the importance of the different sections that require the service provided. For example, during the 2021 extreme weather conditions that led to losses in power production across Texas, facilities that provided emergency

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services such as hospitals and police stations were prioritized for power supply. Strategies that promote managerial flexibility for managing uncertainties like real options can also be applied across different systems to mitigate the efficiency losses due to resilience investments.

CHAPTER VI

CONCLUSIONS

Summary

The role of critical infrastructure in our daily lives cannot be understated, as implied in the word "Critical". Failure of these systems and assets due to disasters can lead to severe consequences felt long after the disaster. This underlines the need to make them more resilient to such disasters. These assets are expensive to run and faced with limited resources; planners frequently have to devise means of increasing output with ever reducing resources. Further complicating investment decisions in any of both is the apparent trade-off between them. This work seeks to understand this problem better and provide insight for approaches to reducing the trade-off, improving both resilience and efficiency without negatively affecting the other. A public health asset system model was used to recreate the problem and identify strategies to address it.

Initial model simulations of strategies where mutually exclusive investments were made in either resilience or efficiency and split allocation of funds where investments were made to both. These simulations supported the problem description and indicated that both held greater benefits than mutually exclusive investments. Innovative managerial strategies that incorporated efficient resource allocation and managerial flexibility were designed and implemented in the modeled system. These strategies were successful to varying degrees in improving one metric's performance without adversely affecting the other.

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When combined, implementing these strategies improved overall system performance and reduced the impact of the trade-off.

The results of this study provide insights and lessons for the practitioner. A sound understanding of the system structure is required as a prelude to strategy design for tradeoff improvement. Understanding the system structure leads to identifying the primary drivers of system performance and high leverage points and designing effective strategies. This understanding can be gained firsthand by the practitioner's own experiences and the elicitation of expert knowledge. Considering that this trade-off is always present in the system, strategy design should improve both resilience and efficiency against a focus in one. The practitioner is encouraged to develop a set of metrics to compare the concepts under investigation. These metrics should be tailored to the particular system under investigation to enable useful comparison. The application of system dynamics or other modeling approaches is encouraged to correctly identify possible policy resistance, as discovered in the increased death rates for the "Severe injuries" section. The combination of different managerial approaches in strategy design and implementation is encouraged for optimal results. These strategies should be flexible to improve the owner's management of the surrounding uncertainty.

This work provides a useful model for the investigation and improvement of the trade-off between efficiency and resilience. It provides a framework for strategy design based on the identification of primary performance drivers. The utility and effectiveness of a

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performance-based metric for research in critical infrastructure performance are shown. The performance-based metric developed and used in this work is useful and adaptable for future investigations of resilience and efficiency in critical infrastructure. This work is limited, as the results were not tested with a case study. Some unit values used in the model were based on the author's mental model and may be inconsistent with the existing system. The severity of the disaster was uniform for all scenarios simulated and is inconsistent with the real system as the severity and occurrence of natural disasters can not be predicted. This model's expansion could prove useful for future work to investigate the trade-off's impact on different infrastructure systems' interactions. Testing this study's results with a case study is necessary for validation and identification of potential shortcomings. Further investigation of the trade-off in different critical infrastructure systems, with different natural disasters of differing severities, is encouraged for a unified framework applicable across all infrastructure systems.

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APPENDIX A

DETAILED DESCRIPTION OF THE HOSPITAL RESILIENCE MODEL

1. **Patient Arrival and processing:** This sector of the model represents an aggregation of patient flows through the system. The discharge rates, patient deaths and transfers are all summed up here. At the end of the patient outflows, there are three stocks. These enable the modeler to estimate actual/hazard performance.

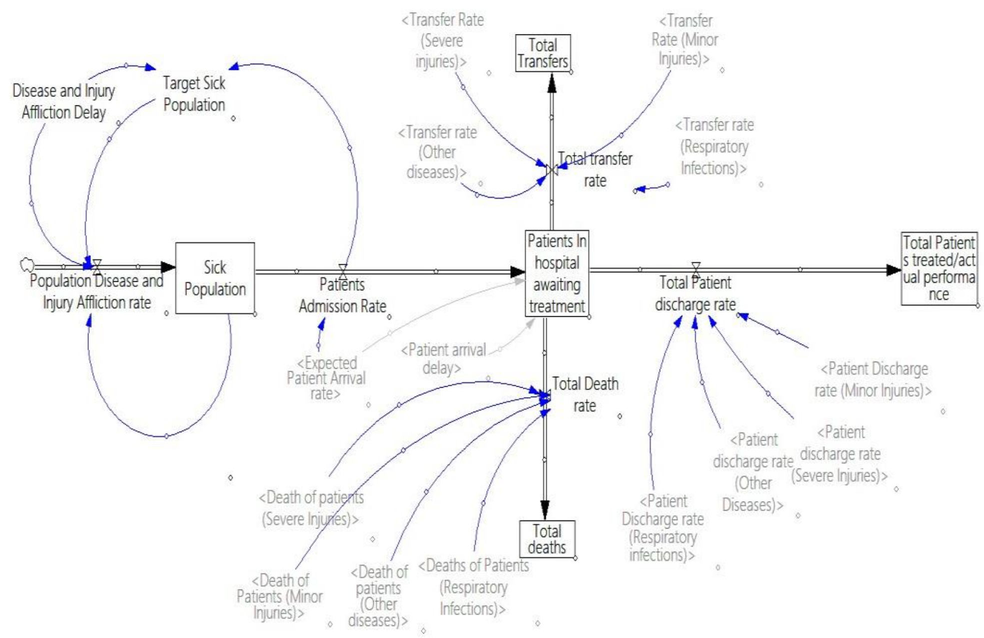

Figure 43: Diagram of patient arrival and Processing

2. **Patient treatment:** These sectors show the patient flows through the different parts of the hospitals. Patients arrive in the hospital and are treated. Some die and some are transferred if the hospital cannot attend to them immediately but only if there are available ambulances. Only patients with severe injuries and other diseases can be transferred. The modeler assumes that every patient who comes in during normal times

