Utrecht University

Graduate School of Natural Sciences

Master Thesis

Optimizing Parking Fees for Park & Ride Facilities

Recalibrating parking fees to incentives short car trips to nearby park & ride stations

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Abstract

The rapid increase in motor vehicle ownership has resulted in significant challenges for city planners. The establishment of Park and Ride (P&R) facilities on the outskirts of cities has proven to be a viable option for alleviating inner-city congestion. However, main road arteries are still congested during rush hour by commuters trying to access these P&R stations. This study aims to extend the benefits of P&R facilities beyond the outskirts of cities by investigating the possibility of encouraging commuters to travel to P&R stations closer to their point of origin. By formulating an optimisation problem and utilizing a Multi-Nominal Logit (MNL) model alongside a Genetic Algorithm, P&R parking fees can be calibrated across the Netherlands with the goal of minimizing the total distance travelled by car. The findings suggest that adjustments to parking fees affect the utility of P&R stations to the commuter. However, the impact is so small that no significant change can be created in the commuter's P&R station choice, resulting in limited reduction of total driven distance. Future research should integrate dynamic demand models and explore additional factors to further promote earlier transfers onto the public transport network and mainly focus on incentivizing commuters who do not already utilize P&R stations as part of their journey.

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1 Introduction

In recent years, the surge in motor vehicle ownership has presented a multifaceted challenge for urban planning. Cities where never designed for this amount of traffic, resulting in daily congestions. However, expansion of existing road infrastructure is often hindered by various constraints such as urban density (Macioszek and Kurek, 2020). Moreover, counterintuitive as it may seem, expanding road capacity has been observed to exacerbate rather than alleviate congestion in numerous instances (Oucham & Gutiérrez Touriño, 2019).

Cities have sought alternative strategies to alleviate urban congestion and mitigate the adverse effects of increased vehicular activity. One such strategy involves the establishment of Park and Ride (P&R) facilities on the outskirts of cities near well connected public transport hubs to encourage people onto the public transport system (Alghazali et al., 2020). The inception of P&R facilities is part of a broader effort to enhance urban liveability by reducing harmful emissions and inner-city congestion. To encourage the use of public transport, cities began implementing measures to disincentivize inner-city car usage, such as imposing exorbitant parking fees (Ji et al., 2007).

It has become evident over the years that people are willing to park their car outside the city and transfer onto the public transport network for the final stretch of their journey. A combination of good parking infrastructure combined with raising inner-city parking charges has made the P&R facility a more viable option for some commuters (Zheng and Geroliminis, 2016). While this has resulted in a reduction of low-density vehicles traveling into the metropolitan area, most of these commuters still travel by car toward the outskirts of the city, often resulting in congestion on main road arteries during rush hour. This raising the question of how commuters can be incentivized to limit their car journey to the nearest station with P&R facilities.

This research aims to extend the benefits of P&R facilities beyond the outskirts of cities by investigating the possibility of financially incentivizing commuters to travel less by car. By calibrating the P&R parking fee for all P&R facilities near train stations in the Netherlands, commuters can be incentivized to travel towards a P&R station closer to their origin. Spreading car trips over a wider road network and limiting the rush hour bottlenecks. Based on this aim, the primary research question emerges as follows:

"What are the optimal prices for Park and Ride facilities in the Netherlands to minimize the total distance travelled by car?"

2 Background

The significant increase in motor vehicle ownership in combination with population and job growth in metropolitan areas has presented a multifaceted challenge for urban planners for decades. Oucham and Gutiérrez Touriño (2019) describe three different fields of measures intended to tackle car congestion. Policy is the first field of measures and can be subdivided into hard and soft policy. Stopher (2004) mentions that a suitable mix of hard and soft policies comparable to “carrots and sticks” can engender a shift in public transport. Where hard policy corresponds to the “stick” that is supposed to nudge the users since hard policies restraint access by users to a product or service by increasing related taxes or reducing subsidies. On the other hand, soft policies focus on the behaviour of users by encouraging them to adopt certain actions without intervening in the set of available choices which corresponds to the “carrot” idea where users are incited to do something (Glaeser, 2006). The second field of measures Oucham and Gutiérrez Touriño (2019) refer to is infrastructure. Measures in this field focus on increasing the capacity of the current road and/or transport network. However, the problem with increased capacity is often an increase in users who switch their travel behaviour as result of new capacity (Parkhurst, 1995). Leading to no real measurable improvements despite increased capacity. The third field of measures is technology and is often referred to as Smart Cities where information and communication technologies are used to make traditional networks and services more efficient (Oucham and Gutiérrez Touriño, 2019).

The inception of Park and Ride (P&R) facilities was intended to offer new parking infrastructure outside cities where it is easier and cheaper to build, thus being an “Infrastructure” measure. In addition, incentivizing people to transfer from low density transportation (cars) to high density transportation (public transport) frees up valuable road capacity and therefor alleviates inner-city congestions. While the success of P&R facilities was confirmed in 1994 after studies were carried out in Oxford and York (Parkhurst, 1995), there has been an on-going academic debate about the real benefits of P&R (Clayton et al., 2014). Nowadays, P&R facilities are not only used as additional parking capacity, but they are essential in limiting the inner-city vehicular traffic. This has been achieved by raising inner-city parking fees in an exorbitant way, making P&R facilities more financially attractive (Zheng and Geroliminis, 2016).

2.1 Pricing of P&R facilities

While most of the P&R facilities where free of charge or priced at the marginal cost upon inception, resulting in very low parking fees. These were measures intended to provide a financial alternative compared to for example inner-city parking fees and encourage a step-change in motorists’ travel behaviour towards using public transport (Clayton et al., 2014). However, dedicated P&R facilities are rarely commercially viable. Rather, they generally receive public subsidy justified by the social function they fulfil. More recently, the economic aspect of P&R facilities has gained more attention, where researchers are pleading against the granted public subsidy (Pierce et al., 2015). The high costs associated with building and operating P&R facilities should not be paid from tax payer's money. Instead, P&R facilities should at least be priced to reach a revenue goal, resulting in higher parking fees, but the operation of the P&R facility can be paid from the additional revenue. Another pricing strategy mentioned by Pierce et al. (2015), is to price the P&R facility at market rate, resulting in a parking fee similar to other parking facilities. This pricing strategy is generally used for commercial businesses, intending to make a profit while competing with other businesses to gain market share.

Despite the high costs associated to building and operating P&R facilities, only a few P&R facilities price to reach a revenue goal and the majority of facilities offer free parking as pointed out by Bos (2004). Lam et al. (2001) concluded that monetary and time savings were the main factors attracting users of P&R facilities. The significance is further highlighted by Guo and Wilson (2004) which concluded that the cost of public transport and parking charges combined must be lower than the total cost of the trip solely travelled by car in order to change the chosen mode of transportation of people. Whilst P&R facilities have gained traction in the Netherlands, commuters only make use of them when they offer clear benefits to the commuter. A combination of cheaper parking costs, plenty of parking capacity and good public transport connectivity can compete with direct car trips into metropolitan areas.

2.2 Price optimisation

The inception of P&R facilities has proven that a change in commuter's travel behaviour can be created. However, a combination of hard and soft policies as discussed by Stopher (2004) is required to achieve this. Focussing on the parking charges of P&R facilities near train stations, the right price must be determined in order to limit the total travelled distance by car. To determine the right price for each P&R station, different combinations must be tested, and the total driven distance must be measured for each combination. An optimisation algorithm aims to find the best solution from a set of feasible solutions, i.e., solutions that satisfy all the constraints of the optimisation problem (Ryan, 2003). The search space, goal, and constraints in which the optimisation algorithm must find the best solution are formulated in the optimisation problem. The decision variables reflect the system's components for which the best value must be found. In an iterative approach, the decision variables are used in some objective function which calculates the desired output value also known as the fitness or objective value. By changing the decision variables, either a minimisation or maximisation in the objective function is sought after. The constraints are the functions that describe the relationships between the system's variables and define the allowable values to be taken by the variables (Ryan, 2003).

