Neural Network-based Forecasting of Energy Consumption due to Electric Lighting in Office Buildings

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Abstract — **This paper presents a novel method to predict the energy consumption due to electric lighting in office buildings, knowing the external daylight. For each month an ideal reference irradiation curve is calculated based on the actual irradiation curves of the days of that month. The office (business) operation hours are seen as a sequence of time intervals (of a few hours) based on the usual office use.**

The system uses as input parameters the day, the time (hour and minutes), the month, the average difference between the actual irradiation curve and the ideal reference irradiation curve in the considered interval, the instantaneous difference between the two curves at that time, and the average actual irradiation in the considered interval. The system predicts the average active power in the following interval. In this way the electric energy consumption is essentially influenced by the quality of the irradiation curve in the considered day. The system was developed as a feed-forward artificial neural network, which was applied to a case study concerning a small office located in Italy. In the experiments, made on the data pertinent to six months, we achieved an average RMSE error which represents 17.25% of the monthly average electric power.

Keywords-electric energy consumption; office buildings; neural networks; short-term forecasting

I. INTRODUCTION

Energy consumption in buildings is one of the fastest growing sectors. It is estimated that the amount of the energy consumed in the European buildings is about 40–45% of the total energy consumption [1]. In particular, as regards office buildings, earlier works have shown that electric lighting is a big component of electricity consumption: it accounts for about 25% of total electricity [2, 3].

The goal of this work is to forecast the electric consumption, due to lighting, in a small office building. The potential benefits of knowing, in real time or even in advance, energy consumptions can be useful for several purposes, ranging from cost reduction, improved energy control, and smarter load scheduling.

The electric energy consumption could be easily estimated knowing the kind and the number of lights and appliances existing in the office and their operating time, but this knowledge is not always easy to achieve. From another point of view, one could expect that the amount of energy consumption due to lighting should be inversely proportional to the amount of natural daylight in the office. Actually, we must take into account the unpredictable component given by occupants' needs and behavior.

Of course, natural daylight depends on the particular building (position and orientation, glazed surface, windows surface kind, etc.) and overall on weather conditions, which can influence the measured value of solar irradiation. Hence, we propose a way of estimating the electric energy consumption, using mainly the solar irradiation data and assuming that the occupants simply try to assure the necessary visual comfort inside the office [4] by paying attention to energy savings.

Several techniques have been traditionally used for energy use forecasting. Among them, we recall some time series analysis classical techniques such as ARIMA [5-6] and regression [7-8]. In the last few years there has been also a growing interest in computational intelligence tools, in particular, neural networks [2, 9-10], expert systems [11], genetic algorithms [12], and hybrid systems [13-14].

Regarding prediction, we need to differentiate between short-term and long-term electric energy forecasting. The former refers to prediction with a horizon of hours, days or weeks. The latter refers to a monthly or even annual horizon. More importantly, long-term prediction usually deals with data that rarely present significant distortions, thus possible irregularities in the data will have very small influence on the overall predicted value. On the contrary, in short-term prediction, an irregularity caused by an unpredictable fact (e.g., a weather phenomenon, an unexpected event, etc.) has a fast and high influence on data [15].

We propose a short-term forecasting method of the energy consumption due to lighting in a small office building. After subdividing the working day into a sequence of time intervals, each corresponding to a specific typical use of the office (which corresponds to a specific, typical use of the lighting system), we build a neural network-based forecasting system, which basically exploits the knowledge about the month, the day of the week, and the solar irradiation in a given time interval, to predict the average energy consumption due to lighting in the following time interval within the working day.

The proposed forecasting method does not need any

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information about the building (such as construction materials, position and orientation), about the lighting equipment (type and number of lights and their operating time), or about the occupancy as usually happens when using simulation tools. In fact, to have to know in advance all these kinds of information may be a drawback [4]. The best exploitation of the proposed system is its application with building-integrated photovoltaic (BIPV) systems.

The paper is organized as follows. Section II describes the experimental data, Section III presents the proposed method to predict the electrical energy consumption due to lighting. Section IV shows the simulations results, and Section V provides concluding remarks and future work.

II. Experimental Data

The data used in this work were collected from the sensors of an office building located in Tuscany, Italy. The data were measured every 15 minutes during 6 months, from April to September 2011. The available data consisted of i) solar irradiation outside the building, ii) sampling timestamp (date and time), and iii) lighting electricity consumption, expressed in terms of active power averaged over 15-minute intervals, which is known to be the real power transformed into work.

