

LOCATION SELECTION OF HYDROGEN REFUELLING STATIONS

by

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ABSTRACT

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The energy resources used today will not be sufficient to fulfil the future demand and the transportation sector will also be affected. Researchers, therefore, study alternative energy sources. Through its advantages, hydrogen energy constitutes one of these alternatives. Hydrogen, which can be used as fuel in vehicles, constitutes an important alternative with electric vehicles for the future. Through its infrastructure advantages, electric vehicles have been on the market before and therefore have a higher rate of sales today. However, with the development of hydrogen technology and the reduction in its costs, it is foreseen that hydrogen vehicles will take their place in the market. This situation is promoted by the countries' support programs published for the development of hydrogen energy, and hydrogen fuel cell vehicle (HFCV) produced by the companies that have an important share in the automobile industry. However, in order for HFCV to become widespread, the number of hydrogen refuelling stations (HRSs) should increase. Electric vehicles can recharge their batteries at points such as homes, which eliminates the need to open a dedicated charging station. However, it is compulsory to open HRSs, where HFCVs can be fuelled. Therefore it is critical to locate HRS. In this thesis, we aim to determine the locations of the HRSs. In this context, the locations of HRSs to be opened in Istanbul are determined using a multi-period p-median model. In order to determine the future demand, the adaptation of demand points (i.e., neighbourhoods) to hydrogen technology is taken into account by using the development indexes of the districts. According to the results, it is observed that in the first periods, the HRSs are opened in the center and they are spread throughout the city in the later periods of a 30-year planing horizon.

ÖZET

HİDROJEN YAKIT İKMAL İSTASYONLARININ YER SEÇİMİ

Günümüzde kullanılan enerji kaynakları gelecek talebini karşılamak için yetersiz kalacak ve bu durumdan ulaşım sektörü de etkilenecektir. Bu nedenle araştırmacılar alternatif enerji kaynağı arayışına girmişlerdir. Sahip olduğu avantajlar sayesinde hidrojen enerjisi bu alternatiflerden birini oluşturmaktadır. Araçlarda da yakıt olarak da kullanılabilen hidrojen, elektrikli araçlarla birlikte önemli bir alternatifi oluşturmaktadır. Sahip olduğu altyapı avantajları sayesinde elektrikli araçlar daha önce piyasaya çıkmış ve bu nedenle günümüzde daha fazla satış oranına sahiptir. Ancak hidrojen teknolojisinin gelişmesi ve maliyetlerinin azalmasıyla birlikte hidrojenli araçlarında da piyasada yerini alacağı düşünülmektedir. Ülkelerin hidrojen enerjisinin geliştirilmesine yönelik destek programları yayınlaması ve otomobil sektöründe önemli paya sahip olan firmaların hidrojenli araç modelleri çıkarmaları bu durumu desteklemektedir. Ancak hidrojenli araçların yaygınlaşabilmesi için hidrojen dolum istasyonlarının sayısının artması gerekmektedir. Elektrikli araçlar pil dolularını ev gibi noktalarda yapabilmekte bu da dolum istasyonunun açılması zorunluluğu ortadan kaldırmaktadır. Ancak hidrojenli araçların yakıt alabileceği hidrojen dolum istasyonlarının açılması zorunludur. Bu zorunluluk hidrojen dolum istasyonlarının nereye açılacağı sorusunu ortaya çıkarmaktadır. Bu tez çalışmasında hidrojen dolum istasyonlarının yerlerinin belirlenmesi incelenmektedir. Bu kapsamda İstanbul'da açılacak hidrojen dolum istasyonlarının yerleri önerilen çok dönemli p-medyan modeli kullanılarak belirlenmiştir. Gelecek talebinin belirlenmesi için ilçelerin gelişmişlik indeksleri kullanılarak talep noktalarının hidrojen teknolojisine adaptasyonu dikkate alınmıştır. Elde edilen sonuçlara göre ilk periyotlarda merkezde açılan hidrojen dolum istasyonlarının 30 yıllık planlama döneminin son periyotlarına gelindiğinde il geneline yayıldığı gözlemlenmiştir.

TABLE OF CONTENTS

ACKNOWLEDGEMENTS	iii
ABSTRACT	iv
ÖZET	v
LIST OF FIGURES	viii
LIST OF TABLES	x
LIST OF SYMBOLS	xii
LIST OF ACRONYMS/ABBREVIATIONS	xiii
1. INTRODUCTION	1
2. LITERATURE REVIEW	5
2.1. Technology Diffusion and S-Curve	5
2.2. Location Selection Problem	7
3. MODEL AND INPUT	16
3.1. Proposed Model	16
3.2. Demand Points: Neighbourhoods	18
3.2.1. Projection of the Number of Vehicles in İstanbul	19
3.2.2. Technology Diffusion of Hydrogen Fuel Cell Vehicles	21
3.2.3. Human Development Index	25
3.2.4. Calculating the Demand of Districts	28
3.2.5. Calculating the Demand of Neighbourhoods	30
3.3. Supply Points: Existing Gas Stations	31
4. RESULTS	34
4.1. Base Scenario Results	36
4.2. Effect of p Values	40
4.3. Effect of Penetration over Demand	49
5. CONCLUSION	52
REFERENCES	56
APPENDIX A: DATA PRE-PROCESSING	63
APPENDIX B: EFFECT OF DEMAND CHANGES	64

APPENDIX C: DIFFERENT P-VALUES	65
APPENDIX D: COMPARISON OF THE $p=90$ and $p=126$	70

LIST OF FIGURES

Figure 2.1.	General structure of technology diffusion (Adapted from [1]). . . .	7
Figure 3.1.	Customer classification at the new technology emergence (Adapted from [2]).	23
Figure 3.2.	The market position of a new technology over the years (Adapted from [2]).	24
Figure 3.3.	General structure of the S-shaped.	24
Figure 3.4.	S-curve of the selected districts.	27
Figure 3.5.	The number of opened stations by periods.	33
Figure 4.1.	The opened stations in the first period (Google Maps [3]).	37
Figure 4.2.	The opened stations in the second period (Google Maps [3]). . . .	37
Figure 4.3.	The opened stations in the third period (Google Maps [3]).	38
Figure 4.4.	The opened stations in the fourth period (Google Maps [3]). . . .	39
Figure 4.5.	The opened stations in the fifth period (Google Maps [3]).	39
Figure 4.6.	Cumulative of the number of common stations obtained by different p-value scenario results.	42
Figure 4.7.	The objective values with different p-values (in steady-state). . . .	43

Figure 4.8.	The maximum distance served by opened stations (in steady-state).	44
Figure 4.9.	The number of neighbourhood served by opened stations (in steady-state).	45
Figure 4.10.	The number of vehicles served by opened stations (in steady-state).	45
Figure 4.11.	The number of stations.	46
Figure 4.12.	The maximum distance by periods.	48
Figure 4.13.	The maximum number of neighbourhood by periods.	49
Figure 4.14.	The demand by periods with different penetration values.	50
Figure 4.15.	The number of stations by periods with different penetration values.	50
Figure 4.16.	The objective values with different penetration values.	51
Figure A.1.	Calculation steps of the neighbourhood demand.	63
Figure C.1.	Examination of the common stations according to the p -value scenarios.	68

LIST OF TABLES

Table 3.1.	The decision variables.	16
Table 3.2.	The sets and parameters.	17
Table 3.3.	The number of vehicles in Turkey and İstanbul in five periods. . .	20
Table 3.4.	The districts and their number of neighbourhoods.	21
Table 3.5.	The vehicle ratio of selected districts.	22
Table 3.6.	The number of vehicle of the selected districts by each period. . . .	22
Table 3.7.	HDI_m value of the selected districts.	26
Table 3.8.	S-Curve ratios of the districts that present the viewpoint of the districts.	26
Table 3.9.	The number of HFCV in district of İstanbul.	27
Table 3.10.	Sample flow data for selected districts as an example.	29
Table 3.11.	The flow of HFCV in the districts in the first period, NHQ_{mn1} . . .	29
Table 3.12.	The estimated demand of the selected districts by periods.	30
Table 3.13.	Population rate of the neighbourhoods in Beylikdüzü district. . . .	31
Table 3.14.	The demand of neighbourhood in Beylikdüzü by periods, g_{it}	32

Table 4.1.	Computational time of examination of effect of number of opened stations.	35
Table 4.2.	Opened stations in the first period.	36
Table 4.3.	Results of the base scenario.	40
Table A.1.	The number of stations by periods.	63
Table B.1.	The demand and stations with different penetration values.	64
Table C.1.	Numerical values of different p -value scenarios.	67
Table C.2.	Number of common stations with p -value scenarios.	69
Table D.1.	Comparison data of $p=90$ and $p=126$	70

LIST OF SYMBOLS

EI_m	Education index of district m
g_{it}	Weight of the demand point i at time period t
HDI_m	Human development index of the district m
I	Set of demand points (neighbourhoods)
II_m	Income index of district m
J	Set of supply points (candidate HRSs)
LEI_m	Life expectancy index of district m
NHQ_{mnt}	The HFCV flow from district m to district n at time period t
p_t	Number of stations to be opened in time period t
T	Set of time periods
TDQ_{mt}	The HFCV demand of district m at time period t
w_{ij}	Distance between demand point i and supply point j
Y_{jt}	1 if supply point j is opened in time period t , otherwise 0
Z_{ijt}	1 if the demand point at i is assigned to supply point j at time period t

LIST OF ACRONYMS/ABBREVIATIONS

AHP	Analytic Hierarchy Process
BEV	Battery Electrical Vehicle
CDF	Cumulative Distribution Function
EI	Education Index
EV	Electric Vehicle
FCV	Fuel Cell Vehicle
GHG	Greenhouse Gas Emission
GIS	Geographic Information System
HDI	Human Development Index
HFCV	Hydrogen Fuel Cell Vehicle
HRS	Hydrogen Refuelling Stations
II	Income Index
ICE	Internal Combustion Engine
IDA	Istanbul Development Agency
LEI	Life Expectancy Index
MIP	Mixed Integer Programming
ND	Normal Distribution
SL	Saturation Level
TUIK	Turkish Statistical Institute (In Turkish: Türkiye İstatistik Kurumu)

1. INTRODUCTION

Currently used energy sources such as fossil fuels will be insufficient to meet the increasing energy demand in the future. The transportation sector, which is one of the most energy-consuming sectors (mostly fossil fuel-powered internal combustion engines, ICE, are used), will also be affected by this deficiency. Therefore, researchers are looking for alternative energy sources. Electric and hydrogen energies constitute two alternatives. Electric vehicles and hydrogen vehicles that we have come across today are seen as two critical potentials for the transportation sector. Hydrogen and electricity, which are secondary energy sources, can be produced from different energy sources such as wind, solar, nuclear, etc. In addition, during the use of both energies, the emission of harmful gases, i.e., CO_2 and Greenhouse Gas (GHG), to the environment is almost zero. These advantages make hydrogen and electricity essential alternatives for the future.

Today, when electric vehicles are mentioned, Battery Electrical Vehicles (BEV) are referred to, while hydrogen vehicles are referred to as Hydrogen Fuel Cell Vehicles (HFCV). The required energy of the BEVs' engine is stored as electricity in the batteries, and then this electrical energy is converted into motion energy and the engine moves. The required power of the HFCVs' engine, on the other hand, is stored with hydrogen energy as fuel, unlike the battery systems of BEVs. Then, this hydrogen fuel is converted into electrical energy, and the movement of the engine is provided. Here, when the basic operating principles of both types of vehicles are examined, they both work with electrical energy. The difference emerges in the fuel used to generate the motion energy required for the engine to run (HFCV uses hydrogen while BEV uses electricity as fuel).

Today, it is observed that BEVs have a higher sales rate in the market, and they are used more widely [4], although there are studies about both BEV and HFCV in the literature. There are two main reasons why electric vehicles have a higher sales rate

in the market: (i) The battery system in BEVs is used in other areas such as mobile devices, fuel cell technology, and (ii) electricity generation and distribution systems have a usable infrastructure [4]. In other words, there is the necessary infrastructure for the development of the BEVs. In contrast, HFCVs are a new technology compared to BEVs, so hydrogen needs more development in terms of infrastructure. Through these infrastructure advantages, BEVs are more widespread. As a result, today, BEVs have a larger market share than HFCVs. However, when we examine the studies on BEV and HFCV technologies, it is predicted that HFCVs have more advantageous, and their use will increase in the future [4, 5]. Comparison of the BEVs and HFCVs reveals better how this situation can be observed. First, both play an essential role in reducing harmful emissions and contribute to countries achieving their targets for future emission reduction. Please note that although the GHG emission in-vehicle use is close to zero, production methods that do not release GHG should be preferred in the production stages of these fuels (In this context, methods such as renewable energy sources and nuclear energy can be used). When the range of the vehicles is considered, it is observed that HFCV vehicles have more range than BEVs and can reach longer distances. In addition, BEVs are not preferred for heavy-duty vehicles, and HFCVs are more suitable than BEVs. Moreover, hydrogen technology can be used in trains, ferries and other vehicles; the availability of hydrogen vehicles is higher than electric vehicles. Finally, another criterion, the fuel filling times, can be used to compare vehicle technologies. To fill 80% of BEV batteries, 1-1.5 hours of charging time is required at high voltage [4]. This time is longer when electric vehicles are charged at home or work. In HFCVs, on the other hand, it takes 3-5 minutes to fill the tanks with hydrogen, slightly longer than the gas tank filling time of the vehicles used in the ICE used today [4]. In other words, this feature offers users an experience close to their current habits. This creates an important advantage in favour of HFCV in the case of choosing between BEV and HFCV. While this shows one of the reasons why HFCVs are successful in the test, just like I am used to test, it gives an idea of why electric vehicles fail this test. In addition to all the HFCVs advantages, i.e., it is efficient [6], low pollutant fuel [6], it improves the safety of primary energy sources [7], it has long storage time [8], it provides longer distance transport [9].

In the process of disseminating HFCVs, governments, institutions, and other stakeholders should have support. These supports include processes such as the development of hydrogen technologies, the creation/development of hydrogen infrastructure, and the opening of hydrogen refuelling stations (HRS). In this context, countries like the United States of America, Japan, China, South Korea, Germany, and France have started supporting studies in these areas to provide spread HFCVs and published programs [4]. Automobile manufacturers such as Daimler, Ford Motor Company, General Motors, Honda Motor, Kia, etc., contribute to the development of vehicle technologies by agreeing on the commercialization of HFCVs. Some of these companies that produce HFCVs have started to take place in the automobile market. In order to increase the demand of these vehicles and become widespread, vehicle users should access fuels easily. That is, HRS should also become widespread. Since the batteries can be filled in electric vehicles at home, workplaces or other places, there is no refuelling station requirement in electric vehicles. In contrast, since the filling of the HFCV tank is not made in the home or other places, the HRS is necessary. Thus, the number of HRS should be increased in order to increase the number of HFCVs [10–13]. The location of each HRS determines how users access these stations, which affects the user experience. Therefore, the determination of the location of the HRS is an important research question.

It is stated that the selection of metropolitan areas would be more appropriate in terms of the widespread use of HFCV [4]. In this thesis, the location selection of HRS for Istanbul, which has one-fifth of Turkey’s population, is studied. The contribution of this thesis is to provide a framework that addresses selecting the optimal locations for HRS in a multi-period setting. In particular, we propose a multi-period mixed-integer programming (MIP) model with 954 demand points and 734 potential HRS points. The potential HRS points are the current gas stations, and demands are calculated at the neighbourhood level by employing the development level of each district. The HFCV adoption level is modelled using an S-Curve which is different for each district.

The rest of the study is organized as follows. In Chapter 2, the related studies about technology diffusion and S-curve and HRS location selection are presented. The proposed multi-period model and required input data to implement this model are addressed in Chapter 3. Chapter 4 gives the results, whereas the interpretation of the results and their evaluation in terms of decision-makers will be given in Chapter 5.

2. LITERATURE REVIEW

In this chapter, the literature review is presented as two pillars: (i) the diffusion of technology and studies involving S-curve and (ii) the location selection methods used to select the HRSs. First, the technology diffusion is presented in Section 2.1. In the technology diffusion literature review, usage of the S-curve is analysed. Then, the literature review about usage location selection for HRS is addressed in Section 2.2.

2.1. Technology Diffusion and S-Curve

Since hydrogen energy is a new technology, which is thought to be an essential alternative for the transportation sector with BEVs in the near future, it will take time for users to adopt and become widespread and reach the saturation level (SL) of its use. The process that new technologies such as hydrogen energy consolidate their position is called *technology diffusion*. Technology diffusion means that it requires a specific time for a technology or innovation to become widespread, and at the end of the defined period, it reaches SL. An example diagram for technology diffusion, which usually follows an *S-shaped* pattern, is given in Figure 2.1.