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is treated immediately and keeps the system in equilibrium. Some die during treatment and the death rate is determined by the number of patients awaiting treatment and a fractional death rate. The rest are discharged. The discharge rate is the difference between treatment rate and the normal death rate. The treatment rate is the daily number of treatments, considering constraints such as utilities, med resources etc. After a disruption, a backlog appears in the stock of the patients waiting to be treated. This stock is reduced as; treatment rate returns to normal and death rates increase as patients are left untreated and transfers to other hospitals.

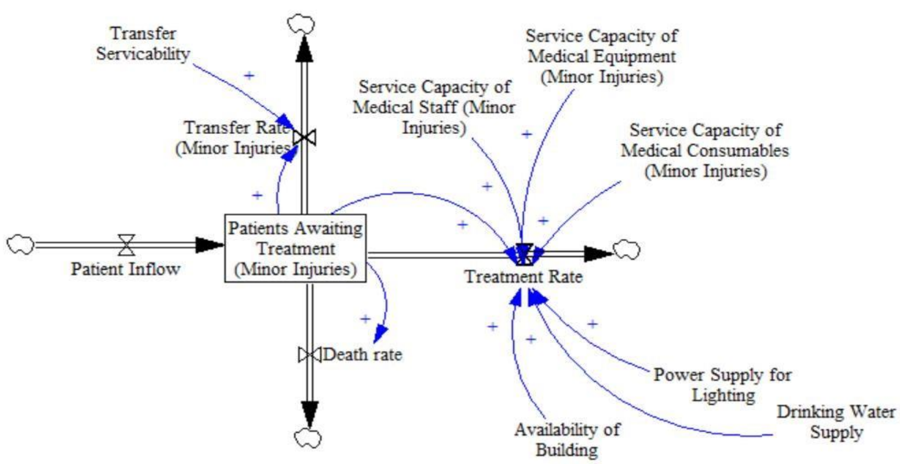

Figure 44: Graph of Patient treatment stock and flows

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3. Dynamics of diseases: This sector of the model contains the medical resources that determine the treatment rate. Medical staff's service capacity is determined by the number of staff, daily treatment capacity per staff, and HIS availability. Medical equipment's service capacity is determined by the number of equipment, daily treatment capacity/machine, rate at which the equipment is used, and medical water availability. Number of beds is determined by patient admission and discharge rates. Service capacity of medical consumables is determined by a consumption rate and a resupply rate. The resupply rate is dependent on the number of consumables in the hospital, the availability of communication and the state of the municipal roads.

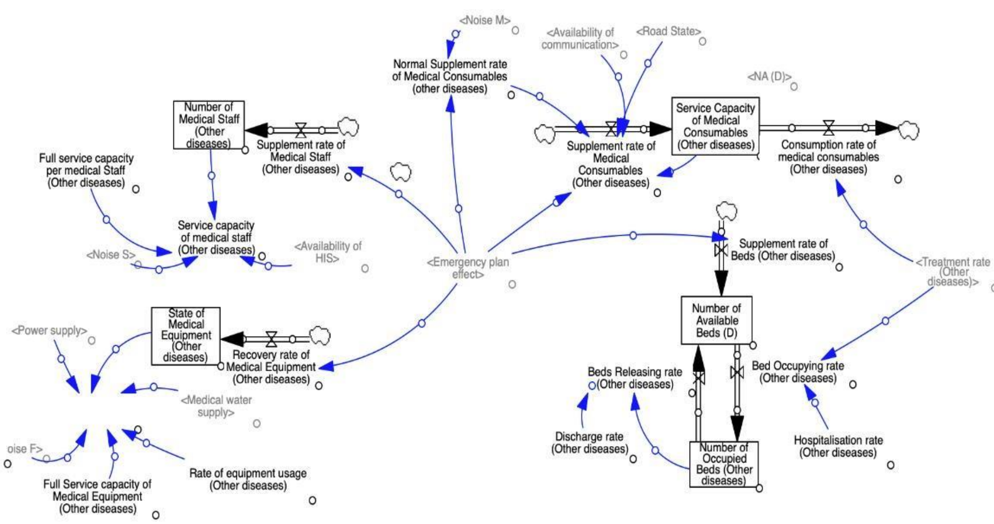

Figure 45: Diagram of Dynamics of Medical Resources

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4. **Dynamics of utilities:** this sector hosts the utilities such as light, water and transportation that the hospital needs to operate. The recovery rates of these utilities can be altered here to reduce or increase medical resources' service capacities. A variable earthquake occurrence time is also available here. To simulate an earthquake, change the value of this constant to any number between 1 and the final simulation time.