We exploited the following input data: *solar irradiation*, *day*, *month*, and *timestamp* (i.e., hour and minute). Regarding the *day of the week*, we chose not to use an explicit information regarding the kind of day (working or weekend) in order to maintain the model as general as possible. Instead, we coded the days of one week from 1 to 7. So doing, we are also able to model further cyclic activities, such as cleaning tasks, periodic meetings, etc. The output parameter is the *average active power* over intervals of a few hours, as better explained in the following.

Moreover, we had some information about the cleaning schedule and about the presence of obstacles in front of the irradiation sensor (see Table I). These data helped us correctly analyze and interpret the experimental results.

III. The Proposed Method

As previously stated, we aim to predict the electric energy consumption due to the use of lighting in an office building. Although the electric power consumption is not the highest one in a building, it is present throughout the working day and it deserves to be taken into account alone.

As we are concerned with a small office, we deal with very small values of consumption if compared with those found in the literature, which are related to big buildings or include the total HVAC (Heating, Ventilation and Air Conditioning) systems consumption. Furthermore, the values we are concerned with are highly irregular.

The correlation between solar irradiation and electric energy consumption is not straightforward. Actually, when a building is in use, the intensity and the stability of the solar irradiation can be considered as the factors that have the greatest influence on the decrease and increase in lighting consumption. By intensity we mean the absolute value of irradiation at every considered instant. The artificial lights are used because the value of the lighting is not enough inside the building. If the solar irradiation had the same time evolution every day, the electric power consumption would not vary significantly from one day to another. Actually, the time evolution of the electric power consumption has many differences between days as Fig. 1 clearly shows. Figure 1 shows the evolution of the electrical consumption and solar irradiation for seven days of a typical Spring week (from Monday May 9th to Sunday May 15th).

Therefore we need to find out how to exploit the available data so as to reproduce the relation between solar irradiation and electrical lighting consumption.

TABLE I. BUILDING CHARACTERISTICS

Characteristic name	Characteristic value
Location	Tuscany, Italy
Obstacles	A tree obscures the irradiation sensor at about 10 a.m.
Usual office operation hours	Monday to Friday: 9 a.m.–9 p.m.
Cleaning schedule	Tuesday to Friday: 7 a.m.–8 a.m.; Saturday morning: actual time not fixed

A. Analysis of Solar Irradiation Trend

The first consideration regards the analysis of the solar irradiation trend. Solar irradiation and thus daylight availability mainly depend on geographic latitude and on climatic contest. In particular, latitude-related variations are caused by changes in the sun position with the latitude. Climate-related variations, also called sky conditions, can be classified as clear, partly cloudy, and overcast [16].

We noticed that clear sky days with high solar irradiation have regular electrical consumption. Instead, overcast or partly cloudy sky days correspond to a mostly irregular electrical consumption (see Fig. 2). It is clear that there is a relation between the daily solar irradiation trend and the electrical consumption due to the use of lighting. Moreover, given the same sky conditions in two consecutive days, we found that the daily solar irradiation curve slightly changes from one day to the following. On the other hand, if the sky conditions in the considered climatic period change, the irradiation curves differ from each other to a greater extent. In any case, over a period of about one month, most irradiation curves appear to be very close to each other.

Based on these considerations, we can consider a single curve representing the climatic period by simply using the curve that best approximates all the curves of the involved days. We will call this curve *ideal typical irradiation curve*. Figure 3 shows the ideal typical irradiation curve for June: this curve represents an ideal "typical" day of that month.

For the purpose of this paper, the chosen period of time is therefore a month. A month can be considered as an important time unit from the weather point of view and many works in the literature often deal with monthly analysis [17].

