Spatial aggregation impact on demand prediction

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Abstract

Dynamic pricing of time windows in retailers' delivery systems is based on the requirements of the place and quantity. Thus, an accurate prediction of order demand benefits to pricing of time windows and construction of delivery services. This project aims to explore different possibilities for spatial and temporal aggregation in order to predict demand accurately and select the optimal model after comparing the performance of different prediction methods.

To obtain effective results, Autoregressive Integrated Moving Average model (ARIMA), Convolutional Neural Networks (CNNs) and Long-Short Term Memory Networks (LSTMs) are applied with depot schedule data in Sydney and its surrounding areas from 3rd July to 21th October 2018. Predicting demand in this case is a three-dimensional problem as it contains a time component, a spatial component and the actual demand. This paper pays more attention to spatial aggregation demand impact on demand prediction. Three geography standards are used for spatial aggregation, which consists of Local Government Area (LGA), Postal Areas (POAs) and State Suburbs (SSCs). The result suggests that forecasting demand at SSCs level by LSTM model can obtain the most accurate demand prediction. This is conducive to the further investigation of logistics delivery system.

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Chapter 1

1 Introduction

This Chapter starts with an introduction of project motivation and objectives through the research and understanding of industry background. In addition, this chapter gives some information about industrial partner and illustrates the commercial context of this project to highlight the importance and value of machine learning algorithm applied in real business word. Finally, a dissertation outline is displayed to show the brief content of each chapter in this thesis.

1.1 Research Motivation

In recent decades, development of e-commerce has a crucial influence on product supply chains. E-commerce pattern is shifting rapidly from the B2B (Business to Business) to B2C segment (Business to Customer) [1]. Numerous retail and service providers are constructing their own logistic delivery systems to satisfy customers' needs of online shopping [2]. For example, numerous traditional grocery retailers now offer their customers the opportunity to shopping online and use their existing distribution networks to deliver items to customers' homes [3]. In the meanwhile, time windows are generally given to customers where they can select a time convenient for them. For instance, Tesco PLC offers their customers one-hour time slot from 6 am to 23 pm every day [4]. Providing time windows to customers can improve customer satisfaction since it allows people to better plan their personal time, but it may lead to ineffective schedules for delivery companies.

To address this problem, dynamic pricing of time windows is proposed to both provide customers with time slot options, alongside taking into account business needs and requirements. Pricing of time slots is a complex business problem which is greatly affected by demand of the area where the order is being made. Thus, predicting demand for a given time slot at a given location is top priority which is a challenging spatial-temporal problem. The combination of Granularity of spatial components and granularity of time windows have a significant impact on accurate demand prediction. Accurately predicting demand can inform window pricing, and in the meantime affect capacity planning for schedules ahead of time.

1.2 Research Objectives

In this thesis, there are total two objectives which is commercial and academic oriented respectively. The first purpose is to predict demand based on past orders which can be used to derive the cost to serve a slot. Predicting demand in this case is a three-dimensional problem as it consists of a time component, a spatial component and the actual demand. Hence, adjusting spatial and temporal dimensions have a significant influence on the output of demand both from a business perspective as well as technical perspective. Thus, in order to predict demand accurately, different possibilities for spatial and temporal aggregation will be explored and the most suitable solution will be found in a business context.

In addition to the commercial objective, this paper also has a more academic goal. It is more research oriented, concentrating on comparing different machine learning algorithms and methods. The result of the algorithm comparison will be evaluated in terms of performance on demand prediction in the context of a B2C (business to consumer) company.

1.3 Industrial partner

This project is handled by Satalia and the specific data is provided by a large grocery store chain in Australia which will be referred as 'WLW' due to the privacy agreement.

Satalia is a London-based optimization and data science consultancy. The main interest of Satalia is optimisation issues. Dr. Daniel Hulme indicates that unique algorithmic techniques and professional services are provided by Satalia to solve industries optimisation problems [5]. In addition, Satalia also focuses on solving various data science problems for their clients. My role in this project is to assist a client of Satalia to address demand prediction problem by data science and machine learning algorithms.

SATΛLIA

The client mentioned above is 'WLW' who is one of the largest grocery store chains in Australia. It has transformed from traditional grocery retailer to e-grocery commerce who offers home delivery service that delivering items from its depot to customers' home. In order to solve the problem of spatial-temporal demand prediction and further investigate the pricing of time window, four months delivery schedule data from Sydney depot is provided by 'WLW' to explore spatial aggregation impact on demand prediction.

1.4 Business Context

The retail industry is developing rapidly because of the changing shopping behaviour of customers [6]. Packages of online order from consumers have increased above one quarter per year over the past decade [7]. For example, the B2C transaction volume in China has raised significantly from 0.2 trillion RMB in 2011 to 2.6 trillion RMB in 2016 [8]. Thus, it is of great commercial value to research on the prediction of logistics delivery demand.

With this project, Satalia aims to demonstrate how data science and machine learning can improve delivery scheduling system by accurately predicting the order demand. Predicting demand can be used to derive the cost to serve a time slot. This may lead to some benefits for businesses, such as more efficient route planning for vans, shorter delivery time and schedule system improvement.

The first benefit is more efficient routing for vans. The logistics route is based on requirements of the place, time and demand. If the order demand is accurately predicted, the routing for vans can be planned more efficiently by knowing order demand in advance [9].

Secondly, another benefit of accurate demand forecast is shorter delivery time. Forecasting the next delivery demand in the B2C ecommerce model is almost equivalent to predicting the next transaction. Efficient order demand prediction not only allows depots to stockpile ahead of schedule, but also allow the logistics system to arrange delivery routes in advance so that customers can receive their products as soon as possible [10].

Finally, schedule system can also be improved. Dynamic pricing of time window based on accurate demand prediction enables the system to find the cheapest slot among all the possible slots within which the delivery could be placed. This is the core of the optimisation algorithm, which can make scheduling efficient by minimizing the total cost. A better estimate of the actual cost of deliveries will enable the optimisation algorithm to make more informed choices as to where to place reservations in the schedule as it is being built.

1.5 Thesis outline

The structure of this study is as follow:

Chapter 2 (Background and Literature Review): An explanation of technical information and machine learning algorithms applied in this thesis, as well as an overview of existing solutions of spatial-temporal prediction problems.

Chapter 3 (Methodology): A description of dataset used and exploratory data analysis, alongside methods for spatial aggregation and order demand prediction.

Chapter 4 (Results and Discussion): An explanation of prediction results including evaluation of spatial aggregation impact on demand prediction and comparison of different prediction methods.

Chapter 5 (Conclusions and further work): The summary of whole project as well as the further planned work.

Appendix: Supplementary tables and figures useful to the interested reader looking for additional information.

Bibliography: A list of all sources cited in this thesis.

1.6 Chapter 1 Summary

In this chapter, the motivation and objectives of this research were firstly discussed. This was followed by an introduction of project industrial partners and the client who provide data. Then, this chapter indicated the business context of this project to show how this work would make a contribution in real business world. Finally, the structure of the rest of this report was presented.

Chapter 2

2 Background and Literature Review

This Chapter contains two sections including background and literature review. In the literature review section, the content of related works is evaluated and existing solutions of spatial-temporal prediction problem are discussed. As for background section, overview of method applied in this study which consists of technical information and machine learning algorithms used are further explained to help readers understand the logic of problem-solving process.

2.1 Existing Solutions of Spatial-temporal Prediction Problems

In this literature review section, related works and existing solutions of spatial-temporal prediction problems are discussed including prediction of delivery demand and other spatial-temporal prediction issues. In addition, the development of methods used in demand forecasting area are also demonstrated from quantitative methods to deep learning algorithm.

2.1.1 Related work about Delivery Demand Prediction

In the past few decades, a variety of spatial-temporal prediction problems were investigated such as crime distribution prediction, weather forecasting and demand for energy use [11]. Although there are numerous existing solutions of spatial-temporal prediction problems, few researches focus on prediction of logistics delivery demand. In the previous studies for demand prediction, some forecasting techniques were used that can be divided into four main classes. The first one is qualitative approaches that are primarily subjective and basically according to human judgment and view to make prediction. Secondly, time-series models utilize historical data to make prediction. Thirdly, causal methods involve assuming that the demand prediction is highly correlated with certain factors in the environment, such as interest rate and the state of the economy. Finally, simulation approaches imitate the consumer behaviours that lead to demand to make a forecast [12].

Most previous investigations applied time-series models and casual models to predict the logistics delivery demand. Firstly, the majority of time-series models used in demand prediction were exponential smoothing, moving-average and the Box-Jenkins method. For example, Chen, Drezner, Ryan, and Simchi-Levi [13] applied a simple moving-average prediction to calculate the mean and variance of supply chain demand. They proved that the bullwhip effect can be dropped by centralizing demand information. In addition, Chen, Ryan, and Simchi-Levi [14] employed exponential smoothing model to predict logistics delivery demand which as well presented a well-performance result.

Secondly, casual models were also applied to solve the problem of demand prediction in the past researches, such as regression and econometric models. For instance, Zhao, Xie and Leung [15] utilized regression model to investigate the logistics delivery demand and impact of prediction models on supply chain performance. They investigated demand prediction and inventory replenishment decisions and supplier production decisions for different demand patterns and capacity constraints.

Although the above quantitative approaches mentioned are effective, they still have certain limitations. Firstly, it is difficult to extract non-linear patterns using quantitative methods. In addition, insufficient expertise may lead to a mis-specification of the functional form that connect independent and dependent variables, causing a poor regression [16]. Finally, outliers may affect the estimation of the model parameters. The limitations mentioned above can be overcome by using neural networks, which have been proved to be universal approximates of functions [17].

2.1.2 Development of deep learning

Before the presence of deep learning, researchers generally applied quantitative methods to forecast logistics delivery demand. Nowadays, deep learning gradually became widely used for demand forecasting with its development in recent years. It allows computational models consisting of multiple processing layers to learn data representations with multiple levels of abstraction [18]. Deep learning has significantly enhanced the application learning performance in solving the problem of demand prediction [19].

Deep learning has been recently applied and effective results have been gained in demand prediction area. In this study, deep learning was applied to construct the prediction procedure of delivery demand including CNN and LSTM. Some previous researches can be found to support these models. Firstly, CNN has been employed in demand prediction in previous work. For instance, Efendigila, Önüta and Kahraman [20] explored how an organization make the informed decisions in time depending on demand information. They applied CNN to estimate the demand for the next period. Eventually, the success of the proposed method to the demand prediction problem was proved using real-world data from a company which is active in consumer durables industry in Istanbul, Turkey. In addition, Chiu and Lin [21] showed how collaborative agents and ANN work together to leverage a computing framework to implement collaborative supply chain planning.

