Master of Science Thesis

Combined model predictive control and parking resource allocation for urban traffic networks

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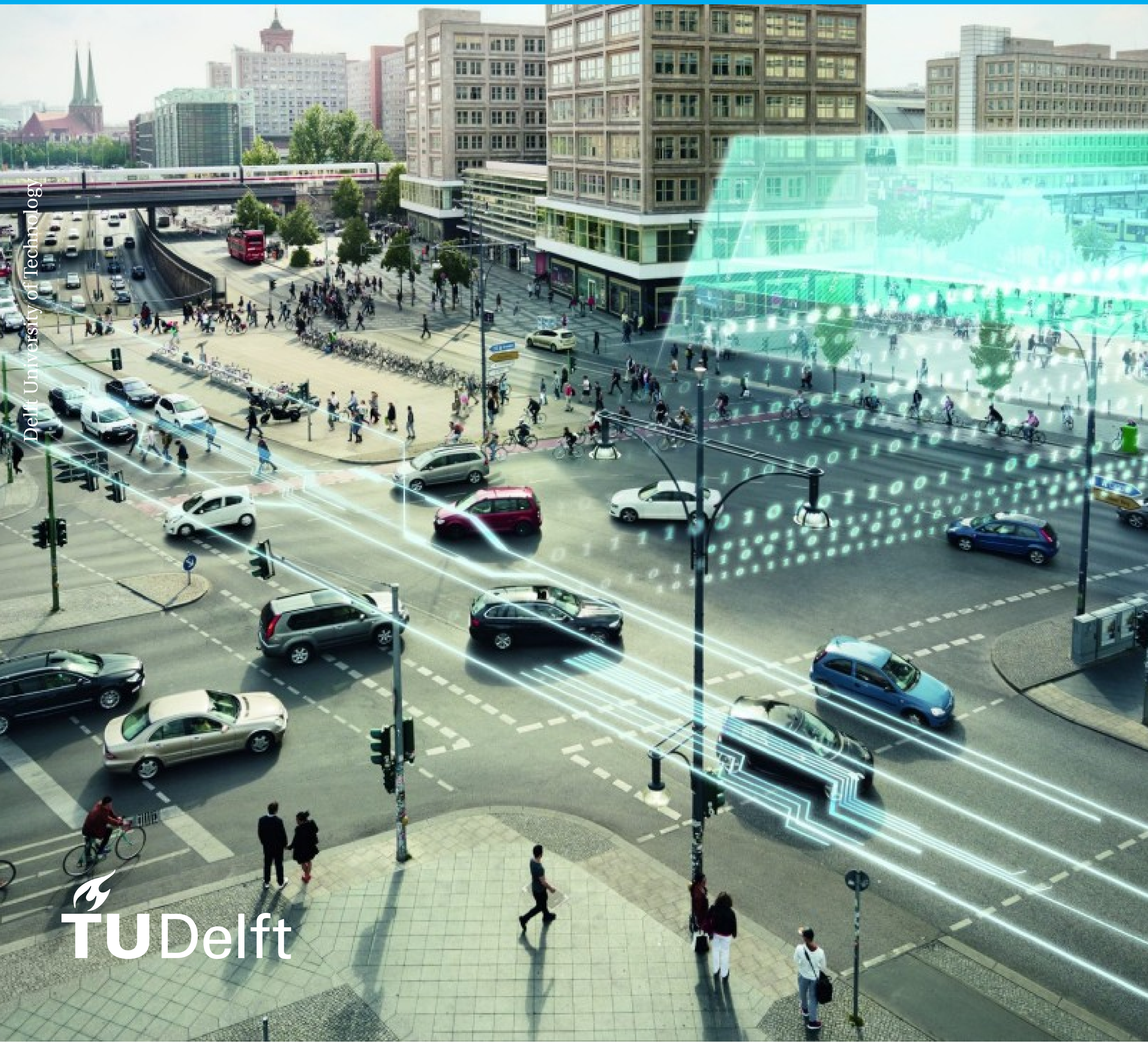

TUDelft

Combined model predictive control and parking resource allocation for urban traffic networks

Master of Science Thesis

For the degree of Master of Science in Systems and Control at
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Summary

Urban areas with many daily commuters often experience a reduction in traffic flow during rush hours. In rush hours, the number of vehicles on the road often exceeds the capacity of the traffic network, resulting in lower traffic flow and consequently longer travel times. In some urban areas where daily traffic congestion occurs, there are popular destinations for leisure that have multiple large parking facilities. On average, vehicles that are searching for a vacant parking spot drive with a lower speed, reducing the traffic flow further. Traffic flow can be improved by using a traffic signal control strategy for the urban areas, and a smart parking solution to increase the speed of vehicles searching for parking spots. The use of Model Predictive Control (MPC) in traffic signal control has resulted in significant improvements over the last years. A parking guidance information system can provide information regarding available parking spots to vehicles. This reduces the number of vehicles that drive with a lower speed due to searching for vacant parking spots. However, the driving behaviour of vehicles then may change from searching to competing for parking spots. When a parking guidance information system is reservation-based, vehicles do not have to compete for a parking area, because it is guaranteed in advance. Moreover, with the use of resource allocation, the travel routes of vehicles can be influenced. This can improve the distribution of vehicles in the traffic network. A reservation-based smart parking solution using resource allocation outperforms a regular parking guidance information system. However, existing papers use an objective for the resource allocation model based on the shortest route. To the best of the authors' knowledge, no resource allocation model to allocate parking areas has as objective to minimise overall travel time. If a resource allocation model to minimise overall travel time and a traffic signal control strategy are exchanging traffic information, the performance of the traffic network could be further improved.

Therefore, this research proposes a combined MPC and novel Parking Resource Allocation Model (PRAM) for urban traffic networks. For MPC, the S-model is chosen as the traffic prediction model. The S-model is a macroscopic traffic prediction model that uses the number of vehicles and the queue lengths in the traffic network as traffic states. The traffic states are used to predict the travel time of routes on the traffic network. A linear approximation of the average vehicle speed on the traffic network is made based on the traffic states, and the average vehicle speed and road lengths of the traffic network are used to predict the travel time of all travel routes. Two different PRAMs are created. The first model allocates vehicles to a parking area based on the predicted travel time. The second model has the same objective with an added objective to evenly distribute the vehicles over different parking areas. This objective prevents parking areas to become full, while other parking areas remain nearly empty. If a parking area is full, vehicles may end up in a full parking area and have to re-enter the traffic network in search of another vacant parking spot. The future distribution of vehicles on the traffic network changes when vehicles are allocated a travel route that is different from their initial travel route. The S-model is therefore modified to consider the future change in the distribution of vehicles.

The performance of the combined MPC and PRAM control strategy is compared using two case studies. In both case studies, the traffic network is a simplified representation of the mall of the Netherlands, located near Leidschendam. The first case study simulates traffic based on the morning rush hours, and the second case study simulates traffic based on the evening rush hours. In both case studies, multiple traffic demands are simulated, based on historical traffic data provided by Rijkswaterstaat. No historical data is provided by the mall of the Netherlands so fictive data is used. The performance of an MPC control strategy, an MPC control strategy with the first PRAM, and an MPC control strategy with the second PRAM is compared with a fixed-time control strategy for these traffic demands.

The results show that the MPC control strategy reduces the total time spent and vehicle time loss of all the vehicles for the morning rush hours, but not for the evening rush hours. For one traffic demand, the added PRAMs further reduce the total time spent and vehicle time loss of all the vehicles, in both case studies. For the other traffic demands, the added PRAMs increased the total time spent and vehicle time loss. There is no significant difference between the two PRAMs in terms of the total time spent and vehicle time loss. Furthermore, the distribution of vehicles to the parking areas is more evenly for the second PRAM. Since the parking demand is fictive, future research is necessary with accurate parking demand to ensure that the combined MPC and PRAM further improves the traffic flow on the traffic network of the mall of the Netherlands. Moreover, future research is needed to more accurately predict the travel time of travel routes.

Acknowledgement

This thesis is a product of seven years of studying at the TU Delft. Working on my thesis project during a pandemic certainly made things difficult and lonely at some times. However, I have had a lot of support during my seven years, especially during my thesis. I am happy and proud that I can present the final results.

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1

Introduction

Nowadays, almost every grown person has experience with traffic congestion. As the number of vehicles on the road exceeds the capacity of the traffic network, the traffic network gets saturated and vehicles slow down. The result often entails longer travel times, frustration, accidents, and more greenhouse gasses emitted. Moreover, traffic congestion results in negative social, economic, and environmental effects [3, 33, 43]. Especially during rush hours, urban areas with many daily commuters experience traffic congestion. Moreover, there are popular destinations for leisure in urban areas that have multiple large parking facilities. On average, vehicles that are searching for a parking spot have a lower driving speed than other vehicles, a habit called cruising. The lower cruising speed during rush hours result in a traffic flow decrease of 25%-40% [45], causing additional traffic congestion. When traffic congestion in urban areas increases, the congestion can propagate back to off-ramps of highways, causing dangerous situations. Therefore, improving the traffic flow in urban areas with destinations for leisure during rush hours is the objective of this thesis.

Possibilities to improve traffic conditions in urban areas are increasing traffic flow e.g. changing the physical structure or better managing traffic [20]. In urban areas, physically changing the road infrastructure to increase the traffic flow is costly, impairs the existing network, and is in some cases not even possible due to lack of physical capacity within the area. Instead, the traffic network can be better managed through the use of Traffic Signal Control (TSC) [31]. Over the years, many different scientific research on TSC strategies has been conducted. At first, TSC involved fixed-time control strategies, i.e. their control strategy is determined offline based on historical data. A more efficient TSC strategy is a traffic-response coordinated control strategy. Traffic-response control strategies can measure the traffic states in the network in real time, and adapt the control scheme according to the current measured traffic states. Traffic-response control strategies include model-based control approaches, one of which is Model Predictive Control (MPC). As one of the most powerful and widely used control technologies, MPC has been employed in the area of TSC in traffic networks and a series of significant results have been achieved in the past 20 years [47].

Another way to increase traffic flow in urban areas with leisure destinations is through the use of smart parking solutions. Smart parking solutions can reduce the amount of cruising for a parking area. An example of a smart parking solution is a Parking Guidance Information System (PGIS). The PGIS provides vehicles with information regarding the parking areas. Although current parking guidance systems increase the probability of finding vacant parking spaces, they have several shortcomings [8]. Drivers may not find vacant parking spots by merely following the guidance system. Furthermore, PGISs change the driving behaviour of vehicles from searching to competing for parking: Several drivers may head towards the same available parking spots resulting in failed parking for some vehicles, forcing re-planning and consequently competition for other parking spots [7]. To remove competition and re-planning, smart parking solutions can be reservation-based, i.e. they provide the vehicles with an option to reserve a parking area in advance of their trip [21]. Moreover, using resource allocation provides more control on the travel route vehicles take. This can increase the efficiency of the traffic network, increasing traffic flow. Resource allocation is a form of strategic planning, where various users (i.e. vehicles) are assigned to a resource (i.e. a parking area or a parking spot). In this strategic planning, the users can have different preferences, while the resource allocation model has an objective, which it tries to optimise. Users can be allocated to a resource in advance (i.e. a reservation of that parking area or spot). There is a significant performance improvement over existing smart parking solutions including the use of a PGIS, when using resource allocation to reserve a parking area or spot in advance where individual vehicles have a preference for cost and walking distance [9].

One element that resource allocation smart parking solutions do not have implemented, is combining resource allocation with a TSC strategy. Moreover, TSC strategies do not account for the use of parking areas on the traffic network. If a TSC and smart parking solution are to communicate, the traffic flow could be improved further. The smart parking solution could adjust their objective according to the current state of traffic.

1.1. Thesis objective

Tackling busy urban areas with large parking facilities, where daily traffic congestion occurs due to daily commuting and the use of these parking facilities remains challenging. Since the number of daily commuters during rush hours often exceeds the traffic networks' capacity, traffic flow decreases. Moreover, the large parking facilities may deteriorate the traffic flow. Combining a TSC strategy with a smart parking solution may be a viable option to further improve traffic flow. The main goal of this thesis will be to investigate the possibilities of a TSC strategy combined with a smart parking solution. This goal can be reached by answering the following main research question:

To what extent can model-based traffic signal control combined with a smart parking solution based on resource allocation further improve traffic flow in a busy urban traffic network with large parking areas?

1.2. Thesis outline

In Chapter 2, theoretical background on model-based control strategies, efficient traffic prediction models, and smart parking solutions is provided. In Chapter 3, the smart parking solution that is used throughout this thesis and the modifications needed for the control strategy and prediction model are explained. In Chapter 4, the performance of the different control strategies is compared by performing a case study. Lastly, this thesis is concluded and suggestions for future work are provided in Chapter 5.

2

Theory behind traffic signal control and parking models

In this chapter, the background information relevant for this research is provided. Different Traffic Signal Control (TSC) strategies are elaborated and the TSC used throughout this thesis is explained in Section 2.1. In Section 2.2, the smart parking solutions are elaborated and the use of resource allocation in smart parking solutions is explained. Lastly, the chapter is concluded in Section 2.3.

2.1. Urban traffic signal control

Over the years, many different TSC strategies have been studied [11, 35, 47]. At first, TSC involved fixed-time control for isolated signalised intersections [44]. The fixed-time control strategy consists of a repeating signal cycle, i.e. a sequence of traffic signal phases where each phase consists of non-conflicting green traffic signals, such that all lanes have enough green time within a signal cycle for vehicles to pass. Each intersection has its optimal signal cycle for the sole purpose of increasing the traffic flow or throughput of that particular intersection. An isolated control strategy can be optimised for one intersection but may lead to congestion somewhere else. In some situations, the overall traffic network may perform worse when the intersections are optimised individually.

Over time, a more coordinated control strategy has been employed to further improve the traffic flow. Instead of optimising an isolated intersection, a chain of intersections is optimised to allow a continuous traffic flow over the intersections, creating a so-called green wave. Often, fixed-time coordinated signal control strategies for multiple time periods are constructed, e.g. for the morning period, the afternoon period, and the late evening or night time period. For these time periods, priority between different roads can be provided, based on historical data. A popular example of a coordinated fixed-time control strategy is MAXBAND, developed by Little et al. in [29]. A downside of fixed-time coordinated signal control strategies is that they cannot cope with unexpected situations: Day-to-day variations in activities are not accounted for (e.g. when a traffic accident occurs).

An alternative TSC strategy is a traffic-response coordinated control strategy. A popular example of a coordinated traffic-response control strategy is SCOOT, developed by Hunt et al. [12]. Traffic-response coordinated control strategies can measure the traffic states in the network in real time, and adapt the control schemes according to the current measured traffic states. Furthermore, traffic-response coordinated control strategies can be model-based. Aboudolas et al. concluded that model-based controllers significantly outperform fixed-time controllers [1]. Model-based control methods (including Model Predictive Control (MPC)) use a traffic prediction model and an online optimisation step to find the best control decisions for the network. When the traffic prediction model is detailed and accurate, the traffic prediction model can accurately predict the traffic flow dynamics in the future, and as a result, enables the controller to look into the future to avoid myopic decisions [26]. Nevertheless, the installation and maintenance costs are much larger compared to fixed-time coordinated control strategies. Intersections with model-based coordinated control strategies require sensors or cameras that provide real-time measurements and communication methods to a central control system. Furthermore, the optimisation problem of model-based coordinated control strategies can become computationally complex when the number of controlled intersections increases. Therefore, the control strategies cannot create the next signal cycle in time and consequently become real-time infeasible.

Even though model-based coordinated control strategies are harder to implement and more expensive, the real-time optimal control feature makes them very attractive. Especially in busy urban areas, model-based coordinated control strategies can further reduce traffic congestion. As one of the most powerful and widely used control technologies, MPC has been employed in the area of TSC in traffic networks and a series of significant results have been achieved in the past 20 years [5, 25, 36]. MPC has some important advantages over traditional optimal control. Optimal control has an open-loop structure. Errors or disturbances can grow increasingly, as there is no feedback. The traffic prediction model has to be very accurate to ensure that the whole simulation has sufficient precision. MPC operates in closed-loop, meaning that the traffic state and the current demand are regularly fed back to the traffic signal controller. Therefore, the traffic signal controller can take disturbances into account and can correct prediction errors resulting from the model mismatch [10]. Moreover, MPC has many degrees of freedom in the choice of the objective function. For different traffic situations, MPC can implement different objective functions, whereas other TSC strategies do not have that possibility. Furthermore, MPC uses a rolling horizon approach. In this rolling horizon approach, traffic is predicted over a horizon of N prediction time steps, and the traffic signals are optimised for that particular horizon in the future. Only the first control input is used, after which the process repeats itself for the next control time step with the same horizon as before. This rolling horizon closes the control loop and provides current decisions based on a long term point of view. Errors do not accumulate very much, because of the finite horizon. Another reason MPC is widely used in TSC is the ability to replace the predictive model. A traffic prediction model that better suits the purpose of the objective can be implemented with little maintenance cost.

The traffic prediction model and the MPC control strategy that are used throughout this thesis, are explained in Sections 2.1.1 and 2.1.2.

2.1.1. Traffic prediction model: S-model

An urban traffic prediction model is introduced to gain more insight into the flow of traffic in urban areas and the influence traffic signals have. This traffic prediction model aims to replicate real-life traffic in a simulation. An important choice to make is whether to use a macroscopic or microscopic traffic prediction model, and whether to use a linear or nonlinear traffic prediction model.

A microscopic model models the behaviour of individual vehicles in the entire network. An advantage of microscopic models is that complex behaviour of individual vehicles can be modelled. However, the traffic states of microscopic models grow increasingly when the number of vehicles increase in the traffic network. For a TSC strategy to be effective in real time, the computation time of the traffic prediction model has to be lower than the sampling time (e.g. if the control strategy is updated every second, the computation time of the traffic prediction model has to be lower than a second to be real-time feasible). Macroscopic models are often derived from the notion of fluid flow [4], or horizontal queuing [18]. In macroscopic vehicles, the individual behaviour is aggregated over the traffic network. The flow of vehicles over a particular road is modelled. The number of traffic states of a macroscopic model grows with the traffic network, not with the number of vehicles. Modelling a busy traffic network with macroscopic traffic prediction models results in lower computation times as opposed to microscopic traffic prediction models. Therefore, for large urban areas, macroscopic models are more suitable.

