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Ensemble based traffic light control for city zones using a reduced number of sensors

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ABSTRACT

Rapid advances in computing, sensing and telecommunication technology offer unprecedented opportunities for artificial intelligence concepts to expand their applications in the field of traffic management and control. Our methodology gravitates around a powerful decision-making method: ensemble-based systems. This technique is used to accurately classify the near future traffic conditions and to make efficient decisions for adapting the traffic lights sequences within an urban area to optimize the traffic flows. The proposed approach requires only measurements provided by traffic sensors located along the principal roads entering the zone. This reduced number of sensors are considered to be enough relevant for classifying the near future state of the traffic and moreover, their measurements can be validated through analytical/hardware redundancy. Our methodology is meant to be implemented within the framework of a wireless sensor and actuator network and is confirmed by computer simulation, including normal or abnormal traffic conditions, for the central part of the city of Timisoara-Romania.

1. Introduction

Urban traffic represents a highly complex phenomenon that becomes more and more a major concern for our everyday life. The escalating demand for people and goods mobility in urban areas (with limited road infrastructure) has caused frequent traffic congestion, with various undesirable consequences: delays, energy waste, noise, pollution or road accidents. Over the years a diverse range of solutions had been applied to reduce the level of traffic congestion and to minimize the consequences. Due to the intricate set of interactions between road infrastructure, diverse types of vehicles, weather conditions and multitude of technologies involved, a general approach has yet to be found.

With the continuous advancements in computing, communication and sensing technology, a series of artificial intelligence concepts had been employed in traffic management and optimization: expert systems (Findler and Stapp, 1992), prediction-based optimization (Tavladakis and Voulgaris, 1999; Liu et al., 2002), fuzzy logic (Tan et al., 1995; Lee et al., 1995), neural networks (Srinivasan et al., 2006; Vlahogianni et al., 2005), evolutionary algorithms (Taale et al., 1998), reinforcement learning (Thorpe and Andersson, 1996; Sutton, 1996), etc. Their direct outcome resides in an overall improvement of traffic flows in both normal and abnormal traffic circumstances.

This paper proposes a new perspective upon adaptive traffic light control in urban areas employing not a single expert system but a mixture of experts (ensemble based system), in order to boost the traffic decision accuracy. Our approach is based on the following premises: *(i) only a small number of roads entering a city zone coagulate the majority of traffic* – the

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situation is similar to the one known from internet network traffic where large "elephant flows" have a much higher effect on the traffic than small "mice flows" (Erman et al., 2007); *(ii) sensors are the traffic devices most prone to malfunctioning* – considering a plethora of sensors to measure the traffic parameters on every unimportant road will complicate the decisional architecture with no relevant results in terms of accuracy; *(iii) for an optimal traffic light control we need a precise evaluator of the near future state of the traffic* – the concept we identified to fit this task is an ensemble-based decisional system (mixture of experts).

As a consequence, we propose an integrated methodology for adaptive traffic light control within a city zone based on an ensemble of classifiers that intelligently process the input data measured by a reduced number of sensors placed only on principal roads entering that zone. This approach can be naturally implemented in the framework of Wireless Sensor/Actuator Network (WSAN) that extends the capabilities of the well-known wireless sensor network to cope with complex control situations.

The rest of the paper is organized as follows. Section 2 presents the kernel of our methodology – the ensemble based system. In Section 3 we present the overall methodology for adaptive traffic light control, accompanied by the system architecture described in Section 4. In Section 5 a relevant simulation case study for traffic light optimization in the central part of Timisoara-Romania is presented, while the last section outlines the conclusions and final remarks.

2. Ensemble of classifiers

Having its roots in the human nature to request two, three or even more qualified opinions every time a complex decision has to be made, the artificial intelligence concept of ensemble of classifiers has rapidly expanded in the automated decision-making research field (Polikar, 2006; Curiac and Volosencu, 2012). The strategy pursued by these ensemble-based systems is to create a group of diverse classifiers and to combine their outputs in a form that significantly improves the generalization feature when compared with single classifiers (Chandra and Yao, 2006). Thus, when carefully designed, these committees of classifiers outperform any individual classifier in the majority of complex applications (Llorca et al., 2012; Geisler et al., 2012), including traffic control.

The general structure for an ensemble of classifiers is presented in Fig. 1.

All of the Q classifiers C_q are formulating their own individual hypothesis h_q, which are later aggregated in an overall decision h:

$$h = f(h_1, w_1, \ldots, h_q, w_q, \ldots, h_Q, w_Q), \tag{1}$$

where w_q are the weights corresponding to each individual hypothesis h_q.

One of the important characteristics that are inherently associated with an accurate mixture of classifiers is the diversity between classifiers (Kuncheva and Whitaker, 2003). Even if individual classifiers are accurately covering different parts of the classification space, their combination must work precisely in the entire space. Between different sorts of ensemble forming and training techniques, two approaches are considered to be the most influential (Ahmed and Abdel-Aty, 2013):

- *Bootstrap aggregating (bagging)* is a model averaging technique that uses randomly extracted subsets of a given training set – obtained through a resampling and replacement procedure – to train different models (Breiman, 1996). The classifiers are trained independently and their outputs are combined by simply averaging or voting to generate the overall ensemble output.
- *Boosting* is a technique that builds the ensemble sequentially by adding new weak learners and train them individually using predominantly the subsets of training data that were previously misclassified by other models (Schapire, 1990; Freund and Schapire, 1997). In order to obtain the ensemble's output, the individual classifiers' outputs are weighted according to their accuracy.

