Adaptive decision algorithms for data aggregation in VANETs with defined channel load limits

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***Abstract*—The main challenges when realizing safety related applications based on vehicle-to-x communication are scalability and reliability. With an increasing number of vehicles, the communication channel must not get congested especially if a large amount of information has to be transmitted over multiple hops to a destination. This challenge can be solved by reducing the data load through data aggregation. In this paper, we present a decentralized congestion control using the channel busy ratio (CBR) on the application layer for an adaptive control of aggregation levels in real time. Adaptive decision algorithms decide which data is aggregated in real time. Two different approaches are compared: One approach relies on two CBR thresholds (min/max) only and one that allows a higher number of CBR thresholds. In both cases, the adaptive aggregation control increases and decreases the data aggregation levels based on these thresholds. Our simulation results show that both approaches are able to adjust the aggregation levels to given channel load thresholds within seconds resulting in improved data quality even in heavy congested situations. Adaptive decision algorithms result in less error introduced by aggregation. The impact of the two aggregation level control approaches is discussed regarding channel load and resulting data precision.**

***Keywords*-Data Aggregation, Adaptive Systems, Adaptive Decision, V2X Communication, VANETs**

I. INTRODUCTION

Cooperative vehicular applications are the next step towards reducing road accidents and improving traffic efficiency. The direct communication of vehicles with each other and with infrastructure units will be based on the ETSI ITS-G5 standard [1]. All vehicles transmit Cooperative Awareness Messages (CAM) [2] based on their position change up to 10 times per second and include sensor data like temporal id, current position, velocity and acceleration. Other vehicles and infrastructure units (Roadside Units, RSUs) receive CAMs within their communication range. In a decentralized system, RSUs can gather sensor information over a road segment and forward this information multihop over several RSUs to a processing application on a Control RSU. This application evaluates traffic situations in real time and warns vehicles upon dangerous situation. This is illustrated in Figure 1.

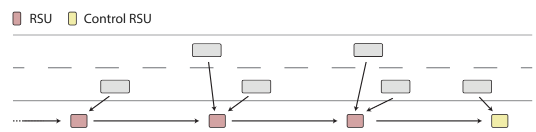


Figure 1. Vehicular Data is Forwarded to Traffic Application

The main communication challenges on a shared wireless channel is scalability and reliability. With an increasing number of transmitting vehicles the wireless channel must not get congested. Data aggregation techniques are used to eliminate data redundancy improving the wireless channel's efficiency. Safety messages must be received in time while other services like forwarding sensor data to an application should adapt to the channel load. Especially in traffic congestion scenarios RSUs cannot forward all collected sensor data to the processing application and need to reduce the information to transmit. The decision component decides which data from the vehicles must be fused to reduce the channel load.

In this paper, we present improvements to the decision and adaptive control component for the aggregation framework developed in [3]. The adaptive standard score and adaptive cost-aware algorithms within the decision component reduce the error caused by fusing various types of data. They adapt its parameters to the traffic situation in real time having essential influence on resulting data precision. Additionally, two new approaches are proposed to adapt aggregation levels at each RSU based on its individual channel busy ratio (CBR). In the Two-thresholds approach, the aggregation levels are only increased and decreased when the individual CBR exceeds the minimum or maximum CBR for several consecutive times. In the N-thresholds approach a higher number of CBR windows is mapped to aggregation levels. Both approaches adapt the aggregation levels in real time.

This paper starts with an overview about related work on data aggregation in Section II. In Section III, IV and V we describe the aggregation framework components, the flexible aggregation scheme as well as the decision and aggregation level control algorithms. All schemes are evaluated in a realistic traffic scenario and the results are discussed in Section VI. The paper is concluded with an outlook in Section VII.

II. Related Work

Data aggregation is used to combine data messages of different sources like the vehicles in a VANETs to eliminate redundant data. RSUs might receive and aggregate vehicular data before it is forwarded to a data sink. Many data aggregation approaches based on infrastructure or RSU have been proposed in recent years. Data aggregation algorithms can be classified into various sections based on the topology for the nodes they require. Tree-based topologies [4], [5] consist of one root node which often represents the data sink. Cluster-based aggregation schemes [6], [7] group the nodes into clusters. Often each of these groups contains one landmark node with special responsibilities called a cluster-head. Other aggregation schemes [8], [9], [10], [11] do not require any specific topology.

