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A possible new adaptive control approach for ramp metering

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January 24, 2016

Rijkswaterstaat
Ministerie van Infrastructuur en Milieu

TU Delft

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Published by	ITS Edulab, Delft
Date	January 24, 2016
Status	Final report
Version number	1.05
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ITS Edulab is a cooperation between Rijkswaterstaat and Delft University of Technology

Preface

"What lies behind us, and what lies before us
are small matters compared to what lies within us."
—Ralph Waldo Emerson

In front of you lies my Master thesis. This thesis is the graduation work that concludes my Master of Science programme Transport and Planning at Delft University of Technology. This thesis is the result of ten months research and the experience I gained during my Master programme. The tuning of parameters of the ramp metering algorithm ALINEA is central to this report. In section 1 the problem will be introduced and research questions will be denoted. Section 2 will evaluate several traffic flow models, ramp meter algorithms and adaptive control approaches based on literature. These evaluations will give answers on some sub questions. The specific traffic flow model, algorithm and adaptive control approach are needed for development and simulation. Section 3 will explain the development for a new adaptive control approach which estimates all parameters of the ramp metering algorithm. Sections 4 and 5 will discuss the simulation set-up and simulation results. Finally in section 6 the findings will be presented and recommendations will be given on further research.

I want to thank several people who helped me during my study at Delft University of Technology. First of all I want to thank my thesis committee consisting of Prof. dr. ir. Serge Hoogendoorn, dr. Victor Knoop, dr. ir. Henk Taale, dr. ir. Mohammad Hajiahmadi and ir. Paul Wiggenraad. Special thanks goes to Victor Knoop who, as daily supervisor, guided me through my Master thesis for the last 9 months. I want to thank him for the positive criticism he gave during our meetings, which helped me to improve my research. Also special thanks to Mohammad Hajiahmadi, because without Mohammad I would not have achieved this thesis which lies before you and I would not have completed this research as I wanted. Mohammad helped me with his knowledge about adaptive control and adaptive control systems which I lacked. Thanks to Mohammad I gained the knowledge on adaptive control needed for this thesis. Mohammad often set me on the right track during our meetings. Therefore many thanks to Mohammad Hajiahmadi. I want to thank Serge Hoogendoorn for his knowledge and enthusiasm during the short meetings we had. Unfortunately, he was not able to attend all meetings, but with his enthusiasm about my subject it gave me that little boost I needed to finish this thesis. I also want to thank Henk Taale who I could always ask questions at the office of Rijkswaterstaat. Henk Taale gave me several information about missing literature about Dutch ramp metering which I needed for this thesis. At last I want to thank Paul Wiggenraad who set me on the right track for the Master programme and the Master thesis steps that had to be taken. I want to thank all of my thesis committee members for their guidance and input during meetings and during the writing of this thesis.
In addition to my thesis committee I also want to thank Goof van der Weg for his METANET model and his help with explaining it to me. I could always get back to him with question about the model, therefore many thanks to Goof. I also want to thank my colleague students for the great time I had during my study at Delft University of Technology. Also many thanks to them for working together during certain courses and helping me with difficulties I had during my Master programme. Special thanks to Niek Lemans, Geert-Jan Wolters and Marios Ntaflos for the great time we had during our

Master programme! I also want to thank my friends, Eric Schreurs, Bart de Jong and Lars Rovers, who where also my fellow students at our previous school Zuyd Hogeschool Heerlen. Thank you for the great time we had in Delft.

At last, and certainly not the least, I want to thank my girlfriend, Laura, who supported me during the past 10 months while writing this thesis. In additions also special thanks to my family who supported me throughout my studies.

M.J.A. Meulenberg

Delft, January 24, 2016

Summary

Traffic management measures are implemented successfully in practice like in the Field Operational Test Integrated Management Amsterdam (*Praktijkproef Amsterdam*). The situation on freeways gradually improves when dynamic traffic management is applied. With increasing congestion every year on Dutch freeways new measures or improvement of existing traffic management measures are necessary. Up till 2020 congestion will keep increasing if no extra measures are taken. A solution on freeways for increasing demand is ramp metering. Ramp metering regulates the inflow from the on-ramp on to the mainline of the freeway.

Introduction and problem formulation

In this research the focus is on traffic-responsive local ramp metering. This ramp metering installation responds to the actual traffic situation and is located on one on-ramp. This thesis will use on-ramps which cause disruptions in the traffic stream on the motorway due to merging and not due to on-ramps close to a bottleneck. The inflow from the ramp to the mainline is regulated by a ramp metering algorithm. A common used algorithm is the ALINEA algorithm, where several traffic variables can be used. A variation of this algorithm is used during the *Praktijkproef Amsterdam* (PPA). This variation, with density as traffic variable, uses a parameter estimator (in Dutch: *Parameterschatter*). The *Parameterschatter* estimates the critical density every time step, which is used to update the target value in the ramp metering algorithm. The gain parameter in this ALINEA algorithm has always been assumed on field experiments, but it is unknown if updating this parameter can improve the current ramp metering approaches. This updating process every time step is called adaptive control. Adaptive control has already been applied in traffic management measures (the *Parameterschatter*), but other types of adaptive control approaches have never been applied to ramp metering. Other adaptive control methods are gain scheduling, model-reference adaptive control, self-tuning regulators and dual control. The problem statement of this research is that with the current knowledge it is unclear to which extent the current ramp metering algorithms can be improved by estimation of the parameters of the ALINEA algorithm by means of conventional adaptive control approaches.

Research approach

The problem will be approached by several literature reviews, development of a possible new approach and simulation of different algorithms. A literature review will be done to investigate the current knowledge on several topics which are needed for evaluations, which are based on literature. One evaluation will be held on several traffic flow models, another evaluation will be held on several existing ALINEA variations and also an evaluation on conventional adaptive control approaches will be held. For either evaluation one variant will be chosen and used in the following steps. Next the new adaptive approach will be developed using MATLAB. The existing methods and the new approach that will be simulated will be compared towards each other based on several indicators. These indicators are Total Time Spent (TTS), Total on-ramp delay (TOD), Average mainline travel time (AMTT) and Total delay. The simulations will be run under stochastic environment.

State-of-the-art

The traffic flow variables are related, which is displayed in a fundamental diagram ($q = \rho * v$). One of the important traffic flow phenomenons for ramp metering is the capacity drop, which is the phenomenon where the capacity in congestion state is lower than the capacity in free flow state. Ramp metering tries to postpone this capacity drop which will lead to improvement of the traffic situation on the freeway in terms of travel time. Spill back from the on-ramp to the underlying network is also taken into account later in this thesis by means of queue control. The capacity drop is an important factor that should be reproduced by the traffic flow model for this thesis. A macroscopic traffic flow model seems most suited for this thesis, where a new ramp metering algorithm will be tested for the first time. From all evaluated macroscopic traffic flow models, METANET seems most suitable for this thesis. This model can reproduce the capacity drop and is sufficient for first time testing a new approach and is therefore suitable for further use in this thesis.

This thesis uses the ALINEA algorithm to keep some relevance with the PPA. ALINEA algorithms with different variables as the target value (flow, density, speed) and upstream and downstream measurement variations will be evaluated. The upstream variations are not inferior to the downstream measurement variation but are only needed in case no downstream measurements are available. In this research there will be available measurements upstream and downstream of the ramp and therefore the downstream variations will be used. From all these variations, the D(density)-ALINEA is one of the most appropriate variation for this thesis, with unique values for different traffic states and it has a certain relevance with the PPA. An other viable variation, is the PI-ALINEA. This Proportional-Integral(PI) variation was only tested in case of distant downstream bottlenecks, where it outperforms the standard (D-)ALINEA. The final choice of the ALINEA variation that will be used is also based on the adaptive control evaluation.

Four different adaptive control approaches are described: gain scheduling, model-reference adaptive control, self-tuning regulators and (suboptimal) dual control. From evaluation the model-reference adaptive control (MRAC) approach seems most suitable for this thesis. The MRAC approach uses a reference model which specifies the desired response of the model. The MRAC approach has been applied to traffic management under emergency evacuation and therefore could be viable for the traffic system. The approach for emergency evacuation is applied with a gradient method which updates the parameters of the control law. The control law in this example looks like the PI-ALINEA discussed before. Other approaches are less suitable for this thesis. The STR approach is inferior compared to the MRAC approach in case of time-varying parameters and will therefore not be considered in this thesis. Gain scheduling is non-feedback and computes parameters off-line which can lead to deterioration of performance when there are unpredictable changes in dynamics, like in changes in traffic flow and is therefore not suitable for this thesis. (Suboptimal) dual control is very complex, it is uncertain if it is possible to implement for ramp metering. And because there is an example for the traffic system with the MRAC approach the MRAC approach seems a more viable option for this thesis.

This thesis uses the MRAC approach with a modified PI-ALINEA as control law similar to the approach with emergency evacuation. The MRAC approach will use the gradient method to update the parameter gains of the PI-ALINEA. The *Parameterschatter* will determine the critical density every time step and updates the target density. The standard D-ALINEA and the standard PI-ALINEA

will be used to compare the new developed approach with.

Development and simulation

METANET and its parameters are calibrated in literature except the critical density, which will be variable over time to show a better response of the *Parameterschatter*. Also the measurements will have noise to create a stochastic environment. The new developed approach, the adaptive ramp metering controller (AD-RMC), will be compared towards the standard D-ALINEA and standard PI-ALINEA. Several criteria are the same for all situations, like the (de-)activation criteria. These are mostly based upon a certain percentage of the capacity or a threshold value for speed. Only the capacity of the AD-RMC will be estimated by the *Parameterschatter* and for the standard variations this value is predefined. The queue control, one of these criteria, is the same for all situations and is based on the queue length, the demand and the maximum allowable queue on the on-ramp.

The first step of developing the AD-RMC is to implement the gradient method, which uses the error between the target density and the downstream measured density. This error is used to update the parameter gains of the PI-ALINEA variation. The gradient method is very unstable because it can lead to zero division and therefore needs some conditions for updating. The parameter gains are not updated when queue control is applied, the error is very high (free flow situation) and when the situation on the freeway does not change over a few time steps (the downstream density does not vary too much). The gains are also not updated when the error converges to zero, because then the previous gains improved the traffic situation on the freeway and are assumed to have a correct value. If these conditions do not apply and there is still zero division, which leads to instability of this method and is therefore applied, the parameter gains in the denominator of the update rule are also updated such that no zero division occurs by changing one of the consecutive parameter gains with a certain percentage. The next step is to update the target density by means of estimating the critical density. The *Parameterschatter* from the PPA is used to estimate this critical density. This method is based on the least squares estimation and determines the derivative of the fundamental diagram. The critical density is updated upward if the derivative is a positive value and greater than the positive threshold value and the previous critical density is smaller than the downstream measured density. The critical density is updated downward if the derivative is a negative value and smaller than the negative threshold value and the previous critical density is greater than the downstream measured density. This way also the critical speed can be determined and with these critical values the actual capacity can also be determined.

The simulation network consist of a stretch of freeway of 30 kilometres with one on-ramp at 20 kilometres. An increasing demand over time is used for the mainline as for the demand on the on-ramp. At the end of simulation time both demands are set to zero such that all vehicles flow out of the network which guarantees the same amount of vehicles at the end of simulation for the no control situation and control situation. The amount of simulation is determined by the variety of the results. The error for all indicators should not be greater than 10 seconds per vehicle. The variations will only be compared towards each other because all variations simulated are already an improvement towards the no control situation. The error for the time the capacity drop took place should not be greater than 2 minutes for statistically reliable results. The simulations will be done under certain circumstances and certain parameter values. In general a more downstream detector is used because the *Parameterschatter* does not work with the first downstream detector of the on-ramp. This

is because in METANET the first downstream segment still has values above critical values for the density, which is in theory not correct. This can cause some errors in the results of this thesis. The D-ALINEA variation will be simulated with different critical density values (30 veh/km/lane and 40 veh/km/lane). The target density in the algorithm is determined by taking a percentage of the critical density. The PI-ALINEA will only be simulated with a critical density value of 30 veh/km/lane because a value of 40 veh/km/lane does not give an improvement at all towards the no control situation. The cause could be that the PI-ALINEA has an extra integral term which tries to keep the response closer to the target value than the standard D-ALINEA. The AD-RMC will be tested in three different ways: only with the *Parameterschatter*, only with the gradient method and a total AD-RMC with the gradient method and with the *Parameterschatter*. The rest of the parameter values will be the same every simulation run. These values need to be defined during test simulations. The adaptation gain values of the update rule for the gradient method are different when used together with the *Parameterschatter* than used without the estimator.

Findings, Conclusions and Recommendations

The AD-RMC with the *Parameterschatter* or the gradient method active gives the best results in terms of TTS and total delay. The PI-ALINEA gives the best results of the standard variations without estimator(s). Unfortunately the total AD-RMC with both estimators gives less good results as the other AD-RMC variations and is also less stable as it needs 140 simulations for statistically reliable results. The results coming from the AD-RMC are promising. In terms of travel time the AD-RMC performs better than the standard variations. Although the improvement is not that large compared to the TTS for the standard variations. Improvements are approximately 58 to 135 hours over all vehicles. For a final check the AD-RMC with the *Parameterschatter* only and with the gradient method only are simulated under different demand. This is also done for the standard D-ALINEA to validate the algorithms. The results coming from validation proof that the algorithms also work under different demand.

The limitations of this research was the used downstream detector which lies 2 kilometre downstream of the on-ramp, this is not in line with actual ramp metering. Other limitations were the use of a macroscopic model, which is less accurate than a microscopic model, and also route choice, emissions and weather effects were not taken into account for first time testing a new ramp metering approach.

It is recommended to not directly implement this new approach in practice. It has potential to be a ramp metering algorithm implemented in practice but further research is recommended. However, the standard PI-ALINEA can be implemented and tested by means of a Field Operational Test (FOT). Although for practice it is recommended to swap the constant variations for adaptive control variations which react better to the actual traffic conditions.

For future research it is recommended to look into the updating conditions for the gradient method. These were not focussed on in this thesis and could be improved in future research. It is further recommended to test the AD-RMC in a more accurate model, a microscopic traffic flow model. It is also worth looking into a more stable parameter gain update method, as this thesis proves that changing the gains every time step has some benefit on the behaviour of ramp metering algorithm.

Samenvatting

Verkeersmanagement maatregelen zijn succesvol geïmplementeerd in the praktijk, zoals in the Praktijkproef Amsterdam. De verkeerssituatie op snelwegen verbetert door het toepassen van dynamisch verkeersmanagement. Door elk jaar toenemende file op Nederlandse snelwegen zijn nieuwe maatregelen of verbetering van bestaande maatregelen vereist. Tot aan 2020 zal de filedrukte toenemen als geen extra maatregelen genomen worden. Een oplossing op snelwegen voor deze toenemende vraag is toeritdosering. Toeritdosering regelt de instroom van de oprit naar de hoofdbaan van de snelweg.

Inleiding en probleem formulering

In dit onderzoek ligt de focus op verkeer-responsieve lokale toeritdosering. Deze toeritdosering reageert op de actuele verkeerssituatie en is gelegen op één oprit. Dit onderzoek gebruikt opritten die storingen veroorzaken in de verkeersstroom door het invoegen van verkeer van de oprit naar de hoofdbaan van de snelweg en niet door opritten dichtbij een knelpunt op de snelweg. Het aantal voertuigen die toegelaten worden op de snelweg wordt berekend met het toeritdosering algoritme. Een veelgebruikte algoritme is het zogenaamde ALINEA algoritme, waarin verschillende verkeersvariabelen gebruikt kunnen worden. Een variatie van dit algoritme is gebruikt tijdens de PPA. Deze variatie, met dichtheid als verkeersvariabele, gebruikt een Parameterschatter. Deze Parameterschatter schat de kritieke dichtheid elke tijdstap en deze is gebruikt om de doelwaarde in het toeritdosering algoritme bij te stellen. De regelparameter in dit algoritme is tot nu toe altijd aangenomen gebaseerd op praktijk proeven, maar het is onbekend of het aanpassen van deze parameter de huidige toeritdosering algoritmen kan verbeteren. Dit proces wordt ook wel adaptief regelen genoemd. Een adaptieve regeling is al eens toegepast in verkeersmanagement maatregelen (de Parameterschatter), maar andere typen adaptieve regelingen zijn nog nooit toegepast op toeritdosering.Andere adaptieve regelingen zijn *Gain scheduling*, *Model-reference adaptive control*, *Self-tuning regulators* en *Dual control*. De probleemstelling van dit onderzoek is dat met de huidige kennis het onduidelijk is in welke mate the bestaande toeritdosering algoritme verbeterd kunnen worden door het schatten van de parameters van het ALINEA algoritme door middel van adaptief regelen.

Onderzoeksaanpak

Het probleem wordt benaderd door verschillende literatuurstudies, ontwikkeling van een mogelijk nieuwe toeritdosering algoritme en simulatie van verschillende algoritmen. Een literatuur studie zal worden gehouden om de huidige kennis over verschillende onderwerpen te onderzoeken die nodig zijn voor verschillende evaluaties. Een evaluatie gaat over verschillende verkeersmodellen, een andere gaat over verschillende bestaande ALINEA variaties en ook een evaluatie over de conventionele adaptieve regelingen zal gegeven worden. Voor elke evaluatie zal een variant gekozen worden en gebruikt worden in de volgende stappen. Daarna, gebaseerd op de resultaten van de evaluaties, zal de nieuwe regeling ontwikkeld worden met behulp van Matlab. De bestaande regelingen en de nieuwe regeling zullen worden gesimuleerd en vergeleken worden met elkaar gebaseerd op verschillende indicatoren. Deze indicatoren zijn Totaal gespendeerde tijd (TTS), Totale vertraging op de oprit (TOD), gemiddelde reistijd op de hoofdbaan (AMTT) en totale vertraging. De simulaties zullen onder een stochastische omgeving plaatsvinden.

Literatuur studie

De variabelen voor verkeersstromen zijn gerelateerd aan elkaar, wat weergegeven wordt in een fundamenteel diagram ($q = \rho * v$). Een belangrijk verkeersstroom fenomeen voor toeritdosering is de capaciteitsval, waar de capaciteit tijdens file lager is dan de capaciteit wanneer vrije afwikkeling geldt. Toeritdosering probeert deze capaciteitsval uit te stellen wat zal leiden tot een verbetering van de verkeerssituatie op de snelweg. *Spill back* van de oprit naar het onderliggende netwerk wordt ook rekening mee gehouden later in dit rapport door middel van een wachtrij regeling. De capaciteitsval is een belangrijke factor, waarbij deze nagebootst dient te worden door het verkeersmodel in deze scriptie. Een macroscopisch verkeersmodel lijkt het meest geschikt voor deze scriptie, waar een nieuw toeritdosering algoritme getest zal worden voor de eerste keer. Van alle geëvalueerde macroscopische verkeersmodellen is METANET het meest geschikt voor deze scriptie. Dit verkeersmodel kan de capaciteitsval nabootsen en volstaat voor een eerste keer testen van een nieuwe regeling en is daarom geschikt voor dit onderzoek.

Deze scriptie gebruikt het ALINEA algoritme om een bepaalde relevantie te houden met de PPA. ALINEA algoritmen met verschillende verkeersvariabelen als doelwaarde (verkeersstroom, dichtheid, snelheid) en benedenstroomse en bovenstroomse metingen worden geëvalueerd. De variaties met bovenstroomse metingen zijn niet minder dan de variaties met benedenstroomse metingen maar zijn alleen nodig in geval er geen meetpunten zijn stroomafwaarts van de oprit. In dit onderzoek zullen zowel benedenstroomse als bovenstroomse metingen gebruikt worden. Van al deze variaties is de D(dichtheid)-ALINEA een van de meest geschikte variatie met unieke waarden voor verschillende verkeerstoestanden. Een andere mogelijke variatie is de PI-ALINEA, welke ook geschikt is voor dit onderzoek. De Proportionele-Integrale(PI) variatie is voorlopig alleen getest voor knelpunten die meer stroomafwaarts gelegen zijn. De uiteindelijke keuze van de ALINEA variatie is ook gebaseerd op de adaptieve regeling evaluatie.

Vier verschillende adaptieve regelsystemen zijn beschreven: *Gain scheduling*, *Model-reference adaptive control* (MRAC), *Self-tuning regulators* (STR) en *(Suboptimal) Dual control*. De MRAC regeling lijkt het meest geschikt voor dit onderzoek. De MRAC regeling gebruikt een referentie model die de gewenste reactie van het model specificeert. De MRAC regeling is toegepast op verkeersmanagement voor nood evacuatie en is daarom geschikt voor een verkeerssysteem. De regeling voor nood evacuatie is toegepast met een gradiënt methode die de parameters van een regeling aanpast. Het algoritme lijkt het meest op de PI-ALINEA die eerder besproken is. De andere regelingen zijn minder geschikt voor dit onderzoek. De STR regeling is inferieur vergeleken met de MRAC regeling in geval van tijd-variërende parameters en zal daarom niet verder worden beschouwd in dit onderzoek. De *gain scheduling* regeling is geen *feedback* regeling en berekent parameters *off-line* wat kan leiden tot verslechtering van de prestatie wanneer er onvoorspelbare veranderingen optreden in de dynamica, zoals bij verkeersstromen en is daarom niet geschikt voor deze scriptie. *(Suboptimal) Dual control* is erg complex en het is onzeker of het mogelijk is om te implementeren voor toeritdosering. En omdat er een voorbeeld is voor het verkeerssysteem met een MRAC regeling, lijkt deze regeling een betere optie voor deze scriptie.

Dit onderzoek gebruikt de MRAC regeling met een aangepaste PI-ALINEA als regelalgoritme, ongeveer gelijk aan de MRAC regeling voor nood evacuatie. De MRAC regeling zal gebruikt worden met de gradiënt methode om de regelparameters van de PI-ALINEA aan te passen elke tijd stap.

De Parameterschatter zal gebruikt worden om de kritieke dichtheid bij te schatten elke tijdstap en daarmee de doelwaarde in het algoritme bij te stellen. De standaard D-ALINEA en de standaard PI-ALINEA zal gebruikt worden voor vergelijking met de nieuwe regeling.

Ontwikkeling en Simulatie

METANET en de bijbehorende parameters zijn gekalibreerd in de literatuur, behalve de kritieke dichtheid die in dit onderzoek variabel zal zijn over tijd zodat de reactie van de Parameterschatter duidelijk zichtbaar wordt. Ook de metingen zullen ruis bevatten om een stochastische omgeving te creëren. De nieuw ontwikkelde regeling, de adaptieve toeritdosering regeling (AD-RMC), zal worden vergeleken met de standaard D-ALINEA en de standaard PI-ALINEA. Verschillende criteria zijn hetzelfde voor alle situaties, zoals de (de-)activatie criteria. Deze zijn meestal gebaseerd op een bepaald percentage van de capaciteit of op een drempelwaarde voor snelheid. Alleen de capaciteit van de AD-RMC zal geschat worden door de Parameterschatter en voor de standaard variaties zal deze waarde vooraf gedefinieërd zijn. De wachtrij regeling, een van deze criteria, is het zelfde voor alle situaties en is gebaseerd op de wachtrij lengte, de verkeersvraag en de maximum toegestane wachtrij op de oprit.

De eerste stap in de ontwikkeling van de AD-RMC is om de gradiënt methode te implementeren, die de fout tussen de doelwaarde en de gemeten waarde gebruikt. De fout wordt gebruikt om de regelparameters van de PI-ALINEA variatie aan te passen. De gradiënt methode is erg instabiel omdat deze regel kan leiden tot nul-deling en heeft daarom bepaalde voorwaarden nodig voor het aanpassen. De regelparameters worden niet aangepast als de wachtrij regel wordt toegepast, de fout heel erg groot is (vrije afwikkeling) en wanneer de situatie op de snelweg niet veel veranderd voor een bepaalde tijd (de stroomafwaarts gemeten dichtheid veranderd niet veel). De regelparameters worden niet aangepast als de fout naar nul convergeert, omdat de vorige regelparameters de verkeerssituatie op de snelweg verbeteren en dan wordt aangenomen dat de regelparameters de juiste waarde hebben. Als deze voorwaarden niet gelden en er is nog altijd sprake van nul-deling, dan worden de regelparameters in de noemer van de aanpassingsregel aangepast, zodat geen nul-deling voorkomt. De volgende stap is om de doelwaarde aan te passen door de kritieke dichtheid te schatten. De Parameterschatter wordt hiervoor gebruikt. Deze methode is gebaseerd op de *least squares* schatting en bepaalt de afgeleide van het fundamenteel diagram. De kritieke dichtheid wordt aangepast naar boven als de afgeleide een positieve waarde heeft en deze waarde groter is dan de positieve drempelwaarde en de vorige kritieke dichtheid kleiner is dan de stroomafwaarts gemeten dichtheid. De kritieke dichtheid wordt naar beneden aangepast als de afgeleide een negatieve waarde heeft en kleiner is dan de negatieve drempelwaarde en de vorige kritieke dichtheid groter is dan de stroomafwaarts gemeten dichtheid. Op deze manier wordt ook de kritieke snelheid bepaald en deze kritieke waarden worden vervolgens gebruikt om de capaciteit te bepalen.

Het gesimuleerde netwerk bestaat uit een strook snelweg van 30 kilometers met op kilometer 20 een oprit. Een toenemende verkeersvraag wordt gebruikt op de hoofdbaan en op de oprit. Op het einde van de simulatie worden de verkeersvragen op nul gezet, zodat alle voertuigen uit het netwerk stromen en dit garandeert dat hetzelfde aantal voertuigen wordt gesimuleerd in geval van geen toeritdosering en wel toeritdosering. Het aantal simulaties wordt bepaald door de variatie in de resultaten. De fout voor alle indicatoren zal niet groter zijn dan 10 seconden per voertuig. De variaties zullen vergeleken worden met elkaar omdat alle variaties al een verbetering zijn ten opzichte van de situatie

zonder toeritdosering. Ook de capaciteitsval wordt rekening mee gehouden. De tijd dat de capaciteitsval is uitgesteld en de tijd dat de capaciteitsval plaatsvindt wordt gebruikt in dit onderzoek. De toegestane fout van de tijd dat de capaciteitsval is uitgesteld is 2 minuten. De simulaties zullen onder bepaalde omstandigheden en bepaalde parameter waarden uitgevoerd worden. In het algemeen zal een meer stroomafwaarts gelegen detector gebruikt worden omdat de Parameterschatter niet werkt met de eerste stroomafwaarts van de oprit gelegen detector. Dit komt omdat in METANET de eerste stroomafwaarts gelegen segment nog steeds waarden voor de dichtheid heeft boven de kritieke dichtheid en dit is in theorie niet juist. Dit kan ook fouten veroorzaken in de resultaten van dit onderzoek. De D-ALINEA variatie zal gesimuleerd worden met verschillende kritieke dichtheid waarden (30 voer/km/rijstrook en 40 voer/km/rijstrook). De doelwaarde voor de dichtheid in het algoritme wordt bepaald door een percentage van de kritieke dichtheid. De PI-ALINEA variatie zal alleen worden gesimuleerd met een kritieke dichtheidswaarde van 30 voer/km/rijstrook omdat een waarde van 40 voer/km/rijstrook geen verbetering geeft tegenover de situatie waar geen toeritdosering wordt toegepast. De oorzaak hiervan kan zijn dat de PI-ALINEA een extra integrale term heeft die probeert de reactie dichter bij de doelwaarde te houden dan de standaard D-ALINEA. De AD-RMC zal getest worden op drie verschillende manieren: alleen met de Parameterschatter, alleen met de gradiënt methode en een totale AD-RMC met beide schattingsmethoden. De overige parameter waarden zullen het zelfde zijn voor elke simulatie. Deze waarden zullen moeten worden bepaald met test simulaties en *trial-and-error* simulaties. De adaptieve parameter waarden van de gradiënt methode zijn anders wanneer deze methode gelijk met de Parameterschatter wordt toegepast.

Bevindingen, conclusies en aanbevelingen

De AD-RMC met de Parameterschatter of the gradiënt methode actief geven de beste resultaten op gebied van TTS en totale vertraging. De PI-ALINEA geeft de beste resultaten van alle geteste standaard variaties zonder schatters. De complete AD-RMC met beide schatters actief geeft helaas minder goede resultaten als de andere variaties van de AD-RMC en is ook nog eens minder stabiel omdat deze AD-RMC 140 simulaties nodig had voor statistisch gezien betrouwbare resultaten te krijgen. Op gebied van reistijd presteert de AD-RMC beter dan de standaard algoritmen. Maar de verbetering is niet heel erg groot vergeleken met de TTS voor deze standaard algoritmen. De verbetering zijn ongeveer 58 tot 135 uur voor alle voertuigen bij elkaar. Als laatste controle wordt de AD-RMC met de Parameterschatter en de AD-RMC met de gradiënt methode gesimuleerd met een andere verkeersvraag. Dit is ook gedaan voor de standaard D-ALINEA om de algoritmen te valideren. De resultaten van deze validatie bewijzen dat de algoritmen ook werken met een andere verkeersvraag.

De beperkingen van dit onderzoek was onder andere de stroomafwaarts gelegen detector die gebruikt is en 2 kilometer stroomafwaarts van de oprit ligt, dit is niet in lijn met de werkelijke toegepaste toeritdosering. Andere beperkingen zijn het gebruik van een macroscopisch model, want deze is minder precies als bijvoorbeeld een microscopisch model.

Het wordt aangeraden om de nieuwe regeling vooralsnog niet te implementeren in de praktijk. De regeling heeft de potentie om als toeritdosering algoritme te dienen in de praktijk maar meer onderzoek is aanbevolen. Daarentegen kan de standaard PI-ALINEA wel getest worden door middel van een praktijkproef. Alhoewel het voor de praktijk aanbevolen wordt om de standaard variaties met constante waarden te vervangen door adaptieve regelingen, omdat deze beter reageren op de werkelijke verkeerssituatie.

Voor toekomstige onderzoek wordt aanbevolen om te kijken naar de aanpassingsvoorwaarden

van de gradiënt methode. Op deze voorwaarden lag geen nadruk in dit onderzoek en kan daarom verbeterd worden in toekomstig onderzoek. Verder is het ook aanbevolen om de AD-RMC te testen in een meer preciezer model, een microscopisch verkeersmodel. Het is het waard om te kijken naar een meer stabielere aanpassingsregel voor de regelparameters, omdat dit onderzoek wel bewijst dat het aanpassen van deze regelparameters voordeel heeft op het gedrag van de toeritdosering algoritme.

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1. Introduction

In the last few years traffic management has been improved. Traffic management measures have been tested and deployed with success. In the Netherlands there has been a large-scale practical implementation of several traffic control measures: the so-called *Praktijkproef Amsterdam* (Field Operational Test Integrated Management Amsterdam). The *Praktijkproef Amsterdam* (PPA) aims at gaining practical experience with applying Integrated Network Management (INM) in a large-scale regional network (Hoogendoorn et al., 2013). INM itself is not new but practical implementation by means of a Field Operational Test (FOT) is new (Hoogendoorn et al., 2013). Several traffic management control measures were tested during this FOT. One of the traffic management measures used during the PPA is a ramp metering installation. Ramp metering tries to improve the traffic condition by preventing congestion on the freeway for a certain time. Ramp metering is done using special traffic lights that allow vehicles to enter the motorway one by one (Middelham and Taale, 2006). This report will mainly be about ramp metering. This section will introduce the topic of this report and will lead to the problem statement and research questions of this report followed by the method to answer these research questions. At the end of this section the structure of this report can be found.

Section 1.1 will give an introduction on congestion as a social problem. This leads to certain measures which are needed to solve this social problem. In section 1.2 measures in the form of Dynamic Traffic Management (DTM) will be introduced and why this is a better solution than building new infrastructure. Section 1.3 will introduce the topic with background information about ramp metering and section 1.4 will introduce adaptive control. Section 1.5 will introduce the problem and will be concluded with the research questions formulated for this research. These research questions need to be answered by a certain method which will be discussed in section 1.6. Finally in section 1.7 the structure of this report will be given.

1.1. The social problem of congestion

According to the VID (in Dutch: *VerkeersInformatieDienst*) in ANP (2014) congestion was reduced between 2007 and 2013 on Dutch freeways but in 2014 there was already an increase. And the prediction in Mackor (2015) is that congestion will increase with 45% from now till 2020 if no extra measures will be taken. According to ANP (2014) the increase of congestion is caused due to the economic recovery. Congestion can lead to irritation among drivers who get heavy delays and will not make it on time at their destination and also their travel times are uncertain. This also can influence traffic safety as drivers get irritated by congestion due to an appointment for example. In addition to time also pollution increases during congestion which is not desired for health and environment. This pollution is caused by fuel consumption which increases when vehicles have to stop and start over and over again like in a traffic jam. The fuel consumption increases which means that car owners also have to pay more money for the same length of road when they are in a traffic jam. For these reasons it is important that new measures will be taken or existing measures are improved to reduce congestion. Many measures have already been developed and will be discussed in the next section.

1.2. Dynamic traffic management

The transportation system has reached its limit due to increasing demand and economic growth. There are several solutions to deal with this problem, like road pricing or building new infrastructure. These solutions are overall quite expensive or time consuming or politically not feasible, therefore traffic management is a better solution to improve the transportation system. To improve the traffic conditions several control measures have been developed in order to handle the demand. Examples of these control measures are ramp metering, variable speed limits, dynamic lane control and Dynamic Route Information Panels (DRIPS). The collection of all traffic control measures is called DTM. The goal of DTM is to improve the transportation system by making it more efficient, effective and safer (Middelham, 2006). The term traffic control refers to a specific form of Intelligent Transport Systems (ITS) that manages or controls traffic with the aim to achieve a certain performance. Examples of purposes of traffic control are to increase safety, reduce congestion, reduce travel time and improve reliability of the transport system (Muller et al., 2013). The control measure ramp metering will be discussed in this report and will be introduced in the next section.

1.3. Ramp metering

Congestion occurs mostly at bottlenecks in the transportation network. Bottlenecks are for example locations in the network where lane narrowing occurs or locations in the network with on-ramps where new traffic is entering the freeway. The last situation can be regulated with ramp metering control. When traffic enters the freeway using an on-ramp, flows will increase on the freeway which can cause congestion downstream of the on-ramp when the capacity of the freeway has been reached. Ramp metering is the most efficient means to regulate the inflow and prevent congestion (for a certain time), whereby a short delay at the on-ramps is the relatively low price to pay (Papageorgiou and Kotsialos, 2000). Several (dis)advantages of ramp metering are mentioned in Elefteriadou (2014). The advantages of ramp metering are the smoother flow of traffic, increased vehicles throughput, increase in average speed, reduction of emissions and reduction of fuel consumption (Elefteriadou, 2014). Disadvantages mentioned by Elefteriadou (2014) are traffic diversion (change of route by avoiding the ramp meter), equity (it could be possibly that some drivers have more benefit from it than others), socio-economic consideration (congestion may shift to another location/bottleneck in the network) and application (if the ramp metering installation is not installed correctly, it may result in worsening conditions). According to its response to real time traffic conditions, ramp metering can be divided into two classes (Zhang et al., 2001):

1. Fixed-time control: Based on historical demands, without the use of real-time measurements
2. Traffic-responsive control: React to actual traffic conditions with the use of real-time measurements.

Besides these two classes based on response, the ramp metering installations can also be divided in three systems (Zhang et al., 2001):

1. Local ramp metering: uses only one ramp meter installation to control the inflow to the freeway
2. Coordinated ramp metering: uses several ramp metering installation to control the inflow to the freeway

3. Integrated systems: combines one or more ramp meters with other traffic control measures.

The focus in this report is on traffic-responsive and local ramp metering. These traffic responsive ramp metering installations are implemented with an algorithm which reacts on the actual traffic conditions based on measurements. All kinds of different algorithms, the strategy to control such systems, have been developed over the years. Examples of algorithms are the Dutch RWS strategy (Middelham and Taale, 2006) and the ALINEA algorithm and its variations (Papageorgiou et al., 1991, Smaragdis and Papageorgiou, 2003, Smaragdis et al., 2004). During the PPA the ramp meters were controlled by a variation of the Asservissement Linéaire d'Entrée Autoroutière (ALINEA) algorithm: Adaptive(AD)-ALINEA. In Smaragdis et al. (2004) there is also an example of an adaptive variation of ALINEA. (AD-)ALINEA is a feedback algorithm that is based on downstream measurements. The density and traffic flow downstream of the on-ramp are measured and used to calculate the ramp flow to be implemented in period k. The ALINEA algorithm used for the PPA is shown in equation 1.1 (Hoogendoorn et al., 2013). The adaptive ALINEA algorithm used during the PPA estimates the critical density with a *Parameter Estimator* (In Dutch: *Parameterschatter*). The *Parameterschatter* determines adaptively the critical density based on actual traffic conditions. The desired value of the density $\hat{\rho}$ is then derived from the critical density (e.g. $\hat{\rho} = \gamma * \rho_{\text{crit}}$ with $\gamma \leq 1$). The *Parameterschatter* also calculates the error of the measured error ($\hat{\rho} - \rho_{\text{out}}(k-1)$). The *Parameterschatter* has the objective to give a reliable estimation of the critical density (See appendix A for associated literature). In addition this estimated critical density is used to also estimate the capacity of the freeway (See appendix A).

$$r(k) = r(k-1) + K_{\text{R}}[\hat{\rho} - \rho_{\text{out}}(k-1)] \tag{1.1}$$

Where

- k = 1, 2, ... the discrete time index
- $r(k)$ = number of vehicles allowed to enter the freeway
- $r(k-1)$ = (Smoothed) number of vehicles entered the freeway in the previous time interval
- K_{R} = Regulator parameter
- $\hat{\rho}$ = Target value of density $\approx \rho_{\text{crit}}$
- $\rho_{\text{out}}(k-1)$ = Density measured downstream of the on-ramp at the previous time interval

In literature the feedback controller ALINEA has been proven to be quite superior compared to other feed forward controllers (Papageorgiou et al., 1991, 2003). Therefore several variations of ALINEA besides the one used during the PPA are developed over the years. These are variations where the density is replaced by occupancy (%), flow (veh/h) or speed (km/h). Even ALINEA algorithms with upstream measurements of the parameters have been researched by Smaragdis and Papageorgiou (2003). There is also a ALINEA variation for distant downstream bottlenecks, PI-ALINEA (Wang et al., 2010). In most practical implementations the parameter occupancy is used. This is because occupancy is closest to density and can be measured from traffic detectors, where density has to be calculated from data (occupancy, flow, speed) coming from the detector. That is why occupancy is often used instead of density. Keeping the density (or occupancy) close to the critical density (or critical occupancy) maximises the throughput of the freeway (Dabiri and Kulcsar, 2014). Because of the density variation used during the FOT in Amsterdam, and to keep a certain relevance to the PPA,

the occupancy variation of ALINEA will be replaced by the density variation as in equation 1.1 for further research in this thesis.

1.4. Adaptive Control

The "adaptive control" used during the PPA and in Smaragdis et al. (2004) are not like the conventional adaptive control approaches as known in systems and control engineering. The methods currently used for ramp metering are estimation methods for the critical density. Adaptive control approaches can also tune other parameters like the regulator parameter in the ALINEA algorithm. To introduce adaptive control first several definitions will be given. One is formulated in Landau et al. (2011): *"Adaptive Control covers a set of techniques which provide a systematic approach for automatic adjustment of controllers in real time, in order to achieve or to maintain a desired level of control system performance when the parameters of the plant dynamic model are unknown and/or change in time".* Äström and Wittenmark (2013) give a more general definition in everyday language: " *'To adapt' means to change behaviour to conform to new circumstances".* From this definition the term 'adaptive controller' can be explained as a controller that can modify its behaviour in response to changes in the dynamics of a process and the character of disturbances (Äström and Wittenmark, 2013). In Äström and Wittenmark (2013) it is discussed what exactly adaptive control is and they came to the conclusion that *an adaptive controller is a controller with adjustable parameters and a mechanism for adjusting the parameters*. Äström and Wittenmark (2013) and Landau et al. (2011) both address the difference between normal feedback control and adaptive control. Feedback control, like the ALINEA algorithm for ramp metering, is used to reject the effect of disturbances upon the controlled variables and to bring them back to their desired target values (Landau et al., 2011). And Landau et al. (2011) defined adaptive control as a control system that measures a certain *performance index* using the inputs, the states, the outputs and the known disturbances. The measured performance index and a target performance index are compared and the adaptation mechanism modifies the parameters in order to maintain the performance index of the control system close to the target performance index. The difference between feedback control and adaptive control is defined as follows: *"While the design of a conventional feedback control system is oriented firstly toward the elimination of the effect of disturbances upon the controlled variables, the design of adaptive control systems is oriented firstly toward the elimination of the effect of parameter disturbances upon the performance of the control system"* (Landau et al., 2011). The scheme of an adaptive controller is given in 1.1.

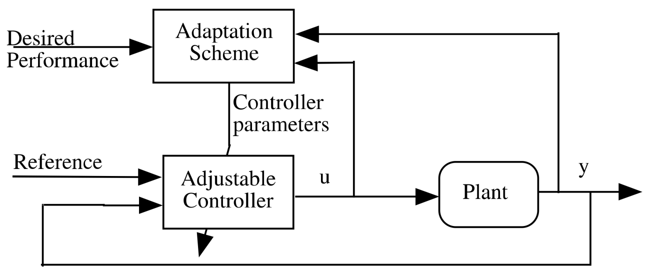


Figure 1.1. – Adaptive Controller (Source: Landau et al. (2011))

Landau et al. (2011) explain when adaptive control should be considered. Adaptive control should be applied when a certain (acceptable) system performance is wanted when large and unknown changes in model parameters can occur. The traffic network is such a system. The traffic states change

over time and are not always predictable. With adaptive control the parameters in the ramp metering algorithm can be tuned and adapted every time step towards the traffic states at hand. If the controller performs better after adaptation the controller should be adjusted the same way, if the controller performs worse after adaptation it should take a 'step back' and be adjusted again and so on.

