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Reducing Wait Time Prediction In Hospital Emergency Room: Lean Analysis Using a Random Forest Model

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I am submitting herewith a thesis written by Gajanan Arha entitled "Reducing Wait Time Prediction In Hospital Emergency Room: Lean Analysis Using a Random Forest Model." I have examined the final electronic copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Industrial Engineering.

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Reducing Wait Time Prediction In Hospital Emergency Room: Lean Analysis Using a Random Forest Model

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Dedicated to my life coach, my grandfather – Mool Singh Arha

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Abstract

Most of the patients visiting emergency departments face long waiting times due to overcrowding which is a major concern across the hospital in the United States. Emergency Department (ED) overcrowding is a common phenomenon across hospitals, which leads to issues for the hospital management, such as increased patient's dissatisfaction and an increase in the number of patients choosing to terminate their ED visit without being attended to by a medical healthcare professional. Patients who have to Leave Without Being Seen (LWBS) by doctors often leads to loss of revenue to hospitals encouraging healthcare professionals to analyze ways to improve operational efficiency and reduce the operational expenses of an emergency department. To keep patients informed of the conditions in the emergency room, recently hospitals have started publishing wait times online. Posted wait times help patients to choose the ED which is least overcrowded thus benefiting patients with shortest waiting time and allowing hospitals to allocate and plan resources appropriately. This requires an accurate and efficient method to model the experienced waiting time for patients visiting an emergency medical services unit.

In this thesis, the author seeks to estimate the waiting time for low acuity patients within an ED setting; using regularized regression methods such as Lasso, Ridge, Elastic Net, SCAD and MCP; along with tree-based regression (Random Forest). For accurately capturing the dynamic state of emergency rooms, queues of patients at various stage of ED is used as candidate predictor variables along with time patient's arrival time to account for diurnal variation. Best waiting time prediction model is selected based on the analysis of historical data from the hospital. Tree-based regression model predicts wait time of

low acuity patients in ED with more accuracy when compared with regularized regression, conventional rolling average, and quantile regression methods. Finally, most influential predictors for predictability of patient wait time are identified for the best performing model.

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Chapter 1

Introduction

In the United States, the total healthcare expenditure for 2015 was an aggregate \$3.2 trillion (USD) against total GDP of \$18.037 trillion(USD) (Martin et al., 2016). The two largest contributors to the growing healthcare expenditures were hospital care (\$1.0 trillion USD) and clinical services (\$634.9 billion USD) (Martin et al., 2016). This increase in healthcare spending was fundamental in the introduction of the Hospital Value-Based Purchasing (VBP) program by the Center for Medicare and Medicaid services (CMS). The VBP program reimburses the acute care hospitals on the basis of the quality of care being provided. This is a marked departure from the existing practice of reimbursing hospitals with respect to the volume of patients receiving treatment. Under the program, the CMS measures the performance of a hospital on the basis of specific, pre-established quality criteria including the clinical process of care, patients experience of the care received, the outcome and efficiency (Blumenthal and Jena, 2013). By changing the factors affecting how hospitals are reimbursed, the program encourages hospitals to provide higher quality and efficient care at lower costs. Therefore, one may argue that the VBP program acts as an external motivator that encourages healthcare providers to engage in quality improvement initiatives at competitive costs.

The VBP program integrates economic gains with operational competence thereby creating a financial pressure across all hospital units. Of all the units in any hospital, its Emergency Department (ED) is arguably the single most crucial unit since it plays a vital role in providing care for the critically injured. EDs serve as the primary point of entry for patients in hospitals across the country (Morganti et al., 2013). In 2013, the total number of ED visits exceeded 130.4 million as compared with only 125.7 million outpatient visits (for Disease Control et al., 2013). Because of the 24/7 operating hours of EDs, there are significant fixed costs and lower profit margins as compared with other departments (Nagasako et al., 2014). The Emergency Medical Treatment and Active Labor Act (EMTALA) mandates the provision of appropriate medical care to all, regardless of whether they can afford treatment, thereby affecting the profitability of the emergency units (Zibulewsky, 2001). Under the VBP program, CMS found that in 2013, of the seventeen measures used to evaluate hospitals performance four were related to care received by patients in the hospital's ED (McHugh et al., 2014). Because of the growing role of emergency departments as factors influencing the hospitals access to reimbursements, there is a significant increase in emergency healthcare. Therefore, it is imperative that one understands and interprets how the performance of a hospitals ED is related to a patient's experience of care and the overall quality of care being provided (McHugh et al., 2014).

Madsen et al. (2015) did a systematic review to compile the key performance indicators (KPIs) that are related to ED measurement and divided them into five categories: satisfaction, process, equity, outcome, and structural or organizational measures. The significant quality indicators for the measurement of the efficiency of hospital-based emergency care identified from study consists of patient satisfaction, the level of ED occupancy, the existence or lack of crowding, time to treatment, ED returns and the patients that Left Without Being Seen (LWBS). In the last decade, there has been a compelling increase in the demand for emergency medical services which correlates with closure of EDs across the US, thus leading to increasingly overcrowded ED units and culminating in a longer wait time for treatments in existing EDs (Burt and McCaig, 2006). The EDs level of crowding, staffing and wait times affect the overall comprehensive measure of quality of care. In ED settings quality of care is measured by patient satisfaction, the ease of access to emergency services evaluated on the basis of number of patients left without being seen by a doctor and efficiency which is assessed by prolonged wait times (Carter et al., 2014). Numerous approaches have been attempted with the aim of increasing the influx of patients through the ED system in a timely manner. These approaches include the introduction of fast track services (Nash et al., 2007), in-room registration process (Gorelick et al., 2005), consultation at triage (Terris et al., 2004), development of holding area in ED (Gantt, 2004) and building multi-disciplinary comprehensive teams that include medical professionals from all departments so as to oversee and implement change to varying degrees of success (Wilson and Nguyen, 2004).

The health care industry is service oriented. As such, the waiting time a patient experiences prior to receiving treatment is a fundamental factor that directly influences a patient's satisfaction (Thompson et al., 1996). In overcrowded ED settings, patients often experience lengthy waits prior to treatment by a senior nurse or doctor, which leads to frustration and has a negative effect on the overall patient satisfaction. While waiting for treatment, the lack of information regarding the time to treatment and unexpected delays can be very frustrating for a patient in an already stressful environment like that of the ED. Extensive wait time is a recurring complaint for patient's visiting ERs. It leads to a decrease in the patients sense of control and increases their levels of stress and anxiety (Mowen et al., 1993). To address this, the first priority of the Press Ganey's ED Pulse Report 2008, was to improve the communication with patients about the waiting time and unexpected delays in their treatment.

1.1 Waiting time (actual Vs perceived)

Two of the major components involved in managing wait times in EDs are reducing the actual wait time while also keeping patients informed about the expected wait time, since it helps in addressing and fulfilling the psychological needs of patients (Shah et al., 2015).The actual wait time in EDs can be minimized by making improvements in the flow of patients through the department, capacity planning, identifying bottle-necks and creating a flexible service enrollment (F. Brian Boudi, July). Of all the factors involved in patient satisfaction during an ED visit, effectively informing patients regarding the wait time is singularly crucial. Providing wait time transparency via informing patients of the expected time of waiting before being triaged or treated by a doctor as well as updating wait time delays digitally can be a key factor in how hospitals can better manage patient's expectations. Prolonged waiting times (perceived versus actual) and the level of communication of information are strongly correlated with patient's satisfaction regarding the quality of their treatment services, in the emergency care environment (Soremekun et al., 2011).

Process changes in ED can bring out the operational performance changes affecting average wait times of patient in the system, but in order to realize patients satisfaction one must investigate two paradigms of patient wait time: actual (verifiable) and perceived (subjective) waiting time (Luo et al., 2004). The perceived wait time is markedly different from the actual wait time that a patient experiences. Recent studies that delved into the psychological aspects of waiting finds perceived wait time is a better predictor of customer satisfaction as opposed to the actual waiting time (Nie, 2000). Some of the ways in which a patient's perception of the waiting time can be influenced include the following: [(Katz et al., 1991); (Hui and Zhou, 1996); (Dubé and Schmitt, 1996)]

- Creating a comfortable wait room environment: By ensuring appropriate seating arrangements in the waiting area the atmosphere can become more inviting and comfortable.
- Providing feedback about expected wait time: Communicate about wait times, provide updates and acknowledge for the delays.
- Engaging Patients during the wait: Check waiting area regularly and demonstrate a personalized approach to patient care.

1.2 Publishing ED wait time

The majority of healthcare providers agree that by providing ED wait time information services to the public may improve a patient's experience (Lateef et al., 2011). A majority of the existing literature supports the argument that improving communication and information delivery is a vital determinant of patient experience in ED setting [Shah et al. (2015);(Press, 2002)]. However, few studies explore how advanced analytical and predictive modeling techniques can help to communicate expected wait times to each individual patient. Patients find waiting less tedious and are more cheerful when the hospital keeps them informed (LARSON, 1987). The accurate communication of predicted wait time, upon arrival, may help in managing patients expectations before being triaged or seen by a doctor. In response to this, many EDs across the country have started publishing estimated wait times on billboards, websites, and smartphone applications (Xie and Youash, 2011). It also serves as an effective marketing tool by driving patients from other EDs, in nearby geographical location, to less busy EDs, thus generating additional revenue for the hospitals (Weiner, 2013). Publicizing wait times within a specific geographical area encourages patient to choose the least overcrowded ED with the shortest wait time, thereby distributing and balancing the workload over nearby EDs (Dong et al., 2015). However, even with technological innovations, the accuracy of predicted wait time remains a topic of debate due to the dynamic nature of activities involved in the ED and the variations in patient arrival rate (of Emergency Physicians et al., 2012). To improve patient experience in the setting of an ED, hospitals across America have implemented numerous initiatives, apart from the communication of wait time, with varying degrees of success.

- Reducing the time for triage by combining doctors and nurses into teams so as to reduce the time needed for performing the triage, medical evaluation and disposal (Subash et al., 2004).
- Encouraging triage nurses to routinely communicate with patients and explain waiting periods and reasons for delays to patients (Nielsen, 2004).
- Multi-faced intervention using patient education films, communication workshops, as well as a nurse for liasoning with patients; for optimal staff patient community communication (Taylor et al., 2006).

- Accomplishing patient's expectations for treatment and care during ED visit (Trout et al., 2000).
- Expressing empathy, keeping patients busy and educating them as to when primary care should be used instead of EDs (Cohen et al., 2013).
- Improving ED operational efficiency, patient flow and increasing throughput (Cohen et al., 2013).
- Using lean techniques to identify and eliminate non -value added processes in the ED (Chan et al., 2014).

1.3 The issue of left without being seen patients

Informing patients about the predicted wait times on screens, within the hospital, influence patient behavior by increasing tolerance and reducing anxiety thereby lowering the likelihood of them abandoning and balking at getting treatment (Jouini et al., 2011). Hospitals have significant revenue losses when numerous patients leave their premises without being treated. LWBS rates vary greatly across hospitals with a range of 0.1% to 20.3% and a median of 2.6% (Hsia et al., 2011).

According to a report in CEP America (2011), the revenue generated by hospitals is approximately $500 USD per patient visiting the ER. Assuming 50,000 patients visiting an ER per annum, a LWBS rate of 4% would yield the loss in revenue of approximately $1 million USD. Emergency department measures on hospital compare, which compare 4,000 Medicare certified hospitals for timely and effective care consists of ED volume, waiting time to see providers, left without being seen volume, wait time to be admitted, wait time for pain medication, time spent in the ED and wait time before imaging results were available for patients with stroke symptoms, hence a high LWBS rate also affects reimbursements under value-based purchasing programs. Aside from the direct financial implications of high LWBS rate for hospitals, there is a tendency for hospitals with high LWBS rates to have a low patient satisfaction score. Dissatisfied patients are more likely to speak negatively about their experiences to friends and family thereby generating negative publicity and diverting traffic from the hospital, which can lead to further financial losses and a loss of potential future customers (Rowe et al., 2006). The declaration of wait time information in EDs can potentially reduce LWBS rates thereby increasing the quality of ED services.

1.4 Emergency Department process flow

Figure 1.1 depicts the flow of patients through a hospital's emergency department. Patients use multiple logistical channels to enter the ED. These include walk-ins (self-transportation) and via the use of ambulances. When patients arrive in the ED, they are evaluated on the basis of the acuity of their concern and classified according to the triage level. There are a series of standard procedures a patient follows including registration, triage, room/ bed assignment, admission and discharge. To calculate wait time, the overall activities involved in emergency rooms as part of the patient's journey can be divided into different sections (as illustrated in Figure 1.1). For a detailed description of legends refer Appendix A.1.

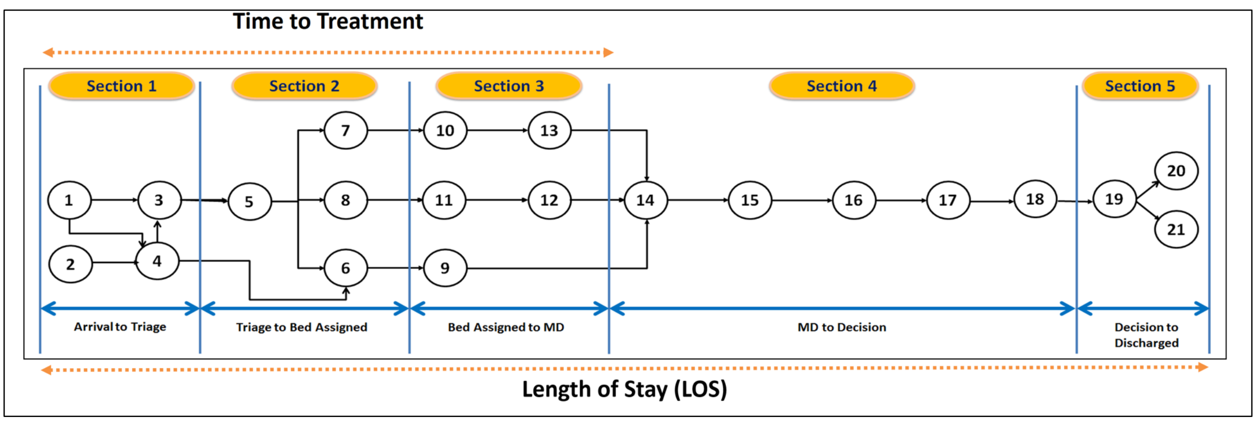


Figure 1.1: Emergency department process flow

1. **Arrival to triage:** After arriving to the ED, depending on the severity of the ailment, a patient may be treated immediately or asked to wait before being attended to by a medical healthcare professional for further triage assessment. A non-critical patient registers with the hospital's reception and provides the requested background

information. Based on the Emergency Severity Index (Wuerz et al., 2000), the patient is then assigned a triage level and categorized into a level of acuity from most urgent (level 1) to least urgent (level 5). This process of triage helps in prioritizing and categorizing the patient on the basis of the urgency of medical treatment required and resource commitment. A non-critical patient waits in a hospital's lobby or designated waiting area before being triaged.

2. **Triage to bed assigned:** After being triaged, the patient is guided to a specific area in the ED where a nurse concludes the process of patient registration. Based on the patient's acuity and the availability of beds, a patient is assigned to a stretcher inside the room where they wait for a doctor to attend to them. Patients with severe medical conditions or with a high risk of mortality (Triage levels 1 & 2) are immediately attended to by a doctor.

3. **Bed assigned to MD:** The patient is evaluated by a physician and based on their assessment, subsequent medical tests are conducted and the patient is treated. A consultant is approached if the doctor decides that the patient would require admission or other care services from different departments.

4. **MD to a decision:** Patients wait in the ED until their test results are available, should they have required tests. Upon receiving the test results, the physician discusses their diagnosis, recommends follow-up appointments and provides information on the various treatment options available to the patient. The final decision regarding the patients discharge, inpatient admission, or referral to other hospitals is taken once the test results are analyzed. Usually, patients with low acuity concerns leave the ED shortly after a diagnosis. Patients with acute medical conditions requiring admission are directed through processes such as admission request, bed assignment and patient transportation.

5. **Decision to discharge:** Since patients with low acuity leave the ED shortly after diagnosis, they are categorized as visitors. The relevant paperwork for their discharge

is completed and transportation is arranged. After being discharged, the patients physically leave the ED.

To reduce ED overcrowding and to ensure that more patients are treated effectively, many hospitals are establishing Fast track centers in an effort to increase ED throughput for low acuity patients (Sanchez et al., 2006). A fast track center comprises of a small team of physicians, nurse practitioners, technicians and radiology staff that operate during the rush hours of the ED. Patients with non-life threatening injuries (Triage Level 4 & 5) are sent to the fast track after triage. They are then diagnosed quickly and discharged or admitted, on the basis of the diagnosis. This helps to maintain the emergency room and makes it available to higher acuity patients leading to a reduction in the total duration of a patient's stay in the ED.