Another notion to consider is the linearity of the traffic prediction models. As traffic behaves highly non-linearly [26], linear models cannot capture the traffic behaviour, and therefore have lower accuracy. However, the online optimisation step of linear traffic prediction models can be solved using efficient convex optimisation algorithms. Linear traffic prediction models (i.e. [48]) are real-time feasible. Nonlinear traffic prediction models can model complex traffic situations, which can result in better control performance. Nonetheless, the constraints of a nonlinear model become nonlinear and non-convex as well. This requires a nonlinear and non-convex optimisation method that may result in multiple local minima, making the optimisation suboptimal. To approximate the global optimum, many local minima have to be examined, which is rather time-consuming. By increasing the simulation time interval, fewer online optimisation steps are required in the same time period, and for real-time computation, this relaxes the maximum computation time per online optimisation that is required. As a result, larger networks can be analysed in real time. Hence, for large urban areas, an accurate traffic prediction model with a large simulation time interval would be ideal for real-time feasibility.

There are various macroscopic traffic models, such as the cell transmission model [4], the link transmission model [38], the BLX-model [23, 39], and the S-model [26]. Every macroscopic model has a trade-off between accuracy and computation time. In the link transmission model, traffic is predicted in a linear fashion. This reduces the computation time significantly. However, the behaviour of traffic cannot be accurately predicted using a linear traffic prediction model. Both the BLX-model and the S-model have been used in combination with MPC [24, 25]. It is preferred to have a traffic prediction model with a larger computation time, as the scope of this research mainly focuses on large urban areas. The S-model is a simplified model originating from the BLX-model with a higher sampling time. The sampling time of the cell transmission model and the BLX-model is somewhere between 1 and 2 seconds, whereas the sampling time of the S-model is the signal cycle of an intersection, often ranging between 1 and 2 minutes. Because of this larger sampling time, fewer computations are needed in the same time interval lowering the computation time. Therefore, the S-model will be used as the traffic prediction model throughout this thesis. The S-model is a nonlinear and discrete-time model and is explained in this section based on [14, 15, 27].

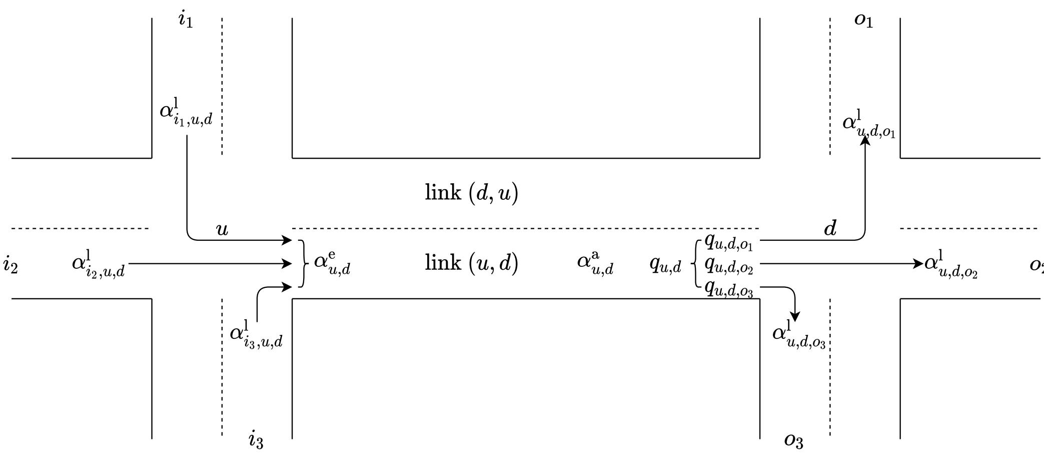


Figure 2.1: A link connecting two traffic-signal-controlled intersections, adopted from [27]

The S-model is defined by a set of nodes J and a set of links L. Each link $(u,d) \in L$ is defined by the upstream node $u \in J$ and the downstream node $d \in J$. The sets of input and output nodes for link (u,d) are $I_{u,d} \subseteq L$ and $O_{u,d} \subseteq L$. Figure 2.1 shows a link connecting two intersections, where $I_{u,d} = \{i_1, i_2, i_3\}$ and $O_{u,d} = \{o_1, o_2, o_3\}$. All intersections are assumed to have equal cycle time c, which is chosen as the sampling time. The corresponding cycle counter is k is time step counter. The state variables of the model are the total number of vehicles $n_{u,d}(k)$ and the queue length $q_{u,d}(k)$ on link (u,d) at time step k. The queue length on link (u,d) can be divided into the queue length going to specific output node $q_{u,d,o}(k)$ with $o \in O_{u,d}$. At every time step k, the total number of vehicles and the queue length are updated:

$$n_{u,d}(k+1) = n_{u,d}(k) + \left(\alpha^{\mathrm{e}}_{u,d}(k) - \alpha^{\mathrm{l}}_{u,d}(k)\right) c, \tag{2.1}$$

$$q_{u,d,o}(k+1) = q_{u,d,o}(k) + \left(\alpha^{\mathrm{a}}_{u,d,o}(k) - \alpha^{\mathrm{l}}_{u,d,o}(k)\right) c, \tag{2.2}$$

$$q_{u,d}(k) = \sum_{o \in O_{u,d}} q_{u,d,o}(k), \tag{2.3}$$

where $\alpha^{\mathrm{e}}_{u,d}(k)$ and $\alpha^{\mathrm{l}}_{u,d}(k)$ are the average entering and leaving flow rates on link (u,d), $\alpha^{\mathrm{a}}_{u,d,o}(k)$ the average arriving flow rate at the tail of the queue on link (u,d) going to node o, and $\alpha^{\mathrm{l}}_{u,d,o}(k)$ the average leaving flow rate on link (u,d) going to node o, in the time interval $[kc,(k+1)c)$.

The leaving flow rate on link (u,d) at time step k is:

$$\alpha^{\mathrm{l}}_{u,d}(k) = \sum_{o \in O_{u,d}} \alpha^{\mathrm{l}}_{u,d,o}(k), \tag{2.4}$$

where the leaving flow rate on link (u,d) going to node o at time step k is defined as the minimum of three flow rates: the saturated, under-saturated, and over-saturated flow rate.

$$\alpha^{\mathrm{l}}_{u,d,o}(k) = \min\left\{\mu_{u,d,o}\frac{g_{u,d,o}(k)}{c}N^{\mathrm{lane}}_{u,d,o},\quad \frac{q_{u,d,o}(k)}{c} + \alpha^{\mathrm{a}}_{u,d,o}(k),\quad \frac{\beta_{u,d,o}(k)}{\sum_{u\in I_{d,o}}\beta_{u,d,o}(k)}\frac{C_{d,o}-n_{d,o}(k)}{c}\right\}, \tag{2.5}$$

with $\mu_{u,d,o}$ the saturated flow leaving link (u,d) going to node o, $g_{u,d,o}(k)$ the green time length of link (u,d) going to node o during $[kc,(k+1)c)$, $\beta_{u,d,o}(k)$ the relative fraction of the traffic on link (u,d) turning to node o during $[kc,(k+1)c)$, $C_{d,o}$ the capacity on link (d,o), and $n_{d,o}(k)$ the total number of vehicles on link (d,o) at time step k.

Vehicles entering link (u,d) will arrive at the tail of the queue after some time delay $\delta_{u,d}(k)$:

$$\delta_{u,d}(k) = \tau_{u,d}(k)c + \gamma_{u,d}(k), \tag{2.6}$$

where $\tau_{u,d}(k)$ is the number of complete cycles of the delay $\delta_{u,d}(k)$, and $\gamma_{u,d}(k)$ the remainder of the delay:

$$\tau_{u,d}(k) = \left\lfloor \frac{\delta_{u,d}(k)}{c} \right\rfloor, \tag{2.7}$$

$$\gamma_{u,d}(k) = \delta_{u,d}(k) - \tau_{u,d}(k)c, \tag{2.8}$$

With the time delay, the average arriving flow rate is given by [15]:

$$\alpha^{\mathrm{a}}_{u,d}(k) = \sum_{i=0}^{|\tau_{u,d}(k)+1-\tau_{u,d}(k+1)|} B_{u,d,i}(k)\cdot\alpha^{\mathrm{e}}_{u,d}\left(k-\max\left(\tau_{u,d}(k+1),\tau_{u,d}(k)+1\right)+i\right), \tag{2.9}$$

where $B_{u,d,i}(k)$ for $i>0$ and $i<|\tau_{u,d}(k)+1-\tau_{u,d}(k+1)|$ equals 1:

$$B_{u,d,i}(k) = 1 \quad \forall i\in\mathbb{N},\quad i>0,\quad i<|\tau_{u,d}(k)+1-\tau_{u,d}(k+1)|.$$

For the end points $i=0$ and $i=|\tau_{u,d}(k)+1-\tau_{u,d}(k+1)|$ three cases occur:

1. In case of $\tau_{u,d}(k)+1>\tau_{u,d}(k+1)$:

$$\begin{aligned} B_{u,d,0}(k) &= \frac{\gamma_{u,d}(k)}{c},\\ B_{u,d,|\tau_{u,d}(k)+1-\tau_{u,d}(k+1)|}(k) &= \frac{c-\gamma_{u,d}(k+1)}{c}, \end{aligned} \tag{2.10}$$

2. In case of $\tau_{u,d}(k)+1<\tau_{u,d}(k+1)$:

$$\begin{aligned} B_{u,d,0}(k) &= -\frac{\gamma_{u,d}(k+1)}{c},\\ B_{u,d,|\tau_{u,d}(k)+1-\tau_{u,d}(k+1)|}(k) &= -\frac{c-\gamma_{u,d}(k)}{c}, \end{aligned} \tag{2.11}$$

3. In case of $\tau_{u,d}(k)+1=\tau_{u,d}(k+1)$:

$$\begin{aligned} B_{u,d,0}(k) &= \frac{\gamma_{u,d}(k)-\gamma_{u,d}(k+1)}{c},\\ B_{u,d,|\tau_{u,d}(k)+1-\tau_{u,d}(k+1)|}(k) &= 0. \end{aligned} \tag{2.12}$$

This average arriving flow rate is divided over the queues heading in different directions based on the turning fraction:

$$\alpha^{\mathrm{a}}_{u,d,o}(k) = \beta_{u,d,o}(k)\alpha^{\mathrm{a}}_{u,d}(k). \tag{2.13}$$

The time delay in (2.6) represents the time it takes for vehicles entering the link to reach the tail of the queue and is dependent on the capacity of the link $C_{u,d}$, the length of the queue, and the distance travelled by a vehicle with constant deceleration $a^{\mathrm{dec}}_{u,d}$ from the free flow speed $v^{\mathrm{free}}_{u,d}$ to the idling speed $v^{\mathrm{low}}_{u,d}$. The capacity of the link (u,d) is given by:

$$C_{u,d} = \frac{l^{\mathrm{lane}}_{u,d} N^{\mathrm{lane}}_{u,d}}{l^{\mathrm{veh}}}, \tag{2.14}$$

with $N^{\mathrm{lane}}_{u,d}$ the number of lanes in link (u,d), $l^{\mathrm{lane}}_{u,d}$ the length of link (u,d), and l^{veh} the average length of a vehicle. To ensure the proper time delay, the distance $\bar{X}_{u,d}$ needed for a vehicle to decelerate from the free flow speed to the idling speed has to be compared to the distance between the beginning of a link and the tail of the queue $\Delta x_{u,d}(k)$. The distance $\bar{X}_{u,d}$ needed for a vehicle to decelerate from the free flow speed to the idling speed is given by:

$$\bar{X}_{u,d} = \frac{1}{2} a^{\mathrm{dec}}_{u,d} \left(\frac{v^{\mathrm{low}}_{u,d} - v^{\mathrm{free}}_{u,d}}{a^{\mathrm{dec}}_{u,d}} \right)^2 + v^{\mathrm{free}}_{u,d} \frac{v^{\mathrm{low}}_{u,d} - v^{\mathrm{free}}_{u,d}}{a^{\mathrm{dec}}_{u,d}}. \tag{2.15}$$

The distance between the beginning of a link and the tail of the queue $\Delta x_{u,d}(k)$ is given by:

$$\Delta x_{u,d}(k) = \frac{C_{u,d} - q^{\mathrm{ave}}_{u,d}(k)}{N^{\mathrm{lane}}_{u,d}} l^{\mathrm{veh}}, \tag{2.16}$$

where $q^{\mathrm{ave}}_{u,d}(k)$ is the average length of the queue in link (u,d) during $[kc,(k+1)c)$, and can be approximated by the queue length at k and $k+1$, or by the output of a predictor-corrector procedure [16]. The time delay is calculated for three different cases. The distance between the beginning of a link and the tail of the queue is either longer, equal, or smaller than the distance needed for a vehicle to decelerate from the free flow speed to the idling speed:

1. In case $\Delta x_{u,d}(k) > \bar{X}_{u,d}$:

$$\delta_{u,d}(k) = \frac{C_{u,d} - q^{\mathrm{ave}}_{u,d}(k)}{N^{\mathrm{lane}}_{u,d} v^{\mathrm{free}}_{u,d}} l^{\mathrm{veh}} - \frac{\left(v^{\mathrm{low}}_{u,d} - v^{\mathrm{free}}_{u,d}\right)^2}{2 a^{\mathrm{dec}}_{u,d} v^{\mathrm{free}}_{u,d}}. \tag{2.17}$$

2. In case $\Delta x_{u,d}(k) = \bar{X}_{u,d}$:

$$\delta_{u,d}(k) = \frac{v^{\mathrm{low}}_{u,d} - v^{\mathrm{free}}_{u,d}}{a^{\mathrm{dec}}_{u,d}}. \tag{2.18}$$

3. In case $\Delta x_{u,d}(k) < \bar{X}_{u,d}$:

$$\delta_{u,d}(k) = \frac{v^{\mathrm{low}}_{u,d}}{a^{\mathrm{dec}}_{u,d}} + \left(\left(\frac{v^{\mathrm{low}}_{u,d}}{a^{\mathrm{dec}}_{u,d}} \right)^2 - 2 \frac{\left(C_{u,d} - q^{\mathrm{ave}}_{u,d}(k)\right) l^{\mathrm{veh}}}{a^{\mathrm{dec}}_{u,d} N^{\mathrm{lane}}_{u,d}} \right)^{0.5}. \tag{2.19}$$

Furthermore, the average flow rate entering link (u,d) is determined by the average flow rate leaving in direction of link (u,d):

$$\alpha^{\mathrm{e}}_{u,d}(k) = \sum_{i\in I_{u,d}} \alpha^{\mathrm{l}}_{i,u,d}(k). \tag{2.20}$$

Note that the average entering flow rate of link (u,d) is not updated when node u is on the edge of the traffic network. If that link is getting saturated, the provided demand of the traffic network could not be reached. Thus an origin queue is implemented to account for the lower average entering flow rate on source nodes. Suppose that there exists a set of source nodes $S \subset J$. The entering flow rate of link (s,d) with source node $s \in S$ is determined by:

$$\alpha^{\mathrm{e}}_{s,d}(k) = \min\left\{\alpha^{\mathrm{dem}}_{s,d}(k) + \frac{q^{\mathrm{source}}_{s,d}}{c}, \frac{C_{s,d} - n_{s,d}(k)}{c}\right\}, \tag{2.21}$$

where $\alpha^{\mathrm{dem}}_{s,d}(k)$ is the demand flow of link (s,d) on the traffic network during $[kc,(k+1)c)$ and $q^{\mathrm{source}}_{s,d}(k)$ the source queue at source node s at time step k. The update equation of the source queue is:

$$q^{\mathrm{source}}_{s,d}(k+1) = q^{\mathrm{source}}_{s,d}(k) + \left(\alpha^{\mathrm{dem}}_{s,d}(k) - \alpha^{\mathrm{e}}_{s,d}(k)\right)c. \tag{2.22}$$

2.1.2. Model predictive control

As was stated earlier, the main advantage of MPC is that the rolling horizon closes the control loop, unlike many other optimal control methods. Therefore, MPC is robust to uncertainties of the traffic prediction model. MPC can easily deal with multi-input and multi-output problems with additional constraints. Another advantage of MPC is that it is modular such that one can freely select and replace the prediction model based on the control requirements or the trade-off between accuracy and computational complexity [26]. The prediction model used in the MPC is the S-model, explained in Section 2.1.1. The states of the S-model are used to calculate the number of vehicles and queues on each link and exit. At every control time step k_{c}, the online optimisation is performed. The S-model is used to predict future states and to calculate a sequence of sub-optimal control inputs over a prediction horizon of N_{p} time steps. Given the control time interval T_{c} and the simulation time interval c, there exists an integer a such that

$$T_{\mathrm{c}} = a \cdot c, \tag{2.23}$$

where T_{c} is the least common multiple of all the intersection cycle times. For a given k, the corresponding value of k_{c} is given by:

$$k_{\mathrm{c}}(k) = \left\lfloor \frac{k}{a} \right\rfloor, \tag{2.24}$$

where $\lfloor x \rfloor$ for x being a real number denotes the largest integer less than or equal to x. A given value k_{c} of the control time step corresponds to the set $\{k_{\mathrm{c}}a, k_{\mathrm{c}}a+1, \ldots, (k_{\mathrm{c}}+1)\,a-1\}$ of simulation time steps. A control horizon $N_{\mathrm{c}} < N_{\mathrm{p}}$ can be used to reduce the number of decision variables. If $N_{\mathrm{c}} < N_{\mathrm{p}}$, the control inputs between N_{c} and N_{p} will be held constant. Then, only the first control input is implemented in the system. This process is known as the rolling horizon principle [2], displayed in Figure 2.2.