1.5. Problem formulation

Despite all the traffic control measures currently deployed congestion occurs more often every year on the freeways in the Netherlands. In begin 2015 the congestion on Dutch freeways increased with 58 percent in comparison to that period in 2013 according to the ANWB in Van Lieshout (2015). But of course it is difficult to compare between these years because of weather conditions and accidents that could affect congestion. According to this article (Van Lieshout, 2015) the grow of congestion on the Dutch freeways is caused by the economic recovery. The VID reported in the same article that weather played a role in this increase of congestion mentioned, which explains the large increase of congestion. But the VID also stated that even in the economic crisis the traffic on Dutch freeways grew with 1 to 2 percent annually (Van Lieshout, 2015).

So with increasing traffic every year, even with small percentages, there is need for improvement (in terms of travel time) of the current traffic control measures or even development of new control measures. For this research the focus will be on trying to improve an existing control measure, ramp metering, and thus the corresponding ramp metering algorithm. This research will also try to keep a certain relevance to the PPA. The *Parameterschatter* and the method in Smaragdis et al. (2004) are currently the only adaptive control approaches for ramp metering. But these methods still differ from the conventional adaptive control approaches as mentioned earlier. There are different adaptive control approaches that are not yet tested or developed for ramp metering. To look into different adaptive control approaches and compare them with each other would be very relevant for the PPA and could benefit the future use of adaptive control approaches for ramp metering. The desired situation that this research wants to achieve will be a longer prevention of the capacity drop, which is caused by congestion, and improve the throughput of the freeway in terms of travel time by means of adaptive control towards the current ramp metering control strategies.

The critical density is updated by an estimation method in Smaragdis et al. (2004) and using the *Parameterschatter* during the PPA. But the ALINEA algorithm consists of more parameters like the *Regulator Parameter* (In Dutch: *Regelparameter*). This parameter has always been assumed based on field results. Research found that the value for K_R of 70 veh/h (for the occupancy variation of ALINEA) provided good results in field experiments (Papageorgiou et al., 1998). Ukkusuri and Ozbay (2013) did research towards different values of the regulator parameter and came to the conclusion that the value should be between 70 veh/h and 240 veh/h. That is a huge gap between the lower bound and upper bound value. Hence, there is room for optimizing this parameter and it should also be included in the adaptive control of ramp metering. With the estimation methods used in Smaragdis et al. (2004) and during the PPA the regulator parameter cannot be tuned to optimize the ramp metering algorithm. Conventional adaptive control approaches are able to estimate this parameter of the ALINEA algorithm. Thus the missing part in literature for ramp metering is the tuning of this regulator parameter. Adaptive control could therefore also be able to better estimate the critical density to update the target density in the algorithm. It is currently unknown to which extent these adaptive control approaches could benefit ramp metering by means of parameter tuning.

Summarized there are several good approaches for ramp metering, which have been tested in sim-

ulation and in practice, to postpone congestion for some time on the freeway. But due to increasing demand on the network there is still room for improvement of these algorithms. One possible way is explained earlier, adaptive control. Conventional adaptive control has not been applied yet for ramp metering and it is therefore unknown if this approach is able to improve ramp metering. It would benefit the transportation network if adaptive control could improve the current ramp metering approaches such that the throughput (overall travel time) of the freeway can be maximised. Adaptive control is a possible way to also update the regulator parameter of the ALINEA algorithm as explained earlier. Thus by applying adaptive control to ramp metering algorithms a new ramp metering control approach could be developed for improving the throughput on the freeway. Therefore the **problem statement** is that with the current knowledge it is unclear to which extent the current ramp metering algorithms can be improved by tuning the parameters of the ALINEA algorithm. In search for a possible improvement in existing ramp metering algorithms, adaptive control can be applied.

The **main research question** that can be derived from this problem statement is as follows:

- *To which extent can adaptive control, by tuning all parameters of the ALINEA algorithm, improve ramp metering in terms of travel time?*

To answer this main question, some prior knowledge is required. Such as how can the new adaptive control approach be evaluated and compared to existing approaches? Which ALINEA variations exist and which is suitable for implementation in this thesis? And which adaptive control approaches are available and are these approaches also suitable for ramp metering? To answer these questions several **sub questions** have been formulated:

A. *Which traffic flow simulation models exist and which one is relevant and suited for implementation and evaluation of a new developed adaptive control approach for ramp metering?*

B. *Which different ALINEA variations exist, what are their advantages and disadvantages and which variation is best suited for implementation in this research?*

C. *Which adaptive control approaches exist, what are their advantages and disadvantages towards ramp metering and which ones are relevant and suited for implementation in this research?*

1.6. Research approach

The method to get an answer on the research questions in section 1.5 will be described in this section. The research approach will consist of a literature review, evaluation for different choices that have to be made, the development of the new control approach, macro-simulation and validation. The following sections will explain the methods that will be used.

1.6.1. Literature review

The current knowledge of the topic was investigated in the previous sections (1.2, 1.3 and 1.4). To finally come to an answer to the research question the several sub question have to be answered. These sub questions will be answered in Section 2, starting with sub question A: *Which traffic flow simulation models exist and which one is relevant and suited for implementation and evaluation of a new developed adaptive control approach for ramp metering?*
To get an answer on this sub question first a literature review on traffic flow theory will be done. The literature review will explain the traffic phenomenons which are needed for the traffic flow model.

Then an evaluation based on literature will be done on different traffic flow models. One type (microscopic/macroscopic) of traffic flow model will be used instead of the other type of traffic flow model, where the reasons for this choice will be explained in the same section. The traffic flow model should be able to reproduce the traffic flow phenomenons capacity drop and spill back. Another criterion for the traffic flow model is accuracy. The traffic flow model should be accurate enough to be able to give some valuable conclusions about the developed adaptive control approach at the end of this report. The choice which type of traffic flow model will be used, will be explained and supported in this section. However, to give a good overview of the research approach the models that will be evaluated are given on beforehand. The different traffic flow models that will be evaluated will be a first order traffic flow model (Papageorgiou, 1998), METANET (Barceló, 2010, Van den Berg et al., 2003) and MARPLE (Taale, 2008, 2013).

The next step of this research is to answer sub question B: *Which different ALINEA variations exist, what are their advantages and disadvantages and which variation is best suited for implementation in this research?*
Prior to the evaluation is a literature overview of several algorithms and why the ALINEA algorithm is the best choice for this research. Then several different variations of the ALINEA algorithm will be evaluated based on literature. The different variations will be evaluated and the one that is most suitable for implementation will be used in the next steps of the research. This is based on literature because a lot of research has already been done on this subject. It is unnecessary to test all variations again and then decide on the one that will contribute best to this thesis' objective because a lot of research already has been done on this subject. The chosen ALINEA algorithm should also be suitable for implementation in the adaptive control approach that will be chosen. The ALINEA algorithms that will be used for evaluation in this step are chosen on beforehand to limit the number of variations. These variations are based on the traffic flow variables density, speed and flow and for every traffic flow variable an upstream and downstream variation (six in total). In addition to these variations also the PI-ALINEA variation will be evaluated.

The next step will answer the last sub question: *Which adaptive control approaches exist, what are their advantages and disadvantages towards ramp metering and which ones are relevant and suited for implementation in this research?*
First the several methods will be introduced and discussed in a general way. These several adaptive methods are chosen beforehand and can be found in Äström and Wittenmark (2013) and are as follows: Gain scheduling, Model Reference Adaptive Control, Self-Tuning Regulators and Dual Control. These four existing adaptive control approaches will be evaluated based on literature and their suitability towards ramp metering. One adaptive approach will be chosen based on this evaluation. The strengths, weaknesses and their suitability for ramp metering control will be evaluated. Based on these results one adaptive approach will be used for further research.

1.6.2. Development and simulation of the control approach

The next steps will give an answer to the main research question: *To which extent can adaptive control, by tuning all parameters of the ALINEA algorithm, improve ramp metering in terms of travel time?*
Based on the findings in previous steps one adaptive control approach will be developed for a chosen ALINEA variation and evaluated with a chosen traffic flow model. MATLAB will be used for implementation of the developed approach. The control approach will be tested on a generated stretch of freeway. This will be a stretch of a few kilometres with 2 lanes and 1 on-ramp. This layout should be enough to test a newly developed control approach. A flow profile will be used with a sudden

increase of ramp and mainline flow over time which will exceed the capacity of the mainline to test the performance of the control approach. The different cases, which will be simulated towards a no control situation and compared to each other are as follows:

- ALINEA algorithm (density based)
- ALINEA variation used
- New developed control approach

The results of the simulation will be evaluated on several performance indicators. These indicators are chosen based on what to expect from a ramp metering algorithm. Ramp metering should increase the overall travel time and throughput of the mainline but in return there will be more delay on the on-ramp(s). This delay on the on-ramp should not exceed some certain threshold value for the need of better throughput on the mainline. Several indicators for evaluating ramp metering are stated by Chu et al. (2004). These indicators are Total Time Spent (TTS), Total On-ramp Delay (TOD) and Average Mainline Travel Time (AMTT). Next to the these three indicators there should also be need for equity. Equity is explained as a certain fairness between the delay on the on-ramp and the efficiency of the ramp meter installation. To account for equity, which also could be a separate study, a certain rule for queue control will be used to ensure waiting times and queues will not be too long. This queue control should prevent that too many vehicles are waiting for the traffic lights. This will only be ensured by a queue control algorithm and will not be checked by an indicator. The TOD can give an indication on the waiting time of vehicles on the on-ramp. The focus in this thesis is not on the equity of a ramp metering installation but more on a possible improvement by parameter tuning and therefore equity will not be issued thoroughly. Next to the previous named indicators, also the total delay will be calculated. The delay will be calculated by comparing the actual total vehicle hours travelled with the travel time those vehicles would have when driving with the free flow speed. Normally there is also an indicator to check if during simulation vehicles never reaches destination or get stuck in simulation. In this thesis there will be a demand profile where at a certain time the inflow is set to zero to let all vehicles flow out of the network. This will ensure that the same amount of vehicle kilometres will be reached during simulation and thus there is no need for this indicator. The indicators used are explained as follows:

- Total time spent (in hours)
  - = Indicator of overall system performance for the whole network; all vehicles, including those having finished their journey and those currently simulated, are considered in this measure.
- Total on-ramp delay (minutes)
  - = Indicator of the effect of ramp control over the on-ramp traffic flows. The measure is calculated by the sum of the difference of the actual travel time that all vehicles experienced on the entranced ramps and free- flow travel time (= travel time without metering and without a queue) on the on-ramps.
- Average mainline travel time (in minutes)
  - = Indicator of traffic conditions on the mainline freeway within the whole simulation process.

- Total delay (in hours)

  = Indicator of the total delay on the network which is based on the difference between the actual total vehicle hours travelled and the total vehicle hours travelled when travelling with the free flow speed.

In addition to previous named indicators, also the time the capacity drop occurs and the time the capacity drop is postponed will be taken into account because this is an important effect of ramp metering (preventing/postponing the capacity drop). Ramp metering tries to postpone the capacity drop which is then the cause of an improvement in travel time. Other impacts on traffic like weather conditions will not be taken into account because it is difficult to simulate these effects with a simulation model. Emissions and route choice will also fall outside the scope of this thesis. These two impacts on traffic flow and ramp metering could be a stand-alone (and further) research. The new developed control approach will be validated using stochastic variables (e.g. other demand profile, variable critical density, noise on measurements) and sufficient simulation runs. Thus the model must not only work for deterministic inputs but should also be able to give reasonable results under stochastic variables. Driving behaviour will not be included in this validation because it is difficult to implement this in a macroscopic traffic flow model. The best way to validate the new control approach would be with a FOT but this will not be feasible during this thesis and will therefore not be done.

1.7. Thesis structure

In section 1 an introduction to the topic is given regarding ramp metering control and adaptive control. In addition to the introduction of the topic also the problem formulation with research questions and the research approach for this thesis are explained. The different research steps that will be taken are explained in detail here. The research approach will be divided in several steps in order to find an answer to the research questions.

Section 2 will involve a literature study about traffic flow theory and an evaluation of different traffic flow models, where one traffic flow model will be chosen for simulation. Also included in this section will be an explanation of ramp metering and the algorithm of the traffic control measure. Several algorithms of local ramp metering will be discussed and explained. Different algorithms, all variations of the ALINEA algorithm will be evaluated and one will be chosen for further research. Further in this section the several adaptive control approaches will be explained in detail. The different adaptive control approaches will also be evaluated to what extend the different approach could be used as a new ramp metering strategy. The evaluations will result in an ALINEA variation, one adaptive control approaches and a macroscopic traffic flow model for further use in this thesis.

In section 3 the results and different methods of the previous section will be combined into a new developed ramp metering approach. This section will first discuss the parameters of the macroscopic model. Next this section will discuss the parameters of the ALINEA algorithm and new developed approach and the indicators for evaluation will be set up. As last part of this section the new approach step will be developed step by step.

In section 4 the simulation set-up will be discussed. The network layout will be discussed as will the amount of simulation needed. Also under which conditions the simulations will be done in the next section will be explained. At last the values of certain parameters that will be used are explained for all variations.

In section 5 the new developed approach will be simulated and compared to a no control situation, a standard ALINEA algorithm (density variation) and the variation that will be chosen from evaluation. The simulation will be under stochastic conditions which shows if also under different conditions there are reasonable results for the new approach. This will be done using sufficient simulations. The results coming from simulations will be presented in this section.

To conclude this research, in section 6 the results coming from previous section will be explained and discussed. Next the main research question will be answered. The research will be concluded with recommendations for future research.

In figure 1.2 the thesis structure for this research, as explained in this section, is given.

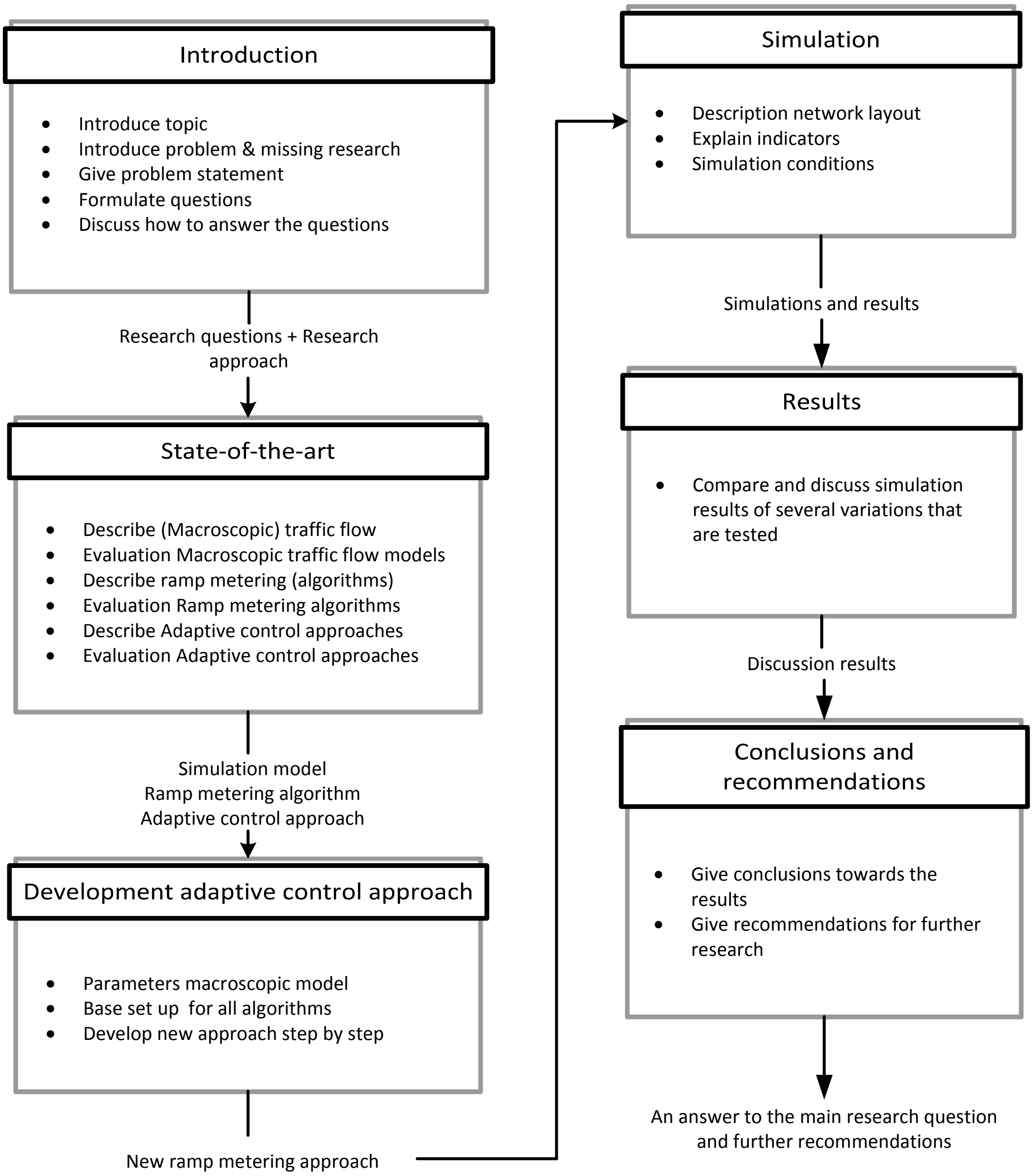


Figure 1.2. – Thesis outline structure

2. State-of-the-art

In the previous chapter an introduction has been given on the problem which resulted in several research questions and a research approach to answer these questions. In this section the three sub questions will be answered:

A. *Which traffic flow simulation models exist and which one is relevant and suited for implementation and evaluation of a new developed adaptive control approach for ramp metering?*

B. *Which different ALINEA variations exist, what are their advantages and disadvantages and which variation is best suited for implementation in this research?*

C. *Which adaptive control approaches exist, what are their advantages and disadvantages towards ramp metering and which ones are relevant and suited for implementation in this research?*

These questions lead to a research approach which is explained in section 1.6. One important part of this research approach is evaluation of traffic flow models, different ALINEA variations and several adaptive control approaches. These evaluation will give an answer to the above listed sub questions. The answer to these questions are given in this section. The results in this section are needed for section 3.

In section 2.1 traffic flow theory will be explained in detail. The traffic phenomenons will be explained that are needed for evaluation of the traffic flow models. The traffic phenomenons as the capacity drop, spill back and rat running will be discussed. After the introduction to traffic flow theory the type of traffic flow model, microscopic or macroscopic, that is most suited for this research will be discussed. An evaluation of several traffic flow simulation models of this type will be given in section 2.2. One of these discussed traffic flow models will be used for simulation purposes. This will conclude sub question A.

In section 2.3 local ramp metering will be discussed and different algorithms will be explained. Especially the different ALINEA variation which are needed for evaluation. The ALINEA algorithm and its parameters will be explained in more detail. This literature review will be followed by an evaluation of the different ALINEA variations in section 2.4. Several variations of the ALINEA algorithm will be discussed and evaluated based on literature. One of the variations will be chosen based on which variation can contribute best to this research. Sub question B will finally be answered after the evaluation of adaptive control approaches in section 2.6 because it is important to know if the ALINEA variation can be implemented in the chosen adaptive control approach. This final choice will be discussed in section 2.7. This will conclude sub question B.

In section 2.5 the adaptive control approaches in general will be explained. Next section 2.6 will give an evaluation of these different adaptive control approaches towards ramp metering and one approach will be chosen to use for development of a new adaptive ramp metering algorithm. This will conclude sub question C.

At last in section 2.7 the final choice for an ALINEA variation will be discussed. Further in this section a overview is given of the different evaluations and its results. These results will be used for the development in section 3.

2.1. Traffic flow

In this section first traffic flow theory will be explained in section 2.1.1 which is of importance for ramp metering and among other criteria, also for the type of traffic flow model. Next in section 2.1.2 the type of traffic flow model that will be used for evaluation will be discussed. The type of traffic flow model should be suited for this research. This is dependent on which phenomenons of traffic flow theory are the most important for this research. For this choice it is also important what the purpose is of these simulations and what this research wants to achieve. This research wants to test a new developed approach for the first time and wants to compare this new approach towards other existing approaches. This thesis will try to verify the working of the new developed approach.

2.1.1. Traffic flow theory

The Fundamental Diagram (FD) shows a relation between certain traffic flow variables. These variables are flow in vehicle per hour (q), density in vehicle per kilometre (ρ) and (time/space) mean speed in kilometres per hour (u). The relation of the variables is denoted as follows: $q = \rho \times u$. An example of a FD which captures one of the traffic flow phenomenons is shown in Figure 2.1. In this figure the *capacity drop* is illustrated with on the horizontal axis the density in vehicles per kilometres and on the vertical axis the flow in vehicles per hour. The capacity drop is caused after congestion sets in at a bottleneck in the network like lane narrowing or where traffic enters the freeway from an on-ramp. The capacity of the freeway after congestion (right hand side of the fundamental diagram) sets in is usually lower than capacity in the free flow state (the left hand side of the fundamental diagram) (Kerner, 2004). This is the so-called capacity drop. Hoogendoorn and Knoop (2012) explain that the capacity drop occurs when drivers are not maintaining the same headway as in free flow state as soon as congestion sets in. Kerner (2004) explains the capacity drop as the difference between freeway capacity in free flow state and the capacity of the situation, where there is synchronized flow upstream and free flow downstream of the bottleneck. By implementing ramp metering this capacity drop phenomenon can be prevented, or at least postponed which means a higher throughput of traffic can be realized.

The capacity drop on freeways is one of the reasons why ramp metering installations get deployed on on-ramps. Other examples of reasons to deploy a ramp meter installation are improving merging traffic at the specific on-ramp and discouraging rat-running traffic, which is explained later. Ramp metering works for improving the throughput on the mainline by preventing/postponing the capacity drop. Ramp metering also shifts the delay from the freeway to the on-ramp. The inflow from the on-ramp to the mainline regulated by the on-ramp is less or is better distributed over time than without ramp metering. Because less vehicles flow into the freeway or there is a better distribution of vehicles over time, the density and flow on the mainline stay lower than without metering. If the ramp metering rate is sufficient to hold the density on the freeway below the critical density, then no congestion will occur and thus the capacity drop is also prevented (Knoop, 2012).

When congestion occurs on the freeway and the ramp meter installation starts metering there is a probability that traffic will *spill back*. This traffic flow phenomenon occurs when the traffic spills back from the freeway to the underlying network or from the freeway bottleneck to other on and off-ramps. The first situation happens at on-ramps where traffic spills back to urban roads because the queue exceeds the maximum storage space at the on-ramp. This is a disadvantage of ramp metering but this can be prevented by using a queue control algorithm and queue detectors on the on-ramp. This queue control algorithm makes sure the ramp meter will stop metering when the queue ex-

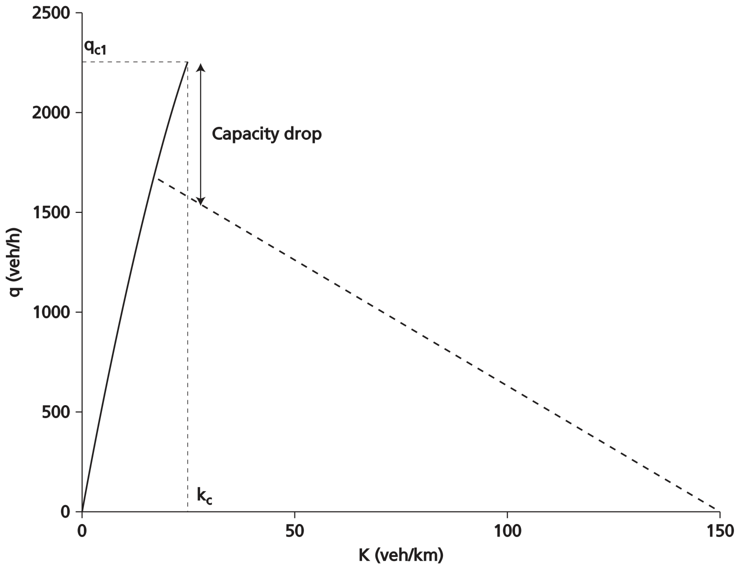


Figure 2.1. – Fundamental Diagram: The capacity drop (Source: Hoogendoorn and Knoop (2012))

ceeds the maximum admissible queue length. An example of a queue control algorithm, based on the ALINEA algorithm, is shown in equation 2.1, 2.2 and 2.3. In these equations is $w(k)$ the current queue length, $d(k)$ the demand flow entering the ramp and $r'(k)$ the flow of vehicles entering the freeway. The w_{max} is the target value for the maximum permissible queue length and $R(k)$ is the proposed ramp metering rate finally applied. The second situation occurs when spill back from the bottleneck towards the upstream (off)-ramps, that causes blocking of these ramps. Ramp metering can prevent this spill back by preventing congestion.

$$w(k+1) = w(k) + T[d(k) - r'(k)] \tag{2.1}$$

$$r'(k) = -\frac{1}{T}[w_{max} - w(k)] + d(k-1) \tag{2.2}$$

$$R(k) = \max\{r(k), r'(k)\} \tag{2.3}$$

Also an additional effect of ramp metering is that of *rat-running*. Rat-running is as drivers choose another on-ramp without metering or a route on urban roads to reach their destination. Drivers will take another route than usual because of the ramp metering installation. This will also decrease the flow on the freeway but have a negative effect on the flows on other road because the flow will increase there and the chance of congestion will rise. Thus a ramp metering installation can cause a shift in congestion from one place to another. This is named as one of the disadvantages of ramp metering by Elefteriadou (2014). Also can rat-running be decreased by ramp metering, which is thus a positive effect. This happens when a ramp metering installation is deployed on an on-ramp which is used by rat-running traffic. This way the flow can be reduced on this on-ramp because drivers do not want to wait in front of the traffic lights. The former rat-running traffic then uses another on-ramp after the installation is deployed, which reduces the rat-running traffic on this on-ramp. The drivers will shift

from on on-ramp to another which can also reduce rat-running.

The next section will determine the type of traffic flow model is relevant for this thesis. Criteria for this is that the model used in this thesis needs to be able to reproduce this capacity drop. Next to this spill back should also be simulated as this is important on the on-ramp, where a queue will occur when the ramp metering installation is activated. This is of minor importance than the capacity drop because spill back on the underlying network is not taken into account. Rat-running is not included in this thesis, because it involves route choice and this is not in the scope of this research. Thus the traffic flow model does not need to include rat-running.

2.1.2. Type of traffic flow model

The traffic flow model should be able to reproduce the capacity drop and should to a lesser extent reproduce spill back. This spill back is needed for the queue on the freeway and the queue on the on-ramp, not for spill back to the underlying network. The new developed approach will be tested for the first time and will be compared to existing ramp metering algorithms. The traffic flow model does need a certain accuracy but for first time testing it is not needed to be as accurate as possible. The type of traffic flow model needs to be sufficient for first time testing a new developed approach to see if there is a possible improvement compared to existing approaches. A lot of simulation runs are needed for comparing and testing several approaches and thus computational time is also a criteria for this choice.

A distinction in traffic flow can be made between macroscopic and microscopic characteristics and models. Microscopic variables are for example time and space headway and individual speeds (Hoogendoorn, 2013). In short all variables belonging to an individual vehicle. On the other hand macroscopic focuses more on traffic flow for a network: it describes the average behaviour of the flow rather than the individual driver (Hoogendoorn, 2013). Microscopic models are very detailed compared to macroscopic models. With microscopic models also driving behaviour, like lane changing and route choice, can be simulated. However, this is not needed in this thesis as it is the first time the new developed approach will be simulated. This research is only interested in the possibility of improvement of ramp metering algorithms by tuning the parameters of a ramp metering algorithm. A microscopic model would require a lot of computational time for the number of simulations in this research and this is out of scope for this thesis. A microscopic model covers a more detailed and realistic traffic situation and could therefore be better than a macroscopic model. A macroscopic model can reproduce the capacity drop which is an important criteria for this thesis. This is a good reason why a macroscopic traffic flow model could be used in this thesis. In addition to this the computational time of a macroscopic model is much less than for a microscopic model and could therefore benefit the number of simulations needed in this thesis. The more simulation runs that can be done, the more results there will be for comparison of the new developed approach compared to the existing approaches. According to Kotsialos and Papageorgiou (2004) a macroscopic model is more suitable for the design of control approaches than a microscopic model, because macroscopic model describe the traffic flow process analytically and demand lower computation effort. This thesis designs a new developed control approach as suggested by Kotsialos and Papageorgiou (2004) to use a macroscopic model in this case. If it turns out that the new approach could give a possible improvement, in future research the new approach could be simulated in a microscopic environment to give a more detailed situation on the working of this method. For now this thesis will use a macroscopic traffic flow model because the accuracy of this kind of models are sufficient for this thesis.

In the next section three macroscopic traffic flow models will be evaluated. One of these models will be chosen for simulation purposes in the following sections.

2.2. Evaluation macroscopic models

In this section different macroscopic models will be evaluated. The following evaluation will result in the macroscopic traffic flow model that will be used for simulation for the new ramp metering approach. The traffic flow model will be chosen based on several criteria. The model should for instance be able to reproduce the capacity drop and spill back (the traffic phenomenons explained in section 2.1). In addition the accuracy of the model is also an important criteria for choosing a simulation model. Also complexity can be an issue with higher accuracy thus there should be a consideration between the accuracy of the model its complexity. In this section a final answer will be given to the following sub question:

- *Which traffic flow simulation models exist and which one is relevant and suited for implementation and evaluation of a new developed adaptive control approach for ramp metering?*

In the previous section it was already explained why a macroscopic traffic flow model will be used in stead of a microscopic traffic flow model. A macroscopic traffic flow model represents the traffic stream in an aggregate manner using characteristics as flow-rate, density and velocity (Hoogendoorn and Bovy, 2001). Macroscopic models can be classified according to the number of partial differential equations and the order of the partial differential equations (Hoogendoorn and Bovy, 2001). The macroscopic models described in this section are the *First-order traffic flow model*, the second-order traffic flow model *METANET* and the dynamic traffic assignment model *MARPLE*.

2.2.1. First order traffic flow model

The first-order traffic flow model is discussed in Papageorgiou (1998) and was introduced by Lighthill and Whitham (1955), called the *LWR-model*. This model can reproduce qualitatively a good amount of real traffic phenomena. For freeway traffic flow the model achieves a certain degree of qualitative accuracy (Papageorgiou, 1998). This model is given by the density (ρ), the corresponding preferred velocity ($V(\rho)$), which is a given non-increasing function of the density, with the density between 0 and some positive maximal density (like ρ_j) (Aw and Rascle, 2000):

$$\partial_t \rho + \partial_x (\rho V(\rho)) = 0 \tag{2.4}$$

Next to the advantages of a certain degree of qualitative accuracy there are also some disadvantages. This model has a few simplifications and it fails to reproduce some real dynamic phenomena observed on freeways (like the capacity drop). The most crucial simplification according to Papageorgiou (1998) is the assumption that the mean speed adjusts instantaneously to traffic density values according to a prescribed relationship. This implies unrealistically high acceleration or deceleration. According to Papageorgiou (1998) this is not enough reason to dismiss this model but it does affect its suitability for optimal design and testing of control approaches for ramp metering. If a first-order model is used to design an optimal ramp metering control approach, it will tend to create limited-length congestion just upstream of the on-ramp, such that no upstream ramps are blocked Papageorgiou (1998). This is an unrealistic behaviour and even if during simulation no upstream off-ramps are

used in the layout of the freeway it is thus not optimal to use a first-order model for spill back. Another view for not using this model is that reduction or avoidance of mainstream congestion cannot increase the mainstream outflow and thus the model misses an important source of improvement of the total time spent on the network (Papageorgiou, 1998). This model misses a certain accuracy which is preferred in this thesis for testing the control approach.

In Papageorgiou (1998) also the first-order models are compared to second-order models. The conclusion, of several other studies and comparisons between the two models, is that evidence indicates clear superiority in terms of accuracy of second-order models compared to first-order models (Papageorgiou, 1998). In short, it is preferable to look at second-order traffic flow models for testing a control approach for ramp metering.

2.2.2. METANET

Second-order models were developed as an attempt to improve the accuracy provided by the first-order models and to circumvent their qualitative deficiencies at the expense of a higher complexity (Papageorgiou, 1998). METANET is such a macroscopic second-order traffic flow model. METANET is a tool for simulating traffic flow phenomena in freeway networks (Kotsialos et al., 2002). METANET is applicable to all kinds of traffic conditions and of capacity-reducing events (incidents) with prescribed characteristics and is also able to take into account control actions such as ramp metering (Kotsialos et al., 2002). The METANET model describes the traffic variables density ($\rho_{m,i}(k)$), mean speed ($v_{m,i}(k)$) and flow ($q_{m,i}(k)$). The basic equations of METANET to calculate the traffic variables for every segment i of freeway link m are denoted in equations 2.5, 2.6 and 2.7 (Kotsialos et al., 2002). In Kotsialos et al. (2002) the equations are explained as follows. Equation 2.5 expresses the vehicle conservation principle. Equation 2.6 is the flow equation which results directly from the definition of the traffic variables and equation 2.8 is the empirical speed equation which describes the dynamic evolution of the mean speed of each segment as an independent variable. Equation 2.8 expresses the fundamental diagram with a static relationship of the speed with the density. T in de equations is the discrete time step, L_m is the length of segment m, and λ_m is the number of lanes. $v_{f,m}$ is the free-flow speed of link m, $\rho_{cr,m}$ denotes the critical density per lane of link m. a_m is a parameter of the FD, τ, a time constant, ν, an anticipation constant and κ are constant parameters which are the same for all network links. $v_{f,m}$, $\rho_{cr,m}$, a_m, τ, ν and κ are constant parameters which reflect particular characteristics of a given traffic system and depend upon street geometry, vehicle characteristics, driver's behaviour etc. (Kotsialos et al., 2002).

$$\rho_{m,i}(k+1) = \rho_{m,i}(k) + \frac{T}{L_m \times \lambda_m}[q_{m,i-1}(k) - q_{m,i}(k)] \tag{2.5}$$

$$q_{m,i}(k) = \rho_{m,i}(k) \times v_{m,i}(k) \times \lambda_m \tag{2.6}$$

$$\begin{aligned} v_{m,i}(k+1) = v_{m,i}(k) + \frac{T}{\tau}\{V[\rho_{m,i}(k)] - v_{m,i}(k)\} + \frac{T}{L_m}[v_{m,i-1}(k) - v_{m,i}(k)] \times v_{m,i}(k) \\ - \frac{\nu \times T}{\tau \times L_m} \times \frac{\rho_{m,i+1}(k) - \rho_{m,i}(k)}{\rho_{m,i}(k) + \kappa} \end{aligned} \tag{2.7}$$

$$V[\rho_{\mathrm{m,i}}(k)] = v_{f,\mathrm{m}} \times \exp\left[-\frac{1}{a_{\mathrm{m}}}\left(\frac{\rho_{\mathrm{m,i}}(k)}{\rho_{\mathrm{cr,m}}(k)}\right)^{a_{\mathrm{m}}}\right] \tag{2.8}$$

In METANET also lane drops and merging phenomena near on-ramps can be modelled according to Papageorgiou et al. (1990). Two additional terms can be added to account for these phenomenons. These additional terms will be added to equation 2.7. The equation 2.9 is to account for the decrease in speed caused by merging (Spiliopoulou et al., 2015, Kotsialos et al., 2002, Papageorgiou et al., 1990). In this equation is δ a constant parameter determined by the validation process, μ is the merging link and m is the leaving link. Second there is an addition to this equation for the speed reduction due to the weaving phenomena resulting from lane drops (equation 2.10) where $\Delta\lambda$ is the number of lanes dropped and ϕ is a constant parameter estimated from the quantitative validation of the model (Spiliopoulou et al., 2015, Kotsialos et al., 2002, Papageorgiou et al., 1990).

$$\frac{-\delta T q_{\mu}(k) v_{\mathrm{m,1}}(k)}{\mathrm{L_m}\lambda_{\mathrm{m}}(\rho_{\mathrm{m,1}}(k) + \kappa)} \tag{2.9}$$

$$\frac{-\phi T \Delta\lambda \rho_{\mathrm{m,N_m}}(k) v_{\mathrm{m,N_m}}(k)^2}{\mathrm{L_m}\lambda_{\mathrm{m}}\rho_{\mathrm{cr,m}}} \tag{2.10}$$

In Kotsialos et al. (2002) the METANET model is validated both quantitative as qualitative. Kotsialos et al. (2002) concluded that the METANET model is able to reproduce traffic congestion built in reality with considerable accuracy and thus making it suitable for evaluating various control approaches and performing further modelling and simulation tasks. Barceló (2010) states that such a simulator like METANET can be used for several purposes as comparison of alternatives (as planned in this thesis) and for development and evaluation of control approaches.

2.2.3. MARPLE

The third evaluation is about the macroscopic traffic flow model MARPLE (Model for Assignment and Regional Policy Evaluation). MARPLE is a dynamic traffic assignment model developed and introduced by Taale (2008, 2013). MARPLE can be used for a freeway network and for an urban network to evaluate the effectiveness of traffic management control measures such as ramp metering (Taale, 2013). MARPLE runs a number of steps as denoted in Figure 2.2.

In Taale (2013) the characteristics of the model are denoted. Travel times on links are calculated with travel time functions. These functions are based on the degree of saturation, where the capacity is determined by certain formulas. There is no direct relation between speed and density. The model takes into account available space on a link and spill back of congestions (Taale, 2013). MARPLE can also be used for ramp metering. In Taale (2013) the step optimisation schemes is described for ramp metering. First the upstream flow has to be determined and the downstream (available) capacity. Secondly the metering cycle time needs to be determined on the basis of the amount of traffic that is allowed to enter the mainline. The maximum and minimum specified metering cycle time should be taken into account. MARPLE does also take route choice into account (Taale, 2013), but this has no further relevance for this thesis. In Taale (2008) MARPLE is developed as an anticipatory control strategy. The anticipatory control strategy is time consuming according to Taale (2008) due to heuristic optimisation method and the use of the Dynamic Network Loading (DNL) model in the

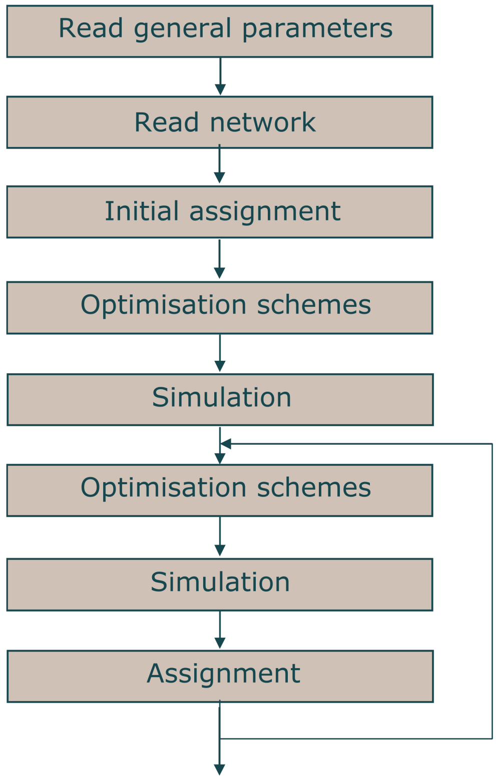


Figure 2.2. – MARPLE steps (Edited from Taale (2013))

method itself. Taale (2008) shows results that indicate that the computation time increases rapidly if the number of parameters to optimise increases, but this should not affect computational time when the focus is on testing a ramp metering installation. The anticipatory control can be used to test all kinds of control approaches, thus also ramp metering (Taale, 2008). MARPLE can be used for testing new ramp metering approaches but is not able to reproduce the capacity drop. However, MARPLE can use the ramp metering installation to influence the capacity, which is like a reversed capacity drop. Marple is a more complex traffic model, which would not be necessary for the purpose of this thesis. Marple also takes into account route choice, which also is not in scope of this thesis. And that is the reason why METANET is more suited for this thesis as a macroscopic traffic flow model than MARPLE.

2.2.4. Evaluation macroscopic traffic flow model overview

In the previous sections several macroscopic traffic flow models have been evaluated. Based on criteria like accuracy and reproducing of several traffic phenomenons the METANET model has been chosen for further use in this thesis. The first-order model explained in section 2.2.1 will not be used in this thesis. This is because second-order models, like METANET, are a better choice for this research in terms of accuracy and reproducing of the capacity drop. Next to METANET, MARPLE also seems a good model for testing ramp metering algorithms but MARPLE cannot reproduce the capacity drop which is required for this thesis. It can however reproduce a so-called reversed capacity drop, as explained before. Due to complexity of this model it is out of scope of this research. In this

thesis the focus is on testing and comparing several control approaches and METANET will be sufficient for the first testing of these approaches. METANET is an often used second-order model for first testing and comparing several traffic control measures according to Barceló (2010), and therefore will also be used in this thesis.

2.3. Local ramp metering

The focus in this thesis is on local ramp metering as mentioned before. Local ramp metering controls one on-ramp at a specific location. At this on-ramp, often a bit downstream of the on-ramp, congestion occurs. According to Middelham and Taale (2006) ramp metering can be applied in two situations:

1. On-ramps close to a bottleneck
2. On-ramps which cause disruptions in the traffic stream on the motorway due to merging.

The first situation occurs when for example just downstream of the on-ramp lane narrowing occurs. This is a bottleneck in the traffic network which causes the capacity to drop due to less lanes. The ramp meter installation in this case will limit the inflow such that the capacity after the bottleneck will not be reached and the flow will be gradually allowed to enter the freeway. The second situation occurs when the flow from the on-ramp causes the flow on the mainline to exceed capacity which causes congestion. This happens during for example peak hours. The ramp meter installation also tries to limit the inflow to the mainline in this case to prevent the capacity drop and to prevent the flow to exceed the capacity of the freeway. This thesis will not represent a certain bottleneck but wants to test a new algorithm for a simple example where the demand exceeds the capacity of the freeway. Thus this research will reproduce a daily occurring situation during peak hours. An increasing demand profile on the mainline and on the on-ramp will be used, which will exceed the capacity of the freeway. This represents the second example. A control algorithm at an on-ramp and traffic lights, controlled by this algorithm, can reduce or avoid congestion at such bottlenecks. These algorithms will be discussed further in this section and evaluated as part of sub question B.

