FORECASTING AND STOCHASTIC PROGRAMMING MODELS TO ADDRESS UNCERTAINTY IN THE TRAUMA SYSTEM CONFIGURATION PROBLEM

by

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DEDICATION

To my family, for their support and encouragement.

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ABSTRACT

Trauma is an essential aspect that must be considered by governing bodies when providing and expanding healthcare services across their jurisdiction. This thesis focuses on analyzing and forecasting physical trauma sustained from accidents, in environments both personal and work related, pertaining to individual injuries and to formulate a stochastic programming model that utilizes recorded injuries as demands to place trauma centers in the most optimal location. The first part of the thesis is to better understand the limitations faced by the existing trauma healthcare infrastructure by forecasting the expected number of people requiring the services of trauma facilities for both rural and urban locations in Texas. Five types of forecasting methods were analyzed to determine the best option to utilize for forecasting for individual data sets. The aim is to identify which forecasting model performs the best for given data sets that can be used to forecast patient demand for a given location and determine the optimal locations for trauma network expansion.

The second part of the thesis proposes a stochastic programming model that considers variable demand in a specific geographical location. Trauma care services are a vital part of all healthcare-based network as timely accessibility is important for citizens. Trauma care access is even more relevant when unexpected events such as the COVID-19 pandemic overload the capacity of the hospitals. Research literature has highlighted that access to trauma care is not even for all populations, especially when comparing rural and urban groups. Historically, the configuration of a trauma system was often not considered as a whole but instead hinged on the designation and verification of individual hospitals as trauma care centers. Recognition of the benefits of an inclusive trauma system has precipitated a more holistic approach. The optimal geographic configuration of trauma care centers is key to maximizing accessibility while promoting the efficient use of resources. This thesis reports on the development of a two-stage stochastic optimization model for geospatial expansion of a trauma network in the state of Texas. The stochastic optimization model recommends the siting of new trauma care centers according to the geographic distribution of the injured population. The model has the potential to benefit both patients and institutions, by facilitating prompt access and promoting the efficient use of resources.

1. INTRODUCTION

1.1. Thesis outline

Physical trauma can be defined as “a body wound produced by sudden physical injury from impact, violence, or accident” [1, 2]. A trauma care center (TCC) is a facility which aims to provide medical services and resources to address individuals involved in traumatic injuries. The spectrum of sustained injuries can range from households to large scale industrial accidents, including but not limited to widespread natural disasters such as hurricanes.

A commonplace of injuries is the result of motor accidents occurring on a regular basis. A study by the American College of Surgeons found that an average of 58.56 per 100,000 population perish due to injuries [3]. Accidents were the 5th leading cause of deaths in 2015 accounting for 4.9% deaths with motor vehicles being the primary cause [4]. Considering the rise in car owners across the country, the total number of motor vehicles registered in 2016 was 268,799,083 as compared to 263,610,219 in 2015 [5]. This represents an increase of nearly 5.2 million more vehicles on the road [6]. In addition, when considering large-scale calamities such as hurricane Harvey which was responsible for at least 70 deaths in Texas, it is essential to strategize the expansion of new facilities to accommodate ever increasing population needs.

This thesis is motivated by real data provided by the Texas Department of State Health Services (DSHS). DSHS oversees the network of trauma hospital for the state of Texas and collects daily data on the number of trauma injuries per zip code. Texas had the biggest increase in population of any state in the country in 2019, according to estimates released on Monday, 30th December 2019, by the U.S. Census Bureau. The data show the number of people in the Lone Star State grew by 367,000 from mid-2018 to mid-2019, bringing the state's total population to almost 29 million [7] This trend is particularly impacting the central Texas regions which reported a 10% increase in population since 2010. Having an accurate trauma injury volume prediction will enable better planning for future expansion of the trauma network of hospitals in Texas.

The goal of the forecasting part of the thesis is to analyze data on trauma injuries in rural Texas and to build robust forecasting models to predict future service demands for different regional locations. The results of this thesis are expected to serve in the decision making for future expansion of state trauma networks. The thesis considers the following factors for a specified area of rural Texas: number of injuries per time per location based on zip codes, environment where the injury occurred, level of the trauma facility destination, and the injury severity score. The results will help in identifying locations which showcase periodic occurrences and that might not have access to a TCC. The results and insights will serve to develop strategies to improve accessibility for potential patients in the state.

The forecasting part of the thesis is organized as follows: Chapter 2, sub-section 2.1 provides a summary of the relevant publications for this research and defines the contribution of the study described here. The methodology followed in this study and the forecasting models are presented in chapter 3 sub-section 3. Chapter 3, sub-section 3.5 presents a case study. Chapter 3, sub-section 3.6 deals with the discussion of the results for the descriptive analysis and sub-section 3.7 discusses the results for time series analysis. The conclusion with a summary and future research areas will be presented and discussed in Chapter 5. As this concludes the forecasting and analysis portion of the thesis, discussions will be undertaken towards formulating an optimization model that takes into consideration the demand from individual locations, determine their distances from trauma centers and formulate a stochastic programming model to determine the optimal locations for facilities in a given geographic region.

Trauma injuries can lead to the death if proper care is not administered to the patient on a timely fashion. Easy access to trauma care centers (TCC) is even more important when considering unexpected events such as the COVID-19 pandemic. TCCs are uniquely impacted by COVID-19 given the need for rapid invasive interventions in severely injured and the growing incidence of community infection [8]. Trauma incidents are one of the leading causes for disability, mortality, and morbidity for patients under the age of 44 in the U.S. and has an economic burden of $671 billion annually [9]. In addition, multiple studies have concluded that access to trauma care centers (TCC) is not even for all populations, especially rural and urban groups [10]. Therefore, trauma is a serious health problem with high social and economic costs.

Providing appropriate care to patients suffering trauma injuries requires smooth healthcare delivery processes. Soon after a trauma injury occurs, healthcare paramedics are dispatched to the scene. The paramedics provide first aid to stabilize the patient and then the patient is transported to a TCC. Delays in patient transportation to a trauma center can impact the patient's survival rate. Clinical intervention is expected within an hour from the moment of an injury incident as a general rule of thumb [11, 12]. A TCC is a hospital that possesses staff, resources, and equipment needed to provide care to severely injured patients [13]. In the U.S., TCCs are classified as Level-I to Level-IV [4, 14]. Level-I and Level-II TCCs offer the highest level of services to patients with traumatic injuries. Level-III and Level-IV are intermediate facilities that help in stabilizing the patient. In this study, Level-I and II TCCs are grouped into Level-I and Level-III and IV TCCs are grouped and referred to as Level-II.

The second part of this thesis studies the design and expansion of the state of Texas trauma care system. The state of Texas plans to expand the availability of high level trauma centers as laid out in the 2019-2020 Texas State Health Plan [11]. The initiative identified the limited availability of high-level trauma care with additional concerns of superabundance of trauma facilities in densely populated urban areas with the focus on Houston-Galveston. The report also recommended a comprehensive study to ascertain the true extent of accessible trauma care for the state particularly for rural zones that have limited road networks to provide access and services. An important result from the report stated that 32.4 percent of Texans live further than 20 miles from a Level-I TCC and 12.1 percent live a distance of more than 50 miles. This shows that improvements in accessibility are required of the current trauma care system to reach a significant portion of the population. In this thesis, a model is developed to guide the expansion of the TCCs in Texas based on three years of data. The results are expected to help the state of Texas government outline its 2025 expansion plan. Although, the numerical results of this study are based on data from Texas, the models developed here could be applied to the design of TCCs in other regions. More generally, the results of this work could also be applied to a group of optimization problems that aim to find the locations of other “fixed servers” (i.e. TCCs) when service needs are constrained by certain time threshold.

The optimal geographic configuration of TCCs is key to maximizing accessibility while promoting the efficient use of resources. The goal of this thesis is to report on the development of a two-stage stochastic optimization model for geospatial expansion of a trauma network in the state of Texas. The stochastic optimization model recommends the siting of new TCCs by level considering the uncertainty in the geographic distribution of the injured population. The novel models also consider the uncertainty in demand created by the COVID-19 pandemic. Previous efforts to produce data-driven solutions to trauma system design have shortcomings, like assuming a deterministic demand and that every trauma facility serves all type of injuries, prompting the development of a novel approach. The models presented in this thesis prove a systematic approach to trauma system design that can help to reassure stakeholders that the best configuration has been chosen.

The stochastic programming chapter of the thesis proceeds as follows. Chapter 2, sub- section 2.2 presents a literature review regarding healthcare facility location problems to be followed by the description of the similar stochastic programming models. Chapter 3, sub-section 3.5 presents the problem description and the parameters associated with the former. Chapter 4, sub-section 4.2 describes the stochastic programming model and its iterations that are modified. These iterations are used in the systems that are tested against the current trauma network to determine their feasibility and performance when observing population coverage. Chapter 4, sub-section 4.3 presents a case study delving further detail for the geographic area under study, the designing of experiments to test the feasibility of the current trauma network and suggested variants. Chapter 4, sub-section 4.4 contains descriptions of the methods used to test the performance of the current trauma network with proposed networks. Chapter 4, sub-section 4.5 contains narrative and illustrative results obtained from testing and with comparisons. Chapter 4, sub-section 4.6 provides the conclusions reached for the study and sub-section 4.7 provides future research prospects and recommendation.

2. LITERATURE REVIEW

The literature review chapter is divided into two sub-sections. Sub-section 2.1 reviews the literature pertaining to the forecasting and analysis of patient arrival at hospital and emergency centers. To determine the location of an optimally placed facility, it is imperative to accurately determine, to the best possible degree of accuracy, the trends of patient arrival at a given location. Sub-section 2.2 reviews the literature on facility allocation programming models that discuss methodologies and approaches to optimally place location in a geographic area when considering patient demand.

2.1. Forecasting and time series analysis of patient demand

This sub-section will focus on reviewing existing literature related to the case of forecasting the arrival of patients to a medical facility. Studies need not be tailored for the problem under study yet proposing models and ideas which can relate to the current research. The unpredictability of patient arrivals lies at the core of managing a care unit to the best of its abilities. Carvalho-Silva. et al. [15] presented an assessment of forecasting models for the arrival of patients at an emergency department. The study was conducted at the Braga Hospital, in Portugal. The authors assessed different forecasting models to test their viability. The study chose the Autoregressive Integrated Moving Averages (ARIMA) model, and the accuracy of the model was based on the Mean Absolute Percentage Error (MAPE) metric. Results favored predictions one week in advance with satisfactory performance. Due to the complex nature of predicting human flows to a facility, comparisons can be made with environments operating under similar circumstances.

Bergs et al. [16] gathered and analyzed data from four Belgian emergency departments in a 6-year period to forecasts patient arrivals for one year ahead. The authors used the exponential smoothening approach for their study laid out by Hyndman et al. [17]. Afilal et al. [18] studied the flow of patient arrival to emergency departments to improve resource allocation of resources and personnel. The authors introduced their patient classification and proposed a forecasting model to predict daily attendance. The model was tested against epidemic data cases and proved to be viable during the epidemic periods. Abraham et al. [19] studied the viability of forecasting the arrival of patients in emergency wards and determine if patterns can be detected to reduce uncertainty regarding admissions and occupancy. The authors concluded that none of their applied models produced viable forecasts resulting in unpredictability. W.T Lin et al. [20] utilized forecasting models to predict patient movements in hospitals selected at random from the state of New York. The authors used Box-Jenkins [21] univariate ARIMA and Tiao-Box [22] multivariate ARIMA models to generate forecasts of patient movements to make better planning decisions. The authors concluded that trends differ by hospitals. They found patterns based on historical data for the same facilities. Champion et al.[23] used exponential smoothing models and ARIMA to forecast the number of patients arriving at an emergency department in regional Victoria for the time between 2000 – 2005. The authors stated that for their study, a simple seasonal model proved to be the best exponential smoothing model awhile the optimal ARIMA model would be a non-seasonal moving average model, displayed as ARIMA (0,1,1). Their results stated that forecasts from the two models were similar.

Jones et al. [24] describe a model that forecasts the daily number of occupied beds due to emergency admissions in a hospital. The authors identified a relationship between the number of beds occupied and two external variables: mean daytime temperature and influenza illness rate. Wargon et al. [25] tried to identify determinants of emergency departments census to assess the performance of long-term forecasts. The authors noted that visits to emergency departments are dependent on factors that are difficult to measure. Boyle et al. [26] used regression models to forecast patient admissions. Their results stated that the highest accuracy was the result of a linear regression, variating monthly, with 11 dummy variables. Jilani et al. [27] developed and tested forecasting models in four emergency departments for long- and short-term predictions. They stated that patient admissions were not purely random and can be predicted with reasonable accuracy. Prediction accuracy would improve as time intervals for forecasting became larger. McCarthy et al. [28] analyzed patient arrivals in an emergency department using a Poisson regression. They stated that the demand is suited well for a Poisson model with few temporal, weather, and diversion predictors.

Juang et al. [29] studied emergency department visits in Taiwan for the time between January 2009 and December 2016. The authors used ARIMA to generate forecasts and determine the model validity in forecasting visits. Their results showed that ARIMA (0,0,1) was appropriate visits for the years 2016 and 2017. D. R. Holleman et al. [30] conducted a study to determine if calendar and weather factors can predict unscheduled visits in a large rural veteran population. They found that weekends, public holidays, federal government check delivery days, and snowfall reduced unscheduled patient arrival volume. It is also decreased when the daily high temperature deviated, towards high and low, from 80 Fahrenheit. Larger patient volume was noted during winter months, except for winter. Seematter-Bagnoud et. al [31] compared different methods of forecasting hospital bed needs. The study emphasized on the need for adequate planning for the hospital under study for a period of twenty years. Even with the usage of different models to forecast the expansion process, there are pros and cons for each and must be chosen according to the requirements of the facility. Practical considerations must be incorporated, as per the policies of the former, to better fit the models.

Ibrahim et al. [32] present an extensive literature review of forecasting models that have been applied to predict the call arrivals at a call center. The authors stated the relevance of having accurate forecasting methods ahead of planning for staff allocations. The authors also commented on the complexity of the system being modelled and how finding accurate forecasting techniques can lead to better operational decisions. Finally, the authors recognize that there often exists a gap between academia and industrial practice which typically limits the capacity of a company since they are unaware of the forecasting techniques that are available to them. Therefore, in this work we wanted to examine whether more traditional forecasting methods could provide a better insight to DSHS in planning for the future expansion of their TCC network.

2.2. Facility allocation programming models

In this sub-section, the review of relevant literature on healthcare facility location is provided. One of the earliest papers discussing the trauma facility location problem is Branas et al. [12]. The authors proposed an optimization model named the Trauma

Resource Allocation Model for Ambulances and Hospitals (TRAMAH). The TRAMAH model was employed to determine the time it takes for a population group to access a trauma center either by ground or aero medical services. Average speeds of 20.1 miles/hour in urban areas, 47.5 miles/hour in suburban areas, and 56.4 miles/hour were considered for drivers. Results also showed that only 69.2% of all residents had access to either a Level-I or II trauma center within a travel time of 45 minutes. The model does not consider Level-III and Level-IV trauma centers. In addition, the study mentioned some limitations such as assuming the problem is deterministic which does not address the uncertainty in patient demand for services.

Jansen et al.[33] proposes an algorithm to improve trauma system configuration utilizing existing network and facility locations. The authors used travel times for both ground and air-based services to every hospital in Scotland. Multi-objective performance measurements were considered to account for conflicting objectives while using geospatial methods to map out the existing framework. The authors discussed the benefits of using an algorithmic based optimization model in combination with geospatial methods to configure strategies for either expansion of existing networks or building a new framework. Wang et al. [34] proposed the use of an evolutionary algorithm to optimize the problem formulated in Jansen et al. [33].

Brown et al. [35] suggested that unregulated growth of new trauma centers within an existing framework could lead to unforeseen consequences and in their paper evaluated trauma center accessibility with injury mortality across the United States. The authors compiled data from different sources including the Center for Disease Control (CDC) relating to injuries, location of trauma centers from the University of

Pennsylvania Cartographic Modeling Laboratory Maps, and the American Trauma Society Trauma Information Exchange Program. The study evaluated the distribution of trauma centers in each state. A Nearest Neighbor ratio (NNR) was devised indicating if the trauma system is clustered or dispersed. The authors calculated NNR as the mean distance between each center and its nearest neighbor while considering the service distributions to be random in each state. The results indicated that the distribution of trauma centers correlates with mortality pertaining to injuries. Clustered trauma centers were associated with lower fatality rates. Possible reasons for this phenomenon could be better access to these centers in large population regions, yet the authors state that further research is necessary and mention the benefits of using geospatial mapping to plan for new trauma centers.

Horst et al. [36] proposed an approach to add new trauma centers to an existing framework using geospatial mapping. The authors used mapping techniques to layer in data from multiple data systems, from the state of Pennsylvania, such as Pennsylvania Trauma Outcome Study (PTOS), Pennsylvania Trauma Systems Foundation (PTSF), Trauma Mortality Predication Model (TMPM). Road networks were used in calculating the travel times in various zip codes. The study identified 38 trauma centers ranging from Level-I to IV within the PTSF database. Carr et al. [37] also analyzed existing gaps in the Trauma System in the United States using geographic analysis and population estimates. The Trauma Information Exchange Program (TIEP) and the American Trauma Society (ATS) databases were used to identify the trauma system limitations. Geographic data, population demographic data, and access figures (using 60 minutes as travel time baseline) were considered. The results showed that 88.3% of the population has access to a higher-level trauma center (i.e. Level-I and II), while 11.7% did not. Carr et al. [37] also discusses the relation between access to trauma care and several factors such as economic, racial/ethnicity, and transportation. The authors concluded that high income population groups that exist within clustered trauma centers have better access to trauma care.

Hashmi et al. [38] studied the relation between access to trauma centers and mortality in population groups in the United States. Their results showed that states with poor access to trauma centers have higher mortality rates at the before hospital admission stage of the process. Although their study did not account for possible scenarios to reduce mortality rates before trauma care, the authors propose the development of a comprehensive database that can track patient outcomes from injury to post discharge to lower mortality outcome statistics. Gomez et al. [39] developed a model to ensure access to trauma care in the state of New South Wales, Australia. The study used the classification criteria based on the American College of Surgeons, viz Level-I to IV, for designating trauma centers. ArcGIS, a geographical information system tool developed by ESRI, was utilized to map locations, and analyze transportation networks. Similar to most studies performed pertaining to trauma care, rotary wing ambulances were used to supplement the travel times between different trauma center designations. The study found that, according to the 2016 Australian Census, 86.1% of the population of New South Wales lives within 60 minutes to the nearest either Regional Trauma Center or Major Trauma Center. The study also concluded that when considering transportation using aircrafts and ground-based ambulances, over a 90-minute time, the population able to receive trauma care surges to 99.5%.

Banerji and Fisher[40] dealt with healthcare facility location in rural India. They propose a hierarchical model which consider multiple type of facilities. Garfinkel et al. [41] proposed a model to locate emergency services and public facilities along a road network. Berghmans et al. [42] dealt with location of healthcare facilities in a new city. The authors propose a quantitative based method classifying the functionalities of all facilities to be similar rather than hierarchical. Cho [43] proposed a multi-objective model seeking the location of medical service centers and the availability of those services. The model aimed to provide comprehensive healthcare services to patients in an efficient manner pertaining to the quality of the services. The paper defines the measures such as consumer welfare, producer welfare, and opportunity to obtain service.

Consumer and producer welfare are dealt by system efficiency and availability of services is measured by the per capita costs such as transportation costs to medical facilities which represent system equity. Rahman et al. [44] proposed a quantitative healthcare facility location-allocation models for developing nations. The authors presented a case study for Guatemala where the *p*-median method was employed taking into consideration population centers and hospital facilities. Mitropoulos et al. [45] proposed a bi-objective model to optimize the location of hospitals and health centers in Greece. The model aimed to minimize the distance between the patient and hospitals and locating adequate facilities to account for multiple population groups and demographics. Hosseini and Ameli [46] implemented the *p*-center method that minimized the maximum distance for all users. The authors expressed that their *p*-median model does not account for emergency services which are needed to operate in rural communities.

Syam and Cote [47] studied the problem of improving the efficiency and effectiveness of the Department of Veterans Affairs (VA) in the United States. They considered various costs incurred by veterans, including family expenditures, and the quality of service provided to veterans. The authors formulated a deterministic optimization model to address the problem. Based on their results, a decentralized system is recommended. Although, it is shown that a decentralized system is more expensive, it offers greater access to population. Kim et al. [48] developed a Lagrange heuristic algorithm to solve the healthcare facility location problem. In their work, they divided patients into groups based on income statistics. Low income groups were restricted to only access public facilities while medium and high-income groups can access public and private facilities. The model assumed that no new facilities will be setup; hence utilizing, to the maximum extent, the use of the existing framework. Their model accomplished the goal of maximizing the number of patients served.

Finally, on a recent literature review on healthcare facility location problems, Ahmadi-Javid et al. [13] discussed papers addressing the location of healthcare trauma facilities. Based on the literature review, the authors propose a facility location model for trauma facilities that maximizes the weighted combination of primary and backup coverage given to demand points. The literature review concludes that only non-dynamic models have been utilized to address the problem of deciding how and where to expand a trauma network (i.e. geographic configuration of TCCs) and those models do not consider uncertainty characteristics. Most papers simply assume deterministic demand and that every trauma facility serve certain type of injuries. Finally, current models do not consider the impact of unexpected events such as pandemics like COVID-19.

3. FORECASTING METHODOLOGY

3.1. Problem background

A study conducted in September of 2018 showed 280 state designated trauma facilities in Texas [49, 50] with four levels of trauma facilities. These range from I to IV with Level-I operationally the most comprehensive facility, capable of treating injuries across all ranges. Currently in Texas, there are 18 Level-I, 23 Level-II, 54 Level-III, and 185 Level-IV trauma centers. The sustainability of the Texas rural trauma services has been a concern of health professionals, policymakers and citizens for many years [50]. Many issues have been documented in the past, but industry leaders and policymakers have performed partial assessments with the available data. Therefore, there is a limited understanding of the current realities of trauma services in rural Texas. This thesis presents the first attempt to identify and quantify areas for the future expansion of trauma system in Texas.

In order to understand the trauma injuries behavior in Texas, this research addresses the following major questions:

1) Does the number of trauma injuries vary over time?
2) Does the number of trauma injuries change as a function of location?
3) After analyzing the performance and behavior of injuries data, which forecasting model provides the most accurate results to quantify the injuries behavior?

Five forecasting methods are evaluated. The results are then analyzed as a function of forecast accuracy and variability. The details of the approach are discussed in the following sub-sections.

3.2. Data collection method

We collaborated with the Texas DSHS to collect statistics pertaining to trauma injuries occurring within a specified geographic region. The department provided data for a period of three years. The records contain several data arrays, yet the study focuses on the data fields which are relevant to the problem at hand. The data fields are listed in Table 1, and include the patient Injury Severity Score (ISS), the regional location of the trauma injury (i.e. county), the level of TCC providing care to the patient (i.e. Level-I, II, III, or IV), environment where the injury took place (i.e. industrial complexes, streets and highways, and public buildings), and injury date. This ISS is given by the trauma facility based on the patient condition at the time of the arrival. The collected data and some of the discussed data fields are used to develop forecasting models to predict future TCC service demands at different locations in Texas.

Table 1. Summary of key fields for trauma accidents

Field	**Description**	**Units**
Regional Location	Regional location of the accident where trauma injury is reported	Location is based on zip codes
Trauma center	Level of TCC providing care to the patient	The trauma center level ranges from I to IV. Level-I provides most comprehensive care
Injury Severity Score (ISS)	Index provided by the trauma facility based on the patient health condition at the time of the arrival.	Score goes from 1 to 75 on an ascending basis
Injury environment	Environment where the injury took place (i.e. industrial complexes, streets and highways, public buildings, etc.)	Environment type designated by codes ranging from 849.0 to 849.9
Injury date	The date the injury was reported	Month, day, year
TCC service demand	The number of trauma injuries reported daily per region. This is the variable of interest which will be forecasted using the models.	Number of injuries expected per region

3.3. Descriptive analysis of trauma injuries

A descriptive analysis of the injury data is considered as part of the methodology to understand the correlation between the variable of interest (i.e. TCC service demand) and the rest data fields listed in Table 1. A class information structure is developed to perform the descriptive analysis. Based on Table 1 four classes are constructed they are listed in Table 2. The classes C_L, C_C, C_T, and C_I are formed to present descriptive statistics to showcase the trends and patterns of the injuries based on the specific data field.

Table 2. Descriptive analysis class structures for trauma accidents

Class (C_i)	**Description**	**Class members** $\{ \boldsymbol{c} \mid \boldsymbol{c} \in \boldsymbol{C_i} \}$
C_L	Injury regional location	(78666, 78640, …)
C_C	Trauma center level	(Level-I, Level-II,…)
C_T	Injury type (based on severity score)	(1, 2, 3, 4, 5,…, 75)
C_I	Injuries environment type	(Homes, industrial, road, public building)

3.4. Predictive analysis of trauma injuries

As stated earlier, the goal of this thesis is to analyze data on trauma injuries in rural Texas and to build robust forecasting models to predict future service demands for different regional locations. Different forecasting methods are evaluated to find the best fit according to each regional location. These models use information on injuries occurring and recorded across the zip codes of study to predict future demand for trauma centers. Since accidents and injuries are present across a year, being recorded daily, time series analysis and time series plots are used to visualize the data and to study the performance of the forecasting methods considered in this study. Table 3 lists the parameters which will be used in subsequent forecasting models. Table 4 summarizes the predictive models investigated in this research.

Table 3. Forecasting models parameters

Parameter	Description
$\hat{Y}_t$	denotes the forecast in time t
Y_t	denotes the observation in time t
$\hat{X}_t$	denotes estimates of the level or systematic component
T_t	denotes estimates of the level or systematic trend
I_t	denotes estimates of the level or systematic seasonality
m	denotes the number of periods in the seasonal cycle
τ	denotes the number of periods in the forecast lead time
b	denotes slope or rate of change of Y given X_{nt}
X_{nt}	denotes a predictor of Y

Table 4. Forecast models

Model	Forecast equation	Parameters
Moving average	$\hat{X}_t = n^{-1}(\sum_{i=1}^{n} Y_{t-1})$ $\hat{Y}_t = \hat{X}_t$	n
EWMA (*simple exponential smoothing*)	$\hat{X}_t = \hat{X}_{t-1} + \alpha(Y_{t-1} - \hat{X}_{t-1})$ $\hat{Y}_t = \hat{X}_t$	α
EWMA-additive trend (*Holt's method*)	$\hat{X}_t = \alpha Y_t + (1-\alpha)(\hat{X}_{t-1} + T_{t-1})$ $T_t = \beta(\hat{X}_t - \hat{X}_{t-1}) + (1-\beta)T_{t-1}$ $\hat{Y}_t = \hat{X}_t + T_t$	α, β
EWMA-additive trend and seasonality (*Winter's method*)	$\hat{X}_t = \alpha(Y_t/I_{t-m}) + (1-\alpha)(\hat{X}_{t-1} + T_{t-1})$ $T_t = \beta(\hat{X}_t - \hat{X}_{t-1}) + (1-\beta)T_{t-1}$ $I_t = \gamma\left(\frac{Y_t}{\hat{X}_t}\right) + (1-\gamma)I_{t-m}$ $\hat{Y}_{t(\tau)} = (\hat{X}_t + \tau T_t)I_{t+\tau-m}$	α, β, γ, m
ARIMA	$\hat{Y}_t = c + \sum_{i=1}^{p} a_i Y_{t-i} - \sum_{i=1}^{q} b_i \epsilon_{t-1} + \epsilon_t$	a, b, c

3.4.1. Moving average and exponential smoothing methods

Forecasting can be defined as ‘ predicting the future as accurately as possible, given all of the information available, including historical data and knowledge of any future events that might impact the forecasts’[51]. A common approach is to observe past data through a time series. This practice is widely used to predict outcomes based on historical trends and data. The first forecasting method to be investigated is the moving average approach. Moving average will smooth out the curve of the data based on past injuries. The moving average length will be analyzed until finding the best fit for the method.

Exponentially weighted moving average (EWMA) or simple exponential smoothing, is the second forecasting method used in this study. Exponential methods of smoothing predict a future value based on a weighted sum of past observations. The key factor is that the model used a weight which decreases exponentially. Table 4 describes the equations and parameters for the exponential smoothing forecasting methods. $\hat{Y}_t$ models the number of patient injuries at a particular region. The time is denoted by t. Y_t denotes the observation of the injury occurrence in a day t. EWMA methods will consider level, trend, and seasonality to get more accurate results. $\hat{X}_t, T_t$, and I_t represent level, trend, and seasonality, respectively. Parameter m will be used to denote seasonality which represents the number of time periods in the cycle. The number of forecast lead time periods will be denoted by π. Presence of levels or trends or both will be the deciding factor in choosing the appropriate modes [52]. Discernible data, if present, will be favored by trend-based methods. This study uses the additive approach, knows as the Holt’s method, even though multiple approaches exist such as multiplicative, damped additive, and additive. If trend and seasonality are present, the application of additive trend and multiplicative seasonality will be used, referred to as Winter's method.

3.4.2. ARIMA method

The study also investigates the Autoregressive Integrated Moving Average (ARIMA) method. ARIMA uses both autoregressive and moving average methods. It is appropriate to use ARIMA if the time series data is correlated with prior observations. The model can be described as follows:

- The number of autoregressive terms 'p'
- The number of past forecast errors 'q'
- The number of difference terms needed to make a non-stationary time series stationary 'd'

Differencing, represented by d, specifies the number of times the series is differenced, to transform a non-stationary series into a stationary one. The model is written as ARIMA (p, d, q). If the data is stationary to begin with, it can be written as $(p\ ,0, q)$. The forecast for patient arrival at time t, $\hat{Y}_t$, is presented in Equation 1.

$$\hat{Y}_t = c + \sum_{i=1}^{p} a_i\, Y_{t-i} - \sum_{i=1}^{q} b_i \epsilon_{t-1} + \epsilon_t \qquad (1)$$

In the equation, a_i and b_i are the correlation coefficients associated with prior observations and random shocks ϵ_t respectively. Prior to fitting an ARIMA model, the modeler must be determined if the data is stationary. This can be confirmed by performing the Augmented Dickey-Fuller unit root test. Differencing will be carried out until the data is stationary. ARIMA models will be determined by matching the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots. The ACF and PACF will be interpreted to determine the autoregressive (p) and moving average (q) terms. The validity of the selected model will be determined by certifying that the residuals are a series of random errors. If the previous statement is true, there should not be any autocorrelations, full or partial, present.

For every model tested, one period forecasts will be generated. These forecasts are represented by $Y_{t+1|t}$ where $Y_{1\dots}Y_t$ are assumed known. The model that has the smallest mean absolute percentage error (MAPE) will be applied to the out of sample data to assess its validity for future time series analysis. Equation 2 is used to compute the MAPE for one time-period in the future.

$$MAPE = T_0^{-1}\left[\sum_{t=T}^{T+T_0}\left|\frac{\hat{Y}_{t+1|t} - Y_{t+1}}{Y_{t+1}}\right|\right] * 100 \qquad (2)$$

3.5. Case study

The scope of the study is limited to a specific number of counties in the state of Texas. Once the subsequent model is determined to be producing the results expected, the scope can be enlarged to the entire state, and perhaps on a national level. Due to patient confidentiality reasons, the injury locations for this study were reported using three-digit zip codes which represent different counties in the state of Texas. The data sets were filtered and analyzed to include these specific counties to determine the trend of trauma injuries over a period of three years viz 2014, 2015, and 2016. Figure 1 shows the counties considered in the case study. Table 5 provides greater detail for the counties under analysis.

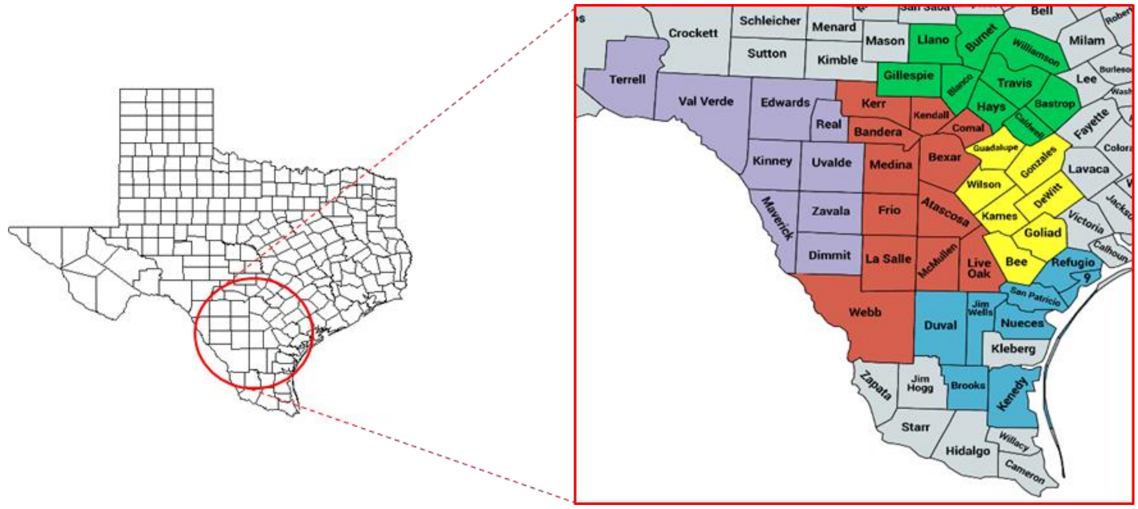


Figure 1. Texas state counties considered in current study

Table 5. Zip code associated with the counties considered in current study

Injury location (3-digit zip code)	Counties
780	Atascosa, Bandera, Bexar, Comal, Frio, Kendall, Kerr, Live Oak, Medina
781	Bee, Bexar, Comal, De Witt, Gonzales, Guadalupe, Karnes, Wilson
782	Bexar, Comal
783	Aransas, Bee, Brooks, Duval, Jim Hogg, Jim Wells, Kenedy, Kleberg, Live Oak, Nueces, Refugio, San Patricio, Webb
786	Bastrop, Blanco, Burnet, Caldwell, Comal, Gillespie, Gonzales, Guadalupe, Hays, Llano, Travis, Williamson
787	Travis, Williamson, Hays
788	Bandera, Dimmit, Edwards, Kinney, Maverick, Medina, Real, Terrell, Uvalde, Val Verde, Zavala

3.6. Descriptive analysis results

In this sub-section a descriptive analysis of the trauma injury data is performed. The goal of the descriptive analysis is to understand the relation between the *TCC service demand* and the following data fields listed in Table 1.

- *Regional location*
- *Trauma center*
- *Injury Severity Score (ISS)*
- *Injury environment*

The following sub-sections will present data plots and insights for each of the data fields (i.e. regional location, trauma center, ISS, and injury environment).

3.6.1. Descriptive analysis for injury regional location

Figure 2 provides a side-by-side comparisons of all injuries in the regions considered in this study for years 2014, 2015, and 2016. The results of our initial analysis show that locations where the highest number of injuries are registered are, 782, 786, and 787. Zip code 787 has Travis county with a population of about 1.274 million in 2019. Travis county contains the city of Austin which has large number of corporations and manufacturing facilities. Zip code 782 includes Bexar county which is home for the city of San Antonio. Bexar county has about 2.0 million of residents and also contains many corporation and manufacturing facilities. Finally, zip code 786 contains the Austin suburbs, a region that has experience an exponential growth in the past ten years[53]. An important insight from this graph is the declining trend for the three regions with the highest numbers. The rest of the regions show an increase in the number of cases from

2014 to 2015 and then a decline from year 2015 to 2016. It is important to consider the variable patterns for regions 780, 781, 783, and 788 since these are mostly rural regions. Understanding the variability in these regions is important for the future expansion of the trauma network in Texas.

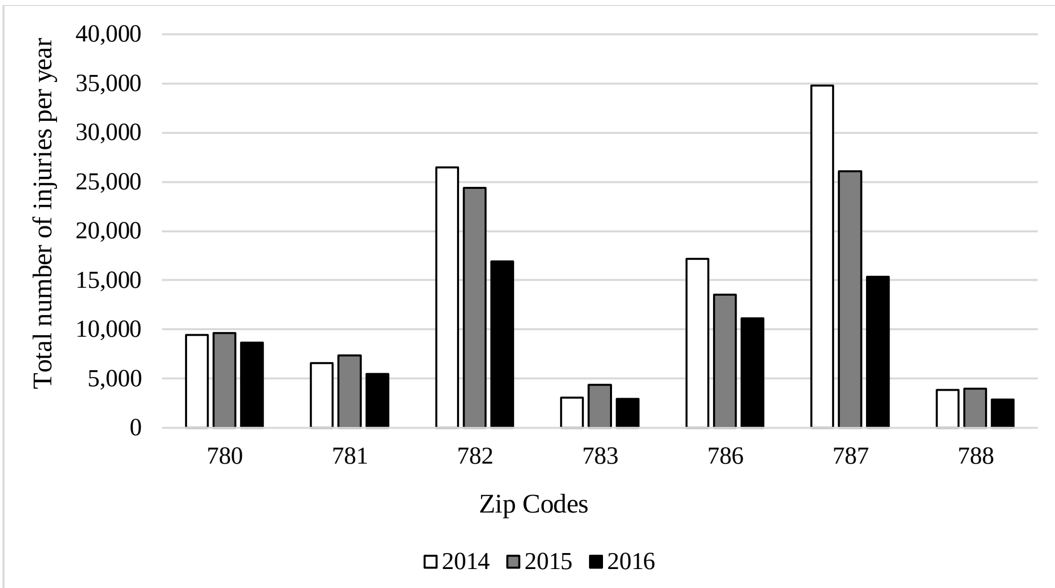


Figure 2. Number of trauma injuries reported per zip code for years 2014, 2015, and 2016

3.6.2. Descriptive analysis for trauma center level

TCCs are designated using four different levels, starting from I to IV. Level-I are *comprehensive* facilities, capable of provide the most extensive care to any injured patient. Only 6% of TCCs in Texas are designated as Level-I trauma facilities. Level-II TCCs are labeled as *major* facilities and only 8% of TCCs in Texas are designated at this level. Level-III TCCs are labeled as *advanced* trauma facilities and only 20% of TCCs in Texas are designated at this level. Finally, Level IV-TCCs are labeled as *basic* trauma facilities and 66% of TCCs in Texas are designated at this level. Therefore, most of the TCCs in Texas (86%) are designated as Level-II or Level-IV facilities.