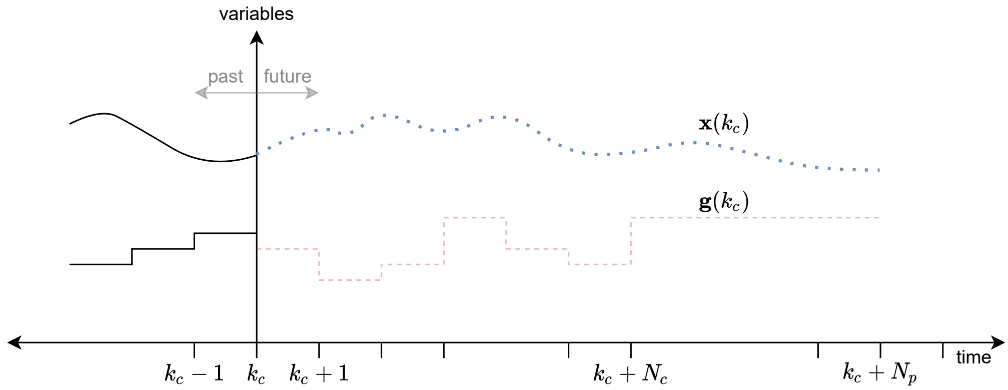


Figure 2.2: Visualisation of the control and prediction horizon N_c and N_p, respectively, and the green times $\mathbf{g}(k_\mathrm{c})$ and state update intervals at every control time step k_c

At every control time step, the sub-optimal control inputs of MPC are calculated by solving the following optimisation problem:

$$\begin{aligned}
&\min_{\mathbf{g}(k_\mathrm{c})} w_\mathrm{TTS}\frac{J_\mathrm{TTS}(k_\mathrm{c})}{\mathrm{TTS^n}} + w_\mathrm{Final}\frac{J_\mathrm{Final}(k_\mathrm{c})}{\mathrm{Final^n}} + w_\mathrm{D}\frac{J_\mathrm{D}(k_\mathrm{c})}{\mathrm{D^n}} + w_\mathrm{Q}\frac{J_\mathrm{Q}(k_\mathrm{c})}{\mathrm{Q^n}},\\
\text{s.t.}\quad & x_{u,d}(k_\mathrm{c}+1) = f\left(x_{u,d}(k_\mathrm{c}), \hat{\mathbf{g}}_d(k_\mathrm{c})\right),\\
&\mathbf{g}_\mathrm{min} \le \hat{\mathbf{g}}(k_\mathrm{c}) \le \mathbf{g}_\mathrm{max},\\
&\Phi\left(\hat{\mathbf{g}}(k_\mathrm{c})\right) = 0,
\end{aligned} \tag{2.25}$$

where TTS stands for the total time spent, with $\hat{\mathbf{g}}(k_\mathrm{c}) = \left[\mathbf{g}^\top(k_\mathrm{c}), \mathbf{g}^\top(k_\mathrm{c}+1), \ldots, \mathbf{g}^\top(k_\mathrm{c}+N_\mathrm{c}-1)\right]^\top$, in which $\mathbf{g}(k_\mathrm{c})$ is a column vector with green times $\mathbf{g}_d(k_\mathrm{c})$ of all intersections $d \in J$ at control time step k_c, the function $f(\cdot)$ represents the S-model, $x_{u,d}(k_\mathrm{c}) = \left[n_{u,d}(k_\mathrm{c}), q_{u,d}(k_\mathrm{c})\right]^\top$ a vector with the number of vehicles and the queue of each link $(u,d) \in L$, w_TTS, w_Final, w_D, and w_Q the weights that describe the importance of the control objectives, $\mathrm{TTS^n}$, $\mathrm{Final^n}$, $\mathrm{D^n}$, and $\mathrm{Q^n}$ the nominal values of the control objectives, $\mathbf{g}_\mathrm{min}$ and $\mathbf{g}_\mathrm{min}$ vectors of the appropriate size with the minimum and maximum phase times, respectively, and $\Phi\left(\hat{\mathbf{g}}(k_\mathrm{c})\right) = 0$ is the cycle time constraint:

$$\Phi\left(\hat{\mathbf{g}_d}(k_\mathrm{c})\right) = c_d - y_d - \sum_{j=1}^{N_d^\mathrm{ph}} g_{d,j}(k_\mathrm{c}), \tag{2.26}$$

where y_d and N_d^ph are the total yellow time and the number of phases of intersection d, respectively.

The traffic prediction model described in Section 2.1.1 uses green time fractions. Instead of modelling individual green times as the decision variables, the phase times are used as decision variables in Section 2.1.2. Figure 2.3 displays the four different phases of each intersection. For a given network with four intersections that each have four phases, there are $16 \cdot N_\mathrm{c}$ decision variables.

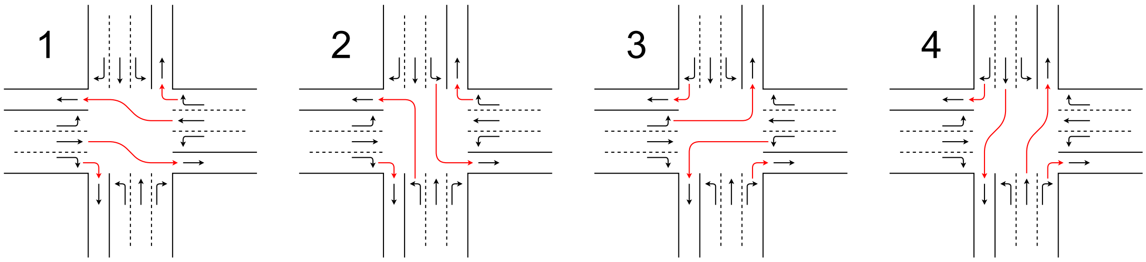


Figure 2.3: Different phases of an intersection, where the red arrows are traffic lights that have right of way

The control objectives, that the MPC tries to minimise, are split into four different parts. At first, the total time spent of all vehicles in the network over the prediction horizon N_p is:

$$J_\mathrm{TTS}(k_\mathrm{c}) = \sum_{(u,d)\in L} \sum_{k_d=k_\mathrm{c}+1}^{k_\mathrm{c}+N_\mathrm{p}-1} c_d \cdot n_{u,d}(k_d), \tag{2.27}$$

the second part of the objective function is a terminal cost to consider the total time spent at the end of the horizon:

$$J_\mathrm{Final}(k_\mathrm{c}) = \sum_{(u,d)\in L} c_d \cdot n_{u,d}(k_\mathrm{c} + N_\mathrm{p}), \tag{2.28}$$

and the third part of the objective function is a cost to prevent large fluctuations of the control inputs between the control time steps:

$$J_\mathrm{D}(\hat{\mathbf{g}}(k_\mathrm{c})) = \sum_{j=0}^{N_\mathrm{c}} \left\| \hat{\mathbf{g}}(k_\mathrm{c} + j) - \hat{\mathbf{g}}(k_\mathrm{c} + j - 1)) \right\|_2^2. \tag{2.29}$$

For the last part of the objective function, a set of nodes K is defined, with all the nodes $i \in K \subseteq J$ that are an intersection. For each intersection i, a set of nodes $K_i \subseteq J$ is defined with all nodes u that have link (u,i) to intersection i. The last part of the objective function is the sum of the longest queue of each intersection over the prediction horizon N_p:

$$J_\mathrm{Q}(k_\mathrm{c}) = \sum_{k=k_\mathrm{c}}^{k_\mathrm{c}+N_\mathrm{p}} \sum_{i\in K} \max_{u\in K_i} \max_{o\in O_{u,i}} q_{u,i,o}(k), \tag{2.30}$$

where $O_{u,i}$ is the set of outgoing nodes of link (u,i). With the sum of the longest queue of each intersection, more green time is given to these queues to more evenly distribute vehicles over the traffic network.

One way to solve the nonlinear optimisation problem of MPC is with a multi-start sequential quadratic programming algorithm [34]. A major drawback of nonlinear MPC is its computational complexity. When the computation time for one control time step becomes greater than the sampling time interval, the MPC becomes real-time infeasible. However, the scope of this thesis focuses on the combination of MPC with a resource allocation model on parking areas to improve the traffic flow. Therefore, reducing the computational complexity of MPC such as [17, 25] will not be considered throughout this thesis.

2.2. Resource allocation in smart parking solutions

On average, vehicles that are searching for a vacant parking spot drive with a lower vehicle speed, a habit called cruising [45]. Smart parking solutions may reduce the amount of cruising and consequently increase the traffic flow. Every driver has their destination and wants to get there as fast as possible. Most drivers do not consider the travel time of other drivers other than themselves. To improve the traffic flow further than reducing the amount of cruising for all drivers, driving behaviour has to be influenced. Smart parking solutions try to influence the behaviour of individual vehicles by providing alternatives that should benefit them, whether it be in price, time or any other value. However, to create a smart parking solution, both the infrastructure (e.g. parking area) and the vehicle have to exchange information.

In general, three types of information flow can be considered in a traffic network: information flow streaming from vehicle-to-vehicle, streaming from vehicle-to-infrastructure and streaming from infrastructure-to-vehicle. In current smart parking areas, the number of available parking spots can be measured through the use of sensors. This information can be displayed for each specific area using a red-yellow-green light, and the total available parking spots can be displayed using a variable-message-sign located near the parking area entries [28]. This is an example of infrastructure-to-vehicle information flow. An example of vehicle-to-infrastructure information flow is to provide information to the parking area where you plan to arrive. An example of vehicle-to-vehicle information flow is to share your traffic route with other vehicles. If vehicles are to be guided to a parking area, infrastructure-to-vehicle information flow is essential. Other information flow such as vehicle-to-infrastructure and vehicle-to-vehicle can be useful to improve the smart parking solution. One example of a smart parking solution that uses infrastructure-to-vehicle information flow is a Parking Guidance Information System (PGIS) [46]. The PGIS provides vehicles with information regarding the optimal parking area. The optimal parking area is derived using the Dijkstra algorithm to find the shortest path. Vehicles are then informed on the optimal path to a parking area. Although current parking guidance systems increase the probability of finding vacant parking spaces, they have several shortcomings [8]. Drivers may not find vacant parking spots by merely following the guidance system. Furthermore, the driving behaviour is changed from searching to competing for parking: More drivers head towards the same available parking spots, and none may be free by the time some drivers arrive, thus forcing re-planning and competition for other spots [7].

Some smart parking solutions are reservation-based, i.e., they provide the vehicles with an option to reserve a parking area before the start of their trip [21]. These reservation-based smart parking solutions reduce the amount of cruising significantly and improve the driver experience. With the use of sensors at every parking spot, a red light could be displaying a reserved parking spot, while green light is an available parking spot. A yellow indicator could provide the arriving vehicle with the information on where to park.

Instead of keeping the choice for the specific parking area with individual vehicles, one could remove the choice. If the smart parking solution could choose the dedicated parking area for vehicles, cruising and traffic congestion could be reduced. This can be done using resource allocation. Resource allocation is a powerful method that is used in many fields of research (e.g. medical, logistic, energy, and manufacturing fields [6, 22, 30, 32]). Resource allocation is a form of strategic planning, where various users are assigned to a resource, based on an objective. Both users and resources can have different preferences or constraints in strategic planning. An advantage of resource allocation is that multiple objectives can be implemented in the model. Resource allocation is therefore very versatile and can optimise the objectives whilst considering the preferences and constraints of individual users or resources. By implementing resource allocation in parking areas, vehicles can be spread out more evenly over the traffic network. Hence, it is interesting to look at the possibilities of resource allocation in urban areas with parking areas during rush hours, where many daily commuters use the traffic network and many daily visitors use the parking areas.

In general, there is a set of users U and a set of resources R. The control input is the choice $x_{u,r}$ to allocate user u to resource r. The cost to allocate user u to resource r is defined as $j_{u,r}$. An example of a linear resource allocation controller is:

$$\begin{aligned}
\min_{\mathbf{x}} \quad & J\mathbf{x} \\
\text{s.t.} \quad & x_{u,r} = \begin{cases} 1, & \text{if user } u \text{ is allocated to resource } r \\ 0, & \text{otherwise} \end{cases} \\
& \text{Additional constraints}
\end{aligned} \tag{2.31}$$

where $\mathbf{x} = \left[x_{1,1}, \ldots, x_{1,r}, x_{2,1}, \ldots, x_{u,r}\right]^\top$ is a column vector with $x_{u,r}$ the allocation of user u to resource r and $J = \left[j_{1,1}, \ldots, j_{1,r}, j_{2,1}, \ldots, j_{u,r}\right]^\top$. Note that the cost $j_{u,r}$ of allocation of user u to resource r may be divided into different control objectives, or preferences of the user (e.g. the shortest travel distance, additional cost of the use of resource r, etc.). Additional constraints may be posed for user u or resource r (e.g. a maximum capacity of resource r or a maximum cost of user u). This optimisation problem is a linear programming problem with binary values, and can be solved using a branch-and-bound procedure.

Geng and Cassandras presented a dynamic resource allocation model for smart parking [9]. Individual vehicles can notify a parking application to be allocated to a parking area. Every user u provides a maximum walking distance D_u and maximum cost of parking M_u. The user also provides a preference of their importance to minimise the walking distance over the cost of parking λ, with $\lambda = 0$ only prioritising the walking distance and $\lambda = 1$ only prioritising the cost of parking. User experience can improve when users can choose their upper bounds. Nevertheless, they may end up not having a resource (i.e. the parking spot) that meets their requirements. If so, the user has to change the constraints and re-apply for allocation to a parking spot. Furthermore, if there is a resource that meets the requirement in time step k, the resource may be unavailable in $k+1$, as the cost of parking is predictive and could change at every time step. This is a limitation of the dynamic resource allocation model that could cause frustration with the user as they have to re-apply with different constraints. The optimisation problem is considered to be a mixed integer linear programming problem that can be solved using a branch-and-bound procedure. The objective of the dynamic resource allocation model is to minimise the total travel distance and the cost of parking. One flaw to be pointed out is that the shortest travel distance may not be the shortest travel time. In partly saturated traffic networks, the shortest travel path may be saturated, while another travel path avoids these congested areas, resulting in significantly lower travel times.

Reservation-based smart parking solutions could also reduce traffic congestion by controlling the parking price [37]. By introducing dynamic pricing in reservation-based smart parking solutions, the total revenue of the parking areas could go up, while the total effective cost of all vehicles is significantly cut, and the overall traffic congestion caused by parking could be eliminated [19]. Vehicles are spread out more evenly along the day, increasing the potential of the parking area. Wang and Wang created a flexible parking reservation system with variable pricing that further reduced the reservation failure rate [43]. However, vehicles that use parking areas for their events (e.g. shopping malls or soccer stadiums) are forced to arrive and leave at a specific time. When that time is during rush hours, the effect of dynamic pricing may not be impressive. Individual vehicles will accept higher pricing simply because they have to be there at a specific time, resulting in higher parking costs. On top of that, some parking areas are free of charge.

In some smart parking solutions, a parking prediction model is used to predict the parking demand in the future [42, 45]. Implementing a parking prediction model provides a better understanding of how to distribute vehicles over the parking areas. In situations where parking spots need to be available in the future for future demand, it is of added value to incorporate a parking prediction model in the smart parking solution. Hence, using a parking prediction model may be beneficial for the smart parking solution, but it is not required.

One thing that is currently not yet implemented in smart parking solutions, is a TSC strategy that works together with the smart parking solution. Having information regarding the traffic signals during rush hours could have a significant effect on the optimal parking strategy. During these rush hours, distributing vehicles evenly along the traffic network can improve the traffic flow on that network. By using accurately predicted travel times of traffic routes, individual vehicles are provided with their desired shortest travel time, while also considering the distribution of the traffic network. Therefore, a novel smart parking solution based on resource allocation that considers the development of traffic is designed in this thesis.

2.3. Conclusions

By implementing a model-based traffic-response controller, congestion can be reduced in urban areas. Over the years MPC has proven to significantly improve traffic flow, consequently reducing traffic congestion. MPC in urban areas uses a TSC strategy to optimise the green time of an intersection. To optimise the green time, an accurate traffic prediction model is needed. One of the main disadvantages of MPC is its computational complexity. A complex traffic prediction model may take too long to find the optimal green times, resulting in real-time infeasibility, i.e. the optimal green times cannot be found within the sampling time of the intersection. Therefore, a trade-off in accuracy and computational complexity is required for the traffic prediction model. Increasing the sampling time interval is found to be an effective way of reducing the computational complexity while still maintaining accuracy. The traffic prediction model used throughout this thesis is the S-model, explained in Section 2.1.1.

More traffic congestion can occur in urban areas with large parking areas used for leisure (e.g. shopping malls, soccer stadiums, or concerts). Many vehicles need a vacant parking spot and often drive slower when searching. The introduction of resource allocation in smart parking solutions improved the possibilities for parking areas. The parking areas could implement control objectives such as travel distance, travel cost, or revenue. For parking areas with time-based leisure, other control objectives may have more benefit during rush hours. Travel time and parking availability could provide a more even distribution of the traffic network, reducing traffic congestion.

There is considerable research on the use of resource allocation in parking areas. The main goal is to minimise the amount of cruising that occurs in the traffic network. Furthermore, individual preferences such as walking distance and parking cost are considered. However, to the authors' best knowledge, no research is done on resource allocation in parking areas with the focus on reducing traffic congestion. Therefore, in Chapter 3, the implementation of a parking resource allocation model together with the TSC strategy is designed and elaborated.

3

Novel smart parking solution: Parking resource allocation model

In this chapter, a novel smart parking solution based on resource allocation is introduced and explained in Section 3.1. The novel parking resource allocation model communicates with the traffic prediction model and traffic signal control strategy, elaborated in Sections 2.1.1 and 2.1.2, respectively, to reduce traffic congestion. The traffic prediction model is consequently modified in Section 3.2 to consider the control strategy of the resource allocation model in the traffic prediction model.

3.1. Parking resource allocation model

The control scheme of both the traffic signal controller and the parking resource allocation model is presented in Figure 3.1. In the control scheme, information regarding the traffic network is input for the traffic prediction model. Sub-optimal traffic signals are calculated with the use of Model Predictive Control (MPC) where the traffic prediction model predicts the traffic states of the future.[1] The sub-optimal traffic signals are used in the traffic network and the process is repeated. After the sub-optimal traffic signals are found, the future traffic states are used to predict the travel times of all routes to a parking area. Vehicles are then allocated to a parking area, based on the predicted travel times and other information regarding the parking areas (e.g. the number of available parking spots).

All vehicles are initialised with a travel route to a parking area based on the shortest distance. When vehicles are allocated to another travel route, this changes the distribution of vehicles on the traffic network. The traffic prediction model is therefore provided with this information to account for the change in the distribution of vehicles.

[1]The optimisation problem is nonlinear nonconvex and requires a multi-start sequential quadratic programming algorithm. Since the global optimum cannot be guaranteed, the algorithm provides sub-optimal control inputs.

