Advanced Street Lighting Control through Neural Network Ensembling

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***Abstract*—In this work, we propose an innovative street lighting energy management system in order to reduce energy consumption. The main goal is to provide 'energy on demand' such that energy, in this case light, is provided only when needed. In order to achieve this purpose it is critical to have a reliable demand model, which in the case of street lighting turns out to be a traffic flow rate forecasting model. Several methods has been compared in order to find out one hour prediction model. In our case studies, Artificial Neural Networks performed best results. Moreover, several control strategies have been tested and the one which gave the best energy savings is the adaptive one we carried out. Experimentation has been carried out on two different case studies. In particular we focused our experimentation on public street of a small and a medium sized cities. Our studies show that with the proposed approach it is possible to save up to 50% of energy compared to no regulation systems**

Keywords-Lighting Efficiency; Energy Management Systems; Adaptive Control; Neural-Network models

I. INTRODUCTION

Since the first international recommendations for the lighting of roads [1], power consumption and environmental aspects have become more and more important and at the same time, the improved performance of luminaires and lamps, and especially the introduction of electronic control gears, has made it possible to introduce adaptive lighting for motorized roads and pedestrians areas.

A structured model has been developed for the selection of the appropriate lighting classes [2] (M, C, or P), based on the luminance concept, taking into account the different parameters relevant for the given visual tasks. Applying for example time dependent variables like traffic volume or weather conditions, the model offers the possibility to use adaptive lighting systems with remarkable energy consumption savings and therefore high financial benefits for those municipalities [3] where street lighting is a high percentage of the electrical bill.

Today, lighting control approaches ranges from simple on/off to regulation systems.

On/off systems include timers, twilight and astronomical clocks. The first one is a static system which turns on and off street lights always according to fixed times. The second one has light-sensitive photocells to turn them on at dusk and off at dawn [5]. The third ones are GPS based street light controllers which operate the on/off of the street light according to the location features (longitude, latitude, sunrise, sunset times).

Regulations systems are based on dimmable LED or high pressure sodium vapor lights [4] and allow to schedule lights on or off and set dimming levels of individual or groups of lights.

All these systems have one common feature: they do not care about the real on-line demand and this is a source of high inefficiency.

Thus, in order to overcome the main lack of the current regulation systems, it has recently started the new Intelligent Street Lighting (ISL) approach which looks very promising [5]-[6]. Therefore, here we propose an ISL approach (Smart Adaptive Control) based on the concept of 'energy on demand', whose goal is to dynamically set the light intensity as function of the foreseen demand, namely the traffic flow rate 1 hour forecast.

Thus, in such context the demand model has a critical role and its accuracy strongly affects the performance of the regulation system.

In the last decade, one of the most widely used method in order to solve modeling problems is that of Artificial Neural Networks (ANN) [7]-[8]. In particular, traffic flow forecasting issue has been tackled through ANN since the nineties [9]-[19]. As example, among the most recent work [19] focuses on traffic flow forecasting approach based on Particle Swarm Optimization (PSO) with Wavelet Network Model (WNM). Pamula [16] reviews neural networks applications in urban traffic management systems and presents a method of traffic flow prediction based on neural networks. Bucur et al. [17] proposes the use of a self-adaptive fuzzy neural network for traffic prediction suggesting an architecture which tracks probability distribution drifts due to weather conditions, season, or other factors.

All the mentioned applications have one feature in common: they use one single global model in order to perform the prediction. Our approach is to use not only one model but an ensemble of models. In Section II an overview of modeling

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methods used is given, in particular statistical and Artificial Neural Network based models and their combination trough ensembling. In Section III we show results obtained on two case studies and then in Section IV we discuss future works.

II. MODELING METHODS

In this section, we shortly describe the modeling and control techniques we compared in the experimentation.

A. Statistical Modeling

One the simplest and most widely used model is to build an average weekly distribution of the traffic flow rate sampled hourly. Thus, from the data we compute for each day the average traffic flow rate hour by hour in such a way that we get an average distribution made of 24X7=168 points.

B. Artificial Neural Networks

Artificial Neural Networks (ANN) are computational models which try to simulate some properties of biological neural networks in order to solve complex modeling problems of non-linear systems. An ANN is an interconnected group of artificial neurons (called also nodes) that uses a mathematical or computational model for information processing based on a connectionistic approach to computation. In more practical terms ANN are non-linear data modeling or decision making tools which can be used to model complex relationships between inputs and outputs or to find patterns in data. ANN are referred also as black-box or data-driven models and they are mainly used when analytical or transparent models cannot be applied. Building such models needs several stages as input analysis and training through algorithms which minimize the error between the real values to be modeled and the ANN output. ANN demonstrated their effectiveness in modeling many real-world applications.

