Electrical Energy Management in five-star Hotel in Lisbon

Daniel Velez Ventura

daniel.v.vent@live.com.pt

Instituto Superior Técnico, Universidade de Lisboa, Portugal

June 2018

Abstract: Building sector is the primary focus of European Union, since the whole sector (residential buildings, public administration, offices and commercial building) accounts for a large percentage of energy consumption (40%) and of CO2 emissions (36%). Within all categories of buildings, hotel industry presents highest energy consumption and greater environmental impact (Priyadarsini, Xuchao, & Eang, 2009). The main goal of this study is to provide efficient energy managing strategies to a five-star hotel unit located in Lisbon without influencing the comfort and service quality.

All the data was provided by hotel unit and used for forecasting, in order to predict the following day energy consumption necessity. Data includes daily energy consumption, hourly temperature in the city of Lisbon and monthly occupancy, from 2013 to 2017, which results in 1.795 observations for each variable. All this data is optimized to provide the study more precision.

Through MatLab software, are developed four forecast models: ARIMA, MLR, kNN and SVR which estimated consumption values for the following day, week and month. For the next, the MLR model unexpectedly had greater accuracy and less error.

Keywords: Energy management in hotel industry; Forecasting for energy consumption

Introduction

With the global population growth and technological development, energy consumption levels have grown exponentially. The solution depends not only on development of new production technologies, but also improvement and adaptation to the new energy efficiency methods, in order to reduce consumption and dependence on natural sources of fossil origin.

This study proposes an analysis of the energy management in a five-star hotel located in Lisbon, Portugal. The main goal is to study possible solutions to increase the energy efficiency of the hotel, combining a good management with machine learning techniques to forecast electrical consumption. In this way, hotel maintenance managers, will be able to respond to the charges imposed by the energy operator and identify possible problems in the electrical system.

The hospitality industry focuses on service quality and comfort of the guests. The requirements imposed on these aspects, are often translated into large, sometimes excessive, high-energy consumption (Wang, 2012).

According to the legislation, the hotel unit under study, fulfils all the requirements in obtaining the five-star rating (Turismo de Lisboa, 2016). Consequently, it falls within the category of hotels with excessive energy consumption, according to the study of Wang (2012).

75% of the energy consumed in a hotel is related to space heating, hot water production, air conditions, ventilation and lighting Tsoutsos et al. (2013). Therefore, this study focuses on electrical energy only, as it represents the highest consumption to provide essential services (Mardani et al., 2016). Energy management is crucial to attenuate environmental problems, reduce energy consumption and increase hotels' sustainability.

Energy Management in Hotel Industry

According to (Mardani et al., 2016), the parameters that influence the energy consumption are several: the geometry of the hotel (usable floor area), the heat transfer coefficient of the building structure, age, geographical location (weather conditions), occupancy rate, services provided, equipment type and efficiency (heating, cooling, hot water, HVAC systems, kitchen and others). In addition to these factors, another aspect to consider is related to the conditions that are offered to hotel guests.

According to Neto (2015), in his research carried out in 4 and 5 star hotels in Portugal, it was verified that the energy performances are strongly related to the parameters: usable floor area and occupancy rate. The author highlights the importance of lighting and heating in hotel energy consumption standards. The estimate of how much energy the hotel has to provide for each guest is 32.27kWh/guest, says the author.

In Portugal, energy consumption in hotels ranges from 99 to 445kWh/m^2, with an average value of 296kWh/m^2/year in 2001 (Bohdanowicz & Martinac, 2007). For 4 and 5 star hotels, the average electricity consumption was 220 and 229kWh/m^2/year in 1999 (Mather & Ogilvy, 2003). More recently obtained results, in a study of 13 hotel units of 4 and 5 star, averaged 196 kWh/m^2/year for 5 stars and 165.9 kWh/m^2/year for 4 stars. It is also mentioned that, on average, expenditures on electricity are 64% of total billed consumption (Neto, 2015).

In order to frame the hotel unit under study into energy panorama of Lisbon's four and five-stars hotels, was created a structures analysis that investigates the behaviour pattern, values and motivations relates do energy efficiency. More precisely, the analysed hotels are in the same geographic, climatic and socioeconomic circumstances of the hotel under study.