Figure 3 depicts the yearly percentage of trauma injuries treated per level of TCC. The plot only considers counties and zip codes presented in Table 5. A total of 53 TCCs facilities were located in the studied region. Four of those facilities are Level-I TCCs, three are Level-II TCCs, and the rest are Level-III and Level-IV. The results show that Level-I TCCs treat at least 35% of the trauma injuries per year, treating more trauma patients than Level-II, Level-III, and Level-IV TCCs. This is relevant because, as stated earlier, only 6% of TCCs in Texas are designated as Level-I trauma facilities. Possible explanations for this phenomenon are that Level-I TCCs are mostly located in large metropolitan areas with high population densities. Also is interesting to notice that Level-II trauma facilities, which are *major* TCCs, treat less patients than Level-III and Level-IV TCCs. A possible explanation for this finding is that only one Level-II TCC is located in the area under study. The number of trauma patients served per year per trauma level does not vary greatly. For instance, the percentage of trauma injuries assisted by Level-I TCCs was between 34% and 37% for years 2014, 2015, and 2016. However, it is important to notice the significant variability among all trauma levels. For instance, Level-II TCCs only serve about 15% of the trauma injuries when compared to about 35% for Level-I TCCs, 27% for Level-III TCCs, and 23% for Level-IV TCCs. The variability could indicate a need for better protocols at the time of selecting the Trauma hospital to transport the injured patients for care. Better trauma hospital selection processes can help in avoiding facilities overutilization or underutilization.

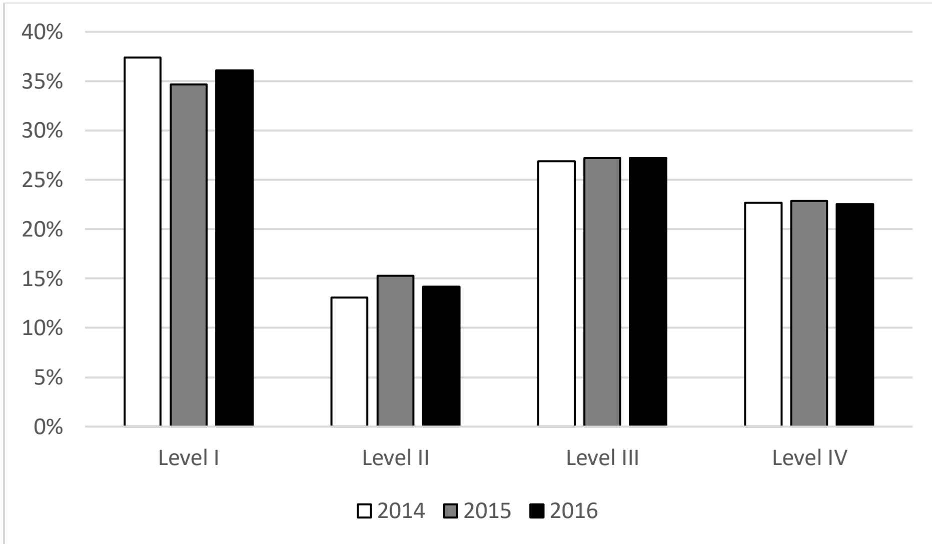


Figure 3. Percentage of trauma injuries assisted by TCC level per year

3.6.3. Descriptive analysis for injury severity score (ISS)

In this sub-section we investigate the average and variance of the ISS for patients treated at TCCs per level for years 2014, 2015, and 2016. These ISS's range from 1 to 75 with the latter being the most extreme case. Since it was observed that some TCCs levels are utilized more than others, it is important to determine the range of injuries received at these facilities. Since TCC Level-I are comprehensive trauma facilities, they are expected to manage mostly severe cases with high ISS. Therefore, the range of the ISS per trauma level could be used to determine if each TCC level is serving patients according to the level of care they can provide. Overutilizing *comprehensive* (Level-I) and *major* (Level-II) levels TCCs with patient cases that are not severe could compromise the trauma network capacity for the state in the event of natural or man-made disasters (i.e. COVID-19).

Figure 4 presents a box plot summarizing the range of ISSs recorded by trauma level for the year 2014. ISSs for trauma Level-I have a median of 9 and a mean value of 9.75. ISSs for trauma Level-II have a median of 6 and a mean value of 8.45. ISSs for trauma Level-III have a median of 5 and a mean value of 7.75. ISSs for trauma Level-IV have a median of 5 and a mean value of 6.78. Figure 4 shows similar patterns among TCC levels for year 2014. Although the variability for trauma Level-I is higher, the plot shows that patients with very low ISS were served at Level-I trauma facilities.

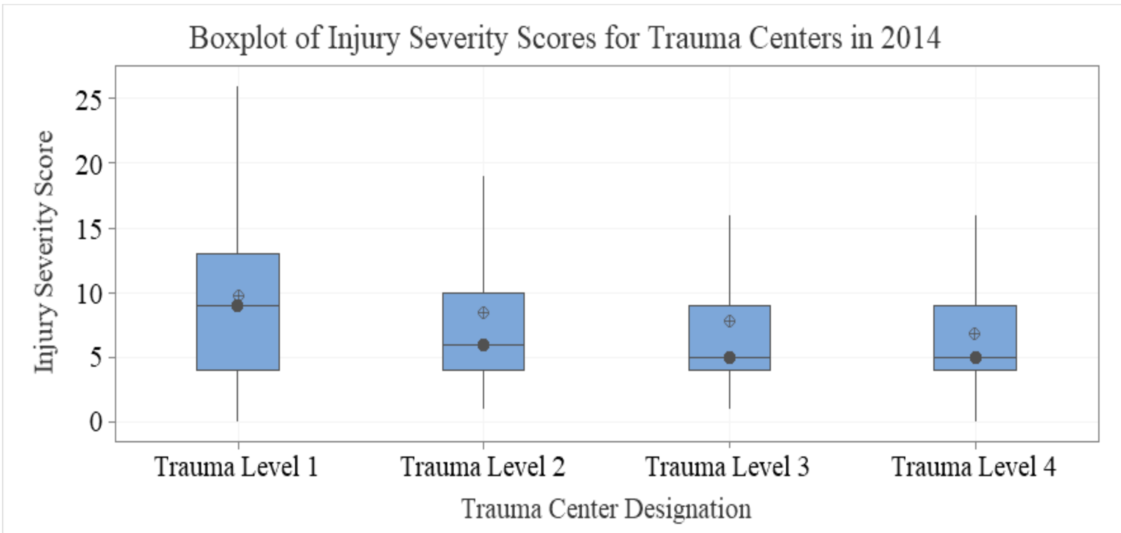


Figure 4. Injury severity scores per trauma level for 2014

Figure 5 presents a box plot summarizing the range of ISS's recorded by trauma levels for the year 2015. ISS's for trauma Level-I have a median of 5 and a mean value of 9.19. ISS's for trauma Level-II have a median of 5 and a mean value of 7.85. ISS's for trauma Level-III have a median of 5 and a mean value of 7.12 and ISSs for trauma Level-IV have a median of 4 and a mean value of 6.20. Year 2016 shows a similar pattern. Figure 6 presents a box plot summarizing the range of ISS's recorded by trauma levels for the year 2016. ISS's for trauma Level-I have a median of 5 and a mean value of 8.76. ISS's for trauma Level-II have a median of 5 and a mean value of 7.42. ISS's for trauma Level-III have a median of 5 and a mean value of 7.10. ISS's for trauma Level-IV have a median of 4 and a mean value of 6.23.

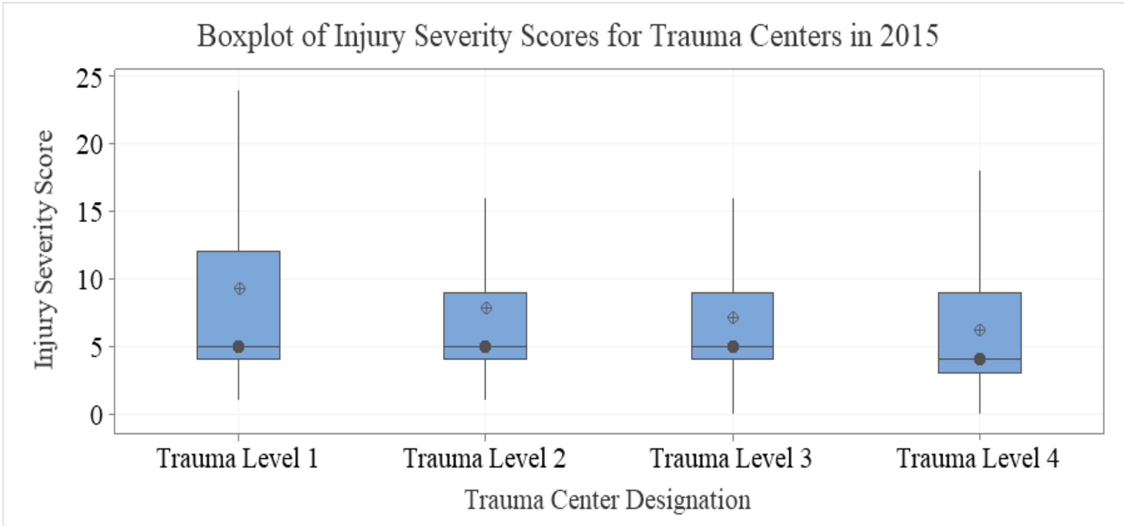


Figure 5. Injury severity scores per trauma level for 2015

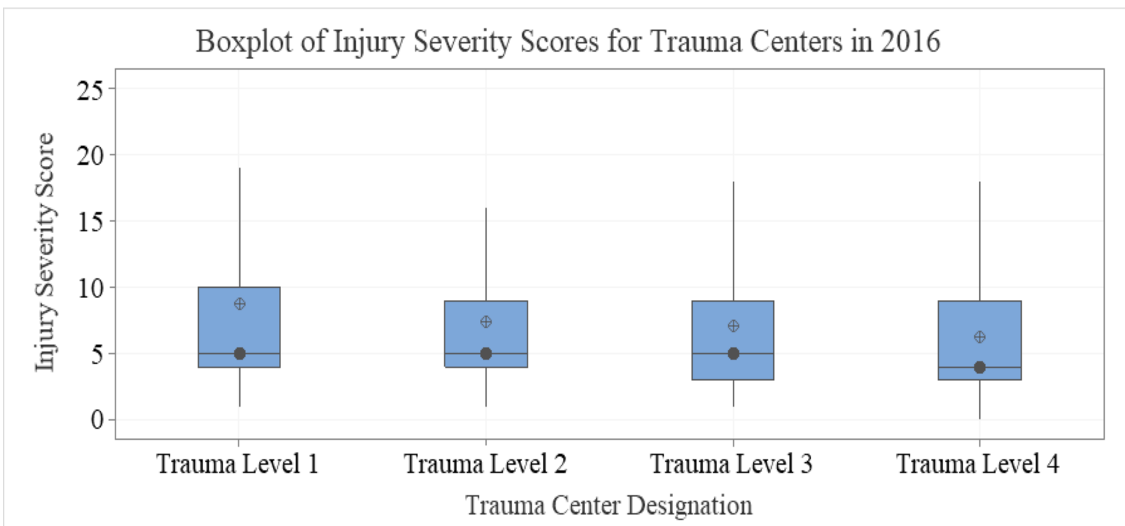


Figure 6. Injury severity scores per trauma level for 2016

It is important to highlight that there is a decrease in the mean and median values for trauma Level-I from year 2014 to years 2015 and 2016. Therefore, the data shows that trauma levels are not necessarily taken into consideration when choosing the facility providing care to the patient. Those decisions should be based on the type of injury sustained by the patient in order to balance the utilization of the trauma network.

3.6.4. Descriptive overall analysis demand behavior considering injury environment

There are ten environment location codes for trauma injuries ranging from 849.0 to 849.9. The different codes represent the type of facility/environment where the injuries occur. The analysis focuses on the four codes that are repeated the most, 849.0 for homes, 849.3 for industrial facilities, 849.5 for street and highway, and 849.6 for public buildings. Figures 7 to 9 contain four boxplots each, one per environment location. Figures 7, 8, and 9 represent the data for years, 2014, 2015, and 2016, respectively. Each boxplot presents the number of injuries per regional location according to the environment location considered.

Figure 7a compares the number of injuries recorded at homes across all zip codes in 2014. Zip code 782 accounts for the highest number of recorded injuries with a median of 1,009 followed by zip codes 786 and 787. Zip code 782 includes Bexar county which is home for the city of San Antonio. Bexar county has about 2.0 million of residents with more than 632,000 households. Similarly, zip codes 787 and 786 includes parts of Travis county, home of the city of Austin, with a population of about 1.274 million in 2019 and more than 550,000 households.

The number of injuries for industrial zones is small when compared to the injuries in the home environment as observed in Figure 7b [54]. For industrial zones, zip codes 782 and 781 account for the highest number of recorded injuries with a median of 9 and 8 injuries, respectively. Zip code 781 includes Bexar county which is home of multiple industrial and manufacturing companies including vehicles and HVAC and refrigeration equipment. Zip code 787 in on third place with 7 injuries. Zip code 787 includes parts of Travis county, home of the city of Austin, which is home of multiple companies dedicated to the manufacturing of computer and peripherals and also to the manufacturing of semiconductors and electronic components.

Figure 7c compares the number of injuries recorded on streets and highways. The top three zip codes with the highest volume of injuries were zip code 787 with a median value of 432, zip code 786 with a median value of 314.5, and zip code 782 with a median value of 268. These three zip codes cover the I-35 corridor that connects San Antonio with Austin. Almost 40 percent of Texans and over 40 percent of Texas jobs were located in the 21 counties along I-35. The population in the counties along the I-35 corridor is expected to increase from 9.7 million in 2010 to 17.7 million by 2040, an increase of approximately 82 percent. The number of crashes in the I-35 corridor is approximately 8.4 percent higher than the statewide urban crash rate for interstate facilities [55] Figure 7d displays the injuries occurring in public buildings across all zip codes. Zip code 787 accounted for the highest number of injuries recorded with a median value of 136 followed by zip code 782 with a median value of 67.5. The rest of the regions showed significantly lower rates. Zip code 787 contains the city of Austin which is home for multiple state government buildings and zip code 782 houses the city of San Antonio which also contains a large number of public buildings.

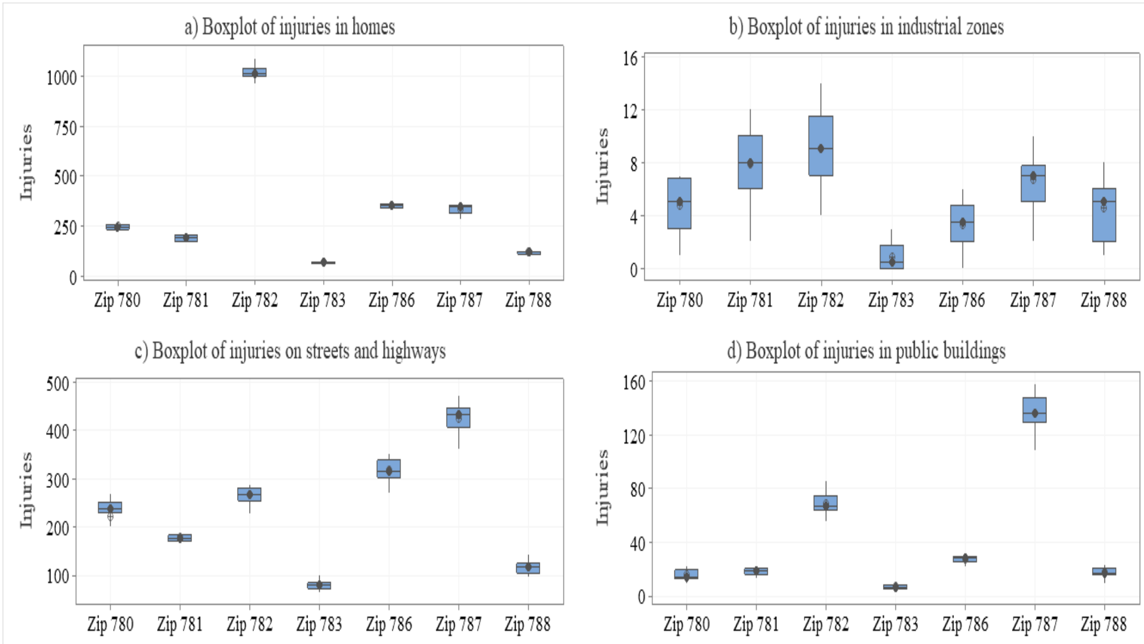


Figure 7. Injuries recorded by injury environment per regional location in 2014

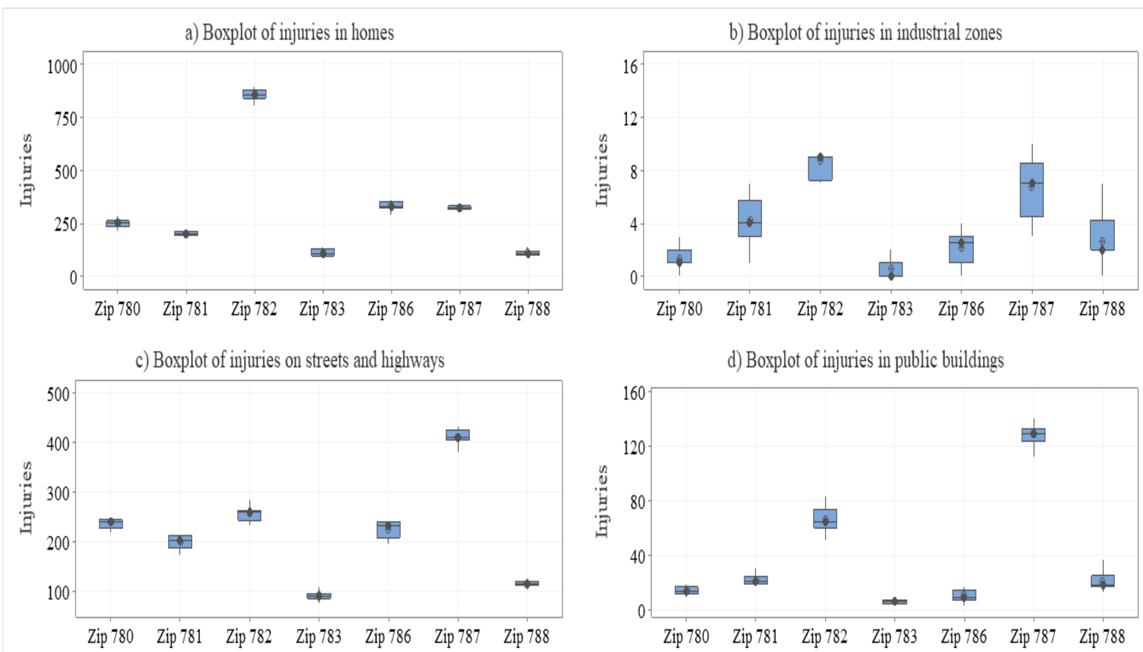


Figure 8. Injuries recorded by injury environment per regional location in 2015

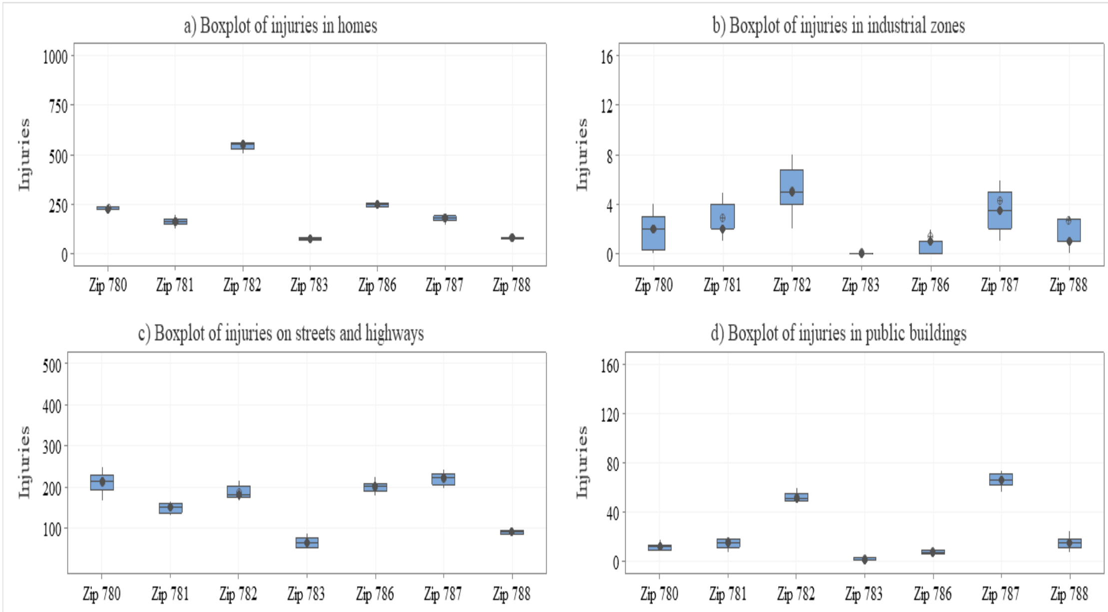


Figure 9. Injuries recorded by injury environment per regional location in 2016

Figure 8 and Figure 9 present the results for years 2015 and 2016, respectively. The trends observed for years 2015 and 2016 were similar to those observed in year 2014. In summary, it is observed that the industrial facilities environment (i.e. code 849.3) accounts for the least number of injuries for any given year. The homes environment (i.e. code 849.0) accounts for the highest number of injuries for any given year with zip code 782 presenting the regional location with the highest number of injuries. Finally, zip code 787 presents the highest number of injuries occurring in the street and highway environment (i.e. code 849.5), and for public buildings environment (i.e. code 849.6).

3.7. Predictive analysis results

In this sub-section different forecasting methods are evaluated to find the best models for predicting the expected number of injuries per regional location. Injuries are considered on a daily base. Time series analysis and time series plots are used to visualize the data and to study the performance of the forecasting models.

3.7.1. Time series analysis per year

Figure 10 presents time-series for the total number of trauma injuries per year for years 2014, 2015, and 2016. The time-series plot is consistent with the results presented in Figure 2 where years 2014 and 2015 present a higher total number of injuries per year when compared to year 2016. Year 2015 shows more variability in the number of injuries reported per day when compared to year 2014. The maximum and minimum number of trauma injuries reported per day in 2015 were 361 and 237, respectively. For 2014 the maximum and minimum number of trauma injuries reported per day were 333 and 245, respectively. Finally, in 2016, the maximum and minimum number of trauma injuries reported per day were 255 and 153, respectively. Year 2016 shows a drop of about 100 trauma injuries reported per day when compared to years 2014 and 2015.

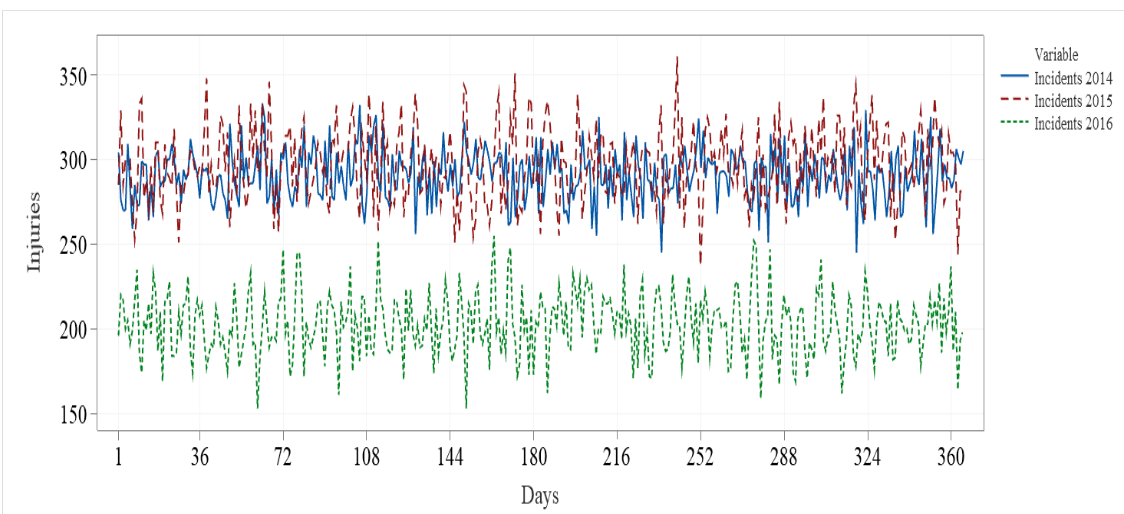


Figure 10**.** Time series plot for injuries for years 2014, 2015, and 2016

3.7.2. Time series analysis considering zip codes per year

Figures 11, 12, and 13 present the time series for all regional locations (i.e. zip codes) for years 2014, 2015, and 2016, respectively. These time-series plots are consistent with the results presented in Figure 2 where zip codes 787 and 782 presented a higher total number of injuries per year. Year 2016 show a decrease in the number of injuries recorded as compared to the previous years but do present similar patterns with respect to the zip codes.

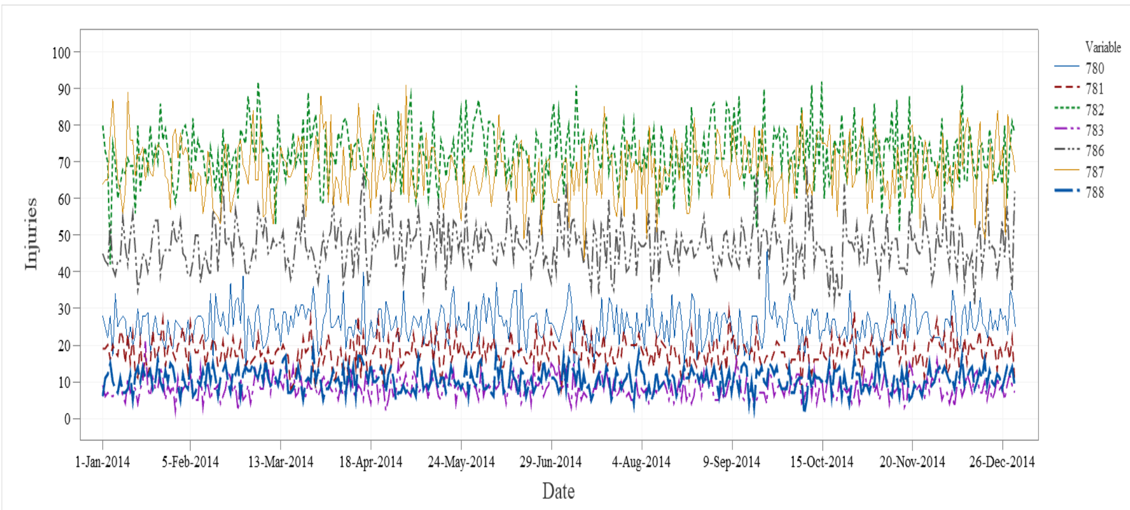


Figure 11. Time series plot for injuries for all zip codes in 2014

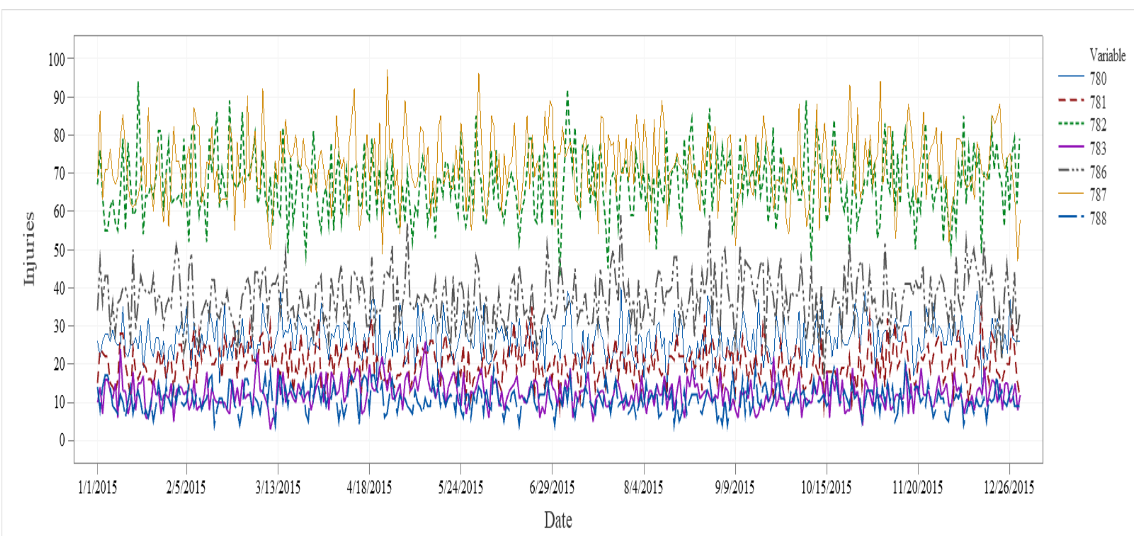


Figure 12. Time series plot for injuries for all zip codes for 2015

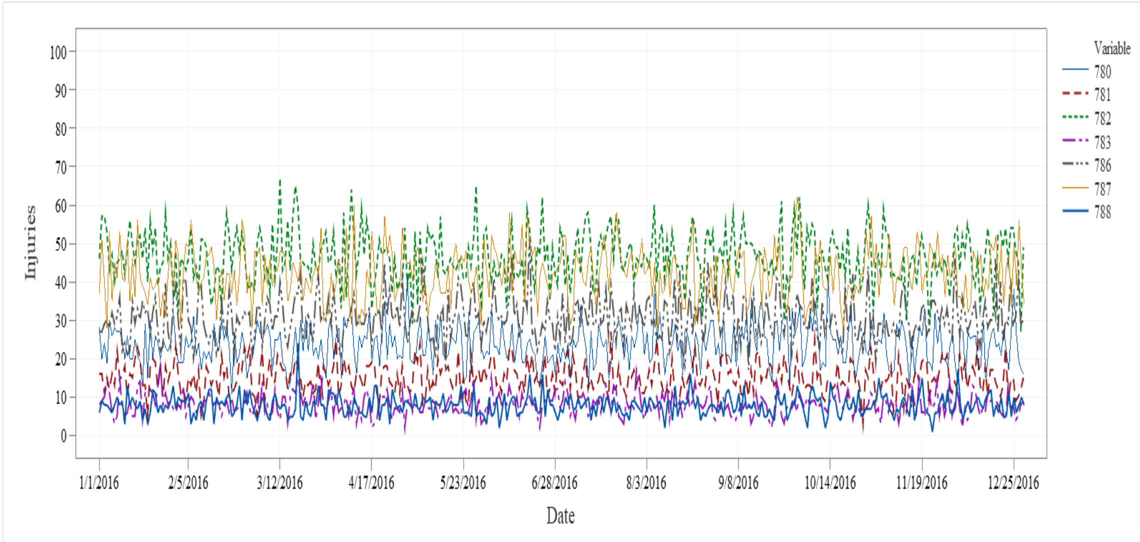


Figure 13. Time series plot for injuries for all zip codes in 2016

As mentioned earlier, zip code 782 contains Bexar county which includes the city of San Antonio, one of the largest cities in Texas, whereas zip code 787 is for Travis County which includes the city of Austin, a major urban location. As these cities are highly populated areas located in the I-35 highway corridor, it is logical to attribute the relation between the number of injuries recorded and location. Zip code 783 accounts for the third highest recording of injuries across all years. Zip code includes Travis, Williamson, and Hays counties. These regions are quite populated since they contain the Austin suburbs, an area that has experience an exponential growth in the past ten years [53].

3.7.3. Forecast model results

Forecasting models, as presented in Table 4, were implemented for the trauma injury data per year. The choice of model will depend on the lowest MAPE. As per the class structure stated prior, C_L denotes the injury location. The five forecasting methods listed in Table 4 were evaluated for each zip code to determine which would result in the lowest MAPE value for each zip code. Table 6 presents the results for the year 2014. The highlighted cells show the lowest MAPE value corresponding to the forecasting model. For the year 2014, it is observed that for most regional locations, ARIMA provides the best performance to use for forecasting. The exception being that for 'Injuries/Day', which includes the data for all zip codes, and 'Zip Code 782'. For those two cases EWMA-additive trend and EWMA provided the best performance, respectively.

Table 6. MAPE results for 2014

Injury location	Moving average	EWMA (simple exponential smoothing)	EWMA-additive trend (Holt's method)	EWMA-additive trend and seasonality (Winter's method)	ARIMA
Injuries/Day	4.82	4.46	**4.45**	4.57	4.46
ZIP Code 780	17.88	16.40	16.39	16.65	**16.32**
ZIP Code 781	20.75	19.18	18.94	19.18	**18.91**
ZIP Code 782	9.53	**8.85**	8.89	9.10	8.88
ZIP Code 783	37.82	34.74	34.76	35.97	**34.64**
ZIP Code 786	12.63	11.28	11.30	11.93	**11.26**
ZIP Code 787	10.84	9.88	9.77	10.46	**9.76**
ZIP Code 788	32.15	30.66	30.57	31.45	**30.55**

Table 7 presents the results for the year 2015. The model selection for this year changed for several regional locations when compared against 2014. For zip codes 780, 783, and 786, the simple exponential smoothing method provided a better performance instead of ARIMA. In addition, the best performer for the aggregated data (i.e. 'Injuries/Day') is now moving average instead of EWMA-additive trend.

Table 7. MAPE results for 2015

Injury location	Moving average	EWMA (simple exponential smoothing)	EWMA-additive trend (Holt's method)	EWMA-additive trend and seasonality (Winter's method)	ARIMA
Injuries/Day	**6.00**	6.02	6.61	6.01	6.02
Zip Code 780	17.95	**16.28**	17.25	17.81	16.71

Zip Code 781	22.15	21.63	21.57	21.94	**21.32**
Zip Code 782	11.23	**10.51**	11.21	10.71	10.73
Zip Code 783	29.24	**27.83**	28.75	29.76	28.40
Zip Code 786	16.71	**16.06**	16.88	17.24	16.12
Zip Code 787	10.90	10.37	10.83	11.24	**10.31**
Zip Code 788	30.76	29.71	30.96	31.54	**29.47**

Table 8 presents the results for year 2016. There are multiple regional locations for which the forecasting model selection remained consistent for every year 2014, 2015, and 2016. For instance, ARIMA was the model selected for zip codes 781 and 788 for all years. Also, EWMA was the model selected for zip code 782 every year. EWMA and ARIMA were provided the best performance for zip codes 780, 786, and 787 in different years. The forecasting model selection for zip codes 783 was different every year and included ARIMA, EWMA, and EWMA-additive trend. Based on the previous results, it can be concluded that EWMA and ARIMA forecasting methods provides the best performance for forecasting trauma injuries in the studied region in Texas. Out of the 24 evaluated time series, EWMA provided the best performance for 9 and ARIMA provided the best performance for 12. The parameters for the ARIMA models are listed in the Appendix.

Table 8. MAPE results for 2016

Injury Location	Moving average	EWMA (simple exponential smoothing)	EWMA-additive trend (Holt's method)	EWMA-additive trend and seasonality (Winter's method)	ARIMA
Injuries/Day	7.37	**7.30**	7.50	7.65	7.34
Zip Code 780	20.82	20.09	20.61	20.91	**20.09**
Zip Code 781	26.32	25.44	25.31	26.27	**25.11**
Zip Code 782	12.90	**12.35**	12.41	13.02	12.37
Zip Code 783	36.82	36.73	**36.21**	37.38	36.22
Zip Code 786	15.58	**14.53**	15.17	15.83	15.14
Zip Code 787	13.84	**13.68**	13.73	14.61	13.71
Zip Code 788	36.81	37.46	35.40	38.07	**35.34**

Table 9 presents descriptive statistics of all data sets for the years 2014, 2015, and 2016. The MAPE values in Table 9 represent the value for the best performing forecasting model. The class designation in Table 9 is explained as follows. Classes I2014, I2015, I2016, denote the total injuries occurring in the years 2014, 2015, and 2016, respectively. A three-digit zip code followed by the year designation contain the descriptive statistics in addition to the MAPE for the best performing forecasting model. 780/2014 row will comprise statistics for all injuries occurring in zip code 780 for the year 2014. This nomenclature is shared by all zip codes in Table 9 for all years.

Table 9. Forecasting models results

Class	CV	MAPE	Minimum	Maximum	Mean	St.Dev.
I2014	5.50	4.45	245	333	290.68	15.97
I2015	7.37	6.00	237	361	297.10	21.90
I2016	9.12	7.30	153	255	202.83	18.50
780/2014	19.27	16.32	12	46	25.795	4.97
781/2014	21.90	18.91	8	29	17.984	3.94
782/2014	10.85	8.85	42	92	72.447	7.86
783/2014	35.05	34.64	2	21	8.342	2.92
786/2014	14.15	11.26	31	69	47.121	6.67
787/2014	11.90	9.76	43	91	67.956	8.09
788/2014	29.54	30.55	1	19	10.578	3.12
780/2015	19.51	16.28	11	40	26.558	5.18
781/2015	21.18	21.32	9	36	20.236	4.89
782/2015	12.97	10.51	43	94	67.082	8.70
783/2015	30.01	27.83	3	26	12.451	3.74
786/2015	18.74	16.06	16	59	37.140	6.96
787/2015	12.47	10.31	47	97	71.712	8.94
788/2015	30.58	29.47	4	20	10.890	3.33
780/2016	22.61	20.09	11	42	23.788	5.38
781/2016	26.79	25.11	3	27	14.984	0.21
782/2016	14.84	12.35	27	67	46.544	6.91
783/2016	35.86	36.21	2	19	8.121	2.91
786/2016	18.65	14.53	17	52	30.574	5.70
787/2016	16.12	13.68	28	62	42.239	6.81
788/2016	35.62	35.34	1	24	7.904	2.82

Figure 14 showcases the relationship between the coefficient of variation (CV) and the MAPE for all zip codes across 2014, 2015, and 2016. It also includes the comparison for the aggregated total of trauma injuries occurring across the same time span. Figure 14 shows that the increase in variability (i.e. CV) results in increase in forecast error. Zip codes 783 and 788 report the largest values for the CV and the MAPE. Those regional locations observed less numbers of trauma injuries, when compared to the rest, for all years considered in this study as observed in Figures 11 to 13. The limited number of observations could be the reason for the observed higher values for CV and MAPE. Better results were obtained for those regional locations with higher number of injuries reported (i.e. 782 and 787). The same analysis applies to the results observed in Figure 14d. A smaller amount of trauma injuries were observed in year 2016, as compared to years 2014 and 2015 as observed in Figure 10. Therefore, the MAPE reported in year 2016 is higher than the values reported for years 2014 and 2015.

