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Green computing: a realistic evaluation of energy consumption for building load forecasting computation

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Abstract

Aim: The methodology proposed in this paper aims at analyzing the energy consumption, electricity costs, computation time, and accuracy associated with each forecasting algorithm and approach. Furthermore, a monitoring infrastructure is considered to provide inputs to the forecasting approach.

Methods: The main objective is to discuss to what extent it is reasonable to increase the consumption of the forecasting approach computation and monitoring infrastructure to achieve more accurate forecasts. Artificial neural networks are used as examples to illustrate the proposed methodology in a building equipped with electricity consumption and other parameters monitoring infrastructure.

Results: It has been shown that collecting many parameters and using very accurate forecasting approaches may cause an energy consumption higher than the energy consumption deviation resulting from the forecasting approach with lower accuracy.

Conclusion: Finally, it has been shown that green computing, or green computation, requires considering the computation of data, the impact of collecting such data, and the need to perform highly consuming computation tasks.

Keywords: Building energy management, green computing, intelligent buildings, load forecast

INTRODUCTION

Green computing aims to reduce the environmental impact of computation to achieve a sustainable environment[1]. Therefore, it targets maximizing energy efficiency while minimizing operational costs. Green computing is integrated into several areas, including proper power management, servers virtualization, data centers design, recycling methods, eco-labeling, environment sustainability design, and energy-efficient resources[2]. Green computing has a positive impact on several activities including business and environmental management, virtualization of businesses, design of information technologies initiative, environment sustainability, energy efficiency, and cost-effectiveness[3]. Green computing technologies are further valued in several application domains due to their potential to improve energy efficiency and scalability, reliability, and high performance at lower costs[4].

The optimization of energy distribution and usage, using smart grid technologies, improves energy efficiency and reduces greenhouse emissions[5]. Smart grids technologies, for example, offer effective management of renewable energy sources. However, from an environmental point of view, it is critical to guarantee energy costs reduction and a decrease in CO_2 emissions[6]. Commercial and institutional buildings research how human intervention may minimize energy losses through the adoption of energy saving techniques[7]. Therefore, it is vital to study both the impact of the user energy choices on the building energy demand and how these choices have the potential to reduce the building energy consumption using information systems[8]. Another application featuring this minimization consists of sorting customers' tasks influenced by their time and power needed to minimize the power consumption when making scheduling decisions[9].

Looking at the electricity demand side, Demand Response (DR) programs are important to reduce greenhouse gas emissions and ensure effective environmental protection. DR programs can, for instance, provide incentives to residential customers encouraging these to reduce the energy load during peak load hours.

Customers' participation in DR programs must be adequately supported with load forecasts, which can use artificial neural networks to predict consumer demand at different times of the day and/or for different days of the week[10]. At the same time, it is necessary to predict future renewable-based local electricity generation levels to take the best advantage of the locally generated energy[11]. Different methods are also used for predicting electricity prices. The unbiased model combines different machine learning techniques and creates clusters to increase prediction accuracy and decrease the categorical bias of these clusters as proposed in[12].

The energy management of data centers, another well-explored topic in the literature, considers two perspectives: minimizing overall energy consumption and reducing peak power demand during demand-response periods[13]. Data centers employ power management strategies to maximize green energy utilization and minimize electricity costs, thus resulting in more sustainable energy management[14]. Moreover, the progress in digital transformation enables data centers to improve the efficiency of electrical energy usage[9].

Cloud data centers can play a quite relevant role in prosecuting energy sustainability using green computing concepts for resource allocation. Basically, the main approaches in the literature can be divided into impact assessment and mitigation approaches. Forecasting is considered for resource needs to anticipate allocation issues[15]. On the other hand, cloud computing manages the green service-level agreements with the customers adequately using expenditure from green energy[16]. In parallel to this, it addresses and mitigates the impact of energy consumption on the environment, namely greenhouse gas emissions. A shadow replication model can help minimize energy consumption and reduce its impact on the environment[17]. A promising way to take advantage of the benefits of cloud computing is to develop a dynamic energy-aware cloudlet-based mobile cloud computing model[18]. Another approach for cloud computing is to focus on reducing the total energy consumption of the electric grid[19].