Once we model an ANN model, we must take into account three basic components. First, the synapses of the biological neuron are modeled as weights. Let us remember that the synapse of the biological neuron is the one which interconnects the neural network and gives the strength of the connection. For an artificial neuron, the weight is a number, and represents the synapse. A negative weight reflects an inhibitory connection, while positive values designate excitatory connections. The following components of the model represent the actual activity of the neuron cell. All inputs are summed altogether and modified by the weights. This activity is referred as a linear combination. Finally, an activation function controls the amplitude of the output. Mathematically, this process is described in Figure 1. From this model the activity of the neuron can be shown to be:

$$y=f_a(\Sigma w_i x_i - \theta) \quad (1)$$

where θ is a threshold called BIAS (Basic Input Activation System) which identifies the sensitivity of the neuron to respond to the external inputs. The most common function used to model f_a are the hyperbolic tangent, the sigmoid and the linear function.

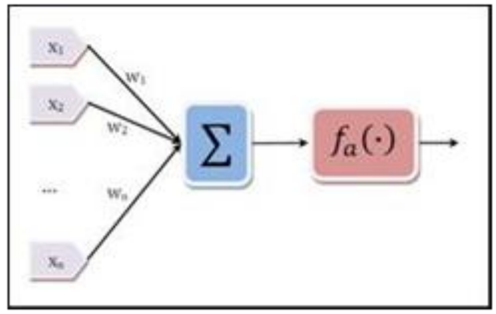

Figure 1. Artificial Neuron Model

Therefore each unit performs a relatively simple job: receive input from neighbors or external sources and use this to compute an output signal which is propagated to other units. Apart from this processing, a second task is the adjustment of the weights. The system is inherently parallel in the sense that many units can carry out their computations at the same time. Within neural systems it is useful to distinguish three types of units: input units which receive data from outside the neural network, output units which send data out of the neural network, and hidden units whose input and output signals remain within the network.

The way units are connected defines the network topology or architecture. In the past years, many of them have been studied and the most widely used and is the feed-forward one. In this network structure, neurons are grouped into layers. There are at least two layers, the input and the output, which gather the corresponding input and output variables. This basic structure is also known as perceptron [20].

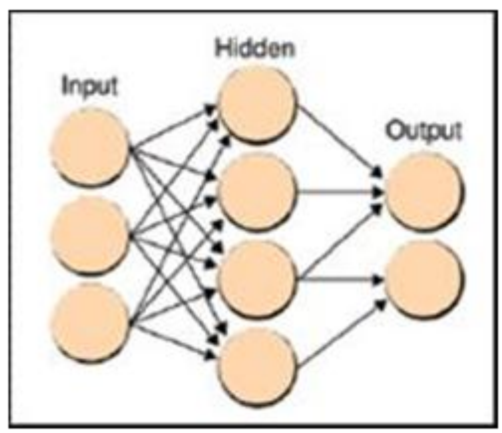

Figure 2. Feed-forward neural network topology

Moreover, in order to let the model cope with non-linear problems, it is possible to add one or more intermediate layers, known as hidden layers. These models are also known as multi-layer perceptrons (MLP) [21].

The flow of data from input to output units is strictly in one direction (forward). The data processing can extend over multiple (layers of) units, but no feedback connections are present, that is, connections extending from outputs of units to inputs of units in the same layer or previous layers.

C. *Ensembling*

The term 'ensemble' describes a group of learning machines that work together on the same task, in the case of ANN they are trained on some data, run together and their outputs are combined as a single one. The goal is obtain better predictive performance than could be obtained from any of the constituent models.