In TAG [4] two data nodes are aggregated by fusing all its contained values using a table as data structure. Thus, two rows of the table structure are merged. CASCADE [6] suggests to store only relative values to a fix point compared to absolute values used in TAG. In CASCADE vehicles are clustered and the center or median of the cluster values is used as fix point. During the decision process, data records are identified for fusion. In SOTIS [9], CASCADE and TAG all data within a certain group is fused to reduce the wireless channel load. These groups can be calculated based on road segments. Another type of aggregation uses mathematical models or complex computations for the decision process in Quantil Digest [5] and Probabilistic Aggregation [10]. The drawback of above aggregation techniques is either the requirement that the of segmentation and grouping has to be done in advance or the increased computational cost. A third decision strategy is used by TrafficView [11]. Its decision component uses a cost function to identify the two data records with least fusion costs. This function takes the distance of the vehicles and the number of vehicles represented by a data record into account. This cost function could solve the problem of missing single extreme values, since the cost of fusing such a data record should be too high for aggregation. However, TrafficViews cost function falls short in considering other metrics than the distance of the vehicles and the number of vehicles represented by a data node. In any case, fusing data by one certain metric usually has disadvantages. Individual extreme values might get lost by fusing over all elements of a group, a safety threat, e.g. a slow car might not be identifiable after fusion.

III. Data Aggregation Framework

The proposed aggregation framework provides a foundation to design adaptive aggregation schemes. It is based on a modular architecture with three main modules: decision, fusion and dissemination. Each phase of the aggregation process is represented by a single module following the generic architecture model for aggregation schemes proposed by Dietzel et al. [12]. Additionally, two modules were defined in [3]. One represents the data structure used in the aggregation process and the other implements the adaptive control of the aggregation process which in enhanced in this work. The implementation of each module defines the properties of an aggregation scheme. An overview of the framework is provided in Figure 2. Following, each of the five modules of the aggregation framework are introduced in more detail.

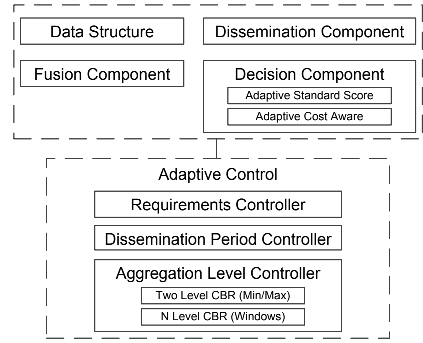


Figure 2. Aggregation Framework Modules

When a RSU receives vehicular information the data is stored in a *data structure*. The data structure stores different data types, combines data of multiple sources into one structure and supports size reduction by data fusion. In our framework we use a tree-based data structure for its flexibility in further processing. The prototype tree of one particular scheme consists of a combination of interval nodes and data nodes in different layers. The *decision component* chooses the most similar data records for fusion to achieve high data precision. It is based on the individual standard score of each metric. The *fusion component* provides a valid aggregation tree to the dissemination component, collects instructions how to aggregate data from the aggregation level control and allows the decision component to determine what data to fuse if necessary. It keeps the aggregation tree valid at all times. The *dissemination component* defines when and how data is disseminated by a RSU to the next RSU in the direction of the data sink. Data is disseminated with an adaptive frequency by the node farthest from the control RSU. Whenever another node receives aggregated data it adds its own data of the requested interval and forwards the combined data immediately. The *adaptive control* with three controllers is responsible for the reliable delivery and the end-to-end delay. It monitors the CBR and triggers an adaptive aggregation schemes aiming at a target CBR to minimize packet loss. The requirements controller defines the required metrics, initial fusion parameters and an initial dissemination frequency. This controller is triggered during initialization of the aggregation process by the application on the Control RSU. Once other nodes receive the requirements, they start to collect the requested data. At runtime, the dissemination period controller observes the delay of incoming information at the Control RSU and adjusts the requested dissemination frequency when the delay exceeds the targeted delay. The aggregation level controller is a decentralized component and is executed on each RSU. It observes the CBR and adjusts the aggregation level if CBR exceeds the targeted ratio.