2.3.1. Local ramp metering algorithms

The ramp meter installation is controlled by an algorithm. Several different types of algorithms have been developed over the years. In this section these several ramp metering algorithms will be explained shortly. This is to give an overview of the algorithms and their working. In the next section the ALINEA algorithm will be explained in detail because this algorithm is relevant for this research.

The purpose of ramp metering is to regulate the inflow from the ramp to the mainline of the freeway. Local ramp metering strategies make use of traffic measurements in the vicinity of an on-ramp (Smaragdis and Papageorgiou, 2003). A good working algorithm could improve the traffic situation gradually in terms of throughput. Thus it is important to have a good working algorithm which will determine the flow from the on-ramp to the freeway. A less working algorithm could even deteriorate the situation on the freeway and it is therefore also important to test a new developed approach first with the help of simulation. In this section several different algorithms will be discussed shortly. Local ramp metering strategies often found in literature are the Demand-Capacity (DC) strategy, Occupancy (OCC) strategy, Fuzzy logic strategy and ALINEA. In the Netherlands there is also a RWS-strategy which is comparable to the DC strategy. These five algorithms will be explained shortly in

the following sections. The ALINEA algorithm, which is important for evaluation in the next section, will be discussed in more detail.

Demand-Capacity strategy

The DC strategy controls the freeway traffic conditions upstream of the on-ramps. This is called feed forward control. The DC strategy calculates the number of vehicles allowed to enter the freeway in time interval k ($r(k)$) by subtracting the last measured upstream freeway flow (q_{in}) from the downstream freeway capacity (q_{cap}) when the last measured upstream freeway occupancy (o_{in} in %) is smaller or equal than the critical occupancy (o_{crit}). When this is not the case the number of vehicles allowed to enter the freeway is determined by the minimum pre-specified ramp flow (r_{min}). The DC strategy is generally known to be quite sensitive to various non-measurable disturbances (Papageorgiou and Kotsialos, 2000). The DC strategy is as follows formulated (Smaragdis and Papageorgiou, 2003):

$$r(k) = \begin{cases} q_{\text{cap}} - q_{\text{in}}(k-1) & \text{if } o_{\text{in}}(k-1) \leq o_{\text{crit}} \\ r_{\text{min}} & \text{else} \end{cases} \tag{2.11}$$

RWS strategy

The RWS strategy is based on the flows on the freeway and on-ramp and the speed of the traffic on the freeway. The RWS strategy aims at a good use of the capacity available. It is a capacity-demand feed forward control algorithm and comparable to the DC strategy. The number of vehicles allowed to enter the freeway ($r(k)$) is determined by the pre-specified capacity of the freeway downstream of the on-ramp (C) minus the measured and smoothed flow upstream of the on-ramp in the previous time interval ($I_{\text{k}-1}$) (Middelham and Taale, 2006):

$$r(k) = C - I_{\text{k}-1} \tag{2.12}$$

The cycle time in seconds (t) of the RWS system is calculated with the following equation, where n is the number of lanes on the on-ramp (Middelham and Taale, 2006):

$$t = \frac{n \times 3600}{r(k)} \tag{2.13}$$

Occupancy Strategy

The OCC strategy is based on the same philosophy as the DC strategy, but it relies on an occupancy based estimation of q_{in} (Papageorgiou and Kotsialos, 2000). The equation assumes a straight line of the left-hand side of the fundamental diagram. The last measured upstream freeway flow (q_{in}) is calculated by the free flow speed (v_f) multiplied by the last measured upstream freeway occupancy (o_{in}) and divided by the g-factor (g) (Smaragdis and Papageorgiou, 2003):

$$q_{\text{in}} = \frac{v_f \times o_{\text{in}}}{g} \tag{2.14}$$

Replacing this equation in the equation of the DC strategy results in (Smaragdis and Papageorgiou, 2003):

$$r(k) = q_{\text{cap}} - \frac{v_f}{g} \times o_{\text{in}}(k-1) \tag{2.15}$$

Also this strategy is a feed forward control strategy but this time based on occupancy. This strategy is even more inaccurate than the DC strategy according to Smaragdis and Papageorgiou (2003). This is because of the linearity of the fundamental diagram. The FD used for the OCC strategy has a more triangular form, with a linear line for the left hand side (as shown in Figure 2.1, but then without the capacity drop).

Fuzzy logic strategy

In Taale et al. (1996) the Fuzzy logic strategy is discussed. It is based on three input variables: speed upstream of the on-ramp, speed downstream of the on-ramp and the time a queue is present on the on-ramp (Taale et al., 1996). The output variable is denoted by the cycle time. The measured value of an input variable is transferred to degrees of membership for certain classes (very low, low, medium, high, very high) in which the input variables are divided (Taale et al., 1996). The fuzzy logic strategy is rule based. One rule as example: **IF** *speed upstream is medium* **AND** *speed downstream is low*, **THEN** *cycletime is long*. The on and off switching of this strategy is different from other strategies according to Taale et al. (1996). It switches on when the calculated cycle time exceeds a certain threshold value and off when it drops below another threshold value. The Fuzzy strategy is different than other strategies like RWS or ALINEA (Taale et al., 1996). The metering time is for example much shorter, but cycle times are longer. In Taale et al. (1996) the fuzzy logic strategy gave good results, but the strategy has some problems with switching on and off too often.

ALINEA

According to Smaragdis and Papageorgiou (2003) it is actually recommended to control the freeway traffic conditions downstream of the ramp. This is called a feedback control strategy. The ALINEA algorithm is such a feedback strategy. The ALINEA algorithm has several variations. The ALINEA equation used for ramp metering during the PPA is as follows (Hoogendoorn et al., 2013):

$$r(k) = r(k-1) + K_{\text{R}}[\hat{\rho} - \rho_{\text{out}}(k-1)] \tag{2.16}$$

The different variables in the equation were already explained in section 1.3. Comparative field-evaluations demonstrated the clear superiority of ALINEA as compared to the DC and OCC strategies (Smaragdis and Papageorgiou, 2003). In Stanescu (2008) also a comparison was made between ALINEA and the RWS strategy. This led to an overall conclusion of different evaluations in literature. The RWS strategy when compared to the ALINEA algorithm is easier to use for traffic operators, shows calmer traffic behaviour, but has a reduced throughput Stanescu (2008). Because in this thesis an improvement of travel time (and thus throughput) is desired, the ALINEA algorithm will be used instead of the RWS strategy. The ALINEA algorithm, the different variations and the different parameters will be explained in more detail in the next section. The different variations will be evaluated and a variation is chosen to use for further research in the next section.

2.3.2. ALINEA variations

The different ALINEA variations will be discussed in more detail here. The variation most suited for this thesis will be chosen based on literature. The ALINEA algorithm does make use of downstream measurements, this means that data measured from detectors downstream of the bottleneck and/or on-ramp are used. Also upstream measurement variations will be evaluated and are denoted with an U in the ALINEA name. In this and the following section an answer will be given to the following sub question:

- *Which different ALINEA variations exist, what are their advantages and disadvantages and which variation is best suited for implementation in this research?*

The variations of ALINEA use different parameters such as the flow (q), speed (V), density (ρ) and occupancy (o). The flow, occupancy and (average) speed can be measured with induction loops on the freeway. Density can only be calculated either from the measured flow and speed or from the occupancy. The density needs to be calculated because inductive loop detectors are point sensors while density is a range concept (Qui et al., 2009). Density is very difficult to measure/estimate accurately in real-time (Qui et al., 2009). The target values ($\hat{o}$, $\hat{q}$, $\hat{\rho}$ and V_s) are mainly determined by a percentage of their critical values (q_{cap}, o_{crit}, ρ_{crit}, V_{crit}). With adaptive control of the algorithm these parameters will be estimated based on real-time measurements.

K_R/K_F in the algorithms is a regulator parameter, used for adjusting the constant disturbances of the feedback control (Chu and Yang, 2003). The regulator parameter is different for the variations. The same value of K_R (Occupancy-ALINEA; D-ALINEA) has been used in all known simulation or field applications of ALINEA without any need for fine-tuning (Smaragdis and Papageorgiou, 2003). As explained in section 1.3 the value for K_R (for occupancy based ALINEA) of 70 veh/h provided good results in field experiments (Papageorgiou et al., 1998). According to Ukkusuri and Ozbay (2013) the value should be between 70 veh/h and 240 veh/h for optimal results. Also according to Papageorgiou et al. (1991) increasing (decreasing) K_R leads to stronger (smoother) reactions of the regulator and regulation times get shorter (longer). In Wang et al. (2014) the value of 40 km/h/lane is used for the regulator parameter of the density variation of ALINEA.

The regulator parameter for V-ALINEA is different from the above described K_R. The K_R for V-ALINEA is a constant in veh/h for a difference in speed of 1 km/h (Middelham and Taale, 2006). And also for FL-ALINEA the value of K_F is different. The parameter regulator value for this algorithm may be chosen equal to 1 or slightly less for a more damped control behaviour (Smaragdis and Papageorgiou, 2003).

Also a bit different form of ALINEA has been introduced: PI-ALINEA (Wang et al., 2010). This ALINEA variation consists of a Proportional (P) and an Integral (I) part. The proportional part has a gain over the error between a measured downstream value one time step earlier and a current measured downstream value. The integral part has a gain over the error of a certain target value and the downstream measured value.

The different ALINEA algorithms developed over the years, with the variables described above, are as follows (Hoogendoorn et al., 2013, Middelham and Taale, 2006, Smaragdis and Papageorgiou, 2003, Smaragdis et al., 2004, Wang et al., 2010, 2014):

1. Occupancy-based ALINEA (ALINEA)

$$r(k) = r(k-1) + K_R[\hat{o} - o_{\text{out}}(k-1)] \tag{2.17}$$

2. Upstream-Occupancy based ALINEA (UP-ALINEA)

$$r(k) = r(k-1) + K_R[\hat{o} - \tilde{o}_{out}(k-1)] \tag{2.18}$$

   - The estimate for the downstream occupancy ($\tilde{o}_{out}$) is given by:

$$\tilde{o}_{out}(k) = o_{in}(k)\left[1 + \frac{q_{ramp}(k)}{q_{in}(k)}\right]\frac{\lambda_{in}}{\lambda_{out}} \tag{2.19}$$

   - $\lambda_{in}/\lambda_{out}$ = the number of mainstream lanes upstream(in)/downstream(out) of the ramp

3. Flow-based ALINEA (FL-ALINEA)

$$r(k) = \begin{cases} r(k-1) + K_F[\hat{q} - q_{out}(k-1)] & \text{if } o_{out}(k-1) \le o_{crit} \\ r_{min} & \text{else} \end{cases} \tag{2.20}$$

4. Upstream-Flow based ALINEA (UF-ALINEA)

$$r(k) = \begin{cases} r(k-1) + K_F[\hat{q} - \tilde{q}_{out}(k-1)] & \text{if } \tilde{o}_{out}(k-1) \le o_{crit} \\ r_{min} & \text{else} \end{cases} \tag{2.21}$$

   - The estimate for the downstream flow ($\tilde{q}_{out}$) is given by:

$$\tilde{q}_{out} = q_{in} + q_{out} \tag{2.22}$$

5. Adaptive control ALINEA (AD-ALINEA)
6. Upstream-measurement based adaptive ALINEA (AU-ALINEA)
7. Speed-based ALINEA (V-ALINEA)

$$r(k) = r(k-1) + K_R[V_s - V(k-1)] \tag{2.23}$$

8. Density-based ALINEA (D-ALINEA)

$$r(k) = r(k-1) + K_R[\hat{\rho} - \rho_{out}(k-1)] \tag{2.24}$$

9. Proportional Integral (PI)-ALINEA

$$r(k) = r(k-1) - K_P * [\rho_{out}(k) - \rho_{out}(k-1)] + K_R * [\hat{\rho} - \rho_{out}(k-1)] \tag{2.25}$$

Adaptive control will be explained in more detail in section 2.5.

2.4. Evaluation ALINEA variations

The ALINEA algorithm has several variations where especially the variable (target/measured) density is replaced. The first ALINEA algorithm, developed by Papageorgiou et al. (1991), uses occupancy (%) instead of density. Several variations on the ALINEA algorithm have been developed where the variables are different (Smaragdis and Papageorgiou, 2003, Smaragdis et al., 2004). Also 'adaptive' control of the ALINEA algorithm has been developed. And instead of downstream measurements,

also ALINEA algorithms have been developed with upstream measurements (which are denoted with an U in the variation name) for different variables

In section 1.6.1 it is already predefined which ALINEA variations will be evaluated. Density is evaluated instead of occupancy, because density is used in the PPA and has thus a greater relevance for this thesis. Also did Chung et al. (2007) compare a density-based control scheme and an occupancy-based control scheme and concluded that density-based scheme had an advantage over the occupancy-based scheme with relation to the capacity drop. The capacity drop, as explained before, is an important factor in ramp metering.

The ALINEA variations will be evaluated based on the working and previous tests in practice or simulation. Also the usage of a certain variable is an important criteria for evaluation. Some traffic variables may be less likely to use in algorithms than others or give less information about the current traffic state which could be important for switching on and off the ramp metering installation. Another important aspect is the relevance towards the PPA, this is also a criteria for evaluation. In this research a certain relevance will be kept towards the PPA. In this thesis, with the METANET model chosen before, upstream and downstream measurements will be available. this could be of importance while choosing between the upstream or downstream variant.

2.4.1. D-ALINEA

D-ALINEA is the variation which makes use of density as target value. The equation was already presented in section 1.3 and 2.3:

$$r(k) = r(k-1) + K_{\mathrm{R}}[\hat{\rho} - \rho_{\mathrm{out}}(k-1)] \tag{2.26}$$

Density is difficult to estimate as it cannot be measured directly from the induction loops, because density is the number of vehicles occupying a stretch of road. Induction loops measure data at a specific point, thus density cannot be measured directly. However, density can be approximated by using speed and flow (Fundamental Diagram). In section 2.3 the data which can be measured and derived from induction loops is explained. The density variation of ALINEA is, for this thesis, preferred over the occupancy variation because density was also used in the PPA. To keep a certain relevance to the PPA it is a good choice as the ALINEA variation. Also the results of a density variation and an occupancy variation should be similar and it is difficult to make a clear distinction between the two besides that the one can be directly measured and the other one can simply not. That is also why the occupancy variation is not considered in this evaluation. However, occupancy can be measured directly by measuring the portion of time during which the detector registers a vehicle presence (Gomes, 2004). The advantage of using density as parameter is that values for density are unique for different traffic states (Stanescu, 2008). The ring-road Amsterdam makes use of downstream detectors for the ALINEA algorithm. The freeway used for the PPA, the ring-road Amsterdam, has both upstream of the ramps and downstream of the ramps dual-loop detectors.

2.4.2. UD-ALINEA

The equation for the upstream measurement variation of the density ALINEA algorithm is the same as for the downstream measurement variation. The upstream density algorithm has not been explicitly discussed in literature, but is similar to the occupancy variation. This variation is discussed and

tested in Smaragdis and Papageorgiou (2003). The equation is also given in section 2.3(only occupancy has changed into density):

$$r(k) = r(k-1) + K_R[\hat{\rho} - \tilde{\rho}_{out}(k-1)] \tag{2.27}$$

$$\tilde{\rho}_{out}(k) = \rho_{in}(k)\left[1 + \frac{q_{ramp}(k)}{q_{in}(k)}\right]\frac{\lambda_{in}}{\lambda_{out}} \tag{2.28}$$

Where $\lambda_{in}/\lambda_{out}$ = the number of mainstream lanes upstream(in)/downstream(out) of the ramp.

The upstream-based ALINEA variations are developed because sometimes it is difficult to implement or test ALINEA in the field due to the lack of detectors downstream of the on-ramp, while detectors are available upstream of the on-ramp (Smaragdis and Papageorgiou, 2003). It is possible to apply a feedback strategy on upstream measurements if suitable estimates for, in the case of occupancy, $o_{out}(k)$ can be made available (Smaragdis and Papageorgiou, 2003). Thus for density a suitable estimate of $\rho_{out}(k)$ should be made available (see equation $\tilde{\rho}_{out}$). All further issues and procedures remain exactly the same as in D-ALINEA (Smaragdis and Papageorgiou, 2003). Smaragdis and Papageorgiou (2003) concluded that there was hardly any difference visible between the upstream variation and the downstream variation of ALINEA. Thus it can be concluded that if there are no downstream detectors, while there are upstream detectors, this upstream measurement variation of ALINEA can be implemented. Note that this variation is only tested in simulation and never in practice.

2.4.3. V-ALINEA

The ALINEA variation using speed has been introduced by Middelham and Taale (2006). The equation was already given in section 2.3:

$$r(k) = r(k-1) + K_R[V_s - V(k-1)] \tag{2.29}$$

The V-ALINEA algorithm is not a closed loop feedback controller. Stanescu (2008) explains the difference between open-loop and closed loop: An open-loop feed forward controller uses the observed inputs to modify the plant input and a closed-loop feedback control system and the controller uses the observed output to modify the plant input. The advantage of using the speed instead of the flow is the same as with density, the observation is unique for both congested and free flowing traffic (Stanescu, 2008). The speed can also directly be measured from the loop detectors. Stanescu (2008) evaluated the speed variation algorithm with the RWS-strategy and came to the conclusion that there were no large differences between the two during preliminary tests. A main disadvantage of using speed is denoted in Stanescu (2008). Speed stays quite the same on the left side of the fundamental diagram, but when congestion sets in the speed will quickly drop. The V-ALINEA is never actually tested in practice, but simulation results gave similar results as the RWS-strategy. There are no real results of the V-ALINEA so it is hard to evaluate this algorithm compared to other algorithms. It can only be assumed that it will have similar results as the RWS-strategy as mentioned in Stanescu (2008).

2.4.4. UV-ALINEA

The upstream measurement ALINEA variation of speed is actually not discussed in literature. But based on assumptions it can explained with the following, and similar as the other upstream variation, equations (Smaragdis and Papageorgiou, 2003):

$$r(k) = r(k-1) + K_{\mathrm{R}}[\hat{V}_{\mathrm{s}} - \tilde{V}_{\mathrm{out}}(k-1)] \tag{2.30}$$

$$\tilde{V}_{\mathrm{out}}(k) = \alpha \times V_{\mathrm{in}} = \frac{\alpha \times V_{\mathrm{in}}}{\rho_{\mathrm{in}}} \tag{2.31}$$

For this upstream variation of the V-ALINEA the same can be said as the V-ALINEA itself. Speed is unique for the different traffic states, but when congestion sets in the speed can quickly drop where the speed stays quite the same on the left side of the FD. Since downstream detectors are available on the ring-road Amsterdam (and overall in the Netherlands) this variation would not benefit this research more than the other variations. Thus the UV-ALINEA is also difficult to evaluate without reliable results and it can only be assumed that the upstream variation will give similar results as the downstream variation and is only relevant when there are no downstream detectors available.

2.4.5. FL-ALINEA

The flow-based ALINEA algorithm has been described in Smaragdis and Papageorgiou (2003). The equation has already been given in section 2.3:

$$r(k) = \begin{cases} r(k-1) + K_{\mathrm{F}}[\hat{q} - q_{\mathrm{out}}(k-1)] & \text{if } o_{\mathrm{out}}(k-1) \leq o_{\mathrm{crit}} \\ r_{\mathrm{min}} & \text{else} \end{cases} \tag{2.32}$$

The flow-based variation is criticised because of the traffic volumes which are not uniquely for different traffic states (Smaragdis and Papageorgiou, 2003). This is caused by the U-shape of the fundamental diagram. The same flows can be found for non-congested and congested traffic. But on the other hand in case of a central network-wide specification of target values, it may be easier to specify set values for flows than for occupancies/densities. For that reason it may be useful under certain conditions to apply the flow-based variation of ALINEA (Smaragdis and Papageorgiou, 2003). The target value $\hat{q}$ should not be close or equal to q_{cap} because the r_{min} of the equation should not be activated too often, else the frequent abrupt switches to $r(k) = r_{\mathrm{min}}$ may irritate the drivers at the on-ramp and will lead to a bursty rather than smooth traffic volume trajectory (Smaragdis and Papageorgiou, 2003). Therefore Smaragdis and Papageorgiou (2003) only recommend this variation if the target value is sufficiently smaller than q_{cap}. Also because q_{cap} is an estimated value, there is a risk that the capacity is actually lower. The equation would then target a value that is not attainable in real traffic and therefore Smaragdis and Papageorgiou (2003) do not recommend FL-ALINEA as a flow-maximising ramp metering algorithm.

2.4.6. UF-ALINEA

The upstream flow ALINEA variation is interesting for the same reasons as the other upstream variations: the non-availability of downstream detectors. The formula is practically the same as for the

other upstream variations, but now flow is used instead of speed/density and the estimate for flow ($\tilde{q}_{\text{out}}$) is calculated as follows (Smaragdis and Papageorgiou, 2003):

$$r(k) = \begin{cases} r(k-1) + K_F[\hat{q} - \tilde{q}_{\text{out}}(k-1)] & \text{if } \tilde{o}_{\text{out}}(k-1) \leq o_{\text{crit}} \\ r_{\text{min}} & \text{else} \end{cases} \tag{2.33}$$

$$\tilde{q}_{\text{out}} = q_{\text{in}} + q_{\text{out}} \tag{2.34}$$

$$\tilde{\rho}_{\text{out}}(k) = \rho_{\text{in}}(k)\left[1 + \frac{q_{\text{ramp}}(k)}{q_{\text{in}}(k)}\right]\frac{\lambda_{\text{in}}}{\lambda_{\text{out}}} \tag{2.35}$$

The disadvantages of the UF-ALINEA algorithm are the same as for the FL-ALINEA. Smaragdis and Papageorgiou (2003) note that when K_F is equal to 1, $q_{\text{ramp}}(k-1)$ is equal to $r(k-1)$ and $\hat{q}$ is equal to q_{cap} this upstream variation of the flow ALINEA becomes identical to the DC strategy (see section 2.3. The results from this UF-ALINEA are virtually equivalent to the FL-ALINEA in Smaragdis and Papageorgiou (2003).

2.4.7. PI-ALINEA

The PI-ALINEA variation has been introduced by Wang et al. (2010). This variation was developed for distant downstream bottlenecks and for a merging bottleneck, because the normal ALINEA variation is less efficient for these cases (Wang et al., 2010). In Wang et al. (2010) the normal ALINEA did not work as good as the PI-ALINEA for the case of distant downstream bottlenecks which makes the normal ALINEA less efficient for this case. The PI-ALINEA was originally developed with the occupancy as target value. In equation 2.36 this variation is denoted with density as parameter:

$$r(k) = r(k-1) - K_P * [\rho_{\text{out}}(k) - \rho_{\text{out}}(k-1)] + K_R * [\hat{\rho} - \rho_{\text{out}}(k-1)] \tag{2.36}$$

The only results available are denoted in Wang et al. (2010). Here the PI-ALINEA is tested on distant downstream bottlenecks and to bottlenecks caused by on-ramp traffic flow that flows into the mainline. The standard ALINEA variation with occupancy was not able of maintaining the maximum throughput when tested on a distant downstream bottleneck (Wang et al., 2010). The PI-ALINEA tested in Wang et al. (2010) had better results in this case. Wang et al. (2010) states that this PI-ALINEA structure is currently only applicable if the bottleneck location is known beforehand, which means that detectors have to be deployed there. In the case of the bottleneck just downstream of the on-ramp both ALINEA variations behaved the same and had satisfactory results (Wang et al., 2010).

2.4.8. Evaluation ALINEA overview

In Table 2.1 an overview is given of the literature review about the ALINEA variation in section 2.4. The exact variation will be chosen also based on the literature review and evaluation of the adaptive control approaches in the following sections. It could be important to know what kind of control law would have more benefit with a specific adaptive control approach. Therefore the definitive choice of an ALINEA variation will be explained in section 2.7.

Table 2.1. – Overview ALINEA variations

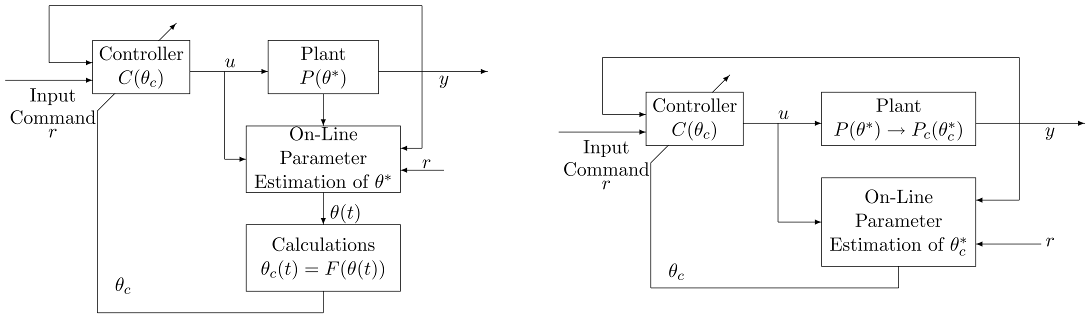
D-ALINEA	Used during the PPA and is a reliable algorithm which works well in practice. Density is unique for different traffic states and therefore reliable to use in an algorithm to prevent the capacity drop.
UD-ALINEA	Simulation results (in literature) are similar to the downstream variation, but never used in practice. Both downstream and upstream detectors are available at the ring-road Amsterdam so it would not have any extra benefit towards other variations.
V-ALINEA	Because the V-ALINEA is an open-loop feed forward algorithm it is not recommended to use in further research. Also no reliable results are known for this variation.
UV-ALINEA	Same as the V-ALINEA variation, but for upstream measurements.
FL-ALINEA	Flow is not unique for different traffic states. But sometimes it may be easier to specify set values for flows than for densities. But it is not recommended to use FL-ALINEA because the equation would target a value that is not attainable in real traffic.
UF-ALINEA	The results from simulation of the UF-ALINEA are similar to the FL-ALINEA. Thus it can be concluded that ALINEA with flow as parameter is not recommended for further use.
PI-ALINEA	The PI-ALINEA was only tested in case of distant downstream bottlenecks, where it outperforms the standard ALINEA. There is not much known about this variation, but in the case of a bottleneck just downstream of the on-ramp it should perform like the standard ALINEA performance-wise.

2.5. Adaptive control approaches

Four types of adaptive control approaches are described by Äström and Wittenmark (2013): gain scheduling, model-reference adaptive control, self-tuning regulators and dual control. Äström and Wittenmark (2013) describe direct and indirect methods. Changyu and Lili (2012) explain the difference between these two methods: Direct methods are ones wherein the estimated parameters are those directly used in the adaptive controller and indirect methods use the estimated parameters to calculate required controller parameters. Both methods are shown in Figure 2.3.

2.5.1. Gain scheduling

Gain scheduling, a direct method, is a useful technique for reducing the effects of parameter variations. This approach is called gain scheduling because the scheme was originally used to measure the gain and then change/schedule the controller to compensate for changes in the process gain (Äström and Wittenmark, 2013). Gain scheduling is an open-loop adaptive control system that can be viewed as having two loops: an inner loop composed of the process and the controller and an outer loop that adjusts the controller parameters on the basis of the operating conditions (conditions wherein a plant operates) (Äström and Wittenmark, 2013). The control scheme is shown in Figure 2.4.



(a) Indirect adaptive control (b) Direct adaptive control

Figure 2.3. – Direct versus indirect adaptive control (Source: Ioannou and Sun (1996))

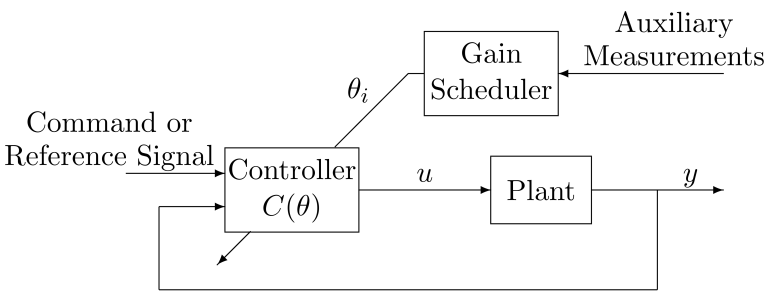


Figure 2.4. – Gain scheduling (Source: Ioannou and Sun (1996))

2.5.2. Model-reference adaptive control

The **Model-reference adaptive control** (MRAC) approach was proposed to solve a problem in which the performance specifications are given in terms of a reference model. This is a direct control method which consists of two loops. The inner loop is an ordinary feedback loop composed of the process and the controller and the outer loop adjusts the controller parameters in such a way that the error, which is the difference between process output y and model output y_{ref} is small (Äström and Wittenmark, 2013). This is shown schematically in Figure 2.5. In Ioannou and Sun (1996) also an indirect MRAC is explained. This adds an extra calculation of the estimated parameters to update the controller.

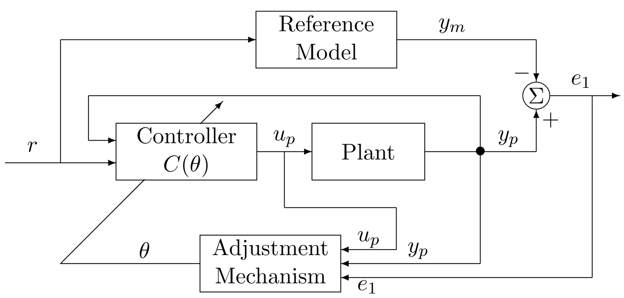


Figure 2.5. – Model-reference adaptive control (Source: Ioannou and Sun (1996))

Model-reference adaptive control automatically adjusts the parameters of a controller so that the

response to command signals is close to that given by a reference model (Äström and Kumar, 2014). A main feature of the MRAC approach is that the system is matched to a reference model which describes the desired response of the control process (Tao, 2014, Äström and Wittenmark, 2013). The goal of the MRAC approach is to drive the error between the reference model and the plant process to zero by adjusting the parameters with an adaptive law (Äström and Wittenmark, 2013). The error between the reference model and the adjustable model is used to estimate the unknown parameters (Maiti et al., 2009). In the original MRAC approach the so-called *MIT rule* was used as adaptive law, where γ is the adaptation gain and $\frac{\partial e}{\partial \theta}$ is the sensitivity derivative of the error (e) with respect to parameter θ (Äström and Wittenmark, 2013):

$$\frac{d\theta}{dt} = -\gamma \frac{\partial J}{\partial \theta} = -\gamma e \frac{\partial e}{\partial \theta} \tag{2.37}$$

$$e = y - y_m \tag{2.38}$$

As explained before the desired behaviour is specified by a reference model and the parameters of the controller are adjusted based on the error, which is the difference between the outputs of the closed-loop system (y) and the reference model (y_m) (Äström and Wittenmark, 2013). Äström and Wittenmark (2013) show that even if the error goes towards zero the parameters do not always converge to their correct values, but this is a characteristic of all adaptive systems. The adaptive law of the MRAC approach searches for the parameters in the control law, such that the response of the plant should be the same as the reference model (Swarnkar et al., 2011). Different methods for the adaptive law according to Swarnkar et al. (2011) are the MIT rule, Lyapunov theory and augmented error theory.

2.5.3. Self-tuning regulators

The **self-tuning regulators** (STR) approach is, in contrast to the previous described approaches, an indirect method. The STR approach is sometimes named Adaptive Pole Placement Control (APPC) in other literature like Ioannou and Sun (1996). The diagram of this method is given in Figure 2.6. The inner loop of the STR approach consists of the process and an ordinary feedback controller and the outer loop adjusts the parameters of the controller. The controller tunes its parameters to obtain the desired properties of the closed-loop system, therefore the name self-tuning regulator. This method is flexible with respect to the choice of underlying design and estimation methods (Äström and Wittenmark, 2013). The controller parameters or the process parameters are estimated in real time using on-line parameter estimation. The STR approach estimates the process parameters and finds controller parameters that minimize a criterion (Äström and Kumar, 2014) and try to reach an optimal control performance (Isermann, 1982).

2.5.4. Dual control

The **Dual Control** approach takes uncertainties in parameters into account. The previous described approaches do not take these uncertainties into account. The controller will take into account the uncertainties of estimated parameters and take special action when it has poor knowledge about the process (Äström and Wittenmark, 2013). The optimal control gives the correct balance between maintaining good control and small estimation errors where the name *Dual Control* comes from

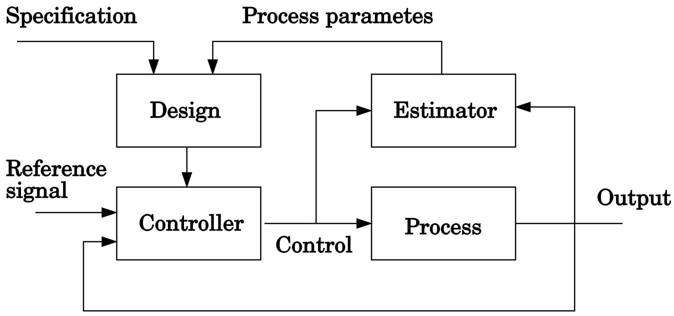


Figure 2.6. – Self-Tuning regulator scheme (Source: Wittenmark (2002))

(Äström and Wittenmark, 2013). This is a complicated approach and it has not been possible to use it for practical problems according to Wittenmark (1995), Äström and Wittenmark (2013). The dual control scheme is given in Figure 2.7.

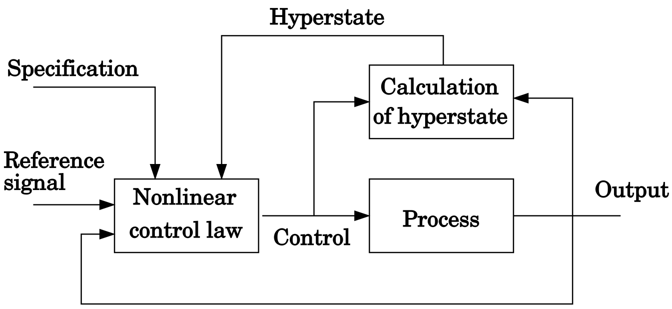


Figure 2.7. – Dual control scheme (Source: Wittenmark (2002))

In Wittenmark (1995) adaptive controllers are classified between non-dual controllers and dual controllers. The non-dual controllers (Gain scheduling, MRAC and STR) are based on the certainty equivalent principle and dual controllers are not. Dual controllers can be divided between optimal dual controllers and **suboptimal dual controllers**. The optimal dual controllers are difficult to compute and implement in practice as discussed before. Therefore these optimal dual controllers will not be considered as adaptive control approach in this thesis. In this thesis it is preferred to design an adaptive control approach that could be implemented in practice. However, the suboptimal controllers are more easy to compute and implement. To solve the complexity of the dual controller, the control laws are derived such that they are practically implementable but also retain the properties of a dual controller (Fabri and Kadirkamanathan, 1998). The suboptimal controllers are in principle non-dual controllers, but with some dual features (Wittenmark, 1995). The suboptimal dual controllers can be divided in different classes, with respect to their modifications towards optimal dual controllers (Wittenmark, 1995): Modifications of the loss function, using serial expansion of the loss function, finite parameter sets and constrain the variance of the parameter estimates. Dual control does not only affect the state of the system but also affects the estimation quality of the estimated parameters (Li et al., 2008). Because the suboptimal dual controllers are not as complex as the dual controllers and can be implemented in practice in contrast to the dual controllers, the suboptimal dual controllers will be evaluated in section 2.6.4.

2.5.5. State-of-the-art adaptive control for ramp metering

Adaptive control of ramp metering has already been done before. The ALINEA algorithm has a variation with adaptive control of the parameters introduced by Smaragdis et al. (2004). The principle of this adaptive control approach is the estimation of the critical occupancy, which will then update the target value for occupancy in the ALINEA algorithm. Smaragdis et al. (2004) named reasons why specification of the critical occupancy may not be feasible when estimated visually from a flow/occupancy-diagram. For those reasons there is an interest in maximizing the freeway flow without having to rely on constant pre-specified target values (Smaragdis et al., 2004). Thus an estimation algorithm was designed to estimate the critical occupancy with real-time measurements. Such an estimation control is visible in the schemes of the self-tuning regulator and model-reference adaptive control as described in previous section. Smaragdis et al. (2004) tested a simple estimation algorithm and a Kalman-filter based derivative estimation algorithm and they also tested an upstream-measurement based adaptive ALINEA. Both downstream and upstream measurements gave similar results (Smaragdis et al., 2004). As explained in section 1.3 the regulator parameter of the ALINEA algorithm has always been assumed fixed and has not been adaptively controlled. In this thesis the ALINEA algorithm with all of its parameters (The gain (K) and critical values of the related states) should be controlled adaptively with methods as described in sections 2.5.1, 2.5.2, 2.5.3 and 2.5.4. Next to possible adaptive ramp metering controllers, one of the methods, the MRAC approach, is used in a traffic control measure for emergency evacuation of traffic in Liu et al. (2007).

2.5.6. Parameter estimation and state estimation

In sections 2.5.1, 2.5.2, 2.5.3 and 2.5.4 several types of adaptive control approaches are explained. In all these schemes a (parameter) estimation 'block' is included in form of gain scheduling, an adaptation mechanism (MRAC), an estimation 'block' (STR) and a hyperstate 'block' (Dual Control). In this section the variables that will be estimated with possible methods and the variables that will not be estimated are explained here. This, parameter estimation, is an important subject of adaptive control and therefore will be explained which methods are appropriate for this thesis and which are not.

In this thesis the objective is to estimate and adjust all parameters for the chosen variation of ALINEA. This includes the regulator parameter and the target values for the variations ($\hat{\rho}$, $\hat{q}$ or V_s). In addition to these parameters, also the capacity of the road and the free flow speed are important parameters. To estimate the critical values methods like the ones in Smaragdis et al. (2004) and Hoogendoorn and Smits (See appendix A) can be used, where the derivative of the fundamental diagram is calculated which is used to update the critical values. These critical values will update the target values of the control law. The critical values can be used to determine the capacity.

The traffic states, density, flow and speed for any segment are not important to estimate in this thesis. The reason for this is as follows. Wang et al. (2008) explains real-time freeway traffic state estimation as follows: "*It refers to the estimating traffic flow variables (flows, space mean speeds, and densities) for a considered freeway stretch or network with an adequate time resolution (e.g. 10 s) and spatial resolution (e.g. 500 m or less) based on a limited amount of available measurement data from traffic detectors*". A traffic state estimation method is often used when limited amount of available measurement data is available as stated in Wang et al. (2008). Thus it is used to estimate unknown states at a certain stretch of freeway. The states are estimated for the desired stretch of road with help of detector data upstream and downstream of this location. Because in the case of the chosen macroscopic model, METANET, at every road segment traffic states will be available. State estimation

is only necessary when certain state information is missing of a certain segment and this information needs to be available for a certain control measure or just for information. Traffic state estimation will therefore not be necessary in this thesis.

For estimating the other parameters, on-line estimation of parameters of a controller is one of the key steps in building an adaptive control system (Landau et al., 2011, Äström and Wittenmark, 2013). Thus one criterion for the control approach that will be developed in this thesis will be that of on-line parameter estimation. In Wang et al. (2008) several advantages where named for on-line model parameter estimation. One of the advantages of the adaptive control approach proposed is that the estimator adapts its model efficiently to changes of certain circumstances (e.g. weather, incidents etc.) (Wang et al., 2008). In Landau et al. (2011) the general *parameter adaptation algorithm* (PAA) of an adaptive control approach is explained. It is a key element for implementing on-line estimation of the parameters of the controller. A PAA is of recursive structure according to Landau et al. (2011) which means that the value coming from the estimated parameters is equal to the previous value (k−1) plus a correcting term. This correcting term is dependent on the most recent measurements (Landau et al., 2011). Several approaches for on-line parameter estimation considered in Landau et al. (2011) are a gradient technique, least squares minimization, stability and rapprochement with Kalman filter.

It can be concluded from this section that there are a lot of different parameter estimation methods. In section 2.6 different adaptive control approaches and estimation methods will be evaluated.

2.6. Evaluation adaptive control approaches

The choice of which adaptive control approach is relevant for further use will be discussed in this section. Different adaptive approaches are mentioned in previous section: Gain scheduling, Model-reference adaptive control, Self-tuning regulators and Dual control. Most adaptive controllers are based on the separation of parameter estimation and controller design (Filatov and Unbehauen, 2004). In that case the *certainty equivalent principle* is applied. The parameters are estimated and then used in the design as if they are the true ones (Wittenmark, 1995). The parameters are estimated based on new measurements. The uncertainty of estimation is not taken into consideration for the controller design (Filatov and Unbehauen, 2004). In this section the following sub question will be answered:

- *Which adaptive control approaches exist, what are their advantages and disadvantages towards ramp metering and which ones are relevant and suited for implementation in this research?*

The adaptive control approaches will be evaluated based on several criteria. It is evaluated in which way it could improve existing ramp metering algorithms such as the PI-ALINEA or the D-ALINEA. Also will be looked into literature for possible similar approaches as (adaptive) ramp metering or with a similar control law. Another important criteria is that the approach is able to be used for ramp metering. If this aspect is uncertain or the approach cannot be applied for ramp metering it drops out of the possible approaches. Also all parameters of the ALINEA algorithm should be adaptively controlled. The gain(s) and the target density in the (PI-)ALINEA should be able to be estimated with the chosen adaptive control approach.

