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Networked Model Predictive Traffic Control with Time Varying Optimization Horizon: the Grenoble South Ring Case Study

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Abstract— **This work discusses the design of a networked traffic control scheme. We refer to the Grenoble South Ring traffic system, as case study, in which the control actions are computed in a control centre far from the traffic system and then sent, through a wireless communication channel, to the actuators placed along the road, i.e. on-ramp traffic lights in the considered case of ramp metering control. The communication channel is affected by delays and packet loss. In order to counteract the effects due to the transmission of the variable over the communication channel, we suggest to adopt a model predictive control (MPC) strategy based on the use of a buffer. Moreover, in order to limit the computational burden and improve the effectiveness of the proposal, the length of the optimization horizon of the predictive control algorithm, and, consequently, the buffer length, is updated relying on a delay estimation. The performances of the proposed approach are assessed in simulation relying on a traffic model the parameters of which are identified using data produced by a commercial microscopic simulator of the Grenoble South Ring traffic system. The capabilities of the considered control scheme when the system parameters vary and the transmitted signals are affected by time delays are highlighted.**

I. INTRODUCTION

Traffic control is a research topic which has recently attracted a new wave of interest by virtue of the technological innovations of the last years, which make applications of control algorithms and monitoring strategies really feasible. Nevertheless, the occurrence of a traffic congestion is more and more regarded as a crucial problem, since it deteriorates quality of life, increases fuel consumption and polluting emissions, as well as the probability of accidents.

In this paper, a real world case study is considered. It is a portion of the Grenoble South Ring traffic system, which is the object of the research on traffic modeling, identification and control carried out within the FP7 Hycon2 Network of Excellence [1]. In Grenoble, the traffic control center is situated downtown, far from the traffic system and the control variables are sent, through a wireless communication network, to the actuators placed along the road (the actuators being, in our case, traffic lights, since, in this paper, we adopt the so-called ramp metering control approach). This is the reason why the effects of transmission delays and packet loss on the controlled traffic system performance can be considerable.

In order to overcome the problems caused by the aforementioned effects, a networked control approach is used and a networked control system is designed. More specifically, the designed controller is of MPC type [11] and it relies on the use of a buffer to compensate for delays and packet loss. In the first part of the paper, we investigate the possibility of implementing a MPC algorithm using a buffer with a constant length, such a length being equal to the optimization horizon, in such a way that the designed traffic networked control scheme provides performance significantly close to those of the ideal case (i.e. the case in which the control variables are not transmitted over the communication channel, but directly fed into the traffic system). In the second part, in order to limit the computational load normally associated with conventional MPC, a different version of the control strategy is proposed, in which the length of the optimization horizon of the MPC algorithm, and consequently the length of the buffer, is updated online according to a delay estimation. Note that the fact of using MPC to control freeway traffic is quite natural since the prediction capability of this methodology is very well suited to the application in question (see for istance [3], [4], [7]). Accordingly, optimal arguments have been invoked to design efficient traffic control algorithms [4], [2], [8]. The originality of the present proposal mainly relies on the idea of adaptively tuning the length of the MPC optimization horizon, and on the formulation of an adaptation mechanism based on a time-varying estimate of the communication channel delay.

The paper is organized as follows. In Section II, the macroscopic mathematical model adopted to describe the traffic system, that is the so-called METANET model [5], is introduced, together with a brief overview of the basic issues relevant to MPC. In Section III the MPC problem is formulated with reference to the considered traffic system. In Section IV the two networked MPC algorithms, the first one characterized by a constant length buffer, the second one with adaptive buffer length, are discussed. A simulation based analysis of the two algorithms is reported in Section V. Note that simulation tests are performed using an instance of the traffic model identified on the basis of data produced by a microscopic simulator of the Grenoble South Ring, which at the present stage of the Hycon2 research, in which the placement of the magnetic sensors on the road is still a work in progress, has to be regarded as the "true traffic system". Final conclusions are provided in Section VI.

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II. Some preliminary issues

In this section, the considered freeway traffic model and the MPC method are briefly recalled.

