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Adaptive street lighting predictive control

Francesco Marino[a*], Fabio Leccese[a], Stefano Pizzuti[b]

[a]Roma Tre University of Rome, Via della Vasca Navale 84, Rome 00146, Italy
[b]ENEA Italian National Agency for New Technologies, Energy and Sustainable Economic Development, Via Anguillarese 301, Rome 00123, Italy

Abstract

In this paper an implementation of a smart predictive monitoring and adaptive control system for the public lighting have been carried out. The vehicular traffic flow acquired using a smart camera has been analyzed and several predictive methods have been studied. Then, a control strategy based on the given traffic forecasts and on the dynamical street class downgrade allowed by the law, has been implemented. Experimental results provided by a real life testbed showed that the proposed strategy has high potential energy savings without affecting safety.

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Keywords: predictive algorythms, public lighting, Basic Ensembling Method, Smart City

1. Introduction

Since world urbanization continues to grow and the total population expected to double by 2050, in order to reduce environmental impact and offer to citizens a high quality life, the request of technologies to make intelligent and sustainable environments is constantly increasing. In the transition from the traditional concept of city toward a new paradigm named Smart City, many challenges have to be addressed in terms of innovation, society, communication and infrastructure networks [1,2].

In this context, street lighting has arisen as a foremost smart cities application attracting the interest of the scientific community. In fact, on one side it is indispensable for road and personal safety and increases the perception of the attractive local landmarks, on the another it is a great electrical energy consumer, consuming as much as 40 percent of a city's energy budget [3, 4]. Therefore, its efficiency is fundamental to reduce the global consumes.

* Corresponding author: Francesco Marino. Tel.: +39 3397636278
E-mail addresses: francesco.ingmarino@gmail.com (F.Marino), fabio.leccese@uniroma3.it (F. Leccese), stefano.pizzuti@enea.it (S. Pizzuti)

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Many street lighting facilities are obsolete and highly inefficient that leads to higher energy requirements and continuous maintenance. In these years the efforts are focused on the use of new lighting technologies as LED and automated and remote management systems combined with smart sensor networks.

There are around 300 million streetlights around the world, most of them in cities and only about 10 percent are LEDs. The advantages of replacing conventional street lighting to LEDs lie in the reduction of carbon dioxide emissions, in a better quality of light, in a longer life time, in a low light pollution due to directional light, in less energy consumption up to 40 percent and consequent higher efficiency.

In 2015 Milan replaced almost all the 140000 point lights for the Expo event with an investment of €91 million, passing from annual 114 millions of kWh to 55 millions of kWh; in 2013 Los Angeles installed 140000 LED street lights and reported energy savings of 63 percent and costs savings of around $8.7 million. In 2014, New York replaced 250000 old lamps with LEDs and since 2017, the city will save $14 million in energy and maintenance costs; Buenos Aires is about to replace the majority of the 125000 existing streetlights with new LED luminaires [5, 6, 7].

Several programs run by different Research Centers showed positive results for PV-powered LED outdoor lighting system for a more sustainable and efficient service, ensuring also photometric performance, energy savings, reduction of light pollution and CO_2 emission [8, 9, 10, 11, 12]. But the use of renewable sources requires reliable power grids and additional investments for the public administration.

Going further, it is possible to connect LEDs to a remote management software but it has been estimated that only 1 percent of the world's street lights are currently connected: the real gains can be made both in cutting energy consumption and costs and in improving the way cities behave. Some experimentations have been conducted in order to create wireless remote control systems, using ZigBee, WiMAX and GPRS sensors' networks demonstrating an increase of efficiency [13, 14, 15, 16, 17, 18].

Cabinet and point lights control systems are commonly used to remotely monitor and manage their operating but in the second case for each street light-point, it is possible to individually set different dimming percentages in relation to the street, the traffic and the environment variables [19, 20]. Working in full power is the least efficient way to provide lighting to users. In better cases, light output can vary according to the scheduled time, using one or more fixed dimming percentages over time; and this is a static control that return energy savings but could determine security issues due to the lighting level that may not meet parameters set by the norms in this field. So, the adaptive street lights' control is a better management way because allows to dimmer or switch off when and where they are not required and to suit the specific needs of each location, considering the variability of external inputs [21]. Several studies have already shown that with an adaptive control system, energy savings are about 30% [19, 21, 22].