Currently, energy efficiency and sustainability are investigated and targeted by many proposed methods and applications; however, the current state-of-the-art still lacks a systematic evaluation of the impact of those approaches regarding the additional energy demand that they need to operate. The use of those solutions, in practice, can negatively impact the efficient use of green energy. A green energy application features forecasting the output performance degradation of proton exchange membrane fuel cells over time caused by impurities of hydrogen or fluctuation. It should be noted that a modified relevance vector machine is more effective in forecasting performance degradation compared to the classic support vector machine[20]. Financial forecasting accuracy and bias application intend to analyze the impact of green and sustainable measures on abnormal stock[21]. Urban scale is essential in energy system modeling for the green energy transition due to the spatial and temporal demand fluctuations as described in[22]. At the same time, cloud data centers aim at improving the quality of services in the field of environmentally sustainable computing. A promising way to achieve this is to minimize the energy consumption of data centers with the support of an optimization metaheuristic algorithm known as Ant Colony[23]. An alternative application proposes an adaptive fuzzy clustering algorithm to minimize energy consumption[24].

Energy management in buildings can be done intelligently with adequate artificial intelligence methods[25]. It is relevant to consider the energy production locally available, the variation of electricity prices along time, and demand response events[26,27]. Load forecasting is particularly important, and different approaches applied to buildings have been widely discussed in the literature. Recent works propose a contextual approach to the forecasting problem, which enables the forecasting methods' accuracy to be as high as possible for a wide range of different contexts[28,29]. It is suggested that different forecasting models should be used in different contexts of building operation instead of the model that is found to be the most accurate on average for all the contexts of building operation. In fact, in many works, the existence of different contexts of building usage is overlooked or considered shallow, and forecasting results might present low accuracy for many actual contexts. Moreover, several other forecasting algorithms have been studied and compared to artificial neural networks-based ones including k-nearest neighbors. The aforementioned research concludes that the artificial neural networks-based method is the more appropriate forecasting algorithm[28,29]. This paper proposes an approach to analyze the energy consumption, electricity costs, computation time, and accuracy associated with each forecasting algorithm. The main objective is to discuss how much it is reasonable to increase the energy consumption of the forecasting approach and the related monitoring infrastructure to achieve more accurate forecasts.

The rest of the paper is organized as follows: First, we present the proposed methodology in Sect. 2. Sect. 3 explains the energy monitoring infrastructure. Results are analyzed in Sect. 4. Finally, the discussion and the conclusions are presented in Sect. 5 and Sect. 6, respectively.

FORECASTING COMPUTATION AND EVALUATION METHODOLOGY

In this section, it is described how the study was conducted methodologically. The main focus is to explain how the load forecast computation and evaluation studies were conducted. The proposed methodology is organized into the following steps:

• Load forecast task

○ Data collection - load consumption and other parameters available to support the load forecast (e.g., temperature, people's presence, *etc.*) are collected from external services or databases.

○ Data processing - raw data are cleaned to correct outliers and missing values, as well as uniformize the size of timestamps, which can be different for distinct parameters.

○ Load forecast - one or more load forecasting algorithms are run for each target period. This task runs independently over time.

Different load consumption forecasting approaches can be used, namely artificial intelligence or statistic-based methods. An artificial neural network-based forecasting model proposed by the study in Ref.[28] has been used in this paper with the support of TensorFlow and Keras libraries. In fact, the authors have previously tested other approaches in research, as the ones published in Ref.[28], and they concluded that neural networks are more adequate for this application. The artificial neural networks model is composed of an input layer with ten neurons, two hidden layers with sixty-four neurons and a rectified linear unit activation function, and finally, an output layer. The input layer receives the variables of ten consumptions placed in sequential periods preceding the consumption output and two additional variables placed in the period preceding the consumption output with CO_2 and light sensors data. The light sensor indicates if there is a light activity in at least one room of the building. The information is presented to the input layer, which is then processed to the hidden layers with the support of the rectified linear unit activation function. The gradient descent algorithm is readapted in this model with a learning rate assigned to 0.001 to perform rigorous searches on how to minimize the forecasting error. A maximum of 500 epochs were used as a parameter to train the artificial neural network-based model with an early stopping procedure that stops the training before the end of the 500 epochs once no training improvements are observed. The output layer depends on the model configuration and can return a single forecasted energy value for a specific period or multiple energy values if the model forecasts multiple periods at once.

