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Off-Street Parking Cost Forecasting Models for Southern California

THESIS

submitted in partial satisfaction of requirements

for the degree of

MASTER OF SCIENCE

In Civil Engineering

By

Biling Liu

Thesis Committee:

Professor Michael McNally

Professor R. (Jay) Jayakrishnan

Professor Wenlong Jin

2014

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ACKNOWLEDGMENTS

Apart from my efforts, the successful completion of this thesis mainly depended on the guidance and encouragement of many others. I would like to take this opportunity to express my deepest appreciation to them.

First, I would like to express my special appreciation to my thesis advisor and committee chair Professor Michael McNally for his excellent guidance, patience and rich experience in transportation planning which inspire me in the future career. I would also like to thank the other two committee members Professor Jayakrishnan and Professor Jin for their brilliant knowledge in transportation area which always leads me forward in my graduate study.

I also want to thank Dr. His-Hwa Hu and Dr. Yongping Zhang from Southern Californian Association of Governments (SCAG) for providing this topic and data for my thesis. Their guidance and encouragement during my thesis and internship provide me precious practice opportunities and help me gain further understanding in transportation modeling.

Lastly, I would like to send my most sincere appreciation to my dear parents, Mr. Jun Liu and Mrs. Aihong Lan, and also to my dear fiancé Ethan Yue Sun. Thank you all for always standing with me in my life!

ABSTRACT OF THE THESIS

Off-Street Parking Cost Forecasting Model for Southern California

By

Biling Liu

Master of Science in Civil Engineering

University of California, Irvine 2014

Professor Michael McNally, Chair

Parking cost is an important and sensitive factor in understanding travel behavior and is typically utilized in the mode choice model of regional demand forecasting models. There are various socio-economics variables that can affect the value of parking cost by employment type, time periods, and trip purposes. In this study, a set of parking cost forecasting models are developed using survey data and local socio-economic data with the objective of identifying parking cost patterns and forecasting future parking costs.

This study first summarizes methods applied in previous parking cost forecasting models. Two categories of models were estimated. The first category does not consider parking space supply as a factor in forecasting TAZ parking; the second category considers both parking space supply and parking demand as explanatory variables. For each category, using current off-street parking cost survey data, linear regression models are built for hourly, daily and monthly pricing for SCAG Tier 2 Transportation Analysis Zones (TAZ) using R and Matlab. Daily parking rates are set as the base rates to generate the hourly and monthly parking cost models. The consideration of parking demand is a major contribution of this study, with demand generated based on home-

based-work trip attractions for commuters by income groups in all models. This study found that daily parking rates can be explained by total employment, the proportion of office to total jobs, and the proportion of multiple to total households. Hourly parking cost can be explained based on daily parking rates and travel behavior associated with education, hospital, finance, entertainment and other employment types. The monthly parking cost model is built base on both daily and hourly parking rates as independent variables. Future work includes integration of on-street parking costs with the current models for off-street parking.

CHAPTER 1. INTRODUCTION

Parking is becoming a major problem in most metropolitan areas, especially in the downtown areas and employment centers. From Annual Rate Survey in 2013, over 40% respondents reported their increase demand for parking service, mainly at off-street Central Business District (CBD), universities and airports. But affected by parking spaces and other socio-economic factors, different parking price may lead to different travel behavior. Thus, more transportation planning institutes begin to take parking price as an important variable in the mode choice model to build the whole Travel Demand Model (TDM) and Activity Based Model (ABM). The charge of parking is not only use to cover the parking facilities construction and operation cost, but also considered as a strategy to control the single vehicle trip rates and balance with the trip attraction desire. Due to the inefficiency use of fuels during parking process, part of parking facilities revenue is also suggested to provide finance support to emission management and transit improvement.

In general, parking price is related to several factors, such as employment density, parking supply, parking demand, time period, trip purposes and the distance between parking facility and final destination. In all parking modes, parking is usually charged by three time periods, hourly, daily and monthly. Here hourly parking rate is set to charge the occasional parking demand. Daily and monthly parking rate is set to charge the employers' and employees' parking demand for daily commuting. In this study, Sothern California Association of Governments (SCAG) region is the study area, including six counties in southern California, and the parking data is

mainly collected from a parking information website ParkMe.com. The study objective is to build parking cost forecasting models by hourly, daily and monthly and use as a part of mode choice model in SCAG regional TDM model and ABM model.

This study totally has five chapters. The first chapter presents an introduction of parking cost study. Chapter 2 reviews the concept of parking rates, parking patterns and previous parking cost models in other transportation study institutions. Study area and available data sources for parking cost model developing are introduced in Chapter 3. Chapter 4 describes the methodology in developing parking cost model. Parking cost models developed with and without parking supply are presented in Chapter 5 and 6 independently. Finally, conclusions and future research suggestions are concluded in Chapter 5.

CHAPTER 2. LITERATURE REVIEW

This chapter provides a review of parking patterns, parking price's significance and charging methods, and also the review of previous parking cost forecasting models built by other transportation planning organizations.

2.1 General Parking Concepts

Parking is a concept comes with the development of vehicles. Actually there were no formal parking garages at the first. Thus drivers can park their vehicles for free everywhere. However, when the buildings and employments clustering in some center areas, disorganized parking always brought congestion and accident problems. Then people began to realize the need of appropriative parking place. Also, the rapid expansion of vehicle numbers leaded parking quickly become a big problem in in United States. In 1920s, some professional parking designs came out, such as car elevator and ramp system (McDonald, 2005). However, the biggest limitation of those designs was the behavior of parking can also be done with the help with profession parking attendants, but not by drivers themselves. By 1950s, modern and convenience parking garages came out and soon brought a construction boom. Nowadays, there are millions of parking garages in United States.

Normally, there are two modes of parking, on-street parking and off-street parking. On- street parking refers that vehicles can be parked on or along the sides of street. This is a convenience parking strategy and can save the cost to build professional parking garages. However, with the disadvantages of narrowing the roads effective width and more safety problems, on-street

parking always has limitation of place and parking time. Most on-street parking in downtown areas can only allow several hours parking and need to be charged by parking meters (Figure 2.1.1).



Figure 2.1.1 On-street Parking with Parking Meters in San Francisco, California (SFMTA, 2009)

The second mode of parking is off-street parking, which refers to professional parking facilities such like parking lots and parking structures (Figure 2.1.2). Off-street parking is now the major parking mode to serve the parking demand in employment centers, CBD, universities/colleges, plazas and hospitals. Compared with on-street parking, off-street parking can meet different parking time demand either by hourly, daily parking or monthly. The facilities for off-street parking can be built both underground or on the land surface, which is more flexible and safety than on-street parking. But on the other side, off-street parking often requires higher construction and operation costs.



Figure 2.1.2 Off-street Parking Lot at Metro's Universal City Red Line Station in Los Angeles, California (StreetsBlog LA, 2014)

2.2 Parking Price

Parking price is a combination price which always includes land cost, parking facility construction and operation cost (Victoria Transport Policy Institute, 2013), and also a reasonable revenue. Typically, a parking space always has a width of 8 to 10 feet and a length of 18 to 20 feet, with totally 144 to 200 square feet land area (Hunnicutt, 2003). But depending on the design, a parking space may need 100 more square feet to ensure parking safety. According to the location, the land cost of parking facilities can vary greatly. In CBD area, land cost for parking facilities can reach as high as millions of dollars per acre. But in rural areas, land cost is as low as thousands of dollars per acre. Construction cost is another important component of parking price which can be affected by different construction level, parking space design,

construction materials costs and labor costs. In 2009, an engineering consultant firm Carl Walker summarized the parking structure construction cost per parking space in the 19 major cities in United States(Figure 2.2.1), which includes two major cities in California States, Los Angeles city ($16,842 per parking space) and San Francisco City($19,253 per parking space) that both above the average rates ($15,552 per parking space).

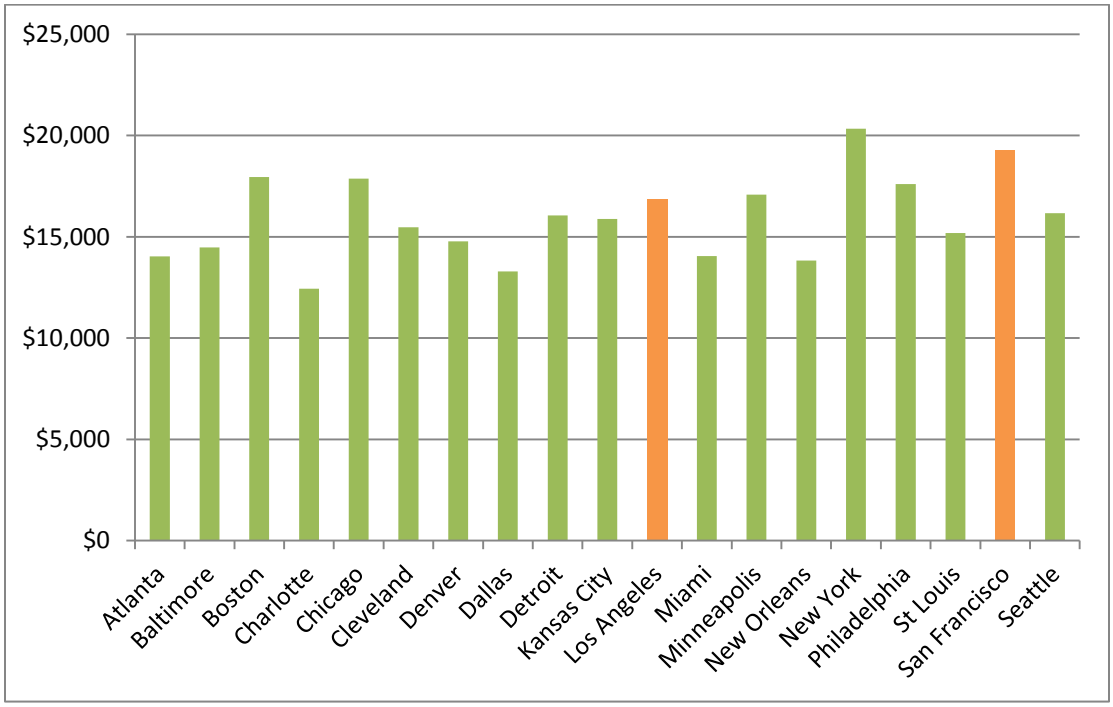


Figure 2.2.1 Parking Structure Construction Cost per Space in 19 cities in United States

Besides construction cost, operation and maintenance cost is also a necessary cost that need to be collected from parking price. In 2005, a survey shows that nearly $500 to $800 maintenance cost is requested per space (Parking Today, 2005). In addition, emission management from low speed driving in parking and appropriate revenue are also important factors in determining final parking price for parking facilities owners.

Although the construction and operation of parking garages requires big cost, but there are still lots of free parking lots existing in the state, especially clustering in shopping centers and plazas

with the objective to attract more consumer. Dr. Donald Shoup, a distinguished professor in urban planning, holds a strongly opposite opinion to free parking and summarized all his parking research in his famous publication *The High Cost of Free Parking* (Shoup, 2011). In his arguments, free parking is such a bad idea that will increase the government's burden and cause more vehicle trips. He suggests that the current parking policy need to be revised and the parking price need to be set more reasonable to meet the requirement of substantial transportation development. Thus, more transportation researchers begin to work on parking cost problems and propose several parking cost models for Transportation-oriented Development (TOD).

2.3 Previous Parking Cost Models Review

The Four-Step Model (FSM) is widely used in transportation planning since the 1950s (McNally, 2000). In the conventional FSM, the four steps are trip generation, trip distribution, mode choice, and trip assignment. Parking cost is just an important explanatory variable in mode choice models and can reflect the sensitivity of parking cost change on travel behavior. Gillen first examined the effect of parking cost on transport modal choice by using binary variable in 1977. After that, Mehranian and Wachs (1987) found that eliminating parking cost subsides was an effective method encouraging ridesharing and reducing congestion in downtown areas. In this study, a comparison between two companies was set to examine the relationship between mode choice of employees and parking cost, since employers and employees were the primary consideration of parking cost. Two later studies by Miller (1993) and Peng (1996) supported this result and concluded that the most sensitive group of people to parking cost changes are commuters. This sensitivity for parking price may finally lead to the abandon of personal trips to transit if the parking price exceeds their tolerance range (Hensher and King, 2001). From then on, more parking cost studies begin to focus on the forecasting the parking price for employment

centers and CBDs, in which commuters clustering. Most parking cost model are generated as a function of employments, socio-economic variables and land use variables. In the following paragraphs, three representative models are reviewed in details.

2.3.1 SCAG Previous Parking Cost Model

Southern California Association of Governments (SCAG) has several attempts using parking cost model. In 2002, SCAG developed a new parking cost forecasting model with the cooperation of TJKM Transportation Consultants to replace the old version that built by Caltrans in 1990 (SCAG and TJKM, 2002). This latest parking cost model was built based on SCAG socio-economic data, land use data and parking survey data in 2000 by transportation analysis zone (TAZ) level in SCAG region. For the records that with no daily price, the missing daily price was covered by:

$$\text{daily maximum} = \frac{\text{minimum price} \times \text{eight hours}}{\text{minimum times in hours}} \tag{2.1}$$

Besides generating employment density from the socio-economic data, this model also considered the level of automobile and transit accessibility of a zone as an explanatory variable. Zonal accessibility indicators were developed based on SCAG's highway and transit planning networks and calculated using the following formula:

$$ACC_{im} = \sum_j T_{ijm} D_{ijm} / \sum_j D_{ijm} \tag{2.2}$$

where:

ACC_{im}= Accessibility level of TAZ i by mode m;

D_{ijm} =Numbers of trips from TAZ i to TAZ j by mode m;

T_{ijm} = Travel impendence by mode m from TAZ i to TAZ

To avoid the arbitrary allocation of parking facilities located in the boundaries to TAZs, this study defined a 0.125 mile area beyond the original boundary of the TAZ which would be used to calculated average parking prize per TAZ. The average daily parking price per TAZ Influence Area (IAP_z) was calculated by the following equations:

$$IAP_z = \sum_{i \in I} p_i A_i TC_i \,/\, \sum_{i \in I} p_i A_i \tag{2.3}$$

where:

IAP_z = average daily parking price of Influence Area of TAZ z;

I = a set of TAZs within the Influence Area of TAZ z

p_i = a percent area of TAZ i inside the Influence Area of TAZ z;

A_i = an acreage of TAZ i;

TC_i = an average daily parking price of TAZ i;

After generating IAP for each TAZ and keeping the effective data, only 323 records reserved. The daily parking price model was developed using a linear regression with square roots of various parking demand variables as independent variables. However, the auto and transit accessibility indicators are not significant explanatory variables of average daily parking cost after regression. The approximate linear relationship between IAP and parking demands was obtained as follow:

$$IAP_z = -0.111 + 1.125 \times SQ_SEVA_z + 0.548 \times SQ_RETA_z \tag{2.4}$$

where,

IAP_z = average daily parking price of Influence Area of TAZ z;

SQ_SEVA_z= a square root of service employment density of TAZ z;

SQ_RETA_z= a square root of retail employment density of TAZ z.

In this daily parking cost model, the goodness-of-fit measure (R^2) of the model is 0.514. Although the two variables included in the model are statistically significant and can be easily gained from SCAG regular socio-economic data, the statistical R-square could be improved using other available variables in the future.

In this old SCAG daily parking cost model, the significant contribution is the idea of generating the influence area price which can better deal with the parking facilities that located on the TAZ boundary. In addition, it took an attempt to develop auto and accessibility indicators, which could be further analyzed in the future study.

2.3.2 A Market-Based Parking Cost Forecasting Framework in Denver

Denver Regional Council of Governments developed a market-based parking cost forecasting framework for CBD in 2004 estimated from longitudinal data (Denver, 2004). Different from most parking cost models, Denver's model estimated the parking costs paid by groups of travelers, not only on the TAZ level. The total parking demand in CBD was estimated based on Home-based-Work (HBW) trip attractions, auto occupancies and mode share and following the formula:

$$\mathrm{D} = \frac{(\frac{HBWA}{2})\times(1-TMS)}{AO} \tag{2.5}$$

where:

D = Total forecasting vehicles parking demand in the CBD;

HBWA = Total forecasting HBW person trip attractions to the CBD;

TMS = Transit mode share for HBW trips attracted to the CBD;

AO = Average auto occupancy for HBW trips attracted to the CBD.

Using the parking demand estimations, the parking cost model for CBD was obtained as a simple log-linear regression model shows below:

$$C=-178.888+ 15.919\times LN(D) \quad (2.6)$$

Here C refers to the weighted average parking cost in the CBD (in 1996 dollars). Full-price parkers, subsidized parkers and free parkers are the three income groups. Their parking cost can be estimated independently using formula 2.6. This model was successfully applied in practice in DRCOG's FSM. In conclusion, Denver's model is a good example using parking demand as a main explanatory variable in determining parking price. However, it may not reflect the true relationship between parking price and employment data due to the less of data.

2.3.3 Parking Cost Forecasting Structure in California Statewide Travel Demand Model (CSTDM09)

The parking cost forecasting model in CSTDM09 was developed by the Institution of Transportation Studies (ITS) in University of California, Davis in 2011 (UC Davis ITS, 2011). There are four parking cost types in the model structure: base parking cost, daily parking cost, hourly parking cost and special parking cost. The available data include land use data, employment data and a CBD parking rate survey. For each TAZ, a 1 mile and a 2.5 mile buffering system were created from the TAZ centroid to provide employment density in different

geographic level. Using linear regression method, parking base cost model was developed based on employment density and population density. The model is:

$$\text{BPC}= 0.0714+1.5 \times 10^{-5} \times \text{TTED1}+1.296 \times 10^{-4} \times \text{TTED25}+1.953 \times 10^{-5} \times \text{PPDen}+5 \times 10^{-5} \times \text{ReDen}+1.197 \times 10^{-5} \times \text{SerDen}+2.487 \times \text{ReSerP} \quad (2.7)$$

where:

BPC = base price cost;

TTED1 = total employment density within 1 mile buffer;

TTED25 = total employment density within 2.5 mile buffer;

PPDen = population density;

ReDen = retail employment density;

SerDen = service employment density;

ReSerP = proportion of employment in retail & service.

This base model has an R-Square of 0.816, which is a good fit and also reasonable generated by employment data. Based on the base cost model, hourly and daily model were developed as follows:

$$\text{HourlyRate} = 0.3698 \times base^{1.1806}, \quad R^2 = 0.7225, \quad (2.8)$$

$$\text{DailyRate} = 5.4773 \times base^{0.5502}, \quad R^2 = 0.6385, \quad (2.9)$$

Both hourly and daily parking cost model can get a good R-Square from the base model. For special parking cost analysis, it represents some additional cost above the base cost in special area, such as airports. Since the data is not enough, this study didn't come out with a special parking cost model. The advantage of CSTDM09 parking cost model is it defined parking cost

classification by time period and additional condition. But limited by the available data, no parking supply or parking demand variable was taken into account in this model.

2.4 Findings from Previous Parking Cost Studies

After reviewing the parking cost studies in other transportation planning organizations, several finding are summarized:

1. Most existing parking cost models were linear regression models in TAZ level and developed from a small set of samples.

2. Employment density variables were normally used as explanatory variables for parking cost.

3. Parking demand, parking supply, auto and transit accessibly, income group and time period are the other possible explanatory variables for parking cost. However, limited by the survey data, it is not easy to consider all these variables at one model. Thus a better parking survey format is needed to meet the requests.

4. Most parking survey data didn't have the classification of on-street and off-street parking. Thus sometimes on-street parking data was also used to generate daily parking cost model, which is not reasonable in real practice.