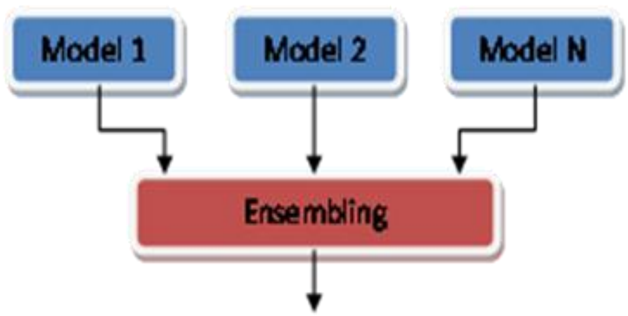

Figure 3. Ensembling

In the last years several ensembling methods have been carried out [22],[23],[24]. The first one, also known as Basic Ensemble Method (BEM), is the simplest way to combine M neural networks as an arithmetic mean of their outputs yi. This method can improve the global performance [25],[26] although it does not takes into account that some models can be more accurate than others. This method has the advantage to be very easy to apply.
A direct BEM extension is the Generalised Ensemble Method (GEM) [25],[26] in which the outputs of the single models are combined in a weighted average where the weights have to be properly set, sometimes after an expensive tuning process.
Other methods are Bootstrap AGGregatING (BAGGING) [27] and Adaboost [28],[29].

III. EXPERIMENTATIONS

In this section, we test and compare the methods presented in the previous sections. We used two test cases: one has concerned Terni and the second regards S.Giovanni in Persiceto.
In the first one, we focused on three different urban streets of Terni (Table I). The data set is made of 3 months (13 weeks) of measurement corresponding to 2184 hourly samples. The data set has been partitioned into training/testing and validation made respectively of 10 and 3 weeks each.

TABLE I. STREET FEATURES

	Maximum traffic flow rate
Street 1	600
Street 2	800
Street 3	950

A. *Modeling*

The basic idea is to set the power level of the following hour as function of the ANN ensemble forecast.

$$P_{t+1} = f(\phi_{t+1}) \qquad (2)$$

where P_{t+1} is the power level normalized in [0,1] to be set for the next hour, ϕ_{t+1} is the traffic flow rate neural forecast which is

$$\phi_{t+1} = anne(\phi_t, \phi_{t-1}, \dots, \phi_{t-n}) \qquad (3)$$

where *anne* is the ANN ensemble result, ϕ_{t-i} is the measured traffic flow rate at time *t-i.*
For Street lighting applications function *f* in (2) can be shaped in different ways, among these we applied a linear profile although international standards [2] suggest a non-linear one that we will apply in future work.

$$\begin{aligned} &\text{If } \phi_k < 0.25 \text{ then } f = 0.5 \\ &\text{If } \phi_k > 0.5 \text{ then } f = 1 \\ &\text{Else } f = 2\phi_k \end{aligned} \qquad (4)$$

where ϕ_k is the predicted traffic flow rate at time *k* (3) normalized in [0,1].
The ANN are feed-forward MLP with 10 hidden neurons and one output (the one hour flow forecast) with sigmoid as activation function for all the neurons. The number of inputs is the same of the dynamics window length (3) and it has been chosen with a preliminary analysis by calculating the validation prediction error, after the ensembling stage, for different number of hourly samples (Table II). Since we obtained the minimum prediction error with a time window of eight hours, we chose the same number of inputs for the ANN, representing the length of time history window. So each input contains the traffic flow of one of eight hours of the time window.
Training has been performed through the Back-Propagation algorithm with adaptive learning rate and momentum stopping after 108 iterations and a 'save best' strategy to avoid overfitting. The reported results are averaged over 10 different runs (with standard deviation in brackets) and the ensemble is therefore made by the same 10 models.
The reported errors are measured as:

$$e = |x-y|/(M-m) \qquad (5)$$

Where x is the real value to be predicted, y is the output model, M is the real maximum value and m is the minimum.

TABLE II. WINDOW HISTORY LENGTH (HOURS) SELECTION

Number of Samples	Street 1	Street 2	Street 3
3	5.72%	6.88%	5.81%
5	3.9%	5.07%	3.99%
8	**3.29%**	**3.43%**	**3.02%**
10	3.54%	4.12%	3.74%

At last, Table III shows the comparison of the models considered in this work in terms of prediction accuracy over the validation set. Figure 4 shows a graphical comparison. We compared real hourly traffic flow rate with prediction provided from statistical and neural network ensemble models. Ensemble models outperforms statistical in all cases.

TABLE III. MODEL COMPARISON

	Statistic	ANN	ANN Ensembling
Street 1	5.90%	3.74% (±0.10%)	3.29%
Street 2	5.56%	3.48% (±0.09%)	3.02%
Street 3	7.14%	4.00% (±0.10%)	3.43%
Average	6.20%	3.74% (±0.10%)	**3.25%**

From this analysis it is clear that in general the ensembling approach outperforms the statistical approach providing a remarkable improvement in prediction accuracy. Such level of precision is very important when dealing with applications like traffic and lighting control where the higher the model accuracy is the more effective the control system is.

