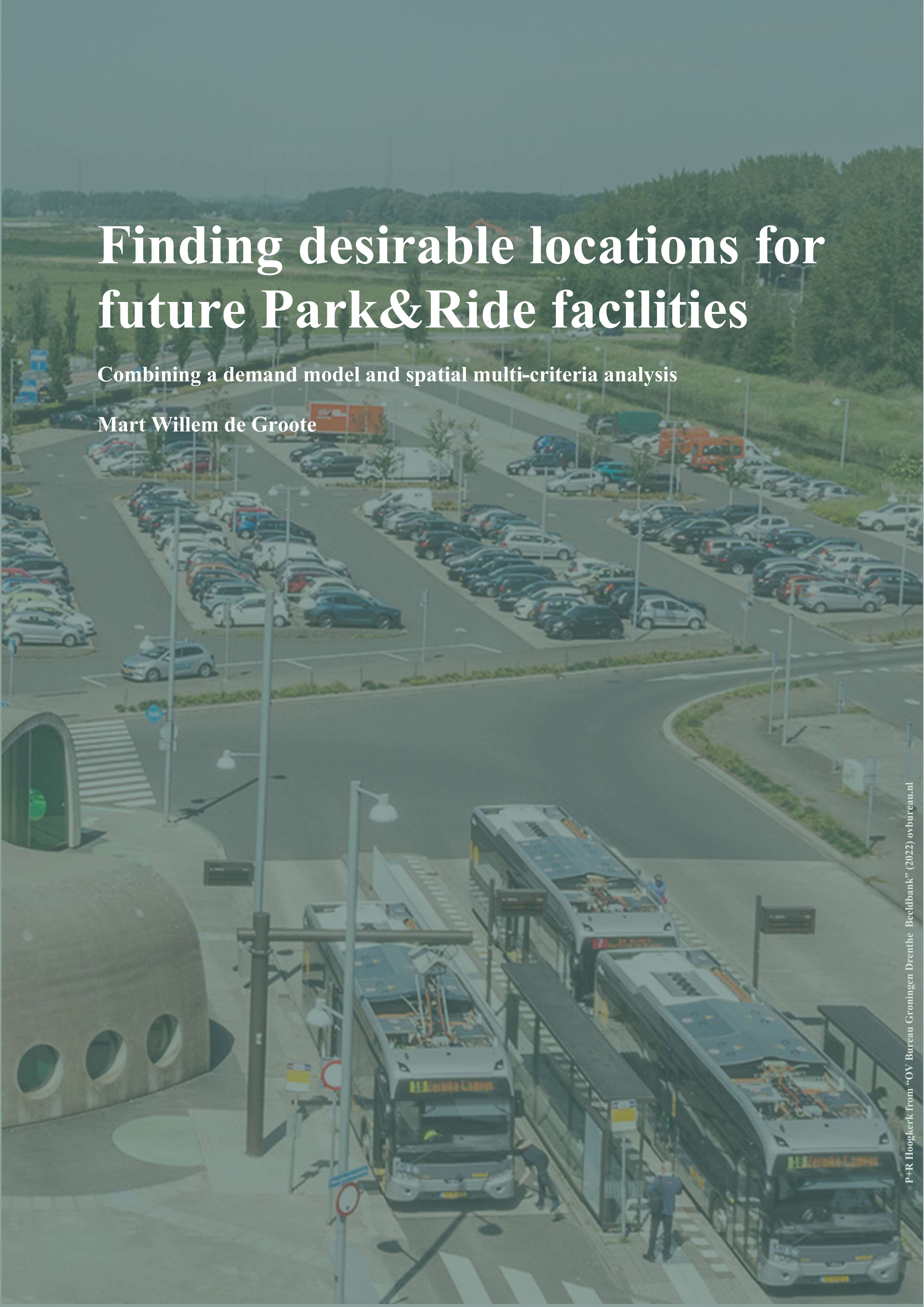

# Finding desirable locations for future Park&Ride facilities

**Combining a demand model and spatial multi-criteria analysis**

**Mart Willem de Groote**

P+R Hoogkerk from "OV Bureau Groningen Drenthe Beeldbank" (2022) ovbureau.nl

# Finding desirable locations for future Park&Ride facilities

Combining a demand model and spatial multi-criteria analysis


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# Preface

This research marks the completion of my master's degree in Civil Engineering. With it, I close an important chapter in Delft, and look forward to completing my second degree at Wageningen University. In this thesis I have taken a deep dive into the academic research aspect of the study and came to grips with performing an independent research, guided by both my supervisors at the university as well as the company.

The initial spark for this research came from a discussion with Fabian Wegewijs at Movares, where we explored the current challenges related to park and ride (P&R) facility locations. In particular how the facility's position within the road network influences its success, a topic that has received limited academic attention. This was the starting point of this research, which has then been expanded to a study on the factors that can predict P&R demand and how this predicted demand can be used in combination with other aspects in a spatial modelling tool to achieve an overall desirability score for new P&R facilities for an entire area.

Even though there were definitely some struggles along the way, I have been surprised by how much I have enjoyed doing this research. I am very thankful for the friendly and interested environment at Movares, and also specifically Fabian for being a great guidance throughout the extent of the research. Your insightful comments and questions during our weekly talks have definitely elevated this research.

The research may be of interest to Movares and similar engineering-consultancy firms, decision-makers like municipalities and provinces, as well as fellow students and those that like to know more about the topic. Additionally, I will publish the research in a paper and present it at the Colloquium Vervoersplanologisch Speurwerk (CVS) 2025 conference.

I like to close of this section by expressing my gratitude towards everyone that helped and supported me throughout the project. Firstly the guidance from Fabian and colleagues at Movares. Fabian has been a great support throughout the project, always trying to highlight the practical side of the research and asking appropriate questions which made me think deeper and get to a better result. I am also grateful to my supervisors - Gonçalo, Jan-Anne and Winnie - for their guidance throughout the research.

On a personal note, I am also very thankful for my friends, housemates and family. Everyone experiences stress at some points throughout their research, and for me it was no different. They have been very supportive and often a great distraction. Lastly I would also like to thank the various parties that have supplied data or information used in this research. Without these sources the research would have been more difficult to conduct.

With this, my thesis journey comes to a close. I hope you enjoy the read.

Mart Willem de Groote

Wageningen, Juli 2025

# Summary


## *Research problem and goal*

Park-and-ride (P&R) facilities serve the increasing need of drivers to reach their end destination via alternative means, as traffic congestion is increasing (Müller, 2024) and cities are increasingly discouraging drivers from entering the urban centers with their private vehicles (Bicycle Dutch, 2021; Elaine Bannon, 2023; Simone Jacobs, 2025). P&R facilities enable the user to park their vehicle and transfer to public transport (PT) to reach the end destination. This way of travel could offer benefits like shorter travel times and, more broadly, reduced road congestion (Cavadas & Antunes, 2019; Memon et al., 2014).

The Netherlands has numerous P&R facilities that exhibit varying usage patterns. Previous research has only partially clarified the reasons for this variation. There is a lack of statistical analyses on influential factors that can quantify their impact, particularly the influence of location within the road network on the demand for P&R facilities, which has not been thoroughly researched. This factor is expected to significantly affect the facility's demand, based on an earlier internal analysis within Movares.

Currently, when planning for new P&R facilities, a local study is conducted on a predetermined set of potential locations that investigates the potential P&R demand per location and the suitability of these locations within its surrounding area, mainly based on expert judgment. A handbook is used for this, developed by the CROW, a knowledge institute in the Netherlands concerning infrastructure, traffic, and transport.

Based on the research problem, the goal of this research is twofold. First, to assess the P&R demand based on a comprehensive set of attributes, including the influence of a P&R facility's position within the road network. Second, to integrate factors, including the P&R demand, that influence the overall P&R facility desirability into a framework that can quantify desirability for new P&R facilities for an entire geographical study area, evaluating all possible locations simultaneously. This framework can facilitate the process of advising and planning for future P&R facility locations. In this instance, the term "desirability" encompasses a wide range of considerations taken by decision makers in the planning of P&R facilities.

## *Methodology*

The research consists of four phases, each supported by a methodology. The first phase is a literature study that evaluates the state of current research on three subjects: (i) the factors that influence the potential demand of a P&R facility, (ii) the factors that determine the overall desirability of a P&R facility, and (iii) methods used to find desirable P&R facility locations. From the literature study, the research gap is formulated and two theoretical frameworks are created, one for the influential factors on P&R demand and one for the influential factors on the overall desirability of a P&R facility.

Through the literature review it is concluded that a spatial multi-criteria analysis (MCA) is the most appropriate method to determine the overall desirability of a P&R facility. Tools that can estimate desirable P&R facility locations based on real-world situations, including straightforward criteria, and that can assess an entire study area at once seem to be lacking. Aquilué Junyent et al. (2024) performed relevant research on the desirability of urban mobility hubs, in which they make use of a spatial MCA; even though this differs from P&R facilities, the study's method can be applied to this research project, as it can guide towards achieving the aforementioned second goal of this research.

In the second phase of the methodology, the theoretical framework of P&R facility demand is used to develop an explanatory model. This model aims to explain the P&R facility demand based on a set of input variables. The statistical method used to find a relationship between multiple independent variables and a dependent variable is regression analysis. The potential demand of a P&R facility is predicted both on a continuous scale and an ordinal scale. With a continuous scale, P&R demand is predicted using multiple linear regression (MLR) and on the ordinal scale, P&R demand is predicted using ordinal logistic regression (OLR). The continuous scale would offer better insight into the exact P&R demand, however it is harder to predict this accurately. The P&R demand prediction based on an ordinal scale is less exact, since you are predicting the demand within certain ranges, but therefore the correct range is more accurately predictable. This introduces a trade-off between the amount of ranges or bins and their sizes, as few bins with a very large size would give a high prediction accuracy for the right bin, but the information gained from this is small compared to a prediction with more bins of a smaller size.

Both the MLR and OLR models are developed following the same four steps. First, the dataset of P&R facilities is created. It includes preprocessing like filtering and cleaning datasets. In the second step, the regression models are developed. This is an iterative process, with different methods and input variable configurations tested. The model development

includes multiple steps: the creation of interaction terms, to capture correlating variables; cross-validation is used to ensure the robustness and reliability of the model performance. In the third step, the performance of the predictive models is assessed based on performance indicators. The significance of variables that explain P&R facility demand is also evaluated. Lastly, the sensitivity of the models to small changes in the input is assessed.

The result is a regression model that predicts P&R facility demand. In the third phase of the research, this predictive demand model is used as one of the input criteria in a spatial MCA. This desirability is determined by multiple factors, of which one is potential demand. Other factors are found in the theoretical framework of P&R desirability. The goal of the spatial MCA is to find the overall desirability of new P&R facilities based on a set of input criteria, assessing an entire study area in which grid cells represent potential P&R facility locations. The input of the spatial MCA consists of three elements: objectives, constraints and alternatives. Objectives are abstract functions representing a specific aspect of the P&R desirability. Constraints determine areas that are infeasible for new P&R facilities. Lastly, the alternatives of the spatial MCA are all grid cells in the study area.

The development of the spatial MCA consists of four elements: value scaling, weight functions, visualization, and sensitivity analysis.

- Value scaling is the concept of translating attribute values to objective scores using specified value functions. These allow for elaborate functions, however, in their simplest form, the value function is the same as normalization.

- The weight functions translate the objective scores from the various criteria into one overall desirability score. These weight functions can see multiple different implementations, from simple linear combinations to spatially dependent functions. In this research, the weighted linear combination (WLC) method is chosen, as it allows for a simple and direct implementation of criteria weights.

- The visualization creates a heatmap that shows the desirability score of the entire study area. The visualization aims to highlight important findings from the overall results. It should be clear and interpretable, also for people with no background in GIS or modeling.

- A sensitivity analysis checks whether small changes in the input weights result in disproportionate changes in the results. The one-at-a-time method is used for this, in which one objective weight is picked and the weight is changed within a specified increment between 0 and 1 (Malczewski & Rinner, 2015). The results are assessed in terms of total desirability score change for the entire study area by looking at the mean and standard deviation of all cell scores. The same is done for the top 10% highest scoring cells, as these are of most interest when planning for new P&R facility locations, as they have the highest desirability scores.

In phase four, the model is verified and validated by applying it to a case study in the region of Groningen. The current P&R facilities in the region are at capacity (Groningen Bereikbaar, 2024), and therefore the municipality is interested in expanding its number of P&R facilities. Two scenarios are developed in this case study, a base scenario with the current PT network and the Nedersaksenlijn (NSL) scenario, in which a new train line is constructed in the southeastern region of the study area. The case study demonstrates how the results in desirability change due to a change in the transportation network.

### *Results*

From the development of the explanatory demand model, it is found that the multiple linear regression model violates the assumption of normality of the residuals. This violation results in unreliable values for the model performance indicators and the significance of the variables. The ordinal logistic regression (OLR) model does fulfill its assumptions and is therefore preferred. The OLR model predicts the potential P&R facility demand within specified ranges (bins): <100, 100-200, 200-400, 400-600, and >600 daily users. The selection of these ranges is based on the trade-off between information and accuracy and is reached in an iterative manner. The model performs well, with a pseudo-$R^2$ of around 0.29, which is an excellent fit (Henscher & Stopher, 1979), an accuracy of around 54% and an average bin error of around 0.5.

**Table I: Significant variables from the OLR model**

| Variable | Coefficient |
|---|---|
| Frequency of connected PT | 0.91 |
| Address density at the P&R facility location | -0.66 |
| Number of reachable workplaces within 60 minutes of travel in PT | 0.97 |
| Distance to the nearest other P&R facility | 1.71 |
| Address density in the surrounding area of a P&R facility | 1.26 |

From the OLR model, it follows that five out of the ten input variables are significant predictors of P&R facility demand. These five variables are shown in table I, alongside their estimated coefficient. The variables have been normalized, such that a direct comparison is possible between variable coefficients. The distance to the nearest other P&R facility has the greatest impact on the P&R facility demand, as it has the highest coefficient. The lowest impact is observed for the address density at the P&R facility, as this coefficient is closest to zero. The position of a P&R facility within the road network is found to be insignificant. Additional factors may significantly influence the P&R demand but were not incorporated in this model due to a lack of data or infeasible implementation. This mainly includes factors at the destination end, such as parking accessibility and traffic congestion in the city.

The spatial MCA combines the potential demand model with other criteria to estimate the overall desirability of P&R locations. The criteria consist of three objective layers and a constraint layer, which are derived from the theoretical framework as a result from the literature study. The three objectives are defined as maximizing potential demand, maximizing connectivity (measured by the travel time ratio, defined as the ratio between the travel time to the end destination with PT and with private vehicle), and suitable spatial embedding, which considers land use suitability (which links the various land use classes to a suitability cost) and distance to the nearest road. The constraint layer consists of four types of areas that are deemed infeasible for the construction of a new P&R facility, these are open water bodies, protected nature areas, national monuments, and residential areas. Open water bodies are technically infeasible, protected nature areas and national monuments are infeasible by law, and residential areas are infeasible as it would have too big of an impact on the local community.

The aforementioned criteria are combined using the WLC method, in which three stakeholder interests are considered: the users, operators, and government. This results in a heatmap of the total desirability of a study area, with weights for each objective layer, 38%, 36%, and 31% respectively for the potential demand, connectivity, and spatial embedding.

To visualize this, the framework is applied to the case study of Groningen. The total desirability score for new P&R facilities within the case study area for the base scenario is shown in figure I. It shows a clear distinction between high-desirability and low-desirability areas. The three objective layers tend to complement each other, meaning that for example high demand areas often also score high on connectivity or spatial embedding. This results in areas with very high desirability and areas with very low desirability. Following from model validation in which zoomed-in analyses are performed on specific locations, the model accurately estimates high desirability scores in areas that experts judged as highly desirable as well, as they are in line with earlier analyses performed by Movares. The analysis of the weight sensitivity in combination with stakeholder scenarios shows that the model is robust in its estimation. The model demonstrates that the total desirability can be effectively estimated with the three objective layers and the constraint layer.

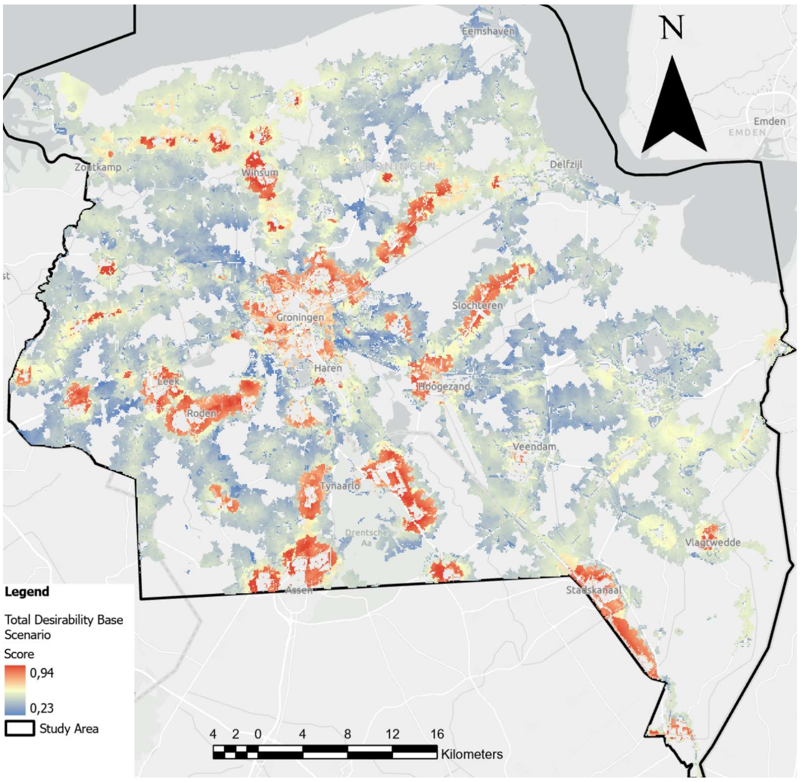


**Figure i: Total desirability heatmap of the case study area in the base scenario**

## *Conclusions and main recommendations*

The first research goal is to develop an explanatory model that explains P&R demand based on a comprehensive set of attributes. From the result, it follows that five variables are found to be significant predictors of P&R facility demand. The model can predict potential demand within specified ranges with an accuracy of around 54%, and an average bin error of around 0.5. The position of a P&R facility within the road network is found to be insignificant in predicting the P&R facility demand, which rejects the previous hypothesis.

The second goal is to employ a framework that can quantify the total desirability of new P&R facilities for an entire study area. The combination of three objectives: maximize demand, maximize connectivity, and suitable spatial embedding, results in an estimate of the total desirability of an area for a new P&R facility. The framework shows flexibility regarding the input criteria, scoring, and weighting of the objectives. The model is shown to be robust as changes in the weights do not change the results of the outcome disproportionately. Overall, the model shows its potential for facilitating in the process of advising and planning for future P&R facility locations.

Both the regression analysis and the spatial MCA can be expanded with additional research. The regression analysis may be limited by the conventional regression methods used in this research (MLR and OLR). Current developments in machine learning, like random forest or neural networks, might yield better predicting models (Bratsas et al., 2020). This might come at the cost of interpretability, so a trade-off must be made.

In the spatial MCA, multiple components are simplified to focus on the core of the method. Further research can look into these components. This includes more realistic value functions describing the relationship between the attribute and objective layers. Additionally, stakeholder involvement, for example by employing the analytic hierarchy process (AHP), can give better insight into appropriate weights. Lastly, the scale of the model can be adjusted to see how the resulting desirability changes. Currently, the grid cells are one hectare in surface area, however, application to different scales is possible in the model.

In terms of the applicability, two aspects are noted. Firstly, the resulting framework is flexible and can therefore be applied to other situations, for example different geographic regions. Secondly, the results from the framework are inherently related to the Netherlands. The Dutch road and PT network design, personal relation to the car, and P&R, all implicitly or explicitly play a role in the results of this research. It is therefore recommended to assess how the results change when applied to a different geographic region.

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# 1. Introduction

A trend is visible in cities where active policies are trying to discourage citizens from reaching the city centers by car and parking in these areas, such as high parking fees and street redesigns (Bicycle Dutch, 2021; Elaine Bannon, 2023; Simone Jacobs, 2025). In combination with increasing overall traffic congestion on the Dutch road network (Müller, 2024), this has led to travelers seeking alternative ways to reach their destinations. One of which is combining private motor vehicle use with public transportation (PT), creating a multimodal journey. Park and ride (P&R) facilities serve this need by enabling users to park their private motor vehicles and transfer to PT. This way of travel could offer benefits like shorter travel times and, more broadly, reduce road congestion, as has been shown by various case studies (Cavadas & Antunes, 2019; Memon et al., 2014). These facilities should therefore be placed in appropriate locations.

Currently, when advising on new P&R facility locations, a local study of a few potential locations is performed on the potential P&R demand and suitability within its surroundings. To determine this, a handbook for P&R facilities is developed by CROW, a knowledge institute in the Netherlands concerning infrastructure, traffic, and transport. Candidate locations are scored, and the most desirable one is chosen. The desirability is affected by numerous variables, including potential demand, local suitability, and construction costs. In this instance, the term “desirability” encompasses a wide range of considerations when planning P&R facilities.

In the Netherlands, numerous P&R facilities exhibit varying usage patterns that cannot always be easily explained. Some facilities seem to be in a high-demand area but see little use, whereas other facilities are expected to have low demand but see much higher demand. Previous research has identified several factors that influence the facility demand (Zijlstra et al., 2015); however, it is unclear whether a complete assessment has been done. The position of a P&R facility within the road network, such as the proximity to a highway, has not been thoroughly investigated. An early internal analysis within engineering and consultancy firm Movares has led to the hypothesis that this factor significantly influences the P&R facility demand. It expects that facilities located closer to major roads, like highways and provincial roads, will experience less demand, as drivers are already on a high-quality transportation network. Conversely, P&R facilities located further away from these major roads are expected to see higher demand. As a result, the assessment may be incomplete when advising on new P&R facility locations. This research therefore aims to assess the P&R demand based on a comprehensive set of attributes, including the influence of a P&R facility’s position within the road network. Furthermore, to facilitate the process of advising on future P&R facility locations, this research aims to compile the influencing factors of P&R facility desirability into a framework that can quantify desirability for new P&R facilities for an entire study area.

## 1.1 Research objectives, questions and scope

Building on that, the objectives of this research are twofold and formulated as:

1. To develop an explanatory model that predicts P&R facility demand, based on a comprehensive set of variables, which includes the position of a P&R facility within the road network. The goal is to assess both the significance of the set of variables as well as the predictive power of the model.
2. To develop a framework that can aid in the advice on future P&R facility locations. This is done by combining the predictive demand model with other factors, identified through a literature study, to estimate the desirability of new P&R facilities within a study area, evaluating all possible locations simultaneously. It is not the goal to decide on what is the most desirable location but rather to show the desirability for all locations.

Various definitions of P&R facility types are used in practice. This research focuses on P&R facilities outside major city centers, excluding ‘last mile’ P&R facilities, as their usage differs from facilities situated further away (Zijlstra et al., 2015). Additionally, the study is limited to P&R facilities within the Netherlands to avoid bias between countries due to differences in the mobility network, (urban) landscape, and culture. The P&R facilities included in the research are connected to varying modes of transport, strengthening the research.

Defining the possible locations is required to estimate the desirability of an entire study area for future P&R facility locations. This is done by creating a grid of the study area in which each grid cell represents a possible future P&R facility location. The scale is chosen to be one hectare per grid cell (100x100m), which is deemed an appropriate size for a P&R facility.

The research objectives and scope are used in the method of unraveling key concepts to come to the following main research question:

*"How can the desirability of new P&R facilities be determined for each geographical location in a grid of a study area?,,*

To support the main research question, seven sub-questions are formulated. The first three questions aim to find the relevant attributes and determine a suitable method for the research. The fourth question looks at finding the importance of the position within the road network on P&R facility demand to check the hypothesis that this would negatively impact the P&R facility demand. The fifth question aims to find an estimate for the potential P&R facility demand. The sixth question develops a framework in which the potential demand prediction is combined with other factors to find the overall desirability of a P&R facility in a location. The seventh question applies this framework to a case study in the region of Groningen.

The seven sub-questions are:
1. What variables influence potential P&R facility demand?
2. What other factors, besides potential demand, influence the desirability of a P&R facility?
3. What methods have been used to find desirable P&R facility locations or similar facility location problems?
4. To what extent does the position within the road network influence the P&R facility demand?
5. To what extent can an explanatory model estimate potential P&R facility demand?
6. How can the combined desirability of various criteria, including potential demand, for a P&R facility in a location be determined?
7. What is the desirability of new P&R facilities within a specific study area?

## 1.2 Methods

The methods used to answer the research questions are briefly addressed in this section. The research objectives, scope, and questions have led to the identification of four research phases. These phases are each characterized by a research method. The first phase aims to answer the first three research sub-questions. The second phase aims to answer the fourth and fifth research sub-questions. The third phase answers the sixth sub-question, followed by the final phase answering the seventh sub-question. The combined results of the four phases answer the main research question. The four research phases are given in table 1.

**Table 1: Research stages and methods**

| Stage | Method | Goal |
|---|---|---|
| 1 | Literature study | To deepen the knowledge on the subject, to identify influential factors on P&R facility demand and overall location desirability, and lastly to determine a suitable method for estimating the desirability of P&R facilities. The factors and method are used in the next stages. |
| 2 | Regression analysis | Develop an explanatory model, estimating potential P&R facility demand based on multiple input variables. This estimated demand is used in the next stage. |
| 3 | Spatial multi-criteria analysis (MCA) | Using Geo-Information Systems (GIS) to produce a heat map. The heatmap combines different spatial layers, representing the influential factors, amongst others the estimated demand, and indicates the total desirability of new P&R locations. A sensitivity analysis is performed on the model results. |
| 4 | Case study | The MCA from the previous stage is applied to a specific case study area. |

The choice of method for phases two and three follows from the literature study. The methodology chapter goes into more detail about these four elements.

## 1.3 Thesis Report Structure

This master thesis initiates in chapter 2 with the literature study on P&R definitions, influential factors on their use and desirability, and what methods have been used to determine these. In chapter 3, the methodology of the four research phases is given alongside data requirements. The development and evaluation of the explanatory demand model are given in chapter 4. After which, in chapter 5, the spatial MCA is performed and applied to a case study. Chapter 6 discusses the overall results and research context, with chapter 7 containing the conclusions and recommendations.

# 2. Literature study

This literature study gathers existing knowledge and identifies the gaps in the literature. This is guided by the first three research sub-questions. However, to do this it is important to first define the various P&R facility types found in literature. In this section, the literature search strategy is explained first, after which the literature is studied. From the knowledge gained from the literature study, the research gap is described. Lastly, a theoretical framework is drawn up. The literature study is done before the methodology chapter because to complete that chapter, the relevant variables and methods must first be identified. The literature study itself is, however, also part of the methodology. Therefore, the literature study methodology is explained here instead of in the methodology chapter.

## 2.1 Literature review strategy

This methodology presents an approach to finding, interpreting, and summarizing the relevant literature that answers the first three research sub-questions. Keywords are used to search for relevant literature on Scopus, Google Scholar, and ScienceDirect, as these sources host the majority of published research papers and other literature. Relevant literature is then added to a Litmaps folder, a tool that shows other related and referenced literature.

A set of keywords is used to find the relevant literature, as shown in table 2. These keywords are selected as they are deemed sufficiently broad but not outside the scope of the research. Search queries are constructed with a combination of facility, definition, factor, or methods using the AND function.

**Table 2: Keywords and search queries used in the literature study**

| Keywords | Facility | Definition | Factors | Methods |
|---|---|---|---|---|
| | Park & ride OR<br>Park and Ride OR<br>Park-and-ride OR<br>P&R OR<br>P+R OR<br>PenR OR<br>P&R facility OR<br>Mobility hub | Definition OR<br>Classification OR<br>Types | Attractiveness OR<br>Demand OR<br>Potential demand OR<br>Desirability OR<br>Suitability OR<br>Feasibility | Location OR<br>Location optimization OR<br>GIS OR<br>MCA OR<br>Multi-criteria analysis OR<br>Traffic assignment model |
| Search queries | Facility AND definition<br>Facility AND Factors<br>Facility AND Methods<br>Facility AND Factors AND Methods | | | |

## 2.2 Literature findings

The literature review first looks at the current definitions used for P&R facilities. This is followed by identifying the factors that influence the demand and desirability of P&R facilities. Thirdly, the methods used to find desirable P&R facility locations are studied.

### 2.2.1 P&R definitions

An early study by Bos (2004) makes a distinction between three types of facilities, categorizing them based on their proximity to the destination. They identify three types: destination P&R, located near the journey's end; origin P&R, located closer to the journey's starting point; and field P&R, which is located midway, often near major highways. This categorization is based on P&R facilities in the Netherlands. The limited number of categories leads to an oversimplification of the diversity and characteristics of P&R facilities. De Graaf et al. (2005) similarly divide P&R facilities into origin and destination categories. This two- or three-tier classification is consistent in Dutch literature and is also used by the CROW.

International studies show different perspectives. Krasić & Lanović (2013) classify P&R facilities based on the type of PT mode used: near railway systems, bus systems, or combined rail and bus systems. This classification, based on a case study in Zagreb, Croatia, introduces a mode-specific approach to defining P&R facilities. Again, the small number of classes can result in an oversimplification of the facility's characteristics.

Zijlstra et al. (2015) performed a meta-analysis on the effectiveness of P&R facilities. In their paper, five different P&R facility types are identified: satellite facilities, which are located in towns at a certain distance from the city; rural facilities, which are located in sparsely populated areas but at the intersection of important transportation crossings; urban fringe facilities, located at the periphery of a city near important access roads; intracity facilities, located near local or regional PT networks within an urban area; and central P&R facilities, located near major PT nodes within an urban area. This implicitly differentiates the facilities concerning their position within the road network.

The definitions used in Dutch literature can be deemed most appropriate, as this research only focuses on P&R facilities within the Netherlands. However, they are limiting as they oversimplify the diversity and characteristics of the P&R facilities. Additionally, more classes allow for more specific selections of facility types. More complex definitions, as used by Zijlstra et al. (2015), are therefore preferred and used in this research.

### 2.2.2 Factors determining P&R facility demand and overall desirability

A multitude of studies have looked into the determining factors of P&R facility demand and desirability, though many fail to capture the full set of factors. The various papers have different goals, as some try to identify the choice behavior of people, and others try to develop mathematical models to determine optimal facility positions. These different goals also lead to different identified factors. These sources are elaborated below. The most important factors, as identified by these various sources, are summarized in table 3.

Faghri et al. (2002) identified a list of criteria for their research on the optimal P&R facility location, applied to the state of Delaware, USA. They have split up the evaluation criteria into three categories, each being decreasingly quantifiable. The most important quantifiable factors are the position relative to the central business district (CBD), negative lot competition, service area population, location relative to the PT station, and PT frequency. Furthermore, they identify less quantifiable criteria, such as site access, location upstream of congestion, and the potential for relocating existing structures. The quantifiable criteria can be used to estimate demand, whereas the more fuzzy and qualitative criteria are better suited for determining the desirability of a P&R facility.

Bos (2004) found the relative importance of different factors influencing the demand for P&R facilities. They identify four main categories, with multiple subcategories: personal characteristics, P&R facility characteristics, connecting PT, and car accessibility at the destination. Factors such as reliability, comfort of travel, information, quality of the facilities, and extra time using a car were found to be significant determinants of P&R usage. This study provides detailed insights, including aspects like P&R supervision, maintenance, and personal characteristics.

Farhan & Murray (2008) investigate three major siting concerns that had not been modeled previously. They employ an optimization framework in which they maximize the population within the catchment area, minimize the total travel time between facilities and major roadways, and lastly maximize the number of P&R facilities. In this setup, they do include the distance to the nearest major roadway; however, their reasoning for this is lacking. This study combines well with their previous work, in which Farhan & Murray (2005) go into detail about delineating the catchment area based on the travel cost ratio and direction of travel. Their research is based in the United States, which is a reason the results may be less appropriate for this research. Major differences are present in the transport network as well as culture, such as the personal connection to the car.

Krasić & Lanović (2013) use the analytic hierarchy process to determine the relative importance of five broadly defined criteria to evaluate current P&R facilities: the size of the area gravitating to the P&R location, the multifunctional character of the P&R location, ease of realization and operation from a technical and financial standpoint, the quality of PT service connected to the P&R facility, and the accessibility to the P&R locations. These five categories both focus on the potential demand as well as overall desirability. The usefulness of these five criteria is questionable, as they are vaguely formulated and hard to quantify.

Zijlstra et al. (2015) performed a regression analysis on seven factors to determine the effectiveness of P&R facilities. These seven factors are: connected public transport mode, the capacity of the P&R facility, headway of the connected PT, the point of intercept (the ratio between the travel time from the origin to the P&R facility and the total travel time of the journey), weekday versus weekend, share of commuters, and location type. They found that the public transport mode, the point of intercept, the capacity of the P&R facility, and the PT headway showed significant results.

Ortega, Moslem, et al. (2020) performed a study using the best-worst method to determine sustainable P&R facility locations, based on a predetermined set of locations. Their study evaluated six main criteria, consisting of nineteen sub-criteria that are regarded as important for decision-makers. They conclude that the five most important sub-criteria are: the frequency of the connected PT, the distance from the P&R facility to the nearest PT stop, the $CO_2$ reduction, the travel distance to the nearest P&R facility, and the increased demand for PT. Furthermore, they have found that accessibility of public transport is considered most important by experts, followed by environmental aspects, such as $CO_2$ reduction and noise pollution. Some of these factors can be related to the P&R facility demand, whereas others are related to the total desirability.

In addition to facility-specific or system-specific factors, personal characteristics also influence P&R usage. Research from various countries and cultures indicates that these factors are region-specific (Macioszek & Kurek, 2020). Ortega et al. (2021) performed a literature review on the planning of a P&R system, concluding that the demand for P&R facilities is more complex than thought at first, as it is also influenced by individual user characteristics and decisions.

Overall, the majority of the identified factors are consistent throughout the various studies, and no contradictory factors are found. The number of factors and the scope of the different studies varied considerably, however this does not seem to change which factors are influential or not. In table 3, the identified factors are listed and indicated if they influence the facility demand (U) or overall desirability (D).

**Table 3: Factors influencing P&R facility demand/usage (U) and overall desirability (D).**

| Reference | Factors | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Personal characteristics | Connecting PT | P&R characteristics | Car accessibility at the destination | Population within catchment area | Accessibility of P&R locations | Nearest neighbor | Point of intercept | Spatial constraints | Congestion on route | Economic incentives | Costs of implementation | Environmental aspects |
| Faghri et al. (2002) | | U | U | | U | U | U | U | D | D | U | D | |
| Bos (2004) | U | U | U | U | | | | U | | | U | | |
| (Farhan & Murray, 2005, 2008) | | U | | | U | | U | U | D | | | | |
| Krasić & Lanović (2013) | | U | U | | U | | | | | | | D | |
| Zijlstra et al. (2015) | | U | | U | | U | | | | | | | |
| Ortega, Moslem, et al. (2020) | | U | | | | U | | U | D | | | D | D |
| Macioszek & Kurek (2020) | U | | | | | | | | | | | | |
| Ortega, Moslem, et al. (2021) | U | | | | | | | | | | | | |

### 2.2.3 Methods used to find desirable P&R facility locations

The position of P&R facilities is studied using several different approaches: GIS-based models, traffic assignment models, multi-criteria analyses, and theoretical location optimization using different mathematical optimization models. These different approaches focus on different parts of the desirability of P&R facilities: GIS on spatial limiting factors for P&R facility desirability; traffic assignment models look at the modal split or decision of an OD pair to use the P&R facility; multi-criteria analyses look to combine several criteria; and optimization models look at the theoretical usage, capacity, pricing, and optimal location. Each of these approaches is elaborated below. A summary of these various methods is shown in table 4.

A GIS-based approach using knowledge-based expert input on the attributes can be useful in predicting desirable P&R locations. The GIS-based approach allows for including different criteria, such as quantifiable variables like position relative to the CBD, but also more fuzzy criteria like the potential for relocation of existing structures (Faghri et al., 2002). This study looked at the United States, so the applicability to the Netherlands is questionable, as their transport infrastructure as well as the personal relation to the private car is very different. Furthermore, the study is relatively old, so there might be new insights to be found using a GIS-based method. The benefit of the GIS-based approach is that it can handle different forms of input variables.

García & Marín (2002) employ a multimodal traffic assignment model, which generates the demand for modes of transport. The physical location of the potential P&R facility locations is determined beforehand, and the model predicts P&R capacity and pricing using a generalized parking link cost. The drawback of this method is that an already existing traffic assignment model is needed, including all route options; additionally, the potential P&R facilities must be located beforehand. Traffic models of the Netherlands used for predicting P&R usage are highly simplified, and therefore their use is limited. The reason for this is the complexity of modeling mobility chains, like the use of a private vehicle to transfer to PT (De Graaf et al., 2005). International methods are more complex; however, they cannot be implemented into Dutch traffic assignment models. De Graaf et al. (2005) therefore developed a model using multimodal logit functions and were able to implement these methods into Dutch traffic assignment models. They note that for origin P&R facilities, the models tend to underestimate the usage numbers.

