Application of linear models, random forest, and gradient boosting methods to identify key factors and predict truck dwell time for a global 3PL company

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ABSTRACT

Driver dwell time is an important challenge the U.S trucking industry faces. High, unplanned dwell times are costly to all stakeholders in the industry as they result in detention costs, declining performance and decreased driver capacity. With the increasing demand for these services, it is important to maximize the driving time of drivers in the industry by minimizing dwell time to free up capacity and provide competitive wages. This project utilizes the data of a third-party logistics company with the goal to understand the factors that influence dwell time, and to construct the model to predict dwell time of a load. In the analysis, linear models, random forest, and gradient boosting methods were explored based on regression and classification approach. Ultimately, the random forest classification model with one-hour bins is the recommended model as it had the highest predictive performance while the one-hour bins was sufficient to meet the business need. Additionally, the analysis concludes that shipper facilities are the most significant driver of dwell time. Hence, understanding and integrating more granular observations on shipper practices within their facilities will allow a third-party logistics company to improve its driver fleet utilization and increase the predictive performance of their dwell time prediction model.

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1. Introduction

1.1 Overview

The U.S truckload industry is a $800 billion industry that accounts for about 80% of the nation's entire freight cost. In 2018, 11.5 billion tons of freight were shipped by trucks around the U.S, accounting for about 70% of the total domestic tonnage shipped (ATA Reports, Trends & Statistics 2018). The industry has seen steady growth and is expected to become a $1.26 trillion-dollar industry by 2030, accounting for 25.6% growth (ATA Latest Freight Forecasts 2019). However, the industry has suffered from a shortage of drivers to fulfill the demand. The shortage was estimated to reach 60,000 drivers for 2018 and is expected to increase to 160,000 by 2028. If unmitigated, these trends will contribute to severe supply chain disruptions resulting in shipping delays, higher shipping costs, and shortages at stores (ATA Driver Shortage 2019).

The sponsoring company for this project is a leading global third-party logistics provider (3PL) focused on matching drivers and shippers in the U.S Truckload Industry. The company competes in a highly fragmented industry with 91% of the driver capacity composed by small to mid-sized entrepreneurs that operate less than 6 trucks each. Similarly, shipper demand is fragmented across multiple manufacturers, retailers, small businesses, and wholesalers with dynamic needs. This creates a highly competitive landscape for the sponsoring company and requires them to build strong relationships with their drivers and shippers to succeed.

The goal of this project is to explore how the sponsoring company can reduce driver dwell time to maximize the driving time of drivers by understanding the main factors that influence dwell time within the sponsoring company's network, and then use statistical and machine learning techniques to predict the dwell time for each stop.

1.2 Motivation

The U.S Trucking industry imposes strict regulations on the numbers of hours driver work per day. In an industry that primarily pays per mile driven, it is important for drivers to optimize their driving time per day to maximize their earning potential. Drivers currently spend about 30% of their work week stuck loading and unloading goods at shipper facilities (OOIDA 2018). Unpredictable dwell times result in unplanned changes to driver arrival times in shipper facilities. These unplanned schedule changes cause around 45% of drivers to lose more than 3 loads per month (OIG 2018). Moreover, these delays increase total transit times to shipper's end customers, not only decreasing delivery service levels, but also reducing profitability and revenue potential.

The sponsoring company aims to accurately predict dwell time at each stop to provide more accurate driver arrival times and increased schedule accuracy to its customers. Moreover, the company aims to understand the main drivers of dwell time to be able to work with its drivers and shippers to preemptively mitigate the root cause of each. Through this, the company will be able to transition from reactive dwell time firefighting to proactive shipper and driver engagement to improve overall fleet utilization and customer satisfaction.

The motivation behind this project is to understand how the sponsoring company can predict dwell time in a shipper facility to assist in updating arrival times, improve delivery service levels, and maximize each driver's hours of service. Reducing dwell time also improves the company's bottom-line by reducing detention costs.

1.3 Problem Statement

This project will focus on identifying the main factors that contribute to long dwell time and predicting dwell time at each shipper's facilities. For this project, dwell time is defined as the total time a driver spends getting loaded and unloaded at these facilities. It is a key driver of on-time driver performance and efficient management of drivers’ fleet in the network. Hence, by spotting the main factors and achieving a more accurate prediction of dwell time, the sponsoring company will be able to provide insightful strategy to reduce unproductive time for shippers as well as increase the efficiency of drivers’ resources.

2. Literature Review

Efficient operations are becoming increasingly important for the truckload industry of the future. The growing demand, increased consumer expectations, and development of firm regulations on the industry require that firms focus on delivering greater efficiency to stay competitive (Leinbach 2007). This literature review will focus on understanding the importance of dwell time on increasing efficiency by exploring the operational and market landscape of the truckload industry, and assessing the current initiatives and approaches used to optimize it. This section starts by providing an overview of the trends and dynamics within the truckload industry, and how they relate to dwell time. Then, it expounds on the business impact dwell time has on the stakeholders involved -- the drivers, shippers, and third-party logistics companies. Lastly, it covers the best practices in industry to mitigate dwell time, and the limitations of each, and discusses current approaches to quantify dwell time through a comparison with the maritime logistics industry.

2.1 Overview of the Truckload Industry

The U.S transportation industry is a multi-billion-dollar industry dominated by trucking; therefore, the potential impact of increasing efficiency in this industry is massive.In 2018, total business logistics costs reached $1.6 trillion, 8% of GDP that year. In 2017, the trucking industry was the largest sub sector reaching $700 billion in revenues accounting for 11 billion tons of goods shipped, making up 80% of overall U.S Freight revenue. The industry is expected to grow by 2.3% year on year from 2019 through 2024 and is expected to reach a total of 15 billion tons of goods shipped by 2045 (U.S Department of Transportation 2019).

Drivers face great complexity in fulfilling shipper delivery requirements.Delivery lead times are shortening due to increased customer expectations driven by same-day and 2-day promises. With the rise of e-commerce, companies such as Amazon are requiring its competitors and other retailers to match its increasingly aggressive delivery promise (A.T Kearney 2018). Aside from increasing the number of products being moved, the booming retail industry has increased the number of shippers on the market. Now, trucking shipper demand is made up of multiple manufacturers, wholesalers, importers, exporters and retailers each with their own locations, and pick-up and drop-off requirements. With this, knowing what, how much, and where to ship is constantly changing for drivers. Moreover, the U.S domestic trucking demand is dispersed across the entire nation.The American Trucking Research Institute suggests that trucking requirements are equally split between short and long-haul distances. Based on regional pickups and deliveries between 100-500 miles account for 37% of the total trip types in 2017, with longer distanced inter-regional, national, and shorter trips taking up about 20% each (American Trucking Research Institute 2018).

To effectively optimize its fleet, carriers in the industry need to forecast and plan the delivery demand required in the industry. As consumer spend drives the demand for domestic freight logistics, the delivery capacity of drivers in the market is required to increase. However, the demand for deliveries in the trucking industry is seasonal. Paired with the increased demand, the volatility in demand for truckload deliveries may result in imbalances in supply and demand that result in sub-optimal pricing in the full truckload and private fleet segments. During peak seasons, tight freight capacity provides leverage for drivers to raise prices and may result in increased transportation costs for shippers. With this, the United States Business logistics costs rose by 6.2% in 2017 and are expected to continue to grow over the next 5 years. Full truckload and private or dedicated fleets are expected to experience the biggest cost hikes of 4.8% and 6.8% 5-yr CAGR respectively (A.T Kearney 2018).

A survey conducted on United States truck drivers by the American Trucking Association suggests that drivers are leaving the industry in search for other jobs because they are unable to maximize their earning capacity driving on the road. Aside from the unattractive long-haul distance and travel times, drivers face inadequate pay compared to other opportunities posed by ridesharing and similar services. Truck drivers are unable to maximize their daily earning potential due to the surprising amount of time spent waiting to be loaded and unloaded by shippers and consignees (Correll 2019). Drivers are paid per mile driven, however, they currently spend over 30% of their work week stuck loading and unloading goods at shipper facilities (OOIDA 2018).

It is becoming increasingly important to retain drivers within the industry, as the need for driver capacity increases. As the labor market in the United States continues to tighten, the industry must maximize the earning potential of drivers to provide an attractive profession and ensure their retention (Monaco 2019). Maintaining equilibrium between consumer demand and driver capacity allows for optimal pricing, an imbalance in this dynamic may result in unfavorable conditions to drivers and shippers in the form of unstable pricing and capacity that in turn affect the carrier performance and customer experience.

2.2 Impact of Dwell Time in the Trucking Industry

Currently, research has quantified the safety and economic impacts of dwell time on truck drivers. It suggests that 37% of truck driver delays are resulting from delays at shipper facilities. Moreover, this follows the release of the U.S. Department of transportation: Office of Inspector General’s (OIG) audit of customer detention impacts, which found that dwell time increased crash risks and reduced incomes for drivers and motor drivers in the for-hire sector (ATA 2019)

The pressure created by this supply crunch is straining the relationship between drivers and shippers.The capacity shortage creates a driver centric market that allows drivers to prioritize routes based on profitability and preference, resulting in higher cancellations and rejections for low density and low profitable routes. Moreover, drivers have the flexibility to reject loads from shippers that take up too much time for loading/ unloading at facilities. Additionally, to increase their potential earnings, drivers are reallocating capacity from long-term contracts to the more lucrative spot markets. As drivers act to maximize their profitability in this market, shippers are experiencing increasing pressure to fulfill customer demand while maintaining trucking costs (American Trucking Research Institute 2018).

The American Trucking Association (ATA) suggests that the capacity deficit leads to a significant shortage in the driver workforce. Currently, carriers are addressing this shortage by increasing their efforts to recruit more drivers on the road. However, another approach to increase the industry capacity is to increase the number of hours drivers spend on the road. A study done by David Correll says that “To make up for the driver deficit, we would have to increase their driving hours to 6.7 hours per day on average — an increase of 0.2 hours or 12 minutes.”

One of the main operational challenges for drivers is to increase the time drivers can spend on the road. This project seeks to address the capacity shortage by increasing driver productivity. It aims to understand the factors that drive dwell time to ultimately predict and decrease dwell time at shipper facilities. By doing so, the project aims to help alleviate the financial pressure on drivers by allowing them to maximize driving time, and provide drivers the opportunity to optimize their daily scheduling. Increasing the productivity of drivers on the road will help stabilize the market dynamic caused by driver shortage. In short, decreasing dwell time at shipper facilities can increase industry capacity by increasing hours each driver spends on the road.