• Energy consumption assessment task

○ Measurement of computation energy consumption - the electrical energy consumption of computers related to the load forecast method/algorithm being run is monitored.

○ Measurement of monitoring infrastructure energy consumption - the electrical energy consumption of the monitoring infrastructure is monitored and stored.

This task can be performed when needed, collecting all the required data, whether it is necessary to estimate the consumption for a day, a week, or a month.

• Discussion of the results

○ Accuracy analysis - the accuracy of the used load forecasting approaches is evaluated and discussed, and the accuracies of the different approaches are compared.

○ Computation time - the forecasting computation time is determined for the used load forecasting approaches and the computation times of the different approaches are compared.

○ Energy consumption analysis - the energy consumption is determined for the used load forecasting approaches and the energy consumption of the different approaches is compared.

○ Electricity cost evaluation - the electricity cost is evaluated for the used load forecasting approaches. The electricity costs of the different approaches are compared too. This evaluation includes the consideration of different electricity tariffs, covering time-of-use and dynamic/real-time tariffs when available.

○ Whenever the consumer is changing the consumption, in response to a demand response event, the respective benefit is assessed during this task. Such an aspect is quite relevant as the accurate calculation of the consumption can enable more intelligent energy management in the context of participation in a demand response event.

As referred to in the load forecast task description, such a task runs independently over time. Additionally, it can be run for several load forecasting approaches to provide an integrated discussion of the most relevant forecasting approach in each building or context of building operation. Such discussion considers the accuracy, energy consumption, electricity cost, and time required for each forecasting approach.

In the end, the key objective is to decide to what extent it is relevant to consume energy in computation and monitoring infrastructures, considering the accuracy obtained for each forecasting approach.

INFRASTRUCTURE

Installation of devices to monitor and control energy in smart buildings is becoming a reality as initiatives and new energy management models are promoted as potential energy savings. However, there is a lack of critical analysis able to examine the relation between the energy consumption of these new solutions versus the energy consumption without a monitoring and control system.

To enable smart, remote, and/or automatic monitoring and control, hardware sensors, usually supported by gateways, are needed to enable the digitalization of smart buildings. In addition, computer infrastructure is also required to enable the processing of data locally or using remote resources, such as cloud computing. Almost every piece of equipment for monitoring and/or control will increase the building consumption, except the devices that work without a communication infrastructure (e.g., WiFi network) and have energy harvesting abilities. Besides the direct energy consumption of the device, there are indirect increases in energy consumption in gateways, routers, and computational infrastructure. Nonetheless, most of the impact studies only focus on the infrastructure acquisition costs, and they are not related to energy consumption.

The building used in this study is a living lab where research activities take place. This building has eleven offices, one meeting room, one server room, one kitchen, two labs, two bathrooms, two halls, and two hallways. The building has a supervisory control and data acquisition (SCADA) system, supported by programmable logic controllers (PLCs), where additional IoT devices are integrated to enable a complete digitalization of the building context (i.e., user and usage context and energy context)[30]. The SCADA system integrates several energy analyzers from Saia Burgess Controls (SBC) (ALE3D5FD10C3A00) that provide a reading every 10 seconds. The building is shown in Figure 1A, the interactive console that allows the partial visualization and control is presented in Figure 1B, and the physical installation of the SCADA system is shown in Figure 1C. The SCADA system also integrates the photovoltaic generation panels installed in the roof, which has a total peak of 7.5 kW. The generation energy is injected into the building without the use of storage units.

