A neuro-fuzzy based approach to cooperative ramp metering

Martin Gregurić, Edouard Ivanjko, Sadko Mandžuka
Department of Intelligent Transportation Systems
Faculty of Transport and Traffic Sciences
University of Zagreb
Vukelićeva 4, HR-10000 Zagreb, P.O. Box 170, Croatia
Email: {martin.greguric, edouard.ivanjko, sadko.mandzuka}@fpz.hr

***Abstract*—To solve today's road traffic congestion problems new solutions in the form of advanced control approaches of existing road infrastructure. Such solutions are from the domain of intelligent transportation systems and include various services. Technologies such as advanced driver assistant systems, and communication between vehicles and the road infrastructure are enabling new possibilities in traffic control. Vehicles can obtain a control input from the traffic management system and become an actuator ensuring that the driver complies to the traffic control system. In this paper, a concept of possible automatic vehicle control in cooperation with neuro-fuzzy based urban highway control systems (ramp metering and variable speed limit control) is described. Implemented urban highway control systems are tested using the CTMSIM simulator assuming that all vehicles support automatic vehicle control.**

I. INTRODUCTION

With the introduction of intelligent transportation systems (ITS) a shift from building new infrastructure to applying various services for the management of the existing road infrastructure happened. Topic of this paper is one area of ITS services related to the road traffic management. Advanced approaches are applied to control traffic lights, route vehicles, optimise schedules of public transportation, etc. Such approaches are examined also in the collaborative project Intelligent Cooperative Sensing for Improved traffic efficiency (ICSI). Its main task is to define a new architecture to enable cooperative sensing in the ITS and to develop a reference end-to-end implementation [1]. The project results will enable advanced cooperative modules. One example is the cooperative learning unit (CLU) described in [2]. It enables application of learning and prediction based methods for traffic control, and cooperation between different control systems using a unified sensor and actuator framework. Learning based methods enable a faster on-line adaptation to new traffic situations or to create a unified control strategy for a wide spectrum of traffic situations [3]. Prediction based methods enable the creation of a prediction horizon and to change the control from a purely reactive approach to an approach that takes into account the future behaviour of the system also.

Effective goal of this paper is to present preliminary results of the pro-active ramp metering algorithm based on the neuro-fuzzy control system. It is assumed that all vehicles (drivers) comply with the control system i.e. support automatic vehicle control. The algorithm proposed in [4] conducts the learning process every 15 minute with respect to minimisation of the total travel spent. Neuro-fuzzy control algorithm proposed in this paper contains a learning component, which has the ability to learn a cooperative ramp metering control strategy from adequate existing ramp metering algorithms. At this point whole mentioned ramp metering algorithm can be considered as an CLU. The pro-active control in ramp metering is enabled using traffic flow prediction, which will be a research subject of this paper also. In order to evaluate the mentioned ramp metering algorithm, several other highway control strategies such as cooperative ramp metering and variable speed limit control (VLSC) are developed using an augmented CTMSIM macroscopic simulator [5]. Mentioned highway strategies will be compared against proposed neuro-fuzzy ramp metering algorithm. Furthermore, this paper provide overall insight in the future migration of the mentioned highway control strategies (ramp metering and VSLC) into the vehicles.

The development of advanced driver assistant systems (ADAS) resulted with vehicles containing an on-board control unit (OBU). In cooperation with the mentioned CLU it can take control over the vehicle in critical areas like speed limit zones, and zones near on- and off-ramps thus creating an additional cooperation potential [3]. In this paper a concept how to include the vehicles into cooperation with an urban highway control system based on a neuro-fuzzy learning framework is described. The proposed concept is based on the possibility of partial automated driving i.e. the vehicle's ADAS control unit can control the vehicle speed or at least inform the driver, and that a control strategy can be learned using several standard approaches as teaching algorithms.