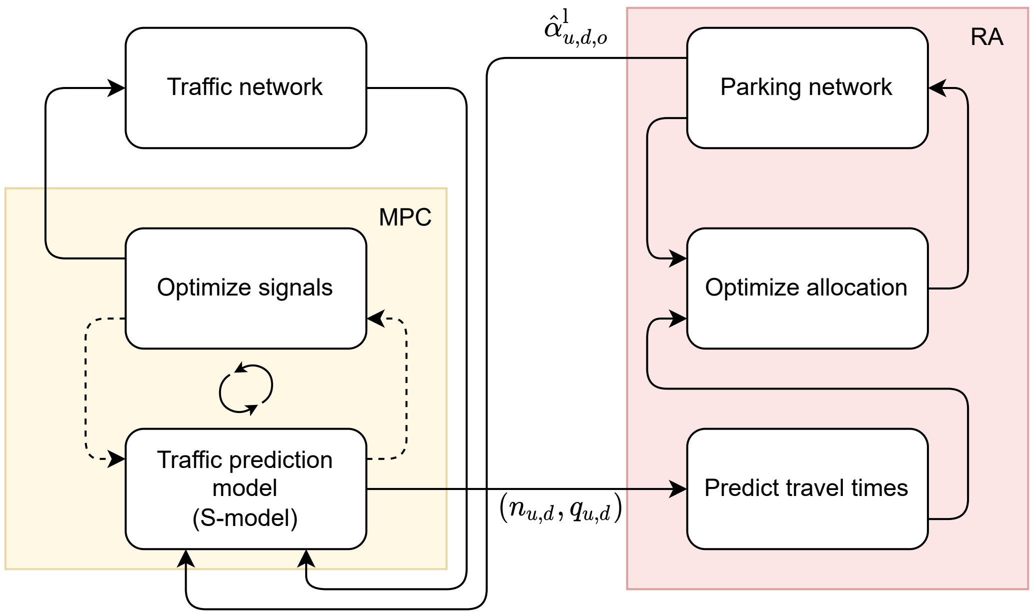


Figure 3.1: Control schemes of MPC and resource allocation where $\mathbf{x}_{u,d}$ are the traffic states from the traffic prediction model and $\hat{\alpha}_{u,d,o}$ is the future change in the distribution of the exits

The parking resource allocation model is defined by a set of users U, a set of routes R, and the same set of nodes J as defined in the S-model presented in Section 2.1.1. The model uses the state variables $n_{u,d}(k)$ and $q_{u,d}(k)$ of the S-model as input. Furthermore, the length of each link $l^{\mathrm{lane}}_{u,d}$ and the simulation time interval c with corresponding time step counter k of the S-model are used. Each user $u \in U$ has a starting node $s_u \in J$, and a real valued starting time t_u. Every starting node s_u of user u has a set of travel routes $R(s_u) \subseteq R$ where each travel route $r_{s,p}$ has a starting node s and the destination of parking area $p \in P$. Each route $r \in R$ has a set of links $L(r) \subseteq L$ that the travel route uses. The predicted travel time $T_r(k)$ of route r at time step k is:

$$T_r(k) = \sum_{i \in L(r)} \frac{l^{\mathrm{lane}}_i}{v^{\mathrm{ave}}_{u,d}(k)}, \tag{3.1}$$

where $v^{\mathrm{ave}}_{u,d}(k)$ is the predicted average vehicle speed of link (u,d) at time step k. The predicted average vehicles speed is explained in more detail in Section 3.2. Parking area p has a total capacity C_p, and a number of available parking spots $S_p(k)$ at time step k. The update equation of the number of available parking spots is:

$$S_p(k+1) = S_p(k) - \alpha^{\mathrm{a}}_p(k) + \alpha^{\mathrm{l}}_p(k) - \alpha^{\mathrm{r}}_p(k), \tag{3.2}$$

where $\alpha^{\mathrm{a}}_p(k)$ and $\alpha^{\mathrm{l}}_p(k)$ are the number of vehicles arriving and leaving parking area p during the time interval $[kc,(k+1)c)$, and α^{r}_p is the number of vehicles that have a reservation to use parking area p, but have not yet arrived during the time interval $[kc,(k+1)c)$. Note that α^{r}_p is controlled by the choice $x_{u,r}(k)$ of the Parking Resource Allocation Model (PRAM) to allocate user u to travel route r during the time period $[kc,(k+N)c)$. Moreover, the available storage is constrained:

$$0 \le S_p(k) \le C_p, \qquad \forall k. \tag{3.3}$$

At every time step k, a set of users $U(k) \subseteq U$ is defined that have a starting time t_u in the time period $[kc, (k+N)c)$. Note that N is the number of time steps that the parking resource allocation model considers to allocate users to a parking area. Hence, all users $u \in U(k)$ are allocated to a parking area p. Note that $N \le N_\mathrm{p}$ must hold because the prediction of the travel time is limited by prediction horizon N_p of the S-model. The optimal control inputs are calculated by solving the following optimisation problem:

$$\begin{aligned}
\min_{\hat{\mathbf{x}}(k)} \quad & \left[\frac{w_\mathrm{drive}}{c^\mathrm{n}_\mathrm{drive}}\mathbf{c}_\mathrm{drive}(k) + \frac{w_\mathrm{parking}}{c^\mathrm{n}_\mathrm{parking}}\mathbf{c}_\mathrm{parking}(k)\right]^\top \hat{\mathbf{x}}(k) \\
\text{s.t.} \quad & \sum_{i \in U(k)} \sum_{r \in R(s_i)} x_{i,r}(k) \le S_{p_r}(k) - \alpha^\mathrm{a}_p(k) + \alpha^\mathrm{l}_p(k), \\
& \sum_{r \in R(s_u)} x_{i,r}(k) = 1, \\
& x_{i,r} \in \{0,1\}, \quad \forall i \in U(k), r \in R(s_i),
\end{aligned} \tag{3.4}$$

with $\hat{\mathbf{x}}(k) = \left[\mathbf{x}_1^\top(k), \ldots, \mathbf{x}_u^\top(k)\right]^\top$ a column vector of $\mathbf{x}_u(k) = \left[x_{u,1}(k), \ldots, x_{u,r}(k)\right]^\top$ where $x_{u,r}$ is the choice of user u to take travel route r with $\forall u \in U(k), \forall r \in R(s_u)$, w_drive and w_parking the weights that describe the importance of the different control objectives, $c^\mathrm{n}_\mathrm{drive}$ and $c^\mathrm{n}_\mathrm{parking}$ the nominal values of the different control objectives, and $S_{p_r}(k)$ the number of available parking spots of parking area p that is reached by using travel route r.

The different segments of the objective function, $\mathbf{c}_\mathrm{drive}(k)$ and $\mathbf{c}_\mathrm{parking}(k)$ describe the travel time of each travel route for each user u, and the number of occupied parking spots of the parking areas:

$$\mathbf{c}_\mathrm{drive}(k) = \left[\mathbf{T}_1^\top(k), \ldots, \mathbf{T}_u^\top(k)\right]^\top, \tag{3.5}$$

$$\mathbf{c}_\mathrm{parking}(k) = \left[\mathbf{A}_1^\top(k), \ldots, \mathbf{A}_u^\top(k)\right]^\top, \tag{3.6}$$

where $\mathbf{T}_u(k) = \left[T_{u,1}(t_u), \ldots, T_{u,r}(t_u)\right]^\top$ is the vector with all travel times of the possible travel routes for user $u \in U(k)$ that departs at $t_u \in [kc, (k+N)c)$ and $\mathbf{A}_u(k) = \left[A_{u,1}(k), \ldots, A_{u,r}(k)\right]^\top$ is the vector of penalties for the number of vehicles occupying the parking area that is reached using travel route $r \in R$ for user $u \in U(k)$. A penalty of a parking area for a particular travel route is:

$$A_{u,r}(k) = \frac{C_p - S_p(k)}{C_p}. \tag{3.7}$$

Some users that have been allocated to a parking area and travel route in $\hat{\mathbf{x}}(k-1)$ may be allocated to a different parking area and travel route in $\hat{\mathbf{x}}(k)$. Furthermore, users that have been allocated to a parking area may have a different travel route than their initial travel route. For these users, a second optimisation decides if these users need to update their travel route and parking area destination. However, it may be undesirable for the user experience to switch travel routes of users after every time step, whilst only a little travel time is lost. Therefore, a weight w_switch is added in the objective function such that only when there is a considerable improvement in travel time, the parking area and travel route is updated:

$$\begin{aligned}
\min_{\hat{\mathbf{x}}^\mathrm{switch}} \quad & \left[\mathbf{T}^\mathrm{switch}(k) - \mathbf{T}^\mathrm{switch}(k-1) + w_\mathrm{switch}\right]^\top \hat{\mathbf{x}}^\mathrm{switch}, \\
s.t. \quad & \mathbf{T}^\mathrm{switch}(k) = \left[T_1^\mathrm{switch}(k), \ldots, T^\mathrm{switch}_{u^\mathrm{switch}}(k)\right]^\top,
\end{aligned} \tag{3.8}$$

where $x_i^{\text{switch}}(k) \in \{0,1\}$ is the choice to switch the user from the prior allocated parking area to the newly allocated parking area with $\hat{\mathbf{x}}^{\text{switch}} = \left[x_1^{\text{switch}}(k), \ldots, x_{u^{\text{switch}}}^{\text{switch}}(k)\right]^\top$ and $T_i^{\text{switch}}(k)$ is the predicted travel time of the respective travel route of user i at time step k.

The distribution of vehicles on the network can change, resulting from the novel parking resource allocation model. The S-model explained in Section 2.1.1 does not account for this change. Hence, the S-model is changed.

3.2. Modified S-model

The novel parking resource allocation model changes the travel route of vehicles heading to a parking spot. Currently, the S-model considers the change in the distribution of vehicles on the traffic network by using the turning fractions $\beta_{u,d,o}(k)$. However, the S-model does not consider the future change in the distribution of vehicles on the traffic network caused by the novel parking resource allocation. Therefore, the turning fraction $\beta_{u,d,o}$ of link (u,d) turning to direction o at time step k is modified.

Furthermore, from the state variables $n_{u,d}(k)$ and $q_{u,d}(k)$, an average vehicle speed $v_{u,d}^{\text{ave}}(k)$ of link (u,d) at time step k can be predicted. Throughout this thesis it is assumed that the average vehicle speed has a linear relation to the state variables:

$$v_{u,d}^{\text{ave}}(k) = \gamma_0 + \gamma_1 n_{u,d}(k) + \gamma_2 q_{u,d}(k). \tag{3.9}$$

where γ are the weights of each state variable. A linear least-squares method is used to find optimal values of γ. The travel time of each travel route can be predicted using (3.1). More complex relations between the average vehicle speed and the traffic states exist, and may have a better performance. However, the analysis of more complex relations are left for future work.

After the parking allocation model has allocated vehicles to a parking area, the set of choices for the optimal travel route for each user is defined as X. A new set of optimal travel routes for each user that deviates from their original travel route is defined as $X^{\text{diff}} \subseteq X$, and the set of exits used in the travel route is defined as E^{diff}.

Every user has a predicted travel time of the allocated travel route to a parking area. Since the travel time is based on the average vehicle speed of each link (u,d), it can be predicted when the user will leave link (u,d) to direction o. Using the starting time t_u, together with the travel time and route of all users $u \in U(k)$, the change in distribution of vehicles on the traffic network of link (u,d) heading to direction o is calculated:

$$\hat{\alpha}^{\text{l}}_{u,d,o}(k) = \frac{\hat{\alpha}^{\text{l,Opt}}_{u,d,o}(k)}{c} - \frac{\hat{\alpha}^{\text{l,Orig}}_{u,d,o}(k)}{c}, \tag{3.10}$$

with $\hat{\alpha}^{\text{l,Opt}}_{u,d,o}(k)$ the number of vehicles leaving link (u,d) to direction o during the time period $[kc,(k+1)c)$ travelling according to their optimal travel route and $\hat{\alpha}^{\text{l,Orig}}_{u,d,o}(k)$ the number of vehicles leaving link (u,d) to direction o during the time period $[kc,(k+1)c)$ travelling according to their original travel route.

Determining the turning fraction $\beta_{u,d,o}(k)$ of the S-model during the prediction horizon is challenging when the turning fractions are time-varying. The case studies of previous research regarding MPC with the S-model as the traffic prediction model use a uniform traffic demand that is time-independent [17, 26, 27]. Consequently, the turning fractions are considered to be known and constant throughout the simulation. However, the turning fractions are time-varying, since the number of vehicles on each travel route changes. Note that the turning fraction $\beta_{u,d,o}(k)$ is the relative fraction of traffic in link (u,d) heading in direction o during the time period $[kc,(k+1)c)$. One way to determine time-varying turning fractions is by using the queue $q_{u,d,o}(k)$ at each link (u,d) heading in direction o. When the turning fractions are not known throughout the simulation, the queue $q_{u,d,o}(k)$ at each link (u,d) heading in direction o explained in Section 2.1.1 can be used to determine the turning fractions.

$$\beta_{u,d,o}(k) = \frac{q_{u,d,o}(k) + \hat{\alpha}^{1}_{u,d,o}(k)}{\sum_{o \in O_{u,d}} \left(q_{u,d,o}(k) + \hat{\alpha}^{1}_{u,d,o}(k) \right)}, \tag{3.11}$$

where $\hat{\alpha}^{1}_{u,d,o}(k)$ is the number of vehicles leaving link (u,d) to direction o during the time period $[kc,(k+1)c)$.

3.3. Conclusions

The use of the novel parking resource allocation model presented in this chapter can reduce the amount of cruising vehicles searching for a parking area in urban areas. Moreover, the model can control the distribution of vehicles on the traffic network. If vehicles are more evenly distributed along the traffic network, traffic flow is increased. The distribution of the vehicles occupying the parking areas can be controlled as well using the novel parking resource allocation model. An even distribution of vehicles over the parking areas prevents one parking area to be full while the others remain almost empty. When a parking area is full and other parking areas remain almost empty, vehicles that arrive at the full parking area have to re-enter the traffic network in search of a vacant parking spot, resulting in additional vehicles in the traffic network. In an already saturated traffic network, additional vehicles on the traffic network reduce traffic flow. The novel parking resource allocation can prevent the unnecessary use of the traffic network.

If the travel route of the vehicles differs from their original travel route, the distribution of vehicles on the traffic network is changed. The S-model explained in Section 2.1.1 is modified to consider the change in the distribution of vehicles on the traffic network caused by the novel parking resource allocation model.

4

Case study: Mall of the Netherlands

The performance of the Model Predictive Control (MPC) control strategy and the Parking Resource Allocation Model (PRAM) is assessed using two case studies. The first case study compares the performance during the morning rush hours and the second case study compares the performance during the evening rush hours. In both case studies, the same traffic network is used, based on the traffic situations of the Mall Of The Netherlands (MOTN). In Section 4.1, the traffic network, performance measures, and demand profiles are explained, and the parameters of both the traffic prediction model and PRAM are identified. The performance of different control strategies for the morning rush hours and evening rush hours are compared in Sections 4.2 and 4.3, respectively. Lastly, the analysis of the results is explained in Section 4.4, and the chapter is concluded.

4.1. Set-up

The traffic network and demand profile for both case studies, the parameter identification of both the S-model and the resource allocation model, and the performance measures on which the different controllers are compared will be discussed in this section.

4.1.1. Urban traffic network

Simulations are performed to compare the performance of the traffic signal controller and the PRAM. The simulations are performed in the traffic simulator VISSIM. VISSIM is a microscopic traffic simulator that is used to model and simulate traffic. With the component object model interface, VISSIM is able to communicate with MATLAB [13]. Information on intersections, links and vehicles is extracted from VISSIM and the green times of the traffic lights can be adjusted. The network that is used in both case studies is shown in Figure 4.1. It is a graphical representation of the situation surrounding the MOTN located in Leidschendam near The Hague. The MOTN is a new large shopping mall located next to a main road that is congested daily. During rush hours (e.g. the morning rush hours and evening rush hours) traffic congestion occurs. The N14, located next to the MOTN is connected to the A4 highway, the busiest highway of the

Netherlands. Rijkswaterstaat is currently investigating new ways of improving the traffic network on the N14. With the opening of the shopping mall, the performance traffic network has deteriorated. The MOTN is a good example of a situation that may benefit from a combined traffic signal control strategy and a PRAM. Therefore, two case studies are performed for both the morning rush hours and the evening rush hours.

The traffic network consists of four controlled four-way intersections, eight entrances and exits, twelve two-way links with two lanes expanding to five lanes at the intersection. Furthermore, five parking facilities with entrances and exits connected to other links are implemented, each with its maximum capacity. The lengths of the links are displayed in Figure 4.1, and the cycle time of each intersection and the control interval of the network are both 60 seconds. Vehicles that enter the network and drive with a free-flow speed of 50 km/h can leave the network in less than 4 minutes. To account for the waiting time in front of the traffic lights, the prediction horizon is chosen to be 8 time steps (i.e. 480 seconds). This prediction horizon is chosen because the vehicles can leave the network within the horizon. For computational reasons, the control horizon is chosen to be 5 time steps (i.e. 300 seconds).

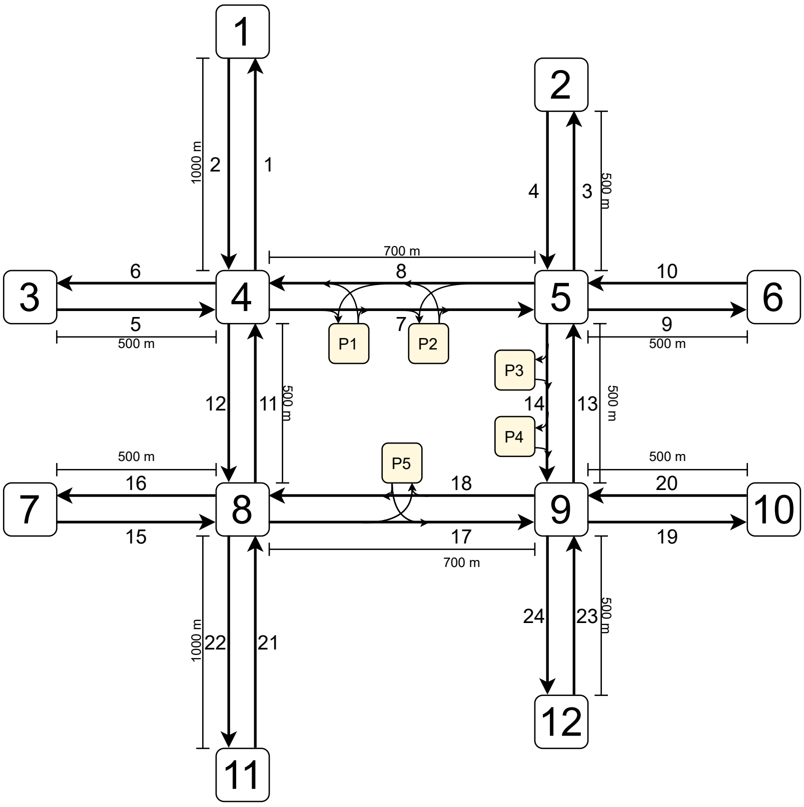


Figure 4.1: Representation of the urban traffic network consistent in the case study

To reproduce the traffic situation of the MOTN during rush hours, historical traffic data of the intersections are needed. Historical data concerning the parking areas are needed as well (e.g. the number of vehicles arriving at each parking area, the number of vehicles leaving each parking area, and the number of available parking spots at a given time). However, the MOTN did not release the historical data concerning the parking areas. Instead, only an estimate of the number of vehicles arriving and leaving all the parking areas is provided by the MOTN. Thus, fictive data is used based on this estimate. The number of vehicles arriving and leaving the parking areas in both case studies is presented in Figures B.1 and B.2. The initial occupancy of all parking areas is 30% and 90% of the full capacity, for the morning and evening rush hours, respectively.