3.8. Decision making using experimental results

In this sub-section, an algorithm is proposed to make decisions using the results and insights from chapter 3, sub-sections 3.6 and 3.7. The descriptive analysis of the data showed that location environments such as homes and proximity to highways are linked to a higher volume of injuries.

Algorithm

For all $\ell \in L$;
    If $p_\ell \geq \omega$;
        $\ell \cup R$;
    Else.
For all $\ell \in R$;
    If $d_\ell \leq \beta$;
        $\ell \cup H$;
    Else.
For all $\ell \in H$;
    If $e_\ell \leq \delta$;
        $\ell \cup I$;

Figure 14. Algorithm

The proposed algorithm is used to identify regional locations with an expected increase of population and located close to highways that have limited access to TCCs. The following notation is used in the algorithm. Let $t \in T$ define the set of TCCs in the current network the former of which is located within the region under study. The algorithm can be scaled from point sources to a general area, but the ideal setup would be to choose a point of study and expand outwards. This can be done by choosing distance radii from the point of origin and encompass the trauma centers that are located with the distance set by the programmer. Let $\ell \in L$ be the set of regional locations considered in the study and p_ℓ the percentage increase in the last 10 years for regional location ℓ. The way to set a defining parameter for population would be to determine eligibility by analyzing the total population of a location to determine a feasible minimum cut off point. It would be preferable to handle it by a case to case basis to obtain better results and even to use *growth rate percentage* as a performance measure. Another method would be to use a range of percentages to allow more flexibility when ascertaining which locations would be eligible to place a trauma center near them. Let set R be a subset of L which defines the regional locations with a population increase $\geq \omega$, where ω is defined by the decision maker. In addition, let d_ℓ denote the travel time from regional location ℓ to the closest major interstate or highway. The travel time must be calculated from a centroid that represents the population of the region. Also, let set H be a subset of R that contains the regional locations ℓ with a travel time $\leq \beta$ from a major highway, where β is defined by the decision maker and let set I be a subset of H that contains the regional locations ℓ with a travel time $\leq \delta$ from a TCC, where δ is defined by the decision maker. Set I will contain the regional locations that must be tracked for future expansion of the TCC network. Figure 14 list the steps of the algorithm.

Applying the proposed algorithm to the data studied in this thesis, the regional location with zip code 786 was identified as having multiple counties with limited access to TCC. Therefore, those counties should be considered for future expansion of the trauma network. Also, the results from the forecasting analysis can be used for capacity analysis. For example, EWMA and ARIMA models can be used to estimate the expected number of injuries for regional location 780. Those results can be used to make a capacity analysis for the TCCs located close the regional location.

An example can be constructed using real time data. Taking zip code 78006, for Boerne, Texas, has had a population growth of 71% since 2010, as per the census report available for 2019 estimates [56]. If the criteria for cut off is set at 50% by the programmer, then it qualifies for the next stage of the process. As the population is considered as a centroid, the distance to the nearest highway or interstate, when using a straight line comes out to be 2.63 miles. If this is less than the limits defined by the programmer then the next phase of the algorithm can be undertaken. Trauma centers within the region of study must be identified and categorized according to their distances from the locations. Table 10 below shows the actual time taken to trauma centers, their names converted to generalized codes to protect identities and is used for presentation purposes only.

Table 10. Time taken to reach trauma centers

Location	Trauma Center	Time in Minutes
78006	TC1	47
78006	TC2	46
78006	TC3	47
78006	TC4	55
78006	TC5	49
78006	TC6	48
78006	TC7	51
78006	TC8	52
78006	TC9	59
78006	TC10	59
78006	TC11	60
78006	TC12	64
78006	TC13	68
78006	TC14	69
78006	TC15	74
78006	TC16	49
78006	TC17	75
78006	TC18	108
78006	TC19	100
78006	TC20	131
78006	TC21	153
78006	TC22	169
78006	TC23	249
78006	TC24	333
78006	TC25	288

If a time limit of 60 minutes is set by the programmer to reach a trauma center, as per the Table 10 above we can see that TC12 and onwards will be rejected due to the constraint provided by the algorithm. There are 11 trauma centers that can serve 78006 within the set time. There are several factors that determine the feasibility of the trauma centers such as capacity, that determines whether they are equipped to handle the demand, services offered, and personnel available but these are out of scope for the current study. If a region has few centers within a certain driving time, then those would be the focus for expansion of the trauma network in that region. As cities and urban population groups expand, there will arise a need for additional trauma centers that can cope up with the rise in demand hence the importance of determining the rise of regional population and the subsequent expansion of ancillary systems such as road networks, industrial and manufacturing hubs, public buildings that are frequented by the population.

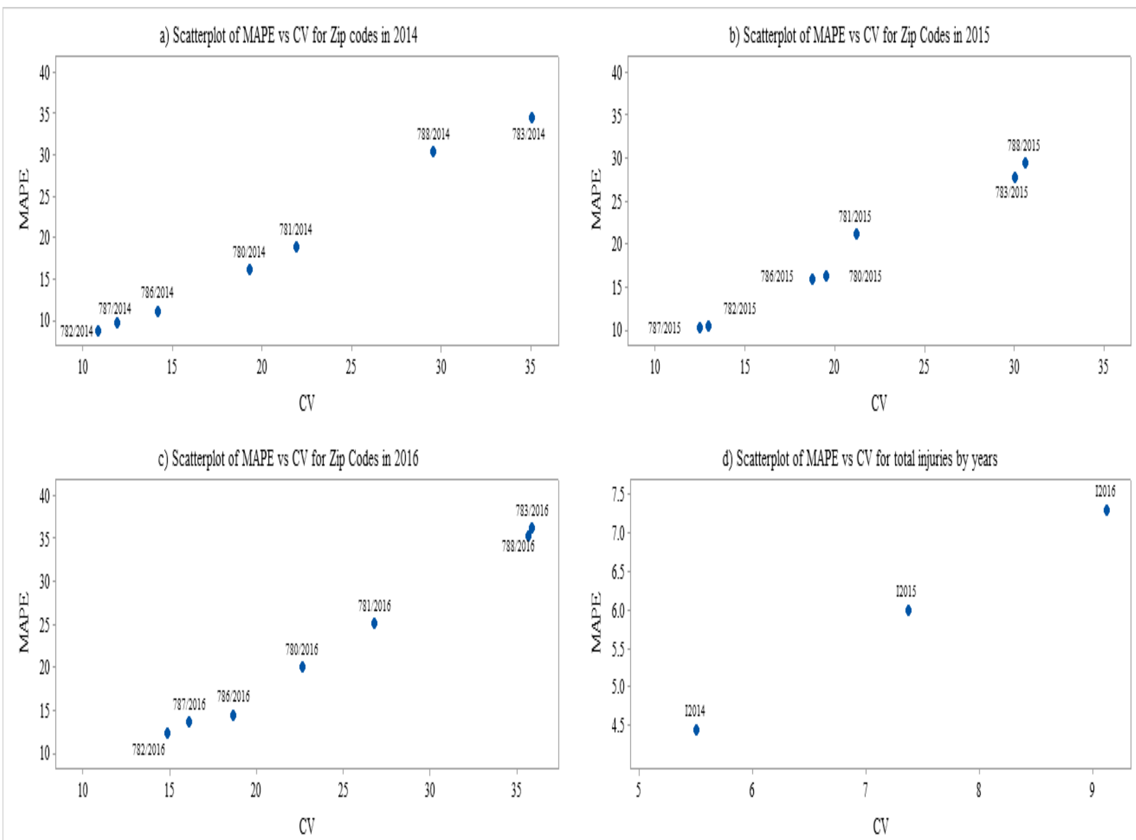


Figure 15. Scatterplot of CV versus MAPE

4. STOCASTIC PROGRAMMING

4.1. Problem description

The problem of maximizing access to TCCs for a population group must consider the location of the population group itself and the location of TCCs that aim to provide services to the concerned group. For the purposes of this study, population groups are identified in terms of their zip code locations for a given geographical region. As is known, the population for any given location, in this case a zip code, is spread across internal communities and zones. Due to this factor, attributing population for the model can be challenging especially when determining which locations can be covered by services. A workaround is to use a population centroid which is the geographical coordinate that represents the entire population of said location. This study utilizes population centroids for zip codes that are subsequently used to determine the distances from zip codes to trauma centers. Let set $i \in I$ represent the set of all zip codes located in the region of study, representing the trauma services demand nodes. These zip codes are located within a service region defined by the state of Texas, known as a Trauma Service Area (TSA). The TSA under study will also have a set of designated TCCs. These are classified as such by the Texas state Department of State Health Services (DSHS) and have a trauma level assigned to them represented by set $\ell \in L$. Every zip code in set I has a demand that is the daily demand by TSA level L associated to it represented by $a_{i\ell}$.

The set of TCCs are represented by set $j \in J$. Some of the TCCs have helipads as part of their infrastructure and are termed as aeromedical depots. These aeromedical depots are represented by set $k \in K$. Clinical intervention is expected within a time S from the moment of an injury incident. Demand region i is geographically covered by an ambulance if there exists a TCC j with $t_{ij}^{G} \leq S$, where t_{ij}^{G} is the driving time from node i to node j. Demand region i is geographically covered by an helicopter if there exists a TCC j with $t_{ki}^{A} + t_{ij}^{A} \leq S$, where t_{ki}^{A} denotes time taken to reach the demand node from the aeromedical depot k and t_{ij}^{A} denotes the time taken to return to TCC j from the demand node i. As a general rule of thumb, S is defined as 60 minutes. Due to this varying demand nature, we modeled the problem as stochastic which consider the uncertainty in the demand for trauma services per regional location. The objective is to find the locations of additional TCCs j and heliports k that will maximize the expected coverage demand within a time a time standard S considering the randomness in the demand.

4.2. Two-stage stochastic programming models

In this sub-section, a two-stage stochastic programming model, named the Stochastic Trauma System Configuration Problem (STSCP), is used to model is presented to model and solve the problem as described in chapter 4 sub-section 4.1. We also present multiple modifications of the STSCP to address different scenarios for the problem. Table 11 below lists the sets, decision variables, and parameters of the proposed optimization model.

Table 11. Decision variables and parameters for proposed optimization model

Sets	
I	Set of injury demand nodes where $i \in I$ (patients in a geographical zone)
J	Set of eligible trauma care center (TCC) locations where $j \in J$

L	Set of trauma center levels $\ell \in L$
K	Set of eligible aeromedical depots (AD) locations where $k \in K$
N_i	$\{j \vert t_{ij}^G \leq S\}$ = TCC sites within the time standard, S, of node i by ground
M_i	$\{(j,k) \vert t_{ki}^A + t_{ij}^A \leq S\}$ = (AD, TCC) pairs within the time standard, S, of node i by air
First Stage Decision Variables	
$x_{j\ell}^{TC}$	=1 if a trauma care center (TCC) level ℓ is sited at node j, 0 otherwise
$x_{k\ell}^{AD}$	=1 if a heliport (AD) is sited at node k with a level ℓ trauma facility, 0 otherwise
$z_{kj\ell}$	=1 if an AD is sited at node k and a TCC level ℓ is sited at node j , 0 otherwise
Second Stage Decision Variables	
$y_{i\ell}^{\omega}$	=1 if demand for level ℓ facility at node i under scenario ω is covered, 0 otherwise
$v_{i\ell}^{\omega}$	=1 if demand for level ℓ facility at node i under scenario ω is covered by ground, 0 otherwise
$u_{i\ell}^{\omega}$	=1 if demand for level ℓ facility at node i under scenario ω is covered by air, 0 otherwise
Parameters	
S	Time standard
p^{TC}	The number of TCCs to be sited
p^{AD}	The number of ADs to be sited
t_{ij}^G	The driving time from node i to node j
t_{ij}^A	The flying time from node i to node j
t_{ki}^A	The flying time from node k to node i
$c_{j\ell}^{TC}$	Cost of opening a trauma center (TC) level ℓ is sited at node j
$c_{k\ell}^{AD}$	Cost of open an aeromedical depot (AD) is sited at node k with a level ℓ trauma facility
r_ℓ	Number of trauma centers that can be placed per level l
Stochastic Parameters	
$a_{i\ell}^{\omega}$	Population demand for a trauma center level ℓ at node i under scenario ω

The STSCP assumes that a TSA is known. In addition, the candidate sites for locating new TCCs are known and finite. In this work TCC candidates are assumed to be existing hospitals in the TSA that are not classified as TCCs. The availability of ground ambulance for the transportation of patients from location i to a TCC j is assumed to be unlimited. Finally, TCC coverage is defined as all zip-codes i within S as explained in chapter 4, sub-section 4.1. The travel times were computed using ArcGIS Pro [57] which has a road network database, and the values are a result of calculations based on real time speed limits. The distances from zip codes $i \in I$ to TCC candidate locations $j \in J$ were computed using geocoded centroids that represent the population for the zip code. The STSCP model is defined by equations $(1a)$ to $(1j)$.

$$\min \sum_{j\in J} \sum_{\ell\in L} c_{j\ell}\, x_{j\ell}^{TC} + \sum_{k\in J} \sum_{\ell\in L} c_{k\ell}\, x_{k\ell}^{AD} - \sum_{\omega\in\Omega} p_\omega * \{\sum_{i\in I} \sum_{\ell\in L} a_{i\ell}^{\omega} y_{i\ell}^{\omega}\} \qquad (1a)$$

Subject to:

$$\sum_{j\in J} \sum_{\ell\in L} x_{j\ell}^{TC} \leq\ p^{TC} \qquad (1b)$$

$$\sum_{\ell\in L} x_{j\ell}^{TC} \leq\ 1,\ \ \forall j \in J \qquad (1c)$$

$$\sum_{k\in K} \sum_{\ell\in L} x_{k\ell}^{AD} \leq p^{AD} \qquad (1d)$$

$$\sum_{\ell\in L} x_{k\ell}^{AD} \leq\ 1,\ \ \forall k \in K \qquad (1e)$$

$$z_{kjl} - x_{j\ell}^{TC} \leq 0,\ \ \ \forall\, j \in J,\ \ \forall k \in K, \forall \ell \in L \qquad (1f)$$

$$z_{kjl} - x_{k\ell}^{AD} \leq 0,\ \ \ \forall\, j \in J,\ \ \forall k \in K, \forall \ell \in L \qquad (1g)$$

$$y_{i\ell}^{\omega} - v_{i\ell}^{\omega} - u_{i\ell}^{\omega} \leq 0,\ \ \forall i \in I, \forall \ell \in L,\ \ \forall \omega \in \Omega \qquad (1h)$$

$$v_{i\ell}^{\omega} - \sum_{j\in N_i} x_{j\ell}^{TC} \leq 0,\ \ \forall i \in I, \forall \ell \in L,\ \ \forall \omega \in \Omega \qquad (1i)$$

$$u_{i\ell}^{\omega} - \sum_{(j,k)\in M_i} z_{kj} \leq 0,\ \ \forall i \in I, \forall \ell \in L,\ \ \forall j \in J,\ \ k \in K,\ \ \forall \omega \in \Omega \qquad (1j)$$

$$\sum_{j\,\in\,J} x_{j\ell}^{TC}\ \leq\ r_\ell,\ \ \forall \ell \in L \qquad (1k)$$

$$x_{j\ell}^{TC}, x_{k\ell}^{AD}, z_{kj\ell}, y_{i\ell}^{\omega}, v_{i\ell}^{\omega}, u_{i\ell}^{\omega} = \{0,1\}$$

The objective function comprises two sections that determine the placement of trauma centers in a geographic area. As stated in previous sub-section 4.2, a cost coefficient is associated with the placement of a trauma center $(x_{j\ell}^{TC})$ at node j for Level-I and placement of a heliport $(x_{k\ell}^{AD})$ at node k for Level-I. Their respective cost coefficients are represented by $c_{j\ell}$ and $c_{k\ell}$ for trauma centers and heliports. The concept behind the function is to balance the cost of opening a facility when covering the maximum demand nodes, represented by zip codes. Greater the coverage will result in a lower objective function value and vice versa. Scenarios (p_ω) have their unique demand values ($a_{i\ell}^{\omega}$) and the summation of these scenarios, according to Table 11, will comprise of all demand nodes covered across all scenarios.

Phase 1 – Facility placement decisions: This stage of the model limits the placement of TCCs and heliports per node per level. Constraint $(1b)$ limits the total number of trauma centers placed according the value (p^{TC}) imposed by the decision maker. No more than one TCC can be placed in a node in set J and this is limited by constraint $(1c)$. The same limitations apply for placing a heliport, as the total number of heliports placed cannot exceed the value (p^{AD}) placed by the decision maker. Constraints $(1e)$ and $(1f)$ check if a trauma facility or a heliport are located to each other or vice versa.

Phase 2 – Node coverage decisions: This stage of the model determines the coverage of facilities with respect to each of the nodes viz I (demand), J (trauma centers), and K (heliports). Constraint $(1h)$ determines if a demand node i is covered by air or ground for scenario $\omega \in \Omega$. Constraint $(1i)$ checks if there is a TCC that can cover demand at node i by ground under scenario $\omega \in \Omega$, as constraint $(1j)$ checks if there is a heliport that can cover demand at node i by air under scenario $\omega \in \Omega$. The final constraint $(1k)$ places a limit as to the number of trauma centers that can be placed at a trauma level.

4.2.1. Model variants

In the following sub-sections different variants of the STSCP model are presented to address different situations associated with the optimal geographic configuration of TCCs. Five different variants of the STSCP model are considered in this study. Sub-section 4.2.1.1 discusses the Benchmark System (BS) model, which goal is to assess the performance of an existing trauma network. Sub-section 4.2.1.2 describes the Free System (FS) model which considers an empty system where none of the TCCs are fixed to a location. This version of the model allows the user to decide the location of all the TCCs that will be part of the trauma network. The FS model imposes no limitations in terms of the number of TCC Level-I or Level-II that can be placed in the trauma network. Sub-section 4.2.1.3 describes the Semi-Constrained (SC) model which is similar to the FS model with one exception. The SC model limits the number of Level-I TCCs that can be placed in the trauma network. Sub-section 4.2.1.4 discusses the Constrained System (CS) model which is similar to the BS in the sense that it only considers the TCCs in the existing trauma network. However, the goal of this model is to assess the reassignment of the levels (i.e. Level-I and Level-II) for the TCCs in the existing trauma network. Finally, sub-section 4.2.1.5 describes the Improvement System (IS) model which is similar to the BS model because the TCCs in the existing trauma network are considered to be fixed. However, this model considers the expansion of the trauma network by deciding where to locate an additional TCC Level-I and an additional TCC Level-II.

4.2.1.1. Benchmark system (BS) model

The goal of the BS model is to assess the performance of an existing trauma network. The idea is to set up a benchmark performance by which we can compare the following model variants. The BS model is defined by equations $(2a)$ to $(2j)$.

$$\min \sum_{j\in J}\sum_{\ell\in L} c_{j\ell}\, x_{j\ell}^{TC} + \sum_{k\in J}\sum_{\ell\in L} c_{k\ell}\, x_{k\ell}^{AD} - \sum_{\omega\in\Omega} p_{\omega} * \{\sum_{i\in I}\sum_{\ell\in L} a_{i\ell}^{\omega} y_{i\ell}^{\omega}\} \qquad (2a)$$

Subject to:

$$\sum_{j\in \hat{J}}\sum_{\ell\in L} x_{j\ell}^{TC} = p^{TC} \qquad (2b)$$

$$\sum_{\ell\in L} x_{j\ell}^{TC} = 1, \ \ \forall j \in \hat{J} \qquad (2c)$$

$$\sum_{k\in \widehat{K}}\sum_{\ell\in L} x_{k\ell}^{AD} = p^{AD} \qquad (2d)$$

$$\sum_{\ell\in L} x_{k\ell}^{AD} = 1, \ \ \forall k \in \widehat{K} \qquad (2e)$$

$$z_{kjl} - x_{j\ell}^{TC} \leq 0, \ \ \forall\, j \in \hat{J}, \ \forall k \in \widehat{K}, \forall \ell \in L \qquad (2f)$$

$$z_{kjl} - x_{k\ell}^{AD} \leq 0, \ \ \forall\, j \in \hat{J}, \ \forall k \in \widehat{K}, \forall \ell \in L \qquad (2g)$$

$$y_{i\ell}^{\omega} - v_{i\ell}^{\omega} - u_{i\ell}^{\omega} \leq 0, \ \ \forall i \in I, \forall \ell \in L, \forall\, \omega \in \Omega \qquad (2h)$$

$$v_{i\ell}^{\omega} - \sum_{j\in N_i} x_{j\ell}^{TC} \leq 0, \ \ \forall i \in I, \forall \ell \in L, \ \forall \omega \in \Omega \qquad (2i)$$

$$u_{i\ell}^{\omega} - \sum_{(j,k)\in M_i} z_{kj} \leq 0, \ \ \forall i \in I, \forall \ell \in L, \ \ \forall j \in J, \ k \in K, \ \forall \omega \in \Omega \qquad (2j)$$

$$x_{j\ell}^{TC}, x_{k\ell}^{AD}, z_{kj\ell}, y_{i\ell}^{\omega}, v_{i\ell}^{\omega}, u_{i\ell}^{\omega} = \{0,1\}$$

In this model, set $\hat{J}$ represents the TCCs that are currently located in the trauma network, $\hat{J} \subset J$. Also, a set $\widehat{K}$ represents the heliports that are currently located in the trauma network, $\widehat{K} \subset K$. The other significant difference between the BS model and the original STSCP model is the elimination of constraint $(1k)$ since the trauma levels are fixed for each TCC in this model. Finally, the equality sign in constraints $(2b)$ to $(2d)$

forces the model to place all trauma centers and heliports to match the number of existing facilities which will be defined in sets $\hat{J}$ and $\hat{K}$.

4.2.1.2. Free system (FS) model

The FS model considers an empty system where none of the TCCs are fixed to a location. This version of the model allows the user to decide the location of all the TCCs that will be part of the trauma network. When compared to the STSCP, the FS model removes constraint $(1k)$ which limits the number of trauma centers that can be placed at a specific level viz Level-I and Level-II, respectively and retains the relation for the maximum facilities that can be placed. The removal of constraint $(1k)$ allows greater flexibility in the model to determine the best possible facility for a given node j that intends to cover a demand node i when considering the distance between nodes. The model is only allowed to place the number of trauma centers for Level-I and Level-II in accordance with the constraints and must comply with the maximum number of either facilities that can be placed as stated by constraints (3b) and (3e). The FS model is defined by equations $(3a)$ to (3j).

$$\min \sum_{j\in J}\sum_{\ell\in L} c_{j\ell}\, x_{j\ell}^{TC} + \sum_{k\in J}\sum_{\ell\in L} c_{k\ell}\, x_{k\ell}^{AD} - \sum_{\omega\in\Omega} p_\omega * \{\sum_{i\in I}\sum_{\ell\in L} a_{i\ell}^{\omega} y_{i\ell}^{\omega}\} \qquad (3a)$$

Subject to:

$$\sum_{j\in J}\sum_{\ell\in L} x_{j\ell}^{TC} \le\ p^{TC} \qquad (3b)$$

$$\sum_{\ell\in L} x_{j\ell}^{TC} \le\ 1,\ \ \forall j\in J \qquad (3c)$$

$$\sum_{k\in K}\sum_{\ell\in L} x_{k\ell}^{AD} \le p^{AD} \qquad (3d)$$

$$\sum_{\ell \in L} x_{k\ell}^{AD} \leq 1, \ \forall k \in K \tag{3e}$$

$$z_{kjl} - x_{j\ell}^{TC} \leq 0, \ \forall j \in J, \ k \in K, \forall \ell \in L \tag{3f}$$

$$z_{kjl} - x_{k\ell}^{AD} \leq 0, \ \forall j \in J, \ k \in K, \forall \ell \in L \tag{3g}$$

$$y_{i\ell}^{\omega} - v_{i\ell}^{\omega} - u_{i\ell}^{\omega} \leq 0, \ \forall i \in I, \forall \ell \in L, \omega \in \Omega \tag{3h}$$

$$v_{i\ell}^{\omega} - \sum_{j \in N_i} x_{j\ell}^{TC} \leq 0, \ \forall i \in I, \forall \ell \in L, \ \forall \omega \in \Omega \tag{3i}$$

$$u_{i\ell}^{\omega} - \sum_{(j,k) \in M_i} z_{kj} \leq 0, \ \forall i \in I, \forall \ell \in L, \ \forall j \in J, \ k \in K, \ \forall \omega \in \Omega \tag{3j}$$

$$x_{j\ell}^{TC}, x_{k\ell}^{AD}, z_{kj\ell}, y_{i\ell}^{\omega}, v_{i\ell}^{\omega}, u_{i\ell}^{\omega} = \{0,1\}$$

4.2.1.3. Semi-constrained (SC) model

The SC model is similar to the FS model with one exception. The SC model limits the number of Level-I TCCs that can be placed in the trauma network. The SC model has an additional constraint when compared to the FS model. The SC model includes constraint $(1k)$ from the original STSCP model and considers all the available hospitals in the TSA as possible locations for TCCs. Constraint $(4k)$ imposes a limit for the number of trauma centers that can be placed per trauma level. The SC model is defined by equations $(4a)$ to $(4k)$.

$$\min \sum_{j \in J} \sum_{\ell \in L} c_{j\ell} \, x_{j\ell}^{TC} + \sum_{k \in J} \sum_{\ell \in L} c_{k\ell} \, x_{k\ell}^{AD} - \sum_{\omega \in \Omega} p_{\omega} * \{\sum_{i \in I} \sum_{\ell \in L} a_{i\ell}^{\omega} y_{i\ell}^{\omega}\} \tag{4a}$$

Subject to:

$$\sum_{j \in J} \sum_{\ell \in L} x_{j\ell}^{TC} \leq p^{TC} \tag{4b}$$

$$\sum_{\ell \in L} x_{j\ell}^{TC} \leq 1, \ \forall j \in J \tag{4c}$$

$$\sum_{k \in K} \sum_{\ell \in L} x_{k\ell}^{AD} \leq p^{AD} \tag{4d}$$

$$\sum_{\ell \in L} x_{k\ell}^{AD} \leq 1, \ \forall k \in K \tag{4e}$$

$$z_{kjl} - x_{j\ell}^{TC} \leq 0, \quad \forall\, j \in J,\ \forall k \in K, \forall \ell \in L \tag{4f}$$

$$z_{kjl} - x_{k\ell}^{AD} \leq 0, \ \forall\, j \in J,\ \forall k \in K, \forall \ell \in L \tag{4g}$$

$$y_{i\ell}^{\omega} - v_{i\ell}^{\omega} - u_{i\ell}^{\omega} \leq 0,\ \forall i \in I, \forall \ell \in L, \forall \omega \in \Omega \tag{4h}$$

$$v_{i\ell}^{\omega} - \sum_{j \in N_i} x_{j\ell}^{TC} \leq 0,\ \forall i \in I, \forall \ell \in L,\ \forall \omega \in \Omega \tag{4i}$$

$$u_{i\ell}^{\omega} - \sum_{(j,k) \in M_i} z_{kj} \leq 0,\ \forall i \in I, \forall \ell \in L,\ \forall j \in J,\ k \in K,\ \forall \omega \in \Omega \tag{4j}$$

$$\sum_{j\, \epsilon\, J} x_{j\ell}^{TC} \ \leq\ r_{\ell},\ \forall \ell \in L \tag{4k}$$

$$x_{j\ell}^{TC}, x_{k\ell}^{AD}, z_{kj\ell}, y_{i\ell}^{\omega}, v_{i\ell}^{\omega}, u_{i\ell}^{\omega} = \{0,1\}$$

4.2.1.4. Constrained system (CS) model

This CS model is formulated to examine an existing trauma network in terms of their trauma level assignments. The idea of this model is to allow the reassignment of trauma levels designations (i.e. Level-I reassigned to Level-II and vice versa) to an existing trauma network. The CS model does not allocate new TCCs. The model only checks if any TCC level designation reassignment provides better service in terms of coverage to the service region. The CS model is defined by equations $(5a)$ to $(5k)$.

$$\min \sum_{j\in J} \sum_{\ell\in L} c_{j\ell}\, x_{j\ell}^{TC} + \sum_{k\in J} \sum_{\ell\in L} c_{k\ell}\, x_{k\ell}^{AD} - \sum_{\omega\in\Omega} p_{\omega} * \{\sum_{i\in I} \sum_{\ell\in L} a_{i\ell}^{\omega} y_{i\ell}^{\omega}\} \tag{5a}$$

Subject to:

$$\sum_{j\in\hat{J}} \sum_{\ell\in L} x_{j\ell}^{TC} = \ p^{TC} \tag{5b}$$

$$\sum_{\ell\in L} x_{j\ell}^{TC} = \ 1,\ \forall j \in \hat{J} \tag{5c}$$

$$\sum_{k\in\hat{K}} \sum_{\ell\in L} x_{k\ell}^{AD} = p^{AD} \tag{5d}$$

$$\sum_{\ell\in L} x_{k\ell}^{AD} = \ 1,\ \forall k \in \hat{K} \tag{5e}$$

$$z_{kjl} - x_{j\ell}^{TC} \leq 0,\ \forall j \in \hat{J}\,,\ \forall k \in \hat{K}, \forall \ell \in L \tag{5f}$$

$$z_{kjl} - x_{k\ell}^{AD} \leq 0, \;\; \forall\, j \in \hat{J}\,, \;\forall k \in \widehat{K}, \forall \ell \in L \tag{5g}$$

$$y_{i\ell}^{\omega} - v_{i\ell}^{\omega} - u_{i\ell}^{\omega} \leq 0, \;\; \forall i \in I, \forall \ell \in L, \forall \omega \in \Omega \tag{5h}$$

$$v_{i\ell}^{\omega} - \sum_{j \in N_i} x_{j\ell}^{TC} \leq 0, \;\; \forall i \in I, \forall \ell \in L, \;\; \forall \omega \in \Omega \tag{5i}$$

$$u_{i\ell}^{\omega} - \sum_{(j,k) \in M_i} z_{kj} \leq 0, \;\; \forall i \in I, \forall \ell \in L, \;\; \forall j \in J, \;\; k \in K, \;\; \forall \omega \in \Omega \tag{5j}$$

$$\sum_{j\,\in\,J} x_{j\ell}^{TC} \; = \; r_{\ell}, \;\; \forall \ell \in L \tag{5k}$$

$$x_{j\ell}^{TC}, x_{k\ell}^{AD}, z_{kj\ell}, y_{i\ell}^{\omega}, v_{i\ell}^{\omega}, u_{i\ell}^{\omega} = \{0,1\}$$

In this model, set $\hat{J}$ represents the TCCs that are currently located in the trauma network, $\hat{J} \subset J$. Also, a set $\widehat{K}$ represents the heliports that are currently located in the trauma network, $\widehat{K} \subset K$.

4.2.1.5. Improvement system (IS) model

The IS model is similar to the BS model because the TCCs in the existing trauma network are considered to be fixed. However, this model considers the expansion of the trauma network by deciding where to locate an additional TCC Level-I and/or an additional TCC Level-II. The Improvement System (IS) model is configured as such to determine the improvements in coverage, if any, in the current trauma network by incrementally increasing the number of trauma facilities per trauma level. This model provides a more practical approach to the problem. When compared to the STSCP model, the (IS) model involves the usage of constraints (6ℓ) and $(6m)$ that fix the location of existing official trauma centers. As these trauma centers will be fixed, the model will have to choose additional TCCs from set J to be added into the trauma network. In this model, set $\hat{J}_1$ represents the TCCs level 1 that are currently located in the trauma network, $\hat{J}_1 \subset J$. Also, set $\hat{J}_2$ represents the TCCs level 2 that are currently located in the trauma network, $\hat{J}_2 \subset J$. Finally, a set $\widehat{K}$ represents the heliports that are currently located in the trauma network, $\widehat{K} \subset K$. The IS model is defined by equations $(6a)$ to $(6l)$.

$$\min \sum_{j\in J}\sum_{\ell\in L} c_{j\ell}\, x_{j\ell}^{TC} + \sum_{k\in J}\sum_{\ell\in L} c_{k\ell}\, x_{k\ell}^{AD} - \sum_{\omega\in\Omega} p_\omega * \{\sum_{i\in I}\sum_{\ell\in L} a_{i\ell}^{\omega} y_{i\ell}^{\omega}\} \qquad (6a)$$

Subject to:

$$\sum_{j\in J}\sum_{\ell\in L} x_{j\ell}^{TC} \le p^{TC} \qquad (6b)$$

$$\sum_{\ell\in L} x_{j\ell}^{TC} \le 1, \ \forall j \in J \qquad (6c)$$

$$\sum_{k\in K}\sum_{\ell\in L} x_{k\ell}^{AD} \le p^{AD} \qquad (6d)$$

$$\sum_{\ell\in L} x_{k\ell}^{AD} \le 1, \ \forall k \in K \qquad (6e)$$

$$z_{kjl} - x_{j\ell}^{TC} \le 0, \ \forall j \in J, \ \forall k \in K, \forall \ell \in L \qquad (6f)$$

$$z_{kjl} - x_{k\ell}^{AD} \le 0, \ \forall j \in J, \ \forall k \in K, \forall \ell \in L \qquad (6g)$$

$$y_{i\ell}^{\omega} - v_{i\ell}^{\omega} - u_{i\ell}^{\omega} \le 0, \ \forall i \in I, \forall \ell \in L, \forall \omega \in \Omega \qquad (6h)$$

$$v_{i\ell}^{\omega} - \sum_{j\in N_i} x_{j\ell}^{TC} \le 0, \ \forall i \in I, \forall \ell \in L, \ \forall \omega \in \Omega \qquad (6i)$$

$$u_{i\ell}^{\omega} - \sum_{(j,k)\in M_i} z_{kj} \le 0, \ \forall i \in I, \forall \ell \in L, \ \forall j \in J, \ k \in K, \ \forall \omega \in \Omega \qquad (6j)$$

$$\sum_{j\,\in\, J} x_{j\ell}^{TC} \le r_\ell, \ \forall \ell \in L \qquad (6k)$$

$$x_{j1}^{TC} = 1, \ \forall j \in \hat{J}_1 \qquad (6l)$$

$$x_{j2}^{TC} = 1, \ \forall j \in \hat{J}_2 \qquad (6m)$$

$$x_{j\ell}^{TC}, x_{k\ell}^{AD}, z_{kj\ell}, y_{i\ell}^{\omega}, v_{i\ell}^{\omega}, u_{i\ell}^{\omega} = \{0,1\}$$

4.3. Case study

The trauma network in TX serves over 28 million citizens. The Texas Department of State Health Services (DSHS) had divided the state into 22 trauma service areas (TSA) [58]. We chose TSA *P* as it encompasses a mix of densely populated urban areas such as Austin and San Antonio in addition to rural areas with lower population densities. This will provide a test base for the models to determine trauma coverage under varied service demands. Figure 16 below shows the counties within TSA *P*.

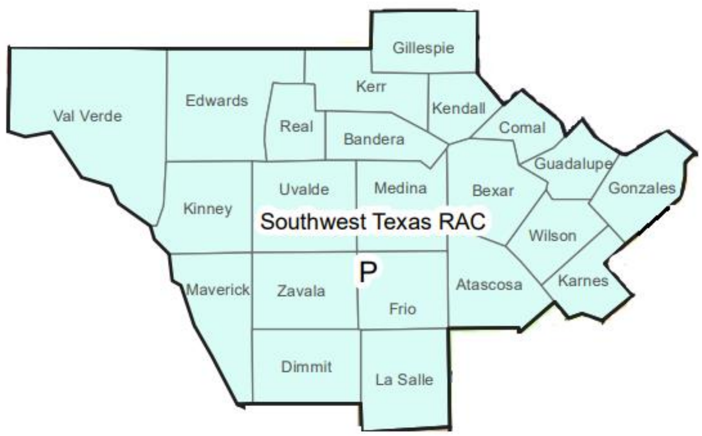


Figure 16. Counties in TSA *P*

Figure 17 shows the locations of the designated trauma level facilities in place as laid out by the DSHS. The red dots depict Level-I facilities and blue for Level-II. Further experimentations will be compared against this benchmark network to showcase the various possibilities of locations that can impact trauma service coverage. The area under study includes 176 unique zip codes and 25 designated TCCs.

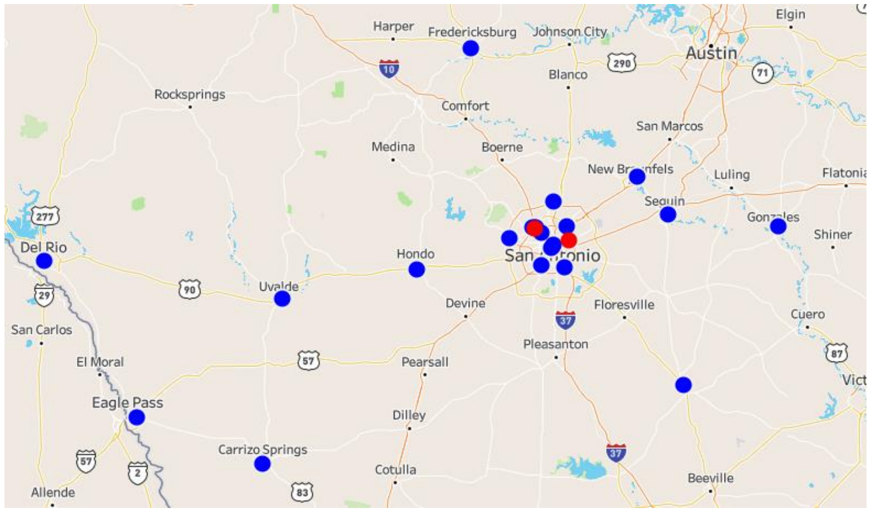


Figure 17. Trauma Network Locations [red-trauma level I, blue-trauma level II]

The current trauma network comprising 25 officially designated TCCs is the Benchmark System (BS). This will be the trauma network to test all recommended networks against in terms of their individual population coverages. We obtained deidentified records of 288,369 trauma incidences for years 2014 to 2016 from DSHS. Table 12 below shows the demand values considered in this case study to develop the demand scenarios for the optimization models. As stated previously, the proposed stochastic models consider the uncertainty in the demand. The case study considers six different scenarios that model the demand variability for region P. These scenarios are the daily average case(s) recorded in each zip code. The first three scenarios are self-descriptive, as they comprise the records for individual years. Scenario 4 is the average of daily average cases for all three years combined. As stated earlier, we also included the COVID-19 surge in demand as part of the scenarios for the stochastic programming models. All COVID-19 cases recorded during the period of study were divided into two sets. These were cases recorded before the reopening order issued on 06/01/2020 and post the same date. Scenario 5 comprises the daily average COVID-19 cases registered between 4/8/2020 to 5/31/2020, termed as pre-opening phase. Scenario 6 considers the COVID-19 cases registered between 6/1/2020 to 7/05/2020, post-opening phase.

