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Ramp Metering with Real-Time Estimation of Parameters

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Abstract—Demand exceeding the capacity of a bottleneck will create congestion upstream of that bottleneck. Once this congestion occurs, the maximum flow through this bottleneck decreases (capacity drop). By limiting the flow towards the bottleneck, one can prevent or postpone the capacity drop and the accompanying congestion. In case the bottleneck is caused by an on-ramp, a common approach is to meter the on-ramp flow. For metering to be effective the algorithm has to be tuned carefully. Normally, the parameters of a metering algorithm are fit for the situation. However, traffic is dynamic and external factors might change, which both lead to changes in parameters of the traffic process. This paper studies how these parameters can be updated dynamically in the control algorithm. It considers various ramp metering algorithms and introduces methods to adapt their parameters. They are tested with simulations using the METANET model. This shows that parameter adaptation improves traffic state. Gains in travel time due to parameter adaptation are typically several percent compared to non-adaptive ramp metering. Road authorities can use these findings to improve ramp metering algorithms and reduce delays.

Index Terms—traffic management, traffic control, ramp metering, parameter adaptation

I. INTRODUCTION

Ramp metering is an important traffic management measure to deal with congestion problems on motorways, particularly the disruptions caused by high demands of traffic entering the motorway from on-ramps. The goal of ramp metering is to restrict demand for on-ramps near a bottleneck or to decrease the number of

disruptions in the traffic stream on the motorway due to the merging process, for example caused by platoons of vehicles coming from an upstream signalized intersection [1]. Ramp metering splits platoons of vehicles into individual vehicles, which can find and fill gaps in the main stream much easier. This is done using a traffic light which allows vehicles to enter the motorway one by one. Not only does this improve the merging process, also the capacity of the motorway can increase if the capacity drop is postponed or prevented. Introducing extra delay on the on-ramp could also cause drivers to choose another on-ramp or even another route, which decreases demand and improves the local situation.

In the Netherlands, ramp metering was first applied on an on-ramp to the ring road of Amsterdam in 1989. More applications followed rapidly, leading to a total number of 122 metering systems throughout the country in 2016 [2]. The control itself is done with special traffic lights. They differ from normal traffic lights in their design (yellow background shield) and in the way the signals are located: as close as possible near the driver (lower and closer to the stop line than normal traffic signals). Another important difference is that in the case an on-ramp has more than one lane the signals operate lane dependent.

The metering system operates using real-time traffic data, collected with induction loops both on the motorway and on the on-ramp. For the motorway data on flows and speeds are collected on two cross-sections, upstream and downstream the on-ramp. On the on-ramp itself loops are used to count vehicles and to detect the

The research was supported by the Netherlands Organisation for Scientific Research and was conducted at the ITS Edulab, a cooperation between Rijkswaterstaat and Delft University of Technology.

presence of vehicles, which is used to control the length of the metering phase and to detect queues. The data is used to feed the control algorithm for two purposes. One purpose is to determine when to switch the system on or off and the other purpose is to calculate the best cycle time for the situation. The cycle time determines the inflow of the ramp to the motorway. Ramp metering proves to be very effective. From the 19 assessment studies that were carried out in the Netherlands in 25 years time [1], [3], it can be derived that due to ramp metering the delay (in terms of lost vehicle hours) decreased on average with about 11%.

The control algorithm for ramp metering has always been an important research topic in the Netherlands. Starting with the demand-capacity Rijkswaterstaat (RWS) algorithm, also the ALINEA algorithm and an algorithm based on fuzzy logic have been tested [4], [5]. Although both ALINEA and the fuzzy logic algorithm produced comparable or even better results, for practical reasons (tuning) the RWS algorithm was chosen as the standard for application in the Netherlands. However, since 2010 the attention for the control aspects of ramp metering renewed, especially with respect to the relation and eventually coordination with other traffic management measures. This was due to the large scale traffic management field trial in and around Amsterdam [6]. This trial applied a variant of the ALINEA algorithm for ramp metering on a network level. The trial showed that adaptation of the control parameters was needed. In this paper we do not consider random effects of vehicle-driver composition, changing within a minute. Instead, we changes of the driving behavior on a longer time scale, for instance due to gradual change of driving education of vehicle technology, or on a medium time scale changing weather conditions. The contribution of this paper is development and testing of a method how parameters can be made adaptive. Note that this paper summarizes the main results extensively elaborated in the thesis of Meulenberg [7].