A deep study on traffic behavior, and the application of analytical methods and data mining techniques that help to foresees it in the next period are fundamental and extremely useful to reach the goal. Different concepts have been elaborated and studied with the aim at traffic forecasting: clustering algorithms for traffic classification [23, 24, 25] and support vector machine (SVM) approaches [26, 27] were proposed and neural network methods were investigated for traffic analysis and forecast [28, 29, 30, 31]. Many different linear time series techniques approaches, especially Auto Regressive and Moving Average, were studied using the Mean Absolute Percentage Error (MAPE metric and Minimum Mean Square Error (MMSE) function to measure and evaluate prediction [32, 33, 34, 35, 36, 37]. In [38] it has been shown a preliminary approach to a complete smart street light management based on the 'energy on demand' approach which provides lighting only when requested or it is really needed, namely when the traffic flow rate is high (Fig.1). Starting from traffic data acquired from cameras installed on poles, after the modelling phase, a smart and dynamic lighting control is obtained which has the dual purpose of increasing the level of road safety providing service delivery lighting proportional to the amount of traffic detected (energy on demand) and always in line with the current regulations (EN 13201) regarding the luminance level of the road. This approach allows to obtain significant savings in energy and operating costs while maintaining road safety offering a high quality service for the citizen.

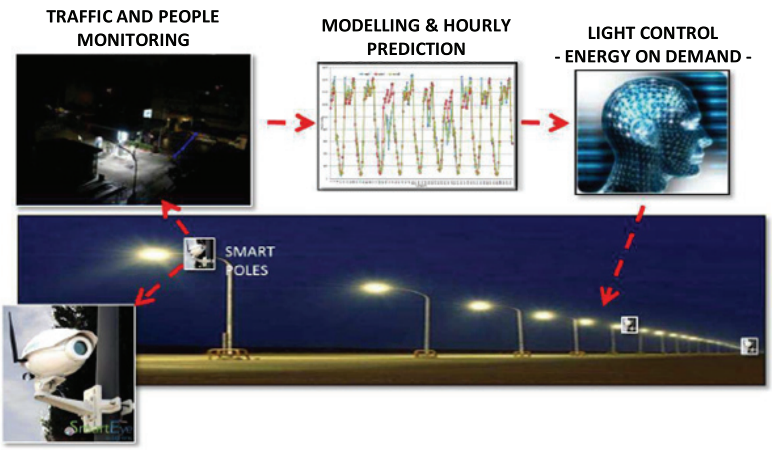

Fig. 1. Energy on Demand approach for public lighting.

In this context, this paper deals with the refinement of the control strategy of the approach proposed in [38] and shows energy saving results from a real testbed. The experimental field is a 5 km length Smart Ring that includes the historic center of the city of L'Aquila, Italy; the test field is limited to a local street named Strinella, 1.2 km length, 3 m width, with one carriageway and two lanes, one for each direction of travel. 53 LED point lights are installed and 3 intelligent cameras Smart Eye, optical sensors installed on street lamps that performs directly on-board the automatic urban scene analysis, considering also weather conditions, able to distinguish cars, heavy vehicles and people. Detecting and monitoring the motorized and pedestrian traffic, smart lighting politics oriented to efficient strategies can be actuated.

The work is divided into four main activities:

- Acquisition and analysis of traffic data
- Study and development of predictive models
- Energy Control
- Energy Savings

Nomenclature

ANN	Artificial Neural Network
ARMAX	Autoregressive-moving average with exogenous terms
BEM	Basic Ensemble Method
LED	Light Emitting Diode
MAPE	Mean Absolute Percentage Error
SmartEye	Optical sensor able to analyse the urban scene

2. Acquisition and analysis of traffic data

The first activity, concerning the acquisition and analysis of traffic data, began in September 2014, and took place in real-time with a 10-minute sampling. A complete examination of the traffic flow, in relation to the individual nodes and to the months, was carried out using a SmartEye able to directly analyze the road scene and traffic flow. Such a system can reduce the energy consumption for public lighting by adapting the lighting level of the road according to its real status and provides interactive services for Smart Cities.