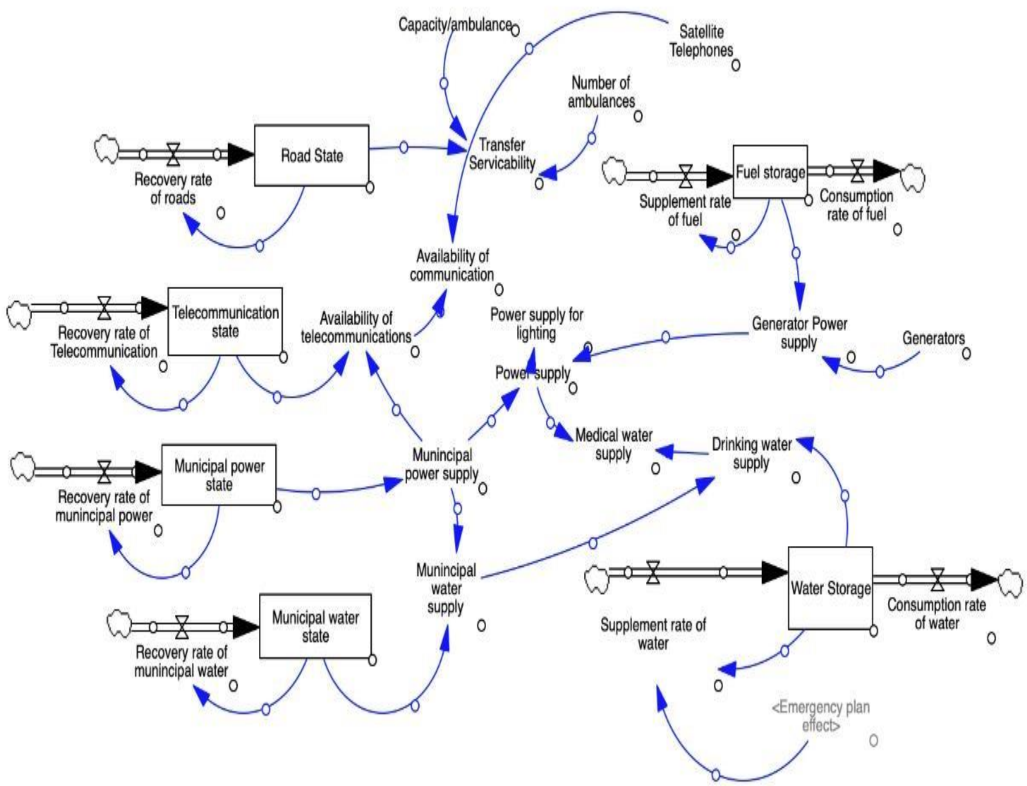

Figure 46: Diagram of Dynamics of Utilities

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5. **Dynamics of hospital Building:** This sector has variables representing the hospital building and HIS(Health Information System). Building recovery rate can be changed by altering the value of the constants "Facility Management team" which represents the facility management staff and their average work capacity "Capacity/Engineer.

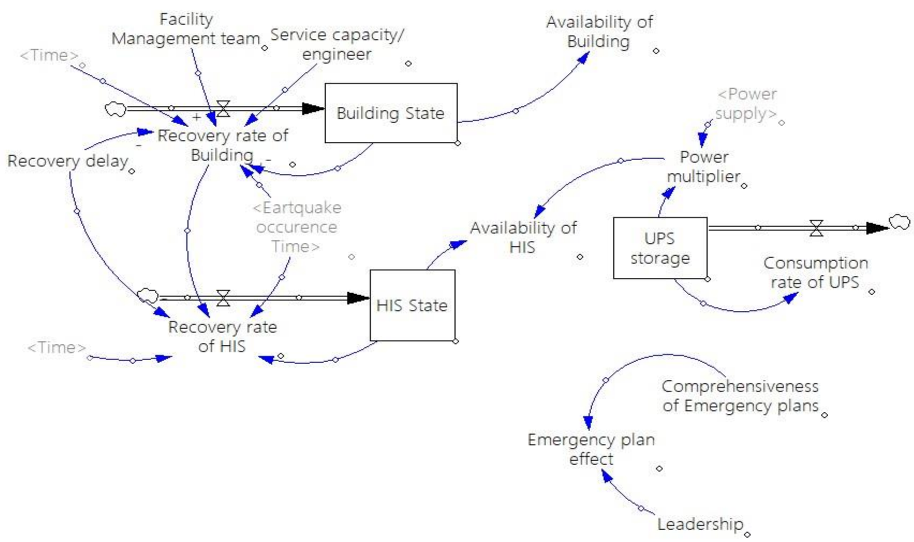

Figure 47: Dynamics of Hospital Building

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APPENDIX B

REVISIONS TO CREATE THE EFFICIENCY/RESILIENCE MODEL

1. **Dynamics of patient inflow:** This sector of the model houses the variables that regulate the patient inflow and allow the model to run in equilibrium. The sum of the sectional expected service capacities determine the Expected patent arrival rate.. The expected service capacity is the service capacity eliminating resource constraints and a disruption. The ratio of the expected service capacity to the patient arrival delay (the average time it takes for a patient to arrive at the hospital from within its service region). The Expected service capacities are all patient inflows in their respective sections. The benefit of these formulations is seen as the treatment rate (Outflow) is always equal to the patient backlog divided by a treatment delay (Stock/outflow delay), which is also equal to the patient admission rate (Inflow) ; keeping the model in equilibrium. This is the case until there is a disruption. performance.