Table 12. Scenarios with demand values

Zip Code	DAC-2014	DAC-2015	DAC-2016	DAC-ALL	Pre-Opening DAC	Post-Opening DAC
78001	1	1	1	3	4	4
78002	1	1	1	3	4	5
78003	1	1	1	3	4	5
78004	1	1	1	3	4	4
78005	1	1	1	3	4	4
78006	2	2	2	6	7	12
78008	1	1	1	3	4	4
78009	1	1	1	3	4	5
78010	1	1	1	3	4	4
78011	1	1	1	3	4	4
78012	1	1	1	3	4	4
78013	1	1	1	3	4	5
78014	1	1	1	3	4	4
78015	1	1	1	3	4	5
78016	1	1	1	3	4	5
78017	1	1	1	3	4	4
78019	1	1	1	3	4	4
78021	1	1	1	3	4	4
78023	2	2	2	6	7	11
78024	1	1	1	3	4	4
78025	1	1	1	3	4	4
78026	1	1	1	3	4	5
78027	1	1	1	3	4	4
78028	2	2	2	6	8	13
78039	1	1	1	3	4	4
78050	1	1	1	3	4	4
78052	1	1	1	3	4	5
78055	1	1	1	3	4	4
78056	1	1	1	3	4	4
78057	1	1	1	3	4	4
78058	1	1	1	3	4	4
78059	1	1	1	3	4	4
78061	1	1	1	3	4	6
78063	1	1	1	3	4	5
78064	1	1	1	3	4	6

78065	1	1	1	3	4	5
78066	1	1	1	3	4	4
78069	1	1	1	3	4	4
78070	1	1	1	3	4	6
78073	1	1	1	3	4	5
78101	1	1	1	3	4	5
78108	2	2	4	8	9	14
78109	2	2	5	9	10	16
78112	1	1	1	3	4	5
78113	1	1	1	3	4	4
78114	1	2	3	6	7	10
78116	1	1	1	3	4	4
78117	1	1	1	3	4	4
78118	1	1	1	3	4	4
78119	1	1	1	3	4	5
78121	1	1	2	4	5	7
78122	1	1	1	3	4	4
78123	1	1	1	3	4	4
78124	1	1	1	3	4	5
78130	3	4	8	15	17	26
78132	1	2	3	6	7	10
78133	1	1	2	4	5	7
78140	1	1	1	3	4	4
78143	1	1	1	3	4	4
78144	1	1	1	3	4	4
78147	1	1	1	3	4	4
78148	1	2	3	6	7	10
78150	0	0	0	0	1	1
78151	1	1	1	3	4	4
78152	1	1	1	3	4	4
78154	2	2	4	8	9	14
78155	3	3	6	12	14	21
78159	1	1	1	3	4	4
78160	1	1	1	3	4	4
78161	1	1	1	3	4	4
78163	1	1	1	3	4	5
78201	3	2	5	10	12	19
78202	1	1	2	4	5	7
78203	1	1	1	3	4	5
78204	1	1	2	4	5	7
78205	1	1	1	3	4	4

78207	3	3	6	12	14	23
78208	1	1	1	3	4	4
78209	2	2	4	8	10	16
78210	2	2	4	8	10	15
78211	2	2	3	7	8	13
78212	2	2	3	7	8	13
78213	2	2	4	8	10	16
78214	2	1	3	6	7	11
78215	1	1	1	3	4	4
78216	2	2	4	8	10	16
78217	2	2	3	7	8	13
78218	2	2	3	7	8	13
78219	1	1	2	4	5	7
78220	1	1	2	4	5	7
78221	2	2	4	8	10	15
78222	1	1	2	4	5	8
78223	3	3	5	11	13	21
78224	1	1	2	4	5	8
78225	1	1	2	4	5	7
78226	1	1	1	3	4	5
78227	3	2	5	10	12	19
78228	3	3	6	12	14	23
78229	2	2	3	7	8	13
78230	2	2	4	8	10	16
78231	1	1	1	3	4	5
78232	2	2	4	8	10	15
78233	2	2	5	9	11	18
78234	1	1	1	3	4	5
78235	1	1	1	3	4	4
78236	1	1	1	3	4	5
78237	2	2	4	8	10	15
78238	2	1	3	6	7	11
78239	2	2	3	7	8	13
78240	3	3	5	11	13	21
78242	2	2	3	7	8	13
78243	1	1	1	3	4	4
78244	2	2	3	7	8	13
78245	3	3	6	12	14	23
78247	3	3	5	11	13	21
78248	1	1	2	4	5	7
78249	3	3	5	11	13	21

78250	3	3	6	12	14	23
78251	3	3	5	11	13	21
78252	1	1	1	3	4	5
78253	2	2	3	7	8	13
78254	3	2	5	10	12	19
78255	1	1	1	3	4	5
78256	1	1	1	3	4	5
78257	1	1	1	3	4	4
78258	2	2	4	8	10	16
78259	2	1	3	6	7	11
78260	2	2	3	7	8	12
78261	1	1	2	4	5	7
78263	1	1	1	3	4	4
78264	1	1	2	4	5	7
78266	1	1	1	3	4	5
78614	1	1	1	3	4	4
78618	1	1	1	3	4	4
78623	1	1	1	3	4	4
78624	2	1	1	4	5	8
78629	1	1	1	3	4	6
78631	1	1	1	3	4	4
78632	1	1	1	3	4	4
78638	1	1	1	3	4	4
78670	1	1	1	3	4	4
78671	1	1	1	3	4	4
78675	1	1	1	3	4	4
78677	1	1	1	3	4	4
78801	4	2	1	7	8	11
78802	1	1	1	3	4	4
78827	1	1	1	3	4	4
78828	1	1	1	3	4	4
78829	1	1	1	3	4	4
78830	1	1	1	3	4	4
78832	1	1	1	3	4	4
78833	1	1	1	3	4	4
78834	2	1	1	4	5	6
78836	1	1	1	3	4	4
78837	1	1	1	3	4	4
78838	1	1	1	3	4	4
78839	2	1	1	4	5	6
78840	9	3	3	15	17	24

78843	1	1	1	3	4	4
78850	1	1	1	3	4	4
78852	9	4	3	16	18	26
78860	1	1	1	3	4	4
78861	3	1	1	5	6	8
78870	1	1	1	3	4	4
78871	1	1	1	3	4	4
78872	1	1	1	3	4	4
78873	1	1	1	3	4	4
78877	1	1	1	3	4	4
78879	1	1	1	3	4	4
78880	1	1	1	3	4	4
78881	1	1	1	3	4	4
78883	1	1	1	3	4	4
78884	1	1	1	3	4	4
78885	1	1	1	3	4	4
78886	1	1	1	3	4	4
78959	1	1	1	3	4	4
Average Demand Value	1	1.341	1.88	4.68	6	8

Scenarios 1 to 4 can be termed as '*nominal operating conditions'* and scenarios 5 and 6 as *pandemic conditions*. A key factor that will provide insight into the results is to observe the relationship between demand probabilities, patient coverage, and TCCs placement. Specifically, we were interested in studying the impact of the COVID-19 pandemic in the future expansion of the trauma network. As shown in Table 13, there are five instances for the demand probabilities per scenario termed as D1, D2, D3, D4, and D5. In D1, the demand for pandemic conditions is 50% and for non-pandemic is 50% as well. This decreases for the former to 10% in D5 and the latter makes up 90% of the total demand weight.

Table 13. Scenario probabilities

Scenario	Demand Probabilities Instances				
	D1	D2	D3	D4	D5
1	0.125	0.15	0.175	0.2	0.225
2	0.125	0.15	0.175	0.2	0.225
3	0.125	0.15	0.175	0.2	0.225
4	0.125	0.15	0.175	0.2	0.225
5	0.25	0.2	0.15	0.1	0.05
6	0.25	0.2	0.15	0.1	0.05

We also determined the location of the 25 designated TCCs in TSA *P* and the remaining 62 non-TCCs. Table 14 lists the TCCs and non-TCCs considered in this study. Every facility has a code assigned to it that is used during programming and later visualized through maps to show the position of said facilities. Codes are used instead of the actual facility name to protect identities and allow for easier visualization when results are to be shown through maps. ArcGIS Pro was used to derive actual ground times from each incidence location to all hospital sites. A total of 177 zip codes are considered in this study. The resulting time matrices, one each for ground and air (177 × 62 cells each), served as a look up table for later use in the estimation of times. Table 15 shows an example of the distance matrix for a single hospital. Table 15 shows the distances between a hospital and all zip codes with the total distance and time taken between them. Usage of '0' and '1' denotes if the zip code is within driving time of 45, 60, and 75 minutes respectively with '1' denoting as covered. The same methodology is undertaken for all hospitals with distances plotted for all zip codes.

Table 14. Hospitals and medical centers in TSA *P*

Hospital Name	City	Code	Trauma Level
CHRISTUS Santa Rosa Hospital	New Braunfels	CA	II
Baptist Emergency Hospital – Hausman	San Antonio	C1	
Baptist Emergency Hospital - Kelly	San Antonio	C2	

Baptist Emergency Hospital – Overlook	San Antonio	C3	
Baptist Emergency Hospital - Schertz	Schertz	C4	
Baptist Emergency Hospital - Thousand Oaks	San Antonio	C5	
Baptist Emergency Hospital - Westover Hills	San Antonio	C6	II
Baptist Emergency Hospital – Zarzamora	San Antonio	C7	
Baptist Medical Center	San Antonio	C8	
CHRISTUS Santa Rosa Hospital - Alamo Heights	San Antonio	C9	
CHRISTUS Santa Rosa Hospital - Medical Center	San Antonio	C10	II
CHRISTUS Santa Rosa Hospital - Westover Hills	San Antonio	C11	II
Connally Memorial Medical Center	Floresville	C12	
Dimmit Regional Hospital (FKA Dimmit County Memorial Hospital)	Carrizo Springs	C13	II
Encompass Health Rehabilitation Hospital of San Antonio (FKA HealthSouth Rehabilitation Institute of San Antonio)	San Antonio	C14	
Fort Duncan Regional Medical Center	Eagle Pass	C15	II
Foundation Surgical Hospital of San Antonio	San Antonio	C16	
Frio Regional Hospital	Pearsall	C17	
Gonzales Memorial Hospital	Gonzales	C18	II
Guadalupe Regional Medical Center	Seguin	C19	II
Hill Country Memorial Hospital	Fredericksburg	C20	II
Kerrville State Hospital	Kerrville	C21	
Kindred Hospital - San Antonio	San Antonio	C22	
Kindred Hospital - San Antonio Central (FKA Select Specialty Hospital - San Antonio)	San Antonio	C23	
Legent Orthopedic and Spine (FKA Cumberland Surgical Hospital)	San Antonio	C24	
Medina Regional Hospital	Hondo	C25	II
Methodist Children’s Hospital	San Antonio	C26	
Methodist Heart Hospital	San Antonio	C27	
Methodist Hospital	San Antonio	C28	
Methodist Hospital - Metropolitan	San Antonio	C29	II
Methodist Hospital - Northeast	San Antonio	C30	II
Methodist Hospital - South (FKA South Texas Regional Medical Center)	Jourdanton	C31	
Methodist Hospital - Specialty and Transplant	San Antonio	C32	II
Methodist Hospital - Stone Oak	San Antonio	C33	
Methodist Hospital - Texsan	San Antonio	C34	II

Methodist Hospital Ambulatory Surgery	San Antonio	C35	
Mission Trail Baptist Hospital	San Antonio	C36	II
New Braunfels Regional Rehabilitation Hospital	New Braunfels	C37	
North Central Baptist Hospital	San Antonio	C38	II
Northeast Baptist Hospital	San Antonio	C39	II
Otto Kaiser Memorial Hospital	Kenedy	C40	II
PAM Specialty Hospital of New Braunfels	New Braunfels	C41	
PAM Specialty Hospital of San Antonio (FKA Promise Specialty Hospital - San Antonio)	San Antonio	C42	
PAM Specialty Hospital of San Antonio Medical Center (FKA Lifecare Hospitals of San Antonio)	San Antonio	C43	
Peterson Regional Medical Center	Kerrville	C44	
Resolute Health Hospital	New Braunfels	C45	
San Antonio Behavioral Healthcare Hospital	San Antonio	C46	
San Antonio Military Medical Center (FKA Brooke Army Medical Center)	Fort Sam Houston	C47	I
San Antonio State Hospital	San Antonio	C48	
Select Rehabilitation Hospital of San Antonio (FKA Global rehab - San Antonio)	San Antonio	C49	
South Texas Spine & Surgical Hospital	San Antonio	C50	
South Texas Veterans Health Care System - Audie L Murphy VA Hospital	San Antonio	C51	
South Texas Veterans Health Care System - Kerrville VA Hospital	Kerrville	C52	
Southwest General Hospital	San Antonio	C53	II
St Luke’s Baptist Hospital	San Antonio	C54	II
Texas Center for Infectious Disease (FKA San Antonio State Chest Hospital)	San Antonio	C55	
The Children’s Hospital of San Antonio	San Antonio	C56	II
University Hospital (AKA University Health System)	San Antonio	C57	I
Uvalde Memorial Hospital	Uvalde	C58	II
Val Verde Regional Medical Center	Del Rio	C59	II
Warm Springs Rehabilitation Hospital of San Antonio	San Antonio	C60	
Warm Springs Rehabilitation Hospital of Thousand Oaks	San Antonio	C61	
Warm Springs Rehabilitation Hospital of Westover Hills	San Antonio	C62	

Table 15. Zip code distance matrix for a single hospital

Zip Code	Hospital	Distance (Miles)	Time Mins.	45 Mins.	60 Mins.	75 Mins.
78001	Baptist Medical Center	105.7	161.5	0	0	0
78002	Baptist Medical Center	20.4	38.7	1	1	1
78003	Baptist Medical Center	45.5	79.4	0	0	0
78004	Baptist Medical Center	35.3	62.5	0	0	1
78005	Baptist Medical Center	42.2	57.1	0	1	1
78006	Baptist Medical Center	30.3	59.3	0	1	1
78008	Baptist Medical Center	54.7	70.1	0	0	1
78009	Baptist Medical Center	25.8	37.6	1	1	1
78010	Baptist Medical Center	55.0	92.2	0	0	0
78011	Baptist Medical Center	46.0	82.8	0	0	0
78012	Baptist Medical Center	46.2	78.7	0	0	0
78013	Baptist Medical Center	45.9	75.3	0	0	0
78014	Baptist Medical Center	88.6	150.6	0	0	0
78015	Baptist Medical Center	25.0	46.2	0	1	1
78016	Baptist Medical Center	33.7	50.0	0	1	1
78017	Baptist Medical Center	70.9	99.8	0	0	0
78019	Baptist Medical Center	115.8	161.2	0	0	0
78021	Baptist Medical Center	75.1	134.0	0	0	0
78023	Baptist Medical Center	16.9	29.3	1	1	1
78024	Baptist Medical Center	81.3	125.6	0	0	0
78025	Baptist Medical Center	71.6	107.3	0	0	0
78026	Baptist Medical Center	39.1	66.0	0	0	1
78027	Baptist Medical Center	43.9	77.8	0	0	0
78028	Baptist Medical Center	64.3	94.3	0	0	0
78039	Baptist Medical Center	24.3	39.8	1	1	1
78050	Baptist Medical Center	25.3	37.8	1	1	1
78052	Baptist Medical Center	26.8	42.6	1	1	1
78055	Baptist Medical Center	62.1	107.8	0	0	0
78056	Baptist Medical Center	28.0	49.9	0	1	1
78057	Baptist Medical Center	41.9	56.8	0	1	1
78058	Baptist Medical Center	87.2	121.6	0	0	0
78059	Baptist Medical Center	29.0	37.4	1	1	1
78061	Baptist Medical Center	54.8	79.3	0	0	0
78063	Baptist Medical Center	39.3	74.5	0	0	1
78064	Baptist Medical Center	31.9	45.5	0	1	1
78065	Baptist Medical Center	26.9	44.8	1	1	1
78066	Baptist Medical Center	28.4	54.1	0	1	1
78069	Baptist Medical Center	20.9	39.8	1	1	1
78070	Baptist Medical Center	32.2	47.1	0	1	1

78073	Baptist Medical Center	18.2	33.7	1	1	1
78101	Baptist Medical Center	19.4	36.3	1	1	1
78108	Baptist Medical Center	21.0	43.1	1	1	1
78109	Baptist Medical Center	12.9	25.8	1	1	1
78112	Baptist Medical Center	19.6	43.2	1	1	1
78113	Baptist Medical Center	45.2	71.1	0	0	1
78114	Baptist Medical Center	26.8	44.2	1	1	1
78116	Baptist Medical Center	53.9	91.3	0	0	0
78117	Baptist Medical Center	48.7	74.5	0	0	1
78118	Baptist Medical Center	54.1	81.3	0	0	0
78119	Baptist Medical Center	61.7	91.2	0	0	0
78121	Baptist Medical Center	27.1	43.8	1	1	1
78122	Baptist Medical Center	55.6	94.2	0	0	0
78123	Baptist Medical Center	31.9	61.6	0	0	1
78124	Baptist Medical Center	24.0	46.6	0	1	1
78130	Baptist Medical Center	31.6	45.9	0	1	1
78132	Baptist Medical Center	33.0	65.8	0	0	1
78133	Baptist Medical Center	40.3	74.1	0	0	1
78140	Baptist Medical Center	51.8	84.0	0	0	0
78143	Baptist Medical Center	46.0	75.6	0	0	0
78144	Baptist Medical Center	53.2	96.5	0	0	0
78147	Baptist Medical Center	37.1	57.9	0	1	1
78148	Baptist Medical Center	15.6	28.7	1	1	1
78150	Baptist Medical Center	16.6	33.4	1	1	1
78151	Baptist Medical Center	67.2	120.2	0	0	0
78152	Baptist Medical Center	18.6	33.5	1	1	1
78154	Baptist Medical Center	18.8	37.8	1	1	1
78155	Baptist Medical Center	34.5	40.3	1	1	1
78159	Baptist Medical Center	59.7	94.7	0	0	0
78160	Baptist Medical Center	39.1	69.9	0	0	1
78161	Baptist Medical Center	30.6	54.3	0	1	1
78163	Baptist Medical Center	23.8	36.3	1	1	1
78201	Baptist Medical Center	3.6	6.7	1	1	1
78202	Baptist Medical Center	2.3	5.4	1	1	1
78203	Baptist Medical Center	2.7	5.9	1	1	1
78204	Baptist Medical Center	2.6	4.9	1	1	1
78205	Baptist Medical Center	0.6	1.0	1	1	1
78207	Baptist Medical Center	2.8	6.2	1	1	1
78208	Baptist Medical Center	2.2	5.3	1	1	1
78209	Baptist Medical Center	4.9	9.3	1	1	1
78210	Baptist Medical Center	3.7	20.3	1	1	1

78211	Baptist Medical Center	6.6	12.7	1	1	1
78212	Baptist Medical Center	2.3	4.9	1	1	1
78213	Baptist Medical Center	6.6	11.6	1	1	1
78214	Baptist Medical Center	5.3	9.5	1	1	1
78215	Baptist Medical Center	1.0	2.4	1	1	1
78216	Baptist Medical Center	7.7	14.2	1	1	1
78217	Baptist Medical Center	9.5	17.2	1	1	1
78218	Baptist Medical Center	9.7	18.0	1	1	1
78219	Baptist Medical Center	7.0	15.4	1	1	1
78220	Baptist Medical Center	5.8	12.1	1	1	1
78221	Baptist Medical Center	7.2	13.0	1	1	1
78222	Baptist Medical Center	8.2	17.0	1	1	1
78223	Baptist Medical Center	7.3	22.9	1	1	1
78224	Baptist Medical Center	8.3	14.9	1	1	1
78225	Baptist Medical Center	4.2	7.6	1	1	1
78226	Baptist Medical Center	5.7	13.5	1	1	1
78227	Baptist Medical Center	10.0	19.0	1	1	1
78228	Baptist Medical Center	5.5	10.5	1	1	1
78229	Baptist Medical Center	7.5	13.5	1	1	1
78230	Baptist Medical Center	9.4	16.5	1	1	1
78231	Baptist Medical Center	10.7	18.9	1	1	1
78232	Baptist Medical Center	11.6	18.9	1	1	1
78233	Baptist Medical Center	12.4	22.4	1	1	1
78234	Baptist Medical Center	4.3	10.1	1	1	1
78235	Baptist Medical Center	7.4	14.0	1	1	1
78236	Baptist Medical Center	11.0	24.3	1	1	1
78237	Baptist Medical Center	5.7	13.1	1	1	1
78238	Baptist Medical Center	9.0	15.9	1	1	1
78239	Baptist Medical Center	11.3	20.4	1	1	1
78240	Baptist Medical Center	9.6	17.5	1	1	1
78242	Baptist Medical Center	11.4	20.1	1	1	1
78243	Baptist Medical Center	9.7	17.1	1	1	1
78244	Baptist Medical Center	9.9	21.1	1	1	1
78245	Baptist Medical Center	13.4	24.9	1	1	1
78247	Baptist Medical Center	12.7	23.5	1	1	1
78248	Baptist Medical Center	12.1	22.0	1	1	1
78249	Baptist Medical Center	12.4	21.5	1	1	1
78250	Baptist Medical Center	13.5	26.3	1	1	1
78251	Baptist Medical Center	12.1	22.4	1	1	1
78252	Baptist Medical Center	15.8	26.6	1	1	1
78253	Baptist Medical Center	18.3	35.1	1	1	1

78254	Baptist Medical Center	16.4	29.2	1	1	1
78255	Baptist Medical Center	19.7	36.0	1	1	1
78256	Baptist Medical Center	16.7	28.4	1	1	1
78257	Baptist Medical Center	24.7	51.3	0	1	1
78258	Baptist Medical Center	15.6	26.7	1	1	1
78259	Baptist Medical Center	16.2	24.8	1	1	1
78260	Baptist Medical Center	20.0	37.3	1	1	1
78261	Baptist Medical Center	18.6	28.8	1	1	1
78263	Baptist Medical Center	13.4	24.8	1	1	1
78264	Baptist Medical Center	18.4	30.1	1	1	1
78266	Baptist Medical Center	19.9	37.2	1	1	1
78614	Baptist Medical Center	64.6	108.8	0	0	0
78618	Baptist Medical Center	92.2	165.7	0	0	0
78623	Baptist Medical Center	51.1	82.5	0	0	0
78624	Baptist Medical Center	67.9	104.2	0	0	0
78629	Baptist Medical Center	66.7	84.3	0	0	0
78631	Baptist Medical Center	85.8	129.9	0	0	0
78632	Baptist Medical Center	66.9	77.6	0	0	0
78638	Baptist Medical Center	45.9	60.0	0	1	1
78670	Baptist Medical Center	50.5	86.3	0	0	0
78671	Baptist Medical Center	66.7	105.6	0	0	0
78675	Baptist Medical Center	80.3	158.2	0	0	0
78677	Baptist Medical Center	67.3	115.7	0	0	0
78801	Baptist Medical Center	83.1	114.4	0	0	0
78802	Baptist Medical Center	87.1	127.7	0	0	0
78827	Baptist Medical Center	113.8	183.8	0	0	0
78828	Baptist Medical Center	122.3	219.7	0	0	0
78829	Baptist Medical Center	81.3	109.5	0	0	0
78830	Baptist Medical Center	96.4	146.9	0	0	0
78832	Baptist Medical Center	122.5	173.0	0	0	0
78833	Baptist Medical Center	116.6	201.4	0	0	0
78834	Baptist Medical Center	114.5	176.2	0	0	0
78836	Baptist Medical Center	117.0	195.1	0	0	0
78837	Baptist Medical Center	189.2	280.8	0	0	0
78838	Baptist Medical Center	86.0	123.6	0	0	0
78839	Baptist Medical Center	107.7	199.5	0	0	0
78840	Baptist Medical Center	152.7	215.1	0	0	0
78843	Baptist Medical Center	147.8	207.7	0	0	0
78850	Baptist Medical Center	51.6	70.1	0	0	1
78852	Baptist Medical Center	139.7	217.1	0	0	0
78860	Baptist Medical Center	143.2	225.1	0	0	0

78861	Baptist Medical Center	41.5	56.0	0	1	1
78870	Baptist Medical Center	73.1	99.5	0	0	0
78871	Baptist Medical Center	225.3	334.0	0	0	0
78872	Baptist Medical Center	97.0	127.0	0	0	0
78873	Baptist Medical Center	96.7	167.7	0	0	0
78877	Baptist Medical Center	145.7	863.3	0	0	0
78879	Baptist Medical Center	94.0	141.4	0	0	0
78880	Baptist Medical Center	136.9	201.6	0	0	0
78881	Baptist Medical Center	63.3	85.7	0	0	0
78883	Baptist Medical Center	63.5	112.3	0	0	0
78884	Baptist Medical Center	78.2	135.2	0	0	0
78885	Baptist Medical Center	82.8	144.3	0	0	0
78886	Baptist Medical Center	49.9	76.3	0	0	0
78959	Baptist Medical Center	76.5	89.5	0	0	0

To model coverage of a TCCs to its nearby population, distances between the candidate and existing TCCs sites and 177 zip-codes in TX were calculated using a road network database in ArcGIS Pro. The coverage matrix ($N_i$and M_i) were prepared a priori based on zip-code information. Population information was obtained from the United States Census Bureau [56] Table 16 shows all the zip codes that are located within the area under study.

Table 16 Demand zip codes in TSA *P*

Zip Code	City	County	Population Count
78001	Artesia Wells	La Salle County	33
78002	Atascosa	Bexar County	8255
78003	Bandera	Bandera County	8689
78004	Bergheim	Kendall County	1183
78005	Bigfoot	Frio County	817
78006	Boerne	Kendall County	27558
78008	Campbellton	Atascosa County	345
78009	Castroville	Medina County	7255
78010	Center Point	Kerr County	3386
78011	Charlotte	Atascosa County	2082
78012	Christine	Atascosa County	436
78013	Comfort	Kendall County	5930
78014	Cotulla	La Salle County	4987

78015	Boerne	Bexar County	9602
78016	Devine	Medina County	9630
78017	Dilley	Frio County	4787
78019	Encinal	La Salle County	1855
78021	Fowlerton	La Salle County	126
78023	Helotes	Bexar County	24334
78024	Hunt	Kerr County	1436
78025	Ingram	Kerr County	4956
78026	Jourdanton	Atascosa County	5861
78027	Kendalia	Kendall County	459
78028	Kerrville	Kerr County	37620
78039	La Coste	Medina County	1657
78050	Leming	Atascosa County	767
78052	Lytle	Atascosa County	6388
78055	Medina	Bandera County	1774
78056	Mico	Medina County	1917
78057	Moore	Frio County	871
78058	Mountain Home	Kerr County	1256
78059	Natalia	Medina County	5387
78061	Pearsall	Frio County	11031
78063	Pipe Creek	Bandera County	9227
78064	Pleasanton	Atascosa County	14102
78065	Poteet	Atascosa County	10831
78066	Rio Medina	Medina County	591
78069	Somerset	Atascosa County	5137
78070	Spring Branch	Comal County	14618
78073	Von Ormy	Bexar County	8171
78101	Adkins	Bexar County	7898
78108	Cibolo	Guadalupe County	27770
78109	Converse	Bexar County	34603
78112	Elmendorf	Bexar County	7941
78113	Falls City	Karnes County	2435
78114	Floresville	Wilson County	20103
78116	Gillett	Karnes County	390
78117	Hobson	Karnes County	545
78118	Karnes City	Karnes County	3976
78119	Kenedy	Karnes County	7680
78121	La Vernia	Wilson County	11381
78122	Leesville	Gonzales County	418
78123	Mc Queeney	Guadalupe County	2397
78124	Marion	Guadalupe County	5609

78130	New Braunfels	Comal County	59546
78132	New Braunfels	Comal County	19139
78133	Canyon Lake	Comal County	16269
78140	Nixon	Gonzales County	3380
78143	Pandora	Wilson County	85
78144	Panna Maria	Karnes County	45
78147	Poth	Wilson County	1919
78148	Universal City	Bexar County	20139
78150	Randolph A F B	Bexar County	11
78151	Runge	Karnes County	1347
78152	Saint Hedwig	Bexar County	2294
78154	Schertz	Guadalupe County	30347
78155	Seguin	Guadalupe County	45341
78159	Smiley	Gonzales County	1023
78160	Stockdale	Wilson County	4273
78161	Sutherland Springs	Wilson County	864
78163	Bulverde	Comal County	9838
78201	San Antonio	Bexar County	45307
78202	San Antonio	Bexar County	11691
78203	San Antonio	Bexar County	6099
78204	San Antonio	Bexar County	11125
78205	San Antonio	Bexar County	1453
78207	San Antonio	Bexar County	55514
78208	San Antonio	Bexar County	3736
78209	San Antonio	Bexar County	39197
78210	San Antonio	Bexar County	36865
78211	San Antonio	Bexar County	31944
78212	San Antonio	Bexar County	28415
78213	San Antonio	Bexar County	40396
78214	San Antonio	Bexar County	23341
78215	San Antonio	Bexar County	1150
78216	San Antonio	Bexar County	40267
78217	San Antonio	Bexar County	32165
78218	San Antonio	Bexar County	31917
78219	San Antonio	Bexar County	15225
78220	San Antonio	Bexar County	15965
78221	San Antonio	Bexar County	35990
78222	San Antonio	Bexar County	19408
78223	San Antonio	Bexar County	50637
78224	San Antonio	Bexar County	17601
78225	San Antonio	Bexar County	13025

78226	San Antonio	Bexar County	6648
78227	San Antonio	Bexar County	46077
78228	San Antonio	Bexar County	58811
78229	San Antonio	Bexar County	28804
78230	San Antonio	Bexar County	39089
78231	San Antonio	Bexar County	7906
78232	San Antonio	Bexar County	35120
78233	San Antonio	Bexar County	43710
78234	San Antonio	Bexar County	7126
78235	San Antonio	Bexar County	357
78236	Lackland A F B	Bexar County	10392
78237	San Antonio	Bexar County	36929
78238	San Antonio	Bexar County	23514
78239	San Antonio	Bexar County	28736
78240	San Antonio	Bexar County	51111
78242	San Antonio	Bexar County	31395
78243	San Antonio	Bexar County	235
78244	San Antonio	Bexar County	30757
78245	San Antonio	Bexar County	56511
78247	San Antonio	Bexar County	49176
78248	San Antonio	Bexar County	13638
78249	San Antonio	Bexar County	49951
78250	San Antonio	Bexar County	54903
78251	San Antonio	Bexar County	49435
78252	San Antonio	Bexar County	7372
78253	San Antonio	Bexar County	29007
78254	San Antonio	Bexar County	44817
78255	San Antonio	Bexar County	10826
78256	San Antonio	Bexar County	6855
78257	San Antonio	Bexar County	3950
78258	San Antonio	Bexar County	40586
78259	San Antonio	Bexar County	22660
78260	San Antonio	Bexar County	24844
78261	San Antonio	Bexar County	13513
78263	San Antonio	Bexar County	4673
78264	San Antonio	Bexar County	12339
78266	San Antonio	Comal County	5591
78614	Cost	Gonzales County	456
78618	Doss	Gillespie County	324
78623	Fischer	Comal County	813
78624	Fredericksburg	Gillespie County	21513

78629	Gonzales	Gonzales County	11887
78631	Harper	Gillespie County	2395
78632	Harwood	Gonzales County	910
78638	Kingsbury	Guadalupe County	2005
78670	Staples	Guadalupe County	168
78671	Stonewall	Gillespie County	654
78675	Willow City	Gillespie County	188
78677	Wrightsboro	Gonzales County	92
78801	Uvalde	Uvalde County	21780
78802	Uvalde	Uvalde County	242
78827	Asherton	Dimmit County	1219
78828	Barksdale	Edwards County	258
78829	Batesville	Zavala County	1207
78830	Big Wells	Dimmit County	786
78832	Brackettville	Kinney County	3598
78833	Camp Wood	Real County	1299
78834	Carrizo Springs	Dimmit County	7829
78836	Catarina	Dimmit County	128
78837	Comstock	Val Verde County	281
78838	Concan	Uvalde County	275
78839	Crystal City	Zavala County	8578
78840	Del Rio	Val Verde County	48149
78843	Laughlin A F B	Val Verde County	336
78850	D Hanis	Medina County	1145
78852	Eagle Pass	Maverick County	53040
78860	El Indio	Maverick County	229
78861	Hondo	Medina County	13701
78870	Knippa	Uvalde County	984
78871	Langtry	Val Verde County	45
78872	La Pryor	Zavala County	1905
78873	Leakey	Real County	1788
78877	Quemado	Maverick County	989
78879	Rio Frio	Real County	264
78880	Rocksprings	Edwards County	1682
78881	Sabinal	Uvalde County	2335
78883	Tarpley	Bandera County	353
78884	Utopia	Uvalde County	1158
78885	Vanderpool	Bandera County	120
78886	Yancey	Medina County	647
78959	Waelder	Gonzales County	1837

A total of 75 problem instances were tested and analyzed (5 models x 5 demand instances x 3 different times allowed to reach TCC); each instance having 6 scenarios, was tested against each time limit, with access threshold as 45, 60 and 75 minutes. Table 17 below summarizes the design of experiments for the case study. As stated in chapter 1 sub-section 1.1 , in this study Level-I will include current and fixed hospitals and trauma care facilities that are classified as Level-I and Level-II while Level-II will include the facilities that are classified as Level-III and Level-IV.

Table 17. Summary for Design of Experiments

Experiment	**Demand Instance**	**Time in Minutes**	**Total Trauma Center Limit**	**Level-I Trauma Center Limit**	**Level-II Trauma Center Limit**
Benchmark System	D1, D2, D3, D4, D5	45, 60, 75	25	Yes	Yes
Free System	D1, D2, D3, D4, D5	45, 60, 75	62	N/A	N/A
Semi-Constrained System	D1, D2, D3, D4, D5	45, 60, 75	62	Yes	N/A
Constrained System	D1, D2, D3, D4, D5	45, 60, 75	62	Yes	Yes
Improvement System	D1, D2, D3, D4, D5	45, 60, 75	62	Yes	Yes

4.4. Experimentation

This research will address access to trauma centers across a designated trauma service area, Area P, shown in Figure 18 as laid out by the Texas Department of State Health Services [58]. The "2019-2020 Update to The Texas State Health Plan" publication lists 280 State designated Trauma centers across Texas [11]. Despite strong attention to facilitate adequate services, Texas residents continue to face inadequacies in access and transportation to such centers.

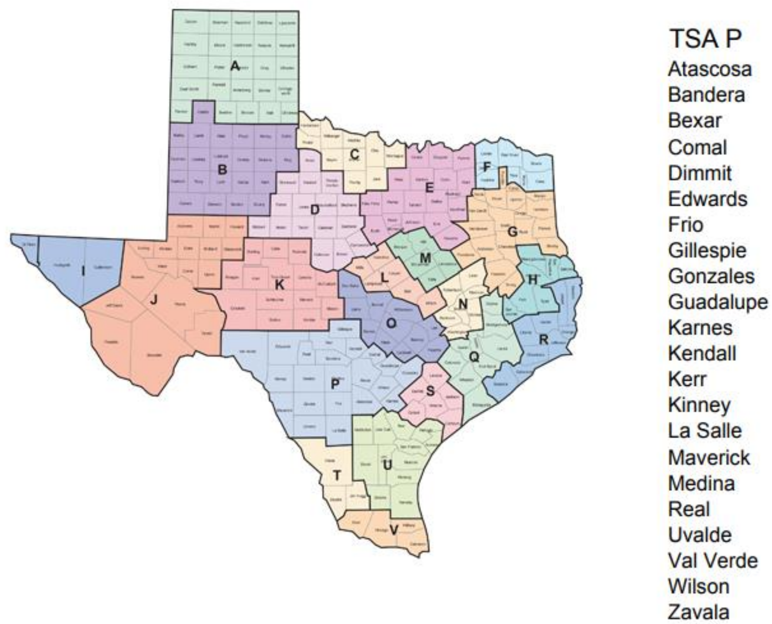


Figure 18. Regional Advisory Council, TSA *P* and counties

It is essential to determine the reach of the current trauma network with respect to the population covered for each time viz 60, 45, and 75 minutes, respectively. The standard time to reach a trauma facility is 60 minutes. There are five designs that were considered by us with the last being the comprehensive system for maximum coverage.

- **Experiment 1 – Benchmark System (BS):** The first step in determining the extent of coverage of the current trauma network. This involves the 25 facilities in TSA *P* of which three are Level-I and the remainder as classed as Level-II according to their official designations. The network is tested for time taken to reach at trauma facility within 60, 45 and 75 minutes respectively and the population covered is calculated in percentages for each level. This method utilizes the iteration of the model as stated previously in chapter 4, sub-section 4.2.1.1 The results obtained will provide the performance parameters for the Benchmark System (B.S).

- **Experiment 2 - Free System (FS):** The second experiment involves creating a new and empty system that is not already classed as Level-I or Level-II. This includes a network of 62 hospitals and medical centers: pre-designated trauma facilities and generic hospitals and medical centers. The demand points remain the same including the parameters for time taken. This comprises the Free System (FS) as discussed in chapter 4, sub-section 4.2.1.2
- **Experiment 3 – Semi-Constrained (SC):** The third experiment places limits on the trauma centers that can be placed for each trauma Level-I, as described in chapter 4, sub-section 4.2.1.3. There being two Level-I trauma centers in the current network with an additional added resulting in three, this involves placing the limit as described in constraint $(4k)$ resulting in only three that can be placed out of the total 62 that are available to the model, albeit the remainder of Level-II trauma center can be placed freely without any limitations. This configuration is essentially the Semi-Constrained System.
- **Experiment 4 - Constrained System (CS):** The penultimate experiment involves placing the exact number of trauma centers that are in the current network (i.e. the model must place 25 trauma facilities but not according to their official designations). The model is free to choose the trauma level designations from the data provided and this allows a different perspective into the performance of the current network when the facility designation can be rotated. This network is named as the Constrained System as discussed in chapter 4, sub-section 4.2.1.4.
- **Experiment 5 - Improvement System (IS):** The final performance measure will

involve the Improvement System, the iteration shown in chapter 4 sub-section 4.2.1.5. With there being only two Level-I trauma centers in the current network, the model is allowed to place an additional facility for Level-I and two additional facilities for Level-II. The idea behind this experiment is to evaluate the performance of a network when facilities are added in a singular fashion which is a more practical perspective.