Fig.2 shows the typical saddle trend: during the night there is a lower number of vehicles, that increases in the central hours of the day but has a small deflection, due to the intensifying of the traffic that reduces the viability.

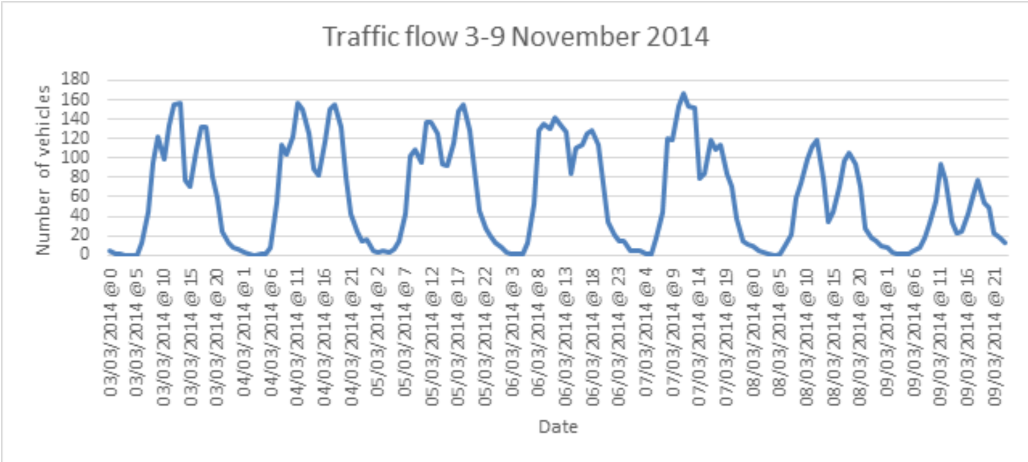

Fig. 2. Weekly traffic flow trend.

3. Study and development of predictive models

The second activity involved the study of predictive models based on vehicular traffic on which is based the implementation of dimming strategies for efficient management of public lighting. The adjustment cannot be performed in real time, due to problems related to the approval of the technicians of the city: therefore, it is needed to have a priori complete profile for each time slot of the considered day that it would be properly implemented.

Relying on the previously acquired data, in order to determine the forecast of the traffic for the following week, statistical methods, regressions and neural networks based algorithms have been taken into account, evaluating their reliability and prediction accuracy calculating the MAPE. It is calculated as the average of the unsigned percentage error and is defined by the formula:

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{A_t - F_t}{A_t}\right| * 100 \tag{1}$$

where A_t is the actual value, F_t is the forecast value and N is the number of observations.

The considered data have been partitioned in training and testing sets for all the modelling techniques considered in this study, therefore the comparison of the different models is coherent. The training set is 75% (about 4800 records) of the whole data set and therefore the testing set is the remaining 25% of data (about 1600 records). The methods that have been considered are described below. In order to forecast the first week of December 2014, the vehicles that transited during the 30 days of November were considered as input:

Method 1: Traffic forecast using statistical model.

The statistical model considers the average of the transiting vehicles for time span for every day of the previous month. Then, for each hourly sample of the first week of December, the difference between the actual value and the forecasted value was calculated; the overall MAPE resulted in 10.79%. This is a relatively a high value because in this forecast the kind of days (weekdays or holidays) wasn't considered but user presence and his behavior on the road is variable depending on them and strongly affect the outcome.

Method 2: Traffic forecast using regression model.

The regression model is a statistical process for estimating how a dependent variable (the criterion variable) is related to and changes as any of the independent variables (or predictors) varies, when the others are hold fixed. This model was implemented in matrix form by coding in Matlab, resulting in a MAPE of 9.65%.

