2018

The influence of external factors on the energy efficiency of public lighting

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Abstract

LED-based technology is transforming public lighting networks, favouring smart city innovations. Beyond energy efficiency benefits, LED-based luminaries provide real time stateful data. However, most of the municipalities manage all their luminaries equally, independently of its state or the environmental conditions. Some existing approaches to street lighting management are already considering elementary features such as on-off control and individual dimming based on movement or ambient light. Nevertheless, our vision on public (street) lighting management, goes beyond basic consumption monitoring and dimming control, encompassing: a) adaptive lighting, by considering other potential influence factors such as work temperature of the luminaries or the arrangement of the luminaries on the street; b) Colour tuning, for public safety purposes and; c) emergency behaviour control. This paper addresses the first component (adaptive lighting) influence factors, in the scope of a real scenario in a Portuguese municipality.

Keywords: public street lighting; random decision forests; energy efficiency

1. INTRODUCTION

In the last years, the concept of Smart City has gained increasing popularity and interest among both research community and society as a whole (Albino et al., 2015). This widespread interest is partly explained by the current worldwide population growth and the general moving of people from the countryside to cities. According to the 2014 revision of the World Urbanization Prospects, compiled by the United Nations, more than half the population (around 4 billion by 2014) currently lives in urban areas, with a tendency to increase: the number is expected to reach 6 billion by 2050 (UN, 2015). This results in increasingly larger cities, with some housing more than 20 million people, namely in Asia, Latin America and Africa (Zhao et al., 2017).

These new demographics raise significant challenges in city management, challenges that can hardly be tackled by human experts alone, given their complexity and scale. It is in this context that the concept of Smart Cities gains relevance. Several definitions for Smart Cities have been put forward by authors from different fields of expertise (Albino et al., 2015). Generally, a Smart City implies the use of Information and Communication Technologies (ICT) to connect its different services and/or resources, allowing data to be collected, analyzed and acted upon in real time (Bakıcı, Almirall, and Wareham, 2013). Evidently, the mere interconnection of these elements is not enough to make a city “Smart”. Thus, a Smart City also implies the use of the collected information for the purposes of improving quality of life (Barrionuevo, Berrone and Ricart, 2012), the efficiency of the city management (Chen, 2010), the management of resources and the sustainability of the city and its growth (Caragliu, Del Bo, and Nijkamp, 2011). Hence, the challenges posed by smart city projects are, typically, socio-technical in nature (Mumford, 2000). Considering that one of the most demanding issues in a Smart City is that of efficient energy management, having into account the consumption issues, neglecting people basic needs related to health and safety, is a thigh solution. Typically, energy management can be addressed at different levels, namely energy generation, energy storage, infrastructure, facilities and transport (Calvillo et al., 2016). More complex approaches may encompass more than one of these levels and, ultimately, research aims at developing a unified model that is able to take into account all these levels and their relationships to provide an accurate and full model of energy management in the city. However, the task is undoubtedly complex, and most research efforts focus on a specific issue (Foley et al., 2010).

In this paper we discuss a specific topic of efficient energy management within cities, that of public lighting management, which might be one of those with the greatest impact on the sense of safety among citizens, as well as the one of the greatest consumption.

Currently the subject of energy efficiency has been focused on all sectors with high energy consumption: industry, housing and public services. Public lighting, in particular, represents a significant percentage of the municipalities’ expenditure with energy. There is nowadays a widespread tendency to replace the conventional High-Pressure Sodium (HPS) lamp-based luminaires by solid state lighting (LED luminaires) with electronic drivers. This, by itself, leads to significant savings. As an example, in Lousada (a municipality in Northern Portugal) 12.500 HPS luminaires were replaced by LED ones, resulting in a decrease of 65% with public lighting costs, equivalent to €500.000/year.

This paper is structured as follows: Section 2 provides an overview of street lighting management and the different approaches that may be followed. Section 3 details the dataset used in this work. This dataset is explored in Section 4, in which a preliminary analysis of its data is put forward. Section 5 details the methodology followed and the results achieved and Section 6 concludes the paper, also stating some limitations of the current work and future lines of research.

