Soft Computing for AdaptiveTraffic Control

Kostandina Veljanovska[1]

[1]Department of Intelligent Systems, Faculty of ICT, University "St. Kliment Ohridski", Bitola, Republic of Macedonia

kostandina.veljanovska@fikt.edu.mk

Abstract:
The aim of this paper is to emphasize the significance of soft computing techniques, to introduce soft computing technique as good functional approximator and to analyze performance of two learning algorithms:one hard computing and one machine learning algorithm. The problem of controlling freeway ramp entrance by reinforcement learning was selected. The aim of this research is to help the local government in reducing air pollution by making influence in the number of vehicles entering the freeway. This way there are possibilities for environmental pollution reduction, fuel consumption reduction and for improving air quality. The results are promising for various dimensions of the cities and intercity freeways since the machine learning algorithms are used and the proposed model is capable of learning from presented data even if they are not precise.

Keywords:
Soft Computing, Artificial Intelligence, Machine Learning, Reinforcement Learning, Q-learning algorithm

1. Introduction

Environmental pollution and how to reduce it has been top priority for both the state and local governments in the Republic of Macedonia for a while. Many studies for air pollution are undertaken and they show that not only heating, but also traffic and transportation is main cause for enormous air pollution in urban areas. Our aim is to contribute to the solution of this problem. This study was undertaken in order to show how transportation control could be performed using soft computing techniques.

Freeway management systems use different control strategies, and many operational activities to keep congestion from occurring in the first place, and shorten the duration of congestion when it occurs. Ramp control on the freeway corridor is the implementation of control devices with the aim of achieving some operational goal. 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 by reducing air pollution.

In urban planning there are possibilities to undertake measures to influence citizens in their way of travel, but in traffic operations there are many ways of influencing drivers in order to control the traffic onsite. The problem is interesting for the local government since addresses the way of behavior of drivers via variable message signs and maintaining optimal throughput on the freeway corridor.

In order to solve the problem of controlling the freeway entrance ramp throughput hard computing techniques were used: 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 demand, but giving no direct consideration to total travel time as a more appealing measure of the effectiveness to traffic operator. It works as a regulator. Papageorgiou et al. [1] have developed METALINE regulator that performs coordinated ramp metering and tries to operate the freeway traffic conditions near some pre-specified set values. The next strategy is AMOC - a macroscopic model [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].

The above mentioned 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. 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 soft computing techniques in freeway management systems could make better use of the existing freeway infrastructure.

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.

Artificial neural networks are widely adopted because they can extract subtle information from training data even if they are noisy and data that cannot be directly obtained by human or other analysis techniques. However, traditional NNs, which are generally trained by back-propagation algorithms, are likely to be trapped in local optimum. Therefore, particle swarm optimization (PSO) has been introduced to train the NN [7].

Deep neural networks and deep learning are relatively newer models, applied mostly so far to pattern recognition and image/voice processing, and for big data analytics. Deep learning schemes have been utilized to develop a framework that use a deep Q-learning in order to perform ramp metering based on traffic video data [8].

For the purpose of fulfilling the aim, we select two different algorithms:hard and soft computing algorithm. We tried to set the problem as solving a control problem. This type of research has not been done in our country using artificial intelligence or soft computing, yet.

2. Soft Computing and Artificial Intelligence

The core reason of establishing the term soft computing is to imitate the human mind. Soft computing, as opposed to traditional computing, deals with approximate models and gives solutions to complex real-life problems. Unlike hard computing, soft computing is tolerant of imprecision, uncertainty, partial truth, and approximations [9]. Soft computing is based on techniques such as fuzzy logic, genetic algorithms, artificial neural networks, machine learning, and expert systems. Some of the scientists have considered it asthe sub-discipline of AI focusing on heuristics, imperfect solutions to complex problems, some of them considered it as subtle intermediate field.