2.3 Importance of Dwell Time on the Driver Experience

Companies aim to optimize the utilization of their fleet to gain a competitive advantage in the industry (Capgemini 2016). Third-party Logistics providers have been focused on using predictive analytics to estimate the on-time delivery of their trips. A study done by Alcoba and

Ohlund in 2016, suggests that the duration a driver spends at the shipper facility (dwell time) is one of the main factors that determine whether a load is on-time or not. Moreover, the relationship of dwell time extends to the ability to predict the estimated transit time of each trip. A study conducted by Gold Truong in 2014, examines the drivers that impact the variability of transit time estimations. The study suggests that there are three main contributing factors: variability in operations within shipper facilities, drivers driving time, and others to include external factors such as weather, accidents, traffic, etc. This study highlights the impact of dwell time on the ability of the drivers to schedule their transit times to further optimize their daily operations. A similar study conducted by Al-Habib and Favier in 2018, shows that a higher dwell time contributes to a higher load cancellation rate, costing each driver $145 dollars per load (~10% of the average total price per load), or costing the industry $4.6 billion per year. Through these examples, it is clear that predicting dwell time per load can provide drivers visibility to plan their daily schedule more flexibly, potential for savings through lower cancellations, and impact their overall experience.

Moreover, other industries have been using predictions in estimated travel times to increase customer experience. The food delivery space uses machine learning models to predict the delivery times for online customer food orders. To do so, they are able to predict the time needed for food preparation, delivery partner transit time, among other factors. The machine learning model is able to then calculate the end-to-end delivery time taking into consideration the amount of time taken at each stage of the order. This study suggests that most dwell time occurs in the restaurant, as the courier waits to receive the food to be delivered. Efforts to mitigate dwell time in restaurants by providing accurate predictions, and identifying key operational processes in restaurants that contribute to dwell time have resulted in improving the customer experience and reducing order cancellation by 7% (Jungle Works, Predicting Arrival Time 2019).

Overall, predicting and estimating dwell time will enable drivers to budget their time more efficiently to account for the time spent at each stop. Thus, providing a better planning experience and driving more ownership of drivers on their daily operations.

2.4 Best Practices in the Industry to Mitigate Dwell Time

According to the importance of dwell time to the trucking industry, there have been multiple approaches to mitigate the dwell time and optimize supply chain efficiency. There are four possible ways to reduce the dwell time (Combined Express, Inc.n.d.)

First, shippers could provide a dock door specifically for live loads. Live load is a type of load that a driver spends time waiting at the facility as the shipper loads up the truck. As live loading is normally slower than loading a dropped trailer, separating these two types of loading will result in shorter wait times and better management of dock.

Second, shippers could require appointments for pickup and delivery time. There have been several studies dedicated to how appointment strategy could decrease dwell time. Huynh (2009) examined the impact of different scheduling policies (individual appointment system and batch appointment system) on the reduction of truck turn-time. The result demonstrates that a terminal without an appointment system could benefit from an individual appointment system by 44 percent improvement in turn time. Moreover, Zhao & Goodchild (2010) conducted the study on utilization of truck arrival time to improve yard operational efficiency and truck dwell time. The result shows that utilizing the information on truck arrival time could reduce truck transaction times within container terminals using revised difference heuristics (RDH) algorithm.

Third, drivers could leverage the trailer dropandhook method to minimize the time drivers have to spend loading and unloading at the facilities. Drop and hook is a situation when the driver drops the trailer at the final delivery location and picks up a new trailer. The detention time is normally lower since the driver does not have to wait to load the pallets into the trailer.

Finally, shippers could set standards to filter valid and responsible drivers. This is to ensure that the selected driver is able to deliver shipping without violating regulations set by Federal Motor Carrier Safety Administration (FMCSA).

2.5 Methodological Approaches to Quantify Dwell Time

Currently, there has been limited research to quantify the amount of dwell time, particularly in the trucking industry. However, there was a similar study in maritime logistics that examined the determinant factors and developed predictive model for container dwell time.

Kourounioti et al.(2016) predicted import containers' dwell time using artificial neural networks. They classified the relevant parameters affecting dwell time into 3 groups; container characteristics, stakeholder's characteristics, and terminal policies. The result of the study showed that the most important determinants of dwell time were (1) the day and month of discharge, (2) the port of origin, (3) the size and the type of container and (4) the type of cargo transferred. Moreover, it is also observed that the more input given into the model, the higher the prediction accuracy. They increased the accuracy of 14.7% in the first model with two variables, i.e., container's size and type, to the accuracy of 65.2%, in their final model with all available variables.

Furthermore, Moini et al. (2012)outlined the framework for developing a predictive model of container dwell time and study the importance of each determinant factors affecting the container dwell time at seaports. In this study, Naïve Bayes, decision tree, and NB-decision tree hybrid algorithm are examined with 10-fold cross validation. There are four evaluation metrics used in the study: correctly classified instances, k-statistics, root mean squared error (RMSE) and processing time. The result shows that the best performing algorithm is the decision tree with the correctly classified instances of 0.82 for both export and import and root mean squared error of 0.19 and 0.16 days for export and import, respectively. While the Naïve Bayes perform worst with the correctly classified instances of 0.35 and 0.41 and root mean squared error of 0.29 and 0.28 days for export and import, respectively. The author suggests that future studies could expand to cover other factors such as shippers' information.

These studies on container dwell time in the maritime logistics industry can be applied to the development of prediction algorithms for trucking dwell time. Several parameters that were examined in these studies, such as container size and type, port of origin, and type of cargo delivered, resemble those that are critical to dwell time duration in the trucking industry.

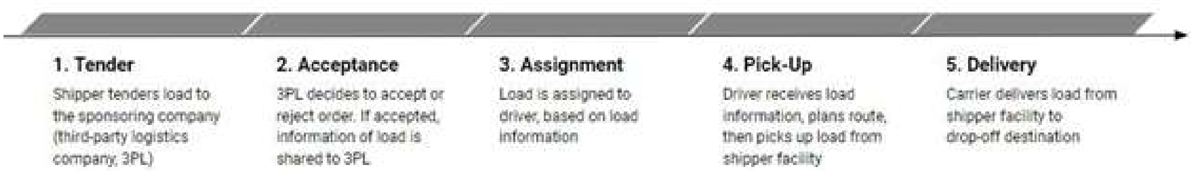
2.6 Section Summary

Customer delivery demand and the increased delivery expectation has placed increasing pressure on drivers in the U.S truckload industry. As drivers are enticed by the increasingly competitive wages and flexibility from roles in other industries, logistics companies may face difficulties in hiring and retaining drivers, thus straining the capacity to deliver goods in the industry. A mismatch between demand and capacity may lead to increasing prices and sub-optimal assignment of loads. With this, it becomes increasingly important to maximize each driver's time on the road and provide a flexible and predictable driver experience. A few common practices to mitigate dwell time are to utilize trailer drop-and-hook and set appointment time. To address the lack of capacity, this project focuses on understanding the factors that drive dwell time at shipper facilities to predict its duration. Moreover, while there has been limited research related to dwell time prediction in trucking industry, the framework of dwell time studies in maritime logistics study provided a valuable guideline for modelling approach as well as a benchmark for measuring predictive performance. This study will expand the scope of existing research to cover important characteristics of the trucking industry and apply the framework to develop a predictive model.

3. Data and Methodology

This section provides an overview of the end-to-end process for load fulfillment while highlighting the key stakeholders, the responsibilities and the impact of each on dwell time to understand how the data used in the analysis is captured along the process. Then, it will discuss how the data is collected, cleaned, and processed, and provide an overview of the types of data used in the analysis of the project. Finally, it will elaborate on the analytical methods used to determine the significant factors that impact well dwell time, the machine learning models used to predict it, and the evaluation metrics used to measure model performance.

3.1 Understanding the Data



3.1.1 Overview of Load Assignment and Delivery Process

Figure 1: Load Assignment and Delivery Process

The load assignment and delivery process consist of four main phases involving multiple stakeholders. Although dwell time occurs during the loading and unloading at customer and shipper facilities, dwell time can be impacted by every stakeholder across every phase. This section provides an overview of the responsibility of each stakeholder at each phase, and their impact on dwell time.

Phase 1: Tender

The shipper is the key stakeholder for this phase. Here, the shipper tenders the load to partnering third-party logistics companies (3PL) and provides details of the load to be delivered. Tendered loads can be long-term contractual agreements that have set terms, or ad-hoc requests in the spot market that are one-off transactions. Upon tender, shippers provide information on each load to be delivered which is shared to the 3PLs. The standard types of information included in the transactions in the industry are:

<u>i.) Physical load attributes:</u> Size, weight, number of pallets, type of items

<u>ii.) Pick-up and delivery schedule:</u> Time and location of pickup and delivery, and special operational instructions required (if any)

<u>iii.)Shipper Information:</u> Shipper who tendered the load

These load details shared upon tender are important to the 3PL, as they are the basis on how the 3PL will assign to its drivers. Moreover, as discussed later in the results section, the load details can be used to predict dwell time, early in the process, to allow fleet owners to further optimize their fleet. Thus, load details must be collected accurately and updated constantly.

<u>Phase 2: Acceptance</u>

The 3PL is the key stakeholder for this phase. Upon receiving the load tender details from the shipper, the 3PL then decides whether to accept or reject the tender. If the load is accepted, the 3PL then negotiates the price to fulfill the load with the shipper. After, the 3PL assigns the load to a driver based on the load details, negotiated price, network utilization (among other factors). Moving forward, the 3PL will own all communications between the shipper and driver including managing changes in load details and scheduled times.

In load acceptance, the goal of the 3PL is to meet shipper demand and to optimize delivery fleet performance. To do so, the 3PL must effectively match drivers who can deliver loads within the cost, time, and other operational constraints provided by the shipper. The acceptance and matching process is critical in managing dwell time, as sub-optimal load assignments may result in increased dwell time within the 3PL's system.