The SCADA system used in the building allows the energy monitoring using detailed readings each second. The data is then stored in a database using 10-second periods. Figure 2 shows the consumption profile, of a day, for three individual zones of the building. The profile considers the month of July 2021. Figure 2 addresses zone 1, zone 2, and zone 3, whose consumptions are represented in Figures 2A-C, respectively. The consumption is divided into three categories: electrical sockets (represented in grey), heating, ventilating, and air conditioning units (represented in blue), and artificial lighting (represented in orange). The consumption of the SCADA system is also measured. The consumption presented on the chart corresponds to a monthly average, representing the building's profile during summertime. Noting that, zone 1 has a meeting room and two offices, zone 2 has a server room and two offices, and zone 3 has three offices. Thus, it is visible a permanent air conditioning in zone 2, which is the refrigeration of the server room. All the zones are from the interior of the building, and there is no ventilation equipment operating. Ventilation is done naturally through the windows. This infrastructure has been used in several research projects for validation and consumer and load modeling, providing a relevant platform for the green computing assessment regarding the running algorithms (e.g., forecasting algorithms).

RESULTS

The case study of this paper is used to evaluate the monthly energy cost of forecasting energy consumption using the artificial neural network-based approach proposed in[29], considering all the needed equipment. The load forecasting application uses TensorFlow platform and is running on a server with four NVIDIA® Tesla® K80, as it is the hardware regularly used in the research facilities for research projects nowadays. Running the forecasting model requires two main steps: accessing the database and executing the forecasting algorithm. The advantage of using this model is that it can be executed for a day-ahead, hour-ahead, 15-min-ahead, or 5-min-ahead. However, the type of execution is dictated by an input variable, and the model's output is only a single value, in kWh, that forecasts the consumption for the targeted period. Figure 3 shows the power related to the energy consumption of the forecasting algorithm training. The grey area represents the baseline load of the server, which consumes 168.00 Wh on standby. All the measurements were monitored using the ALE3D5FD10C3A00 S SBC energy analyzer, read and stored by a Python script.

To test the impact that the monitoring (i.e., SCADA) system and the forecasting models have on the building, six scenarios were considered. First, using the algorithm once per day to provide a day-ahead result; Second, using it for an hour-ahead forecast; Third, using it for a 15-min-ahead; Forth, using a day-ahead forecast with an hour-ahead; Fifth, a 15-min-ahead from 8 a.m. till 8 p.m., for a 5-min-ahead forecast; Sixth, using a day-ahead forecast with an hour-ahead and 5-min-ahead from 8 a.m. till 8 p.m. In these scenarios, the algorithm is used in the indicated frequency, and it is trained every week. In the scenarios where more than one forecasting neural network is used, a trained per network is performed. The calculations were done using the month of July 2021 and considering a flat tariff of 0.22 EUR/kWh.

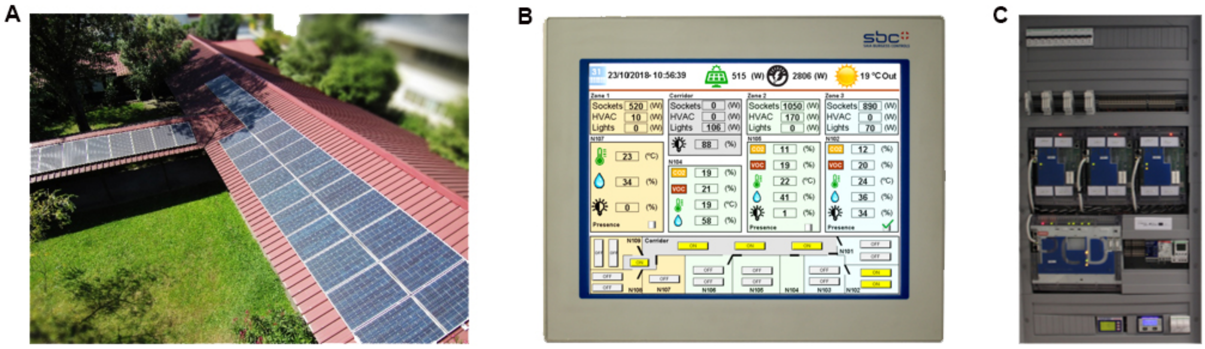

Figure 1. Building infrastructure: (A) the building, (B) the interactive console, and (C) an electrical board with PLCs. PLCs: Programmable logic controllers.