A new technology, which is initially preferred by users who like to take risks, is also preferred by users with different characteristics as time progresses. In HFCV, with the use of vehicles by users with different characteristics, more users are reached, and the spread achieves the SL. Some of the studies in the literature consist of studies conducted to understand the character of this spread. One of these studies is Nieto *et al.* [14]. In that study, technology performance analysis is made over S-curve. The data are analysed in order to indicate the character of the emerging technology. As a result, it is determined that the spread of the emerging technologies is in the S-shaped structure. These studies can also be used to analyse the diffusion of technologies in the energy field. In this context, Rao and Kishore [15] examine how wind energy technology, one of the renewable energy sources, spreads in a designated city of India. In

this context, they use the diffusion model tool to analyse the contribution of different factors. According to the results, it is observed that there is a relationship between the diffusion parameters and the composite policy index. Another study conducted by Rao and Kishore [16] examines the technology diffusion for renewable energy technologies. In that study, they take into account the barrier to renewable energy technology. The aim of their study is the presentation of technology diffusion theory based on the technology diffusion models and their applicability of these models to renewable energy technology. They note that the technology diffusion process follows an S-curve. Moreover, a similar analysis is made by Geroski [17]. In the study of Geroski, which presents a literature review for the technology diffusion models, it is indicated that the usage of new technologies follows an S-curve structure. Thus, the aim is to illustrate what the patterns of S-curve diffusion mean. Another study on energy resources belongs to Kemp and Volpi [18]. They are observed that there is a similar structure in the spread of technologies according to the outputs obtained from these studies, and the technology followed an S-shaped structure regardless of its field. The result, which is the new technology has generally the S-shaped structure, is also obtained from the different studies in the literature. According to these outputs, it is stated that S-curve diagrams are primarily used in the diffusion of technology. In the study of Park *et al.* [19] and Collantes [20], the technology diffusion of HFCVs and their place in the market are shown to follow the S-curve structure.

In other studies in the literature examining the diffusion of technology, models created to show at what rates the technologies to be used will spread according to specified periods or times are covered. In these studies, propagation rates are obtained for the technologies to be used to follow the S-curve structure. As a note, we should add that these rates are examined under the heading of penetration value and are included in finding or analysing the penetration value in the studies carried out. One of the studies carried out in this direction belongs to Schwoon [21]. Their study accepted that the technology follows the S-curve, and they obtain the penetration value from this graph, which ratios would be used according to the periods they determined.

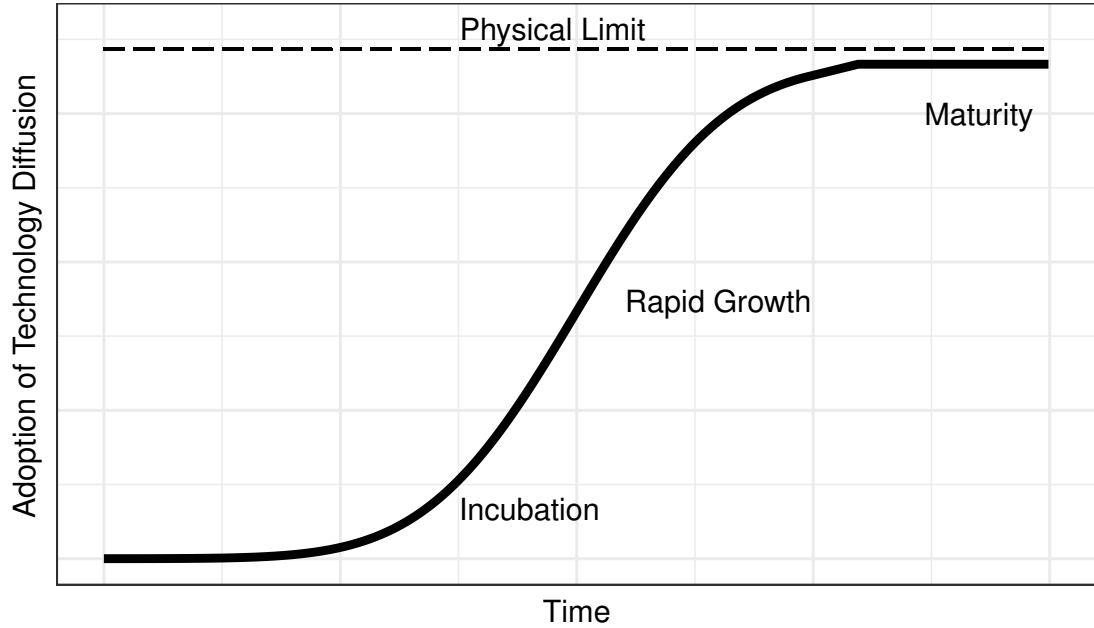


Figure 2.1. General structure of technology diffusion (Adapted from [1]).

In this thesis, the technology diffusion of HFCVs is taken into account to determine the HRSs location. Accordingly, the characteristic structure of the HFCV users within the defined time horizon of thirty years is assumed to follow an S-Curve. In the literature, this structure is generally used as penetration values such as either deterministic values, i.e., 5% of saturation level for the time horizon or functions. In this thesis, we use the normal distribution (ND) function to get penetration value to calculate HFCV demand. Please note that the creation of the S-curve using the normal distribution function and obtaining the HFCV demand are examined in detail in Section 3.2 in Chapter 3. Then, the HFCV demand is used to find where the stations will be opened. In the next section of the literature review, Section 2.2, studies on the methods that can be used to determine the locations of these stations will be presented.

2.2. Location Selection Problem

Location selection has great importance in having advantages such as minimizing costs and being close to the market and the end-user. Moreover, it has strategic signif-

icance as it will affect the processes of companies or institutions in the long run. For these reasons, it has various applications in different areas such as airports, hospitals, schools, computer concentrators, and terminal selections. The reason for this diversity is explained by the following items [22]:

- Location selection occurs at every level where humanitarian organizations are involved.
- The location selection problem is strategic in nature.
- Location selection problems are often difficult to solve optimally. Computational complexity is one of the main reasons for its wide application in the literature.
- The application of the location selection problem is problem-specific. In other words, it is explicitly formed according to the application area.

While the first two items highlight the importance of institutions and their supply chains, the last two items emphasize the technical importance of location selection problems. Furthermore, the ubiquity of local decision-making has led to a strong interest in location analysis and operations research and modelling with management science [22]. In this context, there are location selection instances that are made using different methods in the literature. Current *et al.* [22] classify these location selection models as (i) maximum distance models (set covering location model, maximal covering location model, p-center problem), (ii) the p-dispersion problem, and (iii) total or average distance models (p-median problem, fixed charge location problem, the maximum location problem). The methods used for the location selection problem of HRS, which is the subject of this study, are classified as single-objective and multi-objective methods by Lin *et al.* [23]. Moreover, models with a single objective function are classified as covering, p-median, p-center, and flow capturing models. Although the models in the literature are classified in this way, refuelling station deployment problems are generally examined in three categories: (i) covering model, (ii) flow-refuelling location model, and (iii) p-median model [10]. The covering model focuses on coverage, which is assessed by the travel time or distance between supply and demand points. In the p-median and flow refuelling location model, the aim is to define the

locations of the opened p facilities. The former, the *node-based demand model*, is used to minimize the weighted distance between demand and supply points. The latter, the *path-based demand model*, is used to maximize the flow between origin and destination [10]. According to this information, the studies analysed for the literature study will be given in the form of the flow refuelling location model and the p -median model, respectively. Afterward, studies in which these two methods are examined together will be given. Then the studies with different points of view and studies that are newly proposed models are examined.

Nicholas *et al.* [24] use a geographic information system (GIS) and p -median model to select the location of the HRS. First, they create a composite map of sitting attractions by using GIS. Then, in the second stage, using a p -median model, they use region-wide average driving time to the nearest station to compute trip time. To select the best location, they minimize this objective function. In this model, they assume that people prefer stations from two station options refuel near home or work. They use the available gas stations to transform to HRSs. Using all available stations as inputs in the model requires advanced computer features such as powerful CPU and RAM. For this reason, in their study, they use some part of the data, i.e., they used 309 stations of 701 stations in Sacramento. Then, they implemented different scenarios with one station, two stations, four stations, eight stations, 16 stations, 32 stations, 64 stations, 96 stations, and 319 stations. According to their result, the network reaches about thirty percent of the size of the current gasoline station network in Sacramento County. The study of Nicholas and Ogden [25] is made as an extension of Nicholas *et al.* [24]. As in the referenced study, Nicholas and Ogden also use the p -median model. In their models, vehicle users, which are taken into consideration in the trips between the workplace and home, have been enabled to make the shortest distances. Stephens Romero *et al.* [26] utilize the spatially and temporally resolved energy and environment tool called STREET. Using this tool, they take into account travel time, land use, vehicle travel density, service area zones, and market data on potential FCV customers to determine the number and location of HRSs and a preferred roll-out strategy for those stations, five criteria are applied. Then, using these different criteria, they use the

p-median model to select locations of the HRS in California from available gas stations. According to the results, they propose that a configuration of eight HRSs in the city, if planned strategically, will enable a full-scale fuel cell vehicle (FCV) deployment and concomitant transition to commercialization of FCVs. Brey *et al.* [27] plan the deployment of HRSs in Spain. For this purpose, they characterize each one of the 7959 municipalities of mainland Spain in 2011, by taking a series of criteria: demand criterion, supply criterion, and pollution level by using data envelopment analysis. According to this analysis, they obtain weight and then use it in the optimization model. Itaoka *et al.* [28] use a p-median model to determine the location of the HRS in 2020 and 2025. Moreover, they use a regression model to determine Japan's demand, which is the study's application area. As a result of their GIS analysis, the importance of covering regional center cities (such as governorship capitals) and metropolises is emphasized. In addition, it is stated that 94% of the regional centres are covered with 200 stations until 2020, and all regional centres are covered with 400 stations in 2025. Kim *et al.* [10] aim to create an optimization problem that considers public roads, express ways, and bus refuelling stations throughout the country. For this purpose, they use three mathematical models: the station number determination model, max cover model, and p-median model. By using the first model, they determine the required number of HRS. The last two models, on the other hand, are used to locate and allocate the HRS. Since they consider that HRSs have capacities, all demands are not met fully. For this, to fulfil maximum demand, they use the max cover model. However, this model does not ensure the minimization of the total travel. Thus, they use the p-median model to minimize the total travel time of the customers. Here, since the maximal covering is more important than the p-median model, they use these models sequentially.

Bae *et al.* [29] propose a multi-period optimization model to build on-site HRS and small-sized distributed hydrogen production bases simultaneously. In that study, which is applied to Seoul in urban areas, four stages are considered: energy source, production, transportation, and refuelling stations. Then, they implement three different scenarios: (i) building less initially and building more over time, (ii) building the same increase

rate of the number of HRS, and (iii) building a large number of stations in the early stages. Considering the single-period planning, it is seen that there was no significant change in the locations of the facilities. However, when considered in multiple periods, it is decided when the stations are to be established rather than their locations.

Lin *et al.* [30], in their study, determine the locations of HRS by using multiple data sources (existing station networks, GIS, and economic data, and population data, etc.) and existing station information. They propose a multi-algorithm hybrid solution to solve this problem by combining the genetic algorithm with the greedy algorithm and the annealing algorithm. In that study, in which the application is made for Beijing, the aim is to minimize total demand-weighted distances when the upper bound to the number of opened stations are given. According to their results, it is stated that 16% of the existing stations would be sufficient if the distance to the nearest station is four km. If the distance is determined as three km, it is observed that 31% of the existing stations should be used as HRS. Fuse *et al.* [12] aim to devise near term plan on the location of HRS for 2020-2030 in Yokohama City, Japan. Their study uses three different approaches used in previous studies to understand the relationship between demand and supply. These approaches are (i) optimization models focused on the demand of hydrogen vehicle users (p-median and flow interception models), (ii) models in which life cycle cost is minimized to the supply of HRSs, and (iii) models in which multiple criteria are attempted to be fulfilled. Considering these approaches, they have created their own supply, demand, and supply-demand matching processes by considering safety considerations. In the demand model, they forecast the number of FCVs and estimate the spatial distribution, whereas, in the supply model, they determine HRS numbers and define candidate sites. In the supply-demand matching model, they determine locations of the HRSs by using GIS. Moreover, to accommodate the uncertainty of the adoption of the HFCV, they create three different scenarios: optimistic, intermediate, and pessimistic. According to the results, existing gas stations and mobile HRS can supply the predicted HFCV demand by 2024. He *et al.* [31] make hydrogen energy express-ways planning by using the particle swarm optimization method to minimize life cycle cost. In their study, they determine the location of

HRS by considering constraints such as the HRS's supply radius, the productivity of hydrogen resources and geographical information factor. They apply their study to plan HRS on the Beijing - Zhengzhou between Beijing-Hong Kong-Macao expressways. Another life cycle cost study is conducted by Sun *et al.* [32]. In that study, the siting and sizing of HRSs are found by minimizing the cost. For this purpose, they integrate the Huff model into the location model to estimate the probability of the users' selection of HRS. Then, by using these probabilities, they optimize the size and location of the HRSs. Moreover, for optimization, they use the particle swarm optimization approach and analyse the effect of hydrogen source and demand points on HRS. This cost-based model is applied to Chengdu / China region. Yıldız *et al.* [33] propose a mathematical model that generalizes the deviation flow refuelling location model by Kim and Kuby [34]. Moreover, this mathematical model combines the existing models in the literature. In their study, with the branch and price algorithm, simple path assumption is relaxed. Thanks to this process, the reduction in the solution time concerning models in the literature is obtained as a significant improvement. This study is applied with two particular network topologies: the 25-node road network and the California road network.

Muratori *et al.* [13] provide an overview of the modeling methodologies to project HRS infrastructure requirements to support FCV adoption. For this purpose, they define the methods used in the scenario evaluation and regionalization analysis (SERA) model to address the limitations and provide an approach to prioritize a nationwide FCV infrastructure roll-out. Then, by using SERA, they examine two alternative scenarios as examples. In the first scenario, FCV deployment is limited to California and served major cities in the United States, whereas, in the other FCV reaches widespread adoption across the entire country. Such scenarios can provide guidance and insights for efforts required to deploy the infrastructure supporting transition toward different levels of hydrogen use as a transportation fuel for passenger vehicles in the United States. Lin *et al.* [23] prepare a literature review about location selection of the HRS. According to this research, they provide a classification of the studies by the number of objectives, the spatial dimension of the stations, and the structure of the plan-

ning area. In particular, they classify the studies as covering model, p-median model, p-center model, flow-intercepting model, other models, and multi-objective models. These models provide detailed formulation and different constraint types. Then they examine the advantages and drawbacks of these models. According to the results, the drawbacks of the models can be listed as follows: In the set covering and maximal covering location models, the distance calculation is not considered, whereas, in the p-median model, the traffic flow is not usually taken into account to calculate demand. The demand is not the primary priority in the p-center model. Flow intercepting models, on the other hand, use the origin-destination matrix. However, usage of the flow is the advantage of these problems. The strengths of the other mathematical models can be given as follows. The set covering model can be used for emergency facility location selection because its primary consideration is to maximize the fulfilment of the demand. Moreover, the primary consideration of the maximal covering problem is demand. p-median problems guarantee service convenience, whereas p-center problems ensure a guarantee of the service distance.

In addition to optimization, multi-criteria decision-making methods are also used in studies on HRSs. One of the studies carried out in this context belongs to Messaoudi *et al.* [35]. In the first stage of this study, which consists of two stages, the best locations for wind-powered hydrogen production are evaluated and selected using GIS and the analytic hierarchy process (AHP). In the second stage, petrol stations that can be converted into an HRS using different filtering constraints are determined. To define suitable wind-powered HRS, they use five criteria that are potential of hydrogen production, hydrogen demand, distances to the road, distance to municipalities, and slope. Four suitable stations for wind-powered HRSs are determined in their study for the province of Adrar. Brey *et al.* [27] apply a methodology based on Data Envelopment Analysis to select proper municipalities for setting up HRS in Spain in the early stage of the distribution process. Another study on HRSs is to investigate how users evaluate the position of HRSs. Users' views on how they evaluate the geographic arrangement of HRSs when they decide to purchase FCV are important in the increasing of these stations. In this context, Kelley *et al.* [36] survey early adopters in California, USA

and hydrogen infrastructure planning stakeholders in Connecticut, USA. The data are analysed by t-test and logistic regression, and the customer-demand trade areas are estimated with GIS. As a result of the analysis, it is obtained that it is crucial for most of the participants to have the stations close to their homes, but it is neither necessary nor sufficient for others. In addition to these, station reliability, secondary stations, free way access and convenience to a variety of destinations are stated to be important. Last, it is added that the stations should be close not only to the target consumer, but also to people who can pass there regularly. While Kelley *et al.* [36] evaluate HRS from the point of view of users, Kong *et al.* [37] examine what the development of HRS depends on in their study. In this context, the main problems preventing the increase of HRS in China are examined using In-Depth Analysis. According to the results, it is stated that the HRSs should be supported by the administrations in order to become widespread. In addition, it is emphasized that HFCV should become widespread in the market and it is stated that the construction of hydrogen production facilities is lagging. Like the examination of the point of view of the customers, the sufficiency of the proposed HRS is another research topic in the literature. In the study of Kang *et al.* [11], by using travel patterns with refuelling trips and hydrogen adoption, they make an analysis about the deviation of the refuelling an HFCV with the limited opportunity provided by the 68 proposed HRS in California. Here, they use deviation as a measure of inconvenience for HRS. According to the results, for the worst and best cases, they obtain that these stations provide an average of 2.5 min (2.09 km) and 9.6 min (7.95 km) deviation. That is, when these deviation intervals are compared to the current gas station deviation, it is not different from the current refuelling travel deviation and the HRS provides sufficient accessibility.