With historical data provided by Rijkswaterstaat regarding the traffic network, an origin-destination matrix is constructed that represents the traffic situations in real-life. Note that the number of vehicles that are searching a parking area or leaving from a park area is included in the data provided by Rijkswaterstaat. Therefore, the distribution of vehicles on the traffic network based on historical data is changed to consider the number of vehicles interacting with the parking area. Two origin-destination matrices are thus created for each case study, shown in Tables A.1 and A.2, respectively. Note that both origin-destination matrices of case study B are the transposed of the origin-destination matrices of case study A. Therefore, the total number of vehicles on the traffic network in both case studies are equal. Figure 4.2 captures the traffic demand based on the origin-destination matrices of Tables A.1 and A.2, used as identification data set to identify the parameters of the S-model and the PRAM. After one hour, the traffic demand is increased. Note that only the number of vehicles interacting with the parking areas is increased and all ongoing traffic is kept constant.

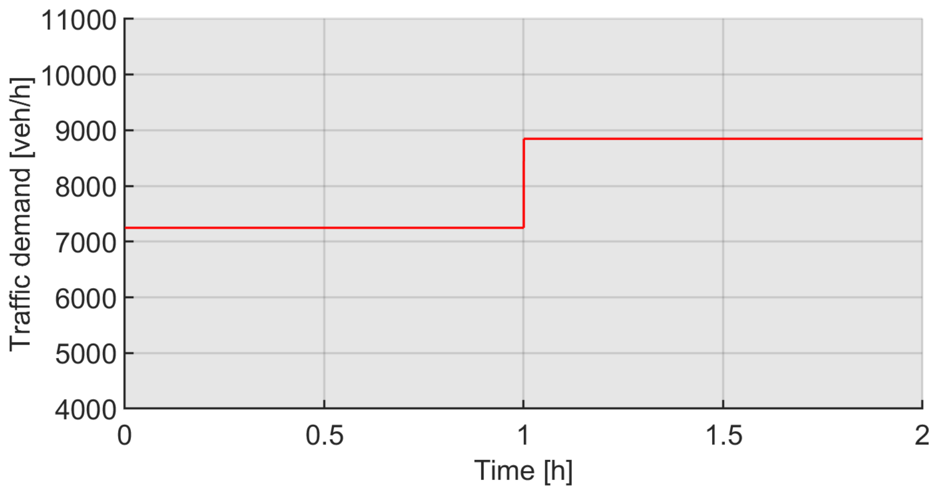


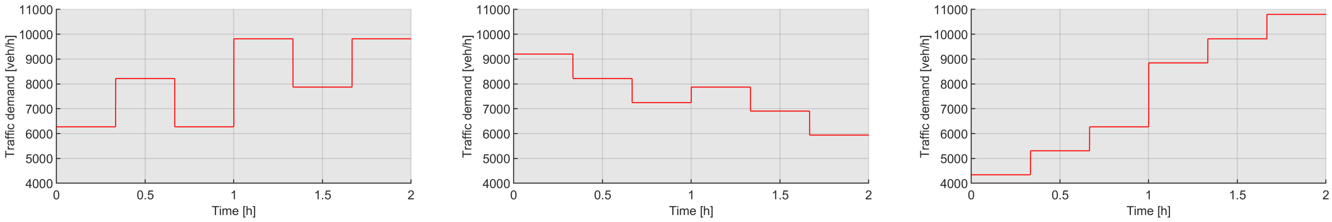
Figure 4.2: Traffic demand flow of all vehicles used as identification demand for the identification of parameters of both case studies

To be able to compare the different controllers, three demand scenarios are generated, based on the origin-destination matrices. The three scenarios i.e. the two-peaks-, declining-, and inclining demand scenarios, are designed and presented in Figure 4.3. In all three scenarios, only the traffic demand of ongoing traffic fluctuates.

All vehicles on the traffic network have a travel route initialised based on the shortest path. If two possible travel routes for an origin-destination pair are of equal length, the travel route that uses link $(4,8)$ or $(8,4)$ is taken as their travel route. For the control strategies that do not use the

PRAM, vehicles will not deviate from their travel route.

The first 30 minutes of each scenario is used for initialisation, such that there is enough past data available for the prediction model.



(a) Two-peaks demand (b) Declining demand (c) Inclining demand

Figure 4.3: Traffic demand flow for the different scenarios in both case studies

4.1.2. Parameter identification

Some parameters should be identified in advance to use both mathematical models of Section 2.1.1 en Section 3.2. Since the identified parameters of the PRAM are dependent on the S-model, the parameters of the S-model are identified first.

In all identification processes, the mean relative error and mean absolute error concerning the simulator output are used as a performance measure. Both errors are provided for the sake of completeness:

$$\text{Relative error} = \frac{N_{\text{Sim}} - N_{\text{Mod}}}{N_{\text{Sim}}}, \tag{4.1}$$

$$\text{Absolute error} = N_{\text{Sim}} - N_{\text{Mod}}, \tag{4.2}$$

where N_{Sim} and N_{Mod} are the number of vehicles on the links (u,d) produced by the simulator VISSIM and the model values, respectively.

The identified parameters are validated on the three scenarios to check if the identified parameters can predict correct outputs for unseen data and to check that the model did not overfit the data on the identification set.

S-model

The following parameters of the S-model are identified: the free-flow and idling speed v^{free} and v^{low}, the deceleration of vehicles a^{dec}, the length of all the links l_i^{edge}, the average length of the vehicles with headway l^{veh}, and the saturation flow rate $\mu_{u,d,o}$ of every link (u,d) to direction o. Note that the free-flow and idling speed, the deceleration of a vehicle, and the average length of a vehicle are chosen to be constant on the traffic network, to lower the complexity of the offline optimisation, and therefore the link subscript (u,d) is removed. The saturation rate is chosen to vary from exit to exit, instead of link to link, because the traffic network consists of links with 2 lanes increasing to 5 lanes.

For the fixed-time traffic signal controller, the green times of each phase for each intersection are shown in Tables A.3 and A.4, and are based on the distribution of vehicles on the traffic network. The cycle time of every intersection is chosen to be 60 seconds. The turning fractions are measured based on the leaving flow rate $\alpha^{l}_{u,d,o}$. The traffic network is initialised for 30 minutes, after which the data is extracted for 90 minutes. The traffic demand, shown in Figure 4.2, is used as calibration data. The number of vehicles and the queue lengths of all the links at every control time step are collected. A nonlinear least-squares problem that optimises the relative error is used. In this optimisation, the number of vehicles and queues of the current time step are used as input to calculate the states for the next 8 time steps. The lsqnonlin solver with the trust-region-reflective algorithm is used in Matlab to solve the nonlinear least-squares problem. Because the traffic prediction model is nonlinear, many local minima can be found. Therefore, multi-start local optimisations are performed, with 1000 random feasible starting points.

Table 4.1: The identified parameters of the S-model during the morning rush hours with $i \in \{3,4,5,6,9,10,15,16,19,20,23,24\}$, $j \in \{1,2,21,22\}$, $k \in \{7,8\}$, $m \in \{11,12\}$, $n \in \{13,14\}$, and $o \in \{17,18\}$. The link IDs i, j, k, m, n, and o correspond to the link numbers in Figure 4.1

Parameter	v^{free} [m/s]	v^{low} [m/s]	a^{dec} [m/ s^2]	l_i^{edge} [m]	l_j^{edge} [m]	l_k^{edge} [m]	l_m^{edge} [m]	l_n^{edge} [m]	l_o^{edge} [m]	l^{veh} [m]
Value	19.34	0.08	-1.68	535.14	1039.71	450.22	400.02	403.81	742.89	9.25

Table 4.2: The identified parameters of the S-model during the evening rush hours with $i \in \{3,4,5,6,9,10,15,16,19,20,23,24\}$, $j \in \{1,2,21,22\}$, $k \in \{7,8\}$, $m \in \{11,12\}$, $n \in \{13,14\}$, and $o \in \{17,18\}$. The link IDs i, j, k, m, n, and o correspond to the link numbers in Figure 4.1

Parameter	v^{free} [m/s]	v^{low} [m/s]	a^{dec} [m/ s^2]	l_i^{edge} [m]	l_j^{edge} [m]	l_k^{edge} [m]	l_m^{edge} [m]	l_n^{edge} [m]	l_o^{edge} [m]	l^{veh} [m]
Value	19.44	1.39	-2.95	450.28	1049.20	457.84	455.02	420.11	629.37	6.61

The values of the identified parameters of both case study A and B are shown in Tables 4.1 and 4.2, respectively. On the calibrated data set, the S-model with the identified parameters has a mean relative error of 10.61%, and a mean absolute error of 8.83 vehicles for the morning rush hours. For the evening rush hours, the mean relative error and mean absolute error on the calibrated data set is 6.44% and 4.22, respectively. The errors with respect to all scenarios are displayed in Tables 4.3 and 4.4. The error in the declining scenario is higher than the other scenarios for both case studies. This may pose problems for the control strategies in that scenario. However, the difference between the calibrated data set and the two-peaks demand scenario is small. Thus the identified parameters are not overfitted on the identification data set. As the S-model is a macroscopic model, errors below 10% are considered reasonable. The model with the found parameters has a somewhat larger error. As a result, the performance of the MPC strategy may be subpar. Note that for another traffic network or traffic demand, the parameters have to be identified again.

Table 4.3: Result of 8 step-ahead prediction of traffic states of the S-model with the traffic demand of Figure 4.2 and Figure 4.3, with the identified parameters of Table 4.1

Error	Identification	Two-peaks	Declining	Inclining
Mean relative error [%]	10.61	9.71	15.84	11.92
Mean absolute error [Veh]	8.83	7.53	10.76	9.90

Table 4.4: Result of 8 step-ahead prediction of traffic states of the S-model with the traffic demand of Figure 4.2 and Figure 4.3, with the identified parameters of Table 4.2

Error	Identification	Two-peaks	Declining	Inclining
Mean relative error [%]	6.44	9.05	13.55	9.17
Mean absolute error [Veh]	4.22	5.93	9.15	6.90

Parking resource allocation model

The prediction of the travel time of all travel routes is made using the traffic states $n_{u,d}(k)$ and $q_{u,d}(k)$ of the S-model. The travel time is calculated by considering an average vehicle speed $v_{u,d}^{\text{ave}}(k)$ on link (u,d) at time step k. On average, the vehicles on link (u,d) at time step k are driving with that vehicle speed.

The states of the S-model with the identified parameters shown in Tables 4.1 and 4.2 for the prediction horizon of 8 steps are used to predict the average vehicle speed during the prediction horizon. The relation between the traffic states of the S-model and the average speed of vehicles on link (u,d), that is assumed in (3.9) and the relation between the travel time and the average vehicle speed that is assumed in (3.1), are recited for completeness:

$$v_{u,d}^{\text{ave}}(k) = \gamma_0 + \gamma_1 n_{u,d}(k) + \gamma_2 q_{u,d}(k), \tag{4.3}$$

$$T_r(k) = \sum_{i \in L(r)} \frac{l_i^{\text{lane}}}{v_{u,d}^{\text{ave}}(k)}. \tag{4.4}$$

Note that the parameters γ_0, γ_1, and γ_2 are constant over all links (u,d) because the relation between the traffic states and the average vehicle speed is assumed to be independent of link (u,d). A linear least-squares problem that optimises the relative error is used. In this optimisation, the number of vehicles and queue lengths of the prediction horizon is used to calculate the average vehicle speed over the prediction horizon. In Matlab, the fitlm solver is used to solve the linear least-squares problem.

The values of the identified parameters for both case studies A and B are presented in Tables 4.5 and 4.6, respectively. What is interesting to note is that the maximum average vehicle speed is much lower than the free-flow speed v^{free} identified in the S-model. The errors of the average vehicle speed with the identified parameters are presented in Tables 4.7 and 4.8. As there is no significant difference in the result between the identification and all demand scenarios, the identified parameters are not overfitted to the identification data set. However, the errors are quite high and can pose a problem for predicting the future travel time of travel routes. Therefore, a comparison of the predicted travel time and actual travel time is needed.

Table 4.5: The identified parameter identification of the parking resource allocation model for the morning rush hours

Parameter	γ_0	γ_1	γ_2
Value	11.303	-0.0264	-0.0354

Table 4.6: The identified parameter identification of the parking resource allocation model for the evening rush hours

Parameter	γ_0	γ_1	γ_2
Value	11.191	-0.0287	-0.069

Table 4.7: Result of the 8 step-ahead prediction of the average vehicle speed with the traffic demand of Figure 4.2 and Figure 4.3, with the identified parameters of Table 4.5

Error	**Identification**	**Two-peaks**	**Declining**	**Inclining**
Mean relative error [%]	18.77	18.87	21.59	18.39
Mean absolute error [m/s]	1.68	1.70	1.76	1.69

Table 4.8: Result of the 8 step-ahead prediction of the average vehicle speed with the traffic demand of Figure 4.2 and Figure 4.3, with the identified parameters of Table 4.6

Error	**Identification**	**Two-peaks**	**Declining**	**Inclining**
Mean relative error [%]	18.96	20.41	22.32	21.36
Mean absolute error [m/s]	1.72	1.75	1.78	1.77

4.1.3. Performance measures

The performance of the controllers is compared. The comparison of the traffic flow is made using the Total Time Spent (TTS). The lower the TTS is, the higher traffic flow is. Another parameter that is important and is widely used in the field of traffic engineering is the Vehicle Time Loss (VTL). The VTL is the total time that is lost by all vehicles in traffic and provides an important base to quantify the economical effects on traffic congestion [40]. The lower the VTL is, the lower the cost of congestion is. The VTL is:

$$\mathrm{VTL} = \sum_{r\in R}\sum_{u\in U}\left(\mathrm{TT}_{u,r} - \mathrm{TT}_r^{\min}\right), \tag{4.5}$$

where $\mathrm{TT}_{u,r}$ is the travel time of user u that uses travel route r and $\mathrm{TT}_r^{\min}$ is the minimum travel time of travel route r. The VTL is used to compare all the vehicles on the traffic network. Moreover, the VTL of all vehicles that use the parking area may be important to see if the PRAM improves the travel time of individual vehicles. Both performance measures of the controllers are compared, and the relative change is calculated:

$$\mathrm{TTS}_{\mathrm{rel}} = \frac{\mathrm{TTS}_{\mathrm{CONTROL}} - \mathrm{TTS}_{\mathrm{FIX}}}{\mathrm{TTS}_{\mathrm{FIX}}} \cdot 100\%, \tag{4.6}$$

where CONTROL stands for the specific controller to compare and FIX for no control at all. In the same way, $\mathrm{VTL}_{\mathrm{rel}}$ is the relative change in VTL. Furthermore, the vehicle distribution on the traffic network and the occupancy of the parking areas are compared.

Throughout the case studies, the optimisation problem from Section 2.1.2 of MPC will be used. For clarity, the objective function is recited:

$$\min_{\mathbf{g}(k_{\mathrm{c}})} w_{\mathrm{TTS}} \frac{J_{\mathrm{TTS}}(k_{\mathrm{c}})}{\mathrm{TTS}^{\mathrm{n}}} + w_{\mathrm{Final}} \frac{J_{\mathrm{Final}}(k_{\mathrm{c}})}{\mathrm{Final}^{\mathrm{n}}} + w_{\mathrm{D}} \frac{J_{\mathrm{D}}(k_{\mathrm{c}})}{\mathrm{D}^{\mathrm{n}}} + w_{\mathrm{Q}} \frac{J_{\mathrm{Q}}(k_{\mathrm{c}})}{\mathrm{Q}^{\mathrm{n}}}, \tag{4.7}$$

with $w_{\mathrm{TTS}}, w_{\mathrm{Final}}, w_{\mathrm{D}}$, and w_{Q} the weights of the objective function. The main objective is to minimise the TTS. However, additional control objectives are used to ensure better traffic states at the end of the horizon, prevent fluctuations of the control inputs, and give extra attention to the largest queue of an intersection. Therefore, the weight of the TTS over the prediction horizon is $w_{\mathrm{TTS}} = 1$, the weight of the TTS at the last prediction time step of the horizon is $w_{\mathrm{Final}} = 0.1$, the weight of the fluctuations of the control inputs is $w_{\mathrm{D}} = 0.01$, and the weight of the longest queue of every intersections is $w_{\mathrm{Q}} = 0.1$.

The cost functions of the TTS, the terminal cost, the switching times, and the cost of the longest queue are as in (2.27), (2.28), (2.29), and (2.30), respectively. For all scenarios, $\mathrm{TTS}^{\mathrm{n}} = 1.00 \cdot 10^{6}$ [s], $\mathrm{Final}^{\mathrm{n}} = 150$[veh], $\mathrm{D}^{\mathrm{n}} = 278$, and $\mathrm{Q}^{\mathrm{n}} = 600$. Note that the nominal values are derived from their values during one prediction window.

Throughout the case studies, the optimisation problem from (3.4) of the PRAM will be used. For clarity, the objective function is recited:

$$\min_{\hat{\mathbf{x}}(k)} \left[\frac{w_{\mathrm{drive}}}{c^{\mathrm{n}}_{\mathrm{drive}}} \mathbf{c}_{\mathrm{drive}}(k) + \frac{w_{\mathrm{parking}}}{c^{\mathrm{n}}_{\mathrm{parking}}} \mathbf{c}_{\mathrm{parking}}(k) \right]^{\top} \hat{\mathbf{x}}(k), \tag{4.8}$$

where $c^{\mathrm{n}}_{\mathrm{drive}} = 100$ [s] and $c^{\mathrm{n}}_{\mathrm{parking}} = 1$ are the nominal values of the control objectives, and w_{drive} and w_{parking} are the weights of the objective function. Two different control strategies are compared. At first, only the shortest travel time is considered as the control objective, resulting in the weights of $w_{\mathrm{drive}} = 1$ and $w_{\mathrm{parking}} = 0$. The second control strategy considers both the shortest travel time, and a uniform distribution of vehicles to the parking areas, resulting in the weights of $w_{\mathrm{drive}} = 1$ and $w_{\mathrm{parking}} = 0.5$.