The sample represents 17 different hotels (4 and 5 stars) which were questioned through an online survey. Each participant is specifically the maintenance director or energy manager. After a pre-selection of participants, the Delphi method was used with the aim of converging to a reasonable consensus among the respondents. This method is structured in consecutive rounds of questionnaires based on Likert's scale. The process ends when all the respondents agree (converge to the same answer) in all questions (Ab Latif, Mohamed, Dahlan, & Mat Nor, 2016).

In this study, all the respondents agree that energy performance certificates contribute to the sustainability of a building, although only 40% of respondents actually have energy certifications issued by ADENE (National Energy Agency), and only one reached an A classification (scale form C to A+++). In case of alternative energies, all respondents totally agree on the importance of these systems for energy efficiency, however only 36,3% of the respondents' use renewable energy sources.

It is also concluded that, when it comes to select an energy saving system, the most important aspects that professionals analyse are: efficiency, price and return on investment. Environmental responsibility is considered an important aspect by 100% of respondents.

The are several management strategies for an efficient use of energy:

Reduction of thermal requirements

Combined Cooling, Heating and Power (CCHP) system can reduce the cooling and heating needs of the building, through direct and automatic energy regulation, reducing its use (Cho, Smith, & Mago, 2014).

Equipment efficiency

The higher energy efficiency of an equipment, higher building efficiency, lower energy expense (Lopes, Hokoi, Miura, & Shuhei, 2005). Gago et al. (2015) developed a study on natural lighting control in buildings, with the aim of increasing the penetration of natural light, thus reducing the use of artificial lighting.

Efficiency of management systems

Energy saving switch, using a card reader to open the room door and control the lights, is one example of management systems. The hotels have great needs for the use of hot water and the heat generated in the refrigeration (chillers, refrigerators) can preheat the water, improving the efficiency of the system. In addition, the cooling system can function freely, thereby reducing the need for energy use in both systems (Mardani et al., 2016).

Renewable energy

Hotels use conventional energy resources known as the sun, wind, biomass, sea and water, which are used mainly in heating, refrigeration, hot water supply and lightning (Mardani et al., 2016). For remote areas the hybrid systems of renewable energy, due to their reliability, are the most appropriate (Fadaee & Radzi, 2012).

Forecast of consumption

Two main factors in foreseeing electrical consumption are improving energy performance through intelligent demand management and fault detection (Fan, Xiao, & Wang, 2014). Development of forecasting models includes engineering methods, grey-box modelling, machine learning and artificial intelligence methods (Hahn, Meyer-Nieberg, & Pickl, 2009).

Building Electrical Energy Consumption Forecasting

One of the strategies currently used in energy management is model predictive control (MPC). MPC is used to anticipate future events and optimize end-use energy. It is a tool that allows to control events in real time, taking into account cost reductions (Ma, Qin, Salsbury, & Xu, 2012). For this, it is essential to have a consumption forecast model.

Some forecasting methods do not depend on a model and can only support data. However, these require a vast amount of building-specific information (Liu & Henze, 2007).

In hotels, some types of charges depend on the number of rooms occupied. Occupation is directly connected to the power consumption, on the other hand, there are fixed services linked to the normal operation of the hotel where charges are independent of the occupation. In addition, outdoor temperature, seasonal variations, etc., are also variables that influence the functioning of the hotel unit (Tarasak, Chai, Kwok, & Oh, 2014). The author specifies that there are variables that can be programmed by specific dates or periods and others that cannot, due to mandatory comfort and quality requirements.

With the focus on short-term energy forecasting, Fan et al. (2014) aimed first to improve gaps in energy consumption data to improve precision. Secondly, data-driven methods are used to select input variables. And thirdly, to improve accuracy and stability of predictions, authors use a more advanced data mining technique, essemble learning.

Fan et al. (2014) analyse consumption data (15 minute intervals) from one year of the highest building in Hong Kong. The aim is to forecast the next-day energy consumption. In order to achieve this outcome, author uses eight prediction models: multiple linear regression (MLR); autoregressive integrated moving average (ARIMA); support vector regression (SVR); random forests (RF); multi-layer perceptron (MLP); boosting tree (BT); multivariate adaptive regression splines (MARS); and k-nearest neighbours (kNN). In this study are used four of the models described above: MLR, ARIMA, kNN and SVR.