In this thesis, there are four contributions. The studies mentioned above are examined the different aspects of the location selection of the HRSs. As can be seen from the literature, the p-median problem used in this thesis study is one of the most used mathematical models. There are different applications to this model. Most of these implementations are related to selecting the stations' locations and are used as a single period time horizon. In addition, although there are a few multiperiod p-

median models [10, 29], in these studies, HRS is considered one part of the hydrogen supply network planning. In other words, these studies take into account HRS and the different supply chains stages such as production, raw material, etc. Nevertheless, there is no multi-period model that only selects the location of the HRS. Moreover, as mentioned before in the literature review of Lin *et al.* [23], not using the flow data in the demand calculation for the p-median model creates a weakness for these models. To eliminate this drawback, the flow data is used in the calculation of the demand. Here, the flow data shows the flow of vehicles between or within the districts. This flow includes commuting from home to work, from home to school, or from home to other areas. These flow data assume that vehicle users get their fuel from stations close to home or workplace. Furthermore, the adaptation to HFCV, the new technology, is taken into account by calculating the human development index (HDI) for each district. Lastly, scenarios to examine the effect of the p-median parameters, i.e., demand and the number of stations, are defined. To summarize the different aspects of this thesis from the literature,

- A multi-period p-median model is proposed. By using this model, the effect of time is taken into account.
- With the help of the multi-period mathematical model, the technology diffusion of the hydrogen energy is reflected in HFCV demand by using HDI.
- By using flow data between and within districts to calculate the demand, the weakness of the p-median model is tried to be eliminated.
- With the scenario analyses, the effect of HFCV demand, the number of opened HRS are examined. Thus, the scenario analyses provide an opinion to strategic decision-makers. Note that the decision-makers here include the managers of fuel company. Considering that gasoline usage will decrease or run out in the future and existing gas stations will be converted to HRS. Thus, this thesis provides a fine starting point.
- Last, this is the first study conducted for İstanbul.

3. MODEL AND INPUT

This thesis aims to determine the locations of HRS to serve the HFCV in İstanbul during the following 30 years. In this context, first, a mathematical model is given in which the classical p -median model is extended to a multi-period p -median model. Then, the required data (parameters of the mathematical model) and preprocessing of data will be presented to enable the application using this model. The pre-processing contains two parts: (i) the framework for determining the demands and (ii) the determination of the candidate station locations.

3.1. Proposed Model

The *p-median problem* is that of locating p facilities to minimize the demand-weighted average distance between nodes and the nearest of the selected facilities [38]. It is used to select the nearest facilities to demand points. The p -median model forms the basis of the proposed multi-period mathematical model in this study. The number of facilities to be selected in this model is given as an input to the model. In other words, in the beginning, it is assumed that the number of facilities that will be opened is known in advance. In addition, each potential site has the same fixed cost, and the candidate sites do not have any capacity constraints. Furthermore, in the p -median model, future time dimensions are not entered into the model. Since the location selection has a long-term effect, we propose a *multi-period p-median model* as a *dynamic model* considering the time dimensions. The decision variables are illustrated in Table 3.1, whereas the sets and parameters of the proposed model are given in Table 3.2.

Table 3.1. The decision variables.

Variables	Definition
Z_{ijt}	1 if the demand point at i is assigned to supply point j at time period t
Y_{jt}	1 if the supply point j is opened in time t , otherwise 0

Table 3.2. The sets and parameters.

Parameters	Definition
i, I	Index and set of demand points (neighbourhoods)
j, J	Index and set of supply points (stations)
t, T	Index and set of time periods
p_t	Number of stations to be newly opened in time period t
g_{it}	Weight of the demand point i at time period t
w_{ij}	Distance between demand point i and supply point j

The proposed mathematical formulation of the multi-period p-median model is as follows:

$$\text{minimize } \sum_{i \in I} \sum_{j \in J} \sum_{t \in T} w_{it} g_{ij} Z_{ijt}, \quad (3.1)$$

subject to

$$\begin{aligned} \sum_{j \in J} Z_{ijt} &= 1, & i \in I, t \in T \\ Z_{ijt} &\leq Y_{jt}, & i \in I, j \in J, t \in T \\ \sum_{j \in J} (Y_{jt} - Y_{j,t-1}) &= p_t, & t \in T, (t-1) \in T \\ \sum_{j \in J} Y_{j1} &= p_1 \\ Y_{jt} - Y_{j,t+1} &\leq 0, & j \in J, t \in T \\ Y_{jt}, Z_{ijt} &\in \{0, 1\} & i \in I, j \in I, t \in T. \end{aligned} \quad (3.2)$$

The objective function given in (3.1) minimizes the weighted average distance of demand points to facilities opened according to periods. Constraint one in equation (3.2) ensures that each demand point is served by a supply point in each period. In

other words, through constraint in equation (3.2), the demand of the demand points are met by a supply point in each period. Constraint two in equation (3.2), on the other hand, ensures that demand points take service from the facilities opened at that time. That is, if a supply point is not opened, it cannot serve any demand points. Constraint three in equation (3.2) gives the number of new facilities to be opened in the specified period, while constraint four in equation (3.2) guarantees the number of facilities to be opened for the first period. The fact that a facility opened in one period remains open in the following periods is provided by constraint five in equation (3.2). For example, a facility opened in the second period is guaranteed to remain open in all subsequent periods in the planning horizon, by this equation. In fact, this is not an equation. It is an inequality. The variables used in the model are assigned as 0 or 1, provided by constraint six in equation (3.2) and it restricts the variables to be binary.

Note that, in the proposed multi-period p-median model, constraint three in equation (3.2) and constraint five in equation (3.2) will be redundant when the number of periods is considered one. Hence, the multi-period model reduces to an ordinary single-period p-median model.

3.2. Demand Points: Neighbourhoods

İstanbul is Turkey's the most crowded city, and one-fifth of Turkey's population live there [39]. For this reason, this city is chosen as a starting point in order to enlarge the use of hydrogen energy in transportation and promote the use of HFCV. One of the factors that increases the demand for HFCV is to offer refuelling stations where users can quickly access hydrogen fuels. Thus, the aim of this study can be given as to determine the locations where HRSs can be opened in İstanbul using the multi-period p-median model. The idea behind the p-median model is to select the supply points to meet the demands of the demand points in a way that optimizes the weighted average distance of demand points to supply points opened by each period. To reach this aim, the number of opened stations is entered into the model. Which supply points to be opened are determined according to the demand points by the p-median model. In this

study, *the neighbourhoods of İstanbul* (954 neighbourhoods) are selected as the demand points, while *the existing gas stations* (734 gas stations) are selected as the (potential) supply points. The aim is to ensure that the neighbourhoods receive hydrogen fuel from the shortest distance to them. In this context, the p-median model constitutively works with three parameters: the coefficients used in the objective function (distance between demand and supply points and demand) and the number of stations to be opened. Accordingly, in this part of the study, the parameters to be used in the model are given. That is, first, the demand of the neighbourhoods of İstanbul in the multi-period is calculated. For this, the following projected factors are used to calculate demand: (i) the number of vehicles in İstanbul, (ii) the number of vehicles in districts, (iii) (HDI) of districts, (iv) the number of HFCV in districts, and (v) the number of HFCV in neighbourhoods. Then, the required number of stations for each period is presented as a solution of the model.

3.2.1. Projection of the Number of Vehicles in İstanbul

This study consists of five periods covering 30 years between 2021 and 2050. Like the multi-period hydrogen supply network studies [7,40], it is assumed that each period consists of six years in this study. Moreover, it is assumed that at the end of the time periods, HFCV will be 20% of whole vehicles parallel to the previous studies in the literature [41–44]. Neighbourhoods are selected as the demand points for selecting the location of the HRS in İstanbul. Please note that the reason behind the use of neighbourhoods as demand points is to reflect the user characteristics to the model better.

The number of vehicles in Turkey for five periods is given in Table 3.3. The row “Period” presents the periods, whereas the row “Turkey” shows the number of vehicles of Turkey that is calculated by exponential smoothing function by using past vehicle numbers in Turkey [39]. The second row, “İstanbul”, illustrates the number of vehicles of İstanbul, which is obtained the multiplication of Turkey vehicle number by the ratio of the current numbers of vehicles in İstanbul to the current number of vehicles in

Turkey (18.08%). We assume that this ratio remains constant throughout periods.

Table 3.3. The number of vehicles in Turkey and İstanbul in five periods.

Period	1	2	3	4	5
Turkey	13,164,016	13,897,265	14,630,514	15,363,764	16,097,013
İstanbul	2,380,620	2,513,223	2,645,826	2,778,429	2,911,032

“Mahallem SEGE”, supported by İstanbul Development Agency (IDA) [45], is a study that provides statistical information on public or urban services at the neighbourhood level in İstanbul. We use the data provided by *Mahallem SEGE* to estimate the demand in the neighbourhoods. The first step is to calculate the number of vehicles in each district.

There are 39 districts and 954 neighbourhoods in İstanbul. Table 3.4 gives the districts and number of neighbourhoods in each district. Adalar, which is covering the islands of İstanbul, is excluded from the scope of the study. Hence, 38 of 39 districts are used for analysis. We illustrate the calculation process by explicitly showing the calculation of some sample districts, in particular Beşiktaş, Beylikdüzü, Kadıköy, Sultanbeyli, and Zeytinburnu are chosen. Note that the districts and the neighbourhoods are represented by the indices m and i , respectively.

We calculate the current ratio of the number of vehicles in each district to the number of vehicles in İstanbul and use it to calculate the projected number of vehicles in each district. The number of vehicles of selected five districts (column 2) and the ratios of these numbers to the total number of İstanbul vehicles (column 3) are given in Table 3.5. The vehicle ratio of Beşiktaş, for example, is calculated as $38,643/1,543,029=2.50\%$. These ratios are assumed to remain constant over the years. Then, district-based vehicle projection is obtained by multiplying these ratios with the projection for the number of future vehicles in İstanbul given in Table 1. For example the projected number of vehicles in Beşiktaş for the first period (59,619) is given by

multiplication of the vehicle ratio of Beşiktaş (2.5%) with the number of (projected) vehicles in İstanbul for the first period (2,380,620). The number of vehicles of selected districts by periods is given in Table 3.6.

Table 3.4. The districts and their number of neighbourhoods.

District (m)	# of Neigh.	District (m)	# of Neigh.	District (m)	# of Neigh.
Arnavutköy	38	Çatalca	39	Pendik	36
Ataşehir	17	Çekmeköy	21	Sancaktepe	19
Avcılar	10	Esenler	16	Sarıyer	38
Bağcılar	22	Esenyurt	43	Silivri	35
Bahçelievler	11	Eyüp	28	Sultanbeyli	15
Bakırköy	15	Fatih	57	Sultangazi	15
Başakşehir	10	Gaziosmanpaşa	16	Şile	62
Bayrampaşa	11	Güngören	11	Şişli	25
Beşiktaş	23	Kadıköy	21	Tuzla	17
Beykoz	45	Kağıthane	19	Ümraniye	35
Beylikdüzü	10	Kartal	20	Üsküdar	33
Beyoğlu	45	Küçükçekmece	21	Zeytinburnu	13
Büyükçekmece	24	Maltepe	18	Adalar	NA

3.2.2. Technology Diffusion of Hydrogen Fuel Cell Vehicles

The next step is to calculate the number of HFCVs in each district. However, this needs a detailed analysis since HFCV is a new technology. The emergence of new technologies does not occur suddenly [46]. It reaches an SL at the end of several stages, which is characterized by consumer behaviour. In general, users of new technology are classified according to their adaptation to the technology, such as innovators, early adopters, early and late majority, and laggards, respectively [44,46]. This classification

is illustrated in Figure 3.1. Since the use of new technology is seen as risky initially, very few users (innovators) start to use this technology. Then, the technology becomes widespread, the use of this technology begins to increase, and after a certain point, this rate of increase will come to a balance [2]. The market penetration of new technology can be illustrated in Figure 3.2. When we analyze Figure 3.1 and Figure 3.2, the consumer characteristic shows a behavior like an ND graph with zero mean, whereas the market penetration can be characterized by an S-shaped structure (i.e., an S-curve) like the cumulative distribution function (CDF) of the ND.

Table 3.5. The vehicle ratio of selected districts.

District	# of Vehicle	Vehicle Ratio
Beşiktaş	38,643	2.50%
Beylikdüzü	47,748	3.09%
Kadıköy	101,149	6.56%
Sultanbeyli	22,585	1.46%
Zeytinburnu	21,748	1.41%
Others	1,311,156	84.98%
Total	1,543,029	100%

Table 3.6. The number of vehicle of the selected districts by each period.

District \ Period	1	2	3	4	5
Beşiktaş	59,619	62,94	66,261	69,582	72,903
Beylikdüzü	73,667	77,77	81,873	85,977	90,08
Kadıköy	156,055	164,747	173,44	182,132	190,825
Sultanbeyli	34,845	36,786	38,726	40,667	42,608
Zeytinburnu	33,553	35,422	37,291	39,16	41,029

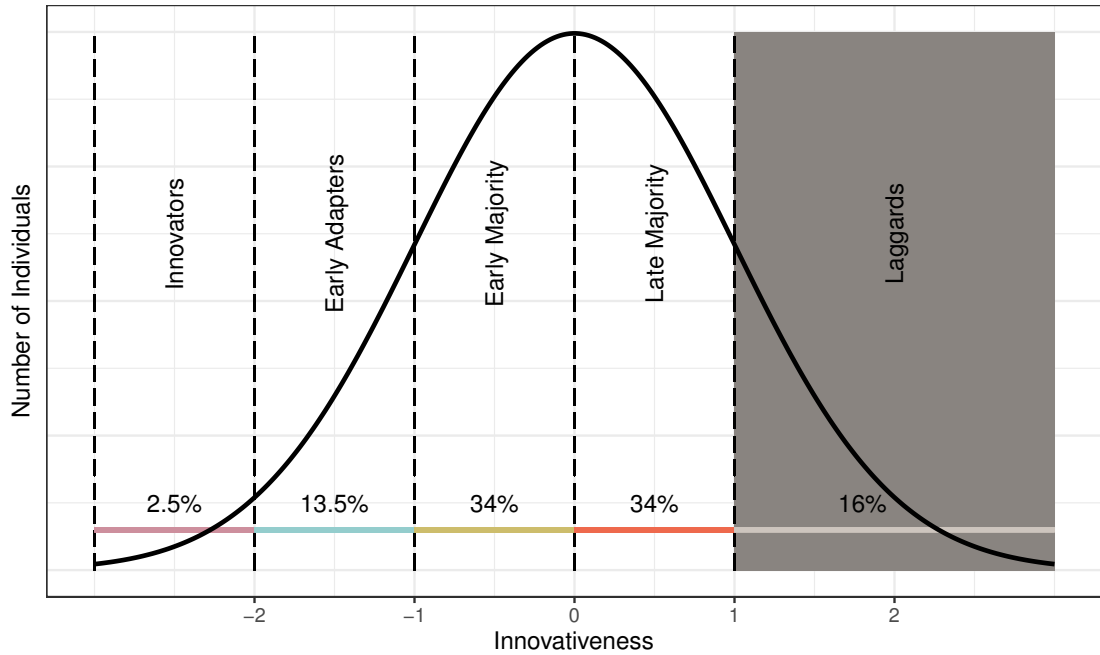


Figure 3.1. Customer classification at the new technology emergence (Adapted from [2]).

The S-curve defines the path from introducing the technology to the SL and is widely used [16,18]. Consider a new technology that reaches its SL by following an S-curve. For example, when five periods are taken into account, the technology reaches SL with the desired penetration SL (saturation level), as shown in Figure 3.3. Here, the level of adoption reaches 0.05 (or 5%) of the SL at the end of the first period, while 50% of the potential consumers start using the new technology when it reaches the middle of the planned time period.

One key issue is to estimate the SL. In the literature on the hydrogen energy supply chain in the transportation industry, this saturation level is characterized by the ratio of the total vehicles [41–44]. In this study, we apply the same procedure, and in parallel to relevant studies, we assume that at the end of five periods, the number of HFCV will be equal to 20% of the total vehicles. That is, when the HFCV comes to its saturation level by following an S-curve, 20% of the whole vehicles in the city will be HFCV by the end of the 30 years.

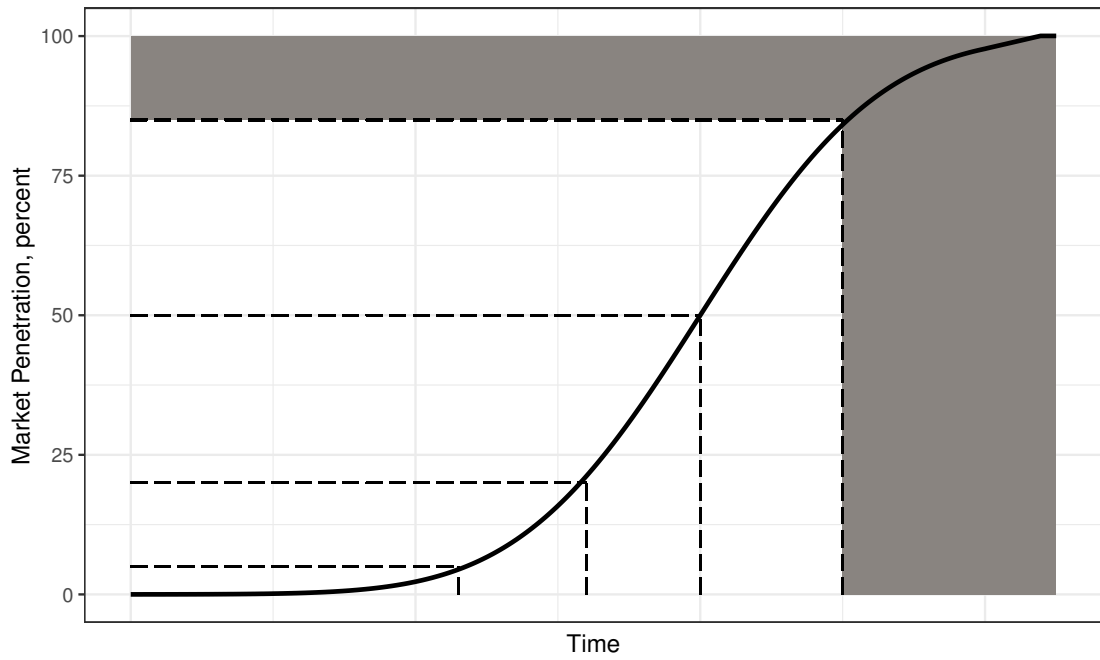


Figure 3.2. The market position of a new technology over the years (Adapted from [2]).