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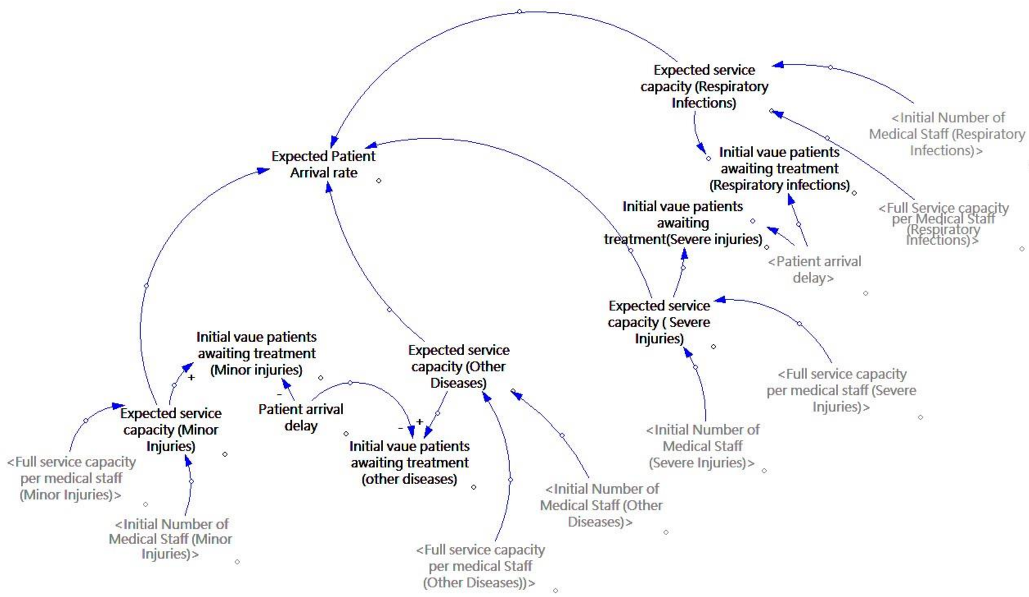

Figure 48: Dynamics of Patient Inflows

2. **Hospital Performance:** This view shows the calculation of the patients left untreated. The non-hazard performance is the total of the expected treatment rates without a disruption or resource constraints. The actual performance is the total number of patients treated during the simulation period. The patients left untreated is the difference between the nonhazard and the hazard/actual performance. The patients left untreated is the measure of resilience. The higher it is at the end of the simulation period, the less resilient the hospital is to disruptions. If all other factors such as service capacities, utilities states and building recovery rate are held constant, the variable's behavior will change if the earthquake occurrence time changes. However, for those same conditions, the final value never changes.

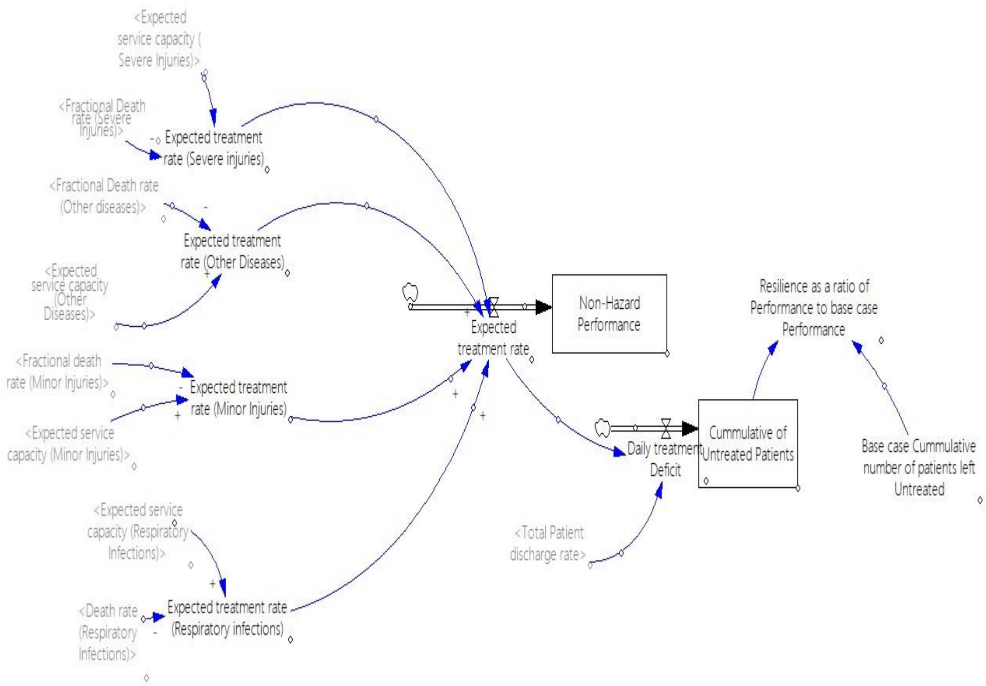

Figure 49: Hospital Performance

3. **Dynamics of Operating costs**: this section of the model sums up the hospital's costs during the simulation period. Due to utility charges, facility maintenance and resource costs like staff wages and equipment maintenance are due to utility charges. The ratio of the total cost to the actual/hazard performance of the hospital gives the unit cost per patient treated. This is the measure of efficiency. The unit cost goes up as efficiency is reduced. If all other factors such as service capacities, utilities states and building recovery rate are held constant, the behavior of the variable will change if the earthquake occurrence time changes. However, for those same conditions, the final value never changes.