Wang et al. (2004) used a model of a linear monocentric city to determine the optimal position and pricing of P&R facilities by using deterministic mode choice. This is an early study using an optimization model, though the simplicity of the model limits its applicability. Aros-Vera et al. (2013) uses a p-Hub approach for the P&R location problem. This approach looks at a predetermined set of P&R facilities and assumes known demand for each origin-destination pair. It analyzes the best position of the P&R facilities to maximize usage. This approach is unsuitable for this research, as the demand for origin-destination (OD) pairs is not known and the number of P&R facilities is not determined beforehand. Henry et al. (2022) apply mixed-integer linear programming with multiple different decision variables to find the optimal P&R facility location, aiming to improve the resilience of the overall urban mobility network. This is a more theoretical model-based approach compared to the goal of this research, which aims for a model that is applied to a real situation.

The analytic hierarchy process (AHP) is used in an multi-criteria decision analysis (MCDA) by Krasić & Lanović (2013) for a case study on the P&R facilities of Zagreb, Croatia. Here, they identified five main criteria that were used in the AHP. They used a relatively simple approach to the AHP, merely doing a pairwise comparison and determining the final weight relationships for a five-by-five matrix. These results were then used in an MCDA to determine the scores of the different location alternatives.
A more complex use of the AHP is done by Ortega, Tóth, et al. (2020) as they use a triangular method, determining the upper bound, lower bound, and average weight for the different criteria. Several other researchers have used the AHP with MCDA for location decision-making for P&R facilities. The overall finding is that AHP is widely used, even though there might be some bias as the expert opinions are subjective (Fierek et al. (2020), Ortega et al. (2023)). Similarly, Ortega, Moslem, et al. (2020) apply the Best Worst Method (BWM) to generate weights for predetermined criteria and sub-criteria. Compared to other methods, this results in fewer pairwise comparisons and a more consistent comparison approach.

Ortega et al. (2023) employ the grey analytic hierarchy process for evaluating the park-and-ride facility location. Primary and secondary criteria are compared in a six-step process. They use a fuzzy triangular method, meaning experts judge an upper and lower bound for the different weights as well. These are then used in an MCDA with a limited set of known alternatives.

Recently Aquilué Junyent et al. (2024) used the AHP together with a GIS-based MCDA for planning shared mobility hubs. Although applied to mobility hubs, this research highlights the potential of using GIS-based MCDA. The results from the research show the desirability of urban mobility hubs with a heatmap, scoring each cell in a grid of the urban area. The paper emphasizes the choice of indicators rather than the choice of the MCDA method. Their research demonstrates the power of GIS as they evaluate the desirability of urban mobility hubs for an entire study area at once. Similarly, Pitale et al. (2022) developed an GIS-MCDM approach in which they included criteria that play an essential role in determining the potential locations for new P&R facilities. Their research however does not include any indicators related to the potential demand and is merely based on spatial data like population density and land use classes. Nevertheless, both these studies show the potential of using GIS in combination with an MCA, as they can effectively locate desirable locations for future facilities. From the assessment of these methods it is therefore found that the combination of GIS with an MCA is most suited to this research. Table 4 shows the benefits and drawbacks from each of the methods.

**Table 4: Overview of various methods and their benefits and drawbacks**

| Reference | Method | Description | Benefits | Drawbacks |
|---|---|---|---|---|
| Faghri et al. (2002) | GIS | Knowledge-based expert judgement and GIS tool to determine the optimal location for P&R facilities | Combine different variables, both quantifiable and fuzzy into a GIS environment. GIS allows for visualization, improving the interpretation of results | Relatively old and simple study, new development in GIS could enable for a more complex analysis. |
| García & Marín (2002), De Graaf et al. (2005) | Traffic assignment models | A multimodal traffic assignment model to determine P&R facility demand | Prediction of P&R facility demand for known locations. | Requires OD pairs and complex route and trip modelling. |
| Aros-Vera et al. (2013) | p-Hub approach | An optimization model to determine the optimal location of p number of P&R facilities, given OD pair demand | Theoretical optimal position of P&R facilities, such that demand is maximized. | The number of hubs is predetermined. The location is not bound by physical constraints (like open water bodies or existing buildings) and demand must be known beforehand. |
| Henry et al. (2022) | MILP | Models entire trip chain from origin to destination, via pick-up and drop-off nodes. A logit model is used to model users' mode choice. Stochastic scenarios are used to represent traffic conditions | Complete trip chain model, which also allows for conclusions about congestion and resilience of the overall road network. | The mathematical formulations are very extensive, limiting their applicability to other situations. More importantly, the OD pair must be known beforehand. |
| Krasić & Lanović (2013)Ortega et al. (2023), Aquilué Junyent et al. (2024) | MCDA - AHP | A multi-criteria decision analysis, determining weights by using the analytic hierarchy process. The goal is to identify and score alternatives based on multiple criteria. | The MCDA allows for both quantifiable as well as fuzzy criteria. Additionally, specific criteria can be added that are already part of other criteria: for example, PT mode, which determines demand, which is also a criterium, but can also be entered as additional criteria. | The demand is only one criterion in the MCDA, whereas this demand is determined by many different factors. Weights are determined by experts, leading to bias in the results. |
| Ortega, Moslem, et al. (2020) | MCDA - BWM | Similarly, a multi-criteria analysis, determining weights by using the best-worst method. | Similar to the MCDA-AHP, where here the best-worst method is used. This provides greater accuracy than the AHP. | Similar to the MCDA-AHP, bias can occur because of expert opinions. |
| Aquilué Junyent et al.(2024) & Pitale et al.(2022) | GIS-based MCDA | An MCDA using GIS where the full study area is considered as possible alternatives. Weights are determined by AHP. | The spatial characteristic of this method allows for assessing the desirability of a full study area, and clearly showing the results in the form of a heatmap. | All data used for the criteria in the MCDA must be available for all locations within the study area. |

## 2.3 Research gap

This literature study shows that the research on the different criteria and the different methods has progressed over time. The assessment of the different influential factors on P&R demand and desirability was done qualitatively by different researchers, covering a wide range of factors. There is, however, a lack of research that quantitatively analyses the importance of the facility's position within the road network on its demand.

Looking at the different methods, where in the early 2000s the models were still quite basic, as Faghri et al. (2002) and Wang et al. (2004) show, in the later 2010s and 20s, more sophisticated methods like optimization models are used, as done by Aros-Vera et al. (2013) and Henry et al. (2022). These are sophisticated models that might be able to predict an optimal position quite well in a modeling environment; however, there is a lack of models that can estimate desirable P&R facility locations based on real-world situations, including straightforward criteria, and that can assess an entire study area at once. Both Aquilué Junyent et al. (2024) and Pitale et al.(2022) have employed a combination of GIS and MCA, which are capable methods for this. However, this study aims to apply these in combination with a potential demand prediction based on an explanatory model, and within a different geographic and network context.

Concluding from the literature study, the position within the road network will be assessed alongside other factors that influence P&R facility demand. This will be done with the development of an explanatory model. This potential demand prediction is then used in a spatial MCA, similar to Aquilué Junyent et al., 2024 & Pitale et al., 2022, to include both quantitative and qualitative criteria so that the total desirability of an area for a P&R facility can be estimated. The choice and justification of methods are explained in more detail in the methodology chapter.

## 2.4 Theoretical framework

The literature study has identified the factors that influence the demand for P&R facilities and the desirability of a P&R facility. An overview of these factors is shown in figures 1 and 2 for the potential demand and desirability, respectively. Here the distinction is made between factors influencing only the demand and the overall desirability. The greyed-out factors shown in the figures are own researcher input. They are thought to have a significant impact on the potential P&R facility demand or overall desirability, but are not derived from literature. Further analysis investigates this hypothesis. The potential demand, as described in figure 1, is one of the major factors determining the overall desirability of a P&R facility location, as shown in figure 2. This is indicated by the blue filling. The factors present in the frameworks are mostly independent from each other, and therefore no relations are indicated between these factors.
In practice, some of these factors cannot be used in the methods used in this research, as no appropriate data exists. This is addressed further in the chapters on these respective methods.

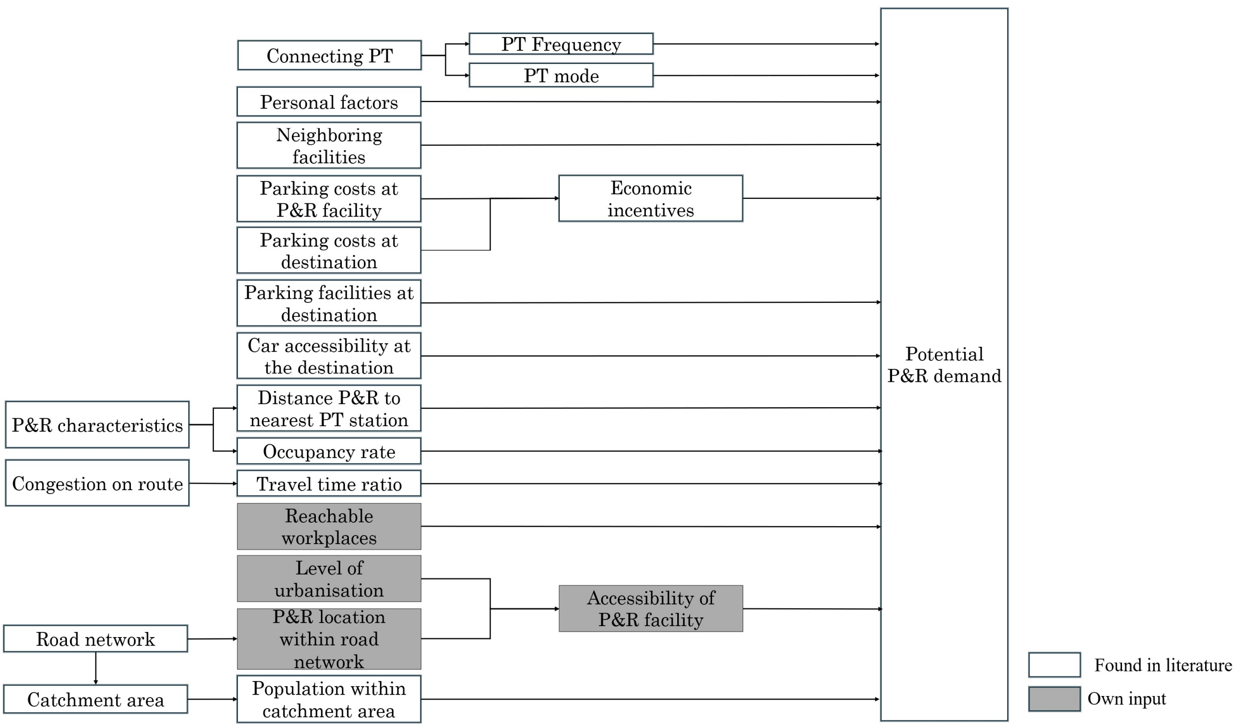


**Figure 1: Theoretical framework potential P&R demand**

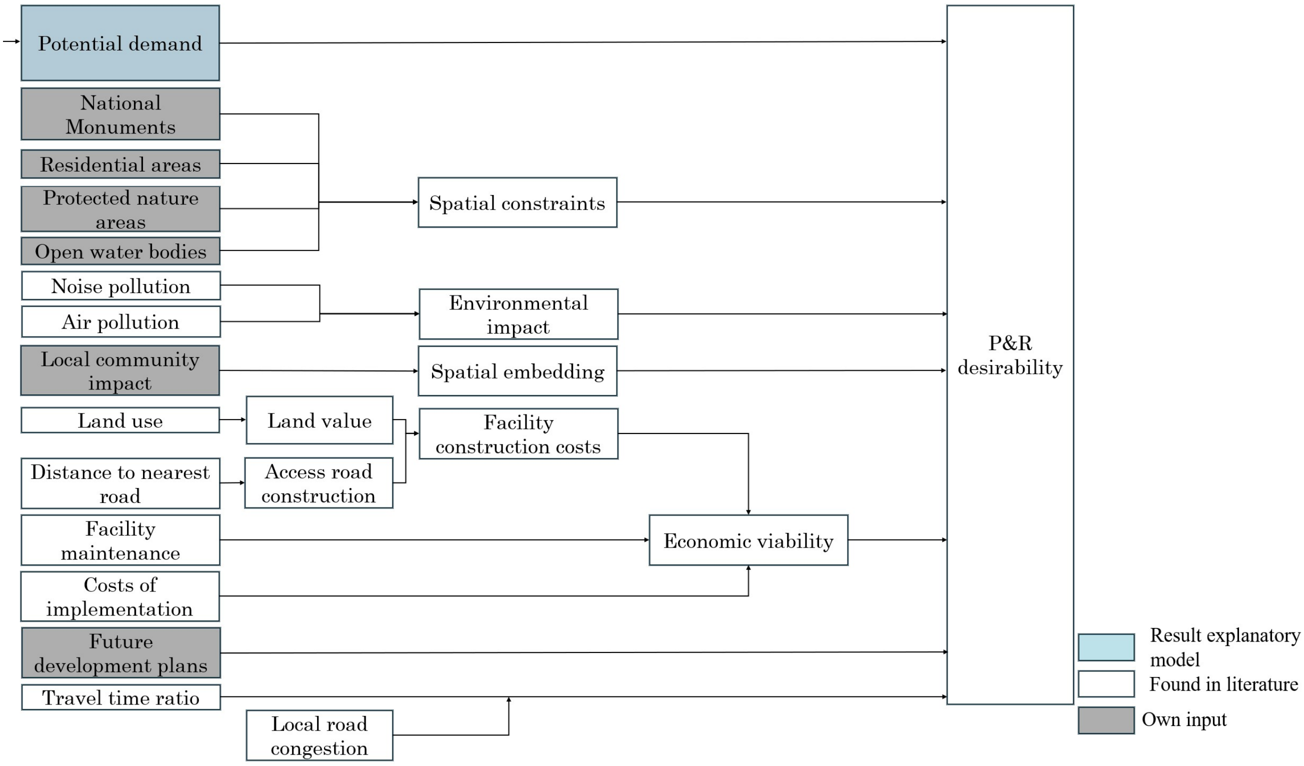


**Figure 2: Theoretical framework overall P&R desirability**

# 3. Research methodology

The research methodology describes the process by which the research questions are answered. It consists of describing the different elements of the methodology and the data and software requirements. The choice of methods is based on the literature study and the availability and shape of the data.

## 3.1 Justification of methods

Traditional mathematical models are difficult to use for assessing the desirability of P&R facilities, as the various factors cannot all be modeled properly (Faghri et al., 2002). Criteria-based methods, such as MCA, are preferred as they allow for multiple criteria and flexibility in assigning weights to these criteria (Aquilué Junyent et al., 2024). Demand is a key factor in the overall desirability of a P&R facility. Other studies employed traffic models or optimization which either already include demand calculations based on origin/destination pairs or do not include the demand factor at all in the consideration of the optimum P&R facility location. However in the case of this research, the demand is unknown for all locations, and therefore, a model is needed to predict this. The demand can be modeled and quantified as the dependent variable resulting from the effects of multiple independent variables. The statistical method commonly used to test whether a relation exists between these variables is regression analysis (Profillidis & Botzoris, 2019). Thus, a regression analysis is performed to predict potential P&R facility demand. This potential demand is then used as one of the input criteria of a spatial MCA. To interpret the results of the spatial MCA, a case study is conducted.

The following four phases are distinguished in this methodology: identification of attributes, explanatory demand model, spatial MCA, and a case study. The sequence and inputs/outputs of these four elements are shown in figure 3. Phase 1 is already concluded in chapter 2. In phase 2, the demand model is developed. This model enters as input for the spatial MCA in phase 3. This is done using a GIS-based model. In this model, space is treated as a grid. Each cell of this grid represents a possible new P&R facility location. The model calculates a desirability score for each cell in this grid. The result from the MCA is a heatmap that shows the estimated desirability score of a new P&R facility for each cell in the grid of the study area. A sensitivity analysis tests the outcome for different weight inputs to ensure the results are consistent. The spatial MCA is applied to a case study to interpret the results. Each of these four elements is explained below in more detail.

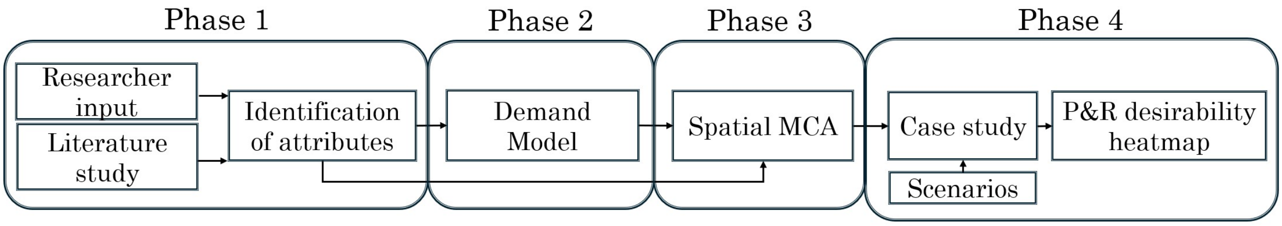


**Figure 3: Research phases and methods**

## 3.2 Phase 2: Potential P&R Demand Model

The explanatory model is used to predict the potential P&R demand at each location within a specific study area. To achieve this, a regression model is developed based on P&R facilities across the entire Netherlands. The model framework, including the inputs, outputs, and steps involved in the development of the model, is shown in figure 4. The inputs consist of the multiple independent variables, as well as datasets needed for the calculations. These include the Dutch road network, locations of current P&R facilities in the Netherlands, and population data. The model development consists of several steps, including preprocessing, cross-validation, and variable selection. These steps are explained in more detail below. The model outputs include β-coefficients that represent the relationship between the independent variables and the dependent variable, as well as values for model performance indicators, which indicate the predictive power of the model.

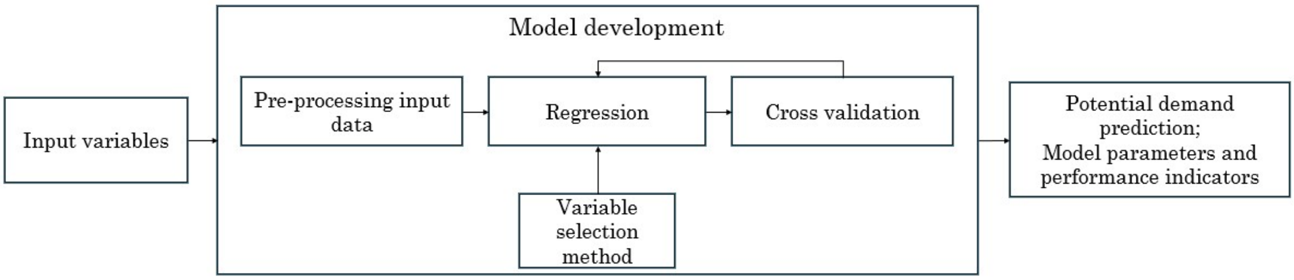


**Figure 4: Framework of the potential demand model**

The model development process consists of four steps. First, preprocessing filters and prepares the data, which includes cleaning the datasets where needed. The characteristics of the dataset are inspected to determine the most appropriate regression method for this data and research.

In the second step, the regression model is set up, which is done in Python. Regression analysis can take many forms, as numerous regression methods exist. The choice of exact regression method is based on the characteristics of the input variables and the goal of the model. The model development is iterative, with different methods and input variable configurations tested. In chapter 4, the characteristics of the data and the choice of regression method are discussed in detail.

The selection of variables is a critical element in regression analysis. Here, it is determined which variables to include or exclude from the model. The process of variable selection depends on the regression method being used. There are three classical approaches to this:

- Forward selection: the selection starts with the null model, which contains only the intercept. Step-by-step each individual variable is added and the model performance is assessed. The best one is selected and added to the null model, after which the process is repeated with a second variable until the model performance does not improve anymore. A drawback of this method is that some variables may become redundant without notice, potentially negatively impacting the model performance.
- Backward selection: this procedure starts with the full model which includes all variables. Step-by-step a variable is removed, after which the model performance is assessed. This is repeated until the model performance does not improve anymore or if all variables are found to be of significant impact on the dependent variable.
- Mixed selection: the third selection procedure is a combination of forward and backward selection. Similar to forward selection, it starts with the null model and adds variables. However, at a certain point, variables may be removed from the model, which could lead to an overall improvement in model performance.

These classical approaches can be applied to traditional regression methods like multiple linear regression and nonlinear regression. For some machine learning methods, all variables are included in the model, and the tuning parameter $\lambda$ is used to reduce or eliminate variables, a process referred to as regularization. In this research the backward selection method is used in the employment of a traditional regression method, as this initially uses all variables and so is better capable of capturing effects caused by multiple variables together.

In the third step, the model is cross-validated to ensure the robustness and reliability of the model performance. For regression methods with hyperparameters, cross-validation is also used to determine their optimal values. K-fold cross-validation splits the dataset into a test set and multiple training sets. The number of subsets determines the name of the cross-validation; for example, four subsets would be called four-fold cross-validation. The model is trained on k-1 training subsets, and model performance indicators are then calculated on the test subset. This results in k estimates of the model performance. The cross-validation estimate is then computed by taking the average of k values. Typically, 5-fold or 10-fold cross-validation is used, as this has been shown to result in neither high bias nor high variance (James et al., 2023).

In the fourth step, the results of the regression analysis are assessed. These include the model parameter values and performance indicators that indicate the quality of the prediction. The specific indicators used depend on the regression method. The regression model has a certain sensitivity to the input variables and parameters. Therefore, a sensitivity check is done to check the impact of small changes in the input of the model on the model results to ensure the model is reliable. After that, the predictive model is ready to be used in the next phase: the spatial MCA.

## 3.3 Phase 3: Spatial MCA

The potential demand model gives insight into the expected demand of a certain location. However, the desirability of a location for a P&R facility is not only governed by its potential demand, as followed from the literature study. A spatial MCA is therefore performed to combine this potential demand with other factors that influence the overall desirability of a location for a P&R facility. Desirability in this case is defined as a combination of several factors, as identified through the literature study.

Various methods exist for performing spatial multi-criteria analyses. These can be roughly categorized into multi-attribute decision analyses (MADA) and multi-objective decision analyses (MODA). MADA uses a predetermined set of alternatives, whereas MODA consists of a continuous solution space. Both methods distinguish between the decision attributes or variables and the decision criteria, linked by an objective function. Based on the characteristics of this analysis, namely a predetermined set of alternatives (all grid cells in the study area) as well as the presence of qualitative and quantitative attributes and constraints, the decision is made to perform a multi-attribute decision analysis. The weight determination is done using the weighted linear combination method (WLC), as this does not require elaborate pairwise comparisons to determine the weights and is open to user input, allowing for different weights depending on the applied case study. Stakeholder scenarios are developed that contain specific weight sets based on the goals of specific stakeholders (Malczewski & Rinner, 2015).

A framework is drawn up of the spatial MCA. The structure of a MADA is used, with the addition of a spatial dimension throughout the framework. Furthermore, the input criteria, value scaling and weight functions that are used are specific to this research. In figure 5, the elements of the spatial MCA are shown as well as the input criteria, alternatives, and scenarios that are used as input for the model. The output is an overall P&R desirability heatmap of the study area.

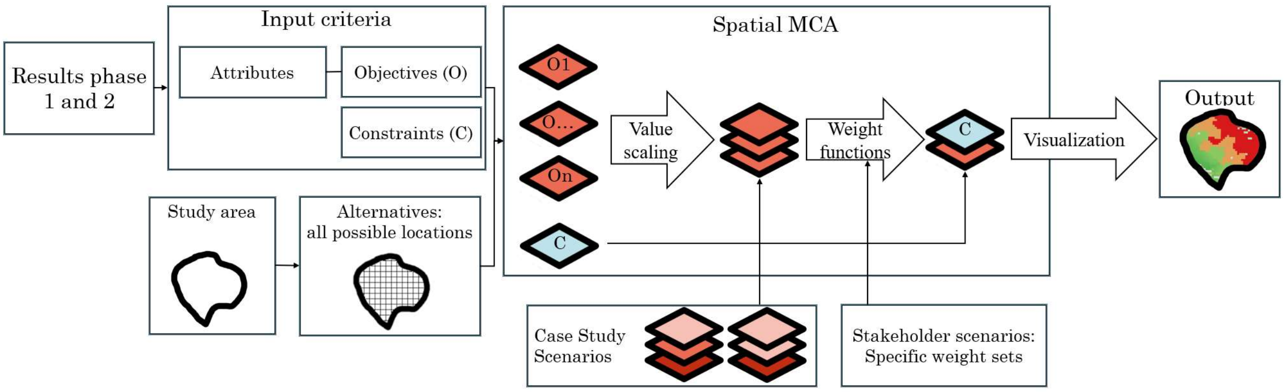


**Figure 5: Framework of the spatial MCA**

### *Model input*

The criteria that are used as input for the spatial MCA consist of the objectives and constraints. Objectives are abstract functions that are to be minimized or maximized, based on their attribute values. Attributes therefore determine the score of the objectives. Constraints are discrete functions that either state if the alternative is suitable (1) or unsuitable (0). These criteria are determined based on the influencing factors, following from the literature study as well as own researcher input, as shown in the theoretical framework in figure 2 in chapter 2.

The other input of the spatial MCA is the alternatives. These are all the possible locations for which the desirability of a P&R facility is to be calculated. In this case, the study area is split up into grid cells, in which each cell represents an alternative. This creates flexibility in the application of the model, as any study area can be split up into similar grid cells. The application of this framework follows in the case study section.

Next, the model is developed using these inputs. This spatial MCA is performed using the ArcGIS ModelBuilder, in which block programming is used to derive the desirability of a P&R facility for each alternative. To achieve this result, several steps are taken in the development of the model. These include value scaling, weight functions, visualization, and a sensitivity analysis, amongst many other smaller modeling steps. These smaller steps follow the modeling cycle basis, which is an iterative approach to reaching the desired result. The main elements of the MCA are drawn from Malczewski & Rinner (2015), however the configuration, modelling and application steps are unique to this research.

### *Value scaling*

Value scaling is the concept of altering the scale of the values of the various attributes that make up the objectives. Value scaling is necessary when implementing a weighting method to determine the relative importance of the objectives, as this requires them to have the same range. Value scaling allows for elaborate functions that can consider spatial variability but also can translate qualitative attributes to quantitative information, determining the score of the objectives. These are also referred to as value functions. In their simplest form, the value function is the same as normalization, which takes the range of the values and divides each entry by its range, resulting in values from 0 to 1. This value function is not necessarily linear; other examples are convex and concave functions. For simplicity, the value functions are taken as linear in this research. Further research can look into whether more complex value functions can achieve a better estimation of desirability.

### *Weight functions*

The weight functions translate the objective score from the various criteria into one overall desirability score. These weight functions can see multiple different implementations, from simple linear combinations to spatially dependent functions. In this research, the weighted linear combination (WLC) method is chosen, as it allows for a simple and direct implementation of criteria weights. This method is a map combination procedure that contains a set of objective weights and value functions. The mathematical formulation of this method is shown in equation 3.1. Weight $w_k$ corresponds to objective k. The value function $v(a_{ik})$ translates the attribute value into the score of the objective.

$$V(A_i) \ = \ \sum_{k\,=\,1}^{n} w_k v(a_{ik}) \qquad (3.1)$$

With $k \in \{1,2, \ldots, n\}$ and n being the total amount of attributes. The sum of all weights is 1.

This WLC method allows for different inputs of weight sets. To take different stakeholder perspectives into account, several stakeholder scenarios are developed, each of which prioritizes a different stakeholder group. These weight sets are then used to give specific results to each stakeholder scenario.

### *Visualization*

The result after the WLC method is an overall desirability layer that has combined all three objective layers. This layer is then overlaid with the constraints, resulting in the final overall desirability layer. This layer is then visualized into a map. The visualization has to suit the application of the model but also convey the true results. The visualization also aims to highlight important findings from the overall results. It should be clear and interpretable, also for people with no background in GIS or modeling. Therefore, the output of the spatial MCA model is a heatmap of the study area, showing the total desirability for each cell in the study area indicated by a blue-red color ramp indicating low desirability in blue areas and high desirability in red areas. Important findings are highlighted by zooming into those specific areas, giving a more detailed look at the desirability there.

### *Sensitivity analysis*

The attribute values are normalized before they are multiplied by their respective weights. For each alternative, thus each cell in the study area, the overall desirability score can then be calculated for different weight sets. The sensitivity analysis checks whether small changes in the input weights result in disproportionate changes in the results. This is important as it can highlight potential bias in the results and show how resilient the outcome is to variations in the inputs. This is done in two ways, to check both first-order and second-order effects. Given the WLC method, to check first-order effects the one-at-a-time method is used, which takes one weight, say $w_1$, and changes its value within a specified increment between 0 and 1. The equation for the calculation of the total desirability of a cell is given in equation 3.2. The other weights are changed ensuring their relative proportionality (Malczewski & Rinner, 2015).

$$V(A_i, w_t) \ = w_t v(a_{it}) \ + \ \sum_{k \neq t} w_{k*} v(a_{ik}) \qquad (3.2)$$

Where:

$w_{k*} \ = \ \frac{(1-w_t)w_k}{\sum_{k \neq t} w_k}$ with $k \in \{1,2, \ldots, n\}$ , n being the total amount of attributes.

$w_t$ = the changed weight t

$V(A_i, w_t)$ = the total desirability of alternative i and weight t

To analyze the sensitivity of the model, the change in mean and standard deviation of the total desirability score over all cells/alternatives and the top 10% of desirability values is assessed. High variation in the results means the model is sensitive to changes in the input, whereas low variation would indicate a more robust model.

The second-order effects are assessed by using Sobol's method in which the effects of each variable and its second order interactions can be calculated (Wan et al., 2015). The calculations for this are shown in equation 3.3 and 3.4.

$$V(y) = \sum_{i=1}^{n} V_i + \sum_{i \leq j \leq n}^{n} V_{ij} + \cdots + \sum_{i \leq n}^{n} V_{1 \ldots n} \qquad (3.3)$$

where V(y) is the total variance of the model output, $V_i$ the first order variance and $V_{ij}$ the second order variance.

With the second-order Sobol index as shown in equation 3.4. This index indicates the proportion of second-order effects with respect to the total variance. This index is calculated for each spatial layer using Python. It ranges from 0 to 1, with low values indicating that only a small part of the total variation is due to second-order effects. The code and results are shown in figure 51 in appendix H.

$$S_2 = \frac{V_{ij}}{V(y)} \qquad (3.4)$$

## 3.4 Phase 4: Selection of case study

The developed model is applied to a case study in the region of Groningen. The goal of the case study is to validate and verify the model and to perform a sensitivity check. The current P&R facilities in the region are at capacity, and therefore the municipality is interested in expanding its number of P&R facilities. Currently, the main P&R facilities are located on the urban fringe of the city of Groningen. Other smaller P&R facilities are also present at several locations near train stations in smaller villages. Figure 6 shows the study area and the geographical locations of the current P&R facilities. The decision is made to extend the study area southwards from the province of Groningen, as this area is located very close to the city of Groningen, so it is of interest to also analyze these areas. In this case study, the model developed in the spatial MCA is applied to this region to predict the overall desirability of a P&R facility. This model allows for assessing many different locations at once.

The case study consists of a base scenario that evaluates the current desirability for new P&R facilities and an alternative scenario, which sees the realization of the Nedersaksenlijn. This scenario evaluates the desirability of new P&R facilities, given this new train line. The choice is made to develop the Nedersaksenlijn, as it is a topic of current public and political debate on whether the line should be constructed. Many stakeholders are in favor of the realization, as it will better connect the Nedersaksen region of the Netherlands and give an economic boost to the region (TwynstraGudde, Studio Bereikbaar, Decisio, MUST Stedebouw, MOVE Mobility, Sweco; 2024). The introduction of these two scenarios allows for the comparison between the resulting differences in desirability scores, leading to insights regarding model validation and sensitivity.

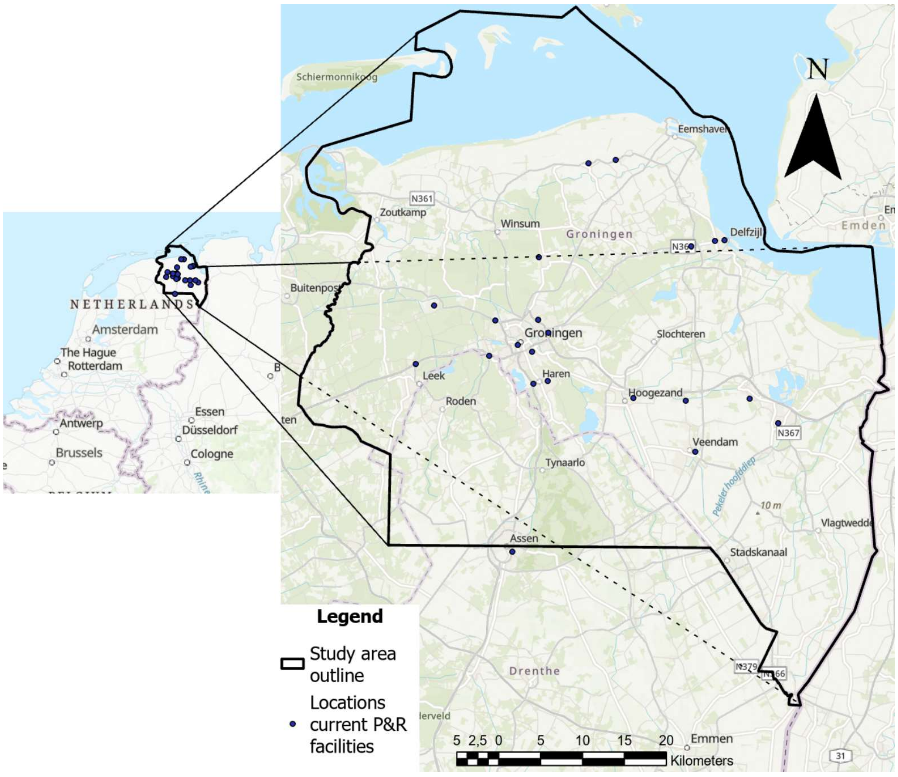


**Figure 6: Case study area including locations of current P&R facilities**

Both scenarios result in a heatmap that shows the desirability of each cell within the study area. This heatmap can then be used to advise on new P&R facility locations. These two scenarios are worked out in more detail in the case study section of the spatial MCA.

## 3.5 Data and software requirements

Both methods, the regression model and spatial MCA, take various data sources as input. It is therefore important to identify the data availability and requirements. Besides that, it is also important to determine the software to be used in the research and the respective agreements regarding the use and acknowledgments of the software authors. Here it is described what data and software is used in the research. To perform similar research, similar data and software is required.

This research uses a combination of open and proprietary datasets. Topographic data, public transport-related information, and P&R usage data are required for developing the regression model. For the spatial MCA, additional datasets are used, including spatial characteristics such as land use and public transport stop locations.

The research requires multiple software tools for data processing and analysis. In this research, Python is used for filtering, preprocessing, regression modeling, and demand predictions. For spatial modeling and analysis, GIS software is required. Multiple options exist, from open-source software to expensive commercial software. In this research, a combination of QGIS and ArcGIS Pro is used. Network analysis computations are performed using a tool from Movares; however, common GIS software can perform similar calculations. genAI software is used in coding assistance as well as clarifying textual content. This approach ensures that the research can be efficiently replicated and verified, given the availability of the required tools and data.

# 4. Potential demand model

A regression analysis is performed to develop a model that predicts potential P&R facility demand based on values of a set of independent variables. To achieve this, the model development follows six main steps. First, the dataset containing P&R facilities and their characteristics is built, which includes data gathering and preprocessing. The content of the dataset is evaluated using descriptive statistics. In the second step, the exact regression method is determined based on the goal of the model as well as the characteristics of the dataset. A resulting input/output overview is given. In the third step, the model estimation is done including supported decisions on certain model components. The model output, consisting of model performance indicators and model coefficients, is evaluated in the fourth step. Here, the assumptions underlying the model are also checked. The fifth step performs a sensitivity check of the model to check the resulting output given certain changes in the model input. Lastly, the discussion and conclusions are given.

## 4.1 Data gathering and preprocessing

The first step of the regression checks the availability of data regarding the factors that influence potential P&R demand as found from the literature study. The theoretical framework is shown in figure 1 in chapter 2. Now, in figure 7, the so-called practical framework is shown. In the figure it is indicated for which variables the implementation as a variable in the explanatory model is possible or not, based on the availability of data regarding these factors.