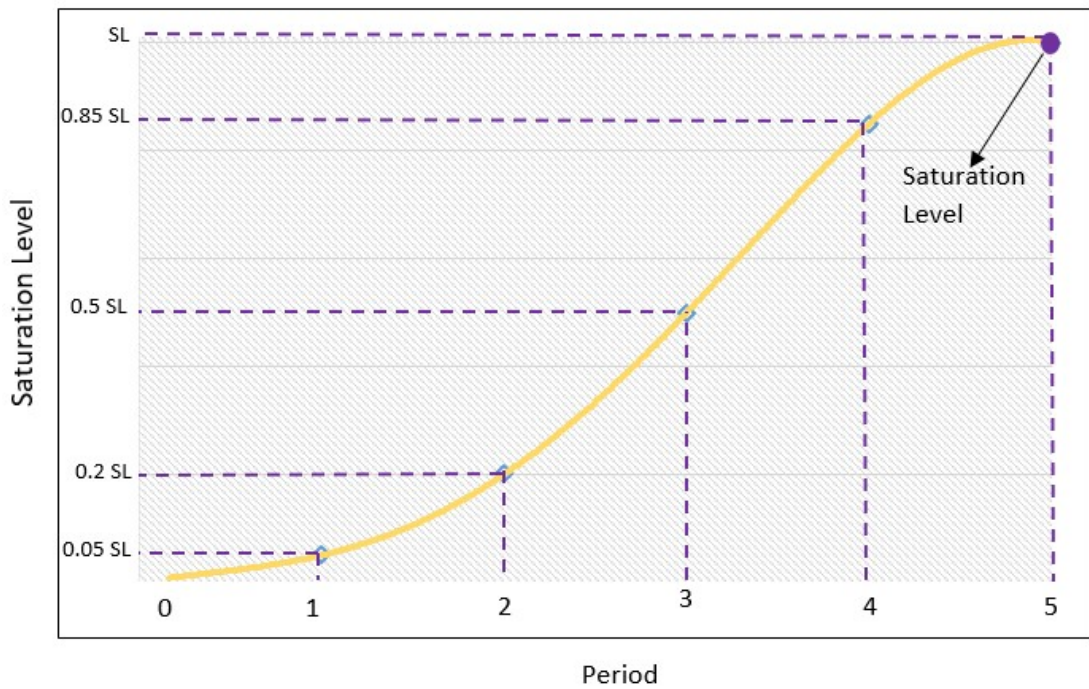


Figure 3.3. General structure of the S-shaped.

3.2.3. Human Development Index

The adoption of new technology by the consumers is characterized by an S-curve. However, the structure of the S-curve can vary for different locations. For example, the number of registered Electric Vehicles (EV) in Norway in 2020 is 330,000, corresponding to 54% of the total vehicles [47]. However, in Turkey, the number of EVs is 1,012, which is only 0.0077% of the total vehicles [48]. Hence several factors like income level or education can affect the structure of the S-curve. Therefore the adaptation level (or S-curve) for each district may not be necessarily the same. This raises the question, “is there a measure that can be used to customize the S-curve?”. Human Development Index (HDI) is an index that shows a measure of average achievement in key dimensions of a country’s human development (Human Development Reports, Access Date: May 6, 2021). It is comprised of economy, education level, and life expectancy of people. We will use HDI to customize the adaptation levels for each district. HDI is given by the geometric mean of life expectancy index (LEI), education index (EI), and income index (II):

$$HDI_m = \sqrt[3]{LEI_m EI_m II_m} \quad m \in M. \quad (3.3)$$

For each country, HDI is reported in the Human Development Report of the United Nations Development Program. Although HDI is calculated at the country level, it can also be calculated and used for cities or districts as well. In this study, we will calculate the HDI values for each district using the data obtained from the “Mahallem İstanbul” study. The HDI values for selected districts calculated by using Equation 3.3 are given in Table 3.7.

The districts with higher HDI will make use of the new technology faster than the districts with lower HDI levels. We will use the HDI levels to characterize the S-curves of each district. In particular, we define the S-Curve of a district by CDF of a normal distribution with a mean value of $(1 - HDI)$ and a standard deviation of one. For selected districts, S-curves are presented in Figure 3.4. In the figure, the horizontal axis

gives time, whereas the vertical axis illustrates the penetration values corresponding to time. Using this graph, we can obtain the penetration values corresponding to the periods determined in the selected districts as a ratio. The S-Curve ratios for selected districts are given in Table 3.8. As can be seen from the graph (Figure 3.4) and table (Table 3.8), the ratios of the districts reach the level of 20% determined at the end of the fifth period.

Table 3.7. HDI_m value of the selected districts.

District(m)	HDI_m
Beşiktaş	0.864
Beylikdüzü	0.614
Zeytinburnu	0.5
Kadıköy	0.846
Sultanbeyli	0.489

Table 3.8. S-Curve ratios of the districts that present the viewpoint of the districts.

District \ Period	1	2	3	4	5
Beşiktaş	0.0053	0.0462	0.1357	0.1904	0.2000
Beylikdüzü	0.0029	0.0324	0.1169	0.1843	0.2000
Zeytinburnu	0.0021	0.0271	0.1080	0.1806	0.2000
Kadıköy	0.0051	0.0451	0.1344	0.1900	0.2000
Sultanbeyli	0.0021	0.0267	0.1071	0.1803	0.2000

When we multiply the ratios obtained from the S-curve (Table 3.8) with the number of vehicles of districts (Table 3.6), we get the number of HFCV for each district by periods (Table 3.9). For example, the number of HFCV of Beşiktaş (315) in the first period is obtained by the product of the number of vehicles in Beşiktaş in the first period (59,619) with the S-curve ratio in the first period (0.0053). Table 3.9 presents

the number of HFCV of selected districts by period. Moreover, in the last row of the table, the number of HFCV in İstanbul according to periods is also illustrated.

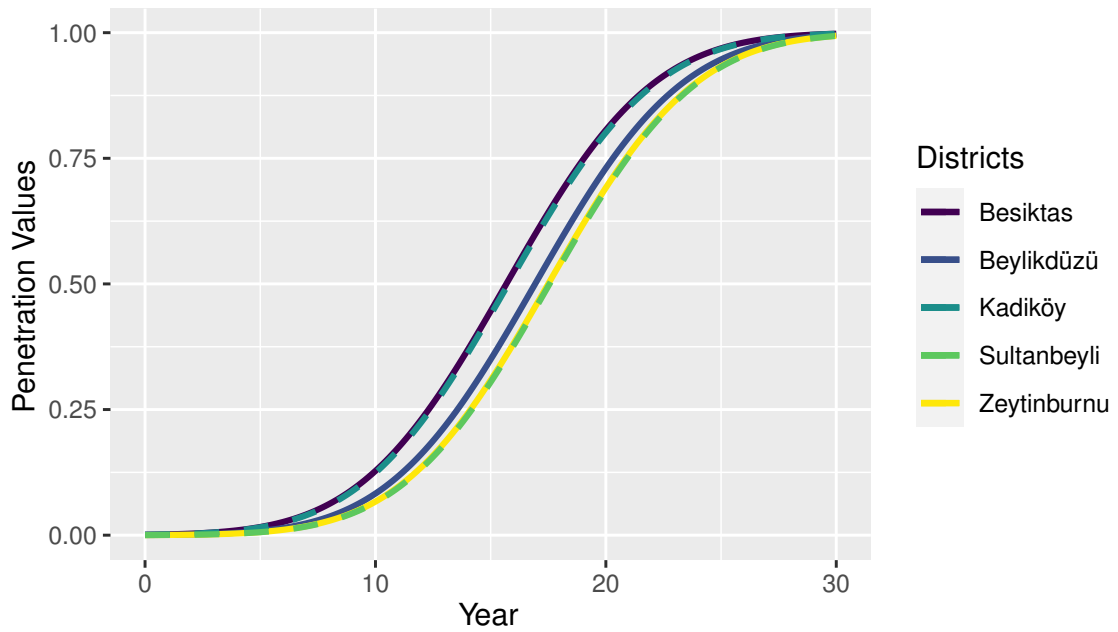


Figure 3.4. S-curve of the selected districts.

Table 3.9. The number of HFCV in district of İstanbul.

District \ Period	1	2	3	4	5
Beşiktaş	315	2,906	8,994	13,248	14,55
Beylikdüzü	212	2,521	9,575	15,842	17,935
Zeytinburnu	72	961	4,026	7,074	8,155
Kadıköy	791	7,428	23,317	34,609	38,08
Sultanbeyli	73	981	4,147	7,331	8,467
Total	<i>6,983</i>	<i>81,461</i>	<i>308,032</i>	<i>510,887</i>	<i>579,451</i>

3.2.4. Calculating the Demand of Districts

Studies in the literature indicate that vehicle owners prefer stations close to their homes or workplaces [24,25]. Therefore, the node-based studies that employ p-median models assume that consumers refill their vehicles from one of these two locations [49]. We will use this assumption to find the demand in each neighbourhood. In particular, we will calculate the demand by finding the inflow and outflow, i.e., the number of vehicles coming into the neighbourhood and going out from the neighbourhood. Mahallem SEGE has a sample flow of vehicles between districts of İstanbul. Table 3.10 shows the flow between our five sample districts adapted from Mahallem SEGE. Please note that, the flow data given here shows a sample and this sample is taken during a certain period of a day. For this reason, it contains missing data, i.e., there are zero values as a flow between districts. In studies where origin-destination pair examinations are made, different methods are used to complete the data for such cases, in other words, in cases where missing or 0 data are observed. These methods are examined under the title of *incomplete data problem* [50] and methods such as Gravity Method and the Deming-Stephan method are used. In addition, calculation errors are avoided by using very small values such as 0.01 and 0.001 instead of 0 in the calculations [51]. In this study, it is decided to use a small number instead of the values that write 0. Since the values in this data set are shown with integers, the value 1 is chosen. Thus, 0 values are removed from the dataset and 1 is used where there is no flow between districts. The rearranged data set was used for further processing.

The intersection of the Beşiktaş and Kadıköy (25), for example, gives the flow from Beşiktaş to Kadıköy whereas, the diagonal of the Beşiktaş (389) presents the flow within the district. We use the flow ratios to calculate the flow of the HFCV between the districts. The flow ratios are the ratios of the flow to the total number of vehicles in the district. For example, the flow ratio for Beşiktaş - Kadıköy flow is $25/986 = 2.54\%$. Here 25 is the flow of vehicles sampled from Beşiktaş to Kadıköy and 986 is the total number of vehicles sampled in Beşiktaş. Then, the HFCV flow from Beşiktaş to Kadıköy is given by the product of this ratio and the projected number of HFCV in

Beşiktaş.

Table 3.10. Sample flow data for selected districts as an example.

District \ District	Beşiktaş	Beylikdüzü	Kadıköy	Sultanbeyli	Zeytinburnu
Beşiktaş	389	4	25	3	6
Beylikdüzü	4	467	3	1	9
Kadıköy	28	2	1,325	18	4
Sultanbeyli	3	1	16	1,019	1
Zeytinburnu	5	9	4	1	877

Table 3.11. The flow of HFCV in the districts in the first period, NHQ_{mn1} .

District \ District	Beşiktaş	Beylikdüzü	Kadıköy	Sultanbeyli	Zeytinburnu
Beşiktaş	124	1	8	1	2
Beylikdüzü	1	115	1	1	2
Kadıköy	9	1	440	6	1
Sultanbeyli	1	1	1	57	1
Zeytinburnu	1	1	1	1	47

After calculating the HFCV flow of districts for each period, we need to calculate the demand of the neighbourhoods by using the HFCV flow. For this, we need a calculation to transform HFCV flow data to the HFCV demand of the districts using the assumption that vehicle owners prefer stations close to their homes or workplaces. Therefore each flow is split into two, and each part is assigned to origin and destination. The formulation of this process is given as:

$$TDQ_{mt} = NHQ_{mmt} + \sum_{n \in M, n \neq m} (NHQ_{mnt} + NHQ_{nmt})/2, \quad m \in M, t \in T. \quad (3.4)$$

Thus, all the movements made in that district are brought together. For example, 124 in Table 3.11 is assigned to Beşiktaş demand since both origin and destination is Beşiktaş. Half of Beşiktaş – Kadıköy flow is assigned to Beşiktaş, and the remaining half is assigned to Kadıköy. This value actually gives us the demand in that district. The demand of the selected districts is given in Table 3.12. The last row of this table shows the total number of HFCV for İstanbul. Note that Table 3.9 shows the number of HFCV of districts, whereas Table 3.13 illustrates the districts' demand.

Table 3.12. The estimated demand of the selected districts by periods.

District \ Period	1	2	3	4	5
Beşiktaş	261	2,499	8,011	12,073	13,345
Beylikdüzü	182	2,171	8,273	13,719	15,543
Zeytinburnu	83	1,074	4,395	7,626	8,760
Kadıköy	689	6,624	21,268	32,029	35,383
Sultanbeyli	82	1,082	4,479	7,830	9,017
<i>Total (İstanbul)</i>	<i>6,983</i>	<i>81,461</i>	<i>308,032</i>	<i>510,887</i>	<i>579,451</i>

3.2.5. Calculating the Demand of Neighbourhoods

The final step is the calculation of the demand in neighbourhoods. We will illustrate the calculation using the neighbourhoods of Beylikdüzü. In Table 3.13, the Neighbourhood column gives the population of neighbourhoods in Beylikdüzü, while the Population column presents the population of these neighbourhoods. Here, for example, the Population Rate of the Cumhuriyet neighbourhood is obtained by using $21,674/314,662=6.6087\%$. When we divide the neighbourhood's population by the total population of the district in which that neighbourhood is located, the Population Rate column is obtained.

By multiplying the population rate (Table 3.13) with the demand of the districts (Table 3.12) according to the periods, we obtain the demand in that neighbourhood for each period. The values given in Table 3.14 show the districts' demand, g_{it} , according to periods, and we can summarize the operations performed to obtain this value by using the formula given as:

$$\begin{aligned}
 \text{Neighbourhood Demand} &= \text{Turkey Projection} \times \text{Istanbul Ratio} \\
 &\times \text{District Ratio} \times 20\% \text{ Penetration} \times S - \text{Curve Percentage} \\
 &\times \text{District Flow Ratio} \times \text{Population Rate}.
 \end{aligned} \tag{3.5}$$

Table 3.13. Population rate of the neighbourhoods in Beylikdüzü district.

Neighborhood (i)	Population	Population Rate
Büyükşehir	20,795	6.61%
Barış	51,9	16.49%
Adnan Kahveci	86,584	27.52%
Cumhuriyet	21,674	6.89%
Gürpınar	19,557	6.22%
Yakuplu	43,962	13.97%
Kavaklı	27,566	8.76%
Marmara	26,537	8.43%
Sahil	4,443	1.41%
Dereağzı	11,644	3.70%
<i>Total (Beylikdüzü)</i>	<i>314,662</i>	<i>100%</i>

3.3. Supply Points: Existing Gas Stations

Supply point information is another critical parameter in the p-median model. Supply points indicate the locations where consumers can buy fuels. In the literature, different alternatives are used as supply points such as social public parking [30], ad-

ministrative office buildings and bus garages [10], existing gas stations [12,24,25,29,30], etc. In this study, available gas stations are selected as the supply points. Note that, these stations contains all gas station companies such as Shell, Opet, Total, Aytemiz etc. In other words, it is assumed that current gas stations will be transformed into HRSs according to the results of the p-median model. In İstanbul, there are 734 stations according to the information obtained from Google Maps during the time of conducting this research. Gas station information consists of the coordinates of each gas station.

Table 3.14. The demand of neighbourhood in Beylikdüzü by periods, g_{it} .

District \ Period	1	2	3	4	5
Büyükşehir	12	144	547	907	1,027
Barış	30	358	1,364	2,263	2,564
Adnan Kahveci	50	598	2,276	3,775	4,277
Cumhuriyet	13	150	570	945	1,071
Gürpınar	11	135	514	853	966
Yakuplu	25	303	1,156	1,917	2,172
Kavaklı	16	190	725	1,202	1,362
Marmara	15	183	698	1,157	1,311
Sahil	3	31	117	194	219
Dereağzı	7	80	306	508	575
<i>Total (Beylikdüzü)</i>	<i>182</i>	<i>2,172</i>	<i>8,273</i>	<i>13,721</i>	<i>15,544</i>

The last parameter required in the p-median model is the number of HRS to opened in each period. Today, there are 734 petrol stations in İstanbul serving a total of 3,386,637 vehicles. This means that one station serves an average of 4,614 vehicles. In this context, when the demand of neighbourhood is divided by the average number of vehicles served by a station, the required number of stations can be calculated. For

example, when the first-period demand (6,983) is divided by the average number of served by a station (4,614), the number of opened stations (2) is obtained. The number of stations required in other periods can be calculated similarly. These results are given in the second row (Number of Stations) of Table A.1. This column illustrates the cumulative number of opened stations. In addition, it is necessary to know the number of opened stations in each period. The number of newly opened stations is given in the third row (Number of New Opened Stations.) of Table A.1. Figure 3.5 presents the number of stations by period. Note that, in this study, it is assumed that the hydrogen stations are uncapacitated. Please note that the neighbourhoods' demand and the number of opened stations obtained, which are the objective function coefficient and parameter of the p-median model, constitute the base scenario parameters.

This study is company neutral, i.e., we ignore the local competition effects of fuel-providing firms.