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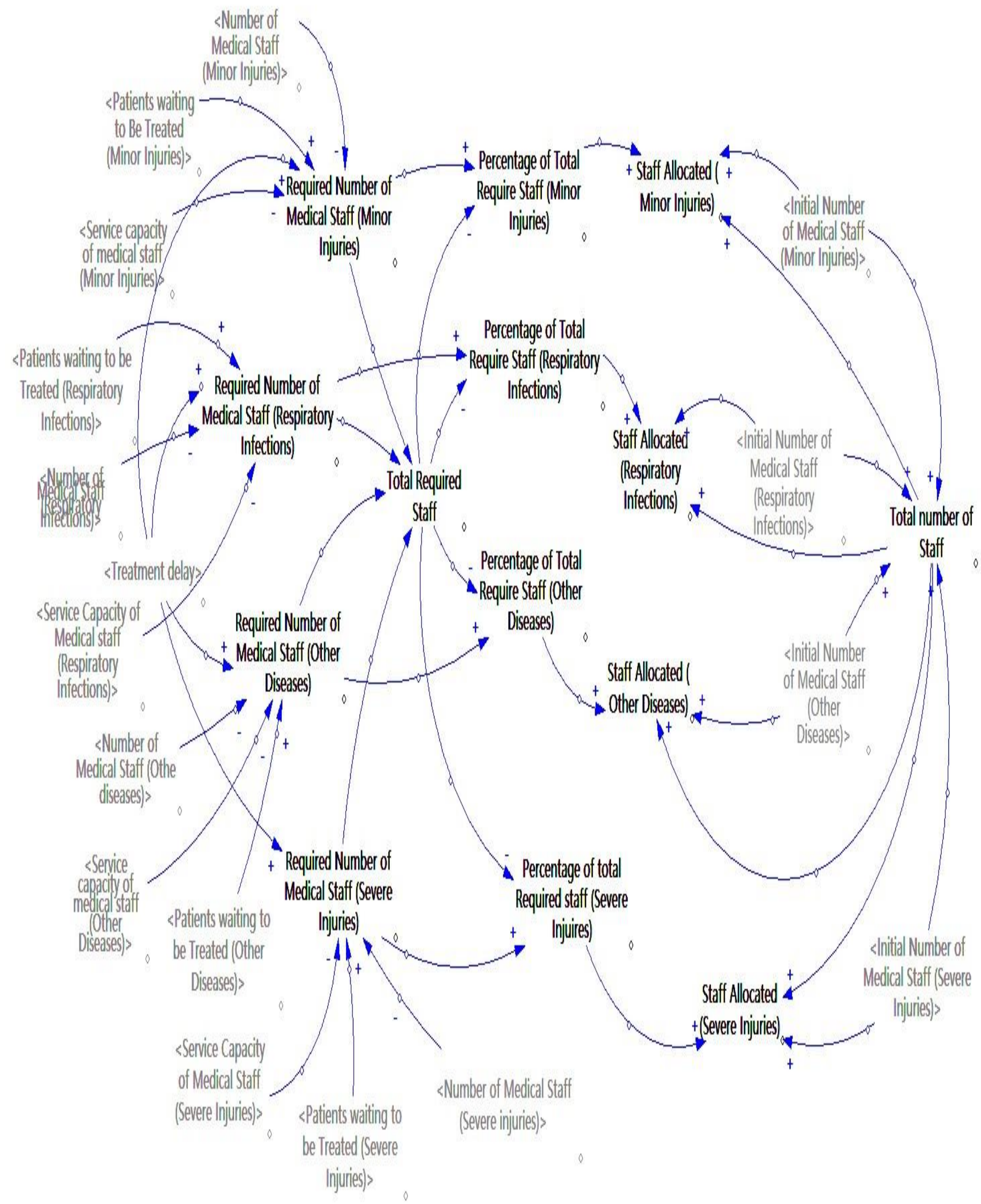

Figure 50: Dynamics of Resource Allocation

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APPENDIX C

MODEL VALIDATION VARIABLE CHANGES

Simulation	Variable name	Normal value	Simulation value
Policy 0	---------------------	-------------------	--------------------
Policy 1	Fuel storage	100%	200%
Policy 2	Number of Beds	80 Beds	40 Beds
Policy 3	Recovery rate of Building	0.0175/day	0.0333/day
Extreme condition 1	Recovery rate of Roads	0.5/day	0/day
Extreme Condition 2	Recovery rate of municipal Power	0.5/day	0/day