Phase 3: Assignment

The driver is the key stakeholder for this phase. Once the 3PL matches a driver to a load, the driver may accept or decline the request. If accepted, the driver then assumes responsibility of managing the operations required to fulfill the pickup or delivery request. Typically, each driver creates a delivery schedule that contains the time and order by which each load is picked-up/ delivered. Since drivers typically manage more than one load per day, it is in the best interest to ensure that they accept load assignments that they can meet the service level agreements for. Drivers have the option to cancel assignments for loads that are difficult and expensive to manage. Moreover, drivers often avoid loads from shippers with poor historical performance (i.e., long wait times) and predictability (i.e., changing schedules and load details). Therefore, if a driver expects a longer dwell time for a specific load, they may be incentivized to cancel the load, and therefore negatively impact the fleet's performance and shippers experience.

Phase 4: Pickup & Delivery

The shipper facilities and delivery customers are the key stakeholders for this phase. Once a load is assigned to a driver, the shippers and customers are responsible for communicating any changes within the load details or pickup/ delivery assignments to the 3PL. Providing visibility on these changes is crucial for 3PLs, as these changes must be relayed to drivers to incorporate into their daily schedule. Changes that are unaccounted for or communicated late to drivers may lead to disruptions in the operations that may contribute to increased dwell time.

Furthermore, shippers and delivery customers own the loading/ unloading operations within their facilities. The processes, equipment, manpower, and other operational resources required are determined and run solely by the shippers and delivery customers. Typically, 3PLs are not involved in determining the operations within these facilities. The length of dwell time within each facility can be directly influenced by multiple factors within a facility's operations such as efficiency, capacity, familiarity, etc. Moreover, dwell time occurs within these facilities during this phase.

3.1.2 Data Collection

The data used in this project is collected from the sponsoring company's internal systems that capture data on a per-load basis. Multiple data points per load are gathered throughout the entire process, starting from when the load is tendered by the shipper until when the load is delivered to the customer. The company's internal systems use both manual processes and automated technologies to capture and record data. As requested by the sponsoring company, both methods of data collection are included in the study.

The raw data set provided includes over 19 million records of loads processed on the company's platform from 2006 to 2019. Each load record contains about 54 unique characteristics specific to the load, and can be categorized into 3 major groups:

i.)Customer: Contains information on the shipper that requested the load and the facility where the load will be processed.

a. Shipper info:This project looks at the industry verticals and primary line of business of each shipper, as they directly impact the type of goods being transported.

b. Facility info:Each facility has a unique ID that has attached information on the location and type of operations within it. This data set covers zip, latitude and longitudinal data to capture location, and hours of operations and other related schedules specific to the facility.

ii.)Load: Contains information on the type of load being processed, and how the load was processed.

a. Physical load attributes: These cover physical attributes of the goods to be handled before driver load acceptance, which drivers may use to evaluate whether to accept the load and to plan their operational schedule. These include the expected size and weight of the items to be delivered, when the goods need to be delivered by, and if the load was processed on the contract or spot market

b. Load processing information:This covers the attributes associated with the processing of each load, including timestamps and operational metrics, generated across each step of the process. Included here are data records on whether the load was delivered on time, how many times the load was rejected before being accepted (bounce count), whether the expected load info matched the initial request, and other operational outcomes associated with the load. The records for each load also include data on the previous and next stop such as the number of miles to the next stop, and the stop number of the current load. Most importantly, the data captures the time when a driver enters and leaves the facility. As discussed in Section 3.2 Data Cleaning, the actual dwell time per load is calculated mainly from these two data points.

iii.)Driver:Contains information on the vehicle used to fulfill the load request. These focus on capturing the type of truck and the equipment used for loading and unloading the load (drop hook vs live load). For data privacy reasons, the sponsoring company is unable to provide specific data on the driver.

All 54 data characteristics were included in the analysis(Appendix A). The goal of the project is to understand the key characteristics that drive dwell time and use them to predict the dwell time for each load.

3.2 Data Cleaning

The raw data provided by the sponsoring company includes over 19 million unique records for each load processed. The data set provided by the sponsoring company was cleaned to ensure consistent and accurate data used in the analysis. Any impurities in the data from missing entries, duplicates, or errors in encoding would result in inaccurate analyses and conclusions from the study. The data was cleaned following multiple steps documented below.

First, the dwell time of each load record was calculated by taking the total time a driver spent in the shipper facility. For unscheduled loads, the dwell time was calculated by taking the difference between the arrival time (ArriveDateTime) and the departure time (DepartDateTime) of the driver in the facility. For scheduled loads, there are three scenarios that may result in different approaches to calculating dwell times -- the driver arrives before the scheduled arrival time, the driver arrives after the scheduled arrival time, or the driver arrives on time. For this project, if the driver arrives before the scheduled time, dwell time is defined as the difference between the scheduled arrival time and the actual departure time of the driver. This was determined by the sponsoring company to ensure highest priority on upholding delivery schedules between shippers and drivers. If the driver arrives on time or after the delivery schedule, dwell time is defined as the difference between the actual arrival time and the actual departure time of the driver, similar to the unscheduled case.

Through this process, the calculated dwell time for each load record varied widely between -780,000 hours to around 2.3 million hours. This wide range of dwell time is due to partially missing arrival time or departure time of some records. As decided with the sponsoring company based on their domain expertise, this project's scope focused on dwell time records between 0–6 hours, capturing the majority of the data (i.e., ~2% loss in 2017-2019 dataset).

Next, due to the size of the data set and time required to process all entries, the analysis focused on the most recent 3 years, to include 2017–2019 data. Then, the data set was cleansed by removing all rows with null, blank, or duplicate entries.

In summary, the data set used in the analysis covers loads records for 3 years, from 2017 to 2019, with dwell times ranging from 0–6 hours, and complete records across all 54 characteristics included in the study. Below is the resulting distribution of dwell time.

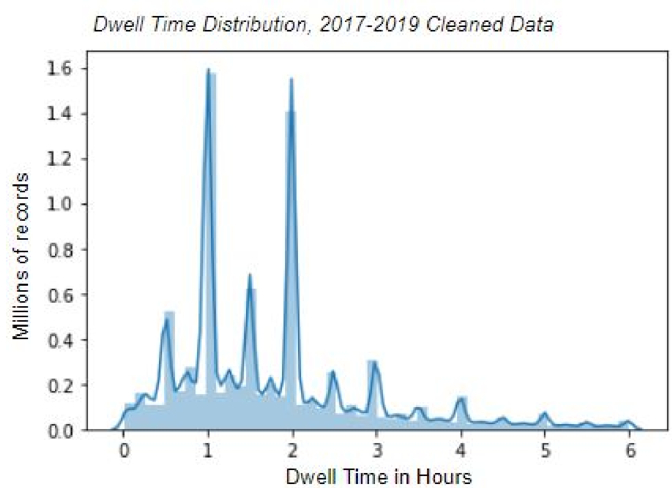


Figure 2 Dwell time distribution in 2017-2019

Note: The dark blue line is the Kernel Density plot of the data. The light blue columns represent the continuous distribution of dwell time

3.3 Data Pre-processing

After data cleaning, data pre-processing or feature engineering is a necessary step required prior to model training. The content of data-preprocessing can be divided into three subsections. First, Section 3.3.1 will explain how to transform time-related variables. Then, Section 3.3.2 will cover aggregated variables generated from the datasets. Lastly, Section 3.3.3 will elaborate on two methods used for handling categorical variables.

3.3.1 Time-related Variables

Time-related variables are calculated from the date and time information when a truck driver arrives at the facility.

a) *Hour of Day* is an integer value indicating the hour, ranging from 0–24, when a truck driver arrives at the facility.
b) *Day of Week* is a variable that represents the day, ranging from Monday to Sunday, when a truck driver arrives at the facility.
c) *Peak Hour* is a Boolean variable indicating if a truck driver arrives at the facility during the peak hour, which is between 6 AM– 4 PM.

3.3.2 Aggregated Variables

Aggregated variables are calculated using different aggregation functions, i.e., sum, unique, average, among other aggregation operations after filtering the load records by different target variables as described below.

a) *Facility Traffic* is the number of load records at each facility at specific hour
b) *Facility Complexity* is the number of unique CarrierID serving specific facility
c) *Carrier Experience* is the number of total load records served by specific driver
d) *Carrier Complexity* is the number of unique FacilityID served by specific driver
e) *Facility Historical Performance*metricsinclude average, median, min, max, and standard deviation of historical dwell time at each facility.

3.3.3 Handling Categorical Variables

There are two types of input variables in the model; numerical variables and categorical variables. While numerical variables can be inputted directly into the model, categorical variables need to be encoded before being input to the training model. Two types of encoding are selected for this capstone project to suit each model used as described below.

i.)One-Hot Encoding for Linear Models

For the nominal variables, without ordinal relationships across categories, one-hot encoding is the common preprocessing method to transform each category into another column with the value of 0 and 1 indicating whether each record falls into that specific category. This project used the one-hot encoding method prior to training the linear models, i.e., ridge regression and logistics regression. This prevents the linear model from mistakenly assigning numerical relationships among different categories when there is none.

ii.) Numerical Encoding for Tree-based Models

While one-hot encoding works well for linear models, its tendency to create a sparse input matrix especially for categorical variables with high cardinality makes it unsuitable for training tree-based models. To cope with this, another encoding technique called numerical encoding is used prior to training tree-based models, i.e., random forest and gradient boosting. Numerical encoding is a preprocessing method that transforms each category into integer values. While this type of encoding is not suitable for linear modes as it forces ordinal relationship between each category when there is none, tree-based models can handle this well as it allows more flexible and numerous splitting points.

3.4 Model Training

The modelling approaches used in this capstone project can be divided into two main categories: regression approach and classification approach. For the regression approach, the predicted dwell time is treated as a continuous variable. While for the classification approach, the predicted dwell time is treated as a discrete variable and split into multiple bins with different binning methods. The details of each modelling technique are referenced from Géron(2019).

3.4.1 Regression Approach

Dwell time is defined as the time the truck driver spends loading and unloading the pallets at each facility and is measured in hours. Hence, the traditional modelling approach is to build a regression model to predict dwell time. There are three types of modelling techniques explored in this approach: ridge regression, random forest regression, and gradient boosting regression.

i.) Ridge Regression

Ridge regression is a type of linear model, which resolves the problems of ordinary least squares in the conventional linear regression. It comprises an ordinary least squares term and an extended regularization term, called L2 penalty. The benefit of using ridge regression, as compared to conventional linear regression, is that it prevents the overfitting of the model and unusually high magnitude of coefficients. The loss function of ridge regression is based on ordinary least squares, which can be expressed as in equation (1).

$$L(\theta) = \frac{1}{2n}\sum_{t=1}^{n}(y^{(t)} - \theta x^{(t)})^2 + \frac{\lambda}{2}\theta^2 \qquad (1)$$

ii.) Random Forest Regression

Random forest regression is a type of ensemble model, which is a combination of multiple decision tree regression models. Unlike linear models which force linear relationships between dependent and independent variables, the decision tree models allow multiple segmentation at each independent variable, providing more flexibility in model building. After segmenting the data, the tree model calculates and outputs the mean value of all the dependent variables within the same segment. The random forest regression works by creating multiple decision trees, each one trained on different datasets using a bagging method as well as different sets of randomly selected independent variables. The outputs from each tree are then averaged to provide the final value of prediction.

iii.) Gradient Boosting Regression

Gradient boosting regression is a type of ensemble model, which is a combination of multiple decision tree regression models. It works by sequentially adding a model that is trained on residual error from the previous prediction model.