First we will analyze some available control concepts for ramp metering (section II). Then, section III explains the proposed method to optimize the parameters of the ramp metering algorithm. Section IV shows how the method will be tested and the results of these tests are described and discussed in section V. Finally, section VI presents the conclusions.

II. CONTROL ALGORITHMS FOR RAMP METERING

As stated before, the purpose of ramp metering is to regulate the inflow from the on-ramp to the mainline of the motorway. Since the introduction of ramp metering,

many algorithms were developed and put into practice. This research is restricted to the local ramp metering strategies used in the Netherlands, being the Rijkswaterstaat (RWS) strategy and the ALINEA strategy.

A. RWS strategy

The RWS strategy is a variant of the demand-capacity (DC) strategy. A standard DC strategy makes use of the motorway traffic conditions upstream of the on-ramp. This is called feed forward control. The strategy calculates the number of vehicles allowed to enter the motorway $r(k)$ in time interval k . If the last measured upstream motorway occupancy o_{in} (in %) is smaller or equal than the critical occupancy o_{crit} , the allowed flow is computed by subtracting the last measured upstream motorway flow q_{in} from the downstream capacity q_{cap} . If the occupancy is higher, the allowed flow is determined by the minimum pre-specified ramp flow r_{min} . The DC strategy is formulated as follows [8]:

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

The strategy is generally known to be quite sensitive to various non-measurable disturbances [9]. To reduce the sensitivity for these disturbances and leaps in the metering rate, the RWS strategy does not use the occupancy upstream as a threshold, but it uses the upstream smoothed flow $\tilde{q}_{in}(k)$ and the measured flow from the previous time interval $q_{in}(k-1)$:

$$r(k) = q_{cap} - \tilde{q}_{in}(k) \quad (2)$$

$$\tilde{q}_{in}(k) = \alpha * q_{in}(k-1) + (1 - \alpha) * \tilde{q}_{in}(k-1) \quad (3)$$

where α is the smoothing parameter [1]. The minimum flow is enforced on $r(k)$ itself, so when $r(k) < r_{min}$ then $r(k) = r_{min}$.

B. ALINEA

According to [8] it is actually the best to control the traffic based on the conditions downstream of the ramp. This is called a feedback control strategy. The ALINEA algorithm is such a feedback strategy. The first ALINEA algorithm, developed by [10], uses the downstream occupancy (%) $o_{out}(k-1)$ as input for the control strategy. ALINEA tries to control the inflow in such a way that the occupancy is held close to a certain desired value \hat{o} :

$$r(k) = r(k-1) + K_R[\hat{o} - o_{out}(k-1)] \quad (4)$$

where K_R is the regulator parameter.

Several variations on the ALINEA algorithm have been developed where the (targeted/measured) variable occupancy is replaced by density, speed or even flow. In this paper we discuss and test two variations which are relevant for the current practice in the Netherlands: D-ALINEA and PI-ALINEA. D-ALINEA [6] uses density and therefore an important parameter is the critical density. PI-ALINEA [11] consists of a Proportional (P) and an Integral (I) part with several parameters. Both algorithms are described in the following subsections.

1) *D-ALINEA*: D-ALINEA is the variation which makes use of density instead of occupancy as the measured variable and the target value. So, equation 4 now becomes:

$$r(k) = r(k-1) + K_R[\hat{\rho} - \rho_{\text{out}}(k-1)] \quad (5)$$

The adaptive part, which was developed during the Traffic Management Trial Amsterdam, estimates the target density $\hat{\rho}$ with a *parameter estimator*. The parameter estimator first determines the critical density ρ_{crit} based on the current traffic conditions. Then the desired value of the density $\hat{\rho}$ is derived from the critical density with $\hat{\rho} = \xi * \rho_{\text{crit}}$ with $\xi \leq 1$. In this way the algorithm tries to prevent that the density exceeds the critical value ρ_{crit} .