The methodology presented in this paper gravitates around the preciseness of classification offered by a carefully constructed ensemble based system (EBS). At every precise moment in time t, EBS receives the measurements $M_i(t)$ from each

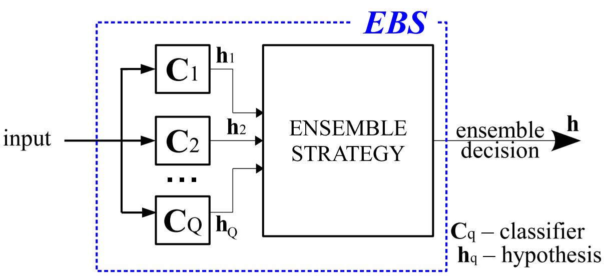

Fig. 1. General structure for an ensemble of classifiers.

of the traffic sensors S_i with $i = 1, \ldots, n$ and precisely selects the most appropriate class $Class_j$, $j = 1, \ldots, p$ which encloses all the time specifications for the traffic lights within the city zone (Fig. 2).

The construction of such an EBS can be done using automatic training procedures implying bagging or boosting methods. During the training process, the ensemble is constructed and configured based on carefully selected input–output sets of the form: $\{M_1(t),\ldots, M_n(t), Class_q\}$ obtained through direct traffic observations and computer simulation. Depending on the type of the classification problem that has to be solved, either bagging or boosting may yield better accuracy (Banfield et al., 2007). In order to identify which method is the most suitable in our case, we conducted an evaluation process started with the selection of decision trees (Karlaftis and Vlahogianni, 2011) as the weak classifiers because of their simplicity, ease of manipulation and general applicability. A decision tree is actually a graphical diagram where every branch is a choice from a set of alternatives and every leaf is a classification decision (Karlaftis and Vlahogianni, 2011). Its input is represented by a series of queries, its output represents the decision (in our case it is the optimal class containing traffic lights phase timings) and the tree depth is defined as the number of branches followed along the path from the root to the farthest leaf.

Analyzing a variety of automated ensemble forming methodologies including AdaBoost, LPBoost, TotalBoost or Bagging, with comparative studies presented in Section 5, we concluded that the most suitable algorithm for solving our problem is TotalBoost (Warmuth et al., 2006). As a consequence, the ensemble used in our adaptive traffic control methodology was developed using this efficient boosting variant (TotalBoost) and classifies the actual traffic conditions for a city zone in classes that correspond to judiciously selected sets of traffic lights phase timings.

TotalBoost is a totally corrective algorithm meaning that in each iteration step it adapts the set of weights (the distribution) to obtain a small edge (i.e. the weighted margin (Grove and Schuurmans, 1998; Warmuth et al., 2007) with respect to all past hypothesis. It uses entropic regularization (Warmuth et al., 2006) by minimizing a variant of the Kullback–Leibler divergence (Kullback and Leibler, 1951) obtained using a quadratic expansion of the divergence.

The relative entropy is defined as follows:

$$D(W, W_0) = \sum_{n=1}^{N} W(n) \cdot \log \frac{W(n)}{W_0(n)}, \tag{2}$$

where W is the current weight distribution (entire set of weights), W_0 is the initial weight distribution considered to be uniform, n is the current input–output pair taken into consideration in ensemble training, N is the total number of input–output pairs, while $W(n)$ and $W_0(n)$ are the weights at the current and first iteration, respectively.

By approximating (2) as a second order Taylor series, in the vicinity of $W_0(n)$, we obtain:

$$D(W, W_0) \approx \sum_{n=1}^{N} (1 + \log \frac{W(n)}{W_0(n)}) \cdot \delta(n) + \frac{1}{2W(n)} \cdot \delta(n)^2, \tag{3}$$

with

$$\delta = W(n) - W_0(n). \tag{4}$$

Each iteration step, the objective function (2) will be minimized with respect to δ using a "vanilla" sequential quadratic programming algorithm (Nocedal and Wright, 2000) and considering the constraint that the edge is lower than a given value.

TotalBoost is efficient in multiclass classifications and exhibits two valuable characteristics: is self-terminating which means that it obtains the best fitting ensemble in a finite time; and it constructs ensembles with very small weights offering the possibility to shrink the resulting ensemble by safely removing some irrelevant classifiers.

The step-by-step methodology is fully described in the next paragraph, implementing details being provided in Section 4.

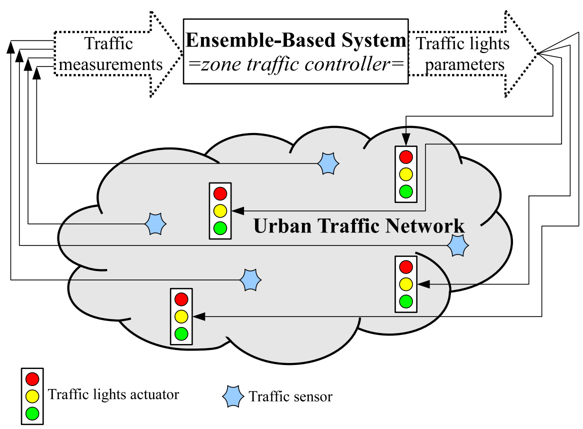

Fig. 2. Ensemble based system as an on-line decision making entity for adaptive traffic lights control.

3. Proposed methodology

Our methodology, designed to optimize the urban traffic in a city zone, relies on the power of ensemble classification to select among different carefully constructed classes (i.e. optimal patterns of traffic flows, described by individualized and interlinked traffic signal schedules for all intersections included in a city zone). It basically implements an adaptive traffic control system characterized by: fixed cycle length common to all traffic signals within the zone; changing traffic signals' timings every time another traffic pattern is identified by the ensemble based system; a control time and a measurement time equal to the fixed cycle length.

Due to different constraints (environment-related – pollution, noise, induced vibrations, maximum size available for road construction, etc.) urban traffic is almost always channelized through a limited road network, recognized as significant for the area in which it is situated. This traffic channelization process was done in an efficient manner by choosing a set of principal roads and a set of principal crossroads.