II. ARCHITECTURE OF THE OVERALL SYSTEM

As described in [3], automated driving connected with the highway management system by vehicle-to-infrastructure (V2I) communication can improve traffic efficiency. In Fig. 1 architecture block scheme of a system that brings vehicles and traffic management into cooperation is presented. Three different parts can be distinguished: (i) urban highway; (ii) highway management system; and (iii) vehicle. The highway management system and the vehicle are both acting upon the urban highway with the same goal, to use it optimally. That means maximal throughput for all users. But this goal can be only achieved if the vehicles are complying with the imposed control information. To ensure this, a cooperative vehicle infrastructure system is being investigated to send the speed limit value directly to the vehicle's control unit [6].

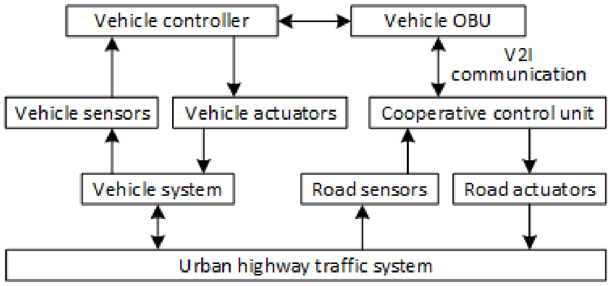

Fig. 1. Block scheme of the overal cooperative system architecture

The highway control part computes the VSLC value that is forwarded to the vehicles in mainstream traffic. So, the vehicle's control unit can automatically adjust the mainstream vehicle speed to the current speed limit. In the same time, the green light signal for the on-ramp's traffic light can be forwarded to the vehicle waiting on the on-ramp. The vehicle's OBU can, in this case, inform the driver to prepare or automatically start the vehicle in the appropriate moment. In both cases, the traffic efficiency can be improved by the established cooperation if appropriate control signals are obtained in the cooperative control unit. The later is the focus of this paper and will be examined in continuation.

III. Short term traffic flow prediction

Short-term prediction for urban traffic flow has become one of the important modules of ITS based services due to its continuous development. Traffic flow presented as a time series contains high amount of randomness and uncertainty. This is the main reason why traditional prediction techniques cannot meet high requirements for prediction precision in practice [7].

In general, short-term traffic flow forecast means real-time forecasts for the next time interval $t+\Delta t$ (where Δt is less than 15 minutes), and even some more time after it, based on the previously collected data [8]. Short-term traffic flow prediction models can be divided into four major categories. First of them are based on the analysis of various mathematical prediction models such as the history average model, linear regressive model, Kalman filtering, etc. The second category of models includes knowledge-based intelligent models. They include non-parametric regressive models and artificial neural networks (ANN). The third group include various traffic simulations which are mainly used to evaluate existing models. The fourth group contains models based on combination between several previously mentioned prediction models.

In this paper, MATLAB neural network toolbox was used to create ANN model for a short term prediction. The ANN model is selected because it provides better prediction results against non-linearity and uncertainty in traffic flow data [8]. Circular feed-forward ANN is selected as the ANN model for prediction of on-ramp traffic demand. This type of ANN model can be described as a recurrent dynamic network with realized feedback, which encloses its outputs with several exogenous inputs. Proposed ANN model in this paper has 180 neurons in the hidden layer. ANN model has learned based on a learning dataset which contains on-ramp traffic demand obtained during 60 working days. On-ramp traffic demand dataset is arranged in the form of a time series. Processing and preparation of the mentioned dataset will be described later with more details.

The ANN predicts on-ramp traffic demand in the form of traffic flow for every on-ramp with a 10 minutes prediction horizon. Length of the prediction horizon can be changed in order to adopt the prediction to the particular application.. Inputs of the ANN for prediction are: code of the working day (1 - Monday, 2- Tuesday, 3 - Wednesday, 4 - Thursday, 5 - Friday), hour of the day (1, 2, 3, ... , 24), code of the 5 minute interval (0, 5, 10, 15, ... , 55) and the current traffic demand value for the observed highway on-ramp. With the first input, it is possible to emphasize unique characteristics of a particular day. Inputs related with the hour of the day and 5 minute interval code enable the ANN to distinguish different parts of each day during the learning process. Using this additional inputs it is possible to increase the prediction accuracy of the existing on-ramp traffic demand prediction approaches [9]. Resilient back-propagation method is used as the learning method. Mentioned ANN adds pro-active control behaviour to the proposed neuro-fuzzy ramp metering algorithm.