2.6.1. Gain scheduling

Gain scheduling is the most simple form of adaptive control. Gain scheduling, in contrast to the other adaptive control approaches, does not use the response of the controller (which indicates that it is not a feedback controller) but only measurements of, in this case, induction loops on the freeway. In theory, measurements would be used to determine the parameters of the ramp metering algorithm. The parameters will be adjusted based on knowledge about the influence of these parameters on the traffic system (Stanescu, 2008). This approach may be able to be implemented as ramp metering control approach. An advantage of gain scheduling is that the controller gains can be changed as quickly as the measurements respond to parameter changes (Ioannou and Sun, 1996). But the rapid and frequent changes may lead to instability of the system according to Ioannou and Sun (1996) and therefore there is a limit to how often and how fast the controller gains can be changed. Another disadvantage named in Ioannou and Sun (1996) is that gain scheduling is non-feedback. The adjustment mechanism of gain scheduling computes parameters off-line (and thus no feedback) and this is not preferred for adaptive control in this thesis. Off-line parameter estimation first collects all input/output data and then estimates the parameters. The parameters cannot vary in time which is a problem when used for ramp metering as the parameters of a ramp metering algorithm do vary in time. Therefore on-line estimation should be more beneficial towards ramp metering. And because of this off-line adjustment mechanism it is a discussion whether gain scheduling can be classified as an adaptive controller like the others named in this section. Unpredictable changes in dynamics (in context of this thesis, changes in traffic flow (parameters)) may lead to deterioration of performance or even complete failure (Ioannou and Sun, 1996). But gain scheduling is still a popular approach for handling parameter variations often used in flight control according to Ioannou and Sun (1996).

2.6.2. Model-reference adaptive control

The MRAC approach makes use of a reference model as explained earlier. The reference model in case of traffic flow and ramp metering should give the desired/maximised outflow. The flow is optimised when the density is kept below the critical density. Thus for example the target density, used in the D-ALINEA variation, could be the reference model which will optimize the throughput on the freeway. One of the advantages of the MRAC model is that it has a high-speed of adaptation (Landau, 1974) and because of the relative short control time of ramp metering fast adaptation would also benefit ramp metering.

In Liu et al. (2007) a MRAC framework is introduced for traffic management under emergency evacuation. This is based on the *gradient method*. The gradient method is another name for the MIT-rule (as explained in section 2.5) and in this thesis the MIT-rule will be further referred to as gradient method. For this thesis the method in Liu et al. (2007) seems most appropriate for a ramp metering strategy, also because Liu et al. (2007) proves that this gradient method works for traffic management (under some assumptions). The control law used in this paper looks a lot like the PI-ALINEA discussed in section 2.4, with two gain factors. Only in the control law in Liu et al. (2007) both gain factors are multiplied by the error and the integral of the error over a time period from 1 to k. The PI-ALINEA variation uses two different errors instead of one similar error for both gains. A good performance will only be achieved after the parameter converged to their correct values. In this paper route choice guidance is the traffic management measure. In this thesis the method will be developed for ramp metering.

The gradient method, used in Liu et al. (2007), can be defined by a loss function given in equa-

tion 2.39, where the gradient J has to be minimized and $\theta = [\theta_1, \theta_2]^T$. θ_i is a parameter that needs to be updated every time step based on the error. The adaptation gain (γ) in the gradient method should be determined by the controller designer (Liu et al., 2007). The adaptation gain should be determined properly to get a stable controller (Swarnkar et al., 2011). Because fast convergence is important for the performance of the approach, this should be taken into account. Thus the correct parameter values will be obtained earlier with fast convergence of the error, this is important for ramp metering because the actual control time is short due to limited storage space on the on-ramp.

$$J(\theta) = \frac{1}{2}e^2(\theta) \tag{2.39}$$

The MRAC approach seems an appropriate approach to use as adaptive controller for traffic control measures (see the example of Liu et al. (2007)), and thus also ramp metering, and therefore a MRAC approach will be developed for ramp metering based on the gradient method as in Liu et al. (2007). The gradient method is the adaptive law in the MRAC scheme (see Figure 2.5). The adaptive law will update the parameters of the ramp metering algorithm. The MRAC example of Liu et al. (2007) indicates that a PI-ALINEA will probably work for this MRAC approach, because of their control law which is of similar structure as the PI-ALINEA.

2.6.3. Self-tuning regulators

According to Ioannou and Sun (1996) this approach is the most general class of adaptive control schemes because of its flexibility in choosing the controller design methodology and adaptive law (parameter estimation method). The STR approach is not much different than the MRAC approach according to Sastry and Bodson (1989). The difference between the MRAC approach and the STR approach is that the MRAC approach uses a reference model. The MRAC approach also uses the gradient method or Lyapunov direct method as adaptive law, whereas the STR approach is free in choosing a parameter estimation method. The purpose of STR approach is to control systems with unknown but constant parameters or slowly varying parameters. The parameters in the traffic network can change rapidly and therefore this approach could not be optimal for a traffic control measure.

The adaptive approach used in PPA for the *Parameterschatter* (See appendix A) is most similar to the STR approach, because of the free choice of a parameter estimation method. In general the PPA uses a parameter estimation method for the estimation of the actual critical density. The STR approach can do the same, where the estimation method is free to choose. Thus the STR approach also uses an estimation method to tune the parameters of the control law, just like the *Parameterschatter* used during the PPA. Thus in theory this STR approach could be applied for ramp metering like the *Parameterschatter* but also with possible other estimation methods for the gain(s) and/or critical density. Recursive parameter estimation methods for the STR approach are discussed in Äström (1975). The methods discussed are the Least Squares method (LS), Extended Least Squares method (ELS) and the Recursive Maximum Likelihood method (RML). For ramp metering the parameters could be estimated by one of these methods and will then update the parameters with these estimated values. Because this approach is inferior compared to the MRAC approach in case of time-varying parameters (the STR approach should control systems with constant or slow varying parameters) the STR approach will not be considered any further in this thesis.

2.6.4. Suboptimal dual control

Suboptimal dual controllers are non-dual controllers with dual features. These type of controllers are very complex. Wittenmark (1995) discusses when to use such a suboptimal dual controller. It can be advantageous when the time horizon is short and when the initial estimates are poor. For ramp metering the time horizon is short, because the storage space on the on-ramp is limited. When the storage space reaches it limits then the ramp meter installation cannot meter according the pre-defined algorithm (e.g. ALINEA). Also when parameters of the process are changing very rapidly dual control should be considered. Process parameters of the traffic system like the critical density do not vary rapidly. Speed, flow and density on the freeway may vary rapidly in certain situations when there is a sudden increase or decrease of demand. Thus suboptimal dual control could be a possible adaptive control approach for ramp metering when parameters are changing rapidly. In Fabri and Kadirkamanathan (1998) more advantages of a suboptimal controllers are named, which follow from the dual features: (i) taking the system state optimally along a desired trajectory, with due consideration given to the uncertainty of the parameter estimate and (ii) eliciting further information so as to reduce future parameter uncertainty, thereby improving the estimation process. The first effect (i) is called caution, because the controller does not use the estimated parameters blindly as if they were true (as the other approaches described above do) (Fabri and Kadirkamanathan, 1998). And the second effect (ii) is called probing because the controller generates signals that encourage faster parameter convergence (Fabri and Kadirkamanathan, 1998).

The suboptimal dual controller looks like a possible approach to adaptively control the ALINEA algorithm because of the short time horizon for the control. It is more complicated than the other mentioned approaches, but also more optimal as can be read in literature (Wittenmark, 1995, Landau et al., 2011, Åström and Wittenmark, 2013, Allison et al., 1995, Reis and Maitelli, 2015). But because there is an example of MRAC with a traffic control measure, which is possible to implement in practice, the MRAC approach is preferred over the suboptimal dual control, which is uncertain if possible to implement for ramp metering, in this thesis. An important criteria for evaluation was that it should be certain the method could be used to estimate the parameters of the ALINEA algorithm. For this adaptive control approach this is uncertain and therefore another reason why this approach will not be used further in this thesis.

2.6.5. On-line estimation

An important step in adaptive control is parameter and/or state estimation. The problem of on-line estimation of model parameters is a generic problem in adaptive control (Landau et al., 2011). There are several methods to estimate the parameters needed for ramp metering control. Because in adaptive controllers the observations are obtained in real time it is desirable to make the computations recursively to save computation time (Åström and Wittenmark, 2013), this is explained earlier in section 2.5.6. Parameters that will need to be estimated are the critical value for the specific ALINEA variation to calculate and update the target value required for the ALINEA variation and the gain(s) (e.g. K_{R}). Aside from these parameters of ALINEA it is also important to estimate the capacity (q_{cap}) of the stretch of road where metering is applied to determine the switch on and switch off thresholds values based on capacity. Several methods have been used before to estimate the critical density. The *Parameterschatter* during the PPA and the two methods described in Smaragdis et al. (2004), simple derivative estimation and Kalman estimation of the derivative, are examples of this. From literature it seems possible to use the methods described in Smaragdis et al. (2004) and the *Parameterschatter*

seems possible based also on practice tests during the PPA. All these methods estimate the derivative of the fundamental diagram. The value is used to determine whether the current critical density value has to be updated or not next time step. The methods are different in the updating rule. All three methods have different equations to update the critical density. The simple derivative estimation update rule is given in equations 2.40, 2.41 and 2.42, where α is a smoothing parameter and Δ is a value for changing the previous critical density.

$$\delta(k) = \frac{q(k-1) - q(k-2)}{\rho(k-1) - \rho(k-2)} \tag{2.40}$$

$$D(k) = \alpha * \delta(k) + (1-\alpha) * D(k-1) \tag{2.41}$$

$$\rho_{\text{crit}}(k) = \rho_{\text{crit}}(k-1) + \begin{cases} \Delta & \text{if } D(k) > D^{+} \\ -\Delta & \text{if } D(k) < D^{-} \\ 0 & \text{else} \end{cases} \tag{2.42}$$

The Kalman derivative estimation update rule is given in equations 2.43, 2.44 and 2.45. In this equations is $\mathbf{H}$ the gain factor, $\mathbf{\Pi}$ the error covariance matrix, $\mathbf{Z}$ and W are the covariance matrices, $\mathbf{c}$ is the matrix $[(\rho_{\text{out}} - \rho_{\text{crit}})\ 1]$, $\mathbf{x}$ is the matrix $[DE]^T$, where D is the derivative which is estimated and E is the capacity of the road downstream of the on-ramp, and the last variable y is the downstream measured flow. The update rule is the same as for the simple derivative estimation in equation 2.42.

$$\mathbf{H}(k-1) = [\mathbf{\Pi}(k-1) + \mathbf{Z}] * \mathbf{c}(k)^T * \frac{1}{\mathbf{c}(k)\,[\mathbf{\Pi}(k-1) + \mathbf{Z}] * \mathbf{c}(k)^T + W} \tag{2.43}$$

$$\mathbf{\Pi}(k) = [\mathbf{\Pi}(k-1) + \mathbf{Z}] - \mathbf{H}(k-1) * \mathbf{c}(k)\,[\mathbf{\Pi}(k-1) + \mathbf{Z}] \tag{2.44}$$

$$\mathbf{x}(k) = \mathbf{x}(k-1) + \mathbf{H}(k-1) * [y(k) - \mathbf{c}(k) * \mathbf{x}(k-1)] \tag{2.45}$$

The *Parameterschatter* uses least squares estimation to determine the derivative of the fundamental diagram. The equations for this method is given in equations 2.46, 2.47 and 2.48, where α is again a smoothing parameter.

$$D(k) = \frac{\sum_{i=k-T}^{T} (\rho(i) - \bar{\rho}) * (q(i) - \bar{q})}{\sum_{i=k-T}^{T} (\rho(i) - \bar{\rho})^2} \tag{2.46}$$

$$\rho_{\text{crit}}(k) = \begin{cases} \alpha * \rho_{\text{crit}}(k-1) + (1-\alpha) * \rho_{\text{out}}(k) & \text{if } \rho_{\text{crit}}(k-1) < \rho_{\text{out}}(k) \\ \rho_{\text{crit}}(k-1) & \text{if } \rho_{\text{crit}}(k-1) \geq \rho_{\text{out}}(k) \end{cases} \tag{2.47}$$

$$\rho_{\text{crit}}(k) = \begin{cases} \alpha * \rho_{\text{crit}}(k-1) + (1-\alpha) * \rho_{\text{out}}(k) & \text{if } \rho_{\text{crit}}(k-1) > \rho_{\text{out}}(k) \\ \rho_{\text{crit}}(k-1) & \text{if } \rho_{\text{crit}}(k-1) \leq \rho_{\text{out}}(k) \end{cases} \tag{2.48}$$

With these methods also the critical speed can be determined the same way. With these estimated

values also the capacity can be calculated from the critical speed value and the critical density value (Capacity = $V_{\text{crit}} * \rho_{\text{crit}}$). The three above discussed methods seem all possible to use as estimation method for the critical density and will therefore be further discussed in section 3.3.

The gain(s) from the ALINEA algorithm has never been tuned with certain methods. From the above evaluations it could be concluded that a MRAC approach can tune this gain(s) as shown in Liu et al. (2007). Because the values of the ALINEA variation that need to be estimated are dependent on the chosen variation and the chosen adaptive control approach, the estimation procedures for the parameters will be further discussed in section 2.7.

2.6.6. Evaluation adaptive controllers overview

The MRAC approach seems the most promising approach for adaptive ramp metering in scope of this research. All strategies seem suitable for ramp metering, but suboptimal dual control is very complex and difficult to implement in practice. The choice for the MRAC approach was also based on which of the four approaches is the most promising approach. The MRAC approach is similar to the STR approach but has the advantage of using the error between the reference output and the plant output, which should achieve a better performance. Therefore the choice for the MRAC approach has been made instead of the STR approach. Suboptimal dual control is less complex than dual control, but still has dual control features. But this approach is still complex compared to the other approaches and it is uncertain if this approach is suited for ramp metering. Below a short summary is given of the different adaptive approaches why it will be used for further research or not.

Gain scheduling makes uses of off-line parameter estimation and is therefore often discussed if it can be classified as an adaptive controller. Because in this thesis the parameters should be estimated on-line, as discussed in section 2.5.6, gain scheduling will not be considered as a possible approach. Also the performance may deteriorate due to sudden changes in the dynamic system (e.g. incidents) and this is not preferred for further use in this thesis.

The **MRAC** approach is a good and popular approach for adaptive control. The error between the reference model and the adjustable model is used to estimate the unknown parameters. This error will converge to zero for optimal parameter estimations. This approach will be used in this research. The gradient method, already tested for evacuation of traffic, is appropriate as adaptive law for the MRAC approach and will therefore be used.

The **STR** approach seems to be similar to already existing approaches for adaptive ramp metering. This approach is meant for control systems with constant or slowly varying parameters, but the traffic system has the possibility of rapidly changing parameters. The MRAC approach seems more promising for further research than the STR approach, because the STR approach is inferior compared to the MRAC approach in case of time-varying parameters.

Suboptimal dual control is more complex than the other approaches, but it has also a better performance than the other approaches according to literature. However, suboptimal dual controllers are difficult to implement in practical situations. Because of this and because it is uncertain if it is suitable for ramp metering this approach will not be considered in this thesis.

2.7. Evaluation overview

In this section a final choice is made for the several evaluations and finally a total overview is given of the evaluations done in this chapter.

The conclusion from the evaluation about traffic flow models is that the macroscopic traffic flow model METANET is the most suitable model for this thesis. A macroscopic type of traffic flow model has been chosen because it is the first time this new adaptive approach will be tested. A macroscopic traffic flow model is sufficient for first time testing an approach.

The ALINEA variation will be chosen based on the adaptive control approach determined in section 2.6.6. From evaluation it seemed that the MRAC approach is a possible approach to use for estimation of all the parameters of the ALINEA variation. The MRAC approach has an example with a traffic control measure in Liu et al. (2007). Adaptive control approaches as described in previous sections are unfamiliar with traffic control measures. From evaluation it seemed that the D-ALINEA and PI-ALINEA were both good ramp metering algorithms. The PI-ALINEA described in section 2.4 has the same structure as the control law in Liu et al. (2007), except that the same error is used in Liu et al. (2007) after both gains and this is not the case for the PI-ALINEA in Wang et al. (2010). For this reason the MRAC approach will be used with a variation of this PI-ALINEA which has the exact same structure as the control law in Liu et al. (2007). The error $(\hat{\rho} - \rho_{\text{out}}(k-1))$ is used in both the integral term (with gain K_{I}) and the proportional term (with gain K_{P}). Because of the complexity of adaptive control approaches and the current knowledge acquired due to literature, this variation of ALINEA is chosen as there is an example for this kind of control law with an MRAC approach. For this reason also a PI-controller is used and not an other type of controller like a PID-controller, where the D stands for derivative. The Integral part corrects for past errors, where the Derivative part corrects for future errors (Araki, 2002). Because there is an example with a PI-controller for an adaptive approach, also in this thesis a PI-controller will be used instead of other possible forms of controllers. This thesis wants to look into the possible improvement of ramp metering algorithms while adaptively control all parameters, therefore following the example of Liu et al. (2007) should be sufficient. The exact PI-ALINEA control law that will be used in this thesis is given in equation 2.49.

$$r(k) = r(k-1) + K_{\text{P}} * [\hat{\rho} - \rho_{\text{out}}(k-1)] + K_{\text{I}} * \int_{1}^{k} (\hat{\rho} - \rho_{\text{out}}(k-1))\, \mathrm{d}k \tag{2.49}$$

The density parameter in the PI-ALINEA is chosen because of the high relevance to the ALINEA variation used during the PPA and because ALINEA with density as parameter has also satisfactory results in practice, therefore see the evaluation in section 2.4. This PI-ALINEA variation will also be tested without the adaptive controller and compared to the D-ALINEA variation in the coming sections to get a good overview of all the different ramp metering approaches. The MRAC approach will update the two gains (K_{I} and K_{P}) of the PI-ALINEA variation with the gradient method as adaptive law. In this thesis also the target density will be updated by estimating the critical density. The critical density will be updated using a least squares estimation (also used in the *Parameterschatter* (See appendix A)), a simple derivative estimation (Smaragdis et al., 2004) and a derivative estimation based on the Kalman filter (Smaragdis et al., 2004) which will update the critical density based on real-time measurements.

The ALINEA variation that will be used, the macroscopic traffic flow model that will be used and the adaptive approach that will be used can be found in Table 2.2.

The adaptive control approach that will be developed is not like the conventional MRAC approach, because for ramp metering this is too complex. Therefore the new approach that will be developed will be referred to as *"Adaptive ramp metering controller"* from here on. For the conventional MRAC approach a reference model has to be developed which determines the desired output, this is a difficult process because it involves linearisation of the traffic system (METANET for example) or a non-linear

Table 2.2. – Total overview

	ALINEA variation	Macroscopic model	Adaptive control approach
1.	PI-ALINEA (variation)	METANET	MRAC based on the gradient method including a critical density estimation method

reference model but that will make the whole process even more complex. In Figure 2.8 the scheme for the adaptive ramp metering controller in this thesis is given as an overview what has to be developed in the next sections. For the next sections the scheme in the figure will be developed and simulated for ramp metering. Initial input values will be used for the PI-ALINEA algorithm. The metering rate will update the ramp meter installation to regulate the inflow from the ramp to the mainline. The output of the traffic network will also be compared to a certain reference model (with a target density, which maximizes the flow output, as output). The adaptive law will use the error between the outputs and the previous values of the gain parameters to estimate these parameters of the PI-ALINEA algorithm for the next step. Then every time step this process will be repeated for the whole control time.

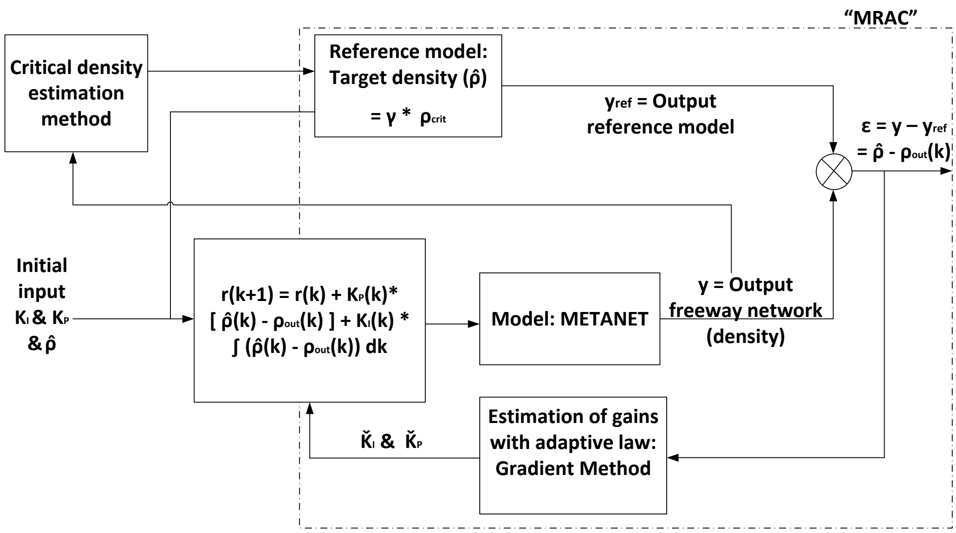


Figure 2.8. – Adaptive ramp metering controller

In the next sections the new adaptive ramp metering controller will be developed. The critical density and both gains of the PI-ALINEA algorithm will be adaptively controlled. The (non-conventional) MRAC part of the adaptive controller is the part where the output of the reference model (the target density) will be used as reference to converge the error between this target density and the downstream density to zero. This will be done with the gradient method as discussed before. The gradient method estimates the gains of the PI-ALINEA in such a way the error between the target density and

measured downstream density converges to zero. The non-conventional MRAC part of this adaptive controller is defined by the gradient method and the reference model. In addition the critical density is also estimated with one of the method discussed in section 2.6.5. The two parts of the controller are indicated in Figure 2.8.

3. Development adaptive control approach

In previous section the sub questions were answered with evaluations. The macroscopic traffic flow model, METANET, will be used to test the new developed approach. A variation on the ALINEA algorithm, named PI-ALINEA, will be used in the adaptive control approach which is a variation on the Model-reference adaptive control. The PI-ALINEA and the variation on the MRAC will be combined as a new ramp metering approach. As concluded in the previous section the new approach that will be developed will be referred to as *"Adaptive ramp metering controller"* in this research. Thus the answers to the sub question, coming from section 2 will be used in this section and also in section 4 and 5 where the developed approach in this section will be simulated.

In this section and the next sections an answer will be given to the main research question:

- *To which extent can adaptive control, by tuning all parameters of the ALINEA algorithm, improve ramp metering in terms of travel time?*

The main research question will be answered in the conclusions and recommendations in section 6. In this chapter the adaptive ramp metering controller will be developed. A PI-ALINEA variation with density as parameter will be used to develop the adaptive ramp metering controller. MATLAB will be used to develop this new adaptive ramp metering approach. The results coming from previous section will be combined and used to develop the new adaptive ramp metering controller which will be simulated and tested using METANET. The developed adaptive ramp metering controller from this section will be used for testing and simulation in section 4 and the results will be discussed in section 5.

In section 3.1 the METANET model is explained with the parameters of METANET used in this thesis and how the data, like speed, flow and density, is collected and measured within METANET. In section 3.2 a set-up as base for development will be explained before developing the adaptive ramp metering controller. This is the base for comparing eventually the results of the adaptive ramp metering controller towards the standard ALINEA and the standard PI-ALINEA algorithm. In section 3.3 the adaptive ramp metering controller will be developed. Section 3.4 will conclude with an overview of the developed adaptive controller.

3.1. METANET

METANET is used as macroscopic model to test the developed adaptive approach. METANET has several parameters that have to be calibrated. This has been done in several literature. The METANET model from Hegyi et al. (2005) is used in this thesis to test the developed approach. For more information about the METANET model see (Hegyi et al., 2005). The parameter values are shown in Table 3.1. The parameter values are used in the equations of METANET, which are mentioned before in section 2.2.2. The equations are repeated below:

$$\rho_{\mathrm{m,i}}(k+1) = \rho_{\mathrm{m,i}}(k) + \frac{T}{\mathrm{L_m} \times \lambda_{\mathrm{m}}}[q_{\mathrm{m,i-1}}(k) - q_{\mathrm{m,i}}(k)] \tag{3.1}$$

$$q_{m,i}(k) = \rho_{m,i}(k) \times v_{m,i}(k) \times \lambda_m \tag{3.2}$$

$$v_{m,i}(k+1) = v_{m,i}(k) + \frac{T}{\tau}\{V[\rho_{m,i}(k)] - v_{m,i}(k)\} + \frac{T}{L_m}[v_{m,i-1}(k) - v_{m,i}(k)] \times v_{m,i}(k) - \frac{\nu \times T}{\tau \times L_m} \times \frac{\rho_{m,i+1}(k) - \rho_{m,i}(k)}{\rho_{m,i}(k) + \kappa} \tag{3.3}$$

$$V[\rho_{m,i}(k)] = v_{f,m} \times \exp\left[-\frac{1}{a_m}\left(\frac{\rho_{m,i}(k)}{\rho_{cr,m}(k)}\right)^{a_m}\right] \tag{3.4}$$

The capacity of the generated stretch of freeway is 2000 veh/h/lane. The values for ν are high when the downstream measured density is higher than the density upstream and otherwise the low value for ν. These different values for ν ensure that the capacity drop is reproduced in the METANET model. The developed adaptive approach shall be tested under stochastic environment. In the METANET model itself the critical density will variate around the value in the table below. This is mainly because this parameter will be estimated by an estimator to update the target density in the algorithm. If the value is constant the response of the estimator on the actual traffic conditions would not representative to the reality. By testing it in a stochastic environment the results are closer to reality, although simulation will never be the same as in practice.

Table 3.1. – Parameters METANET

Parameter	Value	Parameter	Value
L_m	1 km	λ_m	2 lanes
T	0.0028 h	τ	0.0050 h
ν_{high}	65km^2/h	ν_{low}	30km^2/h
κ	5.550 veh/km/lane	$v_{f,m}$	102 km/h
$\rho_{cr,m}$	33.5(+ noise) veh/km/lane	ρ_{max}	160 veh/km/lane
a_m	1.867	δ	0.0122
ϕ	0		

The fundamental diagrams that come from these settings for METANET are shown in Figure 3.1. For different critical density values the fundamental diagram changes a bit. This is shown in this figure, where all the several lines and colors indicate a possible fundamental diagram in the METANET model during simulation. The values are not easily changed as this can lead to instability of the model. Thus for this thesis the above values from Hegyi et al. (2005), with the addition of noise on the critical density parameter, will be used.

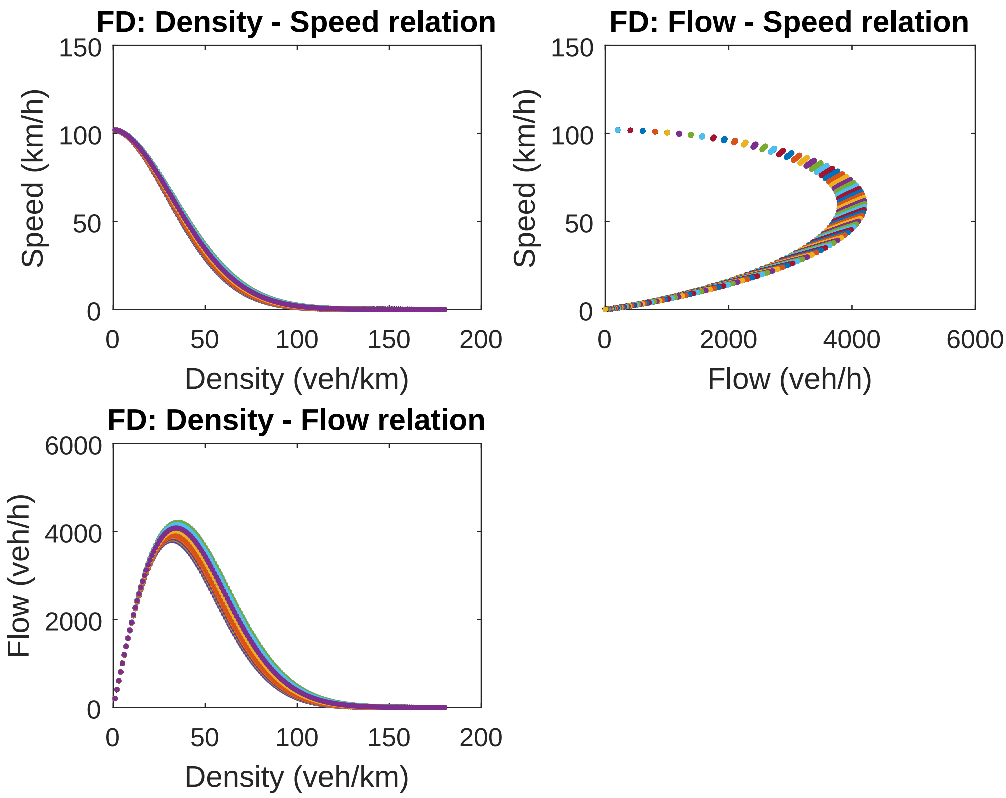


Figure 3.1. – Fundamental Diagrams

3.1.1. Measuring traffic variables

The actual traffic data is measured with so-called induction loops in practice. Detectors on the on-ramp are normally placed near the stop line (the demand detector) and at the end of the on-ramp (the queue detector). Detectors are also located on each lane of the freeway to measure the actual traffic conditions: the mainline detector loops. An induction loop detector can measure if a vehicle occupies the detector. In the Netherlands there are two kinds of detectors: single-loop detectors and dual-loop detectors. Single-loop detectors can measure the fraction of time a detector is covered by a vehicle (occupancy (o)) and the number of vehicles passing per unit time (flow (q)) (Wang and Nihan, 2003). A dual-loop detector consists of two consecutive single-loop detectors several meters apart (Wang and Nihan, 2003) as shown in Figure 3.2. Wang and Nihan (2003) explain that dual-loop detectors can record the time a vehicle used to travel from the first loop to the other loop. If the distance between the loops is predetermined then the detector can calculate the traffic speed. Thus the detector measures the time it takes for the vehicle to travel from the first loop to the second loop and then the detector calculates the speed based on this data. Also the length of the vehicle can be estimated by using the occupancy measured by the single-loop, and thus the vehicle class can be determined based on its length (Wang and Nihan, 2003).

The raw traffic data a detector actually measures is given in Van Lint (2005). Among others, these data consists of the width of the detector, vehicle length, the amount of vehicles occupying a segment, number of passing vehicles in a certain period, the individual local speed per n vehicle and the time

Figure 3.2. – Dual-loop detector (Source: Van Lint (2005, 2014))

spend on the detector. The density however cannot be directly measured from these detectors. They can be derived from other measurements. Mostly this density is then used if needed for a traffic control measure. On Dutch freeways the MoniCA[1] system is used for measurements (Van Lint, 2005).

For this thesis the macroscopic traffic flow model METANET will be used as discussed earlier. Because of the macroscopic model the traffic data will not be acquired per vehicle but more on a macro level. The traffic data (flow, density, speed) will also be acquired immediately from the model and does not have to be calculated as when data is acquired from detectors. Data as density, which normally has to be calculated, is now immediately available from the macroscopic model. Thus METANET, or actually Matlab, gives precise values for speed, density and flow (the real values). Errors of measurements are not actually implemented in Matlab. But with the help of additive white Gaussian noise[2] in Matlab there is a certain measurement error added to the measurements. Gaussian noise has a probability density function that is equal to that of the normal distribution (Barbu, 2013). For more information about Gaussian noise see Barbu (2013). The noise is only added to the measurements (measured flow, measured speed, measured density, measured demand and measured queue length) that come from the 'detectors' of METANET. For every segment of the freeway layout these measurements are available. The METANET itself calculates and uses the values as they actually are (without the noise). So the measurements are used for ramp metering control because in reality also the ramp metering control is dependent on the measurements and it does not use the exact real values. This Gaussian noise will give errors in the measurements, where the control approach has to adapt to. This way a part reality is added to METANET. The parameters of METANET do not have added noise, except the critical density (which is also indicated in the table), and are the exact values as presented in Table 3.1. This METANET set-up should be ideally for testing the new adaptive control approach which will be developed in section 3.3. Due to the stochastic environment every simulation, a sufficient amount of simulation runs will be done for each control situation and the results will be averaged to get a clear view on the performances of the control approach. The number of simulation that are needed will be calculated using the statistics formula used in Kraaikamp and Meester (2005). See equation 3.5, where σ is the standard deviations, $z_{\alpha/2}$ is a number that represents the confidence interval and ε is the error. For this thesis a confidence interval of 95% seems reasonable to get a first glance at the results of the new developed adaptive approach. For this confidence interval the value of $z_{\alpha/2}$ is 1.96 (see table of z-values for confidence interval which can be found in several statistic books). The error will be different for every indicator and is dependent on the allowable error over several simulation. This will be discussed later on in this report. And this also concludes the METANET set

[1] Monitoring Casco: is used on the most freeways in the Netherlands as monitoring system (consists of: induction loops, VIC-net (communication infrastructure) and different data-servers)(Van Lint, 2005)

[2] See mathworks.com for more information about random noise in Matlab (Accessed on 10-07-2015)

up for this thesis.

$$N \geq \frac{\sigma^2 * z_{\alpha/2}^2}{\varepsilon^2} \tag{3.5}$$

3.2. Base set-up

Before the new adaptive approach can be developed a starting point has to be made in Matlab/METANET. The ALINEA-density variation in equation 3.6 and the PI-ALINEA variation in equation 3.7 are written in Matlab. The working of ramp metering is already explained in sections 1.3 and 2.3. The PI-ALINEA also has to be compared to the regular D-ALINEA algorithm because the PI-ALINEA used in this thesis has never been used before. This PI-ALINEA is adjusted, based on the PI-ALINEA introduced in Wang et al. (2010), towards the adaptive ramp metering controller (AD-RMC). The simulation will consist of several comparisons which were already denoted in section 1.6.1: the standard ALINEA (D-ALINEA) with several parameter values, the chosen variation (PI-ALINEA) and several variations of the new developed adaptive approach (AD-RMC). To get a good comparison in behaviour these standard variations will also be tested for different constant value for the critical density. The AD-RMC will also be tested with only the *Parameterschatter* active, only the gradient method active and with both active to get a good view on the behaviour of the estimator with and without each other.

$$r(k) = r(k-1) + K_{\mathrm{R}}[\hat{\rho} - \rho_{\mathrm{out}}(k-1)] \tag{3.6}$$

$$r(k) = r(k-1) + K_{\mathrm{P}} * [\hat{\rho} - \rho_{\mathrm{out}}(k-1)] + K_{\mathrm{I}} * \int_1^k (\hat{\rho} - \rho_{\mathrm{out}}(k-1))\,\mathrm{d}k \tag{3.7}$$

3.2.1. (De-)activation criteria

The ramp meter installation will switch on based on actual traffic conditions on the freeway, which makes it a traffic-responsive ramp metering installation. Criteria for switching on and off are described in Taale and Middelham (1991) and Burley and Gaffney (2013): The switch-on criteria are based on speed, occupancy/density and/or flow. The switch-on criteria are set to relative low threshold value to be sure that the ramp meter starts before the capacity of the freeway is reached (Burley and Gaffney, 2013). Burley and Gaffney (2013) also mentions that this criteria need to be comprehensive to avoid switching on at inappropriate times (e.g. slow moving maintenance vehicles at night). For switching off, stronger criteria are used to ensure signals will not start up again soon after deactivation which will irritate drivers (Burley and Gaffney, 2013). Because in this thesis simulation is done with the METANET model, a macroscopic traffic flow model, the exact green and red time does not have to be determined in the algorithm and are not considered in this thesis. Another switch off criteria is the queue length on the on-ramp. If the queue on the on-ramp exceeds a set threshold value the ramp meter installation will also switch off. To determine when the ramp meter installation is turned on or off some threshold values are defined for in this thesis. The values used in this thesis are similar as the values used in Taale and Middelham (1991), which are used in Dutch ramp metering systems. Below all values will be explained and summarized in Table 3.2.

The ramp meter installation will switch on when the flow on the road downstream of the on-ramp exceeds the threshold value for the capacity (capacity $*0.8$ veh/h) or as the actual speed downstream of the ramp drops below 50 km/h. Also between the lower bound value for speed (25 km/h) and a speed of 45 km/h the ramp metering installation will be activated. If the speed is higher than 70 km/h or lower than 25 km/h the ramp metering system will switch off. If the flow downstream is lower or equal than capacity $*0.7$ veh/h the ramp meter will also switch off. The ramp meter will still be switched off if the speed downstream of the ramp is above 45 km/h and the flow downstream of the ramp is lower than a certain threshold value for the capacity (capacity $*0.6$ veh/h). The capacity that will be used as threshold value will be constant for the PI-ALINEA and D-ALINEA algorithms. This will have a value of 2000 veh/h/lane. For the new approach this value will be variable and dependent on the estimated critical density and critical speed as will be explained in section 3.3. As a final constraint, but certainly not the least, the ramp meter will change the inflow when the maximum queue length is reached. This should account a bit for equity as discussed in section 1.6.2. This queue control should ensure that the TOD value is not too large. It is not desirable to let all vehicles in the queue on the ramp flow in the mainline at once, because this will cause an immediate deterioration of the situation on the mainline. Therefore a certain queue control law will determine the ramp metering rate when the maximum queue length has been reached. Because there is a certain delay between measuring the maximum queue length and the ramp metering rate for the next step, the threshold value for the queue length is 80% of the maximum queue length allowed on the ramp. The ramp metering rate will then be the current queue length (w) plus the demand on the ramp (d) minus the maximum queue length multiplied by 80%. In Table 3.2 an overview is given of the constraints used for ramp metering in this thesis. These constraints are important for switching on and off the ramp metering installation, such that the ramp metering installation is not on or off constantly but reacts to the actual traffic situation. These values are the same for all ramp metering algorithms that will be simulated during this research.

Table 3.2. – Constraint switching on/off for ramp metering

Constraint	**Ramp meter switch on/off**
q >= capacity $*0.8$ veh/h OR v =< 50 km/h	On
v < 45 km/h AND v >= 25 km/h	On
q =< capacity $*0.7$ veh/h OR v >= 70 km/h	Off
v >= 45 km/h AND q < capacity $*0.6$ veh/h	Off
v < 25 km/h	Off
Queue >= 200 vehicles * 80%	$r = w + d - 80\% * w_{\max}$
Capacity value D-ALINEA and PI-ALINEA	2000 veh/h/lane
Capacity value AD-RMC	variable

To prevent the ramp metering installation from switching on and off to fast there is a minimum metering time of 5 minutes. If the ramp metering switches off, it will not turn on again for 5 minutes.

3.3. Adaptive ramp metering controller

The idea behind the AD-RMC is discussed in section 2.7 with guidance of a figure. In this section the AD-RMC will be developed in MATLAB. The first step is the control law for the adaptive controller where both gains and the target density are updated every time step, which is as follows:

$$r(k) = r(k-1) + K_P(k) * [\hat{\rho}(k) - \rho_{out}(k-1)] + K_I(k) * \int_1^k (\hat{\rho}(k) - \rho_{out}(k-1))\, dk \qquad (3.8)$$

The other steps are denoted in the coming sections. In section 3.3.1 the gradient method, and thus the parameter update rule, will be developed and discussed. In the following section, section 3.3.2, the possible critical density estimation methods will be discussed and developed. The gradient method is developed with the help of Liu et al. (2007). The *Parameterschatter* is developed using the Hoogendoorn and Smits (See appendix A).

3.3.1. Gradient method

The next step is to program the gradient method into Matlab. The first step for the gradient method is to create a reference model to compare the target density from the reference model to the downstream density of the real model. The reference model determines the target density, which is around the critical density because the throughput of the freeway is maximized if the density is kept at the critical value (Dabiri and Kulcsar, 2014). The reference model should maximize the throughput of the freeway. This reference model actually exist in the ALINEA algorithm: $\hat{\rho}$. The error between the real model and the reference model is part of the ALINEA algorithm: $\hat{\rho} - \rho_{out}(k-1)$. A certain target density is desired to keep the situation on the mainline ideal. The actual density is measured downstream of the on-ramp and is compared to the desired target value. The conventional MRAC approach tries to converge this error to zero to get the desired state on the freeway. This is also done in the AD-RMC.