A. The traffic model

In this paper the macroscopic model named METANET (see [5]) is considered to describe the freeway flow evolution.

METANET is a second order model, that is it enables to describe the dynamics of the traffic speed, which is required to deal with problems of emissions and fuel consumption [6].

The METANET model represents a freeway system as a directed graph with the links corresponding to freeway stretches. Where a major change occurs on the freeway stretch or in the road geometry (e.g., on-ramp or off-ramp), a node is placed. Each link m is divided into N_m segments of length L_m. The state of the traffic in segment i of link m is characterized by:

- the traffic density $\rho_{m,i}$ (i.e. the number of vehicles in the segment per lane and per length unit);
- the mean speed $v_{m,i}$;
- the outflow $q_{m,i}$ (i.e. the number of vehicles that leave the segment per time unit).

The equations used to compute the traffic states variables for any segment i of a link m are given by:

$$\begin{aligned} q_{m,i}(k) &= \lambda_m \cdot \rho_{m,i}(k) \cdot v_{m,i}(k) \\ \rho_{m,i}(k+1) &= \rho_{m,i}(k) + \frac{T}{L_m \cdot \lambda_m} \cdot [q_{m,i-1}(k) - q_{m,i}(k)] \\ v_{m,i}(k+1) &= v_{m,i}(k) + \frac{T}{\tau} \cdot (V(\rho_{m,i}(k)) - v_{m,i}(k)) + \\ &\quad + \frac{T}{L_m} v_{m,i} \cdot (k)(v_{m,i-1}(k) - v_{m,i}(k)) + \\ &\quad - \frac{\eta \cdot T}{\tau \cdot L_m} \cdot \frac{\rho_{m,i+1}(k) - \rho_{m,i}(k)}{\rho_{m,i}(k) + \kappa} \end{aligned} \tag{1}$$

where τ, η and κ are model parameters representing, respectively, a time costant and two constants accounting for drivers' behavior, T is the discrete time step, λ_m the number of lanes on that link and

$$V(\rho_{m,i}(k)) = v_{free,m} \cdot exp\left[-\frac{1}{a_m} \cdot \left(\frac{\rho_{m,i}(k)}{\rho_{crit,m}}\right)^{a_m}\right] \tag{2}$$

is the so-called Traffic Fundamental Diagram (see [5]), with a_m model parameter. Note that the free-flow speed $v_{free,m}$ in (2) is the average speed that the vehicles assume if traffic is flowing freely, while the critical density $\rho_{crit,m}$ is the density when the maximum flow in the link occurs. Special links are used to model origin and on-ramp links, which receive traffic demand and forward it to the motorway. These links are modeled with a simple queue model

$$w_o(k+1) = w_o(k) + T \cdot (d_o(k) - q_o(k)), \tag{3}$$

where $w_o(k)$ indicates the queue length expressed in number of vehicles, $d_o(k)$ the demand of vehicles to enter the queue, and $q_o(k)$ the outflow at time step k. The outflow depends on the traffic state on the mainstream and, for metered on-ramp, on the ramp metering rate $r_o(k) \in [0,1]$. More specifically, $q_o(k)$ is the minimum of three quantities: the available traffic at time step k (queue plus demand), the maximal flow that could enter the freeway because of the mainstream conditions, and the maximal flow allowed by the metering rate

$$\begin{aligned} q_o(k) = min\Bigg[d_o(k) + \frac{w_o(k)}{T}, \\ Q_{free,o} \cdot min\left(r_o(k), \frac{\rho_{max} - \rho_{\mu,1}(k)}{\rho_{max} - \rho_{crit,\mu}}\right)\Bigg], \end{aligned} \tag{4}$$

where $Q_{free,o}$ is the freeflow on-ramp capacity, i.e., the maximal number of vehicles per time unit that can pass the on-ramp under free flow conditions, ρ_{max} is the maximum density, and μ the index of the freeway link to which the on-ramp is connected. In order to consider the speed drop caused by merging phenomena, if there is an on-ramp then the term