Secondly, the application of LSTM in logistics delivery demand prediction field can also be found in the past papers. For instance, Lin, Zhang and Chang [22] proposed an efficient procedure based on LSTM to predict order demand from the spatial-temporal perspective. In this case, an LSTM network used with two-dimensional input discovered the spatial-temporal correlations among delivery request occurrences and exploited the correlations to make efficient demand predictions. With the simulation study, the prediction performance of the proposed procedure was fairly acceptable.

The related works and existing solutions of spatial-temporal demand prediction problems are discussed in this chapter. For the various methods mentioned above, statistical approaches are only valid for data having seasonal or trend patterns, while neural networks are also efficient for data which are affected by the special case, such as interest rate and promotion. Thus, in this project, both quantitative method and deep learning algorithm will be applied to predict delivery demand including ARIMA, CNN and LSTM. The optimal method will be determined through the comparison of performance of different models with RMSE as evaluation criterion.

2.2 Overview of Methods Used

In this section, the methods employed in this research are further described including their general overview, detailed explanation of mathematical basis and illustration of algorithms used to implement the goal of this investigation.

2.2.1 Spatial Autocorrelation: Global Moran's I

Spatial autocorrelation quantifies the extent to which near observations of a process are more similar than distant observations in space [23]. The measure of autocorrelation used depends on the data type. Usually, spatial autocorrelation indices are used to measure autocorrelation in grid, areal and network data, while the (semi)variogram is used to measure correlation in point data. Larger autocorrelation values indicate stronger correlation, while the opposite is true for semi-variances, where smaller values represent stronger correlations. While autocorrelation can be positive or negative, semi-variance is always positive [24].

A global spatial autocorrelation measure produces a single value that describes the level of autocorrelation across the region of interest in the dataset [25]. The most commonly used global autocorrelation measure is Moran's I which is calculated as equation (2.1):

$$I = \frac{N}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij}(z_i - \bar{z})(z_j - \bar{z})}{\sum_i (z_i - \bar{z})^2} \tag{2.1}$$

In the equation (2.1), i,j = 1,2,…,N refers to the number of spatial units. w_{ij} indicates the elements of the spatial weight matrix W; z are the spatial series [25]. Possible values of Moran's I range between roughly -1 and 1. Values of Moran's I significantly below -1/(N-1) refer to negative spatial autocorrelation and values of Moran's I significantly above -1/(N-1) refer to positive spatial autocorrelation [27]. The result of spatial autocorrelation may affect the performance of CNN algorithm for demand prediction in this investigation, as CNN method takes into account the situation that a polygon is influenced by other adjacent polygons. Therefore, the stronger the spatial autocorrelation in demand, the better the performance of demand prediction using CNN algorithm.

2.2.2 Evaluation Criterion: Root mean squared error (RMSE)

RMSE is a quadratic scoring rule that estimates the average magnitude of the error. It indicates the square root of the average of squared differences between predicted value and observation [28]. RMSE can be calculated as equation (2.2):

$$RMSErrors = \sqrt{\frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{n}} \tag{2.2}$$

In the equation (2.2), n indicates the number of observation units. y_i refers to the observed value for the ith observation; and $\hat{y}$ is the predicted value. The value of RMSE is generally positive, and a value of 0 presents a perfect fit to the observation [29]. In this project, it is clear that the larger the value of RMSE, the worse the performance of demand prediction.

2.2.3 Autoregressive Integrated Moving Average (ARIMA)

ARIMA refers to Autoregressive Integrated Moving Average model, which is one of the most commonly used statistical models and is generally employed to predict space-time processes [30].

The ARIMA model can predict future values based on past and current values of time series [31]. The aim of this project is to forecast delivery demand based on past orders. Therefore, ARIMA model enables to solve this time series problem and can be utilized to make a forecast on logistics delivery demand.

ARIMA model consists of moving average (MA), autoregressive (AR) and integrated(I) [32]. ARIMA is generally denoted ARIMA (p, d, q) where parameters p, d, and q are positive integers or zero [33]. p indicates the autoregressive order of the model which is the number of autoregressive terms in a time series. q refers to the moving average order of the model which is the number of moving average terms. d indicates the number of differences to achieve stationarity of a time series [34].

2.2.4 Convolutional Neural Networks (CNNs)

As a class of deep neural networks, convolutional neural networks (CNNs) applies a mathematical operation called convolution, which is a specialized kind of linear operation [35].

As for this project, CNN algorithm is well suited for solving demand prediction problem as this research focuses on spatial aggregation impact on demand prediction and CNN algorithm takes into account the situation that a polygon may be influenced by other adjacent polygons.

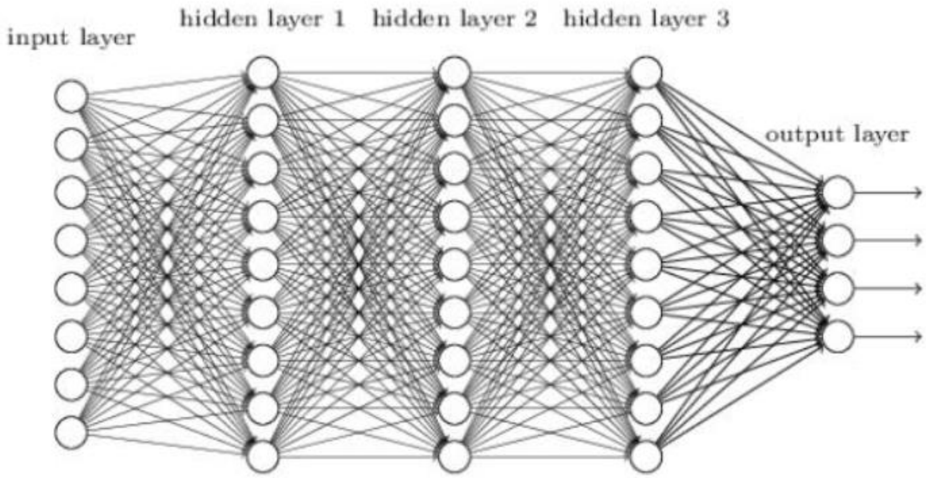

Figure 2. 1: The workflow of CNN

Figure 2.1 demonstrates the workflow and structure of CNN. A convolutional neural network contains an input and an output layer, alongside several hidden layers [36]. In order to improve the efficiency of training intricate data, the CNN model generally employs 3 mapping layers, which are the convolutional layer, pooling layer and the dense layer respectively. Convolutional layers are applied to explore local relationships in inputs, while pooling layer gradually drops the dimension relative to a target variable. Generally, a CNN has several levels of convolutional-pooling layers with several convolution runs performed in each layer. Based on features of input variables, dense layers are utilized to predict a target variable. Nowadays, CNN has proven to be an effective approach for extracting hidden features, utilized to automatically create filters for a variety of data patterns [37].

2.2.5 Long-Short Term Memory Networks (LSTMs)

Long-short Term Memory (LSTM) network is one of deep learning structure and a type of Recurrent Neural Network (RNN) architecture that enable to learn the long-term dependencies [38]. IT was proposed by Hochreiter & Schmidhuber [39], and then was refined and popularized by many researchers in following work.

As one of its greatest advantages, LSTM considers dependence between consecutive events on a relevant time stamp (e.g., minutes or hours) of the same day or another predicting period [40]. Thus, it is effective to apply LSTM in this study for time series forecasting.

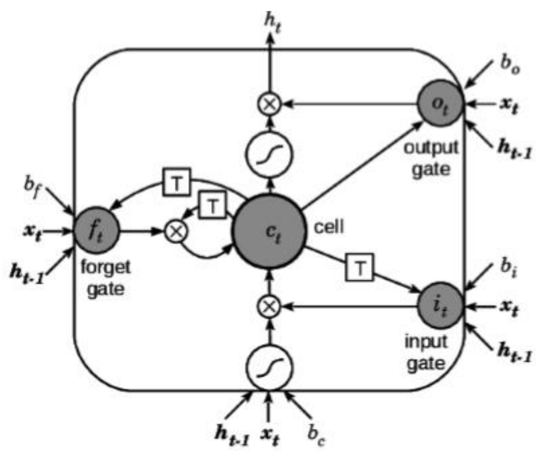

Figure 2. 2: The LSTM single memory cell

Figure 2.2 displays the typical structure of a single LSTM memory cell. The cell demonstrate operates straight down the whole path with some functions of linear combination, which makes it easy to propagate information in time [41]. In addition, as seen in the figure 2.2, LSTM structure contains three gates, an input gate which controls the input of new information to the memory, a forget gate which determines the unnecessary information and an output gate which controls how much the value stored in memory impacts on the output activation of the block [42].

2.3 Chapter 2 Summary

This Chapter started with a literature review section to evaluate the content of related works, investigate existing solutions of spatial-temporal prediction problems and discuss the development of methods used in demand forecasting from quantitative methods to deep learning algorithms. In addition, this chapter also consisted of a description of background with some explanations of technical information and machine learning algorithms used in this research, which contained global Maron's I in spatial autocorrelation, evaluation criterion-RMSE, ARIMA, CNN and LSTM model.

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Chapter 3

3 Methodology

This chapter starts with an overview of dataset used as well as exploratory data analysis. In addition, data pre-processing is demonstrated including spatial aggregation, spatial autocorrelation, data transformation and standardization. Finally, algorithms used in this study containing ARIMA, CNN and LSTM are discussed to predict order demand for a given time period at a given area.

3.1 Used Dataset

The dataset used covers four months of depot schedule data in Australia. It contains the schedule for the depot from 3rd July 2018 to 21th October 2018. Each row in the data is a single delivery completed by a delivery van. The depot investigated in this project is concentrated on customers in Sydney and its surrounding areas. Some of the available variables were as follows:

- **route_id:** Unique id number to identify the van / driver making the delivery.
- **time_flag:** Identification of shift (am or pm)
- **act_arrived_date:** Actual arrival time at customer address.
- **act_ departed_date:** Actual departure time from customer address.
- **slot_start:** Start time of slot selected by customer at point of order.
- **actual_lat:** Actual latitude of delivery location.
- **actual_lon:** Actual longitude of delivery location.

In this research, data from 3rd July to 6th October is used as training set and the rest 15 days data from 7th October to 21th October is treated as testing set.

3.2 Exploratory Data Analysis (EDA)

Some informative and interesting insights are showed through exploratory data analysis (EDA). Figure 3.1 displays daily order quantity from 3rd July to 21th Oct. in 2018. It presents a clear pattern that the demand cycles on a weekly basis. It can be seen that the logistics delivery demand reaches the peak every Monday and regularly fluctuates in the rest of weekday. Furthermore, it seems that the order demand on Sunday is generally higher than that on Saturday.