Agent-based modelling

There are different methodologies to find an optimal solution. For example, Waraich et al. (2013) utilize an agent based approach to simulate the travel behaviour in Zurich, Switzerland, and how different parking prices affect the inhabitants. Each agent has a daily schedule such as for example going to work. Based on a utility function, the model tries to maximize the utility of each agent's daily schedule in an iterative approach. A 10% sample of Zurich's population is used, resulting in roughly 72,000 agents. Detailed information, totalling roughly 266,000 parking spaces divided over public and private, was used. Waraich et al. (2013) tested different parking prices, which were altered in steps of 0.25 Swiss francs, to achieve an 85% occupancy of parking places.

While an agent-based model can yield very accurate results when trying to assess how people respond to interventions, it is very computational expensive which limited the sample size and thus the quality of the results as it simulates the travel behaviour on micro-scale (Waraich et al., 2013). Scaling the agent-based model from an 8 kilometre radius to the entirety of the Netherlands dramatically increases the complexity and computation time to an unreasonable extent. Focussing on a macro-scale model which does not account for every single person in the study area is the only alternative. Utilizing a representative sample of the Dutch socio-demographics to mimic travel behaviour of population groups would alleviate the computational load.

Genetic Algorithm (GA)

Population based search algorithms utilize an initial population which is iteratively altered to create new, and more optimal solutions. The Genetic Algorithm (GA) is inspired by the principles of genetics and evolution, and mimics the reproduction behaviour observed in biological populations (Hassan et al., 2004). It employs the principal of "survival of the fittest" in its search process to select and generate solutions called individuals. Therefore, over a number of generations (iterations), desirable traits (characteristics) will evolve and remain the genome composition of the population. As pointed out by Hassan et al. (2004), the GA is well suited to, and has been extensively applied to, solve complex design optimization problems because it can handle both discrete and continuous variables, and non-linear objective and constraint functions as it does not utilize gradients for finding the optimal solution.

The GA begins its search from a randomly generated population of solutions that evolve over successive generations. In doing so, it employs three functions to propagate its population from one generation to the other. The first function is the "selection" function that mimics the principal of "survival of the fittest". The second function is the "crossover" and mimics the mating in biological populations. This combination ensures that characteristics of better performing solutions propagate into new generations, resulting in a better fitness score on average for these solutions. The third and last function is the “mutation” which invokes random changes in the solutions to promote diversity in the population. This allows for a wide search space and prevents the GA from becoming stuck in local optima (Williams & Crossley, 1998).

Particle Swarm Optimization (PSO)

Another commonly used population based evolutionary heuristic is the Particle Swarm Optimization (PSO). It also starts with a set of randomly generated solutions called the initial swarm and searches through the search space for an optimal solution in an interactive approach just like the GA. However, instead of combining the features of the best performing solutions, it generates solutions (particles) across the wide search space and move them around with the goal of finding the global optimum. This is performed by changing the position of each particle between generations based on a velocity update. The velocity depends on the fitness value of each individual particle and how far off this is from the swarm wide best found fitness value (Williams & Crossley, 1998). The further away a particle is, the higher velocity it will receive in the direction of the best found fitness value. Over generations, this will result in a wide search space followed by the identification of an optimum.

The PSO is very simple and easy to implement and has wide adaptability just like the GA. In addition, it can be run in parallel which can result in a fast convergence rate. However, it can become stuck in a local optima which limits the effectiveness of the results. This is especially noticeable in search spaces with multiple local extremes. A reason for this behaviour is inherent to its search strategy. While it starts with a wide solution diversity due to the randomly allocated particles in the initial iteration, all particles start to move into the direction of the best achieved fitness value in the subsequent generations resulting in a quickly disappearing diversity (Wang et al., 2017). While this can lead to a fast convergence, it does not guarantee that it has found the global optima due to the bias introduced from the start with the swarm’s best fitness value. Contradictory, the GA increases its population’s diversity over generations, resulting in a longer convergence time, but most likely also in a better solution.

3 Methodology

To determine the optimal parking price for P&R facilities that minimize the total distance driven by car, an optimisation model is developed. Figure 1 presents an overview of the process used to develop the P&R parking fee optimisation model. It begins with the creation of synthetic data which to represent the travel behaviour of different population groups. This data, referred to as commuter trip data, is based on the 2021 national traveller survey. It is necessary to create synthetic data since real survey responses could not be used in a public publication due to privacy legislation. Subsequently, an initial solution is created based on the current parking charges for P&R stations. This initial solution is used in a GA to iteratively adjust the parking charges for each P&R facility. For each set of parking fees, the probability that a commuter will use a P&R station is calculated using a Multi-Nominal Logit (MNL) model proposed by Soza-Parra and Ton (2022). This probability is multiplied by the distance to a P&R station and summed for all P&R stations, resulting in the total distance driven while accounting for the probability of using another P&R station. After minimizing the objective function with the GA, the best parking charge for each P&R station in the Netherlands is determined. The proposed model can be used to recalibrate P&R parking charges to minimize the total distance driven by car based on a sample of population group's travel behaviour.

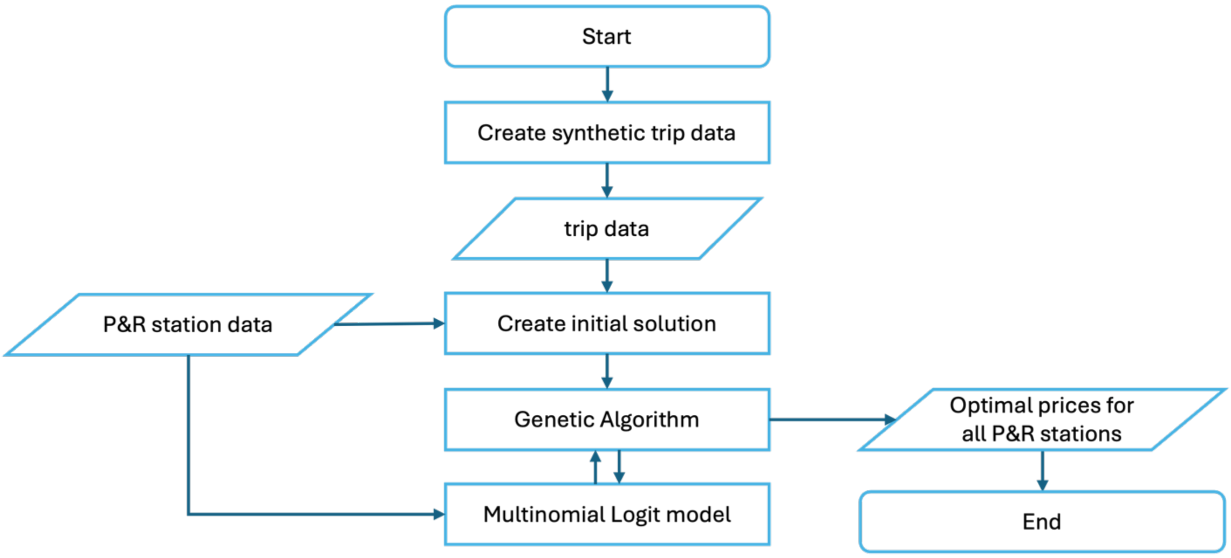

Figure 1. General process overview of the proposed model.

The proposed model is described in three subsections. Chapter 3.1 formulates the optimization problem, followed by the introduction of a Multi-Nominal Logit (MNL) model in Chapter 3.2. The MNL model is used to model the P&R station selection procedure of commuters based on various factors including taste variations and interactions. Chapter 3.3 combines the formulated optimization problem with the MNL model in a Genetic Algorithm, resulting in a model that can minimize the total distance driven by car to reach P&R stations by adjusting the parking fee at each station.

3.1 Formulisation of the optimisation problem

To incentivize commuters to limit their car journey, other options must become more appealing. A variety of hard and soft policies can be used to incentivize public transport usage however, this research focusses on concept of financial incentive. People tend to choose the more affordable option or the one with the greatest benefits. Leveraging this behaviour, the goal is to limit the travelled distance by car by recalibrating the parking charges of P&R stations within the Netherlands. This can be expressed as a minimization problem in Equation 1 subjected to constraint 2 which prevents the parking fees from becoming negative. Equation 1 utilizes a sample of N trips where the distance between each commuter's origin and every P&R station j is multiplied by the probability that the commuter will travel to the P&R station. Here, the assumption is made that each commuter currently uses a P&R station as part of their journey and will continue to do so. As a result, a MNL model, as discussed in Chapter 3.2, is used to model the probability that a commuter will use a P&R station.