5. Monthly parking cost model is another usual mode for commuters, which has not been developed before.

CHAPTER 3. STUDY AREA AND DATA

3.1 Study Area Overview

SCAG region is the study area functioning as the Metropolitan Planning Organization for six counties: Los Angeles county, Orange county, San Bernardino county, Riverside county, Ventura county and Imperial county (Figure 3.1). The region has a population exceeding 18 million and covers more than 38,000 square miles in southern California by the year of 2012 (SCAG, 2012). In SCAG transportation planning process, the zones are divided into two levels of TAZs, Tier 1 TAZs with totally 4,109 records, and Tier 2 TAZs with totally 11,267 records (Figure 3.2). The finally models are built to forecast parking cost in Tier 2 TAZ level.



Figure 3.1 SCAG Region Map

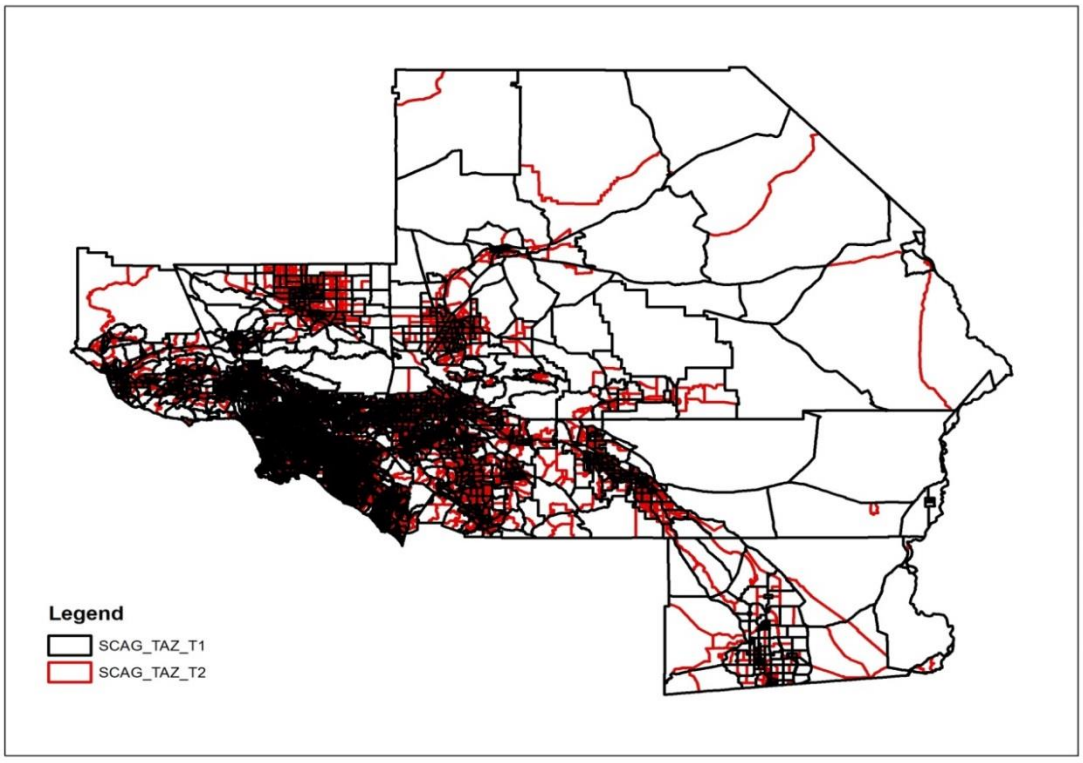


Figure 3.2 SCAG Tier 1 and Tier 2 TAZs

3.2 Study Data

There are two parts of data available to use in this study. The first is SCAG socio-economic data for both Tier 1 and Tier 2 TAZs. In the socio-economic database, there are many useful variables that may contribute in building the parking cost model such as population, number of households, employment by different classifications, income and acreage. The 67% of parking cost data (1966 records) were purchased from ParkMe.com by SCAG in 2013. The other 33% of parking cost data (966 records) were collected by SCAG staff at the same time. The parking cost records summary is listed in Table 3.1 and includes the geographic location of the parking facility, hourly parking rates, daily parking rates, monthly parking rates, and parking capacity. All the

parking cost data are collected only for off-street parking facilities. There is no on-street parking cost data in the dataset.

Table 3.1 Parking Data Summary

Name	Records
SCAG collected	1966
ParkMe.com provided	966
Hourly rates	2386
Daily rates	2369
Monthly rates	899
Location	2932
Parking capacity	1215

From ArcGIS 10.1, the location of each parking facility can be shown directly. Figure 3.3 shows the location distribution of the parking facilities. In this map, the red points represent the parking facilities in SCAG survey, and the blue points are the parking facilities in the ParkMe.com dataset. All the parking facilities in the survey are clustered in the southwest of SCAG region, mainly in Ventura county, Los Angeles county and Orange county. Those locations include CBD, employment centers, plazas, universities/colleges, airports and public recreation places. The details are shown in Table 3.2 for each county. The location information is joined with SCAG Tier 1 and Tier 2 TAZs in ArcGIS and finally each parking facility has both a Tier 1 ID and Tier 2 ID that it locates in. After another join between parking cost data and socio-economic data, the TAZs that involved in the parking cost data have an accumulative population that constitutes about 5% of the total population in SCAG region. The employment, household and acreage in the parking cost survey area account for 23%, 6% and 0.5% of the total employment, household

and acreage of the SCAG region independently (Table 3.3). The parking cost survey area attracts over one fifth of the total employment on the one two-hundredth land of the SCAG region. Thus, this parking cost survey provides a good sample in predicting the parking price in high employment density areas, or called employment centers.

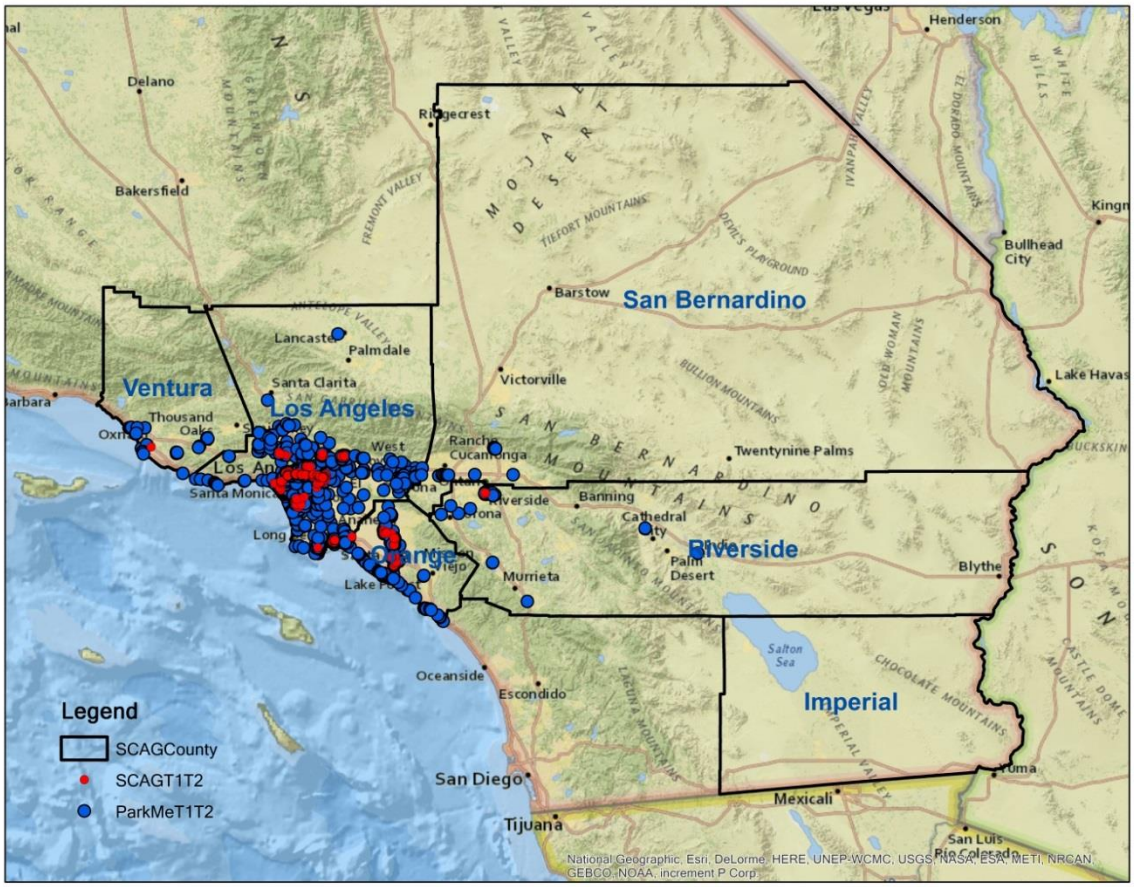


Figure 3.3 Location Distribution of Parking Facilities in the Survey

Table 3.2 Parking Facilities Locations in Each County

County	Representative Place
Ventura	Channel Islands Beach San Buenaventura Beach California State University, Channel Islands California Lutheran University
Los Angeles	Downtown Los Angeles Santa Monica University of California, Los Angeles (UCLA) Beverly Hills Hollywood Long Beach Los Angeles International Airport Pasadena
San Bernardino	LA/Ontario International Airport California State University, San Bernardino
Orange	California State University, Fullerton Anaheim Convention Center Santa Ana College Santa Ana Downtown John Wayne Orange County Airport Newport Beach
Riverside	4th to 12th Street along 91 Riverside Highway University of California, Riverside
Imperial	None

Table 3.3 Basic Parameter Comparison between Parking Cost Survey Area and SCAG Region

Parameter	Parking Cost Survey Area	SCAG Region	Percentage
Population	897219	18405088	4.87%
Employment	1717408	7446910	23.06%
Household	379011	5937560	6.38%
Acreage	125261.08	24615659.74	0.51%

In Chapter 4, some new variables are defined using the current data to better describe parking cost depending on the situation in data preparation step.

CHAPTER 4. METHODOLOGY

Inspired by the previous parking cost studies, this SCAG parking cost models are also developed based on linear regression method. The parking cost models are built by three time periods, hourly, daily and monthly. Here daily parking cost model is considered as the base model for hourly and monthly models. At last, the parking cost models are used to forecast the parking price in each TAZ. The models are developed using R software.

4.1. Linear Regression Model with Constant

Regression analysis is the application of statistical methods to organize and analyze a large number of observational data in order to obtain some inner regularity of the data. Among all kinds of regression model, linear regression model is the most widely used and convenient regression model to process data. In statistics, linear regression is an approach to modeling the relationship between a scalar dependent variable y and one or more explanatory variables denoted X_i. The case of one explanatory variable is called simple linear regression. For more than one explanatory variable, multiple linear regression model is needed.

Given a data set, a multiple linear regression model assumes that the relationship between the dependent variable y and the explanatory x_i is linear. The overall linear model can be written as:

$$y=\beta_0+\beta_1 x_1+\beta_2 x_2+\ldots+\beta_k x_k+\varepsilon \quad (4.1)$$

where:

y = dependent variable;

x_i = independent variable;

k = the number of explanatory variables;

β_k = regression coefficients;

ε_i = error term.

4.2 Linear Regression Model without Constant

As Theil stated in this book *Principles of Econometrics* (Theil, 1971), the constant term usually has little or no significance level in the model and maybe not reasonable if all the independent variables equal to zero. For example, a worker's daily salary can be determined by his work hours and the product amount he produces per day. Using normal linear regression model with constant, the model may be:

$$\text{Daily salary}=20\times\text{work hours}+1.5\times\text{products number}+13 \tag{4.2}$$

If the worker doesn't work one day which refers that both work hour and product number are zero, he can still get $13 this day. However, this is not true in the real world. Thus under this condition, a linear regression model without constant is needed to better fit reality. Besides ordinary least-squares (OLS) regression, there is another regression method called regression through the origin (RTO), which refers to no constant item in the regression model (Eisenhauer, 2003). In the regression process, the final model will be forced to go through the origin. But the formula to calculate R-Square is different from the normal linear regression with constant.

In the normal regression model with constant, the final model is set to cross the mean value of the dependent variable. This rule can be shown in the following formula:

$$(Y_i - \bar{Y}) = \left(Y_i - \hat{Y}_i\right) + \left(\hat{Y}_i - \bar{Y}\right) \tag{4.3}$$

where:

Y_i = observations;

$\bar{Y}$ = the mean of the dependent variable;

$\hat{Y}_i$ = the ith fitted value.

Using OLS, R-Square in normal regression model with constant is defined as the ratio of the sum of squares due to regression (SSR) to the sum of regression due to error:

$$R^2 = \frac{\sum(\hat{Y}_i - \bar{Y})^2}{\sum(Y_i - \bar{Y})^2}$$

or

$$R^2 = 1 - \frac{\sum(\bar{Y} - \hat{Y}_i)^2}{\sum(Y_i - \bar{Y})^2} \quad (4.4)$$

Since $\frac{\sum(\bar{Y} - \hat{Y}_i)^2}{\sum(Y_i - \bar{Y})^2}$ is a nonnegative number, the value of R^2 is between 0 and 1. However, in RTO model, formula 4.4 is not applicable in calculatingR^2. For instance, in Figure 4.1, the red dashed line is the model estimated from the normal linear regression model with constant. But using RTO, the model must be pushed crossing the origin that may lead the model line transformed to the blue line format. Under this condition, the difference between Y_i and $\hat{Y}_i$ will be much bigger than the difference between Y_i and $\bar{Y}$. As a result, $\frac{\sum(\bar{Y} - \hat{Y}_i)^2}{\sum(Y_i - \bar{Y})^2}$ can be close to positive infinity which will finally cause R^2 to be negative according to formula 4.4.

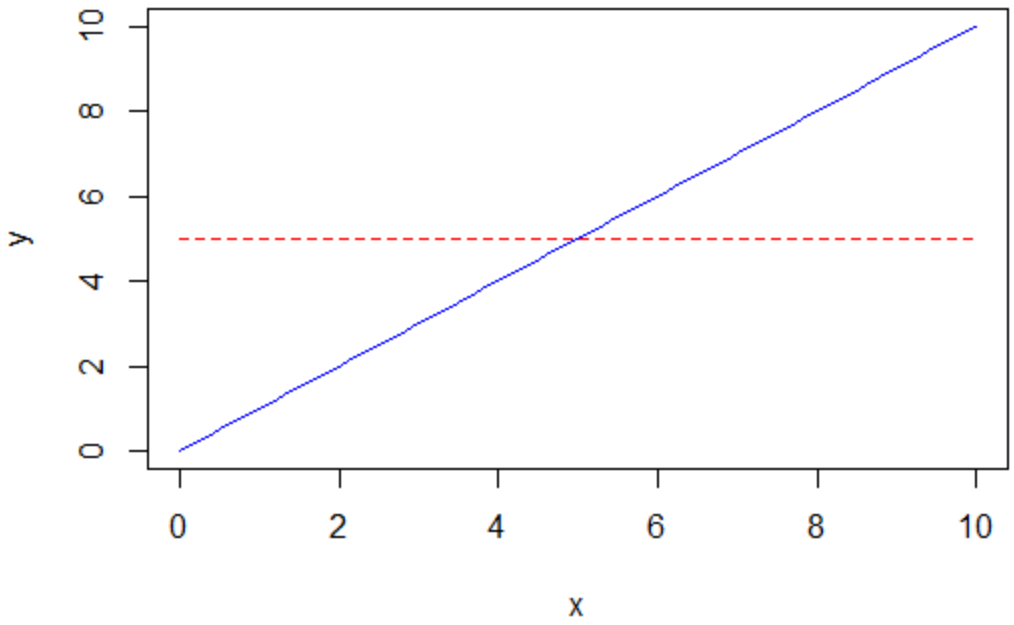


Figure 4.1 An Extreme Example for RTO Model

Thus, R^2 should be calculated by another formula for RTO. Since in RTO, the model should pass the origin but not the mean point, formula 4.4 can be replaced by:

$$R^2 = \frac{\sum(\hat{Y}_i)^2}{\sum(Y_i)^2} \qquad (4.5)$$

Formula 4.5 is the principle to determine R^2 in RTO. In this SCAG parking cost forecasting study, parking cost is supposed to be explained by employment density, population, household numbers and other possible variables. If there is no population and employment in one TAZ, there is no need to charge for parking. Thus RTO is more reasonable than normal linear regression model with constant in predicting parking cost.

4.3 Parking Cost Model Development Process

The objective of this study is to develop parking cost forecasting model by hourly, daily and monthly for commuter purpose. In order to achieve this goal, population, household number, employment density by different types, auto and transit accessibility, parking demand and supply are all the possible variables in determining parking price. However, given limited time and data, the auto and transit accessibility is not able to generate in this study. Then compare to the old SCAG parking price model in 2002, the main improvement in this study is to consider parking demand and supply as explanatory variables for parking price. Parking supply data comes from the survey data and is used directly in the model development. But parking demand data of commuters should be calculated from HBW trip rates. The details will be described in data preparation process. In order to see the contribution of parking supply in determining parking price, the models are developed by two groups, one has parking supply as an explanatory variable, but the other doesn't. The model development flow chart is shown in Figure 4.2.

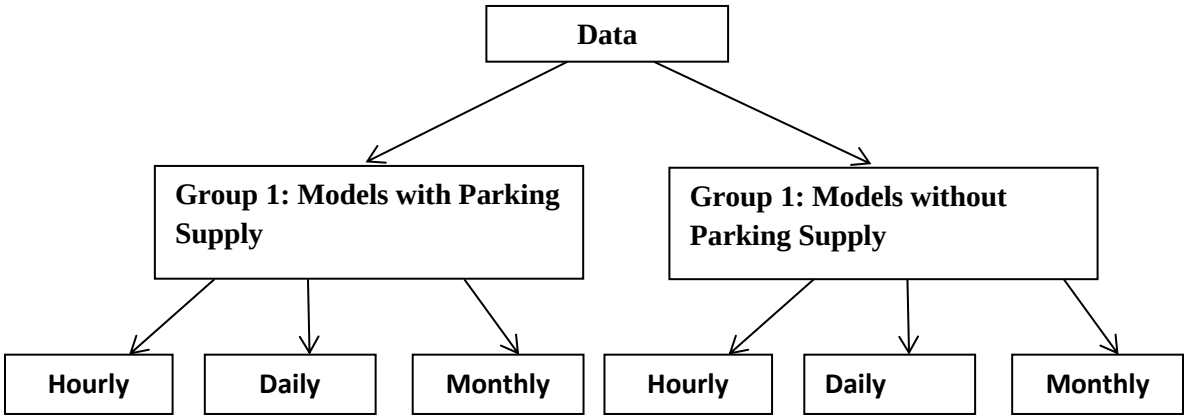


Figure 4.2 Flow Chart of Parking Cost Model Development

CHAPTER 5. PARKING COST MODEL WITHOUT PARKING SUPPLY

Although parking supply is an important variable for parking cost, it is not easy to collect parking supply data for each parking facilities in the study area in real practice. Thus, the significance of parking cost models without supply is to estimate parking cost in all TAZs. However, not each record has hourly rate, daily rate, and monthly rate at the same time. In order to make full use of the available data, some method should be adopted to cover the missing data. At the same time, a set of models that generated directly from the raw data are also built as a comparison. The parking cost models are built in Tier 2 TAZ level.

5.1 Data Preparation

The study data contains two parts: socio-economic data for each TAZ in SCAG region, and parking cost survey for some sample places in SCAG area, which totally has 2932 records. The data preparation process is:

1. Remove the all zero records. In the dataset, there are 419 records don't have any data for hourly, daily and monthly rate at the same time. After removing the all zero records, there are 2513 records left. Save these 2513 records in the file named Parking_without_SP.

2. Select real effective data. From the left 2513 records, there are 835 records that have hourly, daily and monthly rate simultaneously. Save these 835 records in the file named Parking_without_SP_HDM.