4.5. Computational results

4.5.1. Narrative results

This sub-section will showcase the results generated for all systems tested and their performance measures. The parameter that will determine the same is taken as the *Average Population Coverage* (APC) for both trauma Levels-I and II. It is calculated for every zip code that is covered by the TCC for Level-I and II respectively hence, the percentage value will be unique for that trauma level. Zip codes covered in both trauma levels have their populations extracted and a percentage is derived by from the data range. As an example, if 5 out of 10 zip codes are covered by TCC's for Level-I then the percentage of population covered is the performance parameters for the trauma level. The average of percentages for all demand probability instances, as described in Table 13, is the average population coverage for the specific trauma level. Results for the average percentage coverage are presented in Table 18 below. Table 19 below presents the trauma centers that are placed for both trauma levels, including both individual total centers sited across the area of study.

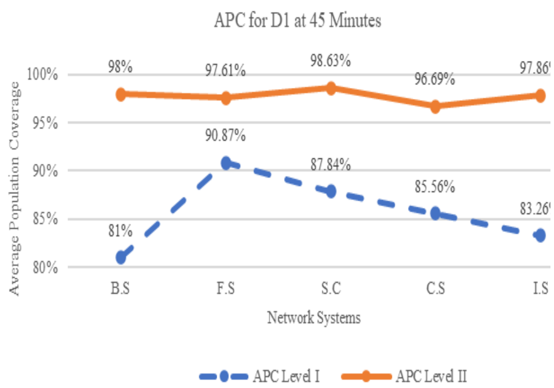
Table 18. Computational results for coverage and cost

Minutes		45					60					75				
System		**B.S**	F.S	S.C	C.S	I.S	**B.S**	F.S	S.C	C.S	I.S	**B.S**	F.S	S.C	C.S	I.S
D 1	APC Level I	81%	90.87%	87.84%	85.56%	83.26%	84%	95.71%	90.30%	89.46%	87.67%	87%	96.47%	92.38%	90.25%	90.18%
	APC Level II	98%	97.61%	98.63%	96.69%	97.86%	98%	98.28%	99.16%	98.05%	99.58%	99%	99.71%	99.70%	99.06%	99.86%
	Cost		-1220	-1231	-1146	-1125		-1342	-1323	-1231	-1211.4		-1419	-1403.5	-1299	-1280
D 2	APC Level I	81%	89.01%	87.84%	85.56%	83.26%	84%	95.71%	90.30%	89.46%	87.67%	87%	96.54%	92.38%	91.25%	90.18%
	APC Level II	97%	97.99%	98.63%	96.69%	97.86%	98%	98.28%	99.09%	98.05%	99.58%	99%	99.69%	99.70%	98.84%	99.73%
	Cost		-1087.5	-1099.8	-1019.6	-999.2		-1198.4	-1185.1	-1097	-1077		-1269.9	-1259.4	-1158	-1140.1
D 3	APC Level I	81%	89.01%	87.84%	85.56%	83.26%	84%	95.71%	90.30%	89.46%	87.67%	87%	96.54%	92.38%	90.25%	90.18%
	APC Level II	97%	97.34%	97.59%	96.69%	97.86%	98%	98.28%	99.13%	98.05%	99.58%	99%	99.69%	99.70%	99.06%	99.73%
	Cost		-955.7	-969.15	-893.2	-873.9		-1054.1	-1047.7	-962.4	-944.15		-1121.3	-1115.6	-1018	-1000.7
D 4	APC Level I	81%	89.01%	87.84%	85.56%	83.26%	84%	95.71%	90.30%	89.46%	87.67%	87%	96.54%	92.38%	91.25%	90.18%
	APC Level II	97%	97.34%	97.59%	96.69%	97.86%	98%	98.28%	99.06%	98.95%	99.58%	99%	99.69%	99.70%	98.84%	99.73%
	Cost		-824.3	-839.1	-766.8	-748.6		-909.7	-910.3	-828	-819.6		-972.7	-971.7	-877.2	-861.3
D 5	APC Level I	81%	87.84%	87.84%	85.56%	83.36%	84%	94.27%	90.30%	89.46%	87.67%	87%	96.54%	92.38%	90.25%	90.18%
	APC Level II	97%	97.59%	97.59%	96.69%	97.86%	98%	98.24%	99.13%	98.05%	99.58%	99%	99.69%	99.70%	99.06%	99.73%
	Cost		-694.05	-709.75	-640.4	-623.3		-767.15	-772.9	-693.8	-677.05		-824.1	-827.85	-736.6	-721.9

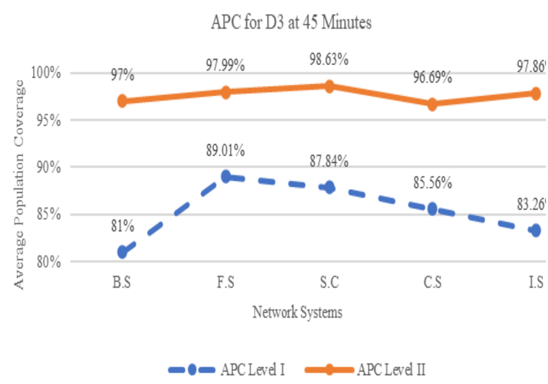
Table 19. Trauma centers placed by trauma levels

Minutes		45					60					75				
System		**B.S**	F.S	S.C	C.S	I.S	**B.S**	F.S	S.C	C.S	I.S	**B.S**	F.S	S.C	C.S	I.S
D1	TCC Level I	2	6	3	3	3	2	7	3	3	3	2	5	3	3	2
	TCC Level II	23	13	15	22	24	23	10	11	22	24	23	9	8	22	34
	TC Sited	25	19	18	25	27	25	17	14	25	27	25	14	11	25	27
D2	TCC Level I	2	4	3	3	3	2	7	3	3	3	2	5	3	3	3
	TCC Level II	23	14	15	22	24	23	10	11	22	24	23	8	8	22	23
	TC Sited	25	18	18	25	27	25	17	14	25	27	25	13	11	25	26
D3	TCC Level I	2	4	3	3	3	2	7	3	3	3	2	5	3	3	3
	TCC Level II	23	13	13	22	24	23	10	10	22	24	23	8	8	22	23
	TC Sited	25	17	16	25	27	25	17	13	25	27	25	13	11	25	26
D4	TCC Level I	2	4	3	3	3	2	7	3	3	3	2	5	3	3	3
	TCC Level II	23	13	13	22	24	23	10	10	22	24	23	8	8	22	23
	TC Sited	25	17	16	25	27	25	17	13	25	27	25	13	11	25	26
D5	TCC Level I	2	3	3	3	3	2	5	3	3	3	2	5	3	3	3
	TCC Level II	23	13	13	22	24	23	10	10	22	24	23	8	8	22	23
	TC Sited	25	16	16	25	27	25	15	13	25	27	25	13	11	25	26

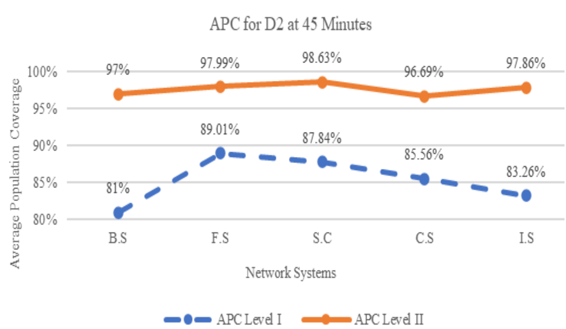
Figure 19 showcase the results presented in Table 18 by comparing the average percentage coverage for each network system as described in chapter 4, sub-section 4.2, comparing the results per time taken to reach viz 45, 60 and 75 minutes.



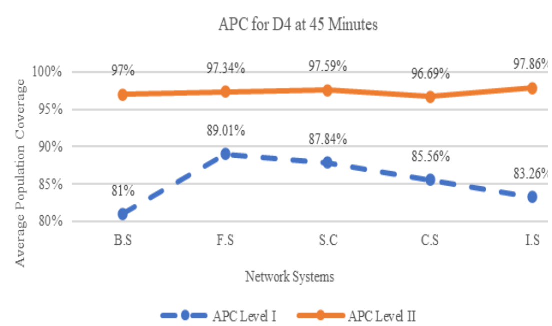
19a) Average Population Coverage for D1 at 45 minutes



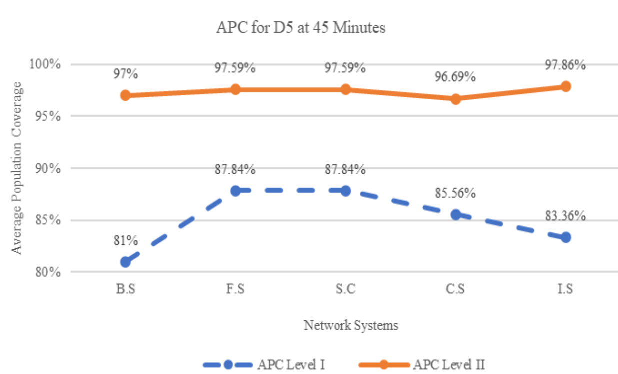
19b) Average Population Coverage for D3 at 45 minutes



19c) Average Population Coverage for D2 at 45 minutes



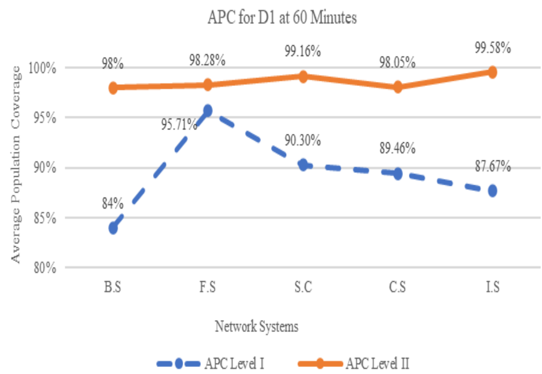
19d) Average Population Coverage for D4 at 45 minutes

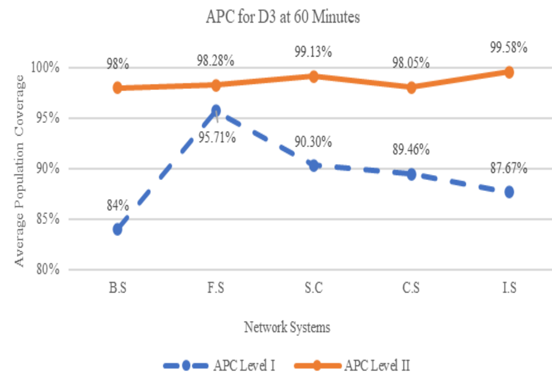


19e) Average Population Coverage for D5 at 45 minutes

Figure 19. Average Population Coverage for 45 minutes

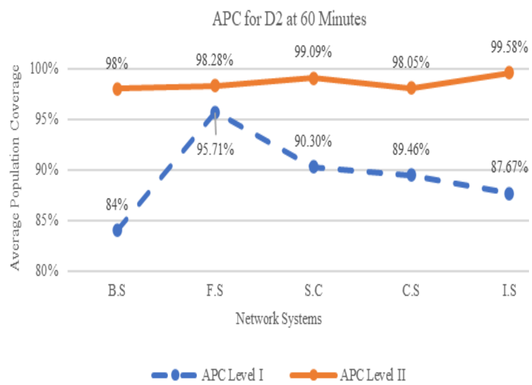
Charts are segregated according to the demand probability instances described in Table 13. Figure 19 displays the performance of the networks compared against each other for all demand probability instances when the expected clinical intervention from the moment of an injury incident is fixed to 45 minutes. For demand D1, the Semi-Constrained system has the highest population coverage at 98.63% for Level-II and the Free-System has the highest coverage at 87% for Level-I. This is attributed to the fact that the Free-System has a higher number of Level-I facilities placed than the rest of the systems due to the absence of bounds within the system itself. This causes fewer Level-II facilities to be placed as the model will seek a balance for the former placed for both trauma levels. As the Semi-Constrained system can place a limited number of Level-I facilities, thus Level-II facilities will have to be increased to maximize coverage. The Semi-Constrained system also has the highest coverage for D2, D3; 98.63% and D4 at 97.59%. respectively. Excluding D5 which is tied with the Semi-Constrained system at 87.84%, the Free-System has the highest performance at 89.01% across D2, D3, and D4 respectively for Level-I. As is seen through D1 to D5 when considering the best performing two systems for their respective trauma levels viz, Free-System and Semi-Constrained System, where D1 represents highest pandemic demand i.e. COVID-19 cases, coverage for the Free-System decreases from 90.87% (D1) to 87.84%(D5) for Level-I coverage. Semi-Constrained System coverage for Level-II decreases from 98.63%(D1) to 97.59%(D5) indicating that higher demand for a trauma level such as D1 will affect the overall decision to place facilities. Figure 20 shows the performance of all network systems when the expected clinical intervention from the moment of an injury incident is fixed to 60-minutes.

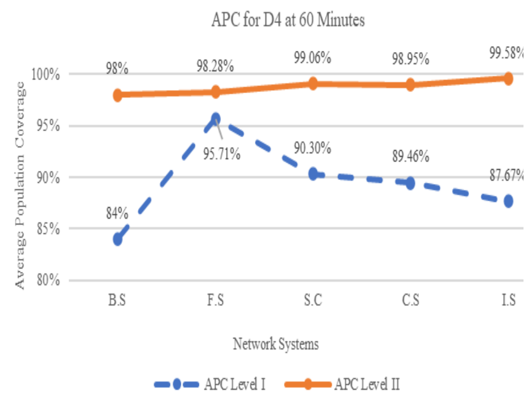




20a) Average Population Coverage for D1 at 60 minutes

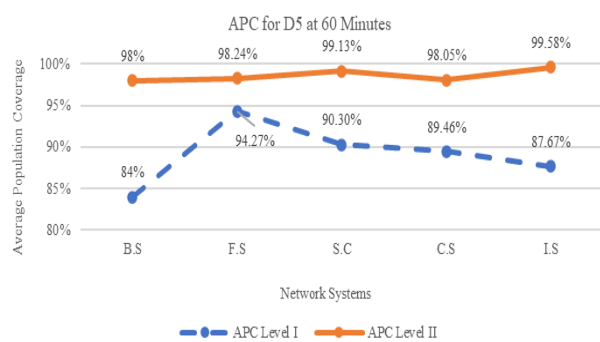
20b) Average Population Coverage for D3 at 60 minutes





20c) Average Population Coverage for D2 at 60 minutes

20d) Average Population Coverage for D4 at 60 minutes

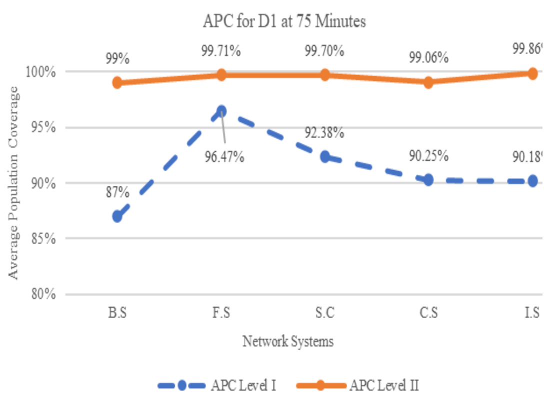


20d) Average Population Coverage for D5 at 60 minutes

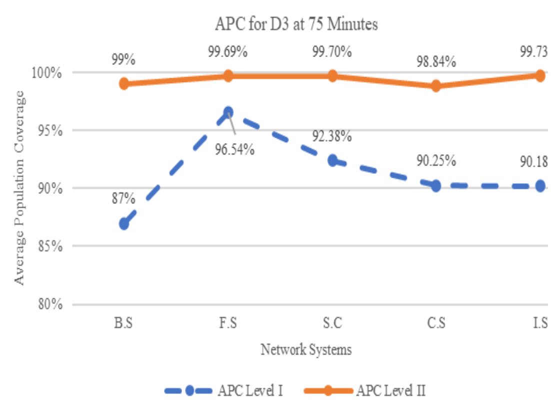
Figure 20. Average Population Coverage for 60 minutes

Across all demand probability instances, D1 to D5, the Improvement-System has the highest coverage at 99.58% for Level-II. This can be attributed to the fact that since the Improvement-System is essentially an improved Benchmark-System the latter of which already shows significant coverage values for Level-II, the addition of more facilities that can be placed within the network will boost coverage in addition to a relaxed time constraint. With the exception of coverage at D5 at 94.27%, the Free-System has the highest coverage across all demand probability instances at 95.71% for Level-I. This provides us the insight that the addition of a handful of facilities into the network when the time taken to reach facilities is at a standard 60 minutes, the coverage improves by almost 4%. The Free-System performs consistently better than all networks across all demand probability instances at a 95.71 % coverage in D1 to D4 and at 94.27% coverage in D5. As is shown through D1 to D5 when considering the best performing system for its respective trauma level viz, Free-System, where D1 represents highest pandemic demand i.e. COVID-19 cases, coverage for the Free-System decreases from 95.71% (D1) to 94.27%(D5) for Level-I coverage thus showcasing that higher demand for a trauma level such as D1 will affect the decision to place the required facilities. It is interesting to note that coverage for the best performing system for Level-II, the Improvement-System, shows consistent coverage at 99.58% for all demands. It can be reasoned that this occurs due to the majority of trauma centers being fixed in their respective locations and the addition of additional trauma centers will improve overall coverage across all demand instances.

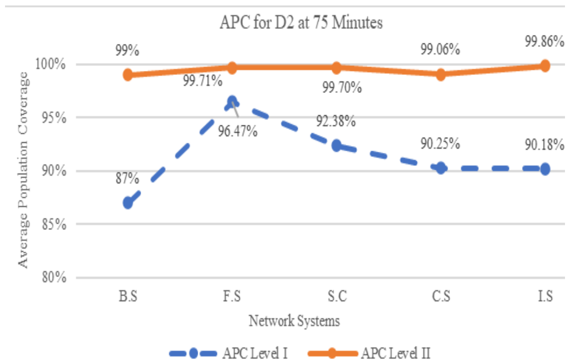
Figure 21 shows the results when evaluating the expected clinical intervention from the moment of an injury incident is fixed to 75 minutes. The Improvement-System has the highest coverage across all demand probability instances at Level-II at 99.86% coverage for D1 to D4 and 99.73% coverage for D5. This can be attributed as per discussions for 60 minutes that due to the fact that the Improvement-System is designed to be an improvement over the Benchmark-System, addition of Level-II facilities will improve the respective trauma level demand. For Level-I and its demand probability instances, the Free-System has the highest coverage at 96.47% for D1 and D2, 96.54% coverage for D3, D4, and D5, respectively. We see higher coverage for the Free-System due to its flexibility in placing Level-I facilities. As the trend shows in previous time limits, coverage for Level-I decreases from D1 to D5, but in this case we see consistent coverages which can be attributed to the fact that time limit has been relaxed to 75 minutes. This change will allow the model to cover a wider area with reduced facilities hence covering all demand instances.



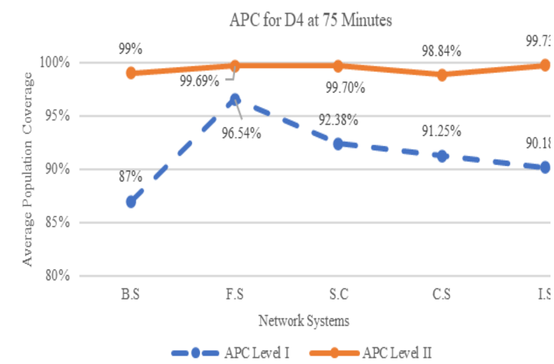
21a) Average Population Coverage for D1 at 75 minutes



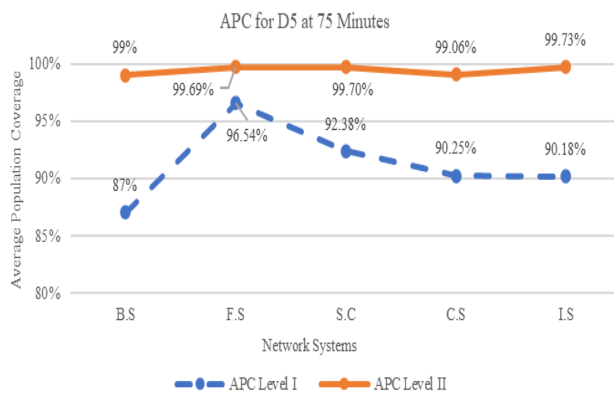
21b) Average Population Coverage for D3 at 75 minutes



21c) Average Population Coverage for D2 at 75 minutes



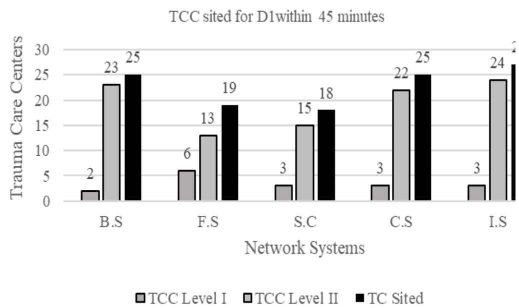
21d) Average Population Coverage for D4 at 75 minutes



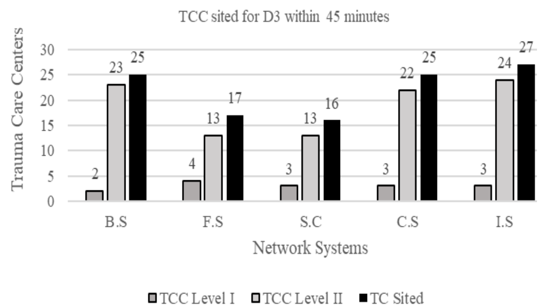
21e) Average Population Coverage for D5 at 75 minutes

Figure 21. Average Population Coverage for 75 minutes

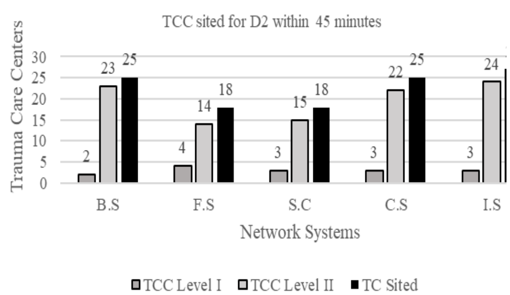
Figure 22 shows the placement of trauma centers for a travelling time of 45 minutes. Trauma centers are fixed for the Benchmark-System, as stated previously, and the comparison of trauma centers across all demand probability instances provides as insight with respect to the facilities that can be placed without sacrificing coverage. Establishing a connection with the data presented in Figure 19 the Semi-Constrained system had the highest coverage for Level-II and here we can see that fewer Level-II facilities are needed to improve coverage for the same level. This can be explained by reasoning that although the number of Level-I facilities are limited in number, the model is allowed to place Level-II facilities based on demand and the distances thus resulting in a more efficient network with fewer facilities. The Free-System had the highest coverage for Level-I, as shown in Figure 19, and seen above, requires considerably fewer Level-I facilities as compared to the Benchmark-System due to the model being bound only by the maximum number of facilities that it can place. This allows it to place a higher number of Level-I trauma centers as compared to the Benchmark-System.



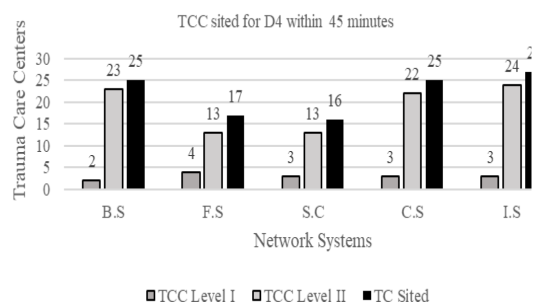
22a) TCC sited for D1 within 45 minutes



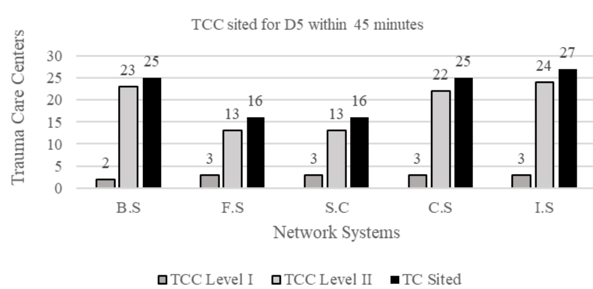
22b) TCC sited for D3 within 45 minutes



22c) TCC sited for D2 within 45 minutes



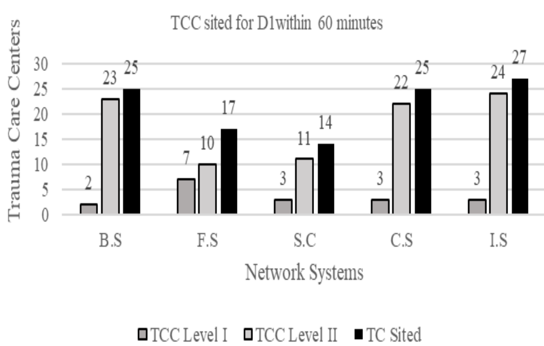
22d) TCC sited for D4 within 45 minutes



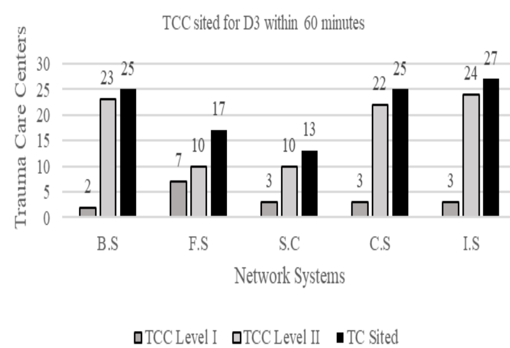
22e) TCC sited for D5 within 45 minutes

Figure 22. Trauma centers placed within 45 minutes

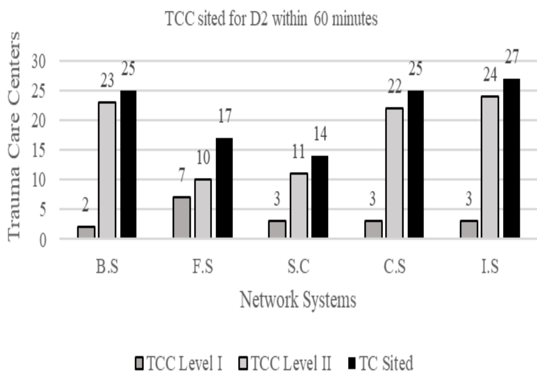
Figure 23 shows the trauma centers placed for trauma levels for a travelling time of 60 minutes. As shown previously in Figure 20, the Improvement-System has the highest coverage for Level-II trauma. This correlation between coverage and trauma facility placement can be seen in Figure 23 as the same network has the highest number of Level-II trauma centers places across all demand probability instances. It being an improvement over the Benchmark-System is allowed to include additional Level-II facilities. The Free-System recorded highest coverage for Level-I and the same correlation can be visualized above as the system places the most Level-I facilities across all demand probability instances. This strengthens the proposition that more facilities do not equate to greater coverage and importance must be given to a more strategic layout.

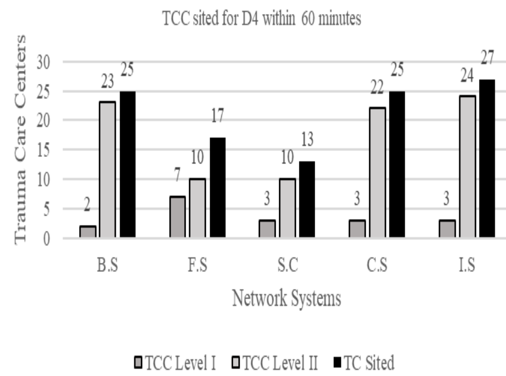


23a) TCC sited for D1 within 60 minutes

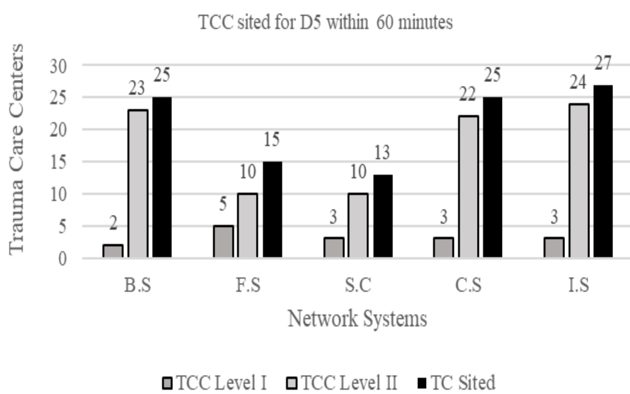


23b) TCC sited for D3 within 60 minutes





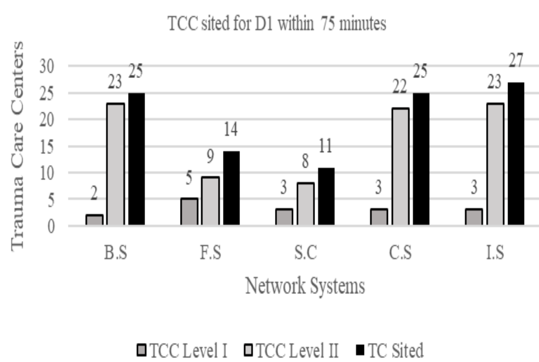
23c) TCC sited for D2 within 60 minutes 23d) TCC sited for D4 within 60 minutes

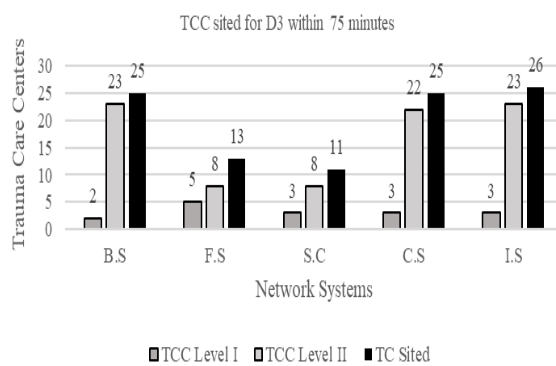


23e) TCC sited for D5 within 60 minutes

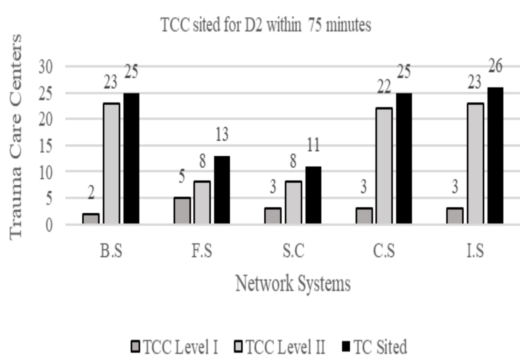
Figure 23**.** Trauma centers placed within 60 minutes

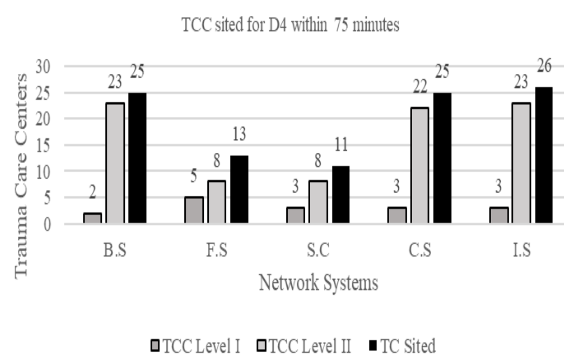
Figure 24 shows the trauma centers placed by trauma levels within a travelling time of 75 minutes. As shown in Figure 21, the Improvement-System has the highest coverage for Level-II and this is represented in Figure 24 where it can be seen that the former has the highest number of Level-II trauma centers placed, but matches with the facilities placed in the Benchmark-System. The Free-System is performing consistently with the highest coverage for Level-I , but due to the relaxed time limit, there are fewer Level-I facilities but still ranks as the highest placed among all systems, across all demand probability instances. This can be attributed for two reasons. The first is due to the time limit being 75 minutes and second because of the absence of constraints that do not limit the number of Level-I facilities that can be placed. Due to the combination of these two factors, the locations of the facilities are such that they cover a wider area with the travel time being higher hence requiring fewer facilities in general. In conclusion to this sub-section showcasing the results for the performance of all systems tested, it is clear that outlined locations and strategy can lead to better coverage with fewer facilities that are placed.



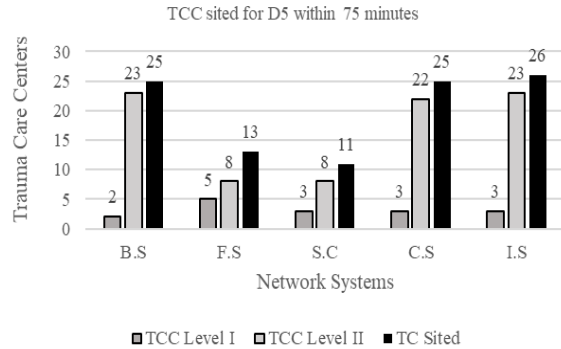


24a) TCC sited for D1 within 75 minutes 24b) TCC sited for D3 within 75 minutes





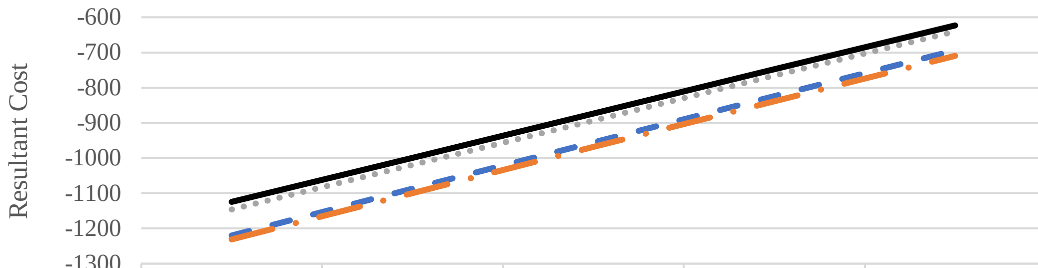
24c) TCC sited for D2 within 75 minutes 24d) TCC sited for D4 within 75 minutes



24e) TCC sited for D5 within 75 minutes

Figure 24. Trauma centers placed within 75 minutes

The objective function of the programming model incorporates a cost coefficient which works in tandem with the demand coverage. In the thesis, it was stated previously, that due to the increased demand during pandemic conditions, which result in greater average daily cases, this will result in a lower cost compared to scenarios which have a lower daily demand. The results in Table 18 when transcribed to a visual perspective, show the desired trend expected from the model decision making. Figure 25 shows the cost versus demand probability instance for systems, excluding the benchmark system for a travelling time of 45 minutes. As stated previously, D1 comprises 50% of the demand from pandemic condition which results to a higher overall demand. Cost values are used as placeholders to represent a numeric association and not the actual value itself. The aim is to confirm the trend and not the resultant value itself as such an initial cost coefficient will vary according to the model programming. The chart shows that higher the demand, D1, has a lower cost and this increase as the demand probability instance decreases to D5. A reminder that demand D5, incorporates just 10% of the pandemic condition values resulting in a lower overall demand. These trends affirm with the objective function that greater the coverage, lesser the resultant cost. Figures 26 and 27 below showcase the trends for 60- and 75-minutes travelling time, respectively.

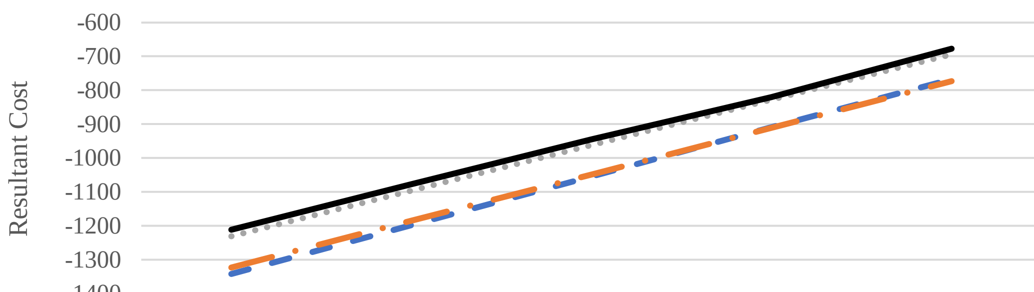


	D1	D2	D3	D4	D5
F.S	-1220	-1087.5	-955.7	-824.3	-694.05
S.C	-1231	-1099.8	-969.15	-839.1	-709.75
C.S	-1146	-1019.6	-893.2	-766.8	-640.4
I.S	-1124.5	-999.2	-873.9	-748.6	-623.3

Demand probability instance

F.S S.C C.S I.S

Figure 25. Cost vs Demand Probability instance for 45 minutes



	D1	D2	D3	D4	D5
F.S	-1342	-1198.4	-1054.05	-909.7	-767.15
S.C	-1323	-1185.1	-1047.7	-910.3	-772.9
C.S	-1230.75	-1096.5	-962.35	-828	-693.75
I.S	-1211.35	-1077	-944.15	-819.6	-677.05

Demand probability instance

F.S S.C C.S I.S

Figure 26. Cost vs Demand Probability instance for 60 minutes

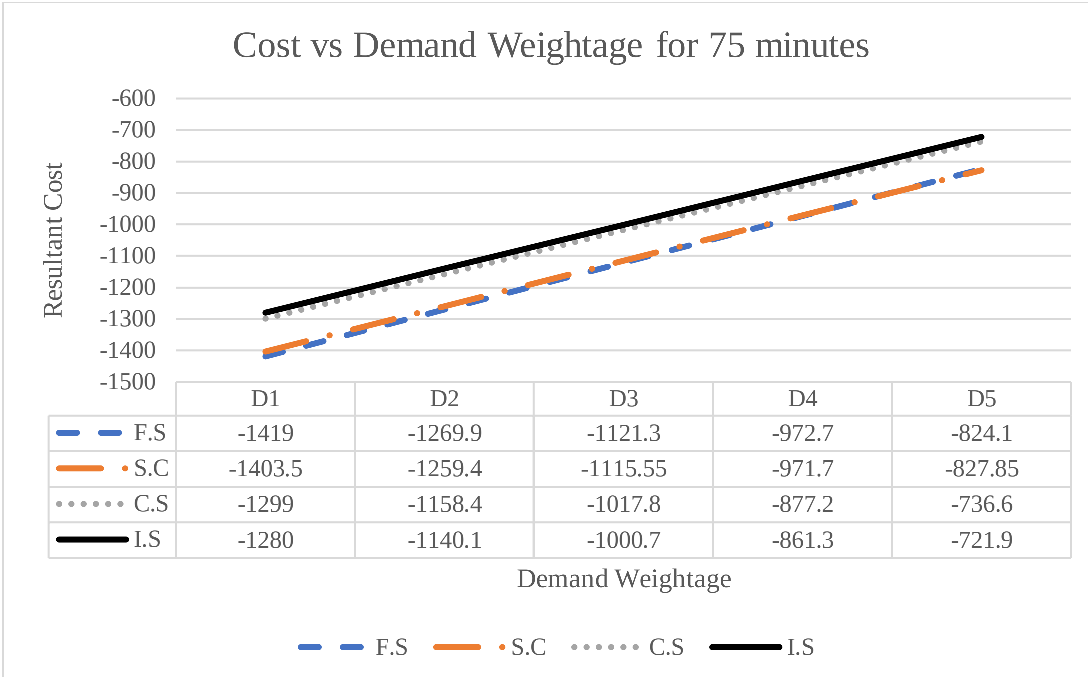


Figure 27**.** Cost vs Demand Probability instance for 75 minutes

Figures 26 and 27 coincide with the results and insights under Figure 25. It is a clear trend among tested systems, for all demand probability instances, and across all travelling times that the placement of facilities by considering higher demand will result in a lower end cost association.