2.1. Soft Computing Techniques

The solution to every problem could be searched in various ways. Numerous techniques for solving problems are divided in two large groups. In classical programming problems are solved by so-called hard computing techniques using precise models that include either symbolic logic reasoning or numerical modelling (Figure 1). The other way is to search for a solution in soft computing way, using approximate models where approximate reasoning could be implemented or where solution could be searched by randomized search techniques using functional approximation. So, soft computing consists of few technical disciplines that are performing behavioural and cognitive modelling of the human brain[9, 10].

Models of approximate reasoning on the other side could be implemented as models that use uncertainty, i.e. probabilistic models or fuzzy models. Probabilistic models as the use of the codes of statistics to data examination and one of the initial methods of machine learning are divided in two smaller groups: Bayesianbelief networks and Dempster Shafer theory of evidence. The best-known algorithm in this group is the Naive Bayes algorithm. Theory of evidence describes research that looks at the beliefs that people hold about the type of evidence that counts in scientific reasoning and changes of those beliefs.

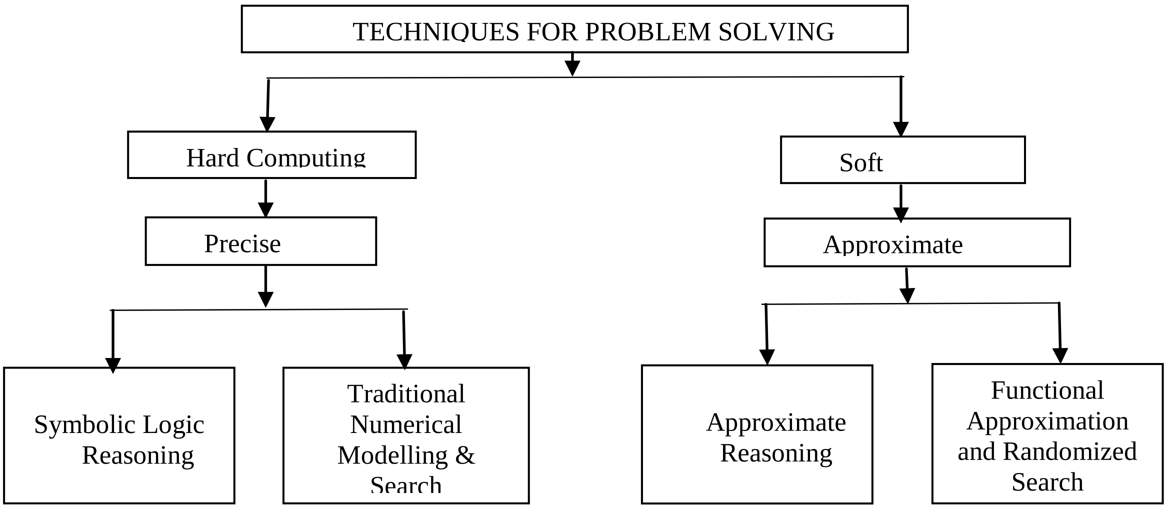

Figure 1: Technical disciplines for problem solving

Dempster Shafer theory of evidence offers an alternative to traditional probabilistic theory for the mathematical representation of uncertainty and it is counted as a generalized schemefor expressing uncertainty. Itconsiders sets of propositions (instead of just single propositions) and assigns to each set an interval within which the degree of belief for the set must lie [11, 12, 13]. The best-known approach in this group is the Belief of Fuzzy Event (Figure 2). K- nearest neighbour is one of the algorithms that use approximate reasoning and could be implemented as probabilistic algorithms that works as simple classifier. Also, the problem of classifying an unseen pattern on the basis of its nearest neighbors in some data set could be addressed from the point of view of Dempster-Shafer theory. Each neighbor that has to be classified could be considered as an item of evidence that supports certain hypotheses regarding the class membership of that pattern. The degree of support could be defined as a function of the distance between two vectors. The evidence of the k nearest neighbors could be pooled by means of Dempster's rule of combination.[14]