Method 3: Traffic forecast using ARMAX model.

ARMAX stands for Autoregressive–moving-average model with exogenous inputs and allows to take account of the stochastic dynamics, useful when dominating disturbances enter early in the process. The application of this model, feature included in the Matlab System Identification Tool, resulted in a MAPE of 8.83%.

Method 4: Traffic forecast using NAÏVE model.

The Naive model produces forecasts that are equal to the last observed value and it is used only for comparison with forecasts generated by more sophisticated methods. This estimation technique predicts that the given time series of samples, for each of them, at time t, is calculated by the following equation $x(t\text{-}e) = x(t)$, where e, always increasing, represents a translation of the model series (by e samples) compared with the real one. Because the greater e is, the greater the offset is, the minimum MAPE computed was 12.08%, corresponding to the case $e = 1$.

Method 5: Traffic forecast using BEM neural model.

The application of the neural model was about a preliminary analysis of a wider range data in order to have a better network training (from March 2014 to November 2014) and to set the optimal number of input and hidden nodes. After choosing 10 hidden nodes, several tests using different number of inputs have been conducted. The neural networks models have been trained on 10 independent runs and then the BEM has been applied to them. BEM is the simple average of the estimations of all the ANNs and allows to obtain better results than those could be obtained from any of the considered neural models. The best result in terms of average and maximum error has been obtained using 24 inputs. Overfitting has been prevented by applying the “save best” approach.

Below is reported the MAPE and max error for both BEM training and testing (Tables 1, 2).

Table 1. BEM Training.

Number of input	MAPE	Max error
2	4,27%	71,26%
4	4,20%	71,49%
6	3,93%	71,58%
8	3,68%	71,68%
10	3,44%	70,18%
12	3,05%	71,74%
16	2,97%	68,45%
20	2,83%	49,51%
24	2,85%	49,19%

Table 2. BEM Testing.

Number of input	MAPE	Max error
2	7,97%	49,64%
4	8,07%	49,83%
6	7,12%	47,49%
8	6,60%	54,04%
10	6,13%	44,77%
12	5,67%	42,51%

16	5,52%	43,40%
20	5,40%	43,03%
24	5,25%	41,76%

The comparison between real and predicted hourly traffic flow is reported in Fig.3.

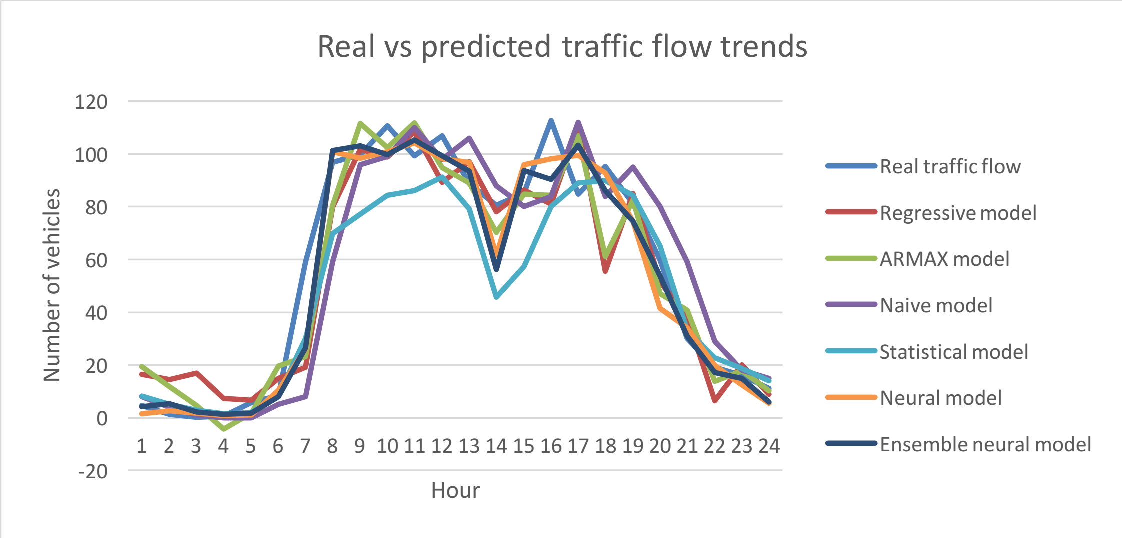

Fig. 3. Real vs predicted traffic flow trends.