1.5 Wait time metrics in ED

In an effort to establish quantitative measures and evaluate the performance of the hospital in term of timely and effective care, the CMS requires hospitals to report the following wait time metrics based on historical data (Welch et al., 2011)

- Median time a patient spends in the ED, prior to their admittance to the hospital (Length of Stay - LOS).
- Median time a patient spends in the ER, once the doctor has made a decision regarding the patient's admittance and prior to their departure for their inpatient room (Length of Stay - LOS).
- Median duration of a patient's visit to the ED before leaving the hospital (Length of Stay - LOS).
- Median time a patient spends in the ED before being attended by a healthcare personnel (Time to Treatment).

Based on the typical stages of patient path in ED, which are separated by waiting times and CMS metrics, the wait times in the ED can be categorized as illustrated in figure 1.1 and are described as follows [(Arkun et al., 2010); (Ghanes et al., 2014)]

- **Time to Treatment:** The time from when a patient arrives into the ER unit and their primary consultation with a healthcare professional. It is also referred to as door-to-doctor time.
- **Length of Stay (LOS):** The time of a patient's journey through the ED calculated from their registration until their discharge, transfer or admission to an internal unit. It is also called “dwell time”.

For this study, the research focused specifically on evaluating the “Time to Treatment”. The overall duration of a patient's ED stay is highly variable because of the series of waiting, consultation, tests and diagnosis involved when compared with “Time to Treatment”. Because of the high variations, the errors in predicting LOS would be significantly large. Moreover, the American College of Emergency Physicians (ACEP, 2012) recommends that hospitals publish patient wait time metric for advertisement purposes should specifically focus on their time to treatment. The posted wait times must be accurate and regularly updated (of Emergency Physicians et al., 2012). According to Boudreaux et al. (2000) a patient's satisfaction during a visit to the ED is significantly correlated to the wait time in the treatment area as compared to the actual length of their stay. Hence, patients are more concerned with the wait time to treatment metric than the time to discharge.

1.6 Wait time for low acuity patients

In this research, the researcher lays emphasis on estimating emergency department wait time for low acuity patients primarily because of all the ED visits across the nation, most comprised of patients seeking non-urgent care (Ruger et al., 2004). Moreover, patients with less acute problems and not seeking an immediate care choose an ED with less wait time even if that requires them to drive to a hospital that is farther, which helps in distributing load among nearby EDs (Dong et al., 2015). A low acuity patient can potentially benefit from wait time information so as to facilitate the decision regarding whether to go to a specific ED or not, choice of ED time of visit. Being aware of the estimated wait time before being attended to by a healthcare professional, while waiting helps in reducing anxiety in low acuity patients when they see high acuity patients requiring urgent care being treated immediately.

The advertisement of the same wait time estimate for patients from all triage levels leads to an underestimation of the wait time for low acuity patients, who are the primary user of the estimate (Ang et al., 2015). In order to address this, hospitals should publish wait times for low acuity patients proceeded by a cautionary note informing them that a change in their wait times is possible due to the prioritization of patients with life-threatening or more serious injuries over them.

1.7 Objective

The objective of this study is to develop a robust statistical model for the estimation of the average expected waiting time experienced by patients in the ED. This will be done on the basis of the parameters of the triage level, the time of day, day of the week, month of the year, occupancy rate and the status of the fast track. The predictive accuracy of the model so developed will be compared against other statistical regression and machine learning techniques. The model developed by the researcher makes use of random forest regression, which is an ensemble learning technique for wait time prediction. The model will help in prioritizing and rank the relevant parameters affecting wait times in EDs. The findings of the study can be potentially useful for hospitals looking to develop strategies for the reduction of wait times and for the improvement of patient satisfaction.

1.8 Organization of thesis

The thesis arrangement is described as follows: Chapter two provides a literature review to understand overcrowding in the emergency department, its impact and causes. Chapter two goes further to discuss types of forecasting techniques used to estimate wait time. The challenges and limitations of forecasting methods are inspected. Chapter three describes stratification of data, the creation of candidate predictor variables, development of wait time model and the validation process to measure accuracy and robustness of the model. Chapter four relates to case study, findings and analysis of results. Chapter five provides conclusion and suggested directions future work can follow.

Chapter 2

Literature Review

This chapter discusses the phenomenon of emergency department overcrowding, its potential indicators, the harmful effects of ED overcrowding and its underlying causes. The relationship between the effects of publishing accurate ED wait times and ED overcrowding is also addressed. The literature pertaining to the various forecasting techniques used for wait time prediction, in queueing systems, with an inclination towards ED management are also examined at length.

2.1 Overcrowding in Emergency Department

Many EDs across the USA deal with the concern of overcrowding, on a regular basis. ED overcrowding primarily occurs due to increasing demand for medical services and a simultaneous lack of healthcare providers. The number of ED visits across the country, for 1999-2013, has increased to 130.4 million from 102.8 million visits annually, i.e. by 27% (for Disease Control et al., 2013). Though one cannot find a formal definition for the phenomenon of ED overcrowding; the American College of Emergency Physicians (ACEP) defines overcrowding as: "crowding occurs when the identified need for emergency services exceeds available resources for patient care in the emergency department (ED), hospital, or both" (of Emergency Physicians et al., 2006). There are numerous factors, internal as well as external, that contribute to the occurrence of overcrowding in the emergency departments.

These include inadequate access to hospital beds and a shortage of healthcare professionals (nursing & physician staff) in the ED units (Di Somma et al., 2015). In the USA, EDs serve as the initial access point for a majority of citizens because of a hospital's legal obligation to treat all patients in need, disregarding their ability to pay for the medical services needed. This pressurizes the ER for the treatment of non-urgent medical conditions of people with limited healthcare insurance or plans.

Asplin et al. (2003) introduced a conceptual Input-Throughput-Output model that can be useful for the evaluation of the factors affecting crowding in EDs. In their model, "Input" refers to factors increasing the need for ER services. "Throughput" is dependent on the numerous processes that influences the efficiency and pace which a patient progresses across the various stages of the ED. Similarly, "Output" refers to, and is driven by, the ED staff's ability to discharge or transfer patients to other departments.

Goodacre and Webster (2005) performed a multivariate analysis to determine the potential factors that contributed to the patient wait times. Their results indicate a strong relationship between the time, the day of the week, the month of the visit and the patient's waiting time. The following should be considered as possible input factors that contribute towards patients suffering a longer wait time in the ED. Other factors such as time to physician (Gilligan et al., 2008), volume of patients waiting (Richards et al., 2000), number of patients that were registered (Han et al., 2007), number of patients awaiting triage (Weiss et al., 2002), and the number of patients at each acuity level (Bullard et al., 2009) have also been found to be significant input factors. Some of common throughput indicators that reflect the efficiency of the ED process are the number of patients being treated (Steele and Kiss, 2008), the volume of patients awaiting their test results (Miro et al., 2003), the time to consultation (Bullard et al., 2009) and the length of stay in the ED (Solberg et al., 2003). There is extensive knowledge in the existing literature regarding the effective ways of measuring the factors affecting the output, including how effectively patients are discharged. These factors include the number of patients admitted to other units within the hospital (Abraham et al., 2009), the number of patients waiting to be discharged (Solberg et al., 2003), the time from when the physician requests admission to the time of the beds assignment

(Ospina et al., 2007), the proportion of the ED that is occupied by in-patients (Lucas et al., 2009) and the time or date of boarding (Falvo et al., 2007). Because overcrowding leads to extremely long waiting times for low acuity patients, this research focuses solely on the pre-determined overcrowding factors that are known to be potential factors influencing ED wait times; while developing an accurate ED wait time model (Cowan and Trzeciak, 2004).

2.2 Causes of ED crowding

Overcrowding has been investigated and discussed by many emergency physicians and researchers alike. Due to its importance in the efficient provision of healthcare services as well as its impact on the hospital's performance, numerous studies, expert panels and surveys have been undertaken. This rich body of knowledge, as presented in the existing literature, helps determine the sources of overcrowding and provides a foundation for generating a feasible solution that can effectively target and address its root causes.

ED Overcrowding is a multifactorial problem. However, in the existing emergency medicine literature, an overwhelming number of studies have identified the lack of adequate inpatient beds as the singular most important cause of overcrowding [(Erenler et al., 2014); (Felton et al., 2011); (Hoot and Aronsky, 2008)]. The lack of an adequate number of critical care beds can potentially lead to high acuity patients being stranded in the ED thereby limiting access, and increasing waiting times, for other individuals needing immediate care. Other causes of ED overcrowding that have been determined are - delays in diagnostic imaging and test results [(Boyle et al., 2012); (Li et al., 2015); (Erenler et al., 2014)], understaffing the ED (Derlet et al., 2001), a delay in access to consultants (Derlet et al., 2001) and an increasing volume of high acuity patients (Derlet et al., 2001).

Providing high acuity patients with effective emergency care is the primary goal of every hospital's emergency department. However, a significant proportion of ED visits, in the country is for non-urgent ailments, by patients with low acuity concerns; thereby leading to an increase in ED occupancy. Numerous studies have strived to determine whether low acuity patients contribute to delays in providing healthcare to high acuity patients by diverting resources from an individual requiring immediate care, and ED overcrowding.In a retrospective study of 4.2 million patients from 110 EDs in Ontario Schull et al. (2007), concluded that patients with low acuity concerns had a negligible impact on the overall ED length of stay and time to treatment of high acuity patients. It is likely because many emergency departments have implemented the development of rapid assessment areas referred to as "Fast-Track". This help to reduce waiting times and length of stay for low acuity patients. The implementation of the fast track encourages quick and efficient treatment of patients with low acuity and non-life- threatening conditions (O'Brien et al., 2006), thereby improving their satisfaction with the services provided by hospitals.

Apart from usage of EDs for non-urgent conditions studies have pointed towards the 1986 federal Emergency Medical Treatment and Labor Act (EMTALA) requiring that hospitals provide emergency treatment, irrespective of the sufferers ability to pay as a major contributor to ED overcrowding (Monico, 2010). EDs are thus, the "last-resort" for the uninsured and those who are unable to afford other healthcare options. EMTALA has led to an increase in inappropriate ED use crippling USA's emergency health care safety net (Bitterman, 1992).

2.3 Impact of ED overcrowding

Crowding of the EDs places an extreme economic burden on the hospital and is detrimental to patients and healthcare staff by affecting the quality of patient care. When overcrowding occurs, all available beds are likely to be occupied and the overflow of patients needing emergency care is often relegated to the hallways while they wait to receive care. In these conditions, emergency healthcare respondents are unable to provide quality care, which poses a further risk to the patient's wellbeing (Derlet et al., 2014). Excluding the critically ill patients, the Centers for Disease Control and Prevention (CDC) reports the median treatment time as 90 minutes for all patients (McCaig and Albert, 2014). This is a significantly long time for treatment. A prolonged treatment time results in delayed medical interventions, leave patients in acute pain for longer than necessary; and also threatens their safety (Bond et al., 2007).

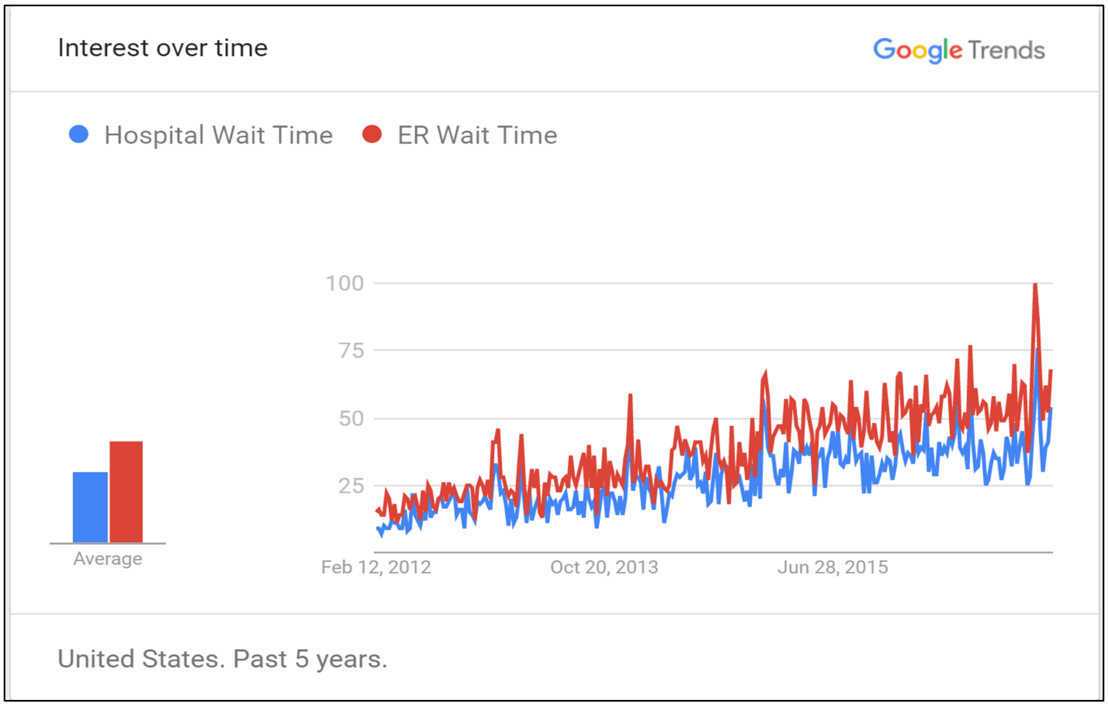
In the case of persistently high ED patient traffic, many hospitals tend to divert ambulances to other EDs. This rerouting provides a temporary break in ED traffic to address existing patient load. This redirecting Emergency Medical Services (EMS) and patients to other nearby EDs has more implications than the obvious obvious revenue loss (Litvak et al., 2001). Continuous ambulance diversions can lead to a domino effect, triggering nearby facilities also to divert other ambulance thereby clogging a local health care system (Derlet, 2002). Studies indicate that ambulance diversions can have a significant effect on patient safety (Schull et al., 2003). Most patients who are transported by ambulances require immediate medical care (Pham et al., 2006) and diversions can increase a patients transition time before arrival at the ED (Schull et al., 2003). In addition to patient safety, ambulance diversions also lead to excessive financial losses. A recent study determined that for each hour of diversion, the hospital lost revenue of over \$1,000 from patients arriving via ambulances. Tellingly, encouraging the use of practices to limited ambulance diversions led to an increase of approximately \$2400,000 per annum (McConnell et al., 2006).

During times of ED overcrowding, patients experience prolonged wait times, which leads to patient dissatisfaction and influences their perception of the quality of service provided by the ED (Derlet, 2002). Long ED wait times are strongly co-related with a higher likelihood of a patient becoming unsatisfied and reporting lower ED satisfaction scores (Pines et al., 2008). Frustrated by long wait times, patients are more likely to leave without treatment (Derlet, 2002). Studies have shown that the numbers of left without being seen (LWBS) patient visits accurately indicate the extent of ER overcrowding. Patents who leave without getting treatment are also more likely to require immediate medical intervention at a later date; and have a higher rate of adverse events and worse outcomes as compared to patients who wait to be treated and discharged (Baker et al., 1991). Communicating with patients regarding the estimate wait times before they are treated by a doctor would better manage their expectations and encourage longer waits (Arendt et al., 2003). Hence, in this study, the researcher focuses on establishing a medium to update patients in real time about their expected wait time status.

2.4 Wait time prediction models

In a service industry, including the medical industry, queues are ubiquitous. Queues develop because of a mismatch between demand and the ability of the system to meet the demand. Researchers have investigated the psychology of waiting and LARSON (1987) describes waiting as a negative experience that causes unhappiness, frustration and anxiety. Scholars have also attempted to discern strategies to reduce the negative effects of the extended wait times. Recently, many service providers have started providing some information related to the expected delay, in providing services, to their customers. For example, Zhang et al. (2013) predicted the future wait time for the customers, on the basis of historical data, at the California Department of Motor Vehicle (DMV) offices, Thiongane et al. (2015) estimated the wait time of customers, on connecting with a customer-care representative in a telephone call center, whereas Simaiakis and Balakrishnan (2015) developed an analytical model to estimate the taxi-out time, at the airport. Similarly, Zhou et al. (2012)predicted the arrival time of public buses on the basis of participatory sensing via mobile phones. Any information regarding wait time can help decrease uncertainty as well as customer's distress [(Bielen and Demoulin, 2007); (Jouini et al., 2011); (Armony and Maglaras, 2004)]. For instance, in a call center model, providing an expected wait time and anticipated delays to arriving customers reduces the rate of abandonment of calls, thereby improving the firm's overall customer satisfaction rates (Yu et al., 2016).

In order to help patients and keep them informed of delays, hospitals are implementing other measures aside from announcements. A growing number of hospitals have started publishing ED wait times on their websites, billboards in their vicinity and developed smartphone applications to keep patients informed. Patients continuously seek information about wait times in EDs, and steady increase can be seen, in the volume of Google queries about “ER or Hospital wait times”; over the past 5 years (Figure 2.1). The factors that influence a patients decision to visit a specific ED include timely provision of treatment along with convenience, location, health insurance status and institutional preferences (Marco et al., 2010). Dong et al. (2015) did an empirical study that analyzed the historical wait times of 211 U.S. hospitals and concluded that patients are increasingly paying attention to ED wait times and use this information while deciding where to go for treatment.