IV. Cooperative ramp metering

In general, a cooperative system can be defined as a system which involves multiple dynamic entities that share information or tasks in order to accomplish a common, though perhaps not singular, objective. In ramp metering several on-ramps can be included into cooperation by sharing traffic information and queuing capacity.

A. Concept of ramp metering

Main purpose of ramp metering is to reduce or completely avoid the impact of a downstream bottleneck on the mainstream highway traffic [4]. Mentioned effect is achieved by the use of special road signals (controlled by a traffic responsive algorithm) at on-ramps which provide control over the rate or size of vehicles platoons entering mainstream traffic [10]. However, while reducing the downstream bottleneck, ramp metering may cause the traffic to spill over onto feeder arterial local roads as the on-ramp queue length increases. Such situation is known as the spillback effect [11]. Both effects (downstream bottleneck and spillback) are shown in Fig. 2 along with an elementary ramp metering installation for one metered on-ramp.

Generally it is possible to divide ramp metering algorithms in two major categories: local (or isolated) and coordinated [11]. Local strategies take into account only the traffic condition on a particular on-ramp and the nearby segment of the highway where they are applied. Most often used standard local ramp metering algorithm is ALINEA. Its basic control idea is to keep the downstream occupancy of the on-ramp at a specified level by adjusting the metering rate [10].

In this paper cooperative and competitive subcategories of coordinated ramp metering algorithms are involved. Detailed elaboration of the mentioned as well as other ramp metering subcategories is provided in [10]. The HELPER ramp metering algorithm, described in [12], is one of the first ramp metering algorithms, which is based on the cooperation between several on-ramps. Main task of cooperative traffic control in ramp metering is to find the combination of control measures that

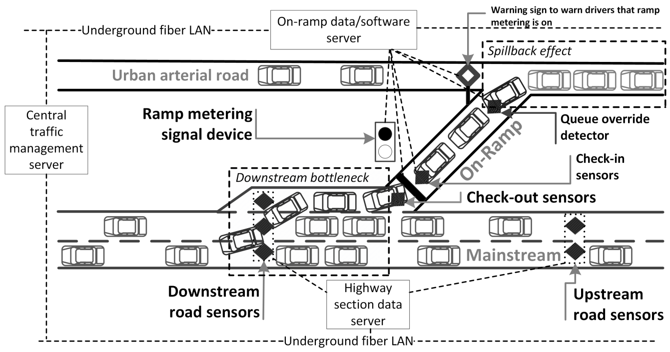

Fig. 2. Illustration of downstream bottleneck and spillback effect location with ramp metering infrastructure [5]

results in high traffic efficiency of urban highways [13]. To achieve that the HELPER ramp metering algorithm firstly detects the place of a major bottleneck and enrols several upstream on-ramps to create virtual on-ramp queues. Virtual queues have the primary goal to stop forwarding additional traffic flow from an on-ramp into mainstream in order to mitigate any downstream congestion. If a bottleneck is not currently present, ramp metering is conducted using the local ramp metering approach. The SWARM ramp metering algorithm, described in [14], is based on competition between the local and global control logics. The more restrictive metering rate value between these two control logic is chosen as the final value.

Latest cooperative ramp metering algorithms include the information about predicted values of important traffic parameters in their final decisions about metering rates. Such a cooperative ramp metering algorithm, which uses prediction data, can be prepared in advance for a particular traffic situation if for example a slow rise in traffic demand is detected. Mentioned data can provide faster response in case when mainstream traffic density has a rising trend. This trend suggests that congestion is rising somewhere downstream and slowly back propagates to the observed part of the highway. In that case, cooperative ramp metering algorithm can reduce the metering rate at several upstream on-ramps in order to reduce impact of possible congestion back propagation.