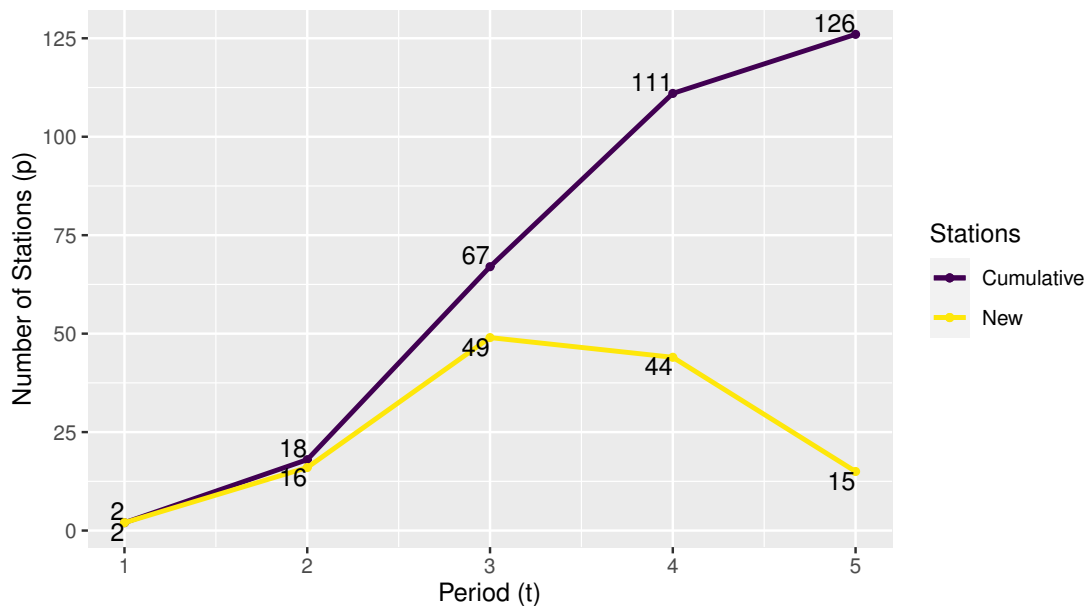


Figure 3.5. The number of opened stations by periods.

4. RESULTS

In this section, we present the results of the multi-period p-median model. For this purpose, first, the base scenario analysis, which is conducted by using the data from Sections 3.2 and 3.3, is examined. The base scenario corresponds to the scenario where HFCVs at SL reach 20% of all vehicles, and a total of 126 stations are opened to meet this demand. In Section 4.1, the results obtained by using the base scenario are presented. Then, to examine the effect of the number of stations and the demand over the model, different scenarios are created using the penetration value changes and the number of opened stations. Last, created scenarios by using these changes are investigated in Sections 4.2 and 4.3, respectively.

We used Python to code and Gurobi to solve the model in an Intel® Core™ i5-10210U CPU with 8 GB RAM computer. Using a computer with these features, a multi-period p-median model obtained with base scenario parameters is initially run. It takes 2781.64 seconds to obtain the results. In addition to this multi-period instance, there are other results obtained from the multi-period p-median problem by using different parameters. First one is obtained in Section 4.2. Here, model with $p = 90$ is run as a multi-period model and the run takes 4544.55 seconds. The last run about multi-period model is obtained in Section 4.3. Here, the multi-period model with different parameters, i.e., different penetration values from 10% to 50% except 20%, and the computational times are obtained as 13382.91 seconds, 868.78 seconds, 1492.61 seconds, and 1140.20 seconds, respectively. The variance observed here is because of the warm-up period. In addition to multi-period model runs, in Section 4.2 to examine effect of number of opened stations, the model is run as single period. The results of these runs are given in Table 4.1. When we compare the multi-period and single period models' computational time, the multi-period models take more time than single-period models. The rows, which are output of the run and give the number of constraints solved by model, increase from 701,191 to 1,658,521. In addition, the columns, which are another output of the model and present the number of variables

in the model, rise from 700,970 to 1,654,480. In other words, the size of the model increases. In addition, these results are also consistent with the computational time complexity that is mentioned in Section 2.2.

Table 4.1. Computational time of examination of effect of number of opened stations.

p Value	Computational Time (sec)	p Value	Computational Time (sec)
5	197.83	105	69.92
10	224.26	110	76.92
15	175.50	115	80.09
20	380.99	120	101.40
25	146.35	125	47.45
30	140.17	130	78.93
35	165.63	135	47.01
40	96.52	140	109.74
45	161.17	145	101.25
50	120.32	150	100.22
55	137.93	155	70.59
60	144.72	160	97.01
65	130.53	165	100.48
70	114.92	170	97.09
75	103.11	175	89.94
80	81.60	180	79.32
85	95.45	185	106.15
90	90.82	190	110.65
95	75.79	195	74.90
100	56.41	200	78.69

4.1. Base Scenario Results

In this section, the results obtained from applying the base scenario prepared in Chapter 3 are presented.

The list of stations that existed in the first period to be converted into HRSs is given in Table 4.2. İstanbul's borders involve two continents, the Asia side and the European side. Therefore, it is expected that one of the two HRS to be opened in the first period will be in the European side and the other on the Asia side. The model results fulfil this expectation. As seen in Table 4.2, the first station shown is opened in Güngören district on the European side, while the HRS on the Asia side is opened in Kadıköy district. Figure 4.1 shows a more understandable representation of the view of the opened facilities on the map.

Table 4.2. Opened stations in the first period.

Opened Station ID	Station Location Information		Number of Served Neighborhood	Number of Served Vehicle
	Neighbourhood	District		
603	Güneştepe	Güngören	565	3,609
698	19 Mayıs	Kadıköy	389	3,374

In the second period, with the increase in the number of new facilities, it is observed that the facilities opened are spread over both continents. Figure 4.2 illustrates the newly opened stations in the second period.

With the number of newly opened facilities being 49 in the third period, it is observed that the places where the facilities were opened have expanded towards the border points of the city. This is consistent with the fact that the population is denser at the center, and the intensity decreases at the city's borders. The HRSs opened in this period are given in Figure 4.3.

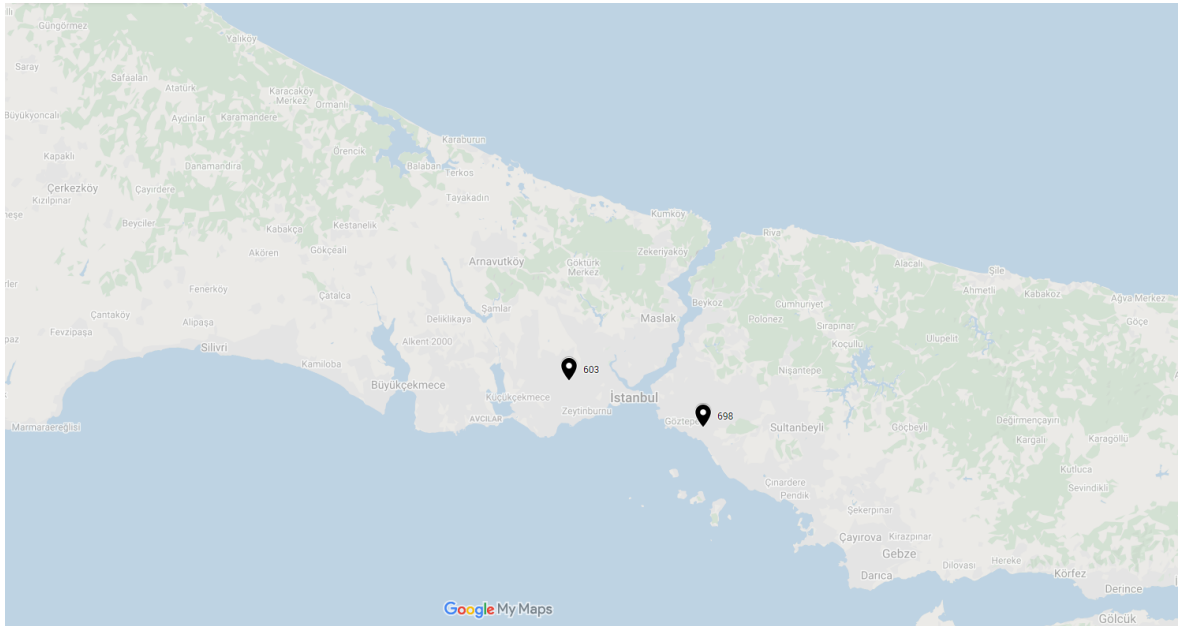


Figure 4.1. The opened stations in the first period (Google Maps [3]).

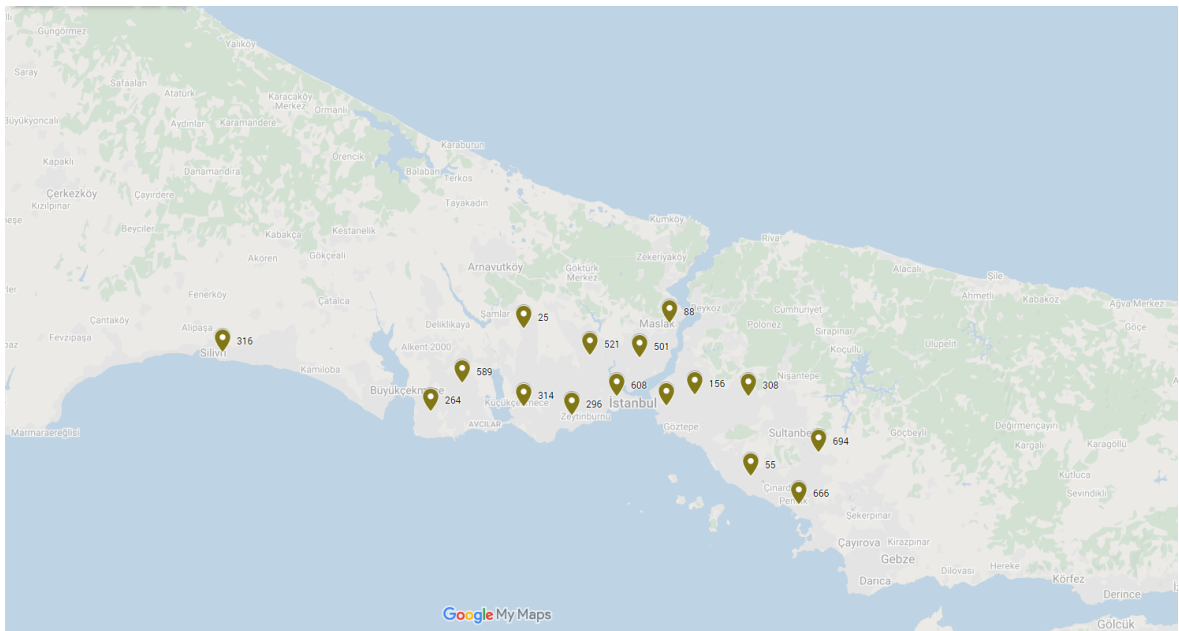


Figure 4.2. The opened stations in the second period (Google Maps [3]).

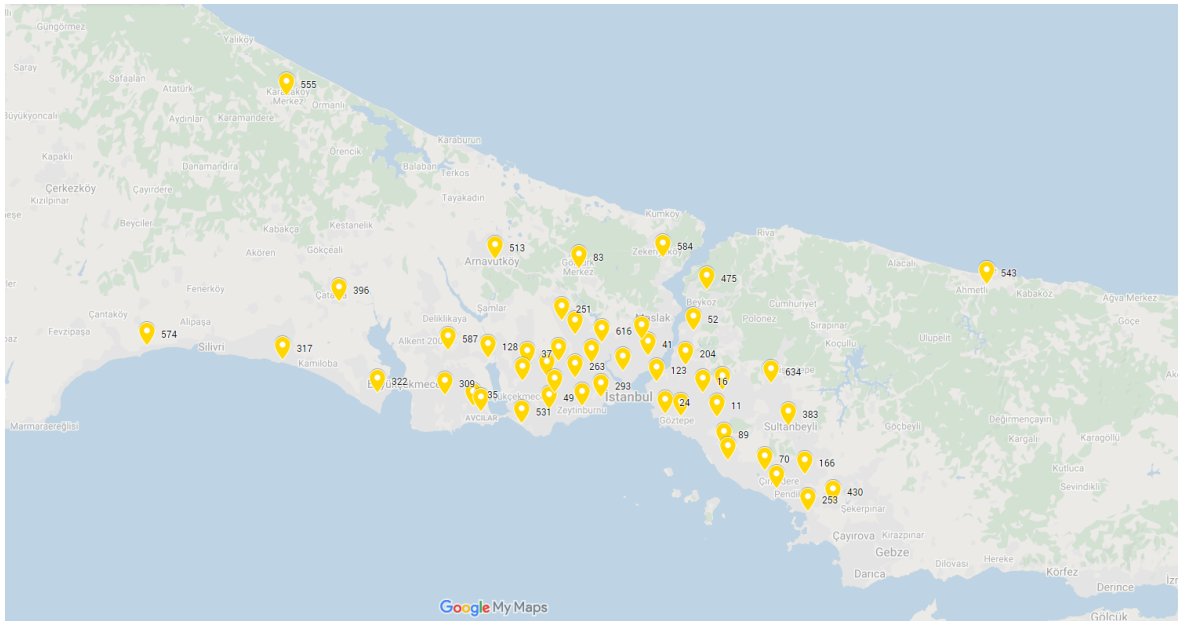


Figure 4.3. The opened stations in the third period (Google Maps [3]).

The facilities opened in the fourth and fifth periods are given in Figure 4.4 and Figure 4.5, respectively. It should be noted here that Figure 4.1 - Figure 4.5 shows only the facilities opened in each period. In other words, stations opened in the previous periods are not shown for a better illustration. Moreover, the numbers in Figure 4.1 - Figure 4.5 give the opened stations, which are identified as unique numbers in the Python model, and these values are used to represent HRSs in the maps. In addition, the stations opened in each period were tried to be indicated by using different colors. For example, opened stations in the first period were indicated by using black. Finally, the stations indicated on these maps show the newly opened stations for that period, the stations from the previous period are not specified.

We can examine the results obtained as a result of the base scenario periodically with the help of different performance measures given in Table 4.3. The “Max Distance (km)” column shows the largest of the maximum distance served by the stations. These values show the maximum of the maximum distances served in each period. It is observed that this distance decreases with the number of stations. The values are given in the column “Number of Neighbourhood” show the maximum number of

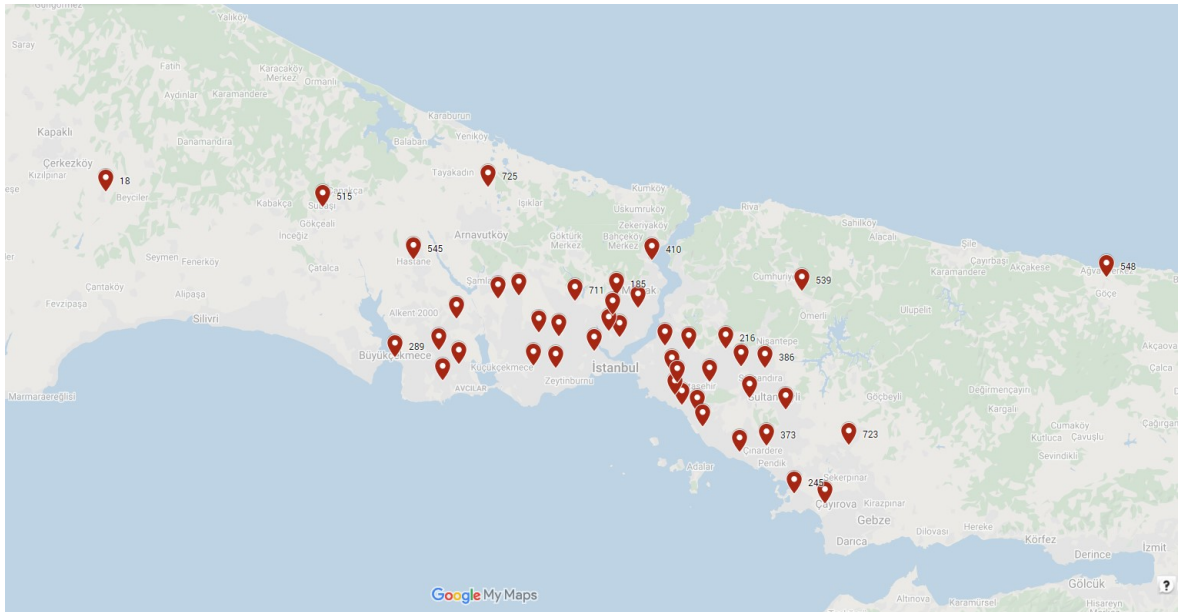


Figure 4.4. The opened stations in the fourth period (Google Maps [3]).