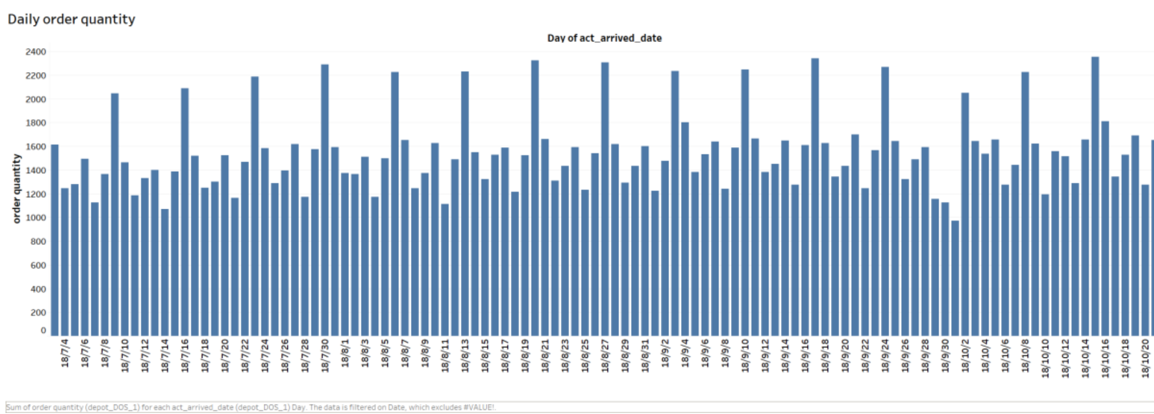


Figure 3. 1: Daily order quantity from 3rd July to 21th Oct. in 2018

Figure 3.2 shows the monthly order demand in the am and pm from 3rd July to 21th October in 2018. It is clear to see that the logistics delivery demand in the am is larger than that in the pm for all four months. In addition, it can be seen that the demand grows from July to September. The value of demand in October in figure 3.2 is the lowest as it only accumulates twenty days' order in this month. Thus, the demand still generally has an increase trend during these four months.

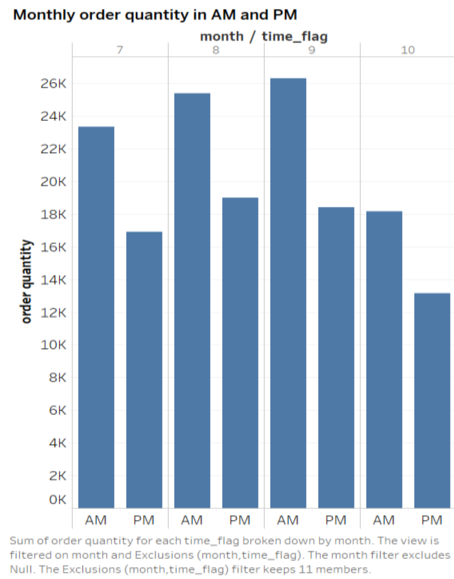


Figure 3. 2: Monthly order quantity in AM and PM from 3rd July to 21th Oct. in 2018

Figure 3.3 indicates total order quantity at different times (hours) of the day. It presents a clear pattern based on timeslot. As for am, it is obvious that logistics delivery demand at 7am and 8am is the greatest, while demand at 5am is the lowest. As for pm, demand significantly increases from 13pm to 16pm and then gradually drops to the bottom at 22pm.

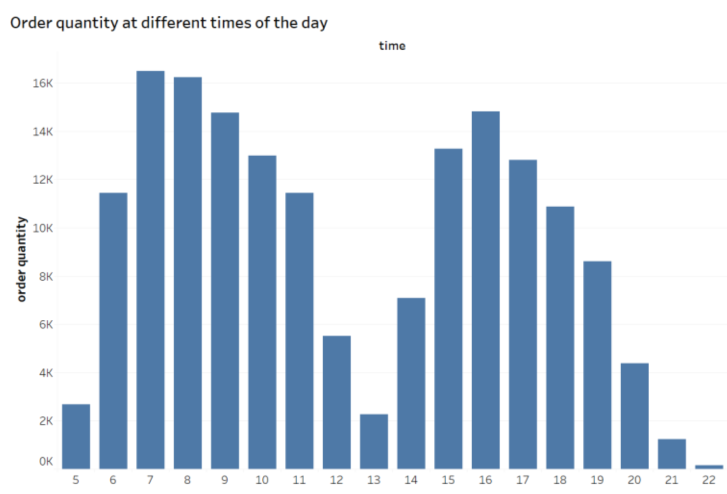


Figure 3. 3: Total order quantity at different times (hours) of the day

3.3 Data Pre-processing

In this section, spatial aggregation according to three different types of geographical division are determined including Local Government Area (LGA), Postal Areas (POAs) and State Suburbs (SSCs). In addition, spatial autocorrelation is implemented to check the distribution state of delivery demand. Finally, dataset is transformed to different structure based on three types of geographical division.

3.3.1 Spatial Aggregation

Predicting demand in this case is a three-dimensional problem as it consists of a time component, a spatial component and the actual demand. The time component for investigation is divided to am and pm. The main interest in this project is spatial component which indicates different types of geographical division where orders are being made. According to the Australian Statistical Geography Standard (ASGS) from Australian Bureau of Statistics (ABS) [43], three types of geographical divisions from large to small are selected which are Local Government Area (LGA), Postal Areas (POAs) and State Suburbs (SSCs).

- **Local Government Area (LGA)**

  LGA is a geographical area under the responsibility of an incorporated local government council, or an incorporated indigenous government council. The boundary for Local Government Areas is composed of distribution of whole Mesh Blocks [44]. Figure 3.4 shows the density of total order demand in four months at Local Government Area (LGA) level. It can be seen that the closer to the inner suburb Sydney, the more demand for orders.

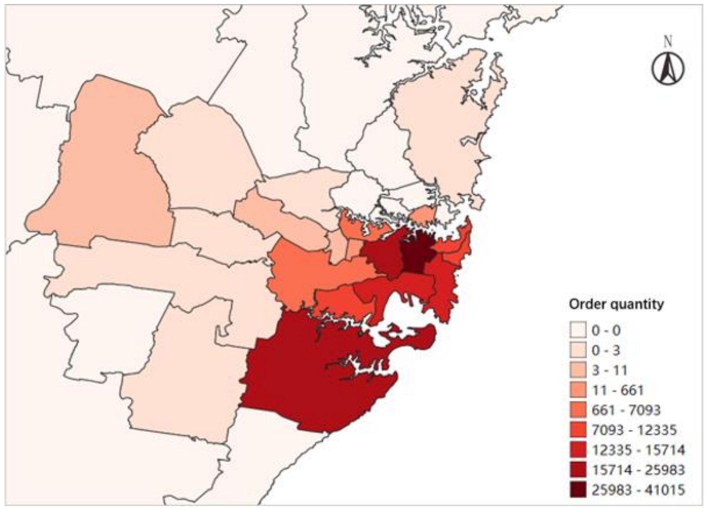


Figure 3. 4: Choropleth Map at Local Government Area (LGA) level

- **Postal Areas (POAs)**

POAs are an approximation of postcodes by ABS, which are created to enable the release of ABS data on areas that, as closely as possible, approximate postcodes. The name of POAs area is defined as the postcode with four- digit number [45]. Figure 3.5 demonstrates the density of total order demand in four months at POAs level. It is clear to see that the number of areas within the geography standard of POAs is more than that within the geography standard of LGA.

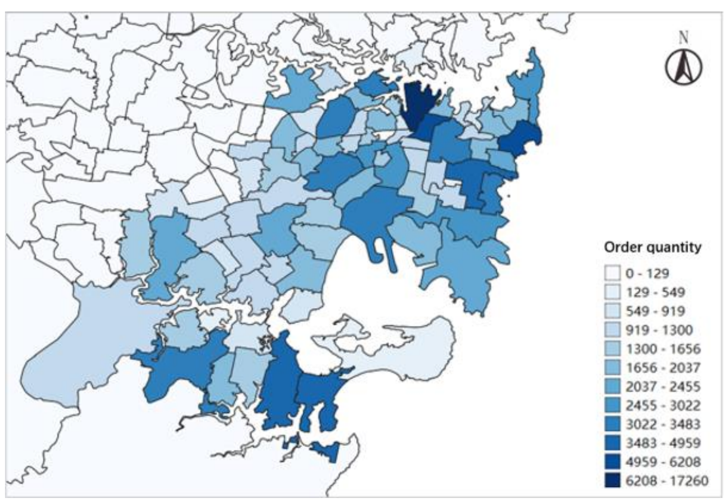


Figure 3. 5: Choropleth Map at Postal Areas (POAs) level

- **State Suburbs (SSCs)**

SSCs are an ABS approximation of gazetted localities, created by allocating one or more Mesh Blocks. For State Suburbs, 'Suburb' includes both suburbs in urban areas and places in rural and remote areas of Australia (suburbs in Australia are purely geographical, not political, divisions) [46]. Figure 3.6 shows the density of total order demand in four months at SSCs level. It is obvious that the number of areas within the geography standard of SSCs is the greatest among three geography standards.

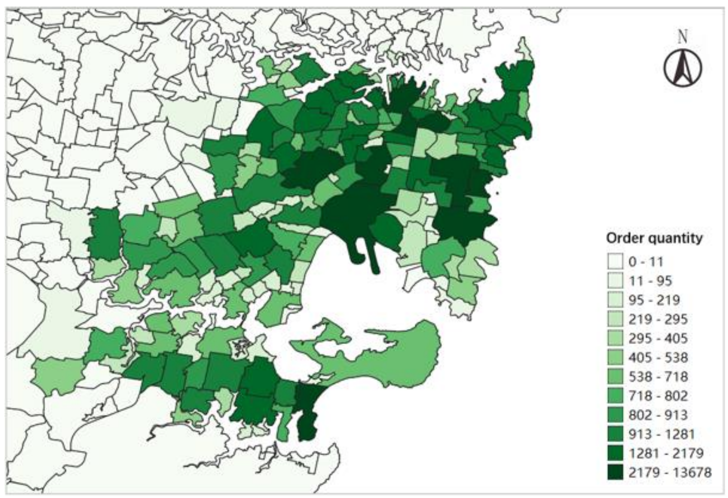


Figure 3. 6: Choropleth Map at State Suburbs (SSCs) level

Overall, Sydney and its surrounding areas are divided according to LGA, POAs and SSCs. Choropleth maps in this section were implemented in QGIS, which is an across-platform desktop geographic information system (GIS) application [47]. Table 3.1 shows the statistics summary of different Australian Statistical Geography Standard (ASGS). It can be seen that POA has the largest daily order demand and average area with smallest number of districts, while SSC has the lowest daily order demand and average area with greatest number of districts.