3.4.2 Classification Approach

According to the discussion with the sponsoring company, their preferred level of prediction output is by the hour. Hence, the classification models are also explored as they could capture the preferred result in a discretized format. Prior to model training, the dwell time data was discretized into multiple bins with different binning methods. There are three types of modelling techniques explored in this approach: logistics regression, random forest classification, and gradient boosting classification.

i.) Binning Methods

Before performing the classification analysis, the dwell time data was binned by using two methods. For the first method, the bins were determined using quantile cutting, which aims to create bins with equal dwell time frequencies. The team used a trial-and-error approach to identify the optimal number of bins that would result in an equal number of dwell time records per bin. Following this procedure resulted in 7 bins with the following divisions:

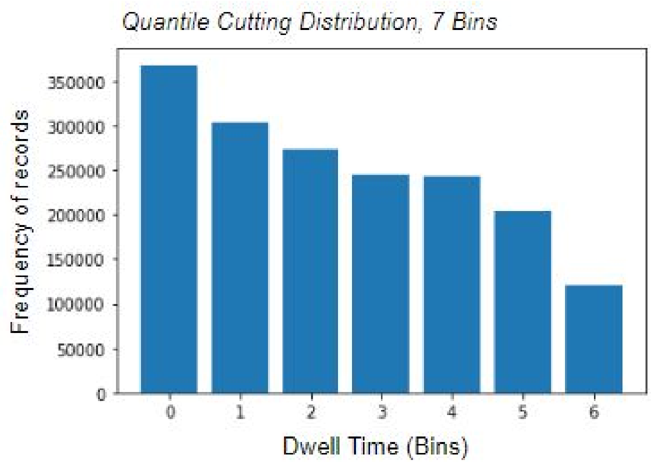


Figure 3 Bar chart showing frequency of dwell time records per bin for quantile cutting

Table 1 Minimum and maximum bounds per bin number and frequency from quantile cutting method with 7 bins

Bin #	Bin Bounds (hrs)	Bin Frequency
0	(0.75, 1.0]	368027
1	(1.833, 2.0]	302949
2	(0.0157, 0.75]	273376
3	(1.333, 1.833]	245299
4	(2.0, 3.0]	243879
5	(3.0, 6.0]	204685
6	(1.0, 1.333]	120624

The second method, as decided with the sponsoring company, was to set bins in 6-minute and 60-minute intervals. The distribution plots are shown in Figure 4 and Figure 5. This was determined based on the level of granularity the sponsoring company required in their daily operations and reporting. It is important to note that there are direct trade-offs to consider in setting the bin size. For example, increasing the number of bins may result in more granular data outputs, but may increase the predictive difficulty and strain model performance. On the other hand, decreasing the number of bins may increase the predictability of the data set, but may result in a loss of information due to discretization. For this analysis, the bin sizes were determined by the nature of the business of the sponsoring company, and the level of granularity required by it.

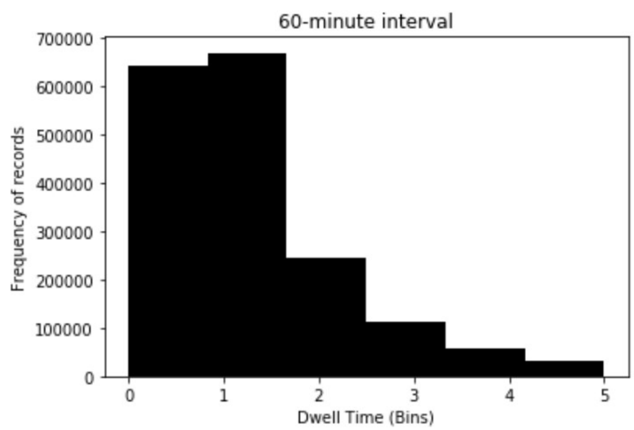


Figure 4 Bar chart showing frequency of dwell time records per bin for 60-minute interval

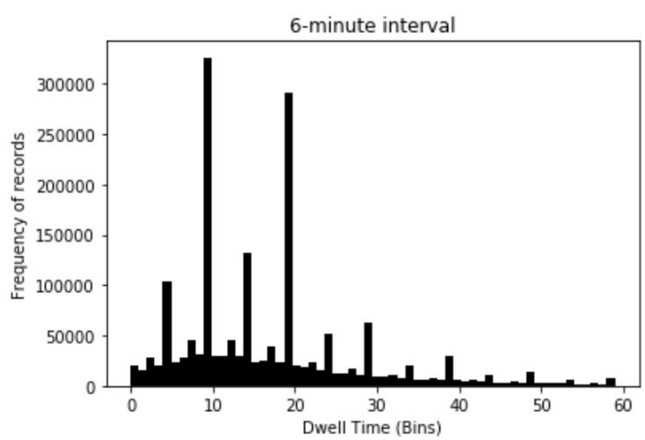


Figure 5 Bar chart showing frequency of dwell time records per bin for 6-minute interval

ii.) Logistics Regression with L2 Penalty

Logistics regression with L2 penalty is a type of linear model, which outputs the probability of occurrence of each prediction bin. The probability is calculated by taking the sigmoid function on the linear combination of independent variables as described in equation (2).

$$\hat{p} = \sigma(\theta x + \theta_0) = \frac{1}{1 + e^{-(\theta x + \theta_0)}} \tag{2}$$

Similar to ridge regression, it comprises a cross-entropy loss term and an extended regularization term, called L2 penalty. Adding the L2 penalty term provides the same benefit as in ridge regression, which is to prevent the overfitting of the model and unusually high magnitude of coefficients. The loss function of logistics regression is based on cross-entropy loss, which can be expressed as shown in equation (3).

$$L(y, \hat{p}) = -(ylog(\hat{p}) + (1 - y)log(1 - \hat{p})) + \frac{\lambda}{2}\theta^2 \tag{3}$$

iii.) Random Forest Classification

Similar to random forest regression, random forest classification is a type of ensemble model, which is a combination of multiple decision tree classification models. However, instead of predicting continuous variables, the model outputs are described by categories instead.

iv.) Gradient Boosting Classification

Similar to gradient boosting regression, gradient boosting classification is a type of ensemble model, which is a combination of multiple decision tree regression models. However, instead of predicting continuous variables, the model outputs are described by categories instead.

3.5 Factor Analysis

After model training, the importance of each factor can be extracted using different techniques depending on the type of models (linear or tree-based). This process is called factor analysis. It is important to analyze and compare across models and understand which variables have high contribution towards dwell time, in order to formulate business suggestions that will potentially decrease the time.

3.5.1 Linear Models

The variable coefficients are the products that come from training linear models. By analyzing the magnitude and sign of coefficients related to each variable, the trend and level of impact each feature has on dwell time can be identified.

3.5.2 Tree-based Models

Feature importance is an impurity-based and common measure for factor analysis of tree-based models proposed by Breiman(2001). However, Strobl et al.(2007)pointed out that this original method is not reliable in situations when the variables vary in terms of scale of measurement and cardinalities. Since the independent variables considered in this project cover high variability of scale and cardinality, the analysis used an alternate method called permutation importance that was demonstrated by Parr et al.(2018). The permutation importance of each feature is calculated by permuting the column and measuring the difference between the baseline and the decrease in overall score. The overall score used in the regression approach is r-squared, while the overall score used in the classification approach is accuracy.

3.6 Model Evaluation

In this project, both the models under regression approach and the models under classification approach are explored. As a result, it is of utmost importance to find common ground to compare the model across different approaches. The evaluation metrics used in this project are thoroughly selected with applied pre-processing tailored for each approach to ensure fair judgement. The detailed calculation of regression and classification metrics are referenced from Géron(2019). While the output pre-processing techniques and special metric for ordinal outputs are proposed by the authors to match sponsoring company's business need.

3.6.1 Regression Metrics

There are two commonly-used regression metrics chosen to evaluate the models: root mean square error (RMSE) and mean error. While the metrics can be straightforwardly applied to models in the regression approach section, for the models under classification approach, the outputs of each bin are transformed into numerical value by using the midpoint value of each bin. For example, the outputs from the 0–1 bin are converted into the value of 0.5. After that, the following two regression metrics are then applied.

i.) Root Mean Squared Error (RMSE)

Root mean squared error is a common measure of model prediction error. It tells how the predicted values differ from the actual values regardless of the sign of the differences. The formula is shown in equation (4).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{4}$$

ii.) Mean Error

Mean error is a common measure of model forecasting bias. Unlike RMSE, apart from prediction errors, it can also capture the event when the predictor gives unusually high or low values as compared to the actual values. The formula is shown in equation (5).

$$Mean\ error\ = \frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y_i}) \tag{5}$$

3.6.2 Classification Metrics

There are three commonly-used regression metrics chosen to evaluate the models: accuracy, F1 score, and confusion matrix. Contrary to section 3.6.1, the outputs from both the regression and classification models require pre-processing to convert them into common ground before comparison. This is achieved by transforming all outputs that fall into a corresponding 1-hour bin to that bin. For example, the output values of 1.05, 1.5 and 1.88 are transformed to 1–2 bin.

i.) Accuracy

Accuracy is a ratio between true positives plus true negatives divided by total observations as described in equation (6).

$$Accuracy\ = \frac{True\ Positives + True\ Negatives}{Total\ Observations} \tag{6}$$

ii.) F1 Score

F1 score is a metric that captures the tradeoff between precision, a ratio between true positives and total predicted positives, and recall, a ratio between true positives and total actual positives. F1 score can be calculated as described in equation (7).

$$F1\ Score\ = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{7}$$

iii.) Confusion Matrix

Confusion matrix is a summary table showing the total number of observations that fall into each combination of actual and predicted bins. The confusion matrix for predicted dwell time is in the following format.