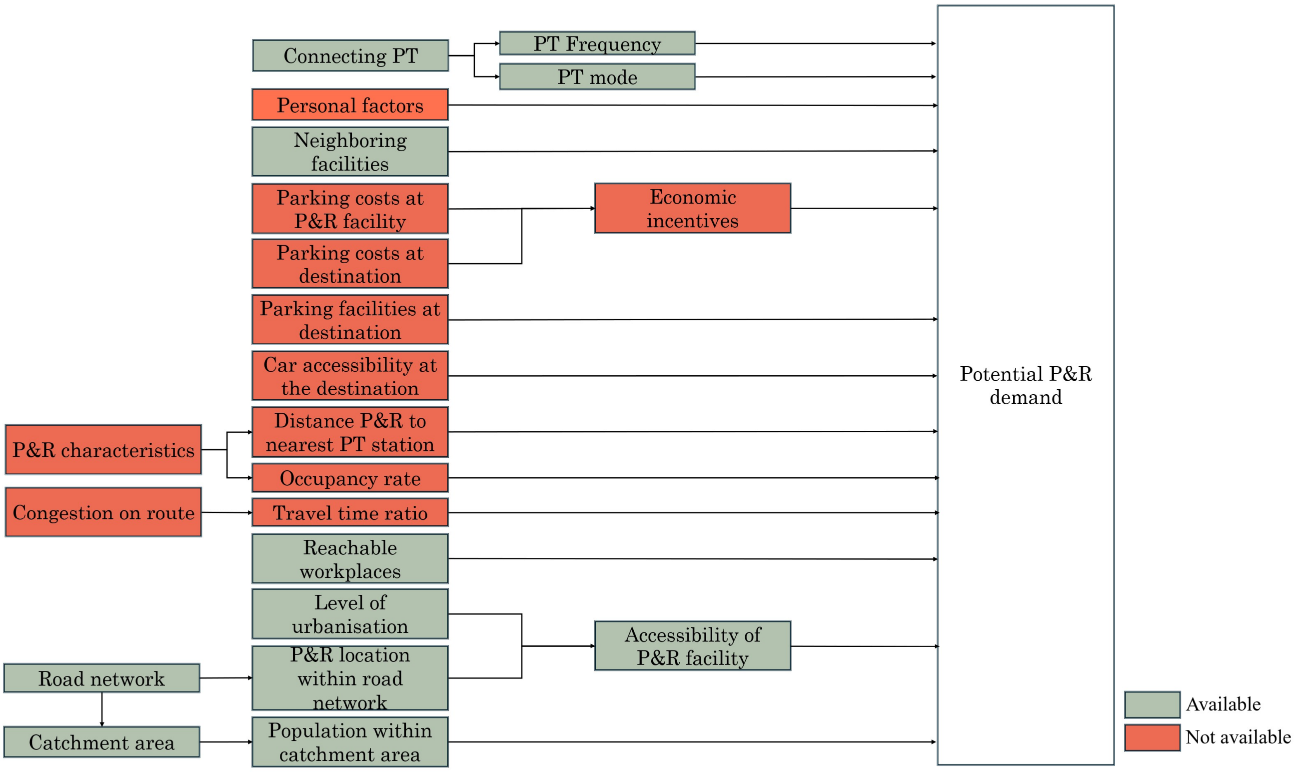


**Figure 7: Practical framework potential P&R demand**

A data handling procedure is used. This procedure consists of three processing steps:

a) Raw data collection and interpretation: the various datasets are collected in one folder, with each file name structured as follows: a_"filename"_"sourcename"."filetype"
b) These datasets are then filtered and cleaned. Columns can be added and datasets combined. These intermediate datasets are saved in a new folder, b_intermediate, to indicate it is an intermediate file. Each file is named accordingly: b_"filename"."filetype"
c) When datasets are in their final form, ready to use in the regression, they are saved in the third folder, c_preprocessed, with corresponding file naming scheme c_"filename"."filetype"

This approach ensures the overview of the different datasets and data sources.

From the literature study, many variables have been identified to impact P&R facility demand. However, this demand model is limited by the availability of data such that some factors cannot be taken into account. This does not mean however that these do not impact potential P&R demand. The P&R usage numbers are aggregated from different data sources, as no complete dataset is available. To perform the analysis, a dataset including P&R facilities and the values of the independent variables is constructed. This dataset contains all the values of the independent variables, for which data is available, and the dependent variable.

Besides the calculations of these independent variables, each P&R facility is also categorized, expanding on the definitions used by Zijlstra et al. (2015). These consist of five P&R facility types, which are defined as follows:

- Rural: outside towns or cities, close to a highway exit/entrance, and/or within a town with a smaller population than 5.000.
- Central: P&R facilities located near the major train stations of cities with a population larger than 50.000 and connected by Intercity trains. If population criteria are met but not connected by intercity trains, this is not a central facility.
- Intracity: any other facility within these cities but not the major train station is classified as intracity.
- Urban fringe: facilities at the edge of central cities, mostly easily accessible by car. Unless it is located in a residential area on the outskirts of the city, this is classified as an intracity facility, as they are focused on a different user group.
- Satellite: all towns and cities that are not classified by the above categories. This includes the majority of P&R facilities. Satellite P&Rs are mostly located centrally near major PT hubs within towns and smaller cities. If there are intracity facilities within satellite cities, they are classified as satellite.

The dataset includes P&R facilities gathered from different sources, including publicly available data from NS and the province of Noord-Holland but also via direct contact with Metropool Regio Rotterdam Den Haag (MRDH) and Groningen Bereikbaar, both supplying usage data for their P&R facilities. The aggregation level is kept the same between these multiple data sources. The usage numbers are based on an average workday in 2019. To calculate the values of the independent variables, various other datasets are required as well. For this, public and proprietary datasets are used. An overview of the various data sources used in the calculations is shown in table 19 in appendix A.

With the base dataset set up, a total of 313 P&R facilities with usage numbers have been collected. With that, the calculations for the independent input variables are done. Derived from the practical framework (see figure 7), nine possible independent variables are drawn up. These are explained one by one below, with a more detailed explanation of the calculations given in table 20 in appendix B.

I. **Mode**: the mode is the PT modality that is connected to the P&R facility. It is determined using publicly available GTFS datasets which contains bus, tram, metro, train and ferry modalities. For this research, the train modality is further split into sprinter and intercity trains. These names are used by the national operator, NS, and indicate whether it is a train travelling mainly between major cities (IC) or if it stops at every station (SPR). Lines of other operators like Arriva and RNET are classified as SPR as they also stop at every station.
II. **Frequency**: the frequency in this case is defined as the number of vehicles that stop at the PT stop within rush hour times (7:00 to 9:00) to which the P&R facility is connected. Similar to mode, the frequency is also derived from GTFS datasets.
III. **Distance to nearest other P&R facility**: the distance to the nearest other P&R facility implements the neighboring facilities factor, as given in the practical framework. It calculates the Euclidean distance to the nearest other P&R facility.
IV. **Address density at P&R facility**: the address density at the P&R facility is calculated by taking the address density from the CBS 500x500m statistics dataset, which contains the address density, and appending it to the corresponding P&R facility. This variable corresponds to the level of urbanization. This dataset is only available in 500x500m cells, instead of the 100x100m grid used in this research.
V. **Surrounding address density**: the surrounding address density is the summed address densities of all locations within a 2.5-1.0 ring buffer around a P&R facility. This ring buffer intersects with the CBS 500x500m statistics dataset and sums over all the values within the ring buffer. Other possibilities in representing the surrounding address density exist, however this approach was deemed most appropriate. This variable also corresponds to the level of urbanization.
VI. **Driving time to nearest highway connection**: the driving time to the nearest highway is one of the two implementations of a variable to check the influence of the position within the road network on P&R facility usage. It calculates the driving time in minutes to the nearest primary road connection, defined as roads with a speed limit of 100km/h or more. This calculation uses a shortest path algorithm in combination with the maximum speed limit to determine the driving time.
VII. **Difference in people in catchment area with and without primary road network**: a second approach to check the influence of the position within the road network is to compare the amount of people that are within the catchment area of a P&R facility. This is done by calculating this number twice, once with the complete road network and once with a road network which excludes all primary roads. This also requires clarifying the

definition of the catchment area of a P&R facility. The catchment area of a P&R facility determines within what distance of the facility people might use the facility. Earlier studies have looked at the shape of this area in a topographic way. Concluding that, in urban areas, the catchment area most closely resembles a parabola (Ortega, Tóth, & Péter, 2020). However, their research has not been applied to more rural located P&R facilities. The CROW developed a handbook P&R, in which they state that all locations that are within a 15-minute drive of a P&R facility fall within its catchment area (CROW, 2016). Considering this information, the choice is made to use the 15-minute drive catchment area as this also considers physical constraints, like waterways, whereas a parabola shape around a P&R would not take this into account.

VIII. **Workplaces**: the number of reachable workplaces is thought to have an impact on the demand of a P&R facility. This variable is calculated by computing the number of workplaces that are reachable with PT within a time of 60 minutes. The workplaces geodataset is a proprietary dataset of Movares.

IX. **Number of neighbors**: a second way to implement the neighboring facilities as a variable is the number of neighbors. This number is calculated by taking a maximum distance of 5km and calculate the number of other P&R facilities which fall within this range.

The calculations for each of these independent variables are explained in table 20 in appendix B. Besides the calculations of the independent variables, multiple other steps are taken in the creation of the dataset. These are also given in appendix B. The result of the preprocessing steps is a complete dataset that includes all P&R facilities and the values for each independent variable. This dataset is ready to use for performing a regression analysis. A sample of the dataset is shown in table 5.

**Table 5: Sample of dataset**

| | Frequency | P&R users | Mode | P&RType | Distance to nearest neighbor | Adress density | Driving time to nearest HW | Name | People in catchment area with HW | People in catchment area woHW | Difference | Workplaces | Number of neighbors | Surrounding adress density |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 61 | 152.0 | SPR | satellite | 2549 | 530.0 | 7 | Abcoude | 74640 | 76100 | 1460 | 407818 | 2 | 586.302326 |
| **1** | 14 | 40.0 | SPR | rural | 4910 | 498.0 | 2 | Akkrum | 14070 | 23555 | 9485 | 77260 | 1 | 76.300000 |
| **2** | 125 | 530.0 | SPR | intracity | 1611 | 2020.0 | 10 | Alkmaar Noord | 195520 | 195220 | -300 | 128311 | 0 | 1917.816667 |
| **3** | 25 | 8.0 | SPR | intracity | 1904 | 2365.0 | 7 | Almelo de Riet | 98250 | 110815 | 12565 | 136285 | 0 | 994.825397 |
| **4** | 72 | 252.0 | IC | intracity | 1667 | 2382.0 | 13 | Almere Buiten | 128800 | 131200 | 2400 | 220768 | 2 | 980.234043 |

## 4.2 Descriptive statistics

Descriptive statistics provide insight into the structure and content of the created dataset. These insights can help in selecting the right regression method and detecting correlations. It also verifies whether some of the assumptions of regression are fulfilled, namely independence and absence of multicollinearity. A more detailed explanation of the regression assumptions follows in section 4.3. The descriptive statistics therefore look into the distribution of P&R types, connected modalities, density plots of the various independent variables, and the correlation matrix, as these can achieve the aforementioned insights.

The distribution of P&R facility users is shown in figure 8, split up into several different bins. It can clearly be seen that between 0-100 and 100-200 daily users is most common. Higher usage numbers occur less often. The proportion of metro and bus modes decreases with higher usage numbers.

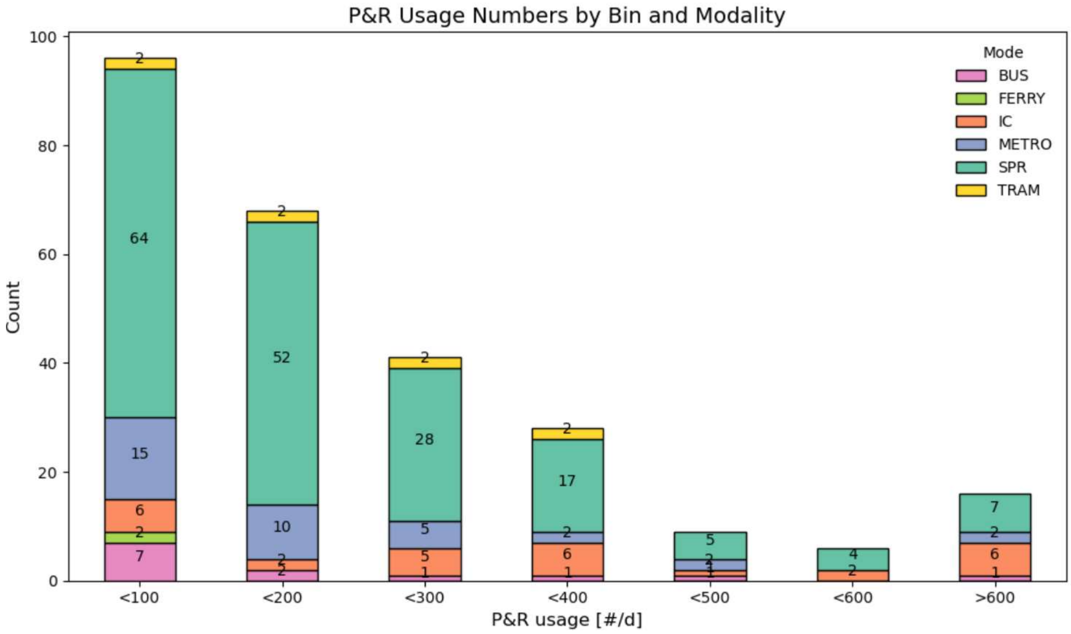


**Figure 8: Distribution of P&R facility usage and modality**

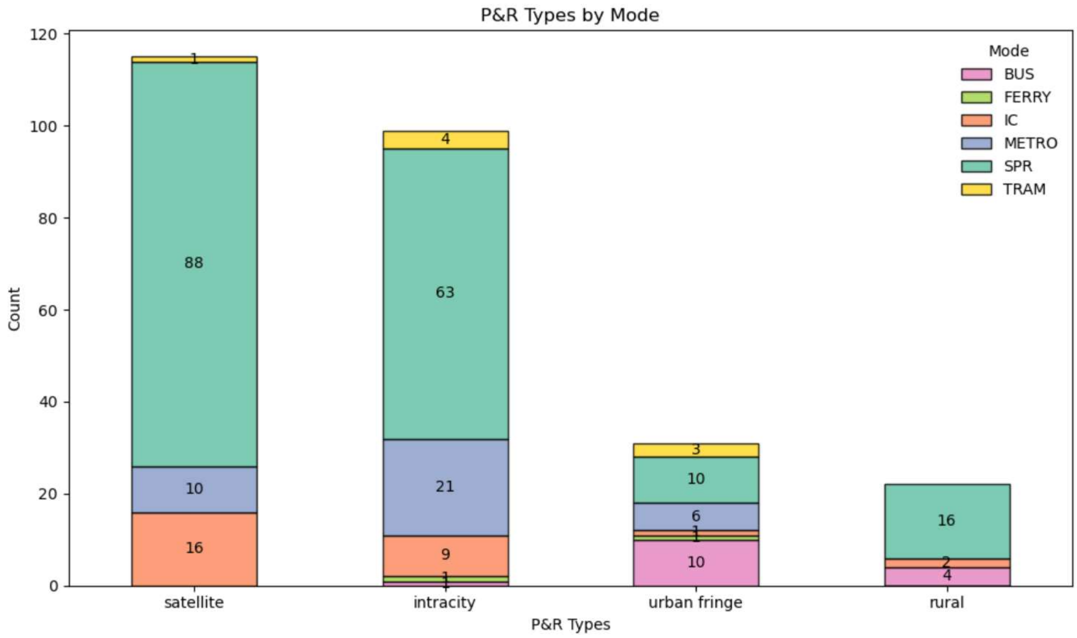


**Figure 9: Distribution of P&R types and modality**

The distribution of P&R facility types shows that satellite and intracity facilities are much more common compared to rural and urban fringe facilities (see figure 9). The distribution of travel modes shows the high number of sprinter (SPR) and the low amount of ferry and tram connected to the P&R facilities. The bus, metro, tram, and ferry modes are underrepresented which could impact the results of the regression analysis. Therefore, when applying cross-validation in the regression methods, it is recommended to use stratified folds to ensure a balanced representation in each fold.

The hypothesis regarding the influence of the road network suggests that the further a P&R facility is from a highway, the more likely people are to use the P&R facility, as they remain on a local road network and may be less reluctant to change to another mode of transportation. The difference in population within the catchment area variable plotted against the P&R usage numbers shows a different story however, as no clear relation can be distinguished. The result is shown in figure 10, where the extreme values have already been filtered to give a better view of the lower values. This suggests that the position within the road network has no influence on the P&R usage numbers. This will be further confirmed by the regression analysis later on.

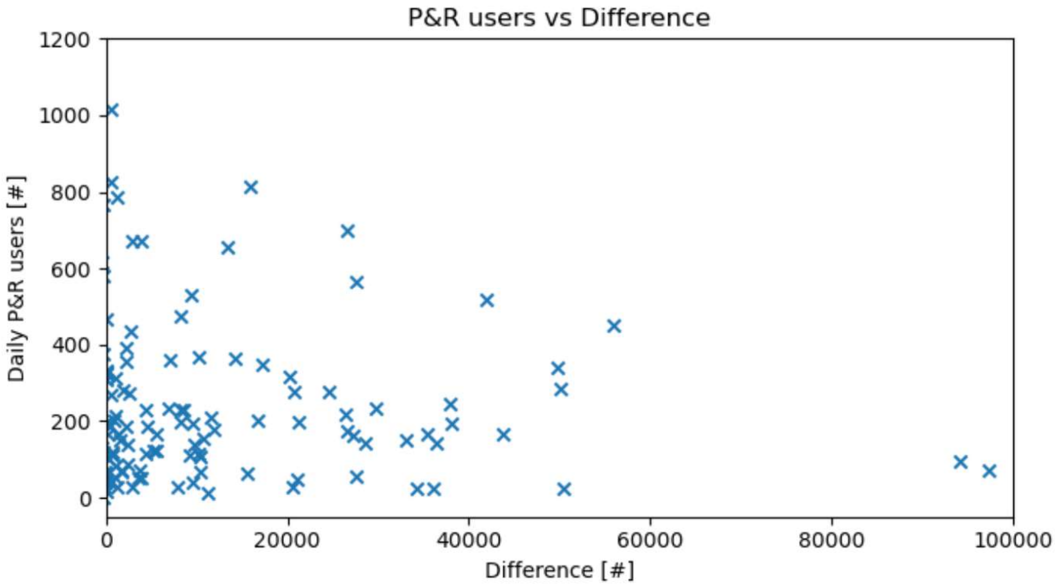


**Figure 10: P&R users vs difference in population in the catchment area with and without highways**

The way independent variables are distributed is important when performing the regression analysis. As can be seen from the histograms in figure 11, not all independent variables are normally distributed. Most distributions more closely resemble a log-normal distribution, with the exemption of the driving time to the nearest highway and the address density at the P&R facility. It is therefore recommended to log-transform these other independent variables when entering the regression model.

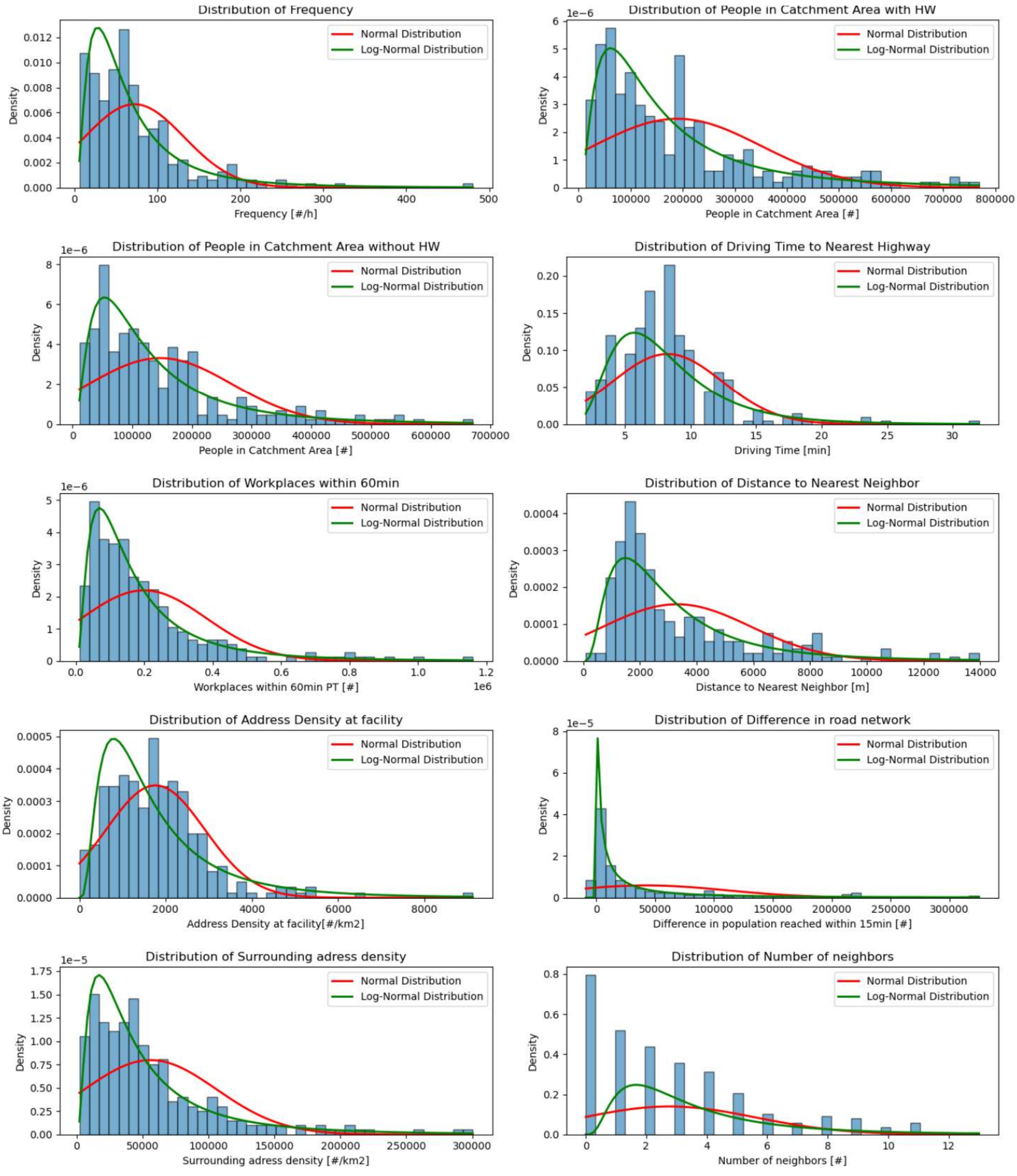


**Figure 11: Distribution of independent variables**

The correlation matrix shows the relationship between the various independent variables and the dependent variable. It gives great insight into specific relationships of variables, two of which are addressed here. A part of the matrix is shown in figure 12, with the complete matrix is shown in figure 38 in appendix D. Metro and frequency show a correlation of 0.42, which makes sense as metro systems often run high frequencies. Secondly, buses show a positive correlation with 'Difference' of 0.61, indicating that when a small difference is found between the number of people within the catchment area with and without the primary road network, this is less often connected to a bus. This also makes sense, as a big difference would be observed around city fringes where facilities are often located near the primary road network and these are often connected with busses to enter the main city. Some strong multicollinearity can be observed between IC and SPR modes, the number of neighbors and distance to the nearest neighbor, and between the people in catchment area calculations. This makes sense as these pairs try to capture the same properties of a P&R facility. This multicollinearity means that only one of these variables should be included in the regression model.

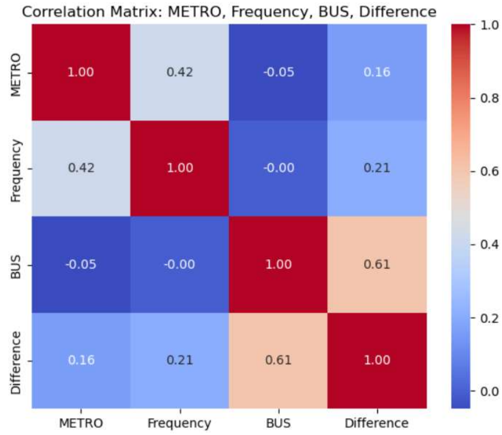

**Figure 12: Partial correlation matrix**

## 4.3 Regression method and input/output overview

With the calculations of the dataset complete and the characteristics analyzed, a choice of regression method must be made. After this, an input/output overview is given to present a clear view of what is used as input and what the results of the model are.

### 4.3.1 Regression method

Many different regression methods exist, so it is important to select the right method for the goal of this research. The selection of the method is done by looking at both the goal of the output and the characteristics of the input data. The goal of the model is to predict potential P&R facility demand, in other words, to predict demand for a location that currently does not have a P&R facility. This prediction is made by estimating coefficients that are multiplied by the values of the independent variables. The model is trained and tested on the existing P&R facility dataset.

Based on the characteristics of the dataset, it is important that the regression method can handle both continuous as well as categorical variables, as for example, the address density is continuous whereas the PT mode is categorical. The method should be able to handle multiple independent variables to predict the dependent variable. And lastly, the method should also be suited to a limited amount of independent variables used as input.

The model is applied to a case study in Groningen where it is used to predict potential P&R demand in areas outside the city. The nature of this application means that the model can be trained and tested on a subset of the P&R facility dataset, filtering for satellite and rural facilities and leaving out urban fringe and intracity facilities. This would still leave a sample size of 137, sufficient to perform a regression analysis (Tabachnick & Fidell, 2007).

The prediction of potential P&R demand can be modeled in two ways; as a continuous variable for which the model predicts potential P&R usage numbers and as an ordinal variable for which the model predicts the range in which the prediction falls, for example between potentially 0 and 100 P&R users. The prediction of continuous demand numbers would be preferred as it would give a more exact demand prediction. However, if the model prediction quality is not sufficient, using an ordinal variable might yield better results. The choice between these two also determines the type of regression. For a continuous dependent variable, multiple linear regression (MLR) is the obvious choice as it is commonly used to find the relationship between multiple independent variables and a dependent variable. For an ordinal dependent variable, ordinal logistic regression (OLR) is best suited as it can relate multiple independent variables of continuous and categorical scale to an ordinal dependent variable (James et al., 2023).

To fit the models to the data, the ordinal logistic regression method uses the maximum likelihood estimation. On the other hand, multiple linear regression traditionally uses the ordinary least squares (OLS) estimation, however, other options exist that might be able to give a better fit. This includes weighted least squares (WLS), which is used in the model estimation alongside the traditional OLS, as this method gives some specific benefits which are addressed later. This means three regression models are developed and assessed.

Both of these regression methods come with a set of assumptions, as stated by Harrell (2015). It is important that these assumptions are checked, either before or during the model estimation, to make sure the model is reliable.
Multiple linear regression assumes:

- Linearity: the relationship between the independent variables and the dependent variable is assumed to be linear, which means that the value of the dependent variable is predicted by a linear combination of several independent variables.
- Independence: the method assumes independence of the input variables. Independence is checked with the correlation matrix that looks at the correlation between the various input variables. A high correlation suggests the variables are correlated and therefore dependent on each other, violating this assumption.
- Homoscedasticity: the variance in the prediction versus the observed values is assumed to be the same over the full range of predicted values. If the variance in the prediction is not the same over the full range of observed values, the variance is heteroscedastic.
- Normality of residuals: the distribution of the residuals is assumed to be normal. This is required to perform statistical tests to evaluate model performance, like the t-test and F-test.
- Heteroscedasticity: The WLS method, in contrast to the OLS, initially assumes heteroscedasticity. The variance in the errors is then weighted, to adjust for the heteroscedasticity. This method is therefore preferred when the initial homoscedasticity assumption is violated.

Ordinal Logistic Regression assumes:

- An ordinal dependent variable: as basis of the ordinal logistic regression, it is assumed the dependent variable is ordinal.
- Proportional odds: it is assumed that the effect of the independent variables is the same across all ranges of the ordinal dependent variable. The assumption must be fulfilled by all input variables. This assumption is checked by performing the Brant test.
- Independence of observations: the OLR method assumes that the observations on which the model is trained are independent. This means that the value of one observation is not influenced by the value of another observation.
- Linearity: the method assumes that the value of the dependent variable can be explained by a linear combination of the independent variables.

Both of these methods are used to develop an explanatory model. The quality of these models is then compared by looking at the performance indicators. After the comparison, a conclusion is drawn on what is the preferred model. This is the final model that is used to estimate potential P&R demand.

### 4.3.2 Input/output overview

An overview of the input and output of the model is shown in figure 13. The input consists of the dependent variable, P&R users, and the independent variables. Some of these variables can see different implementations, as explained in table 20 in appendix B. The choice of implementation is based on the significance of the variable and the overall model quality. The regression model selects the best-performing model, using backward selection as a variable selection strategy. The regression model gives as output both performance indicator values as well as model parameter values. The performance indicators depend on the regression method. For multiple linear regression four indicators are used, namely the adjusted-$R^2$, the root mean squared error (RMSE), the F-statistic, and the AIC. The combination of these four indicators gives a good indication of the model performance since they focus on different aspects of the model performance. Alongside these, the output also includes the coefficients and significance of the independent variables. For ordinal logistic regression, three other indicators are used, namely the pseudo-$R^2$ as well as the accuracy and mean absolute bin error, which are both based on the confusion matrix. These indicators give a good indication of the model performance as they focus on different aspects of the model performance.

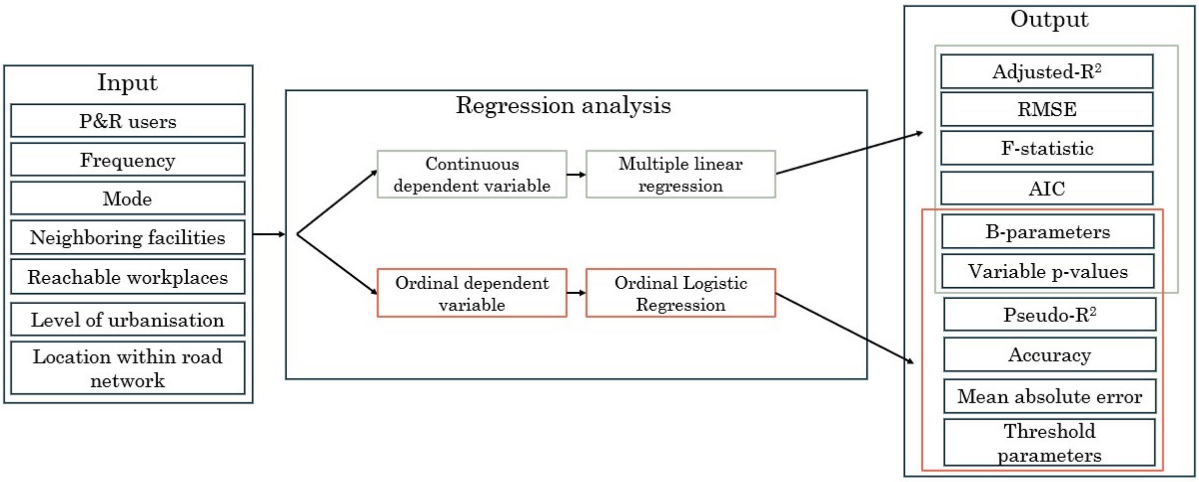


**Figure 13: Regression analysis research process**

## 4.4 Model estimation

With the decision made on the regression method and input variables, the model estimation is done. This is done by using Python. Several programming steps are taken before the model estimation is done, of which the most important ones are:

- Creating dummy variables: the modality variable is categorical as it consists of five categories of PT modality. This cannot be directly implemented into the MLR and OLR, as these methods cannot directly take categorical variables as input. Therefore, this variable is converted into four dummy variables, which state whether the category, for example bus, is present (1) or absent (0) at the P&R facility.
- Logarithmic transformation: as followed from the descriptive statistics, most variables more closely resemble a logarithmic distribution. These variables are therefore transformed to a normal distribution by performing a logarithmic transformation.
- Standardization: to be able to interpret the output parameters of the estimated model, the input variables are standardized. Standardization is the practice of subtracting the mean from the variable value and dividing by the standard deviation.
- Cross-validation: 5-fold cross-validation is used to split the training dataset five times into four training subsets and one test subset. 5-fold is preferred over 10-fold cross-validation, as otherwise, the test subset would become too small. To make sure the distribution of P&R types over the various folds is the same, they are stratified based on P&R type. The model is estimated for each training and test subset, after which the model parameters and performance are computed by taking the average of all five folds.

With these four steps completed, the three regression methods can be modeled. This is an iterative process, where backward selection is used to select significant independent variables. Manual variable selection is preferred over automating the process, as this allows for a better understanding of the variables and their influence. The process for the two regression methods differs in some aspects, therefore they are elaborated on separately below.

### 4.4.1 Multiple Linear Regression

Multiple linear regression comes in many different forms. The first model estimation is done in its basic form, using the independent variables directly and using the ordinary least squares estimation, where all observations are treated equally. A second model uses weighted least squares, to overcome heteroscedasticity. These models are further expanded in different ways to construct a more complicated model, amongst others by including:

- Interaction terms: multiplying two independent variables with each other creates an interaction term. This can result in a better fit, as input variables can have effects on each other and together have a combined effect on the dependent variable. This is then added to the linear combination of variables explaining the dependent variable. This ensures the linearity assumption is not violated.
- Polynomial terms: whereas interaction terms multiply one (or multiple) variables with another, polynomial terms simply raise the power of an independent variable to greater than 1. This term is still part of the linear combination of terms predicting the dependent variable.
- Weight functions: the WLS method allows for the implementation of various weight functions. Most commonly the variance of the OLS model is inversely proportional to the weights in the weight function (James et al., 2023). However, it is also possible to change this weight function, for example dividing by the square of the fitted values.

In this case $w_i$ is taken as $w_i = \frac{1}{\sigma_i^2}$ where $w_i$ is the weight corresponding to the $i^{th}$ observation based on the variance $\sigma_i^2$ of observation i.

After the first estimation, the regression assumptions are checked. When an assumption is violated, a change in the method is needed to overcome this. Other alterations complicate the estimation but perhaps yield a better-performing model. Two multiple regression models have been developed, one using the ordinary least squares estimation and the second one using the weighted least squares calculation. The Python scripts of these final models are given in appendix E.

### 4.4.2 Ordinal Logistic Regression

The development of the ordinal logistic regression model is similar to the MLR model. It also allows for interaction terms and polynomial terms. In contrast to MLR, the OLR requires the dependent variable, P&R usage, to be ordered into bins ranging from the lowest value to the highest value in the dataset. These bins are specified by hand, and as such are subject to own researcher input. Changing the amount of bins and the range of the bins also changes the outcome of the model predictions and model performance. The decision on the ranges of the bins is made by making a tradeoff between the model performance and the usefulness of the results. Therefore this is an iterative process and the bin count and size is discussed in the model results. The same variable selection method is used as for MLR. The model uses the maximum likelihood estimates (MLE) to compute the parameters of the model. The algorithm used for this is the Newton-Raphson method, preferred for its fast calculations and convergence (Akram & ul Ann, 2015). The Python script of the final model is shown in figure 41 in appendix F.

## 4.5 Model results and significance of variables

With the final models constructed, their quality and significant variables can be assessed. As stated earlier, this assessment is done by looking at model performance indicators, which differ for the two different models. The results will therefore be addressed for each regression method separately. Both of the models are estimated on a subset of the P&R facility dataset, including only satellite and rural facilities. This suits the application, as follows in the case study section.

### 4.5.1 Multiple linear regression

Multiple linear regression looks to predict potential P&R facility demand at a continuous scale. The model performance is evaluated first, after which the significant variables are assessed. Following that, the regression assumptions are checked, to make sure the model results are reliable. All independent variables are used as input, after which the variable selection process selects the significant variables. The complete model results are given in figures 42 and 43 in appendix G.

The model performance of the multiple linear regression is evaluated based on four indicators. The results of which are shown in table 6. Each of the four indicators is addressed below.

- The final models have an adjusted-$R^2$ of 0.50 and 0.32 for OLS and WLS respectively. This means that 50% and 32% of the variance in the observations is explained by the model. This is a poor performance for both models, out of which the WLS performs worse. However, looking only at the adjusted-$R^2$ is not good practice, as overfitting can result in a higher adjusted-$R^2$ but not a better model.

- The RMSE of the models are 176 and 185 for OLS and WLS respectively. Both these RMSEs are relatively high, as the range of the dependent variable is between 0 and 1100. The OLS scores better than the WLS.

- The F-statistic tests the overall model significance. It tells whether at least one of the independent variables in the model significantly explains the variation in the dependent variable. A lower value of 28.3 (OLS) compared to 34.0 (WLS), suggests that the OLS model is likely a better fit to the data. The difference is however very small.

- The AIC is a measure of model fit based on the number of independent variables and the maximum likelihood estimate (MLE). The absolute value is not meaningful by itself, but a lower value indicates a better model. The AIC takes into account model complexity, penalizing more complex models. The AIC is slightly lower for the WLS model, indicating a slightly better model.