This research aims to investigate the effect of changing P&R station parking fees on commuter behaviour with the goal of minimizing the total travelled distance by car. Therefore, the parking fee at each P&R station is used as the decision variable. However, the P&R station parking cost is not included directly in the objective function in Equation 1. Instead, the cost is included in the MNL model, affecting the decision process when choosing a P&R station, which in turn affects the probability P_{ij} in the objective function, and thus affects the total driven distance.

$$Minimize\colon \sum_{i=1}^{N} \sum_{j=1}^{M} (D_{ij} \times P_{ij}) \quad (1)$$

Where:

N = the total number of trips
M = the total number of P&R stations
D_{ij} = the distance from the origin of commuter i to P&R station j
P_{ij} = the probability that commuter i would make use of P&R station j

With:

$$C_j >\equiv 0 \quad (2)$$

Where:

C_j = the parking charge for P&R station j

3.2 Multi-Nominal Logit (MNL) model

Before calculating the commuter's travelled distance, it is important to determine to which P&R station the commuter will travel. Since the assumption has been made that all commuters will keep on using a P&R station as part of their journey, a discrete choice must be made by the commuter. Soza-Parra and Ton (2022) created a bi-level Multi-Nominal Logit (MNL) model to identify factors influencing P&R station choice, focussing on those factors that can be influenced by the operator and municipality. This MNL model is based on survey data from the Dutch National Railway as more elaborately discussed in Chapter 4.

The MNL model models the P&R station selection procedure of commuters based on a variety of factors including taste variations and interactions and is based on 41 attributes. The bi-level MNL model includes 11 primary attributes expressing the key influential factors such as the time to reach a P&R station. Each primary attribute includes at least one secondary attribute representing the taste variations and interactions of commuters. For example, transfer time is included as a primary attribute with a negative estimate (Table 1). Indicating that every minute of transfer time results in a lower utility for the commuter. But, if the commuter is travelling for work purpose (the secondary attribute expressing taste variation), the utility becomes even lower for every minute of transfer time.

Table 1. Example of bi-level MNL model attribute estimates and values.

Primary attribute	**Secondary attribute**	**Estimate**	**Value**
Transfer time		-9.09E-03	10 (minutes)
	Work purpose	-7.14E-02	1 (binary)

To calculate the utility of a P&R station to a commuter, the primary attribute estimate is multiplied by the primary attribute value. Subsequently, the secondary attribute estimate is multiplied by the secondary attribute value and multiplied by the primary attribute value. This process is performed for all primary attributes. Finally, everything is summed together to get the final utility value. This example is visualized by Equation 3 for the example in Table 1.

$$utility = (-9.09E^{-03} \times 10) + (-7.14E^{-02} \times 1 \times 10) \qquad (3)$$

These calculations are performed for all primary and secondary attributes included in the bi-level MNL model of Soza-Parra and Ton (2022). Building upon the fitted bi-level MNL model and the associated attribute estimates, as included in Appendix A, saved time since the MNL model was already fitted for commuters in the Netherlands. The required calculations to determine the utility of each P&R station j for each commuter i can be mathematically expressed as Equation 4.

$$U_{ij} = \sum_{p=1}^{P} (\beta_p \times X_{ijp}) + \sum_{s=1}^{S} (\beta_s \times X_{ijs} \times X_{ijp}) \tag{4}$$

Where:

U_{ij} is the utility of P&R station j to commuter i
P is the number of primary attributes
S is the number of secondary attributes
β_p is the estimate corresponding to primary attribute
β_s is the estimate corresponding to secondary attribute
X_{ijp} is the value of the primary attribute
X_{ijs} is the value of the secondary attribute

The utility of a P&R station is not the same as the probability that a commuter will travel to that particular P&R station, as the utility can fall outside the probability range of zero to one. In order to determine this probability, a SoftMax function (Equation 5) can be applied to the utility, normalizing it to a scale between zero and one. This is similar to the method used by Shen et al. (2017). However, this can only be performed for a set of distinct choices. Therefor, the assumption has been made that all commuters in the dataset will continue to use a P&R station as part of their journey.

$$P_{ij} = \frac{e^{U_{ij}}}{\sum_{l=1}^{M} e^{U_{il}}} \tag{5}$$

Where:

U_{ij} is the utility of P&R station j to commuter i
M is the total number of P&R stations
U_{il} is the utility of P&R station l to commuter

By determining the probability of each P&R station and multiplying it by the distance, a more accurate result can be calculated. Otherwise, a single P&R station must be selected as the commuter's choice, but there is no garuantee that the commuter will actually use that P&R station. Therefore, an error measure should be determined for each commuter's trip, complicating the aggreation of the total distance travelled by all trips. This is not necessary when making using probabilities, as the probability already accounts for the error in the decision. For this reason, a more accurate measure can be achieved by multiplying the distance with the probability for each individual P&R station and summing them together.

3.3 Genetic Algorithm

Based on the formulated objective function in Chapter 3.1 and the bi-level MNL model from Chapter 3.2, the total distance driven by car can be calculated for a set of P&R parking fees. Each P&R station represents a decision variable, since each price can be independently adjusted. Combining both with a Genetic Algorithm (GA), creates the proposed P&R parking fee optimisation model which can be used to find the optimal P&R prices that minimize the total distance travelled by car to reach P&R stations.

As discussed in Chapter 2.2, there are different metaherustic optimisation algorithms, each with their own benefits and disadvantages. A GA was chosen for its flexibility and adaptability, which ensured easy itegration within a short project timespan. Additionally, minimizing the total distance driven by all commuters is highely non-linear due to many interacting factors such as varying parking fees and different commuting behaviours. A GA is a particulary good for non-linear problems due to its ability to effectively explore a large search space. Furthermore, the price optimisation is likely to contain multiple local optima, which could affect the quality of the results when using other algorithms such as the PSO. A generic GA, as depicted in Figure 2, is used. It consists out of population selection, cross-over and mutation functions before the objective function calculations as mentioned by Hassan et al. (2004).