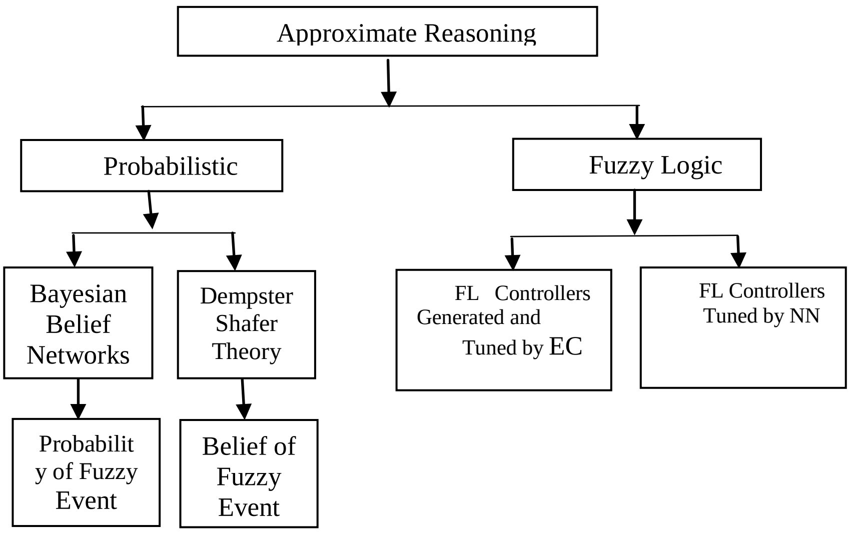

Figure 2: Approximate Reasoning as part of approximate models

Another huge part of approximate models of soft computing is randomized search for the problem solution and finding a solution via function approximation. There are several techniques that could be used and some of the scientists [9, 15] divide them in three groups: evolutionary computing, neural networks and reinforcement learning. The basic biological phenomenon of inheritance and evolution has been used in order to develop so-called evolutionary algorithms [16]. This huge group contains algorithms that could work as evolutionary strategy, evolutionary programming, genetic algorithmsor genetic programming (Figure 3).If we want to simulate hardware of living creatures brain, or even human brain as final aim we could use neural networks.