2) *PI-ALINEA*: The PI-ALINEA variation was developed for distant downstream bottlenecks, because the normal ALINEA variation is less efficient for these cases. This has to do with the time delay involved if a bottleneck is located further downstream the on-ramp than the merging area [11]. In PI-ALINEA, the proportional part gives the gain over the error between a measured downstream value one time step earlier and a current measured downstream value. The integral part represents gain over the error of a certain target value and the downstream measured value. It was originally developed with the occupancy as target value. In equation 6 this variation is denoted with density as the variable:

$$r(k) = r(k-1) - K_P[\rho_{\text{out}}(k-1) - \rho_{\text{out}}(k-2)] + K_I[\hat{\rho} - \rho_{\text{out}}(k-1)] \quad (6)$$

The only results for this variation we know of, are described in [11]. Here PI-ALINEA is tested on distant downstream bottlenecks. The standard ALINEA variation with occupancy was not able to maintain the maximum throughput and PI-ALINEA showed better results. It was also concluded that PI-ALINEA is only applicable if the bottleneck location is known beforehand, which means that detectors have to be deployed there.

C. Discussion

The algorithms described in the previous section all have fixed parameters (target values and regulator parameters), which have to be set if the algorithm is going to be implemented in practice. Experience has shown that this is a difficult and time-consuming task for the traffic engineer. Results from the Traffic Management Trial Amsterdam show that using an adaptive approach to the target density could improve the situation. In the research described in this article we take this a step further and investigate what happens if we make more parameters adaptive. The method how we did that and the results are described in the following sections.

III. A RAMP METERING ALGORITHM WITH PARAMETER ADAPTATION

In our research we focused on the PI-ALINEA algorithm to include parameter adaptation and we named this the Adaptive Ramp Metering Controller (AD-RMC). For AD-RMC the following control law is formulated, where K_I , K_P are parameter gains, which are now time dependent, just like the target density $\hat{\rho}$:

$$r(k) = r(k-1) + K_P(k) * [\hat{\rho}(k) - \rho_{\text{out}}(k-1)] + K_I(k) * \int_1^k (\hat{\rho}(k) - \rho_{\text{out}}(k-1)) dk \quad (7)$$

For updating the parameter gains every time step, we use a gradient method. For the determination of the target density we will estimate the *critical density* ρ_{crit} using a parameter estimator. The target density is defined as $\hat{\rho}(k) = \xi * \rho_{\text{crit}}(k)$, where ξ should be interpreted as the fraction of the capacity of the road that can be filled. In our case we use $\xi = 0.9$.

First this section describes how the parameter gains K_P and K_I are updated (section III-A) and then how the critical density ρ_{crit} is estimated (section III-B).

A. Parameter gains adaptation law

The reference situation on the motorway is obtained when the throughput is optimized. This happens when the density is close to the critical density [12]. To be able to deal with variations, not the critical but a somewhat lower density is set as target, as we explained earlier. The error (e) in the algorithm is the target density $\hat{\rho}$ subtracted by the actual downstream density ρ_{out} . With this, we can rewrite equation (6) as follows:

$$r(k) = r(k-1) + K_P(k) * [e(k) - e(k-1)] + K_I(k) * [e(k)] \quad (8)$$

The gradient method tries to make the error converge to zero by adaptation of the parameter gains. The method is based on the work described in [13]. For adaptation of the parameter gains K_I and K_P , an objective function J can be defined as follows:

$$J(\mathcal{K}) = \frac{1}{2}e(\mathcal{K})^2 \quad (9)$$

where \mathcal{K} is the parameter gain (K_I or K_P) and e the error. To minimize this objective function, the derivative is used. Equation 10 gives the derivation towards the general parameter update rule, in with γ is the adaptation gain.

$$\frac{d\mathcal{K}}{dt} = -\gamma \frac{\partial J}{\partial \mathcal{K}} = -\gamma e \frac{\partial e}{\partial \mathcal{K}} \quad (10)$$

If we discretize this equation we get the the actual update rules for the parameter gains, again with γ as the adaptation gain and T_s the sample time in hours.

$$\mathcal{K}(k) = \mathcal{K}(k-1) - \gamma * T_s * e(k) * \frac{e(k-1) - e(k-2)}{\mathcal{K}(k-1) - \mathcal{K}(k-2)} \quad (11)$$

A non-changing parameter gain leads to an error in this equation. If all of the following conditions hold, there are no updates in the parameter gain:

- Queue control active OR $e(k) > 10$ veh/km
- $|\rho_{out}(k) - \rho_{out}(k-2)| < \alpha_{gains}$
- $e(k) - e(k-1) > \beta_{gains} \wedge e(k-1) - e(k-2) > \beta_{gains}$

where α_{gains} and β_{gains} are threshold values. If the situation occurs that two consecutive realizations of K_P or K_I still have the same value, the value is increased by 10% (if $\mathcal{K} > 0.5$) or decreased by 2% (otherwise). These values, as well as values for γ , α_{gains} and β_{gains} are determined by trial-and-error.

