

## Real-time urban traffic state estimation and prediction using a data-fusion framework based on link neighbors

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### Abstract

Effective ITS and traffic management purposes requires a complete and accurate information about current and predicted traffic states in the transport network. The current state-of-the-art in literature regarding traffic state estimation and prediction yields efforts which mostly focus on highways, which are not bluntly transferrable to an urban environment and do not maximize the utilization of all available traffic data.

This paper describes the development and assessment of a data-driven traffic state estimation and prediction framework for application in an urban environment. It uses the intuitive relationship between past, current and future traffic states on neighboring links to train and improve estimation/prediction accuracy and fill the gaps on those links where no floating car data are available. Additionally, this framework is tested on the well-known Sioux Falls Scenario. When penetration rate of floating cars is 5%, on average 50% of the urban links are estimated within 5 km/h accuracy. For a prediction horizon of 5 minutes, it performs almost equal with a percentage of 49%.

*Keywords: Traffic Data, Data Fusion Framework, Traffic State Estimation, Traffic State Prediction, Urban Traffic Network, Real-Time, Data-Driven Approach, Link-Neighborhoods.*

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## 1. Introduction

Use of information technology (IT) in traffic systems is becoming a hot topic within the traffic research community. It is within this context that IT and traffic, blend together to enable intelligent transportation systems (ITS). Benefits of employing ITS are ample and can range from; increased safety, improved operational performance, enhanced mobility, environmental benefits to boosts of productivity leading to economic and employment growth. One of the practical applications is that actors of a transportation system are allowed to enlighten themselves with information and make better informed decisions through ITS. Second, *the power of prediction* makes it possible for traffic managers to act proactively on future traffic states by, activating the most effective traffic scenarios and evaluating their effectiveness during deployment.

Both examples lean on two key processes, *traffic state estimation* and *traffic state prediction*. Within these processes a robust, complete and accurate picture of the traffic state in the network at any time in the past, present and near-future is generated. Knowledge about this key process is important due to recent developments on bringing more and more information, to the vehicle itself. Research towards improvement of this process is important because the traffic state estimation/prediction process allows use of more and better C-ITS services in a vehicle. In case of autonomous vehicles it is even thinkable that they will pro-actively intervene based on predicted future states. State estimation and prediction are therefore important instruments to understand the daily urban system and its spatial and temporal dynamics, today and in the near future.

Within the research field of traffic state estimation and prediction, the general trend is that only the upper traffic network (generally highways) is researched. Intuitively, a high quality traffic state estimation and prediction algorithm has more benefits if it is also applicable on the larger and more detailed urban road network. These urban networks cover also the important primary and secondary urban arterials. However, when estimating and predicting traffic states in an urban road network, more severe challenges need to be overcome than within the comfort of freeway segments in highway networks. In this paper the following two challenges relating to urban traffic state estimation and prediction are overcome.

The first challenge is lack of full coverage of traffic information sources within an urban network (e.g. limited loop detectors), leading to gaps and errors when no techniques are applied to the available measured data. The second challenge is to perfectly capture the urban nature of the traffic network. An urban environment provides additional challenges as opposed to a freeway only network, due different characteristics e.g.; lower traffic volumes, lower speed limits, more variability in velocities, a higher density of intersections, traffic signals, roundabouts, priority-junctions and dynamic interactions between other modes of transport.

Existing state-of-the-art traffic state estimation techniques can be divided into two large categories, i.e. model-driven approaches, in which the principles of traffic flow theory are modelled, and data-driven approaches in which relations in traffic data are considered, but no traffic-flow-model parameters are estimated. However in an urban environment some additional limitations are experienced. Firstly determination of a realistic fundamental diagram for each segment within the urban network in combination with the impacts of junctions on traffic flows is difficult, due to the inherent capriciousness of traffic in an urban network. Secondly in an urban network, the law of flow conservation does not necessarily hold, e.g. due to on-street parking or side roads that were not included in the network, strengthening the voice for a data-driven approach. Thirdly there are scalability issues, computation times can become too high to use these approaches on larger networks in real time settings. Bottom line; there is no method which outperforms one another in every situation and many of the current state of the art methods seem to be less suitable for detailed *urban* traffic state estimation and prediction. The choice for a certain model should therefore be completely context-dependent.