3. Estimate the missing data in Parking_without_SP dataset. Following the rules in Table 5.1, the missing data are estimated for Parking_without_SP dataset. Since in some recreation places such Hollywood and Universal Studio, there is no hourly parking provided. Vehicles

need to pay the daily parking rates at the parking facilities' entrances no matter how long they really plan to park. Thus the daily parking rate can equal to the hourly parking rate at minimum.

Table 5.1 Estimation Rules for Missing data in Parking_without_SP dataset

Missing data condition	Estimation rules
hourly rate≠0, daily rate=0	daily rate= hourly rate × 8
monthly rate ≠0, daily rate=0	daily rate= monthly rate/20
daily rate≠0, monthly rate=0	monthly rate= daily rate×20
daily rate≠0, hourly rate=0	hourly rate= daily rate/8
daily rate < hourly rate	daily rate= hourly rate

4. Calculate the average parking cost for each TAZ. Since there is no parking supply number consideration, the average parking cost is calculated in arithmetic average of all parking facilities within one TAZ using formula 5.1. After calculating, average parking costs for 741 TAZs are finally obtained from Parking_without_SP dataset, and 269 TAZs' average parking costs are obtained from Parking_without_SP_HDM dataset.

$$\text{Average parking rate}=\frac{\sum parking\ rates\ of\ all\ parking\ facilties\ in\ one\ TAZ}{number\ of\ parking\ facilities\ in\ one\ TAZ} \quad (5.1)$$

5. Remove outliers in Parking_without_SP dataset using the constraints from the Parking_without_SP_HDM dataset. The data in Parking_without_SP_HDM dataset are all the real records from the survey. Thus in the Parking_without_SP dataset, the records with parking cost rates out of the range of parking cost rates in Parking_without_SP_HDM are

considered as outliers and removed from the dataset (Table 5.2). Finally there are 642 effective records saved in Parking_without_SP dataset.

Table 5.2 Constraints and Outliers for Parking_without_SP dataset

Constraints from Parking_without_SP _HDM dataset	Outliers removed from Parking_without_SP dataset
$\mathbf{0.5 \leq hourly\ rate \leq 20}$	6 records removed
$\mathbf{2.5 \leq hourly\ rate \leq 61}$	5 records removed
$\mathbf{30 \leq hourly\ rate \leq 357.5}$	88 records removed

6. Estimate parking demand data for each TAZ. In this study, the parking demand for commuters is the main interest. Thus, the HBW is the trip purpose to estimate parking demand for commuters. In SCAG 2008 Regional Travel Demand Model, SCAG has generated HBW direct trip rates by 3 income groups (Table 5.3). In this step, the income data in both Parking_without_SP and Parking_without_SP_HDM dataset is first converted to 2008 dollar value. Then the parking demand for each TAZ is calculated as the product of HBW trip rate and total household numbers.

Table 5.3 HBW Trip Rate by Income Group

Income group	HBW trip rate
$ 24,999 and less	1.181
$ 25,000 to $ 49,999	1.040
$ 50,000 and more	1.040

$$\text{Parking demand} = \text{HBW trip rate} \times \text{total household numbers} \quad (5.2)$$

In order to find out the true relationship between parking demand and parking cost, the parking demand data are also divided into 3 groups and represented by binary variables.

5.2 Daily Parking Cost Models without Parking Supply

Daily parking is the main parking pattern for commuters and should be considered first. After factor analysis, there are four parameters selected from the database besides the parking demand. The daily model is developed in three variables combination to see the difference. Daily parking cost model without parking demand variable

5.2.1 Daily parking cost model without parking demand variable

There are four variables selected from the database and shown in Table 5.4.These four variables represent employment and household condition in both Tier 1 and Tier 2 TAZ level. Since TAZs in Tier 2 are really small especially in some CBD areas, the influence from Tier 1 TAZs is also significant in determining the Tier 2 level parking cost. The percentage of multiple households can explain the impact of home parking supply to the commercial parking price.

Table 5.4 Variables Description in Daily Parking Cost Model without Parking Supply

Variable Name	Description
P_Mlt_T1	Percentage of multiple households in Tier 1
Share_off	Office job share to total jobs in Tier 2
T2Share	Tier 2 job share to Tier 1
T2EmpDen	Employment Density in Tier 2

After regression using R, the results are shown in table 5.5.

Table 5.5 Regression Results for Daily Parking Cost Model without Parking Demand from Parking_without_SP Dataset

Coefficients	Estimate	Standard Error	t Value	Pr (> | t |)
P_Mlt_T1	6.693055	0.619654	10.801	0.000
Share_off	6.310284	1.009387	6.252	0.000
T2Share	5.875557	0.691800	8.493	0.000
T2EmpDen	0.005502	0.003592	1.532	0.126

Thus, the final model for daily parking cost without parking demand from Parking_without_SP dataset is:

$$Daily = 6.693055 \times P_Mlt_T1 + 6.310284 \times Share_off + 5.875557 \times T2Share + 0.005502 \times T2EmpDen \quad (5.3)$$

In this model, multiple R-Square is 0.7493, and adjusted R-Square is 0.742. From the normal Q-Q plot (Figure 5.1), the residuals fit the normal distribution. However, in the plot of residuals and fitted values, the residuals are not totally randomly distributed around 0 (Figure 5.2). Thus, this model still need to be further improved.

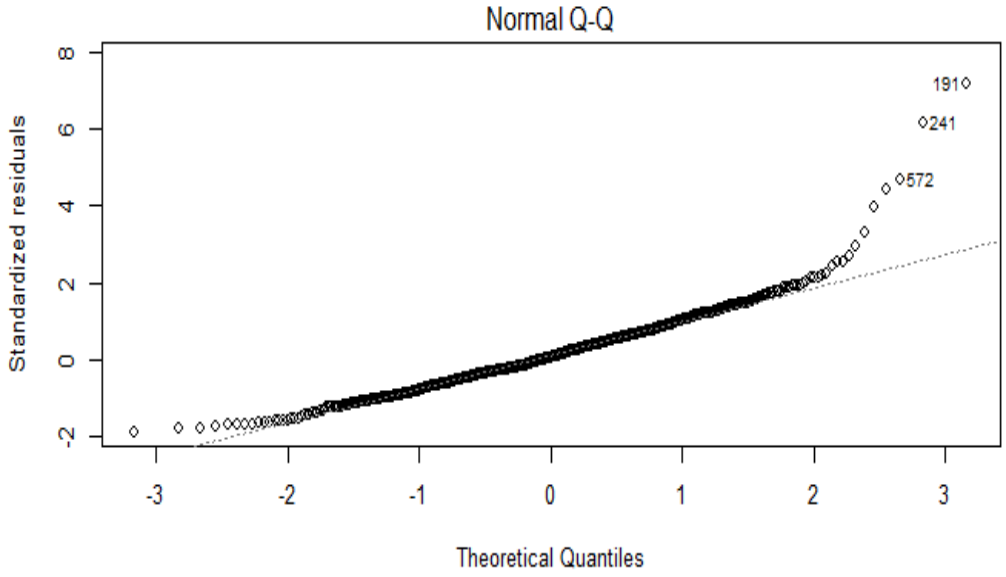


Figure 5.1 Normal Q-Q Plot for Daily Parking Cost Model without Parking Demand from Parking_without_SP Dataset

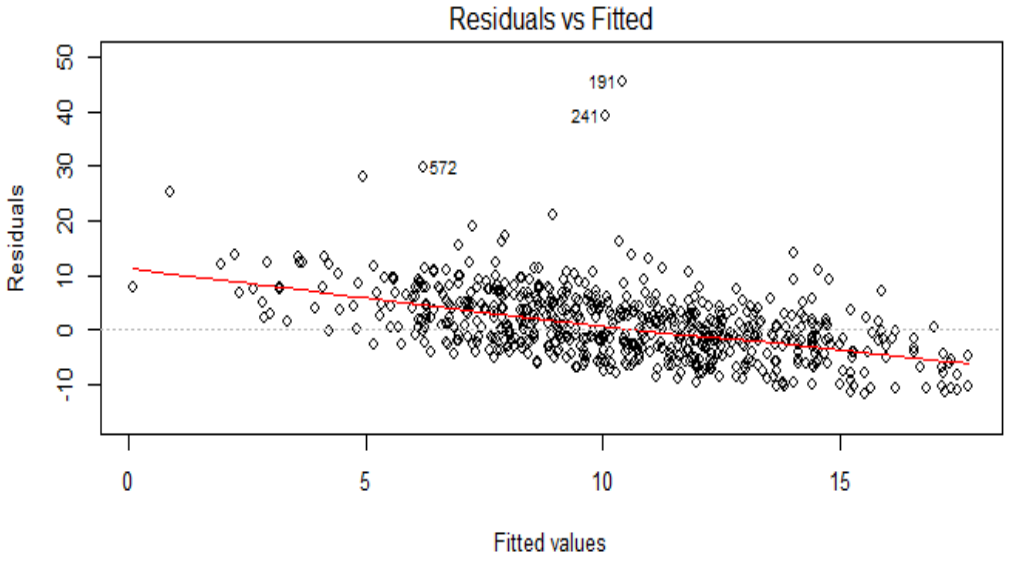


Figure 5.2 Residuals Plot for Daily Parking Cost Model without Parking Demand from Parking_without_SP Dataset

As a comparison, the same variables are also used to build daily model using Parking_without_SP_HDM dataset. The results are shown in Table 5.6.

Table 5.6 Regression Results for Daily Parking Cost Model without Parking Demand from Parking_without_SP_HDM dataset

Coefficients	Estimate	Standard Error	t Value	Pr (> | t |)
P_Mlt_T1	6.365868	1.242014	5.125	0.000
Share_off	6.655341	2.051644	3.244	0.001
T2Share	3.762001	1.494572	2.517	0.012
T2EmpDen	0.019969	0.006324	3.158	0.002

Thus, the final model for daily parking cost without parking demand from Parking_without_SP_HDM dataset is:

$$Daily = 6.365868 \times P_Mlt_T1 + 6.655341 \times Share_off + 3.762001 \times T2Share + 0.019969 \times T2EmpDen \quad (5.4)$$

In this model, multiple R-Square is 0.6563, and adjusted R-Square is 0.6511. So the goodness of fit from raw data is a little lower than the one after filling the missing data. From the normal Q-Q plot (Figure 5.3), the residuals fit the normal distribution. However, in the plot of residuals and fitted values, the residuals are still not totally randomly distributed around 0 (Figure 5.4). Therefore in next step, parking demand should be considered as another explanatory variable in determining daily parking price.

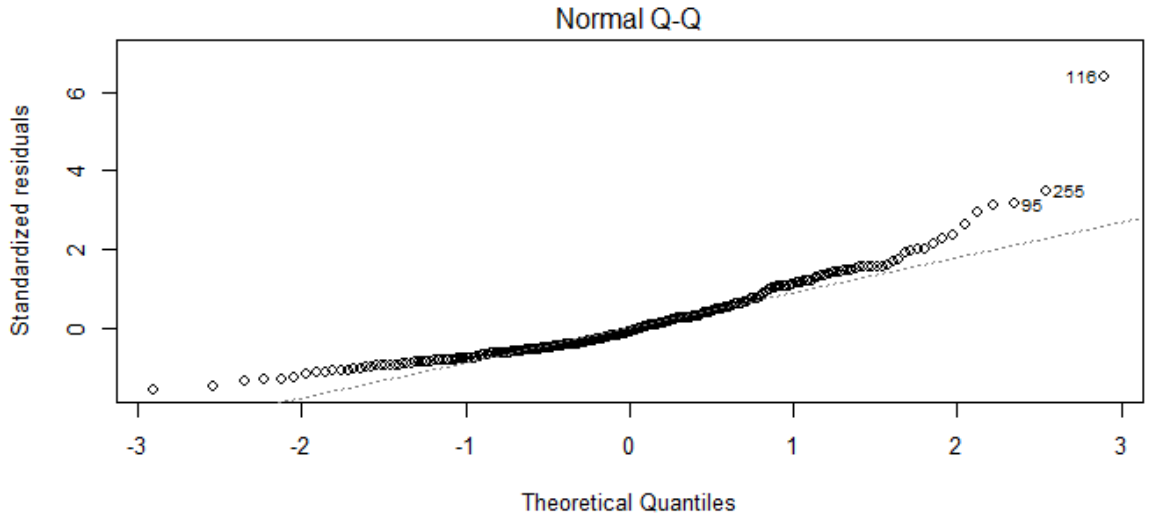


Figure 5.3 Normal Q-Q Plot for Daily Parking Cost Model without Parking Demand from Parking_without_SP_HDM Dataset

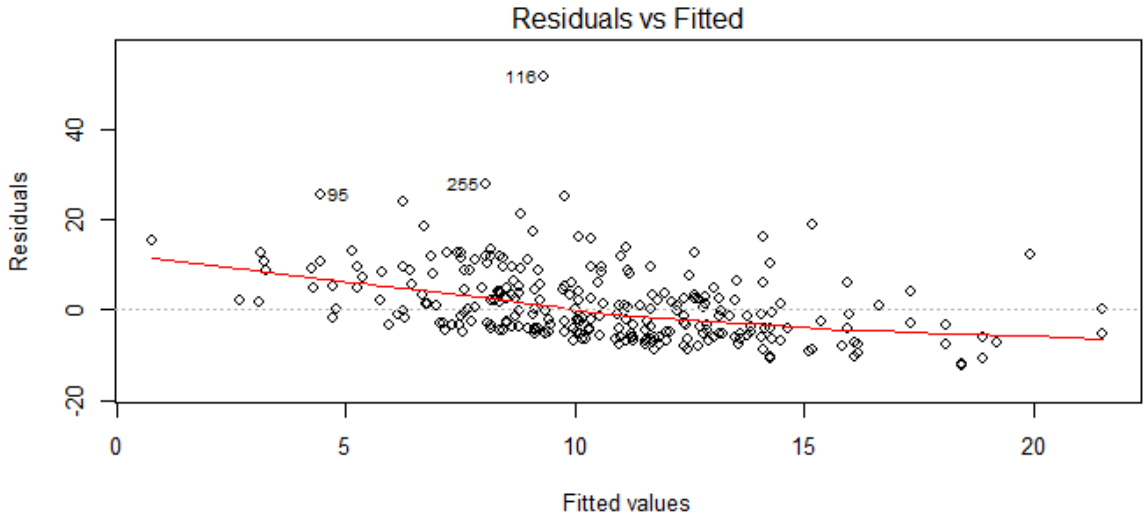


Figure 5.4 Residuals Plot for Daily Parking Cost Model without Parking Demand from Parking_without_SP_HDM Dataset

5.2.2 Daily parking cost model with parking demand variable

By considering parking demand as a new explanatory variable, there are 5 explanatory variables now in determining daily parking price. Using R, the results of new daily parking cost model from Parking Demand from Parking_without_SP are summarized in Table 5.7.

Table 5.7 Regression Results for Daily Parking Cost Model with Parking Demand from Parking_without_SP dataset

Coefficients	Estimate	Standard Error	t Value	Pr (> | t |)
P_Mlt_T1	6.715	0.6215	10.805	0.000
Share_off	6.303	1.01	6.241	0.000
T2Share	5.755	0.7306	7.878	0.000
T2EmpDen	0.003741	0.004966	0.753	0.452
ParkingDemand	0.0000413	0.00008	0.514	0.608

Thus, the final model for daily parking cost with parking demand from Parking_without_SP dataset is:

$$\text{Daily} = 6.715 \times \text{P_Mlt_T1} + 6.303 \times \text{Share_off} + 5.755 \times \text{T2Share} + 0.003741 \times \text{T2EmpDen} + 0.0000413 \times \text{ParkingDemand} \quad (5.5)$$

In this model, multiple R-Square is 0.7437, and adjusted R-Square is 0.7417. Although the adjusted R-Square is good, but the contribution of parking demand in this model is too low. In addition, the R-Square of the current model is just a little smaller than the R-Square of daily cost

model without parking demand, which is not really reasonable. Thus, a binary format of parking demand variable is considered to use to improve the current model. The normal Q-Q plot and plot of residuals and fitted values are shown in Figure 5.5 and Figure 5.6.

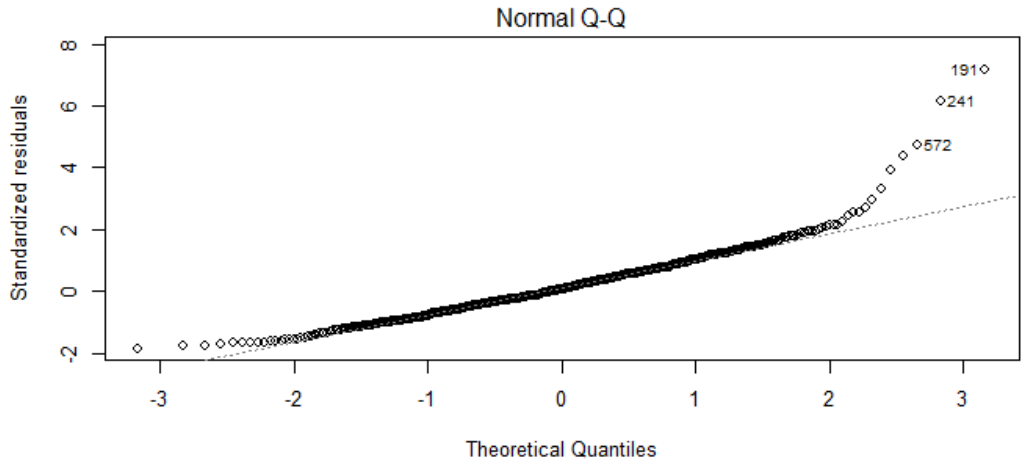


Figure 5.5 Normal Q-Q Plot for Daily Parking Cost Model with Parking Demand (Parking_without_SP)

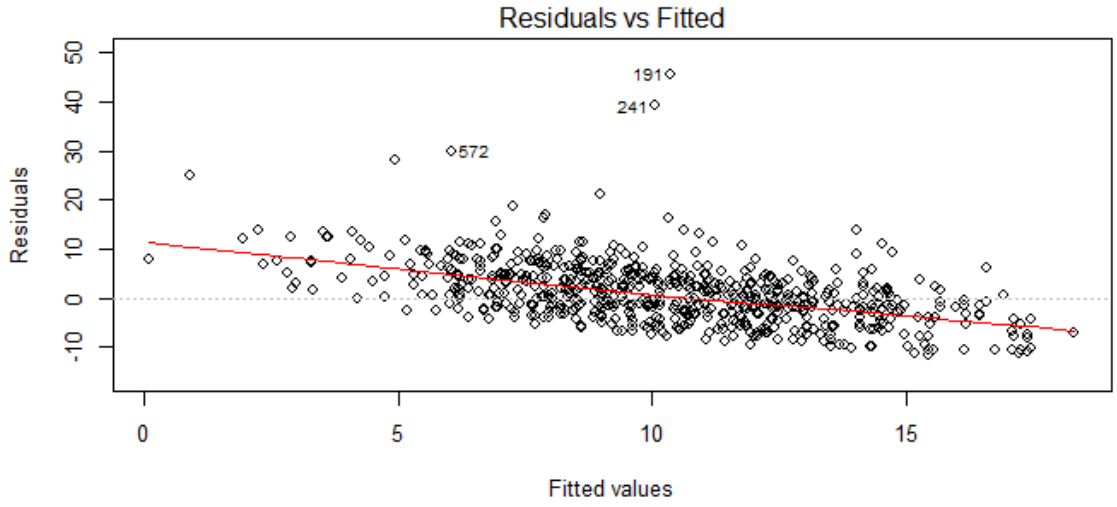


Figure 5.6 Residuals Plot for Daily Parking Cost Model with Parking Demand (Parking_without_SP)

The current variables are also used to build daily parking cost model from Parking_without_SP_HDM dataset. The results are shown in Table 5.8.