**Table 6: Summary of performance indicators**

| Parameter | Model | |
|---|---|---|
| | OLS | WLS |
| Adjusted-$R^2$ | 0.50 | 0.32 |
| F-statistic | 28.3 ($p<0.05$) | 34.0 ($p<0.05$) |
| RMSE | 176 | 185 |
| AIC | 283 | 267 |

The results indicate that the OLS scores better on three out of four indicators compared to the WLS, however neither of the models perform very well. To ensure these model results are valid, the assumptions are checked.

### *Significance of variables*

The variables found to be significant and therefore are included in the final model are shown in table 7 with their corresponding coefficients and p-values. This also includes a constant, representing the intercept of the regression equation. The insignificant variables are not shown, which also include interaction terms. Direct comparison between the coefficients of the independent variables is possible as they have been normalized. For both the OLS and WLS models, the same variables are found to be significant, which strengthens these findings. The distance to the nearest other facility has the biggest influence on the predicted potential demand. The surrounding address density has the lowest impact out of the four significant variables, as it is closest to 0. The position within the road network is not found to be of significant influence on the potential P&R demand in either of the models.

**Table 7: Summary of significant variables**

| Variable | Coefficient | | p-value | |
|---|---|---|---|---|
| | OLS | WLS | OLS | WLS |
| Constant | 4.87 | 4.89 | 0.000 | 0.000 |
| Frequency | 0.40 | 0.32 | 0.000 | 0.000 |
| Distance to nearest other facility | 0.65 | 0.63 | 0.000 | 0.000 |
| Amount of workplaces reachable within 60 min | 0.32 | 0.32 | 0.002 | 0.022 |
| Surrounding address density | 0.26 | 0.28 | 0.019 | 0.012 |

### *Assumptions check*

As stated above, multiple linear regression is based on a set of assumptions. When violated, the results of the regression might be unreliable. The assumption of independence has been tested with the correlation matrix. Now, the assumptions of homoscedasticity and normality can be checked.

Homoscedasticity assumes that the variance of the residuals (the differences between the predictions and the actual observations) remains constant across all levels of the independent variables. The residuals plot can be used to assess this assumption, as it plots the residuals against the fitted values. Figures 14 and 15 show the residual plots of OLS and WLS respectively. As can be seen in the OLS plot, the residuals show heteroscedasticity. This violates the assumption of homoscedasticity. In contrast, the WLS plot shows a more consistent spread of residuals, suggesting that this method results in homoscedastic residuals.

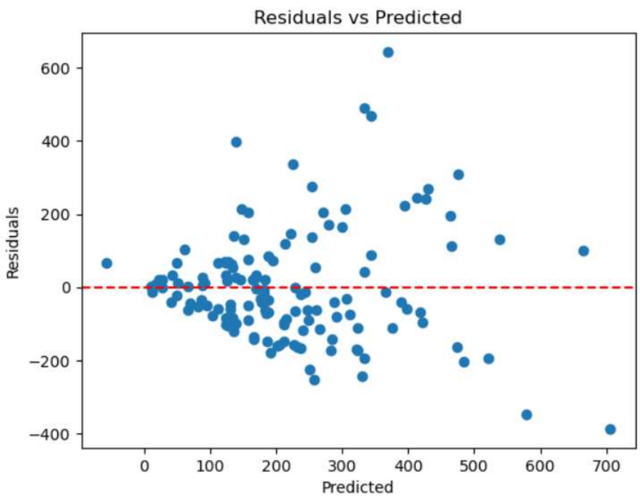


**Figure 14: Residuals plot (OLS)**

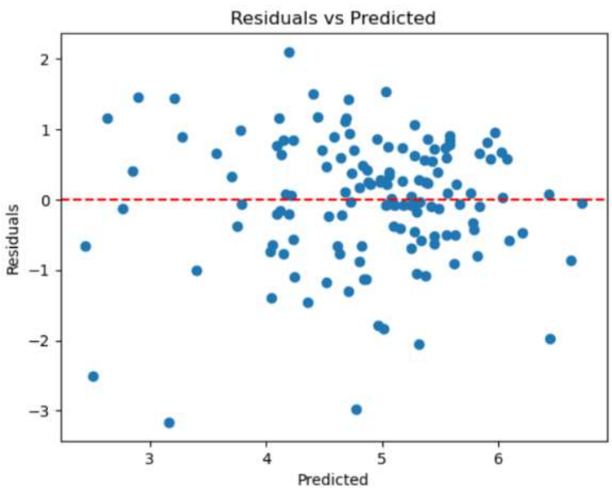


**Figure 15: Residuals plot (WLS)**

The normality of the residuals is another assumption made in multiple linear regression. It assumes that the residuals follow a normal distribution. This assumption can be checked visually by inspecting the QQ-plot, or by a test statistic, namely the Jarque-Bera test. The test statistic is preferred, as this quantifies the check giving a clear answer as to whether the assumption holds. The Jarque-Bera test for the OLS returns a value of 78.0 with a significance of 0.00, indicating that the null hypothesis must be rejected and the residuals significantly deviate from a normal distribution. The Jarque-Bera tests for the WLS return a value of around 118 with a significance of 0.00, indicating that the residuals are not normally distributed. Both regression models violate the assumption of normality, which makes the model performance indicators and variable significance unreliable.

### 4.5.2 Ordinal Logistic Regression

With ordinal logistic regression, the P&R demand is predicted in bins. Therefore, ordinal bins have to be defined. For the final OLR model, the bin selection is: <100, 100-200, 200-400, 400-600, and >600 daily users. These ranges are chosen as they give more detail for the lower P&R usages, whereas the higher bins are larger because in these ranges the model struggles to accurately predict the right bins. For example only using two bins, say more or less than 400 users, yields a high accuracy in the bin predictions but the usefulness of the results is limited. Similarly, the other way around the accuracy would be very low. Bin definition is therefore also an iterative process aiming to strike a balance between information and accuracy. All independent variables are used as input, after which the variable selection process selects the significant variables. The full model results can be found in figure 44 in appendix G. The model performance is assessed first, after which the significant variables are analyzed. Lastly, the assumptions underlying the OLR are checked.

#### *Model performance*

The model performance of the ordinal logistic regression is assessed using the pseudo-$R^2$, accuracy, and the mean absolute error. The values of the pseudo-$R^2$ tend to be much lower than the normal $R^2$. Values of 0.2 to 0.4 for the pseudo-$R^2$ represent an excellent fit (Henscher & Stopher, 1979). This ordinal logistic regression model results in a pseudo-$R^2$ of 0.29 on average for the five folds of the cross-validation. This would indicate an excellent fit, however, other indicators are also relevant. The confusion matrix gives insight into the predictions versus the observation, shown in table 8. It shows that for the majority of the bins, most predictions are placed in the right range (the diagonal). For the higher ranges, there are more incorrect predictions. The model accuracy indicates model performance, as it calculates the percentage of accurate predictions. In this case, 53% of the predictions are correct.

**Table 8: Confusion matrix**

| Actual \ Predicted [#/day] | <100 | 100-200 | 200-400 | 400-600 | >600 |
|---|---|---|---|---|---|
| <100 | 30 | 12 | 0 | 0 | 1 |
| 100-200 | 9 | 21 | 10 | 0 | 0 |
| 200-400 | 0 | 13 | 17 | 0 | 3 |
| 400-600 | 0 | 1 | 8 | 0 | 0 |
| >600 | 0 | 0 | 6 | 0 | 5 |

In addition to these more traditional model indicators, the confusion matrix allows for more tailored indicators that give a better insight into the model performance specific to the P&R demand prediction. The mean absolute bin error is 0.56, meaning that on average the prediction is off by 0.56 bin. By incorporating the bin sizes into the mean absolute bin error calculation, the average prediction error can be interpreted in terms of daily users. When the mean absolute error is based on the midpoints of the bins, it comes down to 97.5 daily users. This value indicates that, on average over all bins, the model prediction is off by 97.5 daily users, related to the specified bins.

#### *Significance of variables*

The independent variables used in the final model are listed in table 9, with their respective coefficients and p-values. As the variables have been normalized, a direct comparison between variables is possible. The distance to the nearest other P&R facility has the highest impact on the potential demand, as it has the highest coefficient. The surrounding address density is the second most impactful variable. A negative relation between the address density at the P&R facility is observed, meaning that when the level of urbanization directly around a P&R facility increases, the potential P&R demand decreases. This variable also has the lowest impact on the prediction, as its coefficient is closest to zero. The influence of the road network on potential demand is not found to be significant.

**Table 9: Summary of significant variables**

| Independent variable | Coefficient | P-value |
|---|---|---|
| Frequency | 0.91 | 0.000 |
| Address density at the P&R facility | -0.66 | 0.024 |
| Workplaces within 60 min | 0.97 | 0.004 |
| Distance to nearest neighbor | 1.71 | 0.000 |
| Surrounding address density | 1.26 | 0.001 |

These variables, along with their coefficients, result in a predictive model as shown in equations 4.1 through 4.5. The predicted bin is determined by $k^*$, the bin with the highest probability.

$$\beta = [0.91 \quad -0.66 \quad 0.97 \quad 1.71 \quad 1.26] \text{ and } X = \begin{bmatrix} Frequency \\ Address\ density \\ Workplaces\ within\ 60\ min \\ Distance\ to\ nearest\ neighbor \\ Surrounding\ address\ density \end{bmatrix} \tag{4.1}$$

$$P(Y \leq k) = \frac{1}{1+e^{-(\tau_k - \beta X)}} \tag{4.2}$$

$$P(Y = k) = P(Y \leq k) - P(Y \leq k-1) \tag{4.3}$$

$$k^* = \underset{k}{\text{argmax}}\ P(Y = k), k \in \{1,2,\ldots,4\} \tag{4.4}$$

$$\tau = [-1.42,\ 0.83,\ 0.80,\ 0.00] \tag{4.5}$$

### *Model assumptions check*

In ordinal logistic regression, it is assumed that the odds are proportional. This means that each independent variable has an identical effect at each bin of the ordinal dependent variable. This assumption can be tested by performing the Brant test statistic. When the p-value is lower than 0.05, the null hypothesis is rejected and the proportional odds assumption is violated. This test is done on each independent variable. From this test, it follows that none of the independent variables violate the proportional odds assumption. For the test results, see figure 45, appendix G.

Another assumption of the model is the independence of observations. Since the observations are taken in spatial dimensions, spatial autocorrelation should be checked. This can be done by performing the Moran's I test. The null hypothesis states there is no significant spatial autocorrelation in the variable, the alternative hypothesis states that there is significant spatial autocorrelation. This test is done for each independent input variable. The results, which are given in figure 46 in appendix G, show that the frequency and distance to the nearest other P&R facility are technically spatially autocorrelated, as their p-value is smaller than 0.05. Moran's I test shows a very weak correlation, as the value is -0.007 whereas 0 would mean no spatial autocorrelation. This spatial correlation is therefore negligible.

## 4.6 Model sensitivity check

All models exhibit a certain sensitivity to their input variables and parameters. It is essential to check the impact of small changes to the input or model on the results to ensure the model is reliable. These changes are specific to the two different regression models; therefore, they are discussed separately.

### 4.6.1 Multiple linear regression

The sensitivity of the MLR model can be assessed in various ways. Here, the choice is made to look at two aspects: the sensitivity to outliers [1], as well as the variation between the five test sets resulting from the cross-validation [2]. The sensitivity to outliers is assessed by finding influential outliers and checking how the model performs with these outliers removed. The outliers are found by computing Cook's distance, a statistical measure that combines residuals and leverage to determine influential outliers in the dataset (Chatterjee & Hadi, 1988). This requires setting a distance threshold, which is commonly calculated by computing 4/n with n being the number of observations (Bobbitt, 2019). This results in eleven influential outliers, as can be seen in figure 47 in appendix G. With these observations removed, the model is run again. A comparison between model results is shown in table 10. What can be seen is that the model significantly lowers the RMSE for both the OLS and WLS models. A considerable decrease in AIC is seen in the WLS, which does not occur in the OLS model. Therefore, the results suggest that the OLS model is less sensitive to the removal of influential outliers compared to the WLS model. The results do indicate that by removing the outliers, a better performing model can be achieved, in terms of RMSE and AIC. The full model results are shown in figure 48 and 49 in appendix G.

**Table 10: Resulting model performance indicator values**

| Alteration | Adjusted-$R^2$ | | AIC | | RMSE | |
|---|---|---|---|---|---|---|
| | OLS | WLS | OLS | WLS | OLS | WLS |
| Original model | 0.50 | 0.32 | 267 | 267 | 163 | 200 |
| Removed influential outliers | 0.49 | 0.27 | 258 | 231 | 116 | 115 |

By assessing the variation in model performance indicators between test sets, resulting from the cross-validation, the sensitivity of the model to the input data can be assessed. Table 11 shows the model performance indicators for five different test sets. These results can also be seen in appendix G, which includes the complete model output. It can be seen that generally the variation between the test sets is small, with an exemption of the RMSE which sees some more significant differences. This is most likely due to the outliers, which have a large impact on the RMSE as assessed above. The adjusted-$R^2$ and AIC show very similar values between test sets, indicating the both the OLS and WLS models are robust in its performance.

**Table 11: Performance indicators for each test set**

| Test set | Adjusted-$R^2$ | | AIC | | RMSE | |
|---|---|---|---|---|---|---|
| | OLS | WLS | OLS | WLS | OLS | WLS |
| 1 | 0.52 | 0.26 | 272 | 260 | 181 | 175 |
| 2 | 0.49 | 0.38 | 289 | 274 | 178 | 187 |
| 3 | 0.52 | 0.22 | 276 | 264 | 143 | 149 |
| 4 | 0.49 | 0.36 | 291 | 270 | 148 | 152 |
| 5 | 0.49 | 0.38 | 286 | 269 | 228 | 264 |

### 4.6.2 Ordinal Logistic Regression

For the OLR model, two alterations are done to the input to check model sensitivity. Firstly, small perturbations are done to the variable with the highest coefficient, the distance to the nearest other P&R facility. These perturbations are done to check whether the model output and performance are sensitive to these small changes in input. The perturbations are set to a random value between -10% and +10% of the initial value. The resulting change in model performance indicators is shown in table 12. It shows that the model performance is impacted only slightly, with a small decrease in the pseudo-$R^2$ and no change in the accuracy. It suggests that the model is not sensitive to small perturbations in the input variable distance to the nearest other P&R facility.

**Table 12: Model performance comparison between original model and changed model**

| | Pseudo-$R^2$ | Accuracy |
|---|---|---|
| Original model | 0.29 | 0.54 |
| Perturbation to distance to nearest other P&R facility | 0.25 | 0.54 |

Secondly, the number of bins and their ranges are a determining factor for the model performance of OLR. Therefore, the bins are altered to observe the impact on model performance. Instead of the current bins (<100,100-200,200-400,400-600,>600), following bins are used: <50, 50-100, 100-150, 150-300, 300-600, >600. This increases the number of bins to six and changes the size of the bins. As a result, the average pseudo-$R^2$ is 0.25, slightly lower compared to the original model of 0.29. The accuracy of the model is decreased to 40%, a considerable change from the initial 54%. The full model results are given in figure 50 in appendix G. These results make sense as the higher the amount of bins, the more precise the prediction has to be to be correct. However, it shows that the model performance is sensitive to the set bins. Therefore, a change to these bins should be carefully considered.

## 4.7 Discussion and conclusion

This section discusses important points of attention following from the creation of the dataset, model development, and outcomes of the different models. A discussion relating the method and results to other studies is given in the overall discussion, in chapter 6. After the points of discussion, conclusions are drawn from the descriptive statistics, model development, and outcomes. These conclusions answer the related research sub-questions.

### 4.7.1 Discussion

The discussion first addresses the input dataset and independent variables. It then goes into the model development and finishes with the model results and sensitivity check.

To begin, in the creation of the dataset and calculations of the variables, it must be noted that the P&R facility usage numbers on which the models have been trained might be different from the actual amount of people that use the P&R facility to transfer to PT and continue their journey. Some P&R facility locations are attractive as end destination parking, and so people tend to use it for this purpose. This is expected to occur mostly in intra-urban areas and thus has a limited impact on this research as the models only include rural and satellite facilities.

This filtering of facility types has resulted in better-performing models than including all P&R facility types in the models. This, however, limits the applicability of the model to predict potential P&R facility demand, as it should only be applied in situations where rural and satellite P&R facilities are possible.

Having addressed data filtering and its implications, attention is now turned to the use of interaction terms in the models. There exists an almost infinite number of possible interaction terms, but it is infeasible to assess all of them. Therefore, only interaction terms that make sense from a PT planning perspective have been tried. An arbitrary interaction term might lead to a significant predictor; however, it might make no sense from a PT perspective.

Building upon the interaction terms, the implementation of both the level of urbanization and the influence of the road network see multiple possible implementations. Once again, those that are the most logical and relevant have been implemented as variables, but it is worth noting that another approach may result in variables with better predictive power.

From the model development, some points of discussion are addressed regarding the OLR[1] model. This method requires manually specified bins, and the configuration of these impacts the model performance. When the bins are too large, the model accuracy may be very high, but the information it provides is limited. A balance must be found between the model's performance and the size and number of the bins. In the current model, this is done on an iterative basis.

Three regression methods were used in the model development; however, many more methods exist that could yield a better predictive model. The descriptive statistics support the selection of these three methods; however, due to the limited timespan of this research, not all potential methods could be tested. Optional other regression methods include quantile regression and machine learning methods.

Moving from the model development to the model results, it is noted that none of the modality variables are significant predictors. This might be unexpected, however looking at the selected subset of satellite and rural facilities, it makes sense. This subset almost exclusively contains P&R facilities that are connected to a train station, either the SPR or IC modality. It is therefore discouraged to use the model for predicting demand for facilities that are connected to different modalities.

Although the OLR model outperforms the MLR[2] models, it also loses prediction information because it only makes predictions for specific bins. The sensitivity analysis shows that the model's performance varies greatly when these bins are changed. This indicates that the model is less desirable since it is sensitive to its input. However, the OLR model meets its assumptions, while the MLR models do not. Thus, both models have advantages and disadvantages. An attempt to employ a different model type could result in better overall outcomes.

MLR models show that removing the outliers can lead to a significant decrease in the RMSE[3]. This is one way of assessing the model sensitivity, however, multiple other options exist. Since the MLR models already violate one of their assumptions, performing an extensive sensitivity analysis is deemed unnecessary.

On the contrary, the OLR does fulfill its assumptions. It is therefore more essential that the sensitivity is properly assessed. Here both the sensitivity to the input bins as well as the input variables are assessed, however, a more in-depth sensitivity analysis would improve the understanding of the sensitivity and model performance. This can include changing the cross-validation procedure and changing the input variables.

### 4.7.2 Conclusion

Two regression methods have been used in this research, which both have strengths and weaknesses. The multiple linear regression models show a decent model fit, with adjusted-$R^2$ values around 50% and 32%. However, upon checking the assumptions, it is found that the assumptions of normality and homoscedasticity are violated. This indicates that the results of the models can be unreliable.

In comparison, the ordinal logistic regression model adheres to its assumptions: an ordinal dependent variable, proportional odds, independence, and linearity. However, the model predicts values within a specific range, making it less useful when exact numbers are required. This is not considered a problem for the application of the model, as the exact numbers of potential P&R users are not of interest. A more accurate model predicting a range in which the potential demand falls is more appropriate for this application. With a pseudo-$R^2$ of around 0.3 and an accuracy of 54%, the model is very good at predicting the potential P&R demand within the specified ranges. Further analysis and tuning of the bins might result in even better predictions.

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[1] Ordinal Logistic Regression
[2] Multiple Linear Regression
[3] Root Mean Squared Error

Out of the eleven possible independent variables, five are found to significantly impact the potential P&R demand using the ordinal logistic regression model. With this information, the fourth research question can be answered: *to what extent does the position within the road network influence the demand for P&R facilities?* As follows from both the multiple linear regression and the ordinal logistic regression models, this influence is insignificant. The two ways this influence was modeled as independent variables do not yield a significant relationship with the P&R demand.

To conclude, the fifth research question can be answered: *To what extent can an explanatory model estimate potential P&R facility demand?*
The potential P&R facility demand can be predicted by five significant variables: the frequency of the connected PT, the address density at the P&R facility, the number of reachable workplaces within 60 minutes, the distance to the nearest other facility, and the surrounding address density. The ordinal logistic regression model uses these variables, along with their corresponding estimated coefficients, to predict the potential demand with an accuracy of 54% and an average bin error of around 0.5 using the following specified bins: <100, 100-200, 200-400, 400-600, >600.

# 5. Spatial multi-criteria analysis applied to a case study

The goal of the spatial multi-criteria analysis is to employ a framework to develop a model that gives an estimation of the desirability of new P&R facilities within a case study area. To achieve an estimation of the desirability, a combination is made with the potential demand model, developed in chapter 4, together with other factors identified through the literature study. To validate the model, it is applied to the case study of the region of Groningen.

The province of Groningen is looking to expand its number of P&R facilities. Currently, the city of Groningen has several urban fringe facilities that see many daily users (Groningen Bereikbaar, 2024). However, there is a lack of proper P&R facilities further away from the city. Some P&R facilities are present, but their capacity is relatively small and are often not actively promoted as P&R facility (Google, 2024). The current P&R facilities within the study area are shown in figure 16. Two scenarios are drawn up, in which the P&R desirability is calculated and visualized for each cell in the study area. This heatmap may then be of use in further P&R facility planning in the province of Groningen.
These two scenarios have been briefly introduced in chapter 3, with additional details given below.

- Base scenario: keeping the current PT network and stops the same to assess the current P&R desirability in the region. The current PT network and stops are shown in figure 17.
- Nedersaksenlijn Scenario: realize the proposed plans of the Nedersaksenlijn (NSL). It extends a train line from Groningen via the southeast to Emmen. Multiple possible routes have been proposed. In this scenario the route via Ter Apel is chosen, as this is expected to have a larger positive impact on the population in the study area. The proposed rail line can be seen in figure 18. The decision is made to use this as a scenario, as it is realistic to assume the realization of this line in the near future. The NSL is constructed such that it forms good connections with the other PT lines. A previous proprietary study within Movares has been used for this. The alterations to the PT network are all done in the Movares Verbindingswijzer network analysis tool.

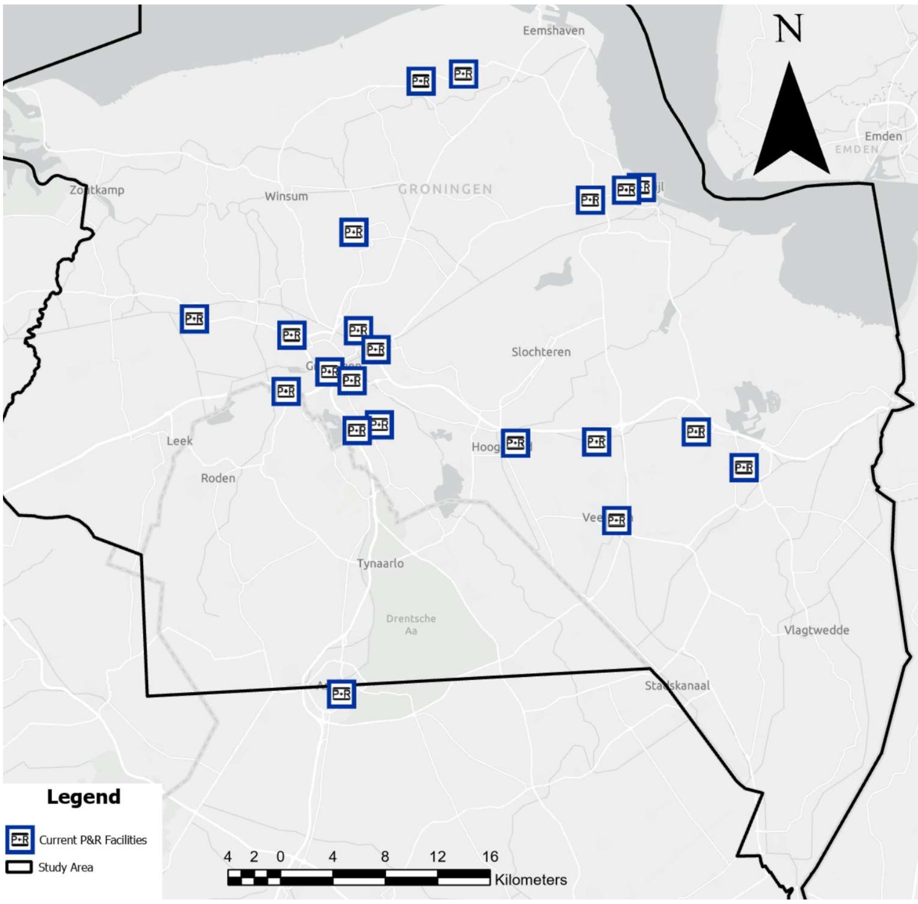


**Figure 16: Overview of current P&R facilities in and around the case study area**

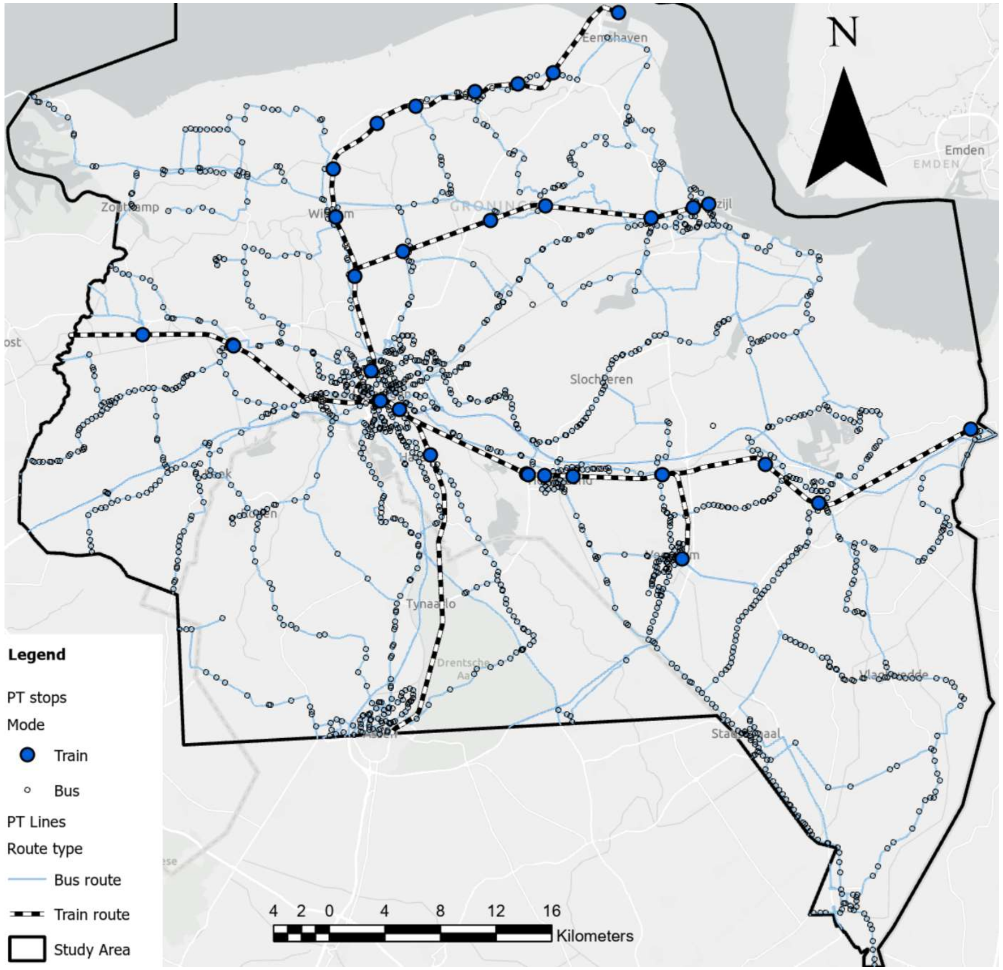

**Figure 17: Base scenario PT network and stops**

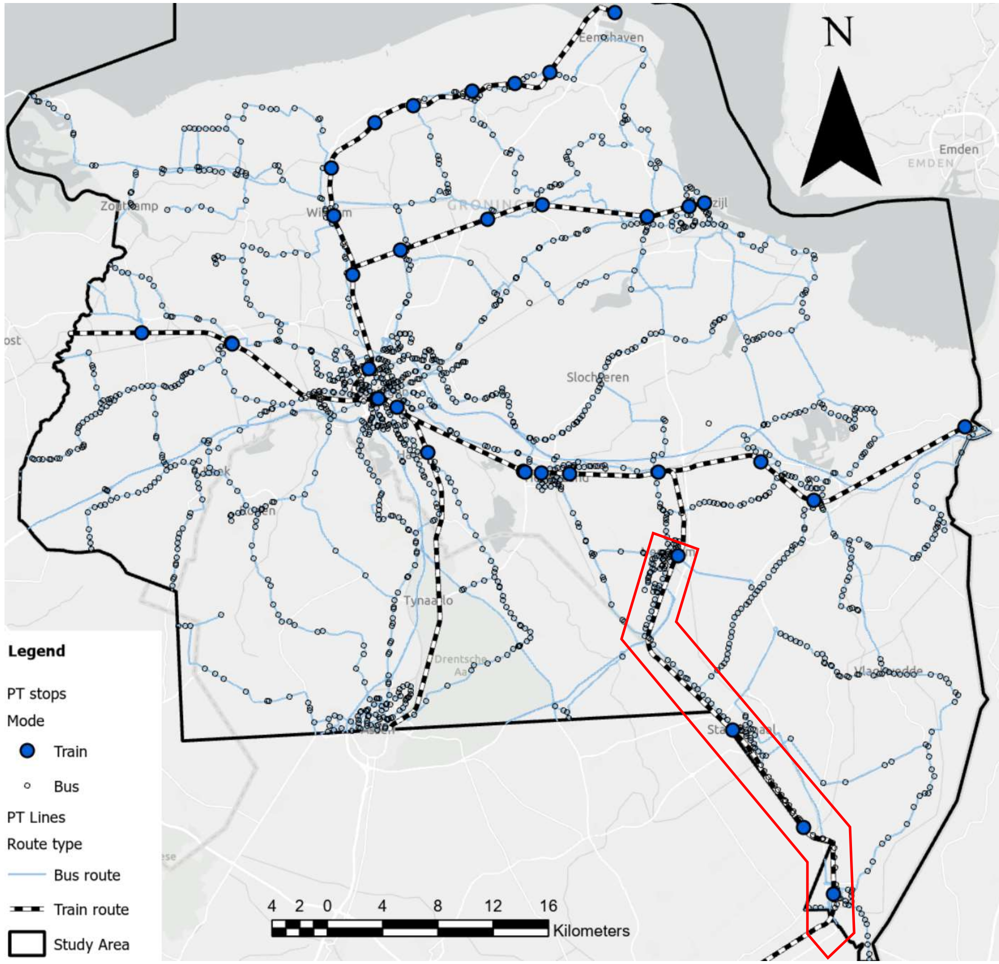

**Figure 18: NSL scenario PT network and stops. Highlighted in red is the addition of the NSL.**

Within the study area, an extensive network of bus and train lines is present. The network is especially dense around the city of Groningen itself. Train lines reach out west to Friesland as well as to the northern and eastern parts of the study area. The southern area sees fewer train lines and is covered more by bus lines. Figure 17 shows this network including the PT lines and stops.

The alterations done to the NSL scenario are highlighted in the red box in figure 18. The rest of the network is kept the same. The introduction of this train line increases the coverage of the rail lines in the southern region of the study area. It offers a faster PT connection to the city of Groningen. The current bus lines in the area are kept the same, for simplicity reasons.

From the literature study, it followed that a certain set of factors influences the desirability of P&R facilities. These are shown in the theoretical framework given in figure 2 in chapter 2. Not all of these factors could be included in a spatial multi-criteria analysis as the required data is not available. The practical framework is therefore given in figure 19, in which the factors are colored green if they are available and red if they are unavailable. This is based on data that is available but also on the feasibility of implementing the factor. An example of this is future development plans. Considering the development plans from the various municipalities within the study area is infeasible. Therefore this factor is deemed unavailable. The travel time ratio, the ratio in travel time between traveling by PT and private vehicle, is added to the framework. This is done as it could not be included in the potential demand model but is expected to have a large influence on the desirability of a P&R location. It could not be implemented in the potential demand model, as the end destination was unknown for the P&R facilities in the dataset. The spatial MCA is applied to a specific case study, in which the end destination is defined, so this factor can be implemented.

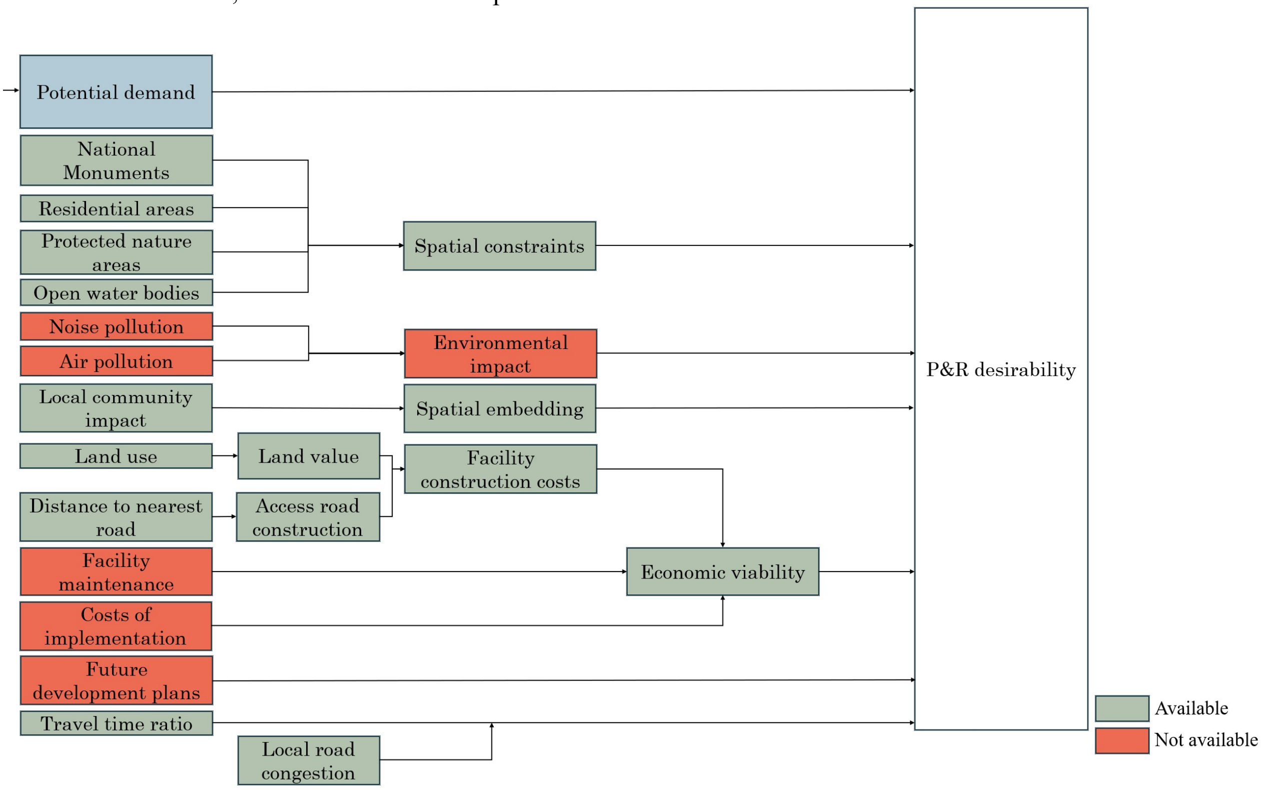


**Figure 19: Practical framework P&R desirability**

These available factors are then translated into criteria. As explained in chapter 3, the criteria consist of the objectives and constraints. Attributes determine the score of the objectives. Table 13 shows an overview of the objectives, attributes, and constraints that are drawn up from the practical framework. The practical framework identifies three objectives: the constraints, including spatial constraints and spatial embedding [1], the connectivity of the area, determined by the travel time ratio [2] and the estimated potential demand, determined by the potential demand model [3]. This leads to three objectives and four constraints. Figure 20 shows these input criteria in the overview of the spatial MCA.