Because the error between target density and the downstream density should converge to zero a certain adaptive law is needed. This is the second step of developing the AD-RMC. The gain parameters of the control law (in this case equation 3.8) will be updated using a gradient method. The gains will be updated by minimizing the following objective function, where e is the error ($e(k) = \hat{\rho} - \rho_{out}(k-1)$):

$$J(\theta) = \frac{1}{2} e^2(\theta) \qquad (3.9)$$

Due to the complexity of this approach, the steps in Liu et al. (2007) are followed in this thesis. In their paper they use a discretized version of the control law and update rule which is better for computer implementation purposes according to Liu et al. (2007). The control law in this thesis is a bit different from the control law used in Liu et al. (2007), because in their paper a h is used and multiplied by K_I. In this thesis this h has no further use as the units add up and this value could be fused within the gain parameter, K_I, itself. This results in the following implemented control law in Matlab:

$$r(k) = r(k-1) + K_P(k) * [e(k) - e(k-1)] + K_I(k) * [e(k)] \qquad (3.10)$$

The gradient method is also implemented in a discretized version in this thesis. The steps from

literature are followed (Liu et al., 2007, Jain and Nigam, 2013) to come to the actual implemented parameter update rule. The first step is to derive the discretized version of equation 3.9. This is shown in equation 3.11, where θ is the parameter gain K_{P} or K_{I} and γ is the adaptation gain γ_P or γ_I:

$$\frac{d\theta}{dt} = -\gamma \frac{\partial J}{\partial \theta} = -\gamma e \frac{\partial e}{\partial \theta} \tag{3.11}$$

The next step is to translate this equation to the discretized version, which will be used in this thesis for implementation. The formulation of this version is as follows (with guidance of Liu et al. (2007)). The parameter from previous time step minus the adaptation gain γ (note that this value can be different for each update rule) multiplied by the sample time (T_s) multiplied by the error ($\hat{\rho}(k) - \rho_{\mathrm{out}}(k-1)$) which is multiplied by the error between two consecutive previous errors divided by the error between the parameter values. In Liu et al. (2007) the T_s is not present in the update formulas. The reason behind this is not clearly stated in their paper, but it could be because it has the value 1 or this value is fused in the adaptation gain. The update formula in discretized form is created with the Euler method ($\frac{K_{\mathrm{I}}(k)-K_{\mathrm{I}}(k-Ts)}{Ts}$), which also results in a sample time. This sample time should be in hours for this update rule because both gains are in km/h. The adaptation gain also makes up for dimensions, which should have the dimension $\frac{km^4}{veh^2 * h^3}$ in this case.

$$K_{\mathrm{P}}(k) = K_{\mathrm{P}}(k-1) - \gamma_P * T_s * e(k) * \frac{e(k-1) - e(k-2)}{K_{\mathrm{P}}(k-1) - K_{\mathrm{P}}(k-2)} \tag{3.12}$$

$$K_{\mathrm{I}}(k) = K_{\mathrm{I}}(k-1) - \gamma_I * T_s * e(k) * \frac{e(k-1) - e(k-2)}{K_{\mathrm{I}}(k-1) - K_{\mathrm{I}}(k-2)} \tag{3.13}$$

The problem with the gradient method of equations 3.13 and 3.12 is instability. When two consecutive values for the gains are the same, the denominator would become zero which leads to instability. This asks for certain conditions which indicate when to update the parameters and a certain condition which indicate what happens when the parameters should be updated but the consecutive values in the denominator for the parameters are the same. With the help of these conditions the zero division should be avoided and it should give more stability to the update rule.

Thus the parameter gains should not be updated under certain conditions. The first one, used for this thesis, is as follows. If the queue control is active or the error ($\hat{\rho}(k) - \rho_{\mathrm{out}}(k-1)$) is greater than +10 veh/km the parameter should not be updated and should have the same value as the previous parameter value. During queue control the error will get very large (very negative mostly), because the inflow of vehicles (on the mainline and on the ramp) is still too large to maintain a stable situation on the freeway but there is simply not enough storage space for vehicles which causes the traffic situation to deteriorate. The queue control just makes sure not all vehicles are directly released from the on-ramp to the mainline. The other condition, when the error is greater than +10 veh/km, is used because in this situation there is a stable situation (at least no traffic state close to congestion) on the mainline and updating the parameter is not needed and also ramp metering is probably not applied during this traffic state.

The second condition is applied when the difference between the downstream density during the current time step and the downstream density two time steps earlier is smaller than a certain value (α_{gains}). This value has to be determined on beforehand based on trial-and-error and the value can be different for certain situations. The choice for using the downstream density two time steps earlier

has to do with the noisy environment. When tested with no noise or only little noise the previous time step $(k-1)$ could also be used instead of two time steps earlier $(k-2)$. In a noisy environment there is a possibility that the measurement is slightly lower or higher than the actual traffic data. By using the two time steps earlier measurement it is better visible if the traffic situation is stable or not and hopefully errors in measurements are corrected this way.

The third and last condition when not to update the parameter gains is based on the improvement of the error. If the difference between two consecutive errors is greater than a certain threshold value the parameter should not be updated because the error has improved compared to the previous error. Also this condition is tested over a longer time period due to the noisy environment. The difference between the error at time step k should be larger than the error at time step $k-1$ but the error at time step $k-1$ should also be larger than the error at time step $k-2$. The difference between these errors should not only be positive but they also have to be greater than a certain threshold value, β_{gains}, which has to be determined on beforehand based on trial-and-error and can also be different for certain situations. By testing this condition for two consecutive errors the possible errors in measurements are hopefully avoided.

If none of the above mentioned conditions hold the parameter gains will be updated with the update rules stated in equation in equation 3.12 & 3.13. In case the two consecutive parameter gains have the same value it leads to zero division and one of these values should be updated to prevent this zero division. During careful testing of the gradient method and vary with several values the rule that seemed most plausible for this thesis is as follows. In all cases, except one, the previous parameter value $(\theta(k-1))$ is updated by taking 98% of the value of two time steps back $(\theta(k-2))$. It should not make a lot of difference if this is turned around and the parameter two time steps back is updated, the update rule should take this into account and converge to the right parameter gain value (after a time steps). It should also not make a lot of difference if instead of 98% a percentage of 102% is used. The values should just not differ too much and the error that is created by the specific percentage should be corrected by the update rule the next time step.

If it happens that these parameter values are very small (less than 0.5 km/h) the previous parameter$((k-1))$ will be updated by increasing $\theta(k-2)$ with 10%. This value is chosen because when the value tends to be small the denominator in the update rule tends to go to infinity which leads to an unstable process. If the value is updated with only a portion of the previous value (like 98%) the update rule will be unstable because the value gets even smaller. This also depends on the chosen initial values. It was found that if the parameter gain should be very small (like 1 or 2 km/h, which is the case for the integral gain K_I) to let the controller get reasonable results the chance that the denominator takes the update rule to infinity is much higher.

The complete algorithm for the gradient method with the before mentioned conditions and what values the parameter gains should get when two consecutive parameter gains have the same value is shown in Algorithm 1.

The MATLAB script for the AD-RMC, with this algorithm for the gradient method, can be found in appendix B.1.

The next step, which will be discussed in the next section, is to develop an estimation method for the critical density to determine the target density even better. The estimated value of the critical density will be used to update the target value in the error $(\hat{\rho} - \rho_{\text{out}}(k-1))$ of the gradient method. For estimating this critical density first three possible methods are tested:

- *Parameterschatter* (See appendix A)

Algorithm 1 Gradient method/Parameter update rule

if Queue control is active $\vee e(k) > 10$ veh/km **then**
    $\theta(k) = \theta(k-1)$
else if $|\rho_{out}(k) - \rho_{out}(k-2)| < \alpha_{gains}$ veh/km **then**
    $\theta(k) = \theta(k-1)$
else if $e(k) - e(k-1) > \beta_{gains} \wedge e(k-1) - e(k-2) > \beta_{gains}$ **then**
    $\theta(k) = \theta(k-1)$
else
    if $\theta(k-1) = \theta(k-2)$ **then**
        if $|\theta(k-1)| < 0.5$ **then**
            $\theta(k-1) = \theta(k-2) * 1.10$
        else
            $\theta(k-1) = \theta(k-2) * 0.98$
        end if
        $\theta(k) = \theta(k-1) - \gamma * T_s * e(k) * \frac{e(k-1)-e(k-2)}{\theta(k-1)-\theta(k-2)}$
    end if
end if

- Simple derivative estimation (Smaragdis et al., 2004)
- Derivative estimation based on the Kalman filter (Smaragdis et al., 2004)

All three aim at estimating the derivative of the fundamental diagram based on real-time measurements and using this derivative to update the critical density for that time step. In the next section these methods will be explained.

3.3.2. Parameterschatter

The *Parameterschatter* is based on a least squares method which is implemented with the guidance of Hoogendoorn and Smits (See appendix A). The equations have been denoted already in section 2.6.5 but will be repeated in this section. Also will the method be discussed more in detail.

To determine the derivative of the fundamental diagram the following linear equation applies where $(x, y) = (\rho, q)$ and $D(k)$ is the derivative of the fundamental diagram:

$$y = D(k) * x + b \tag{3.14}$$

The equation to determine the slope of this function and thus the derivative of the fundamental diagram is denoted in equation 3.15. The derivative is determined in a certain time interval which is denoted by T in this equation. The derivative will be determined over a few (60 seconds averaged) measurements coming from METANET. Because due to the stochastic environment the values coming from measurements are different from the actual values. Thus by taking the derivative over a certain time interval the derivative is taken over a few measurements and this will minimize errors.

$$D(k) = \frac{\sum_{i=k-T}^{T}(\rho(i) - \bar{\rho}) * (q(i) - \bar{q})}{\sum_{i=k-T}^{T}(\rho(i) - \bar{\rho})^2} \tag{3.15}$$

First an initial critical density is set and then the critical density gets updated when the value of the derivative meets a certain threshold value. The updating procedure is as follows as the derivative is greater than a certain threshold value (β^+) and this threshold value greater than zero, where α is a smoothing parameter:

$$\rho_{\text{crit}}(k) = \begin{cases} \alpha * \rho_{\text{crit}}(k-1) + (1-\alpha) * \rho_{\text{out}}(k) & \text{if } \rho_{\text{crit}}(k-1) < \rho_{\text{out}}(k) \\ \rho_{\text{crit}}(k-1) & \text{if } \rho_{\text{crit}}(k-1) \geq \rho_{\text{out}}(k) \end{cases} \tag{3.16}$$

If the derivative is smaller than a certain threshold value (β^-) and this threshold value is smaller than zero, the following equation holds:

$$\rho_{\text{crit}}(k) = \begin{cases} \alpha * \rho_{\text{crit}}(k-1) + (1-\alpha) * \rho_{\text{out}}(k) & \text{if } \rho_{\text{crit}}(k-1) > \rho_{\text{out}}(k) \\ \rho_{\text{crit}}(k-1) & \text{if } \rho_{\text{crit}}(k-1) \leq \rho_{\text{out}}(k) \end{cases} \tag{3.17}$$

Using the *Parameterschatter* also the critical speed can be estimated and thus the capacity can be determined, which value can be used to adjust switch on/off criteria. The determination of the critical speed uses the same update rule (thus also the same thresholds values β^+ and β^-) as for the critical density parameter. Only the smoothing parameter in this update rule for critical speed, which is in this case δ, can have a different value. When the critical density is found with the desired method, the target density in the ramp metering algorithm will be updated with this new critical density. The equation for updating the critical speed is stated in equation 3.18 and 3.19. The capacity is then updated by equation 3.20, where λ is the number of lanes with the critical density in veh/km/lane.

$$V_{\text{crit}}(k) = \begin{cases} \delta * V_{\text{crit}}(k-1) + (1-\delta) * V_{\text{out}}(k) & \text{if } V_{\text{crit}}(k-1) < V_{\text{out}}(k) \\ V_{\text{crit}}(k-1) & \text{if } V_{\text{crit}}(k-1) \geq V_{\text{out}}(k) \end{cases} \tag{3.18}$$

$$V_{\text{crit}}(k) = \begin{cases} \delta * V_{\text{crit}}(k-1) + (1-\delta) * V_{\text{out}}(k) & \text{if } V_{\text{crit}}(k-1) > V_{\text{out}}(k) \\ V_{\text{crit}}(k-1) & \text{if } V_{\text{crit}}(k-1) \leq V_{\text{out}}(k) \end{cases} \tag{3.19}$$

$$q_{\text{cap}}(k) = V_{\text{crit}}(k) * \rho_{\text{crit}}(k) * \lambda \tag{3.20}$$

The other two methods, the simple derivative estimation method and derivative estimation based on the Kalman filter, are introduced in Smaragdis et al. (2004) and the equations were also given in section 2.6.5. The principle for both methods is the same as for the *Parameterschatter*. The derivative of the fundamental diagram is determined in both methods, only the update rule for the critical value is different. During this thesis these two methods were tested and tried to implement as estimator but did not gave reasonable results for the situation in this thesis and will therefore not be used any further. Only the *Parameterschatter* will be used to update the target density of the control law.

The Matlab script for the *Parameterschatter* can be found in appendix B.2.

3.4. Overview development

In this section the development of the new adaptive control approach is given. The used algorithms will be repeated here, to maintain a certain overview.

The control law of the AD-RMC is similar to the existing PI-ALINEA in Wang et al. (2010). The actual control law implemented in this thesis is as follows:

$$r(k) = r(k-1) + K_P(k) * [e(k) - e(k-1)] + K_I(k) * [e(k)] \tag{3.21}$$

This control law will use initial inputs in the first time step. The other time steps the target density ($\hat{\rho}$) and the parameter gains (K_I, K_P) will be adjusted based on the actual situation. The target density will be updated by means of the *Parameterschatter*. Algorithm 2 shows the *Parameterschatter*.

Algorithm 2 *Parameterschatter*

Require: $D(k) = \frac{\sum_{i=k-T}^{T}(\rho(i)-\bar{\rho})*(q(i)-\bar{q})}{\sum_{i=k-T}^{T}(\rho(i)-\bar{\rho})^2}$

if $D(k) > \beta^+ > 0$ **then**

$$\rho_{crit}(k) = \begin{cases} \alpha * \rho_{crit}(k-1) + (1-\alpha) * \rho_{out}(k) & \text{if } \rho_{crit}(k-1) < \rho_{out}(k) \\ \rho_{crit}(k-1) & \text{if } \rho_{crit}(k-1) \geq \rho_{out}(k) \end{cases}$$

$$V_{crit}(k) = \begin{cases} \delta * V_{crit}(k-1) + (1-\delta) * V_{out}(k) & \text{if } V_{crit}(k-1) < V_{out}(k) \\ V_{crit}(k-1) & \text{if } V_{crit}(k-1) \geq V_{out}(k) \end{cases}$$

else if $D(k) < \beta^- < 0$ **then**

$$\rho_{crit}(k) = \begin{cases} \alpha * \rho_{crit}(k-1) + (1-\alpha) * \rho_{out}(k) & \text{if } \rho_{crit}(k-1) > \rho_{out}(k) \\ \rho_{crit}(k-1) & \text{if } \rho_{crit}(k-1) \leq \rho_{out}(k) \end{cases}$$

$$V_{crit}(k) = \begin{cases} \delta * V_{crit}(k-1) + (1-\delta) * V_{out}(k) & \text{if } V_{crit}(k-1) > V_{out}(k) \\ V_{crit}(k-1) & \text{if } V_{crit}(k-1) \leq V_{out}(k) \end{cases}$$

else

Do not update

end if

Simultaneously with the estimation of the critical density, the parameter gains are updated according to algorithm 3, where θ is K_I or K_P and γ is γ_I or γ_P. Values that are not defined in this section will be defined in the following section. The next section will give the simulation set-up including values for certain variables and the variations of ramp metering algorithms that will be compared towards each other.

Algorithm 3 Gradient method/Parameter update rule

if Queue control is active $\vee$ $e(k) > 10$ veh/km **then**
  $\theta(k) = \theta(k-1)$
else if $|\rho_{out}(k) - \rho_{out}(k-2)| < \alpha_{gains}$ veh/km **then**
  $\theta(k) = \theta(k-1)$
else if $e(k) - e(k-1) > \beta_{gains} \wedge e(k-1) - e(k-2) > \beta_{gains}$ **then**
  $\theta(k) = \theta(k-1)$
else
  if $\theta(k-1) = \theta(k-2)$ **then**
    if $|\theta(k-1)| < 0.5$ **then**
      $\theta(k-1) = \theta(k-2) * 1.10$
    else
      $\theta(k-1) = \theta(k-2) * 0.98$
    end if
    $\theta(k) = \theta(k-1) - \gamma * T_s * e(k) * \frac{e(k-1)-e(k-2)}{\theta(k-1)-\theta(k-2)}$
  end if
end if

4. Simulation

In previous section the adaptive ramp metering controller (AD-RMC) was developed using MATLAB. The AD-RMC from section 3 will be used in this section. Also the macroscopic traffic flow model, METANET, determined by an evaluation in section 2.2 will be used for simulation. The variations (standard D-ALINEA and standard PI-ALINEA) that will be used for simulation are given in section 3 and the new AD-RMC algorithm(s) has been summarized in section 3.4 (Algorithms 2 and 3). This section is a continuation on the answer of the main research question:

- *To which extent can adaptive control, by tuning all parameters of the ALINEA algorithm, improve ramp metering in terms of travel time?*

Thus in this chapter the simulation set up and evaluation indicators will be discussed. In the subsequent sections (5 and 6) the results of the simulations will be discussed and the main research question will be answered.

First in section 4.1 the simulation set up, including the network layout will be given. In this section it is also explained how the number of simulation are determined and also the evaluation indicators that will be used to evaluate the simulation runs will be discussed. In section 4.2 it will be discussed how the simulations will be executed and under which conditions and with which parameter values.

4.1. Simulation Set-up

In this section the simulation layout will be given in section 4.1.1. In section 4.1.2 the evaluation indicators will be explained, which will be used to evaluate the results from simulation. Also will be explained how the number of simulation runs are calculated and determined in section 4.1.3.

4.1.1. Network layout

All METANET parameters and settings where given in previous section (3.1). Only the layout of the network was not discussed yet. The layout of the network used for comparing the developed adaptive controllers consists of a stretch of road of 30 kilometres (30 segments of 1 km in METANET), this is used from the pre-defined METANET model of Hegyi et al. (2005). There is also an on-ramp located at 20 kilometres of the mainline. The ramp demand flows in at segment 20 of the network. The road segments are divided in segments of 1 km (L_m). The layout of the freeway is given in Figure 4.1.

The demand profiles for both the mainline and ramp are displayed in Figure 4.2. The demand has the same profile for every simulation run and is therefore not stochastic. Every simulation run (every random seed number) the same number of vehicles are simulated. The demand is set to zero at a certain point to be able to compare the control and no control scenarios. By setting the demand to zero at a certain time all vehicles will flow out of the network and the vehicle kilometres travelled will be equal in all (no-)control situations. This makes sure the comparison will be fair towards each other. This demand results in the freeway situation as shown in Figure 4.3. This situation, with the given demand, is ideal for applying ramp metering. Congestion occurs at the on-ramps on the mainline of the freeway, which indicates that due to a high flow from the ramp the flow exceeds the capacity of

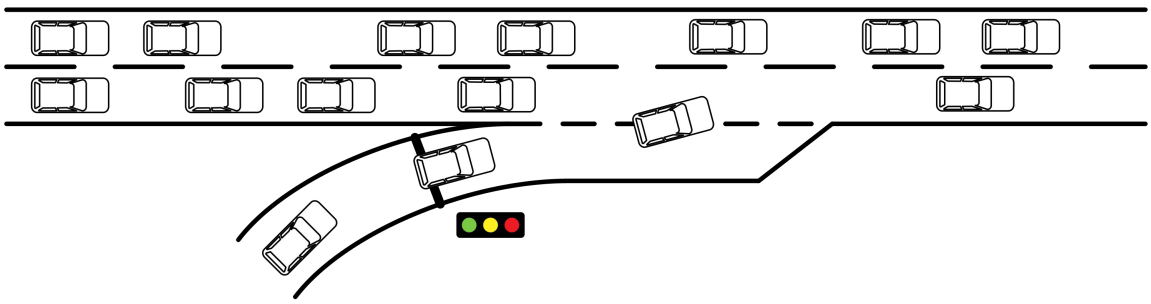


Figure 4.1. – Layout of the freeway during simulation

the road. Ramp metering is able to regulate the inflow from the ramp to postpone this congestion. The traffic management control measure (ramp metering in this case) and the measurements are updated every control time step of 60 seconds and consists of a total of 240 time steps (4 hours) in this METANET model. The METANET model itself is updated more frequently (thus the real/actual flow, speed and density etc.). The METANET model is updated every 10 seconds.

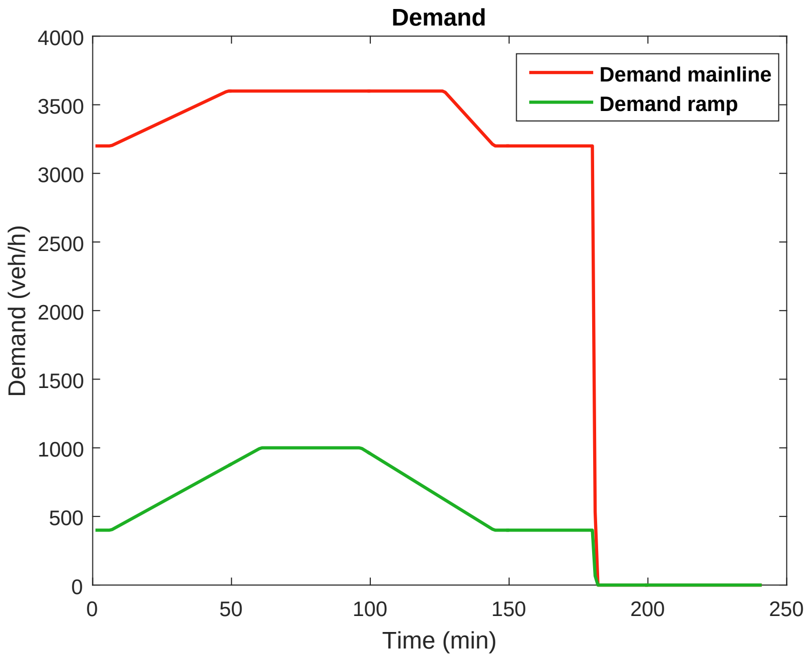


Figure 4.2. – Demand on the freeway

4.1.2. Evaluation indicators

For evaluating and comparing the different ramp metering approaches, the indicators described in section 1.6.2 will be used. The indicators are summarized below:

- Total time spent (in hours)
- Total on-ramp delay (minutes)

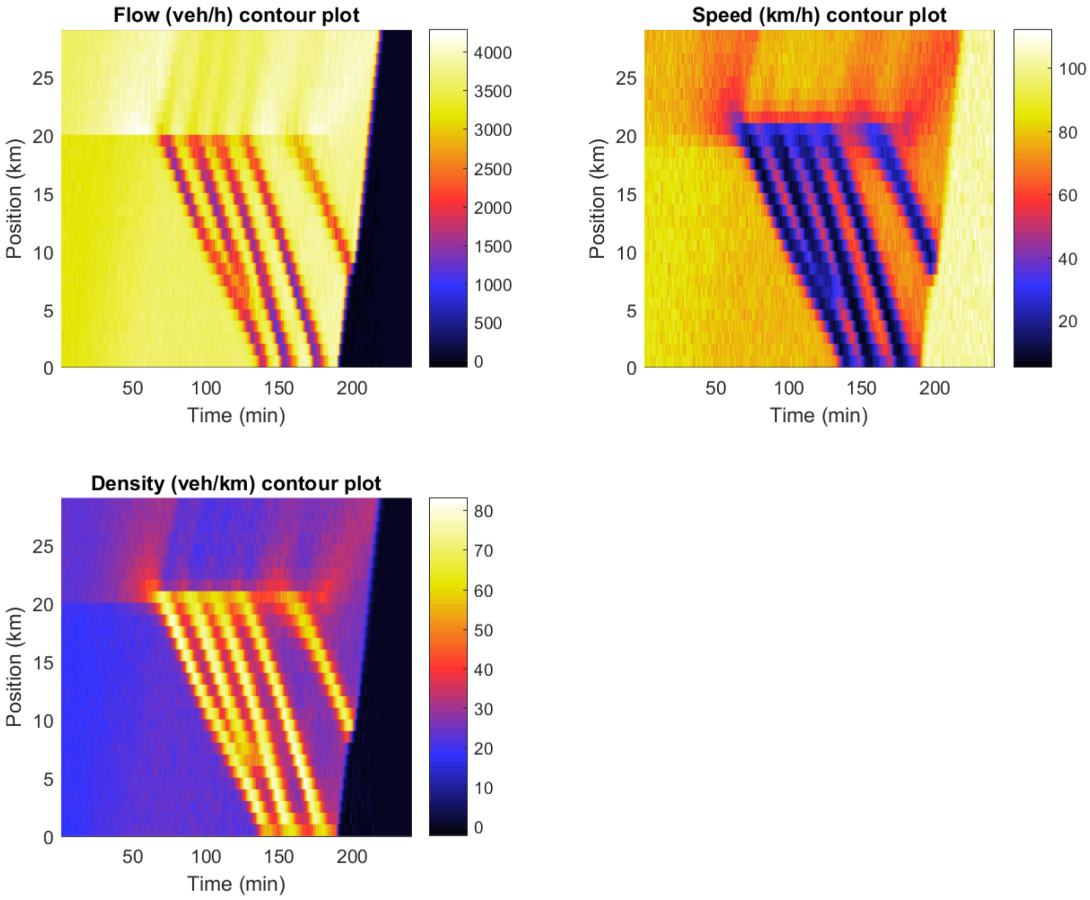


Figure 4.3. – Situation on the freeway in case of no control

- Average mainline travel time (in minutes)
- Total delay (in hours)

The first indicator, Total time spent (TTS), will be calculated with equation 4.1 with T the simulation time parameter of the METANET model, $\rho(:,k)$ the density per lane at every segment, λ the number of lanes, L the freeway length, $w_o(k)$ the queue at the origin and $w_R(k)$ the queue at the ramp.

$$\text{TVHT} = \text{TVHT}(k-1) + T * \left[\sum(\rho(:,k) * \lambda * L) + w_o(k) + w_R(k)\right] \tag{4.1}$$

The second indicator is the total on-ramp delay (TOD). The TOD is calculated as follows. First the number of vehicles (for free flow speed on the ramp and for the control situation) is calculated with equation 4.2. Secondly the areas under the graphs will be calculated and subtracted from each other

(free flow – control) times the simulation time step T (equation 4.3).

$$r_R(k) = r(k-1) + q_R(k-1)/60 \tag{4.2}$$

$$\text{TOD} = \left[\int_1^t (r_{R,v_f} * dk) - \int_1^t (r_{R,\text{Control}} * dk) \right] * T \tag{4.3}$$

The third indicator, average mainline travel time (AMTT), is calculated by the total kilometres length of freeway (L divided by the space mean speed over the whole simulation time and over the whole network ($\sum(\overline{V}_{m,i})$). This multiplied by 60 will give the AMTT per minute for the given situation. Equation 4.4 denotes the AMTT.

$$AMTT = L / \sum(\overline{V}_{m,i}) * 60 \tag{4.4}$$

The last indicator is the total delay. The total delay is calculated by first calculating the Total Free Flow Travel Time (TFFTT) of all vehicles during the simulation and compare this to the free flow travel time of all vehicles. The sum of the free flow travel time of the vehicles during simulation is calculated by taking the difference between the total number of vehicles on the end segment of the freeway and the total number of vehicles coming from the on-ramp ($N(k = 240) - N_R(k = 240)$). This number of vehicles is then multiplied with the travel time from origin to destination ($\frac{30}{v_f}$). The number of vehicles from the on-ramp to the destination are calculated by multiplying the total number of vehicles on the ramp ($N_R(k = 240)$) by the travel time from the on-ramp to the destination ($\frac{30-20}{v_f}$). This is described in equation 4.5. To calculate the total delay the TTS is subtracted by the TFFTT (TTS – TFFTT). This is summarized in equation 4.6.

$$\text{TFFTT} = (N(k = 240) - N_R(k = 240)) * \frac{30}{v_f} + N_R(k = 240) * \frac{30 - 10}{v_f} \tag{4.5}$$

$$\text{Total delay} = \text{TVHT} - \text{TFFTT} \tag{4.6}$$

The first three indicators, TTS, TOD and AMTT are often used for evaluating a ramp metering algorithm (Chu et al., 2004). These indicators are used because they give a good indication on the working of the algorithm and the improvement towards the no control situation when they are compared. The Total Delay indicator will be used to indicate how bad the situation actually is on the freeway and to indicate the improvement of the total delay when the variations are compared towards each other. The purpose of ramp metering is to reduce the delay and improve the TTS. With these indicators a good indication will be given on how much the situation on the freeway can be improved by using a certain ramp metering algorithm. Next to these indicators, which were already defined in section 1.6.2, also the capacity drop will be evaluated. The time the capacity drop occurs in the control situation and the time the capacity is postponed compared to the no control situation will also be taken into account. To determine these values a slanted cumulative curve will be used. From these slanted curves it can be determined at what time the capacity drop took place and how much minutes the capacity drop is postponed compared to the no control situation. Both these values will be in minutes. In section 5 several figures will be shown of slanted cumulative curves which will clearly show at what time the capacity drop took place.

In the next chapter the results will be presented in a certain way. The values will be compared eventually to every other variation and not towards a no control situation. After all, all the simulated variations do improve the traffic situation on the mainline compared to the no control situation unless stated otherwise.

4.1.3. Number of simulations

Because of stochasticity in the simulations, due to variable critical density and noisy measurements, the number of simulation have to be determined to get statistically reliable results. The number of simulation runs are determined by equation 4.7.

$$N \geq \frac{\sigma^2 * z^2_{\alpha/2}}{\varepsilon^2} \tag{4.7}$$

All values will be the same for all approaches that will be simulated which will give a good comparison. The z-value of the associated confidence interval will be 1.96 as explained in section 3.1.1. The standard deviation (σ) is calculated with equation 4.8, where N is the number of simulations and $\bar{x}$ is the sample mean (Kraaikamp and Meester, 2005):

$$\sigma = \sqrt{\frac{\sum(x-\bar{x})^2}{(n-1)}} \tag{4.8}$$

The error (ε) is different for each indicator named in section 4.1.2. For the indicators which are indicated in time (TTS, TOD, AMTT, Total delay) a error is used of 10 sec/veh. This error should be negligible and therefore a good choice. For TTS and total delay this means, with 13640 vehicles per simulation, the allowable error is 38 hours. For the TOD, which is also in hours but only applicable on the vehicles on the ramp (which are 2057 vehicles every simulation), this means approximately an error of 5.7 hours . For the indicator that is already in minutes and averaged over all vehicles (AMTT) the allowable error is $\frac{10}{60}$ min/veh. The minutes the capacity drop is postponed compared to the no control situation will have an allowable error of 2 minutes in this thesis. This also applies to the time the capacity drop takes place. Over a simulation time span of 240 minutes it is reasonable to choose for an error of 2 minutes for these two values. The minimum simulations that will be done will be 30 for this thesis. This will get a good view on the variety of the results, even if less simulations are needed.

4.2. Simulation conditions

In this section the several simulation conditions will be explained. The parameter values used for the different variations will also be discussed. Also why and why not certain variations will be simulated will be explained. For example there will be simulation runs with the same variation but with different values for the critical density. In section 4.2.1 the general simulation conditions will be discussed shortly. In sections 4.2.2 and 4.2.3 the parameter values for the specific variations will be discussed.

4.2.1. General simulation conditions

The random seed numbers used for simulation are the same for all variations. The seed numbers used are from 1, with steps of one, to the minimum number of simulations needed. For test simulation runs (for fine-tuning) random high seed numbers are used above 1000.

For all variations simulated a more downstream detector is used because the *Parameterschatter* does not work with the first downstream detector from the on-ramp and therefore the downstream detector that will be used for all variations and estimators is detector 22 (which is also in segment 22 of the METANET model). This is because of the second-order model METANET traffic where flows may not be represented like actual traffic. A simulation model will still have it flaws. One of them in this thesis seems to be the downstream detector. During test simulations it became clear that the density just downstream of the on-ramp (detector 21, which is still 1 kilometre downstream of the on-ramp) gave densities that exceeded the critical density of the METANET model. According to traffic flow theory the density downstream of a bottleneck does not exceed the critical density (Immers and Logghe, 2002). Thus after a bottleneck, in this case merging from the on-ramp to the mainline, the outflow from this bottleneck should be around the capacity and critical density. This is not the case in the METANET model at segment 21 (where the merging occurs at segment 20). In practice the downstream measurements that are used for ramp metering are just a few hundred meters downstream from the on-ramp/merging section. In the METANET model the segments are 1 kilometre thus the measurements (segment 22) are coming from 2 kilometres downstream of the on-ramp. The traffic variables values at this segment are in theory representative to the in theory correct values (close to the critical values during congested state). This issue can have some effect on the results of this thesis. But because in this thesis a new approach will be tested for the first time it should be enough to give an indication on the working of this algorithm. Also this detector is needed to get a right estimation of the critical density, because the *Parameterschatter* uses the downstream density to track which should be the critical density in case of upstream congestion. Because the *Parameterschatter* does not work properly with detector 21 (or further upstream detectors) in this thesis all algorithms (ALINEA, PI-ALINEA, AD-RMC and the *Parameterschatter*) will be used with the same measurement location (detector 22), which will give a better comparison of results at the end. An attempt was made to recreate an actual practice situation with noise on measurements and the correct measurement data for the *Parameterschatter* and ramp metering algorithms. For an other measurement location the *Parameterschatter* did not work properly in terms of the estimated critical density, which was often too high in test simulations (just like the measured density was greater than the model's critical density).

The value for the number of vehicles that can flow into the mainline is limited to the minimum inflow value as the lower bound value and the capacity of the ramp as upper bound value. The ramp meter rate updates the ramp flow according to the current situation on the mainline and on-ramp. The minimum value for the ramp rate (r_{min}) is set to 240 veh/h (found in Jacobson et al. (2006)), otherwise the ramp flow would be zero until the maximum admissible queue length has been reached and this is not desirable. Note that in the Netherlands the maximum value for the ramp rate in case of one lane on the on-ramp is 300 veh/h, in case of two lanes on the on-ramp this is 240 veh/h. In this thesis the value found in Jacobson et al. (2006) will be used, which therefore represents a two lane on-ramp. The maximum value for the ramp rate is in this case just the capacity of the on-ramp, 2000 veh/hour. In practice the maximum flow is lower and related to the cycle time of the ramp meter installation. In this thesis this is not considered which can give infeasible ramp meter values during simulation. In practice this ramp meter rate is thus also limited to a maximum ramp meter rate. In this

thesis the maximum ramp meter rate is not considered. This is because the response of the (adaptive) controller is important and will be better visible when the ramp meter rate is not limited by an upper value other than the ramp's capacity. The maximum queue length at the ramp is dependent on the ramp storage space. For this experiment the maximum queue length will be set on 200 vehicles. In Hegyi et al. (2005) a value of 100 vehicles is used, which seems reasonable for a one-lane on-ramp. But because in these first tests for a new approach the response will be better visible with a larger storage space, this value will be set on 200 vehicles. These values discussed in this paragraph apply to all variations that will be simulated.

The D-ALINEA and PI-ALINEA will both be simulated with a critical density, a bit lower than the actual density, of 30 veh/km/lane. Also will both algorithms be simulated with a higher critical density than the actual density, 40 veh/km/lane. This is to get a good picture on how well the variation responds to a predefined critical density above the actual critical density and below the actual critical density of the METANET model (which is stochastic). The critical density is used to set the target value of the algorithm. The algorithm tries to keep the density downstream of the on-ramp around this target density. Thus with a target density of for example 40 veh/km/lane, the algorithm tries to keep the downstream density at this value. This research will compare the variations towards each other and not towards the no control situation as long as the variation has an improvement towards the no control situation.

The AD-RMC will be simulated in three different variations. First the AD-RMC will be simulated with only the *Parameterschatter* active, second the AD-RMC will be simulated with only the gradient method active and at last it will be simulated with both estimators active. This is done because the response of both estimators will be visible and the research will show how well they perform alone and together. The AD-RMC with only the gradient method active will have a predefined constant critical density value of 30 veh/km/lane and will not be simulated with a constant critical density value of 40 veh/km/lane. All target values ($\hat{\rho}$) in the variations are defined by the following formula: $0.9 * \rho_{\text{crit}}$.

In section 5 the average results will be presented in a table. These tables will be assisted by a few figures. Not every variation will be assisted by the same figures. The figures that will be shown for some variations are the ramp meter rate, the response of the density and flow and the slanted curve to indicate how the capacity drop is determined. For the variation with estimators also the response of the concerned estimator will be given in a figure.

4.2.2. Parameter values D-ALINEA and PI-ALINEA

The PI-ALINEA and D-ALINEA algorithm used for comparison towards the AD-RMC have a constant value for the gain parameters (K_R = 80 km/h, K_I = 2 km/h, K_P = 80 km/h) and a constant value for the target density ($0.9 * \rho_{\text{crit}}$). The value for the gain of the D-ALINEA is taken from Wang et al. (2010). The occupancy version is used in Wang et al. (2010), but the unit (km/h) of the gain is the same for the density-based ALINEA and the occupancy-based ALINEA. Also 70 km/h is used a lot in other papers, but here is chosen for the value of 80 km/h. Several test simulation runs are done with this parameter value and it seems to give reasonable results for this variation of ALINEA. Thus based on Wang et al. (2010) and test simulation the value of K_R is chosen to be 80 km/h. The values for the gains of the PI-ALINEA are derived from Wang et al. (2010) and adjusted a bit. In Wang et al. (2010) the value for the gain K_I is 8 km/h and for the gain K_P is 200 km/h, but then again this is not the same PI-ALINEA as the PI-ALINEA used in this thesis. Also for these values several test simulations

are run (with different high number of seeds[1]) and the value for K_I = 2 km/h and for K_P = 80 km/h gave reasonable results. The constant critical density that will be used for simulation runs with the D-ALINEA and PI-ALINEA are already discussed in the previous section. In Table 4.1 an overview is given of all used parameter values, discussed in section 4.2.1 and 4.2.2, for the different (standard) variations.

Table 4.1. – Parameter values D-ALINEA and PI-ALINEA

Parameter D-ALINEA	Value	Parameter PI-ALINEA	Value
K_R	80 km/h	K_I	2 km/h
		K_P	80 km/h
ρ_crit	30 or 40 veh/km/lane	ρ_crit	30 veh/km/lane
r_{min}	240 veh/h	r_{min}	240 veh/h
w_max	200 vehicles	w_max	200 vehicles

4.2.3. Parameter values AD-RMC

The values for the parameters that have to be tuned in the algorithms (as shown in section 3.4) of the *Parameterschatter* (Algorithm 2) and the gradient method (Algorithm 3) will be discussed here. These parameters are for example the smoothing parameters and time interval of the *Parameterschatter*. Also the adaptation gains and thresholds value for the updating conditions of the gradient method will be discussed. These values are needed for simulation and it is important to tune these values for a certain situation. The values used in this research could not work entirely well for other case studies as described in this thesis. Most values had to be determined based on test simulation runs (trial-and-error). These test simulations were done in other random seed numbers than the seed numbers that will be used for the simulation runs. The most important values that had to be determined for the gradient method are the adaptation gains (γ_P and γ_I), the threshold values for the conditions (α_{gains} and β_{gains}) and the sample time T_s. The most important values for the *Parameterschatter* are the smoothing parameters (α and δ) and the thresholds values (β^+ and β^-). Another important aspect of the *Parameterschatter* is the value of time step T which is the interval length for determination of the derivative of the fundamental diagram. Also the initial value of the critical density for time step 1 to T has to be predefined.

The most crucial part of the design of the AD-RMC are the adaptation gains (γ_P and γ_I) of the gradient method (visible in equations 4.9 and 4.10). As is stated in Swarnkar et al. (2011) that the choice of this adaptation gain is critical. It is also dependent on the *Parameterschatter*. The adaptation gains are different with the *Parameterschatter* active than without the estimator active. Also when variables for the *Parameterschatter* change, the adaptation gains of the gradient method also have to be adjusted. If only simulation is necessary for the two estimators to work simultaneously, then the *Parameterschatter* should be developed before the gradient method. But because the AD-RMC is also tested and simulated without the *Parameterschatter*, the values for these adaptation gains have to be

[1]Other seed numbers will be used for final simulations than are used for these test simulation runs

determined in case the estimator is active and the case it is not active.

$$K_P(k) = K_P(k-1) - \gamma_P * T_s * e(k) * \frac{e(k-1) - e(k-2)}{K_P(k-1) - K_P(k-2)} \tag{4.9}$$

$$K_I(k) = K_I(k-1) - \gamma_I * T_s * e(k) * \frac{e(k-1) - e(k-2)}{K_I(k-1) - K_I(k-2)} \tag{4.10}$$

The AD-RMC, without the *Parameterschatter*, seems to give reasonable results with the value 0.6 $\frac{km^4}{veh^2*h^3}$ for γ_P and 0.02 $\frac{km^4}{veh^2*h^3}$ for γ_I. The difference between the value of the integral adaptation gain and the proportional adaptation gain has to do with the control law. The integral part should try to keep the control law close to the set value, whereas the proportional part tries the same but does this with more variation. Therefore the value of the integral gain should be kept small and therefore also the adaptation gain of the integral part (γ_I) is smaller than the adaptation gain of the proportional part (γ_P).

But in case the *Parameterschatter* is active, the *Parameterschatter* should be first fine-tuned before determining the values of these adaptation gains of the gradient method. Thus first the parameters of the *Parameterschatter* are defined due some test runs. For these test runs, as stated before, other random seed numbers are used in Matlab than for the actual simulations. The final values that will be used for simulation in the next section are as follows. The time interval T will be 6 and thus the derivative will be determined over six preceding measurements. Some initial values are needed before the critical density and critical speed is estimated. The initial critical density is set on 20 veh/km/lane which seems to give good results when the initial critical density is set low compared to the actual density (which is around 33.5 veh/km/lane). The initial capacity will be set on 2000 veh/h/lane, just as the D-ALINEA and PI-ALINEA will use as a constant. The initial critical speed will be set on 70 km/h, which seems reasonable to use as initial value. After some trial-and-error simulation runs the threshold values, β^+ and β^-, are determined on 10 km/h and -3 km/h, respectively. The absolute value of β^- is smaller than the value of β^+ because of the asymmetric shape of the fundamental diagram (Smaragdis et al., 2004), (See appendix A). In Hoogendoorn and Smits (See appendix A) these values are different (40 and -10, respectively) and they are dependent on the case study and should always be determined based on trial-and-error runs. As for the smoothing parameters, α and δ, there are a lot of possibilities and they are also dependent on time. If the measurements are averaged over a shorter time period (like 20 seconds) these smoothing parameters could be different than when the time period is longer (like 60 seconds as in this thesis). But for this thesis it happens that the smoothing parameters are exactly the same as in Hoogendoorn and Smits (See appendix A), where 20 seconds averaged measurements are used. The δ for the critical speed update equations is therefore 0.9 and the α is 0.8. These are all the values needed for the *Parameterschatter* used in this thesis.