2. Overview on Smart Street Lighting Management Approach

With the advent of the Internet of Things (IoT), we believe that energy savings can be furthered, namely by an individual management of each specific luminary (Gubbi et al., 2013). Indeed, most of the existing approaches look at the public/street lighting system as a whole and treat all luminaries equally. However, lighting could and should be adjusted individually, according to each area's requirements (e.g. people flows) and conditions (e.g. ambient lighting). For instance, luminaries that are in areas with higher luminance (e.g. due to a full moon or to electronic advertisement billboards) could be dimmed in order to save energy while maintaining luminance conditions.

Our perspective on street lightning management follows a human-centered design approach based on IoT and leveraged by machine learning and knowledge representation techniques. This holistic view encloses both social and economic aspects. On one hand, we aim at reducing energy consumption and, on the other hand, we follow an adaptive management approach, having into account people's health and safety, as well as environmental issues. Accordingly, a Smart System for Street Lighting management, fully committed to this approach should address:

- **Consumption monitoring and dimming control** including switch on/off features based on luminaries' internal data;
- **Adaptive monitoring**, based on external factors such as: work temperature of the LED luminaries, the location of the network, the arrangement of the luminaries on the street, the surrounding lightness, the twilight threshold, the daytime and real-time meteorological data;
- **Health and Safety constraints**. This might include color tuning by adjusting the color temperature of the LED for safety and health purposes. Color temperature influences, for instance, the perception of security (Amorim et al., 2016) and the biological clock - known as Circadian rhythm (Revell et al., 2006; Bonmati-Carrion et al., 2014). Indeed, USAI Lighting (a leader in lighting industry in USA) has defined the USAI Lighting Circadian Clock (USAI Lighting, LLC, 2015) with the ideal color led temperature intervals for different periods of the day. Still on the field of safety, it is important to consider, for instance, that the abrupt change between an illuminated place and a place without any illumination, might cause momentary eye disturbances, which could result in a road accident. Typically, luminaries near a dark should have more light intensity, but in the case of a car driver moving from a brighter area to a darker one, probably it would be better to smooth the transition progressively by decreasing the light intensity.

Above we stated the macro requirements or main concerns for an efficient smart system for street lighting management (3SLM), additionally, in what regards to the conceptual architecture, the challenge is not less ambitious. Thus, 3SLM, in the context of environmental monitoring and awareness, needs: i) real-time data collection based on IoT technology and driven by well-defined schemas, shaping the current state of the environment; ii) dynamic and reusable meaning-making models representing the domain knowledge in an inferred and easily retrieve format; iii) learning mechanisms to monitor and dynamically reshape the environment providing, together with i) and ii), a context-dependent decision model to support proactive and more suitable action plans. This conceptual proposal on the problem is, in our opinion, essential to appropriately capture the specificities of such a complex problem and to, therefore, develop a suitable solution.

Understood the overall approach to 3SLM, this paper discusses the meaning of the data provided by the luminaries and explores the different patterns of energy consumption of each luminary, despite the existence of only one strategy for all. We explore this to train a model to predict energy consumption at a luminary level, that will allow an optimized and automatic management of the public network that takes into account the characteristics or environment of each luminary. This will allow to identify those luminaires that have increased costs, allowing city managers to define more efficient lighting strategies, reducing costs and CO2 emissions associated to public lighting.

3. DATASET CHARACTERIZATION

The data described in this paper was collected from two different public lighting settings. The first is the production setting, which includes 305 luminaries in a public lighting network located in a Portuguese municipality. This network is managed by the municipality. The second is the development and test setting and includes two luminaries located in our institution. These luminaries can be controlled by the research team, namely to collect data from different scenarios and test different management models.

In both settings the AQRUILED's ARQUICITY R1 luminary is used. This luminary allows for different data to be collected from its functioning in real time. The dataset collected from the production setting and studied in detail in this paper contains 3.963.730 instances of data. Each instance describes 5 minutes of operation of a specific luminary and includes, among others, data about instant voltage, luminary temperature, instant power, accumulated energy (Wh), uptime or dimming. These data were collected over a period of four months, between the September 5th 2017 and January 3rd 2018.