**Table 13: Overview of objectives, attributes, and constraint and their relation to the practical framework**

| Criteria | Attributes | Factor in practical framework |
|---|---|---|
| Objective 1 Maximize demand | Potential P&R facility demand model that predicts the potential demand within certain ranges. | Potential demand |
| Objective 2 Maximize connectivity | Travel time ratio | Travel time ratio and local road congestion |
| Objective 3 Suitable spatial embedding | Combination of land use suitability and construction of access road. | Local community impact, land use, and distance to the nearest road. |
| Constraint 1 Open water bodies | | Open water bodies |
| Constraint 2 Protected nature areas | | Protected nature areas |
| Constraint 3 Monuments | | National monuments |
| Constraint 4 Residential areas | | Residential areas |

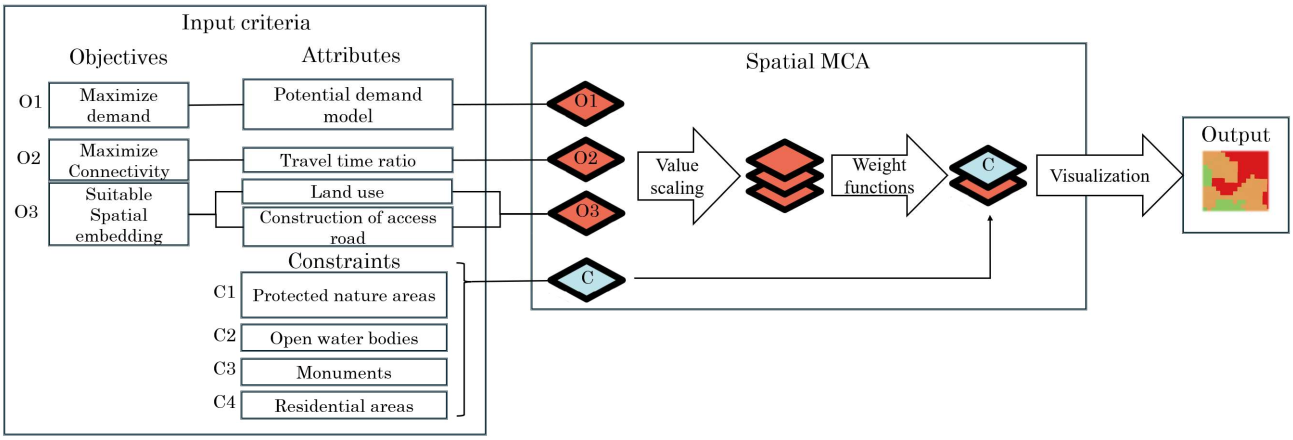


**Figure 20: Input/output overview spatial MCA**

In section 5.1 data gathering and preprocessing are discussed, including setting up file databases, gathering required data, and performing preprocessing steps. This data is then used in the creation of GIS layers for the attributes and constraints, given in section 5.2. The values of these attribute layers are converted into an objective score via a value function. This is done in section 5.3. In section 5.4, the layers are weighted using the WLC method in combination with different stakeholder scenarios, after which they are combined into one layer. Following that, in section 5.5, a sensitivity analysis is done to assess how the output desirability changes with changing input weights. This is followed by the scenario results in section 5.6. Finally, the discussion and conclusion are given in section 5.7 and 5.8 respectively.

## 5.1 Data gathering and preprocessing

Firstly, a file structure for the development of the model is set up. The decision is made to create three file databases, which all focus on a different level of model development. They follow the structure of the model development itself. The overall project consists of several components that each focus on a specific part of the model development. Within these components many smaller calculations are done, called steps. This leads to the following file structuring format:

- The step database includes all files that are a result of within-component calculations. They are intermediate data that can be deleted after the component is completed.
- The component dataset includes all files that are transferred between components, meaning that the output of component 1 which is needed for component 2 is saved in the component dataset. In the development of this model, five components are distinguished: preprocessing (a), layer creation (b), layer scoring (c), sensitivity analysis (d), and visualization (e).
- The project database includes files used as input of the model, such as the study area, and files required for the overall output of the model, in this case, the desirability heatmaps for different scenarios.

With these three databases in place, data can be gathered and preprocessed. Data gathering concerns collecting and cleaning relevant datasets required for the attributes, constraints, and alternatives. These include topographic, socio-geographic, and transport network datasets. A complete overview of all data sources can be found in appendix A.

## 5.2 Creation of layers

The attributes and constraints are realized into spatial layers, using the preprocessed data. The creation of these layers requires setting up the alternatives, based on the study area. Each spatial layer contains the attribute values of each alternative in the study area. A detailed explanation of each objective and constraint is given below. The technical details about the creation of the spatial layers are given in appendix I.

*Objective Maximize potential demand*

This objective tries to maximize the potential demand by utilizing the ordinal logistic regression model, developed in chapter 4 of this research. It is used to make predictions for all grid locations within the study area. The model predicts the potential P&R demand per day within specified ranges. Five ranges are used in the model predictions, in terms of daily users: <100, 100-200, 200-400, 400-600, and >600. The model predicts the bin number based on which bin has the highest calculated probability. This prediction is made for each grid cell in the study area. The expectation therefore is that most cell predictions will be of the lowest bin, as most areas are expected to have a low potential demand. This objective encapsulates multiple factors, as follows from the model development in chapter 4. Its importance is regarded as relatively high compared to the other objectives which focus on one or two factors. The model predictions should however be interpreted with caution, as the model performance indicators show that the model does not have a perfect prediction accuracy.

*Objective Maximize connectivity*

This objective aims to maximize the connectivity of the location. This is determined by the attribute travel time ratio, which is the ratio between travel time to the city center of Groningen by PT and by private car. Values below 1 indicate that PT is faster than the private car. Values higher than 1 indicate that PT takes longer than driving. This travel time ratio takes into account many aspects of the journey. It includes the frequency of the PT, transfer times, and walking times to and from stops/stations. For the driving time, it takes into account local road congestion during rush hours, based on data gathered from Nationaal Dataportaal Wegverkeer. The travel time ratio is calculated using the Movares Verbindingswijzer network analysis tool, which requires a set of input parameters. An explanation of this is given in appendix C.

The objective captures the connectivity of a certain area. The travel time ratio is deemed as an appropriate attribute for this. It does however exclude some other aspects of connectivity, including pricing and physical accessibility for people with disabilities (Rupprecht et al., 2019).

*Objective Suitable spatial embedding*

This objective ensures the suitability of the spatial embedding of a P&R facility. This suitability consists of many aspects, of which two are used as attributes, namely land use and costs of road construction. Land use is a qualitative attribute. To quantify it, it is related to certain suitability values connected to each type of land use using a lookup table. These suitability values are estimated by own researcher judgment since there is no fitting literature available on this. It takes into account both the monetary costs of acquiring the land and building the P&R facility, as well as societal costs that aim to minimize the negative community impacts. The suitability values for different land use classes are given in table 14. Agricultural land gets the lowest suitability cost, as this type of land requires the lowest cost of construction and generally has a relatively low impact on the local community. Natural areas as well as urban greenery also have a relatively low suitability cost of 20 and 30 respectively, as these are non-built-up areas. On the other hand, natural wet areas and religious/cultural/institutional locations have a high suitability cost. Natural wet areas are unsuitable due to high construction costs and religious/cultural/institutional areas are unsuitable due to high societal costs. The costs of road construction is determined by the distance to the nearest road.

**Table 14: Land use suitability costs**

| Land use class | Cost |
|---|---|
| Agricultural | 10 |
| Natural area | 20 |
| Urban Green (incl. sport fields) | 30 |
| Infrastructure | 40 |
| Industrial | 60 |
| Commercial | 80 |
| Recreational | 80 |
| Religious/cultural/institutional | 90 |
| Natural area wet | 90 |

*Physical Constraints*

Physical constraints are areas where the construction of a new P&R facility is infeasible due to technical, administrative, or stakeholder limitations. For this, the decision is made to include open water bodies, national monuments, protected nature and residential areas. Open water bodies are infeasible as the construction cost in these locations would be high. National monuments and protected nature are infeasible due to protection by law. Lastly, constructing a P&R facility in a residential area is infeasible as it would have too big of an impact on the local community. Additionally, parking is often regulated in zoning plans (Lokale Regelgeving Overheid, 2020). Together these areas form the physical constraints.

## 5.3 Layer value functions & scoring

After the attribute layers are created, the objective score can be computed. This is called layer scoring and is determined by the value function. An explanation of the scoring of each objective is given in table 15. A full technical description of the calculations is given in appendix J. The score of the objectives is normalized, such that the range of the output of every objective layer is between 0 and 1. This allows these layers to be combined into one overall desirability score based on weight sets. The range of the normalization is kept the same for both case study scenarios such that a comparison can be made between them.

**Table 15: Layer scoring with value functions**

| Objective | Attribute | Input value range | Value function | Output value |
|---|---|---|---|---|
| Maximize demand | Potential demand prediction | The prediction resulting from the regression model consists of five classes, 0 to 4, which predict P&R usage within a specified range (<100,100-200,200-400,400-600, >600) | The demand classes are valued based on their distance to the nearest PT stop. This means that the predicted demand is scaled with the distance to the nearest PT stop, also known as inverse distance weighting. In this case, for simplicity reasons, this function is taken linear. These values are then normalized. | Between 0 and 1 |
| Maximize connectivity | Travel time ratio | The input value range of the travel time ratio is between 0 and 6.5. | A cut-off value of 5.0 is used as values above this are deemed unrealistic. After this cut-off, the values are normalized from 0 to 1 where 1 is the highest connectivity, meaning the lowest travel time ratio. | Between 0 and 1 |
| Suitable spatial embedding | Land use suitability costs | The input consists of land use (LU) classes. These are qualitative classes. They require a quantization to be used in further calculations. | Using the lookup table given in table 14, the LU classes are translated to values from 10 to 90. The value 90 is given to natural wet areas, the value 10 is given to agricultural land. Other LU classes are valued in between based on their monetary and societal costs. The values are then normalized. | Both attributes are then combined into one objective layer in which the land use suitability costs are multiplied by the distance to the nearest road. |
| | Road construction costs | The Euclidean distance to the nearest road ranges from 0 to a maximum of 1000m, values above 1000m are capped at 1000m. | These distances are normalized, with the lowest distances attaining the lowest suitability cost of 1. The highest distances, 1000m and higher get a suitability cost of 2. | |

## 5.4 Layer weighing and combination

Now that the objective layers are computed and scaled, they can be weighted and combined into one overall desirability layer. The method used for this is the weighted linear combination (WLC) as explained in chapter 3, for which the formula is given in equation 5.1.

$$V(A_i) = \sum_{k=1}^{3} w_k v(a_{ik}) \tag{5.1}$$

With $w_k$ being the weight set consisting of the three objective weights. Four weight sets are proposed based on three stakeholder scenarios. These stakeholder scenarios are focused on the operator, users, and government interests with the fourth scenario the combination of all three. For simplicity, these weight sets are determined based on own researcher judgment and look at the primary interests of the stakeholders. The fourth scenario is the combination of all three stakeholders, in which their interests are all deemed equally important. The sensitivity of the model to these weights is assessed in the sensitivity analysis.

The first scenario is focused on the operator's interests. The operator is mainly focused on making profit and keeping up user satisfaction. Therefore, the potential demand is most important for them followed by the suitability of spatial embedding, as land acquisition may be costly. The connectivity is least important in their case, as long as demand is high. This comes down to a weight set of 60%, 10%, and 30% respectively for weight $w_1$, , $w_2$ and $w_3$.

The interest of the users is mainly to maximize connectivity, as they prioritize shorter travel times. The other two criteria are of much less importance as it is not in their interest to have high demand or low suitability costs. Therefore, their weight set is put to 15%, 70%, and 15% respectively for weight $w_1$, , $w_2$ and $w_3$.

The government is mainly concerned with the integration of the P&R facility within the current built-up landscape. It is also interested in a well-functioning P&R facility, so the potential demand and connectivity are also of importance. Therefore, their interests are balanced between all three criteria. A weight set of 33% for all three criteria is therefore considered appropriate.

Lastly, all three stakeholder scenarios are combined into the fourth scenario accounting for the interest of each of the three stakeholders. It is the average of all three weight sets combined. The four stakeholder scenarios and their respective weight sets are given in table 16. The stakeholder scenarios are used to demonstrate the possibilities of emphasizing certain stakeholder interests. A comparison between the stakeholder scenarios in the results is made in section 5.6. In table 17 an example of how a stakeholder scenario weight set is used as weights in the WLC is given.

**Table 16: Stakeholder scenarios and corresponding weight sets**

| Criteria | Stakeholder scenario 1: operator | Stakeholder scenario 2: users | Stakeholder scenario 3: government | Stakeholder scenario 4: Combined stakeholders |
|---|---|---|---|---|
| Maximize potential demand | 60% | 15% | 33% | 36% |
| Maximize connectivity | 10% | 70% | 33% | 38% |
| Maximize suitability of spatial embedding | 30% | 15% | 33% | 26% |

**Table 17: Implementation of stakeholder scenario 4 weight set into the weight function**

| Criteria | Input value range | Weight function | Output value range |
|---|---|---|---|
| Maximize potential demand | Between 0 and 1 | 0.36 | Between 0 and 0.36 |
| Maximize connectivity | Between 0 and 1 | 0.38 | Between 0 and 0.38 |
| Suitability of spatial embedding | Between 0 and 1 | 0.26 | Between 0 and 0.26 |

## 5.5 Sensitivity analysis

A sensitivity analysis is performed to check whether the previously determined criteria and corresponding weights are in balance and do not show a disproportionate change in the model outcome if adjustments are made in the weights of the criteria. This is done using the one-at-a-time method, explained in chapter 3. One at a time a weight is changed with increments of 0.1. The results are assessed in two ways. First, the mean and standard deviation of the output desirability score are plotted for each weight value. This yields three figures, each showing the change in mean and standard deviation of the desirability score as a result of the change in each of the three weights. Second, the top 10% highest desirability scores are plotted in the same graph, also indicating their mean and standard deviation.

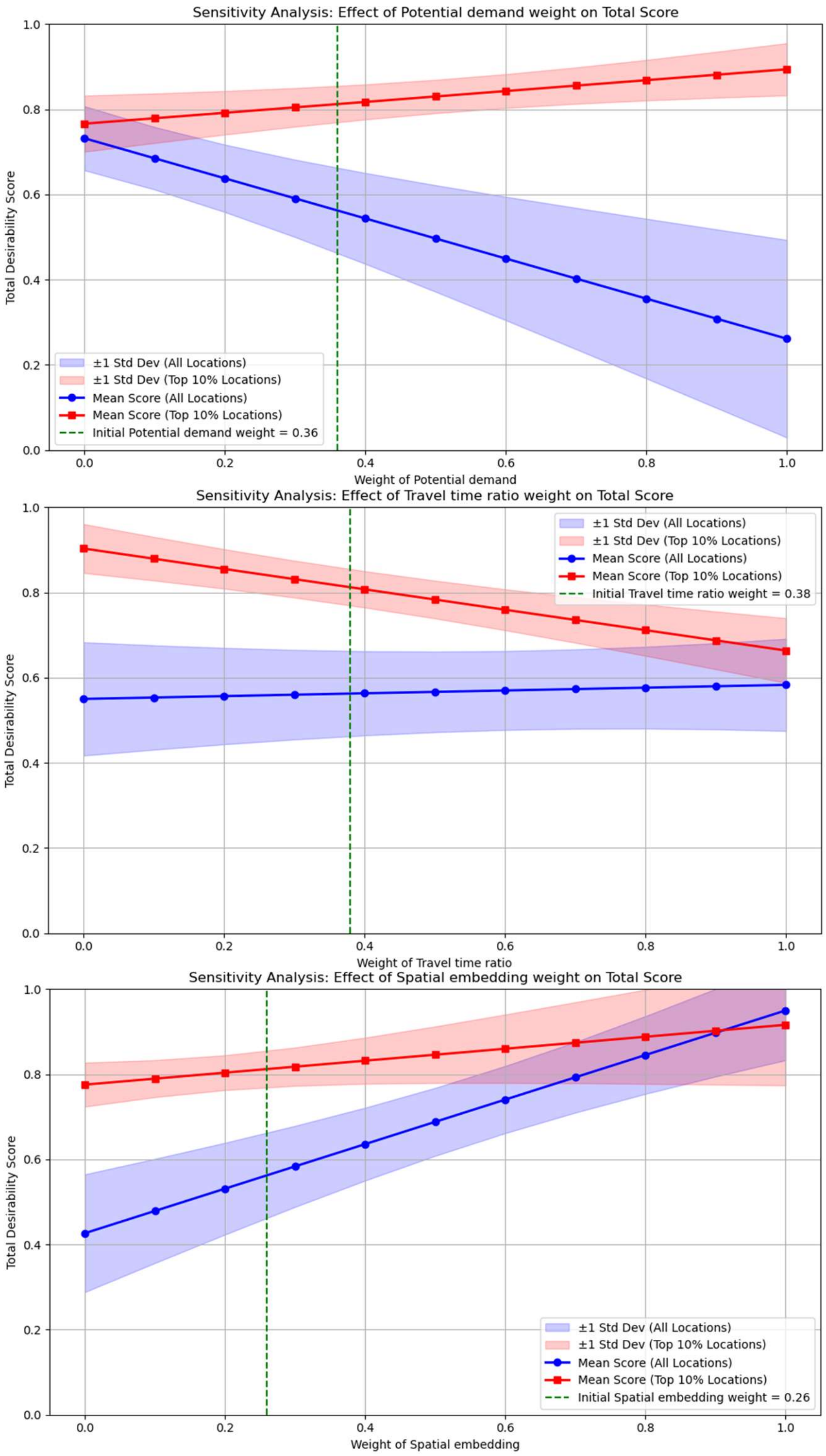


**Figure 21: Sensitivity of total desirability score subject to changes in $w_1$ (top), $w_2$ (middle), $w_3$ (bottom)**

The change in total desirability due to a change in weight values is dependent on which weight value is being changed. This follows from figure 21.

It can be noted that the middle and bottom plots show a different pattern than the top plots, as the top 10% and all locations tend to converge, whereas, for the change in potential demand weight, they show an opposite trend. The desirability of the top 10% locations increases with increased potential demand weight whereas the total desirability for all locations decreases. The increase is small however, which can be due to the top 10% of the potential demand all falling within a small range, as these values will all have originated from the same P&R demand prediction bin.

The standard deviation is shown to be smaller for the top 10% locations compared to all locations combined. This makes sense as the total range of values within the top 10% of the three objectives is also smaller compared to the full range of values.

The results show that for small changes in the potential demand weight and spatial embedding weight, the results remain similar, but larger changes result in large changes in total desirability. A change in weight of the travel time ratio results in smaller changes, as the overall change in total desirability over the full range of the weight is relatively small. The absolute change in total desirability score for the top 10% locations is similar for all three weights.

Besides these first order effects, the use of Sobol' method allows the assessment of second-order effects. The calculations have been addressed in the methodology section. The results of which are shown in table 18. As can be seen, the index shows that the proportion of second-order effects is very small compared to the total variance.

**Table 18: Sobol' Method S2-index**

| Interaction | $S_2$-index |
|---|---|
| Travel time ratio – Potential demand | 0.0089 |
| Potential demand – Land use | 0.0022 |
| Land use – Travel time ratio | 0.0414 |

## 5.6 Scenario results

The complete model is applied to the case study, in which two scenarios are assessed. The input layers are discussed in this section, after which the total desirability score is analyzed. This is followed by a scenario comparison and a zoomed-in analysis on the model performance with the goal to verify and validate the model and its results. Lastly, the results of the three different stakeholder scenarios are analyzed to assess the differences in desirability between scenarios.

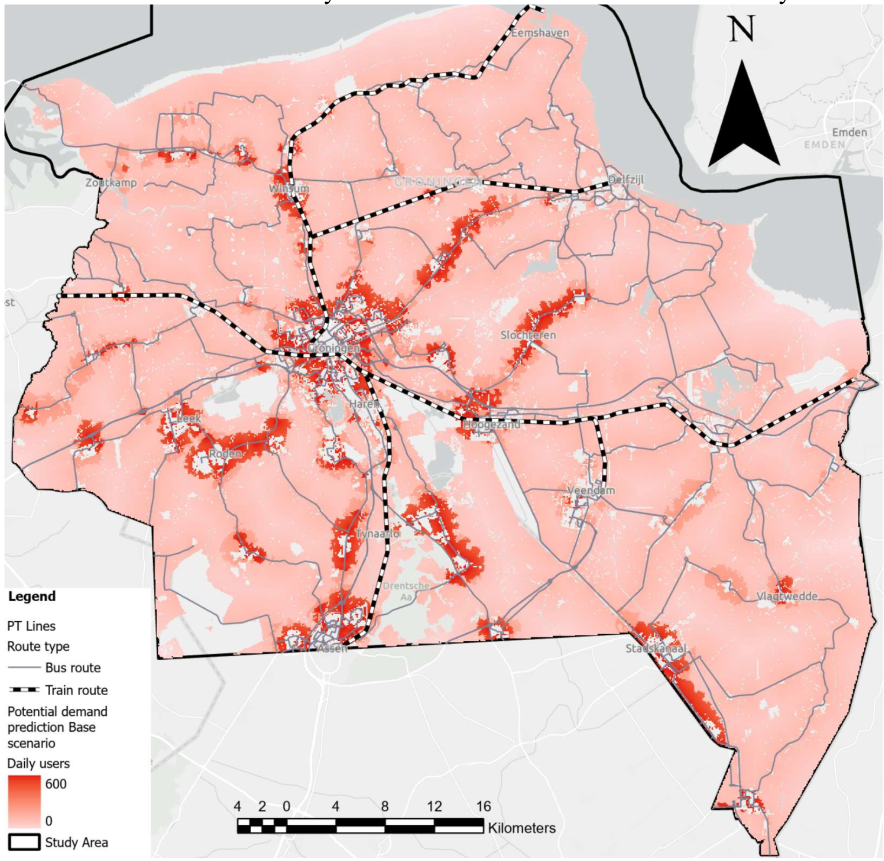


**Figure 22: Maximize demand objective base scenario**

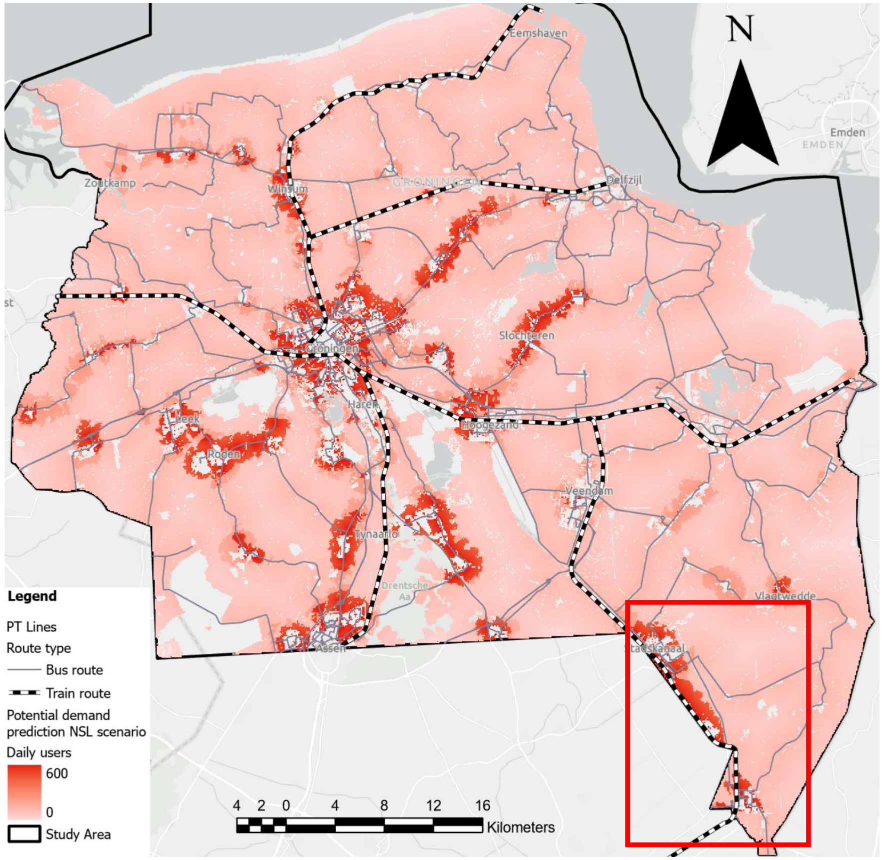


**Figure 23: Maximize demand objective NSL scenario. The red box highlights the changes in demand induced by the new train line.**

The maximize demand objective for the base scenario is shown in figure 22. It can be seen that the demand prediction is done in ranges, as the map shows some very high-demand locations (red) and very low-demand locations (pink). The attribute potential demand, as predicted by the potential demand model, is scaled by the distance to the nearest PT stop. This is visible in the figure by the gradient in the red and pink colors. Since the difference between the prediction classes is high (several hundred daily users difference), the scaling by distance to PT has a relatively small impact. Similarly, the maximize demand objective for the NSL scenario is shown in figure 23. It is subject to the same points of attention as the base scenario. A difference can be observed around the NSL, where some potential demand predictions change to a higher range, highlighted in red. In both scenarios, the area in and around the city of Groningen has high potential demand predictions. These predictions should be neglected as the model is not fit for central, intracity, and urban fringe P&R facility demand, as has followed from the development of the potential demand model in chapter 4.

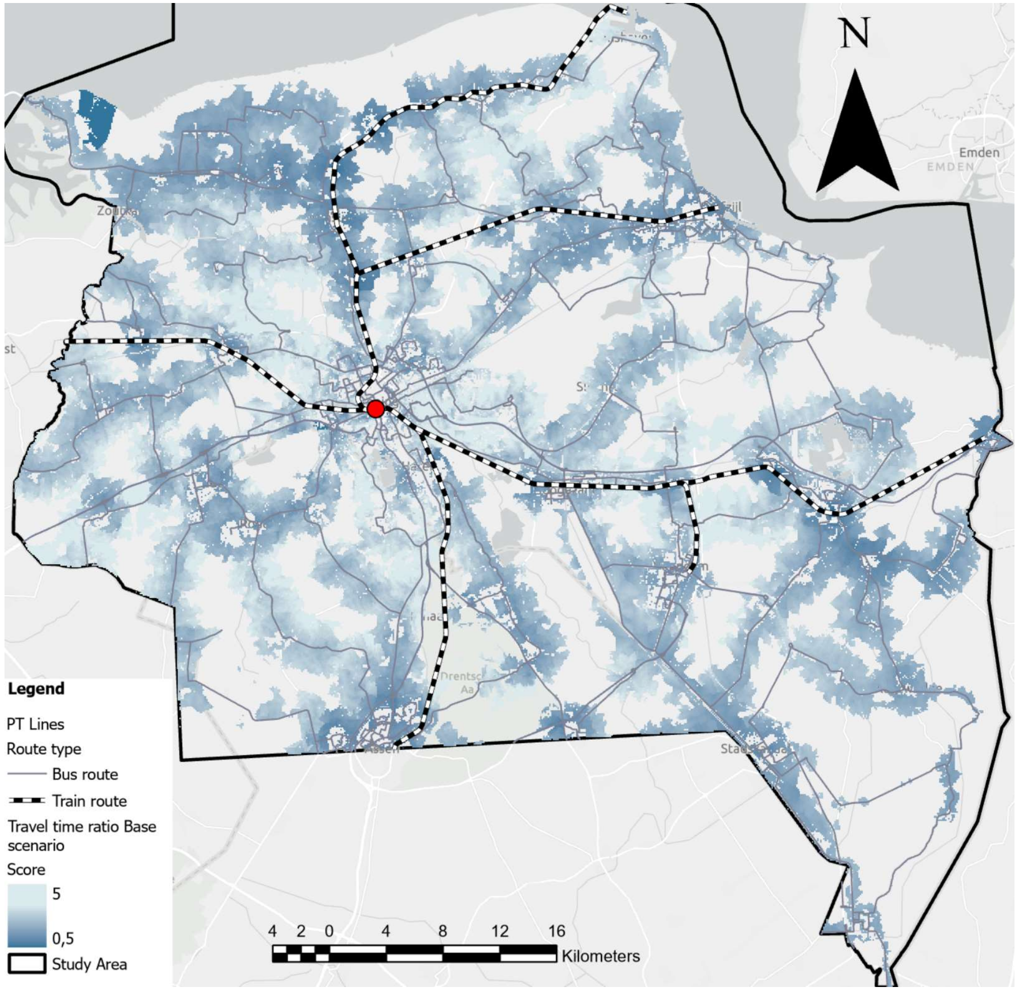


**Figure 24: Maximize connectivity objective base scenario. The end destination is highlighted with the red dot.**

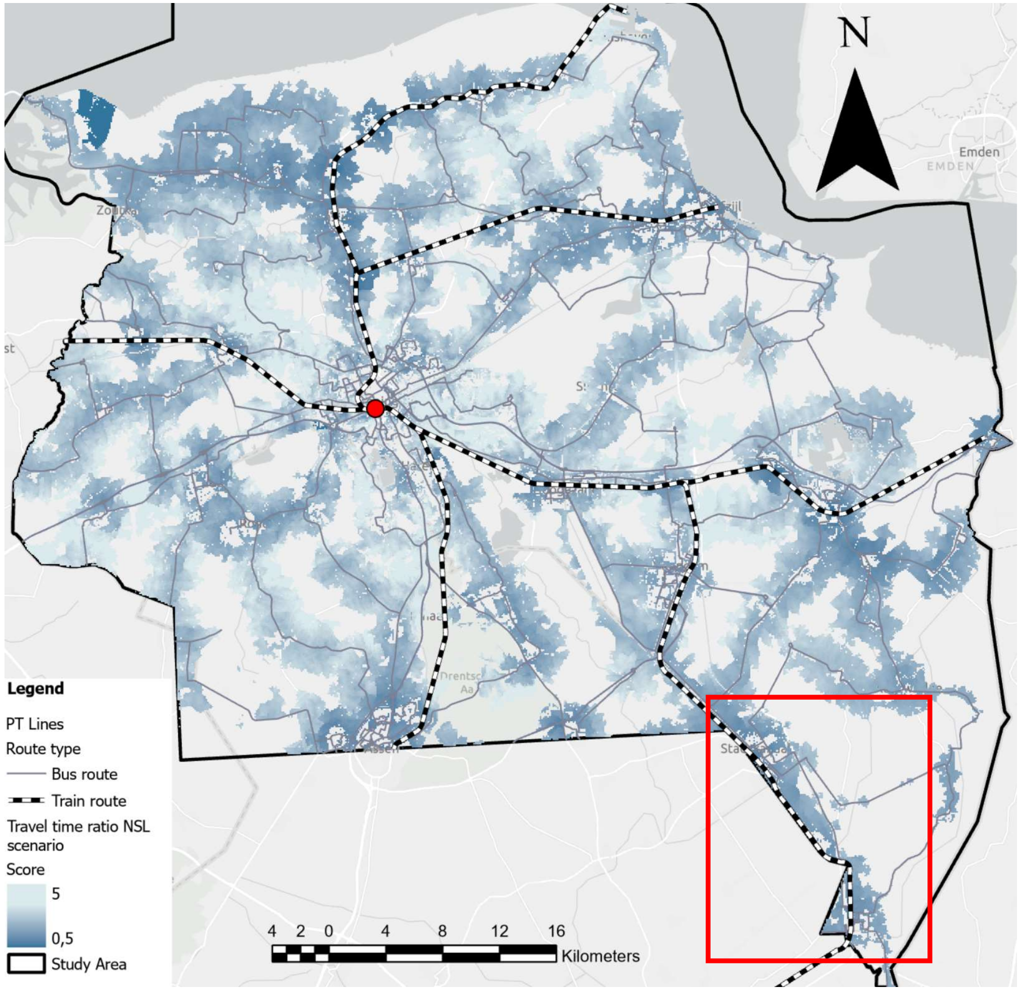


**Figure 25: Maximize connectivity NSL scenario. The end destination is highlighted with the red dot. The red box highlights the changes in connectivity induced by the new train line.**

The connectivity is highly dependent on the proximity of PT lines. Locations far away from a PT stop will inevitably have a high travel time ratio. This can be seen in both figure 24 and figure 25. They show the travel time ratio for the base scenario and NSL scenario respectively. Areas with a low travel time ratio are mostly located near the train lines and some bus lines. Some of these regions see a travel time ratio below 1.0, which indicates that taking PT to the center of Groningen is faster than the private car.

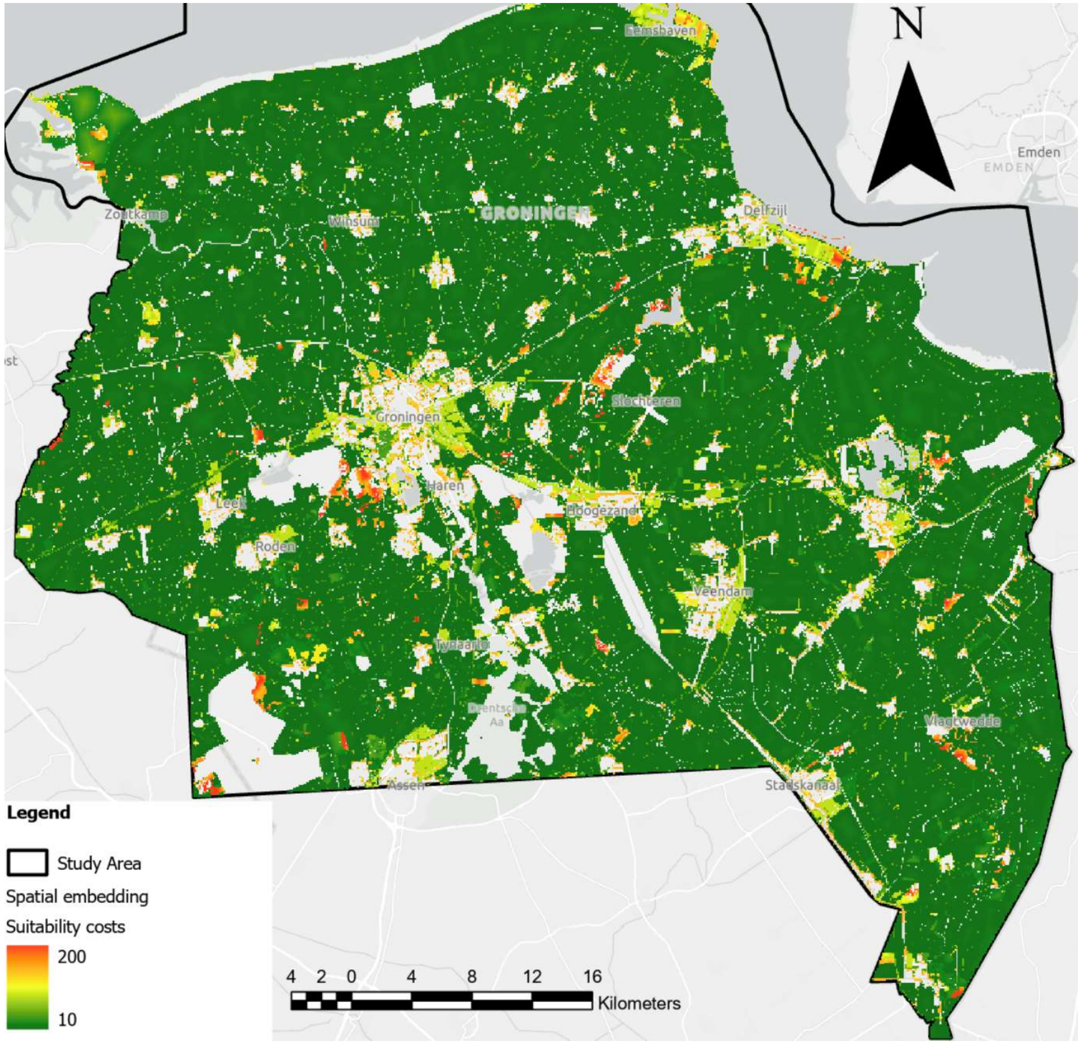


**Figure 26: Suitable spatial embedding objective (Base and NSL scenario).**

The objective of suitable spatial embedding is scored on suitability costs ranging from 10 to 200. As stated before, this layer consists of the various land use class suitability scores in combination with the distance to the nearest road. It results in the suitability costs layer as shown in figure 26. Regions with high suitability costs are indicated in red, these include for example recreational and educational areas. Low suitability costs are shown in green, which is the majority of the study area as it mostly consists of agricultural land or other natural areas. The access road construction cost is also contained within the spatial embedding. This is calculated using the distance to the nearest road. In some parts, a gradient can be seen in areas where the distance to the road network is considerably large. It shows that its impact on the suitable spatial embedding is relatively small.