The last thing to do is to determine the parameter values of the gradient method when the *Parameterschatter* is also active. As stated before these are the most difficult parameters to determine the correct values for, especially the adaptation gains need a lot of fine-tuning. These values can also change dependent on whether the *Parameterschatter* is active or not. Other values are determined easier. The sample time (T_s) of the gradient method should be in hours and has as value the time step in which the control law is updated. This time step the control law is updated is every minute thus the sample time should be $\frac{60}{3600}$ hours. The adaptation gains, γ_P and γ_I, are 1.0 $\frac{km^4}{veh^2*h^3}$ and 0.09 $\frac{km^4}{veh^2*h^3}$ for this thesis, respectively. The threshold values, α_{gains} and β_{gains}, are both 1.5 veh/km. Only

the adaptation gains (γ) are different for the case without the *Parameterschatter*. All these values followed from test simulation runs. The initial values for the gains, K_P and K_I, are the same as for the standard PI-ALINEA, 80 km/h and 2 km/h respectively.

In Table 4.2 and 4.3 the values used for simulation in this thesis are summarized as discussed in this section and section 4.2.1.

Table 4.2. – Parameterschatter parameter values

Parameter	Value
T	6 [-]
β^+	10 km/h
β^-	-3 km/h
α	0.8 [-]
δ	0.9 [-]
$\rho_\mathrm{crit}(1:T)$	20 veh/km/lane
$C(1:T)$	2000 veh/hr/lane
$V_\mathrm{crit}(1:T)$	70 km/h
r_{min}	240 veh/h
w_max	200 vehicles

Table 4.3. – Gradient method parameter values

Parameter	Value
γ_P (without *Parameterschatter*)	0.6 $\frac{km^4}{veh^2 * h^3}$
γ_I (without *Parameterschatter*)	0.02 $\frac{km^4}{veh^2 * h^3}$
γ_P (with *Parameterschatter*)	1.0 $\frac{km^4}{veh^2 * h^3}$
γ_I (with *Parameterschatter*)	0.09 $\frac{km^4}{veh^2 * h^3}$
α_{gains}	1.5 veh/km
β_{gains}	1.5 veh/km
T_s	$\frac{60}{3600}$ h
$K_\mathrm{P}(k=1)$	80 km/h
$K_\mathrm{I}(k=1)$	2 km/h
r_{min}	240 veh/h
w_max	200 vehicles

4.2.4. Validation

To test the simulated variations also under other circumstances a few simulation cases will also be simulated using a different demand profile. This demand profile fluctuates more to see the response of the controller towards sudden changes (instead of the gradually increasing demand profile) in the demand. Figure 4.4 shows the demand for validation purposes.

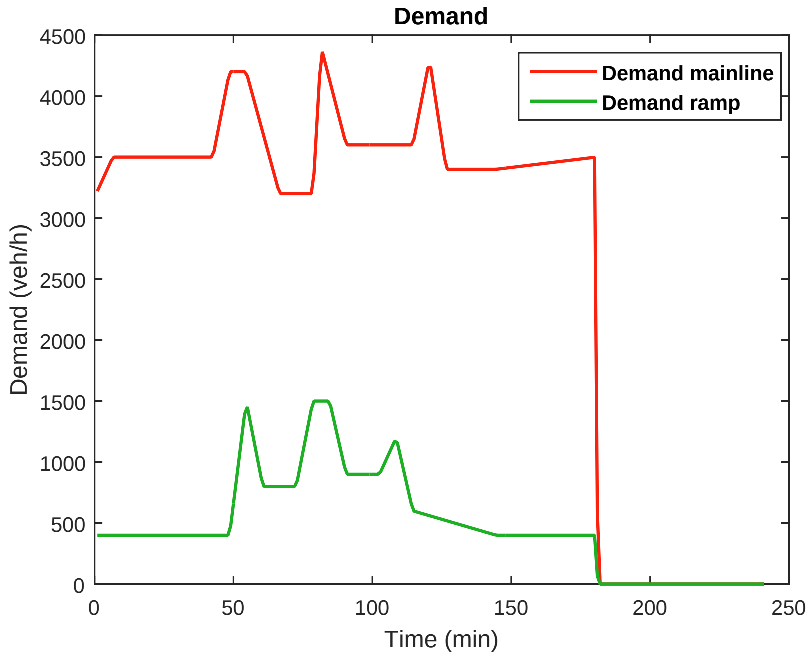
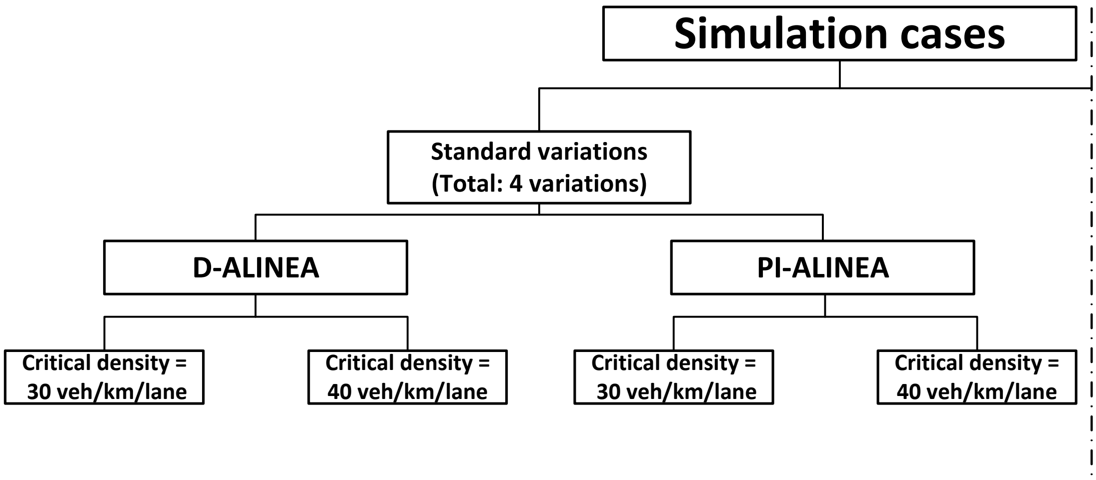


Figure 4.4. – Demand profile for validation

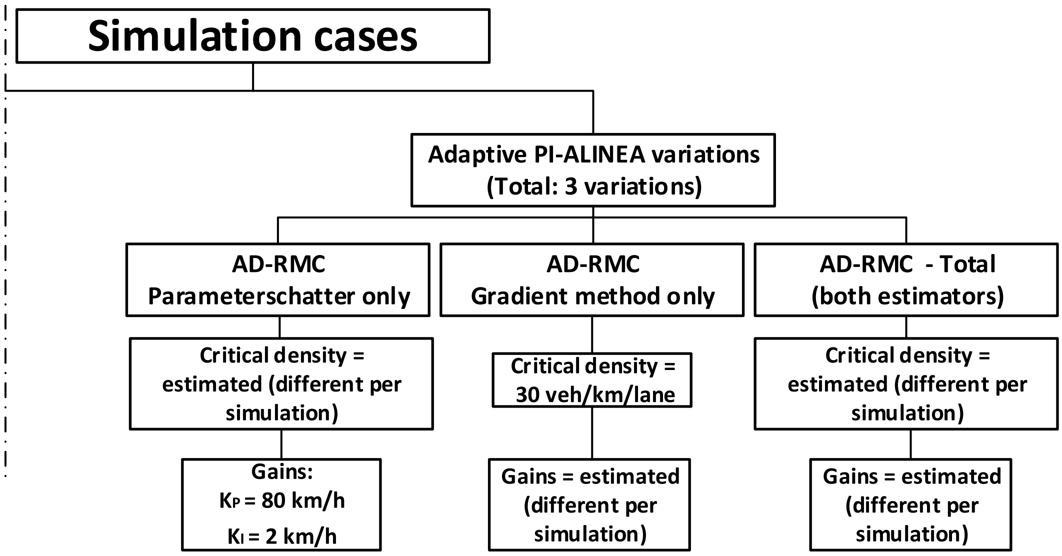
Not all simulated cases will be tested with this new demand. Especially the better performing AD-RMC variations (one or two) will be validated using this demand. For comparison purposes the D-ALINEA with a critical density of 30 veh/km/lane will also be simulated with this demand profile. In contrast to the simulation cases discussed in previous sections, the simulations for validation purposes will take the improvement towards the no control situation into account. This is because the travel time towards the simulation cases is different due to other demand. These validation cases will be compared towards each other by TTS, but towards the simulation cases by the improvement towards the no control situation. The validation cases will not be simulated as much as the simulation cases and will therefore not have statistically reliable results, but they will have an indication on how well the controller performs with a different demand profile. The validation cases will all be simulated ten times with different random seed numbers between 1 and 30.

4.3. Overview simulation experimental set-up

This concluding section will give an overview of the experimental set-up. Several variations will be simulated under several conditions, which is indicated in Figure 4.5. This figure shows all variations that will be simulated with corresponding information about the critical density and/or parameter gains.



(a) Simulation cases - standard variations



(b) Simulation cases - adaptive variations

Figure 4.5. – Simulation cases overview

For the standard variations the parameter gain values were given in previous sections (see Table 4.1). Other parameter values for the adaptive variations, like the adaptation gain of the gradient method, are given in previous sections also (See Table 4.2 and 4.3).

The simulation cases as in Figure 4.5 will be compared towards each other based on the previous mentioned indicators (TTS, TOD, AMTT, Total delay, time capacity drop is postponed and the time the capacity drop took place). Based on these results the cases will be evaluated which one performs best in terms of these indicators. Next to these simulation cases also some variations will be validated with a different demand profile as suggested in section 4.2.4. The standard D-ALINEA variation will be simulated for comparison purposes. The better performing AD-RMC variations will be tested also

using this demand. This is to test the working of the controller under different circumstances. Exact 10 simulations will be done for validation purposes, which give a good indication on the performance of the controller in case of a different demand profile. This concludes this section and also the experimental set-up for this thesis. In the next section the new controller will be simulated and compared to the other variations.

5. Simulation Results

In previous section the simulation set up was discussed. The way simulation is executed for the several variations and for the adaptive ramp metering controller (AD-RMC) that was developed using MATLAB was discussed in previous section. The simulation cases and validation cases were given in previous section. The results of the simulations of the ALINEA variations and the AD-RMC from section 3 will be discussed in this section. This section is a continuation on the answer of the main research question, which will be finally answered in section 6:

- *To which extent can adaptive control, by tuning all parameters of the ALINEA algorithm, improve ramp metering in terms of travel time?*

Thus in this chapter the developed AD-RMC will be simulated and evaluated using the macroscopic second-order traffic flow model METANET. As has been shown in previous sections the METANET model uses standard parameters, except the critical density which is variable. Also the measurements coming from the METANET model does contain noise. The AD-RMC will be compared to a no-control case, a standard D-ALINEA controlled case and a PI-ALINEA controlled case. The results will in particular be presented in this section, where the subsequent section will discuss these results. Also in the subsequent section (6) the main research question will be answered and some recommendations will be given to conclude this research. The expectations are that adaptive control can tune the parameters of the ramp metering algorithm such that the parameters are adjusted the right way and the algorithm will improve the traffic situation compared to standard algorithms.

In section 5.1 and 5.2 respectively, the standard variations, D-ALINEA and PI-ALINEA, and the AD-RMC will be simulated and the results will be discussed. In these sections the results will be presented and some figures will be given. The results between several simulation runs of the variation will be discussed. The actual comparison will be done in the following section, where all variations will be compared towards each other. In section 5.3 a summary of all results of the simulations will be given and the variations will be compared towards each other. Several tables and figures will be given and discussed in this section to show the response and performance of the different simulated variations. To show the working of the better performing AD-RMC variations and for comparison purposes the D-ALINEA (ρ_{crit} = 30 veh/km/lane) these algorithms will be validated with another demand profile as given in previous section. This is discussed in section 5.4.

5.1. Standard variations

In this section the ALINEA algorithm with constant values will be simulated and the results will be evaluated. The value for the regulator parameter (K_{R}) is set to 80 km/h and the target density is set to the critical density downstream of the on-ramp multiplied by 0.9. This simulation will use the values of 30 veh/km/lane and 40 veh/km/lane for the critical density. These values have been discussed in previous section. Also in this section the PI-ALINEA algorithm with a constant value for the critical density will be simulated and the results will be evaluated. The value for the regulator parameters K_{I} and K_{P} are set to 2 km/h and 80 km/h, respectively. Also here the target density is set to the critical density downstream of the on-ramp multiplied by 0.9. This simulation will use the

value of 30 veh/km/lane and 40 veh/km/lane for the critical density, as discussed in section 4.2.

5.1.1. D-ALINEA - $\rho_{\text{crit}} = 40$ veh/km/lane

The Table 5.1 shows the average results coming from 90 simulation runs for the D-ALINEA variations with a critical density of 40 veh/km/lane. This critical density results in a target density in the algorithm of 36 veh/km/lane. This target density is higher than the actual critical density of the METANET model. As explained before, the critical density of the traffic flow model fluctuates around 33.5 veh/km/lane. The average values in the table will be compared towards the other simulated variations in section 5.3.

Compared to the other simulated variations, which will be discussed next, this algorithm needed a lot of simulation runs to get statistically reliable results. This means a lot of diversity was present in the results between simulations. So did one of the best performing simulation runs for this algorithm gave a TTS of 6406 hours, where one of the least performing simulation runs gave a TTS of 6700 hours which is a difference of 294 hours. In total it is a huge difference, per vehicle (with 13640 vehicles over the whole simulation period) it is a difference of 1.29 minutes per vehicle. The total delay variates from 2800 hours to 3095 hours which is a difference of a total delay of 1.30 minutes per vehicle. The AMTT variates a bit less, as it variates between 25.34 minutes to 26.23 minutes and thus a difference of 0.93 minutes per vehicle. The TOD variates between 9.88 hours and 51.87 hours which is a difference of 1.22 minutes per vehicle on the ramp. Another example is the time the capacity drop is postponed compared to the no control situation is only around 10 minutes, where in other simulation runs it is even more than 20 minutes. The time it is postponed is of course in relation with the time step wherein the capacity drop took place. This varies between time step (k) 72 up till time step 86. When the capacity drop is postponed later, the TTS is also lower and thus the algorithm performs better in terms of travel time performance. The time the capacity drop took place and the time it is postponed compared to the no control situation is determined with Figure 5.1 (all other variations determine this the same way). It is visible in this figure that the control line drop much later than the no control line. This drop in number of vehicles indicates the capacity drop. The difference between those drops is the time the capacity drop is postponed compared to the no control situation, the time it drops is the time the capacity drop took place.

Table 5.1. – Average results ALINEA - $\rho_{\text{crit}} = 40$ veh/km/lane

Indicator	Average result (90 simulations runs)
TTS	6522.94 h
TOD	26.87 h
AMTT	25.77 min
Total delay	2914.93 h
Capacity drop postponed	18.51 min
Time capacity drop took place	83.10 min

Some indicators are related towards each other. An example, which is clear from simulation results, is that when the TOD is larger the TTS is overall lower. When the ramp meter installation responds

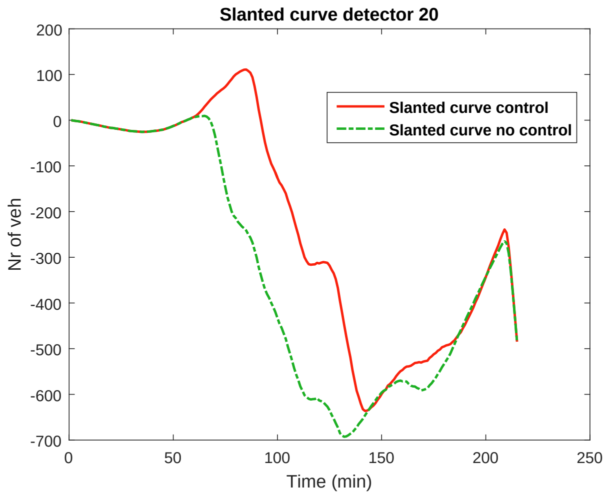


Figure 5.1. – Slanted curve - ALINEA - ρ_{crit} = 40 veh/km/lane - average results

better to the current traffic states it will try to limit the inflow more from the ramp to the mainline which will increase the delay on the on-ramp. The ramp metering algorithm improves the overall throughput by trying to distribute the traffic better over the time period. The ramp meter rate, and thus the response of the ramp meter installation, during average results as in the previous table is shown in Figure 5.2. The ramp meter rate values in this figure (and for coming figures for other variations) are not feasible in practice. In section 4.2.1 it was already explained that for the purpose of this thesis this was not considered. This has to do with the cycle time of the ramp metering installation, which is not considered in this thesis. This figure with ramp meter rate values, compared with Figure 5.3(b), makes clear that the ramp meter installation has some delay in responding to the actual situation and also deactivates early. This is caused by the choice of the critical density which is 40 veh/km/lane and far above the actual critical density. The ramp metering installation is activated when the actual density downstream has exceeded the target value of 36 veh/km/lane. The target value is higher than the actual critical density and this causes the ramp meter installation to respond later than it should. The choice of the target value is therefore crucial. Also the queue control is clearly visible, from approximately time step 80 till time step 125, where the ramp meter rate is constant and when the queue is less the ramp meter rate gradually decreases until below the threshold value (80% of the maximum allowable queue) and then the normal ALINEA algorithm is activated again. This queue control is visible in most these figures for all simulation cases.

The response of the ALINEA algorithm is visible in the Figure 5.3 where the algorithm tries to keep the flow and density around the (average) capacity and target density value (36 veh/km/lane in this case). It is visible that this ALINEA variation tries to keep the flow and density much higher for a longer time period than in the no control situation. The principle, postpone the capacity drop, of ramp metering is therefore visible in these figures. After a while, when the storage space for vehicles on the ramp exceeds the threshold value, the flow cannot be maintained around capacity and will drop just like in the no control case. The lines in these figures for the critical density and the capacity are assumed. They are approximately the average values for the whole simulation period. The critical density is variable (and thus also the capacity as the capacity is the critical density multiplied by the critical speed) as there is noise on this parameter in the METANET model. Therefore these lines only indicate an assumed average value.

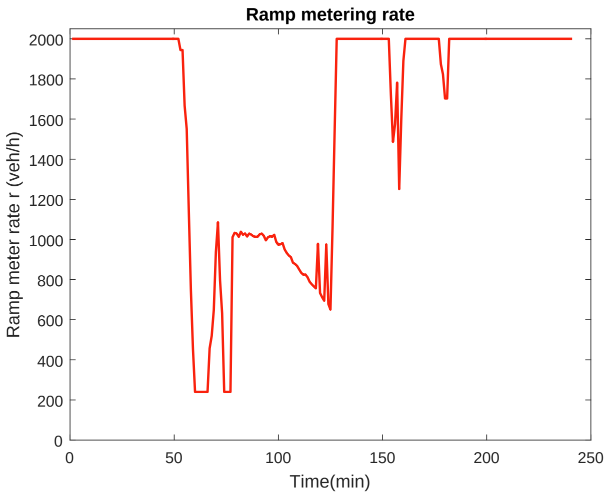
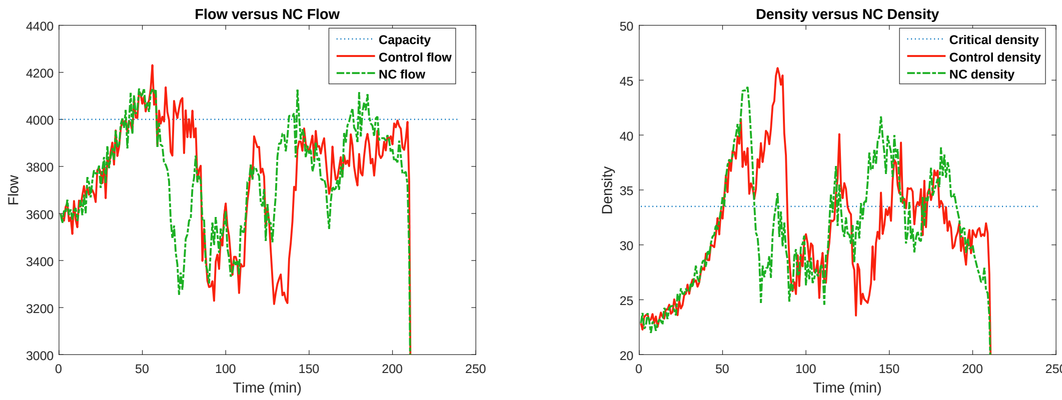


Figure 5.2. – Ramp metering rate - ALINEA - $\rho_{\text{crit}} = 40$ veh/km/lane - average results



(a) Flow comparison (b) Density comparison

Figure 5.3. – ALINEA - $\rho_{\text{crit}} = 40$ veh/km/lane - average results

5.1.2. D-ALINEA - $\rho_{\text{crit}} = 30$ veh/km/lane

The second variation of the D-ALINEA uses a lower target value ($\hat{\rho} = 27$ veh/km/lane) than the actual critical density and is more common to use in practice situations. In Table 5.2 the average results are shown based on 30 simulation runs. Less than 30 runs were enough, but 30 simulation runs are taken as a minimum number of runs to get sufficient results. This variation is therefore very constant in its results and does not variate as much as some other variations tested in this thesis (for example previous variation with a critical density of 40 veh/km/lane). One of the best simulation runs for this variation gave a TTS of 6479 hours, where one of the worst case simulations gave a TTS of 6614 hours which is a difference of 135 hours. In total it is a huge difference, per vehicle (with 13640 vehicles over the whole simulation period) it is only a difference of 0.59 minutes per vehicle. The total delay variates from 2871 hours to 3006 hours which is a difference of a total delay of 0.59 minutes per vehicle. The AMTT variates even less, as it variates between 25.20 minutes to 25.59 minutes and thus a difference of 0.39 minutes per vehicle. The TOD variates between 67.02 hours and 71.23 hours which is a difference

of 0.12 minutes per vehicle on the ramp. It can be concluded that this is a viable variation because the results are predictable and will not have much variation for different situations on the freeway. Despite the better average results of the previous discussed variation, it had a lot of variety in results. Between these two variations it is debatable which one performs better than the other. For a more detailed comparison see section 5.3.

Table 5.2. – Average results ALINEA - ρ_{crit} = 30 veh/km/lane

Indicator	**Average result (30 simulations runs)**
TTS	6543.83 h
TOD	69.38 h
AMTT	25.36 min
Total delay	2934.94 h
Capacity drop postponed	14.53 min
Time capacity drop took place	79.20 min

In Figure 5.4 the average ramp meter rate for this variation is shown. The ramp meter installation activates a bit earlier than for example the previous D-ALINEA variation, because the target value is set lower. This variation is also turned off much later because it is only turned off when the measured density is lower than the target value. Thus the ramp meter installation does regulate the inflow longer than the other D-ALINEA variation with 40 veh/km/lane as critical density. However, this does not immediately mean the performance is better as can be seen in the difference in average TTS between both variations.

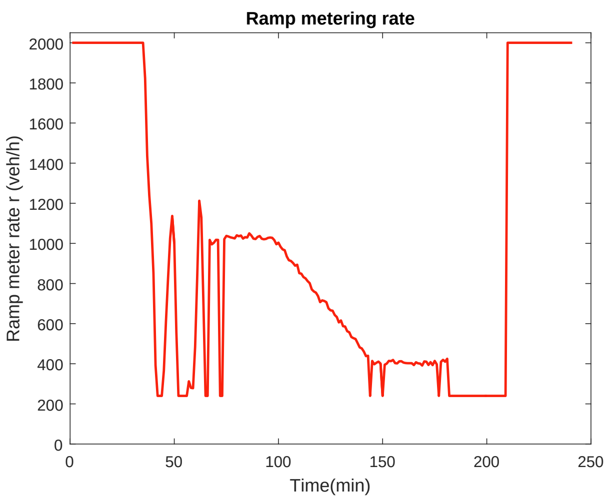
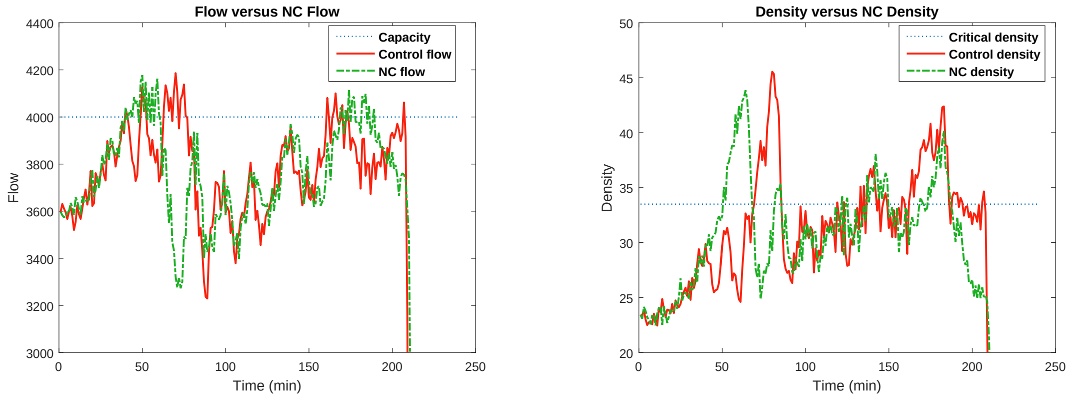


Figure 5.4. – Ramp metering rate - ALINEA - ρ_{crit} = 30 veh/km/lane - average results

Figure 5.5 shows the flow and density that belong to the response of the ramp meter installation. It is clearly visible that ALINEA tries to keep the flow around capacity value until the storage space of the on-ramp has been exceeded. It is also visible that ALINEA tries to keep the density much lower

for a certain time than in the no control situation to postpone the capacity drop and thus congestion. The capacity drop is postponed for 14.5 minutes on an average simulation run. Instead of showing a slanted curve, this can also be seen from Figure 5.5(a). The difference between the time the flow drops below capacity in the no control situation and the control situation is the time the capacity drop is postponed. However, the slanted curve is more precise and more clear. The capacity drop values are determined by observing the slanted curves for every variation.



(a) Flow comparison (b) Density comparison

Figure 5.5. – ALINEA - ρ_{crit} = 30 veh/km/lane - average results

5.1.3. PI-ALINEA - $\rho_{\text{crit}} = 40$ veh/km/lane

The first PI-ALINEA, with a predefined critical density of 40 veh/km/lane (and thus a target value of 36 veh/km/lane), did not give any improvement towards the no control situation during simulations. In all simulation runs (a few simulation runs were done) the ramp metering installation was not activated once. This was also visible in the results of the TOD indicator (it was zero, thus no delay on the on-ramp) and the time the capacity drop is postponed compared to the no control situation (zero hours). Therefore it is also not interesting to show the results in a table as in this thesis only algorithms with an improvement towards the no control situation are relevant. The PI-ALINEA with a predefined critical density higher than the actual density does not activate the ramp metering installation which causes no improvement at all for the traffic situation on the freeway. This situation, where the ramp metering installation is not activated, may happen because the extra integral term in the algorithm tries to keep the actual density closer to the target value ($0,9*$ critical density). In this situation the algorithm tries to keep the density downstream of the on-ramp close to this density value of 40 veh/km/lane. To keep this density high, also the ramp flow should be high. The suggested ramp flow coming from the algorithm could be higher than the capacity of the ramp (2000 veh/h) to reach the target value in the algorithm. This could be happening, which results in no activation of the ramp metering algorithm as the ramp meter rate is bounded by the capacity of the on-ramp in this thesis.

5.1.4. PI-ALINEA - $\rho_{\text{crit}} = 30$ veh/km/lane

This PI-ALINEA uses a lower target value ($\hat{\rho}$ = 27 veh/km/lane) than the actual critical density. In Table 5.3 the average results are shown based on 30 simulation runs, which were more than enough

runs but as discussed before 30 simulation runs is taken as a minimum number of runs to get sufficient results. Just like the D-ALINEA with critical density set to 30 veh/km/lane, this variation is also very constant in its results. The D-ALINEA has a bit less variation. One of the best simulations runs for this variation gave a TTS of 6383 hours, where one of the worst case simulations gave a TTS of 6581 hours which is a difference of 198 hours. In total it is a huge difference, per vehicle (with 13640 vehicles over the whole simulation period) it is only a difference of 0.87 minutes per vehicle. Whereas the D-ALINEA with a critical density of 30 veh/km/lane had a difference of 0.59 minutes per vehicle for the best and worst result. But also this variation is viable for a lot of situations and applicable to different road segments because the results are predictable and will not have much variety in results under different circumstances (in this case different random seed numbers). The other variations between lowest and upper bound values for the indicators are as follows. The total delay variates from 2776 hours to 2972 hours which is a difference of a total delay of 0.86 minutes per vehicle. The AMTT variates between 25.05 minutes to 25.56 minutes and thus a difference of 0.51 minutes per vehicle. The TOD variates between 66.66 hours and 70.36 hours which is a difference of 0.11 minutes per vehicle on the ramp. This is the only indicator which has less variation than the indicators from the D-ALINEA with 30 veh/km/lane as critical density.

Table 5.3. – Average results PI-ALINEA - ρ_{crit} = 30 veh/km/lane

Indicator	Average result (30 simulations runs)
TTS	6465.99 h
TOD	68.12 h
AMTT	25.25 min
Total delay	2856.58 h
Capacity drop postponed	16.5 min
Time capacity drop took place	81.17 min

The ramp meter rate for the PI-ALINEA is visible in Figure 5.6. The ramp meter rate falls fairly fast to the minimum ramp meter rate (240 veh/h), which we have seen for all above variations, and also has not a lot of variation in ramp meter values (not much peaks in this figure).

In Figure 5.7 the same behaviour can be seen as for the previous discussed D-ALINEA (with $\hat{\rho}$ = 27 veh/km/lane). The algorithm attempts to keep the flow around the capacity and attempts to keep the density around the target value. This works well until the queue threshold value is exceeded on the ramp. Queue control sets in and more vehicles flow into the mainline than there is capacity. At that moment also the capacity drop sets in as can also be seen in this figure (the drop of flow under the capacity line). The capacity drop is postponed longer for this variation than for the previous discussed D-ALINEA (with $\hat{\rho}$ = 27 veh/km/lane). The other D-ALINEA (with $\hat{\rho}$ = 36 veh/km/lane) postpones the capacity drop longer than this PI-ALINEA (on average 2 minutes in favour of the D-ALINEA with 40 veh/km/lane as critical density), but as discussed before the D-ALINEA needed more simulations for statistically reliable results. The TTS of this PI-ALINEA is lower than for both D-ALINEA variations. In terms of TTS the PI-ALINEA is performing better than both D-ALINEA variations. But also in terms of AMTT and total delay it performs better than both D-ALINE variations. In section 5.3 an overview will be given of all these indicators compared to other simulation

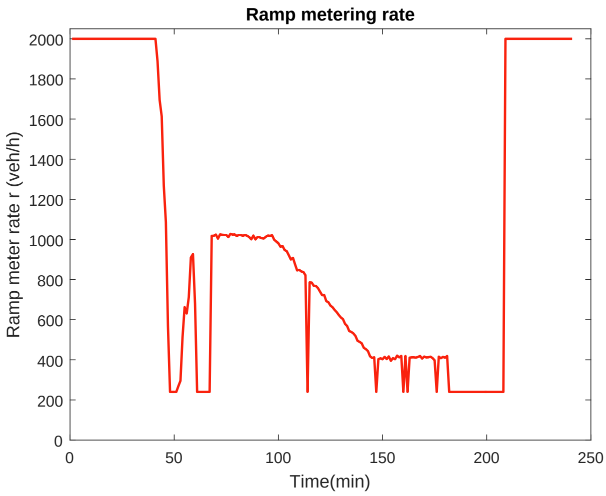
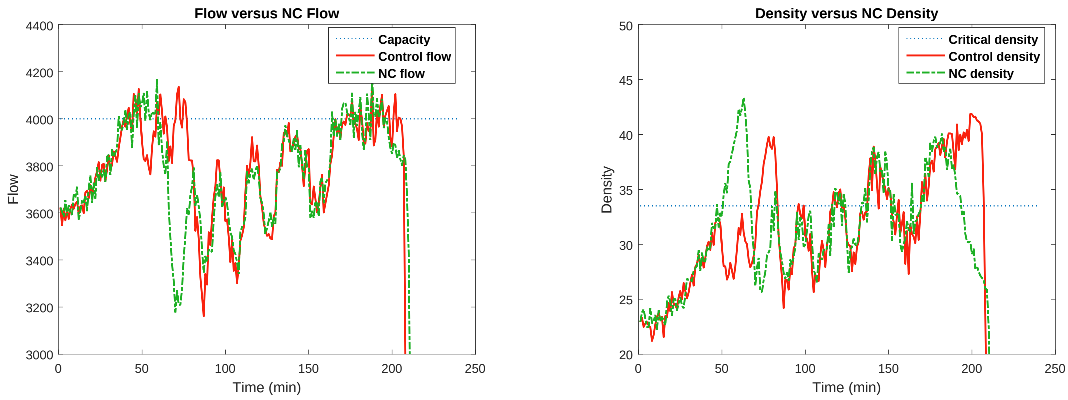


Figure 5.6. – Ramp metering rate - PI-ALINEA - ρ_{crit} = 30 veh/km/lane - average results

cases.



(a) Flow comparison (b) Density comparison

Figure 5.7. – PI-ALINEA - ρ_{crit} = 30 veh/km/lane - average results

It is visible in the Figures 5.3, 5.5 and 5.7 that the choice of the critical density value is determinative. The choice for 30 veh/km/lane also results in lower flow and density values. This contrast can be seen in the figure for D-ALINEA with 40 veh/km/lane as critical density compared to the figures for the D-ALINEA and PI-ALINEA with 30 veh/km/lane as critical density. The density and flow is tried to keep lower when the critical density is set to 30 veh/km/lane. This does not immediately result in better performance in terms of TTS. However, it seems that with 30 veh/km/lane as critical density the results are more constant as the D-ALINEA and PI-ALINEA with this critical density value both only needed 30 simulation. The D-ALINEA with 40 veh/km/lane as critical density needed a lot more simulations (90) and had more variety in terms of TTS.

5.2. Adaptive ramp metering controller variations

In this section the AD-RMC will be tested using only the *Parameterschatter*, only the gradient method and a variation where the estimator and the gradient method are used simultaneously. Section 5.2.1 will show the results of the AD-RMC with only the *Parameterschatter*. Next in section 5.2.2 the AD-RMC with only the gradient method will be discussed. At last in section 5.2.3 the complete AD-RMC will be discussed.

5.2.1. AD-RMC - *Parameterschatter*

This variation is in fact the PI-ALINEA with a critical density estimator, the *Parameterschatter*. The critical density estimator tries to estimate the correct critical density instead of using a constant set value as is shown in previous sections. An average simulation run with the *Parameterschatter* yields the results given in Table 5.4. There were 88 simulation runs needed. One of the best simulations runs for this variation gave a TTS of 6311 hours, where one of the worst case simulations gave a TTS of 6615 hours which is a difference of 304 hours. In total it is a huge difference, per vehicle (with 13640 vehicles over the whole simulation period) it is a difference of 1.34 minutes per vehicle (for comparison: the most stable D-ALINEA has a difference of 0.59 minutes per vehicle). The total delay variates from 2703 hours to 3007 hours which is a difference of a total delay of 1.34 minutes per vehicle. The AMTT variates between 25.03 minutes to 25.86 minutes and thus a difference of 0.83 minutes per vehicle. The TOD variates between 20.88 hours and 66.17 hours which is a difference of 1.32 minutes per vehicle on the ramp. An explanation for this variety (compared to the more constant results of the D-ALINEA and PI-ALINEA) can be that in some simulation runs the estimator did not gave correct values for the critical density which immediately can result in a worse response of the algorithm than with correct values. But most of the time the *Parameterschatter* did estimate the critical density nearly perfect using the earlier specified settings.

Table 5.4. – Average results AD-RMC - *Parameterschatter*

Indicator	**Average result (88 simulations runs)**
TTS	6441.57 h
TOD	42.29 h
AMTT	25.46 min
Total delay	2833.44 h
Capacity drop postponed	19.60 min
Time capacity drop took place	84.20 min

That there is a lot of variation in the results can also be derived from Figure 5.8. The ramp meter rate fluctuates a lot which is caused by the estimation of the critical density. The value changes a lot because the estimator keeps changing the critical density based on the downstream measured density. The target value is derived from this critical density and therefore can explain the fluctuations in the ramp meter rate. As this figure is compared to the figures of the standard variations, there is clearly more variation in ramp meter values. The ramp meter is even active from almost the beginning, instead

of only activated later as in the standard variations (around $k = 50$ for the standard variations). This can happen because the initial critical density is quite low (20 veh/km/lane) and thus the algorithm tries to keep the actual density at that value. In Figure 5.9(b) it can be seen that the actual measured density from the start of the simulation is already almost 25 veh/km/lane.

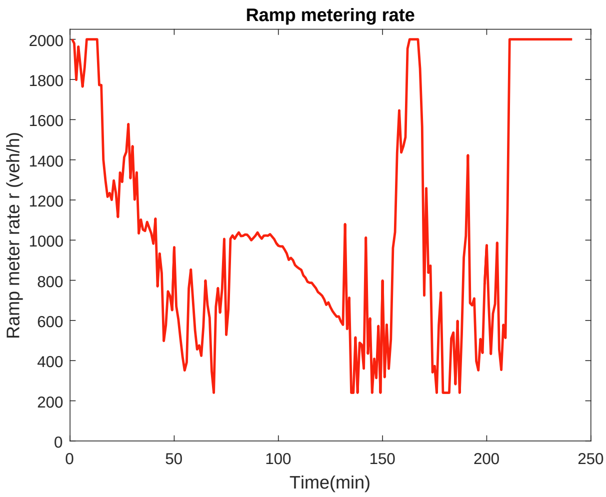
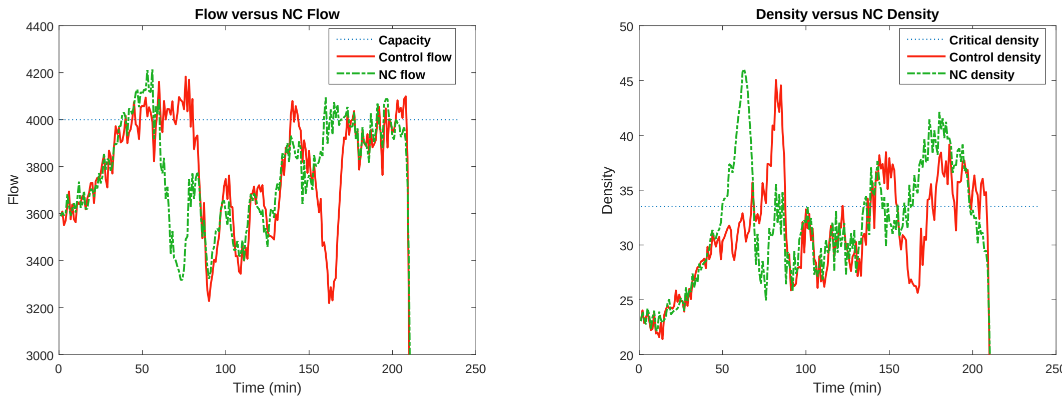


Figure 5.8. – Ramp metering rate - AD-RMC - *Parameterschatter* - average results

Just like the previous discussed variations, in Figure 5.9 the response of the algorithm is visible in the behaviour of the measured flow and measured density. The flow is tried to be kept at an as high as possible value (around the capacity, although the *Parameterschatter* also calculates the capacity itself). The density is tried to keep it below the set value for a while (which is 90% of the critical density). Both the capacity drop (where the control flow drops below capacity) as when the density rises above the critical density value occurs at the same time as can be seen from these figures.

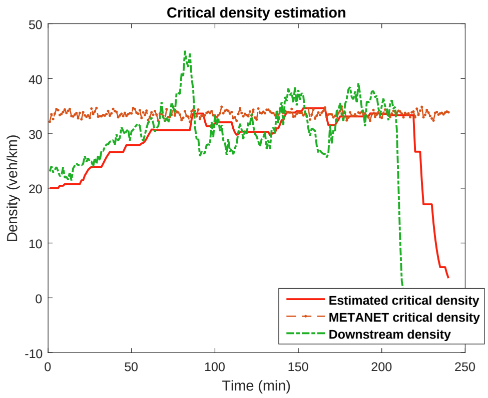


(a) Flow comparison (b) Density comparison

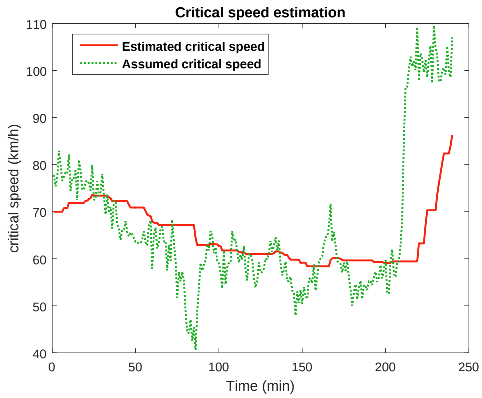
Figure 5.9. – AD-RMC - *Parameterschatter* - average results

The difference between this variation (and the coming variations) and the previous discussed standard variations are the estimators which are active and which estimates certain parameters. In Figure 5.10 the response of the *Parameterschatter* is visible. It is clear that the estimated critical density

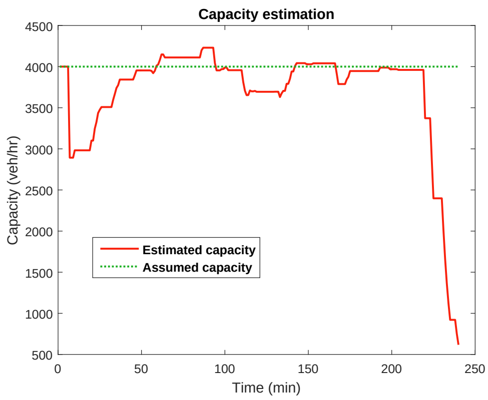
follows the downstream measured density and stays around the actual critical density. That is also why it is important to have a correct downstream measurement location for the *Parameterschatter*. This estimator tracks the measured density and estimates the critical density with this information. Even the capacity is estimated well by the estimator, although the capacity drop sets in a bit later, as it should be around time step 80 and in Figure 5.16(c) it occurs around time step 110. The first part of estimation, the capacity (which also is the case for the critical density) is a bit low, this is caused by the low initial critical density of 20 veh/km/lane. This value was chosen as discussed before because this gave the most reasonable results for the case in this thesis.