Definition 1. *principal road (major road)* – a high-capacity street that attracts the traffic from the surrounding area

The other roads in the zone, with less traffic are called *side roads*.

Definition 2. principal crossroad – intersection between a minimum of two principal roads

The rest of the crossroads are labeled as *secondary intersections*.

Consequently, each city zone is formally characterized by a set of principal roads $\mathfrak{R}$ and a set of principal crossroads $\mathfrak{I}$, with their respective cardinality *card* ($\mathfrak{R}$) and *card* ($\mathfrak{I}$).

Based on knowing the principal roads and principal crossroads in the city, our methodology pursues the following steps:

Step 1: Delimiting the urban area for methodology application.Our methodology is applied on city zone level. In delimiting the area where our methodology will take effect, we will consider the following assumptions:

i) The area will have between 5 and 10 principal roads crossing by $(5 \leqslant card(\mathfrak{R}) \leqslant 10)$ and no more than 20 major intersections $(card(\mathfrak{I}) \leqslant 20)$
ii) The area will be compact and its radius will be between 2 and 4 km. This size of the city zone guarantees the basic objectives of our methodology: *high efficiency of traffic management* by assuring the time-period needed for tuning the traffic signal phase timings in accordance with near-future traffic values; and *low implementation/operation costs*.

Apparently these assumptions may seem restrictive, but, in fact, the methodology can be simply expanded to larger urban areas: we need only to split the region into zones configured according to mentioned prescriptions and after that to apply our methodology for each of these zones.

Step 2: Establishing the position of the traffic sensors.

The traffic sensors will be placed on the exit of the last intersection for all the principal roads entering the investigated zone (Fig. 3). This will add some important time for our precise decision making process and for switching the set of traffic signals' timings to optimize the traffic in the entire zone.

The number of sensors used in our methodology is reduced because we will locate sensors only for monitoring the traffic on major roads entering the zone. Certainly these sensors will need some hardware or analytic redundancy (Chow and Willsky, 1984) in case, for different reasons, they are working incorrectly – either we install more than one sensor on each principal road, or we compute an estimated value for that sensor using measurements obtained from other sensors.

Step 3: Obtaining the ensemble training datasets.

Urban traffic is extremely complex and, as an effect, difficult to be forecasted or simulated (Sun et al., 2005; Istin et al., 2011). The ensemble of classifiers used in our methodology must deal efficiently with the strong volatility and almost chaotic nature of urban traffic. For this reason the training and testing processes of the ensemble have to be done using well-constructed datasets that can envelop various aspects of an intricate reality, provided by two independent sources:

- *real traffic sensors* deployed in the proximity of investigated area – The most important source for training or testing datasets is represented by historical data measured by real traffic sensors. Although, the real measurements may reflect the traffic patterns in usual or unusual circumstances, sometimes they may be statistically inefficient; and
- *computer traffic simulation* – In theory, urban traffic can be simulated to obtain pertinent data for training and testing. This endeavor, even though it has been proven to be error prone, can enlarge the authentic datasets with pertinent scenarios that may not be revealed by collected measurements.

By joining information provided by these two independent sources with sets (classes) of optimal traffic-lights phase lengths for every intersection included in the zone, we can form consistent training and testing datasets.

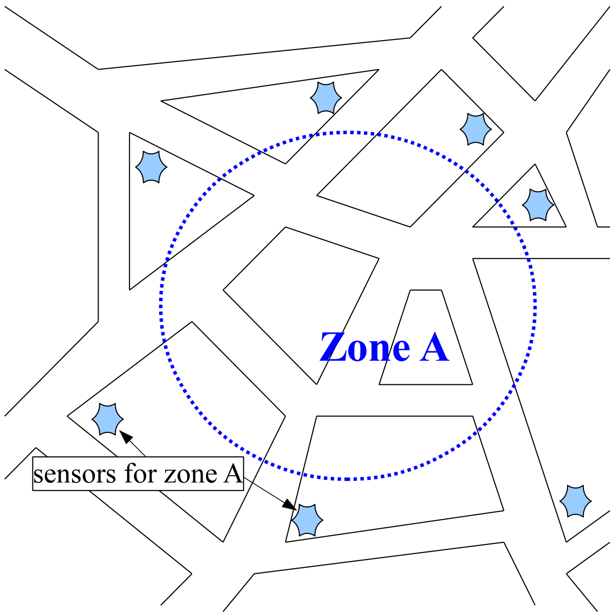

Fig. 3. Example of sensors' locations outside the investigated zone.

Table 1
Structure of the training/testing datasets used in the case study.

Set no.	Input1(2) West [arrivals per cycle]	Input3 West [arrivals per cycle]	Input4 North [arrivals per cycle]	Input5 North [arrivals per cycle]	Input6 East [arrivals per cycle]	Input7 East [arrivals per cycle]	Input8 South [arrivals per cycle]	Optimal class for traffic lights	Training/ testing
1	3	4	5	4	2	6	8	Class 1	Training
2	18	21	5	4	2	6	8	Class 4	Training
3	3	4	26	21	2	6	8	Class 3	Training
4	3	4	5	4	14	28	8	Class 1	Training
5	3	4	5	4	2	6	30	Class 4	Training
6	13	12	16	15	6	19	21	Class 4	Training
7	3	4	5	4	14	28	30	Class 2	Training
...									
60	21	29	7	7	15	33	4	Class 1	Training
61	17	21	5	4	2	2	26	Class 4	Testing
...									
105	21	13	25	4	27	40	1	Class1	Testing

Table 2
Classes containing traffic lights time periods used in the case study.