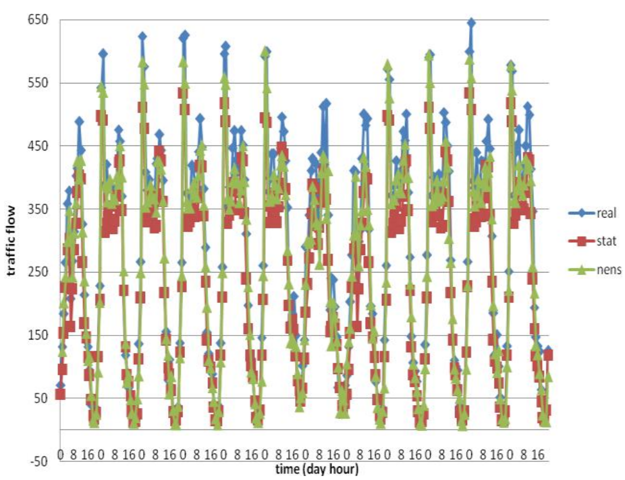

Figure 4. Models comparison

From this graph it is clear that the ANN ensemble model performs much better than the statistical model because, when out of normal conditions the ANN ensembling takes into account the real traffic dynamics (3).

B. Control

In this section, we compare the results of the Static Control (StaC) and the Smart Adaptive Control (SmAC) introduced in Section III.

In the experimentation we calculated the energy saving of the two methods with respect to the no-regulation strategy, namely when lights are always on at 100% of their power for the whole night.

The light on demand control assumes dimmable lights (SAP or LED), on the streets we carried out this study there were no such lamps and data about the real consumptions were not available, therefore the experimentation has been carried out off-line by calculating the potential energy consumptions in the following way. It has been assumed the maximum hourly nominal power consumption to be one, then the following quantities have been calculated :

$$C_{100} = \sum x_1^i \, , \; x_1 \in \{0 \, , 1\} \tag{6}$$

Where x_1^i is the hourly power level for the i^{th} sample according to the no control strategy (night power level always at 100%) and therefore C_{100} is its overall consumption.

$$C_{StaC} = \sum x_2^i \, , \; x_2 \in \{0 \, , 0.5 \, , 1\} \tag{7}$$

Where x_2^i is the hourly power level for the i^{th} sample according to the static control (StaC) strategy (Fig. 4) and therefore C_{StaC} is its overall consumption.

$$C_{SmAC} = \sum x_3^i \, , \; x_3 \in [0 \, , 1] \tag{8}$$

Where x_3^i is the hourly power level for the i^{th} sample (4) according to the smart adaptive control (SmAC) strategy (Fig. 5) and therefore C_{SmAC} is its overall consumption.

These quantities have been calculated over three months of actual traffic flow rates obtained by on street coil sensors. Thus, we computed the consumption saving of the StaC and SmAC strategies with respect to the no control approach in the following way :

$$S_{StaC} = 1 - C_{StaC} / C_{100} \tag{9}$$
$$S_{SmAC} = 1 - C_{SmAC} / C_{100} \tag{10}$$

In Table IV, we report these values for the three considered streets.

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TABLE IV. CONTROL STRATEGY COMPARISON: ENERGY SAVING

	StaC	SmAC
Street 1	25%	44.5%
Street 2	25%	47%
Street 3	25%	37.5%
Average	**25%**	**43%**

Results show that it is possible to save on average 43% of energy, meaning that lamps will work at 57% of their nominal power having as inferior limit 50% (4) and Fig. 5 in order to avoid periods during normal operation with almost no light due to light output drop.

From these results it is clear that the SmAC approach provides a remarkable improvement in terms of energy saving (43% on average) in particular on streets with medium-low traffic flow rate.

Moreover, in Figure 5 it is shown an example of how the two strategies work, where on the Y axis we report the normalized traffic flow rate values and the normalized hourly power consumptions of the different strategies. From Figure 5 it is possible to see that the SmAC strategy is capable to follow the real demand (traffic flow rate) achieving the 'energy on demand' concept. In particular, it is interesting to point out that SmAC improves not only energy efficiency (orange dotted area) but also safety (yellow dashed area) because it provides light when actually needed.