An aggregation scheme consists of particular implementation of each module. The key elements are the prototype data structure, the configuration of the three modules decision, fusion, dissemination and definition of aggregation levels. The flexible aggregation scheme introduced here is shown in figure 3 and uses interval and data nodes. The interval nodes consist of one interval layer each in the tree. The first interval layer

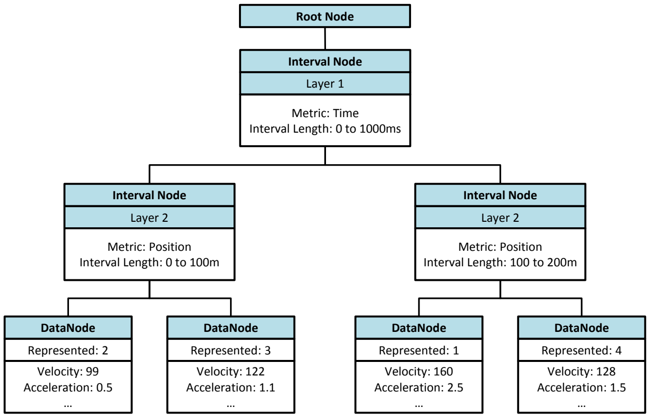


Figure 3. Flexible Aggregation Scheme

uses time-stamp metric, which records the time the parameter set was broadcasted by a vehicle. Second layer defines an interval for the position metric and its interval length (IL) depends on the aggregation level. The length can be anywhere between minimum of 25 meter and maximum road length assigned as shown in Table I. Thus, the imprecision of the position and time-stamp will never be higher than the specified maximal interval sizes. While keeping the limit of maximal children nodes in the tree constant and increasing the length of the interval, the tree shrinks and data nodes are fused. In contrast, when the length of the intervals is reduced, the tree grows. At high channel load and therefore high aggregation level the error will be limited to IL_{max}. Lowering IL_{max} results in higher precision but also higher channel load. The flexible aggregation scheme using two different decision and adaptive aggregation level control schemes is simulated to evaluate the system performance. The precision is expected best with more interval nodes as there will be less fusion of data nodes.

Aggregation Level	0	1	2	...	n-1
Interval Length(IL)	$\frac{IL_{max}}{2^{n-1}} (\geq 25)$	$\frac{IL_{max}}{2^{n-2}}$	$\frac{IL_{max}}{2^{n-3}}$	...	IL_{max}

TABLE I. INTERVAL LENGTH OF FLEXIBLE AGGREGATION SCHEME

IV. ADAPTIVE DECISION COMPONENT

The decision component takes a set of nodes as input and identifies two or more suitable nodes for fusion among the input set. This section introduces two designs for basic decision components: Adaptive standard score and adaptive cost-aware algorithm based on a cost function.

A. Adaptive cost aware decision

The goal of the decision component is to maintain extreme data records while fusing many similar vehicles and thereby maintaining as much precision of the data as possible. Thus, fusing similar objects is preferable. The adaptive cost-aware decision uses a weight function to calculate the fusion costs of two data nodes (vehicles) a and b, considering all contained parameters. Let P denote the set of parameters and a_i be the value for the i-th parameter of node a. Furthermore, let w_i be the weight for parameter i. The parameter $max_{i,t}$ is the maximal value of parameter i in time period t. It is calculated every period t and therefore it adapts to the current situation. Then, the cost can be calculated as indicated in Equation (1).

$$cost = \sum_{i \in P} w_i \times \left|\frac{a_i - b_i}{max_{i,t}}\right| \tag{1}$$

$$w_1 + w_2 + w_3 \ldots + w_i = 1 \tag{2}$$

Using this notation, assuming a system using only two parameters $P = \{vel, pos\}$, let the weights be 0.5 for both the velocity vel and position pos. The weights allow to determine the importance of velocity and position. Furthermore, by varying weights from 0 to 1 can determine the best performance of decision component.

B. Adaptive standard score decision

In the adaptive standard score decision the difference from mean value is described in units of standard deviation from the real time simulation of the metric at each period t. This allows comparing different metrics without using predefined standard deviation values.