Table 5.8 Regression Results for Daily Parking Cost Model with Parking Demand from Parking_without_SP_HDM dataset

Coefficients	Estimate	Standard Error	t Value	Pr (> | t |)
P_Mlt_T1	6.342	1.255	5.052	0.000
Share_off	6.637	2.059	3.223	0.001
T2Share	3.83	1.568	2.443	0.015
T2EmpDen	0.02102	0.009586	2.192	0.029
ParkingDemand	0.0000207	0.0001426	-0.146	0.884

Thus, the final model for daily parking cost with parking demand from Parking_without_SP_HDM dataset is:

Daily = 6.342×P_Mlt_T1+6.637×Share_off+3.83×T2Share+0.02102×T2EmpDen+0.0000207×Parking Demand (5.6)

In this model, multiple R-Square is 0.6563, and adjusted R-Square is 0.6498. The normal Q-Q plot and plot of residuals and fitted values are shown in Figure 5.7 and Figure 5.8.

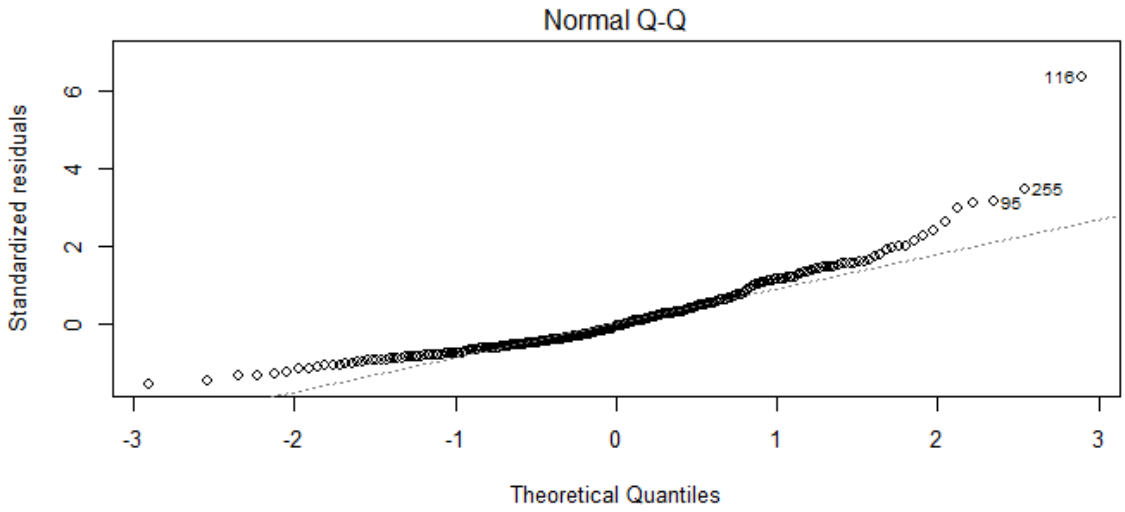


Figure 5.7 Normal Q-Q Plot for Daily Parking Cost Model with Parking Demand from Parking_without_SP_ HDM Dataset

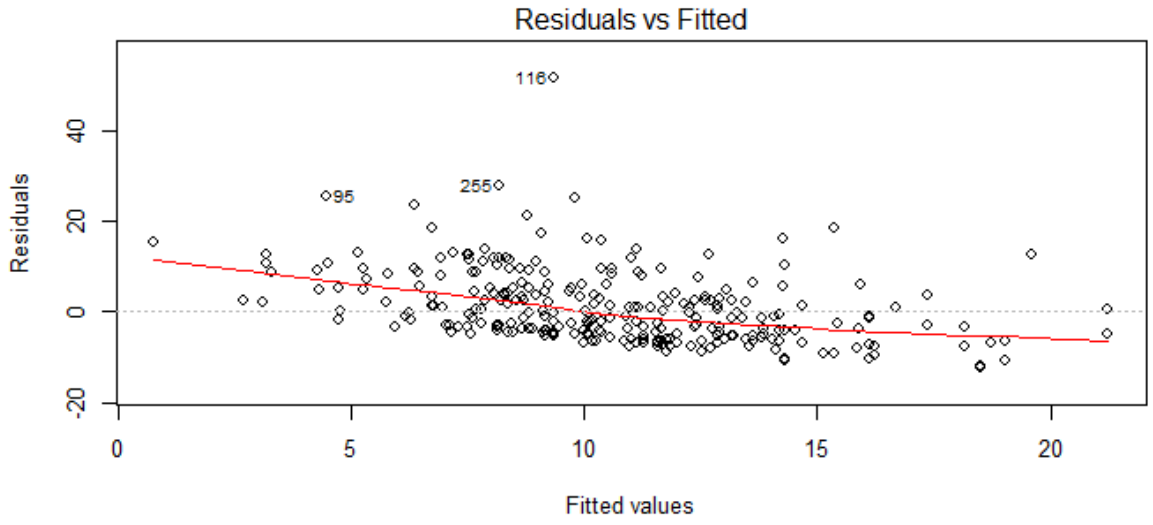


Figure 5.8 Residuals Plot for Daily Parking Cost Model with Parking Demand from Parking_without_SP_HDM Dataset

5.2.3 Daily parking cost model with binary parking demand variables

To better represent the impact of parking demand on daily parking price, the parking demand are divided into three groups as binary variable format: parking demand less than 1000, parking demand between 1000 and 3000, and parking demand over 3000. First, the binary parking demand variables are used to develop daily parking cost model from Parking_without_SP dataset. The results are shown in Table 5.9.

Table 5.9 Regression Results for Daily Parking Cost Model with Binary Parking Demand from Parking_without_SP dataset

Coefficients	Estimate	Standard Error	t Value	Pr (> | t |)
P_Mlt_T1	-0.897742	0.716991	-1.252	0.211
Share_off	-0.619391	0.980447	-0.632	0.5278
T2Share	-0.620284	0.754126	-0.823	0.4111
T2EmpDen	0.007189	0.003379	2.128	0.0337
PD_1000	11.833624	0.755014	15.673	0.000
PD_1000_3000	11.995872	0.867704	13.825	0.000
PD_3000over	12.879548	1.013321	12.710	0.000

Thus, the final model for daily parking cost with binary parking demand from Parking_without_SP dataset is:

Daily =-0.897742×P_Mlt_T1-0.619391×Share_off-

0.620284×T2Share+0.007189×T2EmpDen+11.833624×PD_1000+11.995872×PD_1000_3000

+12.879548×PD_3000 over (5.7)

In this model, multiple R-Square is 0.8162, and adjusted R-Square is 0.8142. Compared with the previous daily parking cost model using parking demand directly, the current model has a higher adjusted R-Square that can better fit the data in the dataset. The normal Q-Q plot and plot of residuals and fitted values are shown in Figure 5.9 and Figure 5.10. From the two figures we can find that the residuals can fit the normal distribution better. And also, the residuals now are randomly distributed around 0. Thus this model is a reasonable model.

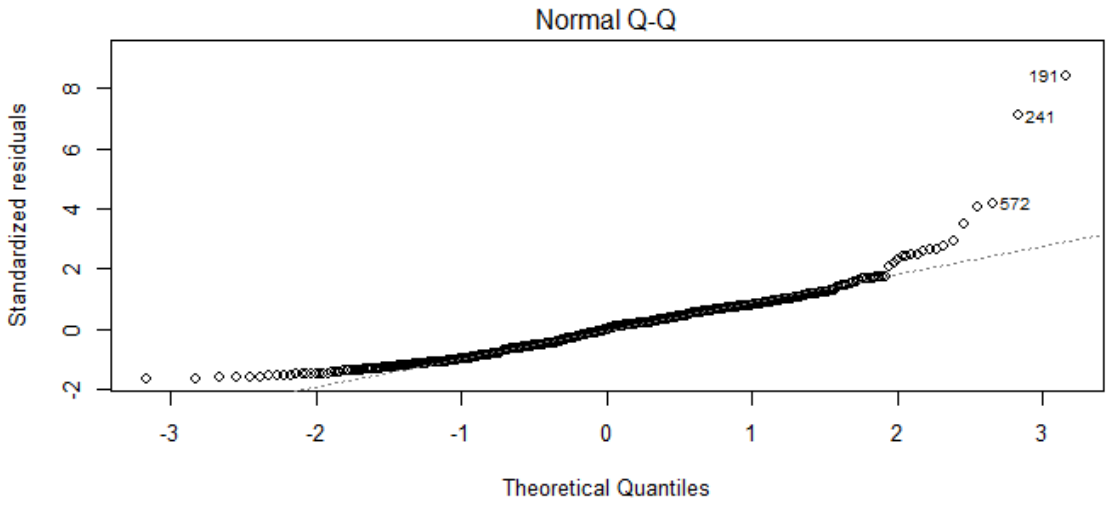


Figure 5.9 Normal Q-Q Plot for Daily Parking Cost Model with Binary Parking Demand from Parking_without_SP Dataset

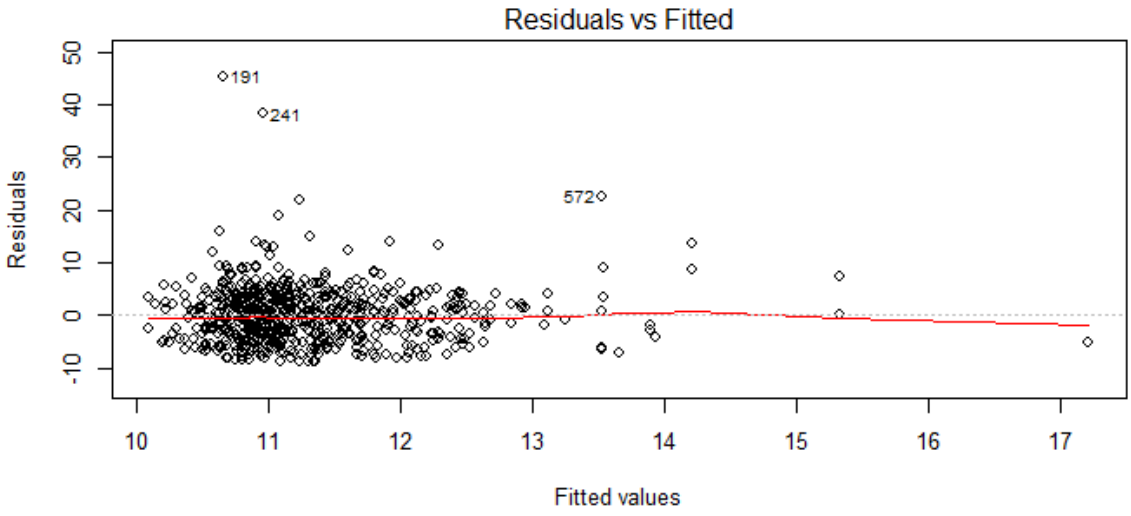


Figure 5.10 Residuals Plot for Daily Parking Cost Model with Binary Parking Demand from Parking_without_SP Dataset

The same variables are also used to build daily parking cost model from Parking_without_SP_HDM dataset. The results are summarized in Table 5.10.

Table 5.10 Regression Results for Daily Parking Cost Model with Binary Parking Demand from Parking_without_SP_HDM dataset

Coefficients	Estimate	Standard Error	t Value	Pr (> | t |)
P_Mlt_T1	-3.23609	1.53609	-2.107	0.036
Share_off	0.25953	1.98033	0.131	0.896
T2Share	-1.81359	1.54757	-1.172	0.242
T2EmpDen	0.02206	0.00645	3.420	0.000
PD_1000	15.17126	1.66037	9.137	0.000
PD_1000_3000	13.06355	1.75229	7.455	0.000
PD_3000over	13.58493	2.05928	6.597	0.000

Thus, the final model for daily parking cost with binary parking demand from Parking_without_SP_HDM dataset is:

Daily =-3.23609×P_Mlt_T1+0.25953×Share_off-1.81359×T2Share+0.02206×T2EmpDen+15.17126×PD_1000+13.06355×PD_1000_3000+13.58493×PD_3000 over (5.8)

In this model, multiple R-Square is 0.7397, and adjusted R-Square is 0.7328. The patterns of normal Q-Q plot (Figure 5.11) and plot of residuals and fitted values (Figure 5.12) are similar to the model generated from Parking_without_SP.

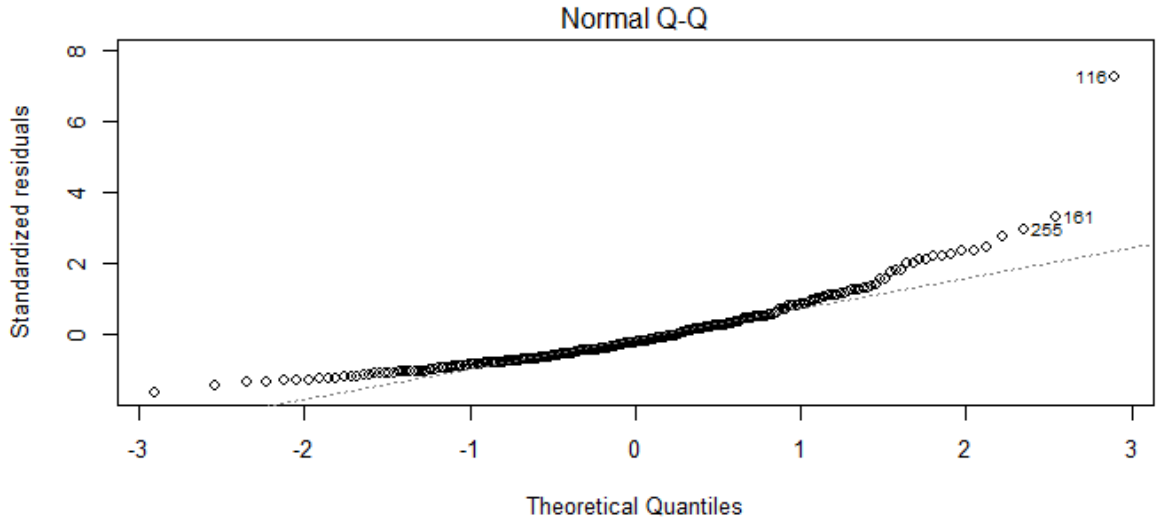


Figure 5.11 Normal Q-Q Plot for Daily Parking Cost Model with Binary Parking Demand from Parking_without_SP_HDM Dataset

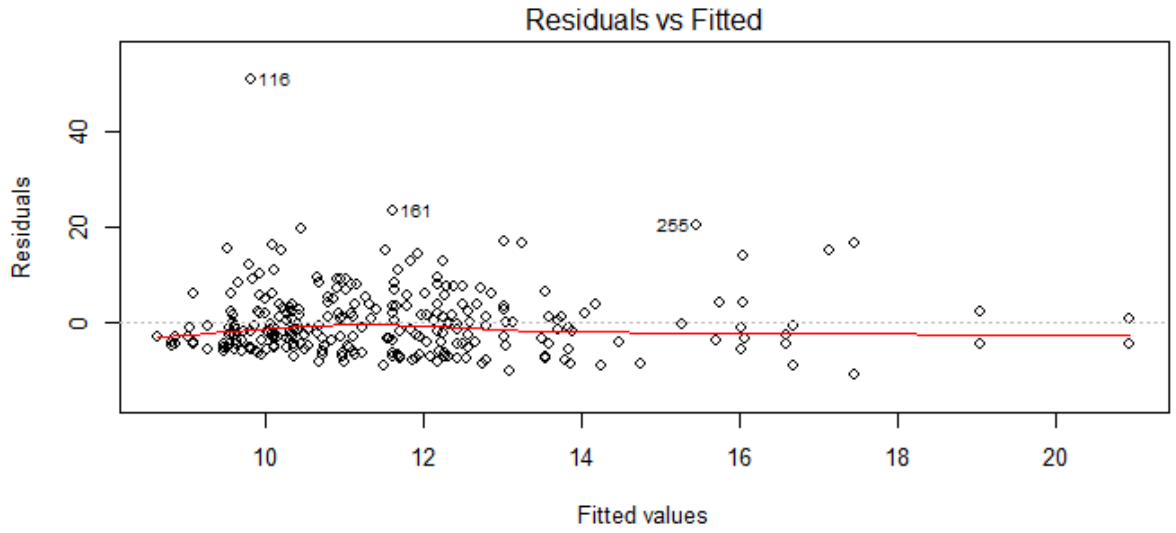


Figure 5.12 Residuals Plot for Daily Parking Cost Model with Binary Parking Demand from Parking_without_SP_HDM Dataset

5.3 Hourly Parking Cost Models without parking supply

The hourly parking cost model is generated based on daily parking rate and other employment variables that refer to occasional parking demand (Table 5.11).

Table 5.11 Variables Description in Hourly Parking Cost Model without Parking Supply

Variable Name	Description
daily	Daily parking rate in Tier 2
FIRE_Den	Finance, insurance, real estate and rental and leasing employment density in Tier 2
EDCU_Den	Educational, health and social services employment density in Tier 2
ARTENT_Den	Arts, entertainment, recreation, accommodation and food services employment density in Tier 2
CBD	Binary variable in Tier 2

The hourly parking cost model generated from Parking_without_SP is summarized in Table 5.12.

Table 5.12 Regression Results for Hourly Parking Cost Model from Parking_without_SP dataset

Coefficients	Estimate	Standard Error	t Value	Pr (> | t |)
daily	0.3698465	0.0155929	23.719	0.000
FIRE_Den	-0.0109435	0.0134501	-0.814	0.416
EDCU_Den	-0.0006821	0.0038418	-0.178	0.859
ARTENT_Den	0.0209189	0.0171689	1.218	0.224
CBD	1.2153109	0.2285953	5.316	0.000

Thus, the final model for hourly parking cost with binary parking demand from Parking_without_SP dataset is:

Hourly =0.3698465×daily-0.0109435×FIRE_Den -

0.0006821×EDCU_Den+0.0209189×ARTENT_Den+1.2153109×CBD (5.9)

In this model, multiple R-Square is 0.7977, and adjusted R-Square is 0.7861. The Q-Q plot (Figure 5.13) and plot of residuals and fitted values (Figure 5.14) are shown below.