B. Parameter estimator

To determine the derivative of the fundamental diagram at time k , $D(k)$, flow and density of the past T time steps preceding time step k is computed based on a linear regression. An initial value for the critical density is set beforehand. When the derivative meets a certain threshold value (β^+ , β^-) the values for the critical density is updated. The update rules for the critical density consist of weighing the previous value with the newly measured density. For the weighing smoothing factors α and δ are used to prevent oscillatory behavior. We separate two cases: undercritical conditions

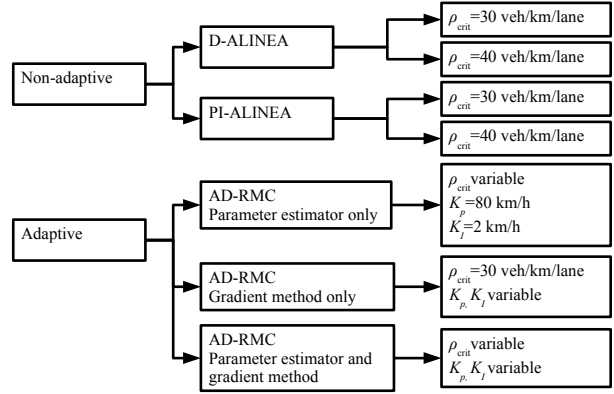


Figure 1. Overview of the tested algorithms

and overcritical conditions. In undercritical conditions, defined as $D(k) > \beta^+ > 0$, the update rule is:

$$\rho_{crit}(k) = \begin{cases} \alpha \rho_{crit}(k-1) + (1-\alpha) \rho_{out}(k) & \text{if } \rho_{crit}(k-1) < \rho_{out}(k) \\ \rho_{crit}(k-1) & \text{if } \rho_{crit}(k-1) \geq \rho_{out}(k) \end{cases} \quad (12)$$

In overcritical conditions, specified by $D(k) < \beta^- < 0$, the update rule is:

$$\rho_{crit}(k) = \begin{cases} \alpha \rho_{crit}(k-1) + (1-\alpha) \rho_{out}(k) & \text{if } \rho_{crit}(k-1) > \rho_{out}(k) \\ \rho_{crit}(k-1) & \text{if } \rho_{crit}(k-1) \leq \rho_{out}(k) \end{cases} \quad (13)$$

The estimated, new critical density will be used to update the target density in the ramp metering algorithm. If the conditions are not undercritical or overcritical then the critical density will not be updated. The values for α , δ , β^+ , β^- , and initial values were determined by means of trial-and-error.

IV. EXPERIMENTAL DESIGN

To test the developed adaptive control algorithms for ramp metering, several scenarios were simulated. This was done for a theoretical case using simulation with a macroscopic traffic model. This case is described, together with the tested algorithms and the performance criteria to assess the different algorithms, in the next sections.

A. Tested algorithms

Figure 1 shows the algorithms which were tested. A first distinction was made between the algorithms for which parameters are fixed and the algorithms with

adaptive parameters. Typically, the first type represents the current practice in which control parameters are adjusted manually to improve performance. The first non-adaptive algorithm is considered to be the reference case. For both D-ALINEA and PI-ALINEA we chose two different settings for the critical density, one just below the critical density used in the simulation model and another one much higher. This might be not the best choices, but the rationale behind this is that the critical density might be estimated wrongly, and a control algorithm should be robust for this. Also the factual density at which capacity is attained in the METANET model is not necessarily the critical density. Sometimes the factual density is larger, therefore the second one is chosen in the upper part of the critical density spectrum.

Two versions of adaptivity can be included: (1) an adaptive critical density, estimated with the parameter estimator, and (2) adapting the gains for the PI controller with the gradient method. It is tested to which extent each of the adaptations improves the traffic performance, and whether or not the combination (variable critical density *and* gains) improves the traffic performance even more.

All tested algorithms use general (de)activation criteria. One criterion is when the maximum storage space of the ramp almost has been reached. To avoid spill back from the ramp to the underlying network a queue control rule is used. Queue control avoids releasing all vehicles at once onto the motorway, but uses the metering rate calculated with $r = w + d - 0.8w_{\max}$, where w is the queue length, w_{\max} is the maximum queue length and d is the demand on the ramp. This ensures that the ramp is not completely occupied with a queue.