Before the data analysis carried out and described in the following section, the dataset was cleaned. This was necessary since the luminaries used have a warm up time of 1 to 4 minutes, a period in which the values read do not correspond to the regular functioning of the luminary. There are also cases in which data was collected from luminaries that had already been turned off (i.e. dimming = 0%), which have also been removed as in these cases the luminary was shutting down and the values also do not reflect their normal operation. During the cleaning operation, 107.912 instances were removed. The resulting dataset thus contains 3.855.818 instances.

Finally, the data from the luminaries was merged with environmental data, also collected at 5-minute intervals from a local weather station. These data include air temperature (ºC), dew temperature (ºC), humidity (%), wind speed (m/s), wind direction (degrees), wind gust (m/s), pressure (mbar), solar irradiance (W/m^2) and rain (mm/h). Thus, for each instance of data collected from each luminary, we also know the environmental conditions at the time. This will allow to study the influence of external factors, such as temperature, on energy efficiency.

4. PRELIMINARY DATA ANALYSIS

As stated in the introductory section, one of the main goal of this work is to determine if there are advantages in managing luminaries individually, namely in terms of energy efficiency, as opposed to what is generally done. In that sense, work started by analysing the power consumption patterns of different luminaires.

We started by analysing energy consumption over several days, for the two luminaries in the test setting. Figure 1 shows the evolution of energy consumption in each of the luminaries in the 10 hours they were on, in three consecutive days, between May 3rd 2018 and May 6th 2018. One first conclusion is evident from the figure: energy consumption in each cycle is not constant for each luminary (although the dimming is kept constant) nor is it necessarily similar between different luminaries (although their dimming is the same).

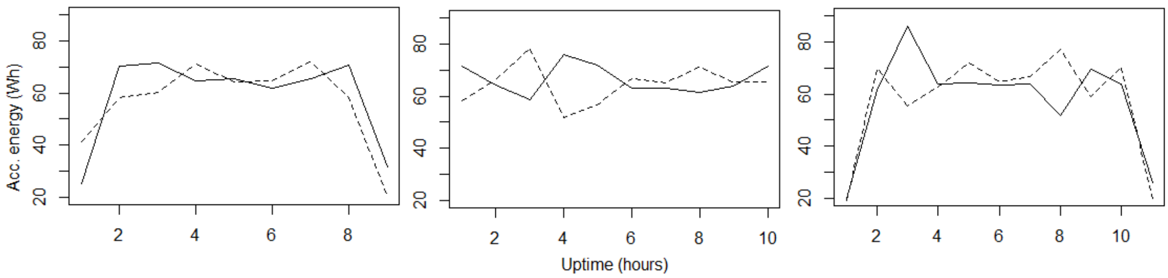

Figure 1 – Energy consumption of the two luminaires in the test setting, in the three nights between May 3rd and 6th 2018, respectively from left to right.

Figure 2 shows the distribution of the data for the same luminaries over the period of one week, between May 1st 2018 and May 8th 2018. It shows that the energy consumption for luminary 8383 is consistently higher than that of the other over this period. Table 1 shows that the values of the mean, median and standard deviation are higher for this luminary. Moreover, the differences observed are statistically significant (ρ-value = 0.000143).

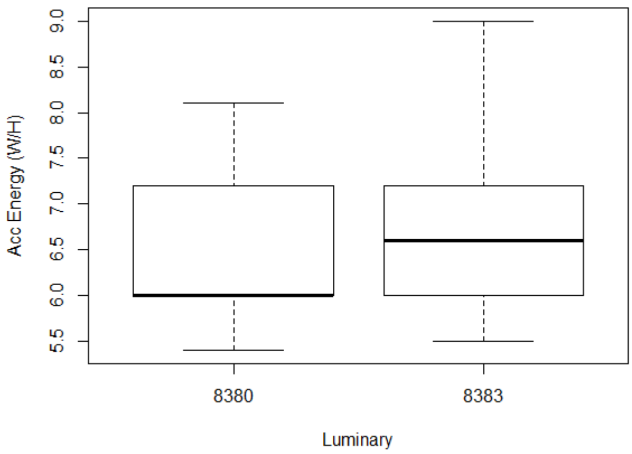

Figure 2 – Distribution of energy consumption over a week, between May 1st 2018 and May 8th 2018, for the two luminaries in the test setting. The differences in the distributions of the data are statistically significant (ρ-value = 0.000143)

LUMINARY	$\bar{x}$	$\tilde{x}$	σ_x
8380	6.30	6	1.03
8383	6.42	6.6	1.38

Table 1 – Differences between the consumption of the two luminaries in the test setting.