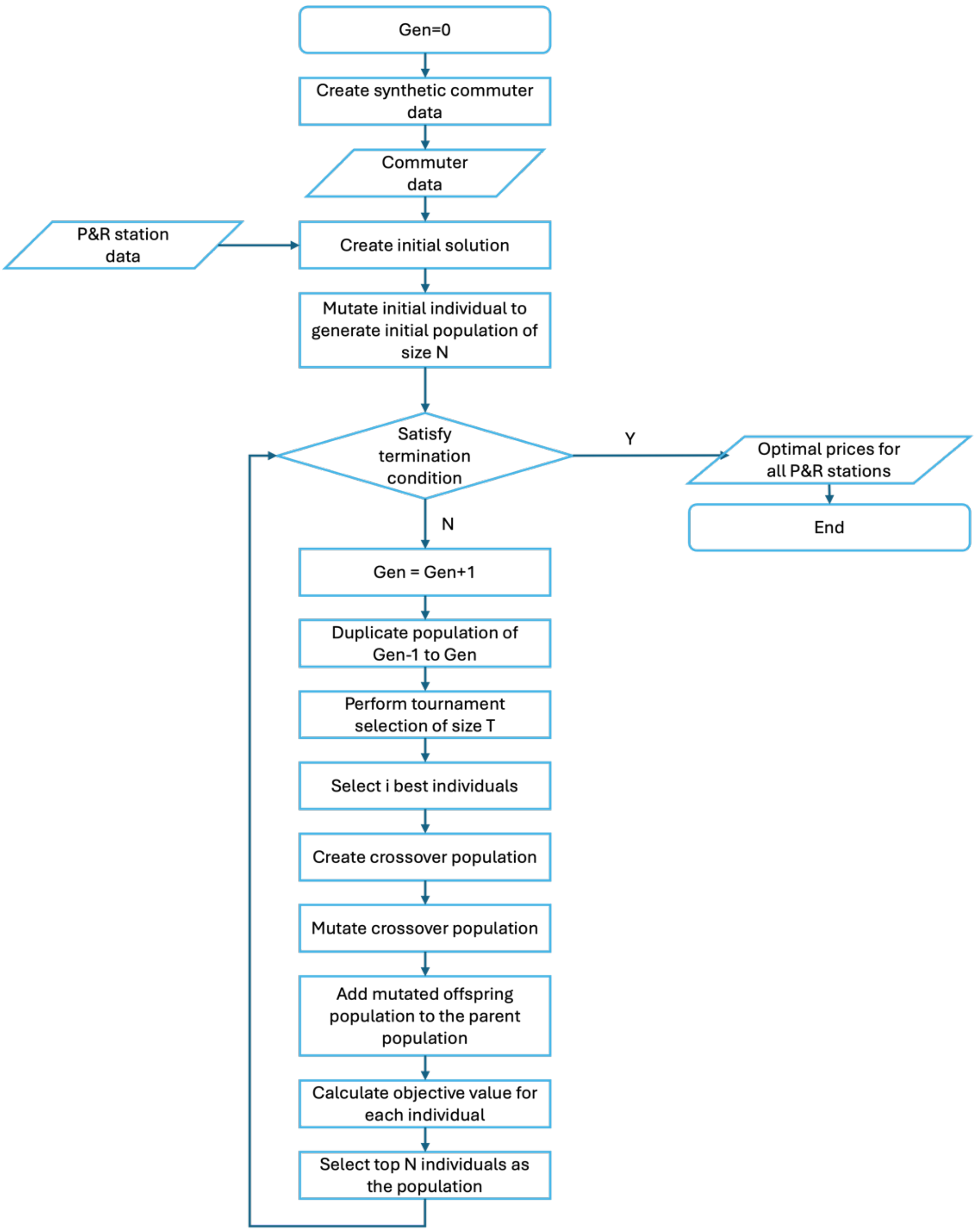

Figure 2. Genetic Algorithm flowchart.

The P&R parking fee optimization model starts by the creation of synthetic data, followed by the creation of an initial solution. In the initial solution, the current parking fees are encoded into a genome. Each number in the genome corresponds to a particular P&R station and represents the parking fee. This initial solution is duplicated and mutated until there are 100 initial solutions, forming the population of the first generation. The number of solutions per generations is defined in the hyperparameter “num_solutions” which can be changed before executing the model.

This initial solution is subsequently used in the GA to create new iterations, also known as generations. Each new generation starts by the previous generation, now called the parent population. From this population, the best performing solutions are taken based on a tournament selection. In this function, T solutions are selected from the parent population and the N best performing solutions, as defined by the “num_solutions” hyperparameter, are chosen as parent solution. The size of the tournament selection depends on the “tournament_size” hyperparameter. Subsequently, for each pair of parent solutions, there is an 80% probability, as defined in the “crossover_rate” hyperparameter, that a cross-over will occur. This probability has been determined to give the best results as discussed in chapter 5. When a cross-over occurs, a random cross-over point is selected, and the genome with P&R parking prices is divided into two for both of the parent solutions. The P&R parking prices after the cross-over point are swapped between the two parent solutions to produce two new offspring solutions. These new offspring solutions are subsequently subjected to the mutation function which randomly mutates the genome of P&R prices based on a normal distribution between €-5 and €5 in 50-cent step size. The lower and upper bound of this normal distribution, as well as the step size, can be changed in the respective hyperparameters. Different values have been tested for these variables, as discussed in Chapter 5, and these values were found to be the best performing. There is a 3% probability that the P&R prices from the offspring are randomly altered based on these variables. This probability is provided in the “mutation_rate” hyperparameter and was found to create enough genetic diversity while ensuring good results. The mutations ensure that the algorithm explores new regions of the search space and does not get stuck in local minimum.

After the offspring population is created, it is added to the parent population of the current generation. For the entire population, the objective value is calculated before the top 100 best performing solutions are selected as the current generation’s resulting population. These solutions will be used as the parent population in the next generation. Finally, a check for convergence is performed to test if the current generation performs better than the previous one. The entire process is repeated until there is no improvement for at least 50 generations as defined in the hyperparameter “patience”. Additionally, a maximum number of generations is provided in the “max_generations” hyperparameter to prevent excessively run execution times without convergence.

3.4 Calibrating the model

Since the P&R parking fee optimisation model is based on a GA, it is important to calibrate the hyperparameters as these have a significant impact on the performance of the model as pointed out by Van Gelder (2002). Different hyperparameter values, as listed in Table 2, have been tested.

Table 2. To be tested hyperparameter values in the grid search.

Hyperparameter	**Test values**
population_size	20 / 100
max_generations	100 / 250
patience	50 / 100
tournament_size	8 / 24 / 48
crossover_rate	0.3 / 0.5 / 0.8
mutation_rate	0.3 / 0.5
step_size	0.15 / 0.5
lower_bound	-2 / -5
upper_bound	2 / 5

To test each possible combinations of hyperparameter values as listed in Table 2, a grid search can be used. This will result in 1.152 possible combinations. With an average execution time of 4 hours and 35 minutes, it would take extremely long to perform an extensive grid search therefore, only a couple of different hyperparameter values have been tested to identify the effect of each individual hyperparameter on the overall fitness.

Two different testing scenarios are created. The first utilizes a fixed "population_size" of 20, while the second scenario utilizes a "population_size" of 100. These scenarios were created to test the effect of "population_size" on the overall fitness of the P&R parking fee optimisation model. The first scenario utilises the following hyperparameter values as the baseline:

population_size:	20	tournament_size:	8	step_size:	0.5
max_generations:	100	crossover_rate:	0.8	lower_bound:	-2
patience:	50	mutation_rate:	0.3	upper_bound:	2

While the second scenario utilises the following hyperparameter values:

population_size:	100	tournament_size:	48	step_size:	0.5
max_generations:	250	crossover_rate:	0.8	lower_bound:	-5
Patience:	50	mutation_rate:	0.3	upper_bound:	5

It can be noted that the second scenario has an increased "tournament_size" and "max_generations" to support the increased population size. Based on these baseline scenario's, different hyperparameter values are tested in Chapter 5. For the best performing model, multiple runs will be executed to capture the run-to-run variance.

4 Data

The data required to run the P&R parking fee optimisation model largly depends on the required attributes for the MNL model. This model is based on 41 attributes, divided over primary and secondary attributes with some occuring multiple times. This results in 24 unique attributes which must be gatherd before the MNL model could be correctly implemented. These attributes can be divided into three categories: P&R descriptive data, journey data and commuter data.

4.1 P&R descriptive data

The first group of attributes is the P&R descriptive data which contains seven attributes that are explicit to each P&R station. These attributes are as follows:

1. pnr_cost
2. pnr_capacity
3. pnr_intercity_service
4. service_interval
5. pnr_wc
6. pnr_coffee
7. pnr_waiting_room

These attributes describe the P&R station itself and the services offered. For example, the attribute “pnr_intercity_service” is a binary variable indicating if intercity trains stop at this P&R station. The attributes “pnr_wc”, “pnr_coffee” and “pnr_waiting_room” are also binary attributes indicating if there is a public restroom, a small food and beverages shop and comfortable waiting areas respectivly. All attributes in this category are static and do not change during the execution of the model. Only if the number of P&R stations changes, new data must be added or old data removed. However, there is one exeption, the “pnr_cost” is the decision variable in the P&R parking fee optimization model, and gets altered in every iteration. Therefore, it is treated separately and is not included as a static attribute.