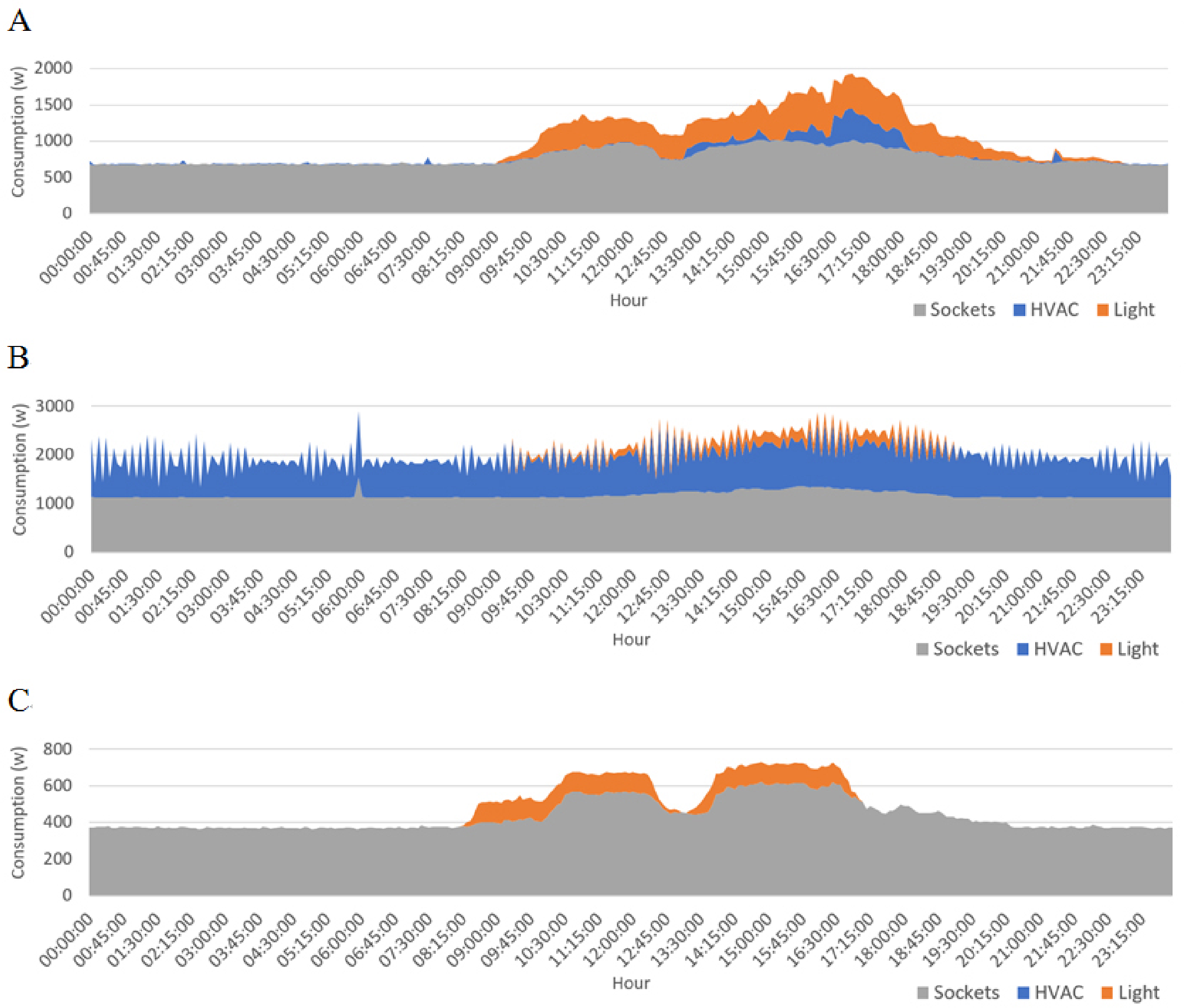

Figure 2. Consumption profile of the building: (A) zone 1, (B) zone 2, and (C) zone 3.

The energy consumption of the PLCs is 31.00 Wh, while the consumption of the interactive console is 10.78 Wh. Therefore, the SCADA system (i.e., PLCs and the console) had a monthly cost of 6.62 EUR. Furthermore, the metering of the SCADA system was made manually using an energy analyzer.