It is within this paper that the relatively un-researched area of a data-driven urban traffic state estimation and prediction method is further explored. In this paper a data-driven traffic state estimation and prediction approach is designed. It is specifically aimed to deliver a robust and complete image for the traffic state now and in the nearby future within an urban environment.

In chapter 2 (background) the state of the art regarding traffic state estimation and prediction is presented. In chapter 3 (method development) the newly developed framework is presented. In chapter 4 the case study for assessment of this new framework is described. Chapter 5,6 and 7 discuss results, conclusions and further research respectively.

## 2. Background

Within the field of traffic state estimation and prediction, a recent shift occurred altering the scope of research from relative comfort of freeway segments in highway networks to larger and more detailed urban road networks. These urban networks cover besides the upper network also the important primary and secondary urban arterials. The first example of such an urban study is the *Instrumented City Project* (Bell et al. 1992). Practical examples of recent urban traffic state studies in The Netherlands are Sensor City Assen (as from 2011) and the Praktijkproef Amsterdam (as from 2013). Within both these projects and in literature the general traffic flow variables of interest are; link wise space mean speeds, travel times, traffic densities and flows (e.g. Snelder & Calvert, 2015; Wang, 2005). Accurately estimating these traffic flow variables for different pre-defined network segments is the ultimate goal for the application of traffic state estimation techniques. Additionally predicting these traffic flow variables is the goal of the traffic prediction counterpart. As the number of unknown traffic flow variables to be estimated and predicted are generally larger than the number of variables that are measured, the relative complex task of deriving an accurate real-time network traffic state for ITS and management purposes, becomes apparent.

As previously mentioned, urban traffic state estimation refers to estimating relevant traffic flow variables such as flows, densities, speed and travel times for links in an urban road network with a certain temporal and spatial resolution based on traffic data available (Wang & Papageorgiou, 2008). Urban traffic state prediction refers to predicting the same traffic flow variables using most current traffic data with a predefined prediction horizon (generally up to 30 minutes). Figure 1 shows the generalized form of a traffic state estimation/prediction method.

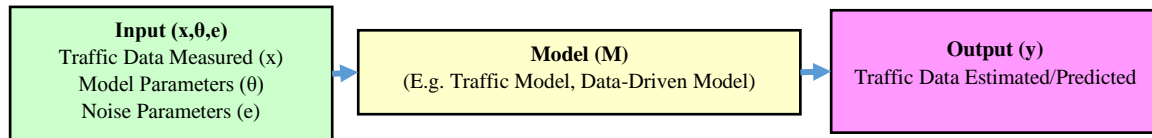


Fig. 1 General form of any traffic state estimation and prediction method. Derived from Van Lint (2011)

Snelder (2015) gives an inexhaustible list of estimation and prediction model types used in literature; e.g. statistical-, dynamical-, microscopic-, macroscopic-, offline-, online-, data-driven, model-driven and deterministic models. Because each type of model has its own advantages and disadvantages there is currently no model which outperforms all other models in every situation. Van Lint (2011) adds that the key difficulty for traffic state estimation and prediction is therefore to find a balance between sophisticated and complex models on one side and smooth, fast, general applicable models on the other side, to make valid estimations and forecasts given the data available. For summary purposes, the categorization proposed in Van Hinsbergen et al. (2007) is adopted in which four categories describe the state-of-the-art regarding each estimation/prediction model.

**The naïve categorization** represents the traffic models in which only the traffic data is used and direct relations are calculated. No model structure or parameters are inputted, which results in favourable low computational complexity and very easy implementation. The naïve method Snelder (2015) uses in the Praktijkproef Amsterdam, is based on the assumption that in short term the traffic situation on the network does not change. It is argued that because of the lack of traffic theory, the results are usually illogical and inaccurate (Van Lint, 2011).

**The parametric categorization** represents models in which the principles behind the Lighthill–Whitham–Richards (Lighthill & Whitham, 1955) model are used. These models are therefore based on plausible theoretical assumptions on traffic behaviour in time (Van Lint, 2011). As these models try to incorporate real world car traffic theory such as e.g. queueing theory, car following theory and/or shockwave theory (Van Lint, 2011), it becomes inevitable that vast calibration of parameters is required as to assure that the model results comply with the real-world. Examples of these model types are; Newell’s simplified kinematic wave model (Newell, 1993), cell transmission models (Daganzo, 1994), the variational kinematic wave theory (Daganzo, 2005), link transmission models (Yperman, 2007) and more recently a Lagrangian based approach (Laval & Leclercq, 2013).