The second optimisation problem from (3.8) of the PRAM is recited for clarity:

$$\min_{\hat{\mathbf{x}}^{\mathrm{switch}}} \left[\mathbf{T}^{\mathrm{switch}}(k) - \mathbf{T}^{\mathrm{switch}}(k-1) + w_{\mathrm{switch}} \right]^{\top} \hat{\mathbf{x}}^{\mathrm{switch}}, \tag{4.9}$$

where $w_{\mathrm{switch}} = 30$ [s] is the minimum travel time loss needed to switch the users from their allocation at time step $(k-1)$ to the allocation at time step k.

4.2. Case study A: Morning rush hours

The effect that different control strategies have on the traffic in the morning rush hours is compared in this case study. The origin-destination matrices shown in Table A.1 will be used together with the three scenarios presented in Figure 4.3 for the traffic demand. Using the identified parameters of the S-model and the average vehicle speed shown in Tables 4.1 and 4.7, the simulation can be performed. The result of the fixed-time control strategy, MPC control strategy, and MPC with the control strategies of the PRAM are compared. The control strategies of the PRAM use the weights $w_{\text{drive}} = 1$ and $w_{\text{parking}} = 0$, and $w_{\text{drive}} = 1$ and $w_{\text{parking}} = 0.5$, respectively.

4.2.1. Results

In Tables 4.9 to 4.11 the system performance by means of the TTS and VTL of the different control strategies is compared. In general, using an MPC control strategy results in a decrease in both the TTS and VTL.

Apart from the declining demand scenario, adding the control strategies of both PRAMs increases TTS and VTL. Only for the declining demand scenario, the TTS is lower when adding the control strategies of both PRAMs. The PRAM control strategy solely focusing on travel time outperforms the PRAM control strategy that focuses on travel time and a uniform distribution the vehicles over different parking areas during the inclining demand scenario.

A reason that the performance of the control strategies of the PRAM does not result in an improvement on the traffic network is presented in Table 4.12. The predicted travel time of all travel routes that are used in the control strategies differs from the actual travel time of all travel routes. Because the travel time prediction is based on the average vehicle speed prediction, this concludes that the error of the average vehicle speed is too large to predict the travel time reasonably.

The development of the occupancy of the parking areas are shown in Figures 4.4, B.3 and B.4, for the two-peaks-, declining-, and inclining demand scenarios, respectively. Adding the control strategy to distribute the vehicles along different parking areas based on their occupancy results in a more even distribution of vehicles over the parking areas. Note that when no control on the distribution of vehicles on the parking areas is provided, the occupancy of parking area 4 remains constant. When adding a PRAM control strategy, the occupancy of parking area 4 increased. Moreover, the most favourable parking area 5 is used less. This results in one parking area not becoming overcrowded while other parking areas remain nearly empty. However, the occupancy of all parking areas never reaches their maximum capacity. Therefore, there are no vehicles that have to re-enter the traffic network in search of another parking area.

The number of vehicles in the traffic network over time are displayed in Figures 4.5 to 4.7. The number of vehicles of the MPC control strategy on average is lower than the fixed-time control strategy. However, during the first half-hour of the simulation, the fixed-time control strategy performs better.

Table 4.9: The result of all control strategies for the two-peaks demand scenario of case study A regarding the total time spent, vehicle time lost, and vehicle time lost of vehicles using parking areas

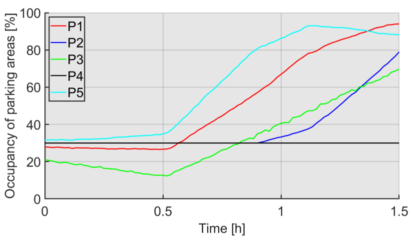
Controller	**TTS [veh · h]**	**$\mathbf{TTS^{rel}}$ [%]**	**VTL [h]**	**$\mathbf{VTL^{rel}}$ [%]**	**$\mathbf{VTL_{park}}$ [h]**	**$\mathbf{VTL^{rel}_{park}}$ [%]**
Fixed-time	845.17	0.00	348.25	0.00	109.97	0.00
MPC	735.27	−13.00	281.56	−19.15	74.30	−32.44
MPC + $\mathbf{PRAM_{TT}}$	783.77	−7.26	348.22	−0.01	90.78	−17.46
MPC + $\mathbf{PRAM_{TT+Cap}}$	771.02	−8.77	347.83	−0.12	94.66	−13.92

Table 4.10: The result of all control strategies for the declining demand scenario of case study A regarding the total time spent, vehicle time lost, and vehicle time lost of vehicles using parking areas

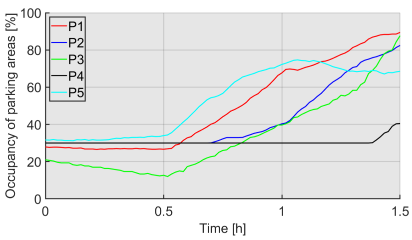
Controller	**TTS [veh · h]**	**$\mathbf{TTS^{rel}}$ [%]**	**VTL [h]**	**$\mathbf{VTL^{rel}}$ [%]**	**$\mathbf{VTL_{park}}$ [h]**	**$\mathbf{VTL^{rel}_{park}}$ [%]**
Fixed-time	927.50	0.00	398.91	0.00	125.95	0.00
MPC	820.22	−11.57	368.10	−7.72	91.49	−27.36
MPC + $\mathbf{PRAM_{TT}}$	800.83	−13.66	396.99	−0.48	106.63	−15.34
MPC + $\mathbf{PRAM_{TT+Cap}}$	777.33	−16.19	361.69	−9.33	94.00	−25.37

Table 4.11: The result of all control strategies for the inclining demand scenario of case study A regarding the total time spent, vehicle time lost, and vehicle time lost of vehicles using parking areas

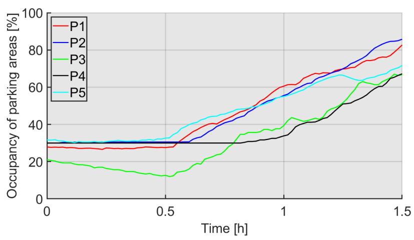
Controller	**TTS [veh · h]**	**$\mathbf{TTS^{rel}}$ [%]**	**VTL [h]**	**$\mathbf{VTL^{rel}}$ [%]**	**$\mathbf{VTL_{park}}$ [h]**	**$\mathbf{VTL^{rel}_{park}}$ [%]**
Fixed-time	776.63	0.00	302.72	0.00	98.11	0.00
MPC	670.22	−13.70	240.90	−20.42	72.88	−25.72
MPC + $\mathbf{PRAM_{TT}}$	756.90	−2.54	336.34	11.11	96.69	−1.45
MPC + $\mathbf{PRAM_{TT+Cap}}$	763.70	−1.67	342.69	13.20	104.52	6.53



(a) MPC without parking control



(b) MPC with parking travel time control



(c) MPC with parking travel time and occupancy control

Figure 4.4: Development of the parking occupancy of all control strategies for the two-peaks demand scenario of case study A

Table 4.12: Error of the predicted travel times of all vehicles for all traffic demand scenarios for both control strategies of case study A

Controller	**Relative error [%]**			**Absolute error [s]**		
	Two-peaks	**Declining**	**Inclining**	**Two-peaks**	**Declining**	**Inclining**
MPC + PRAM$_{TT}$	28.90	28.75	27.13	51.30	59.66	48.15
MPC + PRAM$_{TT+Cap}$	29.94	28.64	26.63	58.49	59.93	48.07

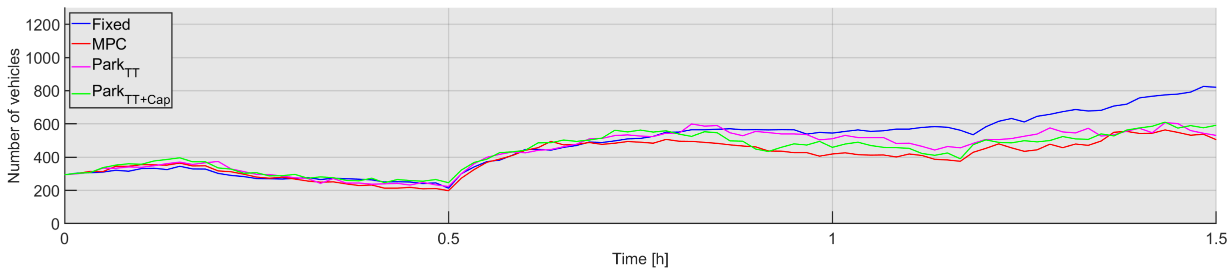


Figure 4.5: The total number of vehicles on the traffic network of all control strategies for the two-peaks demand scenario of case study A

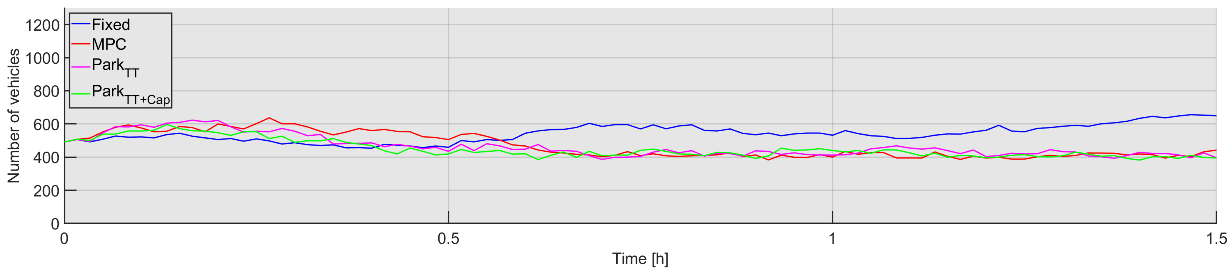


Figure 4.6: The total number of vehicles on the traffic network of all control strategies for the declining demand scenario of case study A

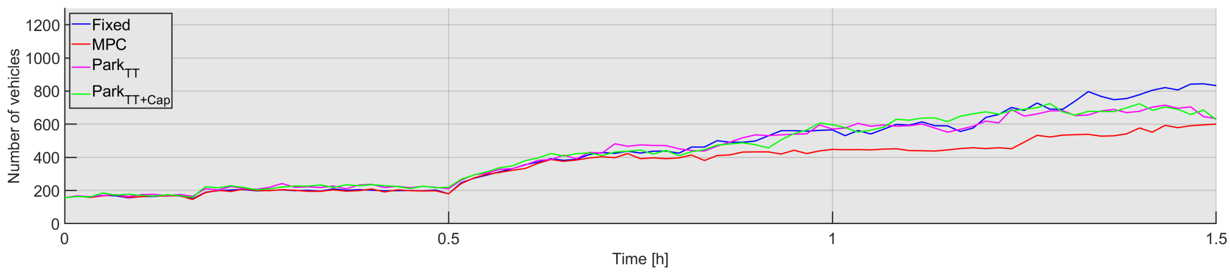


Figure 4.7: The total number of vehicles on the traffic network of all control strategies for the inclining demand scenario of case study A

4.2.2. Conclusions

In this case study, the performance of the control strategies is compared for the morning rush hours. During the morning rush hours, many vehicles require a parking area, offering the control strategy many options to adjust the distribution of the traffic network. The MPC control strategy results in a reduction in TTS of 13.00%, 11.57%, and 13.70% for the two-peaks, declining, and inclining demand scenarios, respectively. Moreover, the VTL is reduced significantly with 32.44%, 27.36%, and 25.72%, respectively. However, the proposed PRAM did not result in an improvement of the traffic network when compared with an MPC control strategy, for the two-peaks and inclining demand scenarios. An explanation could be that the mean relative error of the predicted travel times is on average over 25%. Nevertheless, the PRAM distributes the vehicles to the parking areas more uniform. This potentially reduces the number of vehicles that are re-entering the traffic network.

4.3. Case study B: Evening rush hours

In this case study, the control strategies are compared with traffic demand of the evening rush hours. The origin-destination matrices shown in Table A.2 will be used together with the three scenarios presented in Figure 4.3 for the traffic demand. Furthermore, the identified parameters of the S-model and the average vehicle speed of Tables 4.2 and 4.8 are used. The control strategies of the PRAM use the weights $w_{\text{drive}} = 1$ and $w_{\text{parking}} = 0$ and $w_{\text{drive}} = 1$ and $w_{\text{parking}} = 0.5$, respectively.

4.3.1. Results

In Tables 4.13 to 4.15 the system performances by means of the TTS and VTL of the different control strategies is compared. In general, using an MPC control strategy increases the TTS. This is unexpected behaviour, as a model-based traffic signal controller should be able to outperform a fixed-time traffic signal controller. A possible explanation is that the accuracy of the S-model is too low. Therefore, the found sub-optimal control inputs are worse compared to the fixed-time controller.

Only in the declining demand scenario, the MPC and PRAM control strategy reduced the TTS and VTL. During the declining demand scenario, the PRAM control strategy that focuses on both travel time and uniformly distributing the vehicles along different parking areas performed best.

Comparing the predicted travel time with the actual travel time of vehicles on the traffic network in Table 4.16, the result is unexpected. With a relative error of over 40%, the prediction is worse than in case study A. However, the results of the MPC control strategy combined with the PRAM control strategies both outperform the MPC control strategy by means of the VTL for vehicles interacting with the parking areas. Thus even when the MPC control strategy is not favourable over the fixed-time control strategy, using a parking resource allocation control strategy reduces the VTL of vehicles in need of a parking area.

The development of the occupancy of the parking areas are shown in Figures 4.8, B.5 and B.6. Adding the control strategy to distribute the vehicles along different parking areas based on their occupancy provides little effect. Since the number of vehicles that require a parking area is much smaller than the number of vehicles leaving the parking area during the evening rush hours, there are fewer vehicles to control.

The number of vehicles in the traffic network over time are displayed in Figures 4.9 to 4.11. The number of vehicles of all MPC control strategies performs worse than the fixed-time control strategy. In the first half hour of the two-peaks and declining demand, the combined MPC and travel time and parking distribution focused PRAM performs better.

Table 4.13: The result of all control strategies for the two-peaks demand scenario of case study B regarding the total time spent, vehicle time lost, and vehicle time lost of vehicles using parking areas

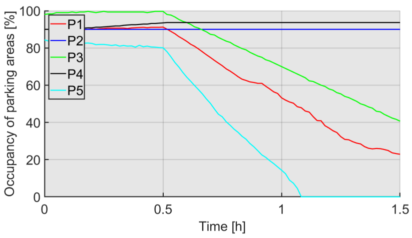
Controller	**TTS [veh · h]**	$\mathbf{TTS^{rel}}$ **[%]**	**VTL [h]**	$\mathbf{VTL^{rel}}$ **[%]**	$\mathbf{VTL_{park}}$ **[h]**	$\mathbf{VTL_{park}^{rel}}$ **[%]**
Fixed-time	782.17	0.00	290.61	0.00	55.72	0.00
MPC	798.63	2.11	297.56	2.39	46.23	−17.03
MPC + $\mathbf{PRAM_{TT}}$	829.05	5.99	374.58	28.89	16.51	−70.37
MPC + $\mathbf{PRAM_{TT+Cap}}$	829.20	6.01	369.68	27.21	15.94	−71.39

Table 4.14: The result of all control strategies for the declining demand scenario of case study A regarding the total time spent, vehicle time lost, and vehicle time lost of vehicles using parking areas

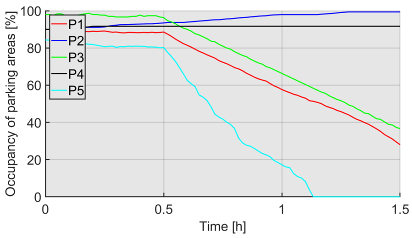
Controller	**TTS [veh · h]**	$\mathbf{TTS^{rel}}$ **[%]**	**VTL [h]**	$\mathbf{VTL^{rel}}$ **[%]**	$\mathbf{VTL_{park}}$ **[h]**	$\mathbf{VTL_{park}^{rel}}$ **[%]**
Fixed-time	822.28	0.00	377.71	0.00	64.65	0.00
MPC	920.63	11.96	461.04	22.06	40.05	−38.05
MPC + $\mathbf{PRAM_{TT}}$	772.92	−6.00	369.73	−2.11	18.70	−71.07
MPC + $\mathbf{PRAM_{TT+Cap}}$	705.12	−14.25	310.73	−17.73	16.23	−74.89

Table 4.15: The result of all control strategies for the inclining demand scenario of case study A regarding the total time spent, vehicle time lost, and vehicle time lost of vehicles using parking areas

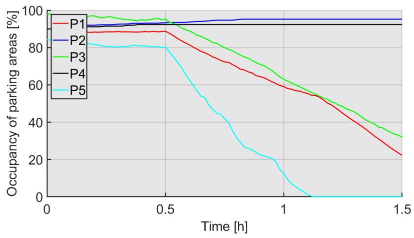
Controller	**TTS [veh · h]**	$\mathbf{TTS^{rel}}$ **[%]**	**VTL [h]**	$\mathbf{VTL^{rel}}$ **[%]**	$\mathbf{VTL_{park}}$ **[h]**	$\mathbf{VTL_{park}^{rel}}$ **[%]**
Fixed-time	826.85	0.00	269.20	0.00	51.13	0.00
MPC	905.15	9.47	335.06	24.47	44.30	−13.36
MPC + $\mathbf{PRAM_{TT}}$	908.65	9.89	348.71	29.53	17.83	−65.13
MPC + $\mathbf{PRAM_{TT+Cap}}$	945.45	14.34	423.87	57.46	23.57	−53.89



(a) MPC without parking control



(b) MPC with parking travel time control



(c) MPC with parking travel time and occupancy control

Figure 4.8: Development of the parking occupancy of all control strategies for the two-peaks demand scenario of case study B

Table 4.16: Error of the predicted travel times of all vehicles for all traffic demand scenarios for both control strategies of case study B

Controller	**Relative error [%]**			**Absolute error [s]**		
	Two-peaks	**Declining**	**Inclining**	**Two-peaks**	**Declining**	**Inclining**
MPC + PRAM$_{\mathbf{TT}}$	44.80	47.07	40.83	99.62	128.37	95.38
MPC + PRAM$_{\mathbf{TT+Cap}}$	47.44	46.46	48.83	101.76	119.80	105.27

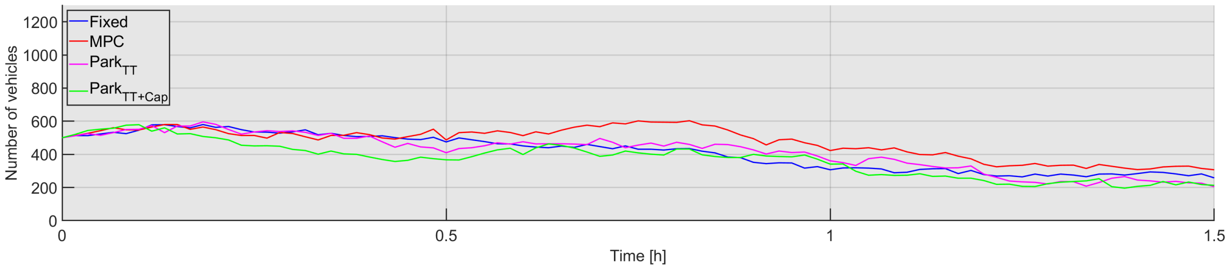


Figure 4.9: The total number of vehicles on the traffic network of all control strategies for the two-peaks demand scenario of case study A