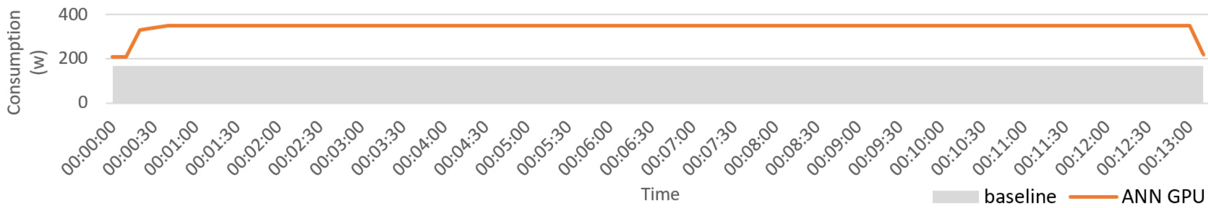

Figure 3. Forecast training model load profile.

The 3 zones of the building have the following monthly energy costs: 157.31 EUR for zone 1, 324.38 EUR for Zone 2, and 74.57 EUR for zone 3. The energy costs 0.22 EUR per kWh and taxes were not included. Table 1 shows the algorithm execution cost for a single execution (and the respective training) and the cost of each of the four scenarios. The column "cost variation" is calculated according to equations (1) and (2):

$$CostVariation = \frac{\Delta_{monthCost}}{buildingMonthCost} \tag{1}$$

$$\begin{aligned}\Delta_{monthCost} = {} & (buildingMonthCost + SCADAcost + forecastCost) \\ & - buildingMonthCost\end{aligned} \tag{2}$$

Where *buildingMonthCost* represnets the monthly energy cost of the building without the SCADA system and the forecasting consumption; *SCADAcost* represents the SCADA monthly energy cost; *forecastCost* represents the forecast energy monthly cost.

This paper considers both the SCADA solution and a forecasting model. Although the results do not consider the needed optimization and scheduling models used to manage energy loads and resources, the use of these models will also increase the computational consumption causing an increase of energy cost.

These results allow us to discuss the green computation of forecasting algorithms, as running the forecast approach several times will increase electricity consumption. Further discussion is provided in Sect. 5.

DISCUSSION

The results of the case study demonstrate that the SCADA system represents an increase of 1.20% in the monthly energy cost and that the forecasting model for 5-min-ahead will increase the monthly cost by 1.31%. These results only consider the server consumption increase during the algorithm execution. Nothing that the server baseline consumption was not regarded in this value calculation, as it is seen as a part of the normal building consumption. The 1.31% increase in the monthly energy cost is not significant in the tested building, which has three independent zones. However, if only zone 3 is considered, having a monthly energy consumption of 338.98 kWh (closer to a residential building), the impact of a SCADA solution with the forecasting execution increases to 10.63%. This critical high value can become an issue when managing energy in smaller buildings as the savings of the management models need to surpass their computational cost.

To lower this impact on the monthly energy costs, it is possible to use a combination of forecasts, avoiding the exclusive use of 5-min-ahead forecasting. The authors propose three alternatives that can lead to lower

Table 1. Energy costs

Scenario	Consumption of forecasting algorithm (Wh)	Trainings in a month	Consumption of the SCADA system (kWh)	Consumption of the building (kWh)	Total energy cost (EUR)	Cost variation (%)
One daily run	38.54	1	30.08	2,498.39	556.27	1.21
Day-ahead forecast - whole month	161.97	4			556.34	1.21
Hour-ahead forecast - whole month	368.97	4			556.30	1.22
15-min-ahead forecast - whole month	1016.97	4			5556.49	1.24
Day-ahead, hour-ahead, and 15-min-ahead (from 8 a.m. till 8 p.m.) - whole month	698.31	12			556.87	1.23
5-min-ahead forecast - whole month	2744.97	4			556.42	1.31
Day-ahead, hour-ahead, and 5-min-ahead (from 8 a.m. till 8 p.m.) - whole month	727.11	12			556.42	1.23

energy costs in a smart building.