To identify the difference between two values in units of standard deviation, the adaptive standard score is used. It is a signed value that describes the difference from the mean in number of standard deviations. This unit of standard deviations allows the comparison of independent parameter values at a particular time t . Let z be the adaptive standard score, x the value of the metric, μ the mean and σ_t the standard deviation of the metric calculated in periodic intervals of time t. Then the adaptive standard score is defined as follows:

$$z = \frac{x - \mu}{\sigma_t} \tag{3}$$

Equation (3) only describes the adaptive standard score of one parameter at a time t. However, to calculate the fusion costs, two values must be considered. These two values are of the same metric, and thus at same time t. For two values x_1, x_2 this difference of the adaptive standard score can be expressed as follows:

$$|z_1 - z_2| \Rightarrow \left|\frac{x_1 - \mu}{\sigma_t} - \frac{x_2 - \mu}{\sigma_t}\right| \Rightarrow \left|\frac{x_1 - x_2}{\sigma_t}\right| \tag{4}$$

The difference between two values can be described in units of standard deviation by simply dividing the difference of the two values by the standard deviation calculated at a time t using Equation (4). The resulting difference in standard deviations can be compared with other metrics calculated at same time t, which is the great advantage of the adaptive standard score. The adaptive standard score decision component aims at overcoming the problem to find standard deviation for each parameter. Instead of dividing the difference with some already assigned or predefined standard deviation, the standard deviation is calculated in real time by using the data that is received by RSU within the time period t.

V. Aggregation Level Control

The aggregation level control shown in Figure 2 decides when to increase or decrease the aggregation level in the framework within each RSU based on its individual CBR measurement. In this paper, we propose two approaches how the CBR is mapped to aggregation levels: Two-thresholds CBR Control and N-thresholds CBR Control. These methods will be described in detail in following sections.

A. Classical Two-thresholds CBR Control

The Two-thresholds CBR Control (2-CBR) method only considers two extreme values - minimum and maximum - of CBR for each RSUs. The aggregation aims to keep the CBR between these two values. In this method, aggregation level of all RSUs starts at level 0 and only increases to a higher level, when the CBR of a particular RSU exceeds the maximum CBR defined for a 2 consecutive times. Same steps are followed to reach the maximum aggregation level possible. If CBR drops below the minimum value for 5 consecutive times the aggregation level is decreased. The hysteresis aims to limit the oscillations of the aggregation level and act more defensively keeping aggregation level high in case CBR is near the thresholds.

B. N-thresholds CBR Control

In N-thresholds CBR Control (N-CBR), the two extreme values that are minimum and maximum value of CBR for each RSUs and the number of aggregation levels are considered. The target CBR window (CBRW) size for each aggregation level can be calculated from Equation (5). Where CBR_{max} is the maximum CBR, CBR_{min} is minimum CBR and n is number of aggregation levels. This method can be explained further using an example, from Table II: n is considered as 5, $CBR_{min} = 0.25$ and $CBR_{max} = 0.40$, following the thresholds in [13]. Similar configuration with 6 aggregation levels is shown in Table III according to the thresholds in [14]. The CBRW size is calculated and each window size is assigned to aggregation level. First each RSU checks its CBR and compares it with the aggregation level. If there is a change then it updates its aggregation level. RSU checks its CBR every $1sec$ and updates its aggregation level accordingly.

$$CBRW = \frac{CBR_{max} - CBR_{min}}{n} \tag{5}$$

Aggregation Level 0	$0 <= CBR < 0.25$
Aggregation Level 1	$0.25 <= CBR < 0.30$
Aggregation Level 2	$0.30 <= CBR < 0.35$
Aggregation Level 3	$0.35 <= CBR < 0.40$
Aggregation Level 4	$0.40 <= CBR < 1$

TABLE II. Mapping of CBR to Aggreg. Levels based on [13]

Aggregation Level 0	$0 <= CBR < 0.19$
Aggregation Level 1	$0.19 <= CBR < 0.27$
Aggregation Level 2	$0.27 <= CBR < 0.35$
Aggregation Level 3	$0.35 <= CBR < 0.43$
Aggregation Level 4	$0.43 <= CBR < 0.51$
Aggregation Level 5	$0.51 <= CBR =< 1$

TABLE III. Mapping of CBR to Aggreg. Levels based on [14]

VI. Evaluation

A. Simulation Setup

The network simulator ns-3.18 was used for evaluation. It was extended by ITS modules enabling simulation of ETSI ITS-G5A [1] and GeoNetworking protocols [15] as well as positioning and mobility modules. The wireless channel assumes Nakagami highway propagation model with 6 MBit/s data rate and 10 MHz bandwidth using the control channel 180 at 5.9 GHz for all communication. Transmission power is 15 dBm for all vehicles and RSUs. The targeted maximal CBR is 0.40, following the channel states from [13]. CAMs are generated by each vehicle with dynamic frequency between 1 and 10 Hz based on the movement of the vehicle, following CAM generation rules [2]. CAM payload size is set to 250 Byte.