(a) Critical density estimation



(b) Critical speed estimation



(c) Capacity estimation

Figure 5.10. – *Parameterschatter* results - AD-RMC - *Parameterschatter* - average results

5.2.2. AD-RMC - *gradient method* - $\rho_{\text{crit}} = 30$ veh/km/lane

The second AD-RMC variation uses only the gradient method. The gradient method tries to update the parameter gains of the control law, PI-ALINEA in this case. The critical density is set to a constant value of 30 veh/km/lane as discussed before and is in this case not updated. The average results coming from 90 simulation runs are given in Table 5.5. There were several large differences between results except for the AMTT, which is the most constant over all these simulation runs (which is also the case for all other simulated variations). This is of course because this is measured per vehicle and

not measured over all vehicles. One of the best simulations runs gave only a TTS of 6270 hours, where one of the least simulations gave a TTS of 6590 hours which is a difference of 320 hours. In total it is a huge difference, per vehicle (with 13640 vehicles over the whole simulation period) it is a difference of 1.41 minutes per vehicle (for comparison: the most stable D-ALINEA has a difference of 0.59 minutes per vehicle). The total delay variates from 2663 hours to 2982 hours which is a difference of a total delay of 1.40 minutes per vehicle. The AMTT variates between 24.93 minutes to 26.01 minutes and thus a difference of 1.07 minutes per vehicle. The TOD variates between 18.95 hours and 65.56 hours which is a difference of 1.36 minutes per vehicle on the ramp. The variety in results of this AD-RMC is a bit larger than the variety of the AD-RMC with the *Parameterschatter*, but the differences are negligible. This variety in results can also, just like with the *Parameterschatter*, be explained that due to not totally correct estimation of the gains, the results can sometimes be a bit disappointing.

Table 5.5. – Average results AD-RMC - *gradient method* - ρ_{crit} = 30 veh/km/lane

Indicator	**Average result (90 simulations runs)**
TTS	6408.11 h
TOD	53.02 h
AMTT	25.29 min
Total delay	2800.11 h
Capacity drop postponed	19.12 min
Time capacity drop took place	83.69 min

The ramp meter rate shows also a lot of variety in values. This is shown in Figure 5.11. Also for this variation does the ramp meter rate fluctuate a lot which in this case is caused by the estimation of the parameter gains. The ramp meter rate changes a lot because the estimator tries to estimate the gains every time step according to the actual traffic situation on the freeway. The gains in the control law are updated by these estimations and therefore a lot of fluctuations in the ramp meter rate can occur. Although comparison between variation will be done in section 5.3 something can be said here about the difference in ramp meter rate fluctuations between two variations. The fluctuations in the ramp meter rate is less for the AD-RMC with the gradient method as for the AD-RMC with the *Parameterschatter* as can be seen when the Figures 5.8 and 5.11 are compared.

Despite a lot of variety in the results, the results still show that there is a definite improvement towards the no control situation and towards other variations. Again, the Figure 5.12 shows the response of the controller. Here the difference between the no control situation and the control situation can be derived. Also for this variation it is clearly visible that the controller tries to keep the flow around capacity and the density just below the critical density. If this is compared to Figure 5.9(a) it can be seen that for this variation, the variety of flow values around the capacity is less than for the variation with only the *Parameterschatter*. Another clear difference is the time the controller can postpone this capacity drop as can also be derived from this figure.

Figure 5.13 shows the estimation of the gains. It is also visible that the gains are not updated every time step. Especially during queue control do the gains stay the same due to given conditions. As stated before the K_{I} has a small adaptation gain and therefore does also not have a lot of variety between values (in the case of the figure between 3 and -3). The gain K_{P} has more variation between

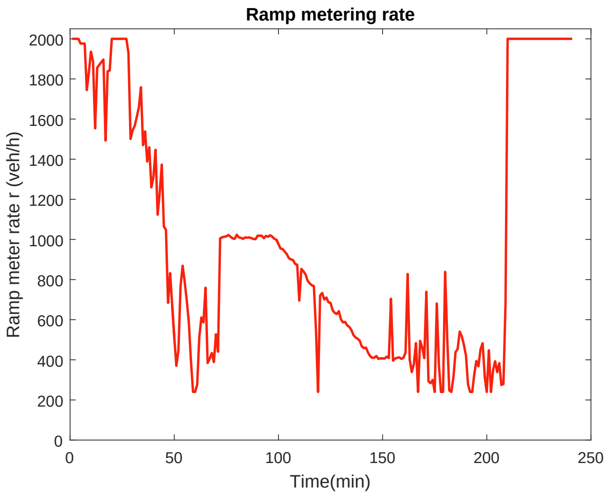
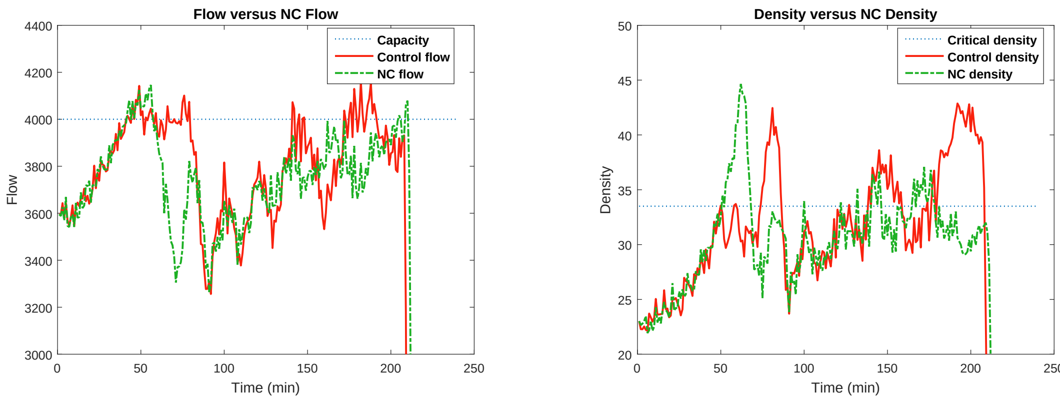


Figure 5.11. – Ramp metering rate - AD-RMC - *gradient method* - ρ_{crit} = 30 veh/km/lane - average results



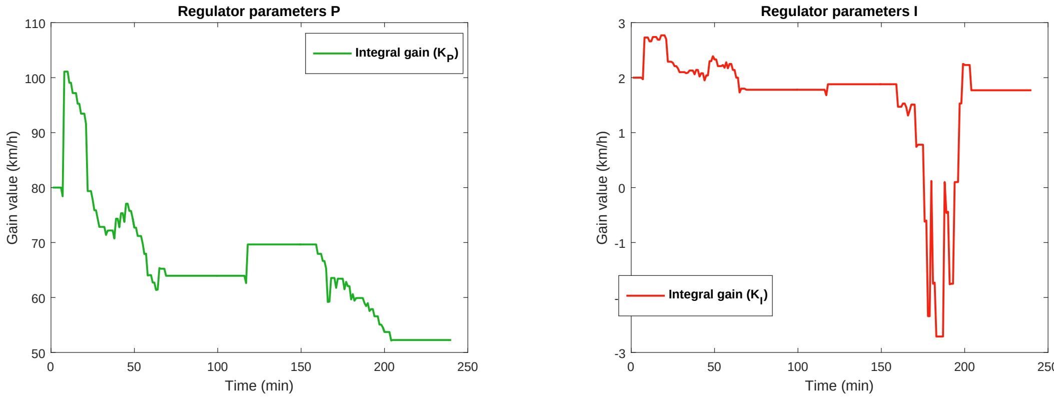
(a) Flow comparison (b) Density comparison

Figure 5.12. – AD-RMC - *gradient method* - ρ_{crit} = 30 veh/km/lane - average results

the values (the value is approximately between 50 and 100). For every simulation run this estimation is different. In contrast to the *Parameterschatter*, which always tries to get close to the actual critical density value, the gains will be estimated dependent on the measured error and this can be different every simulation.

5.2.3. AD-RMC - *Parameterschatter* + *gradient method*

The last AD-RMC variation uses both the *Parameterschatter* and the gradient method. The gradient method is applied, but this time with also variable critical density, which is estimated with the *Parameterschatter*. The average results coming from 140 simulation runs are given in Table 5.6. The most simulation runs were needed from all variations and therefore this variation is not stable at all in results. This can be caused by two estimators. If both estimators give bad estimations at the same time the response of the controller is also not very good. To indicate the difference in indicator values



(a) Flow comparison (b) Density comparison

Figure 5.13. – K_P and K_I estimation - AD-RMC - *gradient method* - ρ_{crit} = 30 veh/km/lane - average results

again the TTS is compared of the best and worst simulation run. One of the best simulations runs gave only a TTS of 6249 hours, where one of the least simulations gave a TTS of 6710 hours which is a difference of 461 hours. In total it is a huge difference, per vehicle (with 13640 vehicles over the whole simulation period) it is a difference of 2.03 minutes per vehicle. As comparison with the AD-RMC with the *Parameterschatter* active had a difference of 1.34 minutes per vehicle and the AD-RMC with the gradient method had a difference of 1.41 minutes per vehicle. Worth mentioning is that the best simulation run, with a TTS of 6249 hours, has the best performance based on travel time of all simulated variations, but the AD-RMC with both estimators active has also the worst performance of all simulation runs with a TTS of 6710 hours. It happened twice during the 140 simulations that this controller gave no improvement at all compared to the no control situation. Other variations between results are as follows. The total delay variates from 2640 hours to 3102 hours which is a difference of a total delay of 2.03 minutes per vehicle. The AMTT variates between 24.90 minutes to 26.37 minutes and thus a difference of 1.47 minutes per vehicle. The TOD variates between 2.10 hours and 66.72 hours which is a difference of 1.88 minutes per vehicle on the ramp. The variety in results of this AD-RMC is much larger than the variety of the AD-RMC with the *Parameterschatter* or gradient method. This can be clearly seen from these differences between results.

Table 5.6. – Average results AD-RMC - *Parameterschatter* + *gradient method*

Indicator	**Average result (140 simulations runs)**
TTS	6437.84 h
TOD	45.19 h
AMTT	25.43 min
Total delay	2829.63 h
Capacity drop postponed	18.73 min
Time capacity drop took place	83.35 min

The ramp meter rate shown in Figure 5.14. Also here a lot of variety in ramp meter rates is shown which can be the cause of the variety in results. It can be clearly seen that the variety in ramp meter values here is more than for the other estimator variations. This has to do with a lot of estimation of the critical density value and the gain parameters which may lead to more variety of ramp meter values. The Figure 5.15 again shows the response of the ramp meter installation in terms of flow and density. It also tries to keep the flow high on capacity value and tries to keep the density below the critical density. But compared to the figures of other AD-RMC variations, the density is not kept as low as it should and it rises pretty fast above critical value. The other AD-RMC variations with only one estimator active does a better job in keeping the density around the target value. This can be the reason that this variation seems not to give as good results as the other variation of the AD-RMC. The time the capacity drop is postponed for this variation is also lower than for the other AD-RMC variations. Although, the difference is not that large as it is only between 0.5 and 0.9 minutes.

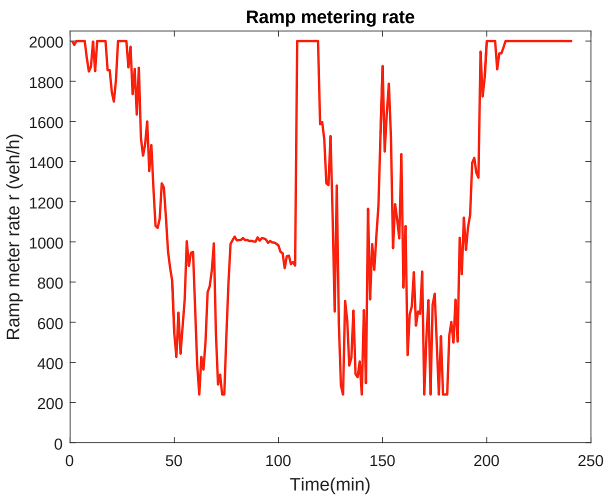
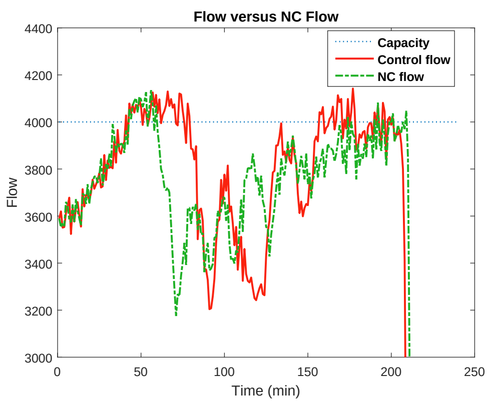
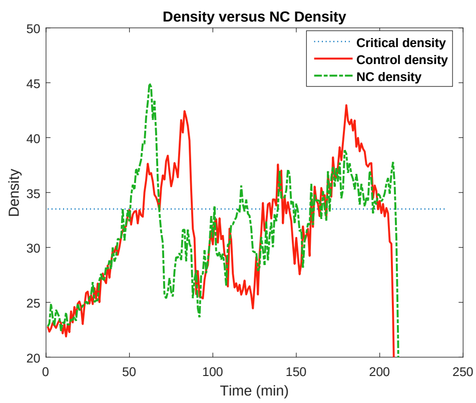


Figure 5.14. – Ramp metering rate - AD-RMC - *Parameterschatter + gradient method* - average results



(a) Flow comparison

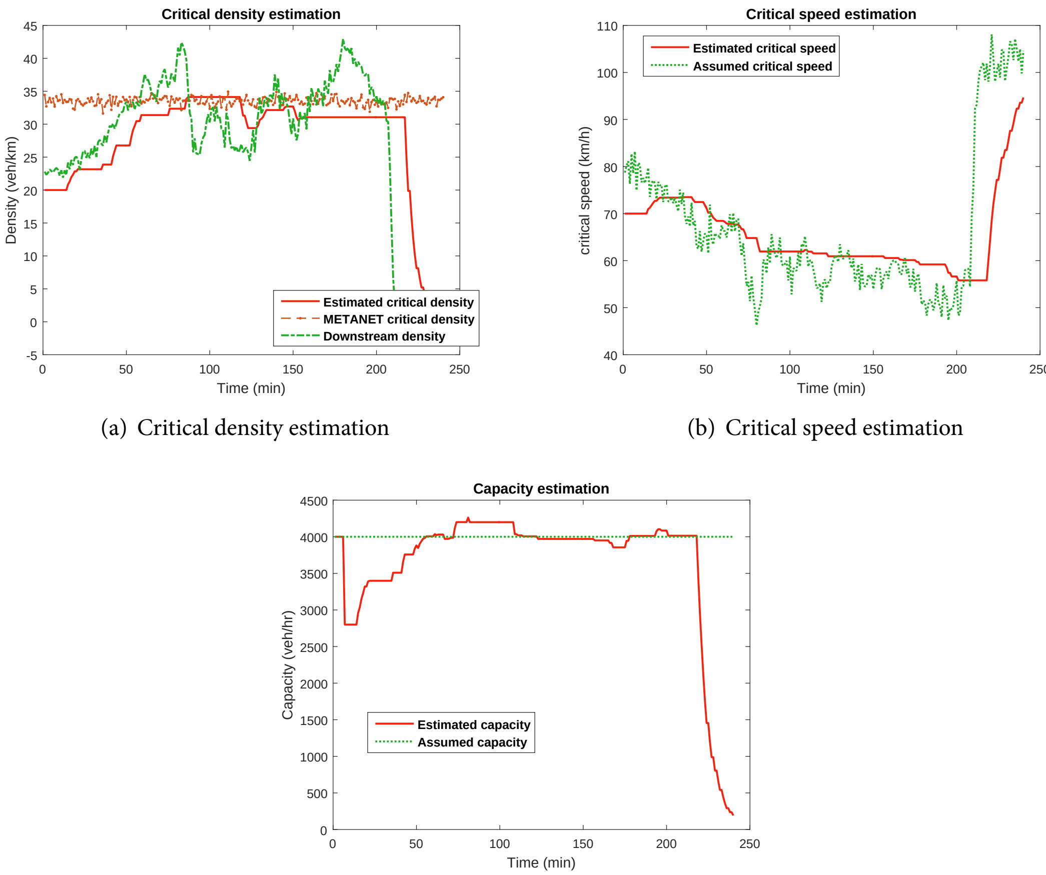


(b) Density comparison

Figure 5.15. – AD-RMC - *Parameterschatter + gradient method* - average results

As last important part of this controller in Figures 5.16 and 5.17 all estimations are visible. What

can be seen, compared to AD-RMC with only the gradient method active, is that there is bigger difference between minimum and maximum values for this variation. The critical density, capacity and critical speed estimation are a bit the same as for the previous discussed variation with only the *Parameterschatter* active. The *Parameterschatter* seems to give correct critical density values for an average result of the total AD-RMC variation.



(a) Critical density estimation

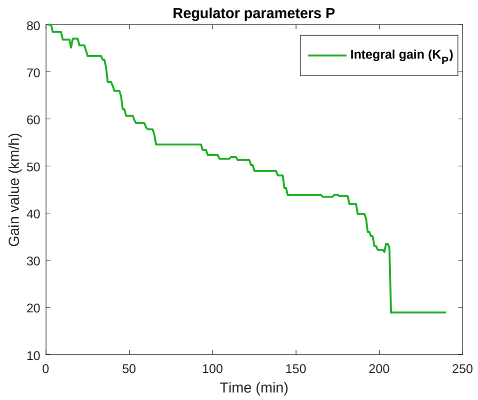
(b) Critical speed estimation

(c) Capacity estimation

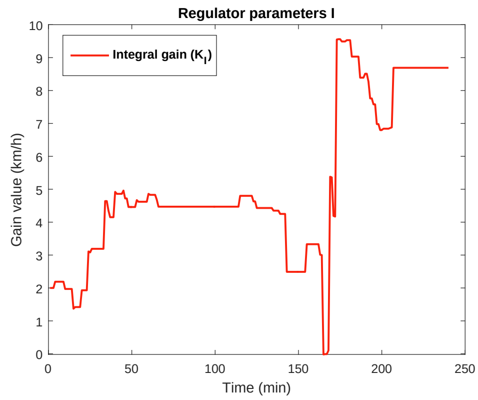
Figure 5.16. – *Parameterschatter* results - AD-RMC - *Parameterschatter* + *gradient method* - average results

5.3. Overview simulation results

All results were discussed with the help of tables and figures in the previous sections. In this section an overview and comparison is given between all those results. In order to give a good picture, all average results are visible in Figure 5.18. The gray scale in this figure indicates which one performed better for a certain indicator. The dark grey indicates the worst result and the light gray indicates the best result for each indicator. The number of simulation runs needed are also of importance because this says something about the variety in results of the control law. The PI-ALINEA with a critical density of 40 veh/km/lane is not included in this figure as it gave no improvement compared to the



(a) Flow comparison



(b) Density comparison

Figure 5.17. – K_P and K_I estimation - AD-RMC - *Parameterschatter + gradient method* - average results

no control situation and is therefore not relevant for comparison with the other simulation cases.

Nr of simulation runs	90	30	30	30
	ALINEA (kcrit 40)	ALINEA (kcrit 30)	PI-ALINEA (kcrit 30)	PI-ALINEA (kcrit 40)
TTS (Hr)	6522,94	6543,83	6465,99	6688,39
TOD (hr)	26,87	69,38	68,12	0,00
AMTT (Hr)	25,77	25,36	25,25	26,28
TOTAL delay (Hr)	2914,93	2934,94	2856,58	3079,01
Cap postponed (min)	18,51	14,53	16,50	0,00
Time cap drop (min)	83,10	79,20	81,17	0,00

Nr of simulation runs	88	90	140
	AD_RMC - Parameterschatter	AD_RMC - gains update (kcrit 30)	AD_RMC - gains + kcrit
TTS (Hr)	6441,57	6408,11	6437,84
TOD (hr)	42,29	53,02	45,19
AMTT (Hr)	25,46	25,29	25,43
TOTAL delay (Hr)	2833,44	2800,11	2829,63
Cap postponed (min)	19,60	19,12	18,73
Time cap drop (min)	84,20	83,69	83,35

Figure 5.18. – Overview simulation results

Standard variations overview

All standard variations, except the PI-ALINEA with a critical density of 40 veh/km/lane, gave improvement towards the no control situation. The PI-ALINEA with a critical density of 40 veh/km/lane does not gave any improvement as discussed before. The other variations did perform fairly well. If the D-ALINEA with 30 and 40 veh/km/lane as critical density and the standard PI-ALINEA variation is compared the following can be concluded. The D-ALINEA variation with 40 veh/km/lane performs a bit better than the D-ALINEA with 30 veh/km/lane in terms of TTS, TOD, total delay but the difference in performance is negligible except for the TOD. The difference between both in case of the time the capacity drop is postponed and the time the capacity drop took place is a bit greater in favour of the D-ALINEA variation with a critical density of 40 veh/km/lane. But this D-ALINEA variation is not very constant in results during this case study. For this small differences in results it seems better to use an algorithm which is more constant and reliable in results. The D-ALINEA variation with a critical density of 30 veh/km/lane only needs 30 simulations and has, together with the PI-ALINEA, the most constant results. However, the PI-ALINEA does perform better in terms

of travel time, AMTT and total delay, where the TOD is about the same. Also the capacity drop is postponed longer and also took place later during simulation in case of PI-ALINEA. Thus the PI-ALINEA performs clearly better than D-ALINEA with 30 veh/km/lane as critical density for this case. And thus the PI-ALINEA also performs clearly better than D-ALINEA with 40 veh/km/lane as critical density for this case, especially in terms of stability but also in terms of TTS.

AD-RMC variations overview

The results of the total AD-RMC (with both estimators active) does give reasonable results. At least 140 simulation runs were needed for statistically reliable results for the total AD-RMC case. Compared to the AD-RMC with only the *Parameterschatter* or only the gradient method active it does not perform better on any of the indicators. There is not much difference between the AD-RMC with the *Parameterschatter* and the AD-RMC with the gradient method. The second one performs better on the TTS, AMTT and total delay indicators but the AD-RMC with the *Parameterschatter* performs better on the TOD, the capacity drop postponed and the time the capacity drop takes place. Although the last two named indicators are negligible in terms of improvement compared to the other variation. Overall both methods with only one estimator active are viable, although also both needed a lot of simulations under the stochastic circumstances for statistically reliable results.

General overview

Of all the simulation results it can be seen that the AD-RMC with only the gradient method or only the *Parameterschatter* seem to give the best results in terms of travel time. But this improvement in travel time comes with the cost of high total on-ramp delay. Although this high TOD is the case for most simulation runs with a good result for the TTS. Both the AD-RMC with the *Parameterschatter* and the gradient method need more simulations than for example the D-ALINEA with 30 veh/km/lane as critical density. The AD-RMC with both estimators active has a lot of variety in the results and the average results are also less than the AD-RMC with only one estimator active. The standard variations have less performance in terms of all indicators (except D-ALINEA with ρ_{crit} = 40 veh/km/lane which performs best on TOD and PI-ALINEA which performs best on AMTT). The only real benefit from the standard variations is that D-ALINEA with a constant critical density of 30 veh/km/lane and the PI-ALINEA are more stable than any other simulated variation. Especially the PI-ALINEA, an algorithm which was never tested before, performs well compared to the other 2 standard variations. In general it can be concluded that the AD-RMC with the gradient method active gives the best results for this case based on the given indicators. Overall the differences between the indicators are not too large, as the difference between the TTS (6408.11 hours) of the AD-RMC with gradient method and the TTS (6441.57 hours) of the AD-RMC with the *Parameterschatter*. Per vehicle in simulation this is only a difference of approximately 9 seconds per vehicle. This small differences can also been seen in the AMTT performance where the average mainline travel time indicator does not differ much for all variations.

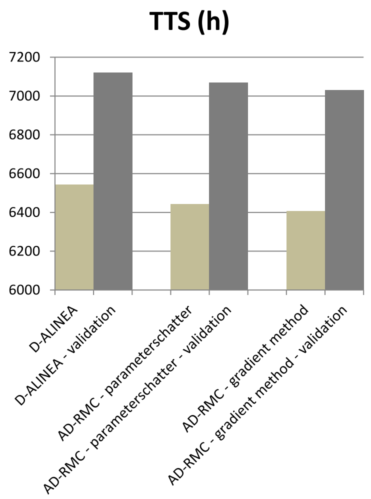
5.4. Validation cases

This section will discuss the results from the validation cases. The D-ALINEA, predefined before, and two AD-RMC variations will be validated using a different demand profile for comparison purposes. The AD-RMC variations that will be simulated depended on the results in the above sections. The

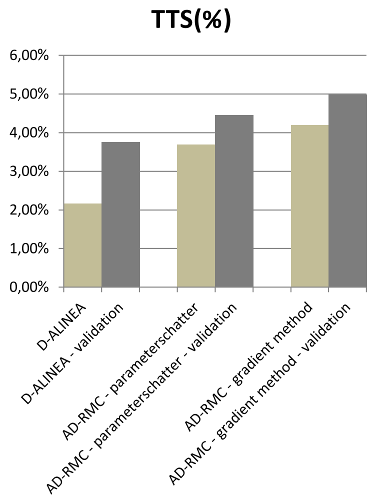
AD-RMC with only the *Parameterschatter* or only the gradient method seem to give the best results of all simulation cases. For this reason will these two cases be validated using the demand profile for validation, which was given in section 4.2.4. The improvement compared to the no control situation is critical in this analysis. Because the TTS is different for this demand profile, the improvement compared to the no control situation will also be analysed. To compare the TTS of the normal simulation cases and the validation cases does not immediately benefit the conclusion as they are not comparable towards each other (in this case the total number of vehicles is larger, 13640 vehicles for the simulation cases, 13930 vehicles for the validation cases).

In Figures 5.19 and 5.20 the differences between the average values of the validation and the simulation cases are given for comparison.

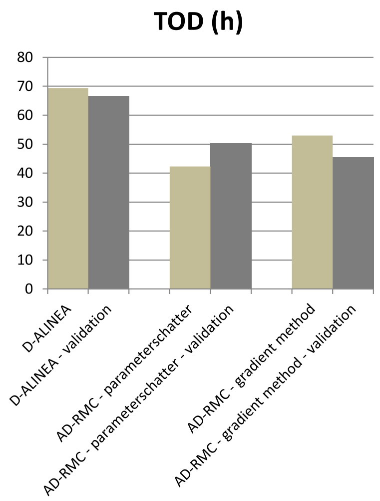
From these figures it can be seen that, just like in the simulation cases the AD-RMC with only the gradient method does perform best in terms of travel time, followed by the AD-RMC with only the *Parameterschatter*. Striking is that for D-ALINEA the time the capacity drop is postponed has improved gradually for this case compared to the simulation cases. However, only 10 simulation were done instead of 30 which could have an influence on the results. It seems that the validation demand profile is more suited for the D-ALINEA variation than the one used for the simulation cases. The AD-RMC variations, used for validation, both have similar results as for the simulation cases. Due to different number of vehicles the actual results for validation are a bit higher. For example the TTS of the gradient method variation in simulation case was 6408.11 hours and in case of validation 7030.46 hours. However, the improvement compared to the no control situation is greater than the simulation cases. It is clear that in case of the validation cases (and the corresponding demand profile) the improvement is greater than for the simulation cases. This could be the cause of a larger TTS in hours for the validation case, which can give also a larger improvement rate (there is more time to improve). Another cause could be that in case of the normal simulations the demand stays fairly high the whole simulation time. The demand for validation has higher peaks, but also decreases at certain times. During these demand drops the controller has time to recuperate and to decrease the queue on the on-ramp, which can lead to more efficient ramp meter rates. This can also be seen within the validation cases. In case of peak 1 of the mainline demand profile (Figure 4.4) the duration is longer than in case of peak 3 (same veh/h as peak 1), which results in the maximum allowed queue on the ramp. This activates the queue control and thus this does result in less efficient ramp meter rates (this applies to all validation cases). Thus the ramp meter installation will react more efficiently to short (in terms of time) peaks in the demand.



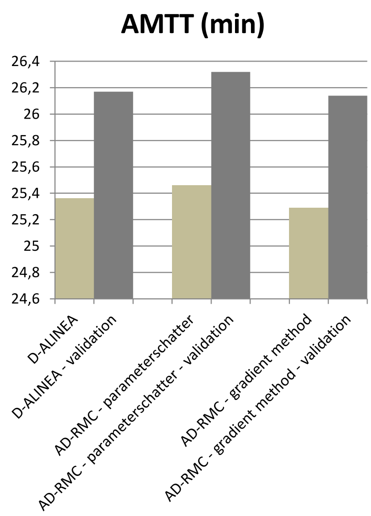
(a) TTS (h)



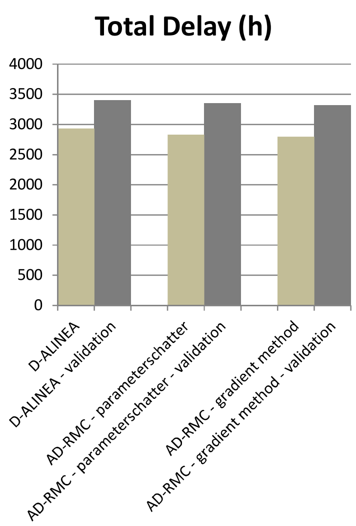
(b) TTS (%)



(c) TOD (h)

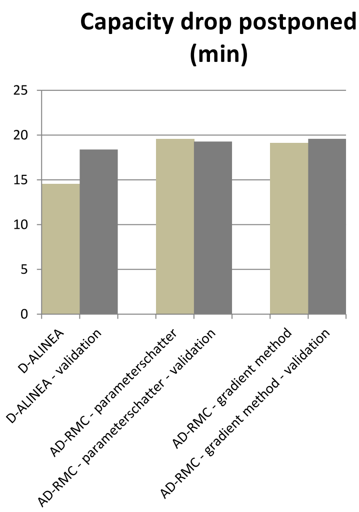


(d) AMTT (min)

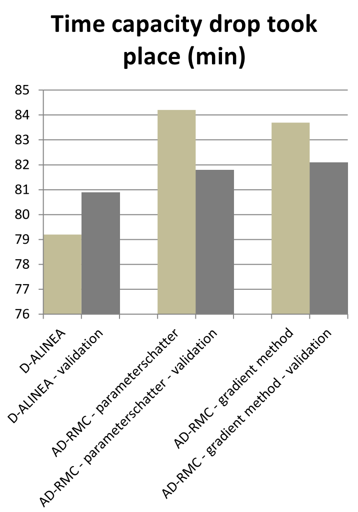


(e) Total delay (h)

Figure 5.19. – Comparison charts of the average results of the simulation cases and the validation cases (1)



(a) Time capacity drop postponed (min)



(b) Time the capacity drop took place (min)

Figure 5.20. – Comparison charts of the average results of the simulation cases and the validation cases (2)

6. Conclusions and Recommendations

In previous sections the adaptive ramp metering controller (AD-RMC) was simulated using MATLAB and the results were compared with the other simulated variations. The results from section 5 will be used in this section. This section will answer the main research question:

- *To which extent can adaptive control, by tuning all parameters of the ALINEA algorithm, improve ramp metering in terms of travel time?*

This thesis will be concluded in this section. In this section the promising findings in this research will be discussed and the final answer on the main research question will be discussed. The sub questions were already answered in section 2 but will be shortly summarized before answering the main research question. At the end of this section several recommendations will be given for practice and future research.

First in section 6.1 the findings of previous sections will be summarized. In section 6.2 the final answer to the main research question will be given. Based on the answer and findings in section 6.3 recommendations will be given for in practice. This section and thus also this research will be concluded with section 6.4 with recommendations for further research.

6.1. Findings

In this thesis a new possible adaptive ramp metering approach has been proposed. This thesis searched for improvement in existing ramp metering algorithms by means of adaptive control. It was expected that adaptive control could tune the parameters in such a way that the algorithm will be improved. This because of the fact that adaptive control adapts the control law and thus the parameters towards the current traffic situation for a better output of the algorithm. The findings in this thesis are based on the results presented throughout this report. The new adaptive ramp metering controller (AD-RMC) was developed with the guidance of Liu et al. (2007). The best way simulate this new developed ramp metering approach for first time testing is with the help of METANET, a second-order macroscopic traffic flow model. The most suitable adaptive control approach for this research was determined in section 2.6. The model-reference adaptive controller was used to develop the new AD-RMC. The AD-RMC (with at least the gradient method active) is therefore based on this conventional adaptive control approach. The D(ensity)-ALINEA and the standard PI-ALINEA were used to compare the new AD-RMC with.

The AD-RMC with only one of the estimators active (the *Parameterschatter* or gradient method) has promising results. However, a high amount of simulations are needed for statistically reliable results. These variations performed best out of all tested ramp metering algorithms in this thesis. From the standard variations, which were all used for comparison with the AD-RMC, the PI-ALINEA performed best. The PI-ALINEA as used in this thesis was never tested before. The PI-ALINEA was derived from the control law for traffic emergency evacuation used in Liu et al. (2007). The PI-ALINEA was very stable in results and gave better results than any of the D-ALINEA (with different target density) variations. This was a surprising result as no literature was found on this variation. This could be the result of the extra integral term used in this algorithm which tries to keep the output closer to the desired value than only a proportional algorithm like D-ALINEA.

Despite the AD-RMC with only one of the estimators active does perform well, the AD-RMC with both estimators active does not perform as well in terms of stability. The total AD-RMC variation does perform reasonable in terms of the indicators. Unfortunately, a lot of simulation runs where needed. The results of all simulations runs (for this variation) were very different. This could be the result of many different estimations which can lead to a lot of uncertainties in the ramp metering algorithm. If both the gradient method and the *Parameterschatter* give poor estimations compared to the actual values the results in terms of travel time will also be poor.

Validation also proved the working of the algorithms under a different demand. Both the D-ALINEA with 30 veh/km/lane as critical density, as the AD-RMC with only one of the estimators active gave promising results under a different demand.

6.2. Answer research questions

At the beginning of this research a problem was discussed and from this problem several research questions where formulated. The sub question have been answered in section 2 and will be summarized shortly here. The answers were as follows for the different research questions.

A. *Which traffic flow simulation models exist and which one is relevant and suited for implementation and evaluation of a new developed adaptive control approach for ramp metering?*

The several macroscopic traffic flow models that have been evaluated are the First-order traffic flow model, METANET and MARPLE. As concluded in section 2.2 METANET has the most benefit in this thesis. METANET is the only traffic flow model which can reproduce the capacity drop and was therefore the most suited model for this research.

B. *Which different ALINEA variations exist, what are their advantages and disadvantages and which variation is best suited for implementation in this research?*

There are a lot of ALINEA variations which have been evaluated in section 2.4. From ALINEA with density as parameter to flow and speed as parameter to even a proportional-integral ALINEA algorithm. The D-ALINEA has been proven to be successful in practice and has been chosen for this to compare towards the AD-RMC in this research. The PI-ALINEA has been chosen based on the most suited variation for an adaptive control approach for ramp metering.

C. *Which adaptive control approaches exist, what are their advantages and disadvantages towards ramp metering and which ones are relevant and suited for implementation in this research?*

Several adaptive control approaches have been reviewed based on literature: Gain scheduling, Model-reference adaptive control, Self-tuning regulators and (suboptimal) Dual control. Model-reference adaptive control seemed the most suitable variation for a traffic network and ramp metering. The paper of Liu et al. (2007) has been followed on the determination of this adaptive control approach and was used as guide for the development of the new controller.

The sub questions have been answered throughout the report. The main research question however, will be answered in this section.

- *To which extent can adaptive control, by tuning all parameters of the ALINEA algorithm, improve ramp metering in terms of travel time?*

This question cannot be answered with one or a few simple sentences. In this research an attempt was made on a possible improvement of the existing ramp metering algorithms, because of annually increasing demand which can cause more congestion. An attempt was made on improving the common used ramp metering algorithm ALINEA. With the guidance of Liu et al. (2007) the new AD-RMC was developed, with as base a PI-ALINEA algorithm. The PI-ALINEA itself, as in the form presented in this thesis, is a new approach for ramp metering and has never been tested before. However, this approach is not adaptive as no variables are updated every time step to react on the actual traffic situation. But this approach has also promising results and seems an improvement compared to the standard ALINEA with density as parameter. The PI-ALINEA has an improvement compared to the D-ALINEA algorithm (with ρ_{crit} = 30 veh/km/lane) of approximately 77 hours in terms of TTS, which is only an improvement of 1.1%.

The results of the AD-RMC coming from simulation are promising, although a lot of variety in the different runs were found. The AD-RMC has been tested in 3 different variations. The AD-RMC with the *Parameterschatter* active gave promising results. The *Parameterschatter* has been implemented in the *Praktijkproef* Amsterdam and this thesis proves its working. And also the AD-RMC with the gradient method active gave promising results. Unfortunately, the combination of both estimation methods active together gave less results than expected and had even more variety in the different simulation runs that was needed for statistically reliable results. Overall the existing ALINEA algorithm can be improved by using adaptive control with the gradient method active in terms of travel time (TTS) by approximately 135 hours (which is 2.1% improvement) over all vehicles simulated compared to the D-ALINEA algorithm (with ρ_{crit} = 30 veh/km/lane) and by 58 hours (which is only 0.9% improvement) compared to the PI-ALINEA algorithm. The difference in TTS between the AD-RMC with the *Parameterschatter* and the AD-RMC with the gradient method is approximately 33.5 hours in favour of the gradient method variation. This means that the improvement of the AD-RMC with the gradient method active compared to the *Parameterschatter* active is 0.5%. But also the *Parameterschatter* is an improvement compared to the standard ALINEA variations. The improvement per vehicle (13640 vehicles were simulated every simulation run) is not that large, but the simulations were also done on macroscopic level. In this thesis the focus is on macroscopic level and therefore also the improvement on total travel time over all simulated vehicles. To conclude the answer, one should keep in mind that fine-tuning of the parameters of the adaptive controller is critical to getting these promising results.

A side note to this answer is that there were some **limitations** in this research and this could have affected the results. One of the limitations was the use of a macroscopic traffic flow model. On microscopic level the simulations are more detailed and the results could then be more reliable. Next to this, another limitation is that a downstream detector 2 segments downstream of the on-ramp had to be used due to some flaws in the METANET model. This could have affected the results as in practice a downstream detectors is used just a few (100) meters downstream of the on-ramp. Another limitation of this research is that the conditions for updating the parameter gains with the gradient method were designed for the first time and because the focus was more on looking for an improvement these conditions could not be optimal for the gradient method. Next to these limitations also route choice, emissions and external effects like weather conditions where not taken into account. These parts of traffic flow are also influenced by ramp metering or they influence ramp metering. The last limitation is that the paper of Liu et al. (2007) was followed as guideline for the approach developed. Maybe also other adaptive control approaches are viable for ramp metering, but this is currently unknown.

This is quite a promising answer on the research question. However, the new approaches lack some stability, in terms of variety, in their results. The results variate a lot and a statistical reliable result was only established after approximately 90 simulation runs. But these algorithms have been tested for the first time in this research and they seem to have potential. And for this purpose these results are quite satisfying. In the following sections recommendations will be given on practice implementation and future research.

6.3. Recommendations for practice

The Matlab scripts of the *Parameterschatter* and gradient method including the PI-ALINEA algorithm are added in Appendix B.1 and B.2. These may be used for future research.

Before the new AD-RMC should be implemented in practice first further research has to be done on the controller. The AD-RMC, as developed in this thesis, is not ready for practice implementation but has potential to be a ramp metering algorithm implemented in practice. The PI-ALINEA variation on the other hand, which performed surprisingly well, seems reliable enough for testing in practice when some more tests are done with a microscopic model for example. This PI-ALINEA could be tested in a FOT. The proposed AD-RMC in this thesis with both the *Parameterschatter* and the gradient method active could be tested in a FOT, as the *Parameterschatter* already have been tested in the PPA. However, it is recommended to first look into more research to try to get less variety in their results. Another recommendation is to test the algorithms with a different road layout as used in this thesis. For example multiple on- and off-ramps, different number of lanes and lane narrowing. The total AD-RMC does have some potential but does need further research because a lot of variety in results. The AD-RMC with only the *Parameterschatter* active could be implemented in practice, as it is also already tested in the *Praktijkproef* Amsterdam. The variables should be fine-tuned for the given situation where the approach is implemented. Overall it is recommended for practice to swap the standard non adaptive algorithms for the adaptive algorithms as these algorithms are an improvement compared to the standard algorithms. However, some of these adaptive algorithms still need some research.

6.4. Recommendations for future research

For future research it is worth looking into the conditions used for updating the parameter gains by means of the gradient method. This research did not focus on the conditions applied to update the parameter gains of the algorithm. And the instability of the AD-RMC, especially the gradient method, asks for improvement of the conditions developed when to update and when not to update the parameter gains.

Another recommendation is to test the AD-RMC with a microscopic simulation model to get a more accurate traffic situation and use a different case study (more lanes, other speed limit etc.). In this thesis the purpose was to first test a new developed approach and a macro simulation model was more suited for that. But now the new developed algorithm is tested for the first time, the next step is to test it in a more accurate traffic flow model. A microscopic traffic flow model is more accurate and can also track driving behaviour and external effects like route choice. This is also an important aspect of ramp metering and should be considered in future research.

Another possible future research, which will cost some more time, could be to try another gain update rule instead of the gradient method. This thesis' purpose was also to test if updating the gains

of the ramp metering algorithm could lead to an improvement. In this research this is the case, so another gain update rule could lead to a more stable controller in comparison with the gradient method.