Note: Numbers represent search interest relative to the highest point on the chart for the given region and time. A value of 100 is the peak popularity for the term. A value of 50 means that the term is half as popular. Likewise, a score of 0 means the term was less than 1% as popular as the peak. Source: (trends.google.com)

Figure 2.1: ED wait times search query over Google trends

Overcrowding is a multifaceted problem, and many solutions have been studied by scholars. Some hospitals have resorted to using queuing models to determine optimal staff allocation, by analyzing the arrival patterns of patients (Green et al., 2006). On the other hand, Batt and Terwiesch (2012) addressed the problem by evaluating the dynamics of an ED. The researcher studied how triage ordered testing helped save time by performing tests parallel to the patient waiting to receive treatment. In another study, Saghafian et al. (2012) uses stochastic models for the management and streamlining of patient flow in the

ED; by separating the patients on the basis of an upfront estimation of their final disposition (admission or discharged). McCusker and Verdon (2006) emphasized on the education of patients regarding when they should choose to visit the ED as opposed to their primary care physician.

Recently, a significant growth of predictive modeling in the medical industry, can be noticed. A primary motivation for the development of prediction models is to understand how historical information can be potentially used so as to make changes to the present operating decisions that can substantially reduce patient's wait times in the ED. Historical data can be used effectively in the determination of seasonal arrival patterns of patients in the ED; and guide operational decision-making so as to reduce ED overcrowding. In the subsequent sections of this chapter, the author explores various forecasting techniques that could be used for the evaluation of wait times of patients in the ED (Figure 2.2). The methods include time series analysis, queuing theory, discrete event simulation as well as numerous statistical methods. The author focuses on statistical methods used in the development of ED wait time prediction models and compares the performance of the conventional rolling average method as well as multiple regression techniques to select the ideal technique for this study. The determination of method's suitability was influenced by considerations of the applicability of methods in the ED environment, the availability of data, predictive performance and technological requirements for implementation of the method.

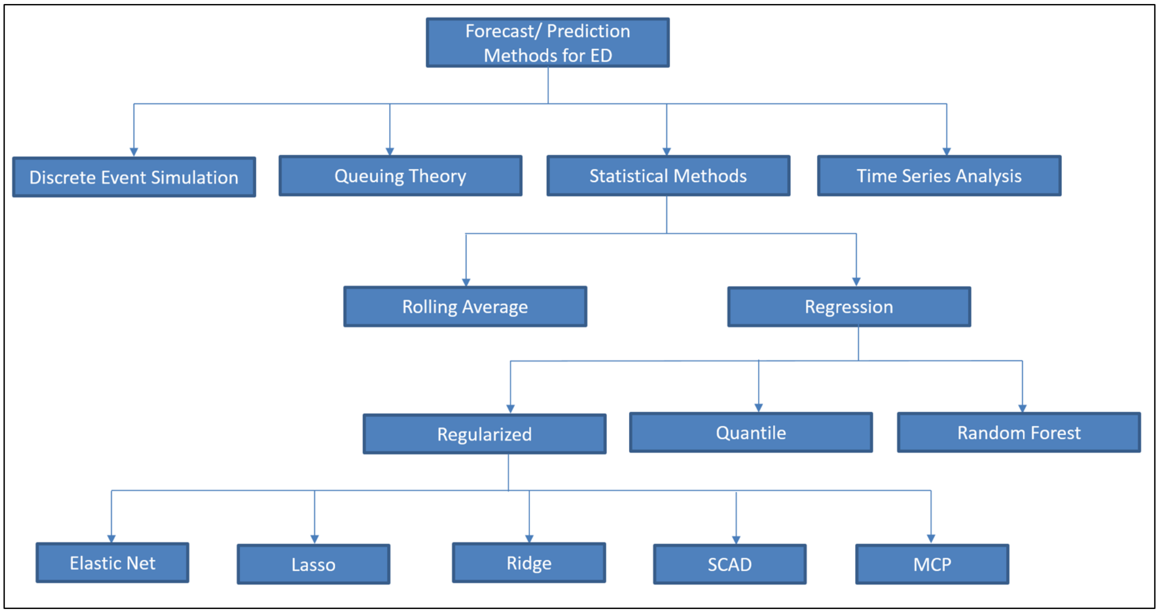


Figure 2.2: Exploratory forecasting methods

2.4.1 Discrete Event Simulation

Discrete event simulation (DES) is a method of simulating the performance of a real-life process by using probabilistic distribution inputs. It helps in evaluating the behavior of complex systems as an ordered sequence of well-defined events, defined at a specific point in time (Katsaliaki and Mustafee, 2011). Due to the stochastic nature and complex dynamics of events, simulation is increasingly being used in health care services. In an ED environment, simulation allows for the investigation of the interaction between patient flow, ED layout, and the procedure and equipment for developing optimal control strategies.

Duguay and Chetouane (2007) use a simulation model for the estimation of the mean and variance of patient wait time in the ED. A study conducted by Hoot et al. (2009) makes use of a DES model to reduce patient's waiting and improve the entire service delivery system and service throughput in an ED. Similarly, Vass and Szabo (2015) uses a DES model to develop a tool to forecast ED crowding as much as 8 hours, in the future. The tool accurately predicted the waiting time, boarding time, length of stay and number of people waiting in the lobby with varying levels of accuracy for a time period of two to four hours in the future.

Connelly and Bair (2004) used discrete event simulation to investigate ED operations at a system level. The developed model predicted the average service times in the range of 10% of actual values.

Despite the numerous successes of using discrete event simulation for predictive modeling, it is computationally more intensive. Therefore, the results of the simulation may not be readily available for the evaluation of an event that may occur instantaneously. Because of the long running times and multiple iterations of such models, the simulation would not be ideal for estimating the wait time of patients, on their arrival at the ED, where decisions are often made under stress and tight time constraints. The DES forecasting models also requires exhaustive quantities of data to be incorporated to model ED activities and necessitates that each stage of a patient's passage though the ER be modeled. Furthermore, in any simulation, it is difficult to specify the initial probability distributions relating to the arrival of patients or their discharge. Therefore, if the inputs are inaccurate, the output is likely to be useless; leading to a classic case of "Garbage in, garbage out."

2.4.2 Queueing Theory

Queueing theory is a simpler method of modeling ED operations for the estimation of wait times of patients. At a fundamental level, the queueing system for EDs can be represented in three basic components (Eitel et al., 2010)

- Arrivals: Patients arriving at the emergency room with some arrival pattern.
- Waiting in queue: The patients wait before being triaged or seen by a healthcare professional.
- Service: Patients receive the required treatment or consultation from a physician and are either being admitted or discharged from the ED.

This system is designed based on queuing disciplines. The most popular disciplines are Last-In-First-Out (LIFO), First-Come-First-Serve (FCFS) and priority. In the setting of an ED, high acuity patients requiring immediate treatment are seen before low acuity patients with non-critical ailments. Many queueing models in research deal with the study of overcrowding in EDs. Vass and Szabo (2015) uses a queuing model to understand the patient flow through the ED. The authors highlight the relationship between ED wait times and allocated resources such as beds and physicians. Wiler et al. (2013) forecasted the number of patients who left without being seen (LWBS) on the basis of patient arrivals, treatment time and ED boarding. Reducing the ED patient boarding time was found to be directly associated with a decline in the LWBS rates. Connelly and Bair (2004) performed a hospital-wide study of patient flow using queuing theories and assessed its impact on the ED.

Despite the simplicity of queueing models, it faces several limitations specifically regarding the forecast of ED populations. Firstly, a majority of queuing models operate on simple queueing disciplines (FCFS or LIFO), which are not appropriate for use with the ED population. In such situations, a model based on priority would be more suited and yield better results. However, it must be cautioned that even a priority queuing discipline might not be modeled at a high level of accuracy for the complex and dynamic cases of an ED. In an ED, a more critical person is prioritized over less critical patients and this process is repeated with the entry of every new patient, thereby changing the priority list repeatedly and leading to a new list of priorities. Secondly, a majority of queuing models work under the assumption that no patient would leave the ED without treatment. However, we know that patients leave the ER, against medical advice, due to long wait times and crowding (Kennedy et al., 2008). Finally, most of the queuing models require the assumption of a steady state in the ED processes i.e. no waiting involved when a patient moves from one state to another, which may not be a case during post triage or consultation or when a patient is waiting for test results (Winston and Goldberg, 2004).

2.4.3 Time Series Analysis

Time series analysis is a method of forecasting future information based on historical data. Time series can serve as an effective tool for modeling ED behavior and help in the prediction of variables related to overcrowding. EDs have used time series analyses to forecast the number of patients visits [(Champion et al., 2007); (Sun et al., 2009)], length of stay (Tandberg and Qualls, 1994), acuity and patient movements in hospitals (Lin, 1989).

Schweigler et al. (2009) uses a seasonal Autoregressive Integrated Moving Average (ARIMA) model to forecast the bed occupancy from four to twelve hours in advance, for three unique ERs. TThe accuracy of the ARIMA model was compared with and found to be more accurate as compared to the hourly historical average and sinusoidal with an Auto Regression (AR) technique. The developed model successfully predicted ED occupancy but was silent on the factors contributing towards ED crowding or the possible solutions for its reduction.

The time series study, as conducted by Tandberg and Qualls (1994),successfully forecasted acuity, length of stay and patient volume. The moving average was found to be most accurate for predicting ED volume and also explained approximately 42% of the variance. The time series model also explained 1% of variation in the LOS or acuity levels of patients visiting the ED. A time series analysis model can effectively capture and predict factors responsible for overcrowding (e.g. patient arrivals, waiting time, Length Of Stay [LOS], boarding time, etc.) through the use of historical data in the long term. But, it fails to take into consideration the short-term variability that creates a surge in the patient's volume arising due to natural disasters or accidents; which is crucial for EDs (Schweigler et al., 2009). Due to these considerations, the researcher did not consider time series analysis as an ideal technique for the establishment of the wait time of patients in EDs.

2.4.4 Statistical Methods

Statistical modelling provides many robust techniques for identifying and describing variables to forecast overcrowding in emergency departments. Statistical methods can be used to model the effects of various independent variables on a certain or collection outcome variables (referred as dependent variables). Numerous statistical methods have been cited in literature related to ED forecasting. Research topics include multiple regression model to estimate patient arrival in ED (Weiss et al., 2004), quantile regression to study ambulance diversion [(Austin and Schull, 2003); (Schull et al., 2004)], logistic regression to estimate overcrowding (Hoot and Aronsky, 2005), regularization models (ridge and lasso) (Ang et al., 2015) and random forest to predict emergency department visits and Length Of Stay (LOS) using regression (Poole et al., 2016).

With reference to the establishment of wait times of patients in the ED, Poole et al. (2016) used quantile regression to predict the waiting time for individual patient's across all the triage levels up to the 95th percentile. Champion et al. (2007) established the wait time through the use of simplest moving or rolling average based on the arithmetic means on an hourly basis. Wenerstrom (2009) captured the wait time using a linear regression model whereas Ang et al. (2015) established the wait time of low acuity patients via the use of a regularized regression model and fluid model estimators. A regularized regression technique, Least Absolute Shrinkage and Selection Operator (LASSO) uses independent factors such as the time of the day, the day of the week, staffing resources of the ED, the status of the fast track program, and the patient's arrival rates to establish dependent factors like time to treatment and triage to treatment time.

This research aims to estimate the wait time prediction of low acuity patients in the emergency department using regularized regression methods (Ridge, Lasso, Elastic Net, SCAD & MCP) along with tree-based regression (Random Forest). In contrast to the independent factors highlighted in Ang et al. (2015), the researcher will also study additional factors such as - the month of the year, and use random forest regression model. The best wait time prediction model is chosen depending on their ability to utilize the historic data from the hospital. The following chapter on the studied methodology discusses the statistical methods in detail alongside the analytical techniques being used.

Chapter 3

Methodology

ED overcrowding is a major concern across hospitals in the country (Carrus et al., 2010). One of the major components that contribute to the long ED wait times is the door-to-doctor time (Arkun et al., 2010). The term is used to refer to the cumulative time since a patients entry in to the ED to the time of their treatment by the doctor and includes the numerous intervals of waiting that the patient experiences. The numerous factors affecting a patients door-to-doctor time have been studied extensively (Arkun et al., 2010). Studies have focused on individual factors like ED volume (Derlet et al., 2001), level of acuity of patients ailments (Hoot and Aronsky, 2008), staffing considerations of the ED unit (Schneider et al., 2001), ED occupancy rates (Forster et al., 2003), daily patient admissions (Olshaker and Rathlev, 2006) and hospital volume (Yancer et al., 2006).

Figure 3.1 highlights the overall steps followed by the researcher, to build the required predictive model starting from variable creation all the way to model validation. To build a reliable predictive model in determining wait times one should incorporate the queues of patients at various stages of ED along with arrival time of patients as candidate predictor variables to accurately capture the conditions of the ED.

The methodology developed for creating candidate predictor follow the procedure suggested in (Ang et al., 2015). The model predicts the wait time for low acuity patients through the use of regression methods. Because of the large number of candidate predictor

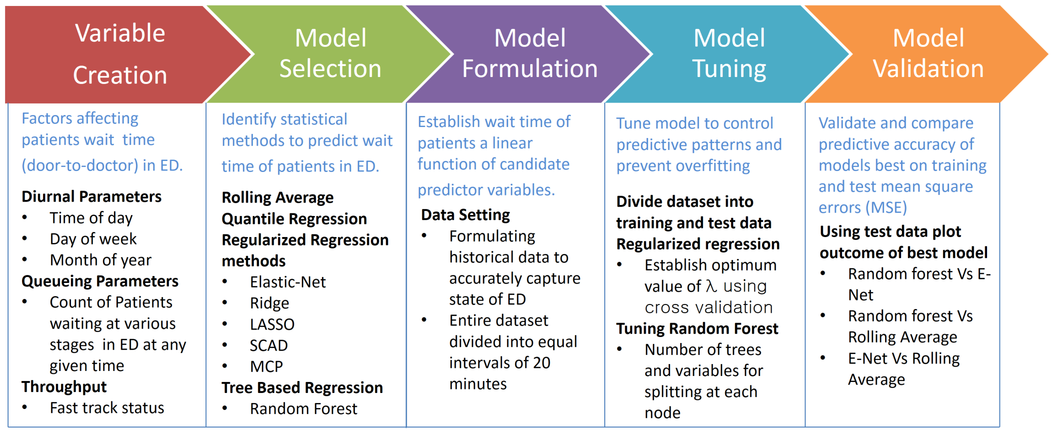


Figure 3.1: Roadmap for developed methodology

variables, the wait time model specifically uses regularized regression techniques along with trees based regression. In order to select the most relevant wait time prediction model, the author compared with the Conventional Rolling Average Method (Dong et al., 2015) as well as Quantile Regression (Sun et al., 2012). These methods are popular in prior studies along with the use of regularized and tree based regression techniques. For the dataset of this study, Random Forest regression gives the best prediction, which is evaluated through the use of Mean Squared Error (MSE) value of test data.

3.1 Variable creation

To effectively model the state of the ED, the right selection of candidate predictor variables is important. To account for the diurnal variation in wait time, the author investigated a set of candidate predictor variables for the time of day along with the day of week and month of the year. Alongside the diurnal set of predictors, the researcher also explored the use of queuing parameters for wait time prediction as used by Armony et al. (2015).

3.1.1 Candidate predictor variables - diurnal parameters

To link the conditions of the ER and the patients arrival times, the researcher attempted to investigate how the arrival pattern of sick people to the ED developed across the day. As is apparent from the graph in figure 3.2; on any particular day, the number of patients visiting the ED increased gradually from 7 A.M to 7 P.M. To capture this variation, the researcher uses 20 minute intervals to capture 71 binary variables based on the time the patient arrived at the ED.

The binary variable takes value of 0 for all time periods excluding the time period in which the patient registers in the ED. For example, if a patient arrives and registers at 8/1/2014 12:14:00 AM; the first 20-minute period from 12.00- 12.20 AM takes a value of 1 and the remaining intervals take the value 0. In general, if instead of 20 minutes one decides to have a period of m-minutes, then there will be $\{[24X60/m] - 1\}$ binary variables.