Data Rate	6 MBit/s
Frequency	5.9 GHz
Transmission power	15 dBm
Minimum CBR	0.25 (0.19)
Maximum CBR	0.40 (0.51)
Propagation model	Nakagami Highway
Highway length	10 km
Number of vehicles	800
Number of RSUs	10
Distance between RSUs	400 m
Speed of vehicles (free)	20 - 40 m/s
Speed of vehicles (jam)	3 - 8 m/s
Traffic jam	3 min
Number of aggregation levels	5 (6)
Max. interval length (IL_{max})	800 m

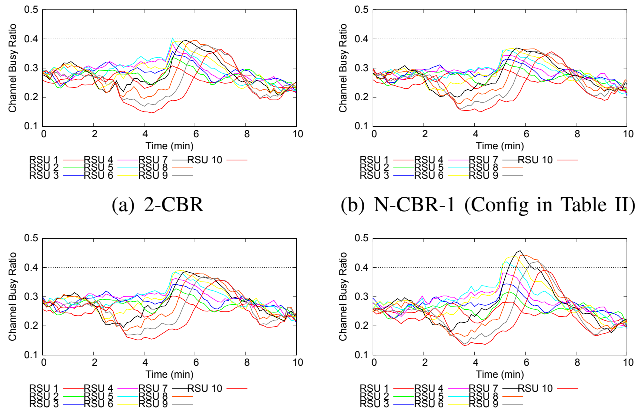
TABLE IV. Simulation setup

A realistic highway traffic scenario is used in the evaluation - a 10 km highway with three lanes in each direction and 800 vehicles randomly distributed on these six lanes. 10 RSUs are placed in a distance of 400 m to each other. The mobility models assume vehicles velocity between 20 - 40 m/s in free traffic flow in both directions. RSUs receive CAMs from vehicles in both direction, but extract only relevant CAMs for further process. After 2 minutes a sudden single directional traffic jam in the middle of the equipped road segment forces the velocity to drop to 3 - 8 m/s. For the next 3 minutes vehicles queue in one direction. Afterwards, traffic jam dissolves slowly for the next 4 minutes, restoring the original velocity distribution. Up to 600 vehicular data records per second per RSU containing 9 different metrics each were received by RSUs and transmitted multihop over 10 RSUs with in-node and in-network aggregation to a processing traffic application. Additional simulation parameters are depicted in Table IV.

B. Simulation Results

The main objective of the adaptive data aggregation is to reduce the load on the wireless channel. We compare the CBR and aggregation level changes of each RSU followed by the trade-off in resulting precision errors.

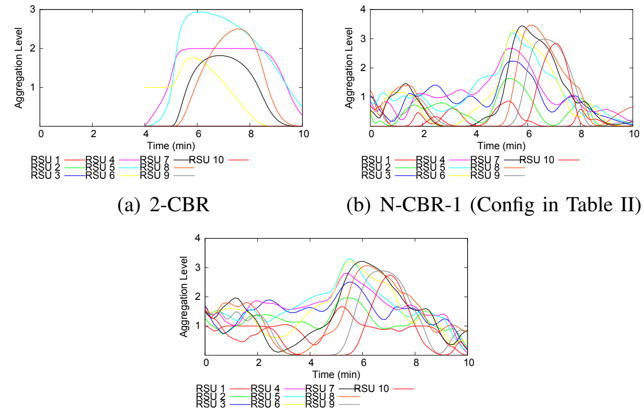
Figure 4(d) shows the CBR of a system that only forwards vehicular data in the tree-based data structure but does not fuse any data. Thus, the channel load can not be reduced and the targeted CBR threshold of 0.40 is exceeded. The smoothed CBRs of the flexible aggregation scheme with 2-CBR and N-CBR control are depicted in Figure 4. In the traffic free flow (0-2 min) the CBR is almost stable around 0.25 for all