4.2 Journey data

The second group of attributes describe the journey of a commuter from the origin to the destination and contains the following five attributes:

1. distance_to_pnr
2. time_to_pnr
3. train_travel_time
4. number_of_transfers
5. transfer_time

These attributes depend on the origin and destination and therefore differ for each commuter. The “distance_to_pnr” and “time_to_pnr” are related to the car journey and must be calculated from the point of origin to each P&R station. These attributes are calculated based on the fastest route in terms of time between the origin and the P&R station. OSRM’s contraction hierarchies are used to find the fastest route between two points. The servers contain pre-processed road graphs and the contractional hierachies enables precomputed routes between major junctions. As a result, it is not necessary to consider each possible road from each junction, dramatically speeding up querying time (Open Source Routing Machine, n.d.).

In addition, the OSRM query makes use of routing profiles representing routing behaviour for different modes of transport (Rajput, 2023). The pre-written profile “car” has been used for this research, determining multiple aspects such as what ways are routable and which speeds to use for different road types. Every road segment between two junctions gets a resistance assigned based on the road type, speed, and length of the road segment. The fastest route between two points is calculated based on the route which has the least total resistance for all road segments.

The remaining three attributes describe the journey by train from the P&R station to the destination. First, a train station close to the destination point must be determined. The closest station is found based on the Euclidean distance. Subsequently, the travel information API from the National Dutch Railway (NS) is used to generate a travel advise between the P&R station and the destination station. This travel advise is based on the timetable of the National Dutch Railway and the possible transfer points. The travel advise is the fastest way to get from the P&R station to the destination station by train. Other modes of public transport such as busses are disregarded. The travel advise provides the total travel time by train, the number of transfers and the transfer time at each transfer station. The latter is summed together for all transfer points to get the total value for the “transfer_time” attribute.

4.3 Commuter data

As third group, the commuter data describes each individual based on some socio-demographic attribute, this category contains the following twelve attributes:

1. business purpose
2. work_purpose
3. leisure_purpose
4. vfr_purpose (Visiting Friends and Relatives)
5. weekly_traveler
6. ns_business_card
7. age_35_to_49
8. age_50_to_59
9. age_60_to_69
10. age_over_70
11. origin_influence_area
12. origin_periphery

All of these attributes are represented by a binary value where one indicates that the commuter is part of the particular attribute. For example, if the “business_purpose” of a commuter contains a one, this means that the commuter is travelling for their business. This also automatically means that the “work_purpose”, “leisure_purpose” and “vfr_purpose” are set to zero, since a commuter has only one travel purpose at the same time. The 11th and 12th attributes represent the area of origin of the commuter. Soza-Parra and Ton (2022) used three different origin regions within the Netherlands based on the population density. These areas are the Randstad, Influence area and the Periphery area ranked from most densely populated to least as depicted in Figure 3. If both the “origin_influence_area” and the “origin_periphery” are expressed by a zero, this means that the commuter originates from the Randstad.

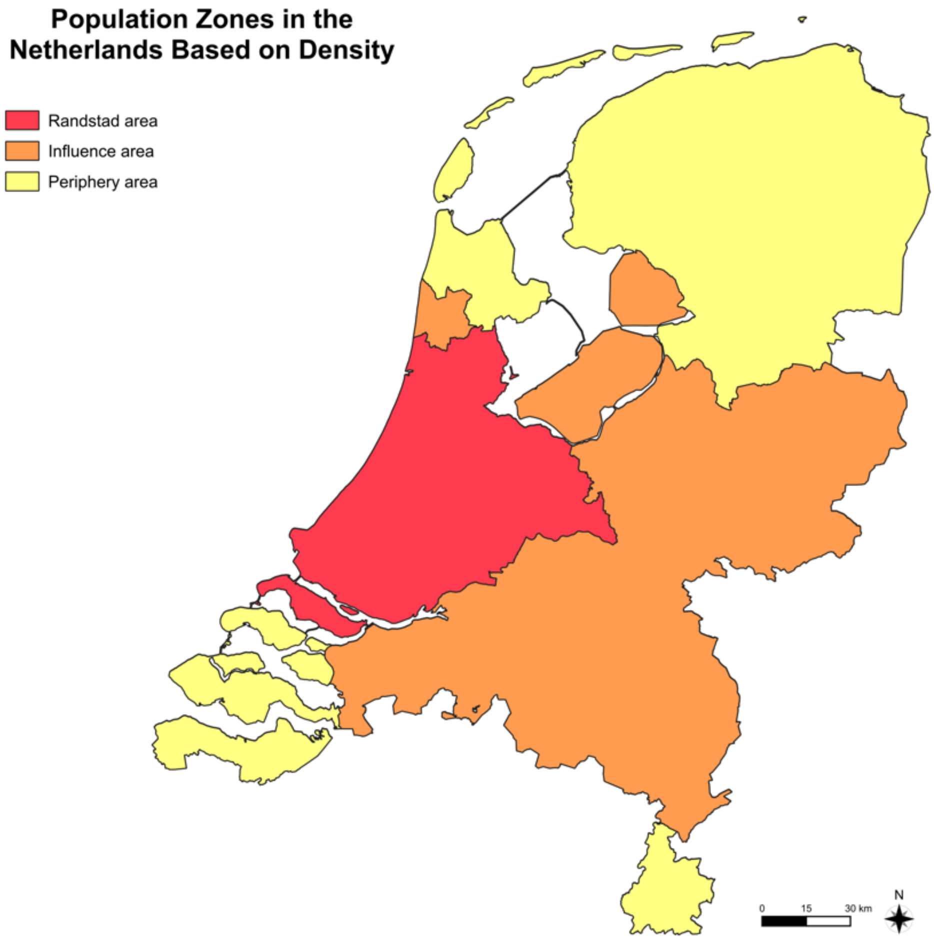

Figure 3. Population zones in the Netherlands based on population density (Dekkers, 2006).

4.4 Data collection

The 24 unique attributes as described in Chapters 4.1 to 4.3 are all required to replicate the bi-level MNL model as developed by Soza-Parra and Ton (2022). These attributes were found to be of significant importance in modelling the P&R station choice of commuters by Soza-Parra and Ton (2022). The research utilized survey data collected by the National Dutch Railway (NS) captured in a major data collection effort in 2019 aimed to capture details and travel behaviour on the door-to-door journey of passengers. This resulted in 50,000 responses, however only 6% of the total trips used a car to access the P&R at the train station, resulting in 2,000 responses detailing information about their trip (Soza-Parra and Ton, 2022).

Since the data was collected from panels and surveys distributed to represent the Dutch socio-demographis, the collected data froms a representative sample of travel behaviour among train passengers. By utilizing this sample in the proposed P&R parking fee optimisation model as discussed in Chapter 3, a fair solution can be generated since it is based on a sample of data representing the Dutch train travel behaviour. However, due to privacy legislation it was impossible to use these survey responses in a public publication. For this reason, publicly available information from the 2021 national traveller survey (Uconsult, 2022) has been used to synthetically generate a similar dataset. While this synthetic dataset does not contain the same data, assumptions have been used to create a representative sample to proof the methodological concept that calibrating P&R station parking fees can incentivizing people to travel less distance by car.

The synthetic data generation process consist out of eight steps, as depicted in Figure 4, whereby these steps are performed for each created trip. The total number of to be generated trips is represented by N and a total of 100 trips have been used during testing as this already resulted in long execution times.