A similar approach, when applied to the data collected from the production setting, holds similar results. Figure 3 shows the distribution of power consumption for 47 of the 305 luminaries, during the 4 months in which data were collected. We show data concerning only 15% of the luminaries, as doing otherwise would render the visualization useless. However, a similar pattern is observed for the rest of the data. Also, for the sake of readability and usefulness, we also do not provide the statistical measures (i.e. mean, median and standard deviation) for each luminary. However, the differences in the distribution of the data are evident from Figure 3.

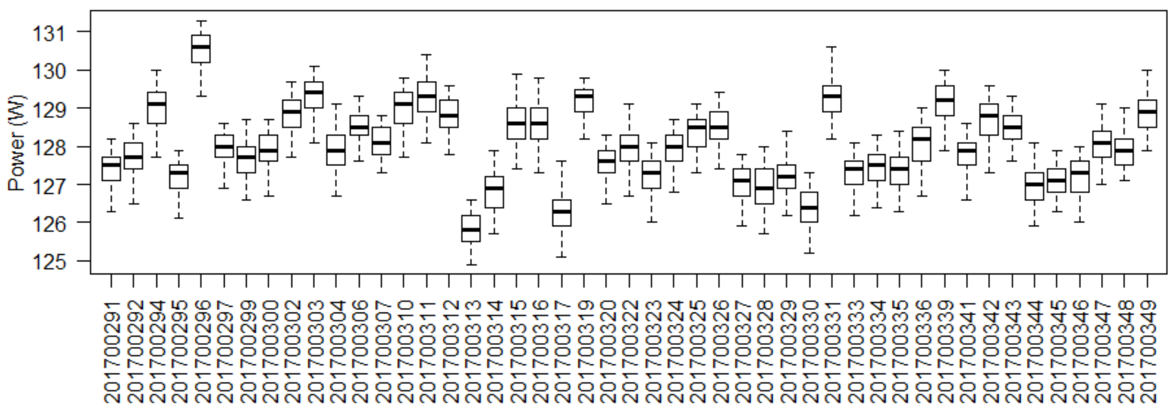

Figure 3 – Distribution of power consumption for 47 of the luminaries (15%, selected randomly) over the 4 months of data collection in the production setting.

Figure 4 shows a different visualization of the data, combining dimming, luminary temperature, and energy consumption (color-coded). This Figure was generated from the data collected from the 305 luminaries in the production setting during the four months of the study.

The first evident conclusion is that energy consumption increases with dimming (i.e. from bottom to top in the Figure). However, it is interesting to note that energy consumption does not depend on dimming alone. That is, for the same value of dimming there are sometimes variations of power consumption. This happens in several ranges but, more markedly, between 80% and 90% of dimming. In this range, it appears that higher values of temperature are associated to lower energy consumptions. This may be relevant for the optimization of energy consumption since 90.31% of the data (3.482.310 instances) were collected from luminaries set to a dimming in this range, that is, this is the most frequent setting for these luminaries.

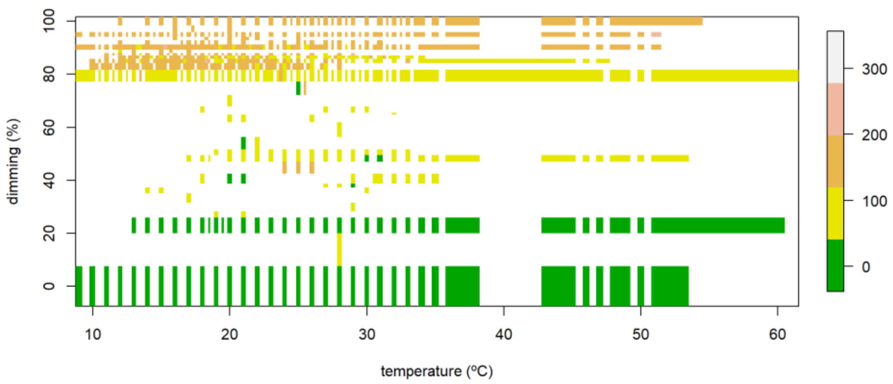

Figure 4 – Heatmap showing the relationship between dimming, working temperature and power consumption.