MLR and ARIMA are both linear methods. Multiple Linear Regression is a statistical method that is used to analyse the relationship between a single response variable (dependent variable) with two or more controlled variables (independent variables) (Oliveira et al., 2017). It is the most common method for linear regression analysis. ARIMA is a clear structure of time series data that describes the time dependent parameter of the mean and residual value (Ding, Duan, Zhang, Wu, & Yu, 2018).

k-Nearest neighbours (kNN) is a non-parametric learning algorithm used for either classification or prediction. It is non-parametric as it does not learn an explicit mapping relationship between inputs and outputs. The parameter k, defines the number of neighbours (closest observations) (Fan et al., 2014).

Support Vector Regression (SVR) is well known for its ability in capturing nonlinearity (in contrast with ARIMA) and depends only on a subset of the training data. SVR uses kernel function to solve nonlinear problems more efficiently (Fan et al., 2014).

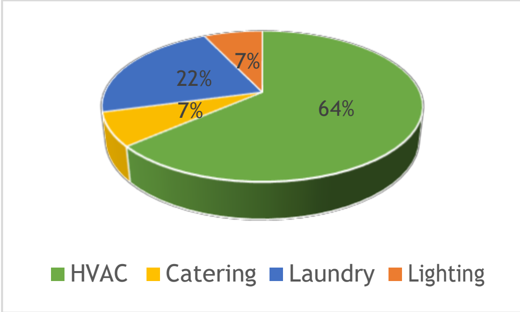
Predictive models' precision is defined by RMSE (root mean square error) and MAPE (mean absolute percentage error).

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{n}}$$

$$\mathrm{MAPE} = \frac{1}{n} \times \sum_{i=1}^{n} \frac{|Y_i - \hat{Y}_i|}{Y_i}$$

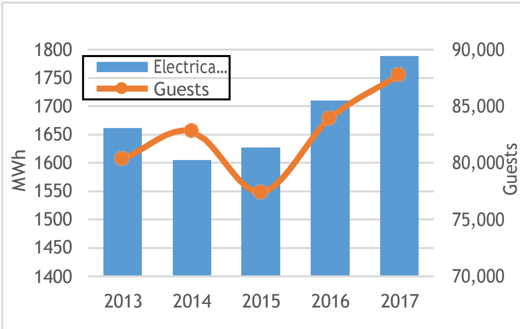
Hotel Unit Analysis

The 5-star hotel under study has a total of 147 rooms, 12 floors and 13.311m^2. All the equipment and building areas were analyzed in order to conclude which ones influence the most the consumption. It is clear that HVAC (heating, ventilation and air-conditioning) represents 64% of total electric consumption, while laundry represents 22%, illumination and catering are both 7%.



Graph 1 - Building Areas Energy Loads

Electric bills, from the last five years (2013, 2014, 2015, 2016 and 2017), provided by the hotel, show the tariff schedule. The price depends on time of day, season, weekday or weekend. Based on these data were created a profile of monthly consumptions in the past five years. There is an increase in consumption in line with the increase in tourism in Lisbon in the past two years.
The same conclusion is verified when the occupation is analyzed.



Graph 2 - Electric consumption VS Guests (Annual)

As is it shown in Graph 2, depending on the increase of guests, increases the energy consumption.

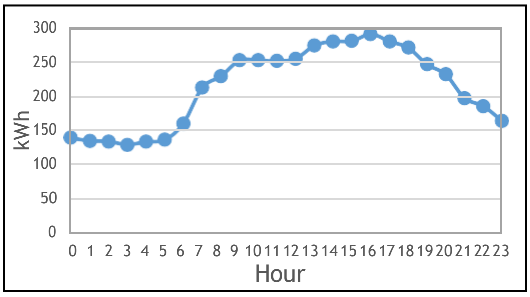
Seasons	Average consumption [KWh]	Average occupancy rate	Consumption by: [kWh]		
			Room	Occupied room	Guest
Winter	138980,73	75%	31,51	41,92	22,78
Spring	134035,20	89%	29,73	33,54	18,64
Summer	151772,33	87%	33,67	38,56	20,54
Autumn	134816,67	88%	30,23	34,44	19,82

Table 1 - Average Consumption per Room and per Person

On average, every year a guest requires 20.45 kWh/guest (**Error! Reference source not found.**) of energy to the hotel. The worst period is related to the winter of 2015 with an occupancy rate of 69% and a consumption per client of 24.47kWh/guest. It means that winter is the season that requiers more energy.