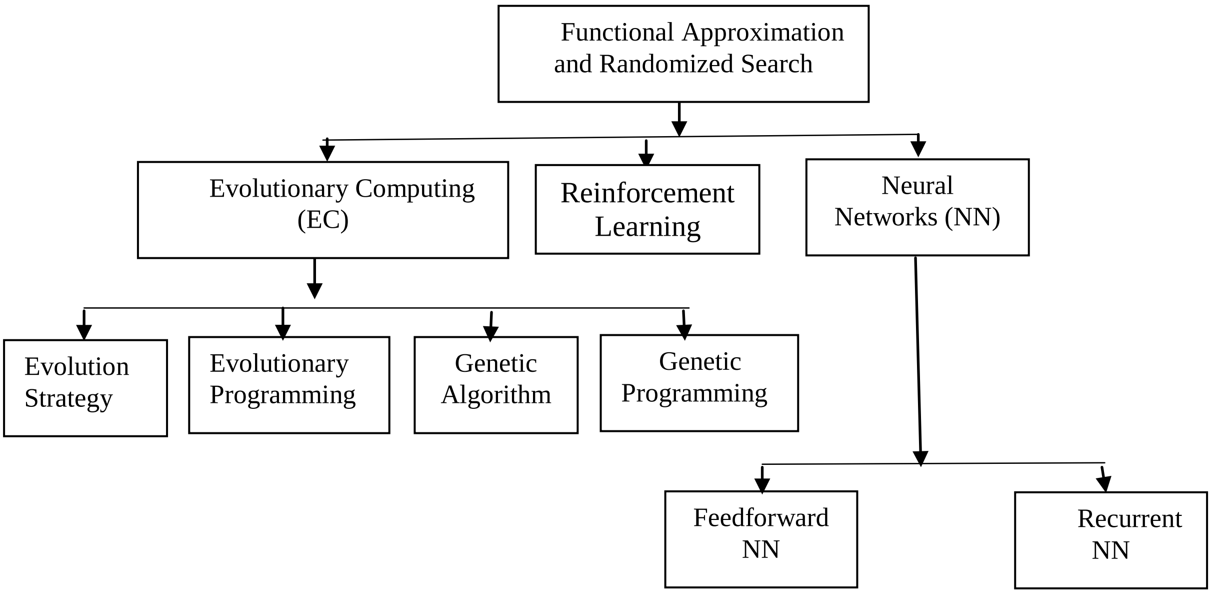

Figure 3: Problem solving by randomized search and function approximation

2.2. Introducing Reinforcement Learning as Soft Computing Technique

The way animals are learning and behave is simulated by reinforcement learning (RL) techniques [16, 17, 18]. Under reinforcement learning as type of machine learning techniques the solution of the problem is done by trial and error through randomized search in problem space. As a result of many years of research in the field of AI and particularly RL we are convinced that RL deserves to be added to the Figure 3. We found it very efficient in doing function approximation [18].

Sometimes, hard computing and soft computing intermingle and they are used together as hybrid computing [15].

2.3. Selecting Soft Computing Algorithms for Strategy Design

Actually, in its classical formulation, soft computing includes most of machine learning, evolutionary computation, and fuzzy logic. Machine learning as the sub-discipline of AI is focused on transforming a large amount of data to a model. Machine learning is the practice of using algorithms to parse data, learn from data, and then make a determination or prediction about some processes or situations in real life. The agent used by soft computing should be “trained” using large amounts of data and algorithms that perform the ability to learn how to act and fulfil some task. The algorithmic approaches over the years included decision tree learning, reinforcement learning, and Bayesian networks among many others.

Machine learning have been widely used for classification and pattern recognition. Some of the implementations are commercially very popular and perform well on numerical and text data like Naive Bayes [19, 20,21]. Neural Networks can handle both discrete and continuous data [19]. There are studies that use NB for determining if smart environment sensor data can be used to predict air quality levels [22], or NB for document classification model [20]. k – Nearest Neighbors (k-NN) is a time consuming method and determining the optimal value has always been an issue [19, 23] even if some specified software is used for the implementation of the algorithm regarding air quality prediction [24]. Using decision tree can reduce the complexity but when it comes to continuous data the DT algorithm is unable to handle them.

2.3.1. Soft Computing Techniques in Traffic

"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." [25] This definition of AI 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." [26]

Intelligent agents systems in traffic control according to Roozemond and Veer [27] have used at most Expert Systems (ES), Neural Networks (NN), Genetic Algorithms (GA) and Fuzzy Logic (FL) all of them soft computing techniques. The emerging soft computing techniques usable in traffic control are learning from experience or reinforcement learning (RL) and multi agent control [28] as a part of Distributed Artificial Intelligence (DAI). These techniques could help update traffic signal timings automatically as a result of response to changing traffic conditions [29], they can detect changes in traffic conditions and also can detect incidents in real-timewith high precision.

3. Strategy Design

The main objective in controlling freeway entrance ramps is to maintain the number of vehicles entering the freeway on such a level that traffic density is kept lower than the critical density which corresponds to capacity of the freeway. Control signals on entrance-ramp are installed in order to reduce total expected delay of the traffic in the freeway corridor, including freeway ramps and local streets.

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 and they are implemented when there is recurring congestion on the freeway, or there is a severe accident hazard at the freeway entrance or severe peak loads of recreational traffic [30, 31].Control strategy implemented in this research is at the same time 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 each ramp on the freeway. It is adaptive because the technique implemented for determining 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. At the end it is optimal control since the control agents learn to maximize system performance and do not rely on some pre-set value.

Q - Learning

Reinforcement learning is known as a machine learning technique that works without supervision [32, 33]. It is goal-directed learning from interaction with an environment, where intelligent agents perform the control strategy and they will learn what to do - how to map situations to actions, in order to maximize a numerical reward signal. 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:

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

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*, $Q\hat{}_{n-1}$ is the previous estimate of the Q-value of taking action *a* while in state *s*, max($Q\hat{}_{n-1}$(*s′,a′*)) is the previously estimated Q-value of following the optimum policy starting in state *s′*.

Training rate which takes values between 0 and 1 is: $\alpha_n = \frac{1}{1+visits_n(s,a)}$ (Eq. 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.

