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Artificial Intelligence in Adaptive Control Strategy Design

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Abstract-Intelligent systems and their theoretical background in artificial intelligence have noticed enormous improvement these years. Their implementation in everyday life is real challenge for the scientists. One of the most present actions in our day–to–day living is use of traffic and transportation. Therefore there are challenges for the researchers to optimize traffic operations. The aim of this paper is to prove the ability of machine learning control technique known as reinforcement learning to respond to variable real-time traffic conditions and adapt while controlling freeway entry access. Learning agents have been implemented as controllers in order to provide optimal performance on the freeway corridor. The algorithm used was Q-learning algorithm. The effectiveness of the agents were measured by several measures: total travel time spend by all the vehicles in the network, delay of the all vehicles in the network, stop time. The results are promising, proving that the Q-learning algorithm is capable for optimal coordinated control of freeway entrance ramps.

Keywords- *Artificial Iintelligence (AI), Intelligent System (IS), Ramp Metering, Optimal Adaptive Real-Time Freeway Entry Ramp Control, Reinforcement Learning, Multi Agent Systems*

I. INTRODUCTION

Transportation professionals have been imposed to a challenge to provide safe, efficient, and reliable traffic and transportation while at the same time minimizing the impact on the environment. Tools that are available are numerous. Artificial intelligence (AI) is one of the most powerful tools to improve safety, efficiency and environment protection for the transportation systems. AI can even encourage us do things we didn't know we wanted to do. Implementing AI techniques in freeway management systems could make better use of the existing freeway infrastructure. Freeway management systems use different control strategies, and many operational activities to keep congestion from occurring in the first place, and shorten the duration and extent of congestion when it does occur. Ramp control on the freeway corridor is the application of control devices with the aim of achieving some operational objective. Devices could be traffic signals, signing and gates and they are used to regulate the number of vehicles entering or leaving the freeway. Typically, the main objective is to balance both demand and capacity of the freeway in order to maintain optimum freeway operation, prevent congestion and protect the environment.

ALINEA was the first local ramp metering control strategy based on straightforward application of classical feedback control theory [1]. The objective of the feedback approach is to minimize deviations from the nominal states, taking into account the traffic evolution, but giving no direct consideration to total travel time, which is a more appealing measure of the effectiveness to traffic operator. Papageorgiou et al. [1] have developed METALINE regulator that performs coordinated ramp metering and attempts to operate the freeway traffic conditions near some pre-specified set values. Further, AMOC a macroscopic model was developed [2] where ramp metering and route guidance are considered simultaneously. Some of the other efforts in corridor control regarding ramp metering algorithms are designing a two-level approaches for the control of freeways [3], a freeway ramp metering using artificial neural networks [4], or genetic fuzzy approach for ramp metering [5].

These ramp metering algorithms, although traffic-responsive, are not really adaptive to changing traffic operating conditions. The development in artificial intelligence starting with artificial neural networks after their blooming in 1993 offered a new tool for designing adaptive traffic-responsive ramp metering algorithms.

The strategy proposed in this paper also uses artificial intelligence technique, i.e. machine learning technique known as reinforcement learning. The proposed strategy tends to learn and to adapt to changing traffic conditions on the freeway and satisfy the objective function to minimize total travel time spent in the system. Most of the existing algorithms for freeway ramp metering, although traffic responsive, are not truly adaptive to traffic parameter changes. Most of them are of local regulator type [6] and not truly adaptive.