$$-\frac{\delta T q_o(k) v_{m,1}(k)}{L_m \lambda_m [\rho_{m,1}(k) + \kappa]} \tag{5}$$

is added to the third equation of (1), where δ is a model parameter. In order to evaluate the evolution equations for a segment, the speed of the last segment of the entering link is simply passed to the first segment of the leaving link

$$v_{m,0}(k) = v_{\mu,N_\mu}(k), \tag{6}$$

where m is the leaving link, μ the entering link, and N_μ the index of the last segment of link μ. Furthermore, the sum of the flows of the entering links equals the inflow of the leaving link

$$q_{m,0}(k) = q_{\mu,N_\mu}(k) + q_o(k) \tag{7}$$

where $q_o(k)$ is the flow from the on-ramp, if there is one, connected to the node, and N_μ is the index of the last segment of the link μ entering the node. The downstream density of the last segment $N_\mu + 1$ of link μ is the density of the first segment of the leaving link m

$$\rho_{\mu,N_\mu+1}(k) = \rho_{m,1}(k). \tag{8}$$

See [5], [8] and [9] for more details about the model.

B. Model Predictive Control

Model Predictive Control (MPC) is a control methodology which explicity uses a process model to optimize the behavior of a controlled system (see, for instance, [10], [11]). The main elements in the design of a predictive controller are:

- the process model used as a predictor;
- a performance index taking into account the reference tracking error and the control input;
- an algorithm to compute future control signals that solves an optimization problem subject to a given set of constraints;
- the receding horizon strategy, according to which only the first element of the optimal control sequence is applied on-line at any sampling time.

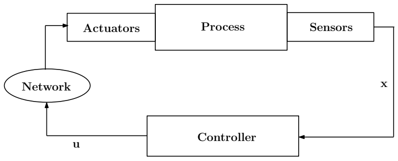

Fig. 1. The control scheme

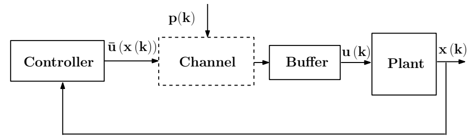

Fig. 2. Closed loop control with a communication channel. $p(k)$ is the binary variable (1 if a packet loss occurs).

III. Optimal control problem formulation

Equations (1)-(8) can be rewritten as a nonlinear dynamic model of the following form

$$x(k+1) = f[x(k), u(k), d(k)], \quad x(0) = x_0 \qquad (9)$$

where x is the state vector, d is the vector of disturbances which consists of the demand at the origins and at the ramps, u is the control vector, i.e. the access rate through ramps ($u_n(k) \in [0, 1]$ for the on-ramp of node n). From the traffic model (9), the following control problem can be formulated: determine at any time step k the control input

$$u^*(k) = \arg\min J[x(k), u(\cdot), k] \qquad (10)$$

where the cost function J is set as

$$J(k) = T \sum_{h=k+1}^{k+N} \left[\sum_{i,j} \rho_{i,j}(h) L_i \lambda_i + \sum_n w_n(h) \right] + \\ + R \sum_n \sum_{h=k}^{k+N-1} \left[u_n(h) - u_n(h-1) \right]^2 \qquad (11)$$

subject to (9), with $0 \leq u_n(k) \leq 1$, where i and j are the indexes of links and segments, respectively, n is the index of the considered on-ramp, and $N \geqslant 1$ is the optimization horizon.

Two main terms compose the cost function: the first measures the Total Time Spent (TTS) of all vehicles in the main stream, while the second penalizes, using the weight R, rapid changes in the control variable, which can be undesirable for the freeway users. The problem is further complicated by the fact that, in order to remain adherent to reality, we consider that a communication channel is present between the controller and the actuators, i.e. the traffic lights situated on the on-ramps of the freeway, as illustrated in Figure 1. In the paper, we assume that the network is affected by delays and packet loss such that the control input u arrives randomly to the system. Then, the aim is to design a networked control system capable of solving problem (10) even in presence of time-varying network delays which can cause a packet loss when they overcome a certain threshold.