Geographical divisions	Number of Districts	Average area (square kilometres)	Time_flag (1=AM, 2=PM)	Average daily order demand
LGA	12	62.18	1.500806	65
POAs	78	4.91	1.495585	10
SSCs	178	2.15	1.485175	5

Table 3. 1: Statistics summary of different Australian Statistical Geography Standards

3.3.2 Spatial Autocorrelation

To explore the autocorrelation of logistics delivery demand among different areas in Sydney, global Moran' I was implemented for different geography standards. Table 3.2 shows the results of global Moran's I for LGA, POAs and SSCs. It can be seen that the values of the Moran's I for all geography standards calculated here are above zero, which suggests positive autocorrelation with clustered distribution in demand. In addition, the statistical significance of the result was tested by p-value. It seems that there is 99% confidence that the level of autocorrelation is not owing to chance because the values of p-value are all below 0.01. Thus, At the LGA, POAs and SSCs level, delivery demand displays significantly positive autocorrelation in Sydney.

Global Moran's I	Moran's Index	z-score	p-value	Autocorrelation result	Distribution
LGA	0.420258	3.7573	0.0002	Positive autocorrelation	Clustered
POAs	0.205805	4.0558	0.0005	Positive autocorrelation	Clustered
SSCs	0.256622	7.0782	0	Positive autocorrelation	Clustered

Table 3. 2: Results of Global Moran's I for different Australian Statistical Geography Standards (ASGS)

Furthermore, the value of the Moran's I statistic at the LGA level of 0.42 is much higher than the value observed at the POAs and SSCs level, which indicates that the degree of observed autocorrelation is greatest at LGA level. However, possible values of Moran's I range between roughly -1 and 1. The value of the Moran's I statistic at the LGA, POAs and SSCs level are all not close to 1 which presents weak positive autocorrelation in demand for all geography standards. This result may affect the performance of CNN algorithm for demand prediction, as CNN method takes into account the situation that a polygon is influenced by other adjacent polygons. The stronger the spatial autocorrelation in demand, the better the performance of demand prediction using CNN algorithm.

3.3.3 Data Transformation

Predicting demand in this project related to time component, spatial component and the actual demand. Time and spatial aggregations are determined in previous sections. However, the original dataset only contains every single delivery completed by a delivery van without actual demand. Thus, a new variable was created which is denoted as order demand. To achieving this, the number of daily single delivery was aggregated and then decomposed by the combination of different time and geography standards.

The above data transformation was conducted by ArcMap, which is a geospatial processing software and is used typically to view, edit, create, and analyse geospatial data [48]. Three main functions were utilized in ArcMap to implement data transformation which contained 'define projection (data management)', 'Join and relates' and 'summary statistics (Analysis)'.

The original one dataset was transformed to three datasets based on three geography standards consisted of LGA, POAs and SSCs. New structure of data in each dataset is shown as follow:

Area name: The name of districts based on its own geography standard in each dataset.

Date: Actual arrival date to customer address.

Time flag: Identification of shift (am or pm)

Order demand: The quantity of order demand for a given time at a given area.

3.3.4 Standardization

Standardization was implemented before predicting demand. The first reason is that data for different areas in each dataset have different scales. For example, at the LGA level, order demand in inner west Sydney is far greater than that in Burwood area. In addition, the second reason is that each dataset for different geography standards also have different scale. For example, average daily order demand for areas at LGA level is 65, which is much larger than that for areas at POAs level with only 10 in average. Thus, standardizing order demand for each dataset can unify the scale of order demand for different geography standards, which can be used to compare the RMSE of demand prediction at LGA, POAs and SSCs level and further choose an optimal geography standard with best performance. Standardization can be estimated as equation (3.1):

$$z = \frac{x_i - \mu}{\sigma} \tag{3.1}$$

In equation (3.1), x_i is order demand in each area for different geography standards. μ is the average demand for each area; and σ is the standard deviation of demand for each area. For example, Sydney has 10 areas at LGA level and dataset covers 111 days of delivery demand. Thus, the data structure after standardization is a matrix of 10*111.

Comparing to training models in each area for a geography standard, it is better to standardize all areas for a geography standard and use all data to train the model because it allows a larger amount of data which may improve the performance of prediction models. Besides prediction of standardized demand, predicted value of original observations was also calculated in a practical sense. To achieving this, indices were given to data after original order demand was standardized. Then, after training the model and obtaining the predicted value of testing data of standardized demand, original observations and their predicted values can be acquired by restoring standardized data with the function of 'test value* standard deviation+ mean' and 'predicted value* standard deviation+ mean' for previous given indices of data. Ultimately, predicted value of original observations can be captured.

3.4 Prediction Model

In this section, the procedure of conducting models for demand prediction are discussed, which consists of ARIMA, Convolutional Neural Network and Long-Short Term Memory Network.

3.4.1 Autoregressive Integrated Moving Average (ARIMA)

Before training data with ARIMA model, time series data should firstly guarantee its stationary. To ensure time series to be stationary, both the rolling statistics including mean and standard deviation should remain time invariant or constant with time. Thus, in order to test whether the data is stationary or not, Augmented Dickey–Fuller test (ADCF) was conducted. Table 3.3 shows the results of Augmented Dickey–Fuller test, it can be seen see that p-value is below 0.05 and, in the meantime, critical values at 1%,5% and 10% confidence intervals are close to the test statistics. Hence, it can prove that the time series at the moment is stationary. If the data is checked to be not stationary, the method of difference can be applied to make it stationary.

Results of Dickey Fuller Test	
Test Statistic	-4.559875
p-value	0.000153
Critical Value (1%)	-3.498198
Critical Value (5%)	-2.891208
Critical Value (10%)	-2.582596

Table 3. 3: Results of Augmented Dickey–Fuller test

After confirming the data is stationary, Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots are created to find value of P and Q for ARIMA. Figure 3.7 and 3.8 displays ACF and PACF plot respectively. The value of Q can be estimated from ACF and P can be determined from PACF, for which value in x-axis, graph line drops to 0 in y-axis for 1st time. After obtaining approximate values of P and Q, the exact values of P and Q can be captured by a function of arma order selection in python. The ultimate values of P and Q can be determined, in which their combination reach the lowest AIC (Akaike information Criterion) or BIC (Bayesian information Criterion).

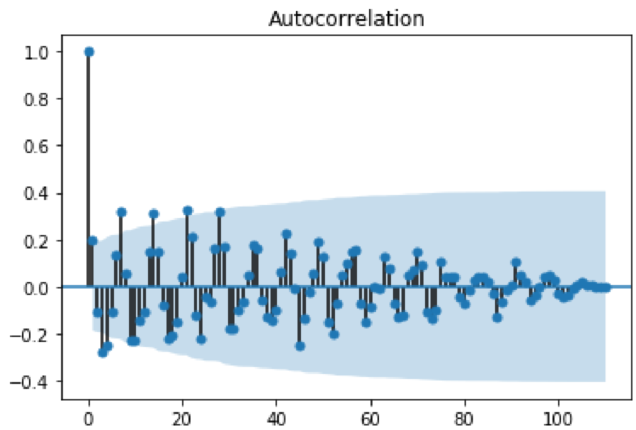


Figure 3. 7: Autocorrelation Function (ACF) plot

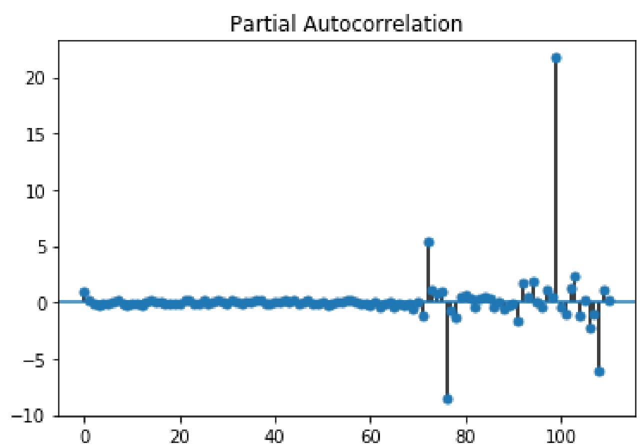


Figure 3. 8: Partial Autocorrelation Function (PACF) plot

After, determining values of P and Q, the ARIMA model can be built to fit the training set and the demand predicting for testing set was smoothly implemented. Delivery demand from 3rd July to 6th October for each area at different geography standards was used as training set and the rest 15 days data was treated as testing set. The procedures illustrated for ARIMA model above were conducted for all three datasets.

3.4.2 Convolutional Neural Networks (CNNs)

CNN algorithm takes into account the situation that a polygon may be influenced by other adjacent polygons. Therefore, CNN is an effective method for solving this spatial-temporal prediction problems.

In previous studies that predict sequence by neural networks, the researchers used to consider the specific area and forecast according to the historical data at this area. Prediction was essentially made on a basis of the time dependency among historical data. In this investigation, it is considered that x_t is a vector denoting demand data at time t for P sub-areas. The input to CNN network is a Q-term series of x_t's, which indicates a matrix x_t with size of P*Q. Thus, the proposed structure could forecast the demand over a large area not only according to spatial data correlations, but also according to temporal data dependencies.

The key idea of this method is to present Q number of historical data with P sub-areas to the network as P*Q matrix. The input matrix with size of P*Q firstly went through the convolutional layer. Then, the output of the convolutional layer fed into a pooling layer to distil the output of the convolutional layer to the most salient elements [49]. This was followed by a flatten layer to reduce the feature maps to a single one-dimensional vector. The next step was to flow to two dense layers that represents the features extracted by the convolutional part of the model.

Furthermore, a loss function is indispensable to have the procedure learn to reach the target value in the training process. Therefore, mean squared error (MSE) was applied as the loss function. Moreover, early stopping callbacks of keras was applied to restore model weights from the end of the best epoch where monitor was set as val_loss and patience was set as 20. After model construction, the model was trained in the training set and the performance of demand prediction can be obtained in the testing set. As for the division of dataset, delivery demand from 3rd July to 6th October for each area at different geography standards was used as training set and the rest 15 days data was treated as testing set.

3.4.3 Long-Short Term Memory Networks (LSTMs)

LSTM is essentially designed to avoid the long-term dependency problem and it has great performance on solving various problems. Compared with the mathematical method in demand prediction problem [50], LSTM is better suited for the time series forecasting.