Table 2 Confusion Matrix Template

Dwell Time		**Predicted**					
		0 - 1 hr	1 - 2 hr	2 - 3 hr	3 - 4 hr	4 - 5 hr	5 - 6 hr
Actual	0 - 1 hr						
	1 - 2 hr						
	2 - 3 hr						
	3 - 4 hr						
	4 - 5 hr						
	5 - 6 hr						

3.6.3 Special Metric for Ordinal Outputs

While the regression metrics enable ordinal output comparison in terms of level of closeness, i.e., 2 is closer to 1 than 5, they provide the error values at excessively high detail level, which does not serve the sponsoring company’s purpose. On the contrary, while the classification metrics can be tailored to provide the evaluation at the right level of granularity (one-hour bin), it does not capture the level of closeness between ordinal outputs. In order to incorporate the benefits of both approaches, special metricfor ordinal outputs, i.e., average error by bin, is created to fulfill this purpose.

i.) Average Error by Bin

Average error by bin is obtained from the confusion matrix by calculating weighted-average value of the difference between actual and predicted data. After assigning the midpoint value to represent each bin, i.e., 1–2 bin is assigned the value of 1.5, the prediction difference for each combination of actual and predicted bin is then calculated and weighted by the number of observations in the bin.

4. Results and Analysis

This section will focus on understanding the preliminary exploratory data analysis and key factors that contribute to dwell time, and evaluating the performance of the statistical models used to predict dwell time. Section 4.1 summarizes the findings and visualizations from exploring the datasets. Section 4.2 uses random forest models to rank the importance of each factor in the analysis, then uses a ridge regression model to explore the correlation of each factor with dwell time. Then, Section 4.3 provide the performance of allof the models.

4.1 Preliminary Exploratory Data Analysis

A descriptive analysis between each independent variable and dwell time was conducted based on the 2019 dataset to understand the correlation of each pair. The results from this exploratory analysis suggest a weak correlation between the raw variables available in the data set provided by the sponsoring company (See Appendix A for data dictionary). To address this, the raw variables were aggregated and transformed based on various time and operational inputs (See Section 3.3.2 for results).

Figure 6 shows the heatmap tables between average dwell time and total number of loads delivered. Table on the left shows average dwell time per hour of day (y-axis), per quarter (x-axis). Table on the right shows the total number of loads delivered per hour of day (x-axis), per quarter (y-axis). The data covers loads delivered in 2019, and shows lower dwell time between the hours of 6am to 3pm, suggesting that facility hours of operations may be a significant factor impacting dwell time This is an example of an aggregated variable.

Dwell Time

TIME OF DAY	Quarter 1	Quarter 2	Quarter 3	Quarter 4
0	5.52	5.82	5.76	6.72
1	4.80	5.07	4.81	4.64
2	4.18	4.43	4.26	4.61
3	3.82	3.95	3.90	3.96
4	3.39	3.57	3.56	3.51
5	3.06	3.08	3.13	3.80
6	2.69	2.71	2.78	3.04
7	2.46	2.42	2.48	2.68
8	2.40	2.36	2.44	2.48
9	2.38	2.36	2.44	2.43
10	2.46	2.43	2.49	2.48
11	2.51	2.52	2.62	2.36
12	2.56	2.64	2.73	2.69
13	2.62	2.72	2.82	2.67
14	2.75	2.86	3.01	3.63
15	3.00	3.16	3.31	3.92
16	3.32	3.57	3.67	4.80
17	3.64	3.85	4.02	6.06
18	3.98	4.30	4.35	4.31
19	4.13	4.65	4.71	4.81
20	4.56	5.10	4.90	5.48
21	4.70	5.30	5.18	7.47
22	4.97	5.67	5.43	5.13
23	5.16	5.55	5.27	6.14

Number of Drops

	Quarter 1	Quarter 2	Quarter 3	Quarter 4
0	6742	8007	8465	161
1	5909	6990	7395	168
2	6221	7069	7537	161
3	6915	7726	7767	153
4	10033	10868	11104	222
5	17919	20237	20114	396
6	32386	37183	37416	630
7	59570	66475	63652	1011
8	79120	85555	83144	1275
9	58507	64935	63467	815
10	64171	70305	68760	705
11	54222	59332	58960	435
12	63990	66812	65131	393
13	52408	55193	54546	252
14	45687	47586	46854	205
15	35047	36846	37029	209
16	23907	25196	25918	140
17	17020	18541	19389	134
18	14392	15869	16892	117
19	11542	13082	14018	91
20	10032	11510	12395	120
21	8212	9535	10443	68
22	7114	8523	8850	85
23	6416	7868	8738	61

Figure 6 Average dwell time and total number of loads delivered per hour of day per quarter

Figure 7 shows the average number of loads fulfilled by each carrier. The x-axis shows the average number of loads fulfilled by a carrier. The y-axis shows the average dwell time for each carrier. This figure suggests that carriers who fulfill more loads have shorter average dwell time. The data covers loads delivered in 2019. This is an example of an aggregated variable.

Shorter average dwell time for 'active' carriers: Carriers who have fulfilled more trips in 2019 have lower average dwell times

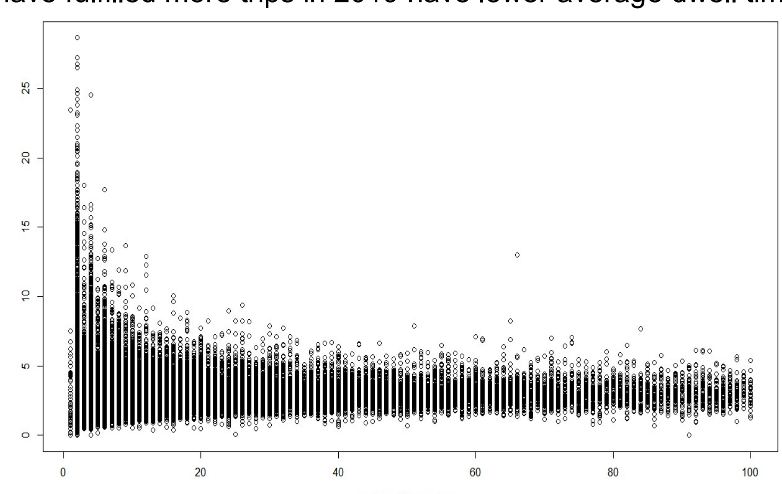


Figure 7 Average number of loads fulfilled by carrier

Figure 8 shows total unique shippers served by carrier. The x-axis shows the total unique shippers served by a carrier. The y-axis shows the average dwell time for each carrier. This figure suggests that carriers who serve more unique shippers tend to have higher average dwell times. The data covers loads delivered in 2019. This is an example of an aggregated variable.

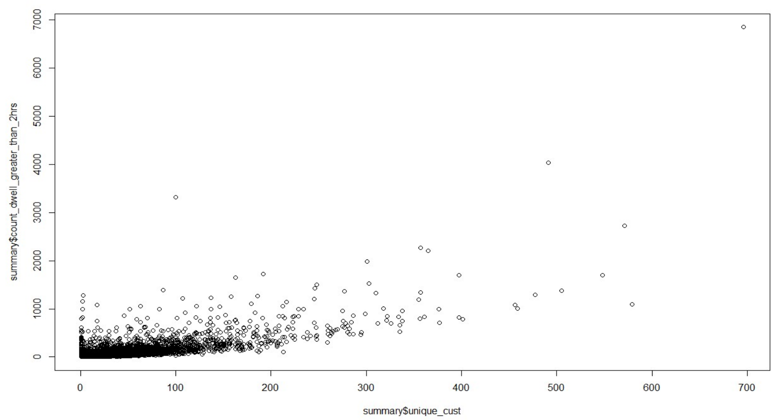


Figure 8 Total unique shippers served by carrier

Figure 9 shows dwell time versus total number of pallets for each load stop type. The x-axis shows the total number of pallets for each unique load. The y-axis shows the average dwell time for each load. This figure depicts a weak correlation between dwell time and total pallets and is an example of a raw variable. The data covers loads delivered in 2019.

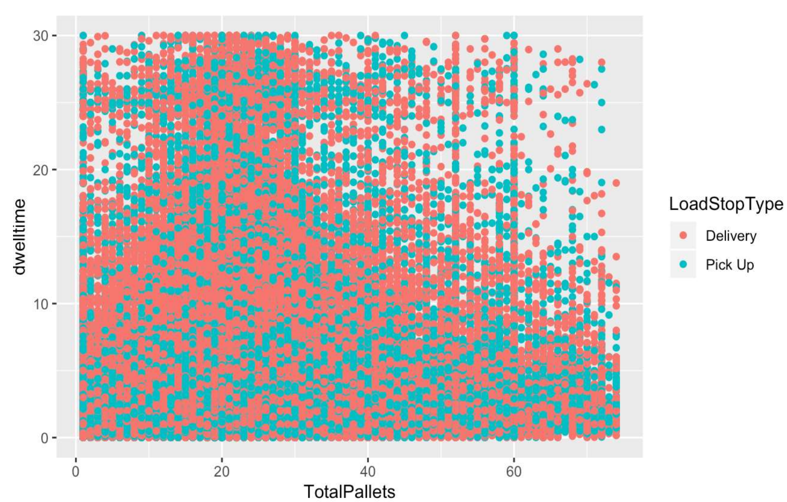


Figure 9Dwell time versus total number of pallets for each load stop type

4.2 Key Factor Analysis

A random forest classifier and regressor were used to determine the importance of each of the factors in the model. Both models suggest that the factors capturing the historical performance of shipper facilities have the highest importance, thus suggesting that facilities play an important role in predicting the dwell time of a load. As seen on Figures 10 below, the median, average, standard deviation and maximum of historical dwell time per facility are major indicators of predicted dwell time of a load. Moreover, this analysis suggests that loads with varying load and driver factors may have the same dwell time, as determined by the facility where the loads are processed. Given that dwell time occurs within facilities, it is not alarming for these factors to be main drivers.

Aside from historical facility performance, ArriveTimeUpdateType, the method by which drivers update their arrival time at a facility, is another major driver of dwell time prediction. For this project, drivers can update their arrival time manually or automatically. Manual updates require drivers to manually input arrival timestamps in their hand-held device which may take more time, and may lead to more human error. Whereas automatic updates may rely on radio-frequency identification (RFID) or other similar technologies attached to the driver's vehicle that captures the exact time of entry and exit of a driver in a facility. Furthermore, the results suggest that loads that are updated automatically tend to have a lower dwell time than manually updates loads.