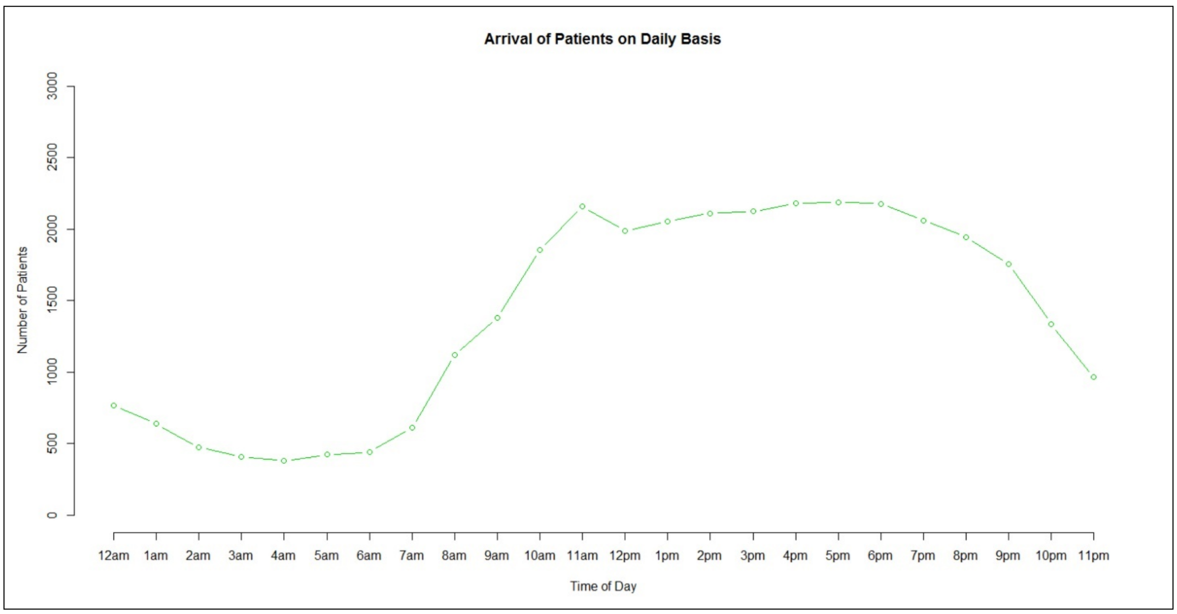


Figure 3.2: Varying volume of People in ED for any given instance of day

In order to capture the volatility of the arrival of patients based on the day of the week; the author investigated the arrival of patients in the ED for the entire week. Arkun et al. (2010) cconcluded that the day of the week had a crucial impact on the waiting time for patients prior to them receiving treatment. From the graph in figure 3.3 oone can see a distinct spike in patient numbers in the ED on Monday whereas there are significantly fewer patients on the weekends. The significant increase in patients visiting the ED on Monday is likely due to the increase in the number of sufferers who fails to seek consultancy from their primary care physician and are then referred to the ED in times of urgency. To account for the day of the week as a candidate predictor variable, the scholar uses 6 binary variables, which take the value of 0 for all days except for the one corresponding to the patient's day of arrival.

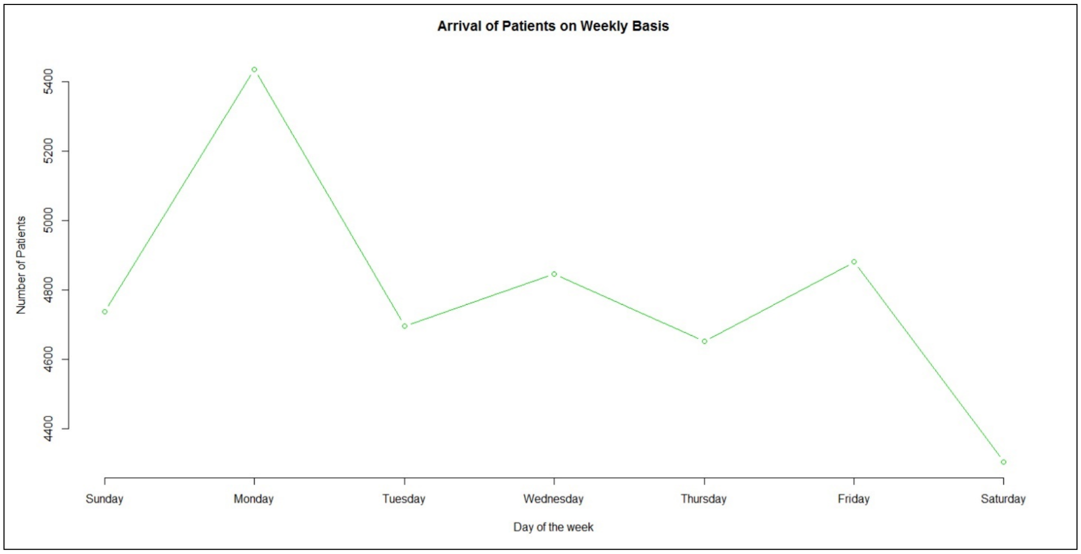


Figure 3.3: Varying volume of people in ER at any given day of the week

Among the numerous factors contributing to ED overcrowding, the seasonal outbreak of influenza is a prominent factor (Hoot and Aronsky, 2008). Seasonal influenza is common in the United States throughout the year. However, an analysis of influenza flu activity for the 34-year period of 1982-1983 through 2015-2016 revealed that influenza activity starts in October and continues through May and peaks in February. This encouraged the researcher to examine the number of patient visiting the ED on a monthly basis, so as to determine whether the suggestion of a direct co-relation was justified. From the graph in figure 3.4 one can identify an almost increase in volume of patients visiting the ED for the months of November through April. Thus, allowing the researcher to address the impact of seasonal influenza on the dataset, thereby adding accuracy to the results of the study. To capture the month of the year as a predictor variable, the author uses 11 binary variables, which take the value of 0 for all months excluding the one corresponding to the patient's month of arrival.

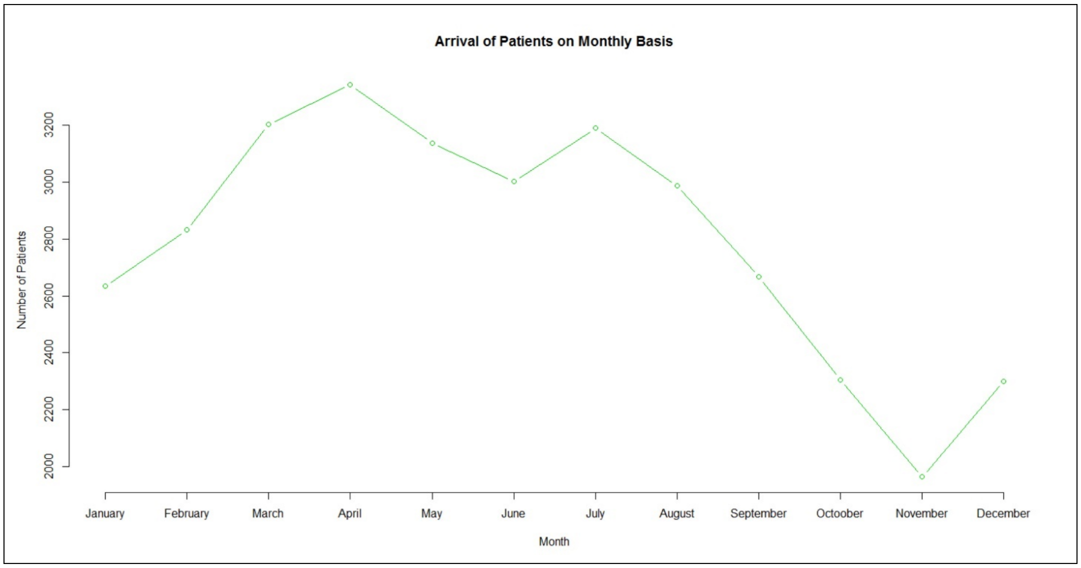


Figure 3.4: Number of people in ED across different months

The ED of the hospital operates a fast track schedule with dedicated resources in an effort to expedite the treatment of patients with non-urgent complaints. These systems help to reduce the wait time of patients visiting the ED, primarily the low acuity patients. The fast track is designed so as to be able to handle a large influx of patients for periods of diurnal fluctuations or seasonal variations (Considine et al., 2008). In the case of the ED under consideration, from figure 3.5 a side-by-side comparison of the average time to treatment for patients with low acuity concerns to the number of people in the ED revealed that there is a continuous increase in the wait time from 12 PM to 12 AM. For this reason, the fast track is staffed for this time period, for seven days of the week. By staffing the fast track with a mid-level practitioner, a registered nurse and a technician, the hospital makes an active effort to reduce the wait time for low-acuity patients. The researcher uses another binary variable to represent whether the Fast Track was in operation at the time of the patient's registration. The binary variable takes value 1 if the patient registers at any time at any time interval 12 PM to 12 AM, and takes the value of 0 if the time of registration falls outside this window.

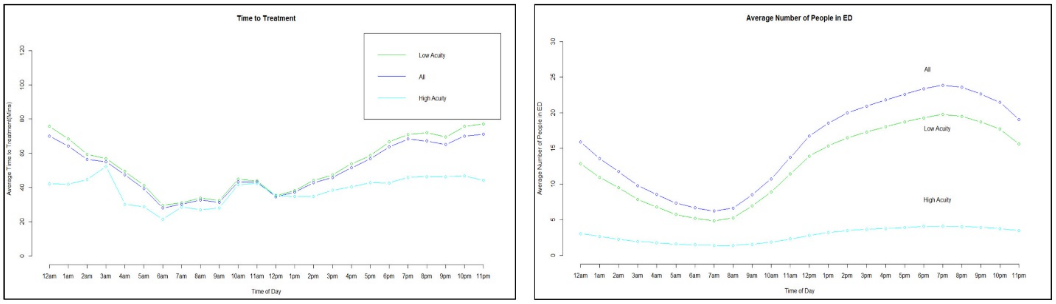


Figure 3.5: Time to treatment and number of people in ED

3.1.2 Candidate predictor variables - queueing parameters

The ED, when evaluated from a queuing systems perspective, can be modeled as multiple server systems. These systems vary over time in terms of arrival rates and number of servers as accompanied by customer abandonment. Ibrahim and Whitt (2011) proposed new predictor variables to be able to predict the wait time of customers, in real time entering such systems. They suggested the use of queue-length based predictors to capture the number of customers in different queues. Queue-length based predictors, in dynamic systems, capture the length of queues which a customer sees before entering the system along with their arrival and process rate in the form of number of servers.

Ang et al. (2015) used fluid model estimators in combination with queue-based predictors to determine the workload in EDs for any given moment of time. It captures the queue of patients waiting at various stages of the ED from registration to disposition, for a fixed interval of time throughout the day. The author makes use of the idea proposed by Ang et al. (2015). To capture the queue length based predictors, the ED was divided into various stages, as seen in figure 3.6. The patient flow procedure in the ED starts with their registration and is followed by triage to assess the severity of their condition. Once triaged based on the condition of the patient they are seen by a physician or referred to waiting area for treatment. The time elapsed between the patient's arrival and their treatment is referred to as the wait time to treatment. Once a physician evaluates a patient, a decision is made to admit or discharge.

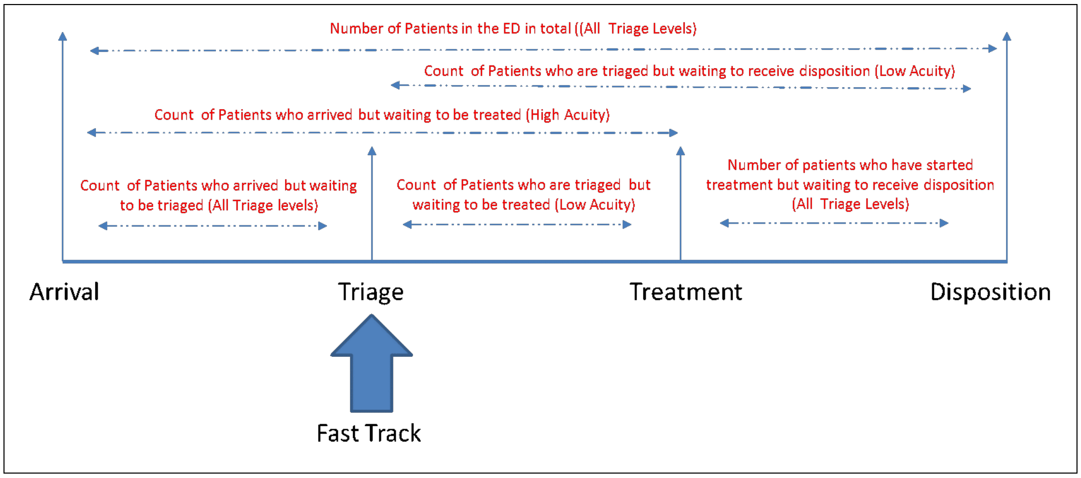


Figure 3.6: Queuing parameters

Based on the triage level, every patient passes through the various stages of ED. The triage levels help in capturing the processing requirements and the kind of resources that need to be used. A patient with a low triage level (1-2) or high acuity needs to be treated immediately thus creating more workload on the ED as compared with a person with high triage level (3-4-5) or low acuity. For patients with high acuity the time lapse between triage and treatment time is minimal, and so a separate count of queue length is calculated. The fast track, with a small team of healthcare practitioners and nurses, helps in prioritizing the treatment of low acuity patient. During the time when the fast track is active, the difference between triage and treatment time for patients with low acuity is relatively small, thereby necessitating the use of a separate count of queue length.

From the time-stamped data, for every 20-minute interval of the dataset, six queue lengths were calculated at various stages of the ED. Since triage level is an important parameter in evaluating the workload imposed by every patient on the ED, the considered queue lengths were further classified by triage level. Therefore, a total of 19 queue length based variables were developed in reference to triage levels and are listed in table 3.1. For example, if a patient arrives and registers on 8/1/2014 at 12:14 AM the queuing indicators from 12.00 - 12.20 AM are linked to the patient's arrival time and so forth.

Table 3.1: Description of queueing parameters

Queueing Parameter	Triage Level	Variable Count
Number of patients in ED in total	All	1
Number of patients who are triaged but waiting to receive disposition	Low Acuity	4
Number of patients who are registered but waiting to be treated	High Acuity	3
Number of patients who are registered but waiting to be triaged	All	1
Number of patients who are triaged but waiting to be treated	Low Acuity	4
Number of Patients who have started treatment but waiting to receive disposition	All	6

3.1.3 Summary

The emergency department is a dynamic process comprising of a lot of external and internal factors affecting the wait time of patients. Hence, to precisely capture the state of ERs and accurately predict the wait time of patients; a total of 108 candidate predictor variables are created (consisting of queue length and diurnal parameters) as discussed in the previous section. Table 3.2 gives a summary of all the essential independent variables reconstructed from ED patient data.

Table 3.2: Summary of candidate predictor variables

Variable Description(s)	Variable Count	Variable Categorization
Time of day	71	Diurnal parameters
Day of week	6	Diurnal parameters
Month of year	11	Diurnal parameters
Number of patent at various stages in ED	19	Queueing parameters
Fast track status	1	Throughput parameters

3.2 Model selection

The prediction of the wait time of patients in any Emergency Department (ED) depends on a large number of predictors. The relationship between patient's wait time before being seen by a doctor, and the candidate predictor variables can be expressed, in its simplest form, by using a multiple linear regression equation. Considering a total of n number of low acuity patients in the ED and p number of candidate predictor variables; one can represent waiting time of patient as:

$$y_i = \beta_0 + \sum_{j=1}^{p} \beta_j x_{ij} \quad + \ \epsilon_i \ , \ i = 1, 2, \ldots, n \tag{3.1}$$

where y_i is the predicted waiting time for i^{th} low acuity patient and x_{ij} is the j^{th} independent predictor for i^{th} patient. β_j are the regression coefficients and ϵ_i is the error term.

Linear regression equation aims to minimize the square of the distance between the actual and predicted wait times. Linear regression is not being used by the researcher as it is sensitive to outliers. Prediction of mean waiting time of patients will be highly skewed leading to underestimation of the predicted wait times (Sun et al., 2012). Furthermore, linear regression is computationally more intensive as compared with other machine learning techniques like regularized regression (James et al., 2013).

3.2.1 Regularized regression models

The author explores other procedures to counter the limitations of linear regression models for model prediction and interpretability. Regularized regression models have been used successfully for Genomic prediction which involves a multiple regression of phenotypic observations (n) on markers (p) where $p >> n$. Ogutu and Piepho (2014) compared the predictive accuracies of genomic prediction using different regularized regression models.

The availability of numerous candidate variables (p) in determining the wait time of patients in EDs encouraged the researcher to use regularized regression methods. Regularized regression methods help in the selection of relevant parameters within the candidate predictor variables while also addressing the concern of multicollinearity. These models evaluate the regression coefficients β_j in equation 3.2 in a manner that minimizes the loss function and penalty function. The loss function comprises of the Residual Sum of Squares (RSS), which is the difference between the sum of the squared differences between the actual and predicted wait time values. By using the notations developed by Ogutu and Piepho (2014) a regularized regression model can be expressed as:

$$F_{\lambda}, \gamma\,(\beta) = \underset{\beta}{^{argmin}} \left\{ \underbrace{\sum_{i=1}^{n} \left(y_i - \sum_{j=1}^{p} \beta_j x_{ij} \right)^2}_{Loss\ Funtion=RSS} + \underbrace{\sum_{j=1}^{p} p_{\lambda,\gamma}(\beta_j)}_{Penalty\ function} \right\} \tag{3.2}$$

where $p_{\lambda,\gamma}(.)$ is the function of regression coefficients β_j in equation 3.2. The tuning parameter $\lambda > 0$, controls the relative impact of the penalty function. γ is the shrinkage parameter determines the type of the penalty function. The varying values of the shrinkage parameter lead to different regularized regression methods. The regularized regression models used to predict the wait time of low acuity patients in EDs include Ridge Regression (Hoerl and Kennard, 1970), Least Absolute Shrinkage and Selection Operator (LASSO) (Tibshirani, 1996), Elastic Net (Zou and Hastie, 2005), Minimax Concave Penalty (MCP) (Zhang et al., 2010) as well as Smoothly Clipped Absolute Deviation(SCAD) (Fan and Li, 2001).