A complete comparison among different models' MAPE is summarized in Table 3.

Table 3. Models' MAPE comparison.

Statistical	Regressive	ARMAX	NAIVE	BEM
10,79%	9,65%	8,83%	12,08%	5,25%

The next phase relates to the definition of weekly lighting profiles, including the dimming percentage of power reduction, in order to provide the right intensity at the right time for road users. This allows significant energy savings and a more sustainable and efficient use of the available electrical resources on the base of the real lighting needed, always respecting security requirements.

4. Energy Control

At the end of the experimentation that lasted 6 months, from December 2014 to May 2015, the estimation of energy and CO_2 savings resulting from the implementation of this strategy was computed. The control strategy is based on the lighting regulations to guarantee safety of road users satisfying all sight needs:

- UNI 11248:2007 Italian standard, named Road lighting - Selection of lighting classes, classifies an outer area intended for the traffic, for the purpose of determination of the lighting category that competes;
- EN 13201-2 European Standard, approved by CEN, named Road lighting - Performance requirements, defines lighting class by a set of photometric requirements aiming at the visual needs of certain road users in certain types of road areas and environment.

The last reported regulation also takes into consideration the possibility of lighting category downgrades as a result of risk analysis (presence of crossing at grade / deceleration devices, conflictual conditions at pedestrian crossings), but also the surrounding visual environment and traffic flow.

The considered roadway in the city of L'Aquila is classified as an urban district road (ME3c), which has 800 equivalent vehicles as nominal flow. As shown in Fig.4, extracted from the EN 13201-2 norm, the average luminance (minimum maintained) of the road surface in dry condition has a value of 1.0 cd/m^2 and that is the main parameter that has to be considered in defining the dimming profile. Moreover, it has no slowing down devices and conflict zones.

Class	Luminance of the road surface of the carriageway for the dry road surface condition			Disability glare	Lighting of surroundings
	L in cd/m^2 [minimum maintained]	U_0 [minimum]	U_I [minimum]	TI in % [maximum]	SR [minimum]
ME1	2,0	0,4	0,7	10	0,5
ME2	1,5	0,4	0,7	10	0,5
ME3a	1,0	0,4	0,7	15	0,5
ME3b	1,0	0,4	0,6	15	0,5
ME3c	1,0	0,4	0,5	15	0,5
ME4a	0,75	0,4	0,6	15	0,5
ME4b	0,75	0,4	0,5	15	0,5
ME5	0,5	0,35	0,4	15	0,5
ME6	0,3	0,35	0,4	15	No requirement

Fig. 4. EN 13201 - Luminance values for each road class.

Consequently, to a reduction respectively of 50% and 25% in the nominal flow of vehicles, a downgrade of the lighting class of one level (ME4b) and 2 levels (ME5) is expected, which correspond to luminance values equal to 0.75 cd/m^2 and 0.5 cd/m^2. The allowed reduction of the luminance's limits opens to the possibility to dynamically decrease the installed power of the point lights on the base of the estimated traffic profile.

A first algorithm which replicates the basic functionality of the lighting calculation software but simplified in input variables (the photometry hasn't been taken into account, for the asphalt reflectance coefficient has been chosen the known 0,217 average factor and the maintenance factor has been set to 0.8), has been developed and subjected to a tuning phase on the base of PDF Reports generated by Dialux SW in order to obtain the same luminance value.