In this project, it is considered that x_t is a vector denoting demand data at time t for P sub-areas. The input to LSTM network is a Q-term series of x_t 's, which indicates a matrix x_t with size of P*Q. LSTM was implemented by Keras which is a high-level API to build and train deep learning models. The input matrix with size of P*Q firstly fed into the LSTM layer.

In addition, a dropout layer was applied to process the output of the LSTM network to avoid overfitted prediction. The overfitting can lead to very high performance in training set but very low performance in testing set [51]. Thus, it is necessary to use dropout layer to prevent model from overfitting. Dropout layer can randomly ignore certain neurons during the training process of neural networks, which could effectively reduce the overfitting scenario. In this research, the dropout rate was set as 0.2 for both input dropout and recurrent dropout.

Furthermore, mean squared error (MSE) was employed as the loss function to have the procedure learn to reach the target value in the training process. In addition, early stopping callbacks of keras was applied to restore model weights from the end of the best epoch where monitor was set as val_loss and patience was set as 20. Then, the model was trained in the training set and the performance of demand prediction can be obtained in the testing set.

3.5 Chapter 3 Summary

In this chapter, the dataset used in this project was described and exploratory data analysis was conducted to find some informative and interesting insights. This was followed by data pre-processing section, which consisted of spatial aggregation, spatial autocorrelation, data transformation and standardization. Spatial aggregation according to three geographical standards were determined including Local Government Area (LGA), Postal Areas (POAs) and State Suburbs (SSCs). In addition, spatial autocorrelation was implemented to check the distribution state of delivery demand and found a weak positive autocorrelation in demand for all geography standards. Besides spatial aggregation and autocorrelation, order demand was created as a new variable and dataset was transformed to different structure based on three types of geographical division. Furthermore, standardization was implemented to unify the scale of order demand for different geography standards. Finally, the procedure of conducting models for demand prediction were discussed including ARIMA, CNN and LSTM algorithm.

Chapter 4

4 Results and Discussion

In this chapter, the results of delivery demand prediction are explained and discussed. This chapter is divided into four sections. The first part is about results of demand prediction for different geography standards. The second part is about evaluation of spatial aggregation impact on demand prediction. The third part compares different prediction methods. Finally, the last section discusses the business influence and value of accurate demand prediction.

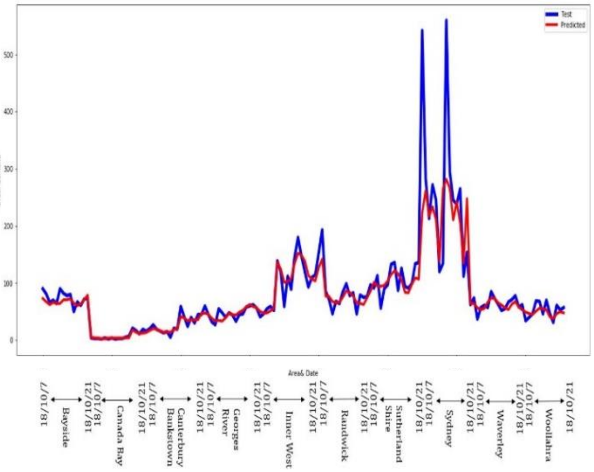
4.1 Results of Prediction for Different Geography Standards

In this section, results of demand prediction for different geography standards are evaluated, which consists of performance of prediction at LGA, POAs and SSCs level respectively.

4.1.1 Performance of Demand Prediction at LGA Level

- ARIMA

  Firstly, ARIMA was applied to predict logistics delivery demand at LGA level. Sydney and its surrounding areas are divided into 10 areas at LGA level, which contains Bayside, Canada Bay, Canterbury-Bankstown, Georges River, Inner West, Randwick, Sutherland Shire, Sydney, Waverley and Woollahra. Figure 4.1 and 4.2 show the testing set result of order demand prediction at LGA level in the am and pm respectively. It can be seen that y axis refers to order demand and x axis is area with date, which indicates 10 areas at LGA level with their 15 days of testing dates for each area. Blue line in figures represents testing data and red line indicates predicted values of observations. It seems that the predicted value of demand generally follows the pattern of values of testing data. The exact value of RMSE for performance comparison will be demonstrated in the next 4.2 section.



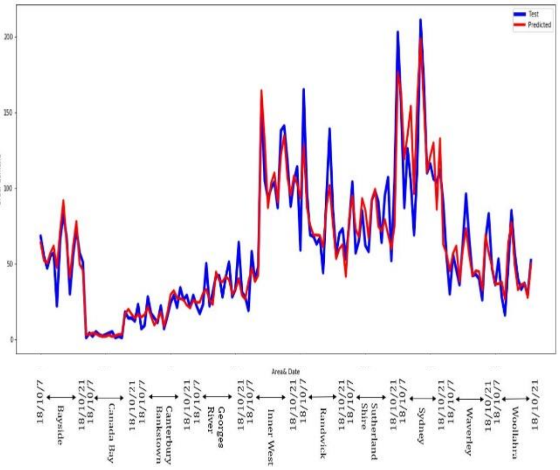


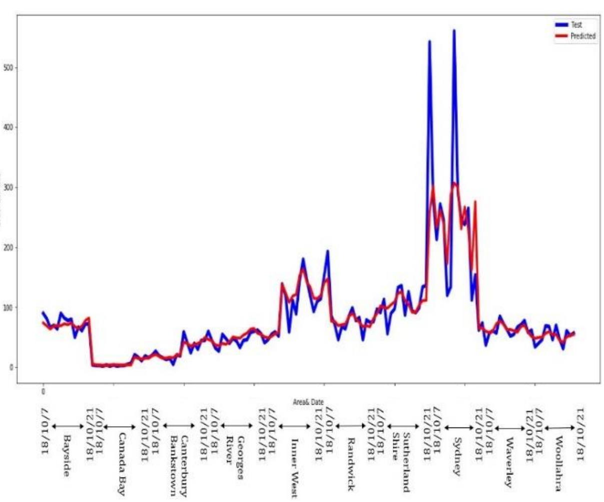
Figure 4.1 Figure 4.2

Figure 4. 1: Testing set result of demand prediction at LGA level in the AM

Figure 4. 2: Testing set result of demand prediction at LGA level in the PM

- CNN

Secondly, CNN algorithm was used to forecast delivery demand at LGA level. Figure 4.3 and 4.4 display the testing set result of order demand prediction at LGA level in the am and pm respectively. It is clear to see that CNN may be well-suited to solve this demand prediction problem since the performance of predicted value for testing set shown in the figures below looks good.



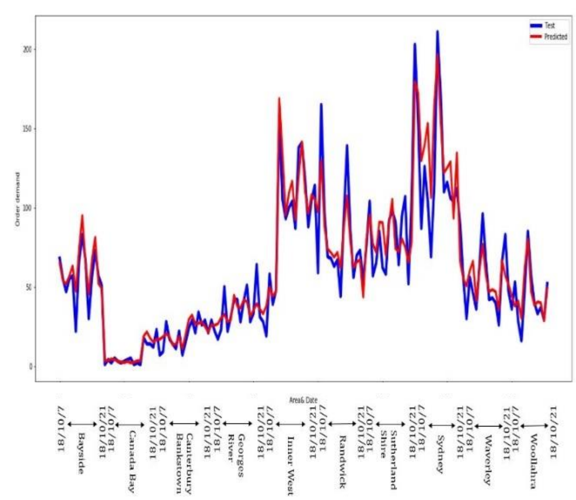


Figure 4.3 Figure 4.4

Figure 4. 3: Testing set result of demand prediction at LGA level in the AM

Figure 4. 4: Testing set result of demand prediction at LGA level in the PM

- LSTM

Finally, LSTM model was also employed to predict delivery demand at LGA level. Figure 4.5 and 4.6 present the testing set result of order demand prediction at LGA level in the am and pm respectively. It seems that the performance of predicted demand using LSTM is better than that by ARIMA and CNN method as the line of predicted demand in the below figures better fits the line of testing data.

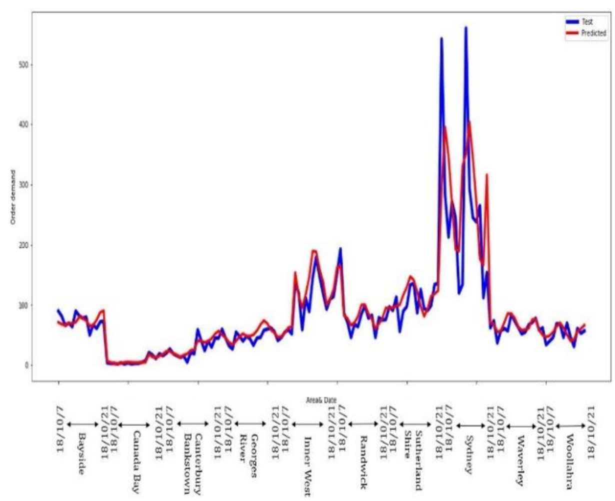


Figure 4.5

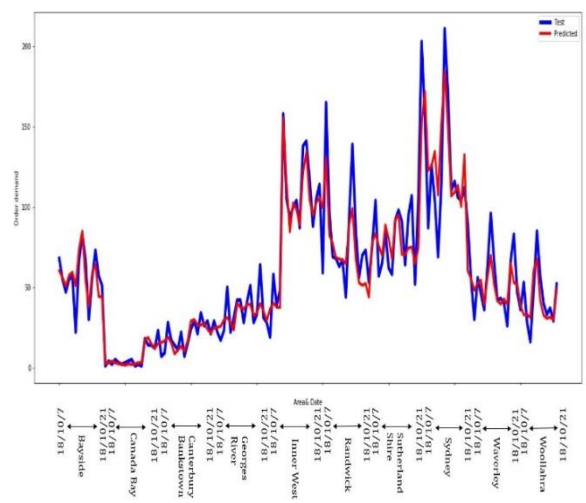


Figure 4.6

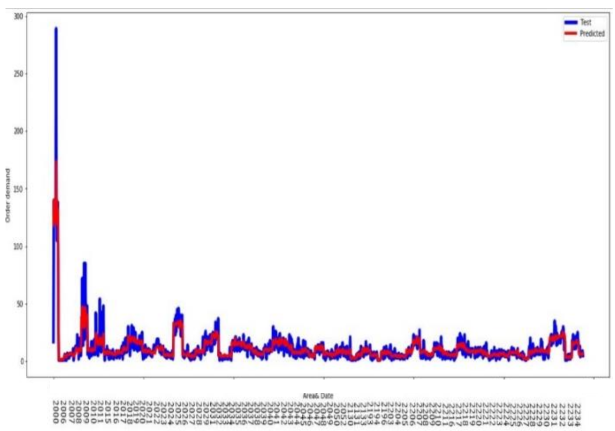
Figure 4. 5: Testing set result of demand prediction at LGA level in the AM

Figure 4. 6: Testing set result of demand prediction at LGA level in the PM

4.1.2 Performance of Demand Prediction at POAs Level

- ARIMA

Firstly, ARIMA was used to predict logistics delivery demand at POAs level. Area name at POAs level is postal code with four digits. Sydney and its surrounding areas are split into 78 areas at POAs level, such as 2000, 2006, 2024, 2047, 2133, 2227 and 2234. Figure 4.7 and 4.8 demonstrate the testing set result of order demand prediction at POAs level in the am and pm respectively. In these figures, y axis refers to order demand and x axis is area with date, which indicates 78 areas at POAs level with their 15 days of testing dates for each area. It can be seen that predicted value has a similar trend with order demand in testing set.