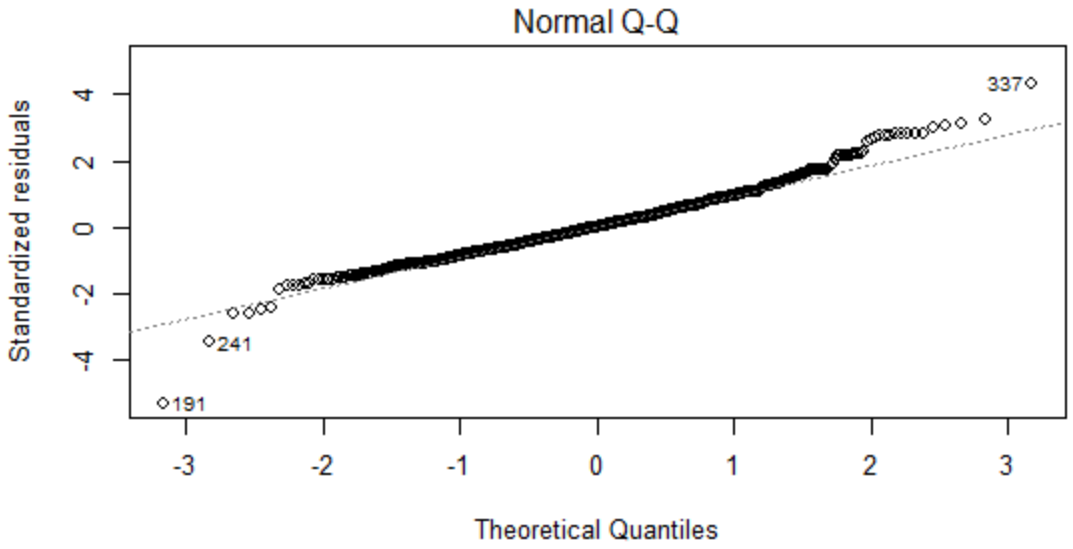


Figure 5.13 Normal Q-Q Plot for Hourly Parking Cost Model from Parking_without_SP Dataset

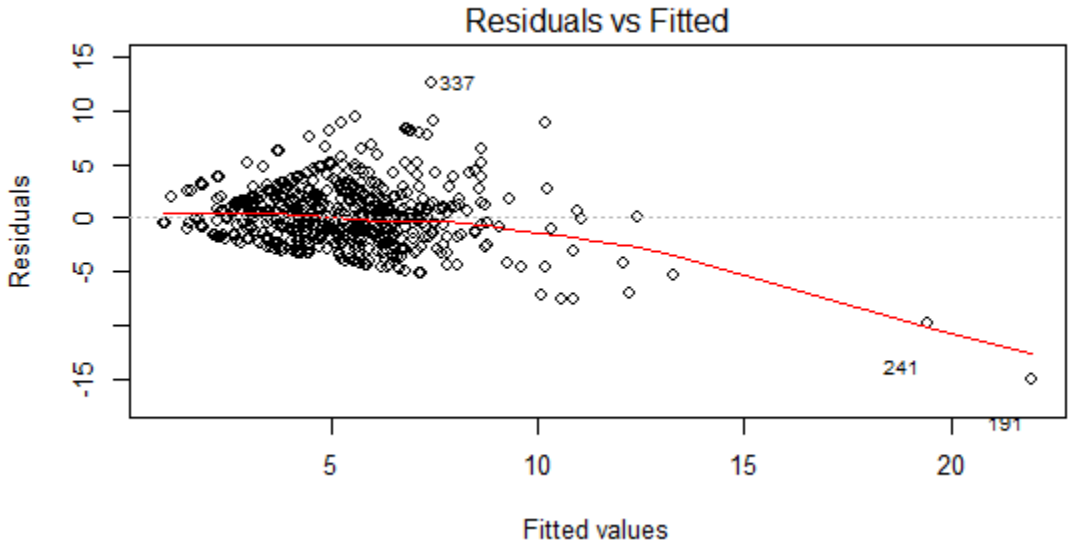


Figure 5.14 Residuals Plot for Hourly Parking Cost Model from Parking_without_SP Dataset

From Parking_without_SP_HDM dataset, the hourly parking cost model is developed and shown below in Table 5.13.

Table 5.13 Regression Results for Hourly Parking Cost Model from Parking_without_SP_HDM dataset

Coefficients	Estimate	Standard Error	t Value	Pr (> | t |)
daily	0.391018	0.020137	19.518	0.000
FIRE_Den	0.017527	0.017546	0.999	0.319
EDCU_Den	-0.001779	0.004095	-0.434	0.664
ARTENT_Den	0.037069	0.023597	1.571	0.117
CBD	1.872293	0.305173	6.135	0.000

$$\text{Hourly} = 0.391018 \times \text{daily} + 0.017527 \times \text{FIRE_Den} - 0.001779 \times \text{EDCU_Den} + 0.037069 \times \text{ARTENT_Den} + 1.872293 \times \text{CBD} \quad (5.10)$$

In this model, multiple R-Square is 0.8669, and adjusted R-Square is 0.8644. The Q-Q plot (Figure 5.15) and plot of residuals and fitted values (Figure 5.16) are shown below.

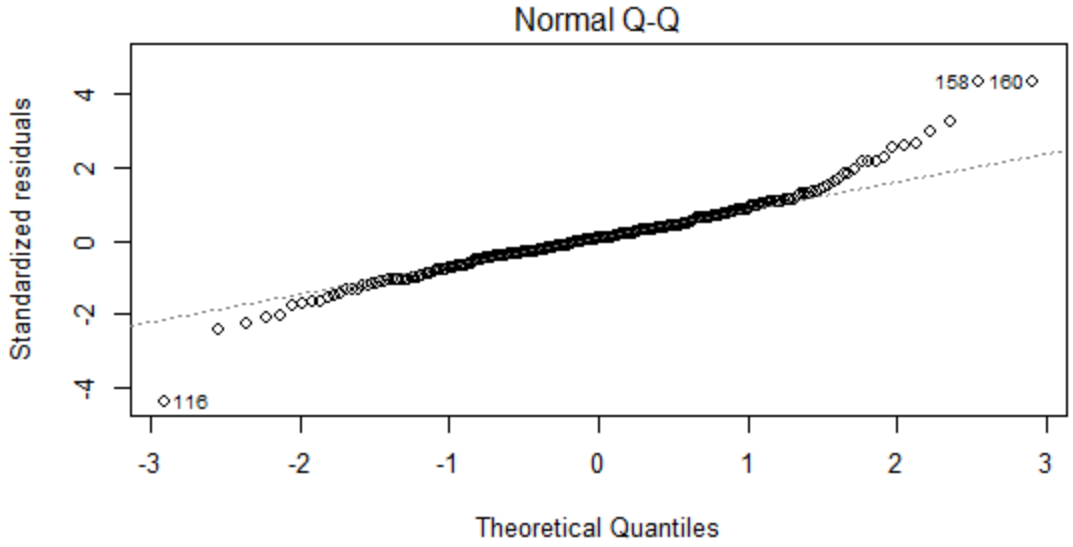


Figure 5.15 Normal Q-Q Plot for Hourly Parking Cost Model from Parking_without_SP_HDM Dataset

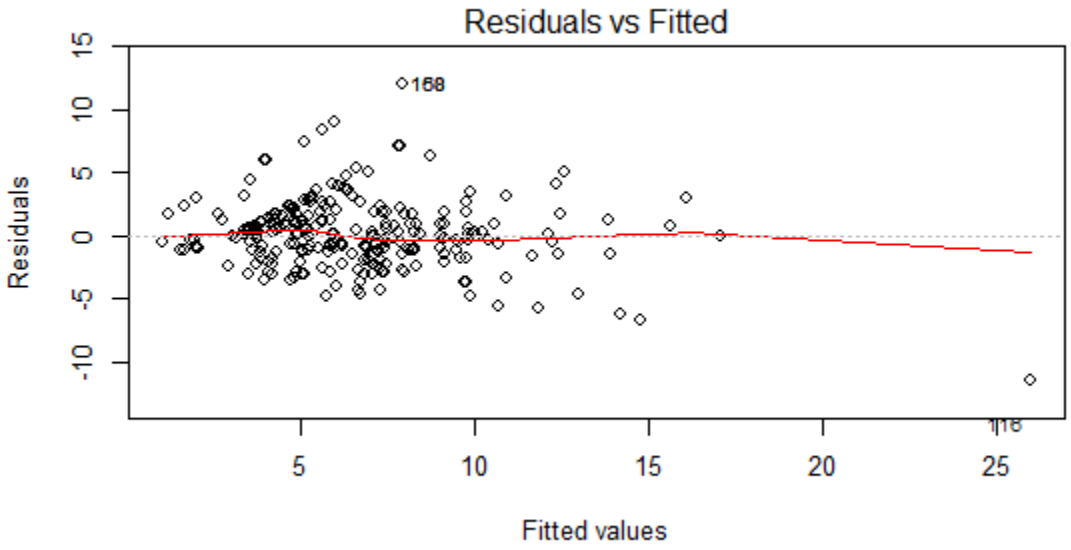


Figure 5.16 Residuals Plot for Hourly Parking Cost Model from Parking_without_SP_HDM Dataset

5.4 Monthly Parking Cost Models without parking supply

Monthly parking cost models are developed from daily and hourly parking rate as a commuter purpose. The results from Parking_without_SP dataset are in Table 5.14.

Table 5.14 Regression Results for Monthly Parking Cost Model from Parking_without_SP dataset

Coefficients	Estimate	Standard Error	t Value	Pr (> | t |)
daily	12.7044	0.4641	23.376	0.000
hourly	6.569	0.9229	7.118	0.000

Thus, the final monthly parking cost model from Parking_without_SP dataset is:

$$Monthly=12.7044\times daily+6.569\times hourly \quad (5.11)$$

In this model, multiple R-Square is 0.8886, and adjusted R-Square is 0.8883. The Q-Q plot (Figure 5.17) and plot of residuals and fitted values (Figure 5.18) are shown below.

The monthly model developed from Parking_without_SP_HDM dataset is summarized in Table 5.15. In this model, multiple R-Square is 0.8646, and adjusted R-Square is 0.8636. The Q-Q plot (Figure 5.19) and plot of residuals and fitted values (Figure 5.20) are shown below.

Table 5.15 Regression Results for Monthly Parking Cost Model from Parking_without_SP_HDM dataset

Coefficients	Estimate	Standard Error	t Value	Pr (> | t |)
daily	4.9282	0.5584	8.825	0.000
hourly	8.1641	1.0065	8.111	0.000

The final monthly parking cost model from Parking_without_SP_HDM dataset is:

$$\text{Monthly} = 4.9282 \times \text{daily} + 8.1641 \times \text{hourly} \quad (5.12)$$

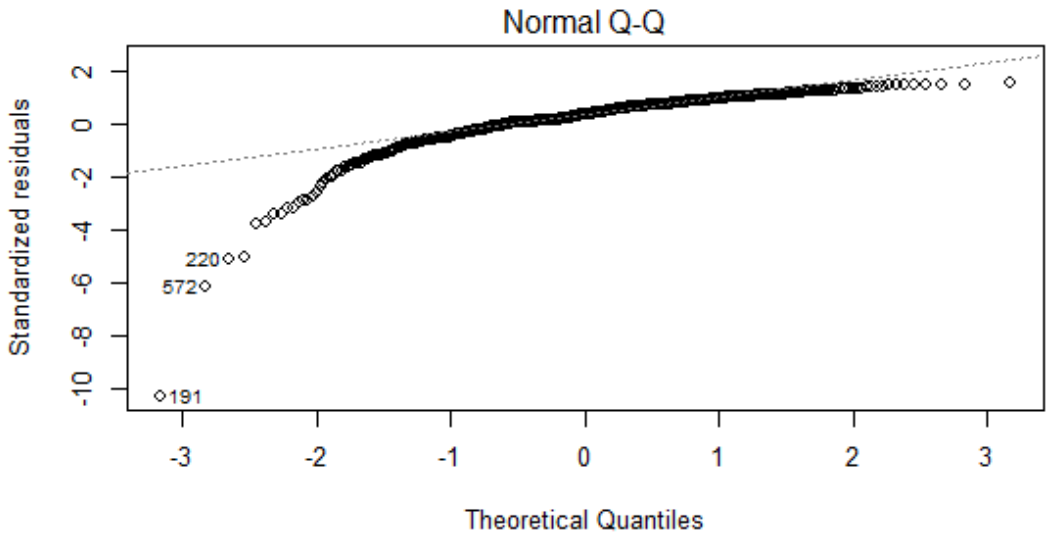


Figure 5.17 Normal Q-Q Plot for Monthly Parking Cost Model from Parking_without_SP Dataset

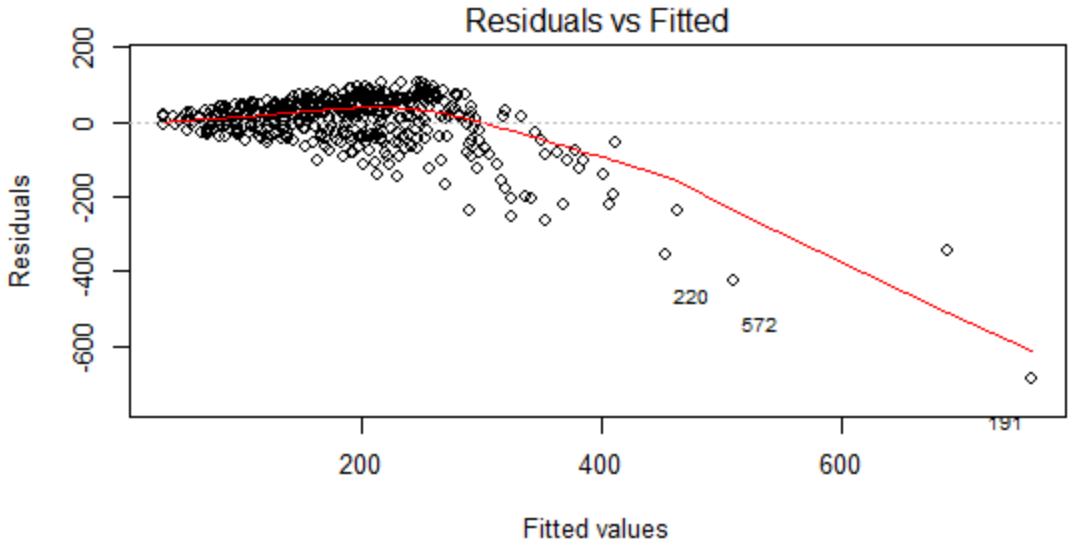


Figure 5.18 Residuals Plot for Monthly Parking Cost Model from Parking_without_SP Dataset

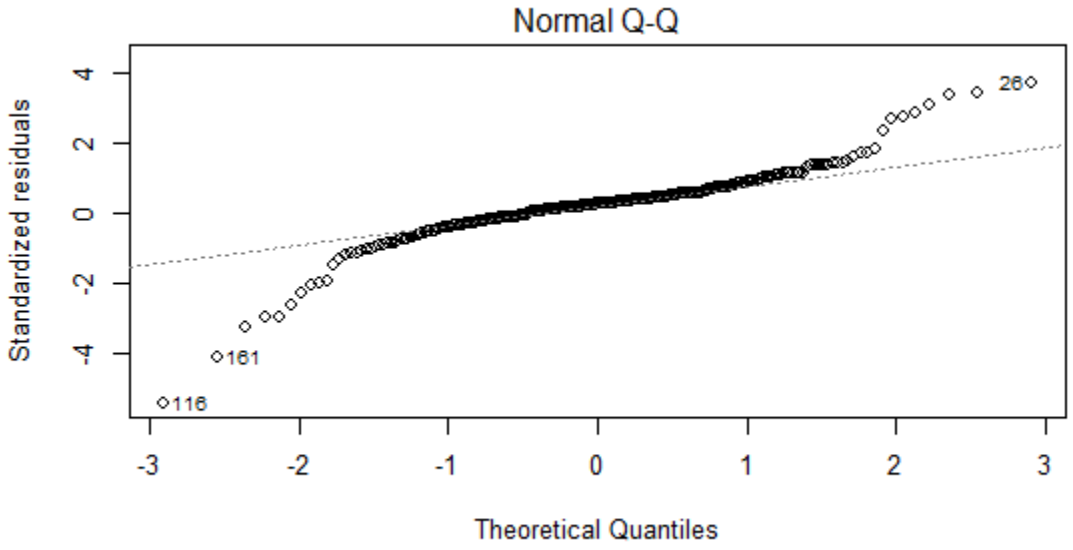


Figure 5.19 Normal Q-Q Plot for Monthly Parking Cost Model from Parking_without_SP_HDM Dataset

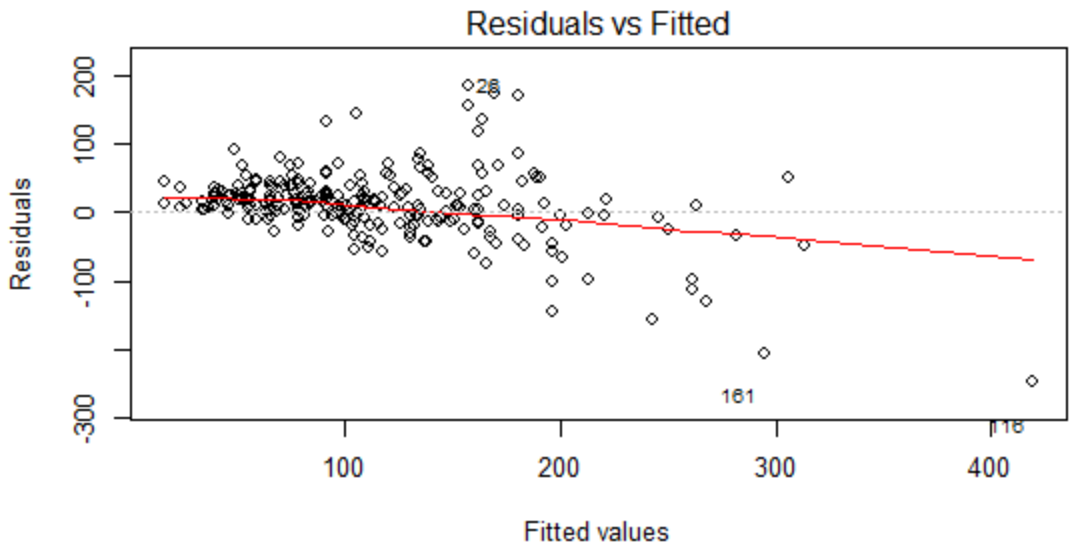


Figure 5.20 Residuals Plot for Monthly Parking Cost Model from Parking_without_SP_HDM Dataset

5.5 Result and Analysis

In this part study, 3 kinds of daily parking cost models without parking supply are developed to forecast the parking cost in all TAZs in Tier 2 (Table 5.16). After comparison, the daily model that has binary parking demand explanatory variables has the highest adjusted R-Square and is chosen to be the final daily parking cost model. Thus, the final hourly, daily and monthly parking cost models without parking supply are finally determined. The next step is to forecast the parking price in each TAZ.

Table 5.16 Daily Parking Cost Models without Parking Supply Comparison

Daily Parking Cost Model without Parking Supply	Adjusted R-Square from Parking_without_SP Dataset	Adjusted R-Square from Parking_without_SP_HDM Dataset
No parking demand variable	0.742	0.6511
Parking demand variable	0.7417	0.6498
Binary parking demand variable	**0.8142**	**0.7328**

CHAPTER 6. PARKING COST MODEL WITH PARKING SUPPLY

Parking supply is another important variable in determining parking price. In this chapter, parking cost models are generated using the available parking supply data in the dataset.

6.1 Data Preparation

The data preparation process is similar to the process in chapter 5, but different in calculating average parking cost in TAZ level.

1. Remove all the records that without parking supply number. After removing, there are 1215 records saved.

2. Remove the all zero records. In the dataset, there are 232 records don't have any data for hourly, daily and monthly rate at the same time. After removing the all zero records, there are 983 records left. Save these 983 records in the file named Parking_with_SP.

3. Select real effective data. From the left 983 records, there are 242 records that have hourly, daily and monthly rate simultaneously. Save these 242 records in the file named Parking_with_SP_HDM.

4. Estimate the missing data in Parking_with_SP dataset. Following the same rules in Table 5.1, the missing data are estimated for Parking_with_SP dataset.

5. Calculate the average parking cost for each TAZ. Since there are parking supply numbers consideration, the average parking cost is calculated in weighted average of all parking facilities within one TAZ using formula 6.1. After calculating, average parking costs for 420

TAZs are finally obtained from Parking_with_SP dataset, and 128 TAZs' average parking costs are obtained from Parking_with_SP_HDM dataset.

$$\text{Average parking rate}=\frac{\sum parking\ rate \times parking\ supply(in\ each\ parking\ facility)}{number\ of\ parking\ supply\ in\ one\ TAZ} \quad (6.1)$$

6. Remove outliers in Parking_with_SP dataset using the constraints from the Parking_with_SP_HDM dataset. The data in Parking_with_SP_HDM dataset are all the real records from the survey. Thus in the Parking_with_SP dataset, the records with parking cost rates out of the range of parking cost rates in Parking_with_SP_HDM are considered as outliers and removed from the dataset (Table 6.1). Finally there are 350 effective records saved in Parking_with_SP dataset.