If this relationship between the luminary temperature and energy consumption is verified, it can be explored to decrease energy consumption. Namely, information about air temperature could be used to determine the best dimming at any given time (e.g. decreasing it when temperatures are lower and energy consumption higher). This goal is realistic since air temperature is one of the factors that most significantly influences the luminaries' running temperature. Specifically, according to our data, the correlation between the air temperature and the luminaries' working temperature is of 0.72. The same correlation is visible in Figure 5, which plots the working temperature of the luminaries in the production setting against the air temperature at the time of the collection of each instance. The vertical gap visible between the 35º and 45º degrees can be explained by the effect of air temperature in moments in which the luminaires were working during the day: as the air temperature rises during the day, the working temperature of the luminaries rises quickly.

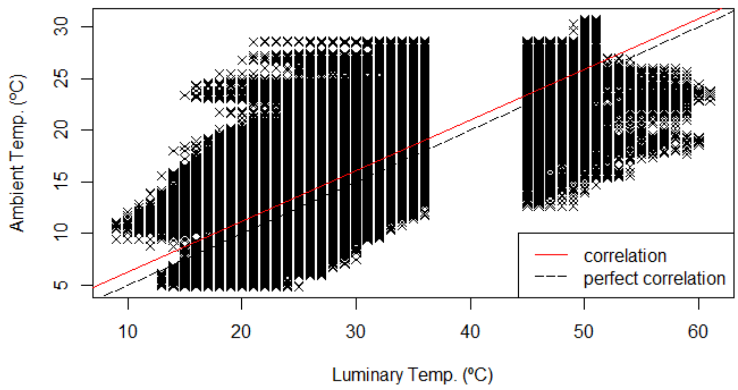

Figure 5 – Scatter plot of air temperature (ºC) versus luminary temperature (ºC) (ρ = 0.72).

5. Methodology and Results

In the section 4, and after the preliminary analysis of the data, we put forward two hypothesis: 1) the energy efficiency of a public lighting network may depend significantly on the characteristics of each individual luminary; and 2) there may be external factors influencing the energy efficiency of each luminary. In this section we try to determine the validity of these hypotheses. As pointed out by Calvillo et al. (2016), energy management/consumption can generally be studied through two main approaches: modelling and simulation. In this work we follow the first. Thus, to assess the hypotheses put forward before, we train 2 different regression models in order to understand the behavior of the public lighting network in terms of energy efficiency.

Specifically, we use the Distributed Random Forest algorithm to model the different aspects of the network. A Random Forest predictor can be used for both regression and classification problems. It uses an ensemble of decision trees to predict the intended value. Generally, the variance tends to decrease as the number of trees increases. Each decision tree is looked as a weak learner, is trained on a random subset of the training set and only uses a random subset of the features. When predicting numeric variables, as is the case, the output is given by the average value predicted by each of the trees.

The following methodology was followed to train each model. Different forests, with different number of trees were trained and evaluated. Each tree is built with 60% of the features of the dataset, selected randomly. For each different number of trees, the deviance and RMSE (Root-Mean-Square Error) were calculated as measures of the quality of the model.

To estimate model performance 5-fold cross validation was used. In each training process six models were built: 1 model on 100% of the training data and 5 cross-validation models that use disjoint holdout validation sets (obtained from the training data) to estimate the generalization of the first model.

At the end, the importance of each variable was also calculated. Variable importance is determined by calculating the relative influence of each variable: whether that variable was selected during splitting in the tree building process and how much the squared error (over all trees) improved as a result.

In order to assess the hypothesis that power consumption varies significantly between luminaries, a first model was trained, with power consumption as the response variable. The goal of this model is to predict power consumption for a given luminary, under given circumstances (e.g. meteorological conditions, uptime, dimming). It is composed of 50 trees with a depth of 20 and an average number of leaves of 56452.86.