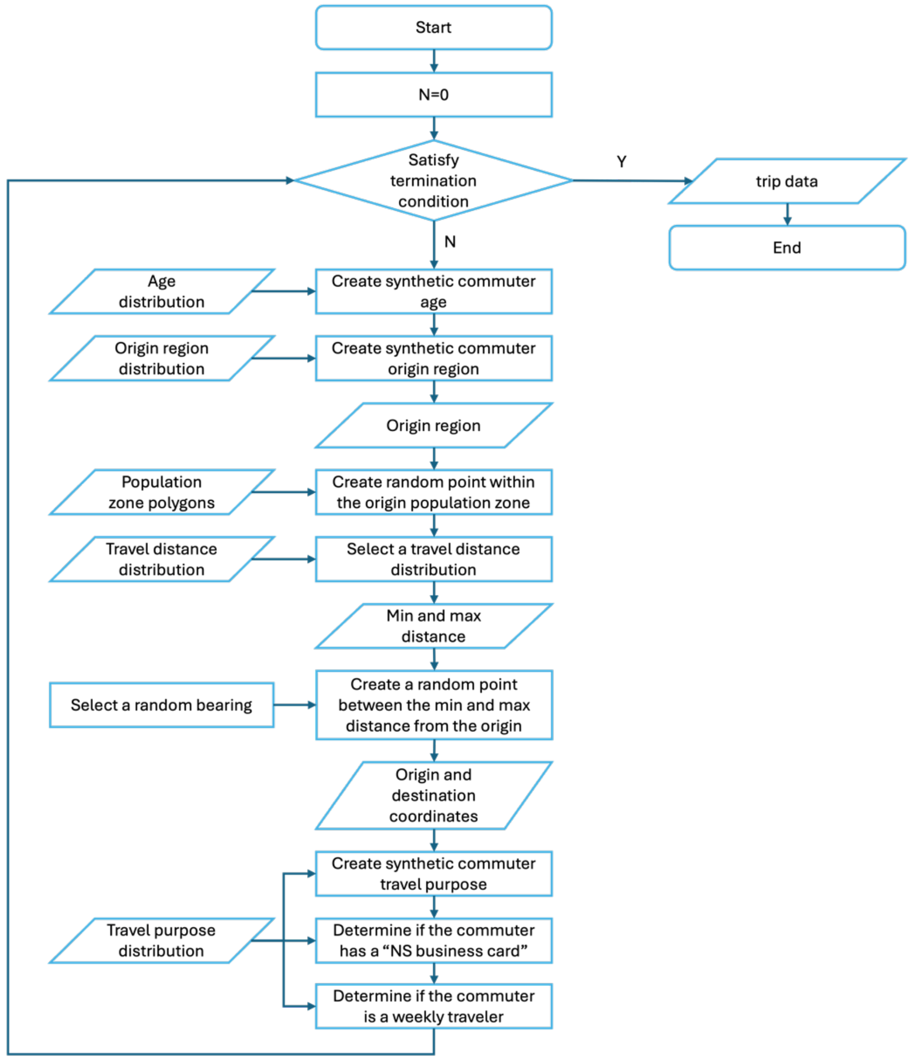

Figure 4. Synthetic data generation process.

The synthetic data replaces the missing survey data from the National Dutch Railway (NS) and contains data about a trip from origin to destination and characteristics of the commuter. The synthetically generated data contains the attributes from the "Commuter data" category as described in Chapter 4.3. It is created to mimic the survey responses utilized by Soza-Parra and Ton (2022) and is a representative sample of people who drive by car towards P&R station before transferring to the public transportation network. Hereby the assumption is made that all commuters keep on using a P&R station to reach their destination but will likely shift their P&R station of choice as the prices change. This way, the demand for P&R stations remains consistent even though the parking fees are changed. This assumption is made to highlight the effect of calibrated parking fees on the total driven distance. In addition, it ensures that the utility of a P&R station to a commuter can be converted in a probability as discussed in Chapter 3.2.

To start the synthetic data generation, the age of a commuter is synthetically generated based on the probability distribution described in Table 3 from the national traveller survey (Uconsult, 2022). However, it should be noted that the national traveller survey utilizes different age categories. Therefore, the distribution has been adjusted to the desired age categories in Table 4. This adjustment is proportionally based on the number of years spanned by each age category.

Table 3. Age distribution in the 2021 national traveler survey.

Age category	Proportion
18 to 30	16.5%
31 to 45	23.9%
46 to 65	40.5%
66 and older	19.1%

Table 4. Age distribution adjusted to the required categories for the MNL model.

Age category	Proportion
35 to 49	25.4%
50 to 59	29.3%
60 to 69	26.8%
70 and older	18.5%

Next, the region of origin must be determined for each commuter. As discussed in Chapter 4.3, Soza-Parra and Ton (2022) used three different origin regions to fit the MNL model. However, the national traveller survey (Uconsult, 2022) makes use of a five-stage region classification which is also based on the population density. To create the mandatory origin regions, the population distribution from the national traveller survey (Uconsult, 2022) in Table 5 is used to derive the required proportions in Table 6. Where "Randstad" contains the entirety of the "Very urban" region as well as half of the "Urban" region. The other half is combined with the "Moderately urban" region within the "Influence area". Finally, the "Periphery area" contains the remaining two population regions from the national traveller survey.

Table 5. Population distribution across regions in the 2021 national traveler survey.

Population region	Proportion
Very urban	20%
Urban	30%
Moderately urban	25%
Low urbanity	15%
Not urban	10%

Table 6. Population distribution across regions adjusted to the required categories for the MNL model.

Population region	Proportion
Randstad area	35%
Influence area	40%
Periphery area	25%

Based on the population region distribution in Table 6, a random point of origin is selected within each area. Subsequently, the destination point is determined based on the travel distance distribution from the national traveller survey (Uconsult, 2022) in Table 7.

Table 7. Travel distance distribution in the 2021 national traveler survey.

Travel distance	Proportion
Maximum of 7.5km	14.7%
Between 7.5km and 15km	20.5%
Between 15km and 30km	32.4%
More than 30km	32.4%

This generates origin and destination pairs for each commuter based on the general probabilities as publicised in the national traveller survey. However, to be a valid pair, both the origin as the destination points must be withing the borders of the Netherlands. For each commuter, their purpose of travel is determined based on the distribution provided by the national traveller survey (Uconsult, 2022) in Table 8. Subsequently, if someone is travelling for either "Business" or "Work", the assumption has been made that they have a 50% change of owning a National Dutch Railways public transit business card (NS business card). In addition, if someone is travelling with a "Work" purpose, there is an 85% change that they are travelling weekly based on the national traveller survey (Uconsult, 2022).

Table 8. Travel purpose distribution in the 2021 national traveler survey.

Travel purpose	Proportion
Business	23.2%
Work	54.8%
Leisure	11%
Visiting Friends and Relatives (VFR)	11%

5 Results and Discussion

For each baseline scenario as described in Chapter 3.4, the P&R parking fee optimisation model is executed a couple of times. For each execution run, a single hyperparameter value was changed to test the effects of this hyperparameter. While testing just a single changed hyperparameter value at the time does not take the interplay between different hyperparameter values into account, it dramatically reduces the total number of tested combinations from 1.152 to 13.

Based on these 13 tests, as included in Appendix B, it could be concluded that the changes in fitness value between each of the 13 tests are very small. Differences were only observed in the order of meters, while the fitness value is expressed in kilometres, resulting in no significant changes. Despite the very small scale, different hyperparameter values result in different fitness values. For example, increasing the maximum number of allowed generations before termination, as tested in combination 2 in Appendix B, did not result in any improvements compared to the baseline scenario in combination 1. After decreasing the crossover rate from 80% to 30% in Combination 3, the fitness value became worse. The same can be concluded when the step size in which the P&R prices are adjusted was changed from €0.5 to €0.15 in combination 5. However, changing the lower and upper bounds of the normal distribution, which is used to alter the P&R prices, to €-5 and €5 respectively, resulted in the first observable improvement of the model in combination 6.

When testing different hyperparameter values for the “population_size” of 100 scenario, better results were achieved across the board. Indicating that an increased population size is preferable, potentially because it provides a wider population diversity and thus search space. Comparing the baseline scenario of combination 7 with combination 8 which has an increased “patience” of 100, a slightly better fitness score is achieved. However, the increased processing time as a result does not justify the improved fitness score. A better fitness score could be achieved when the patience remained at 50 generations and the tournament size was decreased from 48 to 24 as tested with combination 9. A decreased “crossover_rate” was also tested for the second scenario, however, this resulted in worse performance than the baseline just as with the first scenario. Indicating that the model requires a high mutation rate in order to find better solutions. The best performance was achieved in combination 13, by changing the lower and upper bounds to €-5 and €5 respectively. Indicating that greater changes in P&R parking prices could result in more changes in commuter’s travel behaviour.