As seen in Figure 11 and 12, several load and driver specific factors are included in the top 10 important factors that drive dwell time from the random forest regressor model. In this model, the top 2 important factors are average historical dwell time and arrival time update type. Moreover, the regressor model’s weighting is heavily skewed towards these 2 factors with Average Dwell Time (0.842) and Arrival Update Type (0.038), driving 0.88 out of 1.00 of the importance. The other 8 factors, consisting of the driver and load factors contribute to ~0.01 importance each, thus making them less relevant. The classifier model is similar to the regressor model in that the top 2 important factors are facility driven average and median dwell time weighed 0.427 and 0.166 respectively, with arrival time update at 3rd with 0.139. Unlike the regressor model, the classifier model has mostly facility type factors in the top 10, and less variance across the weights of the top 10 factors. In aggregate, the classifier and regressor model assign equivalent weights to Average Dwell Time, Arrival Update Type, and other similar facility historical performance factors that drive over 0.90 out of 1.00 of the importance across the set of over 54 variables.

Currently, the sponsoring company does not have visibility or control over facility operations, as they are determined by each shipper. Therefore, this project will not be able to pinpoint specific operations within a facility that lead to higher dwell time.

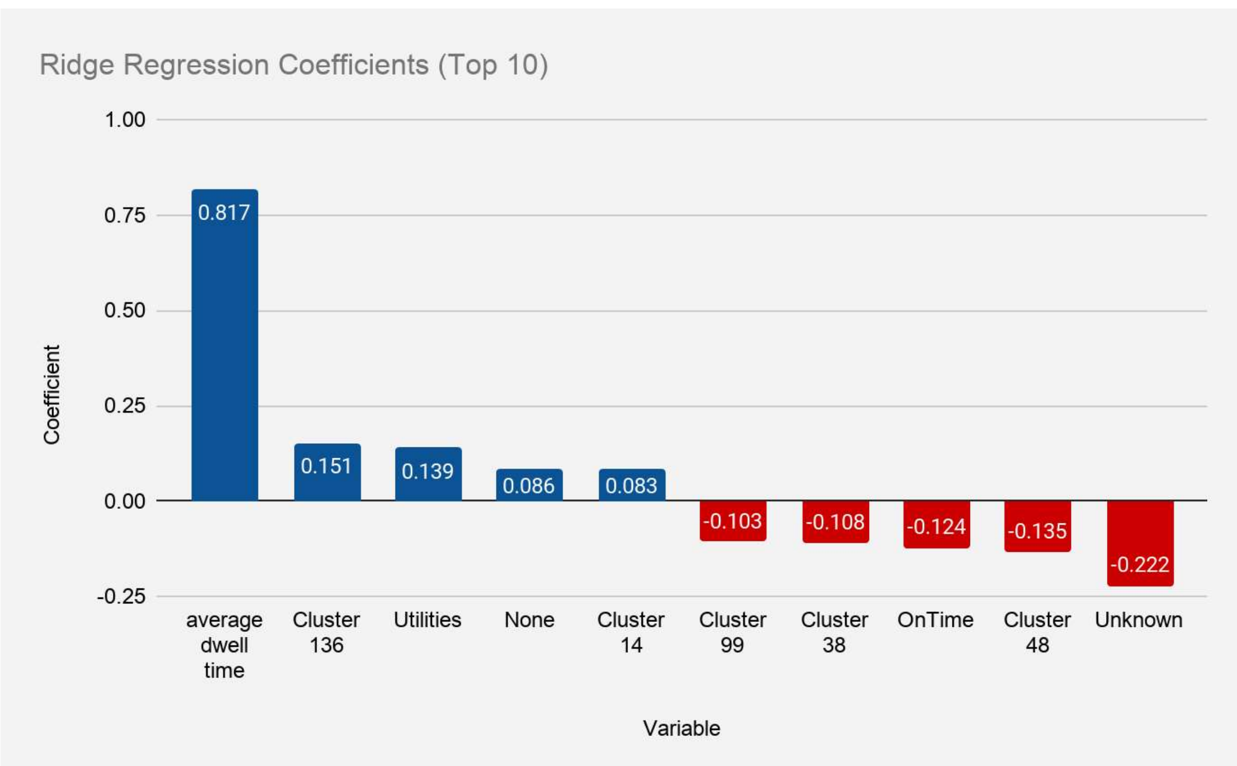


Figure 10 Ridge Regression Coefficients

Notes:-None factor corresponds to the Schedule type 'None' that is assigned to loads with an unknown schedule type (i.e., By Appointment, By Notice, Open Time)

-Unknown factors correspond to the Work Type 'Unknown' that is assigned to loads with an unknown type of work (i.e., No Touch, Driver Loaded, Driver Counted, Lumper, Driver Assisted/ Checked).

- Clusters factors (136, 14, 99, 38, 48) correspond to anonymized geographic regions within the United States created by the sponsoring company

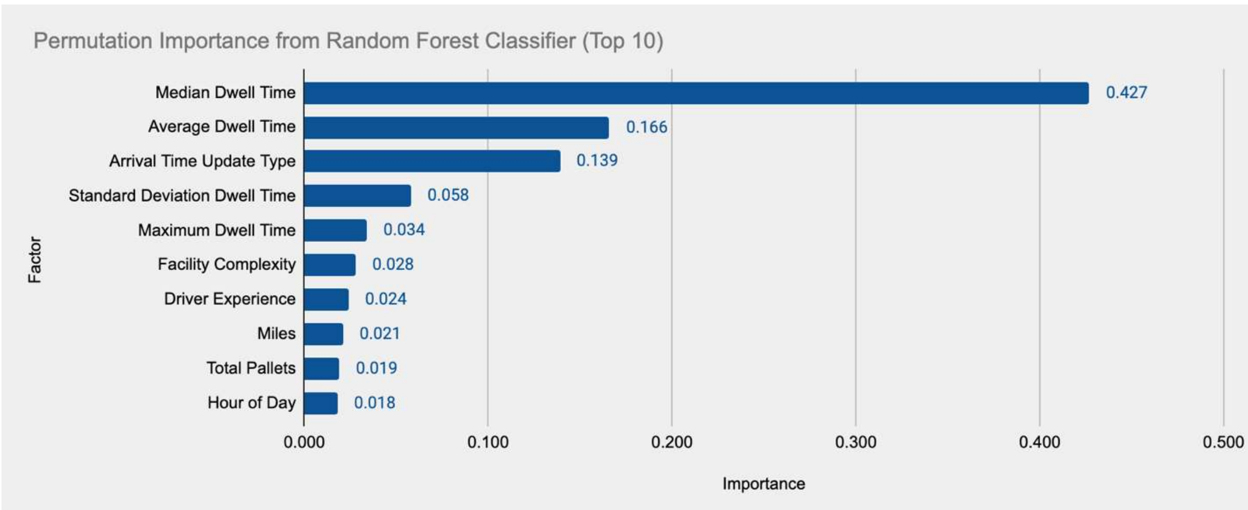


Figure 11 Permutation Importance from Random Forest Classifier

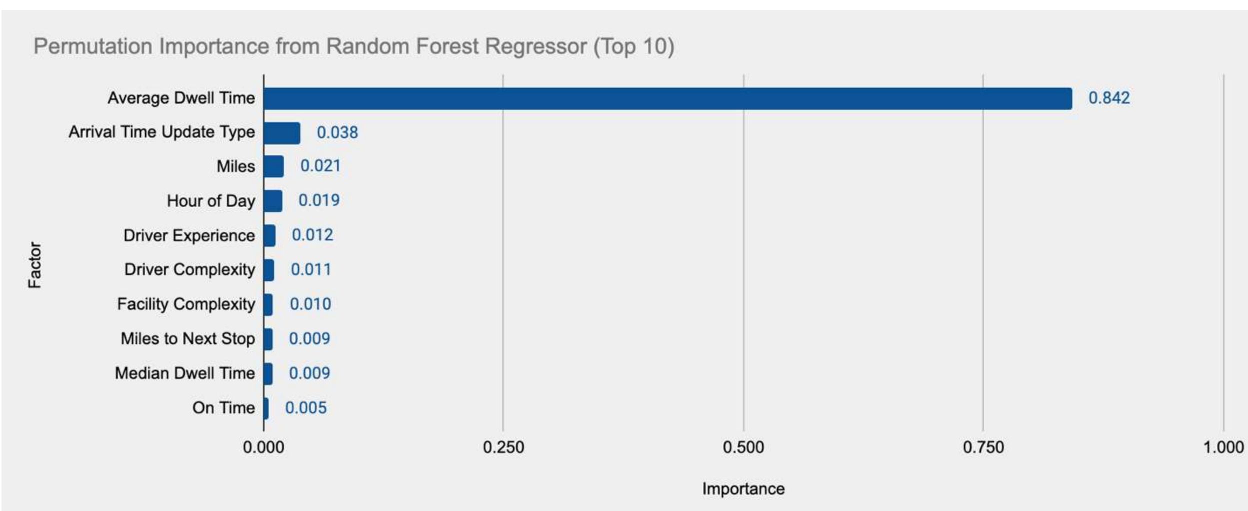


Figure 12 Permutation Importance from Random Forest Regressor

4.3 Model Performance

In this section, the evaluation metrics, i.e., regression metrics, classification metrics, and special metrics for ordinal outputs, of each model will be examined. Section 4.3.1 will show the model performance from the regression approach. Next, Section 4.3.2 will display the model results from the classification approach. Lastly, Section 4.3.3 will summarize and compare the performance of all of the models.

4.3.1 Regression Approach

i.) Ridge Regression

After hyperparameters tuning, the regularization parameter of 0.01 was selected for final model training. The final ridge regression model has RMSE of 1.040, mean error of 0.0005, out-of-sample R2 of 0.165, accuracy of 0.370, F1 score of 0.309, and average error by bin of 0.807. The confusion matrix is displayed in Table 3.