Class	Intersection/phase	7	7	7	7	7	7	7	7	7	7	7	7	7	7
		Cycle duration = 98 s													
Class1	N3/0	G	G	G	G	G	G	G	G	G	G	R	R	R	R
	N3/1	G	G	G	G	G	G	G	G	R	R	R	R	R	R
	...														
	N25/6	R	R	G	G	G	G	G	G	R	R	R	R	R	R
...															
Class4	N3/0	G	G	G	G	G	R	R	R	R	R	R	G	G	G
	N3/1	G	G	G	G	G	R	R	R	R	R	R	R	R	R
	...														
	N25/6	R	R	R	R	R	R	R	G	G	G	G	G	G	G

R-red signal, G-green signal.

The structure of the training and testing datasets is presented in Table 1, where the classes for traffic signals' timings have the shape described in Table 2.

In order to form the optimal set of classes for traffic lights phase timings *Class1*, ..., *ClassN* we started with the analysis of traffic patterns in usual and unusual conditions (traffic events that block a road or intersection, major cultural or sporting events, etc.). As a result, we will choose the number of classes (N) by allocating a class for each significant pattern. Then, based on particular inputs (traffic measurements on each principal road entering the zone) for each pattern we first assigned traffic signals' timings for principal intersections and then for secondary intersections to favor the traffic on principal roads and applying, wherever possible, the 'green wave' strategy (Madireddy et al., 2011). This optimization process to find best traffic-lights phase timings is, for every class, iterative and involves computer simulations, real traffic analysis and even the intuition of human experts.

Step 4: Forming and training the ensemble of classifiers.

The core element of our methodology is represented by a powerful artificial intelligence concept: *ensemble of classifiers*. Basically, such an ensemble combines the decisions made by its individual constituents to obtain an overall accurate decision when classifying new examples. In our case, this committee of diverse classifiers has the crucial goal to accurately select the set of traffic lights phase timings for the entire zone based on traffic sensor measurements.

To accomplish this mission we adopted the boosting method (Freund and Shapire, 1996) to form and train the ensemble. This effective method learns a series of weak base classifiers (in our case the decision trees) through an iterative process focused on correcting the errors made in previous iteration and is currently considered one of the best inductive methods (Hastie et al., 2001) to obtain accurate ensembles of classifiers.

Between multiple boosting methods developed for multi-class classification, we selected the TotalBoost (Warmuth et al., 2006) variant for its simplicity, provable convergence and accuracy and used *ClassificationEnsemble class (Matlab R2012b)* for its computer implementation.

Using the training dataset developed in the previous step of our methodology, we are now able to provide an ensemble of decision-tree classifiers. This ensemble is afterward tested against a totally independent dataset. If this validation process is successful (the classification error is zero) the ensemble is able to be used in adaptive on-line traffic control. If not, we can either modify the number/configuration of the classes (basically we can add new classes) or reconfigure the training dataset and retrain the ensemble within the new circumstances.

Step 5: On-line ensemble-based traffic light control.

Once the ensemble is trained and tested it can be included in an on-line adaptive traffic control strategy that enables adapting the traffic light signals to traffic demands based on three stages:

- *Read the traffic sensors* every t seconds (t – traffic light cycle duration, common for all intersections within the zone), the sensors are providing the number of vehicles that passed on that road in the last time-interval of t seconds;
- *Request the set of traffic lights phase timings from ensemble* based on traffic measurement data, the ensemble will pick the optimal set of traffic signals' timings;
- *Adjust the traffic lights phase timings* after the current cycle duration ends, the traffic lights in each intersection of the zone will be reprogrammed to satisfy the actual traffic demands.

4. System architecture

The traffic control scheme proposed in this paper was thought for an efficient implementation within the frame of Wireless Sensor/Actuator Network (WSAN) architecture Akyildiz and Kasimoglu, 2004; Rezgui and Eltoweissy, 2007; Xia et al., 2007 where traffic sensors and traffic light actuators are all interconnected with a central controller over wireless links (Fig. 4):

The chosen topology for WSAN is cluster-tree. Each cluster of sensor nodes is deployed for measuring the traffic on a specified principal road (Fig. 3). It locally aggregates the measurements (on the cluster-head level) to increase the accuracy. The aggregated traffic values are then sent in a single-hop or multi-hop fashion to the base station where the ensemble based decisional system, acting as a zonal traffic controller, selects the correct parameters for every traffic light and transmits them to the actuators placed in each intersection.

For each principal road entering the zone we allocated a static cluster consisting of three traffic sensor nodes (the redundancy coefficient $r = 2$), one of them acting as a cluster-head and having the measurement aggregation responsibility. The aggregation considered in this paper is a simple and efficient one: it averages the measurements proposed by each sensor within the cluster, excluding the measurement with the greatest absolute deviation. This procedure is proficiently coping with a possible case where one sensor is providing erroneous measurements. Based on the sensor redundancy (the number of cars per cycle length in every location is measured by three different sensors), we can compute a reliable traffic value using the formula:

$$M_{aggregated} = \frac{1}{r} \sum_{i=1, i \neq j}^{r+1} M(i) = \frac{1}{2} \sum_{i=1, i \neq j}^{3} M(i). \tag{6}$$

with

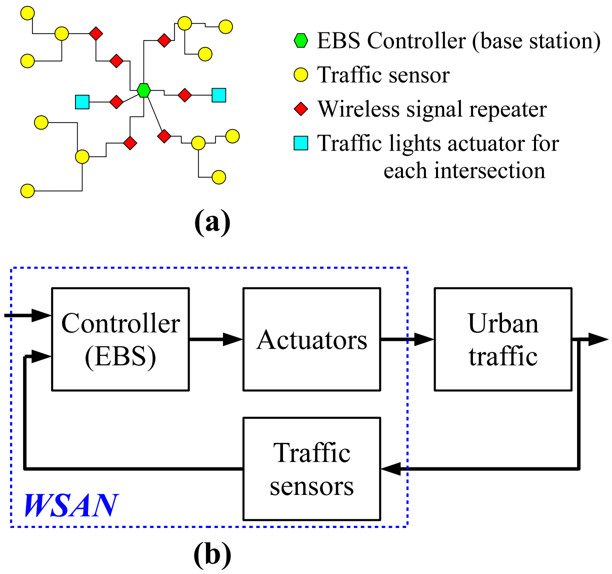

Fig. 4. WSAN architecture with explicit ensemble-based controller. (a) Network general topology, (b) Abstraction of traffic control application.

$$j = \arg\max_i (|\overline{M} - M(i)|). \tag{7}$$

$M(i)$ being the measured value of sensor i, while $\bar{M}$ being the average value of the sensors measuring the traffic in the same location.