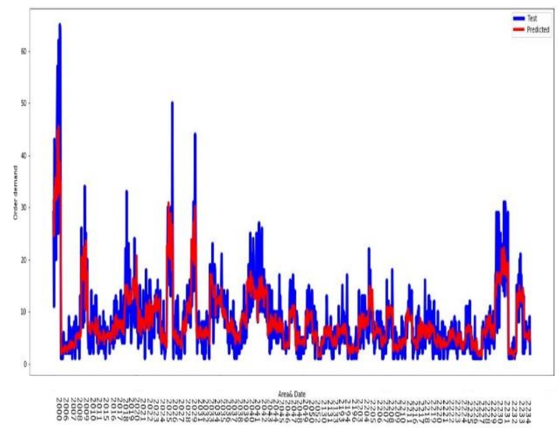


Figure 4.7

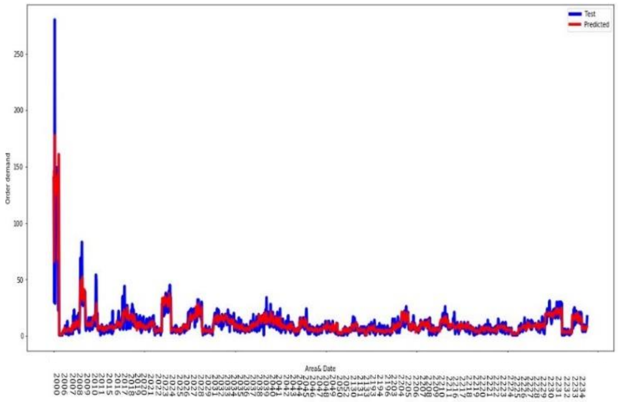
Figure 4.8

Figure 4. 7: Testing set result of demand prediction at POAs level in the AM

Figure 4. 8: Testing set result of demand prediction at POAs level in the PM

- CNN

In addition, CNN mothed was applied for delivery demand prediction at POAs level. Figure 4.9 and 4.10 show the testing set result of order demand prediction for spatial-temporal aggregation at POAs level in the am and pm respectively. It is clear to see that predicted delivery demand overall follows the variation of observations.



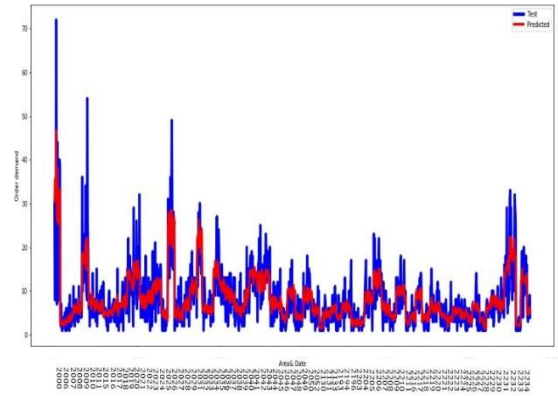


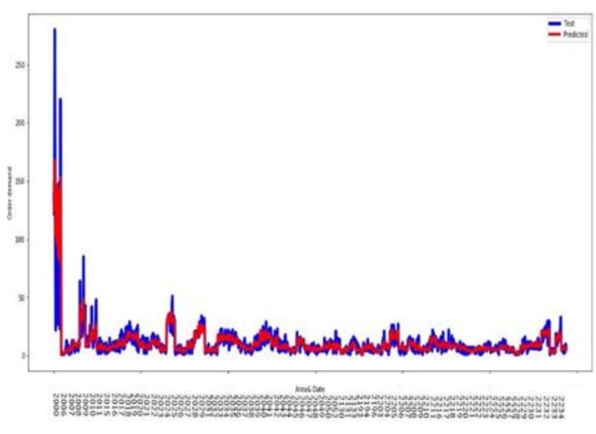
Figure 4.9 Figure 4.10

Figure 4. 9: Testing set result of demand prediction at POAs level in the AM

Figure 4. 10: Testing set result of demand prediction at POAs level in the PM

- LSTM

Furthermore, LSTM model was as well employed to forecast delivery demand at POAs level. Figure 4.11 and 4.12 display the testing set result of order demand prediction at POAs level in the am and pm respectively. It seems that LSTM model has a great performance on demand prediction at POAs level as predicted order demand is close to actual demand.



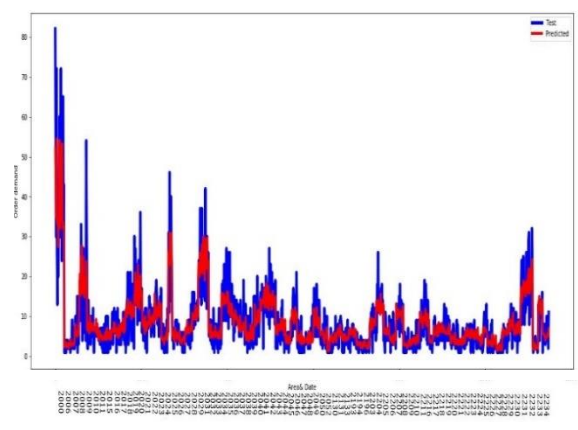


Figure 4.11 Figure 4.12

Figure 4. 11: Testing set result of demand prediction at POAs level in the AM

Figure 4. 12: Testing set result of demand prediction at POAs level in the PM

4.1.3 Performance of Demand Prediction at SSCs Level

- ARIMA

Firstly, ARIMA was utilized to forecast delivery demand at SSCs level. Sydney and its surrounding areas are split into 178 areas at SSCs level, such as Abbotsford, Balmain East, Cronulla, Dulwich Hill, Kyle Bay, Pyrmont and Zetland. Figure 4.13 and 4.14 present the testing set result of order demand prediction at SSCs level in the am and pm respectively. It is clear that y axis refers to order demand and x axis is area with date, which indicates 178 areas at LGA level with their 15 days of testing dates for each area. It is obvious that predicted order demand has a similar trend with value of testing data.

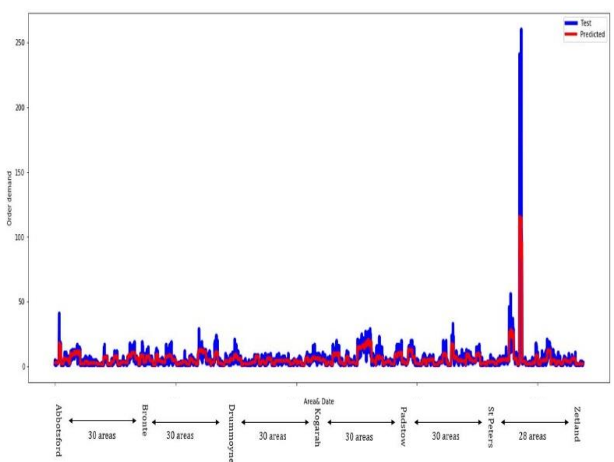


Figure 4.13

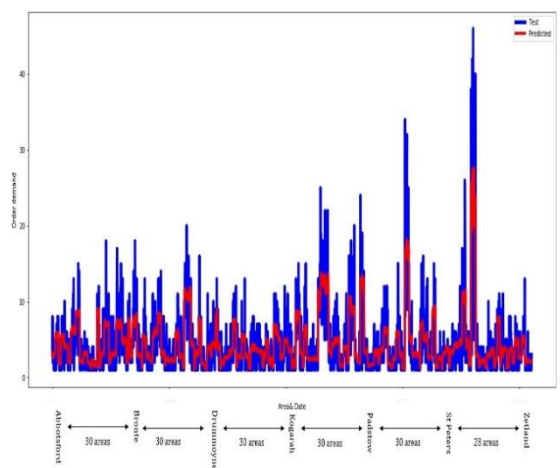


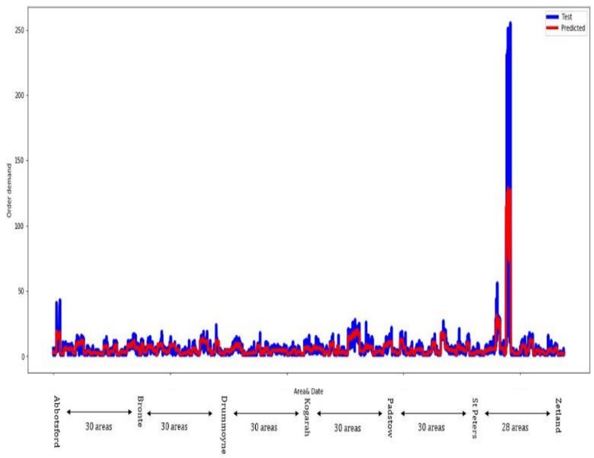
Figure 4.14

Figure 4. 13: Testing set result of demand prediction at SSCs level in the AM

Figure 4. 14: Testing set result of demand prediction at SSCs level in the PM

- CNN

Secondly, CNN algorithm was employed for order demand prediction at SSCs level. Figure 4.15 and 4.16 show the testing set result of order demand prediction for spatial-temporal aggregation at SSCs level in the am and pm respectively. It seems that predicted delivery demand generally follows the pattern of observations.