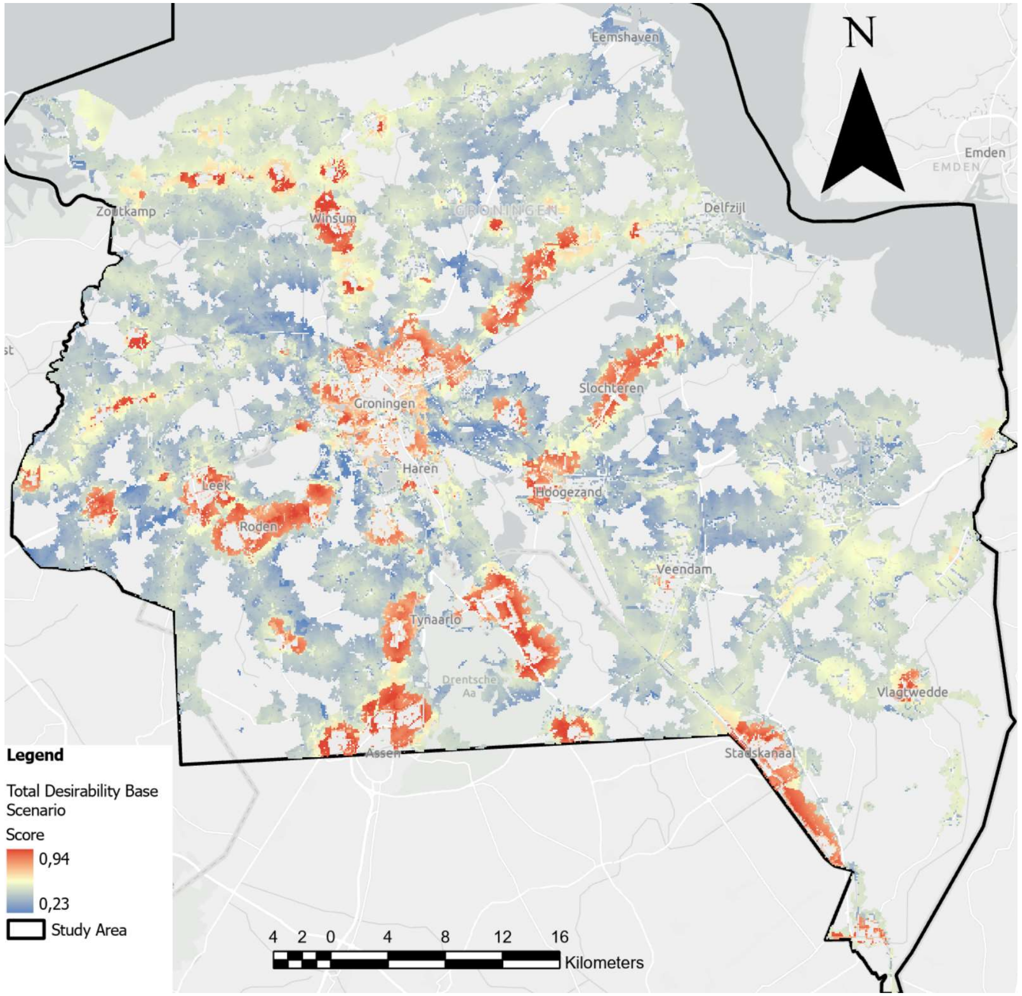


**Figure 27: Total desirability score base scenario**

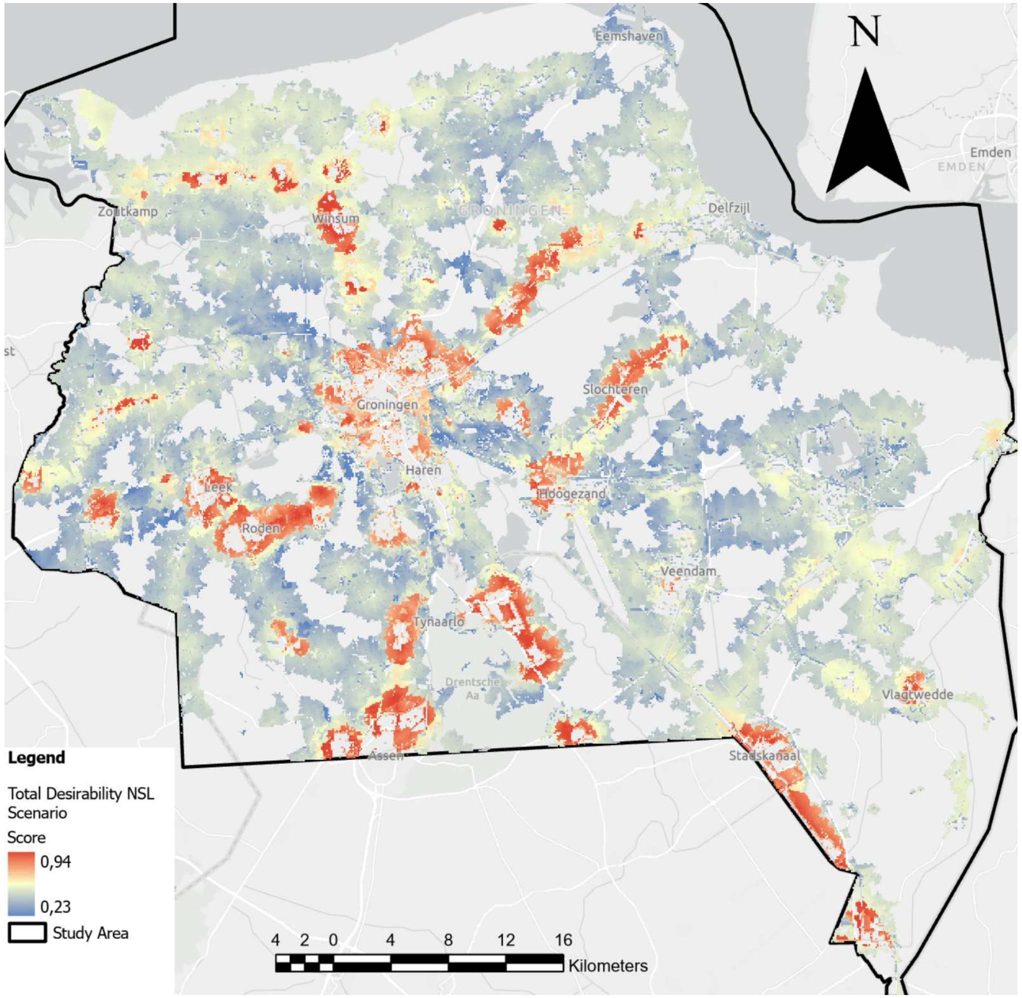


**Figure 28: Total desirability score NSL scenario**

The total desirability score for the base scenario and NSL scenario are shown in figures 27 and 28 respectively. The figures show that higher desirability occurs around the PT network present in the region. The NSL scenario sees some cells/locations with a higher total desirability score, expected to be caused by an increase in demand and connectivity. Low desirability scores are observed in more rural areas, where demand and connectivity are low. Similar to the input objectives of demand and connectivity, the areas with high total desirability largely follow the existing PT network.

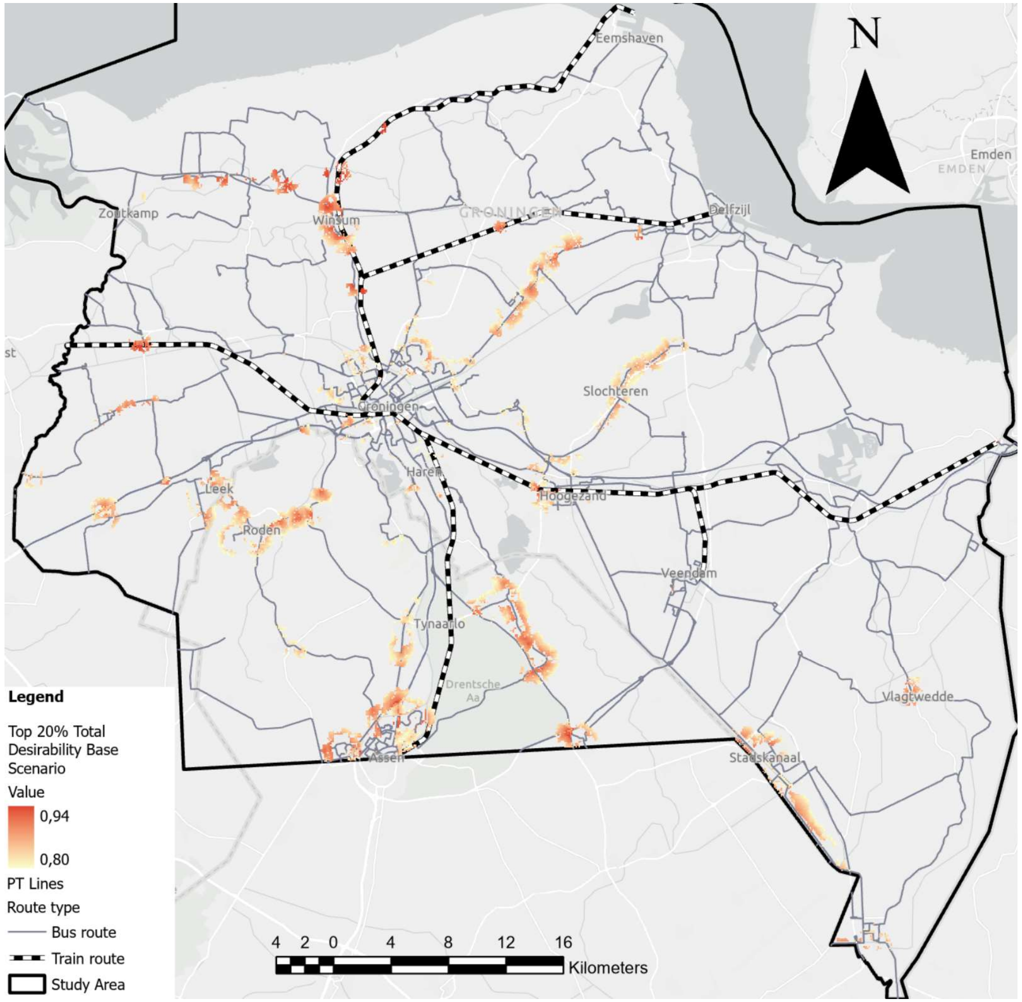


**Figure 29: Top 20% total desirability score base scenario**

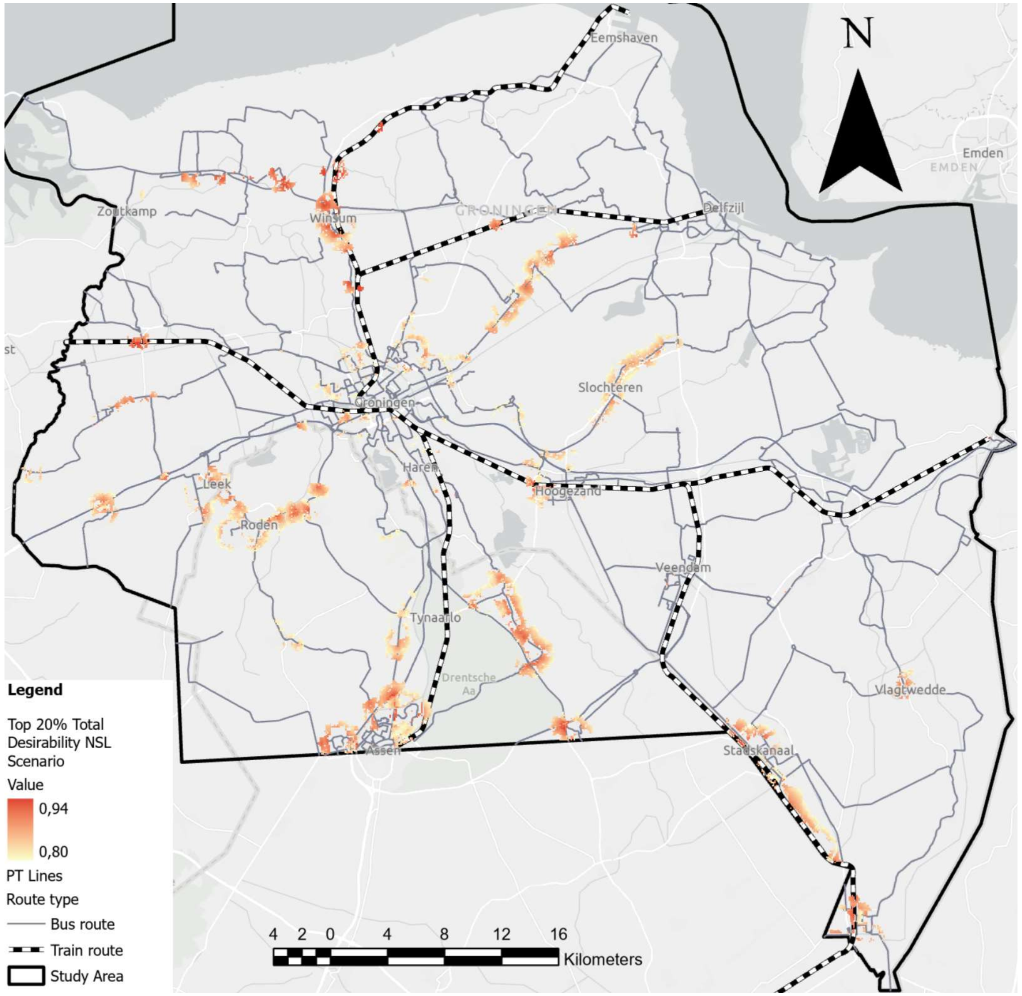


**Figure 30: Top 20% total desirability score NSL scenario**

To have a better look at areas with a high desirability score, figures 29 and 30 show only the top 20% of the total desirability score for the base scenario and NSL scenario respectively. The majority of the study area sees a low total desirability score, with some spots having a high total desirability score. These high desirability scores are located near PT lines, which makes sense as in these areas, the objective layers also score relatively high. Areas close to an already existing P&R facility do not show up as highly desirable as the distance to the nearest P&R facility is used as a predictor in the potential demand prediction.

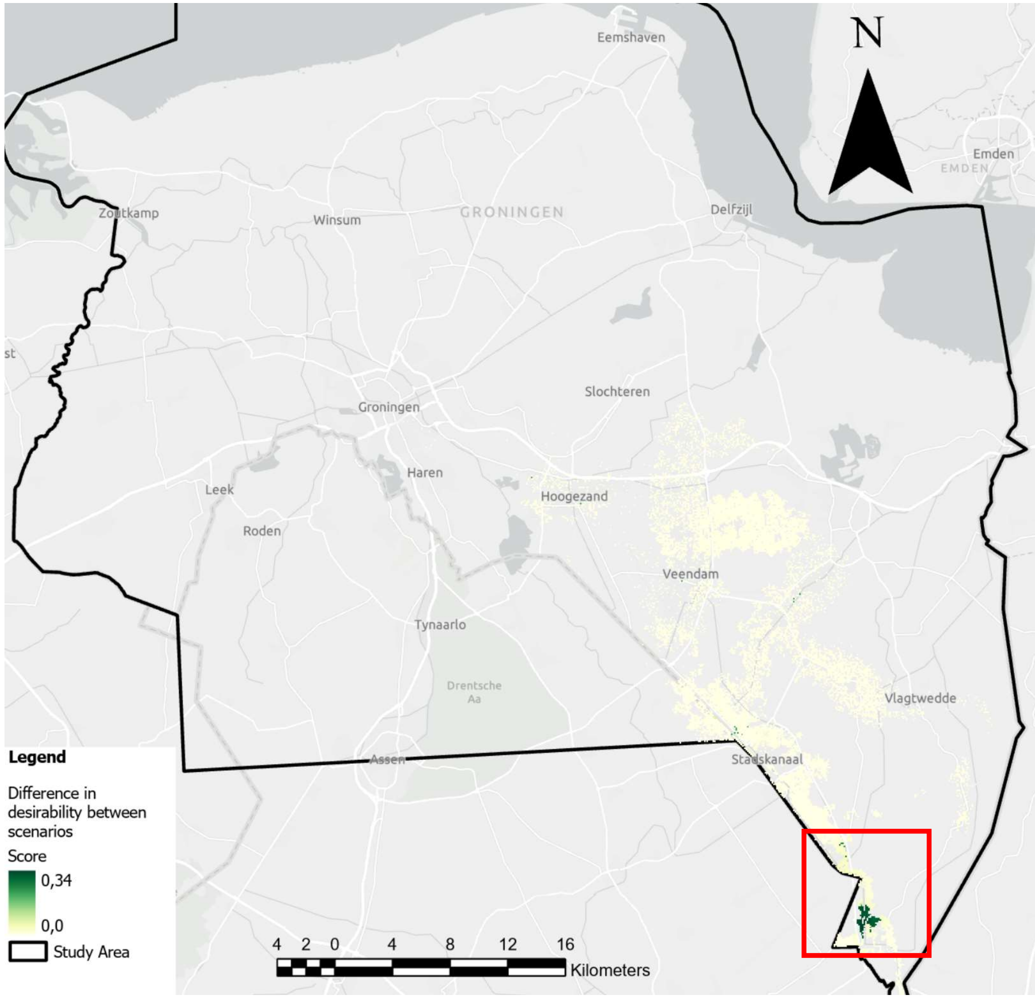


**Figure 31: Difference in desirability score between scenarios. The village of Ter Apel is highlighted in red.**

The difference in desirability between the two scenarios is shown in figure 31. The figure shows that for most of the study area, no difference is observed between the two scenarios. This makes sense as the PT network is only changed in the south east part of the study area. The figure also shows that the larger differences, up to 0.35, are all located in or around the village of Ter Apel which is highlighted in red. Other smaller increases in total desirability are present around the NSL, however, they lead to a low (close to 0) increase in total P&R desirability. The change is most prominent in Ter Apel and less in other areas as this is due to a high quality bus service that is already present in the area and is directly competing with the new rail line in this scenario. Realistically this bus line would be removed with the introduction of the NSL, likely yielding higher differences for other regions like Stadskanaal as well.

### *Validation of model results: zoomed-in locations P&R Gieten and proposed P&R Sauwerd*

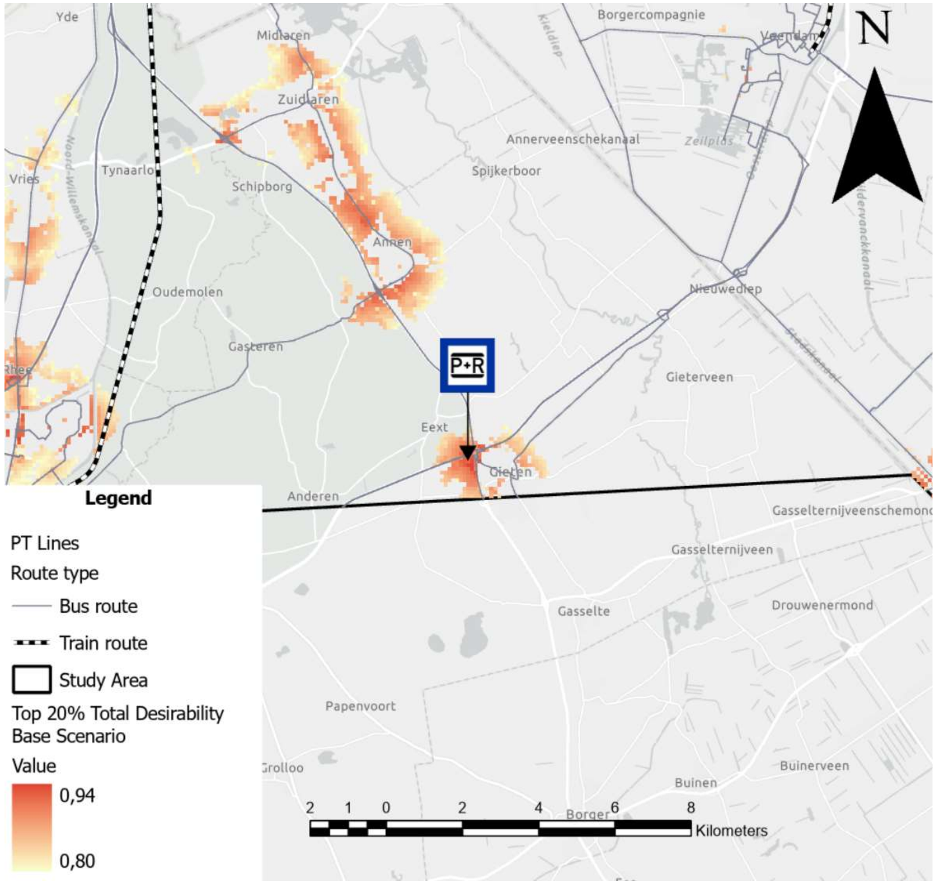


**Figure 32: Top 20% total desirability score in the base scenario, zoomed-in to the town of Gieten. The P&R facility of Gieten is indicated by the icon and is located at the tip of the arrow.**

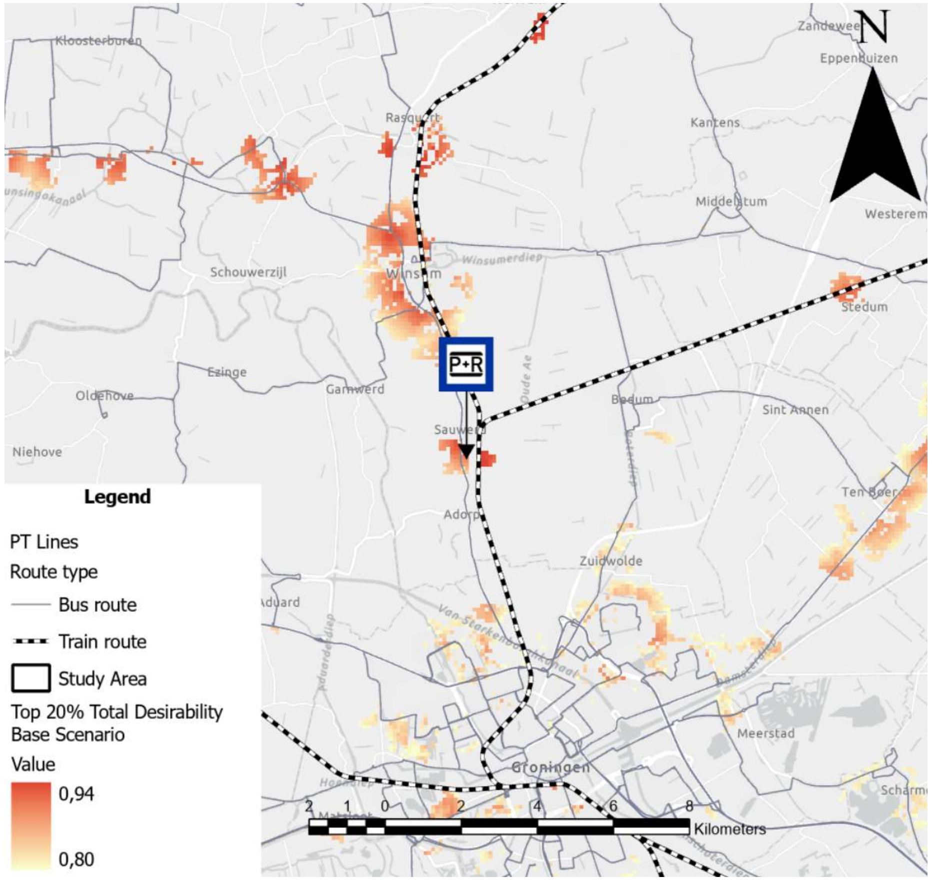


**Figure 33: Top 20% Total desirability score in the base scenario, zoomed-in to the area of Sauwerd. The proposed P&R facility is indicated by the icon and is located at the tip of the arrow.**

Zooming in on two locations within the study area allows for validation of the results, as follows.
A mistake in identifying the current P&R facilities within the study area gives the opportunity to visually check the power of the model. In figure 32 the desirability score in and around the town of Gieten is shown. A P&R facility is present here, at the point of the arrow in the figure, which was not included in the initial dataset. The spatial MCA performs well in predicting the desirability in this area, as it indicates high desirability for a P&R facility in this area.

Another location considered highly desirable for a P&R facility is near the train station of Sauwerd, north of the city of Groningen. The model predicts a high desirability close to the current railway station, as can be seen in figure 33. Movares has been involved in the development of a PT roadmap for the province of Groningen, in which they already advised on the realization of a P&R facility in the same location (Movares, 2025). This further confirms that the developed model is in line with expert judgments.

## *Total desirability output, given three input objective layers*

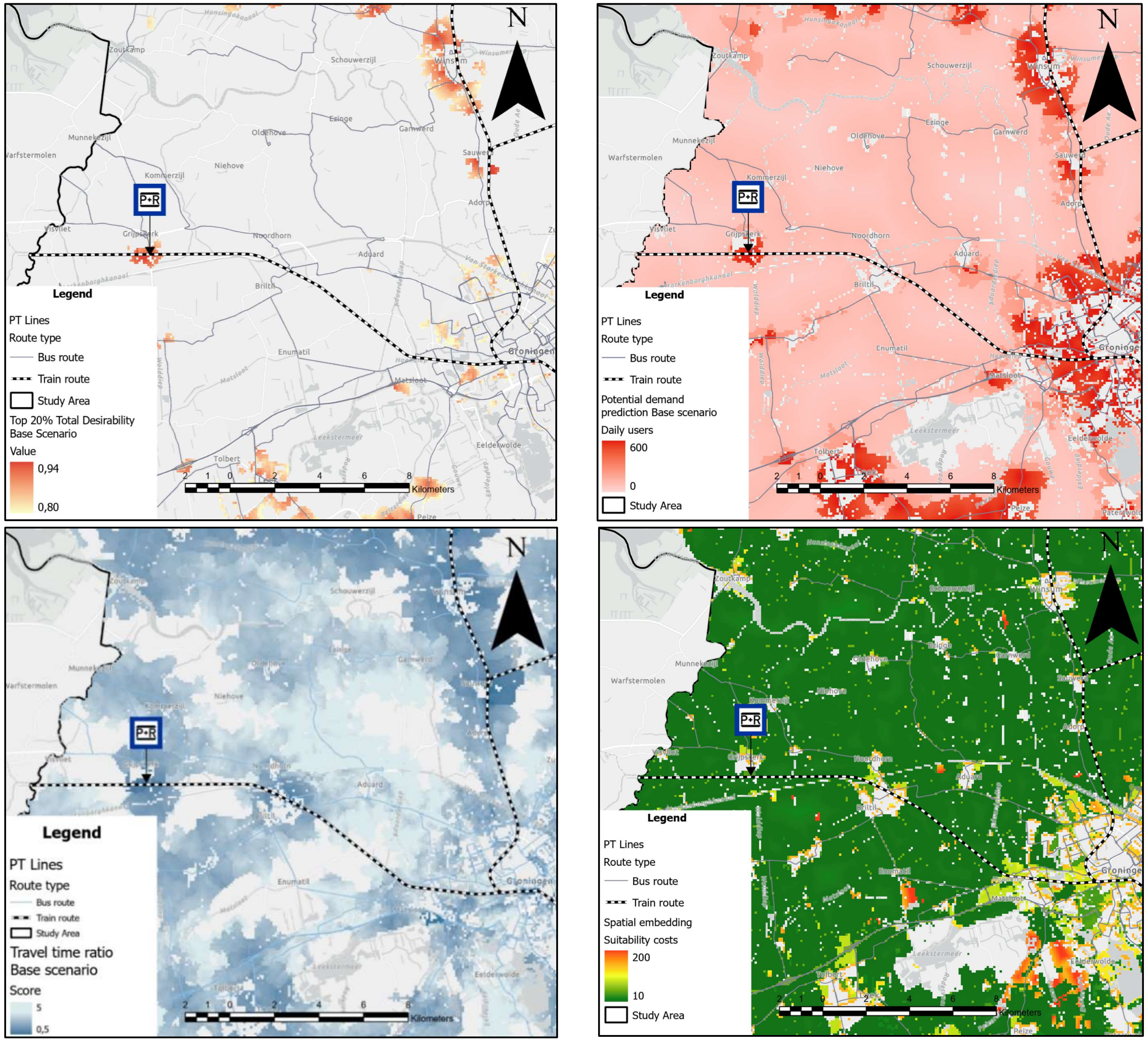


**Figure 34: Western region of study area in base scenario, showing the total desirability score (top left), maximize demand objective (top right), maximize connectivity objective (bottom right) and suitable spatial embedding objective (bottom right).**

To further validate the output of the model, it is necessary to compare it with the input and see whether the results make sense. Here, one example is chosen and assessed. Figure 34 shows the town of Grijpskerk and its surroundings. An area with high total desirability is found near the town of Grijpskerk. A possible P&R facility is located at the tip of the arrow.

The potential demand prediction for this location is high, roughly between 400 and 600 daily users. Looking at the input variables used for the prediction, this makes sense. The area is located near a train line with a station in Grijpskerk. The distance to the nearest other P&R facility is also relatively high. These two factors in combination with the number of reachable workplaces which is most likely quite high since the city of Groningen is close, the model predicts high daily demand.

The travel time ratio is low in this area, attaining a value of around 1.0. This is likely caused by the good train connection to the center of Groningen and the lack of highways in the area.

Lastly, the suitability costs are also low in the areas outside the town. These areas mostly consist of agricultural land, which has a low suitability cost. The distance to the nearest road connection is also small at this location, resulting in a lower suitability cost.

The combination of these three criteria layers has resulted in the total desirability score. Considering that all three layers score well in this area, a high total desirability is expected in the area. The model validates this.

### *Sensitivity check: stakeholder scenario comparison*

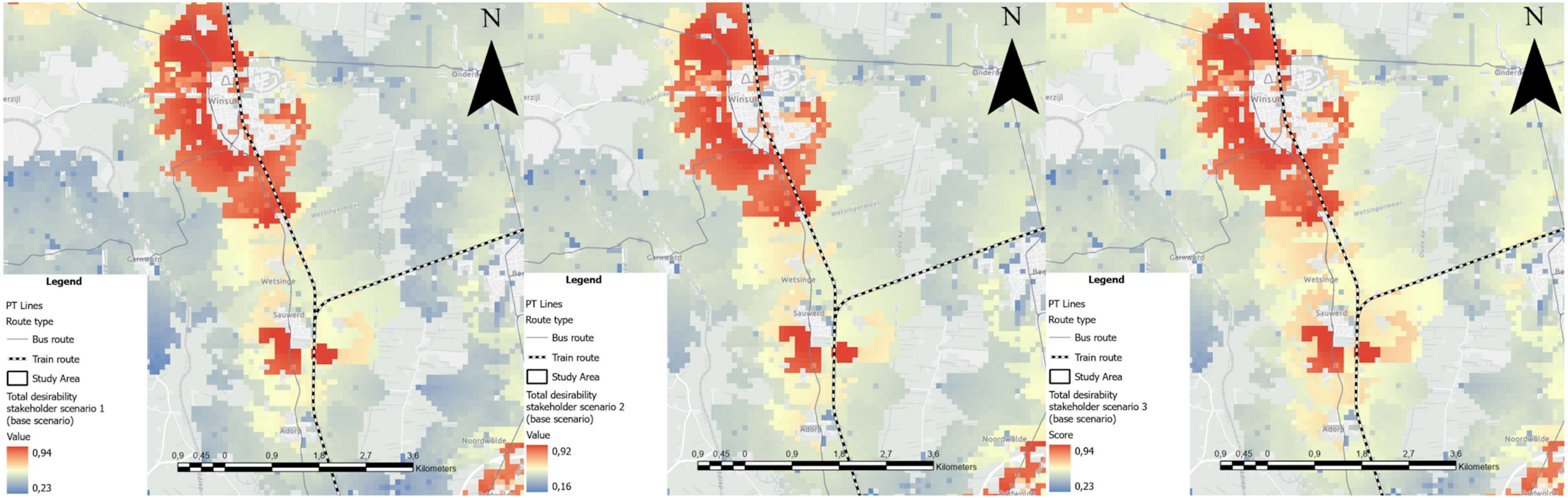


**Figure 35: Zoomed-in total desirability score for stakeholder scenario 1 (left), 2 (middle), and 3 (right) in the base scenario.**

Comparing the three stakeholder scenarios can give insight into the sensitivity of the desirability score, depending on what interest from what stakeholder group are considered. Figure 35 shows the total desirability score in the base scenario for each of the three stakeholder groups: the operator (1), users (2), and government (3). The desirability differs only slightly between the stakeholder groups, with the largest differences observed in areas with low or middle desirability scores. High desirability scores do not seem to differ between the stakeholder scenarios. These are expected results from the sensitivity analysis, which has also looked at the changes in total desirability subject to changes in the weights. It shows that the model results are not sensitive to the input weights. Most likely this is caused by the fact that the three objective layers complement each other in most locations.

## 5.7 Discussion

Several assumptions, simplifications, and constraints affect the model's development and resulting total desirability maps. Here these are discussed alongside the implications of the model application. The discussion is structured per modeling component, covering specific assumptions and limitations.

### *Input layers*

Starting with the input layers of the model, the potential demand model only predicts three out of the five bins, which is unexpected. The middle bins of 200-400 and 400-600 users per day do not occur. This might be due to the characteristics of the study area, which may only include regions with either low demand (0-100, 100-200) or very high demand (>600). Another possibility is that the calculated probability of the bins is too close together, causing predictions to overlap and yielding unexpected results. Additionally, for a small number of locations, the model predicts high demand (>600) in areas where this does not make immediate sense, such as rural areas. This issue is due to the model's nature, which considers only the five significant variables included. If an area is located far away from other P&R facilities, its demand prediction may be high, even if the area itself is not desirable in terms of PT connection. Lastly, the middle bins might have a considerable probability; however, they may be overshadowed by much higher probabilities of the lower and higher bins.

Since the model has only been applied to one study area at one scale, it is unclear whether it scales well across different sizes of study areas. The current application has used a grid size of 100m by 100m, yielding an area of 1 hectare per alternative. Increasing this size results in fewer alternatives and, therefore, faster computation times, though it might yield very different predictions. This change would likely require a remodeling in the base of the GIS model.

The availability of data, which also depends on the size of the study area, limits the input criteria used for the model. Data aggregation is easier for smaller areas. However, limited data availability results in an oversimplification of P&R desirability, meaning this model cannot be used as a standalone tool and must be combined with locally specific factors that depend on the stakeholders. Additionally, the model requires the data to be available for all alternatives within the study area.

The constraint layer, which consists of feasible and infeasible areas, lacks more nuanced constraints that could be applied in specific cases. For example, residential areas are deemed infeasible for constructing P&R facilities, but areas immediately adjacent to neighborhoods are also less preferred. The current implementation is therefore simplistic, and the use of a more complex three-stage constraint layer could yield more realistic P&R desirability calculations.

The attribute layers are subject to value functions that convert their values into objective scores. These value functions allow for a wide range of implementations. This is done in three different ways in the current model, as explained in section 5.2. The decision is made to simplify these value functions, as tuning these is a research topic in itself. This simplistic view on these value functions means the model is easier applicable, however some effects may not be captured. Non-linear relationships could therefore be examined, for example, between the potential demand and the inverse distance weighting used to scale this demand. Currently the weighting is linear, though other functions, such as accessibility curves (van Nes et al., 2018), are used in literature.

Similarly, the land-use suitability costs are determined by researcher judgment and are assigned on a scale of 10 to 100. The resulting suitable spatial embedding score should therefore be approached with a critical view. No relevant literature is available regarding the suitability of P&R facilities in different land-use areas, making this a potential topic for further research.

### *Weight function and sensitivity analysis*

Stakeholder scenarios are a proposed way to incorporate various stakeholder interests. Weight sets were determined by researcher judgment, though a more realistic view could be obtained by interviewing the various stakeholders and constructing well-representing stakeholder groups. The model allows for this, as the objective weights are model inputs that can be adjusted accordingly. What is noted from the sensitivity analysis is that the final desirability output is largely unaffected by the weights of the layers. It follows that all three layers largely coincide with each other, yielding this result. This is a weak point of this model. The addition of more criteria layers or more complex value functions may overcome this.

In addition to the stakeholder scenarios, the weight function linearly combines the three objective layers. However, this may result in biased total desirability scores, as the layers have different distributions of objective scores. While normalization is consistent, if the assumption of a linear relationship between the actual scores and normalized scores is incorrect, results may favor certain objectives. This bias is expected for the maximization of the demand objective, as high total desirability scores largely coincide with areas of high demand prediction.

### *Scenarios*

The introduction of the Nedersaksenlijn in the second scenario results in a slightly higher total desirability score in the areas along that train line, particularly in the southern parts of the study area. The effect of this train line's construction is influenced by the area's existing bus network, which is designed to take up the potential demand for this train line. These bus lines and other parts of the PT network would need adjustment to truly assess the effect of the Nedersaksenlijn on the total desirability score.

The current implementation of the NSL scenario is relatively simple. However, with minor alterations to the PT network, more complex scenarios could be developed. The model is flexible enough to handle different PT networks for the calculations.

### *Results*

The resulting total desirability scores range from low to high desirability, though no decision is made on what is the most desirable location. High desirability cells tend to be clustered together, which makes sense as the characteristics of the area are similar close together. However, this means that selecting the top five scoring cells alone is insufficient for determining the best location. Instead, results should be used as guidance towards potential locations and not for immediate decision-making.

Overall, the model demonstrates that combining the three objective layers yields total desirability scores. Additional objective layers could be added, which can diversify the results. Further collaboration with the provincial and municipal stakeholders could provide better insights into which factors are prioritized for regional PT planning.

The input criteria, value functions and weight sets used in the model represent a straightforward approach that may overlook certain aspects. However, their simplicity makes implementation and application relatively easy. This is important, as the goal of the model is to be used as a practical tool in P&R facility locating advice. An overly complex model would therefore be less desirable.