The selected light sources are 137 W power and luminous flux 10275 lm (luminous efficiency of 75 lm/W) and determine the average luminance value (minimum maintained) 1.02 cd/m^2, that matches the limit ($\geqslant$ 1.0 cd/m2), as well as the other photometric requirements. The algorithm adjustment returns a rough and conservative indication of power reduction percentage in case of lighting downgrades: for a one-level, power can be reduced up to 67% and for two levels up to 45%. For this evaluation were taken into account parameters concerning

- Road configuration:
  - Width of carriageway
  - Number of lanes
  - Spacing between luminaires
  - Road surface type
- Lighting design:
  - Mounting height of the luminaire
  - Installed power
  - Luminous flux (or alternatively the luminous efficiency)

- Angle of light incidence
- Overall maintenance factor
- Boom length
- Luminaire tilt

Obviously, if it is acceptable (although you would use more power than necessary, while ensuring regulatory limits) that predicted derating range is equal or greater than the real derating range, it would be illegal in the opposite case. So, conservative derating thresholds were chosen, by considering an uncertainty value ± ε that was set equal to twice the error of the forecasting model (about 5-6%).

5. Energy Savings

The daily energy consumption is obtained using the following formula:

$$DailyEnergyConsumption[kWh] = InstalledPower[kW] \cdot WorkingHours[h] \quad (2)$$

Relatively to December 6, for each luminaire, the daily energy consumptions, in presence and absence of dimming regulations, are computed below:

$$NoDimmedDailyEnergyConsumption[kWh] = 137W \cdot 14\ h = 1.918\ kWh \quad (3)$$

$$DimmedDailyEnergyConsumption = 137W \cdot 4\ h + 91\ W \cdot 1\ h + 61\ W \cdot 9\ h = 1.188\ kWh \quad (4)$$

with energy savings of

$$EnergySavings = 1.918 - 1.188 = 0.73\ kWh \quad (5)$$

Because the camera covers a straight stretch of the road, in which 18 lamps insist and no relevant entries come from the residential side streets, the total energy saving would be

$$EnergySavings = 0.73 \cdot 18 = 0.73\ kWh \quad (6)$$

After this first tuning phase, the analysis and implementation was extended to get energy and cost savings in the long run. At the end of 6 months during which the algorithm calculated the dimming profiles, the theoretical energy savings that would be obtained for each month are reported. Energy savings in spring are less than in winter because of the daylight saving time and the change of the sunrise and sunset times. In addition, the month of May is considered until 29. The energy cost was set equal to 0.17 €/kWh while for CO_2 savings, a value of 382 g/kWh was considered.

Table 4. Results.

	December	January	February	March	April	May
System ignition	17	17	17	18 / 19	19	20
System shutdown	8	8	7	7	7	6
Working hours [h]	465	465	392	400	360	290
Energy consumption (No Dimming) [kWh]	945.81	945.81	797.328	813.6	732.24	589.86
Energy consumption (Dimming) [kWh]	684.054	678.366	565.092	563.49	503.91	400.356
Energy savings [kWh]	261.756	267.444	232.236	250.11	228.33	189.504
Energy savings [%]	27,67	28,27	29,13	30,74	31,18	32,12
CO_2 savings [kg]	100	102.2	88.7	95.6	87.2	72.4

6. Conclusions

This activity concerning a project in the field of smart lighting took place over the course of 12 months, from 1 July 2014 to 30 June 2015. In the first months, the collected traffic data by the cameras installed on the road were analyzed and a series of computations, with data consistency and diagnostics activities. For the next 6 months, prediction methods, statistical, regression and neural were studied and tested and their MAPE were compared to determine the reliability, also in the long run. Through the selected predictive model and subsequently implemented, considering the road configuration in place, from December 2014 to May 2015, weekly dimming profiles have been defined. At the end of the experimentation, energy consumption with and without the application of smart adaptive strategies for the installed power reduction were evaluated, achieving energy savings of the order of 30%.

Future directions will comprehend the study and development of more sophisticated modelling methodologies, also related to the prediction of traffic flow for single day, in order to improve the accuracy of vehicles transiting forecast. A more reliable forecast could be obtained using a longer training period in which a lot of data would be acquired and processed. Finally, combining lighting with integrated services as value-added, i.e. dynamic jams' management, traffic lights and offenses supervision, will lead to a Smart Street including a complete lights' regulation system for a real Smart City.

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