Figure 6 (left) shows the evolution of deviance and RMSE with different number of trees. The final value of RMSE is satisfactory considering the distribution of the response variable. Figure 6 (right) shows the relative importance of each variable to predict power consumption, scaled to the interval [0..1]. According to the results, the variable with the highest importance when predicting power consumption is the identifier of the luminary, followed by its dimming, the uptime, the date and the temperature (both working temperature and air temperature). First, it is important to note that the importance of the date is most likely due to its relationship to temperature, which is higher during the day and lower at night. Second, these results show indeed that energy consumption varies from luminary to luminary. However, as addressed in Section 5, these results must be interpreted with care. Indeed, we did not expect such a high relevance of the device_id variable, especially when compared to dimming. This may be explained by the low variability of the dimming variable: 90% of the data was collected with luminaries working with a dimming between 80% and 90%. This is a limitation of this work, and is further explored in Section 6.

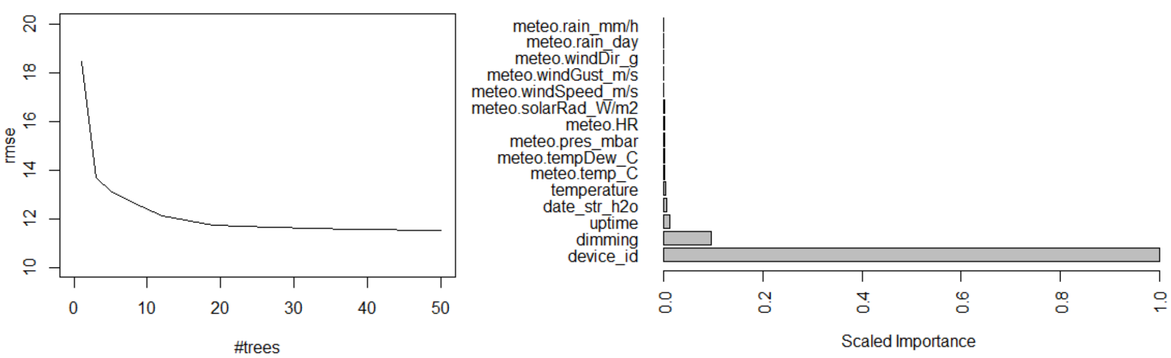

Figure 6 – Evolution of RMSE with increasing number of trees (left); Relative importance of each variable in the prediction of power consumption (right).

A similar approach was followed for modelling the working temperature of the luminary. The resulting model is composed of 50 trees with a depth of 20 and an average number of leaves of 112988.92. Figure 7 (left) shows the evolution of the RMSE during the training of the 50 trees that compose the model. The final RMSE of 1.0348 ºC achieved with 50 trees shows that the model is well adjusted. Figure 7 (right) shows the most important variables for determining the luminaries' working temperature. The image shows that the most important variables are the date and the air temperature. As previously stated, this similar importance is expected since these two variables are strongly related. Results also point out that other ambient variables have some significant importance, such as dew temperature, uptime, device identifier and humidity. It is interesting to note that the device identifier is one of the relevant variables to determine the luminaries' temperature. Once again, we believe that this is due to factors such as the placement of each luminary (e.g. location on the street, orientation towards the sun.

If the working temperature truly influences the luminaries' energy efficiency as our data suggests, then knowledge about the factors that influence this temperature (such as the ambient variables used in this paper) may prove relevant for improving energy consumption in public lighting networks.

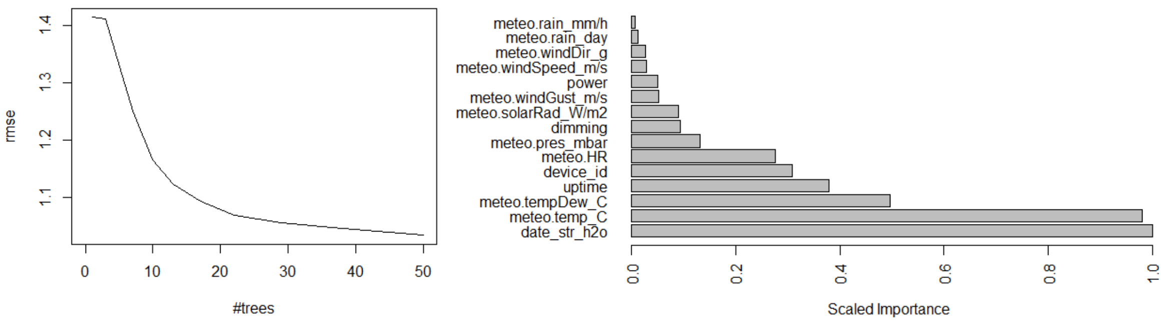

Figure 7 – Evolution of RMSE with increasing number of trees (left); Relative importance of each variable in the prediction of working temperature (right).