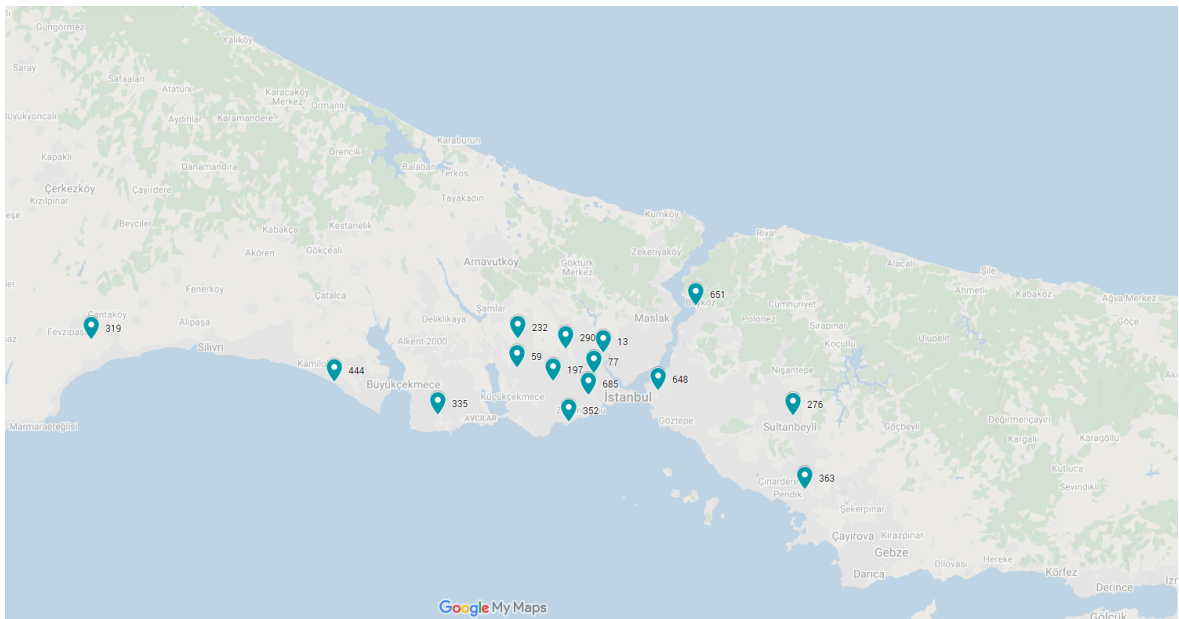


Figure 4.5. The opened stations in the fifth period (Google Maps [3]).

neighbourhoods served by the stations opened in that period. In both measures, the neighbourhoods served by the stations opened in a certain period are examined. In the first criterion, the number of neighbourhoods served is considered, and the highest number of neighbourhoods served by each station for that period is reported. In the other criterion, the longest distance served by each opened station is calculated, and then the largest distance is selected among these distances. This process is done for each period, and the services provided are measured. It is observed that the maximum number of neighbourhoods that the HRS serves has decreased due to the increasing number of stations in recent periods.

Table 4.3. Results of the base scenario.

Period	Max Distance (km)	Max Number of Neighbourhood
1	71.97	565
2	53.98	97
3	26.15	60
4	20.27	43
5	20.27	43

4.2. Effect of p Values

One of the assumptions in the p -median model mentioned before is that the number of facilities to be opened is a parameter, i.e., it is not a decision variable set by the model. Hence the number of stations to be opened in each period is calculated in advance and given as an input to the model. Here, an alternative approach will be used to define the p -value. The model is run for different p -values for the last period. We choose the last period since it is the period where the HFCV demand saturates. Then different p values are evaluated concerning defined performance measures such as objective value, maximum distance served by the opened stations in the scenario, the number of served neighbourhood the opened stations by scenarios, etc. Thus, a

single-period p -median model is run in 40 different scenarios ($p \in \{5, 10, \dots, 200\}$) in steady-state conditions. Like the base scenario, to get results for each p -value, it is assumed that the demand will be twenty percent of all vehicles at the SL.

By using the scenarios, we present two primary analyses about the number of stations to be opened. In the first analysis, we look at how many of the opened stations are common. In the second, we will evaluate the scenarios using different performance measures to choose a proper p . Here, we follow an approach similar to the elbow graph employed in the k-means algorithm [52]. In the k-means algorithm, we try to separate observations into pre-specified clusters. To select the appropriate number of clusters, the algorithm is run with several cluster numbers. As soon as the severity of the error decreases in these graphs, it is decided that the optimal number of clusters is that. The method is named as such because the resulting graphic resembles an elbow.

When we compare the HRS opened in each scenario, it is observed that 407 of the 734 stations are not used in any scenario. Station 396, on the other hand, is opened in 37 of 40 scenarios. Note that the first part of the common station examination is given in Figure C.1 in Appendix C. Then, all stations are examined according to the scenarios. That is, we observed which stations are opened in each scenario. Thus, information is obtained on how many scenarios a station is opened. The cumulative values required for the histogram are created by gathering these numbers. After that, the histogram in Figure 4.6 is obtained. For instance, one common station in 37 scenarios indicates that this station is opened in the 37 scenarios out of 40 scenarios. This means that it can be interpreted as a station with strategic importance as it helps to meet the demand in most of the scenarios. For example, 99 stations are opened in 18 different scenarios, and these stations are included as common stations in these scenarios.

After examining the common stations, the scenarios can be evaluated with the performance measures, i.e., maximum distance served, the maximum number of neighbourhoods served, and the maximum number of vehicles served. The number of HRS

can be evaluated based on these performance measures. The first performance measure is the objective value (the total distance travelled by the vehicles) obtained by each scenario and is illustrated in Figure 4.7. As expected, the objective function concavely decreases as the number of stations increases.

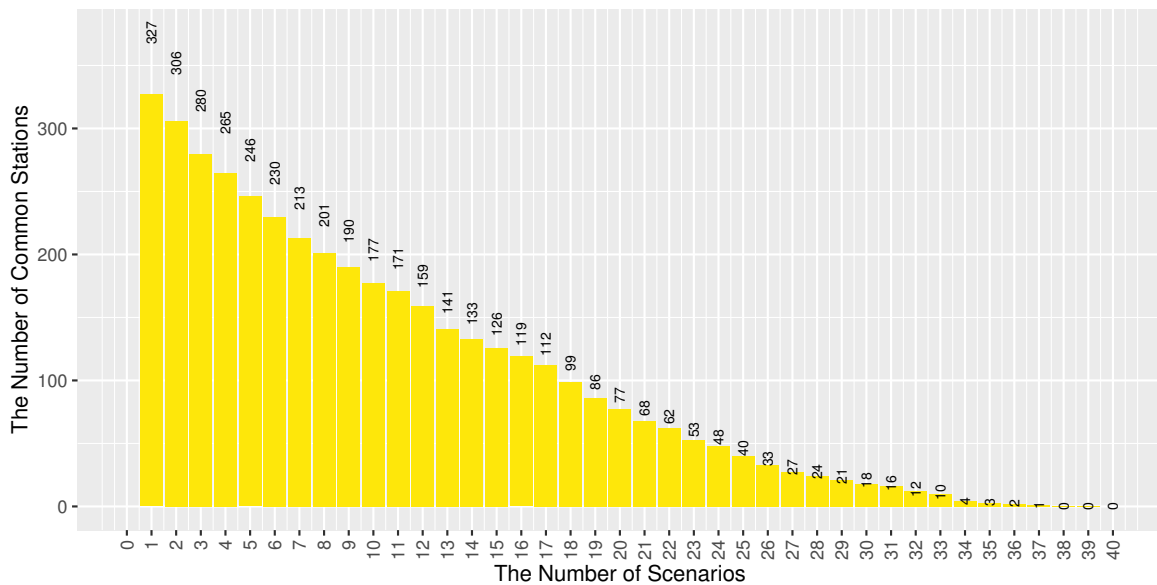


Figure 4.6. Cumulative of the number of common stations obtained by different p-value scenario results.

The second performance measure is the distances (minimum, average and maximum) served by the stations. The maximum distances served by the opened stations in each scenario are obtained. The maximum distance served in that scenario is obtained by taking the largest distance among these distances. For example, in the scenario where p is five, the maximum distance between the neighbourhood and its station is 59.87 km. Afterward, this process is done for all scenarios, and the maximum distance served in each scenario is taken. These maximum distances are expressed in green in the graph given in Figure 4.8. The yellow line shows the smallest of the maximum distances in the scenarios. The average line is shown by taking the average of the maximum distances served by the stations opened in that scenario. Figure 4.8 can be interpreted in two ways. First, the distances served by the stations opened in each

scenario can be compared. From here, it is understood that some stations serve distant neighbourhoods, while others serve their immediate surroundings. The other is that as the number of stations opened increases, the maximum distances decrease. In other words, as the number of stations opened increases since stations can be opened to different points, the furthest neighbourhoods served by the stations come closer to the stations. However, one point to note here is that this decreases after a specific p-value.

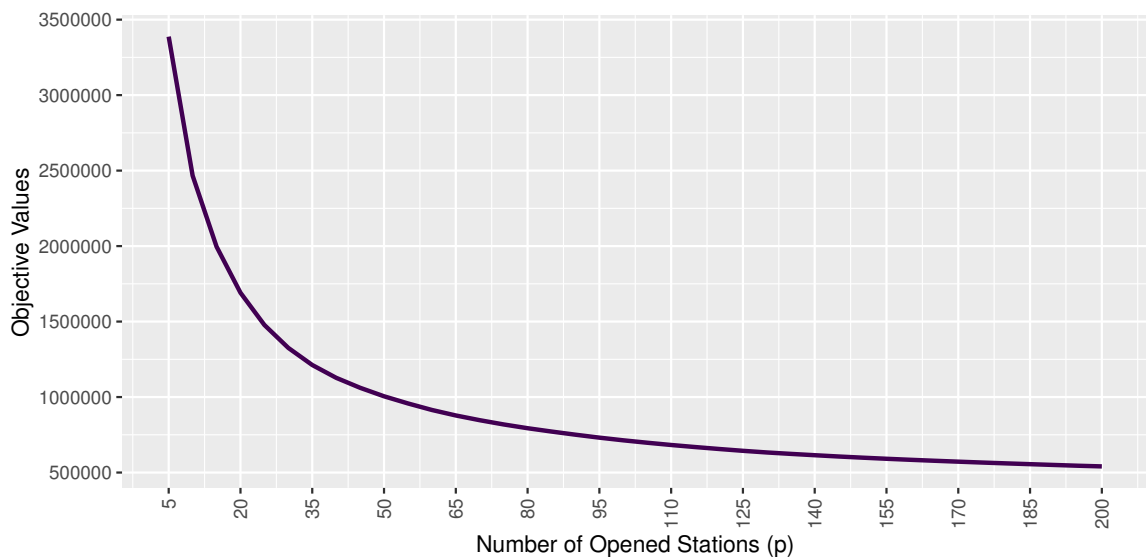


Figure 4.7. The objective values with different p-values (in steady-state).

In the previous performance measure, the maximum distance served by a station is examined. Here, the numbers of neighbourhoods served by the opened stations in each scenario are found. Then, the maximum, minimum, and average values are taken from these data. While the maximum number of neighbourhoods served in the scenarios is shown in green in Figure 4.9, the minimum number of neighbourhoods among the values kept is shown in yellow. The purple line in Figure 4.9 shows the average number of neighbourhoods that the neighbourhoods will serve in that scenario. For example, in the scenario where p is five, an opened station serves 284 neighbourhoods, while the other station serves 149 neighbourhoods, which is the minimum number in this scenario.

The average number of neighbourhoods in this scenario is obtained from 5 out of 954 neighbourhoods. The reason for giving the average value in this graph is to express how much more the station serving the neighbourhood serves more than the average. Like maximum distance analysis, as the number of stations opened increases, the maximum number of neighbourhoods served decreases, and the number of neighbourhoods served by the stations reaches the average.

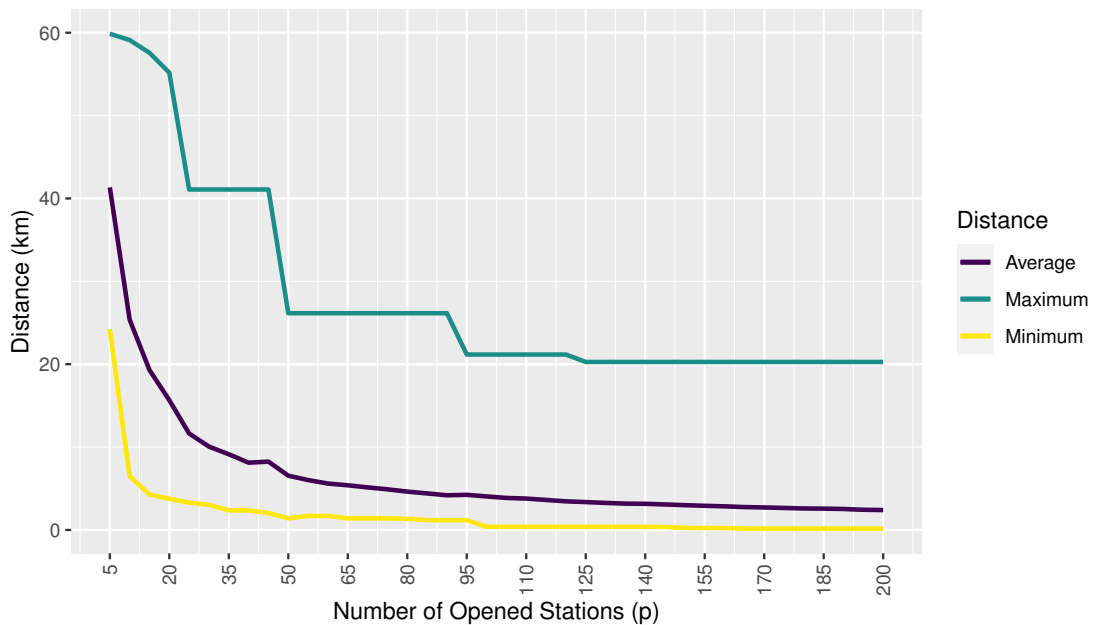


Figure 4.8. The maximum distance served by opened stations (in steady-state).

The number of vehicles served is given in Figure 4.10. The maximum value shows the maximum number of vehicles served by the stations opened in that scenario, while the minimum value shows the minimum number of vehicles. The average is obtained by dividing the demand, the number of vehicles, by the number of stations opened. When we interpret the graph here, as in the last three performance measures, as the number of stations opened increases, the maximum and the minimum number of vehicles served by the opened stations decreases.

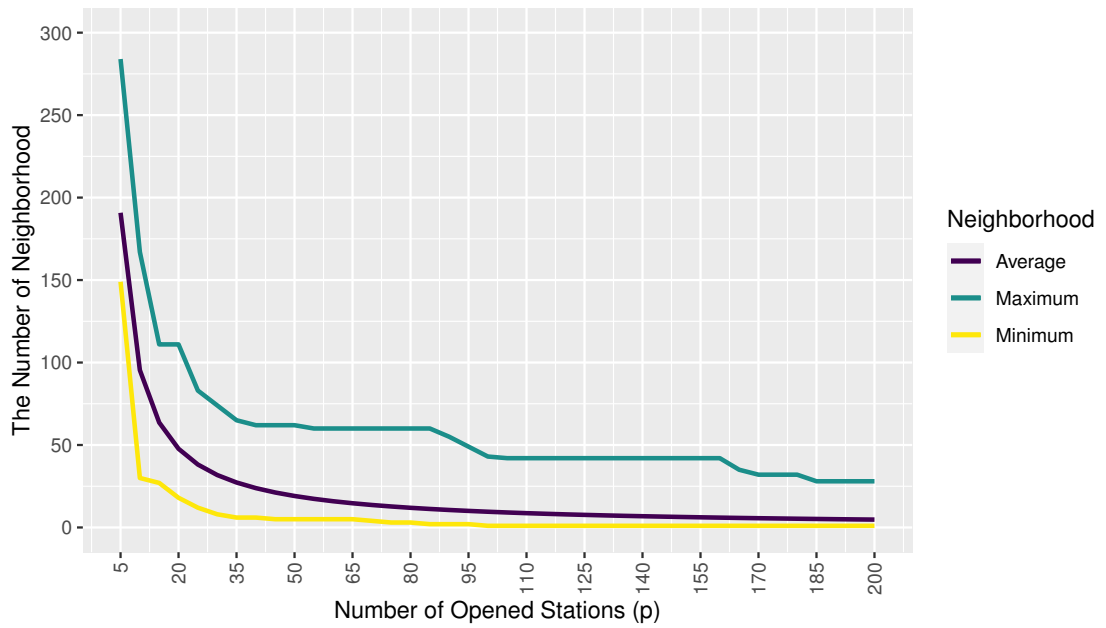


Figure 4.9. The number of neighbourhood served by opened stations (in steady-state).

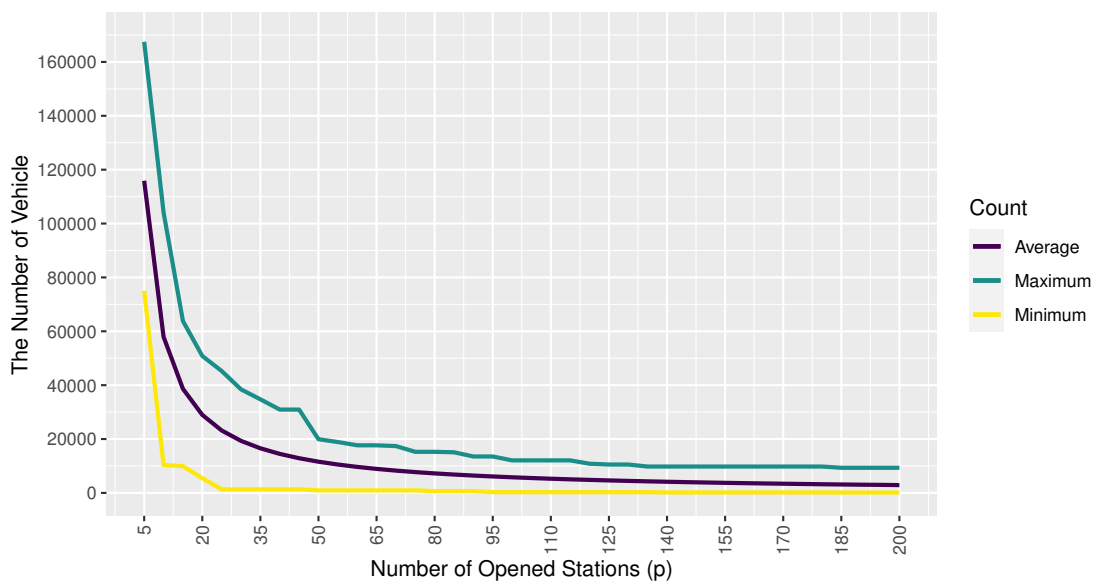


Figure 4.10. The number of vehicles served by opened stations (in steady-state).