As can be seen from Eqs. (6) and (7), this aggregation technique requires a set of simple operations and can be easily implemented on the cluster-head sensor nodes.

Our implementation proposal within the WSAN framework includes the following set of wireless equipments: traffic sensors grouped in clusters, actuators for each intersection equipped with traffic lights, wireless signal repeaters and one base station (a laptop class device) running the EBS software. While the number of sensors (NS) and the number of traffic-lights actuators (NA) are given by (8) and (9) formulas, in the case of wireless signal repeaters we can compute a maximum number of repeaters (MNR) using (10). The number of repeaters in real implementations may be less than MNR if some repeaters are used for two or more adjacent braches of the cluster-tree architecture:

$$NS = (r+1) \cdot card(\Re), \tag{8}$$

$$NA = no.\ of\ crossroads\ equipped\ with\ traffic\ lights, \tag{9}$$

$$MNR = \sum_{i=1}^{card(\Re)} \frac{dist(cluster\_head_i, base\_station)}{wireless\_range} + \sum_{j=1}^{NS} \frac{dist(actuator_j, base\_station)}{wireless\_range}, \tag{10}$$

where r represents the redundancy coefficient (number of backup sensors for each traffic sensor), $dist(A,B)$ is the Euclidian distance between the locations A and B, $wireless\_range$ is the range in which the repeaters are reliably working.

As can be seen from (8), the number of sensor nodes included in our methodology is a reduced one, even if applying hardware redundancy, due to their placement only on principal roads entering the zone.

5. Case study – simulations and experiments

In order to validate the presented approach we developed a complex case study addressing the crowded traffic in the city center of Timisoara, Romania. This urban area is characterized by various traffic magnitudes induced by daily events like home-to-workplace or home-to-school travels or by exceptional conditions including major cultural and sport events or even traffic collisions. The road network of the investigated area, presented in Fig. 5, comprises seven principal and eight side roads, six major and five secondary intersections which are spread on an area of around 12 square kilometers.

Our method is intended to be implemented within the framework of a wireless sensor and actuator network. In this case, the WSAN deployment must include seven clusters of sensors nodes to capture the traffic flow on all principal roads entering the zone, six actuators for all crossroads equipped with traffic lights, four signal repeaters (we considered a reliable wireless range of up to 750 m in open area) to assure reliable communication flows and a base station which runs the ensemble-based decision software, as depicted by Fig. 5.

Fig. 5. Investigated area in the center of Timisoara with WSAN deployment.

We used a fixed cycle length of 98 s (divided in 14 blocks of 7 s as in Table 2), maintained the same for all intersections. For obtaining the cycle length value, the following three steps have been performed: (i) compute the minimum cycle length for each intersection (the overall cycle length must be greater than these values); (ii) compute the optimal cycle length for the most critical intersection (approximately 92 s for intersection N25) using the classic Webster's method (Webster et al., 1958); (iii) obtain the final value of the cycle length, which is a little bit larger than the optimal cycle length for N25, using a recursive tuning/validation procedure based on computer simulations.

Fifteen major scenarios were considered for traffic light control optimization. They correspond to the most relevant traffic patterns observed in the studied area in both normal and abnormal conditions. The traffic magnitude measured in the seven input points varies from an average of 2 to 6 cars per minute on calm periods (e.g. on Sunday) to heavy traffic corresponding to 26 to 40 cars per minute during peak hours. Each of the already mentioned scenarios is exemplified by seven independent sets of traffic volumes (sub-scenarios) measured in real traffic conditions in the seven input points. The collection of the traffic measurements grouped in sub-scenarios form the training and testing datasets, as presented in Table 1.

For each intersection equipped with traffic lights, we allocated between 2 and 7 phases per cycle (total cycle duration of 98 s) depending on the number of input and output lines. Fig. 6 depicts the traffic signal phase allocation for the six major intersections (*N3*, *N17*, *N13*, *N22*, *N23* and *N25*).

One of the main aims of the optimization process was to obtain a "green wave" for major roads, on the sections between major crossroads, in all considered scenarios. By applying the traffic-responsive urban control strategy proposed in Diakaki et al. (2002) for all major scenarios in a combination with the k-mean clustering method for class reduction we obtained a condensed set of only four classes as presented in Table 2. Each of these classes contains an overall phasing plan for all intersections within the investigated zone. The construction of each phasing plan started with an initial version that was based on green time allocation for every crossroad, traffic flow parameters, zone's geometry and cycle length value, and was later fine-tuned through extensive computer simulations.

As an optimization parameter, we use the total queue length (TQL) Almejalli et al., 2009 at a given moment t over the considered area:

$$TQL(t) = \sum_{\gamma=1}^{\Gamma}\sum_{\psi=1}^{\Psi} QL_{\gamma,\psi}(t), \tag{11}$$

where $QL_{\gamma,\psi}(t)$ represents the number of vehicles at a time t on the lane γ entering intersection ψ, having speed less than 5 km/h and therefore considered as waiting in a queue. This parameter is expressed in number of vehicles waiting in all Γ area's intersections at a certain moment in time and has a major impact on other important parameters like total waiting time, total travel time and fuel consumption for all traffic participants.