6. LIMITATIONS AND FUTURE WORK

It is accepted that the setting of a smaller dimming in public street lighting will result in several advantages that contribute to the sustainability of the city, namely in terms of smaller emissions of carbon dioxide (Radulovic, Skok, Sand Kirincic, 2011) as well as on decreasing costs related to power consumption. However, the problem is not so simple and there are also disadvantages associated to such a practice.

On the one hand, there is the subjective perception of pedestrians of safety and well-being. Indeed, Peña Garcia, Hurtado and Aguilar-Luzón (2015) conducted a survey of 275 pedestrians in the city of Granada (Spain), concluding that the perception of security and well-being is influenced by factors such as the color of the lighting (e.g. white, yellow-sodium) or the average illuminance on the street. Moreover, the authors also conclude that white light (with a high content of blue) is associated to a higher melatonin inhibition and cortisol release, both indoors as outdoors.

On the other hand, there are also objective measures associated to different intensities and forms of lighting. Painter (1996) conducted a study in which the street lighting was upgraded in three urban streets and a pedestrian footpath considered to be crime and fear prone. The impact of the street lighting programme was assessed using attitudinal and behavioural measures, through ‘before’ and ‘after’ surveys of pedestrians. The results provide convincing evidence that sensitively deployed street lighting can lead to reductions in crime and fear of crime and increase pedestrian street use after dark.

These issues show, as addressed in the introductory section, that energy efficiency in public lighting is a complex phenomenon as it affects many relevant spheres of the society including safety (subjective and objective), well-being, the cities’ budgets. These different strands often have conflicting objectives, making it difficult to achieve a consensus that can satisfy all constraints.

In this paper we do not mean to solve this complex problem. Our goal was, rather, to contribute with additional paths for potentially improving the energy efficiency of public street lighting systems and, in doing so, facilitating the satisfaction of its constraints. Specifically, we show that energy consumption varies from luminary to luminary, and also that it may be influenced by measurable and predictable external factors such as air temperature. Machine Learning techniques, together with knowledge about these factors, may support the development of more fine-grained management strategies, that autonomously manage each individual luminary to optimize energy consumption.

However, there are also limitations in this work that must be pointed out. Namely, we used a single solid state luminary model. Other models could behave differently and other types of luminary (e.g. High-Pressure Sodium) would definitely behave differently. We thus need to repeat this study with other models to determine if these conclusions can be generalized, at least, to other LED luminaries.

Another limitation of this work results from the collection of data from a production environment: as detailed in Section 3, 90% of the data was collected from luminaries set at a dimming between 80% and 90%. This makes the representativity of the remaining ranges of dimming very low. However, given the already addressed effect of luminance on crime, safety perception or well-being, we could not change the settings of the network for the purpose of this research. In the future we will address this issue by acquiring more luminaries for the test setting, an environment in which we can freely adjust their settings without risking anything.

Finally, in future work we will also try to isolate the factors that influence energy consumption in each luminary. While the intrinsic characteristics (namely hardware) of each luminary may explain, to some extent, the observed differences, we believe that other external factors must play a more important role. Specifically, we will determine the orientation of each luminary as it affects the surface of the luminary that is hit by the sun and may, therefore, influence its temperature throughout the day. We will also estimate, for each luminary, the amount of sunlight received during the day as this may be influenced by obstacles such as high trees or buildings. Finally, we are also modeling the relationship between ambient luminance and the luminance under the luminary, to determine the influence of each level of dimming for specific degrees of ambient luminance. With all these efforts combined we are confident that we will be able to significantly improve the energy efficiency of public lighting without compromising safety and well-being.

ACKNOWLEDGEMENTS

This work is co-funded by Fundos Europeus Estruturais e de Investimento (FEEI) through Programa Operacional Regional Norte, in the scope of project NORTE-01-0145-FEDER-023577.

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