(a) 2-CBR (b) N-CBR-1 (Config in Table II)

(c) N-CBR-2 (Config in Table III) (d) No Aggregation

Figure 4. Channel Busy Ratio



(a) 2-CBR (b) N-CBR-1 (Config in Table II)

(c) N-CBR-2 (Config in Table III)

Figure 5. Aggregation Level

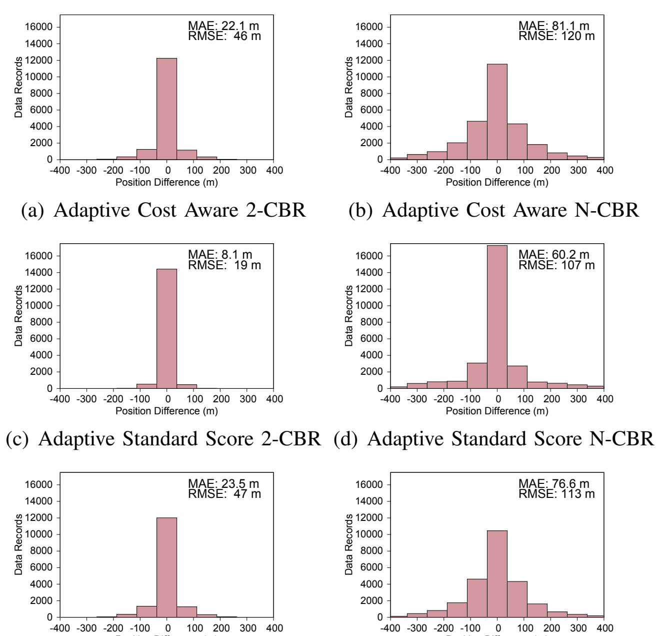
RSUs. As the traffic jam starts in the middle of the road section the CBR rises for affected middle RSUs and later also lower RSUs experiencing dense traffic. The CBR decreases for higher RSUs having low traffic down to 0.15 for RSU10. As the traffic jam moves on in the direction of higher RSUs at min 4-7 every RSU is effected and their CBRs rise having a peak at min 5-7. Both 2-CBR and N-CBR control adapt to the channel load and change their aggregation level accordingly. 2-CBR control slightly peak over the target limit of 0.40, N-CBR control keeps under the limit at all times. While the traffic jam dissolves, CBR lowers for all RSUs back to the initial value.

Increasing and decreasing of aggregation levels regulates the channel load of aggregated data. Figures 5(a) and 5(b) show the aggregation levels for the two control approaches corresponding to the CBR in Figure 4. In the 2-CBR control the aggregation levels start to rise quickly at RSUs 5-6 as soon as CBR reaches the target of 0.40. While the traffic jam moves slowly forward, the aggregation levels rise also at RSUs 7-9. Beginning with min 7 the traffic jam starts to dissolve and the aggregation levels quickly decrease back to zero. The N-CBR control reduces some additional channel load from the start, as lower and middle RSUs (4-6) already rise their aggregation level significantly from min 2. RSUs 5-10 reach their peaks in min 5-7 and are back to initial values at min 8. The early increase of aggregation levels causes the CBR to stay below the target limit at all times.

N-CBR with configuration from Table III (N-CBR-2), shown in Figure 5(c) includes one additional level compared to N-CBR from Table II (N-CBR-1), shown in Figure 5(b). The first threshold in level 1 is lower, therefore the aggregation level is increased earlier and the following CBR relaxes earlier at the cost of the precision. The thresholds are wider apart in N-CBR-2 and the level will not change as early as in N-CBR-1. The adaptive data aggregation is more flexible towards higher CBR in N-CBR-2 because of the higher upper threshold.

Data precision is an important performance indicator to evaluate decision schemes. The data fusion introduces an error that each decision scheme aims at keeping low. The error introduced by each scheme is compared in two metrics: position and velocity error. Each figure states the number of data records received with a certain error, the average difference from true value (Mean Absolute Error - MAE) and the Root Mean Square Error (RMSE). During free flow traffic both control approaches deliver data precision with almost no errors because of low CBR. During the traffic jam peak (min 4-7), however, the data fusion introduce different errors which are presented next.