Table 3 Confusion Matrix of Ridge Regression Model

Dwell Time		Predicted					
		0 - 1 hr	1 - 2 hr	2 - 3 hr	3 - 4 hr	4 - 5 hr	5 - 6 hr
Actual	0 - 1 hr	21,274	141,161	29,648	337	4	0
	1 - 2 hr	2,902	144,632	52,208	907	11	0
	2 - 3 hr	350	43,428	28,632	731	28	0
	3 - 4 hr	92	15,995	17,216	741	33	0
	4 - 5 hr	33	6,613	10,093	738	43	2
	5 - 6 hr	16	3,161	6,031	524	64	4

ii.) Random Forest Regression

After hyperparameters tuning, the maximum depth of 10, minimum sample leaf of 3, number of trees of 300 were selected for final model training. The final random forest regression model has RMSE of 1.032, mean error of 0.0006, out-of-sample R2 of 0.179, accuracy of 0.372, F1 score of 0.307, and average error by bin of 0.800. The confusion matrix is displayed in Table 4.

Table 4 Confusion Matrix of Random Forest Regression Model

Dwell Time		**Predicted**					
		0 - 1 hr	1 - 2 hr	2 - 3 hr	3 - 4 hr	4 - 5 hr	5 - 6 hr
Actual	0 - 1 hr	19,817	144,745	27,495	363	4	0
	1 - 2 hr	2,201	147,968	49,507	964	20	0
	2 - 3 hr	227	44,239	27,762	906	35	0
	3 - 4 hr	56	16,233	16,830	911	46	1
	4 - 5 hr	21	6,662	9,875	909	53	2
	5 - 6 hr	14	3,172	5,901	635	77	1

iii.) Gradient Boosting Regression

After hyperparameters tuning, the maximum depth of 5, number of trees of 30, and learning rate of 1 were selected for final model training. The final gradient boosting regression model has RMSE of 1.031, mean error of 0.0004, out-of-sample R2 of 0.180, accuracy of 0.380, F1 score of 0.327, and average error by bin of 0.794. The confusion matrix is displayed in Table 5.

Table 5 Confusion Matrix of Gradient Boosting Regression Model

Dwell Time		**Predicted**					
		0 - 1 hr	1 - 2 hr	2 - 3 hr	3 - 4 hr	4 - 5 hr	5 - 6 hr
Actual	0 - 1 hr	26,182	137,655	27,866	688	25	8
	1 - 2 hr	3,699	144,488	50,830	1,574	64	5
	2 - 3 hr	445	42,862	28,372	1,419	63	8
	3 - 4 hr	126	15,643	16,793	1,438	66	11
	4 - 5 hr	55	6,499	9,566	1,295	97	10
	5 - 6 hr	29	2,993	5,751	900	103	24

4.3.2 Classification Approach

For the classification approach, three different binning methods, as discussed in Section 3.4.2, were explored for each model. It is observed that the outputs from one-hour binning method have the highest accuracy. Hence, one-hour binning method was selected for the final model training and the evaluation metrics for each model are displayed in this section.

i.) Logistic Regression

The final logistic regression model has RMSE of 1.336, mean error of 0.638, accuracy of 0.420, F1 score of 0.357, and average error by bin of 0.840. The confusion matrix is shown in Table 6.

Table 6 Confusion Matrix of Logistic Regression Model

Dwell Time		Predicted					
		0 - 1 hr	1 - 2 hr	2 - 3 hr	3 - 4 hr	4 - 5 hr	5 - 6 hr
Actual	0 - 1 hr	90,840	101,379	205	0	0	0
	1 - 2 hr	69,768	130,630	260	2	0	0
	2 - 3 hr	21,697	51,391	80	1	0	0
	3 - 4 hr	9,435	24,620	21	1	0	0
	4 - 5 hr	4,692	12,819	11	0	0	0
	5 - 6 hr	2,537	7,256	7	0	0	0

ii.) Random Forest Classification

After hyperparameters tuning, the maximum depth of 10, minimum sample leaf of 3, number of trees of 300 were selected for final model training. The final random forest classification model has RMSE of 1.216, mean error of 0.513, accuracy of 0.470, F1 score of 0.401, and average error by bin of 0.743. The confusion matrix is displayed in Table 7.

Table 7 Confusion Matrix of Random Forest Classification Model

Dwell Time		**Predicted**					
		0 - 1 hr	1 - 2 hr	2 - 3 hr	3 - 4 hr	4 - 5 hr	5 - 6 hr
Actual	0 - 1 hr	83,919	108,322	169	11	2	1
	1 - 2 hr	37,285	162,795	556	23	0	1
	2 - 3 hr	9,281	62,745	1,045	63	6	29
	3 - 4 hr	3,379	30,124	376	187	6	5
	4 - 5 hr	1,510	15,742	202	43	24	1
	5 - 6 hr	759	8,895	95	19	7	25

iii.) Gradient Boosting Classification

After hyperparameters tuning, the maximum depth of 10, number of trees of 30, and learning rate of 1 were selected for final model training. The final gradient boosting classification model has RMSE of 1.263, mean error of 0.487, accuracy of 0.467, F1 score of 0.424, and average error by bin of 0.773. The confusion matrix is displayed in Table 8.

Table 8 Confusion Matrix of Gradient Boosting Classification Model

Dwell Time		**Predicted**					
		0 - 1 hr	1 - 2 hr	2 - 3 hr	3 - 4 hr	4 - 5 hr	5 - 6 hr
Actual	0 - 1 hr	97,970	88,888	3,224	1,310	548	484
	1 - 2 hr	50,675	140,716	5,872	1,841	861	695
	2 - 3 hr	14,488	50,594	5,640	1,480	558	409
	3 - 4 hr	5,989	23,059	2,819	1,398	480	332
	4 - 5 hr	2,886	11,510	1,550	761	518	297
	5 - 6 hr	1,537	6,227	900	555	245	336

4.3.3 Model Performance Summary

The summary table of evaluation metrics for each model, i.e., RMSE, mean error, accuracy, F1 score, and average error by bin, is displayed in Table 9 below.

Table 9 Evaluation Metrics Comparison Summary

Models / **Evaluation Metrics**	**Regression**			**Classification**		
	Ridge Regress	**Random Forest**	**Gradient Boost**	**LogisticR egress**	**Random Forest**	**Gradient Boost**
RMSE	1.040	1.032	1.031	1.336	1.216	1.263
Mean Error	0.0005	0.0006	0.0004	0.638	0.513	0.487
Accuracy	0.370	0.372	0.380	0.420	0.470	0.467
F1 score	0.309	0.307	0.327	0.357	0.401	0.424
Error by bin	0.807	0.800	0.794	0.840	0.743	0.773

It can be observed that the regression models produce lower RMSE and mean error than the classification models. Since the RMSE and mean error are calculated by the difference between predicted and actual values, the classification models, which provide the average value of each bin for calculation, are expected to have higher errors. On the contrary, the result shows that the classification models give higher accuracy and F1 score than the regression models. This occurrence is interesting, since it implies that optimizing the model over a higher level of granularity, i.e., using R-squared rather than accuracy, does not necessarily result in higher accuracy. This trade-off between model accuracy and predictive error should be taken into consideration while choosing the model to correspond with measurement objective.

Moreover, it can be seen that a random forest classifier has the best performance among classification models, while a gradient boosting regressor has the best performance among regression models. Since the distribution of dwell time is positively skewed (right-skewed) as depicted in Figure 2, this results in lower-than-actual portion of predicted bins between 4 and 6 hours, especiallyfor random forest regression modelas observed in Table 4. The possible rationale might be the fact that the model calculates and outputs the mean value of all dwell time records in each segment. This results in lower-value bins dominating the mean output, resulting in the majority of the prediction in lower-value bins. On the contrary, while gradient boosting models have a lower accuracy, the prediction tends to cover a wider range of the dwell time bins.

In addition, while logistic regression has relatively high accuracy at 0.420, it has the highest average error by bin at 0.840. This occurrence indicates that the high accuracy does not take into account the level of difference of ordinal variables, which is highlighted by higher RMSE and mean error of the model at 1.336 and 0.638, respectively. It implies that for this research question, neither the regression metrics, i.e., RMSE and mean error, nor the classification metrics, i.e., accuracy and F1 score, should be examined separately. As a result, the average error by bin metrics, which incorporate both regression and classification metrics, is selected for model comparison.

Finally, to correspond with the business requirement to model dwell time predictor at bin size of an hour, the average error by bin is examined. It is observed that random forest classifier has the lowest average error by bin at 0.743 hour, followed by gradient boosting classifier and gradient boosting regressor at 0.773 and 0.794, respectively.

5. Discussion

This section provides an explanation of the results from the descriptive statistics and machine learning models in Section 4, and how they interact with the business operations of the sponsoring company. Section 5.1 will outline the key factors that influence dwell time, their implications for the business, and the limitations of the analysis. Then, Section 5.2 will compare the different modelling techniques applied to arrive at a recommended model that best fits the needs of the sponsoring company.

5.1 Impact of shipper facility factors on dwell time

Ridge regression analysis, random forest classifier, and random forest regressor models were used to analyze the importance of each independent variable on the dwell timeper load.The three models unanimously found that a facility's average historical dwell time is the most important indicator in predicting the dwell time of a load.The historical median and standard deviation of dwell time of the facility are also significant to dwell time prediction. Aside from the historical measures of central tendency, the arrival update type is observed to be another significant driver. Generally, driver arrival times that are updated automatically observe a lower dwell time than those that are manually updated.

For manually updated loads, drivers have the responsibility and autonomy to indicate when they arrive and leave shipper facilities. Because of this, it is important to note that manually updated arrival times may be subject to human error and judgement that may lead to the differences in dwell as compared to automated arrival updates.

It is not surprising that dwell time is driven by shipper facilities since dwell time occurs and is measured when drivers are physically present within these facilities. Moreover, these results echo the survey conducted by the Office of the Inspector General (as cited in Section 2.1) suggesting that a significant portion of driver delays originate from shipper facilities. With this, itis clear that shipper facilities have the greatest influence on dwell time. However, in our analysis, it is unable to explain why this is the case due to the lack of data on the operations within each facility. Each facility dictates its own internal processes, staffing capacity, hours of operation, and other operational nuances that both drivers and third-party logistics providers have no control over.