Based on the fact that the model performs better with a larger range between the lower and upper bounds, as well on the fact that increased patience does not significantly improves the results, the following hyperparameter values were used as the best performing model:

population_size:	100	tournament_size:	48	step_size:	0.5
max_generations:	250	crossover_rate:	0.8	lower_bound:	-5
Patience:	50	mutation_rate:	0.3	upper_bound:	5

A total of 5 runs have been performed were the initial couple of generations show generational improvements, followed by an ever increasing number of generations without improvement as can be observed in Figure 5. Indicating that some minor improvements can potentially be achieved at the expense of increasing computation times. This corresponds to the improvements observed when testing a larger value for the “patience” hyperparameter. Run 4 achieved the best fitness value at generation 4 after which there was no further improvement for the following generations. For this reason, it can be concluded that the P&R parking fee optimisation model achieved convergence at generation 4. While run 4 performed the best, its performance also differs the most from the other four runs. For this run, the average driven distance per commuter was reduced from 11.76533 kilometres in the initial solution to 11.76448 kilometres at convergence. This marginal reduction of 0.007% is neglectable on the grand scheme.

Figure 5. Generational fitness over multiple runs of the P&R parking fee optimisation model based on the best performing hyperparameter values.

The marginal reduction achieved by the P&R parking fee optimisation model indicate that almost all commuters are not changing their P&R station of choice, despite increases in price. This can be explained by the fact that the most commuters seem to already travel towards the nearest P&R station as their point of transfer onto the public transport network. Only resulting in reduced driven kilometres when there are multiple P&R stations at almost the same distance from the point of origin. Something what happens most often in the suburbs of larger cities.

In addition, the marginal improvement might hint at the relative low importance of parking price in the P&R station choice of the commuter. Since the MNL model accounts for a variety of different factors in the P&R station selection procedure of commuters, a combination of different factors might result in a larger reduction of driven kilometres. This is further substantiated by the fact that the optimal solution changes the current parking fees by as much as 15 euro's. Indicating that the price must be significantly increased for some P&R stations to incentivise commuters to choose a different P&R station. Figure 6 provides an overview for how often each P&R price occurs in the current situation. Comparing this to the distribution provided in Figure 7 for the newly determined P&R parking prices indicates a change in pricing. It occurs more often that P&R stations are priced above €3 and sometimes even as high as €15. While this poses no problem in the P&R parking fee optimisation model, it is unreasonable to assume that commuters would continue to use a P&R station if the parking price is increased to 15 euro, while other modes of transport are most likely cheaper at this point. For this reason, it is important to disregard the assumption of fixed demand in further studies and incorporate dynamic demand modelling. This way, a complete picture can be created for the total cost of a trip depending on several factors and how this cost affects the mode of transport choice.

Figure 6. Distribution of current P&R prices.

Figure 7. Distribution of newly calculated P&R prices.

Visualising the difference between the current and new parking fees for each P&R station in Figure 8 provides an overview of where the more expensive P&R locations are located.

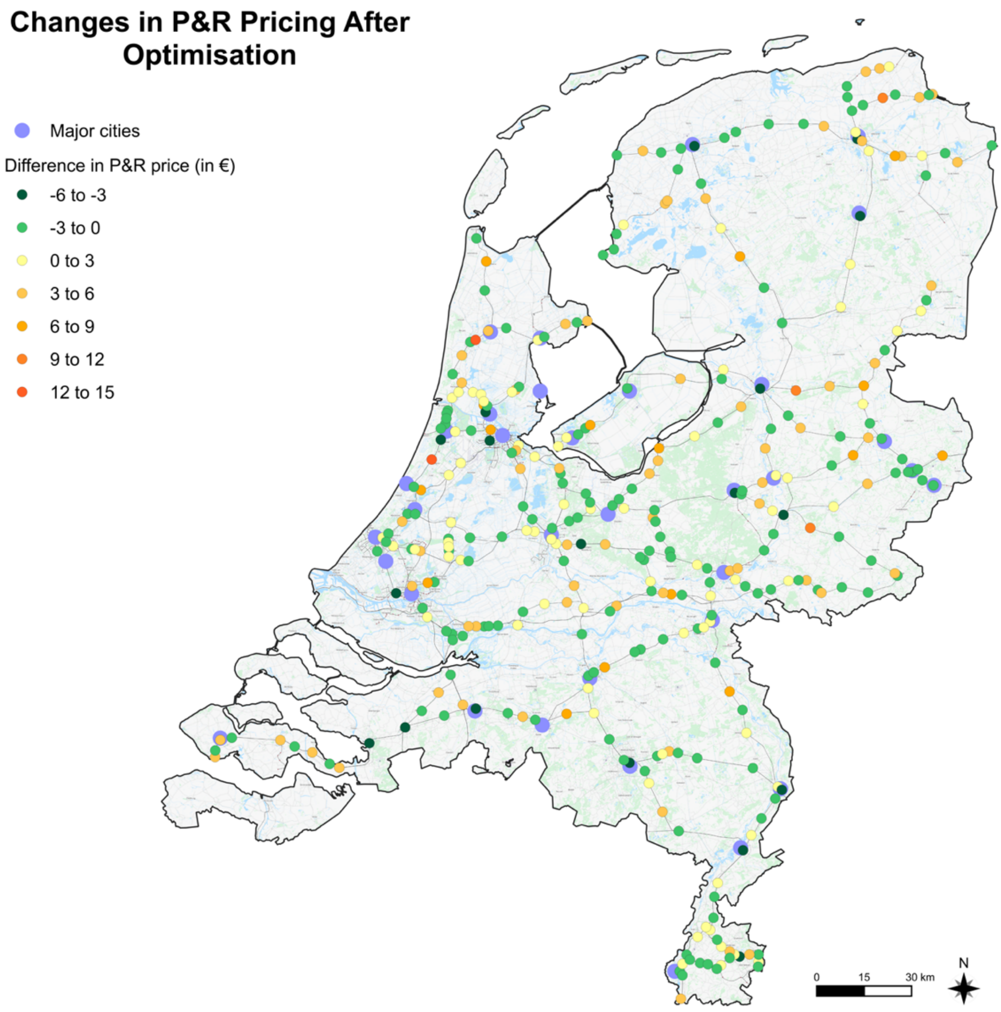

Figure 8. Difference between the new and old P&R parking fee.

Upon visual inspection, there is no clear trend visible. While some P&R stations nearby major cities have become more expensive, as indicated by a yellow to orange colour, there are also plenty of P&R stations nearby major cities which have become cheaper. Most of the P&R stations located further away from cities have generally become cheaper with most of the exceptions being situated on the right-hand side of the Netherlands. This result falls partially in line with the expectations, since monetary and time savings were the main factors attracting users to P&R stations as concluded by Lam et al. (2001). By increasing the P&R prices near major cities and decreasing the prices into the more rural areas, commuters can be nudged to P&R stations located farther away from their destination points, as these have become more viable. This behaviour corresponds to the conclusion drawn by Guo and Wilson (2004) which concluded that people generally gravitate towards the cheaper alternative. Creating a cheaper but still fast and comfortable alternatives closer to commuter's origins will result in reduced kilometres driven by car.

However, this trend does not appear to hold true for every P&R station near large cities. Some P&R stations near cities such as Leeuwarden appear to have received a reduction in parking price. This might be explained by the fact that reducing the total travelled distance by car does not directly translate into forcing car users away from cities. Most cities are surrounded by suburbs and villages, resulting in increased population centres around major cities. While it might be beneficial to increase parking fees and force people away from larger cities, the inhabitants also require appropriate parking facilities. Transferring these commuters onto the public transport network via P&R stations around the major cities might be the best solution to reduce the total number of driven kilometres. Combining this with the earlier drawn conclusion that commuters generally already choose the closest P&R station to their point of origin, might explain why most of the price increases are seen by cities with multiple P&R stations close by. As only commuters with multiple alternatives at almost the same distance from their point of origin are likely to change their P&R station of choice after changing the parking price.

While the results suggest that commuters can be incentivized to travel less distance by car by changing P&R parking fees, it also demonstrates the complexity associated to changing people's behaviour. Despite a marginal reduction in driven kilometres invoked by implementing a hard policy such as price increases, other factors are most likely required to create a significant difference in total driven kilometres. Reduced train fairs, increased inner-city parking prices and intercity services at more remote stations are examples of factors which should potentially be considered in order to effectively change commuting behaviour. Further research into the interplay between different factors and their effect on the total driven distance is required before implementation and only a suitable mix of measures, ranging from policies to infrastructure, can lead to success as pointed out by Stopher (2004).