Eventually, also a study could be done on the route choice and external conditions, like weather and emissions. Route choice and other external conditions have not been considered in this research. The route choice can be tested with an underlying network and more on- and off-ramps on the freeway. The AD-RMC could affect the route choice of drivers and emissions or be affected by weather. It would be interesting to know how the AD-RMC affects the route choice of drivers.

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Appendices

Appendix A. Literature *Parameterschatter*

Functionele specificatie Parameterschatter

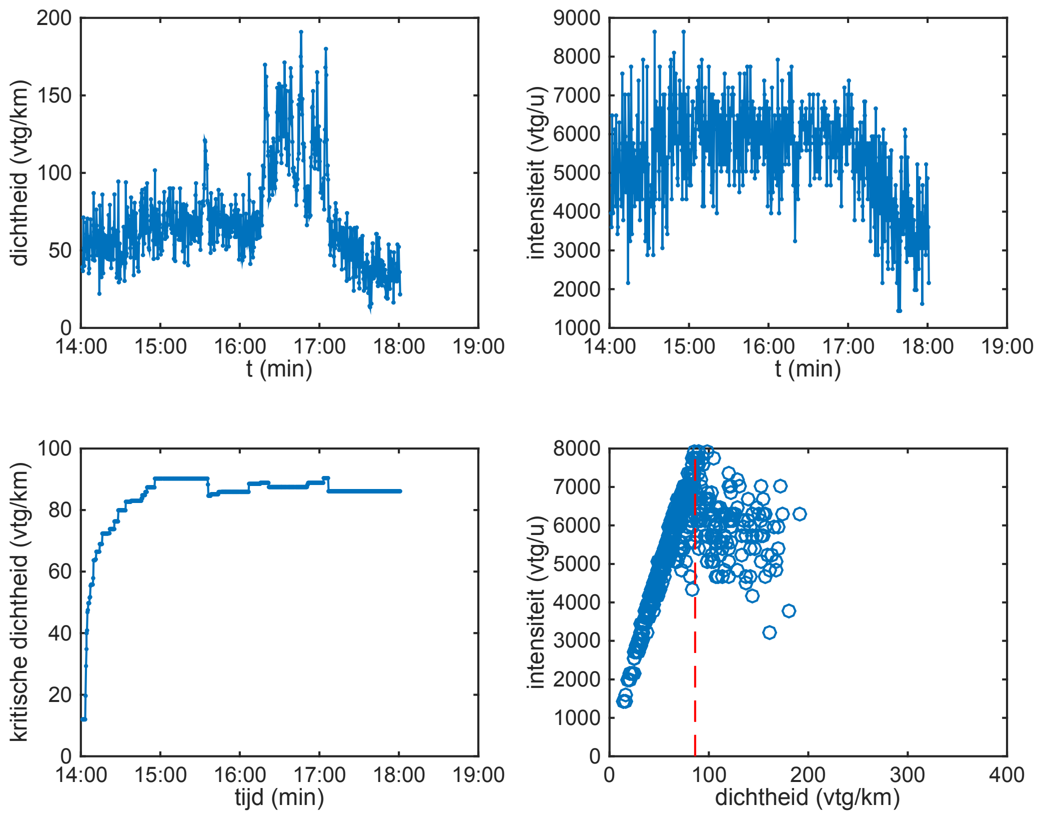
Van:	Serge Hoogendoorn, Erik-Sander Smits
Datum:	Vrijdag, 3 april 2015
Functie:	Parameterschatter

1 Inleiding

Deze functionele beschrijving behelst de Parameterschatter.

1.1 Doel en functie

De parameterschatter beoogt een betrouwbare schatting te geven van de *kritische dichtheid* en (hiervan afgeleid) de capaciteit, met als doel het kunnen bepalen van de doelwaarde van het adaptieve toeritdoseeralgoritme. Hierbij gaan we uit van het ALINEA algoritme, al kan het RWS-C algoritme ook zinvol gebruik maken van de geschatte doelwaarde (i.c. de capaciteit).



Bovenstaande figuren illustreren de werking van de nieuwe methode op grond van 20s data afkomstig van de detector stroomafwaarts van de TDI bij de s101. De figuur linksonder laat de geschatte waarden zien voor de kritische dichtheid als functie van de tijd. De figuur

rechtsonder geeft schetst de waarde in relatie tot het fundamenteel diagram. De figuren laten zien dat de hier voorgestelde methode zeer goed functioneert.

Een belangrijk uitgangspunt is dat we gebruik kunnen maken van intensiteiten, harmonische snelheden en - daarvan afgeleid – correct bepaalde waarde voor de dichtheid. De gegevens die afkomstig zijn van de TDI detectoren zijn hiervoor zeer geschikt; de data uit de meetraaimanager wellicht minder (snelheden zijn niet harmonisch gemiddeld, maar rekenkundig gemiddeld[1]).

1.2 Context

Onderstaande figuur toont de functionele architectuur, met daarin de positie van de Parameterschatter en de relatie met de andere functies binnen de PPA.

PM

2 Verkeerskundige werking

Doel van de parameterschatter is het bepalen van de kritische dichtheid. Dit is de dichtheid waarbij de capaciteit van de weg wordt gerealiseerd (die ook op grond van de geschatte kritische dichtheid kan worden afgeleid). Deze kritische dichtheid ρ_c wordt gebruikt om de doelwaarde ρ^* van het ALINEA algoritme te bepalen:

$$q_{doseer}(k+1) = q_{doseer(t)} + K \cdot \left(\rho^* - \rho(k)\right)$$

volgens $\rho^* = \xi \cdot \rho_c$.

Het bepalen van de kritische dichtheid gebeurt op grond van dichtheid-intensiteit waarnemingen $\left(\rho(k), q(k)\right)$ waarbij de dichtheid is afgeleid van de harmonisch gemiddelde snelheid $u(k)$ volgens $\rho(k) = q(k)/u(k)$.

2.1 Werking op hoofdlijnen

De gedachte is nu als volgt. Stel dat we een schatting hebben voor de kritische dichtheid $\hat{\rho}_c(k-1)$ bepaald in de vorige periode $k-1$. We hebben ook de afgeleide $Q'(k)$ van het fundamenteel diagram bepaald in de laatste gemeten waarde van de dichtheid $\rho(k)$. Er kunnen zich nu twee situaties voordoen.

In de eerste situatie geldt $Q'(k) > 0$, dat wil zeggen dat de huidige dichtheid in de vrije tak van het fundamenteel diagram zit. In dit geval *zou moeten* gelden: $\hat{\rho}_c(k-1) > \rho(k)$ (de huidige dichtheid moet lager zijn dan de kritische dichtheid). Geldt dit niet, dan moeten we de schatting voor de kritische dichtheid naar boven bijstellen.

---

[1] In sommige gevallen wordt de harmonisch gemiddelde snelheid benaderd door het harmonisch middelen van de rekenkundige gemiddelde snelheid *per rijstrook*. Nader onderzoek moet uitwijzen in hoeverre deze *pseudo harmonische snelheid* afwijkt van de harmonisch gemiddelde snelheid.

In de tweede situatie geldt $Q'(k) < 0$, met andere woorden: de huidige dichtheid zit in de congestietak van het fundamenteel diagram. In dit geval zou moeten gelden dat $\hat{\rho}_c(k-1) < \rho(k)$ (de huidige dichtheid is groter dan de kritische dichtheid). Geldt dit niet, dan moeten we de kritische dichtheid naar beneden bijstellen.

In hoofdstuk 4 wordt de werking nader uitgewerkt.

Nota bene: de parameterschatter geeft alleen een betrouwbare schatting van de kritische dichtheid indien de data die wordt gebruikt afkomstig is van de kiemlocatie. Desondanks is ervoor gekozen om de Parameterschatter toch op *alle meetpunten toe te passen binnen het regelgebied waarvoor de meetgegevens beschikbaar zijn.*

Een betrouwbare schatting kan alleen worden afgegeven in de volgende situaties:

1. Bij een kiem die ontstaat bij een toerit. In dit geval maken we gebruik van de gegevens van de TDI, te weten de TDI lus op de ASW stroomafwaarts van de toerit. Dit zijn ook de gegevens die de TDI zal gebruiken bij het regelen.
2. Bij een kiem die ontstaat elders in het netwerk (wegversmalling, weefvak, etc.). In dit geval maken we gebruik van gegevens van de meetraaimanager. Ook hier maken we gebruik van de gegevens van de dichtstbijzijnde detector stroomafwaarts van de kiem.

Bij het gebruik van de schatting moeten we hier dus expliciet rekening mee houden!

3 Notatie

De onderstaande tabel toont de verschillende parameters en variabelen relevant voor de parameterschatter.

Symbool	Eenheid	Beschrijving	Default	Range
k	-	Tijdsindex (per 20 sec, per minuut, afhankelijk van databron)	-	{0,1,2,3,…}
$\rho(k)$	Vtg/km	Actuele dichtheid (rijbaan)	-	[0…9999]
$q(k)$	Vtg/u	Actuele intensiteit (rijbaan)	-	[0…9999]
$u(k)$	Km/u	Actuele harmonische snelheid (rijbaan)	-	[0…999]
T	-	Intervallengte voor bepalen afgeleide	7	[0…999]
$\hat{Q}'(k)$	Km/u	Schatting van de afgeleide van het fundamenteel diagram in het punt $\rho(k)$	-	[0…999]
$\hat{\rho}_c(k)$	Vtg/km	Geschatte kritische dichtheid voor periode *k*	$25 \cdot n_{rstr}$	[0…9999]
$\hat{u}_c(k)$	Km/u	Geschatte kritische snelheid voor periode *k*	80	[0…999]
$\hat{C}(k)$	Vtg/u	Geschatte actuele capaciteit voor periode *k*	-	[0…9999]
α	-	Smoothings parameter	0.8	[0…1]
γ	-	Smoothings parameter	0.9	[0…1]
β^+	Km/u	Grenswaarde voor afgeleide fundamenteel diagram op grond waarvan schatting wordt aangepast	40	[0…99]
β^-	Km/u	Grenswaarde voor afgeleide fundamenteel	-10	[-99…0]

		diagram op grond waarvan schatting wordt aangepast		

4 Algoritme

In dit hoofdstuk beschrijven we de algoritmiek voor de Parameterschatter. Het algoritme bestaat uit een drietal componenten:

1. Pre-processing van de data, afhankelijk van het type data (direct vanuit de TDI of vanuit de meetraaimanager)
2. Bepalen van de afgeleide $Q'(k)$
3. Bepalen van de nieuwe schattig voor de kritische dichtheid
4. Bepalen van de bijbehorende waarde voor de capaciteit

Onderstaande stappen worden uitgevoerd voor alle beschikbare detectordata! Hieronder worden de stappen *per detector beschreven*.

4.1 Voorbewerken van de data

We maken hier onderscheid tussen twee databronnen:

1. Data afkomstig van de TDI
2. Data afkomstig van de meetraaimanager (MRM)

4.1.1 TDI data

De TDI bepaalt harmonisch gemiddelde snelheden $u(k)$ voor iedere 20 s. Indien deze op rijstrookniveau beschikbaar zijn, dan moeten we de waarden harmonisch middelen over de rijstroken *r*, i.e.:

$$u(k) = \frac{q(k)}{\sum q_r(k)/u_r(k)}$$

met de rijbaanintensiteit:

$$q(k) = \sum q_r(k)$$

De dichtheid kan nu worden geschat via $\rho(k) = q(k)/u(k)$.

4.1.2 MRM data

De MRM geeft rekenkundig gemiddelde snelheden per rijstrook voor iedere 60 s. Deze gegevens zijn *in principe minder geschikt dat de harmonisch gemiddelde snelheden van de TDI*. Om het harmonisch gemiddelde zo goed mogelijk te benaderen gebruiken we ook hier[2]:

[2] We moeten nog onderzoeken in hoeverre deze benadering de vorm van het fundamenteel diagram voldoende behoudt en derhalve leidt tot goede gegevens voor de parameterschatter.

$$u(k) = \frac{q(k)}{\sum q_r(k)/u_r(k)}$$

met de rijbaanintensiteit:

$$q(k) = \sum q_r(k)$$

De dichtheid kan ook nu worden geschat via $\rho(k) = q(k)/u(k)$.

4.2 Bepalen van de afgeleide van het fundamenteel diagram

De gekozen methode bestaat uit het schatten van een regressielijn door de laatste *T* metingen. Er geldt dan:

$$y_i = \hat{Q}'(k) \cdot x_i + b$$

waarbij $(x_i, y_i) = (\rho(i), q(i))$ met $i = k - T, \ldots, k$. In de meeste gevallen zal normale regressie volstaan en is geen robuuste regressieanalyse nodig. Er geldt dan dat:

$$\hat{Q}'(k) = \frac{\sum_{i=k-T}^{T} (\rho(i) - \bar{\rho}) \cdot (q(i) - \bar{q})}{\sum_{i=k-T}^{T} (\rho(i) - \bar{\rho})^2}$$

Voor de eerder getoonde resultaten hebben we *T* = 7 gekozen, wat tot goede resultaten leidt. Dit is wel afhankelijk van de kenmerken van de gebruikte gegevens (e.g. 20 sec of 60 sec gemiddelde gegevens).

4.3 Schatten van de kritische dichtheid

Gegeven de vorige schatting voor de kritische dichtheid $\hat{\rho}_c(k-1)$ bepaalt door de parameterschatter. Indien deze niet beschikbaar is ($\hat{\rho}_c(k-1) = -1$), dan kiezen we een redelijke initiële waarde $\hat{\rho}_c^0 = 25 \cdot n_{rijstrook}$.

Bij het bepalen van de nieuwe schatting bepalen we eerst op grond van de geschatte afgeleide $\hat{Q}'(k)$ welke van de twee situaties zich voordoet.

<u>Situatie 1: $\hat{Q}'(k) > \beta^+ > 0$ huidige dichtheid zit in de vrije tak van het fundamenteel diagram.</u> In dit geval moet gelden: $\hat{\rho}_c(k-1) > \rho(k)$ (de huidige dichtheid moet lager zijn dan de kritische dichtheid). Geldt dit niet, dan moeten we de schatting voor de kritische dichtheid naar boven bijstellen. Dit kunnen we op verschillende manieren doen, bijvoorbeeld stapsgewijs:

$$\hat{\rho}_c(k) = \begin{cases} \alpha \cdot \hat{\rho}_c(k-1) + (1-\alpha) \cdot \rho(k) & \hat{\rho}_c(k-1) < \rho(k) \\ \hat{\rho}_c(k-1) & \hat{\rho}_c(k-1) \geq \rho(k) \end{cases}$$

met $0 \leq \alpha \leq 1$ een te kiezen wegingsparameter. Nota bene: indien we $\alpha = 0$ kiezen, dan geldt de volgende eenvoudige vorm:

$$\hat{\rho}_c(k) = \max\{\hat{\rho}_c(k-1), \rho(k)\}$$

Uit de laatste formulering kunnen we opmaken dan indien de huidige waarde van de dichtheid in de vrije tak zit van het fundamenteel diagram (d.w.z. $\hat{Q}'(k) > 0$), de beste schatting voor de kritische dichtheid gelijk is het maximum van de vorige waarde van de kritische dichtheid en de huidige dichtheidswaarde.

Situatie 2: $\hat{Q}'(k) < \beta^{-} < 0$ huidige dichtheid zit in de congestietak van het fundamenteel diagram. In dit geval zou moeten gelden dat $\hat{\rho}_c(k-1) < \rho(k)$ (de huidige dichtheid is groter dan de kritische dichtheid). Geldt dit niet, dan moeten we de kritische dichtheid naar beneden bijstellen. Dit kunnen we net als in situatie 1 doen:

$$\hat{\rho}_c(k) = \begin{cases} \alpha \cdot \hat{\rho}_c(k-1) + (1-\alpha) \cdot \rho(k) & \hat{\rho}_c(k-1) > \rho(k) \\ \hat{\rho}_c(k-1) & \hat{\rho}_c(k-1) \le \rho(k) \end{cases}$$

met $0 \le \alpha \le 1$ een te kiezen wegingsparameter. Nota bene: indien we kiezen $\alpha = 0$, dan geldt:

$$\hat{\rho}_c(k) = \min\{\hat{\rho}_c(k-1), \rho(k)\}$$

Uit de laatste formulering kunnen we opmaken dan indien de huidige waarde van de dichtheid in de congestietak zit van het fundamenteel diagram ($\hat{Q}'(k) < 0$), de beste schatting voor de kritische dichtheid gelijk is het minimum van de vorige waarde van de kritische dichtheid en de huidige dichtheidswaarde.

4.4 Bepalen van de capaciteit

Het bepalen van de capaciteit gebeurt indirect, via het bepalen van de kritische snelheid. Voor de kritische snelheid gebruiken we dezelfde systematiek als voor de kritische dichtheid.

4.4.1 Bepalen van de kritische snelheid

Ook hier maken we onderscheid tussen twee mogelijke situaties.

Situatie 1: $\hat{Q}'(k) > \beta > 0$ huidige dichtheid zit in de vrije tak van het fundamenteel diagram. We gebruiken:

$$\hat{u}_c(k) = \begin{cases} \gamma \cdot \hat{u}_c(k-1) + (1-\gamma) \cdot u(k) & \hat{\rho}_c(k-1) < \rho(k) \\ \hat{u}_c(k-1) & \hat{\rho}_c(k-1) \ge \rho(k) \end{cases}$$

met $0 \le \gamma \le 1$ een te kiezen wegingsparameter.

Situatie 2: $\hat{Q}'(k) < -\beta < 0$ huidige dichtheid zit in de congestietak van het fundamenteel diagram. We gebruiken nu:

$$\hat{u}_c(k) = \begin{cases} \gamma \cdot \hat{u}_c(k-1) + (1-\gamma) \cdot u(k) & \hat{\rho}_c(k-1) > \rho(k) \\ \hat{u}_c(k-1) & \hat{\rho}_c(k-1) \le \rho(k) \end{cases}$$

met $0 \le \gamma \le 1$ een te kiezen wegingsparameter.

4.4.2 Bepalen van de capaciteit uit de kritische dichtheid en snelheid

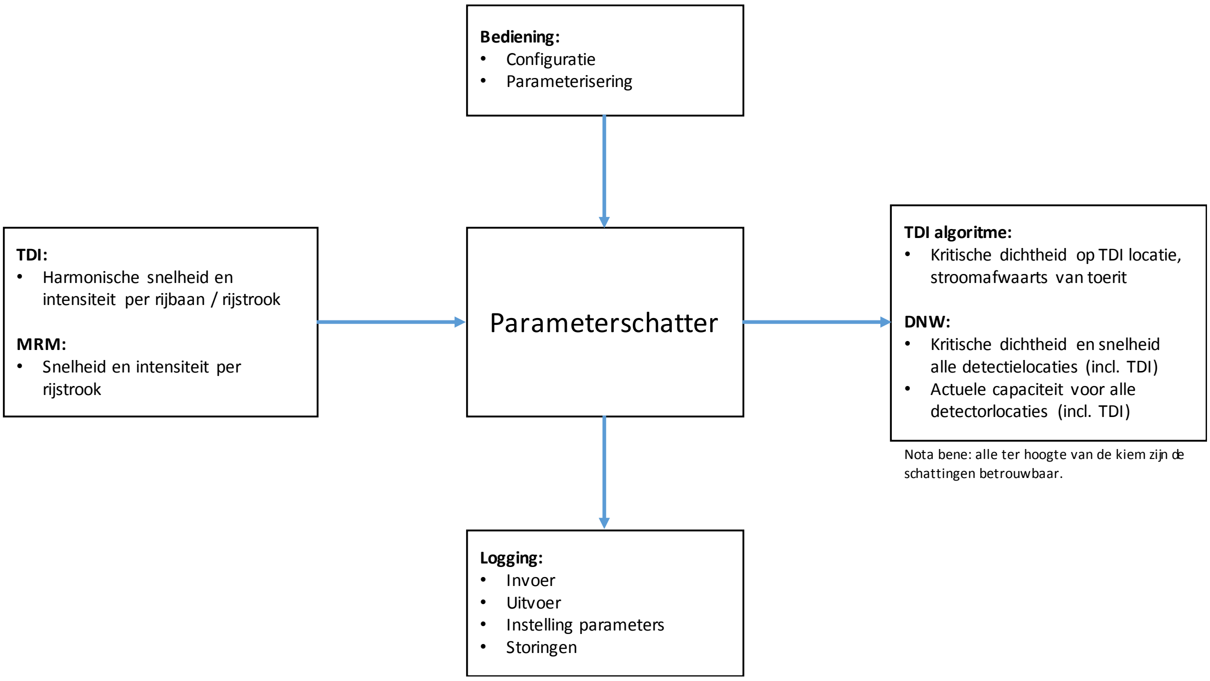
Wanneer de kritische snelheid en de kritische dichtheid zijn bepaald, is het berekenen van de actuele capaciteitswaarde eenvoudig:

$$C(k) = \hat{\rho}_c(k) \cdot \hat{u}_c(k)$$

Nota bene: het algoritme bepaalt de actuele capaciteit. Dit betekent dat zolang we onder vrije afwikkeling meten, de capaciteit wordt opgestuwd naar de vrije capaciteitswaarde. Zodra we in de congestietak belanden wordt de capaciteitswaarde aangepast richting de afrij capaciteit. In combinatie met het RWS-C algoritme heeft dit als voordeel dat de actuele capaciteitswaarde kan worden gebruikt om te regelen i.p.v. een vooraf ingestelde vaste waarde.

5 IO relaties

Onderstaande figuur toont de IO voor de Parameterschatter.



5.1 Input en output relaties

De Parameterschatter maakt gebruik van gegevens afkomstig van de TDI en van de MRM. *Dit is een aanpassing ten opzichte van de Parameterschatter uit fase 1*. De Parameterschatter levert uitkomsten aan het TDI algoritme en aan de DNW.

5.2 Bediening en logging

Voor de configuratie zijn met name de parameters voor smoothing en het aanpassen van de schattingen relevant. Onderstaande tabel geeft hiervan een overzicht. De logging bestaat uit de invoer en de uitvoer, de instellingen van de parameters en eventuele storigen.

Symbool	Eenheid	Beschrijving	Default	Range
T	-	Intervallengte voor bepalen afgeleide	7	[0…999]
α	-	Smoothings parameter	0.8	[0…1]
γ	-	Smoothings parameter	0.9	[0…1]
β^{+}	Km/u	Grenswaarde voor afgeleide fundamenteel diagram op grond waarvan schatting wordt aangepast	40	[0…99]
β^{-}	Km/u	Grenswaarde voor afgeleide fundamenteel diagram op grond waarvan schatting wordt aangepast	-10	[-99…0]

6 Kwaliteits- en performance eisen aan de monitoring systemen

De algoritmiek is getest met harmonisch gemiddelde snelheden en intensiteiten afkomstig van de TDI detectoren, stroomafwaarts van de toerit, in geval er sprake is van een kiem. We verwachten dat we ook goede schattingen kunnen bepalen indien er in plaats van 20 s gemiddelde gegevens, 60 s gemiddelde gegevens worden geleverd.

Vooralsnog is niet zeker of de aanpak ook werkt met rekenkundig gemiddelde snelheden.

7 Prototype code

```
% Testje eenvoudige parameterschatter
% We gebruiken de data uit de 0/1 meting:
close all;

v0 = 120;
kj = 150;
ccong = 18;

load('projFile_1meting');
for idag = 1:7
    figure(idag);
    t = Proj(idag).Control.tTdi;
    q = Proj(idag).Control.Data.tdi_i_rwsa_vth;
    v = Proj(idag).Control.Data.tdi_v_rwsa_kmh;
    tdi_labels = Proj(idag).Control.ObjectTdi;

    itdi = 1;
    q = q(itdi,:); index = find(~isnan(q)); q = q(index);
    v = v(itdi,:); v = v(index);
    t = t(index);
    k = q./v;

    % Nu maar een paar plaatjes...
    subplot(3,2,1);
    plot(t,k, '.-');
    xlabel('t (min)');
    ylabel('dichtheid (vtg/km)');
    datetick('x');

    subplot(3,2,2);
    plot(t,q, '.-');
    xlabel('t (min)');
    ylabel('intensiteit (vtg/u)');
    datetick('x');
```

```
subplot(3,2,5);
plot(k,q,'o');
xlabel('dichtheid (vtg/km)');
ylabel('intensiteit (vtg/u)');

% Nu de kiemenspeurder eens testen...
eps = 0.0;
alfa = 0.8;
gamma = 0.9;

T = 7;
kkrit(1:T) = 12;
ukrit(1:T) = 50;

m = length(q);

for i = T+1:m
    i0 = max(1,i-T+1);
    Q = q(i0:i);, K = k(i0:i);

    p = polyfit(K, Q, 1);
    % Bepaal de afgeleide:
    % Qprime = (q(i) - q(i-1)) / (k(i) - k(i-1));
    % Qprime = beta * Qprime + beta * (1-beta) * QprimeRuw;
    Qprime = p(1);

    % Pas de kritische dichtheid (doelwaarde) aan:
    disp(Qprime);
    if Qprime < -0.5 * ccong
        if k(i) < kkrit(i-1)
            disp('Naar beneden bijstellen...');
            kkrit(i) = alfa * kkrit(i-1) + (1-alfa)*(k(i) - eps);
            ukrit(i) = gamma * ukrit(i-1) + (1-gamma)*(v(i) - eps);
        else
            kkrit(i) = kkrit(i-1);
            ukrit(i) = ukrit(i-1);
        end;
```

```
    else
        if Qprime > 0.5 * v0
            if k(i) > kkrit(i-1)
                disp('Naar boven bijstellen...');
                kkrit(i) = alfa * kkrit(i-1) + (1-alfa)*(k(i) + eps)
                ukrit(i) = gamma * ukrit(i-1) + (1-gamma)*(v(i) + eps);;
            else
                kkrit(i) = kkrit(i-1);
                ukrit(i) = ukrit(i-1);
            end;

        else
            kkrit(i) = kkrit(i-1);
            ukrit(i) = ukrit(i-1);
        end
    end

end;

subplot(3,2,3);
plot(t, kkrit(1:length(t)), '.-');
ylabel('kritische dichtheid (vtg/km)');
xlabel('tijd (min)');
datetick('x');

    subplot(3,2,4);
plot(t, ukrit(1:length(t)), '.-');
ylabel('kritische dichtheid (vtg/km)');
xlabel('tijd (min)');
datetick('x');


subplot(3,2,5);
hold on;
plot([kkrit(m)  kkrit(m) ], [0 10000], 'r--');
plot(kkrit, kkrit .* ukrit, 'rx-');
ylim([0 8000]);
xlim([0 400]);
```

Appendix B. Matlab scripts

B.1. Matlab code PI-ALINEA including gradient method

```
function [ MRAC_RMcontrol, R ] = Compute_MRAC_RMcontrol( k, EST, P, d_M, ...
    S, d, R_para)
%%ALINEA control computes the inflow that is allowed to enter the mainline
%  the input rho_hat comes from rho_crit, K_r is a constant, rho_out is
%  measured value previous time step, r(k) is the regulated inflow ...
    previous time step

%% initial inputs
R.det_loc_plots = 22; % detector location downstream of ramp for plots ...
R.det_loc = 22; %detector location downstream of ramp
R.wmaxallowed = 200; % maximum value for queue on ramp
R.wmax = R.wmaxallowed * 0.8; %threshold value for queue control
R.minimum_flow = 240; %minimum ramp meter flow in veh/h
MRAC_RMcontrol = zeros(1,P.Nm); %make matrix with zeros for rmcontrol
EST.capacity(EST.det_loc,1:P.Nm) = 4000; %activate if Parameterschatter is
%not active
R.thresholdcap_on = EST.capacity(EST.det_loc,k) * 0.8; %(de-)activation ...
    criteria
R.thresholdspeed_on = 50; %(de-)activation criteria
R.thresholdcap_off = EST.capacity(EST.det_loc,k) * 0.7; %(de-)activation ...
    criteria
R.thresholdspeed_off = 70;%(de-)activation criteria
R.threshold_lowcap_off = EST.capacity(EST.det_loc,k) * 0.6; ...
    %(de-)activation criteria
R.threshold_lowspeed_off = 45;%(de-)activation criteria
R.threshold_lowestspeed_off = 25;%(de-)activation criteria

R.ADAPTGAIN_P = 0.6; %adaptation gain Proportional gain - needs fine tuning!
R.ADAPTGAIN_I = 0.02; %adaptation gain Integral gain - needs fine tuning!
R.beta = 1.5; %threshold value gradient method - needs fine tuning!
R.alpha = 1.5; %threshold value gradient method - needs fine tuning!
R.K_I = zeros(1,P.Nm);
R.K_P = zeros(1,P.Nm);
R.K_I_0 = 1*S(R.det_loc).n_l; %initial value integral gain
R.K_P_0 = 40*S(R.det_loc).n_l; %initial value proportional gain


%% MRAC ALINEA algorithm

R.rho_crit = zeros(EST.det_loc,P.Nm); % make zero matrix
R.rho_crit(EST.det_loc,k) = 30; %EST.rho_crit(EST.det_loc,k);
%determine critical density, set to constant value if parameterschatter ...
    is not active
R.h =  1;
R.T_s = 60/3600; %sample time gradient method
R.rho_hat(EST.det_loc,k) =  S(R.det_loc).n_l * R.rho_crit(EST.det_loc,k) ...
    * 0.9; % target density
```

```
R.Error(k) = (R.rho_hat(EST.det_loc,k) - ...
    d_M.rho(R.det_loc,k)*S(R.det_loc).n_l ); %Error = target density - ...
    downstream density

if k > 1
R.DIFFERROR(k-1) = R.Error(k) - d_M.Error(k-1); %determine difference in ...
    error
end

R.K_P(1:2) = R.K_P_0; %initial value gains for first 2 time steps
R.K_I(1:2) = R.K_I_0;

% Updating K_P & K_I
if k > 2
    if d_M.wR(k) ≥ R.wmax || R.Error(k) > 10
        % if queue exceeds threshold value or error is very positive
       R.K_P(k) = d_M.K_P(k-1);
       R.K_I(k) = d_M.K_I(k-1);
      elseif (abs(d_M.rho(R.det_loc,k)*2 - d_M.rho(R.det_loc,k-2)*2) < ...
          R.alpha )
        % if traffic situation is stable, no big differences in density
       R.K_P(k) = d_M.K_P(k-1);
       R.K_I(k) = d_M.K_I(k-1);
      elseif (R.DIFFERROR(k-1) > R.beta && d_M.DIFFERROR(k-2) > R.beta)
       % if difference in error (for 2 time steps) is positive and ...
           greater than threshold
       R.K_P(k) = d_M.K_P(k-1);
       R.K_I(k) = d_M.K_I(k-1);
    else
        %first update K_P / K_I if consecutive time steps have the same
        %value
            if d_M.K_P(k-1) == d_M.K_P(k-2)
                if abs(d_M.K_P(k-2)) < 0.5
                 d_M.K_P(k-1) = round(d_M.K_P(k-2)*1.10,2);
                else
                d_M.K_P(k-1) = round( 0.98*d_M.K_P(k-2),2);
                end
            end
            if d_M.K_I(k-1) == d_M.K_I(k-2)
               if abs(d_M.K_I(k-2)) < 0.5
                d_M.K_I(k-1) = round(d_M.K_I(k-2)*1.10,2);
                else
                d_M.K_I(k-1) = round( 0.98*d_M.K_I(k-2),2);
               end
                if d_M.K_I(k-1) < 0.1 && d_M.K_I(k-2) < 0.1
                    d_M.K_I(k-1) = 0.1;
                end
            end
            %update parameter gains according update rule
            R.K_P(k) = round(d_M.K_P(k-1) - R.T_s * R.ADAPTGAIN_P * ...
                (R.Error(k)) * (d_M.Error(k-1) - ...
               d_M.Error(k-2))/(d_M.K_P(k-1) - d_M.K_P(k-2) ),2);
             R.K_I(k) = round(d_M.K_I(k-1) - R.T_s * R.ADAPTGAIN_I * ...
                 (R.Error(k)) * (d_M.Error(k-1) - ...
                 d_M.Error(k-2))/(d_M.K_I(k-1) - d_M.K_I(k-2) ),2);
     end
```

```
end

if  d_M.wR(k) ≥ R.wmax
    %other RMcontrol at certain queue length at ramp (segment 20)
    if d_M.wR(k) > 0.3*R.wmax
    MRAC_RMcontrol(k+1) = d_M.dR(k) + d_M.wR(k) - R.wmax;
    end
%disp('update queue control')
elseif d_M.q(R.det_loc,k) ≥ R.thresholdcap_on || d_M.v(R.det_loc,k) ≤ ...
    R.thresholdspeed_on
    % activating ramp metering at ramp (segment 20) at certain threshold ...
        value

    if k == 1
    MRAC_RMcontrol(k+1) = d_M.RM_Rate(:,k) + R.K_P(k) * ...
        (R.rho_hat(EST.det_loc,k) - d_M.rho(R.det_loc,k)*S(R.det_loc).n_l ...
        - R.rho_hat(EST.det_loc,k)...
         + d_M.rhoss(R.det_loc)*S(R.det_loc).n_l) + R.h * R.K_I(k) * ...
             (R.rho_hat(EST.det_loc,k) - ...
             d_M.rho(R.det_loc,k)*S(R.det_loc).n_l );
   else
    MRAC_RMcontrol(k+1) = d_M.RM_Rate(:,k) + R.K_P(k) * (R.Error(k) - ...
        d_M.Error(k-1)) + R.h * R.K_I(k) * (R.Error(k));
   end
%disp('update rm rate 1')
elseif d_M.q(R.det_loc,k) ≤ R.thresholdcap_off || d_M.v(R.det_loc,k) ≥ ...
    R.thresholdspeed_off
    % deactivating ramp metering at ramp (segment 20) at certain ...
        threshold value
    MRAC_RMcontrol(k+1) = R_para.Q0;

elseif d_M.v(R.det_loc,k) ≥ R.threshold_lowspeed_off && ...
    d_M.q(R.det_loc,k) < R.threshold_lowcap_off
    % deactivating ramp metering at ramp (segment 20) at certain ...
        threshold value
    MRAC_RMcontrol(k+1) = R_para.Q0;

elseif d_M.v(R.det_loc,k) < R.threshold_lowestspeed_off
    % deactivating ramp metering at ramp (segment 20) at certain ...
        threshold value
    MRAC_RMcontrol(k+1) = R_para.Q0;

elseif d_M.v(R.det_loc,k) < R.threshold_lowspeed_off && ...
    d_M.v(R.det_loc,k) ≥ R.threshold_lowestspeed_off
    % activating ramp metering at ramp (segment 20) at certain threshold ...
        value

    if k == 1
    MRAC_RMcontrol(k+1) = d_M.RM_Rate(:,k) + R.K_P(k) * ...
        (R.rho_hat(EST.det_loc,k) - d_M.rho(R.det_loc,k)*S(R.det_loc).n_l ...
        - R.rho_hat(EST.det_loc,k)...
         + d_M.rhoss(R.det_loc)*S(R.det_loc).n_l) + R.h * R.K_I(k) * ...
             (R.rho_hat(EST.det_loc,k) - ...
             d_M.rho(R.det_loc,k)*S(R.det_loc).n_l );
   else
```

```
        MRAC_RMcontrol(k+1) = d_M.RM_Rate(:,k) + R.K_P(k) * (R.Error(k) - ...
            d_M.Error(k-1)) + R.h * R.K_I(k) * (R.Error(k));
      end
    %disp('update rm rate 2')
  else
        MRAC_RMcontrol(k+1) = R_para.Q0;
  end

  %% certain value preventing to switch on to fast
  %minimum metering time (=5 min)
  %if ramp metering turns on, it does not turn off for X minutes to prevent
  %flashing
  if k > 4 && MRAC_RMcontrol(k+1) ≥ R_para.Q0 && d_M.RM_Rate(:,k) < ...
      R_para.Q0 && d_M.wR(k) < R.wmax
  if d_M.RM_Rate(:,k-1) ≥ R_para.Q0 || d_M.RM_Rate(:,k-2) ≥ R_para.Q0  || ...
      d_M.RM_Rate(:,k-3) ≥ R_para.Q0
        MRAC_RMcontrol(k+1) = d_M.RM_Rate(:,k);
  end
  end
  %minimum time off after metering
  %ramp metering turns off, than it stays off for X minutes
  if k > 1 && d_M.RM_Rate(:,k) ≥ R_para.Q0 && d_M.RM_Rate(:,k-1) < ...
      R_para.Q0 % k-('#') < k < P.Nm+1
   % (k-)'#'+1 minutes RM = 1 if RM = 0 at timeinterval [k-('#'),k-1]
      MRAC_RMcontrol(k+1) = R_para.Q0;
  end
  if k > 2 && d_M.RM_Rate(:,k-1) ≥ R_para.Q0 && d_M.RM_Rate(:,k-2) < ...
      R_para.Q0 % k-('#') < k < P.Nm+1
   % (k-)'#'+1 minutes RM = 1 if RM = 0 at timeinterval [k-('#'),k-1]
      MRAC_RMcontrol(k+1) = R_para.Q0;
  end
  if k > 3 && d_M.RM_Rate(:,k-2) ≥ R_para.Q0 && d_M.RM_Rate(:,k-3) < ...
      R_para.Q0 % k-('#') < k < P.Nm+1
   % (k-)'#'+1 minutes RM = 1 if RM = 0 at timeinterval [k-('#'),k-1]
      MRAC_RMcontrol(k+1) = R_para.Q0;
  end
  if k > 4 && d_M.RM_Rate(:,k-3) ≥ R_para.Q0 && d_M.RM_Rate(:,k-4) < ...
      R_para.Q0 % k-('#') < k < P.Nm+1
   % (k-)'#'+1 minutes RM = 1 if RM = 0 at timeinterval [k-('#'),k-1]
    MRAC_RMcontrol(k+1) = R_para.Q0;
  end

  %% boundary values
  if MRAC_RMcontrol(k+1) ≥ R_para.Q0
          MRAC_RMcontrol(k+1) = R_para.Q0;
  elseif MRAC_RMcontrol(k+1) ≤ R.minimum_flow
            MRAC_RMcontrol(k+1)= R.minimum_flow;
  end


  end
```

B.2. Matlab code Parameterschatter

```
function [ EST ] = Compute_rhocrit( k, d_M, P, S )
%In this function script the critical density will be estimated for the
%ALINEA algorithm in the MRAC-scheme.
%   The estimated critical density is used to update the target density in
%   the ALINEA algorithm.

EST.rho_crit = zeros(P.N_Seg,P.Nm); % make an intitial matrix for faster ...
    matlab runs


%% least squares estimation
T=6; %Time interval
alpha = 0.8; % smoothing parameter, tuneable
gamma = 0.9; % smoothing parameter, tuneable
EST.det_loc = 22;
EST.beta_plus(1:P.Nm) = 10; % upperbound threshold value for updating the ...
    critical density
EST.beta_min(1:P.Nm) = -3; % lowerbound threshold value for updating the ...
    critical density
EST.rho_crit(EST.det_loc,1:T) = 20;
EST.v_crit(EST.det_loc,1:T) = 70;
EST.capacity(EST.det_loc,1:T) = 4000;
EST.Qprime(1:T) = 1;

for k = T+1:P.Nm; % run for k = 1 till #runs

%Determine derivative of fundamental diagram
i0 = max(1,k-T+1);
Q = d_M.q(EST.det_loc,i0:k);
K = d_M.rho(EST.det_loc,i0:k)*S(EST.det_loc).n_l;
EST.p = polyfit(K, Q, 1);
EST.Qprime(k) = EST.p(1);

eps = 0;

if EST.Qprime(k) < EST.beta_min
if EST.rho_crit(EST.det_loc,k-1) > d_M.rho(EST.det_loc,k)
      EST.rho_crit(EST.det_loc,k) = alpha*EST.rho_crit(EST.det_loc,k-1) + ...
          (1-alpha)*(d_M.rho(EST.det_loc,k) - eps);
      EST.v_crit(EST.det_loc,k) = gamma*EST.v_crit(EST.det_loc,k-1) + ...
          (1-gamma)*d_M.v(EST.det_loc,k);
elseif EST.rho_crit(EST.det_loc,k-1) ≤ d_M.rho(EST.det_loc,k)
    EST.rho_crit(EST.det_loc,k) = EST.rho_crit(EST.det_loc,k-1);
    EST.v_crit(EST.det_loc,k) = EST.v_crit(EST.det_loc,k-1);
end
elseif EST.Qprime(k) > EST.beta_plus
if  EST.rho_crit(EST.det_loc,k-1) < d_M.rho(EST.det_loc,k)
EST.rho_crit(EST.det_loc,k) = alpha*EST.rho_crit(EST.det_loc,k-1) + ...
    (1-alpha)*(d_M.rho(EST.det_loc,k) + eps);
EST.v_crit(EST.det_loc,k) = gamma*EST.v_crit(EST.det_loc,k-1) + ...
    (1-gamma)*d_M.v(EST.det_loc,k);
elseif EST.rho_crit(EST.det_loc,k-1) ≥ d_M.rho(EST.det_loc,k)
    EST.rho_crit(EST.det_loc,k) = EST.rho_crit(EST.det_loc,k-1);
    EST.v_crit(EST.det_loc,k) = EST.v_crit(EST.det_loc,k-1);
end
```

```
else
EST.rho_crit(EST.det_loc,k) = EST.rho_crit(EST.det_loc,k-1); % in all ...
    other cases
EST.v_crit(EST.det_loc,k) = EST.v_crit(EST.det_loc,k-1);
end

% if EST.rho_crit(EST.det_loc,k) > d_M.rho(EST.det_loc,k)
% EST.capacity(EST.det_loc,k) = 4000;
% else
EST.capacity(EST.det_loc,k) = ...
    EST.rho_crit(EST.det_loc,k)*S(EST.det_loc).n_l*EST.v_crit(EST.det_loc,k);
% end


end
end
```