**The non-parametric categorization** represents the traffic models in which relations in traffic data are considered, but no traffic flow parameters are estimated. They estimate traffic state based on real-time traffic data with some relation abstracted from historical traffic data. This relationship can be spatial and/or temporal. E.g. a simple regression approach tries to approximate output by using weighted combinations of input data and is generally classified as an autoregressive–moving-average (ARMA) model. Expansions of ARMA are again possible by

considering e.g. locally weighted regression in which each data point is weighted proportionally to its proximity to the investigated data point (which is also in basis used in the Adaptive Smoothing Method (Treiber & Kesting, 2012), or a linear combination of historical and current states (ATHENA; Aron & Danech-Pajouh (1991)) or recent measurements to be weighted more heavily as opposed to more historical measurements (SETAR; Watson et al. (1992)). These models have in common that while their complexity is low and therefore they can easily be run in real-time speed, their accuracy is according to Van Lint (2011) generally low.

**The hybrid categorization** represents traffic models which take elements from the different categories. Examples of popular parametric models which also apply some non-parametric techniques are mostly based on Kalman Filtering (KF)(Kalman & Bucy, 1961) e.g. EKF, UFK, PF, DEKF (Van Lint et al., 2008). These models are already quite well performing (e.g. Wan & Merwe, 2000; Ristic et al., 2004; Wang et al., 2005). The advantages of hybrid parameterized models are numerous as these traffic models allow decision support, scenario analysis and real-time traffic control (Van Lint, 2011). The limitations are related to the designed complexity as demands, turning rates, on-street parking rates, route choice patterns, traffic signal cycles and the vast amount of parameters to be calibrated. And as this calibration requires the outputted (real) traffic states as main ingredient, a vicious circle is potentially designed. Additionally computation complexity increases and therefore these models might forfeit the real-time prediction ability (Van Lint, 2008; Snelder, 2015).

From all these models, a hybrid data-driven approach seems, at least theoretically, to be best suitable for usage within a dynamic urban environment. These type of models run well within in real-time and are simple yet complex enough to cope with a heterogeneous urban traffic network. By including conditional dependencies and memorization of patterns in previous outputs, naïve approaches are outperformed. As a prerequisite this does require some existing intuitive relationship as to give direction to the weight layers and a starting point for further research. At first thought, an obvious relationship is that of travel time correlation between neighboring links. This relationship is already extensively researched and confirmed in literature (e.g. Gajewski & Rilett, 2003; Sen et al., 1997). Research on correlation of velocities for neighbouring links already delivered two separate frameworks developed by Morita (2010, 2011) and Esawey (2012), with both showing promising results. A more elaborate relationship is used by Inrix, in which data from adjacent links are considered informative for the current and future state of other links. These approaches are classifiable within the hybrid category where they combine naïve, non-parametric and perhaps even slight hints of parametric ideas. It has already shown in previous research to outperform naïve approaches (Wismans et al., 2017). It is within this line of reasoning, that the idea of correlation of traffic flow variables between neighbouring links is deemed an worthy area for further exploration within urban traffic state estimation and prediction research. This paper fills this gap by developing a real-time data-fusion framework, in which data from link neighbours and different data-sources is fused.

### **3. Method development**

Within this research the previously mentioned frameworks of Morita (2011) and Esawey (2012) are used as a basis for the development of a new Link Neighborhood Method (NLM). Currently these aforementioned frameworks only output estimations along the dimension of space (and not time) and do so with room for improvement. Additionally these frameworks differ in detailed approach and mathematical techniques, such that careful comparison is required to select best cherries of each approach. Lastly the frameworks currently only output velocity/travel time. Extension and redesigning is therefore required to include intensities and densities as output.

The backbone of the newly developed NLM method, proposed in this research, is based on weighting data of neighbor links and to fill in the gaps of links with no data by using the data from its' neighbors. Without going into details here (a complete step-for-step explanation is provided later on), it stores newly received traffic data in a traffic database and uses a newly designed neuron layer which outputs traffic data of each link in the network.