IV. Networked model predictive control

The control scheme adopted in this paper is composed of two main elements: the model predictive controller and a buffer. The first is used to generate a set of future control inputs, the second to compensate for the possible network delays or packet loss by using, as new control action, when the optimal one at the current time istant has not been received, the elements subsequent to the first one of the last control sequence which has been received. Clearly, the higher is the probability of having significant delays, the longer must be the buffer length. This latter in our proposal coincides with the optimization horizon N. For these reasons, in presence of the network, it is logical to vary N as a function of the estimated delay to improve the computational aspects of the algorithm [12], giving rise to the proposal of a Networked MPC with adaptive buffer length which will be described in Subsection IV-B. For the sake of simplicity, the network time delay τ_k in the forward channel is random but bounded (the number of consecutive packet loss in bounded), while the network time delay in the feedback channel is assumed to be negligible.

A. Networked model predictive control with costant N

This networked control scheme is based on the use of a buffer in analogy with [13]. Note that in [13] the context was different, and the use of a buffer-based MPC to control freeway traffic systems is original. As before, at each time step k, the control input is computed by using the conventional MPC algorithm, but the complete optimizing sequence $\overline{u}(k)$ is sent to the actuator. The received packets are buffered, providing the plant inputs, see Figure 2. For that purpose, the buffer state is overwritten whenever a valid (i.e., uncorrupted and undelayed) control packet arrives. Actuators values are passed on to the plant sequentially until the next valid control packet is received. In that case the first element of the new control sequence is applied. After N consecutive events of packet loss, the last element of the control sequence is hold and is actuated until a new packet containing an updated control sequence arrives.

B. Networked model predictive control with adaptive N

The networked MPC with constant buffer introduced in the previous subsection can be a sound approach to deal with the presence of network delays even in the case of freeway traffic control. Yet, it obviously needs to rely on a conservative selection of the buffer length N (i.e. of the optimization horizon). But in the applicative cases like the one considered, where the communication network can be shared with other traffic supervision devices which, in an asynchronous and unpredictable way, could need to transfer big files (e.g. video or images), the risk is that the value of N is unnecessary high in most of the time instants. Since, at least in a first approximation, the computational load of the MPC algorithm is tied to the size of N, and this value also influences the amount of data transmitted over the communication channel, thus contributing to its overload

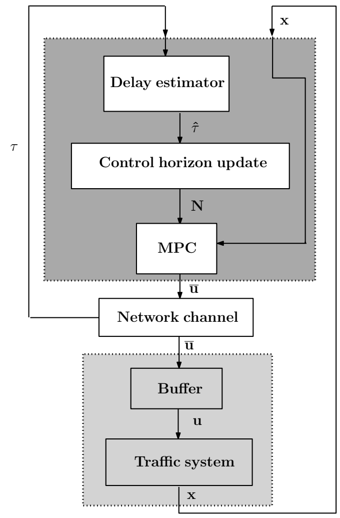

Fig. 3. Closed loop control scheme with adaptive buffer length

and the consequent performance degradation, it would be benefical to keep N to a minimum.

In order to achieve, at least in principle, this objective, in this paper we propose a mechanism to tune the value of N giving rise to a Networked MPC with adaptive buffer length. The idea is to update the buffer length, i.e. N, at any time step k, on the basis of an estimate of the network delays. Various kinds of delay estimators can be found in the literature (see [14]). In this paper, to allow for a comparison, six different delay estimation algorithms are used. Three algorithms (Mean Value Estimation, Median Value Estimation, and Max Value Estimation) are based on simple statistical considerations. While, the so-called Exponential Averaging and the Kalman Filter algorithms are based only on the current system state. In the following we will briefly describe the delay estimators used in our case.