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APPENDIX D

SIMULATION GRAPHS

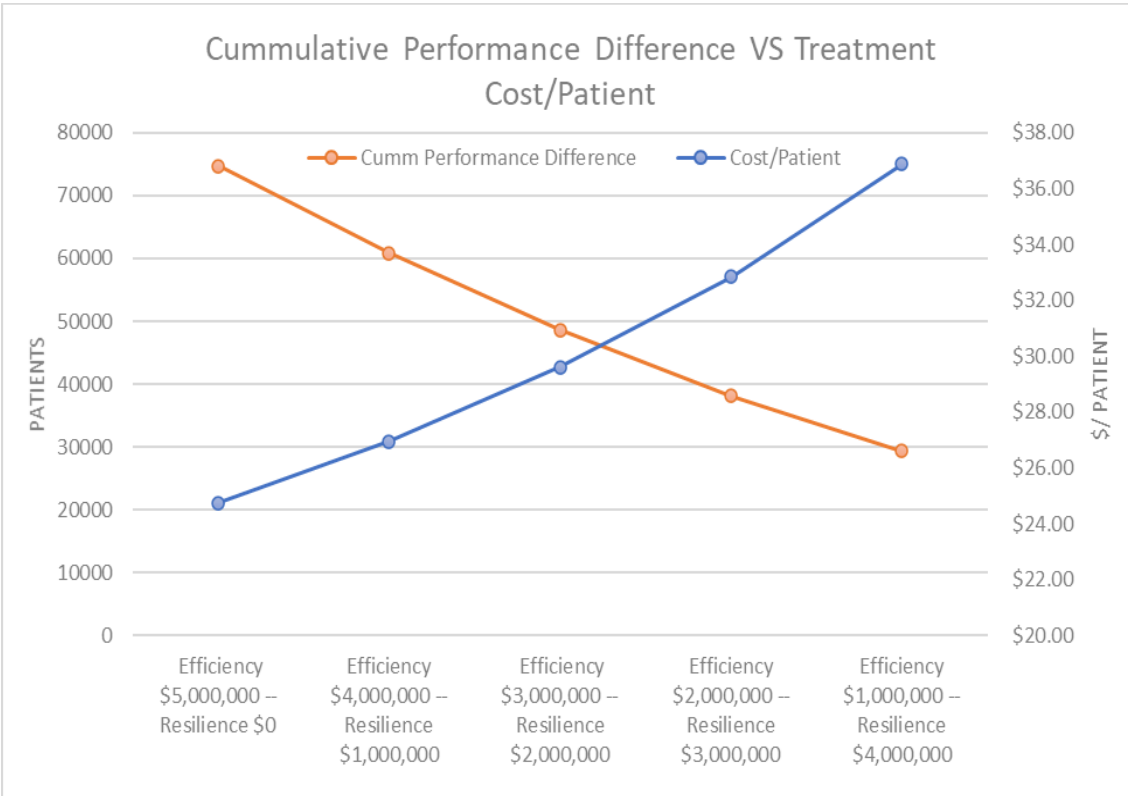

Figure 51: Graph of Cumulative performance difference versus Treatment cost/patient for Varied investments

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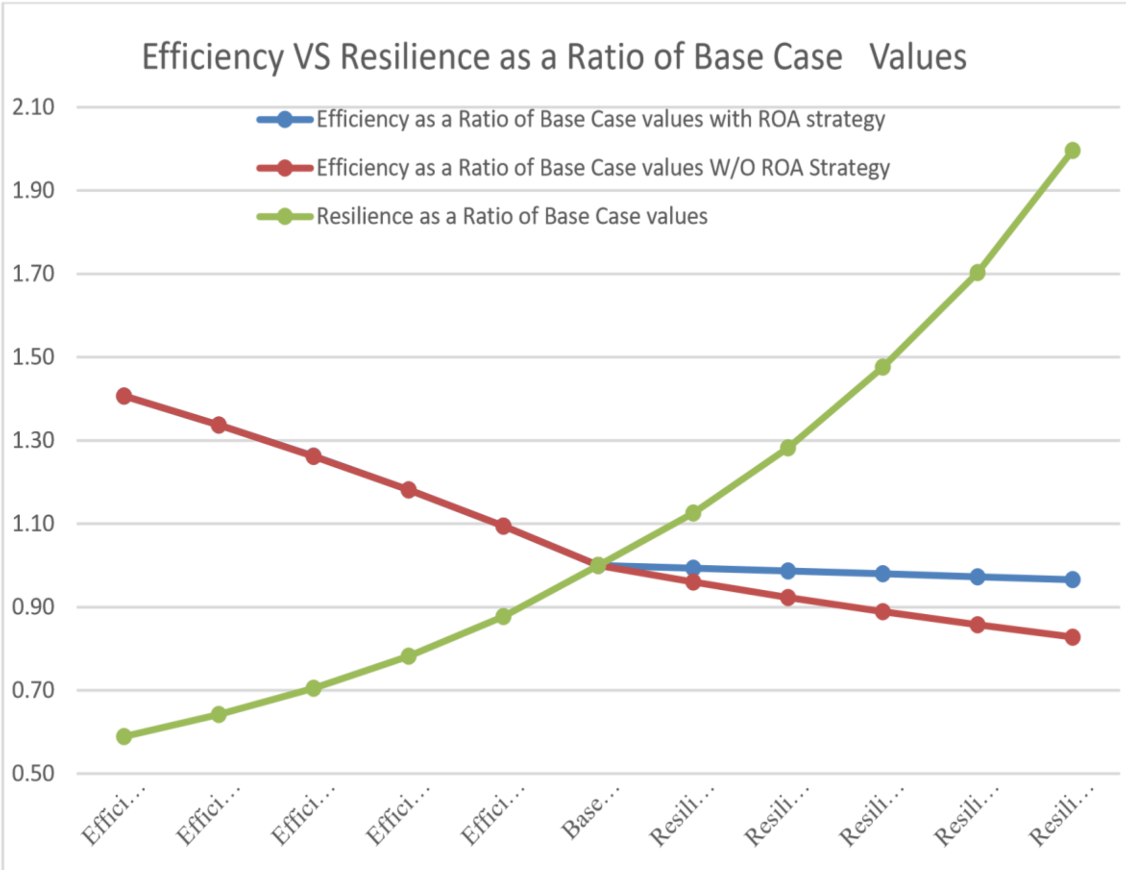

Figure 52: Graph of Efficiency Vs Resilience for Mutually exclusive investments (Real options Inspired Strategy)

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Table 9: Table of final values of important model variables in real options inspired mutually exclusive investments