Next, the interpolation method used to derive the traffic state estimation is discussed in more detail. It is branded the "Neighbor Link Method" (NLM) as is based on the idea that by using patterns in historical traffic data, the current traffic state of links can be used as indicators for the traffic state on neighboring links. However, these segments are not necessarily easily found (Esawey, 2012). They can be simple adjacent, preceding and succeeding segments, parallel segments, intersecting segments or even segments on opposite sides of the network. The goal of NLM is therefore to not only find the appropriate neighborhood for each link, but also to derive the robust, complete and accurate picture of the urban traffic state on all links in the network.

NLM does so by fusing and enriching both historical traffic data and neighboring link data to compensate for the less accurate estimations derived from a limited sample rate of floating car data (FCD) and the limited or even absent coverage of loop detectors. NLM adopts the approach of a ‘data-driven black box’ with an artificial neural network and regression model at its core. The artificial neural network aims to find not only the neighboring links of each link, but also a suitable weighting to express the solidity of the relationship. The global structure of NLM is therefore based on two of these dynamic artificial layers. The first layer is the neighborhood layer, which identifies the links which are most likely showing the same traffic behavior over time. The second layer is the weight layer, which optimizes weights for the neighboring links such that the relation of mirroring-behavior between links is quantified.

Within this research, multiple approaches were tested for each layer. For example: binning of data (e.g. separating peak hour shoulders from the real peak period), excessive neighborhood space refreshing (e.g. every minute instead of only once every rush hour period) and limiting the historical traffic database size). This paper describes the framework compliant to the best performing settings found.

### 3.1. NLM Data fusion framework

In the next few paragraphs, the content of each step of the NLM framework is explained in more detail. The order of calculation steps is visualised in the figure below. For traffic state prediction part, steps 6 and 7 are omitted due to the most recent data being of time  $t$ , and not of time in the future.

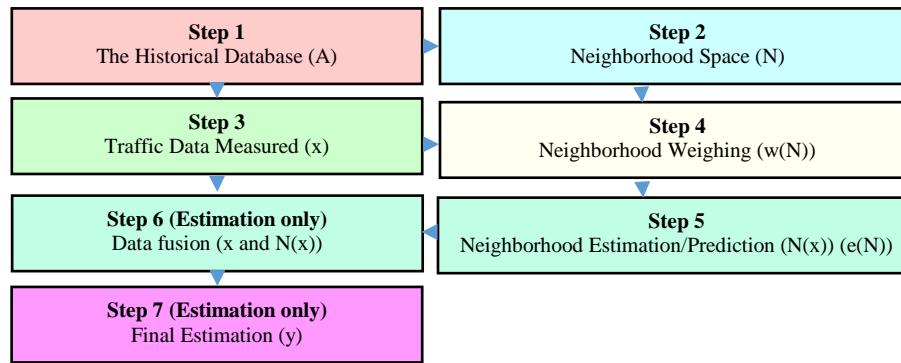


Fig. 3 Step by step structure of the NLM framework for estimation/prediction

**Step 1: The historical database** contains the data of available floating cars and loop detector data sources, which provides the data for the actual state estimation/prediction. The floating car data is generated per time step of 0.5 seconds. Within the database the data is aggregated to one minute mean values. Additionally the historic database stores for each interval ( $t$ ) an estimated link density by comparing the penetration rate of probe vehicles with the number of vehicles that pass the loop detectors. For links without loop detectors a global moving average is used. When the database is filled with up to three days of data, the data from the oldest day is omitted.

**Step 2: The neighborhood space** ( $N_x(t)$ ) contains the links which can be used as indicators for a current (time  $t$ ) traffic state on a link ( $x$ ). The size of the neighborhood space is set to 4 links, which seems a reasonable cut-off value without losing estimation accuracy (Esaway, 2012). The selection procedure for links to be included in this neighborhood space is determined by calculating the Pearson’ correlation coefficient ( $r$ ) of the traffic data on the link in question to the traffic data on every other link. The neighborhood space ( $N_x$ ) at a time  $t$ , of link  $x$  is then filled with the 4 links ( $x_1, x_2, x_3, x_4$ ) which give the highest correlation in respective measurements, throughout the historic database.

For the prediction part the correlation is instead determined over a 5 minute interval. So the link is compared with the traffic data from its neighbours with a 5 minute shift in data. As this operation can become quite time consuming suggested is to follow the recommendation of Esaway (2012) to not bluntly refresh the neighbourhood space every minute but once every rush hour period.

