Home Energy Management System in an Algarve Residence. First Results

A. Ruano[1,2(✉)], K. Bot[1], and M. Graça Ruano[1,3]

[1] CINTAL, Universidade do Algarve, 8005 Faro, Portugal
aruano@ualg.pt
[2] IDMEC, Instituto Superior Técnico, Universidade de Lisboa, Lisbon, Portugal
[3] CISUC, University of Coimbra, Coimbra, Portugal

Abstract. Home Energy Management Systems (HEMS) are becoming progressively more researched and employed to invert the continuously increasing trend in (electrical) energy consumption in buildings. One of the critical aspects of any HEMS is the real-time monitoring of all variables related to the management system, as well as the real-time control of schedulable electric appliances. This paper describes a data acquisition system implemented in a residential house in the South of Portugal. With the small amount of data collected, a Radial Basis Function (RBF) model, designed by a Multi-objective Genetic Algorithm (MOGA) framework, to forecast total electric consumption was developed. Results show that, even with these little data, the model can be used in a predictive control scheduling mechanism for HEMS.

Keywords: Home energy management systems · Electric energy consumption forecasting · Neural networks · Multi-objective optimization · IoT acquisition systems · Non-intrusive load monitoring

1 Introduction

The goal of a Home Energy Management System (HEMS) is to manage the flow of electricity efficiently in the house, to reduce the electricity consumption (and consequently the energy bill) while increasing or maintaining the comfort of its occupants. Despite the substantial interest of the research community, due to the complexity and diversity of the systems, as well as the use of suboptimal control strategies, energy consumption is still higher than necessary, and users are unable to yield full comfort in their homes [1]. Energy monitoring is a key point of a HEMS; it can be done installing measuring devices at every load of interest or using Non-Intrusive Load Monitoring (NILM) methods, which desegregate the overall electricity usage, using a measure of the load at the utility service entry [2].

The authors would like to acknowledge the support of Programa Operacional Portugal 2020 and Operational Program CRESC Algarve 2020 grant 01/SAICT/2018. Antonio Ruano also acknowledges the support of Fundação para a Ciência e Tecnologia grant UID/EMS/50022/2020, through IDMEC, under LAETA.

J. A. Gonçalves et al. (Eds.): CONTROLO 2020, LNEE 695, pp. 332–341, 2021.
https://doi.org/10.1007/978-3-030-58653-9_32

A first step in reducing energy use is to create awareness of the energy consumption rate among the occupants. This can be done much more effectively using the disaggregation of energy achieved by the NILM algorithms. Classifying the appliances as schedulable or non-schedulable enables the use of scheduling algorithms to improve the efficiency of a HEMS. Assuming that renewable sources of energy and/or battery storage are available in the home, several Demand Response strategies can be used to further improve the efficiency of a HEMS, such as time-of-use pricing, critical peak pricing, real-time pricing and peak-time pricing. Furthermore, if forecasts of the consumption profiles as well as electrical energy data are available, Model-Based Predictive Control (MBPC) can be employed to derive optimal schedules for the schedulable appliances (for each HVAC systems), as well as to manage efficiently the flow of electricity between PV installation, battery storage, grid and house, in such a way that the electricity usage or its bill will be minimized. Recent approaches of the use of MBPC in HEMS can be found in [3–5].

All these aspects will be considered in a Portuguese FCT-funded project, NILMforIHEM, which is currently being executed. This paper aims to introduce the first steps of the project, having as objectives to describe the case study considered, comprised of the selected home and the technical description of the acquisition system implemented, and to present the model developed to forecast the total electricity consumption of the household, based on the preliminary data obtained,. The forecasting model developed is a RBF neural network, designed using by a Multi-Objective Genetic Algorithm (MOGA) framework.

The case study is described in Sect. 2. Section 3 describes the model design methodology and the results obtained are discussed in Sect. 4. Conclusions and guidelines for future work are drawn in Sect. 5.