Table 6.1 Constraints and Outliers for Parking_with_SP dataset

Constraints from Parking_without_SP _HDM dataset	**Outliers removed from Parking_without_SP dataset**
$\mathbf{0.5 \leq hourly\ rate \leq 20}$	12 records removed
$\mathbf{2.5 \leq hourly\ rate \leq 48}$	3 records removed
$\mathbf{30 \leq hourly\ rate \leq 350}$	55 records removed

7. Estimate parking demand data for each TAZ. The estimating method is the same as the method in Chapter 5.

6.2 Daily Parking Cost Models with Parking Supply

In daily parking cost models development, three daily models are built separately to see the difference after involving parking supply and parking demand as explanatory variables. In addition, daily parking cost models are built independently from both Parking_with_SP dataset and Parking_with_SP_HDM dataset.

6.2.1 Daily parking cost models without parking supply and parking demand

The variables are the same as the daily parking cost models in chapter 5, including P_Mlt_T1, Share_off, T2Share and T2EmpDen. First, from Parking_with_SP dataset, the daily parking cost model results without parking supply and parking demand are shown in Table 6.2.

Table 6.2 Regression Results for Daily Parking Cost Model without Parking Supply and Parking Demand (Parking_with_SP)

Coefficients	Estimate	Standard Error	t Value	Pr (> | t |)
P_Mlt_T1	6.409971	0.89413	7.151	0.000
Share_off	6.455732	1.453074	4.443	0.000
T2Share	5.782531	0.976690	5.921	0.000
T2EmpDen	0.005816	0.005252	1.107	0.269

Thus, the final model for daily parking cost without parking supply and parking demand from Parking_with_SP dataset is:

$$\text{Daily} = 6.409971 \times \text{P_Mlt_T1} + 6.455732 \times \text{Share_off} + 5.782531 \times \text{T2Share} + 0.005816 \times \text{T2EmpDen} \quad (6.2)$$

In this model, multiple R-Square is 0.7015, and adjusted R-Square is 0.698. Similar to the result in chapter 5, in the normal Q-Q plot (Figure 6.1), the residuals fit the normal distribution. But in the plot of residuals and fitted values, the residuals are not totally randomly distributed around 0 (Figure 6.2). Thus, this model still need to be further improved.

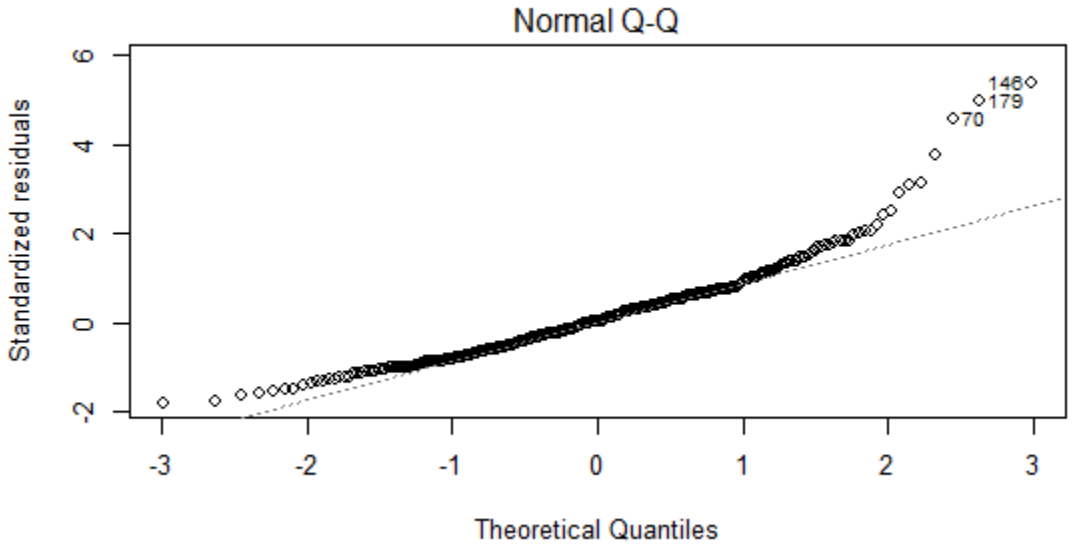


Figure 6.1 Normal Q-Q Plot for Daily Parking Cost Model without Parking Supply and Parking Demand from Parking_with_SP Dataset

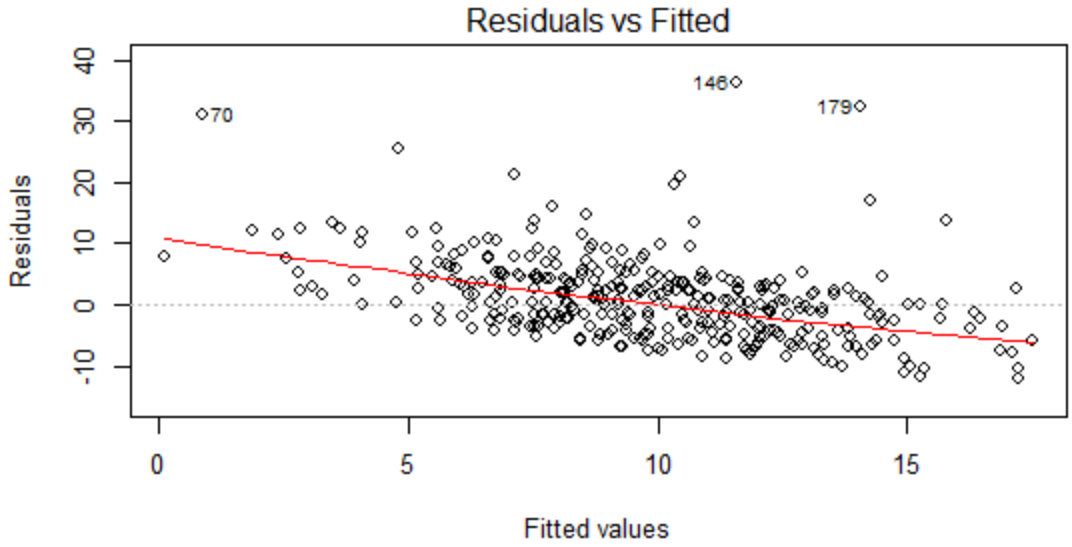


Figure 6.2 Residuals Plot for Daily Parking Cost Model without Parking Supply and Parking Demand from Parking_with_SP Dataset

As a comparison, the same variables are also used to build daily model using Parking_with_SP_HDM dataset. The results are shown in Table 6.3.

Table 6.3 Regression Results for Daily Parking Cost Model without Parking Supply and Parking Demand from Parking_with_SP_HDM dataset

Coefficients	Estimate	Standard Error	t Value	Pr (> | t |)
P_Mlt_T1	5.86794	1.92184	3.053	0.003
Share_off	7.61301	3.00007	2.538	0.012
T2Share	5.28607	2.14570	2.464	0.015
T2EmpDen	-0.01008	0.01191	-0.846	0.399

Thus, the final model for daily parking cost without parking demand from Parking_with_SP _HDM dataset is:

$$Daily = 5.86794 \times P_Mlt_T1 + 7.61301 \times Share_off + 5.28607 \times T2Share - 0.01008 \times T2EmpDen \quad (6.3)$$

In this model, multiple R-Square is 0.6224, and adjusted R-Square is 0.6102. So the goodness of fit from raw data is a little lower than the one after filling the missing data. From the normal Q-Q plot (Figure 6.3), the residuals still fit the normal distribution. However, in the plot of residuals and fitted values, the residuals are still not totally randomly distributed around 0 (Figure 6.4). Therefore in next step, total parking supply and parking demand should be considered as additional explanatory variable in determining daily parking price.

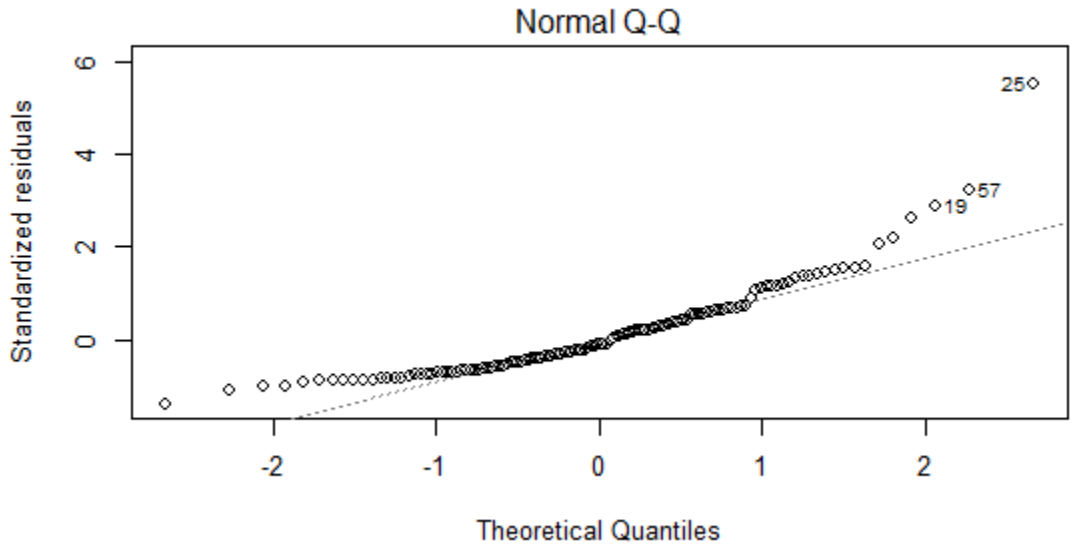


Figure 6.3 Normal Q-Q Plot for Daily Parking Cost Model without Parking Supply and Parking Demand from Parking_with_SP_HDM Dataset

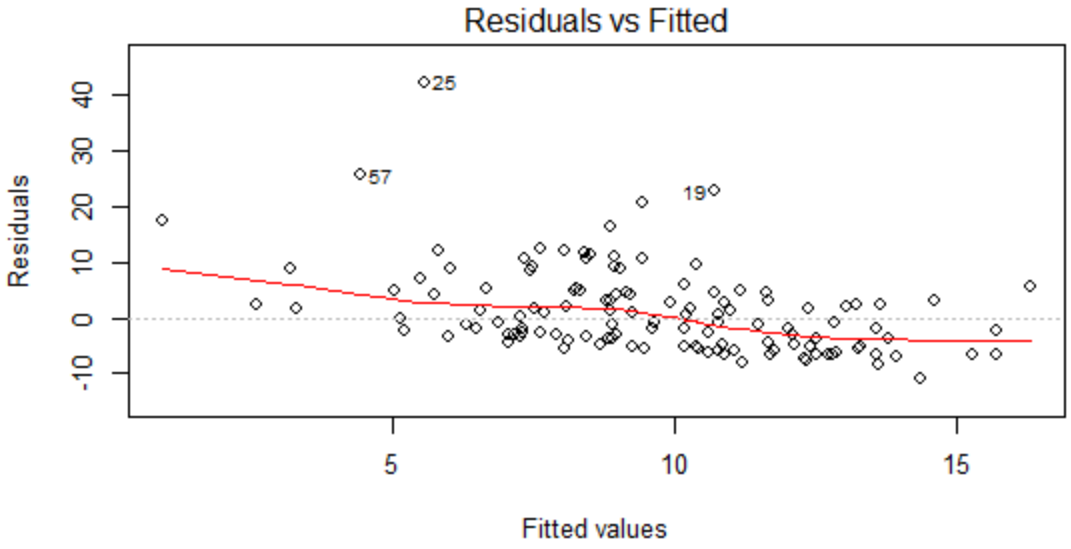


Figure 6.4 Residuals Plot for Daily Parking Cost Model without Parking Supply and Parking Demand from Parking_with_SP_HDM Dataset

6.2.2 Daily parking cost models with parking supply and parking demand

In this part, total parking supply number and parking demand are new explanatory variables for daily parking cost models. First, the results of daily parking cost model from Parking_with_SP dataset are shown in Table 6.4.

Table 6.4 Regression Results for Daily Parking Cost Model with Parking Supply and Parking Demand from Parking_with_SP Dataset

Coefficients	Estimate	Standard Error	t Value	Pr (> | t |)
P_Mlt_T1	5.695	0.8675	6.564	0.000
Share_off	6.412	1.387	4.622	0.000
T2Share	4.6	0.9996	4.601	0.000
T2EmpDen	0.003206	0.00705	0.455	0.65
TT_SP	0.001704	0.0002858	5.963	0.000
ParkingDemand	-0.00001381	0.0001126	-0.123	0.902

Thus, the final model for daily parking cost with parking supply and parking demand from Parking_with_SP dataset is:

$$\text{Daily} = 5.695 \times \text{P_Mlt_T1} + 6.412 \times \text{Share_off} + 4.6 \times \text{T2Share} + 0.003206 \times \text{T2EmpDen} + 0.001704 \times \text{TT_SP} - 0.00001381 \times \text{ParkingDemand} \quad (6.4)$$

In this model, multiple R-Square is 0.7295, and adjusted R-Square is 0.7248. The normal Q-Q plot is shown in Figure 6.5, and the plot of residuals and fitted values is shown in Figure 6.6.

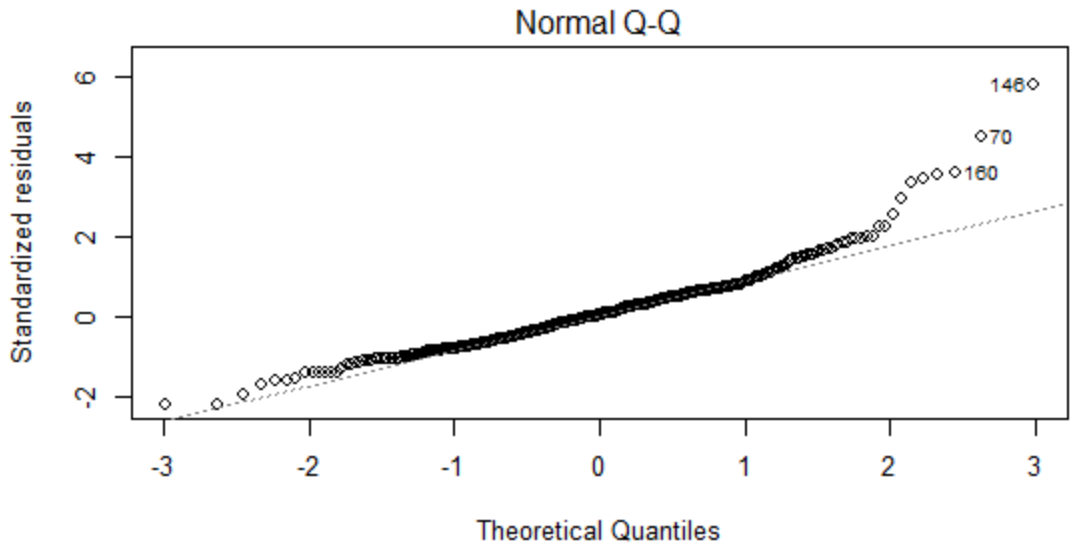


Figure 6.5 Normal Q-Q Plot for Daily Parking Cost Model with Parking Supply and Parking Demand from Parking_with_SP Dataset

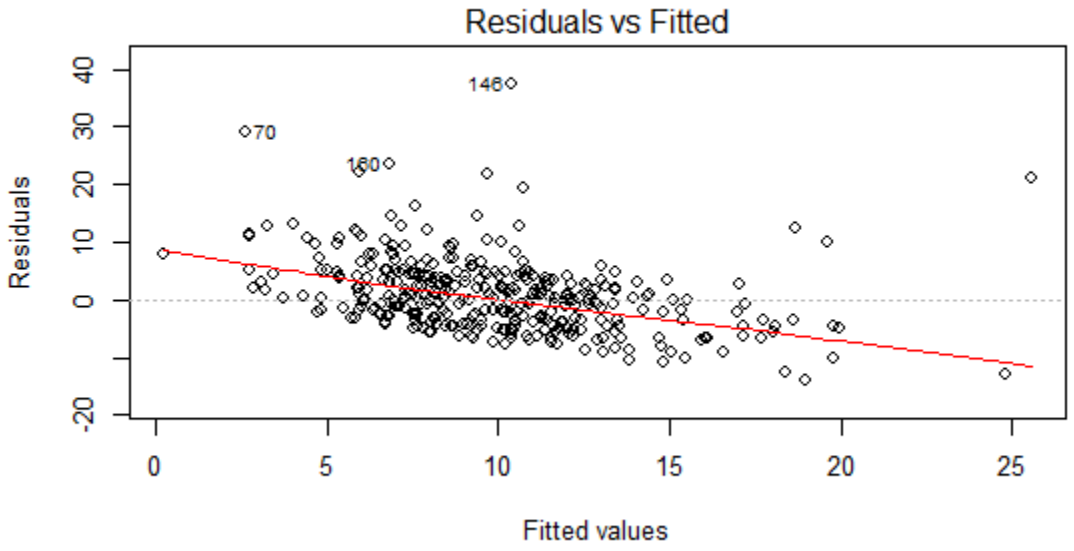


Figure 6.6 Residuals Plot for Daily Parking Cost Model with Parking Supply and Parking Demand from Parking_with_SP Dataset

As a comparison, the same variables are also used to build daily model using Parking_with_SP_HDM dataset. The results are shown in Table 6.5.

Table 6.5 Regression Results for Daily Parking Cost Model with Parking Supply and Parking Demand from Parking_with_SP_HDM dataset

Coefficients	Estimate	Standard Error	t Value	Pr (> | t |)
P_Mlt_T1	4.9463223	1.8213895	2.716	0.007
Share_off	7.0374624	2.8176472	2.498	0.014
T2Share	4.7151153	2.0958684	2.250	0.026
T2EmpDen	-0.0042272	0.0157844	-0.268	0.789
TT_SP	0.0030439	0.0007057	4.313	0.000
ParkingDemand	-0.0001619	0.0002342	-0.691	0.49

Thus, the final model for daily parking cost without parking demand from Parking_with_SP _HDM dataset is:

$$\text{Daily} = 4.9463223 \times \text{P_Mlt_T1} + 7.0374624 \times \text{Share_off} + 4.7151153 \times \text{T2Share} - 0.0042272 \times \text{T2EmpDen} + 0.0030439 \times \text{TT_SP} - 0.0001619 \times \text{ParkingDemand} \quad (6.5)$$

In this model, multiple R-Square is 0.6733, and adjusted R-Square is 0.6572. The normal Q-Q plot is shown in Figure 6.7, and the plot of residuals and fitted values is shown in Figure 6.8.