Daily Electric Consumption Profile

Data provided to create a daily electric profile refers to hourly consumptions from one day in different building areas, between 07/09/2017 and 12/09/2017.



Graph 3 - Daily Electric Consumption Profile

In the graph above is visible the beginning of daily activity in the hotel with the increase of the consumption around 07:00am. The time of greatest consumption takes place between 13:00 and 18:00, it is when the lunches are served, the check-ins are made and other services are taking place. After 18:00 consumption is gradually decreasing, most of the services are finished, the number of staff and the activity of the guests is reduced.

Forecast Models

The data used for forecasting includes daily energy consumption, hourly temperature in the city of Lisbon and monthly occupancy, from 2013 to 2017, which results in 1.795 observations for each variable.

In order to optimize data entries, all the observations under 2000kWh and above 7000kWh (16 observation) were replaced by their own mean value.

Temperature data were organized into four variables: Maximum Temperature, Minimum Temperature, Medium Temperature and Degree Day.

<u>ARIMA</u>

Three parameters, which define the numbers of autoregressive terms, differencing order, and moving average terms, were optimized for ARIMA models. The corresponding values are (5, 1, 4).

<u>MLR</u>

No parameter needs to be optimized for MLR, however to increase accuracy, a linearity test of all variables is performed. In this way, was identified the optimum number of previous days which will be used to create the model.

<u>kNN</u>

The value k was optimized for kNN models and the optimized value is 472.

<u>SVR</u>

In order to optimize the parameters were used Radial Basis Function (RBF) kernel. 30 iterations are performed and the best value observed according to Kernel Scale was 5,1165 and according to Epsilon (ε) was 78.783.

<u>Results</u>

To facilitate data interpretation, the results were divided into three groups: evaluation of the consumption forecast of 30% of the input data; assessment of the next day consumption forecast; assessment of the next month consumption forecast.

The evaluation of the 30% of input data is done by the root mean square error (RMSE) method and by the MAPE (absolute mean error), that evaluates the forecast of each observation, which makes a total of 540 observations evaluated by the model. In the case of ARIMA, 534 were evaluated because 16 observations of the initial data were removed.

Model	RMSE	MAPE (%)
ARIMA	12756,00	8,97
MLR	5273,10	10,14
kNN	6931,70	11,72
SVR	3015,60	5,91

Table 2 - Forecast estimation for 30% of the input data

Table above shows that the most precise model is SVR, within the models used, the results are parallel with study by Fan et al. (2014). In the other hand, models presented worse performance when compared to the Fan et al. (2014) study. This decrease in accuracy may be a consequence of the type of data used and the processing of the input data.

In order to obtain a more empirical evaluation, the forecast for the next day (01/12/2017) was executed.

Model	RMSE	MAPE (%)
ARIMA	260,65	5,85
MLR	2,67	0,06
kNN	397,00	8,97
SVR	332,68	7,52

Table 3 - Forecast evaluation for the next day

At the previous table, MLR model has an accurate forecast of actual consumption for that day. The SVR, that stood out as the best previously, in this case had reduced its accuracy, while all other models improved their precision. One of the explanations that can describe this great variation can be related with model optimization. More precisely, taking away the MLR, the optimization was done to the entire data set. The optimized MLR only uses 43 earlier observation to create the model. This model throughout the year has several fluctuations in the results, certain periods with bad and good results that occur in the period under analysis.

Finally, to understand forecasts' precision for a month, was made the evaluation for the total consumption of December 2017. Here all models reach quite satisfactory performances as it is shown at the next table. The ARIMA model did the best forecasting performance.

Model	RMSE	MAPE (%)
ARIMA	71,32	0,30
MLR	706,32	4,76
kNN	1518,90	6,00
SVR	956,05	3,77

Table 4 - Forecast evaluation for the next month

The kNN algorithm always obtained the worst performance in all evaluations made. In this type of models, it is extremely important to structure a set of optimal data entry, that is, to remove unnecessary information and define the relevant variables. This type of treatment increases model efficiency, as well as the computation time.