1) Mean Value Estimation Algorithm: This tecnique predicts the current delay by the mean value of last γ measured delays

$$\hat{\tau}_{\bar{k}+1|\gamma} = mean\{\tau_{\bar{k}}, \tau_{\bar{k}-1}, ..., \tau_{\bar{k}-\gamma+1}\}$$

2) Median Value Estimation Algorithm: This model predicts the current delay by the median value of last γ measured delays

$$\hat{\tau}_{\bar{k}+1|\gamma} = median\{\tau_{\bar{k}}, \tau_{\bar{k}-1}, ..., \tau_{\bar{k}-\gamma+1}\}$$

3) Max Value Estimation Algorithm: This algorithm selects the larger value between the mean and the median of last γ measured delays

$$\begin{aligned}\hat{\tau}_{\bar{k}+1,\gamma} \quad = \quad & \max\left\{mean\left\{\tau_{\bar{k}}, \tau_{\bar{k}-1}, ..., \tau_{\bar{k}-\gamma+1}\right\},\right. \\ & \left. median\left\{\tau_{\bar{k}}, \tau_{\bar{k}-1}, ..., \tau_{\bar{k}-\gamma+1}\right\}\right\}\end{aligned}$$

4) Markov Chain Estimation Algorithm: This method predicts the delay range by using a probabilistic distribution on the basis of the previous dynamic events (see [18]).

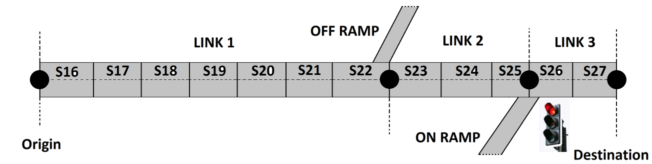

Fig. 4. Schematic Illustration of the considered freeway part

5) Exponential Averaging Estimation Algorithm: The technique allows to predict the delay on the basis of the previous prediction as well as the current network load, i.e.

$$\hat{\tau}_{\bar{k}+1} = \alpha(\tau_{\bar{k}}) + (1-\alpha)\hat{\tau}_{\bar{k}}$$

where $\hat{\tau}_{\bar{k}}$ is the previous prediction, $\tau_{\bar{k}}$ is the current measurement, and α $(0 \leq \alpha \leq 1)$ is a constant used to weight the two contributions (for more details see [15]).

6) Kalman Filter Estimation Algorithm: This is basically a predictor-corrector type estimator that is optimal in the sense that it minimizes the estimated error covariance (for more details see [16]).

Relying on the delay estimation attained by applying one of the previous algorithms, the value of N is updated as follow

$$N(k+1) = \mathcal{N}(\hat{\tau}(k+1)) \qquad (12)$$

where $\mathcal{N}(\hat{\tau}(k+1))$ is the first integer number such that $\mathcal{N}(\hat{\tau}(k+1)) \geq \frac{\hat{\tau}(k+1)}{T_u}$, where $\hat{\tau}(k+1)$ is the delay estimated at time step $k+1$ and T_u is the controller sampling time. where $\hat{\tau}(k+1)$ is the delay estimated at istant $k+1$ and T_u is the controller sampling time.

The scheme of the complete networked MPC with adaptive buffer length is illustrated in Figure 3.

V. APPLICATION TO THE CASE STUDY

We now consider a case study which is part of the traffic show case studied by the researchers involved in the FP7 Network of Excellence HYCON2 (Highly-Complex and Networked Control Systems). The selected road is part of the Grenoble South Ring or "La Rocade Sud" including exit number 4, which corresponds to Saint-Martin-d'Héres, with a total length of about 2.9 km. The considered portion, depicted in Figure 4, is composed of twelve segments, three links and includes an off-ramp and an on-ramp. Table I reports a description of the segments, along with their length and number of lanes.

The METANET model parameters have been identified relying on the data produced by a microscopic simulator of the considered freeway portion by using the procedure proposed in [17].