2 Case Study Description

This work uses data collected from a residential house, situated in Gambelas, Faro, in the south of Portugal. It is a detached house, with two floors and with 20 different spaces (including garden, halls, and so on). The house has a PV installation, composed of 20 Sharp NU-AK panels [6], arranged in two strings, each panel with a maximum power of 300 W. The inverter is a Kostal Plenticore Plus converter (KI) [7], which also controls a BYD Battery Box HV H11.5 (with a storage capacity of 11.5 kWh) [8]. Several electrical appliances exist in this house, and a json file was created according to the format used by the NILM Toolkit [9]. The house electric panel is a Schneider panel consisting of 16 monophasic circuit breakers, plus a triphasic one. The house also has available a few TP-Link HS100 Wi-Fi Smart Plugs (SP) [10], one Intelligent Weather Station (IWS) [11], and a few Self-Powered Wireless Sensors (SPWS) for measuring room climate variables [12].

An acquisition system was afterwards implemented to monitor several electric variables. The data that will be used for NILM identification is supplied by a Carlo Gavazzi (EM340) 3 phase energy meter [13]. This meter is a class X certificated device, and electrical measurement is done using a 2 wires Modbus RTU connection. EM340 supplies 45 different electric variables, sampled at 1 Hz. Additional electric variables are measured for every circuit breaker to provide approximate ground truth for the NILM identification. The measurement devices, in this case, are Circutor Wibeees (WB) [14], which are plug and play wireless devices to measure electric consumption. Each one provides a hotspot to perform the first configuration using a mobile app from the manufacturer. By default, a WB sends data acquired to a free manufacturer web service. This behaviour can be disabled, and the data acquired is still available using an internal web interface/service or using the Modbus IP protocol. The devices use Hall Effect technology, and, because of that, some calibrations are required for correct measurements. Measurements of voltage, current, frequency, active reactive and apparent power, power factor, active inductive reactive and capacitive reactive energy are obtained every second for the 16 monophasic circuit breakers, the same number for each phase of the triphasic one, together with totalized values. In total, 198 variables are sampled by the WBs every second. Please note that as the measurement devices are not synchronized, the instants of time for each breaker are different.

Variables related with the energy produced by the PV, stored in the battery and injected in the grid are available either from the inverter or from a Kostal smart energy meter (KEM) [15]. Measurements of home electrical consumption are also available in the inverter. In total, 21 variables are obtained by KEM and 47 by KI, at a sampling interval of 1 min. The data access is done using a cable IP network using the Modbus IP protocol. Smart Plugs are used for on/off control of some equipment. Additionally, they allow sockets belonging to the same CB to be measured individually. This type of devices connects to an existing wireless network using an initial access point and a manufacturer mobile app. They can be read/controlled using a cloud API or directly using an internal web service, which is the case here. At present 3 SPs are employed, enabling the measurement of 6 variables every second for each plug.

The IWS a device that measures the air temperature and relative humidity, and global solar radiation, and predicts their evolution within a self-defined prediction horizon. To enable these forecasts, a two stages strategy is employed. When small measured data are available, a nearest neighbor algorithm is employed. When enough data are available, neural networks predictive models are automatically off-line designed and uploaded to the IWS, for real-time use. More details of the IWS can be found in [11]. Finally, SPWS devices are used for measuring room data, such as air temperature and relative humidity, status (open/close) of doors and windows, walls temperature, light and room movement. They are Ultra-Low-Power devices and communicate via ISM radio band working on 2.4 GHz or 868 MHz frequencies. They will be used to measure thermal comfort for usage in predictive control of some air-conditioners in the house. For more information on the use of SPWS for HVAC predictive control, please see [16].