B. Traffic model

To assess the performance of the algorithms we use simulations with the METANET model [14] [15]. This is a second order macroscopic model, requiring a fundamental diagram and a relaxation towards the speed matching the fundamental diagram. The METANET model provides a capacity drop, due to the relaxation of speeds. This is an essential property for testing the effectiveness of a ramp metering installation. For the merging process, we also follow the original METANET formulation. The ramp metering is modeled by limiting the flow of the last cell of the on-ramp. The critical density is input to the METANET model. Therefore estimating it could be an easy task. To introduce more realism in the simulation for every run the critical density is stochastically varied, representing the stochasticity

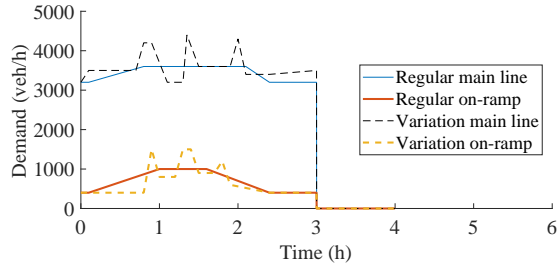


Figure 2. Demand profiles for the simulations

of traffic as well as the uncertainty in the estimation process.

C. Simulation setup

For the case study, we consider a two-lane road stretch of 30 km, with an on-ramp at 20 km. The network is divided into cells of 1 km, and the progression of traffic is computed with a time step of 10 seconds. The on-ramp and the mainline have separate demand profiles, which all end up at the same destination. The demand profiles are shown in figure 2. Note that both demands reduce to zero, such that the network can empty at the end of the simulation. Consequently, in all scenarios, the same number of vehicles arrive, which makes the average travel times comparable. This is a theoretical case designed to show the effects of adaptive control parameters. Therefore, the demand profiles and model parameters are chosen in such a way that congestion occurs at the on-ramp, which extends upstream for 15 kilometers and resolves after the drop in demand at 120 minutes or at the end of the simulation.

Apart from the runs with a normal demand profile, additional runs are done with a different demand profile, see also figure 2. This will show to which extent the ramp metering algorithm can handle variations in demand, and is not fitted for one case only. In case of no metering, the peaks in the demand will induce congestion and trigger the capacity drop. This matches normal traffic conditions, where demand is stochastic by nature due to departure patterns, but also due to traffic influences like traffic signals or congestion upstream on local roads.

The simulation is stochastic. During each run the critical density of the merging section varies stochastically each minute. Its value is drawn from a normal distribution with a mean value of 33.5 veh/km/lane (obtained from measurements on motorways in the Netherlands), with a mean of 0.5 veh/km/lane. The number of runs required depends on the standard deviation, a specified confidence level of (95%) and an allowed error of

Table I
SIMULATION RESULTS

	ρ_{crit} veh/km/lane	TD veh-h	TOD veh-h	AAMT min	Runs #
No control		3079	0	26.3	30
D-ALINEA	30	2935	69	25.4	30
D-ALINEA	40	2915	27	25.8	90
PI-ALINEA	30	2857	68	25.3	30
PI-ALINEA	40	3079	0	26.3	30
AD-RMC	Par. est.	2833	42	25.5	88
AD-RMC	Grad. meth.	2800	53	25.3	90
AD-RMC	Both est.	2830	45	25.4	140

(10 sec/veh) [16]. The resulting required number of runs change, and are indicated in table I. Neither of the setpoints for the controller (30 or 40 veh/km/lane) coincides with the mean capacity. This reflects the fact that the critical density will evolve from the setpoint with time anyway.

D. Performance criteria

To assess the different algorithms the following performance indicators are used:

- Total delay in the network (TD, in vehicle-hours). We compute so by adding the delays encountered in each cell (compared to free flow travel time).
- Total on-ramp delay (TOD, in vehicle-hours). This is the total delay encountered on the on-ramp, before merging to the main line.
- Average mainline travel time (AMTT, in minutes): for every time step the travel time on the mainline is calculated and these are averaged to obtain a value for the whole simulation period.

The indicators show the balance between the delay for drivers on the main road and on the motorway. From a policy perspective, this could be an essential part for consideration of fairness.

V. RESULTS

This section discusses the results: first for the regular demand profile, and then for the more variable demand.