The combination of Python and ArcGIS for model development results in a less streamlined approach. Certain elements require computations in Python, whereas the majority of the modeling is carried out in the ArcGIS Pro ModelBuilder. This combination of code, manual work, and GIS modeling means the process is not entirely seamless.

## 5.8 Conclusion

This chapter proposed a framework that performs a multi-criteria analysis to find the overall desirability of new P&R facilities, by combining multiple factors that influence P&R desirability, as identified through the literature study. Creating spatial criteria layers, allowing for extensive value scoring and weighting to ultimately achieve an overall desirability heatmap for new P&R facilities within the case study area. The spatial MCA can thereby give an answer to the sixth and seventh research sub-question.

*How can the combined desirability of various criteria, including potential demand, for a P&R facility in a location be determined?*

The total desirability of a P&R facility can be computed by combining three objectives: maximizing potential demand, maximizing connectivity, and suitable spatial embedding. Each objective is linked to quantified spatial attributes and transformed via value functions into objective scores. These are combined using the weighted linear combination method that results in a heatmap of the total desirability scores for an entire case study area. The assessment of the resulting heatmap shows that this is a suitable method for finding the combined desirability for a P&R facility for each location within an entire study area.

*What is the desirability of new P&R facilities within a certain study area?*

The spatial MCA is applied to a case study in the region of Groningen. By applying the spatial MCA to a real-world area, the desirability of new P&R facilities within that study area can be estimated. The results show a clear distinction between high-desirability and low-desirability areas. The three objective layers tend to complement each other, meaning that for example high demand areas often also score high on connectivity or spatial embedding. This results in areas with very high desirability and areas with very low desirability.

Following from zoomed-in analyses, the model accurately estimates high desirability scores in areas that experts judged as highly desirable as well. The analysis of the weight sensitivity in combination with stakeholder scenarios shows that the model is robust in its estimation, however it also suggests that the effect of the three combined layers is low as they tend to complement each other. Overall, the model shows its potential for facilitating in the process of advising and planning for future P&R facility locations, however several aspects can still be improved.

The spatial MCA is modeled in a way that allows for user input at several steps in the analysis. Firstly, the method allows for the addition of multiple criteria layers. These can be specific to the study area or more general criteria. The scoring of the objectives is open to user input, determining what value functions are used to translate attribute values to objective scores. Lastly, the use of the weighted linear combination allows for the input of objective weights. The proposed implementation of stakeholder scenarios results in different weight sets. Other weight sets can be entered into the model.

# 6. Discussion of overall research approach

Since this research consists of two main parts, the potential demand model and spatial multi-criteria analysis (MCA), a discussion specific to these parts was given in their respective sections. This chapter contains an overall discussion, containing a comparison of the results of this research to that of other studies found in literature as well as a discussion regarding the dependence of the spatial MCA on the potential demand model. It also contains a discussion of the practical limitations of this approach and its results and how this can be handled appropriately in practice.

The prediction of the potential demand for a P&R facility has been researched in multiple cases using various methods. From using deterministic choice models (Wang et al., 2004) to simple linear regression (Zijlstra et al., 2015), these studies show that the findings from the research reported in this thesis agree with what was found earlier regarding influential factors like the travel time ratio and the frequency of connected public transport (PT). The model developed in this thesis achieves the implementation of many influential factors that were deemed difficult to include in mathematical models (Faghri et al., 2002).

The second part of this research has previously been attempted in a similar way by Pitale et al.(2022), in which they used a spatial MCA including weight determination with the analytic hierarchy process (AHP) to find desirable locations of new P&R facilities. They applied their framework to a highly urban area with objectives that differ from the ones used in the research presented in this thesis. However, their conclusions line up with the findings of this research: the flexibility of the model to take multiple different input criteria, value functions, and weight sets. Additionally, the addition of more stakeholder interests into the weight set determination would strengthen the model and therefore the decision-making capabilities using the model. Aquilué Junyent et al. (2024) have found that the data requirements are a limiting factor in the applicability of the decision support tool. This is also found in the results of this research. While the application to the case study was straightforward, applying this to a new case study area could pose the same data requirement challenges. They also highlight that previous research pre-selects specific locations to be scored, whereas their method evaluates an entire area. This approach is also one of the key advantages of the framework applied in this research.

However, merely finding the desirability of a P&R facility does not directly mean a P&R facility will function well in that location. Besides the factors included in both the explanatory model and the spatial MCA, many more factors influence demand and desirability, which could not be included in the models. Therefore, the results of this study should be combined with information regarding these additional factors when deciding on new P&R facility locations. Such factors include personal characteristics, such as car ownership, age, and gender, as well as social safety, parking costs at the facilities, the parking policies and car accessibility of the end destination (Bos, 2004).

Bos (2004) also found that the communication and advertising of a P&R facility is essential for a well-functioning P&R facility. This includes signs on major roads indicating the availability of parking as well as general communication on time and cost savings when using the P&R facility. To extend this, a connection can be made with a common trend in PT planning and practice: mobility as a service (MaaS). MaaS offers an online platform for a multitude of activities, like reserving a parking spot or paying in advance for your tickets (Maas, 2022). By integrating the P&R facilities into such platforms, the barrier to using these facilities might be significantly lowered.

The way in which this research has been set up results in a dependence of the spatial MCA on the explanatory model. The regression analysis offers valuable findings related to the significance of variables that explain P&R demand. The spatial MCA uses these findings, adding value to this research by finding the overall desirability of a new P&R facility. However, without the regression analysis, the value of the spatial MCA may be limited, as it would solely rely on literature and expert judgment regarding the relevance of the objectives. The combination of these two methods adds considerable statistical value to the overall process of finding desirable P&R facility locations, a strong point of this research.

The combined models can give a desirability score for new P&R facilities within a study area. However, it is not flexible for policy interventions and their influence on the P&R desirability. Only effects that can be connected to one of the input factors can be assessed. An example of this can be a municipality that is interested in changing its parking policy in the city center and would like to understand how that would change the P&R desirability. The current approach does not allow for easy integration of these kinds of policies, mainly because the parking accessibility is not modeled. In this case, a more sophisticated optimization model may offer this ability.

# 7. Conclusions

To reiterate, this research presents a framework that combines two commonly used analysis methods, regression analysis and multi-criteria analysis (MCA), to combine multiple factors that influence park and ride (P&R) facility demand and desirability into one overall desirability score. The method is applied spatially, in which a geographical study area is split up into grid cells leading to all possible locations being assessed simultaneously.

The regression analysis gathers all factors that influence P&R demand and develops an explanatory model to use these factors to predict P&R demand. It assesses which variables are significant predictors, and to what extent they can accurately predict P&R demand.

An MCA is employed to combine the P&R demand with other factors that influence overall P&R desirability. The predictive model for P&R facility demand is entered as one of the criteria in the MCA, resulting in a dependence of the MCA model on the regression model. What follows from the MCA, is that the total desirability can be estimated by looking at the potential demand, the connectivity, and the suitable spatial embedding of a location.

The model is applied to the region of Groningen, which is looking to expand their P&R facility network and is therefore looking for desirable locations to place new P&R facilities. The model results show that specific locations show high desirability whereas other, at first sight also reasonable, locations do turn out to be less desirable. The application of the model demonstrates it agrees with expert judgment and is a powerful tool in estimating the P&R desirability. This highlights the model's potential for supporting decisions in planning for future P&R facilities.

The combination of a statistical model that predicts park-and-ride (P&R) facility demand and a spatial MCA that combines that demand with other criteria is the first of its kind and therefore offers a unique tool to support P&R facility locating advice by PT planners and decision-makers. Compared to mathematical optimization models (Aros-Vera et al., 2013; Henry et al., 2022; Holguí n-Veras et al., 2012), the approach taken in this research contains a statistical base for potential P&R demand predictions while combining it with other factors to estimate total desirability. This research puts forth a framework that is simpler in its application while remaining powerful in estimating the desirability of locations for new P&R facilities.

The employed framework addresses the knowledge gap identified in existing literature, which is twofold. Firstly, the assessment of factors that influence P&R demand is found to be incomplete, as there is a lack of studies assessing the significance of the position of a P&R facility within the road network on its facility demand. The regression analysis combines this factor with other factors and assesses their significance in predicting P&R facility demand, resulting in a complete assessment of a full set of factors. Secondly, a lack of models is identified that can estimate desirable P&R facility locations in real-world situations based on a limited set of criteria. The spatial MCA addresses this gap by finding the estimated overall desirability of a P&R facility within a study area based on the potential demand model in combination with the connectivity and the suitable spatial embedding. It demonstrates that the desirability can be accurately estimated based on this limited set of criteria, highlighting its practical applicability.

## 7.1 Answers to research questions

In this section, the research questions are presented and answered.

*What variables can be found in literature that influence potential P&R facility demand?*

Various factors determine the demand for P&R facilities. Key factors include the quality of the connected public transport (PT) in terms of frequency, mode, and capacity. Facility-specific characteristics such as occupancy rate and distance to the nearest other P&R facility play a significant role. The location of the facility within its surroundings is also considered of influence, which includes factors like accessibility of the P&R facility, nearby road congestion, the population that lives within the catchment area, and the distance to the end destination. Additionally, personal characteristics like car ownership, age, and personal preferences influence the P&R demand. Economic aspects, such as parking costs at the facility and the end destination also impact demand. Lastly, the accessibility of the end destination and the respective travel times with the private vehicle and public transport (PT) are determining factors. Overall, the identified factors were consistent throughout the various studies, though the number of factors considered and the scope of each study varied considerably.

*What other factors, besides potential demand, that can be found in literature, influence the desirability of a P&R facility?*

Besides the potential demand, literature identifies several other factors influencing the overall desirability of P&R facilities. Extending beyond demand, desirability also depends on spatial, economic, and environmental aspects. Spatial constraints, such as protected nature or open water bodies, determine whether a location is feasible or not. Economic aspects such as land value and operational costs are important determinants for desirability as the construction and exploitation have to be economically viable. Lastly, the environmental aspects are also important for the desirability of a P&R facility. Noise- and air pollution due to high traffic volumes to and from a P&R facility close to residential areas would negatively impact the desirability of that facility.

*What methods have been used to find desirable P&R facility locations or similar facility location problems?*

Various methods have been used to find desirable P&R facility locations. These range from complicated mathematical optimization models to straightforward multi-criteria analyses of a predetermined set of possible locations. GIS-based methods are powerful in evaluating spatial constraints and location-specific variables, allowing for quantitative and qualitative inputs. On the other hand, traffic assignment models are powerful in simulating many aspects, however, require complex mobility chain modeling, predefined facility locations, and origin-destination data. Besides these models, optimization models are often used. They range from simple deterministic models to complex mixed-integer linear programming. They focus on mathematical optimization, often balancing capacity, pricing, and network resilience. They are mostly focused on finding the theoretical optimum and are less applicable to real-world situations. Lastly, multi-criteria decision analyses (MCDA) are widely applied to weigh and compare various criteria. Various methods are commonly used, such as the best-worst method and analytic hierarchy process. Recent studies increasingly combine GIS with MCDA to combine the benefits of GIS, the spatial capabilities, with the weighting and scoring of MCDA methods.

*To what extent does the position within the road network influence the P&R facility demand?*

The explanatory model includes a set of variables out of which two were related to the position of a P&R facility within the road network. These two variables were implemented as:

1. The total driving time from a P&R facility to the nearest primary road, defined as roads with a speed limit equal to or higher than 100km/h.
2. The difference in the population that lives inside the catchment area of a P&R facility, which is defined as 15 minutes by car, with and without the primary road network.

Both variables were used in the development of the predictive demand model. The results of the model show that neither of the two variables is a significant predictor for P&R facility demand. This result goes against the hypothesis that a facility located further away from the primary road network would see a significantly higher demand.

*To what extent can an explanatory model estimate potential P&R facility demand?*

An explanatory demand model is developed that can estimate potential P&R facility demand, based on a set of independent variables. These independent variables are gathered from the literature study and entered into a regression model. Regression analysis comes in many different forms, of which two were used in this research. A multiple linear regression model is developed that can predict potential P&R facility demand on a continuous scale. This method however violates the assumption of normality, resulting in unreliable model performance. Therefore, an ordinal logistic regression (OLR) model is employed. This method predicts the P&R facility demand within specified ranges of demand (bins). This reduces the prediction accuracy but improves the overall model performance in predicting the correct range. This OLR model fulfills all its assumptions, resulting in a valid model. The OLR model is used in combination with the coefficients of the significant variables, and the thresholds that determine what bin to assign to a certain probability, to predict potential P&R demand. The performance of the OLR is determined by the pseudo-$R^2$, which ranges from 0.2 to 0.4, the accuracy of the predictions and the average bin error. The OLR model achieves a pseudo-$R^2$ of 0.31, an accuracy of around 54% and an average bin error of 0.5. This indicates that the model performs well in predicting potential demand.

*How can the combined desirability of various criteria, including potential demand, for a P&R facility in a location be determined?*

The combined desirability for a P&R facility in a location can be determined using a spatial MCA that combines three main objectives:

I. Maximize demand: the predictive model developed in chapter 4 is entered as an attribute in the spatial MCA. This potential demand model predicts the daily usage within prespecified bins, ranging from 0 to 600 users per day. This attribute is multiplied by the normalized distance to the nearest PT stop. This rescaled potential demand prediction is the objective score.
II. Maximize connectivity: the connectivity of a location is determined by the attribute travel time ratio, which is the ratio in travel time between PT and private vehicle to the destination or center of the study area.
III. Suitable spatial embedding: spatial embedding is the third objective, which is concerned with finding the suitability of a location for a P&R facility. It combines two attribute layers: the various land use types connected to a suitability cost, and distances to the nearest road to determine the overall suitability of the spatial embedding. A lower suitability cost means a higher overall desirability.

By employing appropriate value functions for each objective layer and using the weighted linear combination method, a final total desirability heatmap of the case study area is achieved. To conclude, the total desirability for a P&R facility is a linear combination of the demand objective, connectivity objective, and suitable spatial embedding objective.

*What is the desirability of new P&R facilities within a certain study area?*

The spatial MCA is applied to a case study in the region of Groningen. By applying the spatial MCA to a real-world area, the desirability of new P&R facilities within that study area can be estimated. The results show a clear distinction between high-desirability and low-desirability areas. The three objective layers tend to complement each other, meaning that for example high demand areas often also score high on connectivity or spatial embedding. This results in areas with very high desirability and areas with very low desirability.

Following from zoomed-in analyses, the model accurately estimates high desirability scores in areas that experts judged as highly desirable as well. The analysis of the weight sensitivity in combination with stakeholder scenarios shows that the model is robust in its estimation. The model demonstrates that the total desirability can be effectively estimated with the three objective layers and the constraint layer. Overall, the model shows its potential for facilitating in the process of advising and planning for future P&R facility locations.

The spatial MCA is modeled in a way that allows for user input at several steps in the analysis. Firstly, the method allows for the addition of multiple criteria layers. These can be specific to the study area or more general criteria. The scoring of the objectives is open to user input, determining what value functions are used to translate attribute values to objective scores. Lastly, the use of the weighted linear combination allows for the input of objective weights. The proposed implementation of stakeholder scenarios results in different weight sets. Other weight sets can be entered into the model.

## 7.2 Recommendations for practical use

Starting with practical recommendations for future users that aim to advise on future P&R facility locations, there are some important considerations to take into account. To begin, the determination of the weight sets should be done by involving various stakeholders and determining their interests and, with that, their objective weights. Stakeholder scenarios should then be developed that include several stakeholders. This should be used as weight sets in the spatial MCA. Additionally, by involving stakeholders in the application, other objectives can be defined, which might be prioritized by the stakeholders.

It is not recommended to only employ the spatial model as a decision support tool, as the combination with the demand model enables its powerful estimation of desirable P&R facility locations. Additionally, the user must be aware that the results from the model cannot be simply interpreted as the truth but rather should be used as an aid in combination with other parts of the decision-making. The tool can give initial guidance on what are desirable locations, but to decide what is the most desirable, other elements should be taken into consideration, such as the involvement of citizen participation, include demographic data from the region like car ownership, gender or age, and incorporating future development plans. To be able to assess policy changes related to transportation and mobility, it is advised to employ more sophisticated models.

Another important consideration for future decision-makers is that the current models are based on the Netherlands, which has a characteristic mobility network, and the results, therefore, are characteristic of this country. When applying this tool to another country, it is recommended to re-evaluate the importance of the various influencing factors for both the potential demand estimation as well as the overall desirability.

Finally, the model's current application focuses on evaluating grid cells measuring 1 hectare in size. The results show that at this scale, the model predictions are in line with expert judgments and current P&R facility desirability, as followed from the validation of the results in section 5.6. It is, however, unclear how the quality of the results changes with a change in the scale of the assessment. It is unsure whether a change in scale will result in realistic desirability scores. It is therefore unrecommended to change the scale of the analysis or to be cautious of unrealistic desirability scores when doing so.

## 7.3 Recommendations for future research

Even though the current combination of the two models offers a powerful way of determining the overall desirability of P&R facilities, several improvements have been identified that could increase its performance, usefulness, and generalizability.

The regression analysis has employed relatively straightforward models. These models are interpretable but do not ensure the best possible model performances. In recent years, machine learning methods have been used more and more often. Machine learning is shown to significantly improve model performance in certain situations (Bratsas et al., 2020). It is therefore recommended to attempt other machine learning methods in developing a better predictive model for potential P&R demand.

In the spatial MCA, multiple components are simplified to focus on the core of the method, however they are noted for future research. These include determining more realistic value functions describing the relationship between the attributes and objective layers. An example is the potential demand prediction, which in this model is converted into an objective by multiplying it by the distance to the nearest PT stop. This is taken as a linear function, however, further research can look into other functions that may be able to result in a more realistic implementation.
The linear weighted combination is used in this model to combine the objective layers into one overall desirability layer. Multiple other, more sophisticated, weight combination methods are available. A comparison should be made between these different weighting methods to determine their impact on the results and to see which one is most appropriate. Other methods include the analytic hierarchy process and the best-worst method.

Building on that, the current weights are determined by taking the average weights of three stakeholder scenarios. This is a simple approach, and more complex methods exist to include several stakeholder groups in the decision-making process. These methods are referred to as group decision-making methods (Malczewski & Rinner, 2015). Future research can investigate whether an implementation of these methods into the model can yield a better representation of stakeholder interests and group decision-making.

The current models are applied to one study area. The results show the power of predicting P&R desirability for that area. By expanding the analysis to multiple study areas, researchers can assess the robustness of these findings and further refine the framework for broader applications. Application in another geographic region, for example, another country, should assess whether similar results are found. The same applies when adjusting the case study's scale, either by zooming in or out and by increasing or decreasing the grid cell size.

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# Appendix A: Data sources

Table 19 lists the open data sources used for calculations for both the regression analysis and the spatial MCA.

**Table 19: Data sources used for the regression analysis**

| Data | | | | | |
|---|---|---|---|---|---|
| **Name** | **Description** | **Source** | **Shape** | **Used for** | **Retreived at** |
| P+R capaciteit Noord Holland.pdf | Table of 60 P+R stations in NH, Flevoland and Utrecht. Includes occupancy(%) | https://www.google.nl/url?sa=t&source= | pdf | Finding P&R usage numbers | 30-10-2024 |
| Rapportage P+R MRA.pdf | PDF with table including around 50 P+R facilities. It includes name, capacity and occupancy rate | https://www.google.nl/url?sa=t&source= | pdf | Finding P&R usage numbers | 30-10-2024 |
| All PT stops in NL | Dataset with all pt stop locations, operator, name and town | http://data.openov.nl/haltes/ | csv.gz | Unzip with python, use in QGIS as shp. Used for calulcations of frequency and mode | 5-11-2024 |
| All P&R facility locations | Datasets containing the coordinates of all 280 P&R locations in the Netherlands. This inculdes P&Rs near | https://www.anwb.nl/verkeer/routeplanner?displayType=map&expoints=rp_map | WebApp | Converted to csv file. Used for locating P&R facilities. | 5-11-2024 |
| All NS stations with usage numbers | This dataset includes the coordinates of all NS and mixed stations, the usage numbers for NS and the previous mode of travel, of which car driver is important as they will have used a P&R facility | Reizigersgedrag \| NS Dashboard | WebApp | Converted to csv file. JSON to CSV. Used for P&R usage numbers. | 1-11-2024 |
| CBS 100x100m raster data 2021 | This is a raster layer that comprises of 100x100m cells of the entire Netherlands. A cell is filled in, if the population is 5 or bigger. This data will be used to determine the amount of people in the P&R catchment area | https://www.cbs.nl/nl-nl/dossier/nederla | Geopackage | Determining amount of people within P&R catchment area | 1-11-2024 |
| CBS 500x500m raster data 2021 | This is a rastert layer that comprises of 500x500m ceels of the entire Netherlands. This dataset contains data on many different factors. | https://www.cbs.nl/nl-nl/dossier/nederla | Geopackage | Determining the level of urbanisation at a P&R facility | 1-11-2024 |
| Stationvoorzieningen 2014 | Station amenities in 2014 | http://data.openov.nl/ns/stationsvoorzieningen-2014-07.csv | csv | Criteria in MCDA; amenities at station | 6-11-2024 |
| All PT lines | Dataset with all PT lines in NL, this dataset includes mode, operator and frequency(weekday and weekend) | http://data.openov.nl/lijnnetkaart/20240402.zip | .shp | Mathcing mode and frequency with nearest P&R facility, ensuring highest quality is prioritized | 6-11-2024 |
| All roads in NL | Dataset including all primary, secondary and tertiary roads in the | https://service.pdok.nl/rws/nwbwegen/atom/nwb_wegen.xml | .gpkg | For calculating driving distance from each P&R to nearest highway | 14-11-2024 |
| GTFS NL | Improved GTFS | https://busmaps.com/en/netherlands/Ovapi/gtfs-nl | .zip | Easier calculation of mode and frequencies | 23-12-2024 |
| OSM kaart Nederland | Up to date map of the Netherlands | https://download.geofabrik.de/europe/netherlands.html | .osm.pbf | Create network without highways, used for analysis in Verbindingswijzer analysis tool | 10-1-2025 |
| Cultuurhistorische kaart | Dataset containing the location of national monuments. | https://service.pdok.nl/rce/ps-ch/atom/v1_0/ps-ch.xml | .gml | Creating the spatial constraint layer for national monuments | 10-3-2025 |
| Toekomstvisie Groningen Maart 2025 | Future development plan of the province of Groningen | https://www.provinciegroningen.nl/actueel/nieuws/nieuwsartikel/nieuwe-omgevingsvisie-dit-wordt-groningen/ | .pdf | Determine the future development plans of Groningen used in developing the NSL Scenario in the spatial-MCA | 10-3-2025 |
| Natura 2000 | Dataset containting geographic locations of Natura 2000 protected nature areas. | https://www.pdok.nl/introductie/-/article/natura2000-inspire-geharmoniseerd- | .gml | Computing the protected nature constraint in the spatial-MCA | 10-3-2025 |
| CBS Existing Land Use | Dataset containing the land use information of the whole of the Netherlands | https://www.pdok.nl/introductie/-/article/cbs-existing-landuse-inspire-geharmoniseerd- | .gml | Computing land use suitability costs in the spatial-MCA | 10-3-2025 |
| Top10NL Open water | Dataset containing open water bodies in the Netherlands | https://www.pdok.nl/introductie/-/article/basisregistratie-topografie-brt-topnl | .gpkg | Compute the open water bodies constraint layer for the spatial-MCA | 10-3-2025 |

# Appendix B: Calculations of independent variables and other preprocessing steps

Table 20 explains the calculation of the dependent and independent variables. This is a textual description of the calculations rather than formulas since for most calculations no simple formulas are used but rather a set of steps in Python or GIS software.

**Table 20: Variable calculation explanation**

| Influental Factor | Variable | Unit | Calculation |
|---|---|---|---|
| P&R users | P&R users | [#/day] | The P&R usage numbers consist of four different data sources. The major source is from the NS dashboard. Here traveller counts for each NS station are given for an average work day in 2019. The access travel mode is also given as a percentage. Multiplying the car access percentage with the traveller counts gives the daily P&R users for the station. The other datasets (MRDH, Provincie Noord-Holland and Groningen Bereikbaar) simply include the P&R facility and corresponding occupancy. |
| Connecting PT | Frequency | [#/day] | The frequency of the PT is calculated by translating GTFS.zip data folder by unpacking and reading the JSON format in python. The frequency for each line is given with the stop_ids. The routes are aggregated on stop id and then the frequency is summed over all routes that use the corresponding stop in a timespan of 2 hours, from 07:00 until 09:00. This time window is chosen as it calculates the frequency during morning rush hours, in which it is the busiest both in terms of frequencies and PT users. |
| | Mode | - | Similar to the frequency, the PT mode also follows from the GTFS.zip dataset. This is used for the modes BUS, TRAM, METRO and FERRY. For the train stations, the type of train station was manually entered. The station is either a sprinter station (SPR), where only sprinter trains stop, or an intercity (IC) station where both intercity and sprinter trains stop. |
| Neighboring P&R facilities | Distance to nearest other facility | [m] | There are two possible implementations for taking into account the neighboring P&R facilities. This first option calculates the euclidean distance to the nearest other P&R facility. This calculation is done in Python using Geopandas. |
| | Number of neighbors within 5km | [#] | A second option is calculating the amount of neighboring P&R facilities within a range of 5km. This calculation is also done in Python using Geopandas. |
| Level of urbanisation | Adress density at facility location | [#/km2] | The level of urbanisation is implemented in two possible ways. First, the adress density directly around the P&R facility can be used. This adress density is sourced from the CBS 500x500m dataset, which is a grid of 500x500m cells containing the adress density within that cell. |
| | Adress density around facility | [#] | The second possible implementation is the adress density around a certain area around the P&R facility. This area is between the range of 2.5 and 1.0km from the P&R facility. Each of the cells is summed, giving a total adress density. This could give better predictions as more of the catchment area density is captured in this way. This calculation is done in Python using Geopandas |
| Population in catchment area | Population within a 15min drive of a P&R facility | [#] | The population that can reach the P&R facility within 15 minutes by car. This calculation is done by using the Movares Verbindingswijzer network analysis tool in combination with the CBS 100x100m grid dataset containing population counts. |
| P&R Location within road network | Driving time to nearest highway | [min] | The location within the road network sees two possible implementations. First, the driving time is calculated to the nearest highway entrance/exit. This calculation is done using the Movares Verbindingswijzer tool that can use two datasets as input and calculates the shortest driving times from each point in input set 1 to the nearest point in input dataset 2. Set 1 is the P&R facility dataset, and set 2 is a dataset containing all primary roads in the Netherlands |
| | Difference in the amount of people within catchment area with and without highway network | [#] | The second possible implementation is to calculate the amount of people within the catchment area with and without the primary road network. This calculation can also be done using the Movares Verbindingswijzer tool. A bigger difference would suggest that the highway would have a lower impact on the user numbers of a P&R facility compared to a lower difference. |
| Reachable workplaces | Reachable workplaces within 60 minutes of travel with PT | [#] | This variable is fully calculated by the Movares Verbindingswijzer, calculating how many workplaces can be reached from each P&R facility within 60 minutes of travel with PT, based on the work locations and P&R facility locations. |

Besides the calculation of the independent variables, several other preprocessing steps have been done. These are listed below.

- Combining datasets: because of the various sources of P&R usage data, they are combined into one, and duplicates are removed from the dataset.
- Deleting wrong P&Rs: with the automatic process of creating the P&R dataset, some facilities are added that are actually no P&Rs. These are removed from the dataset. Additionally, in the calculations of the PT mode and frequency, sometimes a wrong mode is appended to the P&R facility. This requires manual adjustments.
- Verbindingswijzer network analysis tool: the network analysis tool requires specific data structures. This requires proper preparation of the datasets for use in the Verbindingswijzer. The tool also requires setting input parameters. A detailed explanation for this is given in appendix C.
- It is assumed that those that use the P&R facility, transfer on to PT to continue their journey. In reality, there will be people who use the facility as their final destination, however, this cannot be taken into account for this research as it is impossible to know what percentage of improper use occurs.

# Appendix C: Movares Verbindingswijzer analysis tool

The Movares Verbindingswijzer analysis tool is used to perform network calculations needed for the calculations of some variables. The tool requires a specific structure of the input tables as well as input parameters.

The input tables, for example, the P&R facility locations, have to have four columns, “id”, “count”, “lat” and “lon”. The first is the index column and the second is a value column, the last two are the coordinates. The value in the “count” column is arbitrary for the calculations done in this research. The output of the tool will be the same “id” and “count” with additional calculation results as column. Calculations done using the Verbindingswijzer include the population within the catchment area, both with and without the primary road network, the number of reachable workplaces, and the travel time ratio, used in the spatial MCA.

The model takes multiple input parameters, which are explained by way of an example. To calculate the amount of people living within the 15-minute catchment area of each P&R facility, the input parameters are relatively simple. When selecting driving as a transport mode, all other input parameters become irrelevant. The calculation layer is set to the CBS 100x100m dataset, which contains the amount of people living in each cell of this grid. The calculations use the pre-loaded Dutch road network. The 15-minute threshold is set in the regional analysis sub-tab. The calculations result in a dataset containing each P&R facility and the number of people reachable within 15 minutes. The interface of the tool is shown in figure 36.

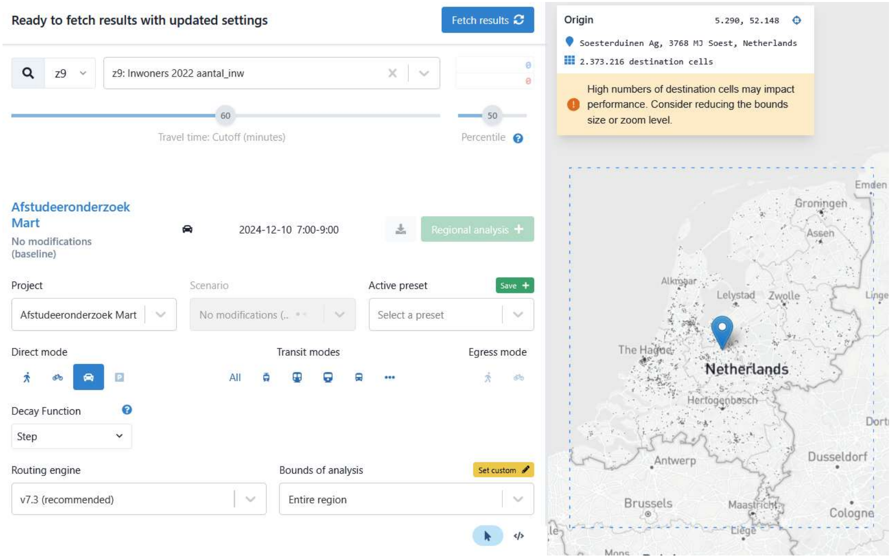


**Figure 36: Movares Verbindingswijzer parameter input**

For calculations using the PT network, various other parameters are required. This includes the start and end time, amount of transfers, walking speed, and maximum walking time. In the calculations for the independent variables using the transport network, for example for the number of reachable workplaces, the rush hours between 07:00 and 09:00 are used, 1 transfer, a walking speed of 5km/h, and a maximum walk time of 20 minutes are set. The date is set to the second Tuesday in December 2024. The access and egress modes are kept to the default, walking. The interface of the tool is shown in figure 37.

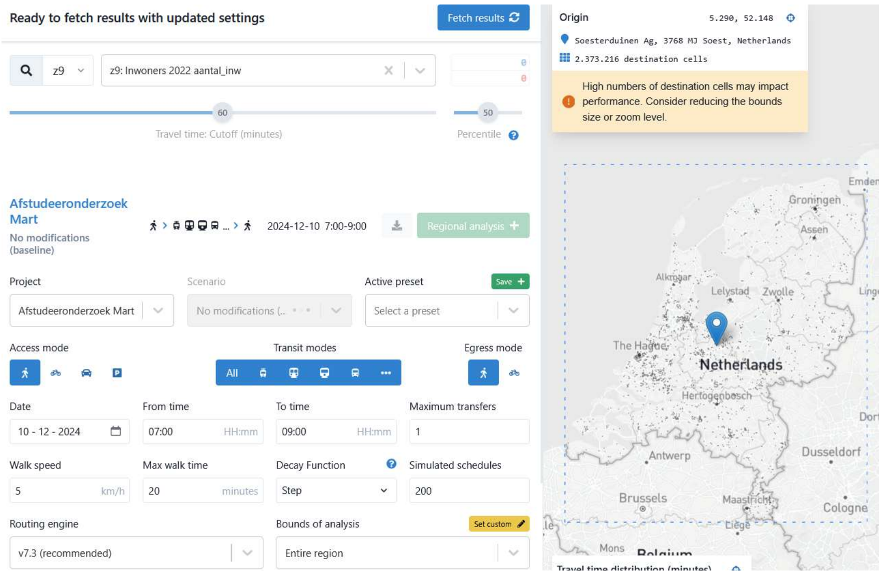


**Figure 37: Movares Verbindingswijzer parameter input**

The output of the analysis tool is a .csv file that contains for each origin ("id"), in this case, P&R facility, the corresponding value of the variable. This file is then imported into the Python notebook.

# Appendix D: Correlation matrix

The correlation matrix is given in figure 38.

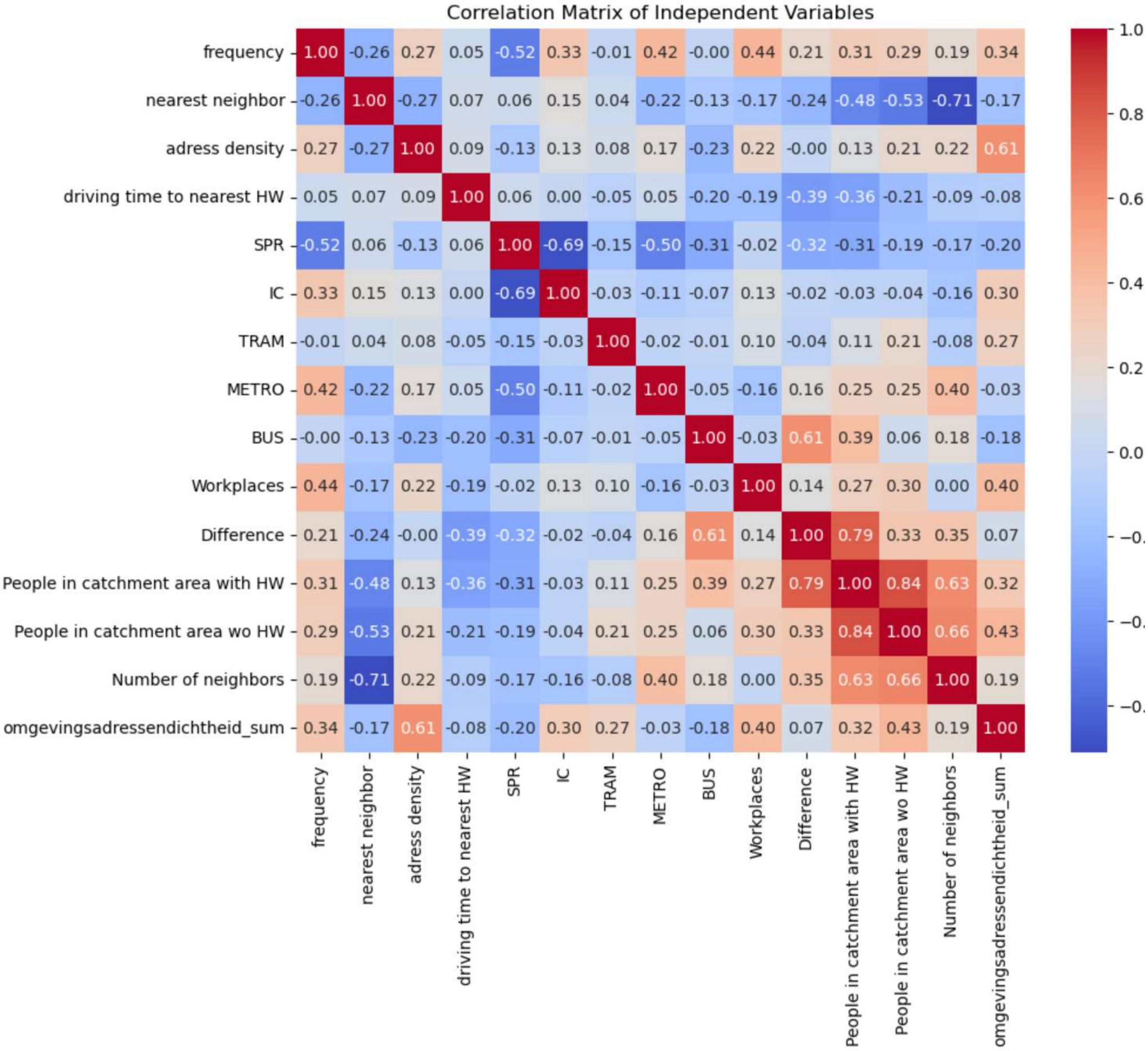


**Figure 38: Correlation matrix of the independent variables**

# Appendix E: Python script Simple Linear Regression

Figure 39 shows the python script for OLS. Figure 40 shows the python script for WLS.