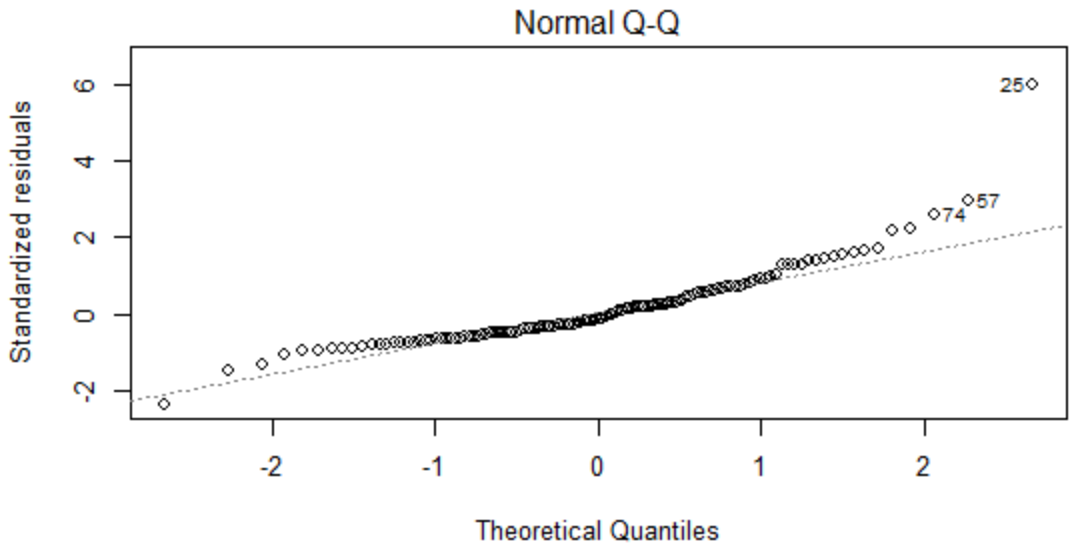


Figure 6.7 Normal Q-Q Plot for Daily Parking Cost Model with Parking Supply and Parking Demand from Parking_with_SP_HDM Dataset

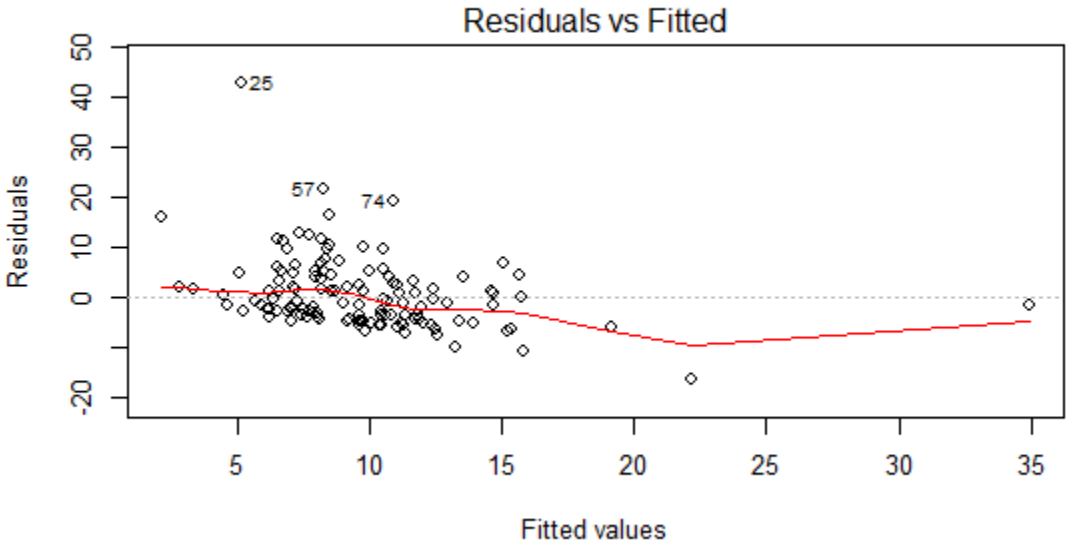


Figure 6.8 Residuals Plot for Daily Parking Cost Model with Parking Supply and Parking Demand from Parking_with_SP_HDM Dataset

6.2.3 Daily parking cost models with parking supply and binary parking demand

Parking demand should be an important explanatory variable in determining daily parking cost. However, the result in last part is not as good as expected. Thus in this part, binary parking demand variables are considered to replace direct parking demand number. The classification of binary parking demand is the same as the classification in chapter 5. First, the model results from Parking_with_SP dataset are shown in Table 6.6.

Table 6.6 Regression Results for Daily Parking Cost Model with Parking Supply and Binary Parking Demand from Parking_with_SP Dataset

Coefficients	Estimate	Standard Error	t Value	Pr (> | t |)
P_Mlt_T1	-1.05771	1.0322966	-1.025	0.306
Share_off	-0.1055261	1.4320515	-0.074	0.941
T2Share	-1.0733624	1.0938290	-0.981	0.327
T2EmpDen	0.0081258	0.0049374	1.646	0.101
TT_SP	0.0014724	0.0002548	5.778	0.000
PD_1000	10.3670843	1.0656917	9.728	0.000
PD_1000_3000	10.7461655	1.2632315	8.507	0.000
PD_3000over	11.0086197	1.5348576	7.172	0.000

Thus, the final model for daily parking cost with parking supply and parking demand from Parking_with_SP dataset is:

Daily =-1.05771×P_Mlt_T1-0.1055261×Share_off-

1.0733624×T2Share+0.0081258×T2EmpDen+0.0014724×TT_SP+10.3670843×PD_1000+10.

7461655×PD_1000_3000+11.0086197×PD_3000over (6.6)

In this model, multiple R-Square is 0.7895, and adjusted R-Square is 0.7846. The normal Q-Q plot is shown in Figure 6.9, and the plot of residuals and fitted values is shown in Figure 6.10.

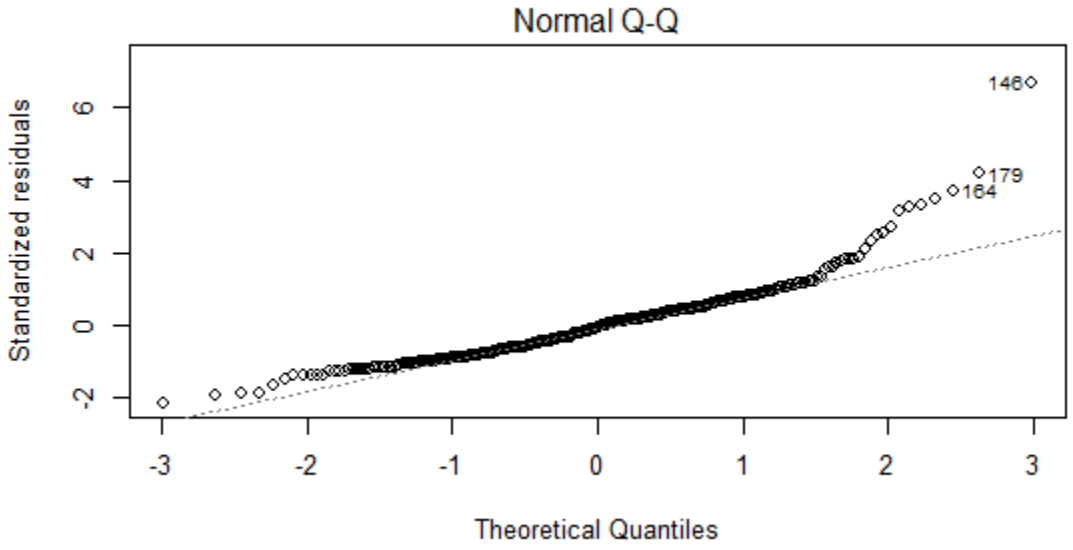


Figure 6.9 Normal Q-Q Plot for Daily Parking Cost Model with Parking Supply and Binary Parking Demand from Parking_with_SP Dataset

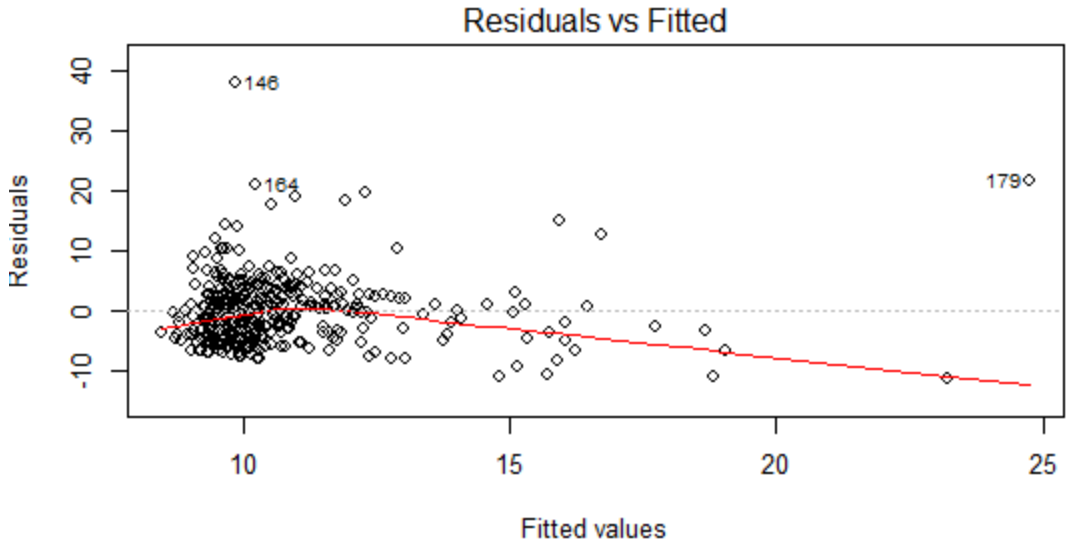


Figure 6.10 Residuals Plot for Daily Parking Cost Model with Parking Supply and Binary Parking Demand from Parking_with_SP Dataset

As a comparison, the same variables are also used to build daily model using Parking_with_SP_HDM dataset. The results are shown in Table 6.7.

Table 6.7 Regression Results for Daily Parking Cost Model with Parking Supply and Binary Parking Demand from Parking_with_SP_HDM dataset

Coefficients	Estimate	Standard Error	t Value	Pr (> | t |)
P_Mlt_T1	-3.3446239	2.2258110	-1.503	0.135555
Share_off	0.7980065	2.7827613	0.287	0.774785
T2Share	-0.4378933	2.1876045	-0.2	0.841686
T2EmpDen	-0.0009377	0.0115877	-0.081	0.935638
TT_SP	0.0026285	0.0006383	4.118	0.000
PD_1000	12.4365749	2.2106822	5.626	0.000
PD_1000_3000	11.3744198	2.4388011	4.664	0.000
PD_3000over	11.5691185	3.0238878	3.826	0.000

Thus, the final model for daily parking cost without parking demand from Parking_with_SP _HDM dataset is:

$$\text{Daily} = -3.3446239 \times \text{P_Mlt_T1} + 0.7980065 \times \text{Share_off} - 0.4378933 \times \text{T2Share} - 0.0009377 \times \text{T2EmpDen} + 0.0026285 \times \text{TT_SP} + 12.4365749 \times \text{PD_1000} + 11.3744198 \times \text{PD_1000_3000} + 11.5691185 \times \text{PD_3000over} \quad (6.7)$$

In this model, multiple R-Square is 0.7431, and adjusted R-Square is 0.7259. The normal Q-Q plot is shown in Figure 6.11, and the plot of residuals and fitted values is shown in Figure 6.12.

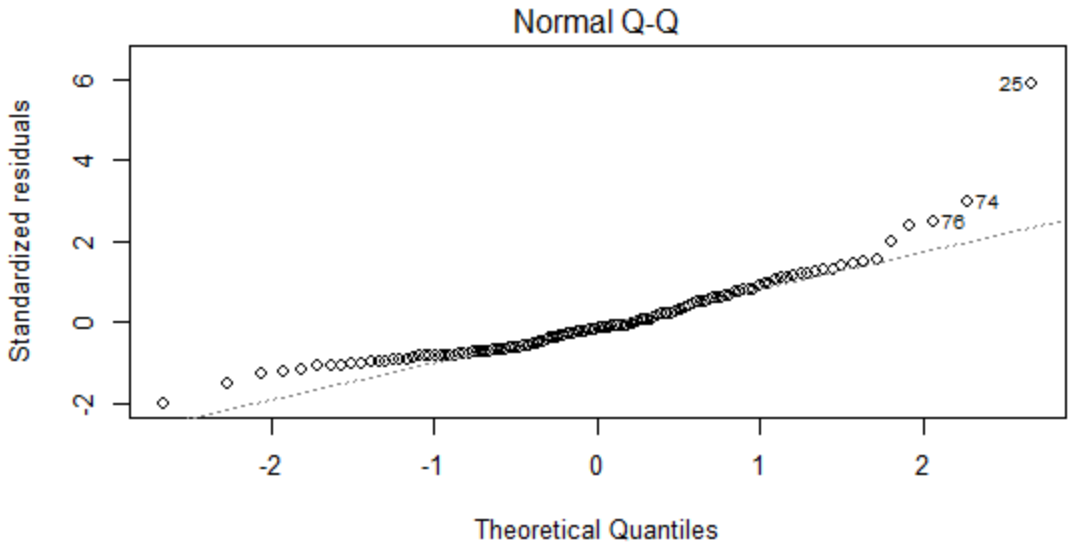


Figure 6.11 Normal Q-Q Plot for Daily Parking Cost Model with Parking Supply and Binary Parking Demand from Parking_with_SP_HDM Dataset

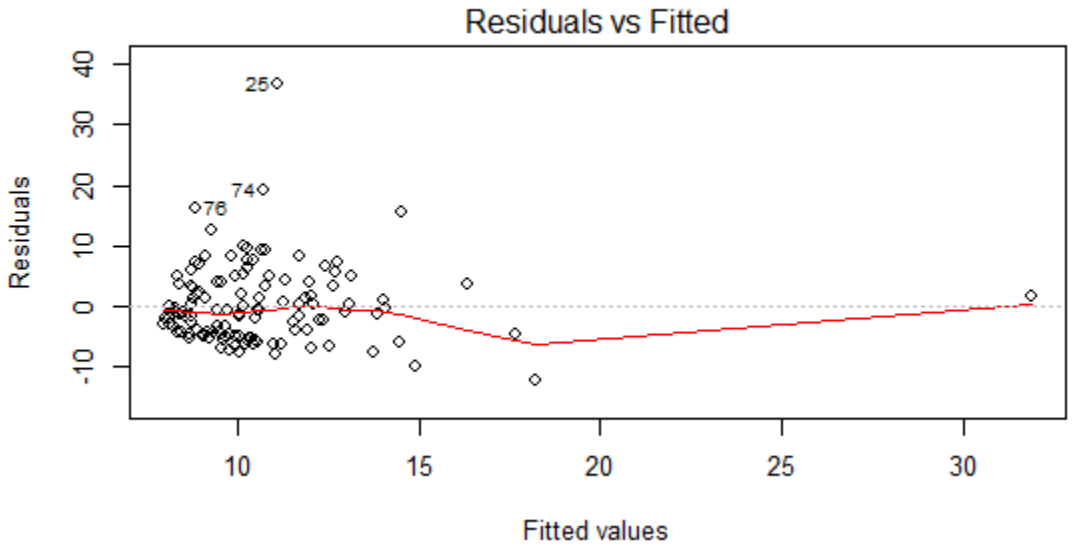


Figure 6.12 Residuals Plot for Daily Parking Cost Model with Parking Supply and Binary Parking Demand from Parking_with_SP_HDM Dataset

6.3 Hourly Parking Cost Models with Parking Supply

Hourly parking cost model is developed using the same variables in chapter 5. The model results from Parking_without_SP is summarized in Table 6.8.

Table 6.8 Regression Results for Hourly Parking Cost Model from Parking_with_SP dataset

Coefficients	Estimate	Standard Error	t Value	Pr (> | t |)
daily	0.368118	0.022535	16.335	0.000
FIRE_Den	-0.029676	0.024944	-1.19	0.235
EDCU_Den	-0.000401	0.006252	-0.064	0.949
ARTENT_Den	-0.012644	0.026324	-0.48	0.631
CBD	1.577994	0.343551	4.593	0.000

Thus, the final model for hourly parking cost with binary parking demand from Parking_with_SP dataset is:

$$\text{Hourly} = 0.368118 \times \text{daily} - 0.029676 \times \text{FIRE_Den} - 0.000401 \times \text{EDCU_Den} - 0.012644 \times \text{ARTENT_Den} + 1.577994 \times \text{CBD} \quad (6.8)$$

In this model, multiple R-Square is 0.7243, and adjusted R-Square is 0.7203. The Q-Q plot (Figure 6.13) and plot of residuals and fitted values (Figure 6.14) are shown below.

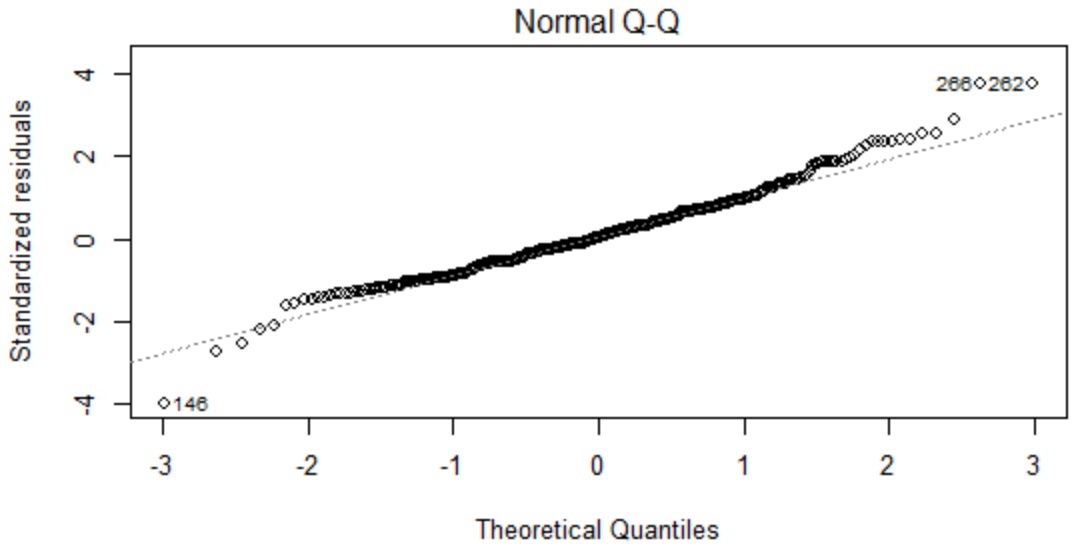


Figure 6.13 Normal Q-Q Plot for Hourly Parking Cost Model from Parking_with_SP Dataset

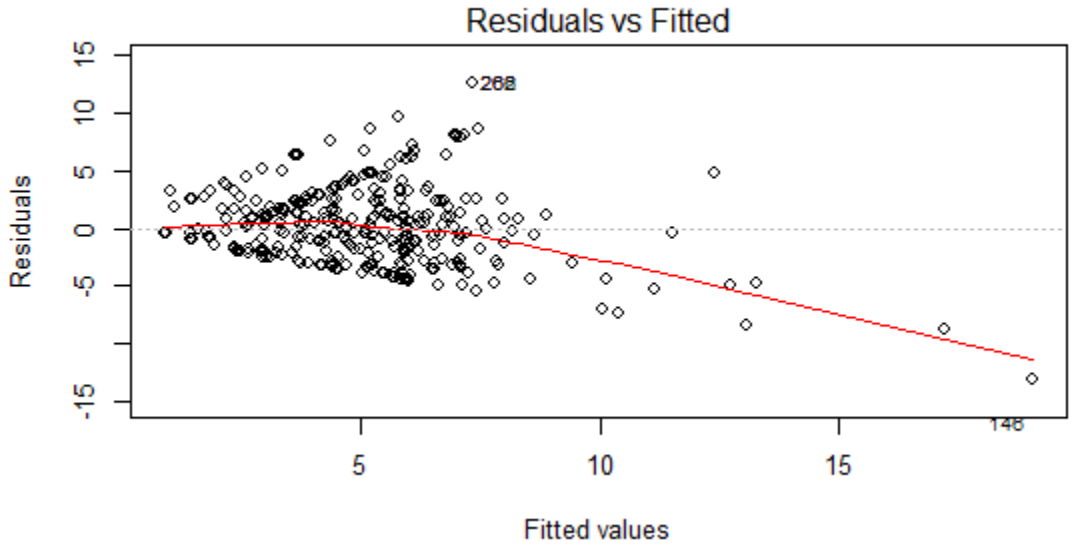


Figure 6.14 Residuals Plot for Hourly Parking Cost Model from Parking_with_SP Dataset

From Parking_with_SP_HDM dataset, the hourly parking cost model is developed and shown below in Table 6.9.