Ridge Regression

The Ridge regression model penalty function in equation 3.2 with $\gamma = 2$ reduces to (Hoerl and Kennard, 1970):

$$Ridge\,(\beta) = \underset{\beta}{^{argmin}} \left\{ RSS + \lambda \sum_{j=1}^{p} \beta_j^2 \right\} \tag{3.3}$$

As $\lambda \to \infty$, the impact of the shrinkage penalty grows, and the estimated ridge regression coefficients will approach zero thereby leading to a decrease in variance but an increase in bias. For varying values of λ we observe different solutions. λ acts as the shrinkage parameter and controls the size of the coefficients or the amount of regularization. For this reason, the selection of an optimal value of λ is critical. The optimal value of λ that minimizes the mean squared error is chosen via the process of cross-validation. The penalty used by the ridge regression model is referred to as the l_2 regularization.

Least Absolute Shrinkage and Selection Operator (LASSO)

The LASSO estimator penalty function in equation (3.2) with γ= 1 reduces to (Tibshirani, 1996):

$$Lasso\,(\beta) = \underset{\beta}{argmin}. \left\{ RSS + \lambda \sum_{j=1}^{p} |\beta_j| \right\} 0 \tag{3.4}$$

This is similar to the ridge regression penalty estimator. The LASSO model also shrinks the estimated coefficients to zero. However, the LASSO penalty function can force some of the coefficient estimates to be exactly equal to zero in situations where the value of λ is sufficiently large. This property of the model enables it to be used for the purpose of performing a variable selection. Due to this, the LASSO estimator yields a sparser model, which is easier to interpret as compared with a ridge regression model. However, as in a ridge regression model, choosing an optimal value of λ for LASSO is equally important. The penalty used by LASSO is referred to as l_1 regularization.

Elastic Net

The elastic net regularized regression model combines the ridge regression model as well as the LASSO regression model thereby incorporating both l_1 and l_2 penalties. The elastic net penalty function in equation (3.2) can be written as (Zou and Hastie, 2005):

$$[E - Net\,(\beta) = \underset{\beta}{argmin}. \left\{ RSS + (1-\alpha) \sum_{j=1}^{p} |\beta_j| + \alpha \sum_{j=1}^{p} \beta_j^2 \right\} \tag{3.5}$$

$$\alpha = \lambda_2/(\lambda_1 + \lambda_2) \tag{3.6}$$

Where is a hyper-parameter and takes a value ranging from 0 to 1. By controlling how much l_1 or l_2 is regularized, takes the value of 0 for ridge regression and 1 for LASSO. λ_2 and λ_1 are the shrinkage penalties for the ridge regression and LASSO model respectively that were selected through the process of cross-validation. In the case of a high degree of collinearity, LASSO regressions tend to perform poorly compared with ridge regression. On the one hand, where there is a high degree of pairwise correlations within variables, the LASSO model selects only one of the variables thus affecting the quality of variable selection. On the other hand, ridge regression models lack variable selection technique. The elastic net regression model with hybrid properties from both elastic net and lasso helps in generating a sparser model with l_1 regularization and addresses the limitation of the number of selected variables using l_2 regularization thereby leading to better prediction performance.

Smoothly Clipped Absolute Deviation (SCAD) and Minimax Concave Penalty (MCP)

Both SCAD and MCP are nonconvex penalties which can be used to diminish bias in penalized regression methods. Both penalties focus on eliminating the irrelevant variables from the model while retaining the important estimators. The penalty for MCP and its derivative can be written for the interval [0,∞) as [(Zhang et al., 2010); Breheny and Huang (2009)]:

$$p_{\lambda,\gamma}(\beta) = \left\{ \begin{array}{c} \gamma\beta - \frac{\beta^2}{2\gamma}\ ,\ if\ \beta \leq \gamma\lambda, \\ \frac{1}{2}\ \gamma\lambda^2\ ,\ if\ \beta > \gamma\lambda \end{array} \right\} \tag{3.7}$$

$$p'_{\lambda,\gamma}(\beta) = \left\{ \begin{array}{c} \gamma - \frac{\beta}{\gamma}\ ,\ if\ \beta \leq \gamma\lambda, \\ 0 \quad\ ,if\ \beta > \gamma\lambda \end{array} \right\} \tag{3.8}$$

Where $\lambda \geq 0$ and $\gamma > 0$. The derivative of MCP penalty shows that it applies same rate of penalty as lasso till $\beta > \gamma\lambda$. The smoothly clipped absolute deviation (SCAD) penalty and its gradient is defined by [(Fan and Li, 2001); (Breheny and Huang, 2011)]:

$$p_{\lambda,\gamma}\left(\beta\right)=\left\{\begin{array}{cc}\lambda\left|\beta\right| & ,if\left|\beta\right|\leq\ \lambda \\ -\frac{\beta^2-2\gamma\left|\beta\right|+\lambda^2}{2(\gamma-1)} & ,\ if\lambda<\left|\beta\right|\leq\gamma\lambda, \\ \frac{(\gamma+1)\lambda^2}{2} & ,\ if\ \left|\beta\right|>\gamma\lambda\end{array}\right\} \tag{3.9}$$

$$p'_{\lambda,\gamma}\left(\beta\right)=I\ \left(\beta\leq\ \lambda\right)+\ \frac{\left(\gamma\lambda-\beta\right)}{\left(\gamma-1\right)\lambda}+I\left(\beta>\lambda\right)for\ some\ \gamma>2\ and\ \beta>0 \tag{3.10}$$

Where $\lambda > 0$ and $\gamma > 2$. This corresponds to a second order spline function with knots at λ and $\gamma\lambda$. This corresponds to a second order spline function with knots at λ and $\gamma\lambda$. SCAD tends to shrink small coefficients to zero while retaining the large coefficients. Thus, SCAD can produce a sparse set of solutions with unbiased large coefficients. Both MCP and SCAD have oracle properties as both tend to fit an unpenalized model in which non-zero predictors are known in advance (Zhang, 2007).

3.2.2 Random Forest

Random forest is an ensemble learning method that can be used for the purpose of classification as well as regression problems (Breiman, 2001). In an ensemble learning method like random forest, the output of multiple methods is combined and collectively evaluated to reach final conclusions (Brown, 2011). Random forests combine as well as generate binary decision trees while also aggregating their results (Breiman et al., 1984). Decision trees in random forest are constructed using a bootstrap sample of the training data and randomly choosing a subset of predictors at each node. This is in contrast to the Classifcation and Regression Trees (CART) model building process. After fitting individual trees by using bootstrap samples in the ensemble, the final output is achieved by averaging the output of the ensemble. In statistical terms, this process is known as bagging and helps in improving the prediction and accuracy of the model, reducing variance while also avoiding overfitting (Hastie et al., 2009).

Out-of-Bag (OOB) errors can be defined as the training error associated with the points that are not contained in the bootstrap straining sets. The training of random forest is stopped once the OOB error stabilizes. The two important parameters that need to be determined while tuning a random forest are the number of trees to grow; and the number of variables available for splitting at each tree node. The researcher chose both the parameters via the process of cross-validation for the purpose of predictions.

A random forest regression is known to have comparable, if not better, predictive accuracy than other regression models (Zhu et al., 2015). This is because random forest can efficiently deal with both numerical and ordinal variables, and does not require any assumptions about the distribution of data. This is in sharp contrast to other regression models (Joly et al., 2012). Random forest comprehensively captures the non-linearity between the set of candidate predictors and the dependent variables (Smith et al., 2013). Furthermore, it can also handle missing values efficiently along with an automatic variable selection feature.

The algorithm for random forest regression with N being the number of trees and p being the number of input variables at each split is as follows (Dudek, 2015).

1. For $i = 1$ to N:
   (a) Draw a bootstrap sample B of size S from the training data.
   (b) Grow a random-forest tree T_i to the bootstrapped data, by recursively repeating the following steps for every node of the tree until the minimum node size m is reached.
      i. Select p variables at random from the n variables.
      ii. Pick the best variable/split-among from the p.
      iii. Split the node into two daughter nodes
2. Output the ensemble of trees $\{T_i\}$ $where\ i = 1$ to N

The prediction of new point x is made by using

$$f\left(x\right) = \frac{1}{N}\sum_{i=1}^{N} T_i(x) \tag{3.11}$$

3.2.3 Quantile Regression

Quantile regression models help define the relationship between a set of candidate predictor variables and the specific quantiles of the response variables analogous to a linear regression, which investigate the mean value of response variables for a given set of predictor variables (Bassett Jr and Koenker, 1978). Quantile regression leads to a more comprehensive analysis by estimating the changes in specific quantiles of the response variables with respect to predictor variables, providing relationship at different points in the conditional distribution of response variable (Mak et al., 2010).

During the modeling process of quantile regression, the data is divided into specific proportions, where quantile $q \in (0, 1)$ is that value of y which is split between q below and $1 - q$ above for median $q = 0.5$ the quantile regression estimator for quantile q minimizes (Baum, 2013)

$$F(\beta_q) = \underset{\beta}{argmin}. \left\{ \sum_{i:y_I \geq x_i\beta}^{N} q\,|y_i - x_i'\beta_q| + \sum_{i:y_I < x_i\beta}^{N} (1-q)|y_i - x_i'\beta_q| \right\} \tag{3.12}$$

where the conditional median quantile function of y for the given co-variates of x is $x_i'\beta_q$.

Quantile regression is preferred over linear regression when the extremes of the data are important. Unlike linear regression, quantile regression does not require distribution assumptions, is more robust to outliers and more comprehensive. For these reasons, it is ideal for estimating the predicted wait time for low acuity patients in EDs; because it allows the researcher to address the likelihood of significant variations because of the dynamic environment of ED units (Sun et al., 2012).

3.2.4 Rolling Average

The rolling or moving average is a method by which data points are analyzed by creating a continuous set of averages, from consecutive subsets of a full dataset. There are several types of moving averages based on the method of calculation. The most commonly used moving averages are simple, weighted, exponential and cumulative moving averages (Dash, 2013). They are used widely for interpreting the associated patterns in any given dataset.

In this study, the researcher focused on using the simple moving average. For a given dataset, a fixed subset size is selected for which the average is calculated. The subset is decided based on the type of data and its application. For a time-series data, the subset can be determined either on the basis of a fixed time (m *minutes*) or a fixed number of entries (k *points*). A moving average helps in smoothing the dataset by removing short-term variations. For a dataset of m points and t fixed subsets of k entities, the moving average can be calculated as (Weisstein, 2013):

$$r_l = \frac{1}{k} \sum_{i=1}^{k} m_i \ , \ l = 1, 2, \ldots, k \tag{3.13}$$

where r_l is the rolling average of l^{th} subset. The rolling average is a conventional method, and it has certain disadvantages when compared with more advanced statistical analysis techniques. The primary disadvantage of the rolling average is that it takes into consideration historical information but ignores future changes; leading to inconsistencies over the period of time. The use of rolling averages can be seen predominantly in understanding the behavior of stock markets and share prices, measuring computer performance and the prediction of wait times in hospitals [(Cook et al., 2011); (Dong et al., 2015);(Conti and Walkowicz, 1977)].

3.3 Model formulation

The ED of a hospital is a complex and dynamic system. It involves extreme volatility and sensitivity. Therefore, to accurately capture the state of the emergency room, one needs to dynamically capture and update the number of patients present in the ED at any given moment of time. To accurately predict the waiting time for low acuity patients, using the one-year historical data from EMR database, the entire dataset was divided into intervals of 20 minutes. To evaluate the waiting time of low acuity patients, the entire dataset is formatted as (Ang et al., 2015)

$$(y_1, \overline{P}_1), (y_2, \overline{P}_2) \ldots\ldots(y_n, \overline{P}_n) \tag{3.14}$$

Where y_i is the actual time to treatment for the i^{th} low acuity patient, $\overline{P}_i \in R^M$ is the vector value of predictor variables for a 20-minute period, M is the total number of candidate predictor variables and n refers to the number of low acuity patients visiting ED. As highlighted in the previous section, a total of 108 candidate predictor variables are created comprising of 19 queueing, fast track status and 89 time based-estimators to accurately predict the wait time of low acuity patients in ER.

3.4 Model tuning

Model tuning is used to enhance the predictive performance of regularized and tree based regression models as well as accurately estimate the wait time of low acuity patients. Model tuning enables us to identify the best parameters for a machine learning algorithm and optimize its performance for a given set of data. For the data under consideration, the researcher explicitly used time-series based cross-validation as recommended by Bergmeir et al. (2015) in order to establish the tuning parameters for the statistical model. For the purpose of cross-validation, the entire dataset is split into two sets in chronological order; training and test subsets with no overlap. The training set constitutes 80% of the data while remaining 20% comprised of test data. The training dataset is further split into five equal subsets in which the first 80% of patient visits is used for training and remaining 20% as the validation set to forecast the prediction of wait time of patients. The same step is repeated for entire training set by adding validation set to training set and treating next 20% of data points as a new validation set. An overview of this procedure is highlighted in the figure 3.7

3.4.1 Tuning Regularized Regression models

Tuning regularized regression models involves choosing an optimum value of λ using cross validation. Using glment package in R software, the author chooses different values of λ

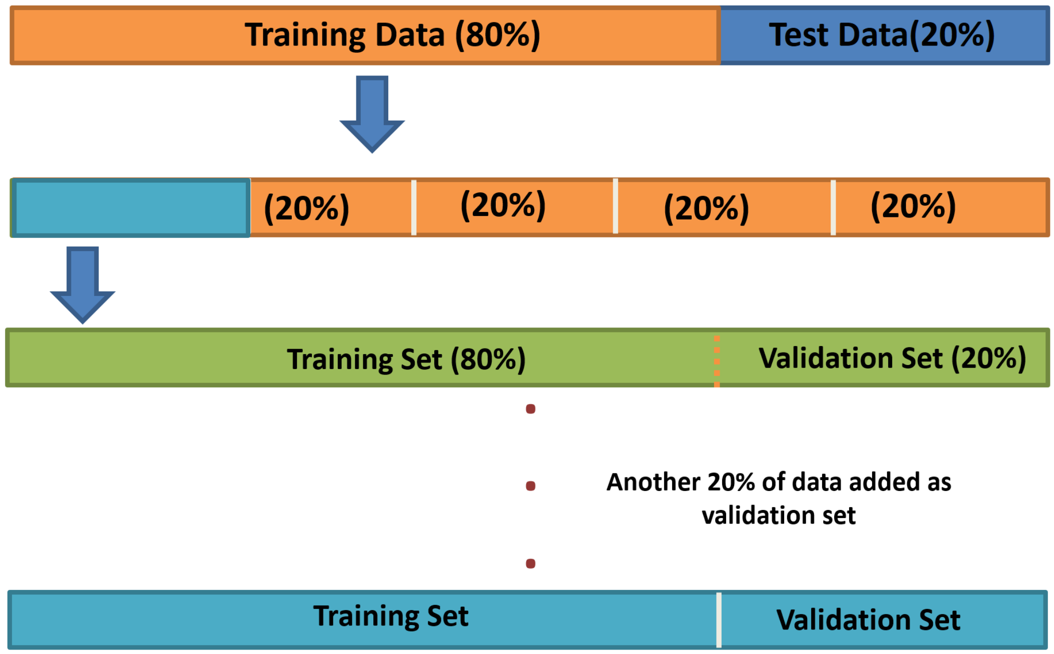


Figure 3.7: Overview of cross validation for time series data

ranging from 0 to point where a minimum MSE is observed over the training set. This identified value of λ is used to make predictions for validation set and corresponding MSE is evaluated. The same process is then repeated across different subsets of the training set. The most optimum value of λ is than decided based on the lowest MSE which is used for making prediction for test data set.

3.4.2 Tuning Random Forest models

There are many parameters that control the predictive accuracy of the random forest model. The two specific tuning parameters having the biggest impact are – number of variables to randomly sample as candidate predictors for each split (mtry) and the number of trees to grow (ntree). A baseline for mtry is calculated by taking the square root of the number of candidate variables. Using the caret package in R software multiple tuning of multiple parameters is evaluated by choosing different values of mtry and ntree over training data. Using repeated cross-validations, the optimal value of tuning parameters is chosen for the

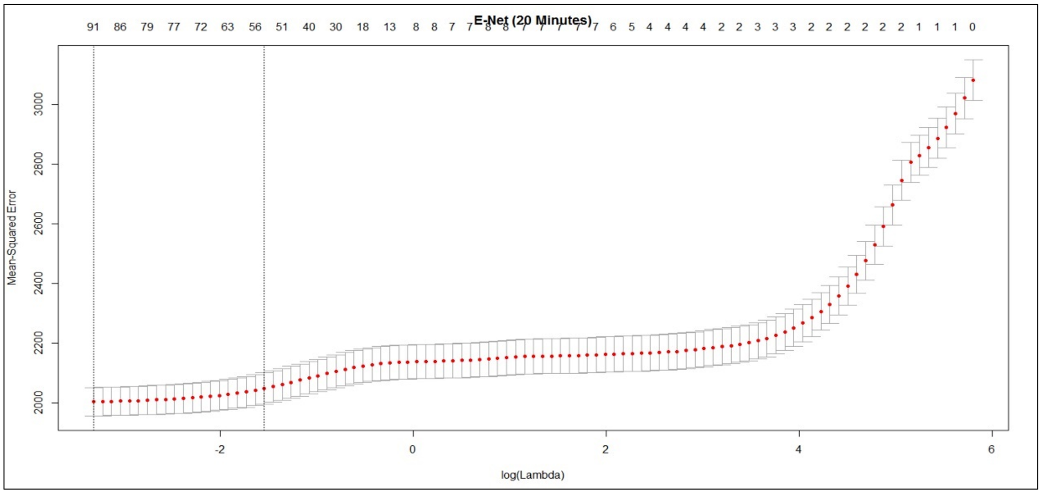


Figure 3.8: Tuning of Elastic-Net model over training data

lowest value of root mean square error (RMSE) as illustrated in figure A.2. The identified tuning parameters is than used in establishing the wait time of patients for test data set.