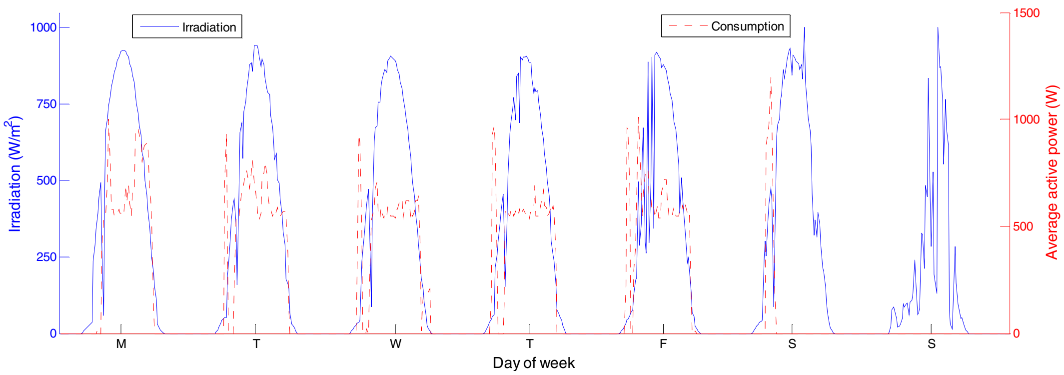

Figure 1. Evolution of consumption (dotted line) and irradiation (solid line) from Monday May 9th to Sunday May 15th.

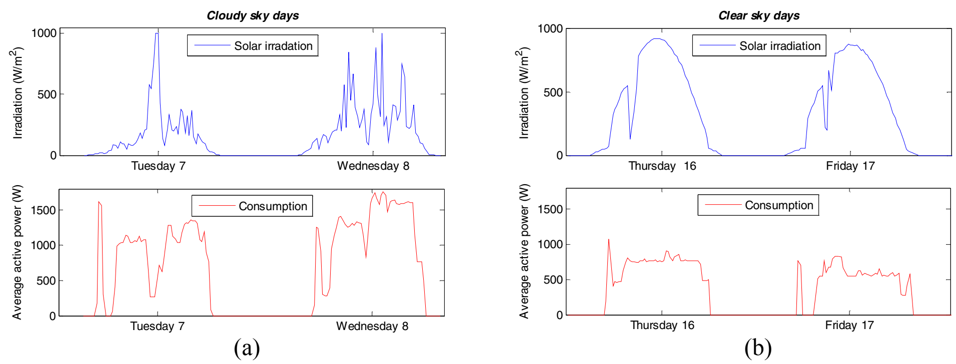

Figure 2. Electrical consumption with different sky conditions for four days of June. (a) Cloudy sky days. (b) Clear sky days.

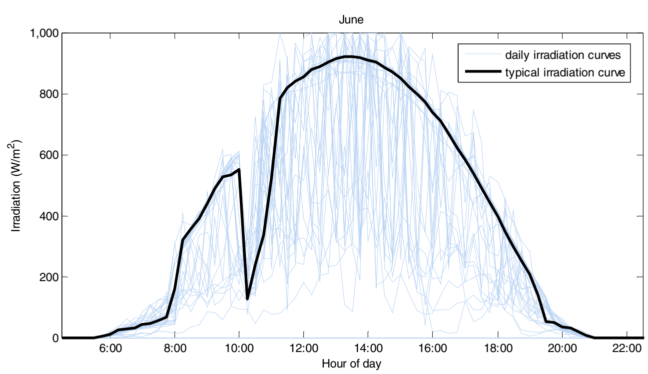

Figure 3. Daily irradiation curves for June, and corresponding typical ideal irradiation curve.

More precisely, from an operation point of view, for each month we have performed the following steps. After superimposing the irradiation curves relative to all days of that month (as done in Fig. 3), we have noticed that most curves almost coincide, in the sense that their difference is very small in all points. So, after removing the few curves that represent outliers, we have generated the curve that best approximates all the involved curves.

In Fig. 4 we show the typical ideal irradiation curves for the 6 months from April to September. We can notice that the discontinuity present in all curves at about 10 a.m., due to the presence of a tree that obscures the irradiation sensor, slightly changes as a result of the movement of the sun.

Our choice to keep this discontinuity in the ideal typical curves stems from the will to use this curve to faithfully model the particular spatial context of the building.

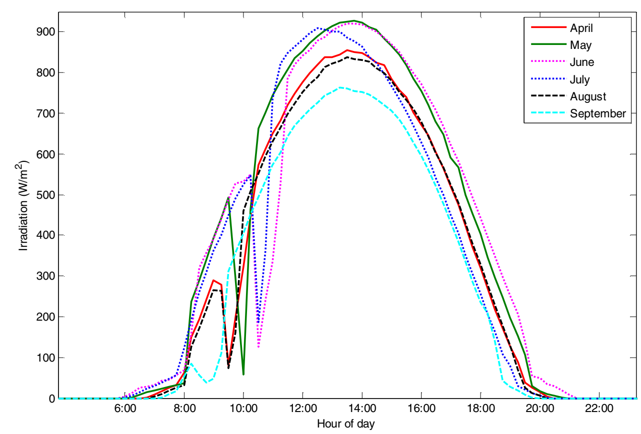

Figure 4. Typical ideal irradiation curves for the 6 months.