Model Predictive Control (MPC) is the most used methodology for predictive based cooperative ramp metering algorithm design. In [13], MPC is based on the Advanced Motorway Optimal Control (AMOC) optimization method which computes metering rates according to the obtained real-time and predicted traffic parameters. MPC uses a closed-loop structure in order to enable feedback of the controlled traffic parameters and the current traffic demands to the MPC based controller. This feature provides ability to take disturbances into account in form of traffic demand prediction errors and provide adequate corrections for prediction errors. Prediction errors are the results of difference between the current traffic model and MPC model output.

B. ANFIS based cooperative ramp metering

Rapid development of control methods based on machine learning (e.g. reinforcement learning, fuzzy inference systems (FIS) and ANN) has enabled its application for cooperative ramp metering. Latest approaches in learning based cooperative ramp metering include the use of hybrid intelligent systems such as fuzzy-neural control systems [4]. Mentioned systems are mainly used in order to perform adaptive mitigation of congestion which is varying in strength and in time. In [15], a conceptual design of a Fuzzy Neural Network Control based ramp metering for joint consideration and coordination between eight on-ramps is presented. Furthermore, recent work described in [16] and [4] includes use of an Adaptive Neural Fuzzy Inference System (ANFIS) based ramp metering algorithm for cooperative ramp metering.

The ANFIS based ramp metering algorithm, proposed in [4], contains two parts: an inference control system and an ANN to tune the parameters of the control inference system [17]. In order to tune parameters of the control inference system, ANFIS is put in a learning process using a learning dataset containing situations with significant differences in traffic demand. The learning dataset contains a set of traffic solutions (input traffic parameters and output metering rates) for one particular traffic scenario derived from different control strategies. These control strategies are used as teaching strategies. Three different ramp metering strategies are selected: ALINEA, SWARM and HELPER. ALINEA incorporates good knowledge about local traffic control, SWARM includes some predictive behaviour and the HELPER algorithm has primary role to teach ANFIS algorithm how to identify and react upon the traffic situation which demands a cooperative ramp metering strategy. Mentioned learning process will perform self-tuning in order to satisfy the following criteria function [4]:

$$f(r) = 0.6 \cdot TT + 0.4 \cdot D, \tag{1}$$

where *f(r)* is the metering rate function, *D* is Delay and *TT* is travel time. Delay is defined as the difference between the actual time spent by all vehicles on a congested highway and the time spent in case they have travelled at free flow speed [18]. Delay also considers vehicles which are waiting in on-ramp queues or in mainstream queues caused by the bottlenecks. TT is a simple measure which can answer the question of how much time one vehicle needs to travel through an observed highway segment. This measure is related to mainstream traffic only. Inclusion of weights assigned with TT and Delay in the criterion function allows the user to put emphasis on the higher mainstream flow or to enable higher on-ramp flows. In this paper emphasis is set on the higher mainstream flow. This is done by multiplying TT with a larger weight.

The control inference system at this point will have reactiveness on various traffic scenarios based on newly formed knowledge learned from the teaching ramp metering control strategies. Details about the ANFIS learning process can be found in paper [19]. One has to consider that the criteria function (1) is related to the learning data set preparation and not to the ANFIS learning process itself. During the learning process, classic minimization of the output error is used. ANFIS basic control idea for cooperation between on-ramps is shown in Fig. 3.

As mentioned, this paper presents an augmented version of the cooperative ANFIS ramp metering algorithm, which