**Step 3: Considering the real-time data** is the next step in this algorithm. It is applied to consider the traffic data measured at a time ( $t$ ) at which a state estimation is required. This traffic data comprises for each link ( $x$ ) out of aggregated floating car and loop detector data which are used to calculate raw mean speed  $\bar{v}(x, t)$  and mean

densities  $\bar{p}(x, t)$  on each link. For flow the trivial multiplicative property of speed and density is used.

**Step 4: The neighborhood space weighting** uses an algorithm to find for each link ( $x$ ) a linear weighting of the links in the neighborhood space ( $w_v(N_x)$ ) such that the indicator of velocity ( $\bar{v}(x, t)$ ) is reached as closely as possible for all times ( $t$ ) in the database. Additionally a second, completely separate weighting scheme ( $w_p(N_x)$ ) is required, which aims towards reaching the indicator of density  $\bar{p}(x, t)$  as closely as possible for all times ( $t$ ). The optimization problem for finding these weights is a special case of the *least squares problem* (Morita, 2012). In formula form, the following two problems are solved:

$$\min_{w_v(N_x)} \left\| A_{N_{v,x}}(t) * w_v(N_x) - \bar{v}(x, t) \right\|_2^2, \quad [1]$$

$$\min_{w_p(N_x)} \left\| A_{N_{p,x}}(t) * w_p(N_x) - \bar{p}(x, t) \right\|_2^2. \quad [2]$$

This step is repeated for each link, such that for each link two weight layers  $w_v$  and  $w_p$  are calculated. For the traffic state prediction, we again introduce a time shift equal to the prediction horizon ( $t$  is replaced by  $t+5$ ).

**Step 5: The neighborhood space estimation/prediction.** The neighborhood estimation of the velocity and density can be calculated by using the weighting from the previous step by multiplying the indicators for velocity/density with this weighting. In formula [3]  $v$  can be replaced by  $p$  to yield the density formula:

$$\hat{v}(N_x, t) = \sum_{i=1}^{|N_x|} \bar{v}(N_{x,i}, t) * w(N_{x,i}, t). \quad [3]$$

In which:

$\hat{v}(N_x, t)$  = Neighborhood velocity estimation of link  $x$  at time  $t$  (or  $t+5$  for prediction)

For traffic state prediction purposes, it is noted that there is obviously no traffic data available for the time of prediction  $t_f$ . Therefore for prediction its weight is set to zero (omitting it). However, the algorithm might include its own link in its neighbourhood space and weigh its relevance accordingly. Step 5: The neighbourhood space prediction is therefore the outputted final prediction, whereas for estimation the following steps are taken.

**Step 6: The data fusion framework.** The intermediate data available up until this step is considered to contain two datasets. The first set is the previously determined neighborhood estimations:  $\hat{v}(N_x, t)$  and  $\hat{p}(N_x, t)$ . The second set is the data from the link itself:  $\bar{v}(x, t)$  and  $\bar{p}(x, t)$ . A weighting scheme is required to assure that the final estimation for the link maximizes the utility of both data sources.

Chosen in this research is to weigh the velocity estimations using the respective variances of the estimations, to account for the reliability of the estimations. Whereas for density no variances are available (they are unknown), a simple straight average is proposed. Trial simulations with different weighting schemes did not disprove the conclusions of Esaway (2012), though using both the data from the link itself and the neighborhood yields better results than using solely the data from either sources.

For velocity the variance in the mean velocity of the all traffic data  $s^2_{\bar{v}}(x, t)$  is therefore calculated on each link, using the standard statistical formula for variance:

$$s^2_{\bar{v}}(x, t) = \frac{1}{n(x,t)-1} \sum_{a=1}^{\tilde{n}(x,t)} (v_a(x, t) - \bar{v}(x, t))^2. \quad [4]$$

! When  $\tilde{n}(x, t) \in (0,1)$ ,  $s^2_{\bar{v}}(x, t)$  is defined to be equal to  $v_{max}(x)$ .