	Total/Nonhazard Performance *1000(Patients)	Hazard Performance *1,000 (Patients)	Cumulative Performance difference (Patients)	Operational Cost *1000 ($)	Treatment cost/Patient ($/Patient)
Efficiency $5,000,000 Investment	1,176	1101	74654	29,094	24.8
Efficiency $4,000,000 Investment	1,079	1011	68522	28,094	26.0
Efficiency $3,000,000 Investment	982	920	62389	27,094	27.6
Efficiency $2,000,000 Investment	886	829	56256	26,094	29.5
Efficiency $1,000,000 Investment	789	739	50123	25,094	31.8
Base Case	692	648	43990	24,094	34.8
Resilience $5,000,000 Investment	692	675	16789	24,344	35.2
Resilience $4,000,000 Investment	692	678	14387	24,594	35.5
Resilience $3,000,000 Investment	692	680	12186	24,844	35.9
Resilience $2,000,000 Investment	692	682	10298	25,094	36.3
Resilience $1,000,000 Investment	692	684	8557	25,344	36.6

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Table 10: Table of Final values of the important model variable for mutually exclusive investments and dynamic resource allocation

	Total/Nonhazard Performance * 1000(Patients)	Hazard Performance *1,000 (Patients)	Cumulative Performance difference (Patients)	Operational Cost *1000 ($)	Treatment cost/Patient ($/Patient)
Efficiency $5,000,000 Investment	1,176	738.781	25795	29094.4	24.7
Efficiency $4,000,000 Investment	1,079	829.384	24504	28094.4	26.0
Efficiency $3,000,000 Investment	982.	919.987	23213	27094.4	27.6
Efficiency $2,000,000 Investment	886	1010.59	21922	26094.4	29.5
Efficiency $1,000,000 Investment	789	1101.19	20631	25094.4	31.8
Base Case	692	648.178	19340	24094.4	34.8
Resilience $5,000,000 Investment	692	670.135	16789	25094.4	36.3
Resilience $4,000,000 Investment	692	666.344	14387	26094.4	37.7
Resilience $3,000,000 Investment	692	662.367	12186	27094.4	39.1
Resilience $2,000,000 Investment	692	657.867	10298	28094.4	40.6
Resilience $1,000,000 Investment	692	653.1	8557	29094.4	42.03

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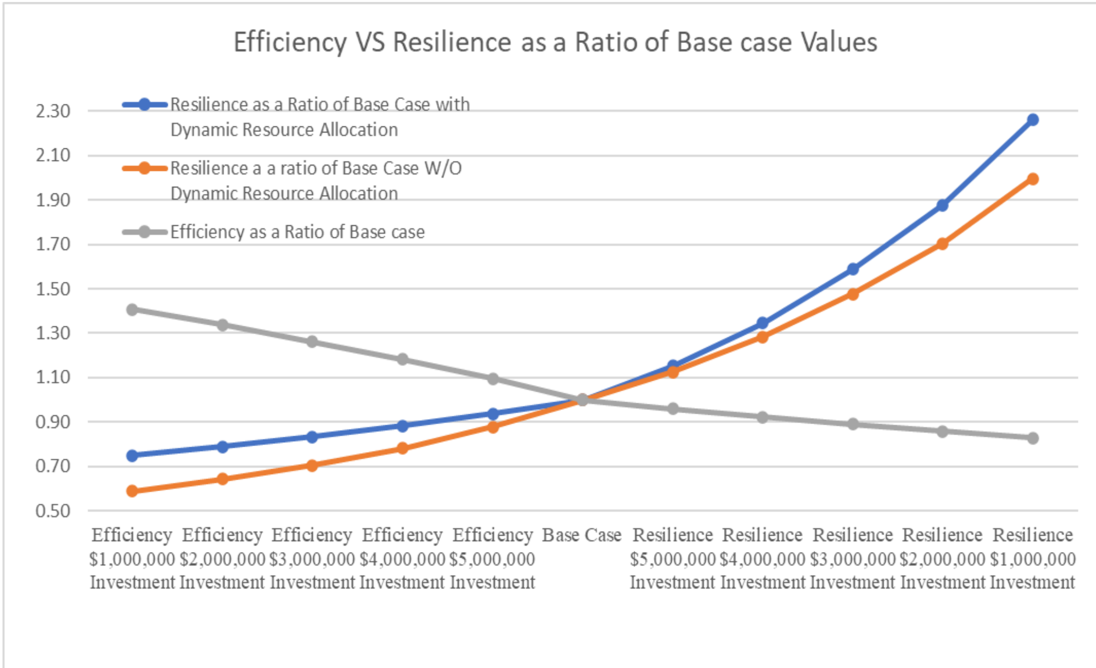

Figure 53: Graph of efficiency VS resilience as a ratio of the base case values for mutually exclusive investments with dynamic resource allocation