A. Regular demand profile

The results of the regular demand profile are given in table I. It shows the absolute values of the performance indicators for all scenarios and also the number of simulations needed to obtain a 95% confidence level. The no-delay travel time equals 3609 veh-hrs, so the delays equal approximately half the total time spent.

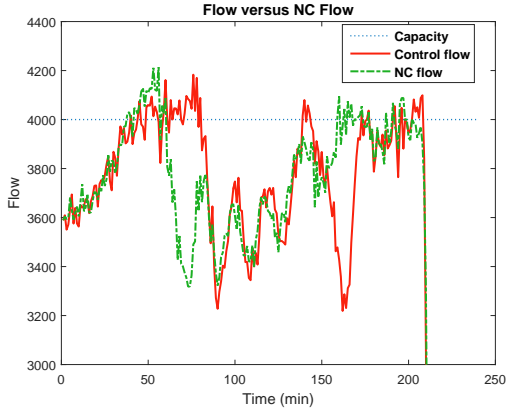
Table I shows that non-adaptive algorithms perform fairly well in comparison with the no-control (NC) case:

up to 7% less delay. The D-ALINEA algorithm with a critical density of 40 veh/km/lane performs slightly better than the variant with a critical density of 30 veh/km/lane. The total delay is somewhat lower (-1%) and there is also less delay on the on-ramp, but the mainline travel time is a little longer. It seems that this variation makes a better use of the available capacity, but this comes with a cost: there is more spread in the results from run to run. Therefore, this scenario needed more simulation runs for statistically reliable results. The non-adaptive PI-ALINEA with a critical density of 40 veh/km/lane did not give any improvement compared the NC case. There is no metering, hence no delay on the on-ramp, and exactly the same performance as in the no-control case. However, the PI-ALINEA with a critical density of 30 veh/km/lane has the best performance among the non-adaptive algorithms, yielding the lowest total delay.

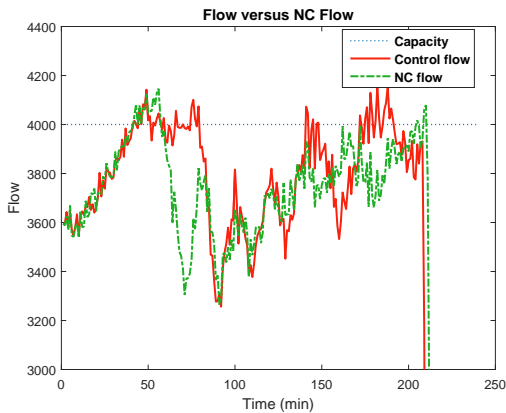
The AD-RMC was tested in three different scenarios. Results of the algorithm with adaptation of the parameter gains or the critical density show improvement compared to the NC case, but also compared with the non-adaptive scenarios. The AD-RMC with the parameter estimator had an average total delay (TD) of 2833 vehicle hours (-8%), where the AD-RMC with the gradient method had an average TD of 2800 vehicle hours (-9%) compared with the NC-case. Comparing adaptive with non-adaptive methods: the best adaptive strategy (AD-RMC with gradient method) improved delay with 4.0% compared with D-ALINEA and 2.0% compared with PI-ALINEA. This improvement comes on top on the results already obtained when introducing ramp metering. Compared to no control, total the delay decreases with 9.1%.

Results of the algorithm with a combination of both adaptation methods show considerable variation. Therefore, many more simulations were needed for statistically reliable results. This scenario had an average delay of 2830 vehicle hours, comparable to the scenario with only the parameter estimator active. This could be the result of situations where estimators oppose instead of strengthen each other. This also means that this algorithm is less stable.

The improvement is for a large part due to the postponement of the capacity drop. To illustrate that figure 3 shows the traffic flow during the NC case and the flow with the two different AD-RMC algorithms. As can be seen the capacity drop still occurs due to the onset of congestion, which cannot completely be prevented by ramp metering, but occurs much later. The time the capacity drop is postponed is clearly visible in these



(a) AD-RMC - Parameter estimator - flow



(b) AD-RMC - Gradient method - flow

Figure 3. Traffic flow with Parameter adaptation compared to no control

figures. For both AD-RMC scenarios the capacity drop occurs at approximately 80 minutes. For the NC case the capacity drop occurs at approximately 50 minutes, which explains the savings in total delay.