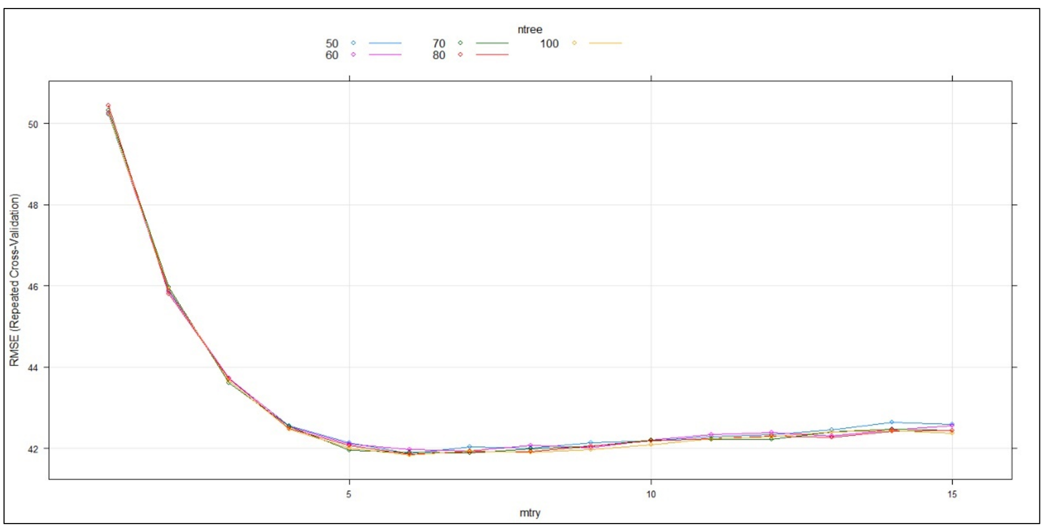


Figure 3.9: Tuning of random forest model over training data

3.5 Model Validation

Two non-overlapping distinct datasets were used to train and test the outcome of the developed model. The patient information was partitioned as per the time series based cross-validation technique described in previous section. For all the statistical techniques used in this research, the training set consisting of first 80% of data is used to fit and tune the model. The trained function is then used to predict the wait time of low acuity patients using the test data. The predictive accuracy of the model was evaluated by mean square error (MSE), which measures the average of the squares the difference between predicted and actual wait times. The statistical technique with least MSE is the best performing model with high predictive accuracy in determining the wait time of patients. Model validation with comparison between different methods is discussed in detail in chapter 4.

Chapter 4

Case Study

This chapter presents the case study undertaken by the researcher, and discusses the findings of the implementation of the study's wait time prediction model. The case study was developed to test and validate the predictive accuracy of the model developed using existing literature. The findings are presented with a brief description of the study site along with the exploratory data analysis. The case study also allowed the researcher to compare different wait time models with sensitivity analysis so as to determine the best performing model.

4.1 Study setting

This study was conducted using the data for one of the nine Acute Care Hospitals within the Covenant Health Care systems. Covenant Health is a community owned not-for-profit healthcare system headquartered in Knoxville, USA. The ED under consideration has a capacity of 40 beds with approximately 49,000 patients visiting annually. The unit operates throughout the week and irrespective of the day of the week; the facility also operates a 10-bed fast track unit for the treatment of low acuity patients.

4.2 Data collection

The archived data of patient's records was extracted from the Emergency Medical Record (EMR) database of the ED facility under consideration. The EMR acts as a centralized database for capturing information from each ED including records related to patient's registrations, medication prescribed, triage details, consultation and mode of payment. The data from the dataset was extracted for a one year period from August 2014 to July 2015. The total dataset comprised of approximately 50,000 entries. The EMR also records the time and date stamps entered by a medical healthcare professional or administration as patients transition through the various stages of the ED from registration to disposition. All sensitive and identifying information of the patient's demographics were suitably removed by the concerned hospital staff prior to the data's use for the study. The data was extracted from the fields listed below.

4.3 Data screening

The raw data as extracted from the EMR database included several corrupt and incomplete records. There were a significant number of missing data points, double entries and inaccurate information of patients records. Therefore, the author implemented the following steps so as to make the data more applicable

1. The data for 1,145 patients who left the ED without being seen, was deleted from the raw data.

2. For a substantial number of records (6,054), the time of treatment was missing. These records were also removed from the data.

3. In order to ensure that there were no negative values for time taken for treatment, the data was checked for consistency

$$Arrival \leq Triage \leq Treatment \leq Disposition$$

Table 4.1: EMR data field description

Columnar Header	Description
Internal ID	Unique primary key for identifying record in EMR database
LOS	Total length of stay of patient in Emergency Room
Age	Age of registered patient
Sex	Gender of patient
Chief Complaint	Chief complaint recorded for patient at time of triage/ registration
Triage Category	Triage level assigned to patient by triage nurse
Disposition	Status whether the patient was discharged or admitted
FAC	Name of facility
Department ID	Department ID (EDP) for which the data was captured
Arrival DTTM	Date-time when the patient arrived and registered themselves in the ED
Triage DTTM	Date-time when the patient was assessed by the triage Nurse
Assigned Bed DTTM	Date-time when the patient was assigned a bed
Chart DTTM	Date-time when the patient was charted
MD DTTM	Date-time when the patient was first seen by a physician
Decision DTTM	Date-time when the decision regarding the patient's admission or discharge is taken
Disposition DTTM	Date-time when the patient leaves the ED via; discharge or admission
MOA	Mode of arrival of the patient (ambulance or walk-in)

Continued on next page

Table 4.1 – continued from previous page

Columnar Header	Description
Miscellaneous	Status whether the patient left without being seen (LWBS), was admitted, discharged, transferred declared Dead on Arrival (DOA) or eloped

4. The author found approximately 2,000 duplicate entries which were further deleted from dataset.

After the process of data screening was implemented, the number of patient records reduced from the original 51,000 data points to a final sample of 34,000.

4.4 Data exploration

To focus on the number of patients who Left Without Being Seen (LWBS) as well as those who left/ eloped from the ED against medical advice, the author used data exploration techniques on the sample. The medical records of 50,963 patients, over a one year period, revealed that a total of 1,582 (3.10%). Patients left without being seen or eloped from the ED against medical advice. A majority of the patients, around 86% of those visiting the ED, were low acuity patients with triage level 3, 4 and 5. This is in stunning contrast to a mere 13% of those visiting the ED, being high acuity patients with potentially life-threatening conditions and triage levels 1 and 2. A patient with high acuity requires immediate medical care while also using more resources (Wuerz et al., 2000). Figure 4.1 is a pictorial representation of the number of patients that visited the ED and segregated based on their triage level.

The average time to treatment for all patients was observed to be 54.24 minutes. High acuity patients requiring immediate medical attention had a lower average time to treatment

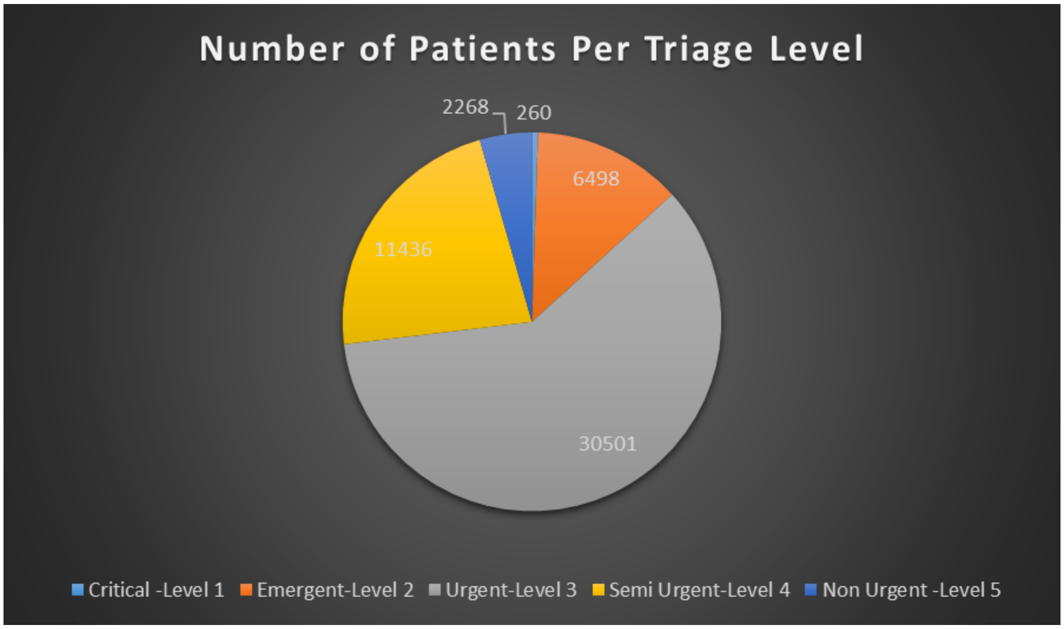


Figure 4.1: Patients per triage level

of 41.53 minutes whereas low acuity patients had a higher average time to treatment of 56 minutes.

Figure 4.2 is a graphical representation of the average time to treatment for various patient groups for any given day. The average time to treatment of patients is directly related to the EDs occupancy as well as staffing consideration at any given time of the day. The ED facility, used for the study, employs more resources from 6 A.M to 6 P.M as opposed to other times of the day. It is evident from Figure 4.2 that both low and high acuity patients have relatively lower times to treatment when more staff are employed in the ED.

Table 4.2 lists the description of data in terms of triage level, gender, rooming and decision. From the table, we find that 73% of the patients that visited the ED were discharged after being treated by a doctor or nurse. 24% percent of the patients were either admitted or transferred. This strengthens the argument that the majority of ED visits culminate in the discharge of the patients.

The average number of patients visiting the ED varied for different times. However, at any given time of the day, the number of high acuity patients in the ED was relatively constant as opposed to the number of low acuity patients. This is evident in Figure 4.3. As

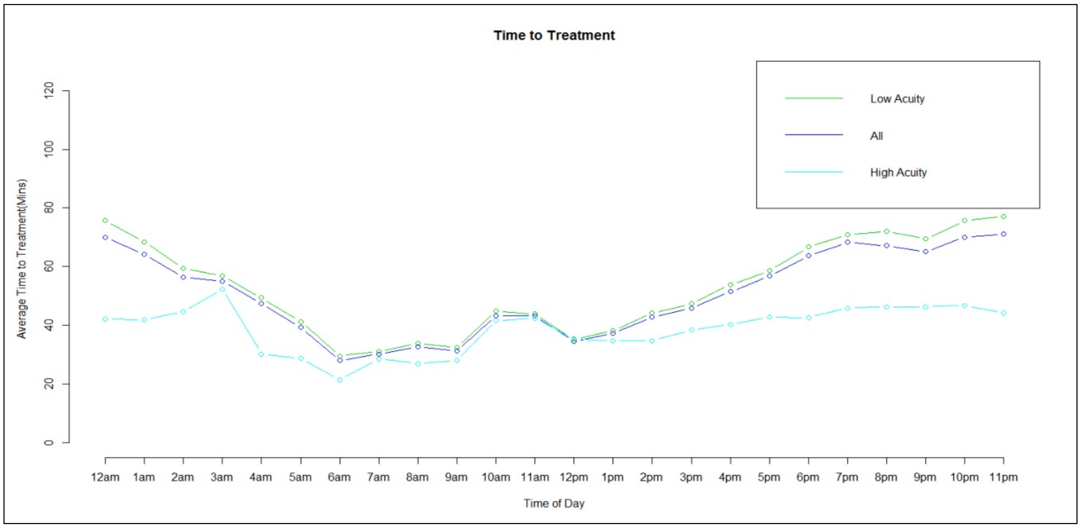


Figure 4.2: Average time to treatment of patients across day

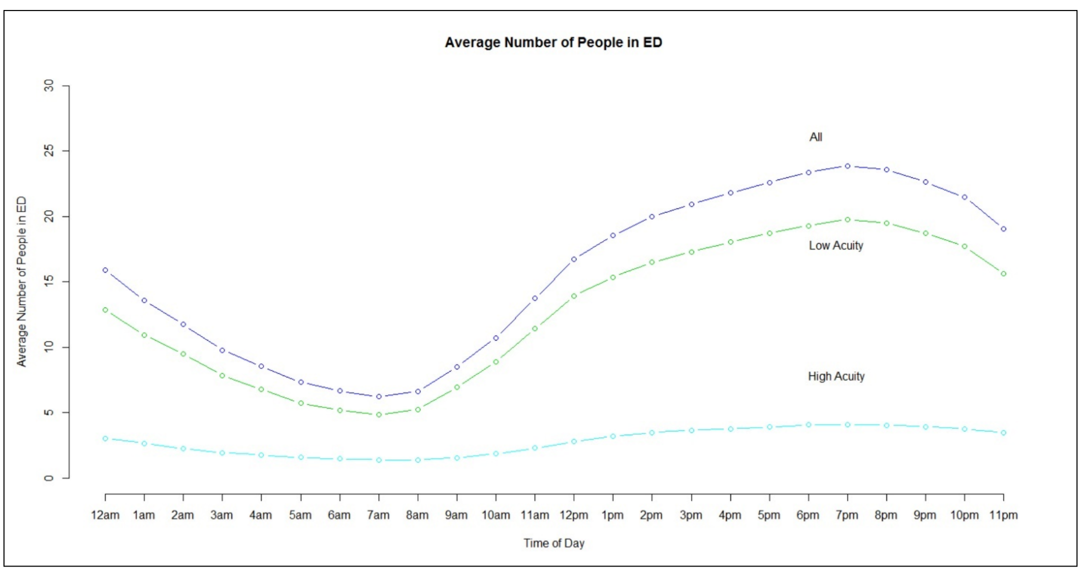


Figure 4.3: Average number of people in ED at a given time of day

Table 4.2: Description of data

Data Characteristic	**Count(Percent)**
Total Number of ED Visits	50,963
Left ED	
Left Without Being Seen	1,145 (2.25%)
Left Against Medical Advice	437 (.85%)
Mode of Arrival	
Ambulance	6,385 (12.5%)
Law Enforcement	16(<1%)
Walked in/ Private Transportation	32,335 (63.44%)
Missing Data Points	12,227 (23%)
Gender	
Male	28,999 (57%)
Female	21,964 (43%)
Triage Category	
Critical -Level 1	262 (0.51%)
Emergent-Level 2	6,498 (12.75%)
Urgent-Level 3	30,506 (59.85%)
Semi Urgent-Level 4	1,1439 (22.14%)
Non Urgent -Level 5	1,431 (2.8%)
Rooming	
ER1-ER17	21,415 (42.02%)
ER18-ER27	8,047 (15.78%)
ER28-ER37	11,733 (23.02%)
CC Rooms	3,235 (6.34%)
Others (Triage Room, Lobby, etc.)	1,616 (3.17%)
Missing Data Points	4,916 (9.64%)
Decision	
Admitted	11,133 (22.23%)
Discharged	37,233 (73.05%)
Transferred	683 (1.34%)
Others (Dead on Arrival, Registration Error, etc.)	326(<1%)

mentioned earlier, the number of low acuity patients in the ED varied through the time of day, with the number increasing steadily as the day progressed from 7 AM to 7 PM. However, it decreases at a slower rate during the remaining parts of the day.