STRATEGY TESTING

Research was conducted by programming the functions in API of VISSIM microsimulator in order to implement the technique of reinforcement learning by multi agents. The simple network created in the simulator 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, few experiments were performed. The most promising results gave the experiments where measurements were taken downstream at each freeway entry, 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 proposed 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 a hard computing technique. The results from the experiments 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.

4. Discussion of the Results

Experiments were implemented with traffic parameters measured on the mainline downstream of the each ramp and unknown traffic demand with two types of testing: testing without traffic congestion, and testing with traffic congestion on the corridor. 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 which could be explained with the fact that there is no recurrent congestion on the corridor, making the strategy inferior compared to ALINEA.

For the hard computing strategy (ALINEA) there are some parameters calibrations needed for the particular geometry of the freeway and the corresponding traffic demand, while for the proposed strategy, the calibrations are not needed and testing is performed on unknown traffic demand. Regarding travel time savings, increasing the speed and increasing the number of vehicles that exit the network ALINEA is not very promising.

During the second test phase (with 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 1)

Table 1:
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

Improvements are almost doubled compared to ALINEA results as shown in Table 1. It was evident that the strategy adjusts itself to the changing traffic conditions, which shows that it is adaptive and responds to the traffic demand in real-time. Considering all the measures of effectiveness, the best results are gained for control strategy implementation on unknown traffic demand, with recurrent congestion. That shows that suggested strategy is feasible for coordinated freeway ramp metering and it performs optimal, adaptive and traffic responsive control.

Experiments of the proposed strategy that uses Q-learning agents with data where there is recurrent congestion on the corridor 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 hard computing technique 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.

5. Conclusion

By selecting soft computing algorithms, we are able to perform problem solution search, prediction and control similar to human mind reasoning, using imprecise and uncertain data, partial truth, and approximations. According to the results of the testing of proposed strategy in this research where reinforcement learning was implemented it can be concluded that this technique is feasible for performing coordinated freeway ramp metering control. 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.

We would like to emphasize that proposed strategy which uses soft computing technique is better compared to hard computing technique taking into account the average stop time per vehicle and average number of stops per vehicle during the rush hour that allows smoothness of the traffic flow with no interruptions in terms of “stop-and-go”. This leads to reduced air pollution, reduced fuel consumption per vehicle and reduced pollution of the environment.

There are few steps in terms of future research that will make the reinforcement learning technique faster and improved in the matter of optimization of the algorithm in faster learning such as implementation of Q-learning with function approximation instead of look-up table.

It is shown that reinforcement learning technique is feasible in finding a solution for traffic control which is very simple, and truly adaptive and have the cognitive ability to learn effectively. Thus reinforcement learning deserves to be counted as significant component of soft computing techniques.

References:

[1] Papageorgiou, M., (1991) Automatic Control Methods in Traffic and Transportation, Operations Research and Decision Aid Methodologies in Traffic and Transp Management, NATO ASI Series, Springer