There are three recommended next steps to further understand the specific conditions within facilities that influence dwell time, and reduce it. First, the sponsoring company may consider clustering shipper facilities with similar historical mean dwell times. Then, it may compare the operational processes, policies, infrastructure, and other conditions within each cluster to understand the differences between a facility with high and low dwell time, among other classes. Second, the sponsoring company may consider building on their shipper facility data that may be added as additional independent variables in the statistical models above. Lastly, using the cleansed data provided, the sponsoring company may work directly to facilities to mitigate dwell time. To start, the sponsoring company may select facilities with high dwell time that control majority of the loads processed on their platform, then deep dive into the facility specific operations to understand and mitigate the bottlenecks that contribute to higher dwell time

5.2 Random forest classification model

Classification and regression performance metrics were used in conjunction to evaluate the performance of each model. As described in Section 3.6, the classification metrics aim to measure the accuracy and precision of the models in predicting bins, while the regression metrics aim to measure the errors in predicting numerical values. Together, these two groups of metrics provide a more holistic method of evaluating the models used in the analysis.

This project used a logistic and ridge regressions to establish baseline models for comparing predictive performance. A random forest regressor and classifier were used to handle the complex and large number of independent variables obtained from the raw and aggregated data. Although random forests typically work best with complex input variables, they do not provide visibility on how variables are correlated with dwell time. This lack of visibility was addressed by the ridge regression analysis, which determined the magnitude and direction of the correlation of each independent variable with dwell time. The combination of these models allowed for an in-depth analysis of the main factors that drive dwell time by evaluating the correlation and importance of each. Moreover, it provided a basis for comparison on the predictive power of each model.

The random forest classifier model is most suitable for the sponsoring company to use. The model outperforms the random forest regressor and ridge-regression models across all performance metrics, thus indicating that it is superior in predicting dwell time values. Also, the model uses one-hour bins to classify dwell time. The sponsoring company decided to implement one-hour bins as this offered sufficient granularity required in its day-to-day scheduling operations and their detention cost planning. The random forest classifier performed better than the regression models because the regression models had a difficult time with the continuous distribution of dwell time. The continuous distribution of dwell time (See Figure 2: Section 3.2) has a long tail and contains sparse data that is harder to predict. Binning the continuous data in one-hour bins smoothens the distribution by increasing the frequency of data points per bin. This helps train and test the classification model and results in higher prediction accuracy. Moreover, the raw data contains manually recorded records that are roundedoff by the hour. Fitting these points into ordinal data points may result in an inaccurate approach (See Figure 13 and 14)

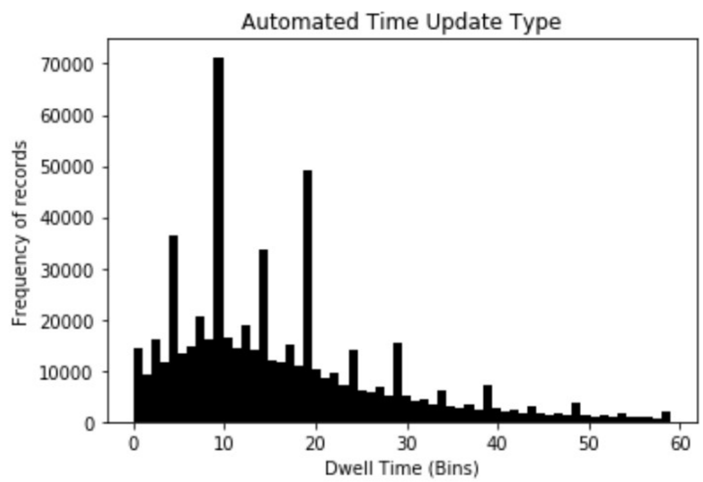


Figure 13 Dwell time distribution for automated time update type

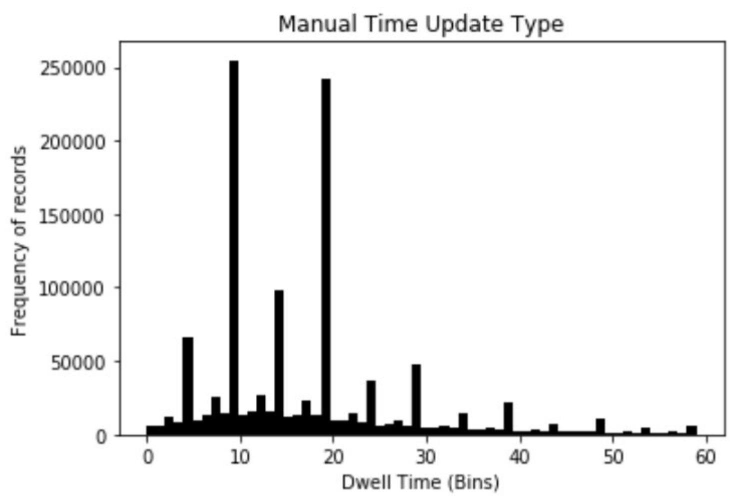


Figure 14 Dwell time distribution for manual time update type

Note: Manually updated loads usually fall into discrete hourly bins. Data captured covers cleansed load data from 2017 – 2019

There are two recommended ways forward to improve model predictive performance. First, time-series characteristics of dwell time can be incorporated during modelling. The current models view each load record independently. However, as both shippers and carriers can demonstrate performance improvement as they operate, it subsequently impacts dwell time as a function of time. Second, more complicated modelling techniques such as neural network can be explored. However, the tradeoff between predictive performance and the interpretability of the model must be taken into account when choosing the model. While neural network can be fine-tuned to provide the model with high predictive accuracy, it is difficult to extract insights on factor impactfrom the model. Nevertheless, if the priority is to achieve the model with the best predictive performance, the neural network model is recommended for further investigation. Finally, the time-series model could be combinedwith modern neural network method, i.e., recurrent neural network, to leverage the benefits of the two methods in constructing predictive model as proposed in the study by Laptev et al. (2017).

6. Conclusion

Driver dwell time is an important challenge the U.S trucking industry faces. High, unplanned dwell times are costly to all stakeholders in the industry as they result in detention costs, declining performance and decreased driver capacity. With the increasing demand for these services, it is important to maximize the driving time of drivers in the industry by minimizing dwell time to free up capacity and provide competitive wages. This project utilizes data from a third-party logistics company with the goal to understand the factors that influence dwell time, and to determine if dwell time of a load can be predicted. The analysis used a combination of descriptive statistics and machine learning models, composed of categorical and regression models.

The analysis identified that shipper facilities have the most impact on the dwell time of a load, and that a facility's average historical dwell time is the strongest predictor of its future performance. The historical dwell time of the facilities included in the analysis behaved independently of factors such as location, industry, and time of year. The negligible impact of load, driver, and external factors of dwell time suggest that dwell time can be reduced by understanding the internal practices unique to each shipper facility. As next steps, we recommend clustering the shipper facilities based on average historical dwell time, comparing their internal practices, and then evaluating the impact of each on dwell time. Once the best practices within the high performing cluster have been identified, the sponsoring company may work to adopt them within the underperforming groups. This facility driven approach requires that the sponsoring company integrate a more granular view on shipper practices with its efforts to predict and reduce dwell time.

Six models were used in the analysis to provide a mix of classification and regression techniques, and linear and ensemble learning methods. Each model has tradeoffs between its predictive performance and interpretability of its results. The logistics and ridge regression models produced lower predictive performance but offered clearer insights on the correlation and relative impact of each factor on dwell time. On the other hand, both random forest and gradient boosting methods had greater predictive performance, but lacked the interpretability of the direct impact of each factor. Furthermore, the analysis used a combination of classification and regression performance metrics to evaluate each model. The classification models had a slightly higher error than the regression models due to the propagation of error from the transformation of categorical bins to ordinal values. Conversely, the former had a better accuracy, F1 score, and bin error. Ultimately, the random forest classification model with one-hour bins is the recommended, as it has the highest predictive performance while the one-hour bins was sufficient to meet the business need. To improve model predictive performance, time-series characteristics of dwell time can be incorporated and more complicated models, i.e., neural networks, can be explored.

The operations required to deliver loads in the U.S Trucking Industry are complex, as most loads delivered require the coordination across drivers, shippers, and third-party logistics providers. Shipper's and their facilities play an important role in sustaining the inflow of demand into the industry. Understanding and mitigating the key drivers of dwell time is the foundation for reducing the efficiency gap within the industry. Thus, stakeholders in the industry must collaborate to share information that will allow for more accurate planning, efficient operations, and stable pricing.

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Appendix A

Below is the data dictionary from sponsoring company's database used in the project.

1) LoadId: The ID of the shipment

2) LoadDate:

3) ParentCustomerID: The ID of parent customer

4) CustomerID: The ID of customer

5) CarrierID: The ID of carrier

6) DnBIndustry

7) ReportingIndustryVertical: Industry Type

8) PrimaryLineofBusiness: Primary line of business of customer

9) NormalizedCustomerLoadRank: Backup, Primary, Spot

10) CarrierLoadRank

11) Miles: Travel distanced in miles

12) Team

13) HRHV

14) Hot: Urgency of load

15) EquipmentType: R (reefer), V (van)

16) EquipmentLength:Length of equipment in feet

17) TotalPallets:Number of pallets

18) TotalWeight: The load weight

19) ShipmentType: Warehouse, CrossDock, Direct, ThroughTrailer, Transload, IntraMX, Unknown

20) LoadStopID

21) LoadStopSequence

22) LoadStopType: Pick Up, Delivery

23) MilesToNextStop: Distance to next stop in miles

24) FacilityID

25) StopAddress

26) CityID

27) StopLocation

28) StopZipCode

29) ClusterId: Sponsoring company’s specific code by geographic location and other internal factors

30) ClusterName:

31) Latitude: Latitude of the stop

32) Longitude: Longitude of the stop

33) TrailerDropped

34) ScheduleType: Appt, Open, Notice, None

35) WorkType: No Touch, Lumper, Driver Count, Assist/Check, Driver Load, Unknown

36) ScheduleOpenTime: The start of appointment time

37) ScheduleCloseTime: The end of appointment time

38) FacilityWindowStartDateTime: The open time of the facility

39) FacilityWindowEndDateTime: Close time of the facility

40) ArriveDateTime: The actual arrival time

41) ArriveTimeUpdateType: Manual, Automatic

42) DepartDateTime: The actual departure time

43) DepartTimeUpdateType: Manual, Automatic

44) OnTime

45) StopExpectedWeight: Expected weight at stop

46) StopExpectedPallets: Expected pallets at stop

47) StopExpectedPieces: Expected pieces at stop

48) BounceCount: Count of times the load gets rejected

49) DetentionLoadingCustomer

50) DetentionUnloadingCustomer

51) LumperChargeCustomer

52) DetentionLoadingCarrier

53) DetentionUnloadingCarrier

54) LumperChargeCarrier