Conclusion

The objective of this work was to study, through different approaches, the energy characteristics of 4 and 5-star hotels in Lisbon and to develop a methodology to support energy management, based on the electric consumption forecast, of a specific hotel.

The approaches were composed of scientific research, through articles investigated on the Internet, survey to the hotels in the city of Lisbon and inspection of hotel equipment and characteristics (audit).

All this process was essential in the development of the study, since it allowed to identify all the parameters essential to the proposed development of four models of machine learning.

- **ARIMA** (autoregressive integrated moving average)
- **MLR** (multiple linear regression)
- **kNN** (k-nearest neighbors)
- **SVR** (support vector regression)

High occupancy rates and the mandatory comfort requirements in this type of buildings provide the ideal scenario for a large demand for electricity. About 64% of the total billed consumption is related to electricity (Neto, 2015). To respond to this problem and increase energy efficiency in the hotel, a set of prediction models has been developed, which has been subjected to three main steps:

1. Characterization and processing of data
2. Optimization of Models
3. Evaluation and precision of the models

During the data treatment, were identified parameters that influence hotels' energy consumption, such as: usable floor area, structural characteristics of the building, meteorological conditions, occupancy rate, equipment efficiency and services. In addition to studying these parameters, a survey was carried out to analyse energy patterns and behavior of 4 and 5 star hotels in the city of Lisbon. The main conclusion was that energy efficiency strategy is a trend of most hotels. The hotel under study is not the most efficient one in the region, but it seeks do find solutions to improve.

The culmination of modeling is to evaluate forecasting in three different scenarios. The first is an evaluation of 30% of the input data; second is according to the following day's evaluation; and last one according to an evaluation of the following month.

At the first scenario, with a greater number of days predicted, it is possible to verify that the SVR was the one that obtained the best performance. The MLR and kNN models had the worst performance. The ARIMA and MLR models do not perform better because the set of variables used are generally non-linear, reflecting fluctuations throughout the year in the forecasts.

In the second scenario, the MLR is the best against the previous results, it is a period where the MLR algorithm performs well. This performance is due to the large linear correlation of the variables, which occurs at this time of year. Within the previous results, only the kNN remains the worst performance, although it has improved somewhat. The SVR of all in this scenario was the only one that lowered performance.

Finally, in the third and last scenario, all models significantly improved their performances with greater distinction of the ARIMA model. This scenario was only counted the total energy of the month, not the days during the month, this approach causes a reduction in the error and does not reflect the forecast of the days of the month, but of the month.

In short, these models may have better performance in forecasting and computation time, if available, a selection of appropriate input data. This selection should drastically reduce the number of observations and remove inconsistent or irrelevant data for the model. The process of creating the models is computationally time-consuming, but with the created models making the forecast based on new data is a fairly quick process.

The application of this type of management technique can help to take previous measures on days where high consumption is expected. helps to identify faults in electrical systems, thus reducing the time of perception. And it can help identify possible changes in the various branches of the hotel in order to increase the energy efficiency of the building.

References

Ab Latif, R., Mohamed, R., Dahlan, A., & Mat Nor, M. Z. (2016). Using Delphi Technique: Making Sense of Consensus in Concept Mapping Structure and Multiple Choice Questions (MCQ). *Education in Medicine Journal*, *8*(3), 89–98. http://doi.org/10.5959/EIMJ.V8I3.421

Bohdanowicz, P., & Martinac, I. (2007). Determinants and benchmarking of resource consumption in hotels-Case study of Hilton International and Scandic in Europe. *Energy and Buildings*, *39*(1), 82–95. http://doi.org/10.1016/j.enbuild.2006.05.005

Cho, H., Smith, A. D., & Mago, P. (2014). Combined cooling, heating and power: A review of performance improvement and optimization. *Applied Energy*, *136*, 168–185. http://doi.org/10.1016/j.apenergy.2014.08.107

Ding, C., Duan, J., Zhang, Y., Wu, X., & Yu, G. (2018). Using an ARIMA-GARCH Modeling Approach to Improve Subway Short-Term Ridership Forecasting Accounting for Dynamic Volatility. *IEEE Transactions on Intelligent Transportation Systems*, *19*(4), 1054–1064. http://doi.org/10.1109/TITS.2017.2711046