II. ARTIFICIAL INTELLIGENCE TECHNIQUES IN TRAFFIC AND TRANSPORTATION

"Artificial intelligence is that activity devoted to making machines intelligent, and intelligence is that quality that enables an entity to function appropriately and with foresight in its environment." [7] The definition of AI mentioned above might be the useful one, because practitioners, researchers, and developers of AI are guided by a rough sense of direction and an imperative to "get on with it." Still, the lack of a precise, universally accepted definition of AI probably has helped the field to grow, blossom, and advance at an ever-accelerating pace. Many of the AI research trends such as: large-scale machine learning, deep learning, computer vision, natural language processing, robotics, collaborative systems, Internet of Things, reinforcement learning etc. find their implementation in everyday life. "Transportation is likely to be one of the first domains in which the general public will be asked to trust the reliability and safety of an AI system for a critical task." [8]

This statement is valid for all the implementation of AI in traffic and transportation, no matter weather is vehicle, infrastructure or planning in question. Intelligent agents systems in traffic control according to Roozemond and Veer [9] have used at most Expert Systems (ES), Neural Networks (NN), Genetic Algorithms (GA) and Fuzzy Logic (FL). The emerging artificial intelligence techniques usable in traffic control are learning from experience or reinforcement learning (RL) and multi agent control [10] as a part of Distributed Artificial Intelligence (DAI). AI techniques could help update traffic signal timings automatically as a response to changing traffic conditions [11] and can also detect changes in traffic conditions and incidents in real-time and precisely.

III. MODELLING THE CONTROLLER

The main objective in freeway entrance ramps control is to regulate the number of vehicles entering the freeway in such a way that traffic density is kept lower than the critical density which corresponds to capacity of the freeway. Installation of control signals on entrance-ramp may appear when it results in a reduction of the total expected delay to the traffic in the freeway corridor, including freeway ramps and local streets. It should fulfil either one of the conditions: there is recurring congestion on the freeway, or there is a severe accident hazard at the freeway entrance or there is a recurring congestion. The signals are needed to reduce sporadic congestion on isolated sections of freeway caused by short-period peak traffic loads from special events or from severe peak loads of recreational traffic [12, 13].

Proper metering rate could be provided when signal timing is adjusted according to many factors: grade, vehicle mix, specific geometry on-site, driver's behaviour. Two types of traffic lights settings exist: one car per green and control via red phase duration, and traffic cycles. Control strategies compute proper on-ramp volumes.

Control strategy implemented in this research is traffic responsive adaptive and optimal coordinated control strategy. It is traffic responsive because of self-corrective feedback provided with measurements of the system states downstream the ramp on the freeway. It is adaptive because the technique implemented to determine the metering rates is capable of continuous learning. It means that the control policy itself is continuously changing in response to temporal changes in inherent systems characteristics. Optimal control can be performed as the control agents learn to maximize system performance and not rely on a pre-set value.

A. Q - Learning

In the school of Behaviorism, learning is a complex process of responses to several kinds of distinct stimuli. Learning is defined as a three-term system comprised of a discriminative stimuli, a response, and a reinforcing stimulus.

Reinforcement learning as a machine learning technique which can work without supervision [14, 15]. It is goal-directed learning from interaction with an environment, technique that will learn what to do - how to map situations to actions, in order to maximize a numerical reward signal. Technique used in the proposed control strategy is performed by intelligent agents. Agent as a result of taking action *a* in state *s* receives a reward or reinforcement *r(s,a)*, which depends on the effect of this action on the environment. The combination of state *s*, action *a*, and reward *r(s,a)* is used to recursively update the previous estimate (as of time n-1) of the Q-value:

$$\hat{Q}_n(s,a) \longleftarrow (1-\alpha_n)\hat{Q}_{n-1}(s,a) + \alpha_n[r + \max_{\alpha'} \hat{Q}_{n-1}(s',a')] \quad (1)$$

Where *s* and *a* are the state and action updated during the n-th iteration, *r* is the reward received for taking action *a* while in state *s*, $Q\wedge_{n-1}$ is the previous estimate of the Q-value of taking action *a* while in state *s*, $\max(Q\wedge_{n-1}(s',a'))$ is the previously estimated Q-value of following the optimum policy starting in state *s'*.

Training rate takes values between 0 and 1 is:

$$\alpha_n = \frac{1}{1 + visits_n(s,a)} \quad (2)$$

Where $visits_n(s,a)$ is the total number of times this state-action pair has been visited up to the n-th iteration. When α_n is 1, this rule is suitable for deterministic case. By reducing α_n at an appropriate rate during training, convergence of the Q values can be achieved. Also, a discount factor is taken for future rewards, which reflects the higher value of short-term future rewards relative to those in the longer term. The updated estimate of Q-value is stored in look-up table [16].