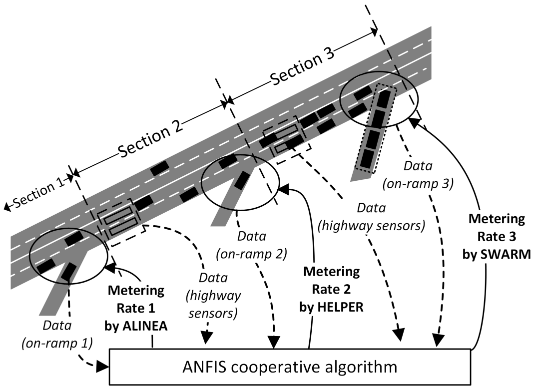

Fig. 3. ANFIS basic control idea for cooperation between on-ramps

enable correction of the computed metering rate based on the predicted traffic demand. Correction is conducted based on the set of four simple IF-THEN rules. If part of each rule compares metering rate computed by the original ANFIS, and the on-ramp traffic demand prediction related with particular on-ramp. Mentioned part of the rule considers comparison between critical density and current density of the highway segment related with particular on-ramp also. Then part of the rule decreases or increases metering rate computed by the original ANFIS ramp metering algorithm. Difference between originally computed metering rate and traffic demand prediction for particular on-ramp can be subtracted or added to mentioned metering rate value with respect to the comparisons made in the if part of the particular rule. Augmented ANFIS based on traffic demand prediction is shown in Fig. 4.

V. Simulation Results

To verify the developed short term prediction and ramp metering approach, a simulation of a section of the Zagreb bypass has been implemented in an augmented version of the simulator CTMSIM [5]. For comparison no control case, several standard ramp metering algorithms (ALINEA, SWARM, HELPER) and VSLC were used.

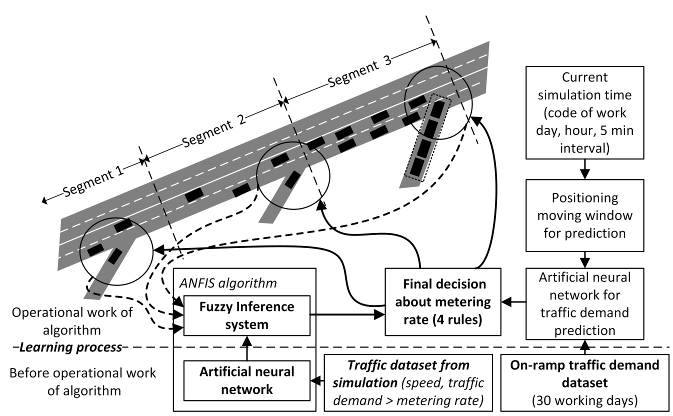

Fig. 4. ANFIS with included traffic demand prediction

A. Simulation setup

CTMSIM is a macroscopic simulator for simulation of interactions between highway traffic flows [18]. Macroscopic traffic model used by CTMSIM is based on the Asymmetric Cell Transmission Model (ACTM) which is described in detail in [18]. To enable simulation of cooperative ramp metering approaches two modifications have been made to CTMSIM [5]. First modification enables cooperative control between all cells (small parts of the modelled highway segment) of the simulation model, by adding an additional step after every simulation iteration. This additional step according to the traffic data from all cells can provide final control decisions about, metering rates for the all cells with an on-ramp. Second modification involves implementation of VSLC for every cell in the simulation model. This augmentation enables its standalone application and cooperation with ramp metering.

Created use case model uses constructional parameters of Zagreb bypass between the nodes Lučko and Jankomir [4]. Segment of the Zagreb bypass between mentioned two nodes has similarities with the other urban bypasses regarding their periodical traffic patterns (e.g. strength and time of the peak hours, traffic load increase at summer tourist season). On-ramps traffic demand characteristics are presented as a hourly traffic flow dataset. Mentioned dataset is interpolated in 5 minute interval on-ramp traffic demand dataset. One typical working day from the mentioned dataset is used in the simulation.

In order to verify operational work of the cooperative highway management strategies, penultimate cell is set to generate high traffic demand. Such step creates a downstream congestion resulting in a "shock wave" propagating upstream. With such a simulation setup the creation of upstream virtual queues can be observed during simulation.

B. Prediction results

Interpolated on-ramp traffic demand dataset is divided into two groups. First group of 60 working days from this dataset is used for the learning process, while other 5 working days are used for validation purposes. Traffic data for Saturday and Sunday are not included into the prediction due to the fact that the traffic demand is low on these days so ramp metering is not applied. Prediction horizon of 10 min has been chosen.