The variance of the neighborhood estimation ( $s^2_{\hat{v}}(N_x, t)$ ) can be derived using the normalized weights ( $w_{norm}$ ) from step 4:

$$s^2_{\hat{v}}(N_x, t) = \sum_{i=1}^{|N_x|} s^2_{\bar{v}}(N_{x,i}, t) * \left( w_{norm}(N_{x,i}, t) \right)^2. \quad [5]$$

With now  $s^2_{\bar{v}}(N_x, t)$  and  $s^2_{\bar{v}}(x, t)$  known, the final estimation is calculated by minimizing the variance of both estimations and thus weighting each with their inverse variance. In formula form:

$$\ddot{w}(\dot{v}(N_x, t)) = \frac{\frac{1}{s^2_{\dot{v}}(N_x, t)}}{\frac{1}{s^2_{\dot{v}}(N_x, t)} + \frac{1}{s^2_{\bar{v}}(x, t)}}, \text{ and } \ddot{w}(\bar{v}(x, t)) = 1 - \ddot{w}(\dot{v}(N_x, t)). \quad [6][7]$$

For density derivation the straight average is used.

**Step 7: The data fusion framework** is the last step. Within the estimation is calculated for all links the weighting from the previous step. Arbitrarily  $v$  can be replaced in [8] by  $p$  to yield the density formula. Flow is calculated from multiplications of both the speed and density estimation.

$$\hat{v}(x, t) = \dot{v}(N_x, t) * \ddot{w}(\dot{v}(N_x, t)) + \bar{v}(x, t) * \ddot{w}(\bar{v}(x, t)). \quad [8]$$

#### 4. Case

For assessing the performance of the method proposed, we choose to simulate the ground truth using the microsimulation package Paramics. The case study for this research is the Enriched Sioux Falls Scenario firstly introduced by Morlok et al. (1973) as a traffic equilibrium network. It has been adopted as a benchmark and test scenario for many publications. Professor Hillel Bar-Gera from Ben-Gurion University of the Negev supplies the open source data for this network (Bar-Gera, 2014). In this chapter the reasoning for choosing this network, as well as the specific network layout, network demand and trip distribution are discussed.

##### 4.1. Enriched Sioux Falls Scenario

The choice for the Enriched Sioux Falls Scenario is based on the following considerations. For this research a small-scale scenario with realistic demand and a high level of disaggregated information is needed to test and demonstrate the newly proposed approach. Therefore it is required to find a scenario that is computationally manageable (in this case study setting, without access to optimized/advanced soft- and hardware). An additional requirement is that it should be compiled out of open source data in order to ensure both comparability and free public access. Furthermore, the network should resemble a real world scenario, but without necessarily exactly mimicking a biased location. Recently Chakirov (2014) developed an enriched version of the Sioux Falls Scenario with the purpose of mimicking socio-demographic characteristics and spatial distributions. This lead to the development of a scenario which serves as a convenient test-case for developers of agent-based simulation tools. It therefore aligns with the aim of this research. The test scenario used in this research is therefore the original Sioux Falls test scenario (Morlok, 1973) enhanced with the Enriched Sioux Falls Scenario (Chakirov, 2014).

The Enriched Sioux Falls Scenario network consists out of the original 24 zones with 24 nodes and 76 links. A 25% reduction in node distances is applied (new area size = 9,6 km<sup>2</sup>) due to licensing limits of the used microsimulation-package Paramics. The original zone placement on the actual nodes is changed to be on the links directly adjacent to the node, allowing (at random) disappearance and appearance of vehicles on links itself, mimicking real world behaviour. The length of all links is set to be equal to the Euclidian distance between nodes, yielding an average link length of 1290 meters. For the setting of physical road parameters such as road length, number of lanes and a legal speed limit, the two types of road links defined by Chakirov (2014) are copied to Paramics. These are highways (2x3 lanes (width: 11m) with an imposed speed limit of 110 km/h) and urban roads (2x2 lanes (width: 7,3m) with an imposed speed limit of 50 km/h).

Nodes between highway and urban roads are modelled as simple priority junctions in PARAMICS. The nodes between urban roads are modelled as signalized junctions, with a very simple non-actuated cycle of 30s green time for each opposing direction (allowing left turns in conflict). The cycle and green times are therefore independent of the actual traffic demand. Additionally every link leading to a signalized junction is equipped with dual loop detectors. Regarding vehicle characteristics, it is chosen (for simplicity) to model a unimodal vehicle mix consisting of passenger cars only. For modelling in Paramics, the default values for behavioural parameters are kept unchanged.