IV. STRATEGY TESTING

Research was conducted with direct programming of the functions in VISSIM microsimulator in order to implement the technique of reinforcement learning by multi agents.

A simple network was created in the simulator. The simple network consists of one segment of a freeway with three lanes and three ramps with one on-ramp lane. Detectors were located upstream the on-ramp entrance, on the freeway downstream of the ramp and before the end of the freeway segment, at the destination zone. System state data were gathered directly by the simulator. The timing plans of the ramp signal controllers were updated at the end of the fixed intervals.

In order to test the control strategy, a few scenarios were divided into two test phases: first phase - coordinated control was performed with parameters' measurements taken at the freeway exit and traffic demand on the main line was known and second phase - where measurements were taken downstream at each freeway entry (Figure 1), and coordinated control was performed and traffic demand on the main line was unknown. During this test phase two types of scenarios were developed: testing when there is no traffic congestion and testing when there is traffic congestion on the corridor.

The feasibility of the suggested strategy for optimal adaptive coordinated control of the freeway entry ramps was estimated in such a way that the results from the learning agents were compared to the results of the case without control strategy and to the results of the case with ALINEA control.

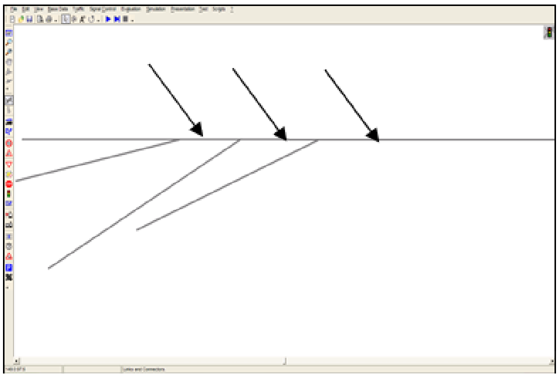

Figure 1. Second phase layout

The results from the simulations without control strategy were taken as the base case. Testing was conducted according to the rules of Q-learning i.e. after sufficient number of iterations with different numbers of states and after Q-values convergence.

V. ANALYSIS OF THE RESULTS

Within the *first test phase* improvements were as follows: decreased average stop time per vehicle (37%), decreased average number of stops per vehicle (35%), decreased delay (26%), decreased travel time (15%) and increased number of vehicles exiting the network (14%).

It was also, evident that this type of control strategy needs longer learning phase for the agents, which makes the strategy not enough efficient.

Therefore, second phase of the testing was implemented, with traffic parameters measured on the mainline downstream of the each ramp and unknown traffic demand. During this phase two types of testing were performed: testing without traffic congestion, and testing when traffic congestion on the corridor exists.

After the testing without traffic congestion, it was noticed: decreased average stop time per vehicle (78%), decreased average number of stops per vehicle (80%), decreased delay (30%), decreased travel time (3%) and increased number of vehicles exiting the network (3%). This shows that traffic flow is smooth and after one hour of travel, travel time and delay decrease is noticeable. But, travel time, number of vehicles exiting the network have very little improvement. It was evident that the strategy follows real-time traffic parameters changes, especially during the transition from the state of congestion to the normal state.

The implementation of ALINEA for the same effectiveness measures shows similar results with the suggested control strategy. That could be explained with the fact that there is no recurrent congestion on the corridor, which makes the strategy inferior compared to ALINEA.

For the ALINEA strategy there are some parameters calibrations that need to be made for the particular geometry of the freeway and the corresponding traffic demand, while for the suggested strategy for coordinated control, the calibrations are not needed and testing is performed on unknown traffic demand. Regarding travel time saving, increasing the speed and increasing the number of vehicles that exit the network ALINEA is not very promising. Therefore, in the case where there is no traffic congestion for the suggested strategy prior to the implementation learning performed with similar traffic demand could be implemented.