[2] Kotsialos, A., et al. (2002) Coordinated and Integrated Control of Freeway Networks via Non-linear Optimal Control, Transportation Research Part C, Vol. 10, Elsevier Sc. Ltd, GB, pp. 65-84
[3] Alessandri, A., et al. (1995) A Two-Level Approach for the Control of Freeways, Applications of Advanced Technologies in Transportation Eng. - Proc of the 4th Internat. Conf, Capri, IT, 429-433
[4] Zhang, H. et al,(1997) Freeway Ramp Metering Using Artificial Neural Networks, Transportation Research Part C, Vol. 5, No. 5, Elsevier Science Ltd, Great Britain, pp. 273-286
[5] K. Bogenberger, et al., (2000) Design of a Genetic Fuzzy Approach for Ramp Metering", IEEE Intelligent Transportation Systems, USA
[6] X. Wang, et al., (2010) Reinforcement Learning On-Ramp Metering with or without Complete Information", ASCE
[7] Xiao, G. et al, (2015) Travel Mode Detection Based on Neural Networks and Particle Swarm Optimization, Information 2015, 6, 522-535
[8] Liu, B et al, (2019) A Deep Reinforcement Learning Approach for Ramp Metering Based on Traffic Video Data, Transportation Research Board Annual Meeting, USA
[9] Dogan, I. (2016)An Overview of Soft Computing, Procedia Computer Sc,Elsevier, Vol 102,34–38
[10] Konar, A. (2000). Artificial Intelligence and Soft Computing: Behavioral and Cognitive Modeling of the Human Brain (1st ed.), CRC Press
[11] Koslowski, B. (2008) Theory and Evidence – The Development of Scientific Reasoning, MIT Press
[12] Zadeh, L. (1986) A Simple View of the Dempster-Shafer Theory of Evidence and its Implication for the Rule of Combination, AI Magazine Volume 7 Number 2
[13] Sentz, K. et al. (2002)Combination of Evidence in Dempster-Shafer Theory, Sandia Nat. Labs, CA
[14] Denœux, T. (1995) A k-nearest neighbor classification rule based on Dempster-Shafer Theory, IEEE Transactions on Systems Man and Cybernetics 219(5):804 – 813
[15] Kumar Das, S. et al. (2013) On Soft Computing Techniques In Various Areas, CSIT, 3(59), 166
[16] Veljanovska, K. (2009) Artificial Intelligence – Lecture Notes, University St. Kliment Ohridski
[17] Veljanovska, K. (2017) Artificial Intelligence in Incident Detection, International Journal of Emerging Research in Management &Technology, 6-4, pp:225-229
[18] Veljanovska, K. (2017) Artificial Intelligence in Adaptive Control Strategy Design, International Journal of Science and Engineering Investigations, 6-63, pp.: 112-115
[19] G. Kaur et al, (2014) A Review Article on Naive Bayes Classifier with Various Smoothing Techniques, International Journal of Computer Science and Mobile Computing, Vol.3 Issue.10, October- 2014, pg. 864-868
[20] S.L. Ting, W.H. Ip, Albert H.C. Tsang, (2011) Is Naïve Bayes a Good Classifier for Document Classification?, International Journal of Software Engineering and Its Applications Vol. 5, No. 3
[21] D. Soria, et al., (2011) A 'non-parametric' version of the naive Bayes classifier, Knowledge-Based Systems, Elsevier, Vol.24, Issue 6, pages 775-784.
[22] S. Deleawe, et al., (2010) Predicting Air Quality in Smart Environments, J Ambient Intell Smart Environ. 2(2): 145–152.
[23] Y. Zhao, et al. (2013) Comparison of Three Classification Algorithms for Predicting pm2.5 in Hong Kong Rural Area, Journal of Asian Scientific Research, 3(7):715-728
[24] Dragomir, E.G. (2010) Air Quality Index Prediction using K-Nearest Neighbor Technique, BULETINUL Universităţii Petrol – Gaze din Ploieşti, Vol. LXII No. 1/2010, pages 103 – 108.
[25] Nilsson, N. (2010) The Quest for AI: A History of Ideas and Achievements, Cambridge Univ Press
[26] Stone, P. et al., (2016) One Hundred Year Study on AI (AI100), Stanford University
[27] Roozemond, D. et al, (1999) Usability of Intelligent Agent Systems in Urban Traffic Control, Delft University of Technology, Delft, The Netherlands
[28] Katwijk, P. et al., (2005) Test Bed for Multiagent Control Systems in Road Traffic Management, Transportation Research Record, No. 1910, Washington, D.C., 2005.
[29] Genders, W. et al. (2016) Using a Deep Reinforcement Learning Agent for Traffic Signal Control, *Cornell University Library*, arXiv: 1611.01142
[30] Carvel, JD et al, (1997) Freeway Management Handbook, Texas Transport, US Depart Transport

[31] W.S. Homburger, et al, (1996) Fundamentals of Traffic Engineering, Univ of California, Berkeley
[32] Sutton, R. and Barto, A.(1998) Reinforcement Learning-An Introduct, MIT Press,Cambridge, MA
[33] Mitchell, T. (2016) Machine learning, McGraw-Hill, New York, USA, 1997 and 2016 (2nd edition).