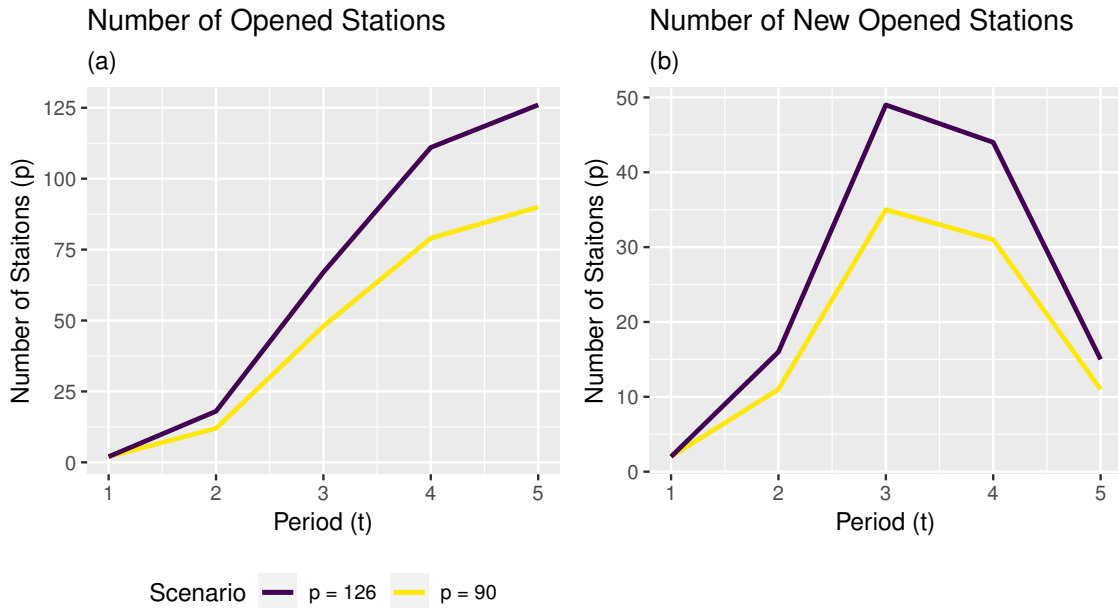


Figure 4.11. The number of stations.

After examining the common stations by scenarios, the aforementioned performance measures can be presented to select a convenient number of opened stations. In all performance measures examined, it is observed that the rate of improvement in the values of the measures starts to decrease after a certain point. For example, the rate of improvement achieved when p is moving from 5 to 10 is much greater than in the scenario where p is from 95 to 100. Since these performance measures constitute the cost values for p -median, it raises the question of whether such stations can be opened for a slight improvement. The reason behind this situation is that as more stations are opened, the service is closer to the end-user. Moreover, the decrease in the objective function is getting slower after the one point that can be called “*elbow*” similar to the cost reduction in the k -means algorithm. The slowdown in the improvement of the objective function can aid the determination of the value of p . In other words, to what point is the reduction in improvement in objective function acceptable? Therefore, it concludes that the trade-off between the objective value and the number of stations opened should be well understood. As can be seen from the graph, while improvement occurs rapidly in small p values, it is observed that this improvement is observed less

in scenarios where p is 90 and greater. As a result, in the next step, if 90 stations are opened, an answer to the question of how multi-period analysis will change will be sought.

After the number of stations to be opened at the end of five periods is determined as 90, the number of stations to be opened in each period must be determined to perform a multi-period analysis. The last period demand and the total number of stations to be opened can be used to determine the stations to be opened. In the steady-state analysis, where 90 stations are obtained, and here, the total demand is 579,452. When we divide this value by 90, we get the number of vehicles served by a station as 6438. When we divide the demand for each period by the number of vehicles served by a station, the number of required stations in that period can be obtained. The number of stations required for each period and the number of new stations to be opened in the periods are given in Figure 4.11 together with the base scenario data. While Figure 4.11 (a) shows the required number of stations, Figure 4.11 (b) shows the number of new stations to be opened according to the periods.

After running the model, whose number of opened stations is 90, p values can be evaluated by comparing the model's outputs using two data sets. When the stations opened in both scenarios are examined, it is observed that 598 stations are not included in both outputs. In addition, objective values are obtained 2,379,964 and 2,028,116 for $p = 90$ and $p = 126$, respectively. That is, if the number of stations is 126, an improvement of 14.79% is obtained in the objective value compared to 90 stations. In addition to this measure, these scenarios can be compared using the criteria used to determine the p -value. For this purpose, the maximum distance and the number of the neighbourhood by period are examined for both two runs.

As we mentioned before, the maximum distance performance measure gives the distance travelled of the neighbourhood that comes the farthest to get fuel from the opened station. Here, we use this measure to take the maximum distance for each period. In each period, the maximum distance between the neighbourhood and its

stations is gathered. Figure 4.12 shows this measure for both scenarios. When the graph in Figure 4.12 is analysed, at the first three periods, the distance in $p = 90$ is decreasing faster compared to the scenario where $p = 126$. That is, the improvement in this measure is seen more obvious in $p = 90$. However, in the last periods, the maximum distance served is close to each other in both scenarios.

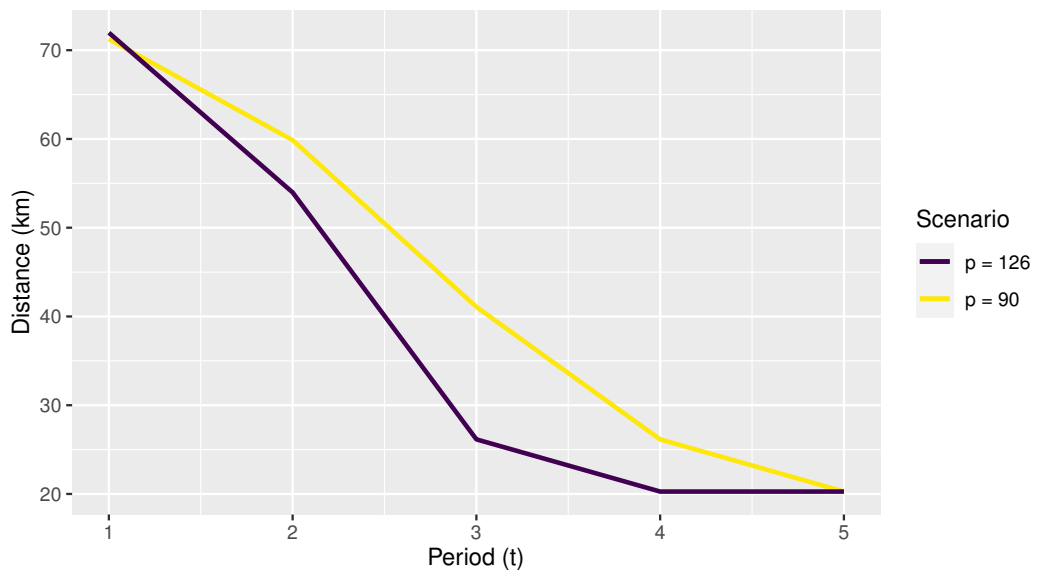


Figure 4.12. The maximum distance by periods.

Another criterion examined is obtained by measuring the maximum number of neighbourhoods served by stations opened in periods. The graphic of this measure is included in Figure 4.13. In both scenarios scenario, the two stations share the neighbourhoods. Therefore, in the $p = 90$ scenario, a faster transition is made to the number of neighbourhoods served in the next period. In contrast, when it comes to the last periods, it is observed that the maximum number of neighbourhoods served is close to each other for both scenarios. Note that the numerical values, figured out in Figure 4.12 and Figure 4.13, are presented in Table D in Appendix D.

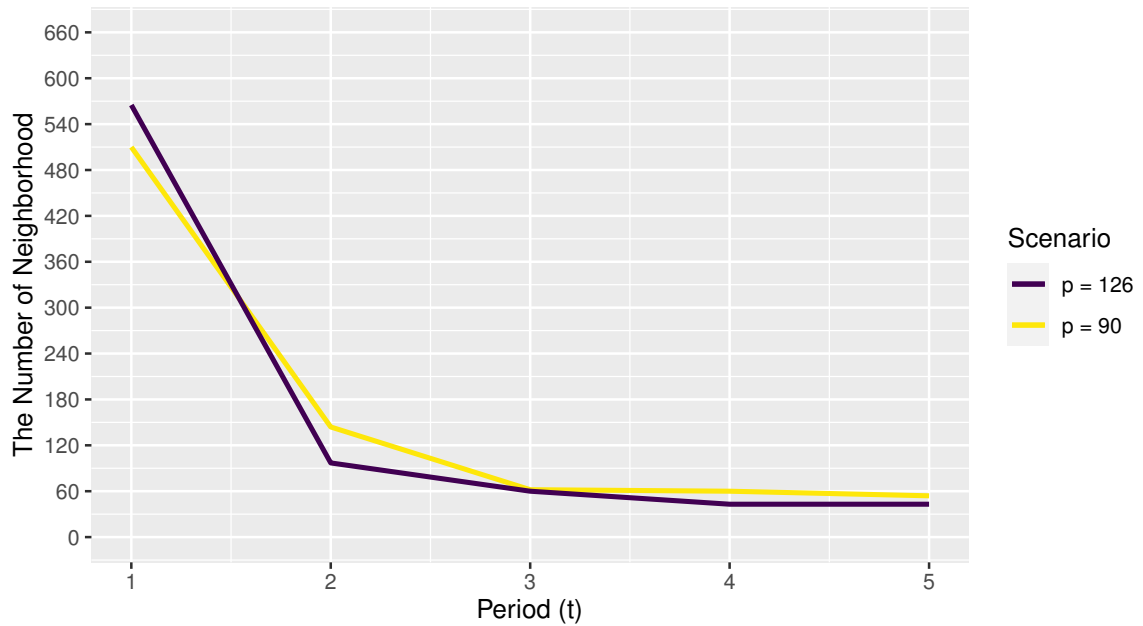


Figure 4.13. The maximum number of neighbourhood by periods.

4.3. Effect of Penetration over Demand

We have analysed the case results, which assume that the final penetration rate of HFCV is 20%. In this section, we examine different penetration values. The data set created for each penetration value here can be referred to as a *scenario*. In this context, four scenarios are created with penetration values between 10% and 50% with an increase of ten units by using the same data preprocessing steps in the base scenario. A graphical representation of the datasets obtained by periods is given in Figure 4.14. Note that the data set shown in olive-green illustrates the base scenario. The reason behind presenting this data set is to show its relationship with the other datasets. Like the demand calculation of each scenario, the number of stations to be opened is determined by using demand divided by an average number of vehicles served by one station, i.e., 4,614 vehicles. The number of stations is given in Figure 4.15 (a), whereas the number of new stations to be opened in each period is presented in Figure 4.15 (b). The total demand by periods for each scenario and the number of opened stations by periods are given in the appendix in Table B.1.

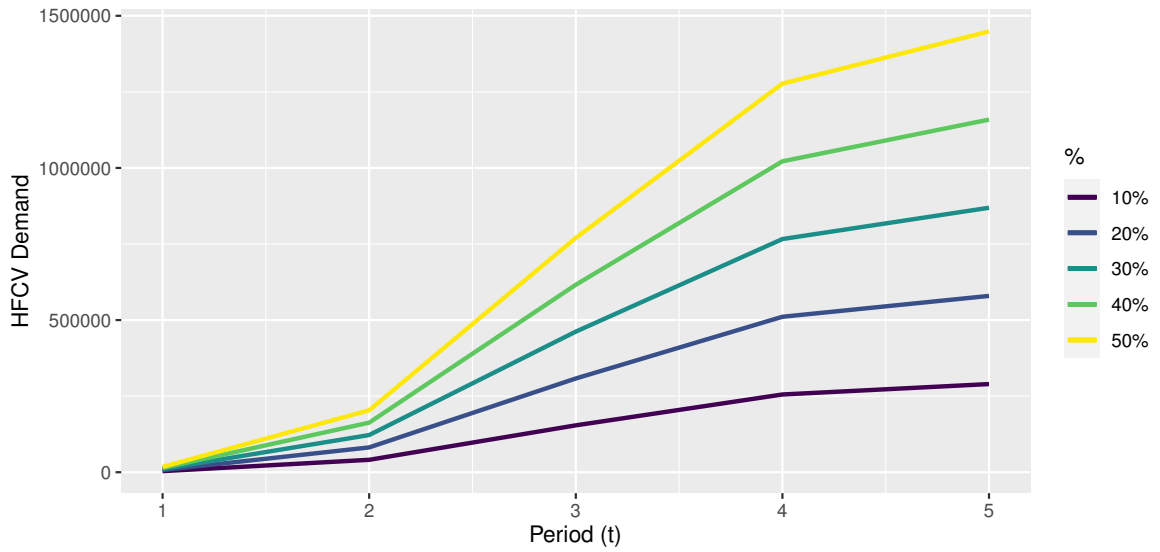


Figure 4.14. The demand by periods with different penetration values.

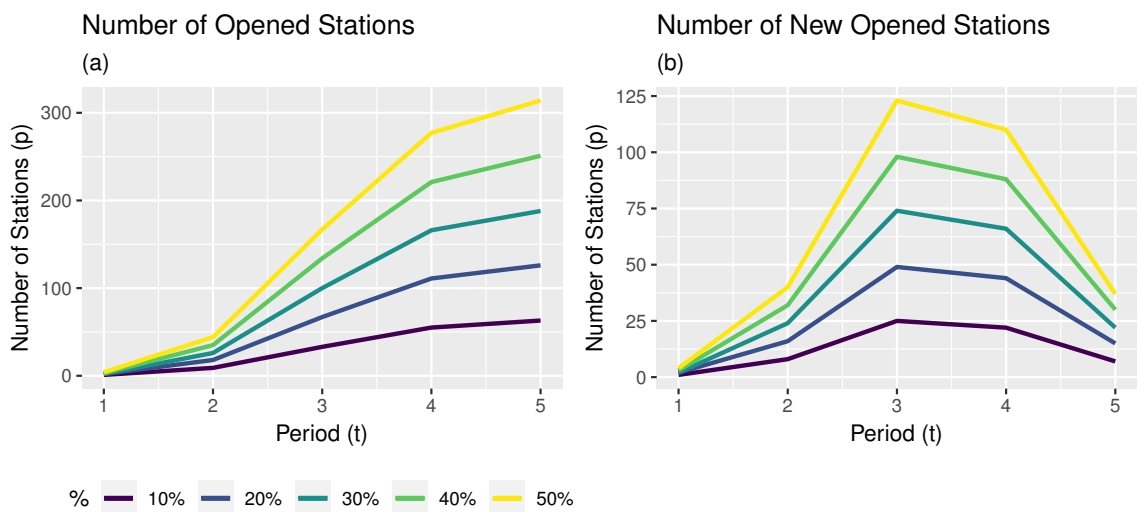


Figure 4.15. The number of stations by periods with different penetration values.

As can be seen from the graphs given in Figure 4.14 and Figure 4.15, the demand and number of stations proportionally change parallel to the penetration changes. Accordingly, the results obtained with the objective function should be expected to have a certain characteristic. Objective function values obtained from the scenarios are given in Figure 4.16. The yellow line in this graph illustrates the objective values obtained from each scenario. The purple dash line, on the other hand, shows the line fit as a linear function. This graph proves that the objective functions obtained from five scenarios almost exhibit a linear structure. This shows that the effect of proportionally varied penetration values is also in a linear direction.

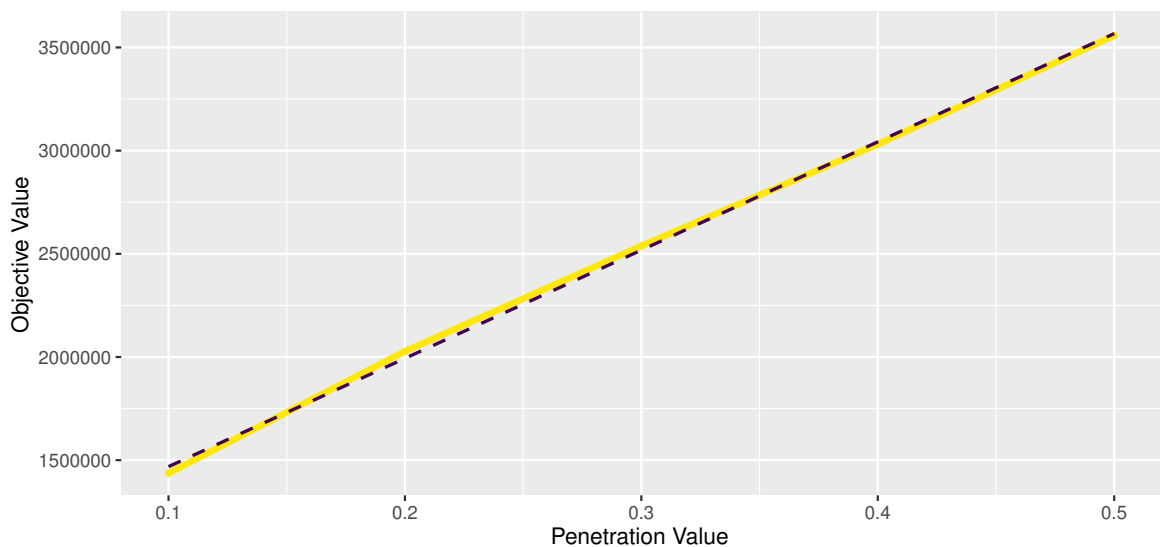


Figure 4.16. The objective values with different penetration values.