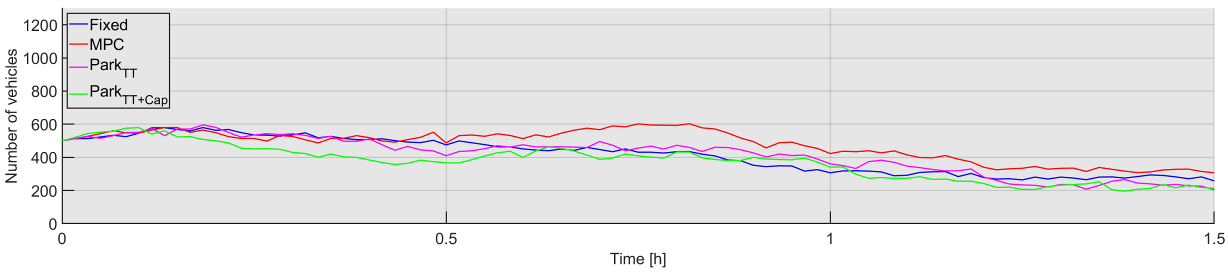


Figure 4.10: The total number of vehicles on the traffic network of all control strategies for the declining demand scenario of case study B

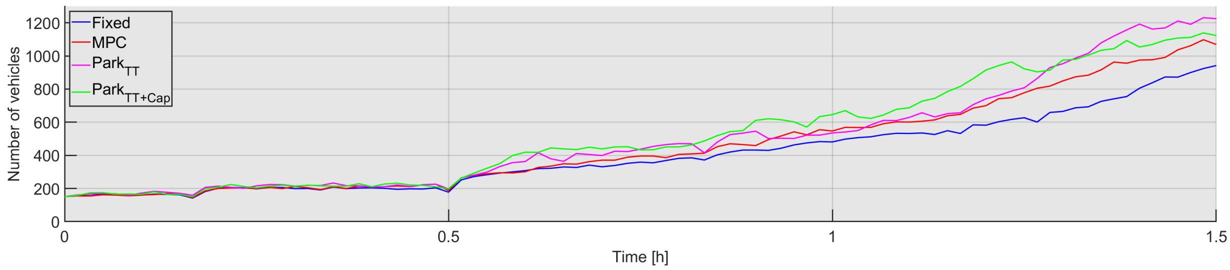


Figure 4.11: The total number of vehicles on the traffic network of all control strategies for the inclining demand scenario of case study B

4.3.2. Conclusions

In this case study, the performance of the control strategies is compared for the evening rush hours. The MPC control strategy results in an increase in TTS of 2.11%, 11.96%, and 9.47% for the two-peaks, declining, and inclining demand scenarios, respectively. However, for the declining demand scenario, implementing a combined MPC and PRAM control strategy with the focus of travel time and a uniform distribution of vehicles along different parking areas resulted in a decrease of the TTS of 14.25%, VTL of 17.73%, and VTL for vehicles interacting with a parking area of 74.89%. Moreover, the VTL of the control strategies with the PRAM is reduced for vehicles interacting with the parking area, when compared to the MPC control strategy for all demand scenarios. Even though the predicted travel time of travel routes has an accuracy of over 40% over the actual travel times, there is a decrease in VTL.

4.4. Analysis of results

In both case studies A and B (i.e. the simulations of the morning and evening rush hours, respectively), the result for the declining demand scenario is promising. The combined MPC and PRAM control strategy with the focus on both travel time and a uniform distribution of vehicles along the parking areas performs best. Moreover, the PRAM control strategy that solely focuses on travel time outperforms the MPC control strategy without PRAM. For the two-peaks and inclining demand scenarios, the MPC control strategy outperforms all other control strategies in case study A. Consequently, implementing a PRAM control strategy leads to an increase in TTS and VTL. In case study B, all control strategies perform worse than the fixed-time control strategy, for the two-peaks and inclining demand scenarios. Moreover, both PRAM control strategies have a negative effect on the TTS and the VTL. Applying a PRAM control strategy in case study B reduces the VTL of vehicles that are searching for a parking area. Note that in case study B, the number of vehicles searching for a parking area is lower than in case study A, as shown in Figures B.1 and B.2. Applying the PRAM with the focus of both travel time and a uniform distribution of vehicles on the parking areas results in a more uniformly distribution of vehicles towards the parking areas, shown in Figures 4.4, B.3 and B.4.

Based on the results of this research it is interesting to consider an MPC control strategy with PRAM, with the focus on both travel time and a uniform distribution of vehicles towards the parking area. The parking areas are then more uniformly filled with vehicles. This ensures that vehicles will not re-enter the traffic network in search of a vacant parking spot. The user experience of vehicles using the PRAM is increased. Moreover, if the vehicle demand matches the declining demand scenario, the TTS and VTL are reduced. A lower TTS and VTL implies that the traffic flow on the traffic network is higher, consequently reducing traffic congestion. The vehicles on the traffic network, local residents, and the MOTN all benefit from a reduction of traffic congestion.

However, the results of the two-peaks and inclining demand scenarios with the MPC and PRAM control strategies are not an improvement on the traffic network. The main reason is the travel time prediction. The relation assumed throughout this thesis is linear. However, the traffic dynamics behave in a highly nonlinear fashion [26]. For example, the traffic network that is used throughout the case studies has links arriving at an intersection that expands from 2 lanes to 5 lanes. If the traffic network is saturated, the queue of one link can block exits for other vehicles. An example is presented in Figure 4.12. A large queue of vehicles blocks vehicles for the right exit. Especially if the queue lengths of a saturated link are different across the exits, one exit can be blocked by the queue length of another exit. With a relatively low queue length, the average vehicle speed can be low, due to this blocking behaviour. Hence, the relation between the traffic states of the S-model and the average vehicle speed on a link that is assumed is simplified too much. The mean relative error of the travel time prediction and the actual travel time is over 25% and 40% for both case studies, respectively.

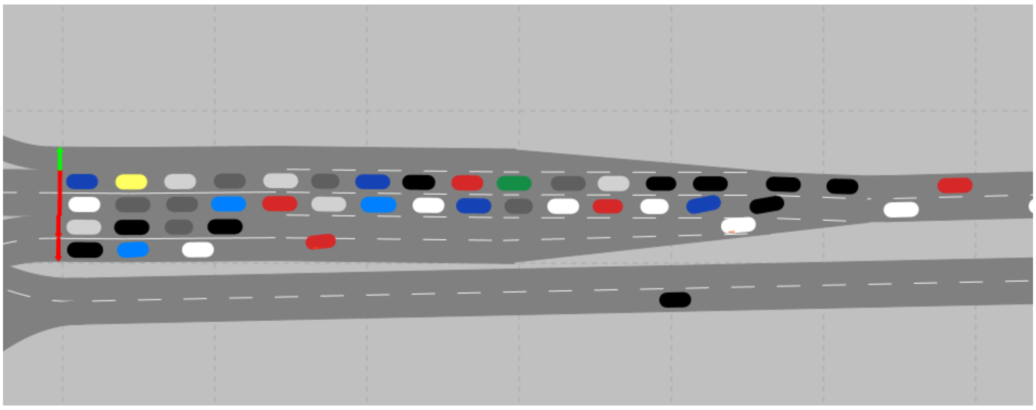


Figure 4.12: An example where the long queue of one exit physically blocks another exit

4.5. Conclusions

In this chapter, the control strategies of MPC and MPC combined with the PRAMs are compared. The performance of these control strategies are compared on the TTS, the VTL, and their distribution of vehicles to the parking areas, by performing two case studies.

For both cases, parameters are identified for the traffic prediction model and the PRAM. The mean relative error of the predicted 8 step-ahead traffic states of the S-model is around 10%, which is considered reasonable. The mean relative error of the predicted average vehicle speed used in the PRAM is over 18%, which may lead to problems in predicting the travel time of travel routes. In case study A, the MPC outperforms all other control strategies, for the two-peaks and inclining demand scenarios. In case study B, all control strategies perform worse than the fixed-time control strategy, for the two-peaks and inclining demand scenarios. For the declining demand scenario, the combined MPC and PRAM control strategy focusing on travel time and a uniform distribution of vehicles towards the parking areas performs best in both case studies. This control strategy reduces the TTS and the VTL of vehicles on the traffic network and uniformly distributes the vehicles towards the parking areas. The result is promising because it consequently reduces traffic congestion and avoids re-entering of vehicles on the traffic network. Unfortunately, the MPC and PRAM control strategies do not perform well in other demand scenarios. One explanation is that the mean absolute error of the predicted travel time of travel routes is over 48 [s] and 95 [s] in case studies A and B, respectively. Despite the large error in predicting the travel time, the MPC and PRAM control strategies in the declining demand scenario perform well. If the error of the predicted travel time can be reduced, traffic congestion for other demand scenarios can be reduced as well with this control strategy.

5

Conclusions and discussion

In this thesis, a combined Model Predictive Control (MPC) strategy with Parking Resource Allocation Model (PRAM) is proposed to improve traffic flow in urban areas with destinations for leisure. An extensive case study is done on an urban traffic network during rush hours with multiple parking areas that attract many vehicles. Three different control strategies are compared during the morning rush hours and the evening rush hours. In this chapter the research question is answered, final conclusions are drawn, and recommendations for future research are given.

5.1. Conclusions

This research focuses on the combination of the PRAM and model predictive traffic signal control strategy in urban traffic networks with parking areas. The research question of this thesis is defined as:

To what extent can model-based traffic signal control combined with a smart parking solution based on resource allocation further improve traffic flow in a busy urban traffic network with large parking areas?

The case studies show promising results. The combined MPC control strategy with the travel time and vehicle distribution focused PRAM outperforms all other control strategies by means of the Total Time Spent (TTS) and Vehicle Time Loss (VTL), for the declining demand scenario. A reduction in TTS and VTL generally means an improvement in traffic flow. Moreover, the distribution of vehicles towards the parking areas is more uniformly when applying the PRAM. This ensures that vehicles will not arrive at a full parking area, while other parking areas remain near empty, reducing the re-entering of vehicles on the traffic network. However, the other demand scenarios are less favourable. The MPC control strategy without a PRAM performs best for these demand scenarios in case study A, while the fixed-time control strategy outperforms all other control strategies in case study B. Adding a PRAM to an MPC control strategy results in an increase in TTS and VTL for both case studies.

The main cause that may have affected the undesired outcome is travel time prediction. The mean absolute error of the predicted travel time of travel routes is over 48 and 95 seconds in case studies A and B, respectively. This can affect the choice of travel routes for vehicles searching for a parking area. One travel route is perceived as the shortest travel time, while in reality, another travel route has a shorter travel time. Throughout this thesis, the travel time prediction of travel routes is based on a linear relation between the traffic states of the S-model and the average vehicle speed of links, and a linear relation between the average vehicle speed of links and the travel time. A linear relation does not capture the nonlinear traffic behaviours such as blocking (i.e. the physical blocking of an exit due to a large queue length of another exit, explained in Section 4.4). A nonlinear relation could be assumed to improve the travel time prediction. Other information of the S-model (e.g. the time delay or queue length per exit) may improve the accuracy of the travel time prediction. Therefore, it is recommended for future research to compare the performance of more complex relations between the traffic states and the travel time of travel routes.

Implications for practice

The combined MPC control strategy with PRAM cannot be employed directly on the traffic network of the Mall Of The Netherlands (MOTN). Instead, future research on the performance of the MPC control strategy with PRAM is needed on the traffic network of the MOTN. The traffic demand used in the case studies is based on real-life traffic demands. However, fictive parking demand is used. The number of vehicles arriving and leaving the parking areas is uniform. In real life, the parking demand may change over time. To comprehend the real-time performance of the traffic network with a combined MPC control strategy and PRAM, a real-life parking demand study has to be performed. Additionally, the traffic demand scenarios based on the traffic network of the MOTN are simplified. An extensive traffic demand research may provide the combined MPC and PRAM with more realistic traffic demands. Furthermore, there is a significant difference between the number of vehicles using the parking areas during the morning and evening rush hours. More vehicles are searching for vacant parking spots during the morning rush hours. Roughly 30% of vehicles on the traffic network is heading towards the parking areas during the morning rush hours, while roughly 12% of vehicles on the traffic network is heading towards the parking areas during the evening rush hours, based on Figures 4.2, B.1 and B.2. When more vehicles on the traffic network use the PRAM, the options to uniformly distribute vehicles over the traffic network increase. Since the combined MPC and PRAM outperforms the fixed-time control strategy in case study A but not in case study B, it is recommended to focus mainly on the morning rush hours. Therefore, the main recommendation to the MOTN is to compare the combined MPC and PRAM with real-life traffic and parking demands for the morning rush hours.

The same recommendations hold for other urban areas. For urban areas with large time-based destinations of leisure, a combined MPC and PRAM can be promising. Note that throughout this thesis, the rush hours of both the traffic demand and the parking demand overlap. Examples of time-based destinations of leisure are concert halls or soccer stadiums. When the destinations of leisure are held (e.g. a concert, or a soccer match) during the morning or evening rush hours, it could be beneficial for the performance of the traffic network to implement a combined MPC and PRAM. A combined MPC and PRAM may not be necessary for the urban area when the destinations of leisure are not held during the morning or evening rush hours. Solely implementing a PRAM to more uniformly distribute vehicles to the parking areas may be enough for these urban areas to improve the traffic flow, and better distribute vehicles towards the parking areas.

In conclusion, the main recommendation is to improve the accuracy of the travel time predictions. The performance of more complex relations between the traffic states of the traffic prediction model and the travel time of travel routes have to be compared. Moreover, future research concerning real-life traffic and parking demands during the morning rush hours is needed for the traffic network of the MOTN. The combined MPC and PRAM during the morning rush hours can then be implemented with real-life traffic situations. For other urban areas with time-based destinations of leisure, it is important to analyse the rush hours of the traffic on the traffic network and the rush hours of vehicles toward the parking areas. When the rush hours of traffic and the parking areas coincide, the performance of the combined MPC and PRAM with real-life traffic and parking situations can be analysed and may benefit the performance of the traffic network.

5.2. Future work

There are multiple suggestions for future work on the topics of this thesis:

Improvements to the framework

The main recommendations would be to improve the framework of MPC with the PRAM. Some improvements are:

- **Alternative relation of travel times:** The travel time prediction of this thesis is based on a linear relation of the traffic states of the S-model. However, there exist more complex relations that may improve the accuracy of predicting the travel time of travel routes.

  An option to consider is to include other variables of the S-model such as the the flow rates $\alpha^{\mathrm{l}}_{u,d}$, $\alpha^{\mathrm{e}}_{u,d}$, and $\alpha^{\mathrm{a}}_{u,d}$ of link (u,d). The time delay $\delta_{u,d}$ of link (u,d) could also be used. However, this variable is difficult to validate as there are no measurements available.

  Another option is to consider the relation between the traffic states and the average vehicle speed as a linear time-invariant system. A state-space model from input and output measurements can be identified using subspace identification methods [41, Chapter 9].

- **Accurate parking demand:** If an analysis of the historical demand of the parking areas during rush hours could be done, a better match can be made in real-life.

- **Adding a blocking parameter:** Throughout this thesis, blocking behaviour occurred. Vehicles are physically being blocked by another large queue and are unable to exit the link, even while the queue of its exit is low. The traffic prediction model perceives the queue to be small enough that all vehicles leave the intersection. However, this is not possible in real life. If a blocking parameter is added, results could improve. This blocking parameter could be an integer that is 1 when a queue $q_{u,d,o}(k)$ at time step k becomes larger than a said threshold:

$$\text{Blocking}_{u,d,o}(k) = \begin{cases} 1, & \text{if } \max_{i \in O_{u,d}, i \neq o} q_{u,d,i} > \text{Threshold}, \\ 0, & \text{otherwise.} \end{cases} \tag{5.1}$$

The blocking parameter in turn can restrict the leaving flow rate $\alpha_{u,d,o}(k)$ of the other exits.

- **Include re-entering of vehicles on the traffic network:** It can be assumed that unnecessary use of the traffic network results in a lower traffic flow. However, the effect that the re-entering of vehicles on the traffic network has on traffic flow is unknown, because it is not implemented in the simulation. If this behaviour is implemented, an extensive study on the effect that the PRAM will have on reducing the re-entering of vehicles can be done. Moreover, the effect that the re-entering of vehicles on the traffic network will have on traffic flow can be studied.

- **Consider another traffic prediction model:** Instead of using the S-model as the traffic prediction model, different traffic prediction models could be considered. For instance, the BLX-model has a lower sampling time [23, 39]. With a lower sampling time, more traffic dynamics could be captured. Moreover, a lower sampling time could take green waves into account. Especially in busy urban areas where the distance between intersections is small, green waves could provide an improvement. Moreover, if the BLX model also includes the blocking of vehicles in their traffic dynamics, complex traffic networks could be analysed more accurately.

- **Study the effect on partial use of PRAM:** Throughout this thesis, the assumption is made that all vehicles participate in the resource allocation model. However, many vehicles do not always participate. A study on the effect of a PRAM when only a part of the vehicles uses that model is interesting. It can be interesting to know how many vehicles have to participate for a PRAM to be effective.

A parking resource allocation model to allocate parking spots

Throughout this thesis, a parking area is considered to have multiple parking spots. If vehicles arrive at a parking area, they automatically receive a parking spot. The traffic dynamics within a parking area is not considered. Moreover, only a parking area is provided. It is interesting to implement traffic routes inside a parking area. Especially for busy parking areas, providing an optimal traffic route may reduce problems inside the parking area.

Multi-modal traffic networks

When a multi-modal traffic network is considered, the alternative options can be compared. Moreover, a study can be performed to provide the parking areas with measures to reduce the use of vehicles on the traffic network and increase the use of public transport.

Combined MPC and PRAM in freight transport

For freight transport, it can be interesting to use a combined MPC control strategy and PRAM. Alternative travel routes for trucks may be provided to deliver packages or supplies.

Combined MPC and resource allocation in railway management

The global railway management problems can be solved using an MPC approach. The travel time of the travel routes can be predicted, and alternative travel routes can be provided to individual users through a resource allocation model. Consequently, the delay of individual users may affect the decision variables of the MPC control strategy.