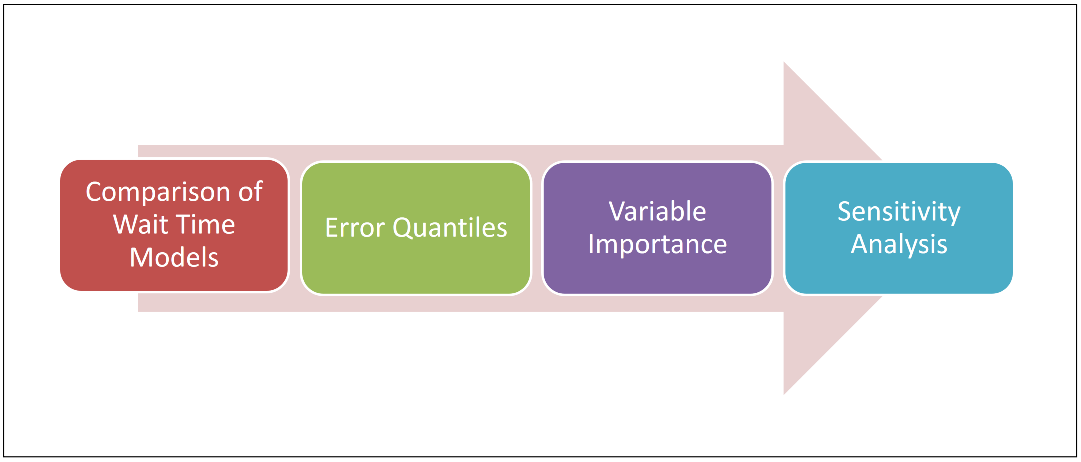


Figure 4.4: Organization of analysis and results section

4.5 Results and analysis of case study

This section of the chapter highlights the findings of the wait time model, as presented in the previous methodology chapter. The outcome of the model, as developed for the study, is evaluated and compared with the findings from different prediction methods that are based on the Mean Square Error (MSE)/Root Mean Square Error (RMSE) methods. The accuracy of the prediction methods is further assessed in terms of error quantiles. For the best performing wait time model, the most important predictor variables are determined on the basis of statistical significance followed by a sensitivity analysis so as to identify the important variables that can be influenced to reduce wait times. The results of the wait time models discussed in the subsequent sections of the thesis are developed via the use of free and open source R programing language. The researcher uses the ***glment*** package for regularized regression models, ***quantreg*** package for quantile regression and ***randomforest*** package for random forest regression models respectively. The information is organized and presented as shown in the figure 4.4

4.5.1 Comparison of wait time models

To compare and validate the wait time across different models, the data is split into training and test datasets with no overlap. First 80% of the patient visits, in chronological order,

Table 4.3: Training and test Mean Square Error (MSE) and Root Mean Square Error (RMSE) in minutes for wait time prediction of low acuity patients

	MSE		**RMSE**	
Forecasting Method	**Training**	**Test**	**Training**	**Test**
LASSO	1173.08	1811.93	34.25	42.56
Ridge	1144.16	1838.94	33.82	42.88
E-Net	1172.31	1809.2	34.23	42.53
SCAD	1171.47	1829.69	34.22	42.77
MCP	1171.04	1829.69	34.22	42.77
Quantile Regression	1271.68	2201.8	35.66	46.92
Rolling Average	1543.43	2570.68	39.28	50.7
Random Forest	1550.25	1708.78	39.37	41.33

accounted for the training dataset and the remaining 20% of the patient visits were used for test data. Table 4.3 shows MSEs and RMSEs for regularized regression models (Lasso, Ridge, E-Net, SCAD & MCP), conventional rolling average, as well as quantile and random forest regression models for both datasets. From this table, we see clearly that the Random Forest Regression model is more accurate than all the other prediction methods with the least test MSE of 1708.78 followed by E-Net with a 5% increase in error value. When compared with the rolling average, which is conventionally used by hospitals for the purpose of publishing the wait time, the random forest model achieves greater accuracy by reducing test MSE by 33%. No unusual variation in Test MSEs was observed for all regularized regression models.

Figure 4.5 graphically visualizes and compares patients wait times across different models on the basis of the information presented in Table No. 4.3. To evaluate the accuracy of predicted waiting times, across different times of day, the output of the two best performing models (Random forest and E-Net) are compared against the conventional rolling average which is used by most hospitals to determine and publish the wait time of patients in the emergency room.

Rolling Average Vs Elastic-Net

To visualize the accuracy of patients, wait time model using elastic-net against rolling average; mean of actual and predicted wait times across different times of day over 20

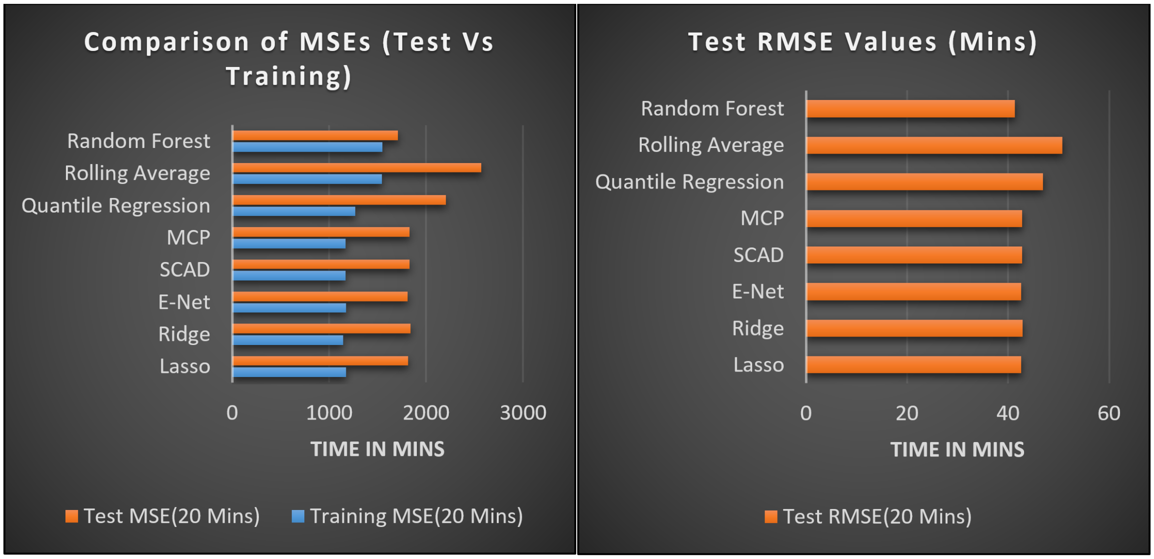


Figure 4.5: Training & Test Mean Square Error (MSE) and Root Mean Square Error (RMSE) comparison

minutes period is presented in the figure 4.6. As seen in figure 4.6, the rolling average tends to overestimate the wait time during the period of midnight to 7 AM and underestimates the wait time for the rest of the day due to the inability to effectively capture the diurnal variation. However, predictions from the elastic-net model overestimate the wait time of patients for almost all times of the day thus allowing patients to be seen before the actual predicted time. A patient is expected to have a higher rate of satisfaction when they are treated before the cited time as compared to the situation where they have to wait much longer than the estimated wait time. While looking back at the arrival rate of patients into the ED in figure 4.3, a majority of low acuity patients visited the ED between 11 pm to midnight. This period aligns with the time during which the rolling average method potentially underestimated the wait time. Hence, the majority of patients visiting the emergency room would likely see underestimated wait times thereby leading to more frustration and anxiety.

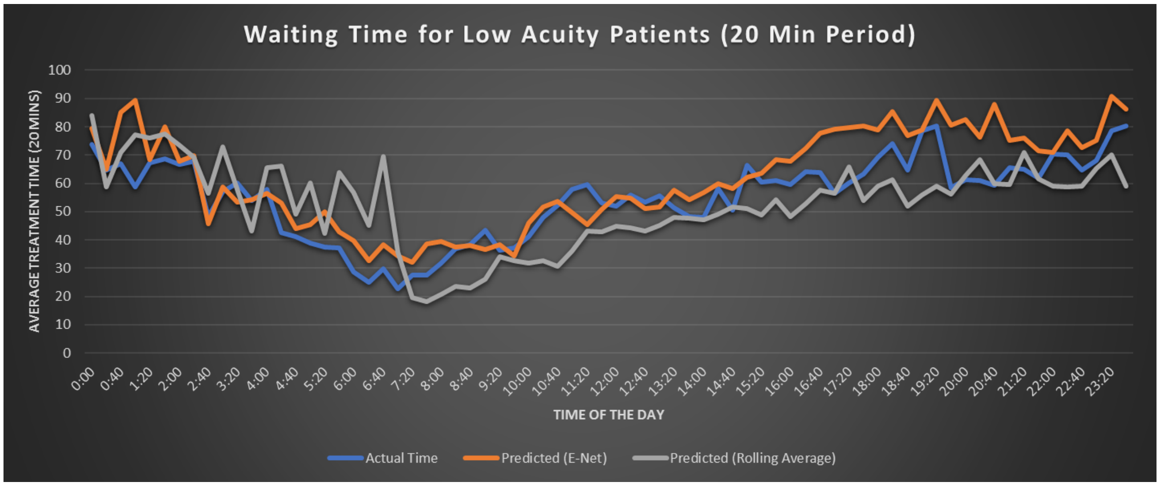


Figure 4.6: Comparison of Rolling Average Vs Elastic-Net

Rolling Average Vs Random Forest

As shown in figure 4.7, similar to the Elastic Net model, the random forest model also tends to overestimate the waiting time for patients, but with lesser variation across different times of the day except for the period between 10 pm to 4 am in morning. While comparing the random forest model with the rolling average we find that the rolling average tends to overestimate in situations where the actual wait time is less and underestimates when the actual wait time is more. However, the wait time predicted by the random forest model is tied closely with the actual wait time for 20 mins period across the day as evident from figure 4.3. By updating the candidate predictor variables every 20 minutes, the random forest model can capture the changes in ED dynamics with more accuracy in contrast to conventional rolling average method, which relies heavily on historical data.

Random Forest Vs Elastic-Net

As shown in figure 4.8, both random forest and elastic-net capture the wait time with good accuracy. However, the random forest model supersedes the elastic-net model with a low MSE value. The analysis of the actual vs predicted wait times for both the models, across different times of the day, reveals some interesting insights in terms of capturing the variability in patient's time-to-treatment. Relative to the random forest model, which

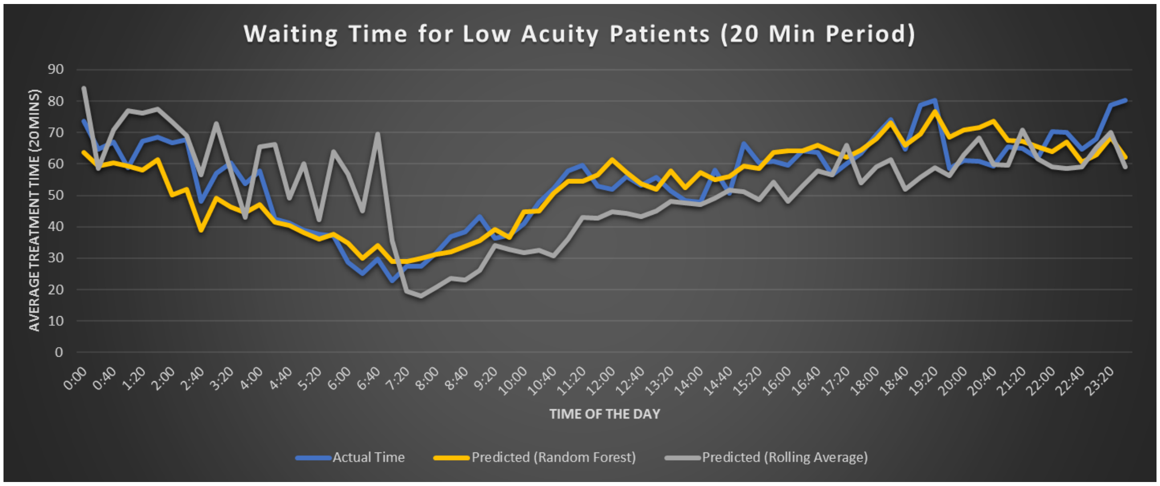


Figure 4.7: Comparison of Rolling Average Vs Random Forest

overestimates the predicted wait time during certain periods in the day (4 AM to 10 PM), the elastic-net model tends to overestimate the wait time of patients for almost all times of the day. In the case of overestimation of the wait time, a patient may be happy to be seen before the predicted time (Rae et al., 2008). However, the misrepresentation of wait times is also likely to encourage patients to leave the ER without being seen by a healthcare professional. There is the additional concern that an underestimation of wait time could lead to anxiety amongst low acuity patients over the delays to their treatment. The random forest model tends to solve the associated problems by evenly distributing underestimation and overestimation across the day and predicting the expected ED wait times more accurately.

4.5.2 Error quantiles

Table 4.4 specifies the proportion of distribution of error in the predicted and actual wait times of low acuity patients for all the methods across different quantiles. Since a huge variation can be observed in the actual wait times for low acuity patients across different times of the day, the quantile errors can help identify extreme values by classifying errors in different quantiles. As seen from the values in table 4.4 the wait time is underestimated for 25% of patients and overestimated for the rest of data points in the test data set for all the forecasting methods (except quantile regression & conventional rolling average method). As

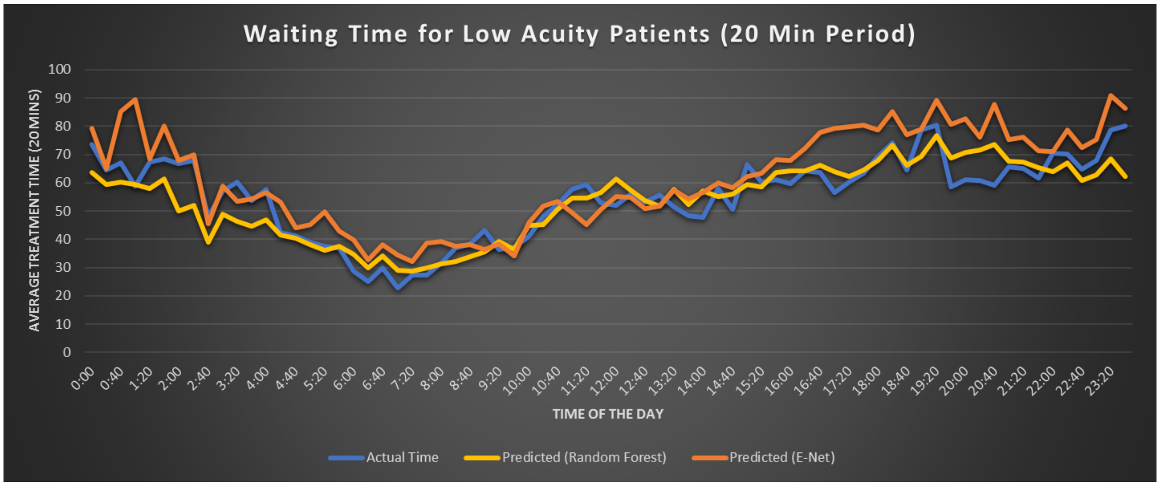


Figure 4.8: Comparison of Elastic-Net Vs Random Forest

expected, the wait time for approximately 50% of the patients were underestimated by using the conventional rolling average method whereas the underestimation count for patients was as high as around 75% for the quantile regression forecasting technique. The random forest method mitigates the problem of extreme underestimation and overestimation by uniformly distributing the error estimates across different quantiles. A comparison of the wait time prediction for low acuity patients using the random forest technique and the conventional rolling average method for the extreme ends of test data (10% & 95%) and the median (50%) yields interesting insights. For instance, for 10% and 95% of patients respectively with less acuity, there is a difference of approximately 15 minutes in the predicted time to treatment for the rolling average and random forest methods with the latter being more accurate with less error. Additionally, the random forest method has the least overestimated estimation of around 7 minutes for the median.

4.5.3 Variable Importance

To identify the important factors contributing towards the accurate estimate of the wait time prediction importance of variables is computed for the best performing model i.e. random forest. As detailed in the methodology section of the thesis, a total of 108 candidate predictor variables are created including 19 queueing, fast track status and 89 time based estimators

Table 4.4: Error quantiles for test data in mins

	Error Quantiles (Mins)				
Forecasting Method	**10%**	**25%**	**50%**	**75%**	**95%**
Rolling Average (20 Min)	-60.6	-25.5	-2.0	17.0	67.0
Quantile	-77.3	-53.9	-34.5	-15.3	31.5
LASSO	-44.0	-13.9	7.5	24.9	56.1
E-Net	-40.2	-10.2	11.5	29.3	64.5
Ridge	-44.4	-13.6	8.0	24.4	57.0
SCAD	-39.7	-10.1	11.7	29.5	61.8
MCP	-39.9	-10.2	11.5	29.4	61.6
Random Forest	-45.5	-14.7	7.2	22.5	53.5

so as to accurately predict the wait time of low acuity patients in the emergency room figure 4.9 shows the relative importance of the top twenty variables identified based on the Gini Impurity Index for the random forest regression method. Table 4.5 provides the reader with a detailed description and categorization of the top twenty variables identified by the researcher. From the tabulated information, the top 20 important factors identified for model accuracy consist of fast track status, 14 queueing parameters and 5 diurnal based parameters. Based on the conceptual model introduced by Asplin et al. (2003) the largest influencers of wait time are further categorized into input, output and throughput factors.

The important estimators identified for model accuracy could potentially help the ED's management and administration in deciding the significant factors leading to excessive wait time. The largest influencers of wait time consist of low acuity patients who are triaged and awaiting treatment in waiting rooms. The count of high acuity patients arriving and waiting for treatment as well as the total number of people in the ED at any given time also had a significant impact on ED wait times. The identified predictors as detailed in table 4.5 were consistent with the findings from the discrete time event study conducted by McCarthy et al. (2009) in which, the long wait time of patients in the ER room correlates with the total number of people waiting for treatment.