Gateways and a Technical Network are responsible for the data transmission from/to the measurement devices. A technical IP-cabled and a wireless network have been created using a network router located inside an extension of the electric board case. This router separates the home network from the technical network. All devices, except the SPs and SPWS, are connected to that network. To perform the data acquisition from the existing devices EasyGateway devices are used. EasyGateway [12] is a fault-tolerant IoT gateway that supports a variety of reception/acquisition protocols such as Modbus, SNMP, Easy modules and serial http, as well as a set of Data Delivered Connectors (DDC) commonly used on IoT environments, such as Mqtt, and Ampq. To try to guarantee the acquisition rates required, five of these gateways are used within the electric board case, and the WBs, EM340, KI and KEM measurements were distributed among them. The weather station has its own internal gateway. An additional EasyGateway is located on a centralized position in the house, to enable communications of the SPWS. The data transmission of the EasyGateways is always performed at a 1-min base, which means that the data acquired by the measurement devices related to each gateway are packed and transmitted at that rate.

The gateways can also send data to up to three different DDCs. Here, 2 DDCs and 2 IoT Platforms are used. One platform is used inside home, employing an EasyMqs DDC and another, using a Generic Ampq DDC, is in the cloud. The same IoT platform is used inside home and in the cloud. It receives data from the configured message queue servers. The data arrived pass by a set of configured plug-ins for each type of entities configured on the platform. The application provides a web page where the end-user can configure a set of definitions related to data storage and management. It also allows data visualization using plots grouped by sensors category, and data download in 4 standard formats, csv, xlsx, mat and npz. For a more detailed description of the IoT platform, please see [12]. A diagram of the acquisition system is presented in Fig. 1. On the right side of the figure images of the IoT platform are displayed.

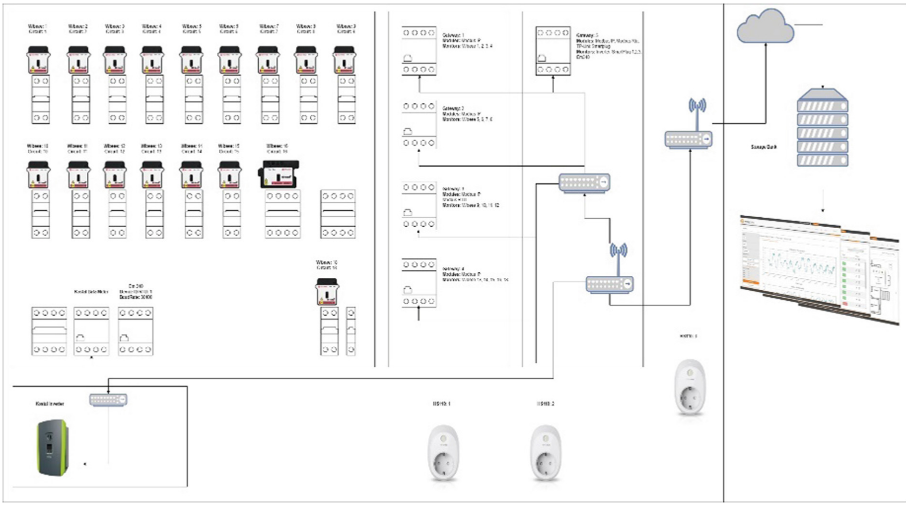

Fig. 1. Data acquisition diagram.

3 Home Consumption Model Design

Data collected from 27 November 2019 to the 31st of January was available for model design. The electric data employed was the active power, obtained from the EM340 device, which has been averaged in 15 min periods. This time step is employed due to the technical requirements for interchanging energy information between prosumer and energy suppliers [17] in the Portuguese market. In addition to electric power, two exogenous variables were employed: a codification of each day, within a week, considering holidays and their position within the week [18], and the occupation within the period considered. Future work will also employ external weather data. The objective of the model is to forecast the home electrical consumption, within a period of 12 h (48 steps-ahead). For such, a 1-step model will be designed, and the forecasts within the desired Prediction Horizon (PH) are obtained in a multi-step fashion (Fig. 2).