5. CONCLUSION

Current energy resources such as fossil fuels will not be enough to meet energy demand in the future has led researchers to seek alternative energy resources. Properties of hydrogen energy, such as being an efficient energy source, allowing long-term transportation and storage, have made it one of the alternative energy sources. In addition to these features, hydrogen energy, which can be produced from different energy sources such as wind, water, nuclear, coal, and biomass, highlight as a low polluting fuel. In this context, it is thought that hydrogen vehicles, along with electric vehicles, will significantly impact the future of the transportation sector. Furthermore, hydrogen energy support programs published by countries such as the United Kingdom, USA, and South Korea and hydrogen vehicles produced by companies such as Ford, General Motor, and Kia, which have an essential share in the automobile market, provide information about the future of this technology. However, in order for HFCV to become widespread, the number of HRS must also increase. In this respect, one of the differences between hydrogen vehicle and electric vehicle technology emerges. BEV can provide the necessary electrical energy by charging their batteries at different points such as home and office. In other words, BEVs do not need any refuelling station in order to provide the required fuel. A different situation is valid for hydrogen technology. It is mandatory to have HRS to supply hydrogen fuel. This necessity raises the question of where to open HRS. This research question also consists of the subject of this thesis study. In this study, we look for an answer to the determination of locations of HFS in İstanbul, where one-fifth of Turkey's population lives. In order to answer this question, a multi-period p-median method, which is one of the frequently used methods for location selection in the literature, is employed. In this context, the future HFCV demand of İstanbul between 2020-2050, which involves thirty years, is determined. Since hydrogen energy is a new technology; it is a fact that the neighbourhoods, which are defined as demand points, do not use this technology simultaneously. According to the assumption, to reflect differences between the neighbourhoods, the development index is calculated for each district, and to use these values S-Curve structure is ap-

plied to the data preparation stage. The normal distribution is selected to construct the S-curve, and the development index is used as the mean of the normal distribution function by $(1 - \text{development index})$. Thus, with the help of the development index added to the S-Curve, the diffusion of the hydrogen energy for each district is represented in the model parameters. By using this district information, neighbourhood HFCV demand is calculated. Moreover, it is assumed that at the end of the planning horizon, which contains five periods, the number of HFCV will reach 20% of the whole vehicles in Turkey. Considering all this information, the demand of the neighbourhoods is obtained. Then, to fulfil the neighbourhoods' demand, the existing gas stations are determined as candidate sites, preferred in the previous studies conducted in the literature. That is, the existing 734 stations are used to select the location of the HRS's in İstanbul. In other words, it is accepted that the proper stations from among the existing gas stations are converted into the HRSs in the future. In this way, with the proposed model, HRSs to be opened are determined by selecting from existing facilities by minimizing the distances weighted with demand according to the periods.

According to the results obtained from the base scenario, it is observed that the facilities opened in the first periods are located in the center. As the periods progressed, there is an increase in the number of stations to be opened in order to meet the increasing demand and as a result, the stations start to spread from the center to the locality. Thus, the HRS opened have started to get closer to the neighbourhoods that are the demand points. These results show existing gas stations that can be converted for the next five periods. However, the p-median model is based on three basic assumptions: (i) the number of facilities to be opened in each period is known at the beginning, (ii) the fixed cost of each refuelling station is the same, and (iii) the stations to be opened have no capacity restriction. In order to examine the effects of the first assumption, different ratios in penetration value are examined and the results are analysed. It is observed that different penetration values formed proportionally create a similar effect on demand. In other words, proportional demand values are obtained with these penetration values. Objective function values obtained also support this result. The effect of proportionally increasing penetration values shows a similar structure in

the objective function, and the relationship between them is obtained linearly. This relationship also affects the number of stations opened. The number of stations to be opened by periods used in the base scenario is obtained by using the average number of vehicles served by a station today. As in demand, a linear relationship is obtained in the number of opened stations according to the different penetration values. The first assumption is also analysed by using different p-values as another scenario in addition to the different penetration value scenarios. In this context, 40 different p-value scenarios are created, starting from 5 to 200, increasing by five. According to the results, it is observed that 407 of the 734 existing stations are not selected to convert into HRS in any scenario. In addition, the scenarios are evaluated using performance measures such as the objective values, the distance to the farthest neighbourhood served by opened stations, the maximum number of neighbourhoods served by opened stations, and the maximum number of vehicles served by the stations opened. Then, the most appropriate p-value is selected to perform a multi-period analysis. According to the results obtained by the defined performance measures, it is found that the improvement in the performance measures for the p values at the beginning is higher, whereas there is a decrease in the improvement rate with the increase of the p-value. It is determined that the improvement rate in the measures approached almost zero for the bigger p-values. For example, it is observed that if the p is higher than 85-95, no significant improvement could be obtained. Thus, the p=90 is selected. In this model, 90 shows the number of stations to be opened in the last period. By using this value, the number of stations by period is determined. Then, the results obtained from this model are compared with the base scenario where p is 126. Although there are differences in both scenarios in the initial periods according to the defined performance measures, it is observed that the performance measure values are very close to each other, especially in the last two periods. The result obtained here can be interpreted in two different ways. If the number of stations to be opened is to be determined by considering the cost, a p = 90 scenario in which fewer facilities are opened may be preferred. If users are asked to buy hydrogen fuel from nearby stations instead of fuelling from long distances, the scenario with p=126 can be chosen. Thus, users can buy fuel from closer stations starting from the first period.

An analysis is made for decision-makers about where the HRS can be opened with the results obtained with this thesis. In these analyses, using the HDI, the results for the locations of the stations were obtained by taking into account the districts that may have the potential to use HFCV before. In addition, alternative scenarios different from the base scenario were taken into account, and where the HRS to be opened could be opened as a result of differentiation was examined.

With the analyses, implicit demand is added to the study. However, since it is assumed that the facilities have no capacity, explicit demand is not used. Therefore, the effect of explicit demand is not analysed directly. For this reason, in future studies, studies can be conducted by assuming the stations to be opened have different capacities, the results obtained in this study can be examined under capacity constraints. In addition to the capacity assumption, it is accepted that the cost of each opened station is the same. However, differences in fixed costs may be observed depending on the number of pumps opened and the capacity. Moreover, since these analyses are made in the long run, the discount rate can be entered into the model with the different fixed costs analyses. Thus, costs can be analysed by adding this difference to the model, and how the costs affected the stations opened can be investigated. Furthermore, different distance measurement methods can be used instead of the Euclidean distance used to calculate the distance between the neighbourhood and the station, which is used as the coefficient value of the objective function. In order to make these measurements more realistic, calculations can be made using real data (for example, Google data), or non-Euclidean functions can be used. Finally, the development index can be added by using a different approach to data pre-processing.

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APPENDIX A: DATA PRE-PROCESSING

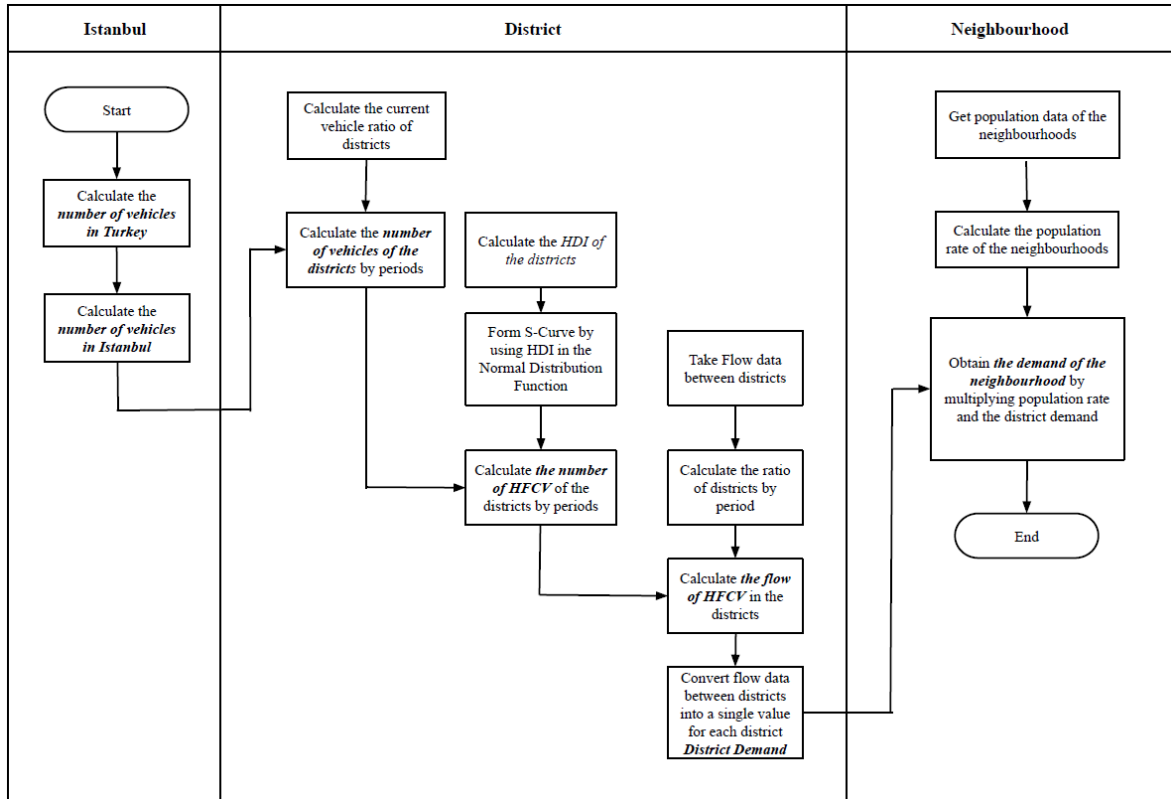


Figure A.1. Calculation steps of the neighbourhood demand.

Table A.1. The number of stations by periods.

Period	1	2	3	4	5
Number of Stations	2	18	67	111	126
Number of New Opened Stations	2	16	49	44	15

APPENDIX B: EFFECT OF DEMAND CHANGES

Table B.1 shows the demand by periods for each scenario and the number of stations required for that period. While the number on the left shows the demand, the value on the right shows the number of stations to be opened. For example, while the demand in the third period at 30% penetration value is 616063 vehicles, the number of stations required to meet this demand is 134. In order to calculate the number of stations to be opened periodically, the procedures in the base scenario should be applied.

Table B.1. The demand and stations with different penetration values.

Period \ Penetration	10%	30%	40%	50%
1	3492/1	10475/2	13967/3	17459/4
2	40730/9	122191/26	162921/35	203651/44
3	154016/33	462047/100	616063/134	770079/167
4	255443/55	766330/166	1021774/221	1277217/277
5	289726/63	869177/188	1158903/251	1448629/314

APPENDIX C: DIFFERENT P-VALUES

The values given in Table C.1 include the numerical values used for plotting the graphs shown in Chapter 4. The objective column in Table C.1 is used to obtain the graph in Figure 4.7. The values under the title Distance are used to create a graph in Figure 4.8, and the subtitles have the same meaning as in Figure 4.8. The Values in Neighbourhood and Vehicle columns also correspond to Figure 4.9 and Figure 4.10, respectively.

As a result of the models operated using different p values between 5 and 200, the stations opened in each scenario are examined and the common stations opened in the scenarios are analysed. In other words, this analysis looked at which of the 734 stations are opened in which scenarios. Afterward, the stations are listed in descending order according to the number of common stations obtained from the stations opened in the scenarios. A part of this sequence obtained is given in Figure C.1. The rows illustrate the stations in the given table, whereas the columns show the p values in the scenarios. A value located at the intersection of the station and p -value indicates that that station is opened in the specified scenario. For example, in all scenarios, station 396 is opened except for three scenarios where the p values are 5, 10 and 15. In other words, it takes place in 37 of 40 scenarios. After performing this analysis for all stations, the values in the Total column are counted and shown as a histogram with Figure 4.6 in Chapter 4 according to the common stations.

The stations opened are examined using the results obtained from the scenarios created according to p values. In this context, by using 734 stations, the opened stations in each scenario are examined. Afterward, the number of scenarios in which the stations opened is determined. Some of these values are given in Figure C.1. 94, 162, 213, 531, 545, and 603 stations, for example, are opened in 26 different scenarios. Note that, in this analysis, the scenarios can be either the same or different. That is, although stations 94 and 162 appear in 26 scenarios, scenarios involving station 94 and

station 162 may be different. Then, the scenario values of the stations are counted. In the example, six stations take place in the 26 scenarios. Thereby, the number of 26 common stations is equal to six. Using this calculation, scenarios from 0 to 40 are counted and kept in the *Count* column in Table C.2. The sum of the counts is presented under the *Cumulative* column used to create a histogram graph given in Figure 4.6 of Chapter 4.

Table C.1. Numerical values of different p -value scenarios.

p	Objective	Distance (km)			Neighbourhood			Vehicle		
		Minimum	Average	Maximum	Minimum	Average	Maximum	Minimum	Average	Maximum
5	3387577	24,23	41,33	59,87	149	191	284	75055	115890	167471
10	2466779	6,50	25,37	59,11	30	95	167	10386	57945	104126
15	1996559	4,27	19,30	57,58	27	64	111	9929	38630	63812
20	1690901	3,76	15,66	55,18	18	48	111	5482	28973	50845
25	1477373	3,29	11,64	41,08	12	38	83	1317	23178	45252
30	1325586	3,02	10,06	41,08	8	32	74	1317	19315	38434
35	1212404	2,37	9,13	41,08	6	27	65	1306	16556	34753
40	1127574	2,34	8,12	41,08	6	24	62	1306	14486	30938
45	1061449	2,05	8,24	41,08	5	21	62	1306	12877	30938
50	1005107	1,40	6,55	26,15	5	19	62	925	11589	19930
55	957700	1,69	6,02	26,15	5	17	60	925	10535	18888
60	914445	1,69	5,60	26,15	5	16	60	925	9658	17669
65	878110	1,40	5,39	26,15	5	15	60	925	8915	17669
70	846705	1,40	5,13	26,15	4	14	60	925	8278	17380
75	818639	1,40	4,90	26,15	3	13	60	925	7726	15247
80	793549	1,35	4,62	26,15	3	12	60	671	7243	15247
85	771476	1,17	4,41	26,15	2	11	60	671	6817	15083
90	750735	1,17	4,18	26,15	2	11	55	671	6438	13527
95	731058	1,17	4,24	21,16	2	10	49	268	6099	13527
100	713474	0,38	4,04	21,16	1	10	43	268	5795	12076
105	697460	0,38	3,86	21,16	1	9	42	268	5519	12076
110	682502	0,38	3,78	21,16	1	9	42	268	5268	12076
115	668821	0,38	3,62	21,16	1	8	42	268	5039	12076
120	656050	0,38	3,45	21,16	1	8	42	268	4829	10836
125	643906	0,38	3,36	20,27	1	8	42	264	4636	10537
130	633013	0,38	3,26	20,27	1	7	42	264	4457	10537
135	623673	0,38	3,17	20,27	1	7	42	264	4292	9785
140	614764	0,38	3,15	20,27	1	7	42	181	4139	9785
145	606262	0,35	3,08	20,27	1	7	42	181	3996	9785
150	598500	0,23	2,99	20,27	1	6	42	181	3863	9785
155	591214	0,23	2,91	20,27	1	6	42	181	3738	9785
160	584488	0,23	2,85	20,27	1	6	42	181	3622	9785
165	578091	0,16	2,76	20,27	1	6	35	181	3512	9785
170	572032	0,16	2,71	20,27	1	6	32	181	3409	9785
175	566241	0,16	2,65	20,27	1	5	32	181	3311	9785
180	560747	0,16	2,59	20,27	1	5	32	181	3219	9785
185	555408	0,16	2,57	20,27	1	5	28	144	3132	9325
190	550143	0,16	2,53	20,27	1	5	28	144	3050	9325
195	545150	0,16	2,43	20,27	1	5	28	144	2989	9325
200	540642	0,16	2,40	20,27	1	5	28	144	2897	9325

Table C.2. Number of common stations with p -value scenarios.

Number of Common Stations	Count	Cumulative	Number of Common Stations	Count	Cumulative
40	0	0	19	9	86
39	0	0	18	13	99
38	0	0	17	13	112
37	1	1	16	7	119
36	1	2	15	7	126
35	1	3	14	7	133
34	1	4	13	8	141
33	6	10	12	18	159
32	2	12	11	12	171
31	4	16	10	6	177
30	2	18	9	13	190
29	3	21	8	11	201
28	3	24	7	12	213
27	3	27	6	17	230
26	6	33	5	16	246
25	7	40	4	19	265
24	8	48	3	15	280
23	5	53	2	26	306
22	9	62	1	21	327
21	6	68	0	407	734
20	9	77			

APPENDIX D: COMPARISON OF THE $p=90$ and $p=126$

Table D.1. Comparison data of $p=90$ and $p=126$.

Scenario	Measure \ Periyot	1	2	3	4	5
p=90	Maximum Distance	71.2479	59.8705	41.08156	26.15128	20.269627
	Number of Neighbourhood	510	144	62	60	54
p=126	Maximum Distance	71.97284	53.97721	26.15128	20.26963	20.26963
	Number of Neighbourhood	565	97	60	43	43