5.1. Road traffic simulation for investigated area

The urban traffic for the investigated area was simulated using the Simulation of Urban Mobility (SUMO) software package. This well-known traffic simulator is heavily involved both in research and industrial projects (Behrisch et al., 2011) and uses the SUMO-Krauβ microscopic space-continuous car-following model developed inside the safe speed paradigm (Krauß, 1998; Krauß et al., 1997). To model the traffic demand we used a static flow parameter to obtain controllable and reproducible testing scenarios. The flow rate parameter (Rakha and Gao, 2010) specifies the average input measured in cars per hour

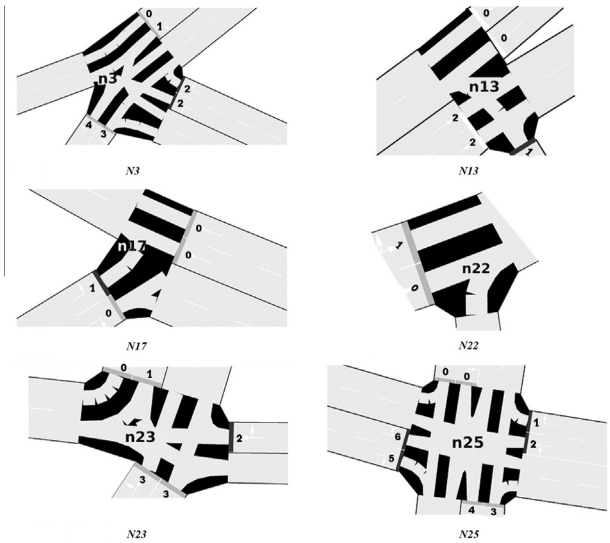

Fig. 6. Crossroads' configurations in investigated area.

entering each intersection. This parameter was computed as a mean value of several measurements on the seven input points during relaxed or peek intervals.

During model calibration and validation we used the SW zone of the investigated area, delimitated by N25 and In7, with the assumption that driving behavior is homogeneous inside the entire scenario's area. For calibration we used root mean square error analyses between the simulation output and observation. Calibration data were collected at N25 and In7 during two 20 min. intervals, one with heavy traffic on Monday 9:00 AM and one with light traffic on Sunday 3:00 PM. The goal was to find the best SUMO parameter combination in order to minimize the mean square error for speed data. The model's parameters were acceleration, deceleration, σ and τ. The first two parameters refer to maximum acceleration and deceleration of simulated vehicles. Corresponding to typical compact cars, predominant in investigated traffic, they were approximate to 2.5 m/s^2 and 3 m/s^2, respectively. The σ represents the driver imperfection related with human behavior expressed as a real number in the interval 0.0–1.0. The τ parameter models the driver reaction time in seconds. For calibration we consider the σ values in the range 0.1–0.9 with a 0.1 step and the τ values in the range 1.0–3.0 with a 0.3 step. After calibration we found the best values as $\sigma = 0.4$ and $\tau = 1.8$ s. For model validation we collected data during six 20-min intervals covering various traffic conditions. The resulting root-mean-square error (RMSE) for traffic leaving the area was 12.35 km/h, which is acceptable considering the measured traffic speed in the considered lane is in the range of 40–56 km/h.

The roadmap area representation was imported in SUMO from OpenStreetMap (Zilske et al., 2011). The maximum speed for all lanes was set to 50 km/h, representing the legal speed for the considered segments.

We simulated 15 traffic scenarios, each of them comprising of seven sub-scenarios which implement diverse traffic conditions on each major road, from low to medium or even to extreme traffic conditions. They include 60 sub-scenarios used for ensemble training and also 45 testing sub-scenarios. Moreover, we prepared five SUMO network settings corresponding to the four traffic light control classes (*Class1, Class2, Class3* and *Class4*) plus one setting having all traffic lights switched off. Afterward, we use these four traffic light control settings and the special setting with no traffic control to simulate all the 105 sub-scenarios. Simulations have been run for 30 min with 10 min allocated for traffic stabilization. We run the ensemble in parallel with simulation for each scenario and compare the resulting class with the simulation output. To simplify the simulation, we considered the number of vehicles that stop inside the case study area as equal to the number of vehicles leaving parking space on the same area. To compute TQL from SUMO simulation output file we developed some extra Java modules. They extract all cars that have a velocity less than 5 km/s in a certain moment of time and therefore are considered as waiting in queues.

5.2. Identifying the most suitable algorithm for ensemble construction and training

In order to identify the most suitable algorithm for constructing and training the ensemble of classifiers, we analyzed four different algorithms (AdaBoost Freund and Schapire, 1997, TotalBoost (Warmuth et al., 2006), LPBoost (Warmuth et al., 2006) and Bagging (Breiman, 1996). For this, we developed a Matlab program based on *ClassificationEnsemble class (Matlab R2012b)* to study the efficiency of each mentioned algorithms in terms of resulted classification error and resources needed to run the trained ensemble. Using the training and testing datasets presented in Table 1 we started the automated training