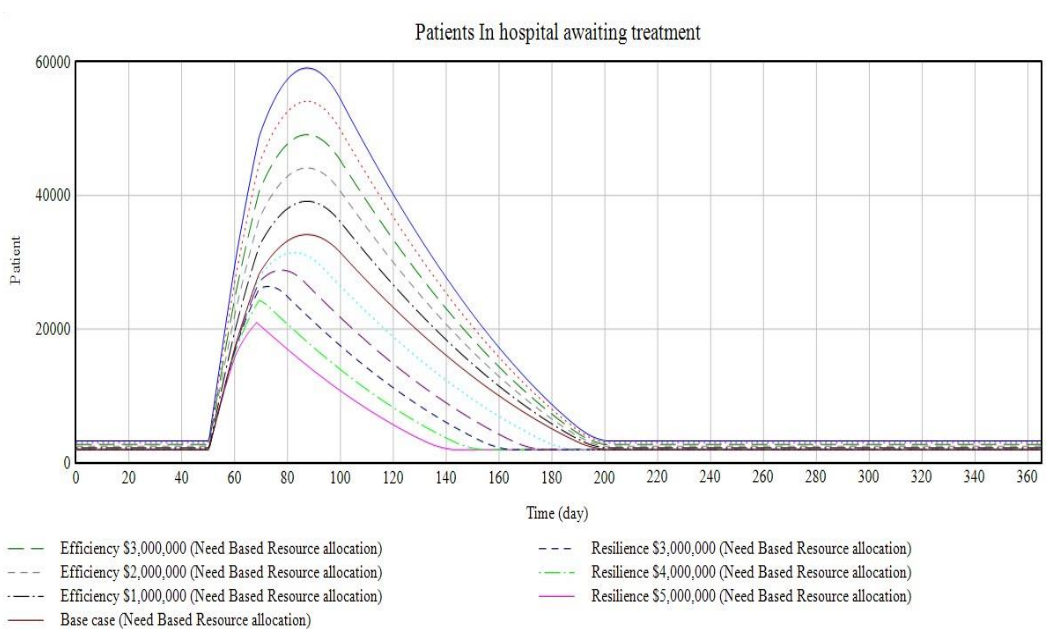

Figure 54: BOTG of Patient Backlog Mutually exclusive investments with Dynamic Resource Allocation)

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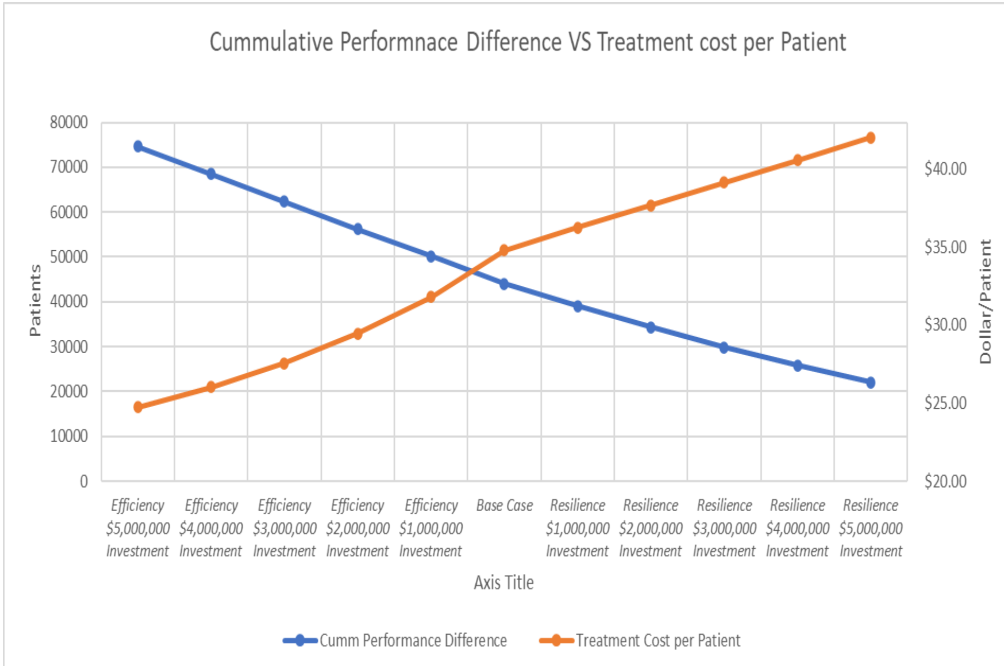

Figure 55: Graph of Cumulative Performance difference VS treatment cost per patient for mutually exclusive investments

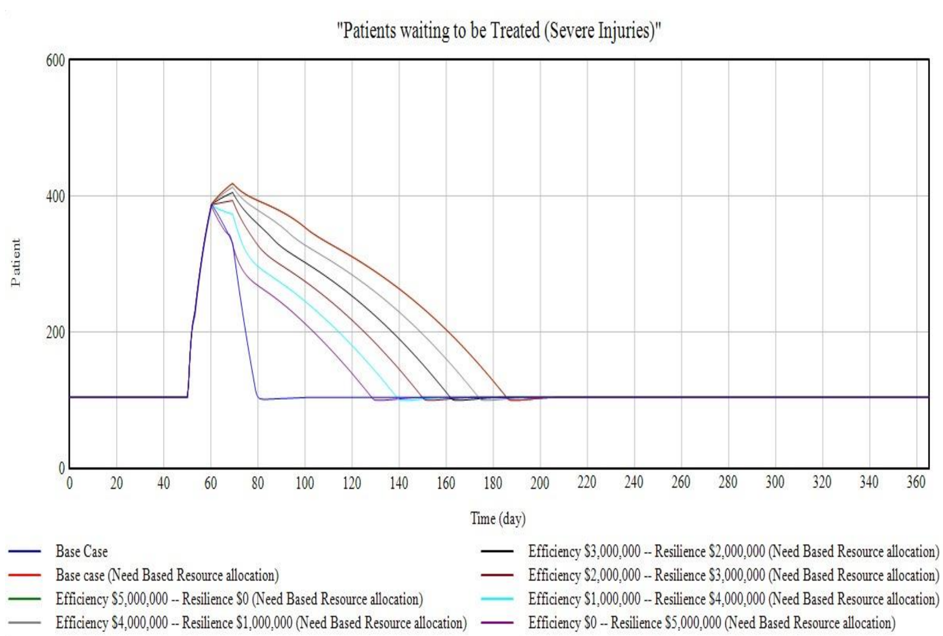

Figure 56: BOTG of patient Backlog (severe Injuries) Varied investments with Dynamic Resource Allocations