The adaptation of one type (parameter gains or critical density) leads to the best results in terms of total time spent or total delay. The improvements are obtained at the cost of a higher on-ramp delay, but in total the network performs better. The non-adaptive PI-ALINEA with a critical density of 30 veh/km/lane has an improvement of 2.7% over the D-ALINEA with the same critical density in terms of total delay. The AD-RMC with the parameter estimator for the critical density has an improvement of 3.5% over the D-ALINEA in terms of total delay. The AD-RMC with the gradient method for the parameter gains performs best in terms of total delay. This variation reduces TD with of 4.6% compared

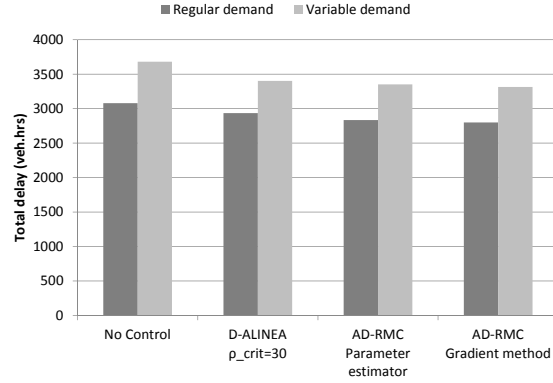


Figure 4. Average total delay for the regular and variable demand profile

to D-ALINEA.

B. Variable demand profile

The results for the total delay with the variable demand are shown in figure 4. The control algorithms with variable demand show the same pattern, but the improvements are a bit higher compared to the NC case. For example the AD-RMC with gradient method has an improvement in total delay of 10% compared with the NC-case. For the regular demand this was 9.1%. Overall, the results show that the AD-RMC algorithm with gradient method performs best for both demand profiles.

VI. CONCLUSIONS AND FURTHER RESEARCH

In this paper we developed and tested a new approach to ramp metering strategies. Instead of finding the fixed (set point) parameters for a ramp metering algorithm, the contribution of this paper a method to make these parameters adaptive. This saves effort for finding the optimal fixed value, and avoids the problem that the same fixed value is not optimal for all situations. The method is incorporated in a new adaptive ramp metering controller (AD-RMC) in which up to three parameters are continuously updated to fit the ever changing circumstances in traffic. The AD-RMC was tested by simulation, using METANET, a second-order macroscopic traffic flow model, and was compared with existing variations of the ALINEA metering algorithm: the D(ensity)-ALINEA and the standard PI-ALINEA (PI for proportional integral).

From the research it can be concluded that the AD-RMC with only one of the estimators active gives promising results. These two variations performed best in

terms of less delay (up to 4.6%), for the situation chosen. Another conclusion is that from the standard algorithms the non-adaptive PI-ALINEA performed best. The PI-ALINEA, as specified in this paper was never tested before and it showed very stable and better results than any of the D-ALINEA algorithms. This was a surprise as the only known research of a PI-ALINEA algorithm was done only with the proportional term. In this paper the algorithm has been extended by adding an integral, which lead to this good result. Probably this is due to the fact that this term tries to keep the measured output closer to the desired value than a proportional only algorithm.

For the tested situation, the AD-RMC with both estimators active did not perform as expected. In terms of total delay, the performance is as good as one with only one estimator active, but in terms of stability it performed much less: fluctuations between runs were very high. This could be the result of the combination of different estimations which could have opposite effects.

The conclusions derived from the simulations with a regular demand profile were confirmed by the simulations with a more variable demand profile. Both the non-adaptive D-ALINEA as well as the two AD-RMC variants with only one of the estimators active even showed somewhat higher improvements.

For future research it is recommended to investigate the conditions used for updating the parameter gains by means of the gradient method. This could improve the stability of the AD-RMC, especially the one with the gradient method. It is also recommended to test other gain update rules instead of the gradient method. This could lead to a more stable controller.

Another recommendation is to test the AD-RMC with a microscopic simulation model to get a more accurate traffic situation and a more realistic environment to test ramp metering strategies. With a microscopic model it is also possible to track driving behavior and external effects like route choice. This is also an important aspect of ramp metering and can be tested with an urban network and more on- and off-ramps on the motorway. It is known that ramp metering affects the route choice of drivers and it would be interesting to know this works out for the AD-RMC. Furthermore, microscopic simulation would also make it possible to combine ramp metering algorithms with new developments in cooperative, connected and automated driving. Finally, microscopic simulation could reveal the stochastic effects of vehicle composition in critical density. The adaptation of control parameters to this stochasticity should also be further

investigated.

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