The precision error regarding the position metric is illustrated in Figure 6. The adaptive standard score with 2-CBR control performs best (MAE = 8.1m) followed by adaptive cost-aware with 2-CBR (MAE = 22.1m). Both the adaptive decision algorithms show less precision error with 2-CBR control compared to N-CBR. While keeping the channel load low, the N-CBR approach rise the aggregation level more often and therefore cause increase in precision error. Both adaptive decision algorithms result in higher data precision compared to non-adaptive algorithms because the algorithms adapt their parameters to receiving values in real time. Figure 7 shows the precision error analysis of the velocity metric with equivalent results.

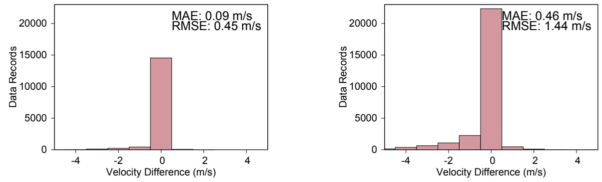


(a) Adaptive Cost Aware 2-CBR (b) Adaptive Cost Aware N-CBR

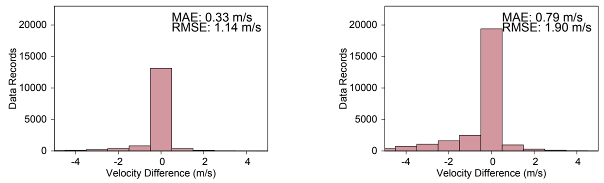
(c) Adaptive Standard Score 2-CBR (d) Adaptive Standard Score N-CBR

(e) Standard Score 2-CBR (f) Standard Score N-CBR

Figure 6. Position Precision Error

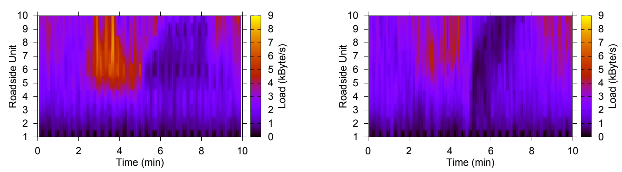


(a) Adaptive Cost Aware 2-CBR (b) Adaptive Cost Aware N-CBR



(c) Adaptive Standard Score 2-CBR (d) Adaptive Standard Score N-CBR

Figure 7. Velocity Precision Error



(a) 2-CBR (b) N-CBR

Figure 8. Aggregated Data Load

The resulting channel load caused by additional aggregation data load is depicted in Figure 8. In 2-CBR approach a higher amount of aggregation data is transmitted between RSU 5-10 during the traffic jam (min 2-5) resulting in higher data quality in this road section. Less aggregation data is transmitted in N-CBR approach because the channel load already exceeded first limit resulting in increasing the aggregation level. In both cases, the aggregation data load is heavily reduced after the traffic jam dissolves and vehicles start to move with high velocity again causing high channel load based on CAMs.

VII. Conclusions

In our paper we presented two adaptive decision algorithms within the aggregation framework which decide which data is aggregated in real time. Furthermore, two different approaches for aggregation level control were described and evaluated in a traffic scenario. Simulation results show that both adaptive algorithms had lower precision errors than non-adaptive algorithms especially in dynamic traffic scenarios where the vehicular data change rapidly.

Additionally, the simulation results show that both aggregation level control approaches are able to adjust the aggregation levels to current channel load thresholds within seconds resulting in improved data quality even in congested traffic situations. The 2-CBR control keeps the precision error lower compared to N-CBR approach but may exceed the targeted CBR limit for the magnitude of seconds. This approach might be useful in use cases with one optimal CBR threshold where exceeding this threshold for short time frame does not affect the performance of the system significantly. The N-CBR adjusts its aggregation level earlier and manages to keep the CBR below the target limit at all times. This approach might excel in use cases where exceeding certain CBR limit has severe negative impact on the whole system.

We observed that the aggregation level control has natural limits for its impact on the regulation of the channel load - it does not influence the base line CBR based on CAMs. However, with increasing number of applications and therefore increasing channel load based on these applications we expect even more impact on aggregation schemes regulating the channel load.

In further simulations, the decentralized congestion control (DCC) on application layer of this framework will be combined with DCC for access layer [13], where all nodes adjust their transmit power and other parameters dependent on CBR. An evaluations with more complex street topology, mobility models and traffic scenarios will follow.

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