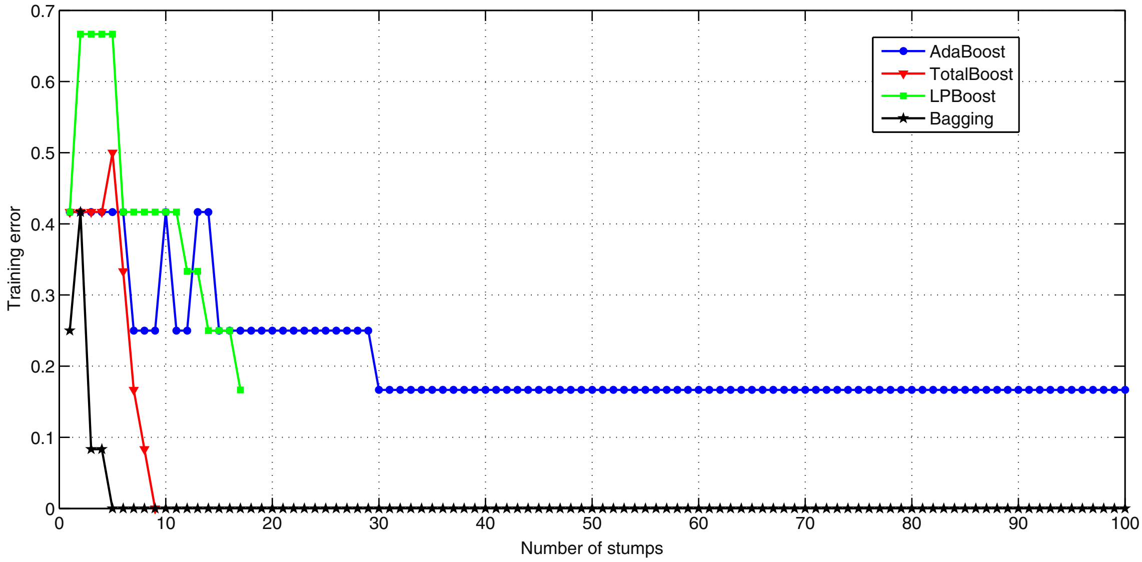

Fig. 7. Ensemble error during training.

Table 3
Comparison between the four algorithms.

Criterion	AdaBoost	TotalBoost	LPBoost	Bagging
Percentage of classification error for the testing dataset [%]	2	0	2	4
Number of trees for resulted ensemble	100	9	17	100
Maximum tree depth	1	1	1	5
Memory needed for resulted ensemble [KB]	275.13	42.60	63.76	393.26

Table 4
Testing sub-scenarios involving high traffic.

Testing sub-scenario	Mean traffic inputs	Ensemble output	Mean TQL [no. of cars]			
			Class1	Class2	Class3	Class4
WMSH	{15,15,4,4,2,2,26}	Class4	79	154	182	52
WHNHEM	{25,42,28,28,10,14,6}	Class4	104	186	208	82
WMNHSM	{9,10,32,47,3,3,10}	Class3	98	121	88	92
NHEHSM	{3,4,36,34,14,28,18}	Class2	189	103	168	136
EHSH	{5,4,2,5,16,28,60}	Class2	112	102	177	188
NHEM	{2,2,42,26,15,15,2}	Class3	102	143	46	154
WMEH	{15,15,5,4,27,40,1}	Class1	89	114	109	131
EMSH	{3,8,4,5,20,16,52}	Class2	112	73	177	81
NHSH	{6,8,44,25,2,2,61}	Class3	119	184	92	94
WHNH	{25,50,32,47,10,6,4}	Class4	132	121	133	112
WMNMEH	{21,13,25,4,27,40,1}	Class1	101	184	195	128

process of each algorithm with 100 decision stumps. The error decrease in the training process is illustrated in Fig. 7, while some relevant comparative data are presented in Table 3.

The conclusion is that TotalBoost outperforms the rest of the investigated algorithms needing only 9 stumps to accurately classify all entries of the training set, while LPBoost needs 17. The rest of the investigated algorithms need to train all 100 stumps to get a minimum classification error. Moreover, in the testing process, the ensemble constructed by TotalBoost was the only one that obtained a zero error for all 45 sets of the testing dataset. By selecting TotalBoost we not only significantly decrease the memory demand (42.6 KB for Totalboost and a minimum of 63.76 KB for the other algorithms), but also sped up the decision-making process due to the smallest number of classifiers included in the resulted ensemble.

5.3. Methodology evaluation

As expected, the ensemble traffic state classification was 100% accurate for all 60 scenarios used in ensemble training. It also holds its accuracy for the 45 low, medium and extreme traffic conditions used for testing.

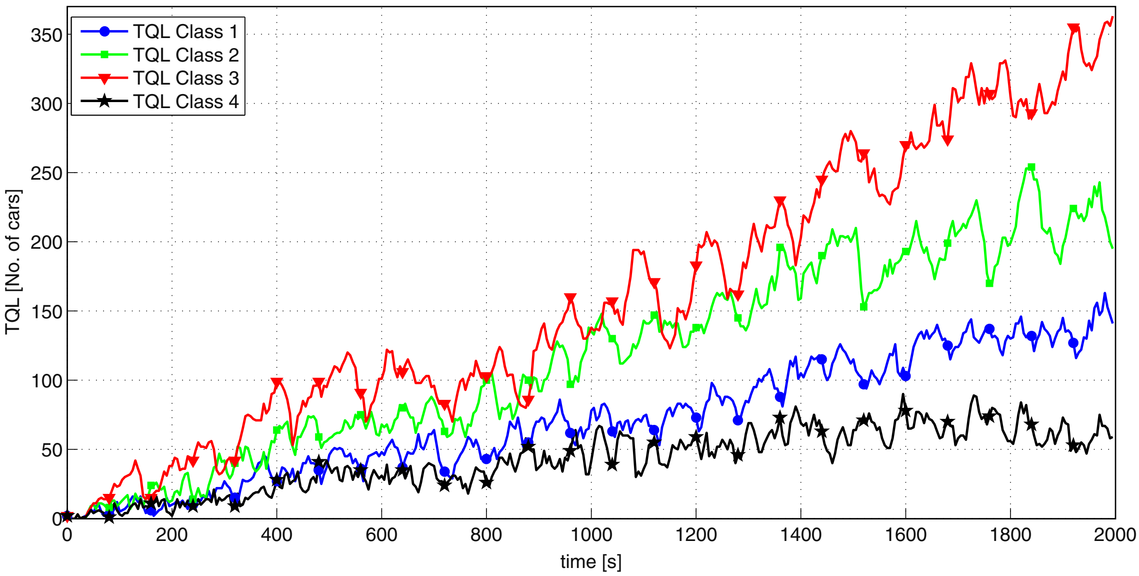

Fig. 8. Total queue length for WMSH sub-scenario.