A

Supportive tables

Table A.1: Traffic demand of case A: Morning rush hours

(a) Traffic demand of first hour of simulation in [veh/h]

OD	1	2	3	6	7	10	11	12	P1	P2	P3	P4	P5
1	0	41	7	45	125	79	651	139	268	0	0	0	0
2	85	0	44	0	7	0	7	0	0	0	32	0	0
3	156	27	0	27	17	58	107	19	101	0	0	0	0
6	135	0	83	0	7	0	81	0	0	0	74	0	0
7	9	7	7	0	0	7	344	0	0	0	0	0	90
10	273	0	179	0	7	0	156	7	0	0	0	0	152
11	359	27	65	474	271	408	0	100	0	0	0	0	421
12	107	0	73	0	7	57	7	0	0	0	0	0	62
P1	278	0	112	0	0	0	0	0	0	0	0	0	0
P2	0	0	0	0	0	0	0	0	0	0	0	0	0
P3	0	23	0	135	0	0	0	0	0	0	0	0	0
P4	0	0	0	0	0	0	0	0	0	0	0	0	0
P5	0	0	0	0	104	151	333	65	0	0	0	0	0

(b) Traffic demand of second hour of simulation in [veh/h]

OD	1	2	3	6	7	10	11	12	P1	P2	P3	P4	P5
1	0	40	7	45	124	79	650	138	460	224	24	7	0
2	85	0	44	0	0	0	0	0	0	0	86	0	0
3	156	26	0	27	16	58	106	18	176	83	9	7	0
6	134	0	82	0	0	0	80	0	0	0	196	7	0
7	8	0	7	0	0	7	344	0	43	67	10	7	120
10	273	0	179	0	7	0	155	7	0	186	10	7	205
11	359	27	64	473	270	408	0	100	230	269	28	7	591
12	106	0	73	0	7	57	7	0	7	81	7	7	77
P1	185	0	74	0	0	0	0	0	0	0	0	0	0
P2	0	0	0	0	0	0	0	0	0	0	0	0	0
P3	0	16	0	90	0	0	0	0	0	0	0	0	0
P4	0	0	0	0	0	0	0	0	0	0	0	0	0
P5	0	0	0	0	70	100	222	43	0	0	0	0	0

Table A.2: Traffic demand of case B: Evening rush hours

(a) Traffic demand of first hour of simulation in [veh/h]

OD	1	2	3	6	7	10	11	12	P1	P2	P3	P4	P5
1	0	85	156	135	9	273	359	107	278	0	0	0	0
2	41	0	27	0	7	0	27	0	0	0	19	7	0
3	7	44	0	83	7	179	65	73	112	0	0	0	0
6	45	0	27	0	0	0	474	0	0	0	117	18	0
7	125	7	17	7	0	7	271	7	0	0	0	0	104
10	79	0	58	0	7	0	408	57	0	0	0	0	151
11	651	7	107	81	344	156	0	7	0	0	0	0	333
12	139	0	19	0	0	7	100	0	0	0	0	0	65
P1	268	0	101	0	0	0	0	0	0	0	0	0	0
P2	0	0	0	0	0	0	0	0	0	0	0	0	0
P3	0	32	0	74	0	0	0	0	0	0	0	0	0
P4	0	0	0	0	0	0	0	0	0	0	0	0	0
P5	0	0	0	0	90	152	421	62	0	0	0	0	0

(b) Traffic demand of second hour of simulation in [veh/h]

OD	1	2	3	6	7	10	11	12	P1	P2	P3	P4	P5
1	0	85	156	134	8	273	359	106	185	0	0	0	0
2	40	0	26	0	0	0	27	0	0	0	16	0	0
3	7	44	0	82	7	179	64	73	74	0	0	0	0
6	45	0	27	0	0	0	473	0	0	0	90	0	0
7	124	0	16	0	0	7	270	7	0	0	0	0	70
10	79	0	58	0	7	0	408	57	0	0	0	0	100
11	650	0	106	80	344	155	0	7	0	0	0	0	222
12	138	0	18	0	0	7	100	0	0	0	0	0	43
P1	713	0	270	0	0	0	0	0	0	0	0	0	0
P2	0	0	0	0	0	0	0	0	0	0	0	0	0
P3	0	86	0	197	0	0	0	0	0	0	0	0	0
P4	0	0	0	0	0	0	0	0	0	0	0	0	0
P5	0	0	0	0	241	404	1124	165	0	0	0	0	0

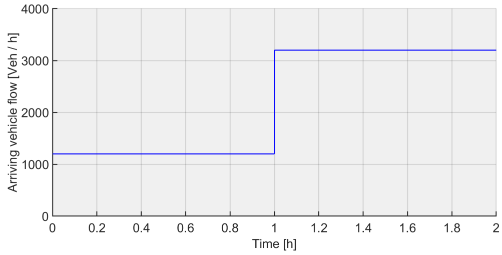
Table A.3: Phase time of intersections during morning rush hours

Phase time	**Phase 1**	**Phase 2**	**Phase 3**	**Phase 4**
Intersection 1	6.8	8.5	6.4	26.3
Intersection 2	23.5	9.8	9.8	4.9
Intersection 3	9.4	10.3	7.5	20.8
Intersection 4	26.2	9.7	7.0	5.1

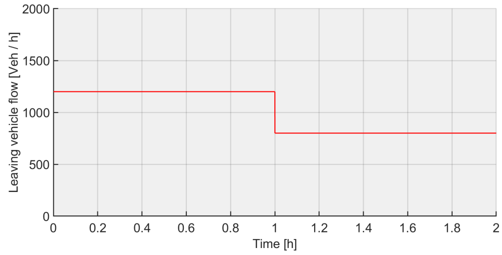
Table A.4: Phase time of intersections during evening rush hours

Phase time	**Phase 1**	**Phase 2**	**Phase 3**	**Phase 4**
Intersection 1	7.9	9.2	9.7	21.2
Intersection 2	26.7	6.4	11.2	3.7
Intersection 3	3.0	8.9	20.6	15.5
Intersection 4	25.4	10.2	5.9	6.5

B
Supportive figures

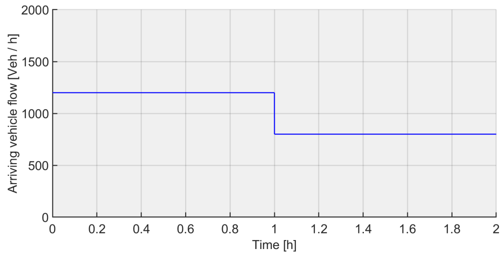


(a) Arriving flow rate of parking areas

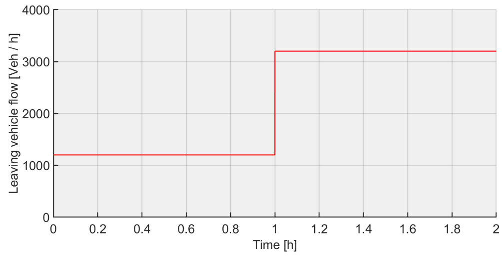


(b) Departing flow rate of parking areas

Figure B.1: Arriving and departing flow rate of the parking areas during the morning rush hours

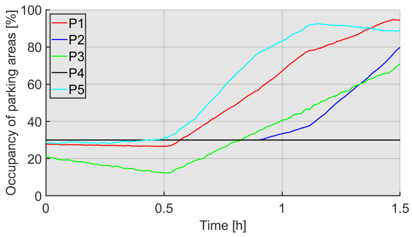


(a) Arriving flow rate of parking areas

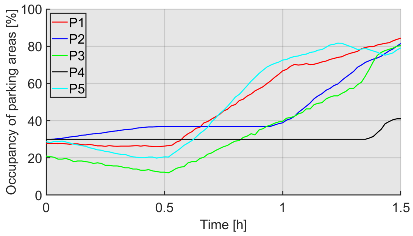


(b) Departing flow rate of parking areas

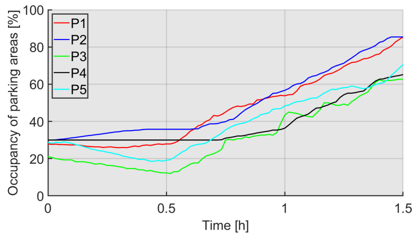
Figure B.2: Arriving and departing flow rate of the parking areas during the evening rush hours



(a) Model Predictive Control (MPC) without parking control

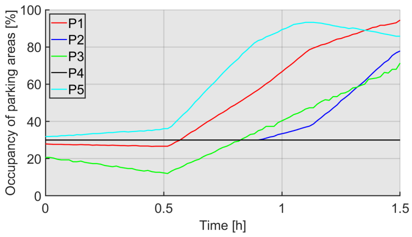


(b) MPC with parking travel time control

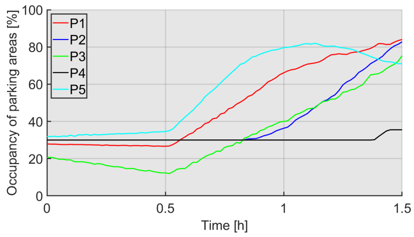


(c) MPC with parking travel time and occupancy control

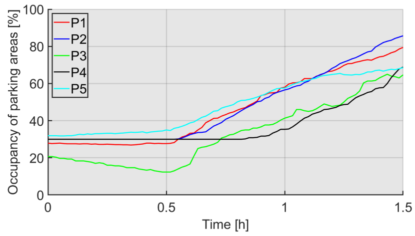
Figure B.3: Development of the parking occupancy in scenario 3 during the morning rush hours for each control strategy



(a) MPC without parking control

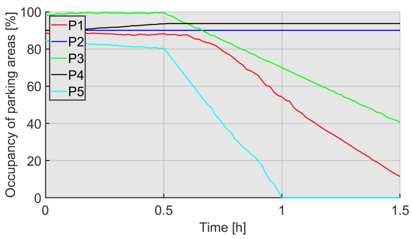


(b) MPC with parking travel time control

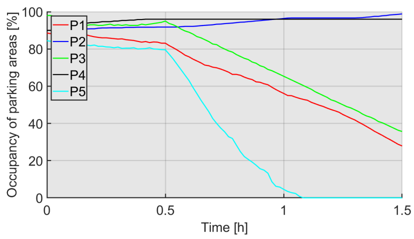


(c) MPC with parking travel time and occupancy control

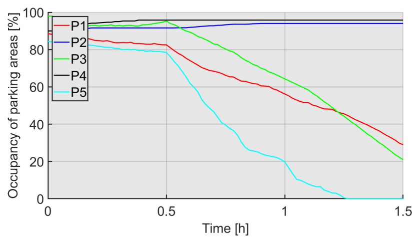
Figure B.4: Development of the parking occupancy in scenario 2 during the morning rush hours for each control strategy



(a) MPC without parking control

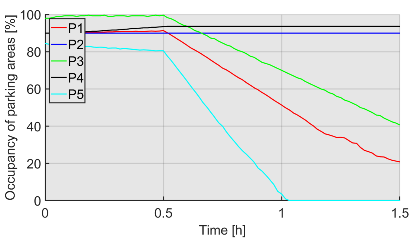


(b) MPC with parking travel time control

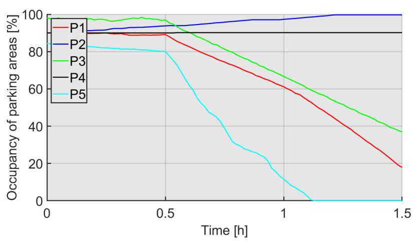


(c) MPC with parking travel time and occupancy control

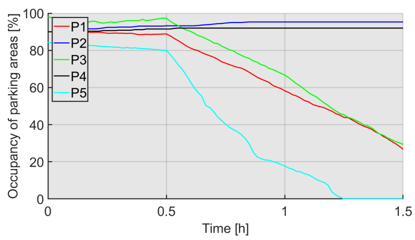
Figure B.5: Development of the parking occupancy in scenario 3 during the evening rush hours for each control strategy



(a) MPC without parking control



(b) MPC with parking travel time control



(c) MPC with parking travel time and occupancy control

Figure B.6: Development of the parking occupancy in scenario 2 during the evening rush hours for each control strategy

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List of Symbols

Symbols used in S-model

c	cycle time of an intersection
J	set of nodes
L	set of links
K	set of intersections
l^{veh}	average length of a vehicle
$I_{u,d}$	set of upstream cells of link (u,d)
$O_{u,d}$	set of downstream cells of link (u,d)
$n_{u,d}(k)$	total number of vehicles on link (u,d) at time step k
$q_{u,d}(k)$	the queue length of link (u,d) at time step k
$q_{u,d,o}(k)$	the queue length of link (u,d) at time step k heading to node o
k	simulation time step
$\alpha^{\text{e}}_{u,d}(k)$	entering flow rate on link (u,d) during the time interval $[kc,(k+1)c)$
$\alpha^{\text{l}}_{u,d}(k)$	leaving flow rate on link (u,d) during the time interval $[kc,(k+1)c)$
$\alpha^{\text{a}}_{u,d}(k)$	arriving flow rate at the tail of the queue on link (u,d) during the time interval $[kc,(k+1)c)$
$\alpha^{\text{l}}_{u,d,o}(k)$	leaving flow rate on link (u,d) heading to node o during the time interval $[kc,(k+1)c)$
$\alpha^{\text{a}}_{u,d,o}(k)$	arriving flow rate at the tail of the queue on link (u,d) heading to node o during the time interval $[kc,(k+1)c)$
$\mu_{u,d,o}$	saturation rate on link (u,d) heading to node o
$g_{u,d,o}(k)$	green time on link (u,d) heading to node o during the time interval $[kc,(k+1)c)$
$N^{\text{lane}}_{u,d,o}$	number of lanes on link (u,d) heading to node o
$N^{\text{lane}}_{u,d}$	number of lanes on link (u,d)
$\beta_{u,d,o}(k)$	turning fraction on link (u,d) heading to node o during the time interval $[kc,(k+1)c)$
$C_{u,d}$	total capacity of link (u,d)
$\delta_{u,d}(k)$	time delay on link (u,d) during the time interval $[kc,(k+1)c)$
$\tau_{u,d}(k)$	number of complete cycles of time delay on link (u,d) during the time interval $[kc,(k+1)c)$
$\gamma_{u,d}(k)$	remaining time delay on link (u,d) during the time interval $[kc,(k+1)c)$
$a^{\text{dec}}_{u,d}$	average deceleration of vehicles on link (u,d)
$v^{\text{free}}_{u,d}$	free flow speed on link (u,d)
$v^{\text{low}}_{u,d}$	idling speed on link (u,d)
$l^{\text{lane}}_{u,d}$	length of link (u,d)
$\bar{X}_{u,d}$	distance needed for a vehicle to decelerate from the free flow speed to the idling speed

$\delta x_{u,d}(k)$	distance between the beginning of link (u,d) and the tail of the queue on link (u,d)
$q_{u,d}^{\text{ave}}$	average length of the queue on link (u,d) during the time interval $[kc,(k+1)c)$
$\alpha_{s,d}^{\text{dem}}(k)$	demand flow on link (s,d) with source node s during the time interval $[kc,(k+1)c)$
$q_{s,d}^{\text{source}}$	the source queue on link (s,d) with source node s during the time interval $[kc,(k+1)c)$
$v_{u,d}^{\text{ave}}(k)$	average vehicle speed on link (u,d) at time step k
γ	weights of the state variables
$\hat{\alpha}_{u,d,o}^{\text{l}}(k)$	change in distribution of vehicles on link (u,d) heading to node o during the time interval $[kc,(k+1)c)$
$\hat{\alpha}_{u,d,o}^{\text{l,Opt}}(k)$	number of vehicles leaving link (u,d) heading to node o during the time interval $[kc,(k+1)c)$ travelling according to their optimal travel route
$\hat{\alpha}_{u,d,o}^{\text{l,Orig}}(k)$	number of vehicles leaving link (u,d) heading to node o during the time interval $[kc,(k+1)c)$ travelling according to their original travel route

Symbols used in Model Predictive Control

k_c	control time step
N_c	control horizon
N_p	prediction horizon
$x_{u,d}$	vector with the states of the S-model
$\mathbf{g}_d(k_c)$	vector with the green times of intersection d at control time step k_c
$J_{\text{TTS}}(k_c)$	part of the objective function that depends on the total time spent at control time step k_c
$J_{\text{Final}}(k_c)$	part of the objective function that includes the final cost at control time step k_c
$J_{\text{D}}(k_c)$	part of the objective function that calculates the cost of switching times at control time step k_c
$J_{\text{Q}}(k_c)$	part of the objective function that calculates the longest queue of intersections at control time step k_c
$\Phi(\mathbf{g}_d(k_c))$	equality constraint on the phase times at intersection d and control time step k_c
w	weights of the different objectives in the cost function
TTS_{rel}	relative change in the total time spent of the controller
VTL_{rel}	relative change in the vehicle time lost of the controller

Symbols used in Parking Resource Allocation Model

R	set of travel routes
U	set of users
P	set of parking areas
t_u	starting time of user u
$v_{u,d}^{\text{ave}}(k)$	average vehicle speed on link (u,d) at time step k
$T_r(k)$	predicted travel time of route r at time step k
$S_p(k)$	the available parking spots of parking area p at time step k
C_p	total capacity of parking area p
$\alpha_p^{\text{a}}(k)$	number of vehicles arriving at parking area p during the time interval $[kc,(k+1)c)$
$\alpha_p^{\text{l}}(k)$	number of vehicles leaving parking area p during the time interval $[kc,(k+1)c)$
$\alpha_p^{\text{r}}(k)$	number of vehicles reserving parking area p during the time interval $[kc,(k+1)c)$
$x_{u,r}(k)$	the choice of user u to choose travel route r at timestep k
$J_{\text{drive}}(k)$	part of the objective function that includes the travel time at time step k
$J_{\text{parking}}(k)$	part of the objective function that ensures an even distribution of vehicles towards the parking areas at time step k
w	weights of the different objectives in the cost function
$A_{u,r}$	penalty for user u to take travel route r by means of the available parking space of the parking area
$x_{u,r}(k)$	choice of user u to use travel route r at time step k
x_u^{switch}	choice to switch user u from the prior allocated parking area to the newly allocated parking area
T_u^{switch}	predicted travel time of user u that may choose to switch to another parking area

List of Acronyms

MOTN	Mall Of The Netherlands
MPC	Model Predictive Control
PGIS	Parking Guidance Information System
PRAM	Parking Resource Allocation Model
SQP	Sequential Quadratic Programming
TSC	Traffic Signal Control
TTS	Total Time Spent
VTL	Vehicle Time Loss