4.5.2. Illustrative results

4.5.2.1. Benchmark system

The Benchmark-System comprises the officially designated trauma facilities in TSA P. Figure 28 below is a map of the trauma centers in the network along with their level designations. Red dots present Level-I trauma centers and blue dots represent Level-II trauma centers. The representation shows that the majority of facilities are clustered within the city of San Antonio. The remainder of the facilities in the network, when considering TSA P, are spread far between, clearly reinforcing the notion that coverage can be improved. Table 20 presents the codes for the trauma centers placed for the Benchmark-System.

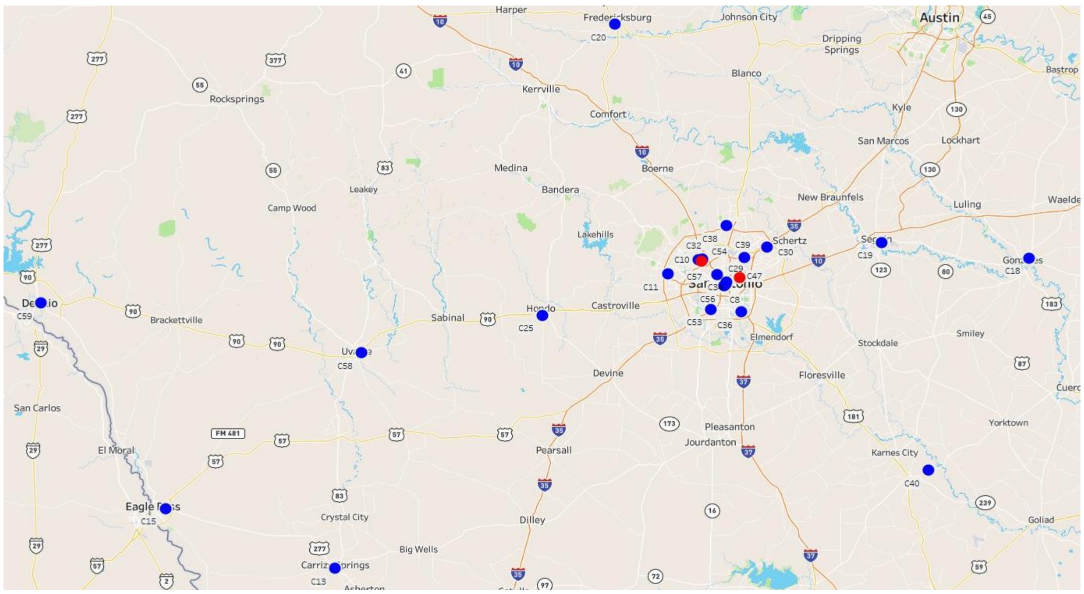


Figure 28. Trauma centers placed for Benchmark-System

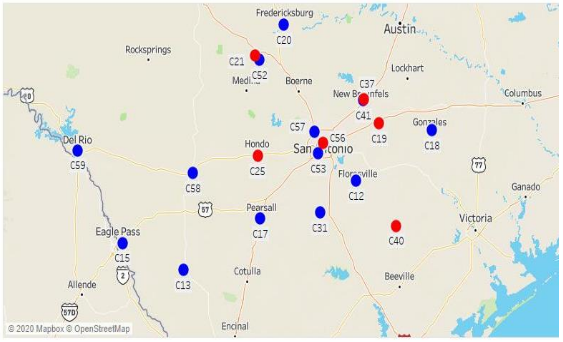
Table 20. Trauma Centers placed for Benchmark-System

D1/D2/D3 D4/D5	Level I	C47, C57
	Level II	C56, C20, C25, C18, C32, C34, C29, C36, C39, C30, C40, C38, C53, C54, C8, CA, C11, C10, C13, C15, C19

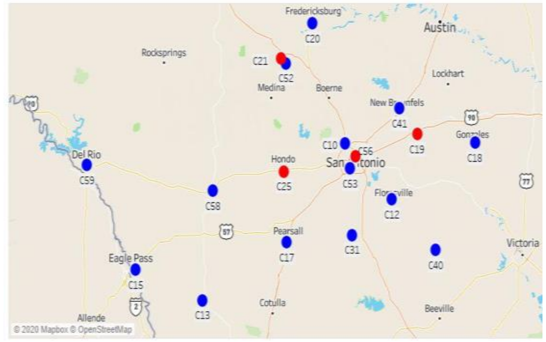
As shown in Table 18, the Benchmark System has its coverage by Level-I trauma centers to 84% when considering the standard travel time of 60 minutes. This improves to 87% when relaxing the time limit to 75 minutes, which is not a very significant increase. The coverages for Level-II trauma centers at 60 minutes is at 98% which requires Level-II trauma centers to be placed at locations closer to rural areas. Coverage improves to 99% when the time limit is relaxed to 75 minutes. For 45 minutes the coverage for Level-I reduces to 81%. These coverages show that there is room for improvement for Level-I.

4.5.2.2. Free system

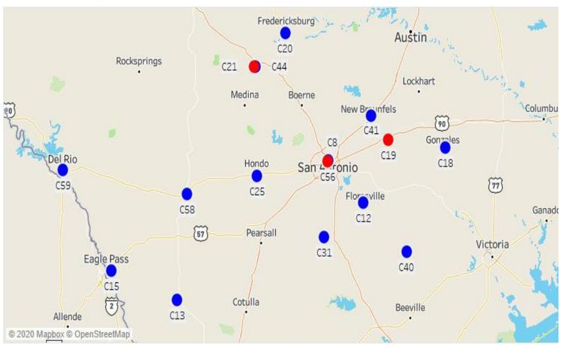
Figure 29 shows the first visual representation of the facility placement decision for the Free-System. Four panels represent the facilities placed according to the demand probability instances within a travel time of 45 minutes. Moving clockwise from the top left, the first panel shows the facilities placed for demand D1. There are a significant number of Level-I (red dots) facilities placed, as compared to the benchmark system, with a wider spread of Level-II (blue dots) facilities. The second panel, for demand D2, shows a reduced number of Level-I facilities, yet the spread of Level-II facilities remains consistent with the previous panel. The third panel, for demand D3 and D4 as the placement is the same for both probability instances, shows the facilities for both trauma levels with a consistent spread. The last panel, for demand D5, shows the least number of Level-I facilities placed with Level-II having a consistent spread. Table 21 below shows the codes for trauma centers placed, in correlation with Figure 29, for individual demands for both trauma levels.

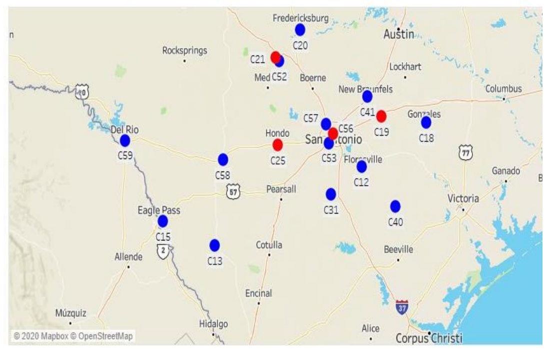


29a) TCC placed in demand D1 within 45 minutes



29b) TCC placed in demand D2 within 45 minutes





29d) TCC placed in demand D5 within 45 minutes

29c) TCC placed in demand D3 and D4 within 45 minutes

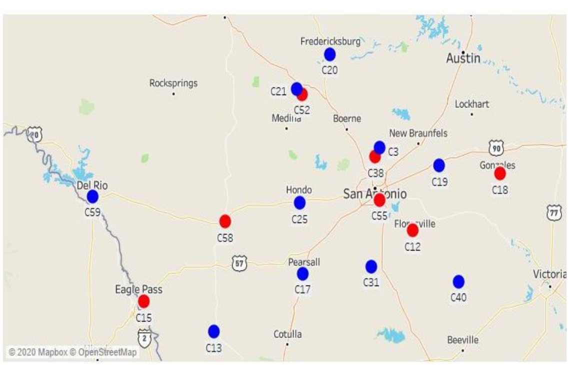
Figure 29. Trauma centers placed for Free-System within 45 minutes

Table 21. Trauma Centers placed for Free-System in 45 minutes

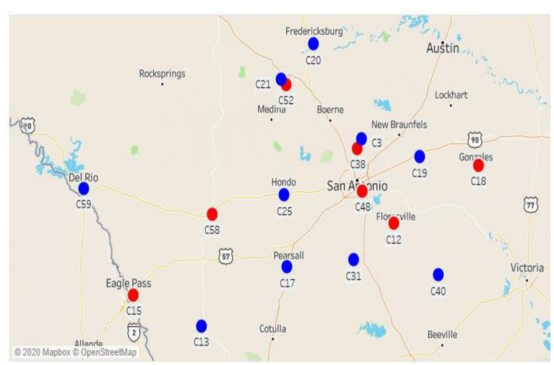
D1	Level I	C19, C21, C25, C37, C40, C56
	Level II	C12, C13, C15, C17, C18, C20, C31, C41, C52, C53, C57, C58, C59
D2	Level I	C19, C21, C25, C56
	Level II	C10, C12, C13, C15, C17, C18, C20, C31, C40, C41, C52, C53, C58, C59
D3/D4	Level I	C19, C21, C25, C56
	Level II	C12, C13, C15, C18, C20, C31, C40, C41, C52, C53, C57, C58, C59
D5	Level I	C19, C21, C56
	Level II	C12, C12, C15, C18, C20, C25, C31, C40, C41, C44, C58, C59

When considering the driving time of 45 minutes, the Free-System improves Level-I coverage to an average of 89.15% which is a significant increase from the previous Benchmark system value of 81%. Coverage for Level-II is at an average value of 97.57% which is lower than the Benchmark-System, but the facilities are not clustered within San Antonio.

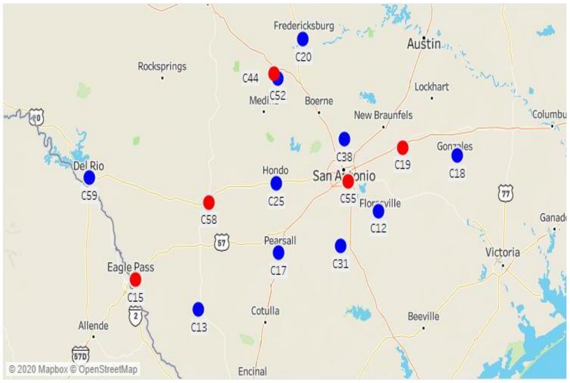
Figure 30 below shows the trauma centers placed within 60 minutes of travelling time. Red dots represent Level-I trauma centers and blue dots represent Level-II trauma centers. Moving clockwise from the top eft panel, the first indicator is the increased number of Level-I centers in comparison to the 45-minute time limit. Certain facilities that were designated as Level-II for 45 minutes, are now placed as Level-I, such as C15, C58, which are designated as Level-I across all demand probability instances. The third panel combines D3 and D4, for the centers placed are the same. We can see that the spread of centers throughout the area remains consistent. Table 22 below shows the codes for trauma centers placed, in correlation with Figure 30, for individual demands for both trauma levels.



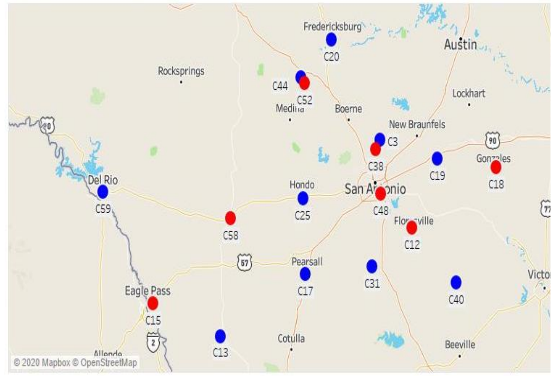
30a) TCC placed in demand D1 within 60 minutes



30b) TCC placed in demand D2 within 60 minutes



30d) TCC placed in demand D5 within 60 minutes



30c) TCC placed in demand D3 and D4 within 60 minutes

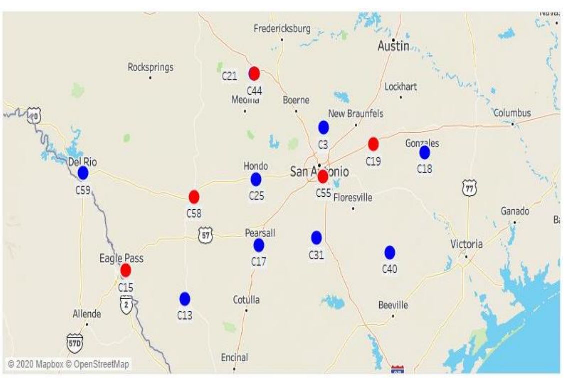
Figure 30. Trauma centers placed for Free-System within 60 minutes

Table 22. Trauma Centers placed for Free-System in 60 minutes

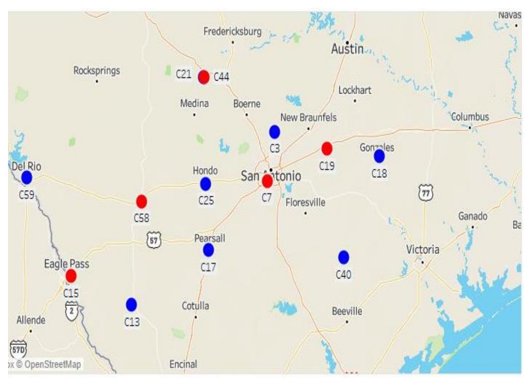
D1	Level I	C12, C15, C18, C38, C52, C55, C58
	Level II	C13, C17, C19, C20, C21, C25, C31, C3, C40, C59
D2	Level I	C12, C15, C18, C38, C48, C52, C58
	Level II	C13, C17, C19, C20, C21, C25, C31, C3, C40, C59
D3/D4	Level I	C12, C15, C18, C38, C48, C52, C58
	Level II	C13, C17, C19, C20, C25, C31, C3, C40, C44, C59
D5	Level I	C15, C19, C44, C55, C58
	Level II	C12, C13, C17, C18, C20, C25, C31, C38, C52, C59

For 60 minutes Level-I coverage increases to an average value of 95.42% which is a significant increase over the Benchmark-System (84% for Level-I) and Level-II coverage has an average value of 98.27% which is consistent with the latter yet the facilities aren’t clustered around San Antonio. Its limitations are primarily based on the cost association of opening facilities and the quantity that can be placed. Modification of these parameters can improve coverage for both trauma levels.

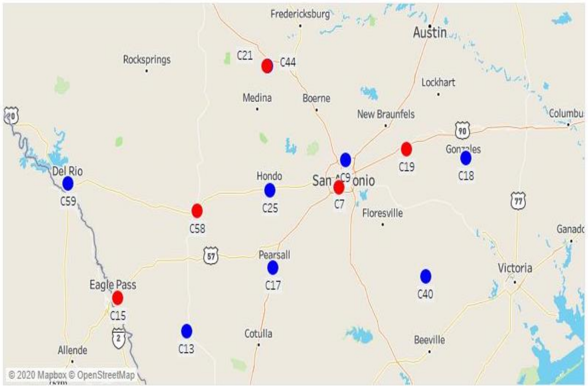
Figure 31 below shows the trauma centers placed within a travelling time of 75 minutes. Due to the relaxed limit of time required to reach a trauma center, there are fewer facilities places as compared to previous time limits of 45 and 60 minutes respectively, yet the spread of facilities inside the area of study remains consistent and not clustered in any specific region. Moving clockwise from the top left panel, the first panel shows the centers placed for demand D1 and subsequently D2. The third panel shows the centers for demand D3, D4 and D5 are presented in the same panel as the facilities placed are the same. A pattern can be immediately visualized as all demands have the same facilities, both in name and number, placed. An interesting perspective as high-level centers are essentially the same, suggesting that merely changing the location of Level-II facilities can be considered to improve coverage. Table 23 below shows the codes for trauma centers placed, in correlation with Figure 31, for individual demands for both trauma levels.



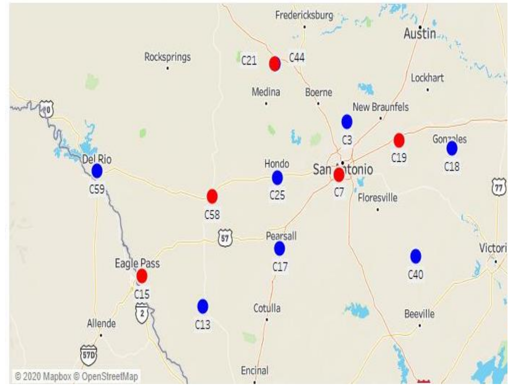
31a) TCC placed in demand D1 within 75 minutes



31b) TCC placed in demand D2 within 75 minutes



31d) TCC placed in demand D4 and D5 within 75 minutes



31c) TCC placed in demand D3 within 75 minutes

Figure 31**.** Trauma centers placed for Free-System within 75 minutes

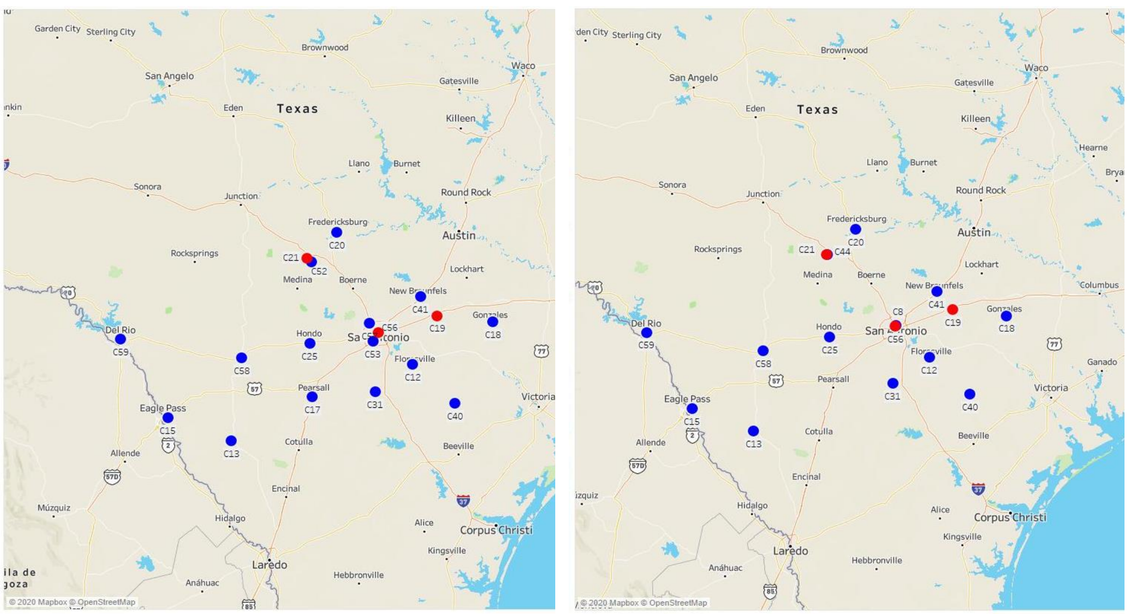
Table 23. Trauma Centers placed for Free-System in 75 minutes

D1	Level I	C15, C19, C44, C55, C58
	Level II	C13, C17, C18, C21, C25, C31, C3, C40, C59
D2	Level I	C15, C19, C44, C58, C7
	Level II	C13, C17, C18, C21, C25, C3, C40, C59
D3	Level I	C15, C19, C21, C58, C7
	Level II	C13, C17, C18, C25, C3, C40, C44, C59
D4/D5	Level I	C15, C19, C21, C58, C7
	Level II	C9, C13, C17, C18, C25, C40, C44, C59

The average coverage values for Level-I and Level-II are 96.53% and 99.69% which can be attributed to the relaxed time limit in place. These are improvements over average coverage values of 87% and 99% for Level-I and Level-II for the Benchmark-System. If the focus of the study is geared towards coverage when considering 75 minutes as the time limit then the system will perform better than its predecessors, viz 45 and 60 minutes respectively, with facilities being spread over a larger area rather than being clustered.

4.5.2.3. Semi-constrained system

Figure 32 below comprises two panels that display the trauma centers placed for the Constrained-System within a travel time of 45 minutes. Moving from the left, the first panel combine centers placed in demand D1 and D1 since the facilities placed are the same in each demand. The second panel combines the same for demands D3, D4, and D5. As this system will place three Level-I trauma centers regardless of demand or time, the resultant network will involve rotating Level-II facilities to respond to demand probability instances. Table 24 below shows the codes for trauma centers placed, in correlation with Figure 32, for individual demands for both trauma levels.



32a) TCC placed in demand D1and D2 within 45 minutes

32b) TCC placed in demand D3, D4, and D5 within 45 minutes

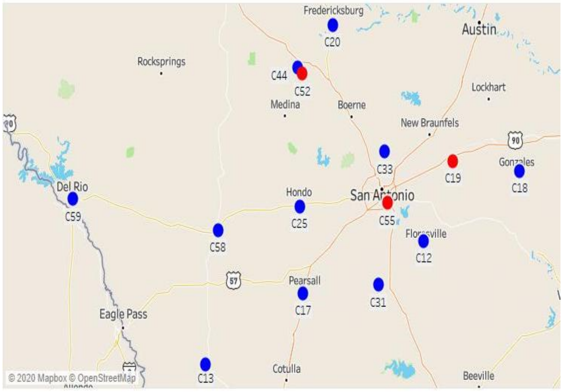
Figure 32**.** Trauma centers for Semi-Constrained System within 45 minutes

Table 24. Trauma Centers placed for Semi-Constrained System in 45 minutes

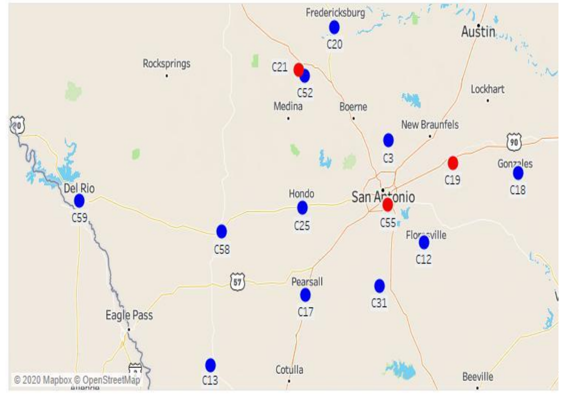
D1/D2	Level I	C19, C21, C56
	Level II	C12, C13, C15, C17, C18, C20, C25, C31, C40, C41, C52, C53, C57, C53, C57, C58, C59
D3/D4/D5	Level I	C19, C21, C56
	Level II	C12, C13, C15, C18, C20, C25, C31, C40, C41, C44, C58, C59, C8

The average coverage values for Level-I and Level-II are 87.84% and 98.01% which is an improvement for Level-I and similar to Level-II when compared against the Benchmark-System which has average coverage values of 81% and 97% for Level-I and Level-II respectively. Even with the reduced time limit, there is no clustering to an extent seen in the Benchmark-System and coverage is determined by time taken and number of facilities that can be placed.

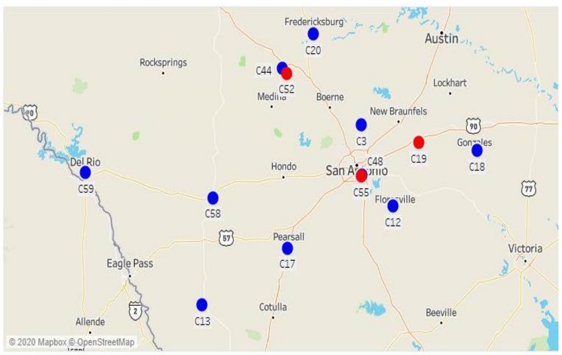
Figure 33 below shows the trauma centers placed for the Constrained-System within a travel time of 60 minutes. Moving clockwise from top left, the first panel shows the trauma centers placed for demand D1, D2, D4, and D3 combined with D5 for both have the same trauma centers placed between them. There are three Level-I facilities placed with the rotation being prioritized for Level-II centers. The placement of trauma centers is slightly skewed towards the east coast. Table 25 below the codes for trauma centers placed, in correlation with Figure 33, for individual demands for both trauma levels.



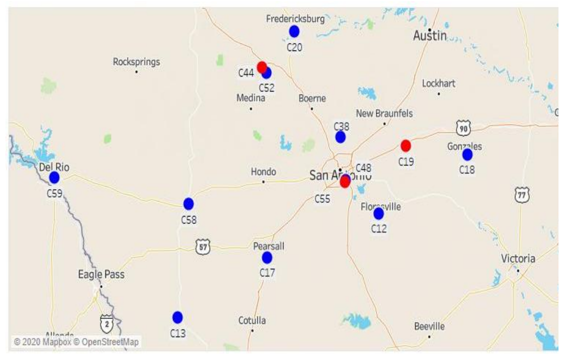
33a) TCC placed in demand D1 within 60 minutes



33b) TCC placed in demand D2 within 60 minutes



33d) TCC placed in demand D4 within 60 minutes



33c) TCC placed in demand D3 and D5 within 60 minutes

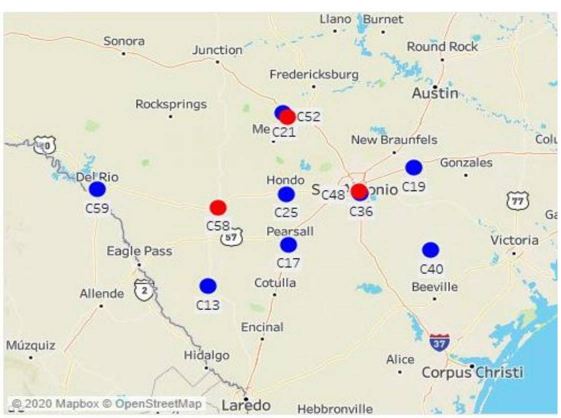
Figure 33. Trauma centers placed for Semi-Constrained System within 60 minutes

Table 25. Trauma Centers placed for Semi-Constrained System in 60 minutes

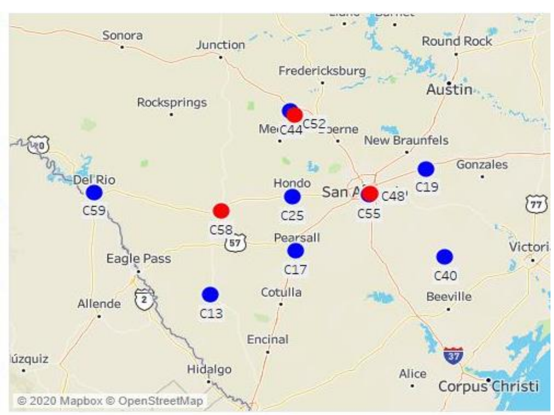
D1	Level I	C19, C52, C55
	Level II	C12, C13, C17, C18, C20, C25, C31, C33, C44, C58, C59
D2	Level I	C19, C21, C55
	Level II	C12, C13, C17, C18, C20, C25, C31, C3, C52, C58, C59
D3/D5	Level I	C19, C44, C55
	Level II	C12, C13, C17, C18, C20, C38, C48, C52, C58, C59
D4	Level I	C19, C52, C55
	Level II	C12, C13, C17, C18, C20, C3, C44, C48, C58, C59

For the standard driving time of 60 minutes, Level-I and Level-II coverage increase with an average value of 90.30% and 99.11%, respectively, which are significant improvements over the Benchmark-System: 84% for Level-I and 98% for Level-II. This suggests that although Level-II facility coverage is adequate and will require very fine tuning to improve its coverage, the network needs more Level-I facilities to cover more ground. The limit enforced is three Level-I facilities, but incremental additions will likely improve the coverage to a greater extent or redesignating pre-existing Level-II facilities to Level-I will also affect coverage.

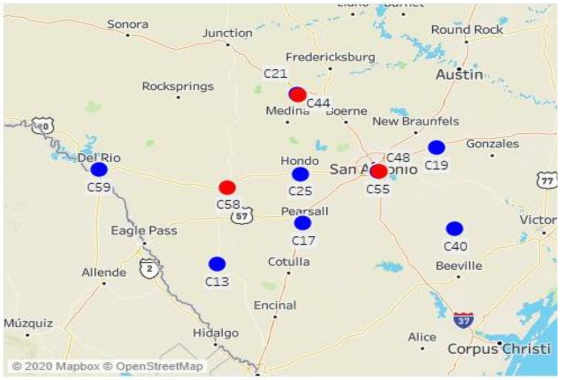
Figure 34 below shows the placement of trauma centers within a travel time of 75 minutes. All demand probability instances have their respective panels. An immediate indication pertaining to the difference between 75 minute and the remainder is the relocation of Level-I facilities and the absence of the skewed nature of location as compared to Figure 33. Table 26 below the codes for trauma centers placed, in correlation with Figure 34, for individual demands for both trauma levels.



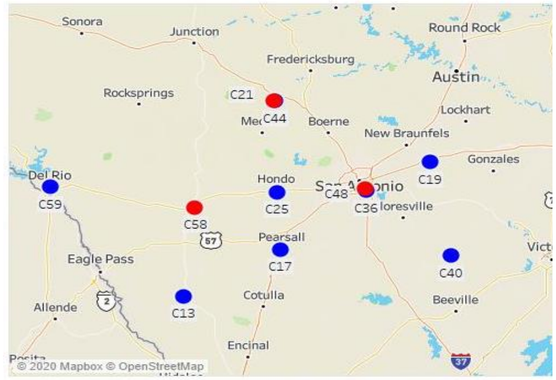
34a) TCC placed in demand D1 within 75 minutes



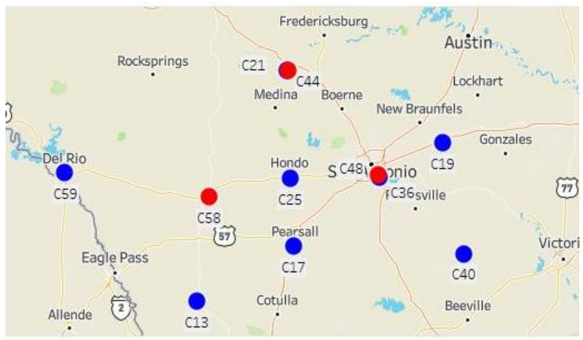
34b) TCC placed in demand D2 within 75 minutes



34d) TCC placed in demand D4 within 75 minutes



34c) TCC placed in demand D3 within 75 minutes



34e) TCC placed in demand D5 within 75 minutes

Figure 34. Trauma centers placed for Semi-Constrained System within 75 minutes

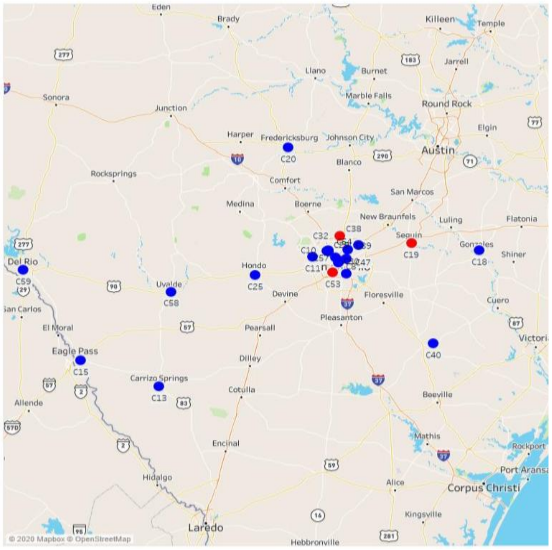
Table 26. Trauma Centers placed for Semi-Constrained System in 75 minutes

D1	Level I	C48, C52, C58
	Level II	C13, C17, C19, C21, C25, C36, C40, C59
D2	Level I	C48, C52, C58
	Level II	C13, C17, C19, C25, C40, C44, C55, C59
D3	Level I	C21, C48, C58
	Level II	C13, C17, C19, C25, C36, C40, C44, C59
D4	Level I	C44, C48, C58
	Level II	C13, C17, C19, C21, C25, C40, C55, C59
D5	Level I	C44, C48, C58
	Level II	C13, C17, C19, C21, C25, C36, C40, C59

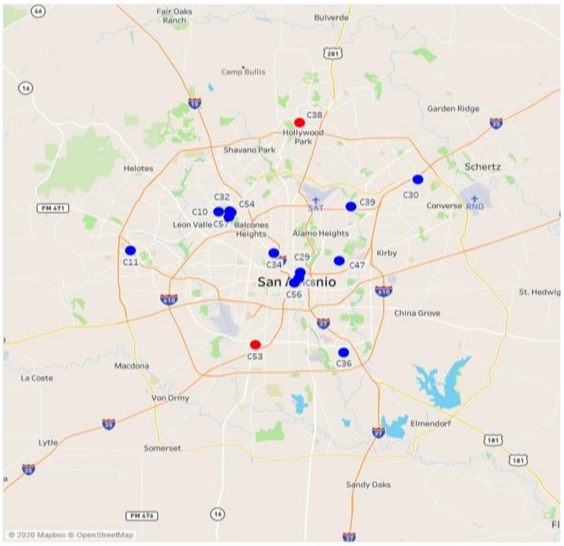
With a limit of 75 minutes, we can see coverage for Level-I and Level-II improve to an average value of 92.38% and 99.70% showcasing significant increases compared to the Benchmark-System; 87% for Level-I and 99% for Level-II. Level-II coverage needs tuning at an incremental level to cover the entire population under study, but Level-I coverage will require more facilities to improve its population coverage. This can be seen in terms of injuries that are not critical in nature and do not require immediate attention can benefit from this system as coverage is almost at a 100%.

4.5.2.4. Constrained system

Figure 35 below comprises the trauma centers placed for the Constrained-System within a travel time of 45 minutes. As the locations of centers placed are the same across all demand probability instances, there is only a need for a singular panel. To avoid cluttering, a second panel to the right was added which enlarges the area of San Antonio where a significant number of trauma centers are placed to allow for clarity. This is repeated for Figure 36 as well. Table 27 below shows the codes for trauma centers placed, in correlation with Figure 35, for individual demands for both trauma levels.



35a) TCC placed for all demands, D1 to D5, within 45 minutes



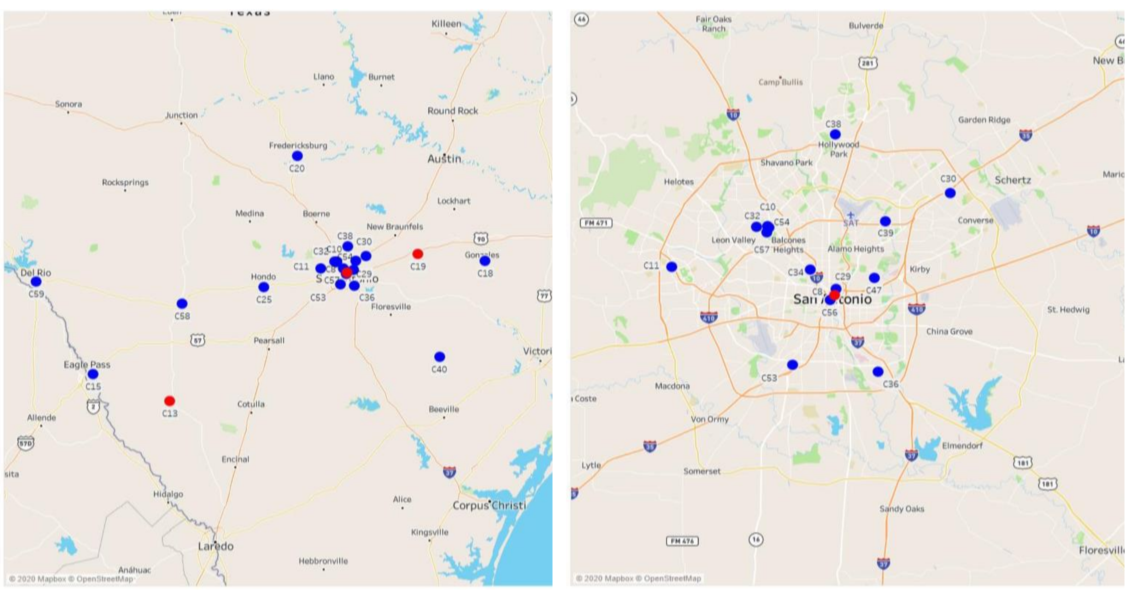
35b) Enlarged area of San Antonio with TCC placed

Figure 35. Trauma centers placed for Constrained System within 45 minutes

Table 27. Trauma Centers placed for Constrained System in 45 minutes

D1/D2/D3/D4/D5	Level I	C38, C53, C19
	Level II	C47, C57, C56, C20, C25, C18, C32, C34, C29, C36, C39, C30, C40, C54, C58, C59, C8, CA, C11, C10, C13, C15

For 45 minutes as the time limit, average coverage values for Level-I and Level-II are 85.56% and 96.69% which is an improvement over the Benchmark-System; 84% for Level-I, but remains almost the same for Level-II i.e. 97%. This shows us that the current trauma network coverage can be improved by re-designating existing facilities of their trauma levels. Figure 36 shows the trauma centers placed within a travel time of 60 minutes. As can be noted, the location varies from the previous figure for a Level-I trauma center is placed down south near Eagle Pass (i.e. C15). Table 28 below the codes for trauma centers placed, in correlation with Figure 36 for all demands for both trauma levels.