For each month we use the corresponding typical ideal irradiation curve to characterize each given day in the month. More precisely, we compare the ideal curve with the actual daily irradiation curve, so as to highlight how the considered day differs from the "typical" day of that month. Figures 5(a) and 5(b) show, respectively, the typical ideal irradiation curves and actual irradiation curves for three days (from Tuesday September 6th to Thursday September 8th), and the corresponding differences. From Fig. 5 we can notice that in clear days (like September 8th) the actual irradiation curve perfectly follows the ideal curve. On the contrary, in cloudy days (like September 6th and 7th) there are quite a lot of variations in the irradiation values (probably due to weather fluctuations) between the ideal and actual curves. We used the difference between the daily actual irradiation curve and the typical ideal curve as further input parameter to our system.

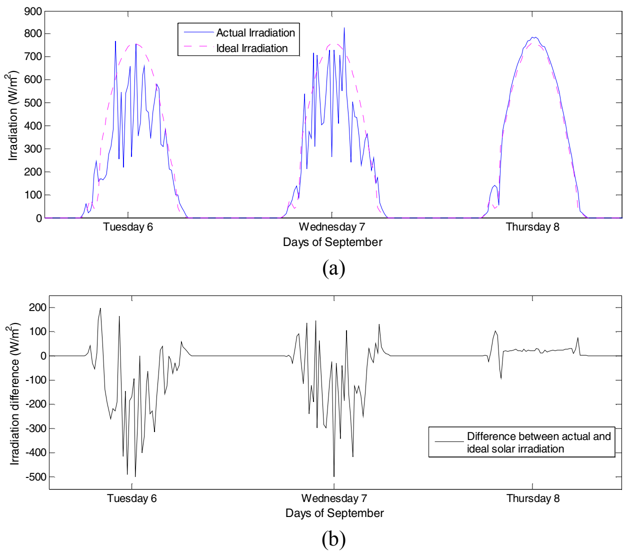

Figure 5. (a) Typical ideal irradiation curve and actual irradiation curve for September 6th - 8th. (b) Difference between the two irradiation curves.

B. *Analysis of Energy Consumption Based on Office Use*

The second consideration concerns the analysis of the energy consumption in relation with the specific use of the office taken into account.

Considering the energy consumption trend of a typical working day, we have split each day into a small number of intervals with the aim of taking into account the use of the office building in the various parts of the day. In order to identify the most appropriate number of these intervals, we have tried several combinations and we finally found out that the working time, from 9 a.m. to 9 p.m., can be profitably subdivided into three intervals of 4 hours each. Indeed, we aim to predict the average energy consumption of a given time interval based on information pertinent to the previous interval. Of course, in order to predict the electrical consumption related to the first interval, we added a service interval, called *interval 0*, from 5 a.m. to 9 a.m..

By analyzing the weekly consumption trend, we noticed that the consumption data present daily and weekly cyclicity during the whole year: from Monday to Friday there is a considerable variability of electric power consumption in the working hours, and on Saturdays there is only consumption in a little span of one hour. In addition, in four days a week (from Tuesday to Friday) there is a peak, relative to a high electric power use during one hour before the beginning of working hours, in correspondence with the cleaning time of the office. The same peak occurs on Saturday morning at a non-fixed time.

A further consideration regards the fact that in most cases we decided to use the average value within each considered time interval instead of all the instantaneous values. The reason is that this is the usual practice found in the literature, although relative to daily average values [2].

Summarizing, the input parameters to our system are: day, month, time (hour and minutes), average irradiation difference for the considered interval, instantaneous difference between actual and ideal irradiation at that time, average actual irradiation for the considered interval. All these input parameters are pertinent to a given time interval. The output parameter from our system is the average energy consumption, expressed in terms of average active power, for the following interval. Table II shows the inputs and output of the network, and their units of measurement.