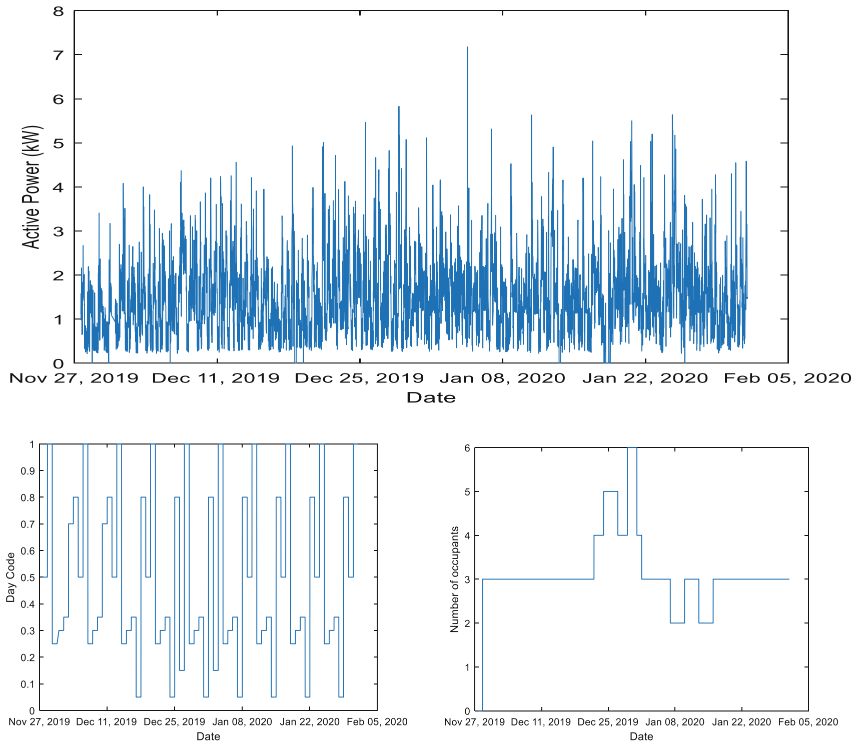

Fig. 2. Data for model design: top) active power, bottom left) day code, right) occupation

3.1 Methodology for Model Design

The models employed are RBF neural networks, in a Nonlinear AutoRegressive with eXogenous inputs (NARX) configuration. As mentioned above, two exogenous variables (day code and occupation) and their delays are used as inputs to the RBF, together with delays of the modelled variable (electric power). For data selection and dataset construction, the ApproxHull algorithm proposed in [19] is employed. ApproxHull is an incremental randomized approximate convex hull algorithm applicable to high dimension data that treats memory and computation time efficiently. The convex hull vertices obtained are compulsorily introduced in the training set so that the model can be designed with data covering the whole operational range. According to user partition preferences, the rest of the training set is obtained by a random selection of the rest of the design data, as well as the testing and the validation sets.

These data sets are supplied to a Multi-Objective Genetic Algorithm (MOGA) design framework. According to the user-specified set of objectives (which will be minimized or met as restrictions), range of neurons and range of inputs, the genetic algorithm part of MOGA will search for the best set of inputs and neurons of model individuals that solve the optimization problem. Each model in the population is trained by an improved version of the Levenberg-Marquardt algorithm. After MOGA execution a model is selected from the non-dominated solutions obtained, considering the values of the objectives and possible additional performance criteria. For a detailed explanation of the MOGA framework please consult [20]. In this work, the objectives to minimize are the RMSEs of the training set (ε_{tr}), the testing set (ε_{te}), the model complexity (O) and the forecasting error (ε_p). This last criterion is useful as we intend to design a predictive model and uses for its computation a subset (D), with p data points, of the existing time-series. It is computed as:

$$\varepsilon(D, PH) = \sum_{i=1}^{PH} RMSE(E(D, PH), i) \tag{1}$$

$$E(D, PH) = \begin{bmatrix} e[1,1] & e[1,2] & \cdots & e[1,PH] \\ e[2,1] & e[2,2] & \cdots & e[2,PH] \\ \vdots & \vdots & \ddots & \vdots \\ e[p-PH,1] & e[p-PH,2] & \cdots & e[p-PH,PH] \end{bmatrix} \tag{2}$$

In this work, MOGA is executed with 100 generations, population size of 100, proportion of random emigrants of 0.10 and a crossover rate of 0.70. The training set is used for model parameter estimation, the test set for early-stopping and the validation set used in final model selection, using its RMSE (ε_v). Each model design involves typically two iterations of MOGA. The first uses an unconstrained approach, while in the second some objectives are used as restrictions, taking into consideration the unconstrained results.