36a) TCC placed for all demands, D1 to D5, within 60 minutes

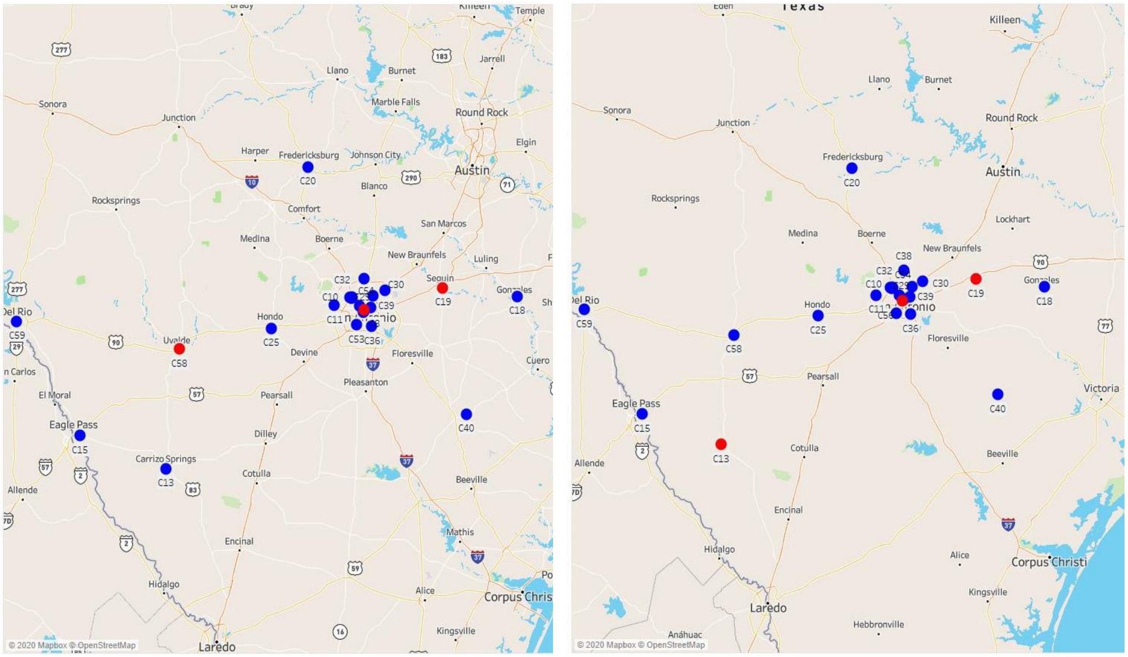
36b) Enlarged area of San Antonio with TCC placed

Figure 36. Trauma centers placed for Constrained System within 60 minutes

Table 28. Trauma Centers placed for Constrained System in 60 minutes

D1/D2/D3/D4/D5	Level I	C8, C13, C19
	Level II	C47, C57, C56, C20, C25, C18, C32, C34, C29, C36, C39, C30, C40, C38, C53, C54, C58, C59, CA, C11, C10, C15

When considering 60 minutes as the standard driving time, average coverage values for Level-I and Level-II are 89.46% and 98.23% which showcase improvements for the former yet similar to the latter when compared against the Benchmark-System; 84% for Level-I and 98% for Level-II. This reinforces the statement made for 45 minutes driving time that redesignating existing Level-I facilities will improve coverages. A factor that must be considered is that clustering of facilities can be seen in San Antonio hence requiring additional hospitals and medical centers to be considered as trauma centers to ensure adequate spread in land area. Figure 37 below shows the trauma centers placed for demands D1, D3, and D5 in the left panel, D2 and D4 in the right panel. A significant number of trauma centers are clustered in San Antonio. Table 29 below the codes for trauma centers placed, in correlation with Figure 37, for individual demands for both trauma levels.



37a) TCC placed for demands D1, D3, and D5, within 75 minutes

37b) TCC placed for demands D2 and D4 within 75 minutes

Figure 37. Trauma centers placed for Constrained System within 75 minutes

For 75 minutes, average coverage values for Level-I and Level-II are 90.18% and 99.76% which are improvements when compared against the Benchmark-System; 87% for Level-I and 99% for Level-II. These improvements assert the fact that re-designation for trauma levels of existing facilities and adding more hospitals to the network will improve coverage.

Table 29. Trauma Centers placed for Constrained System in 75 minutes

D1/D3/D5	Level I	C29, C58, C19
	Level II	C47, C57, C56, C20, C25, C18, C32, C34, C36, C39, C30, C40, C38, C53, C54, C59, C8, CA, C11, C10, C13, C15
D2/D4	Level I	C56, C13, C19
	Level II	C47, C57, C20, C25, C18, C32, C34, C29, C36, C39, C30, C40, C38, C53, C54, C58, C59, C8, CA, C11, C10, C15

4.5.2.5. Improvement system

Figure 38 shows the trauma centers placed in the Improvement System for a travel time within 45 minutes. For all demand cases, clustering of facilities can be seen in San Antonio with a spread similar to what the Benchmark System shows. Table 30 below the codes for trauma centers placed, in correlation with Figure 38 for all demands for both trauma levels. Clustering can be observed in San Antonio with average coverage values for Level-I and Level-II being 83.28% and 97.86% respectively, which especially is an improvement; considering Level-I, when compared against the Benchmark-System, which has an average coverage of 81% and 97.57% for Level-I and Level-II respectively. For Level-I, facility C21 has been placed to cater to the required trauma demand for the driving time. For Level-II, facility C30, C31, C52, and C59 were added to facilitate demand within the driving time. It is clear that coverage for Level-II does not change, rather shows a very slight decrease mainly due to the time limit of 45 minutes which does restrict coverage.

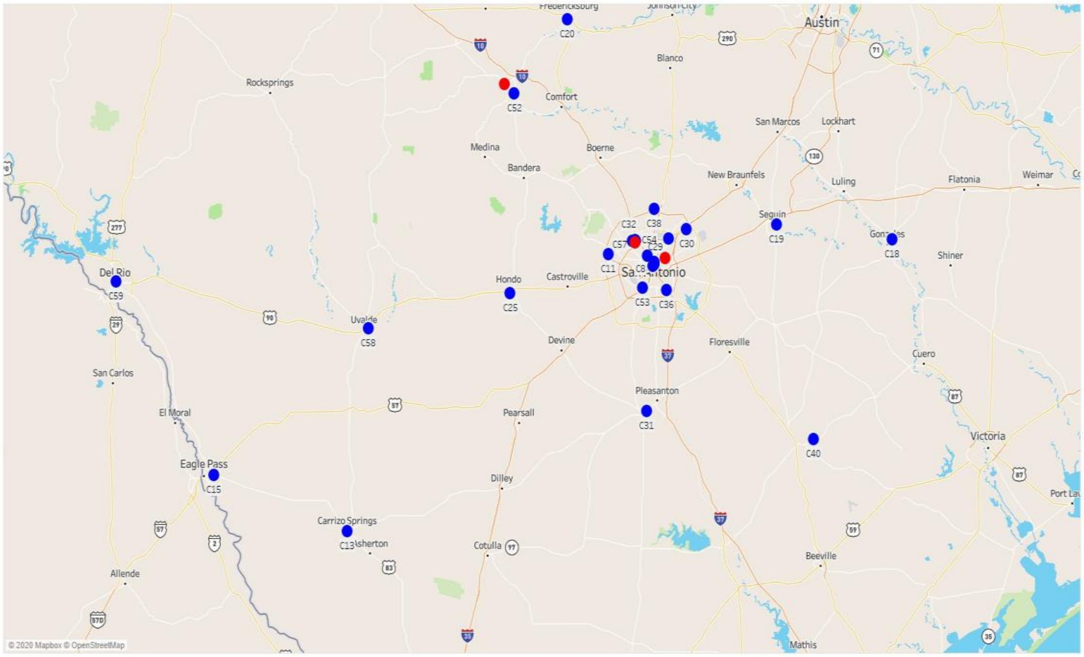
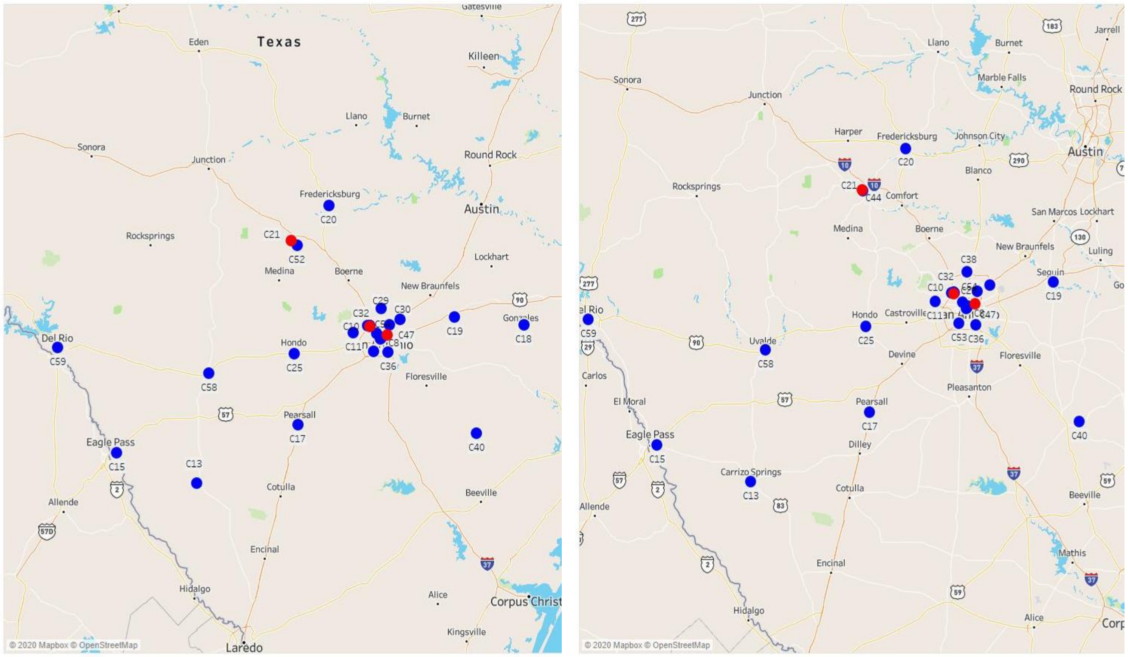


Figure 38. Trauma centers placed for Improvement System within 45 minutes

Table 30. Trauma Centers placed for Improvement System in 45 minutes

D1/D2/D3/D4/D5	Level I	C21, C47, C57
	Level II	C10, C11, C13, C15, C18, C19, C20, C25, C29, C30, C31, C32, C34, C36, C38, C39, C40, C52, C53, C54, C56, C58, C59, C8

Figure 39 below shows the trauma centers placed within a travel time of 60 minutes. The clustering effect seen previously is present, similar to centers within 45 minutes. Table 31 below the codes for trauma centers placed, in correlation with Figure 39, for individual demands for both trauma levels. For the standard driving time of 60 minutes, average coverage values for Level-I and Level-II are 87.67% and 99.58% respectively, which are improvements over the Benchmark-System which has average coverage values of 84% and 98% for Level-I and Level-II respectively. For Level-I, facility C21 is placed in addition to the existing centers and for Level-II C52(D1) and C44(D2 to D5) to cater demand outside of highly populated areas. Clustering can be seen in and around San Antonio suggesting additional Level-I facilities must be placed outside urban areas to improve coverage for rural areas and other towns/cities. When considering the placement of trauma facilities due to the pandemic demand, initial analysis of cases showed increase in the number of cases recorded during the pre-opening phase and post-opening phase around the area of Kerrville and Fredericksburg in addition to San Antonio, which is expected due it being a major city. As is such the demand instance D1 incorporates greater demand for COVID-19, the placement of a Level-I trauma center, C21, in the location of Kerrville and Fredericksburg affirms the decision of the model to provide service to the demand location. Even when considering the lowest demand instance for COVID-19 i.e. D5, the model still places a Level-I facility and places center C44 instead of C52 which can be reasoned that the model would consider the distances between trauma centers and demand nodes to better facilitate the demand. It would seem that the model still considers the large cases recorded in an area to be given priority over others, with changing demand instances, to evaluate the demand over all instances and place the trauma centers accordingly. If demand in the area discussed would be lower than shown, the model would not have deemed fit to place a high-level trauma center.



39a) TCC placed for demand D1 within 60 minutes

39b) TCC placed for demands D2, D3, D4, and D5 within 60 minutes

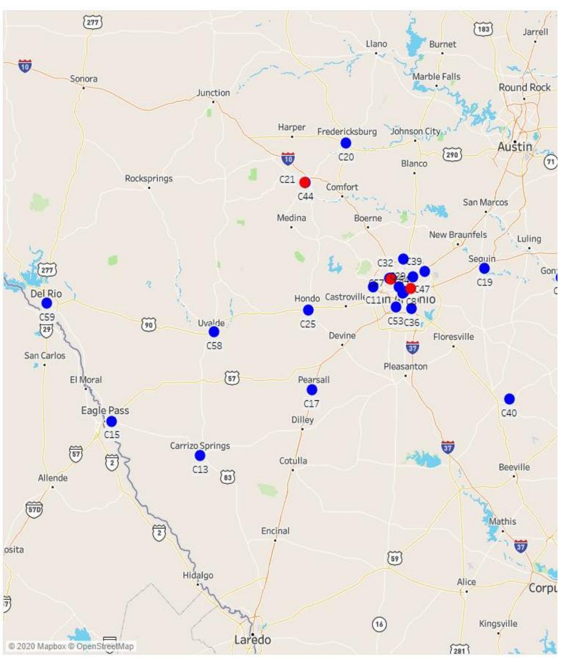
Figure 39. Trauma centers placed for Improvement-System within 60 minutes

Table 31. Trauma Centers placed for Improvement System in 60 minutes

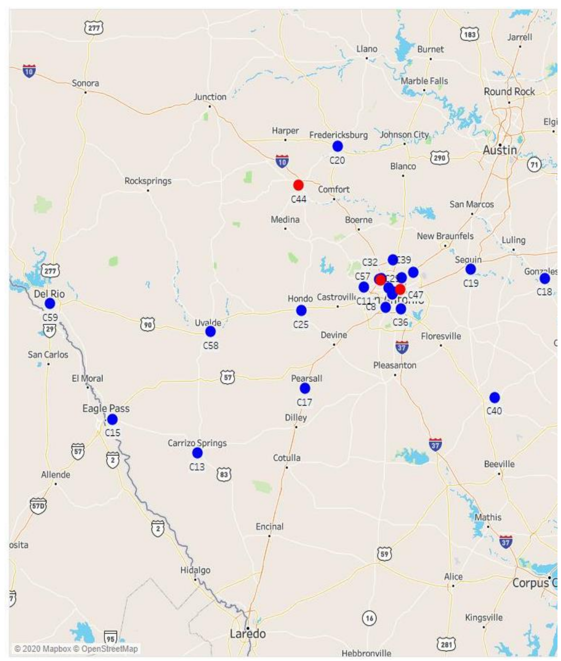
D1	Level I	C21, C47, C57
	Level II	C10, C11, C13, C15, C17, C18, C19, C20, C25, C29, C30, C32, C34, C36, C38, C39, C40, C52, C53, C54, C56, C58, C59, C8
D2/D3/D4/D5	Level I	C21, C47, C57
	Level II	C10, C11, C13, C15, C17, C18, C19, C20, C25, C29, C30, C32, C34, C36, C38, C39, C40, C44, C53, C54, C56, C58, C59, C8

Figure 40 below shows the trauma centers placed within a travel time of 75 minutes. Clustering can be seen clearly, similar to centers within 45 and 60 minutes. Table 32 below the codes for trauma centers placed, in correlation with Figure 40, for individual demands for both trauma levels. When considering a driving time of 75 minutes, average coverage values for Level-I and Level-II are 90.18% and 99.76 %

respectively when compared to the Benchmark-System which has average coverage values of 87% and 99% respectively. For Level-I, facility C21(D1) and C44(D2 to D5) is placed in addition to the existing centers and for Level-II it is interesting to point out that C44 which was a Level-II facility in D1 is placed as a Level-I for D2 to D5 with a reasoning that due to the lower demand from D2 and onwards, it would be better utilized as a higher level center, thus removing the need to find a replacement facility for the same demand instance. This refers to improvements when compared against the Benchmark-System asserting the statement that additional Level-I facilities are needed outside San Antonio to avoid clustering and improve coverage. Improving Level-II coverage is already significant, hence minute improvements will require closer scrutiny over incremental additions to the trauma network.



40a) TCC placed for demand D1 within 75 minutes



40b) TCC placed for demands D2, D3, D4, and D5 within 75 minutes

Figure 40. Trauma centers placed for Improvement-System within 75 minutes

Table 32. Trauma Centers placed for Improvement System in 75 minutes

D1	Level I	C21, C47, C57
	Level II	C10, C11, C13, C15, C17, C18, C19, C20, C25, C29, C30, C32, C34, C36, C38, C39, C40, C44, C53, C54, C56, C58, C59, C8
D2/D3/D4/D5	Level I	C44, C47, C57
	Level II	C10, C11, C13, C15, C17, C18, C19, C20, C25, C29, C30, C32, C34, C36, C38, C39, C40, C53, C54, C56, C58, C59, C8

5. CONCLUSION

The conclusion part of the thesis is divided into two sub-sections. Sub-section 5.1 will discuss and summarize the findings for the forecasting and analysis part of the thesis in addition to providing recommendations for future research. Sub-section 5.2 will discuss and summarize the observations and results obtained for the stochastic part of the thesis while providing recommendations for future research.

5.1 Forecasting analysis conclusions

Trauma care access is an important public health issue that must be considered by Texas public officials in an ongoing basis due to the continuous increase in population experienced by the state in the last few years. The focus was on analyzing and forecasting physical trauma injuries in rural areas of the state. Five types of forecasting methods were analyzed to determine the best option to utilize for forecasting for individual data sets. The following insights were obtained from a descriptive analysis of the data. The results show that regional locations around Travis and Bexar counties reported the highest number of injuries. Those two counties are home to major cities such as Austin and San Antonio. The results also showed high variability in the number of trauma injuries reported per year in regions 780, 781, 783, and 788 which are mostly rural regions. Ongoing analysis of the variability of these regions is important for the future expansion of the trauma network in Texas.

In terms of trauma center levels, the results showed that Level-I TCCs treat at least 35% of the trauma injuries per year, treating more trauma patients than Level-II, Level-III, and Level-IV TCCs. These findings are relevant because only 6% of TCCs in Texas are designated as Level-I trauma facilities. Possible explanations for this phenomenon are that Level-I TCCs are located in large metropolitan areas with high population densities. In addition, it could indicate that there is a need for better protocols at the time of selecting the Trauma hospital to transport the injured patients for care. Better trauma hospital selection processes can help in avoiding facilities overutilization or underutilization.

Level-I TCCs are comprehensive trauma facilities and they are expected to manage mostly severe cases with high ISS. Although the ISS for patients served at TCCs Level-I were highly variable, the results showed that patients with very low ISS were served at Level-I trauma facilities. This finding supports the recommendation of developing better protocols for deciding where to transport patients (i.e. TCC level) when they have suffered accidents. In terms of injury environment, it was observed that the industrial facilities environment (i.e. code 849.3) accounts for the least number of trauma injuries for any given year. The homes environment (i.e. code 849.0) accounts for the highest number of trauma injuries for any given year with zip code 782 presenting the regional location with the highest number of injuries.

The following insights were obtained from the predictive analysis of the data. The EWMA and ARIMA forecasting methods provided the best performance for forecasting trauma injuries in the studied region. Out of the 24 evaluated time series, EWMA provided the best performance for 9 and ARIMA provided the best performance for 12. It was also observed that the increase in variability (i.e. CV) in the time series resulted in an increase in the forecasting error. Zip codes 783 and 788 reported the largest values for the CV and the MAPE. Those regional locations observed less numbers of trauma injuries, when compared to the rest, for all years considered in this study. The limited number of observations could be the reason for the observed higher values for CV and MAPE. Better MAPE results were obtained for those regional locations with higher number of injuries reported (i.e. 782 and 787).

In terms of future research, we propose to formulate a stochastic programming (SP) optimization model to study the expansion of the TCC network in the studied regions. The SP model will utilize the forecasting results and models to predict future needs. The results of the ISS analysis will be used to test different assignment patient-hospital protocols to prioritize the assignment of trauma facilities based on their capabilities to allow for maximum utilization. The combination of all these constraints will provide a more dynamic, non-deterministic approach to develop policies for public health decisions related to the expansion of the trauma network. Appendices A and B contain additional information required that pertains to the data and results for the study. Appendix A contains the ARIMA model parameters. Appendix B contains total trauma level visits for all years, injury severity score insights, fitted values against injuries per data sets for the best performing models.

The primary limitation faced with this aspect of forecasting was the lack of exact data pertaining to the trauma injuries location. Two data sets were provided by DSHS. The data set with injury locations contained data at the county level providing only three digits zip codes, while the other set contained the injury data in terms of trauma level designation and injury severity score statistics. There was no way to determine a link between these sets, as there were no unique identifiers. Since the data sets cannot be linked, the study did not want to assume trends and extrapolate patterns without any concrete foundations. If the complete sets can be made available in the future, correlations between data sets can be made to determine the actual patterns and yearly trends for specific locations in Texas.

5.2 Stochastic programming conclusions

The goal of the stochastic programming part of the thesis was to analyze and determine the performance, in terms of population coverage, for *Trauma Service Area ‘P*’ as shown in chapter 4, sub-sections 4.2 and 4.4. Zip codes within the region were identified and categorized as demand nodes and trauma centers, both officially designated and general hospitals and medical centers, were also identified. Distances between demand nodes and trauma centers were calculated to construct a matrix which would determine if a given demand node was in reach of trauma centers within 45, 60, and 75 minutes driving time, respectively. Demand was divided into instances which comprised six scenarios withing each instance. Scenarios would represent daily average cases recorded according to the data available from the DSHS for the years 2014 to 2016 and recent COVID-19 cases. Demand instances would change their weightage in a decreasing order where instance D1 would represent 50% of the demand attributed to COVID-19 while instance D5 would represent just 10% of COVID-19 demand and the remainder 90% of the demand would be the cases recorded during nominal operations. A two-stage stochastic programming model was introduced along with its variations of which the latter are modified versions of the original model that are used to represent modified networks of the current trauma network to determine their coverage. The current trauma network was termed as the Benchmark-System, the network to test all proposed networks against. The Free-System would develop a new network with a wider assortment of hospitals and medical centers available at its disposal. The Semi-Constrained System had to limit its Level-I facility placement to three and the Constrained System had to place both Level-I and Level-II facilities according to the numbers in the current trauma network. The Improvement-System was developed to determine changes in coverage when facilities were added incrementally to the current trauma network and observe improvements. The results obtained were showed as both narrative and illustrative based to provide insights and discuss relationships between numerical and visual aspects.

The Benchmark system is the current trauma network of which all proposed systems are tested against. When considering population coverage for Level-I facilities, the Free-System has the highest coverage percentage across all demand probability instances and for all time limits, with the exception of coverage at demand D5 at 45 minutes where it is tied with the Semi-Constrained System. The Free-System also has the highest number of individual Level-I trauma centers placed when compared to all systems across all demand probability instances and for all time limits, which makes sense due to its relaxed bounds for placing trauma centers not inhibited by placing limits on individual trauma levels. The Improvement-System has the highest overall population coverage for Level-II facilities yet does not have the same performance when it comes to coverage at Level-I. It is a clear indication that the Benchmark-System can be redesigned and planned with fewer trauma centers to improve coverage. We have also seen that incremental increase of facilities in the current network produces an improvement of almost 4% in coverage for Level-I trauma centers when comparing the Benchmark and Improvement Systems, the latter of which is considered to be more pragmatic approach to coverage improvement rather than the complete restructuring of the current network. As coverage pertaining to Level-II facilities was already significantly high, the remainder 1% - 2% gap in coverage is a challenge within itself and will require more facilities to be considered. The cost with respect to coverage relationship brings into foray the desired performance; greater coverage reduces resultant cost, especially pertaining to the Free and Semi-Constrained System which do better than the rest, albeit the cost coefficients vary system to system. Every system apart from the Benchmark-System improves Level-I coverage while Level-II will require closer scrutiny, in terms of increased facility numbers, to provide maximum coverage. Even if we consider the comparisons between the Benchmark System and the Improvement System, we see improvements from 84% to 87% for Level-I, from 98% to 99.69% for Level-II, when considering the standard time of 60 minutes. As discussed in previous sub-sections, improvements for Level-II coverage will require greater scrutiny and analysis of demand at a case by case level for exact locations to be placed at.

The next evolutionary stage of this model is to be scaled up to cover more land, in terms of counties. Entire states with their trauma networks can be mapped and analyzed to determine their performance and recommend strategies for either expansion or re-designation. A desired scenario would be to cover the state of Texas to determine its overall population coverage. This model can theoretically be scaled up to cover a country provided the necessary computing power and exact databases for distances are available.

There are several additions to the decision-making model that can improve the outcome significantly. The model does not include characteristics of the facilities themselves such as bedding capacity, available personnel, and equipment available. The model can be tailored to plan medical services in disaster prone areas to prepare for inevitable natural calamities so that administrations are prepared to meet the challenges of providing rapid and accessible care to residents. Additions that involve micro-management of facilities that are combined with macro-based factors will undoubtedly improve the decision-making process of the model proposed. An aspect that although is contained in the model, but not being a focus for study, is the location for heliports that can provide rapid access to patients over larger distances in a short span of time. Several trauma centers have access to helipads and airborne EMS services yet fall under the responsibility of said trauma center. What can be done is to place these heliports and designate them as their own separate entities that operate independently from the trauma center to provide coverage for far flung rural areas.

Disaster prone areas are a viable location to make use of the programming model. It can be altered to suit the demands of locations that are subject to calamities by using forecasting to determine the extent of services needed and thus plan for either redesignation or expansion from scratch. Using low cost facilities for areas with restricted access and utilizing the programming model with resource allocation can assist in setting up new healthcare services in developing regions that do not require large scale facilities initially.

APPENDIX SECTION

APPENDIX A

ARIMA model Parameters

Zip Code/Year	ARIMA Model Parameters
780 /2014	(1,0,6)
781/2014	(1,0,18)
783/2014	(1,0,3)
786/2014	(1,0,0)
787/2014	(1,0,3)
788/2014	(1,0,14)
781/2015	(1,0,14)
787/2015	(1,0,1)
788/2015	(1,0,8)
780/2016	(1,0,9)
781/2016	(1,0,3)
788/2016	(1,0,4)

APPENDIX B

Total Trauma level visits

Trauma Level	**2014**	**2015**	**2016**
Level I	39,616	38,151	43,115
Level II	13,861	16,828	16,919
Level III	28,498	29,950	32,466
Level IV	24,047	25,197	26,873
Total	106,022	110,126	119,373

Data analysis revealed an interesting aspect of facilities assigning injury scores. Three specific scores accounted for the largest percentage of injuries for all three years. The table below presents these observations in percentages.

Injury Severity Score Percentages

Injury Severity Score	Percentage in 2014	Percentage in 2015	Percentage in 2016
1	17.05	18.39	19.48
4	21.62	22.32	21.79
9	22.87	20.45	20.04
Sum	61.54	61.16	61.31

Figures 1 to 24 present the fitted values for the best performing forecast model with respect to the number of injuries. Figures are presented in a yearly basis; example, Figure 1, and by individual zip codes; example, Figure 2. The fitted values were calculated in Minitab© and the software uses the fitted values in the formula to calculate the MAPE. These figures are presented to showcase the comparison of the best suited model performance to the respective data set

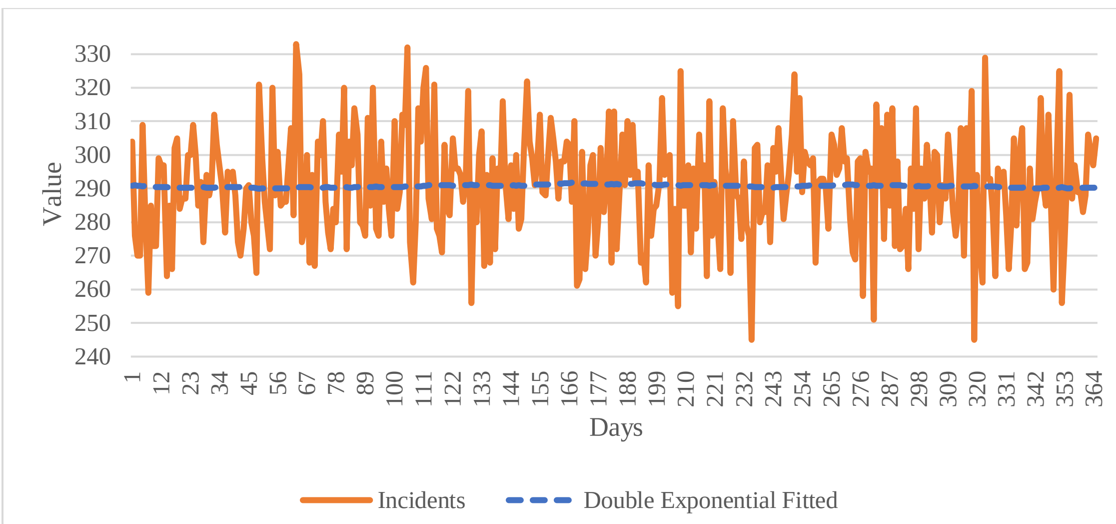


Figure 1. Fitted Values value comparison for Total Injuries in 2014

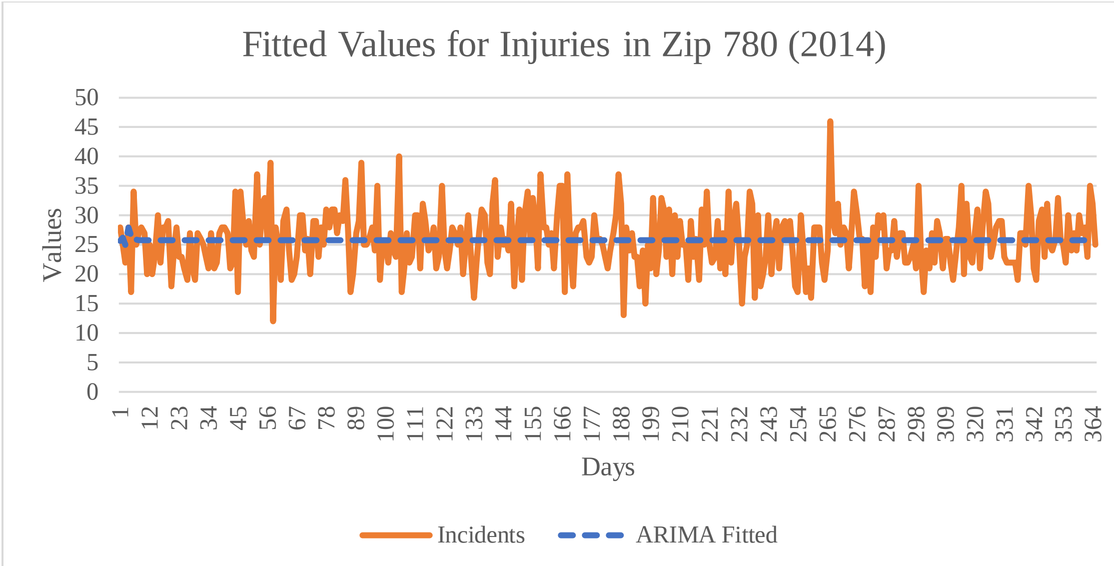


Figure 2. Fitted Value for injuries for zip code 780 in 2014

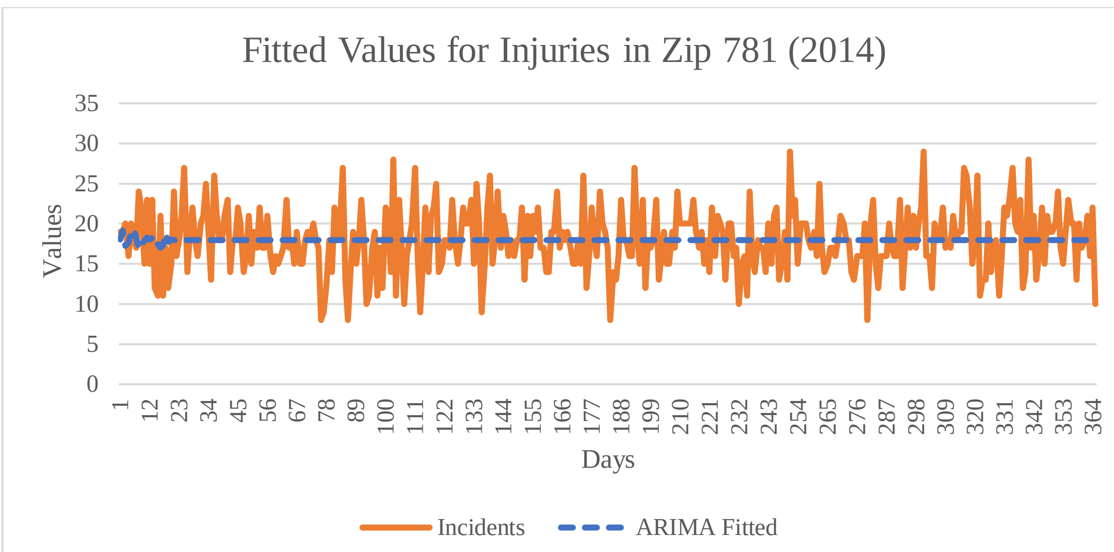


Figure 3. Fitted Value for Injuries in Zip Code 781 (2014)

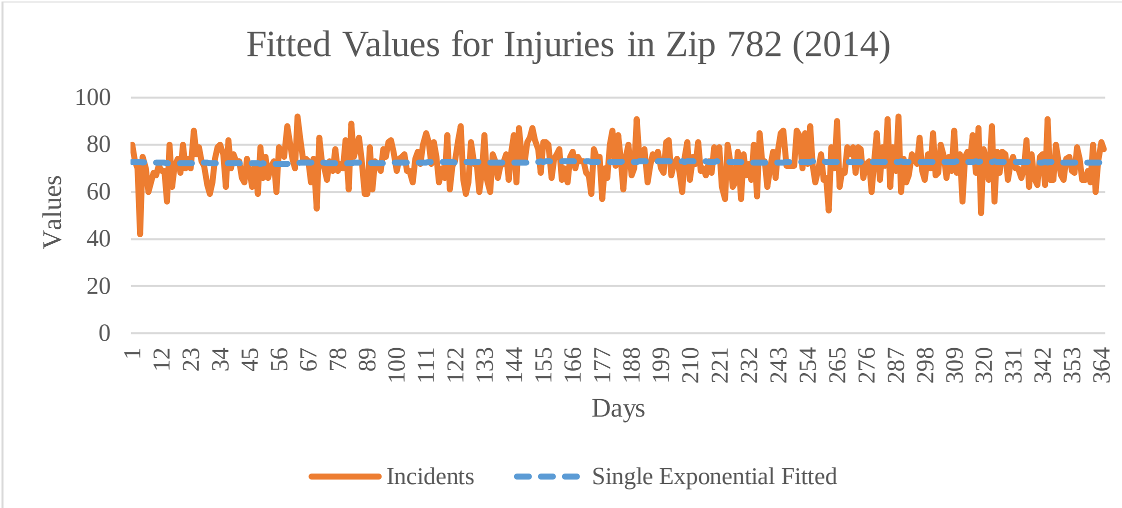


Figure 4. Fitted Value for Injuries in Zip Code 782 (2014)

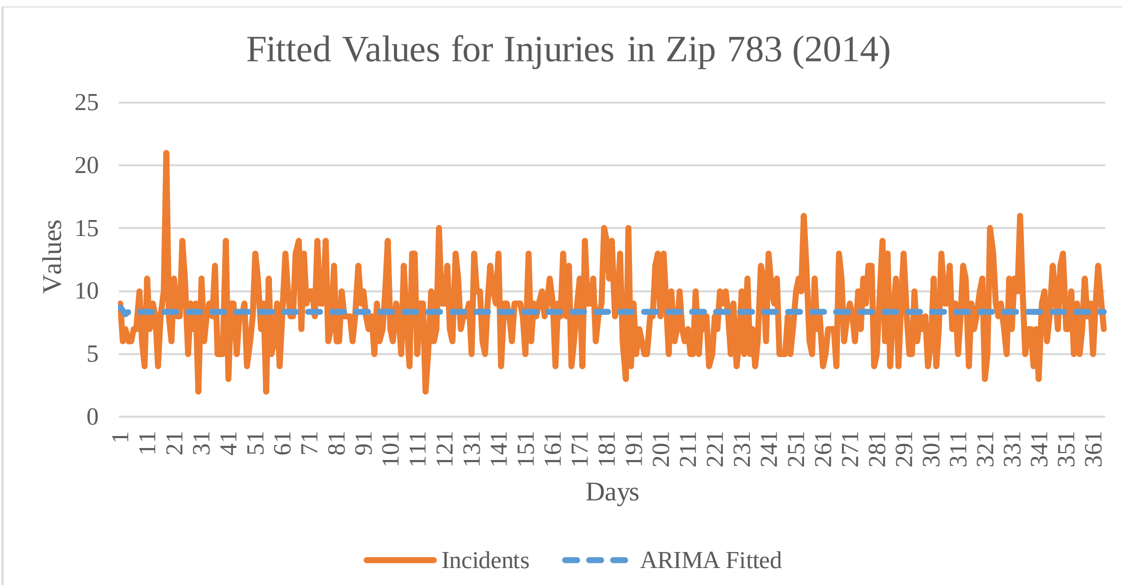


Figure 5. Fitted Value for Injuries in Zip Code 783 (2014)