From the triage perspective, since the study focused on establishing the wait time of low acuity patients only, it follows that the number of low acuity patients waiting for triage had

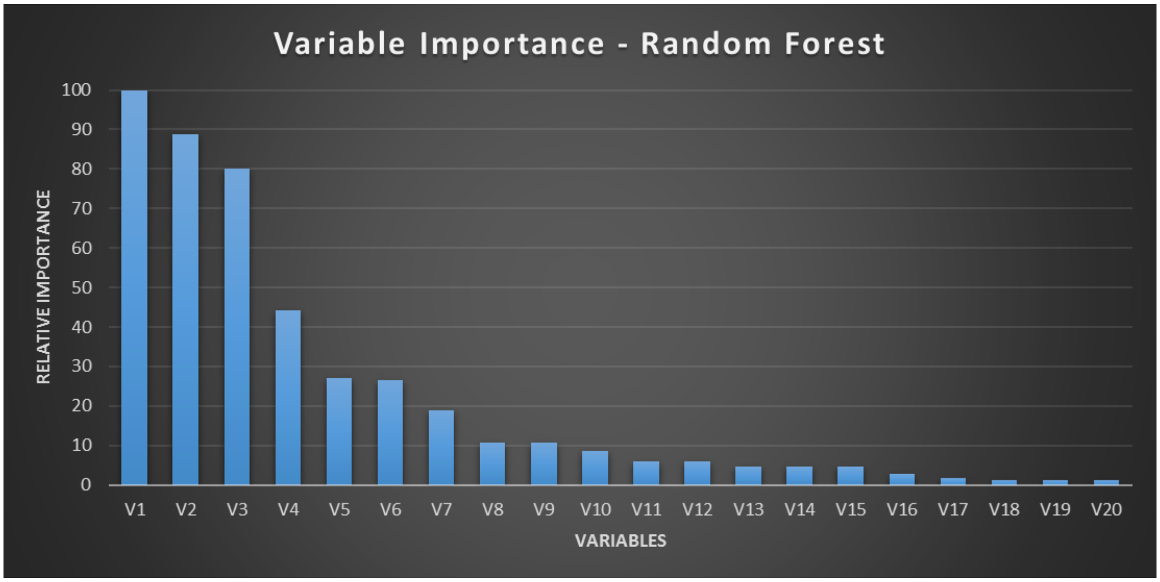


Figure 4.9: Variable importance plot random forest (Top 20 estimators)

the highest impact on wait times. The number of patients with life-threatening injuries is the second most important factor contributing towards the wait time estimates as high acuity patients are immediately triaged and rushed for treatment thereby consuming more ED resources and leaving low acuity patients in the waiting room. Hence, in terms of urgency, the patients with all triage levels are the indicators of wait time in the emergency room.

The predictors associated with the output consist of all the patients waiting for disposition (either being admitted or discharged) after triage or treatment. In the ED process, the provider or consultant is responsible for making a final decision as to whether a patient is to be admitted or discharged after treatment. If a consultant decides to admit a patient after initial treatment, there are many follow up processes that need to occur, which can increase the patient's overall length of stay in the ER. For the ER of the hospital being studied, approximately 23% of all ED patients are admitted to the hospital. This population adds to the waiting time of other patients in the ED by occupying inpatient beds while they are in the process of final consultation. To reduce delays when admitting patients, the ED administration may consider focusing on streamlining the admission process. This can be done by encouraging communication between the physicians and the consultant staff responsible for admitting patients into the hospital. This suggestion is rooted in the results of the study conducted by Howell et al. (2004) and Quick (1999), which showed that effective communication between the ED physicians and in house hospitalists could significantly reduce admission cycle time.

At the time of the patient's arrival into the roomer, throughput factors leading to a long wait time comprise of the total number of people in ED and the status of the fast-track initiative. For hospital under consideration, approximately 86% of the total patients visiting the ED were low acuity patients. Therefore, to have maximum impact in improving the throughput and operational efficiency of the ED, the ED managers could explicitly focus on operational innovations around low acuity patients. The implementation of a rapid triage system, staffed with a physician and nurse so as to quickly examine and treat low acuity patients, could help reduce the patient's length of stay in the ER. Furthermore, by assigning a dedicated staff for radiology and laboratory services during the periods of a surge in low acuity patients, the hospital can further reduce the overall length of stay of their patients in the ED.

4.5.4 Sensitivity analysis

Sensitivity analysis is performed to determine the set of independent variables that specifically impact the wait time of patients for the best performing model. The MSE for the random forest model is evaluated for a certain set of candidate predictor variables, and proceeds to sequentially incorporate other variables. The set of candidate variables used start with 19 queueing based parameters (Queue); 71 parameters based on the time of day (Day); 6 day of the week parameters (Week); 11 month of the year (Month) parameters and 1 status of fast track parameter (Fast-track).

Table 4.6, reports the MSE for the different sets of candidate predictor variables. The researcher finds that including queueing-based parameters alone gives remarkably high predictive accuracy, and incorporating the day-based parameters and fast-track status further reduces the MSE. However, incorporating the day of the week and the month of the year parameters as predictor variables does not lead to a significant reduction of the MSE.

Table 4.5: Variable importance plot & description for random forest model (top 20 estimators)

Variable Description	Relative	Variable	Reference
Low acuity triaged, but waiting for treatment	100	Queueing Parameters (Input)	V1
High acuity arrived, but waiting for treatment	88.874	Queueing Parameters (Input)	V2
Triage level 3, Waiting to Start treatment	80.085	Queueing Parameters (Input)	V3
Total number of people in ED at any time	44.324	Queueing Parameters (Throughput)	V4
Triage level 5, waiting to start treatment	27.062	Queueing Parameters (Input)	V5
All patients (registered, but waiting to be triaged)	26.646	Queueing Parameters (Input)	V6
Low Acuity waiting for treatment (Triage -4)	18.905	Queueing Parameters (Input)	V7
Low acuity, who triaged but waiting for disposition	10.732	Queueing Parameters (Output)	V8
People treated, but still waiting for disposition (Total)	10.732	Queueing Parameters (Output)	V9
Low acuity waiting for treatment (Triage -2)	8.489	Queueing Parameters (Input)	V10

Continued on next page

Table 4.5 – continued from previous page

Variable Description	Relative	Variable	Reference
People treated, but still waiting for disposition (Triage-3)	5.852	Queueing Parameters (Output)	V11
Triaged, but waiting for disposition (Triage-3)	5.852	Queueing Parameters (Output)	V12
December	4.562	Diurnal Parameters (Input)	V13
Treated, but waiting for disposition (Triage-3)	4.536	Queueing Parameters (Output)	V14
Treated, but waiting for disposition (Triage-1)	4.536	Queueing Parameters (Output)	V15
Fast Track	2.68	Fast track Status (Throughput)	V16
8:40 PM	1.66	Diurnal Parameters (Input)	V17
10:20 PM	1.212	Diurnal Parameters (Input)	V18
11:40 PM	1.178	Diurnal Parameters (Input)	V19
1:00 PM	1.138	Diurnal Parameters (Input)	V20

Another important insight from the table 4.6 is that the incorporation of only the queuing-based candidate variables yields a more accurate prediction than the conventional rolling average method. When comparing output from the conventional rolling average method and

Table 4.6: Test MSE (in Mins) for different set of predictor variables

Variables	MSE
Queue	2017.698
Queue+Day	1837.251
Queue+Day+Week	1849.044
Queue+Day+Week+Month	1818.04
Queue+Day+Week+Month+Fast-track	1708.784

the random forest model, the random forest model with queueing-based parameters alone reduces the MSE by 22%. Thus, even if the hospitals incorporate only the queuing based parameters, they are likely to implement a better wait time prediction system that accurately captures the dynamic state of an ER.

It is also worth noting that it is beneficial to capture the diurnal variation in the arrival of patients by the process of recording their time of the day based parameters. The inclusion of 71 binary variables of 20-minute intervals, on the basis of the time at which the patient arrived at the ED, along with the queueing-based parameters reduced the MSE by approximately 9%. Updating the entire dataset after every 20 minutes helps in capturing the volatility and sensitivity associated with ED operations.

Additionally, the availability of the fast track in the ED helps in increasing throughput and reducing patient's overall length of stay in the ER. Therefore, incorporating the availability of the fast track status as an independent variable during the estimation of the wait time of patient yields significantly improved prediction accuracy.

Chapter 5

Conclusions and Future Work

5.1 Conclusion

A robust predictive model that accurately estimates the wait time of low acuity patients using random forest regression model is presented in this thesis. The developed model established the wait time of patients in almost real time by accurately capturing the changing ED conditions and through the use of diurnal and queueing parameters. For every patient arriving at the ED, data from the Emergency Medical Records (EMR) is mined to specifically calculate the number of patients of different triage levels at various stages of the ED along with candidate predictor variables related to fast track status, time of day, day of week and month of year. The predictive accuracy of the developed model is compared to the conventional rolling average, quantile and regularized regression methods (Ridge, Lasso, Elastic Net, SCAD & MCP) through the use of mean square error.

Random forest regression model achieves better accuracy by uniformly distributing underestimation and overestimation across different times of the day as compared to the E-Net model (second best performing model), which tends to overestimate the wait time to treatment. Relative to the conventional rolling average method, there is a significant increase in the predictive accuracy of the developed model because of its accounting for diurnal variation and patient flow across various stages of the ED. Predictors with the largest effect on wait time estimates were identified using variable importance plot. The biggest contributors comprised of a number of patients waiting in the lobby for treatment. By identifying the most important indicators leading to long wait times, ED administrators can specifically modify their strategies that are aimed at reducing long delays. The ED staff and management can also effectively manage their resources by studying the arrival patterns of patients in to the ER.

Sensitivity analysis helped in detecting important sets of candidate predictor variables that could be used in estimating wait times. Instead of using all the intendent variables, a hospital can specifically rely on a specific set so as to achieve the desired accuracy. This identification is a key step because when the hospital is implementing a system to estimate the wait time of patients in almost real time, one has to query the live database to retrieve the information, which can significantly take a long computation time. Therefore, by specifically identifying the key set of predictor variables, a more efficient and reliable system with real time information can be developed requiring lower computational time.

Implementing the wait time model will also help in managing the expectations of the patients waiting for treatment. Providing patients with a predicted wait time positively affects patient's behavior by increasing their tolerance for waiting, which leads to increased patient satisfaction and reduces the likelihood of them leaving before being seen by a doctor. It also helps the ED staff to efficiently deal with anxious patient awaiting consultation with a doctor. Providing an estimate of the wait time also gives the ED administrators an opportunity to be informed regarding the volume of patients in the ED for any point in time thus helping them to allocate their resources more efficiently during a surge.

5.2 Future Work

5.2.1 Model

The developed predictive model may be further extended to improve predictive accuracy by incorporating the staffing schedule of physicians and nurse practitioners as potential candidate predictor variables. Thus, helping to accurately capture the throughput indicators in the ED for any given time. There also exists a potential to accommodate real time traffic data from sources like Google & Nokia maps. Information captured from the traffic data can be added to the estimated wait time thereby giving low acuity patients a better estimate of the total time (waiting + travel time) before being seen by a healthcare professional.

5.2.2 Software and web interface

The presented model can also benefit by integrating with the existing ED software tools used by the staff to register a patient on arrival. By allowing receptionists or greeters to manage the patient's expectations by informing them well in advance about the estimated wait time, the patient's satisfaction levels can be improved. The same information can further be published on the hospital's website or on a screen the in waiting area in the ER, providing patients with updated information. Showing real time information regarding ER wait times publicly, on the website, can further help patients to choose an ED with lower wait time thus distributing patient load in nearby EDs.

5.2.3 Mobile application

The developed wait time model can be implemented as an application for mobile devices. This will enable patients to retrieve information in real time and locate an ER with shortest waiting time. Using location feature on mobile devices patients can be further assisted in providing directions to nearby EDs.

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Appendix

Appendix A

Emergency Department process flow

A.1 Patient flow through ED

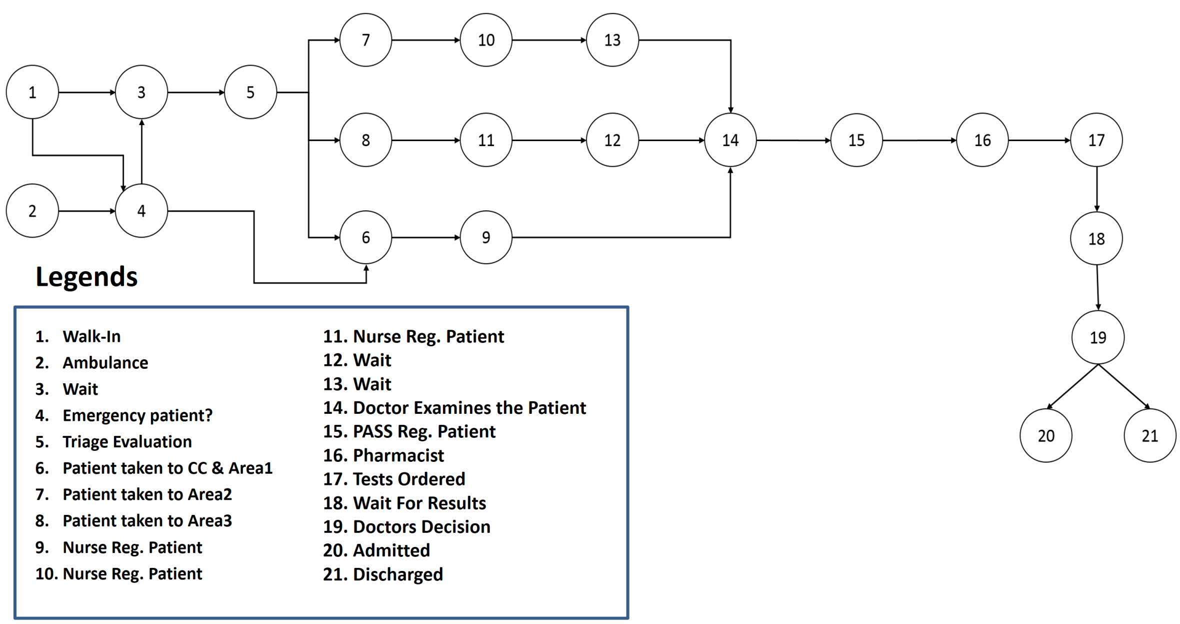

Figure A.1: Patient flow through ED

A.2 Data flow through ED

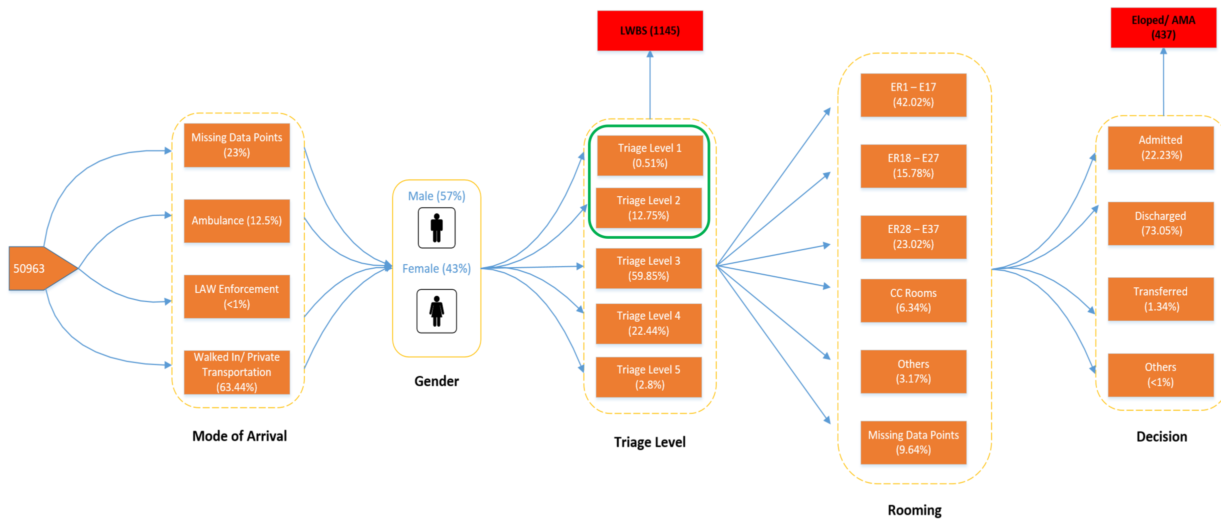

Figure A.2: Data flow through ED

Vita

Gajanan Arha was born on the 5th of April 1988; in Pali-Marwar, a small town in the western state of Rajasthan, India. In 2012, he completed his five-year dual degree in Electric and Electronics Engineering and Masters in Mathematics from Birla Institute of Technology and Science, Pilani. He spent the next two years working in the product management department of an organization in Hyderabad, India. In 2014, Gajanan joined the graduate program at the University of Tennessee, Knoxville in the Industrial and Systems Engineering Department to pursue his second Masters degree, where he accepted a graduate research assistantship in the Center for Advanced Systems Research and Education (CASRE) group. Currently, he is employed as a business analyst at Mayo Clinic in Rochester, Minnesota where he is working in outpatient practice optimization services and also working towards finishing his Masters Degree in Industrial Engineering. He will be graduating in May 2017.