##### 4.2. Case assessment framework

The case assessment framework is shown in figure 4. Within this framework a two hour peak period is adopted

within the Enriched Sioux Falls dynamic case study environment. This rush hour period is simulated for five simulation days, to mimic daily variation in traffic using Paramics' random decision process regarding the release of vehicles, vehicle parameters and choice processes. Each simulation therefore has a unique random generated seed. The output of each simulation are the log files which contains 100% accurate vehicle positions. From the FCD we derive the ground truth. The NLM framework then yields state estimations and predictions as close to the ground truth as possible, while having access to only a subset of floating car data. For this study a 5% penetration rate of probe vehicles is simulated, by randomly removing 95% of the floating cars' data from the database. This percentage is in favourable conditions already achievable. Assumed for this selection is that there is no sample bias present, which might not be true for real world conditions. Examples of possible reasons for bias in real world conditions are; (1) Some road types might be more frequently travelled by GPS equipped vehicles; (2) longer trips might be logged more; (3) certain destinations might attract more GPS equipped vehicles and (4) at certain times the coverage rate is more than average, while at other times less. The prediction horizon is set to 5 minutes.

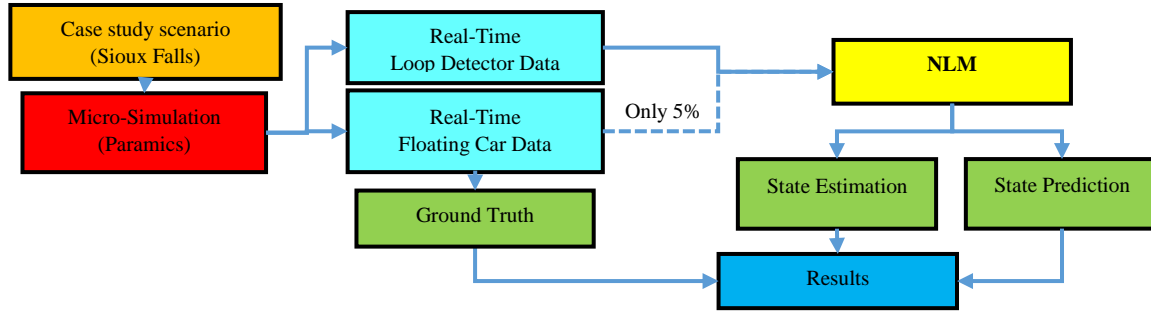


Fig. 4 NLM Assessment framework

For comparing the urban traffic state estimations ( $\hat{v}(x, t)$ ) to the actual observed ground truth ( $v_{GT}(x, t)$ ), the MSE (Mean Square Error) and  $r$  (Pearson's correlation) are adopted. These statistics are calculated for all estimations and predictions in comparison with the ground truth. For velocity an example is provided:

$$MSE_v(x, t) = \frac{1}{|x|} (\hat{v}(x, t) - v_{GT}(x, t))^2 \quad [9]$$

$$r = corr(\{\hat{v}\}, \{v_{GT}\}) \quad [10]$$

Additionally three (arbitrary) accuracy thresholds defined for each of the traffic flow variables. These are then used to describe the average accuracy of the estimation/prediction. Respectively for velocity, density and flow;

For velocity: C1(v): <5 km/h, C2(v) <10 km/h and C3(v): <15 km/h,  
 For density: C1(p): <7.5 veh/km/lane, C2(p): <15 veh/km/lane and C3(p): <24 veh/km/lane.  
 For flow; C1(q): <100 veh/h/lane, C2(q): <200 veh/h/lane and C3(q): <300 veh/h/lane.

## 5. Results

The results are shown per variable in the tables below. Table 1 shows estimation accuracy, Table 2 prediction. It shows that NLM outputs on average for 50% of the links in the network, a traffic state estimation within 5 km/h of the ground truth. The traffic state prediction accuracy is slightly lower with 49% respectively. Additionally the correlation between ground truth and estimations/predictions of the traffic flow variables of velocity and density score all above 0.85. It is concluded that flow accuracy needs to be improved.