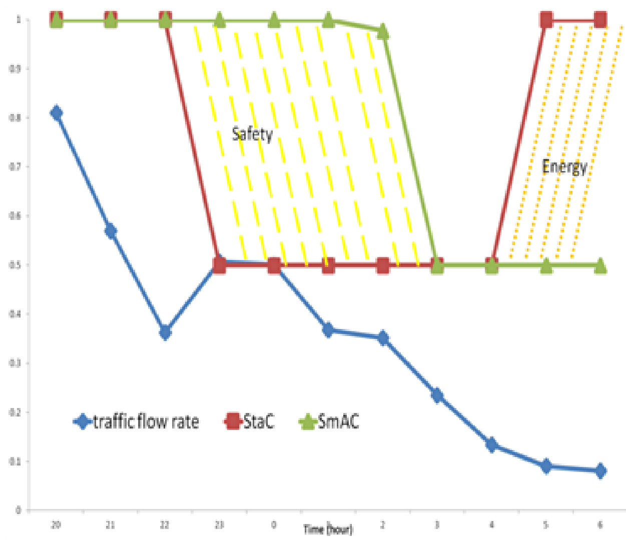

Figure 5. Control strategy comparison

Tests performed on S.Giovanni in Persiceto are based on a dataset of 123 days, sampled hourly, for a total of 2952 hours. Once again we compared different forecasting system:

- *Actual hour*: next traffic flow prediction based on previous hour traffic flow
- *Previous week*: forecast based on the same hour and the same week day of the previous week
- *Statistic model*: averaged hourly profile
- *Neural Ensembling*: neural network ensembling based model

TABEL V. COMPARISON OF FORECASTING MODELS ERRORS

	Actual Hour.	Previous week	Statistic model	Neural Ensembling
Error	8.77%	7%	5.53%	4.39%

Results show that also in this case Neural Ensemble outperforms other methods.

Then we compared three different control described above: constant, static and adaptive. As shown in Fig. 6 constant control does not take in account the traffic flow, static control does not overcome the variability of traffic flow meanwhile adaptive control provide energy to lighting spot proportional to traffic flow.

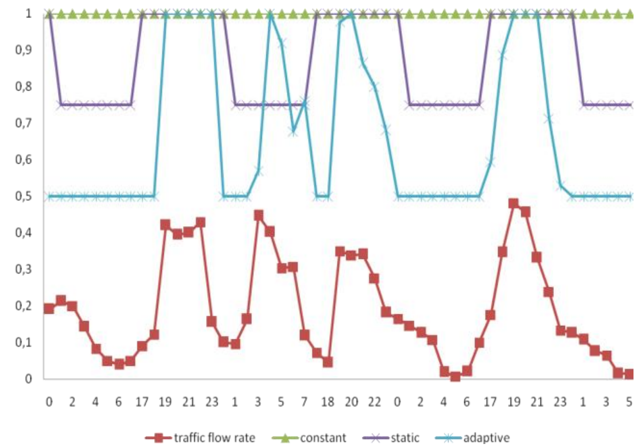

Figure 6. Comparison of control strategies

TABLE VI. CONTROL STRATEGY COMPARISON (ENERGY SAVING)

Static Control	Adaptive Control
-12%	-34%

Energy saving show in Table VI is a theoretical evaluation respect of constant control.

IV. CONCLUSIONS AND FUTURE WORKS

In this work, we proposed a new approach for adaptive street lighting control based on the 'energy on demand' idea. In order to achieve this goal it is critical to have a reliable demand model, which in the case of street lighting turns out to be a traffic flow rate forecasting model.

Thus, we showed a modeling approach based on Artificial Neural Networks Ensembling in order to provide a one hour forecast of urban traffic flow rates. Experimentation has been carried out on three different classes of real streets and results showed that the proposed approach clearly outperforms the statistical methods (6% prediction error) achieving a 3% prediction error. The reason for that is that the neural ensembling model is capable to provide more reliable estimations when out of standard conditions because it considers the real traffic dynamics.

Moreover, the proposed adaptive control strategy has been tested and compared to a traditional regulation system on the same streets. Results showed that the adaptive control provides, on average, energy savings almost doubled (43% vs 25%).

Future work will firstly focus on dimming profiles according to international standards, then further modeling improvements (using more sophisticated ensembling methods as well as trying to develop hybrid models) will be investigated and lastly, the economic impact of the proposed methodology will be carried out.

Moreover further forecasting model can be taken in account in order to validate the quality of results obtained.

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