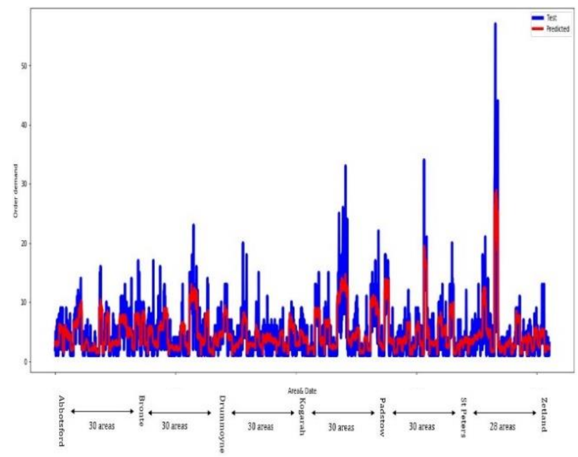


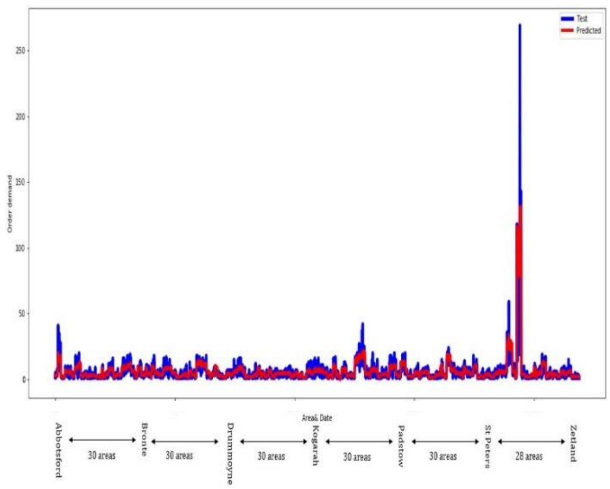
Figure 4.15 Figure 4.16

Figure 4. 15: Testing set result of demand prediction at SSCs level in the AM

Figure 4. 16: Testing set result of demand prediction at SSCs level in the PM

- LSTM

Moreover, LSTM model was also applied to forecast delivery demand at SSCs level. Figure 4.17 and 4.18 demonstrate the testing set result of order demand prediction for spatial-temporal aggregation at SSCs level in the am and pm respectively. It can be seen that LSTM is also well-suited to address this demand forecasting issue as the performance of predicted demand for testing set shown in the figures below is quite well.



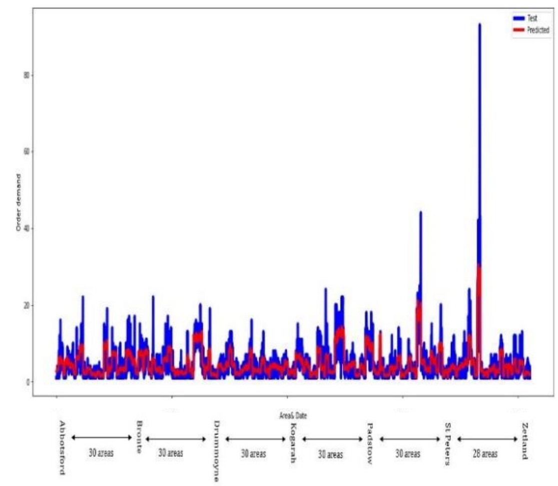


Figure 4.17 Figure 4.18

Figure 4. 17: Testing set result of demand prediction at SSCs level in the AM

Figure 4. 18: Testing set result of demand prediction at SSCs level in the PM

4.2 Evaluation of Spatial Aggregation impact on demand prediction

This section evaluates different spatial aggregation impact on demand prediction and finds the most suitable spatial aggregation from LGA, POAs and SSCs. Table 4.1 shows the comparison of spatial aggregation impact on demand prediction. Average RMSE in below table indicates the mean of prediction error for ARIMA, CNN and LSTM algorithm at LGA, POAS and SSCs level respectively. RMSE of the prediction models for standardized demand was used to compare the spatial aggregation impact because the scales of demand at different geography standards were unified after standardization and can be capable of comparison. As seen in the table 4.1, the average RMSE of delivery prediction models is greatest at LGA level with 1.1766, while RMSE reaches the lowest at SSCs level with 1.0186. Hence, in order to predict the demand more accurately, SSCs is chosen as the most efficient solution of spatial aggregation.

RMSE (standardized demand)	LGA	POAs	SSCs
ARIMA	1.1786	1.0496	1.0279
CNN	1.1758	1.0461	1.0157
LSTM	1.1754	1.0228	1.0121
Average RMSE	**1.1766**	**1.0395**	**1.0186**

Table 4. 1: Comparison of spatial aggregation impact on demand prediction

4.3 Comparison of Different Prediction Methods

In order to determine the optimal method, the results and performance of different prediction methods conducted in this project are compared using RMSE as evaluation criterion. Table 4.2 presents comparison of ARIMA, CNN and LSTM model results. Average RMSE in below table indicates the mean of prediction error for LGA, POAS and SSCs level using ARIMA, CNN and LSTM algorithm respectively. It can be seen that the performance of ARIMA model is worst with highest average RMSE at 1.0854, while the performance of LSTM model is best with lowest average RMSE at 1.0701. In addition, average RMSE for CNN algorithm is larger than LSTM and smaller than ARIMA model. Therefore, it can be concluded that the optimal method for demand prediction in this study is LSTM model.

RMSE (standardized demand)	LGA	POA	SSC	Average RMSE
ARIMA	1.1786	1.0496	1.0279	**1.0854**
CNN	1.1758	1.0461	1.0157	**1.0792**
LSTM	1.1754	1.0228	1.0121	**1.0701**

Table 4. 2: Comparison of ARIMA, CNN and LSTM model results

The reason why LSTM is the optimal model in this project may be because an LSTM network with two-dimensional input can discover the spatial-temporal correlation among delivery request occurrences and utilize this correlation to make efficient demand forecasts. As for CNN algorithm, the performance of demand prediction using CNN is worse than that using LSTM. This may result from weak spatial autocorrelation in demand for all three geographical standards. CNN method takes into account the situation that a polygon is influenced by other adjacent polygons. The performance of demand prediction applying CNN algorithm may be better if the spatial autocorrelation is stronger in demand. In the case of ARIMA, the performance of demand prediction using ARIMA is less effective than that using CNN and LSTM. The reason why prediction results employing ARIMA is the worst is that non-linear patterns are difficult to capture using ARIMA model, which can be extracted by CNN and LSTM algorithms.

4.4 Business Impact and Value

Previous sections discuss about how to predict logistics delivery demand more accurately and the result is to predict demand at SSCs level by LSTM model. Accurate demand prediction can lead to a variety of business values. Firstly, efficient demand prediction has a positive influence on route planning for vans. The delivery route is based on requirements of the place, time and demand. Thus, an accurate forecast of order demand might benefit to route planning.

Moreover, the real cost of servicing a reservation at the time the customer is booking it can be estimated according to the order demand for given time at given areas. Knowing the marginal cost of servicing a customer reservation is quite useful. It allows the routing and scheduling system to know whether a delivery can be fitted within an existing schedule within a given time slot, without breaking vehicle capacity or working regulations. Then the system knows whether or not it can offer that time slot to the customer. In addition, it enables the system to find which slot is the cheapest, among all the possible slots within which the delivery could be placed. This is at the core of the optimisation algorithm and allows the schedules to be made efficient by minimising their overall cost. Getting better estimates for the real cost of deliveries would enable the optimisation algorithm to make more informed choices as to where to place reservations in the schedule as it is being built. Furthermore, the business can give incentives to customers to choose a time when their delivery is the most cost effective. For instance, customers can be charged a premium for time slots during which their delivery has a high cost compared to other available slots, which may direct them towards slots where the business can service the delivery at a lower cost.

4.5 Chapter 4 Summary

In this chapter, the results of delivery demand prediction were explained and discussed. Firstly, the results of demand prediction for different geography standards and spatial aggregation impact on demand prediction were evaluated. It indicated that the performance of demand prediction was greatest when forecasting at SSCs level. Moreover, different prediction methods were compared and LSTM was proved to be the optimal model for demand prediction. Finally, this chapter also discussed the business influence and value of accurate demand prediction, which consisted of improvement of route planning and delivery time.

Chapter 5

5 Conclusion

The following chapter is split into two sections including summary and further work. The first section is to recap and summarize the objectives, procedure and results of this project. As for the second section of this chapter, the planed follow ups to the project and possible extensions to the research are discussed.

5.1 Summary

In conclusion, the purpose of this project is to explore different possibilities for spatial and temporal aggregation in order to predict demand accurately and select the optimal method after comparing the performance of different prediction methods. To attain effective results, ARIMA, CNN and LSTM methods are applied with depot schedule data in Sydney and its surrounding areas from 3rd July to 21th October 2018. Predicting demand in this case is a three-dimensional problem as it consists of a time component, a spatial component and the actual demand. This paper pays more attention to spatial aggregation demand impact on demand prediction. Three geography standards are used, which consists of LGA, POAs and SSCs.

In order to gain effective results on the investigated topic, the research procedure was implemented as follows. Firstly, a variety of related literatures were reviewed to deepen the understanding of spatial-temporal demand prediction problem, and find the feasibility of estimating the spatial aggregation impact on demand prediction. Secondly, background was discussed to explain technical information and machine learning algorithms applied in this thesis. Then, exploratory data analysis was conducted to find some interesting insights. Next step was spatial aggregation. In this study, three geographical standards were selected for spatial aggregation which consisted of Local Government Area (LGA), Postal Areas (POAs) and State Suburbs (SSCs). This was followed by data creation and transformation, which were implemented by aggregating number of daily single delivery for given time at given areas. After this stage, appropriate methods for demand prediction were chosen to achieve the objective of the project. ARIMA, CNN and LSTM were employed to solve demand prediction problem. Final step was to run the methods above using transformed data to examine the spatial aggregation impact on demand prediction.

After completing above procedures, some interesting results were found. Firstly, in order to predict the logistics delivery demand more accurately, SSCs is chosen as the most efficient solution of spatial aggregation. Secondly, the optimal method for demand prediction in this study is LSTM model. In addition, the analysis performed in this thesis can also benefit to delivery time improvement, route planning for vans and schedule system improvement. Overall, forecasting delivery demand at SSCs level by LSTM model can obtain the most accurate demand prediction.

5.2 Further Work

After obtaining accurate delivery demand prediction, serval further works are still planned to implement for research extension in the future. Firstly, dynamic pricing of window slot can be further explored because pricing of time slots is greatly affected by demand of the area where the order is being made. Thus, accurately predicting demand can inform window pricing which can be applied in real business world.

In addition, shorter time segment can be conducted in the future research. The study completed in this thesis pays more attention to spatial aggregation and only divide time window into am and pm time slot. Hence, for further investigation, time slot can be split much shorter. For example, daytime can be divided into six parts on a basis of two hours timeslot.

Finally, in practice, the prediction result of the order demand can be the basis for constructing the logistics route. The logistics route is based on requirements of the place, time and demand. Therefore, for further application, an accurate prediction of delivery demand can be utilized to plan routes for vans and further improve the delivery system.