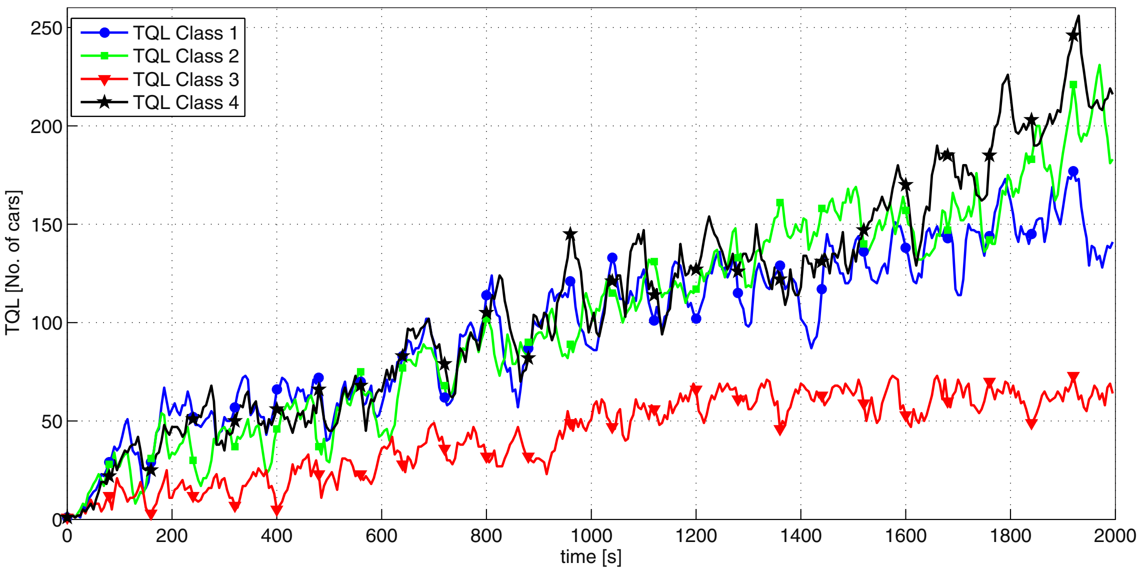

Fig. 9. Total queue length for NHEM sub-scenario.

To exemplify the accuracy of our presented method, between the scenarios that included extreme traffic conditions (Table 4), we will present two comparative analyses corresponding to WMSH and NHEM sub-scenarios used during the testing process.

Fig. 8 presents the TQL parameter evolution corresponding to all four traffic lights control classes for the WMSH sub-scenario involving high traffic from South, medium traffic from West and low traffic from North and East. The output of the ensemble in this case was *Class4*, which corresponds to the lowest development of TQL in the graphic.

In the case of NHEM sub-scenario implying high traffic from North and medium from East, the ensemble output points to *Class3*. This option was proved to minimize the total queues length over considered area as shown in Fig. 9.

As can be seen from Fig. 8 and Fig. 9, only the optimal class of traffic lights parameters (the one chosen by EBS – *Class4* for Fig. 8 and *Class3* for Fig. 9) assures a bounded TQL, the rest conducting to increasing queues and even to intersection blocking.

In order to underline the impact of our method, we compared the number of sensors and their total operational cost during lifetime (includes the sensors' purchase price and the costs for maintenance during entire sensors' lifetime) for different

Table 5
Total costs for sensors during expected sensors' lifetime.

Method	Number of inductive loop sensors	Sensor purchase cost (Klein et al., 2006a) ($)	Annualized maintenance cost/sensor (Klein et al., 2006b) ($)	Expected sensor's life (Klein et al., 2006b) (years)	Total cost expected for sensors' lifetime (per zone) ($)
Actuated control of isolated intersections	43	500	62	10	48,160
ATLC MI (Zhou et al., 2011)	86	500	62	10	96,320
Our method	12	500	62	10	13,440

methods tackling the traffic control in the investigated zone. As depicted by Fig. 5, the area covers seven major input points with a total of twelve lanes, six major intersections (presented in Fig. 6) comprising 27 lanes and ten minor intersections with an amount of 16 lanes. In case of choosing an approach based on actuated control of isolated intersections (Liu et al., 2002), 43 inductive-loops are needed to cover all lanes entering major or minor crossroads using an inductive-loop per lane. We also investigated a more complex adaptive traffic signal control approach for multiple intersections, described in Zhou et al. (2010, 2011), where two inductive-loops are used for each lane entering the crossroads. The results are summarized in Table 5 and demonstrate the efficiency of our method in terms of total costs over expected sensors' lifetime.

6. Conclusions

This paper introduces an integrated methodology for adaptive traffic signal control within a city zone. Its efficiency is based on three pillars: proficient traffic control decisions using an ensemble based system; efficient traffic measuring, using sensors located only on principal roads entering the zone; and a cost-effective implementation using wireless sensor and actuator network architecture. Validation through extensive computer simulations for a group of 16 intersections in the central zone of Timisoara-Romania gave plausible results proving significant performances for a set of 105 different traffic scenarios. The methodology, being implemented in a generic manner, can be customized according to the needs of any given urban area with a radius under 4 km.

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