During the second test phase (without traffic congestion on the freeway and entry ramps), the Q-learning agents show extraordinary good results after relatively small number of iterations (about 1500) with unknown traffic demand: decreased average stop time per vehicle (38%), decreased average number of stops per vehicle (35%), decreased delay (26%), decreased travel time (15%) and increased number of vehicles exiting the network (10%) and increased speed (10%).

TABLE I. IMPROVEMENTS DURING THE SECOND TEST PHASE

	New strategy		ALINEA	
Measurement	Decrease (%)	Increase (%)	Decrease (%)	Increase (%)
Travel time	15		8	
Delay	26		13	
Average stop time per vehicle	38		20	
Average number of stops per vehicle	35		19	
Number of vehicles exiting the network		10		6
Speed		10		4

According to Table I. improvements are almost doubled compared to ALINEA results. It was noticeable that the strategy adjusts itself to the traffic conditions, i.e. it is adaptive and responds to the traffic demand in real-time.

As Figure 2. Shows the best improvement was gained for the average stop time per vehicle and average number of stops per vehicle in the case of implementation of the control with non-congested data.

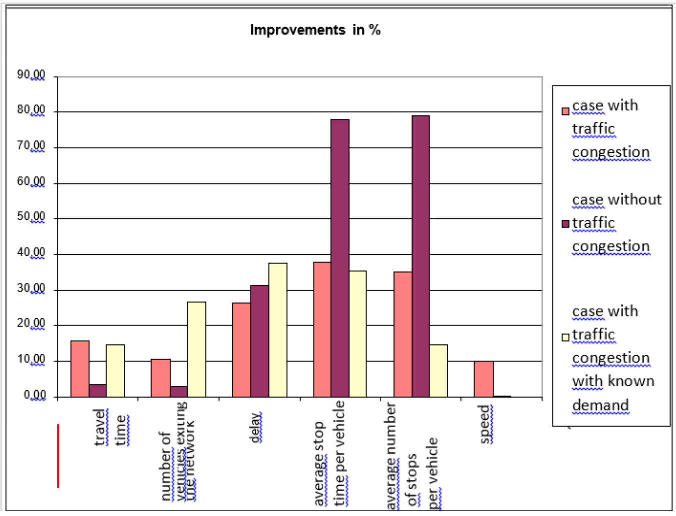

Figure 2. Improvements comparison according to measurements of effectiveness in respect to base case (no control strategy)

Regarding all the measures of effectiveness, the best results with control strategy implementation on unknown traffic demand, with recurrent congestion, are gained. That shows that suggested strategy is feasible for coordinated freeway ramp metering and it performs optimal, adaptive and traffic responsive control.

After the testing with data where there is recurrent congestion on the corridor, the proposed strategy that uses Q-learning agents shows extraordinary good results after relatively small number of iterations with unknown traffic demand. Thus, it is shown that it is feasible and efficient.

Coordinated control implemented with new proposed strategy is better compared to ALINEA taking into account the average stop time per vehicle and average number of stops per vehicle during the rush hour. This allows smoothness of the traffic flow with no interruptions in terms of "stop-and-go" which leads to reduced air pollution, reduced fuel consumption per vehicle and also, reduced pollution of the environment.

VI. CONCLUSSIONS

According to the results of the strategy testing, it can be concluded that optimal adaptive coordinated freeway ramp metering control is feasible for performing coordinated freeway ramp metering control. Thus, it can be concluded that reinforcement learning technique is feasible for implementation in traffic control. This research is one step towards creating intelligent freeway in terms of creating the strategy which is very simple, and truly adaptive. Also, it could be concluded that while creating the strategy, prior to implementation there is no need to model the environment. On the other side, the supervision is not necessary and there is no need for traffic parameters' prediction.

Still, there are next steps in the research that will make the reinforcement learning technique faster and improved in terms of optimization of the algorithm in faster learning, implementation of Q-learning in cases where there is non-recurrent congestion on the freeway and also, to explore the strategy performance after its implementation.

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