Fadaee, M., & Radzi, M. A. M. (2012). Multi-objective optimization of a stand-alone hybrid renewable energy system by using evolutionary algorithms: A review. *Renewable and Sustainable Energy Reviews*, *16*(5), 3364–3369. http://doi.org/10.1016/j.rser.2012.02.071

Fan, C., Xiao, F., & Wang, S. (2014). Development of prediction models for next-day building energy consumption and peak power demand using data mining techniques. *Applied Energy*, *127*, 1–10. http://doi.org/10.1016/j.apenergy.2014.04.016

Gago, E. J., Muneer, T., Knez, M., & Köster, H. (2015). Natural light controls and guides in buildings. Energy saving for electrical lighting, reduction of cooling load. *Renewable and Sustainable Energy Reviews*, *41*, 1–13. http://doi.org/10.1016/j.rser.2014.08.002

Hahn, H., Meyer-Nieberg, S., & Pickl, S. (2009). Electric load forecasting methods: Tools for decision making. *European Journal of Operational Research*, *199*(3), 902–907. http://doi.org/10.1016/j.ejor.2009.01.062

Liu, S., & Henze, G. P. (2007). Evaluation of Reinforcement Learning for Optimal Control of Building Active and Passive Thermal Storage Inventory. *Journal of Solar Energy Engineering*, *129*(2), 215. http://doi.org/10.1115/1.2710491

Lopes, L., Hokoi, S., Miura, H., & Shuhei, K. (2005). Energy efficiency and energy savings in Japanese residential buildings - Research methodology and surveyed results. *Energy and Buildings*, *37*(7), 698–706. http://doi.org/10.1016/j.enbuild.2004.09.019

Ma, J., Qin, J., Salsbury, T., & Xu, P. (2012). Demand reduction in building energy systems based on economic model predictive control. *Chemical Engineering Science*, *67*(1), 92–100. http://doi.org/10.1016/j.ces.2011.07.052

Mardani, A., Zavadskas, E. K., Streimikiene, D., Jusoh, A., Nor, K. M. D., & Khoshnoudi, M. (2016). Using fuzzy multiple criteria decision making approaches for evaluating energy saving technologies and solutions in five star hotels: A new hierarchical framework. *Energy*, *117*, 131–148. http://doi.org/10.1016/j.energy.2016.10.076

Mather, & Ogilvy. (2003). *Eficiência Energética nos Edifícios*. *Direcção Geral de Energia Ministério da Economia*. http://doi.org/http://www.adene.pt/NR/rdonlyres/00000092/zaxpmqlrayniuusffzenbctcmilxaxam/Efici%C3%AAnciaEnerg%C3%A9ticanosEdif%C3%ADcios.pdf

Neto, P. (2015). *Metodologia integrada de gestão de energia em hotelaria*. Instituto Superior Técnico.

Oliveira, M. M., Camanho, A. S., Walden, J. B., Miguéis, V. L., Ferreira, N. B., & Gaspar, M. B. (2017). Forecasting bivalve landings with multiple regression and data mining techniques: The case of the Portuguese Artisanal Dredge Fleet. *Marine Policy*, *84*(July), 110–118. http://doi.org/10.1016/j.marpol.2017.07.013

Tarasak, P., Chai, C. C., Kwok, Y. S., & Oh, S. W. (2014). Demand bidding program and its application in hotel energy management. *IEEE Transactions on Smart Grid*, *5*(2), 821–828. http://doi.org/10.1109/TSG.2013.2287048

Tsoutsos, T., Tournaki, S., Santos, C. A. de, & Vercellotti, R. (2013). Nearly Zero Energy Buildings Application in Mediterranean Hotels. *Energy Procedia*, *42*, 230–238. http://doi.org/10.1016/j.egypro.2013.11.023

Turismo de Lisboa. (2016). Análises desta edição. *Observatório Do Turismoa de Lisboa*. Retrieved from https://www.visitlisboa.com/sites/default/files/2017-02/OBS-RTL N.157.pdf

Wang, J. C. (2012). A study on the energy performance of hotel buildings in Taiwan. *Energy and Buildings*, *49*, 268–275. http://doi.org/10.1016/j.enbuild.2012.02.016