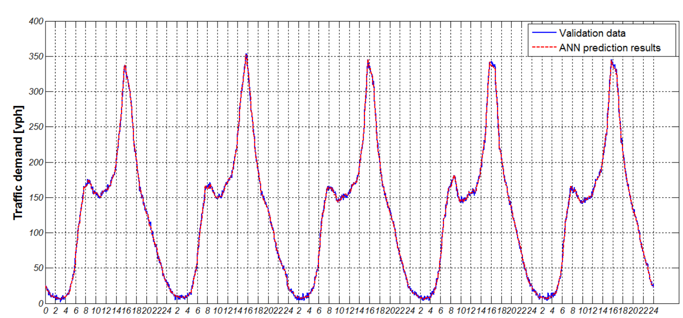

Fig. 5. Traffic demand prediction results for 5 consecutive working days

Prediction results are graphically presented in Fig. 5. The ANN has achieved a 2.60 Root Mean Square Error (RMSE) for the 10 minute long prediction horizon. In the accuracy analysis, 5 working days, as presented in Fig. 5, were used. Furthermore, mentioned ANN achieved 2.05 Mean Absolute Error (MAE) and 0.05 Mean Relative Error (MRE) values. Detail description of the mentioned measures can be found in [20].

C. Ramp metering results

In this section comparative analysis between several different highway management strategies is presented. They are all simulated using the same previously described simulation use case model for a typical working day (24 hours). Results are presented in Table I. The proposed ANFIS based approach without prediction has produced the second lowest average TT value compared to the other ramp metering algorithms involved in the analysis. Best average TT is achieved by the SWARM algorithm due to its longest average and maximal on-ramp queue. The proposed ANFIS based approach with prediction has produced slightly higher value of TT compared to the ANFIS without prediction. On the other hand, ANFIS with prediction has achieved lower average value of Delay and lower average number of vehicles in on-ramps queues compared to the ANFIS algorithm without prediction.

This is an important result since the ANFIS without prediction has produced highest Delay values compared to the other ramp metering algorithms. Both types of ANFIS algorithms produce results which include smaller average TT over Delay. The reason for that is the higher value of the weight assigned with TT in contrast to the coefficient assigned with Delay in the criteria function presented in equation (1).

Lowest Delay was achieved in the simulation scenario without ramp metering and with the use of the standalone VSLC. This result can be explained with the simulation settings enabling immediately merging of on-ramp flows with mainstream under the condition that in a current cell maximal mainstream capacity is not exceeded [18]. Such behaviour induces absence of on-ramps queues but significantly increases traffic density of mainstream, which increases average TT also [4].

The cooperative strategy of the HELPER teaching ramp metering algorithm maintains increased mainstream throughput by distributing vehicles and consequently the waiting time to the "slave" on-ramps queues. This behaviour causes longer queues at "slave" on-ramps and consequently extends average Delay at the controlled segment of highway. This reduces the impact of congestion back-propagation on the mainstream throughput, which consequently decreases TT. Since both ANFIS algorithms have values of average and maximal on-ramp queue length within the value range of HELPER algorithm, it is possible to conclude that ANFIS algorithm has learned a ramp metering strategy based on cooperation between on-ramps.

From Fig. 7 can be concluded that ANFIS, which uses prediction, creates higher Delay before congestion starts. Mentioned behavior indicates its ability to detect congestion in the near future and with respect to this information, to reduce metering rates at all upstream (or "slave") on-ramps compared to the future congested one. As the consequence of this action Delay produced in time of congestion by the ANFIS algorithm with prediction, is significantly lower compared to the ANFIS algorithm which does not use predictions. ANFIS algorithm with prediction reduces mainstream density by restricting the access of the on-ramp flows to the mainstream, before congestion arise. With that control action the algorithm prepares the mainstream flow for the upcoming congestion. Fig. 6 shows that ANFIS algorithm with prediction produces higher TT in time of a congestion breakdown, and produces a minimal increase in average TT compared to ANFIS without predictions.