Table 1. State estimation accuracy per traffic flow variable and expressed in % of links in the network per threshold (C1, C2, C3)

	MSE	r	C1	C2	C3
Velocity	31,5	0.912	50%	71%	90%
Density	235	0.934	90%	92%	95%
Flow	16197	0.781	60%	70%	82%

Table 2. State prediction accuracy (5 min horizon) per traffic flow variable and expressed in % of links in the network per threshold

	MSE	r	C1	C2	C3
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Velocity	37,3	0.877	49%	69%	83%
Density	403	0.870	80%	90%	92%
Flow	51833	0.677	20%	41%	89%

The above results show the average accuracy for the whole 2 hour peak period. Minute-to-minute results within these two hours vary due to the traffic state transitions present in a rush hour period. Whereas the start of rush hour and the actual congestive phase of a link are relatively easily estimated/predicted, the most difficult period to be estimated and predicted is during the traffic recovery phase of a link. The traffic demand during this recovery period decreases, while on neighbouring links congestion is likely to be still present. Capriciousness vehicle velocities on recovering links, coincide with increasing variances of the mean traffic data received from this link. Therefore when weighting the traffic data from both the neighborhood space and the link itself, it is the data from the neighborhood space which coincidentally fully dominates the result. This implies that during this period it is key that links which show exact the same behaviour are included in the neighborhood space. Due to day-to-day-variabilities in the traffic, it is however not necessarily true that if two links show exact the same minute-to-minute behaviour yesterday, that they will do so today. Subsequently a higher than average MSE is the result. Logically binning or partitioning comparable day's (by characteristics, e.g. weather, workday etc.) should overcome this issue, yet a first attempt with binning data within this research did not yield a more accurate result. The second most difficult period is found to be the shoulders of the rush hour period, related to the characteristics of FCD in general. In this research, on average only 100 vehicles were present in the network during the start/end of the morning rush hour. With a 5% FCD coverage rate, most links in the network therefore were not sampled. As with few vehicles on each link, the heterogeneous traffic dynamics of vehicles plays an important role, the ground truth is already highly capricious. Assuming that with no samples, the travelled velocity is  $v_{max}$  and both density and flow are zero, the ingredients are created for lesser estimation and prediction accuracy.

The determination of the neighborhood space is key within the NLM framework. During this research clues were found that using the adopted approach of linear correlation in the raw traffic data might not be the most rewarding. Firstly because using Pearson's correlation coefficient for linear correlation, does not necessarily guarantee finding a neighborhood space in which a relatively good weighting for the traffic data can be found. Secondly, difficulty arises due the fact that the neighborhood space needs actual neighbours to function properly. For traffic state estimation the weighting scheme can compensate for a slight mismatch in the timing of the traffic phases on neighbouring links (e.g. a neighbouring link might be fully congested some minutes earlier or later, therefore together with the traffic data from the link itself, still describing more or less the correct situation). In the traffic state prediction the first link which (in time) experiences a traffic breakdown or recovery, has no neighbour links which foresee this event and thus create a time lag equal to the prediction horizon for these links. Density and flow predictions are as a result less accurate.

## 6. Conclusion

This research shows that the designed NLM framework can yield very reasonable traffic state estimation results in a modelled and simulated environment. Due to the fact it is simple in essence and algorithmically not very complex, NLM can be easily transferred to real world scenarios. Additionally other traffic data sources can be implemented effortlessly in the process, which improves estimation accuracy even more. For traffic state prediction the results show a more clouded image, as specifically flow accuracy (as a result of stacking of errors of both velocity and density predictions) is deemed low. Especially traffic states transitions, i.e. from congested to non-congested and vice versa, are more difficult to predict with NLM in its current form.

The advantages of utilizing the state estimation part of NLM in ITS and traffic management are however already ample; (1) NLM delivers a complete and robust overview of the urban traffic network, showing what's going on anywhere in the city by providing real-time travel times, velocities, densities, flows for every link in the network; (2) NLM enables the controller to communicate more effectively to the users by allowing for real-time dynamic routing and load balancing via e.g. VMS (Treiber, 2012); (3) NLM enables the users of the traffic network to make dynamic real-time route choices via e.g. traffic-dependent navigation devices and (4) NLM provides tactical information on (real-time) fixes possible in the city, e.g. where to improve traffic flows by tweaking traffic lights or whether to impose variable speed limits.

## 7. Further Research

In this paper the performance of NLM's traffic state estimation and prediction is assessed. The ground truth is derived from a dynamic traffic scenario (Sioux Falls). However, some traits that typically describe a real world urban environment were because of the scope of this research, not (fully) included or worked out e.g. user-interaction, mode-interaction, a heterogeneous vehicle mix, dynamic traffic lights and a bigger data set (in terms of more than five days). Further work is therefore needed to proof, improve and test the current implementation into the more complex and realistic environment of real world urban traffic network cases.

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