TABLE II. INPUTS AND OUTPUT VARIABLES OF THE NETWORK

Input variable name	**Unit of measurement**
Day	Encoding: from 1 to 7
Month	Encoding: from 1 to 12
Timestamp (hour, minute)	Encoding: hour:minute
Mean difference for the considered interval between actual and ideal irradiation	W/m^2
Difference between actual and ideal irradiation for the considered timestamp	W/m^2
Average actual irradiation for the considered interval	W/m^2
Output variable name	**Unit of measurement**
Average energy consumption for the following interval	W

IV. SIMULATIONS AND RESULTS

We implemented the proposed approach with a feed-forward neural network with one hidden layer. The transfer functions for the hidden and output neurons are the default ones in the Matlab® environment, i.e., respectively, hyperbolic tangent sigmoid and linear functions. Likewise the training algorithm is Levemberg-Marquardt.

Regarding the number of hidden neurons, we tried different neural configurations by varying the number of hidden neurons from 10 to 30 with step 1. For each of the training, validation and test sets, the same number of samples is randomly extracted for each month so as to keep balanced sets. The percentages of samples extracted for each month are 60%, 10% and 30%, respectively, for the three sets.

Each kind of experiment was repeated 30 times. The best configuration was a neural network with 28 hidden neurons.

The aim of the simulations was the comparison between the actual electrical consumption in a given time interval and the predicted electrical consumption in the same interval. For each month, we computed the monthly MSE (Mean Squared Error) considering the three time intervals included in the operation hours of the office for all the days of the month. Then we obtained the average monthly MSE (MSE_{av}) by averaging the monthly MSEs over the 30 trials of the experiment related to the best neural configuration.

We also computed both the RMSE (Root Mean Squared Error) and the normalized RMSE as follows:

$$RMSE_n = \frac{1}{EP_{av}} \cdot \sqrt{MSE_{av}}\,, \qquad (1)$$

where EP_{av} and MSE_{av} are, respectively, the average monthly electric power and the average monthly MSE.

Table III shows the average monthly MSE, the RMSE, the monthly average electric power, and the normalized RMSE for the six months. Please note that in the available data there are some missing days in correspondence with sensor maintenance. In particular, there are 6, 1, 6 and 6 missing days for April, May, August and September. Obviously, these numbers have been taken into account for computing the MSE value.

As we can see from Table III, we achieve good results for April, May, June and July. Poorer results are obtained in August and September. In both cases, the high error is most likely due to the presence of frequent weather changes within the same day, as we observed by analyzing the irradiation curves of August and September. In such conditions the electric power consumption can be sensibly different from what expected, thus causing an increased prediction error. Further, in August, we must also take into account the partial, non regular daily occupancy of the office building during summer vacation, as testified by the low monthly electric lighting consumption. This situation obviously increases the prediction error.

TABLE III. AVERAGE MONTHLY MSE (MSE_{AV}), RMSE, MONTHLY AVERAGE ELECTRIC POWER (EP_{AV}), NORMALIZED RMSE ($RMSE_N$)

Month	MSE_{av}	*RMSE* (W)	EP_{av} (W)	$RMSE_n$ (%)
April	548.1	23.41	483.13	4.84
May	2058.9	45.37	408	11.12
June	2647.3	51.45	487	10.56
July	1816.8	42.62	307.24	13.87
August	340.72	18.45	48.23	38.27
September	12113	110.05	443.23	24.83

Therefore, we can state that the RMSE error ranges from 4.84% to 38.27% of the monthly average electric power, with an average value of 17.25%. In absolute terms, the minimum and maximum RMSEs are 18.45 W and 110.05 W, obtained for August and September, respectively.

To assess our results we applied the persistence method assuming as target value of the forecasted average energy consumption of a given interval the average energy consumption of the same interval of the previous day. We achieved an average monthly MSE one order of magnitude greater than the values shown in Table III.

V. CONCLUSIONS

We have described a novel method to predict the energy consumption due to electric lighting in a small office building, mainly based on solar irradiation. The forecasting system, implemented as a feed-forward artificial neural network, predicts the average active power in a given time interval of the working day exploiting the difference between an *ideal* irradiation curve (for a given month) and the actual irradiation curve in the previous time interval.

In the experiments the average RMSE error represents 17.25% of the monthly average electric power.

As a future work, we aim to extend the presented analysis to the heating and cooling consumption, in order to build a system able to estimate the total HVAC consumption of an office building. We are also planning to study this problem as a NARX model.

ACKNOWLEDGEMENT

We wish to acknowledge Samares, Via Giuntini, 25, 56023, Navacchio di Cascina, Pisa (Italy), for having provided the set of data used in the present paper.

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