## Multiple linear regression (OLS)

```
# Select variables from the satellite and rural facilities subset (df_Gro)
X = df_Gro[['frequency','nearest neighbor', 'Workplaces', 'surrounding adress density']].copy()
# Log transform selected columns
columns_to_log_transform = [col for col in X.columns if col not in ['IC','TRAM', 'SPR','BUS','METRO', 'adress density', 'driving time to nearest HW']]
X[columns_to_log_transform] = np.log1p(X[columns_to_log_transform])
# Store column names
feature_names = ['const'] + list(X.columns)

X = np.nan_to_num(X.values, nan=0.0, posinf=0.0, neginf=0.0) # Replace NaN values

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)  #Standardize the input variables.
X_scaled = sm.add_constant(X_scaled)
X_scaled = np.array(X_scaled)

y = np.log1p(df_Gro['P&R users']+1)
y = np.array(y)

stratify_labels = np.array(df_Gro['P&RType']) # Stratify on P&R type

cv_results = []
observed_values = []
all_residuals = []
f_statistics = []
coefficients = []
p_values = []

skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=12) # Set up 5-fold stratified cross-validation
for train_index, test_index in skf.split(X_scaled, stratify_labels):
    X_train, X_test = X_scaled[train_index], X_scaled[test_index]
    y_train, y_test = y[train_index], y[test_index]

    model = sm.OLS(y_train, X_train).fit()

    y_pred = model.predict(X_test)
    residuals = y_test - y_pred

    observed_values.extend(y_test)
    all_residuals.extend(residuals)

    condition_number = np.linalg.cond(X_train)
    rmse = np.sqrt(mean_squared_error(np.expm1(y_test), np.expm1(y_pred)))
    aic = model.aic
    f_statistic = model.fvalue
    f_statistics.append(f_statistic)
    r_squared = model.rsquared_adj

    coef = pd.Series(model.params, index=feature_names)
    pval = pd.Series(model.pvalues, index=feature_names)
    p_values.append(pval)
    coefficients.append(coef)

    variables_info = {}
    for var, coef, t_stat, p_val in zip(feature_names, model.params, model.tvalues, model.pvalues):
        variables_info[var] = {'Coefficient': coef, 't-statistic': t_stat, 'p-value': p_val}

    cv_results.append((r_squared, residuals, condition_number, rmse, aic, f_statistic, variables_info))

# Aggregate and display results
average_r_squared = np.mean([result[0] for result in cv_results])
average_condition_number = np.mean([result[2] for result in cv_results])
average_rmse = np.mean([result[3] for result in cv_results])
average_aic = np.mean([result[4] for result in cv_results])
average_f_statistic = np.mean(f_statistics)
# Calculate average coefficients and p-values
average_coefficients = pd.concat(coefficients, axis=1).mean(axis=1)
average_p_values = pd.concat(p_values, axis=1).mean(axis=1)
print(f"\nAverage adjusted-R-squared from 5-fold cross-validation: {average_r_squared:.3f}")
print(f"Average Condition Number from 5-fold cross-validation: {average_condition_number:.3f}")
print(f"Average RMSE from 5-fold cross-validation: {average_rmse:.3f}")
print(f"Average AIC from 5-fold cross-validation: {average_aic:.3f}")
print(f"Average F-statistic from 5-fold cross-validation: {average_f_statistic:.3f}")
print("\nAverage Coefficients:")
print(average_coefficients)
print("\nAverage P-values:")
print(average_p_values)
```

**Figure 39: Python script of the multiple linear regression (OLS)**

```python
X = df_Gro[['frequency', 'nearest neighbor', 'Workplaces', 'surrounding adress density']].copy() # Input variables
feature_names = ['const'] + list(X.columns)# Store column names

columns_to_log_transform = ['frequency', 'nearest neighbor', 'Workplaces', 'surrounding adress density'] # Logarithmic Transformation: Apply log transformation to columns
X[columns_to_log_transform] = np.log1p(X[columns_to_log_transform])
X = np.nan_to_num(X.values, nan=0.0, posinf=0.0, neginf=0.0)

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
X_scaled = sm.add_constant(X_scaled)
X_scaled = np.array(X_scaled)

y = np.log1p(df_Gro['P&R users'])
y = np.array(y)

stratify_labels = np.array(df_Gro['P&RType'])

# Initialize storage lists
adjusted_r_squared_values = []
rmse_values = []
aic_values = []
condition_numbers = []
significance_values = []
jarque_bera_values = []
f_statistics = []
all_residuals = []
coefficients_all = []
t_stats_all = []
p_values_all = []

# Set up 5-fold stratified cross-validation
skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=12)

# Run the stratified cross-validation with WLS
for fold, (train_index, test_index) in enumerate(skf.split(X_scaled, stratify_labels)):
    X_train, X_test = X_scaled[train_index], X_scaled[test_index]
    y_train, y_test = y[train_index], y[test_index]

    # Initial OLS model to get residuals for weighting
    initial_model = sm.OLS(y_train, X_train).fit()
    y_pred_initial = initial_model.predict(X_train)
    residuals = y_train - y_pred_initial
    abs_residuals = np.abs(residuals)
    abs_resid_model = sm.OLS(abs_residuals, X_train).fit()
    predicted_abs_resid = abs_resid_model.predict(X_train)
    predicted_abs_resid = np.maximum(predicted_abs_resid, 1.0e-6)

    # Weights are inverse of predicted squared residuals
    weights = 1 / (predicted_abs_resid**2)

    # Apply WLS with individual observation weights
    wls_model = sm.WLS(y_train, X_train, weights=weights).fit()
    y_pred_test = wls_model.predict(X_test)
    all_residuals.extend(y_test - y_pred_test)
    # Calculate adjusted R-squared manually for test data
    ss_total = np.sum((y_test - np.mean(y_test)) ** 2)
    ss_residual = np.sum((y_test - y_pred_test) ** 2)
    adjusted_r_squared = 1 - (1 - (1 - ss_residual / ss_total)) * (len(y_test) - 1) / (len(y_test) - X_test.shape[1] - 1)
    adjusted_r_squared_values.append(adjusted_r_squared)

    # RMSE calculation - converting back from log space
    rmse = np.sqrt(np.mean(((np.exp(y_test) - 1) - (np.exp(y_pred_test) - 1)) ** 2))
    rmse_values.append(rmse)

    # Store model statistics
    aic_values.append(wls_model.aic)
    condition_number = np.linalg.cond(X_train)
    condition_numbers.append(condition_number)
```

```python
    # Create Series with proper indices for parameters and p-values
    coef = pd.Series(wls_model.params, index=feature_names)
    pval = pd.Series(wls_model.pvalues, index=feature_names)
    tstat = pd.Series(wls_model.tvalues, index=feature_names)
    # Store statistics
    significance_values.append(pval)
    coefficients_all.append(coef)
    t_stats_all.append(tstat)
    p_values_all.append(pval)
    jb_test = sm.stats.jarque_bera(wls_model.resid)      # Test for normality of residuals
    jarque_bera_values.append(jb_test)
    f_statistics.append(wls_model.fvalue)
# Calculate average metrics
average_adjusted_r_squared = np.mean(adjusted_r_squared_values)
average_rmse = np.mean(rmse_values)
average_aic = np.mean(aic_values)
average_condition_number = np.mean(condition_numbers)
average_f_statistic = np.mean(f_statistics)
# Calculate average coefficients, t-statistics, and p-values
average_coefficients = pd.concat(coefficients_all, axis=1).mean(axis=1)
average_t_stats = pd.concat(t_stats_all, axis=1).mean(axis=1)
average_p_values = pd.concat(p_values_all, axis=1).mean(axis=1)
# Display results
print("\n===== Cross-Validation Results =====")
print(f"Average Adjusted R-squared across 5 folds: {average_adjusted_r_squared:.4f}")
print(f"Average RMSE across 5 folds: {average_rmse:.4f}")
print(f"Average AIC across 5 folds: {average_aic:.4f}")
print(f"Average Condition Number across 5 folds: {average_condition_number:.4f}")
print(f"Average F-statistic across 5 folds: {average_f_statistic:.4f}")
print(f"Average Jarque-Bera Test Statistic: {average_jb_statistic:.4f}")
print(f"Average Jarque-Bera Test P-value: {average_jb_pvalue:.4f}")
# Create a summary DataFrame
results_df = pd.DataFrame({
    'Coefficient': average_coefficients,
    't-statistic': average_t_stats,
    'P-value': average_p_values})
print("\n===== Variable Coefficients and Statistics =====")
print(results_df)
```

**Figure 40: Python script of the multiple linear regression (WLS)**

# Appendix F: Python script Ordinal Logistic Regression

The Python script of the ordinal logistic regression model is shown in figure 41.

```python
data = df_Gro # Select satellite and rural facilities subset (df_Gro)
y = data['P&R users']
y = y.dropna().astype(int)
bins = [-1, 100, 200, 400, 600, y.max()] # Manually specifying bins
labels = [0, 1, 2, 3, 4]
y_bins = pd.cut(y, bins=bins, labels=labels).astype(int)
y_bins_series = pd.Series(y_bins, index=y.index)

X = data[['Frequency', 'Adress density', 'Workplaces', 'Distance to nearest neighbor', 'Surrounding adress density']] # Selection of input variables
X = X.astype(int).clip(lower=0)
columns_to_log_transform = [col for col in X.columns if col not in ['IC', 'TRAM', 'BUS', 'METRO', 'Adress density', 'Driving time to nearest HW']] # Log transforming the appropriate input variables
X[columns_to_log_transform] = np.log1p(X[columns_to_log_transform])

X = X.loc[y_bins_series.index]

pseudo_r2_sum, accuracies, conf_matrices, coefficients, z_values, p_values, means_list, stds_list = ([] for _ in range(8))

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X) # Standardizing input variables
X_scaled = np.array(X_scaled)

y_bins_array = np.array(y_bins_series)
stratify_labels = np.array(data.loc[y_bins_series.index, 'P&RType']) # Stratified cross-validation on P&R type

skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=12) # Setting up 5-fold cross-validation
for train_index, test_index in skf.split(X_scaled, stratify_labels):
    X_train, X_test = X_scaled[train_index], X_scaled[test_index]
    y_train, y_test = y_bins_array[train_index], y_bins_array[test_index]

    # Corrected variable names
    means_list.append(scaler.mean_)
    stds_list.append(scaler.scale_)

    model = OrderedModel(y_train, X_train, distr='logit') # Training the OLR
    result = model.fit(method='newton', disp=False) # Fitting the OLR
    y_pred_prob = result.predict(X_test)
    y_pred = np.argmax(y_pred_prob, axis=1)
    residuals = y_test - y_pred

    # Calculate metrics
    ll_model = result.llf
    ll_null = result.llnull
    pseudo_r2 = 1 - (ll_model / ll_null)
    pseudo_r2_sum.append(pseudo_r2)
    accuracies.append(accuracy_score(y_test, y_pred))
    conf_matrices.append(confusion_matrix(y_test, y_pred, labels=labels))

    # Store coefficients, z-values, and p-values
    coefficients.append(result.params)
    z_values.append(result.tvalues)
    p_values.append(result.pvalues)

# Calculate mean values from stored lists
mean_values = np.mean(means_list, axis=0)
std_values = np.mean(stds_list, axis=0)

# Print the results with variable names
variable_names = X.columns
print("\nMeans for each variable:")
for name, mean in zip(variable_names, mean_values):
    print(f"{name}: {mean:.4f}")
print("\nStandard deviations for each variable:")
for name, std in zip(variable_names, std_values):
    print(f"{name}: {std:.4f}")

mean_accuracy, mean_pseudo_r2, mean_conf_matrix, mean_coefficients, mean_z_values, mean_p_values = (np.mean(accuracies),np.mean(pseudo_r2_sum),
    np.sum(conf_matrices, axis=0),np.mean(coefficients, axis=0),np.mean(z_values, axis=0),np.mean(p_values, axis=0))

# Print the results
print(f"Mean Accuracy: {mean_accuracy:.4f}")
print(f"Mean Pseudo-R2: {mean_pseudo_r2:.4f}")
print("Mean Confusion Matrix:")
print(mean_conf_matrix)
print("Average Coefficients:")
print(pd.Series(mean_coefficients))
print("Average Z-values:")
print(pd.Series(mean_z_values))
print("Average P-values:")
print(pd.Series(mean_p_values))
```

**Figure 41: Python script of the ordinal logistic regression**

# Appendix G: Regression model results

This appendix includes the model outputs of the regression analyses as well as the outputs of the assumptions checks and sensitivity checks.

```
[0.5248260345872096, 0.48960863647670283, 0.519695251479831, 0.4876538274522767, 0.49272667822463934]
[271.96923917917115, 288.62482952622616, 276.0397837491159, 290.84695747513626, 285.98909698868306]
[181.4368557645219, 177.8116269546054, 143.38454081227925, 148.0977553073533, 227.82574357186894]

Average adjusted-R-squared from 5-fold cross-validation: 0.503
Average Condition Number from 5-fold cross-validation: 1.963
Average RMSE from 5-fold cross-validation: 175.711
Average AIC from 5-fold cross-validation: 282.694
Average F-statistic from 5-fold cross-validation: 28.317

Average Coefficients:
const                        4.882491
frequency                    0.406479
nearest neighbor             0.638355
Workplaces                   0.327137
surrounding adress density   0.252918
dtype: float64

Average P-values:
const                        1.377270e-80
frequency                    9.942124e-05
nearest neighbor             6.059441e-11
Workplaces                   3.596255e-03
surrounding adress density   4.193615e-02
Jarque-Bera test statistic: 78.0489
Jarque-Bera test p-value: 0.0000
The residuals significantly deviate from a normal distribution (reject null hypothesis).
```

**Figure 42: Results multiple linear regression (OLS), including test for normality of residuals (Jarque-Bera)**

```
[0.26476880721982365, 0.3759645718632333, 0.21992316272804469, 0.3606276895667435, 0.3822791846088923]
[260.1565613946402, 274.0339561803363, 263.6833026524596, 269.75785894249157, 269.2155887648227]
[174.85786766218803, 186.98268798226084, 148.57204945133554, 151.62680221081834, 264.4905371489299]

===== Cross-Validation Results =====
Average Adjusted R-squared across 5 folds: 0.3207
Average RMSE across 5 folds: 185.3060
Average AIC across 5 folds: 267.3695
Average Condition Number across 5 folds: 1.9628
Average F-statistic across 5 folds: 33.9750
Average Jarque-Bera Test Statistic: 117.7237
Average Jarque-Bera Test P-value: 0.0000

===== Variable Coefficients and Statistics =====
                            Coefficient  t-statistic       P-value
const                          4.892249    58.977243  2.011271e-81
frequency                      0.318723     3.662490  2.014242e-03
nearest neighbor               0.631155     7.649163  5.872500e-11
Workplaces                     0.316730     3.647881  2.170174e-02
surrounding adress density     0.276672     3.372676  1.202546e-02
```

**Figure 43: Results multiple linear regression (WLS)**

```
Descriptive Statistics for Input Variables:
                   Variable      Mean  Standard Deviation
                  Frequency    3.7556              0.7513
             Adress density 1270.5515            701.5836
                 Workplaces   11.6356              0.7382
Distance to nearest neighbor    8.1847              0.7098
  Surrounding adress density   10.0063              0.7496

Regression Summary:
                   Variable  Coefficient  Z-value  P-value
                  Frequency       0.9135   3.7057   0.0006
             Adress density      -0.6621  -2.6047   0.0238
                 Workplaces       0.9688   3.6363   0.0014
Distance to nearest neighbor       1.7051   6.0299   0.0000
  Surrounding adress density       1.2558   4.1474   0.0006
                Threshold 1      -1.4217  -4.8443   0.0000
                Threshold 2       0.8266   5.1504   0.0000
                Threshold 3       0.8018   4.5486   0.0000
                Threshold 4       0.0001   0.0481   0.7207

Model Performance:
  Mean Accuracy    : 0.5370
  Mean Pseudo-R²   : 0.2937

Mean Confusion Matrix:
[[30 12  0  0  1]
 [ 9 21 10  0  0]
 [ 0 13 17  0  3]
 [ 0  1  8  0  0]
 [ 0  0  6  0  5]]
```

**Figure 44: Results ordinal logistic regression**

```
Brant Test Results:
                     Predictor          Chi2  p-value  Violates Assumption
0                    Frequency  1.267651e-01  0.988443                False
1               Adress density  2.479992e-08  1.000000                False
2                   Workplaces  1.619817e-02  0.999454                False
3  Distance to nearest neighbor  3.167836e-01  0.956842                False
4    Surrounding adress density  1.871947e-01  0.979630                False
```

**Figure 45: Results Brant-test to test the proportional odds assumption**

```
Summary of Moran's I Results:
                              Moran's I  P-value   Z-score  \
Frequency                     -0.007353    0.006 -3.081313
Distance to nearest neighbor  -0.007353    0.010  2.734280
Adress density                -0.007353    0.171  0.851448
Workplaces                    -0.007353    0.355  0.440304
Surrounding adress density    -0.007353    0.079 -1.165466

                              Standard Deviation  Significant Spatial Pattern  \
Frequency                           3.659383e-18                         True
Distance to nearest neighbor        4.441046e-18                         True
Adress density                      4.074761e-18                        False
Workplaces                          3.939831e-18                        False
Surrounding adress density          4.465313e-18                        False

                             Pattern Type
Frequency                       Dispersed
Distance to nearest neighbor    Dispersed
Adress density                     Random
Workplaces                         Random
Surrounding adress density         Random
```

**Figure 46: Results Moran's I test to test the independence of observations**

## Sensitivity analysis MLR

```
model = sm.OLS(df_Gro['P&R users'], sm.add_constant(df_Gro[['frequency', 'nearest neighbor', 'Workplaces',
                                                            'omgevingsadressendichtheid_mean']])).fit()
influence = model.get_influence()
cooks_d = influence.cooks_distance[0]
threshold = 4/len(df_Gro['P&R users'])
influential_points = [i for i, dist in enumerate(cooks_d) if dist > threshold]
print("Influential Points:", influential_points)
```

```
Influential Points: [6, 16, 20, 27, 33, 48, 51, 113, 117, 129, 133]
```

```
dfx = df_Gro.reset_index(drop=True)
observations = influential_points  # Column indices to drop
dfx = dfx.drop(index=observations)
```

**Figure 47: Cook's distance calculation for determining outliers**

```
Average adjusted-R-squared from 5-fold cross-validation: 0.491
Average Condition Number from 5-fold cross-validation: 1.889
Average RMSE from 5-fold cross-validation: 116.368
Average AIC from 5-fold cross-validation: 257.765
Average F-statistic from 5-fold cross-validation: 24.911

Average Coefficients:
const                       4.770714
frequency                   0.407071
nearest neighbor            0.664002
Workplaces                  0.312290
surrounding adress density  0.272821
dtype: float64

Average P-values:
const                       6.945891e-73
frequency                   1.231159e-04
nearest neighbor            2.587816e-10
Workplaces                  4.443824e-03
surrounding adress density  1.868136e-02
```

**Figure 48: Results OLS with outliers removed**

```
===== Cross-Validation Results =====
Average Adjusted R-squared across 5 folds: 0.2733
Average RMSE across 5 folds: 115.2545
Average AIC across 5 folds: 231.2174
Average Condition Number across 5 folds: 1.8895
Average F-statistic across 5 folds: 58.4145
Average Jarque-Bera Test Statistic: 117.7237
Average Jarque-Bera Test P-value: 0.0000

===== Variable Coefficients and Statistics =====
                            Coefficient  t-statistic       P-value
const                          4.796521    57.389448  1.235835e-74
frequency                      0.297081     3.687209  9.616504e-04
nearest neighbor               0.593924     7.771027  1.080741e-10
Workplaces                     0.301540     3.739428  4.998859e-04
surrounding adress density     0.291601     3.705467  5.213320e-04
```

**Figure 49: Results WLS with outliers removed**

```
Descriptive Statistics for Input Variables:
                    Variable      Mean  Standard Deviation
                   Frequency    3.7692              0.7581
              Adress density 1287.0882            707.3347
                  Workplaces   11.6718              0.7481
Distance to nearest neighbor    8.1714              0.7119
  Surrounding adress density   10.0348              0.7867

Regression Summary:
                    Variable  Coefficient  Z-value  P-value
                   Frequency       0.9076   4.0892   0.0000
              Adress density      -0.6183  -2.4923   0.0127
                  Workplaces       0.9148   3.4313   0.0006
Distance to nearest neighbor       1.3564   5.5262   0.0000
  Surrounding adress density       1.3346   4.6628   0.0000
                 Threshold 1      -2.4305  -6.8678   0.0000
                 Threshold 2       0.0691   0.2586   0.7960
                 Threshold 3       0.0018   0.0074   0.9941
                 Threshold 4       0.7292   4.3574   0.0000
                 Threshold 5       0.7890   3.6793   0.0002

Model Performance:
  Mean Accuracy    : 0.4412
  Mean Pseudo-R²   : 0.2490

Mean Confusion Matrix:
[[50  0  0 20  0  0]
 [30  0  0 10  0  0]
 [30  0  0 20  0  0]
 [ 0  0  0 70 30  0]
 [ 0  0  0 40 20  0]
 [ 0  0  0  0 10 10]]
```

**Figure 50: OLR model results subject to different bins**

# Appendix H: Sensitivity analysis spatial model

Figure 51 shows the code and results of the sensitivity analysis on the second-order effects using Sobol' Method.

```python
import numpy as np
import rasterio
from SALib.sample import saltelli
from SALib.analyze import sobol

layer_paths = [
    'TTR_sens.tif',
    'PotentialDemand_sens.tif',
    'Landuse_sens.tif'
]

# Load all raster layers directly
layers = []
for path in layer_paths:
    with rasterio.open(path) as src:
        data = src.read(1, masked=True).astype(np.float32)
        layers.append(data)
# Stack layers into a 3D array and create a mask for valid pixels
layers = np.stack(layers, axis=0)
valid_mask = ~np.isnan(layers).any(axis=0)
# Extract valid pixels
valid_pixels = layers[:, valid_mask].astype(np.float32)
# Define Sobol problem
problem = {
    'num_vars': len(layer_paths),
    'names': [f'{i+1}: {path}' for i, path in enumerate(layer_paths)],
    'bounds': [[0, 1]] * len(layer_paths)
}
# Generate samples using Saltelli method
N = 1000
param_values = saltelli.sample(problem, N=N, calc_second_order=True)
param_values = param_values / np.sum(param_values, axis=1, keepdims=True)

# Compute the model output for each set of weights
def model_output(weights, layers, valid_pixels):
    wlc_values = np.sum(valid_pixels * weights[:, np.newaxis], axis=0)
    return np.mean(wlc_values)
Y = np.array([
    model_output(w, layers, valid_pixels)
    for w in param_values
])
# Compute Sobol indices
Si = sobol.analyze(problem, Y, calc_second_order=True, print_to_console=False)
# Print second-order Sobol indices (S2)
S2 = Si['S2']
print("\nSecond-order Sobol indices (S2):")
for i in range(len(problem['names'])):
    for j in range(i + 1, len(problem['names'])):
        if not np.isnan(S2[i, j]):
            print(f"{problem['names'][i]} & {problem['names'][j]}: {S2[i, j]:.4f}")
```

```
Second-order Sobol indices (S2):
1: TTR_sens.tif & 2: PotentialDemand_sens.tif: 0.0089
1: TTR_sens.tif & 3: Landuse_sens.tif: 0.0022
2: PotentialDemand_sens.tif & 3: Landuse_sens.tif: 0.0414
```

**Figure 51: Python code execution of Sobol' Method and results**

# Appendix I: Technical documentation attribute calculations

The attribute calculations use a combination of Python, QGIS, and ArcGIS Pro ModelBuilder. An explanation is given for each attribute individually below.

## *Potential demand*

The potential demand attribute is calculated using both Python and ArcGIS ModelBuilder. It makes use of the ordinal logistic regression (OLR) model. This requires five input variables:

- Frequency of the closest PT line: the frequency is derived from GTFS datasets. From each cell of the study area, the closest PT stop is searched, using Geopandas. The corresponding PT frequency at that stop is then appended to the corresponding grid cell.
- Adress density at the P&R facility: the address density for each cell in the study area is found by clipping the cell with the CBS 500x500m dataset that contains address densities for 500x500m cells. This is a different aggregation level. This means that multiple grid cells will have the same address density. This calculation is also done in Python using Geopandas.
- Reachable workplaces within 60 minutes of PT travel: similar to the calculation for that of the current P&R facilities, this is calculated using the Movares Verbindingswijzer for each cell in the study area. The network analysis tool considers the distance to the nearest PT stop in its calculation. If it takes more than 20 minutes to reach a PT stop, the number of reachable workplaces is limited to those reachable within 20 minutes of walking.
- Distance to nearest other P&R facility: the current P&R facilities within the study area are used in this calculation. From each cell in the study area grid the distance to the nearest existing P&R facility is calculated using Python with Geopandas.
- Surrounding address density: the surrounding address density is calculated for each cell in the study area grid by first creating ring buffers of 2.5km – 1.0km for each cell. This is then clipped with the CBS 500x500m dataset, which is then summed over all the cells in the 2.5-1.0km ring buffer.

These five variables are all combined into one dataset containing all grid cells in the study area. This is then put into the OLR, which predicts the potential demand bin for each grid cell. This prediction is then saved as new .csv and imported into ArcGIS in which it is spatially joined with the study area grid, resulting in the final potential demand prediction as a spatial layer. The code for making the predictions is given in figure 52.

```python
complete = gdf_main[['frequency', 'Address density at facility', 'Workplaces', 'Distance to nearest neighbor', 'Surrounding address density']]
X_raw = complete.to_numpy()
def predict_bin_vectorized(X_raw, means, stds, betas, taus):
    # 1. Log transform (except address density)
    X_transformed = X_raw.copy()
    log_mask = [True, False, True, True, True]  # Mask for which columns to log transform
    X_transformed[:, log_mask] = np.log1p(X_raw[:, log_mask])

    # 2. Standardize
    X_standardized = (X_transformed - means) / stds # Standardize based on OLR model training data

    # 3. Calculate X*beta for all samples at once
    Xb = np.dot(X_standardized, betas)

    # 4. Calculate cumulative probabilities for all thresholds
    # Reshape Xb to allow broadcasting with taus
    Xb = Xb.reshape(-1, 1)
    logits = taus - Xb
    probs_cumulative = 1 / (1 + np.exp(-logits))

    # 5. Calculate category probabilities
    probs = np.zeros((len(X_raw), len(taus) + 1))
    probs[:, 0] = probs_cumulative[:, 0]
    probs[:, 1:-1] = np.diff(probs_cumulative, axis=1)
    probs[:, -1] = 1 - probs_cumulative[:, -1]
    # 6. Find the index of the bin with the highest probability for each sample
    predicted_bins = np.argmax(probs, axis=1)  # This gives the index of the highest probability for each sample

    return predicted_bins, probs

##### Input parameters from Ordinal Logistic Regression model:
means = np.array([3.7556, 1270.5515, 11.6356, 8.1847, 10.0063])
stds = np.array([0.7513, 701.5836, 0.7382, 0.7098, 0.7496])
betas = np.array([0.913468, -0.662096, 0.968836, 1.705097, 1.255827])
taus = np.array([-1.422, 0.8266, 0.8018, 0.0001])

predicted_bins, probs = predict_bin_vectorized(X_raw, means, stds, betas, taus)
complete['Predicted_Bin'] = predicted_bins
print(complete)
```

**Figure 52: Making predictions with the OLR model**

## *Travel time ratio*

The travel time ratio is calculated by dividing the travel time with PT to the center of the study area, in this case Groningen city, by the travel time by private car. These travel times are calculated using the Movares Verbindingswijzer. The division is done using Python, importing the .csv files from the Verbindingswijzer. The travel time ratio is then saved as .csv and imported in ArcGIS in which it is spatially joined with the study area grid, creating the travel time ratio as a spatial layer.

### *Suitable land use*

The suitable land use is fully calculated within ArcGIS. The land use dataset is found on pdok.nl and includes polygons of the entire study area for various land use classes. A lookup table is created based on these classes, used for assigning a suitability value to a qualitative land use class. The land use classes are then joined to the suitability cost field in the lookup table, using the ArcGIS ModelBuilder. An illustration of this is given in figure 53 which shows the calculation, alongside an explanation of the ModelBuilder. The new land use suitability cost layer is then used for further calculations.

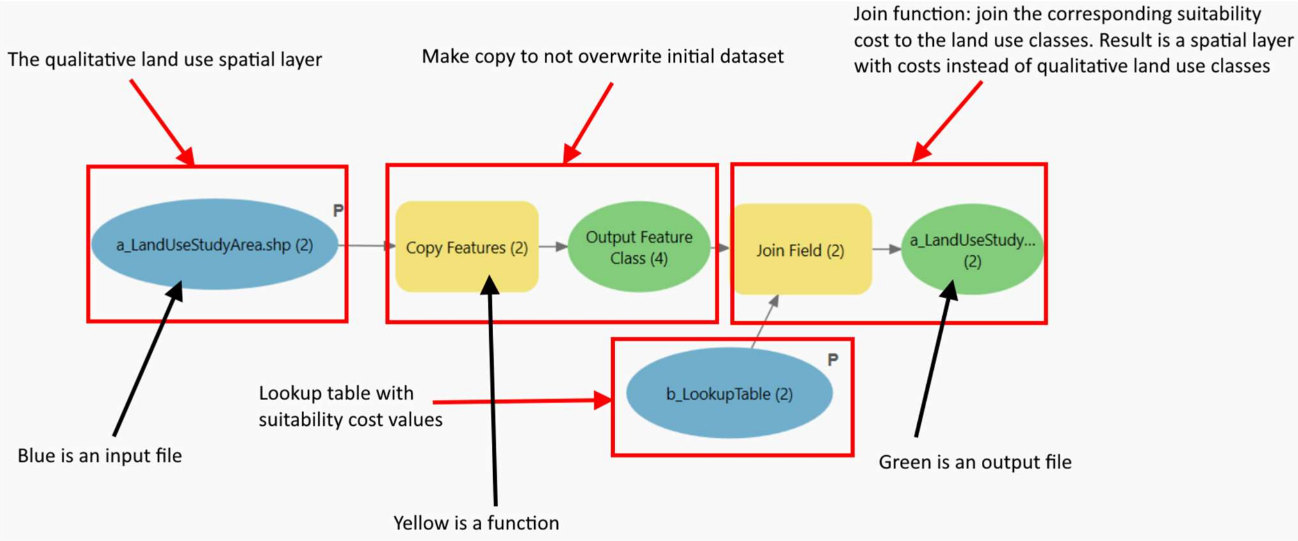


**Figure 53:ModelBuilder explanation and suitability cost calculation**

### *Distance to the nearest road*

The distance to the nearest road is calculated in the same way as the distance to the nearest current P&R facility. The calculation is done in Python using Geopandas and takes the cells of the study area grid as origins and the road network as polygons as destinations. It then finds the nearest road alongside the Euclidean distance to this road. This is saved as a table to be imported into ArcGIS.

The calculations for the potential demand prediction and the travel time ratio are done for both the base scenario and NSL scenario of the case study. The suitable land use and the distance to the nearest road do not change with the change in scenario. The result of these four attribute calculations is used in the layer scoring and weighting. This is explained in appendix J.

# Appendix J: Technical documentation of layer scoring and weighting

First, the attribute layers are scored, resulting in the objective layers. These objective layers are then weighted to estimate the final overall desirability score.

## *Objective layer scoring*

The process of layer scoring starts with importing the appropriate attribute layers, as shown in figure 54.

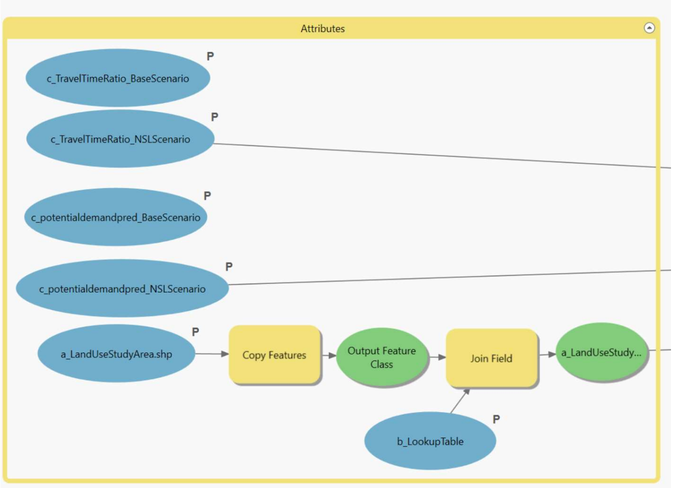


**Figure 54: Importing attribute layers in ModelBuilder**

All three attribute layers are subject to a specific value function. These are explained one by one below.

First the travel time ratio value function. For this attribute, the objective score is calculated by setting all values higher than 5.0 to 5.0, as higher values are unrealistic, and result from the characteristics of the calculation and not from the real-world situation. High travel time ratio values are observed very close to the end destination, where the network analysis tool struggles to compute realistic driving times as it rounds up to the minute. After the values are capped at 5.0, they are normalized, after which they are ready for layer weighting.

The potential demand model is subject to a value function that incorporates the distance to the nearest PT stop. The distance to the nearest PT stop is calculated using the grid cells and the PT stop dataset from GTFS. The distance is calculated in Python using Geopandas, of which the result is a table including all cells in the study area and the corresponding distances. The maximum distance is 5000m, if the distance is higher than 5000m, the cell is removed. The table is converted to a raster, after which it is rescaled to a range from 1 to 0, resulting in the inverse distance weight. It is then multiplied by the potential demand prediction. This process is shown in figure 55.

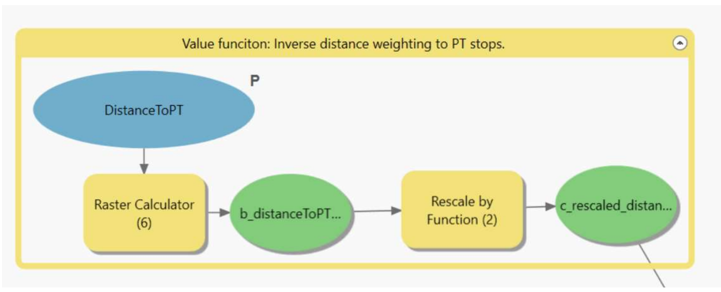


**Figure 55: Value function of potential demand prediction**

The final value function is simply the normalization of the combined values of the land use suitability cost attribute and the distance to the nearest road attribute. After the normalization, the combined attribute layer can be used in the layer weighting.

## *Objective layer weighting*

The weighting of the objective layers is done using the ArcGIS ModelBuilder, as shown in figure 56.

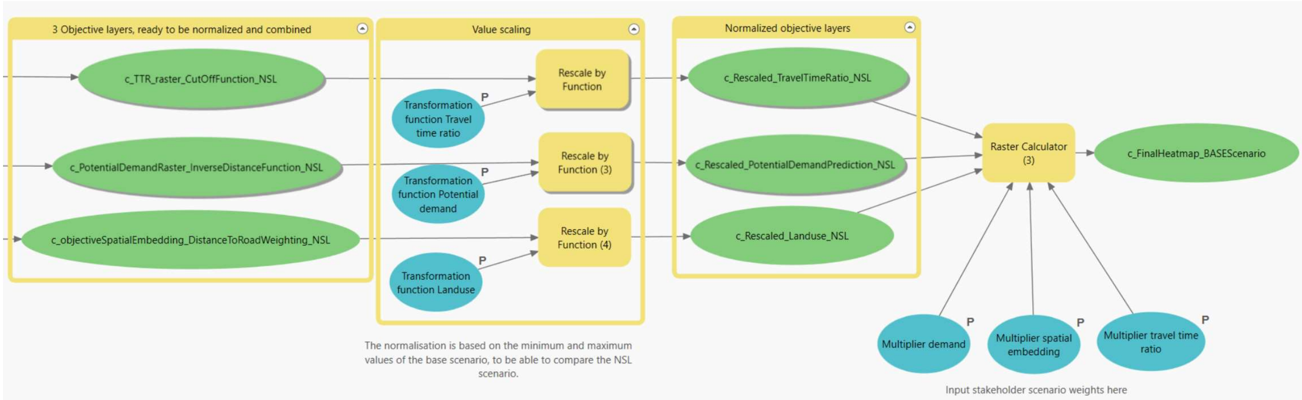


**Figure 56: Objective layer normalization and weighting**

First, the three normalized objective layers are positioned, they are normalized using a transformation function that is the same for both case study scenarios. They are then combined using the raster calculated in which each layer is multiplied by its respective layer weight. The output is one overall desirability score, calculated for each cell within the study area.