VI. Conclusion and future work

This paper proposes a cooperative ramp metering control structure, which is designed using a learning framework. The ANFIS algorithm is used as the learning framework and can provide appropriate control inputs for a cooperative

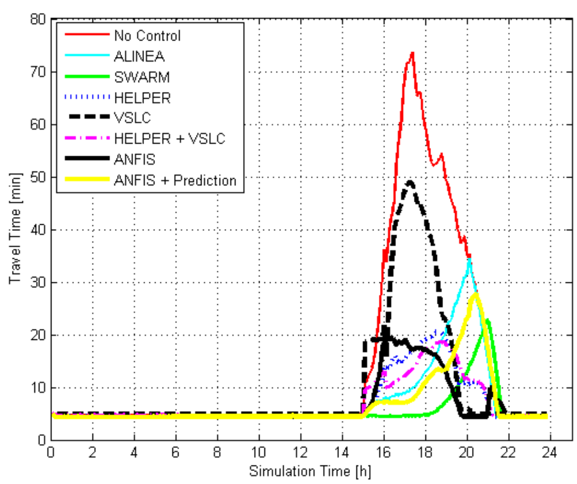

Fig. 6. Comparative analysis according to TT

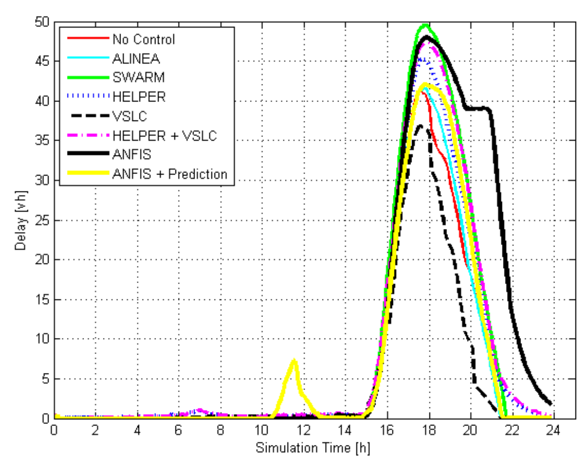

Fig. 7. Comparative analysis according to Delay

TABLE I. RESULTS OF COMPARATIVE ANALYSIS BETWEEN DIFFERENT RAMP METERING ALGORITHMS

	No Control	ALINEA	SWARM	HELPER	VSLC	HELPER + VSLC	ANFIS	ANFIS + prediction
Average TT [min]	14.46	7.39	5.58	6.82	10.5	6.80	6.48	6.69
Average Delay [vh]	6.06	6.8	8.03	7.29	8.05	7.59	10.18	7.03
Average queue [veh]	0	16	18	17	13	18	19	16
Maximum queue [veh]	0	40	49	40	15	42	42	42

ramp metering structure and vehicles equipped with an OBU for automated driving. Two types of ANFIS algorithms are designed. One of them uses on-ramp traffic demand predictions for the correction of its originally computed metering rates for every on-ramp, while another ANFIS type does not. Simulation results achieved by the proposed ANFIS algorithms are compared with results achieved by its teaching ramp metering algorithms. Additionally, both types of ANFIS algorithm are compared against each other. They are also compared with the situations based on cooperation between VSLC and HELPER, and standalone VSLC. The Zagreb bypass between nodes Lučko and Jankomir is used as highway simulation model for situational evaluation of analysed ramp metering algorithms.

Both ANFIS algorithms show promising results in effective balance between values of TT and Delay, compared to the other involved highway management strategies. ANFIS algorithm with predictions compared to the ANFIS algorithm without predictions, produces lower value of Delay and lower average on-ramp queue as well. ANFIS algorithm with predictions creates shorter virtual queues long before the congestion arise on the "slave" on-ramps. This action decreases density of the upstream traffic, before congestion arise and consequently reduces average on-ramp queue length.

Described control strategy combines cooperative and proactive ramp metering control into one ramp metering algorithm. Future work involves development of more robust and comprehensive cooperative ramp metering logic, which uses traffic demand predictions. Additionally, future work will include further improvement of the traffic demand prediction accuracy.

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