The communication network is modelled as a communication channel, which operates at the same sampling rate as the controlled system. We characterize transmission effects via the following discrete Bernoulli process (see Figure 2)

$$p(k) = \begin{cases} 1 & \text{if packet loss occurs at istant } k \\ 0 & \text{if packet loss does not occur at istant } k \end{cases}$$

Segment	Type	Length [m]	Lanes
S16	Standard (Barrier)	260	2
S17	Standard	220	2
S18	Standard	220	2
S19	Standard	230	2
S20	Standard	230	2
S21	Standard	230	2
S22	Off-Ramp	310	2
S23	Standard	300	2
S24	Standard	300	2
S25	On-Ramp	140	3
S26	Standard	210	2
S27	Standard	205	2

TABLE I
FREEWAY SEGMENTS DESCRIPTION

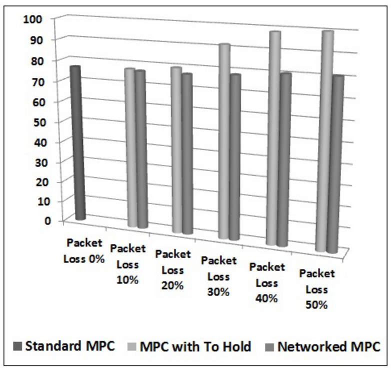

Fig. 5. Confrontation of normalized control performance index I between standard MPC (no packet losses), MPC with to hold mechanism and networked MPC with constant buffer length in presence of packet loss in the communication channel

A. Analysis of the performance of ramp metering in presence of the communication channel

We now compare the performance of a standard MPC applied to the considered freeway under the assumption of zero packet loss with an MPC equipped with an hold mechanism (the control input computed at the previous step is used if packet is lost), and with the networked MPC with costant buffer length, relying on an index I which depends on the values of the cost function assumed at any time step k. This index can be expressed as

$$I(k_f) = \sum_{i=k_0}^{k_f} J(i) \tag{13}$$

where k_0 and k_f are, respectively, the first and final simulation time step and $J(k)$ is defined in (11). Note that the MPC with to hold mechanism and the networked MPC with constant buffer length are tested assuming that packet losses are randomly generated during simulation. Figure 5 shows the effectiveness of the networked MPC proposal which provides values of the index I close to that obtained in the case of zero packet loss (denoted as "standard MPC").

B. Analysis of the robustness properties of MPC

Robustness analysis plays a key role in the control system design: given a control system, it is important to evaluate the performance degradation due to plant parameters variations. The parameters of the traffic system, defined in Section II, are

$$\tau,\ \eta,\ \kappa,\ a_m,\ v_{free,m},\ \rho_{crit,m}.$$

We suppose that the each parameter is subject to the same variation for all the segments. The considered percentage modifications for each parameters are:

Case 1:
$\Delta\tau_1 = +10\%$, $\Delta\eta_1 = -10\%$, $\Delta\kappa_1 = +20\%$, $\Delta a_{m_1} = +10\%$, $\Delta v_{free,m_1} = -15\%$, $\Delta\rho_{crit,m_1} = +20\%$.

Case 2:
$\Delta\tau_2 = -10\%$, $\Delta\eta_2 = +10\%$, $\Delta\kappa_2 = -20\%$, $\Delta a_{m_2} = -10\%$, $\Delta v_{free,m_2} = +15\%$, $\Delta\rho_{crit,m_2} = -20\%$.

Case 3:
$\Delta\tau_3 = +15\%$, $\Delta\eta_3 = -10\%$, $\Delta\kappa_3 = -15\%$, $\Delta a_{m_3} = -15\%$, $\Delta v_{free,m_3} = +15\%$, $\Delta\rho_{crit,m_3} = +10\%$.

	N=1	N=5	N=10	N=50	N=100
Case 1	120	115	115	101	100
Case 2	119	116	115	103	100
Case 3	127	120	120	102	100

TABLE II
NORMALIZED COST FUNCTION INDEX VALUES I WITH SYSTEM PARAMETERS AND OPTIMIZATION HORIZON VARIATION

In Table II normalized cost function index values I are reported with different optimization horizons in the three considered simulation scenarios.