5.3 Chapter 5 Summary

This chapter firstly recapped the objectives and methodology used in this research. Then, the research procedure to capture effective results on the investigated topic was summarized. This was followed by the research results, which consisted of the evaluation of spatial aggregation impact on demand prediction, comparison of different prediction methods and the business values of accurate demand prediction. Finally, further works planned to conduct were discussed including pricing of window slot, shorter time segment and logistics route formulation.

Appendices

Appendix A: Exploratory data analysis

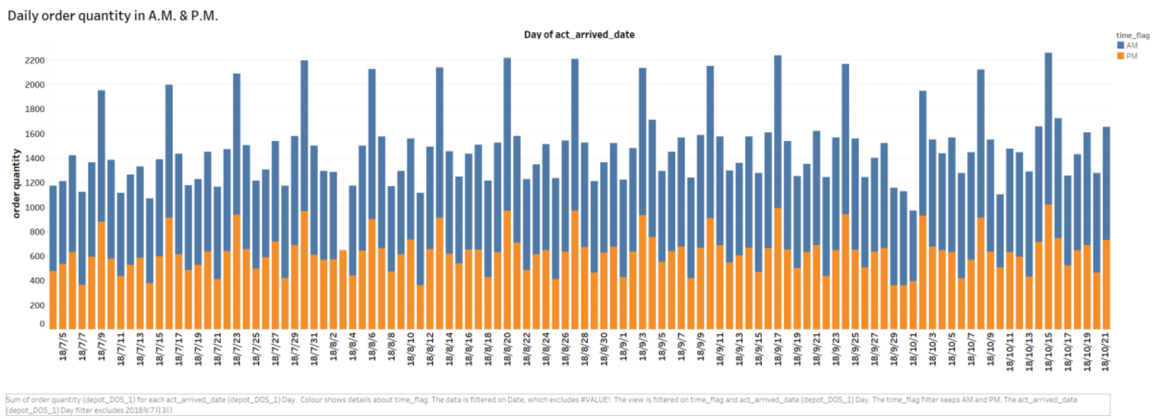


Figure A. 1: Daily order quantity in AM and PM from 3rd July to 21th Oct. in 2018

	month			
time_flag	7	8	9	10
AM	23,325	25,380	26,318	18,163
PM	16,917	19,006	18,401	13,146

order quantity: 13,146 – 26,318

Table A. 1: Statistics of monthly order quantity in the AM and PM from July to Oct.

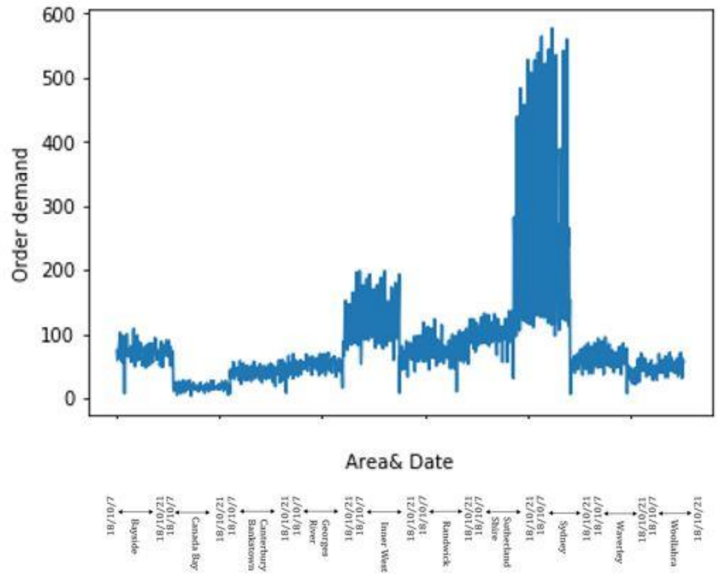


Figure A. 2: Actual demand at LGA level in the AM

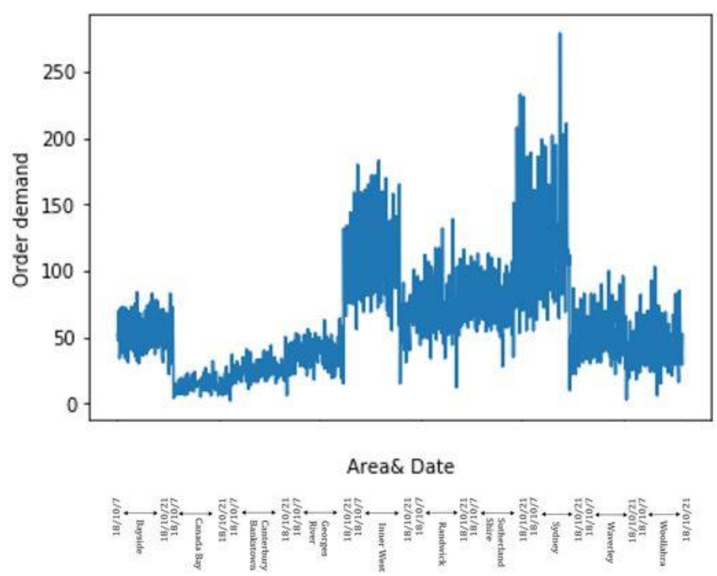


Figure A. 3: Actual demand at LGA level in the PM

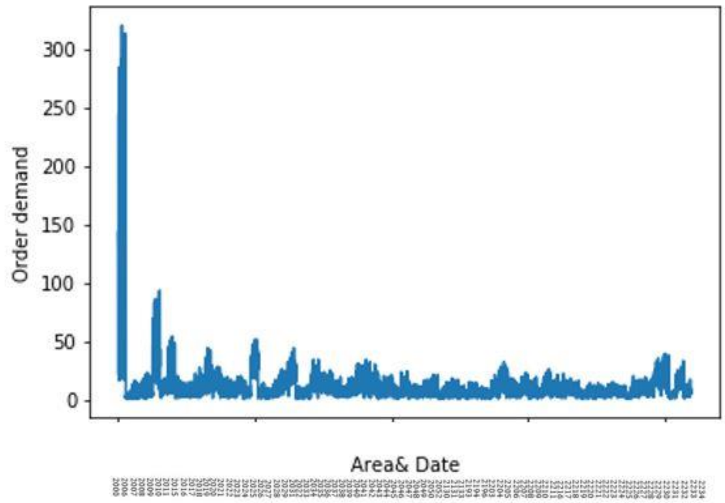


Figure A. 4: Actual demand at POAs level in the AM

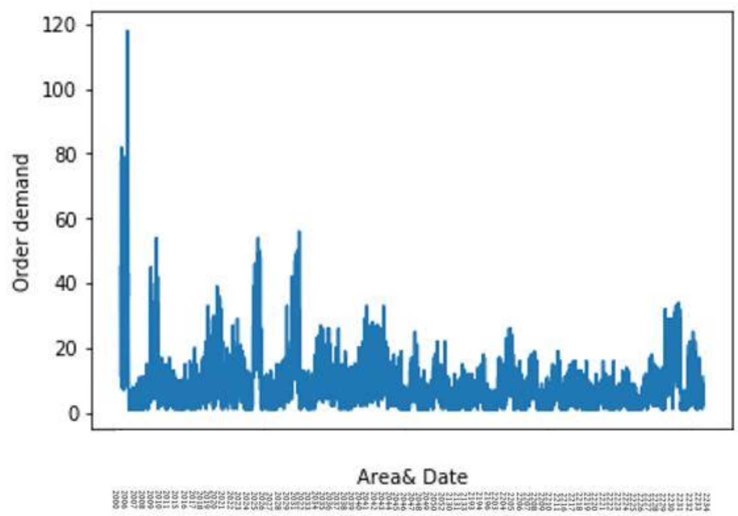


Figure A. 5: Actual demand at POAs level in the PM

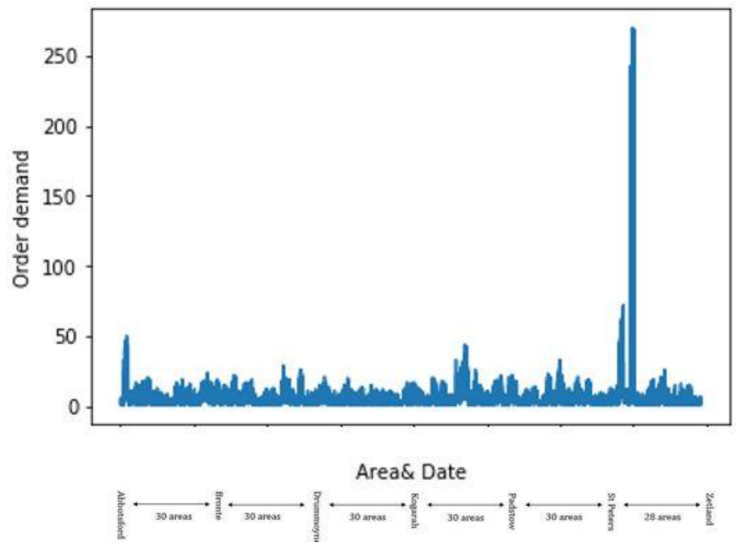


Figure A. 6: Actual demand at SSCs level in the AM

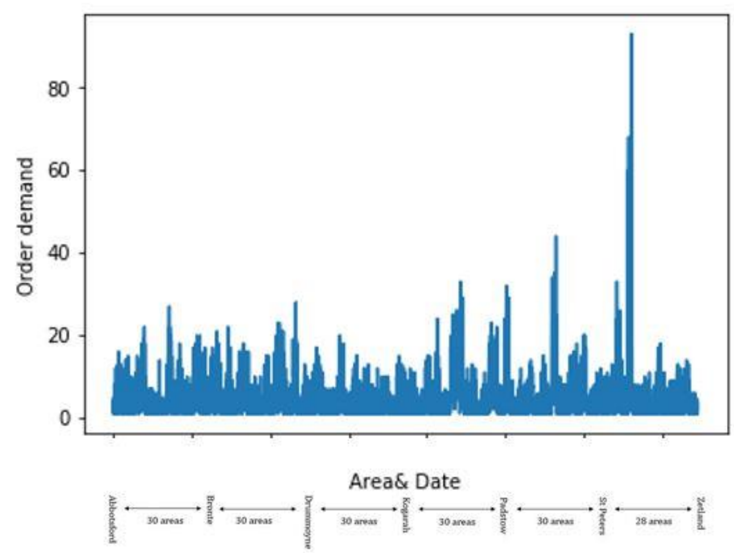


Figure A. 7: Actual demand at SSCs level in the PM

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