Table 6.9 Regression Results for Hourly Parking Cost Model from Parking_with_SP_HDM dataset

Coefficients	Estimate	Standard Error	t Value	Pr (> | t |)
daily	0.465004	0.034196	13.599	0.000
FIRE_Den	0.043655	0.028032	1.557	0.122
EDCU_Den	0.009593	0.027261	0.352	0.725
ARTENT_Den	-0.044582	0.045145	-0.998	0.325
CBD	1.528827	0.551399	2.773	0.006

$$\text{Hourly} = 0.465004 \times \text{daily} + 0.043655 \times \text{FIRE_Den} + 0.009593 \times \text{EDCU_Den} - 0.044582 \times \text{ARTENT_Den} + 1.528827 \times \text{CBD} \quad (6.10)$$

In this model, multiple R-Square is 0.8315, and adjusted R-Square is 0.8246. The Q-Q plot (Figure 6.15) and plot of residuals and fitted values (Figure 6.16) are shown below.

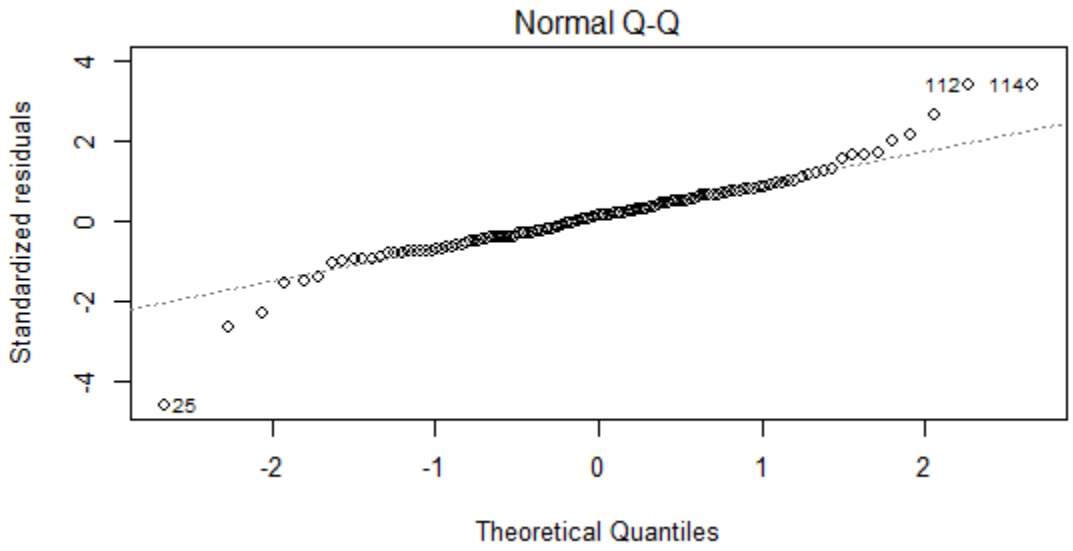


Figure 6.15 Normal Q-Q Plot for Hourly Parking Cost Model from Parking_with_SP_HDM Dataset

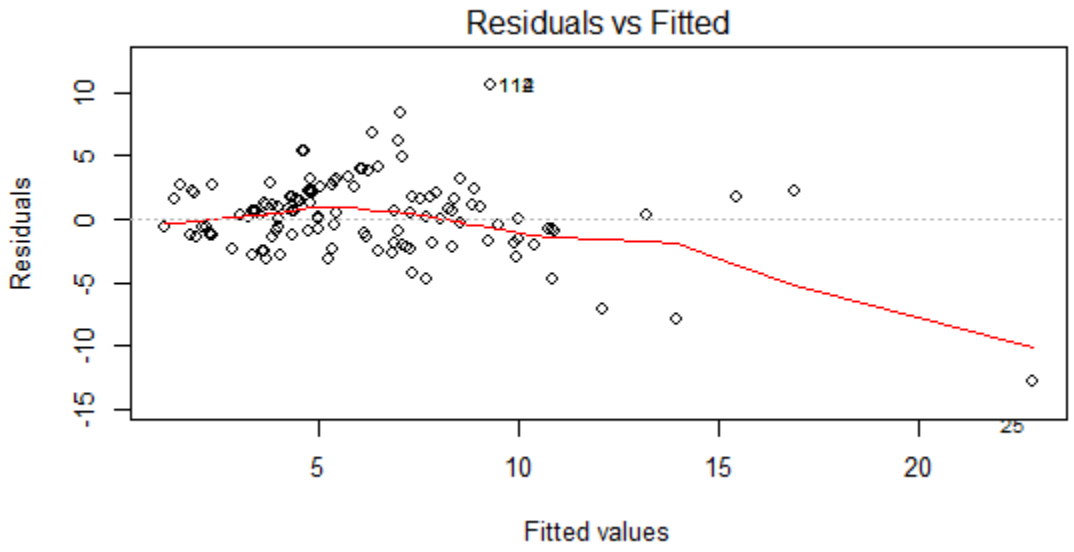


Figure 6.16 Residuals Plot for Hourly Parking Cost Model from Parking_with_SP_HDM Dataset

6.4 Monthly Parking Cost Models with Parking Supply

Similar to the monthly model in chapter 5, the monthly parking model with parking supply is also developed from daily and hourly parking rate. The model results from Parking_without_SP dataset are in Table 6.10.

Table 6.10 Regression Results for Monthly Parking Cost Model from Parking_with_SP dataset

Coefficients	Estimate	Standard Error	t Value	Pr (> | t |)
daily	12.066	0.5805	20.784	0.000
hourly	6.4902	1.118	5.805	0.000

Thus, the final monthly parking cost model from Parking_with_SP dataset is:

Monthly=12.066×daily+6.4902×hourly (6.11)

In this model, multiple R-Square is 0.8675, and adjusted R-Square is 0.8667. The Q-Q plot (Figure 6.17) and plot of residuals and fitted values (Figure 6.18) are shown below.

The monthly model developed from Parking_without_SP_HDM dataset is summarized in Table 6.11. In this model, multiple R-Square is 0.8766, and adjusted R-Square is 0.8747. The Q-Q plot (Figure 6.19) and plot of residuals and fitted values (Figure 6.20) are shown below.

Table 6.11 Regression Results for Monthly Parking Cost Model from Parking_with_SP_HDM dataset

Coefficients	Estimate	Standard Error	t Value	Pr (> | t |)
daily	4.7334	0.7302	6.482	0.000
hourly	8.4637	1.2231	6.92	0.000

The final monthly parking cost model from Parking_with_SP_HDM dataset is:

Monthly= 4.7334×daily+8.4637×hourly (6.12)

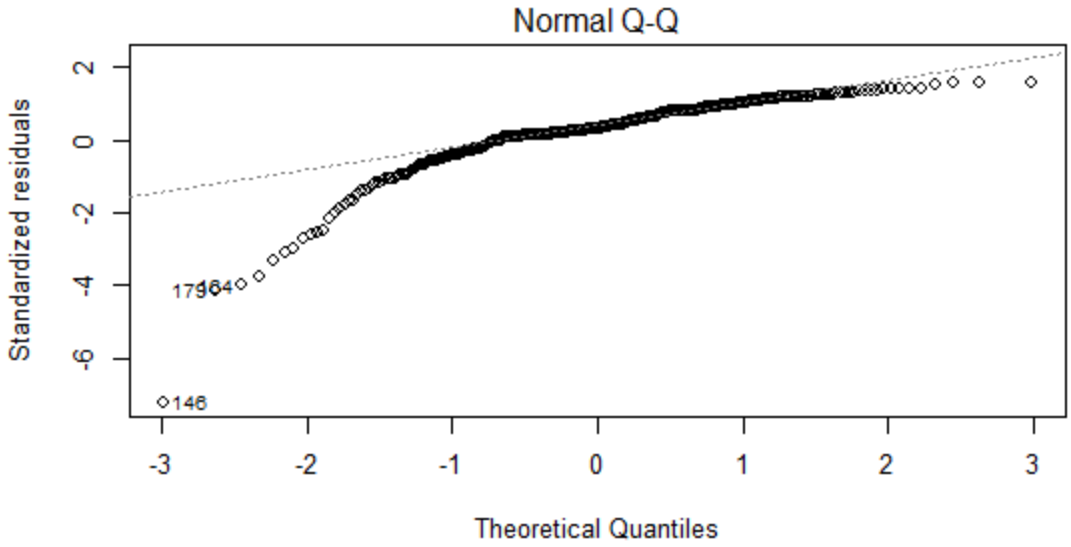


Figure 6.17 Normal Q-Q Plot for Monthly Parking Cost Model from Parking_with_SP Dataset

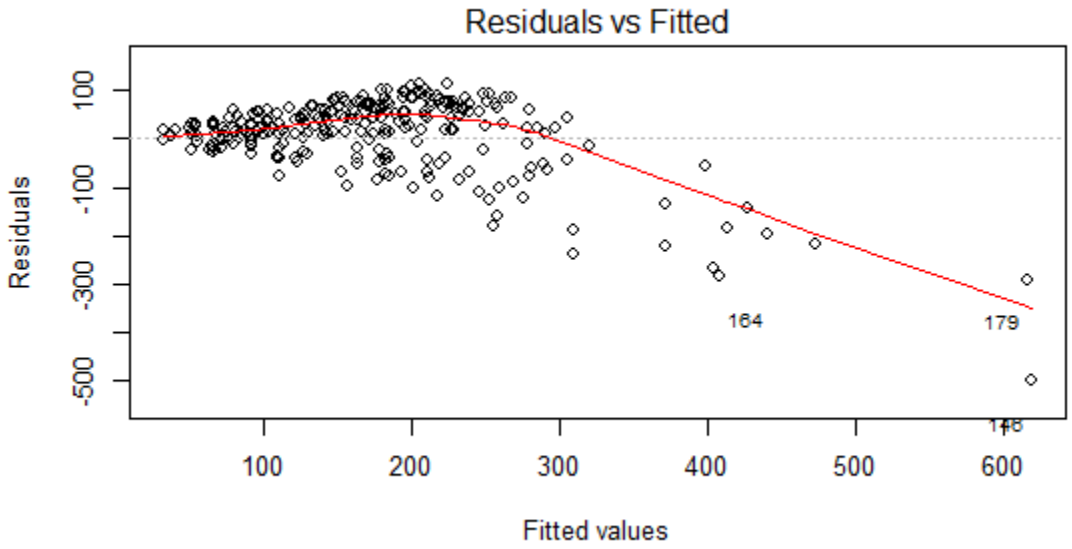


Figure 6.18 Residuals Plot for Monthly Parking Cost Model from Parking_with_SP Dataset

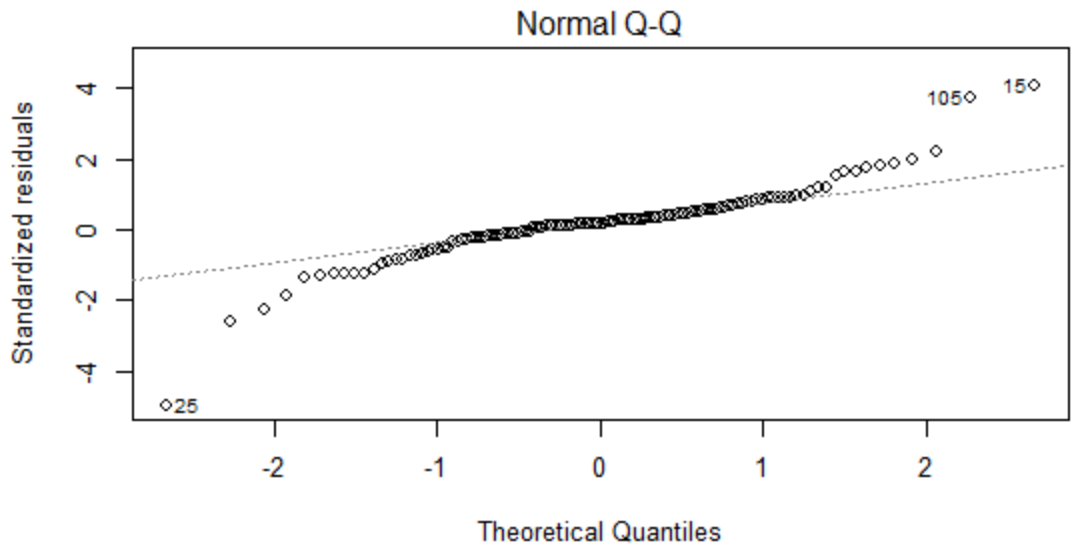


Figure 6.19 Normal Q-Q Plot for Monthly Parking Cost Model from Parking_with_SP_HDM Dataset

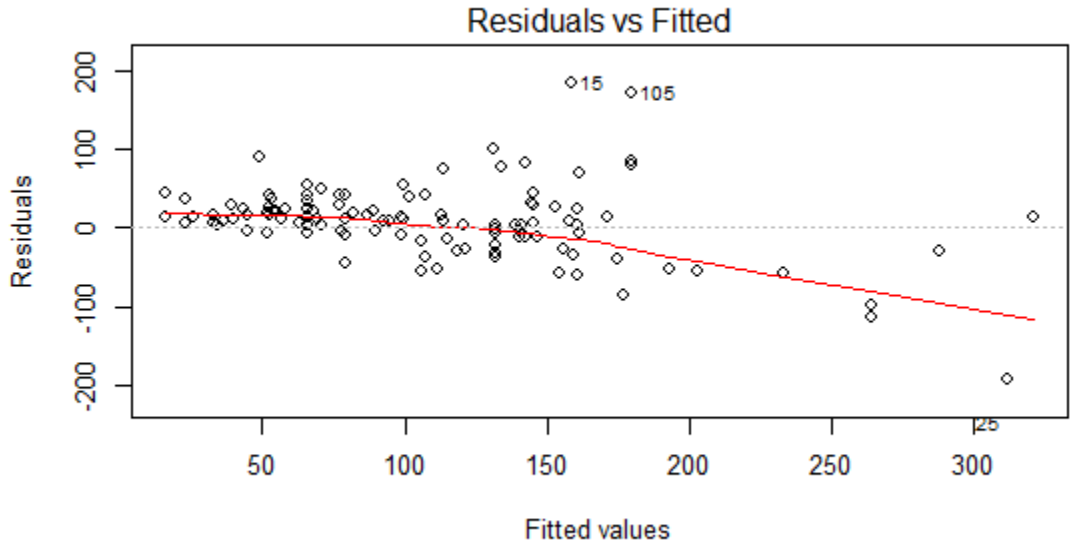


Figure 6.20 Residuals Plot for Monthly Parking Cost Model from Parking_with_SP_HDM Dataset

6.5 Results and Analysis

In this part of the study, three types of daily parking cost models without parking supply are developed to forecast the parking cost in all TAZs in Tier 2 (Table 6.12). After comparison, the daily model that has both total parking supply and binary parking demand explanatory variables has the highest adjusted R-Square and is chosen to be the final daily parking cost model. Thus, the final hourly, daily and monthly parking cost models with parking supply are finally determined. However, this model cannot be applied to forecast parking cost in each TAZ since it requires parking supply number.

Table 6.12 Daily Parking Cost Models with Parking Supply Comparison

Daily Parking Cost Model with Parking Supply	Adjusted R-Square from Parking_with_SP Dataset	Adjusted R-Square from Parking_with_SP_HDM Dataset
No total parking supply and parking demand variable	0.698	0.6102
Total parking supply and parking demand variable	0.7248	0.6572
Total parking supply and binary parking demand variable	**0.7846**	**0.7259**

CHAPTER 7. CONCLUSIONS AND RECOMMENDATIONS

7.1 Conclusions

This study aims to develop parking cost models for off-street parking facilities in Tier 2 TAZ level from current socio-economic database and parking cost survey using linear regression in R. With the consideration of parking supply variable, this study develops two groups of models, one with parking supply, the other not. To conclude this study, the models comparison tables are shown in Table 7.1 and 7.2. From the model results we can find that employment information is still the most important variable in determining parking price. In addition, parking supply and parking demand are also significant independent variables. From the model results, binary parking demand variables can fit better than the direct parking demand number. R-Squares from dataset after filling the missing data are always higher than the R-Squares from raw dataset. It refers that the method of filling missing data is reasonable. However, although the models with both parking supply and parking demand are more reasonable in real life, it cannot be used to forecast parking price in each TAZ level since it is not possible to get the parking supply number in each parking facility. Thus, according to current condition, parking cost models developed in chapter 5 can be used directly in SCAG Mode Choice Model to estimate parking price in Tier 2 TAZs. The main contributions of this study are:

1. Use binary parking demand variable in determining parking price;

2. Develop two groups of models as comparison and for different use;

3. Build daily, hourly and monthly parking price models using reasonable explanatory variables.

Table 7.1 Parking Cost Models without Parking Supply Comparison

Parking Cost Model without Parking Supply	Independent Variables	Adjusted R-Square from Parking_without_SP Dataset	Adjusted R-Square from Parking_without_SP_HDM Dataset
Daily model without parking demand variable	T2share, P_Mlt_T1, Share_off, T2EmpDen	0.742	0.6511
Daily model with parking demand variable	T2share, P_Mlt_T1, Share_off, T2EmpDen, Parking Demand	0.7417	0.6498
Daily model with binary parking demand variable	**T2share, P_Mlt_T1, Share_off, T2EmpDen, PD_1000, PD_1000_3000, PD_3000over**	**0.8142**	**0.7328**
Hourly model	**daily, FIRE_Den, EDCU_Den, ARTENT_Den, CBD**	**0.7861**	**0.8644**
Monthly model	**daily, hourly**	**0.8883**	**0.8636**

Table 7.2 Parking Cost Models with Parking Supply Comparison

Parking Cost Model without Parking Supply	Independent Variables	Adjusted R-Square from Parking_with_SP Dataset	Adjusted R-Square from Parking_with_SP_HDM Dataset
Daily model without parking demand variable	T2share, P_Mlt_T1, Share_off, T2EmpDen	0.698	0.6102
Daily model with parking demand variable	T2share, P_Mlt_T1, Share_off, T2EmpDen, TT_SP Parking Demand	0.7248	0.6572
Daily model with binary parking demand variable	**T2share, P_Mlt_T1, Share_off, T2EmpDen, TT_SP PD_1000, PD_1000_3000, PD_3000over**	**0.7846**	**0.7259**
Hourly model	**daily, FIRE_Den, EDCU_Den, ARTENT_Den, CBD**	**0.7203**	**0.8246**
Monthly model	**daily, hourly**	**0.8667**	**0.8747**

7.2 Recommendations

Limited by the available data, this study build hourly, daily and monthly parking cost models mentioned above. In the future, there are still many challenges to further improve the current models:

1. Different from off-street parking, on-street parking models can also be developed if the data is available;

2. Auto and transit accessibility is another possible explanatory variable for parking price and can be studied in the future;

3. This parking demand is calculated only based on HBW trip rates for commuter purpose. In the future study, TAZs can be divided into different groups by purpose, such as employment centers, recreation centers, universities and so on. Depending on different TAZ group, the parking demand should be calculated using different trip purpose rates, not only HBW trip rates.

4. With the development of driverless car, the impact of driverless car should also be taken into account in developing parking cost models;

5. All the parking cost models now are not perfect limited by the available data. Thus, a better parking cost survey should be designed with all information related to parking price, such as auto ownership for each traveler, trip purpose and parking subsidy.

6. From Table 7.2 we can find that, after considering total parking supply as a new variable, the improvement is not so significant. An alternative method is to generated average parking supply per person as a new independent variable and can be achieved in the future.

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