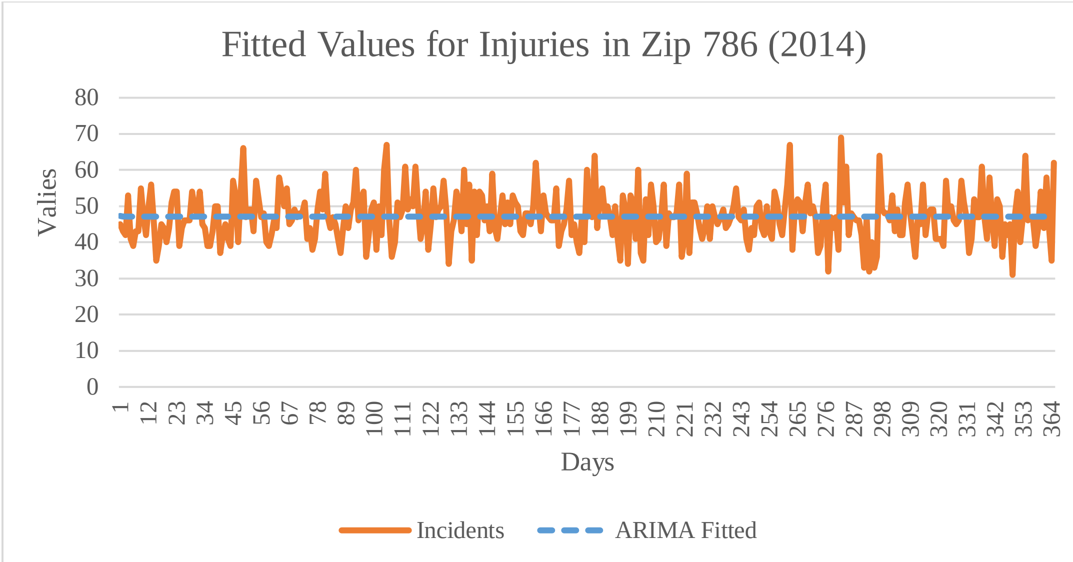


Figure 6. Fitted Value for Injuries in Zip Code 786 (2014)

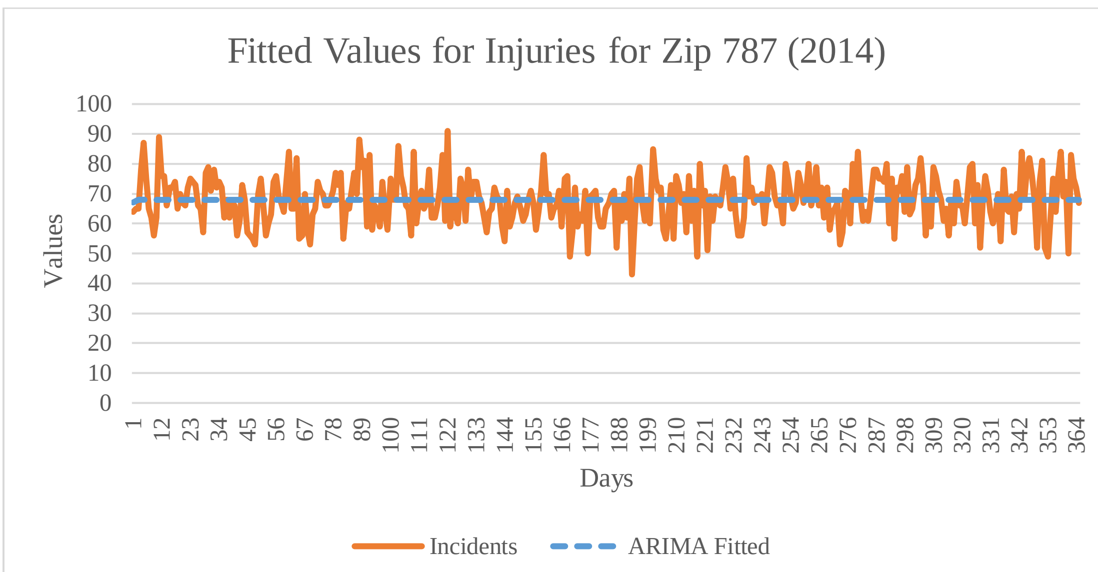


Figure 7. Fitted Value for Injuries in Zip Code 787 (2014)

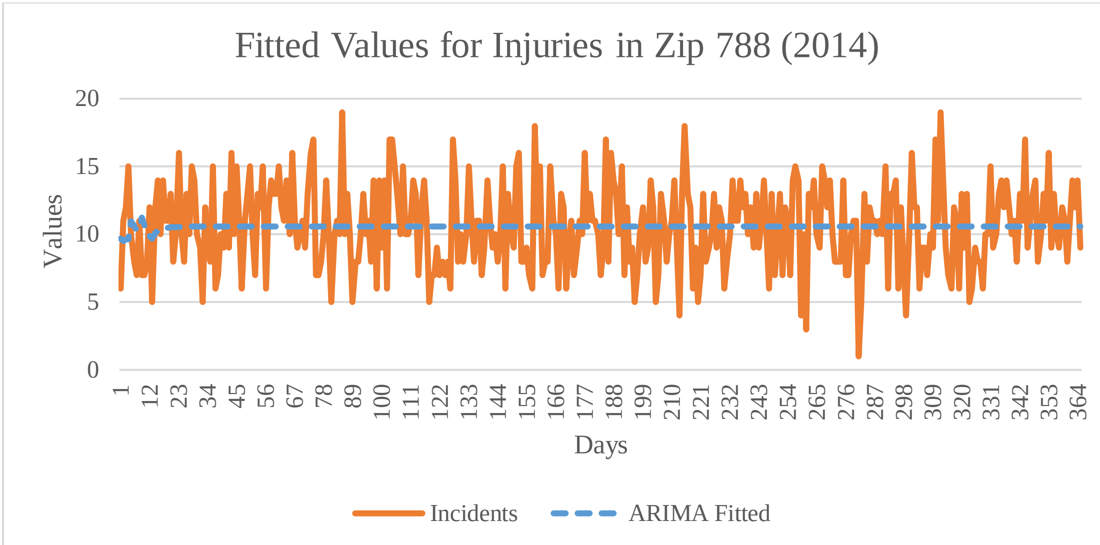


Figure 8. Fitted Value for Injuries in Zip Code 788 (2014)

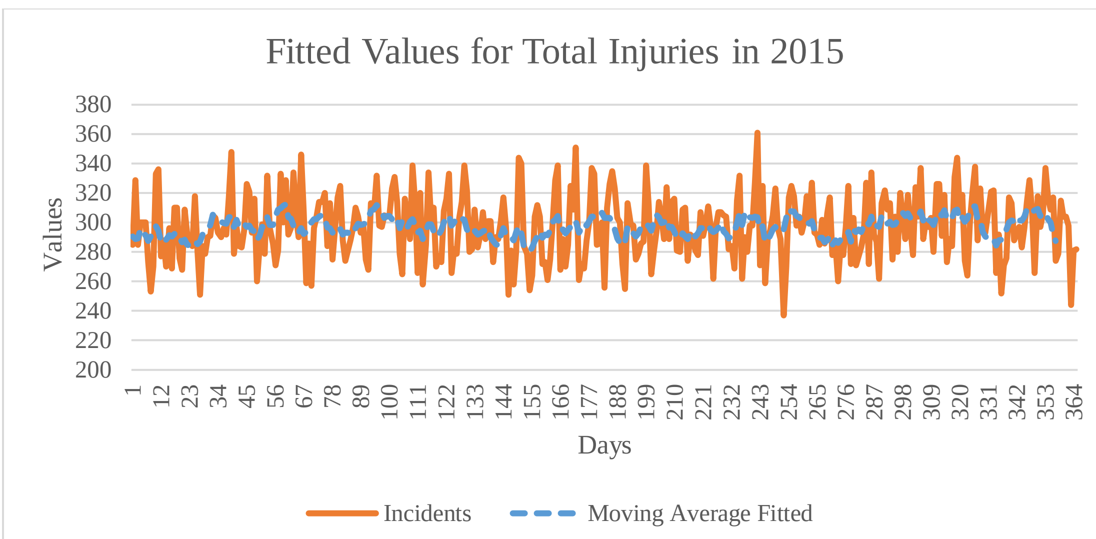


Figure 9. Fitted Value for Total Injuries in 2015

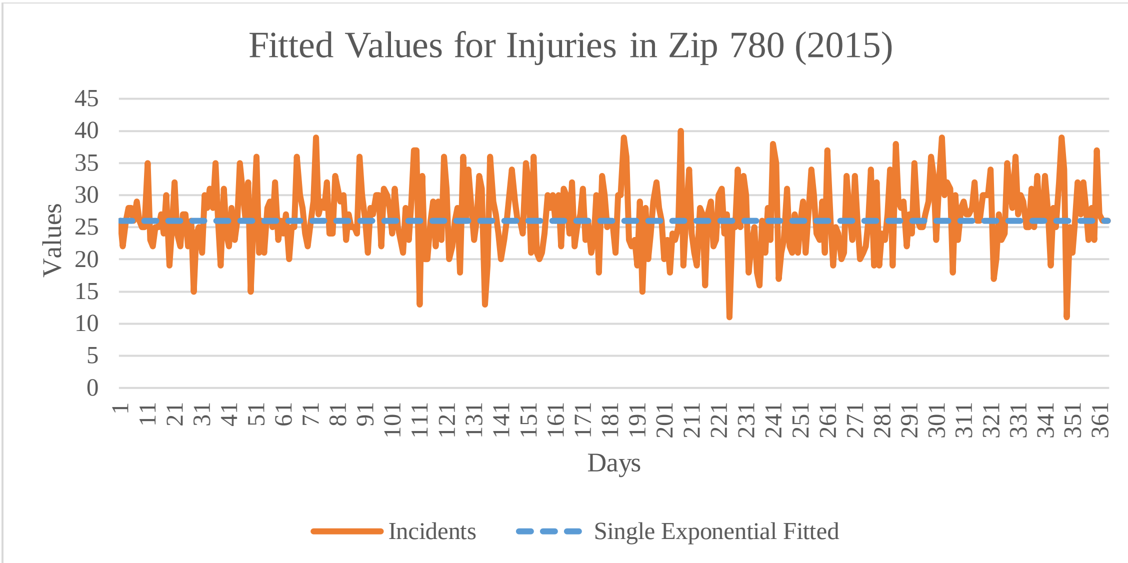


Figure 10. Fitted Value for Injuries in Zip Code 780 (2015)

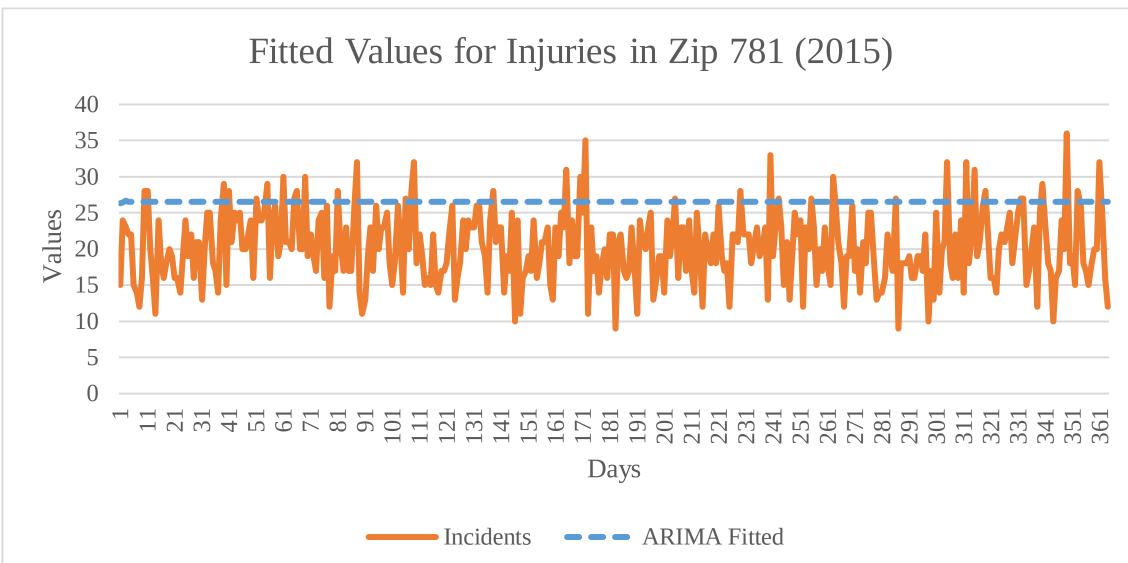


Figure 11. Fitted Value for Injuries in Zip Code 781 (2015)

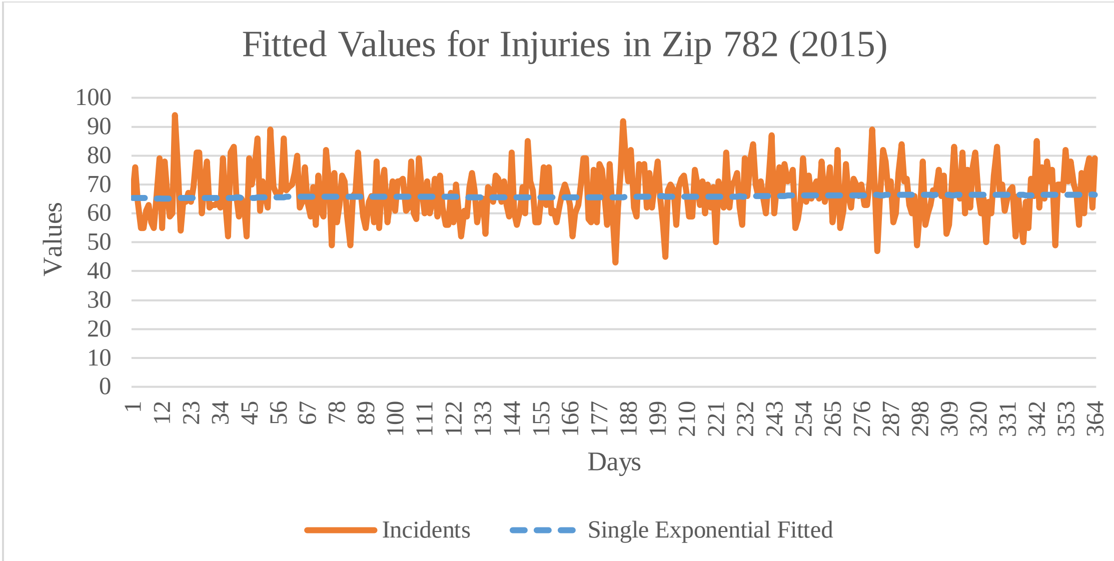


Figure 12. Fitted Value for Injuries in Zip Code 782 (2015)

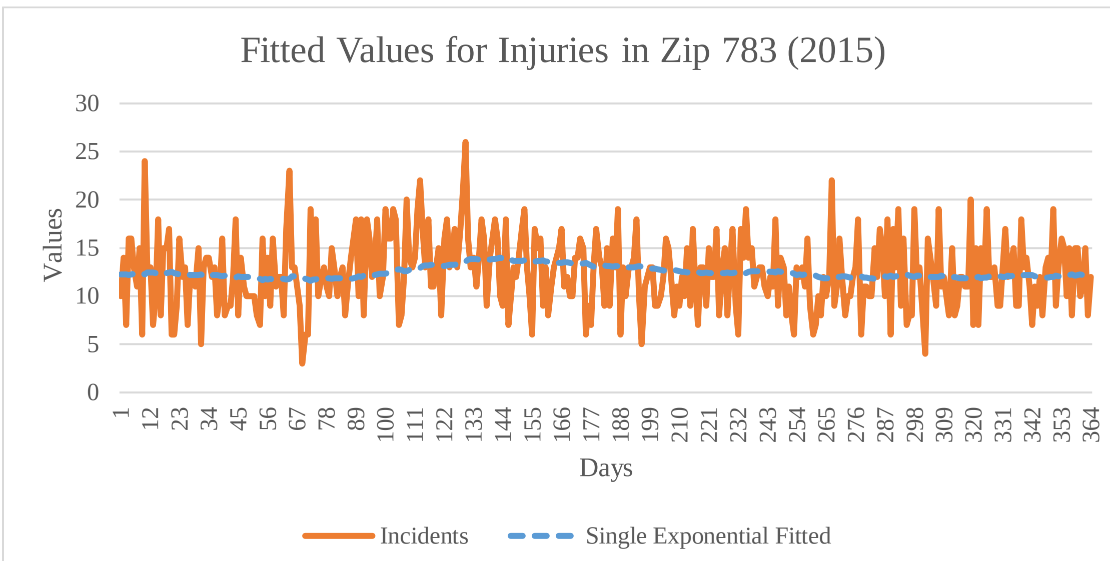


Figure 13. Fitted Value for Injuries in Zip Code 783 (2015)

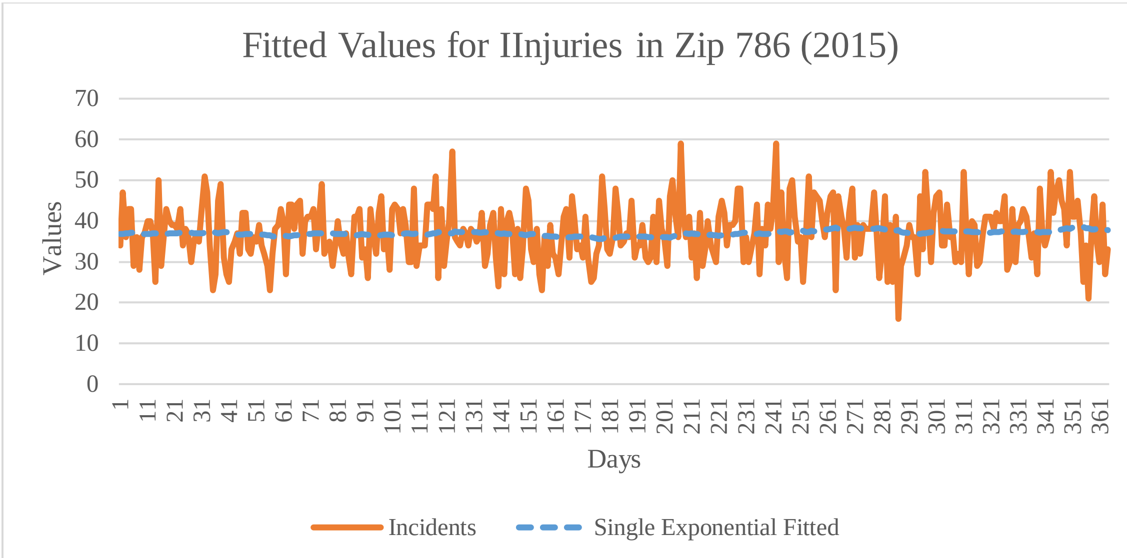


Figure 14. Fitted Value for Injuries in Zip Code 786 (2015)

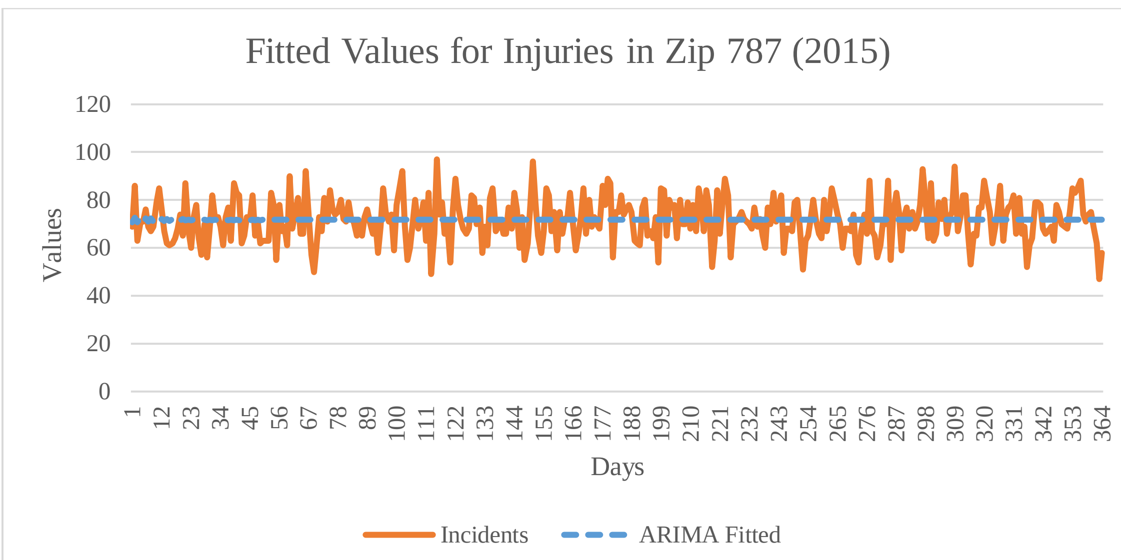


Figure 15. Fitted Value for Injuries in Zip Code 787 (2015)

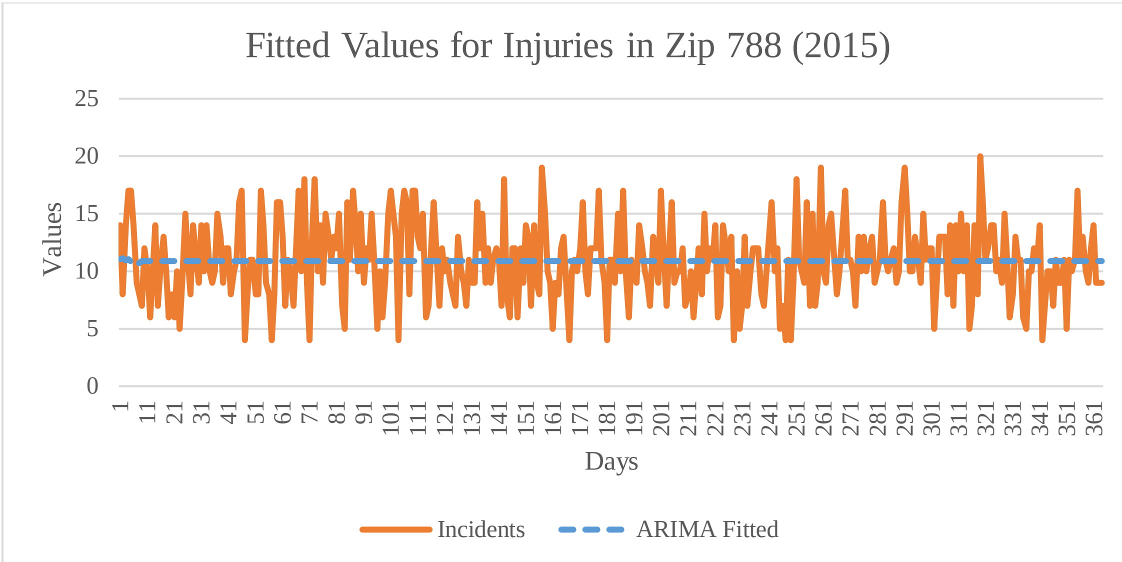


Figure 16. Fitted Value for Injuries in Zip Code 788 (2015)

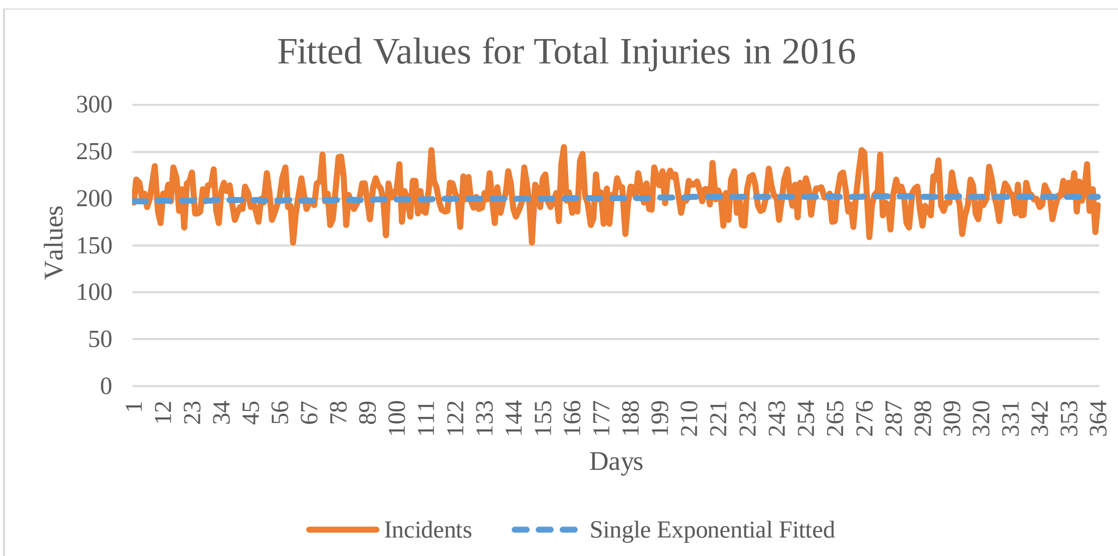


Figure 17. Fitted Values for Total Injuries in 2016

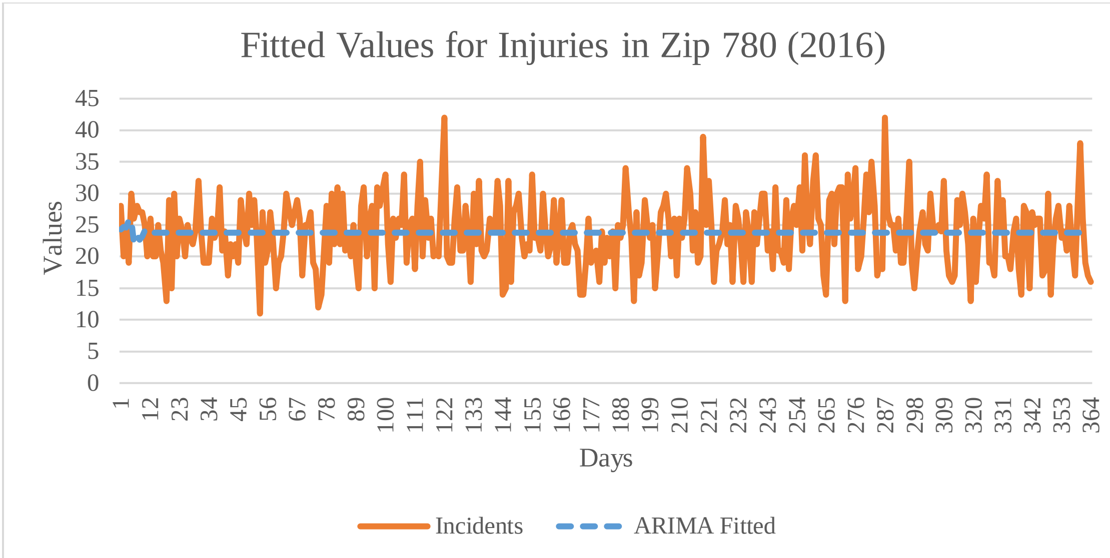


Figure 18. Fitted Value for Injuries in Zip Code 780 (2016)

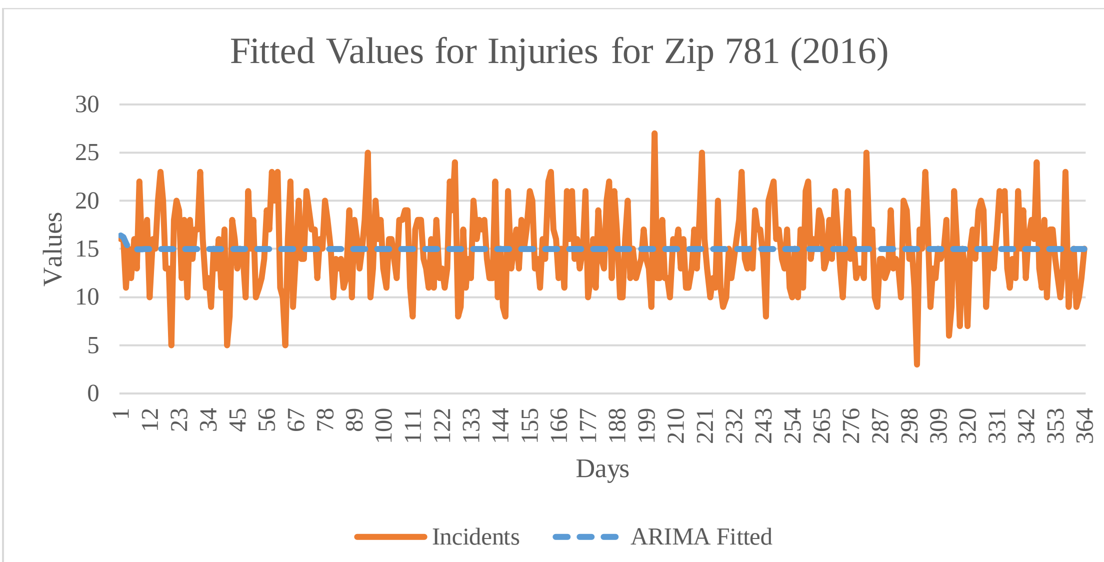


Figure 19. Fitted Value for Injuries in Zip Code 781 (2016)

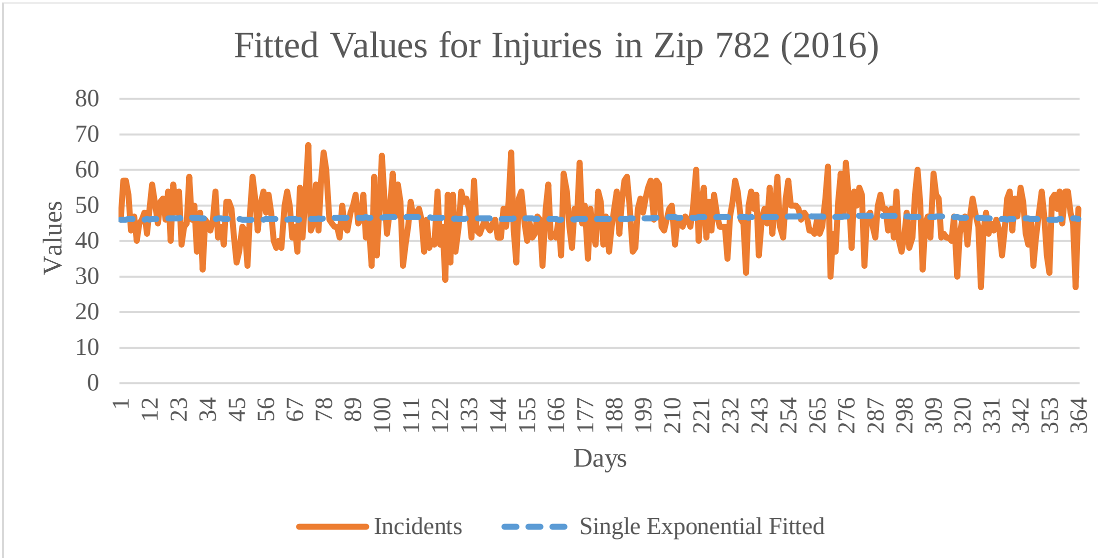


Figure 20. Fitted Value for Injuries in Zip Code 782 (2016)

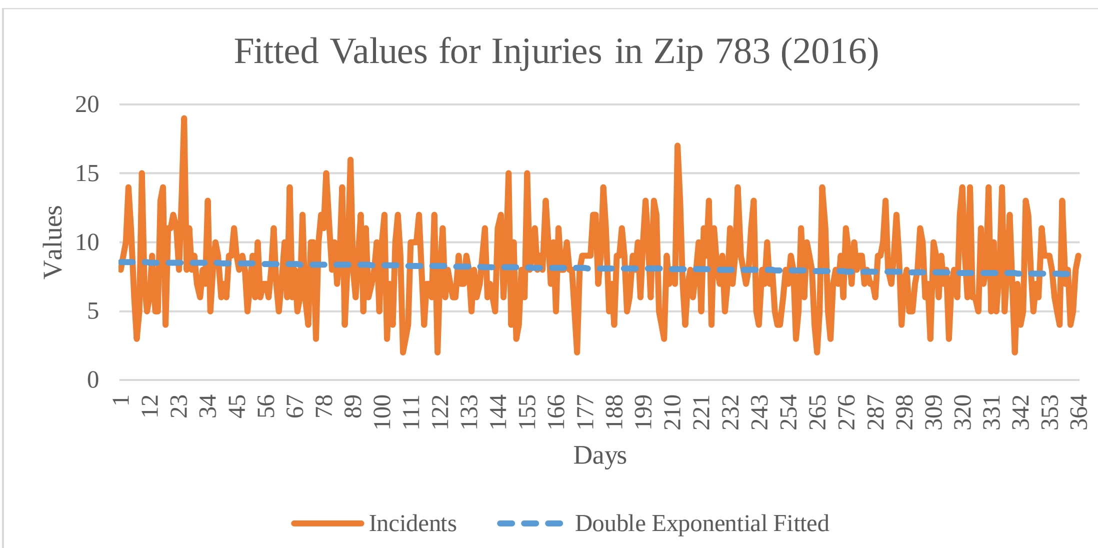


Figure 21. Fitted Value for Injuries in Zip Code 783 (2016)

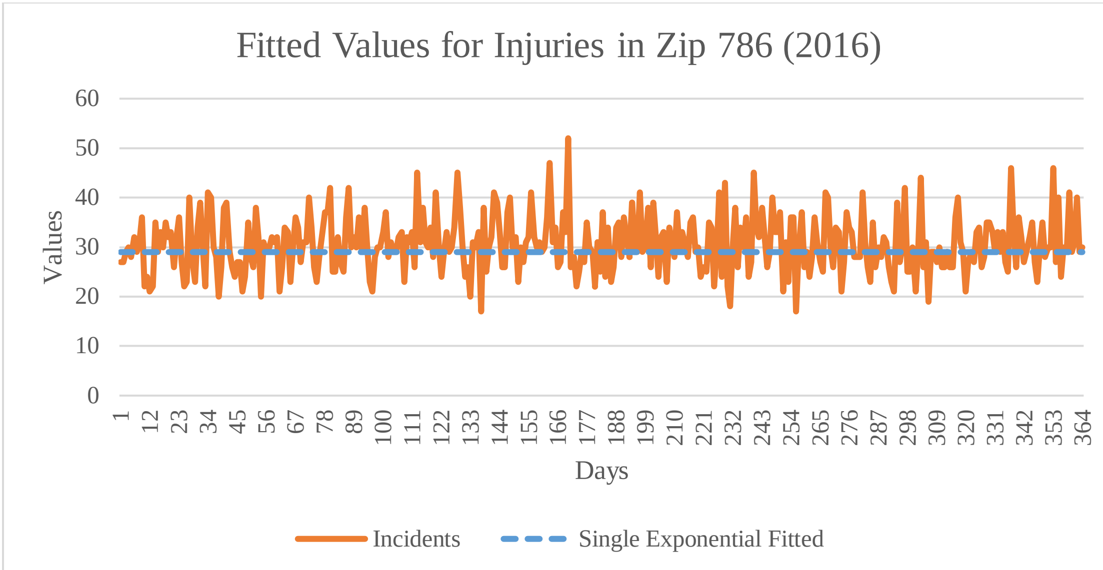


Figure 22. Fitted Value for Injuries in Zip Code 786 (2016)

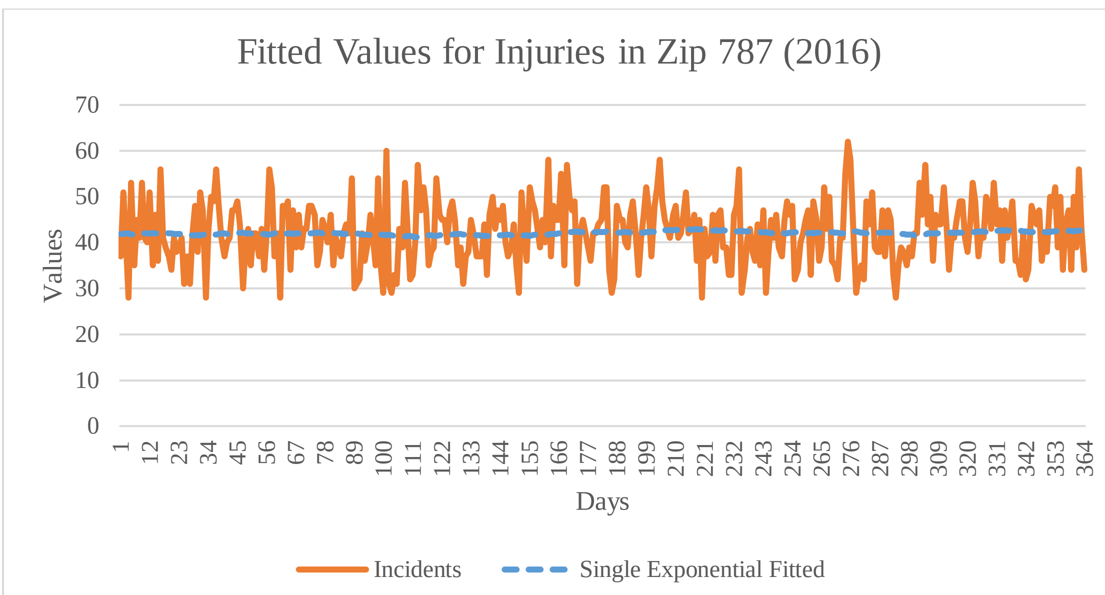


Figure 23. Fitted Value for Injuries in Zip Code 787 (2016)

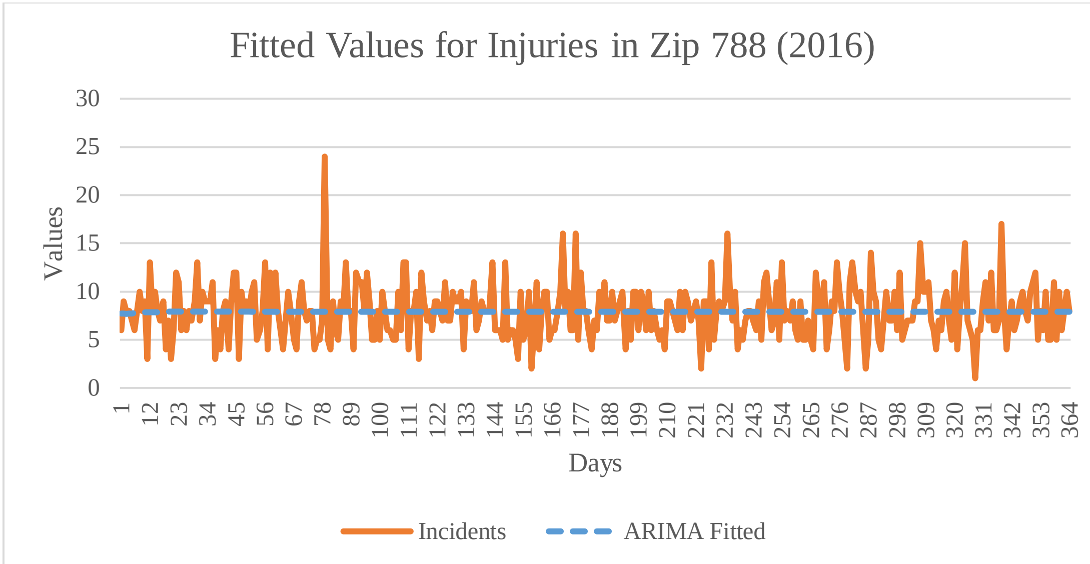


Figure 24. Fitted Value for Injuries in Zip Code 788 (2016)

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