The forecast of energy can be done using a combination of ahead periods depending on both the needs of the building and on the error values obtained in the last executions. For instance, if the night periods have lower forecast error, then the hour-ahead algorithms can be used. However, in periods with higher variation, such as the beginning and end of the working day, the 5-min-periods can be used. It is worth noting that this will decrease the number of forecasting executions. Another approach is to have the forecasting algorithm running according to the needs of external events, such as demand response programs where careful management of the building must be made.

This work proposes a second alternative in which the forecast runs during periods where the local renewable generation surpasses the building's consumption. To apply this solution, the forecasting algorithms must be adapted to allow execution at any time. For instance, the hour-ahead forecast for 12:00 p.m. could be executed at 02:00 p.m. where and if the local generation allowed. This scheduling of forecasts can be applied using energy prices indexed to the market prices (i.e., real-time pricing or hourly prices) too.

Furthermore, our work introduces a third alternative which is monitoring devices' management, turning them off when not needed, or when the forecast shows smaller errors. Turning off the monitoring system in the used infrastructure is not an applicable solution because the monitoring system has a lower consumption than the forecasting algorithm. However, for more complex systems, the monitoring system can have a consumption above the forecast algorithm. In these cases, and only for periods where forecasting errors are close to zero, the forecast algorithm can predict the consumption while the monitoring system is turned off. However, suppose forecasting errors are far from zero. In that scenario, it is recommended to keep the monitoring system on to closely monitor the smart building consumption and to allow efficient real-time management of its loads and resources.

These three alternatives are still in research progress, where some results have already been obtained. Preliminary results, comparing the Symmetric Mean Absolute Percentage Error (SMAPE) and training time dedicated to historic training and cleaning operations with the support of two forecasting algorithms have been obtained. At the same time, artificial neural networks and k-nearest neighbors based algorithms were also compared.

The forecasting errors of the first alternative propose two possible approaches: one to predict for different periods either for 5 min intervals, only during activity hours, where the consumption has a high variation, or on hour schedules for night hours where the consumption has a low variation. Using SMAPE as the featured error metric, both for artificial neural networks and k-nearest neighbors based algorithms, the forecasting error was lower than 7.35%. In parallel to this, an hour ahead forecasting on night hours resulted in higher precision with SMAPE forecasting errors equal to 4.98% and 5.06%, and a computation time of 3400s and 13s for artificial neural networks and k-nearest neighbors, respectively. Similarly, for 5 min ahead forecasts on activity hours resulted in less precision, with SMAPE forecasting errors equal to 7.35% and 6.25% for artificial neural networks and k-nearest neighbors based ones, respectively. On the other hand, the second alternative updates the historic training and saves it to the storage disk before events where the local renewable generation surpasses the building's consumption. During these events, forecasting executions are required with the training loaded in RAM. The forecasting is very precise for this approach on hour schedules presenting forecasting errors of 3.88% and 3.05% for artificial neural networks and k-nearest neighbors based algorithms, respectively.

CONCLUSIONS

This work focuses on analyzing the energy consumption, electricity costs, computation time, and accuracy associated with each forecasting algorithm or approach, proposing a methodology to perform such analysis. A monitoring infrastructure was presented, which provided inputs to the forecasting approach. Artificial neural networks have been used as an example to illustrate the proposed methodology in a building equipped with electricity consumption and other parameters monitoring infrastructure. It can be concluded that collecting many parameters and using very accurate forecasting approaches can cause an energy consumption higher than the energy consumption deviation resulting from the forecasting approach with lower accuracy. Therefore, contributing to green computing, it is required to consider the computation of data, the impact of collecting such data, and the need to perform highly consuming computation tasks. Furthermore, increasing the consumption related to forecasting algorithms' computation will increase the electricity bill, possibly above the cost paid without optimizing energy management. Above all, the use of energy should be optimized so that the one only uses the needed energy, even if it comes from green energy sources. Such energy can be used for other relevant purposes instead of irrelevant computation tasks.

DECLARATIONS

Authors' contributions

Made substantial contributions to conception and design of the study and performed data analysis and interpretation: Vale Z, Gomes L, Ramos D, Faria P.

Availability of data and materials

Data will be made available upon request.

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Conflicts of interest
All authors declared that there are no conflicts of interest.

Ethical approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

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