C. Adaptive networked MPC with random delay and model parameters variation

Now we assume that both the transmission delay and that the traffic model parameters vary. In [12] it is observed that the complexity of MPC is linear with the horizon length in the best case. In general, it is not easy to assess the computational complexity of model predictive control algorithms but, in our case, it is useful to define an index to analyze the computational aspects of the proposed solutions. In analogy with (13), we define the following index

$$Q(k_f) = \sum_{i=k_0}^{k_f} N(i) \tag{14}$$

where $N(\cdot)$ is the length of the MPC optimization horizon at any simulation step. The aim of the present test is to assess the performance of the networked MPC with adaptive buffer length based on the six different delay estimators with respect to that of the networked MPC with constant buffer length. The capability of two different estimators to track the actual network delay is shown, to give an idea, in Figure 6.

In Table III the normalized values of the performance index I and of the computational cost index Q are reported

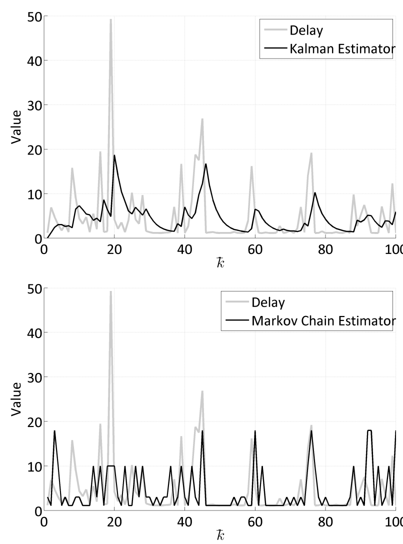

Fig. 6. Delay predictions using the considered estimators

	10% P.L.	30% P.L.	Delay estimator
Case 1	I=110, Q=102	I=115, Q=102	Mean
Case 1	I=108, Q=101	I=110, Q=102	Exp. average
Case 1	I=106, Q=101	I=110, Q=100	Kalman
Case 1	I=105, Q=100	I=108, Q=100	Markov chain
Case 1	I=100, Q=45000	I=100, Q=45000	-
Case 2	I=111, Q=102	I=114, Q=102	Mean
Case 2	I=108, Q=102	I=111, Q=100	Exp. average
Case 2	I=107, Q=100	I=110, Q=101	Kalman
Case 2	I=106, Q=101	I=108, Q=101	Markov chain
Case 2	I=100, Q=45000	I=100, Q=45000	-

TABLE III

NORMALIZED COST FUNCTION INDEX VALUES I, NORMALIZED COMPUTATIONAL COST INDEX VALUES Q WITH SYSTEM PARAMETER VARIATION, DIFFERENT DELAY ESTIMATION AND PACKET LOSS (P.L.) IN THE COMMUNICATION CHANNEL

showing the capability of the networked MPC with different estimators in Case 1 and Case 2, with and without packet losses (P.L.). Note that in Table III all the rows, apart from the fifth and the tenth ones, refer to the application of Networked MPC with adaptive buffer length. The fifth and the tenth rows refer to the case of Networked MPC with costant buffer length and, in this case, the value of N is set equal to 50 which is greater than the maximum number of consecutive packet losses. In case of adaptive buffer length, the computational cost index Q is remarkably less than the value obtained in the costant buffer case.

VI. CONCLUSIONS

In the present paper, two networked MPC algorithms are discussed and analyzed in simulation, making reference to a real world case study. Both the algorithms relies on the use of a buffer so as to circumvent the drawbacks due to the presence of a communication channel between the control center and the traffic system itself. The first algorithm is characterized by a constant buffer length, while the second one by a buffer length which is adaptively tuned on the basis of an estimate of the transmission delay. A simulation analysis of the two algorithms is performed using an instance of the adopted traffic model identified on the basis of data produced by a microscopic simulator of the Grenoble South Ring, this traffic system being the object of the research on traffic modeling, identification and control carried out within the FP7 Hycon2 Network of Excellence. Simulation evidence relevant to the considered case study confirms the validity of the idea, and encourages us to proceed with the experimental test phase, as soon as the sensors will be positioned on the road.

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