6 Conclusion

Overall, it can be concluded that the total driven distance to reach P&R stations are not significantly affected by changing P&R parking fees. While the utility of each P&R station to the commuter is changed when the P&R parking prices are altered, it often does not result in any actual changes in P&R station choice, as most commuters are already travelling to the nearest P&R station. While some reductions are achieved by the proposed model, the reductions are neglectable with only 0.007%. While this research proves the fact that the total driven distance to reach P&R stations can be reduced by making use of the concept of financial incentive, it does not create significant changes purely based on different P&R parking prices.

Further research could be performed into different factors influencing the commuter's choice in P&R stations and how these factors can result in a reduction in total distance travelled by car. In addition, a combination of factors would most likely result in better results. Other areas for further research are the incorporation of dynamic demand modelling instead of assuming that all commuters in the dataset will keep on using the P&R stations as part of their journey while it is much more likely that commuters will switch to other modes of transport at different thresholds based on the benefits they provide. Focussing on the cost of a trip for different modes of transport and how financial incentive affects these choices could provide valuable insights and potentially reduce the total distance travelled by car to reduce congestion on main road arteries leading into the city.

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Appendix A

Primary variable	Secondary variable	Estimate	Std.err.	t-ratio
Time to P&R		-4.23E-03	2.40E-04	-17.62
	Business purpose	3.66E-04	2.10E-04	1.74
	Origin influence area	-1.11E-03	1.87E-04	-5.93
	Origin periphery	-1.13E-03	1.81E-04	-6.24
	Age between 35 and 49	-6.94E-04	2.74E-04	-2.54
	Age between 50 and 59	-6.80E-04	2.39E-04	-2.85
	Age between 60 and 69	-1.37E-03	2.35E-04	-5.84
	Age over 70	-1.66E-03	2.36E-04	-7.03
	NS business card	-5.86E-04	1.82E-04	-3.23
	Travelling weekly	-4.18E-04	1.94E-04	-2.15
	Distance to P&R	1.91E-02	8.58E-04	22.24
P&R cost		3.58E-04	1.74E-04	2.06
	Origin influence area	-1.55E-03	3.35E-04	-4.63
	Origin periphery	-1.24E-03	4.37E-04	-2.84
P&R capacity		2.79E-03	2.45E-04	11.40
	Origin influence area	-2.02E-03	3.59E-04	-5.64
	Travelling weekly	6.99E-04	3.87E-04	1.80
P&R intercity service		-1.53E-01	1.27E-01	-1.21
	Business purpose	5.30E-01	2.04E-01	2.60
	Origin influence area	1.24E+00	1.80E-01	6.90
	Origin periphery	1.52E+00	1.96E-01	7.74
P&R wc		1.35E-01	9.19E-02	1.47
	Origin periphery	3.64E-01	1.87E-01	1.95
P&R coffee		1.70E-01	1.07E-01	1.59
	Visiting friends and family purpose	4.41E-01	1.61E-01	2.74
	Origin periphery	-3.56E-01	2.10E-01	-1.69
P&R waiting room		2.97E-01	7.19E-02	4.13
	Visiting friends and family purpose	2.49E-01	1.54E-01	1.62
Train travel time		-7.84E-02	6.14E-03	-12.75
	Work purpose	-1.19E-02	5.32E-03	-2.24
	Business purpose	-1.94E-02	7.56E-03	-2.57
	Distance to P&R	3.93E-01	3.28E-02	11.99
Transfer time		-9.09E-03	1.09E-02	-0.84
	Work purpose	-7.14E-02	1.81E-02	-3.94
Number of transfers		-2.08E-01	1.14E-01	-1.82
	Leisure purpose	-9.88E-01	3.78E-01	-2.62
Service interval		1.84E-02	9.59E-03	1.92
	Origin influence area	2.84E-02	1.11E-02	2.55
	Origin periphery	7.97E-02	1.08E-02	7.37
	Travelling weekly	1.61E-02	1.12E-02	1.43
	Distance to P&R	-3.25E-01	6.69E-02	-4.86

Appendix B

Combination: 1		**Fitness value: 11.76474047**		**Convergence generation: 50**	
Hyperparameter values:					
population_size	20	tournament_size	8	step_size	0.5
max_generations	100	crossover_rate	0.8	lower_bound	-2
patience	50	mutation_rate	0.3	upper_bound	2

Combination: 2		**Fitness value: 11.76467867**		**Convergence generation: 50**	
Hyperparameter values:					
population_size	20	tournament_size	8	step_size	0.5
max_generations	400	crossover_rate	0.8	lower_bound	-2
patience	50	mutation_rate	0.3	upper_bound	2

Combination: 3		**Fitness value: 11.76482326**		**Convergence generation: 50**	
Hyperparameter values:					
population_size	20	tournament_size	8	step_size	0.5
max_generations	100	crossover_rate	0.3	lower_bound	-2
patience	50	mutation_rate	0.3	upper_bound	2

Combination: 4		**Fitness value: 11.76475294**		**Convergence generation: 50**	
Hyperparameter values:					
population_size	20	tournament_size	8	step_size	0.5
max_generations	100	crossover_rate	0.8	lower_bound	-2
patience	50	mutation_rate	0.6	upper_bound	2

Combination: 5		**Fitness value: 11.76480758**		**Convergence generation: 50**	
Hyperparameter values:					
population_size	20	tournament_size	8	step_size	0.15
max_generations	100	crossover_rate	0.8	lower_bound	-2
patience	50	mutation_rate	0.3	upper_bound	2

Combination: 6		**Fitness value: 11.76469196**		**Convergence generation: 50**	
Hyperparameter values:					

population_size	20	tournament_size	8	step_size	0.5
max_generations	100	crossover_rate	0.8	lower_bound	-5
patience	50	mutation_rate	0.3	upper_bound	5

Combination:	Fitness value:	Convergence generation:
7	**11.76463952**	**50**

Hyperparameter values:					
population_size	100	tournament_size	48	step_size	0.5
max_generations	250	crossover_rate	0.8	lower_bound	-2
patience	50	mutation_rate	0.3	upper_bound	2

Combination:	Fitness value:	Convergence generation:
8	**11.76463395**	**100**

Hyperparameter values:					
population_size	100	tournament_size	48	step_size	0.5
max_generations	250	crossover_rate	0.8	lower_bound	-2
patience	100	mutation_rate	0.3	upper_bound	2

Combination:	Fitness value:	Convergence generation:
9	**11.76462811**	**50**

Hyperparameter values:					
population_size	100	tournament_size	24	step_size	0.5
max_generations	250	crossover_rate	0.8	lower_bound	-2
patience	50	mutation_rate	0.3	upper_bound	2

Combination:	Fitness value:	Convergence generation:
10	**11.76477786**	**50**

Hyperparameter values:					
population_size	100	tournament_size	48	step_size	0.5
max_generations	250	crossover_rate	0.5	lower_bound	-2
patience	50	mutation_rate	0.3	upper_bound	2

Combination:	Fitness value:	Convergence generation:
11	**11.7646858**	**50**

Hyperparameter values:					
population_size	100	tournament_size	48	step_size	0.5
max_generations	250	crossover_rate	0.8	lower_bound	-2
patience	50	mutation_rate	0.5	upper_bound	2

Combination: 12		**Fitness value: 11.76462328**		**Convergence generation: 50**	
Hyperparameter values:					
population_size	100	tournament_size	48	step_size	0.15
max_generations	250	crossover_rate	0.8	lower_bound	-2
patience	50	mutation_rate	0.3	upper_bound	2

Combination: 13		**Fitness value: 11.76435613**		**Convergence generation: 100**	
Hyperparameter values:					
population_size	100	tournament_size	48	step_size	0.5
max_generations	250	crossover_rate	0.8	lower_bound	-5
patience	100	mutation_rate	0.3	upper_bound	5