4 Results and Discussion

This section presents the data concerning the data set creation and model design, as well as the performance of the forecasting model.

4.1 ApproxHull

During the available 66 days of data, in three periods there was lack of data: 18-Dec-2019, 14:37:30 to 17:52:30, 13-Jan-2020, 12:52:30 to 16:07:30 and 18-Jan-2020, 02:37:30 to 12:52:30. Therefore, fours periods of data were available for model design. Additionally, as we shall use lags of power consumption immediately before the current sample (20), lags centred on the sample 24 h before (9) and one week before (9), the largest lag is 676. As the four periods of available data had 1978, 2475, 718 and 587 samples, only the first two were employed. As the first 676 cannot be used from each period (they are the necessary lags), 3005 records were employed by ApproxHull. 802 convex hull vertices were found and incorporated in the training set. As we considered 60%, 20% and 20% of the data for training, testing and validation, these three sets had 1803, 601 and 601 samples, respectively. All the data are scaled in the range [−1, 1].

4.2 Moga

As the work aims to use the model for forecasting, a prediction set D was also supplied to MOGA, comprising data from 21-Dec-2019, 20:52:30 to 05-Jan-2020, 03:37:30. In the first MOGA run the 4 objectives were minimized, and the ranges of neurons and inputs allowed were [2, 10] and [1, 20], respectively. There were 315 models in the non-dominated set. The minimum values of ε_{tr}, ε_{te}, ε_{v} and ε_{p} are shown in the first line of Table 1. Analysing the results, model 3163 was chosen. It has a structure shown in Eq. 3, which means that this model did not employ any of the exogenous variables and incorporated lags of the modelled variable around 24 h and one week before. The errors obtained by this model are shown in the 1st line of Table 2.

$$y(k) = f\begin{pmatrix} y(k-1), y(k-2), y(k-3), y(k-5), y(k-6), y(k-11), \\ y(k-13), y(k-14), y(k-15), y(k-17), y(k-93), y(k-96), \\ y(k-97), y(k-670), y(k-673), y(k-675), y(k-676) \end{pmatrix}, \quad (3)$$

Table 1. Non-dominated sets

Problem	ε_{tr}	ε_{te}	ε_{va}	ε_{p}
1st	0,152	0,139	0,147	9,997
2nd	0,156	0,139	0,146	9,836

Table 2. Selected models result.

Problem	Features	Neurons	ε_{tr}	ε_{te}	ε_{va}	ε_{p}
1st	17	10	0,163	0,147	0,1784	10.62
2nd	19	9	0,163	0,145	0,1175	9,83

The predictive performance of the chosen model was evaluated in a different segment of the active power time series, with samples from 8-Dec-2019, 09:52:30 to 18-Dec-2019, 02:22:30. Figure 3a) illustrates the evolution of RMSE, over the prediction horizon, for the period considered, and the 1-step-ahead forecast, compared with the real values of active power. After having analyzed the results, MOGA was executed again, this time using the values of 0.17 and 0.16 as goals for ε_{tr} and ε_{te}, respectively, and reducing the maximum allowable value for input terms to 18. The non-dominated set had 256 models, and the number of prefered models (that also met the restrictions) was 127. The 2nd row of Table 1 illustrates performance values for the prefered set. It can be concluded that a smaller value of the prediction error was obtained. Having analysed the results, model 5371 was chosen. It has a structure very similar to the one chosen in the previous MOGA iteration:

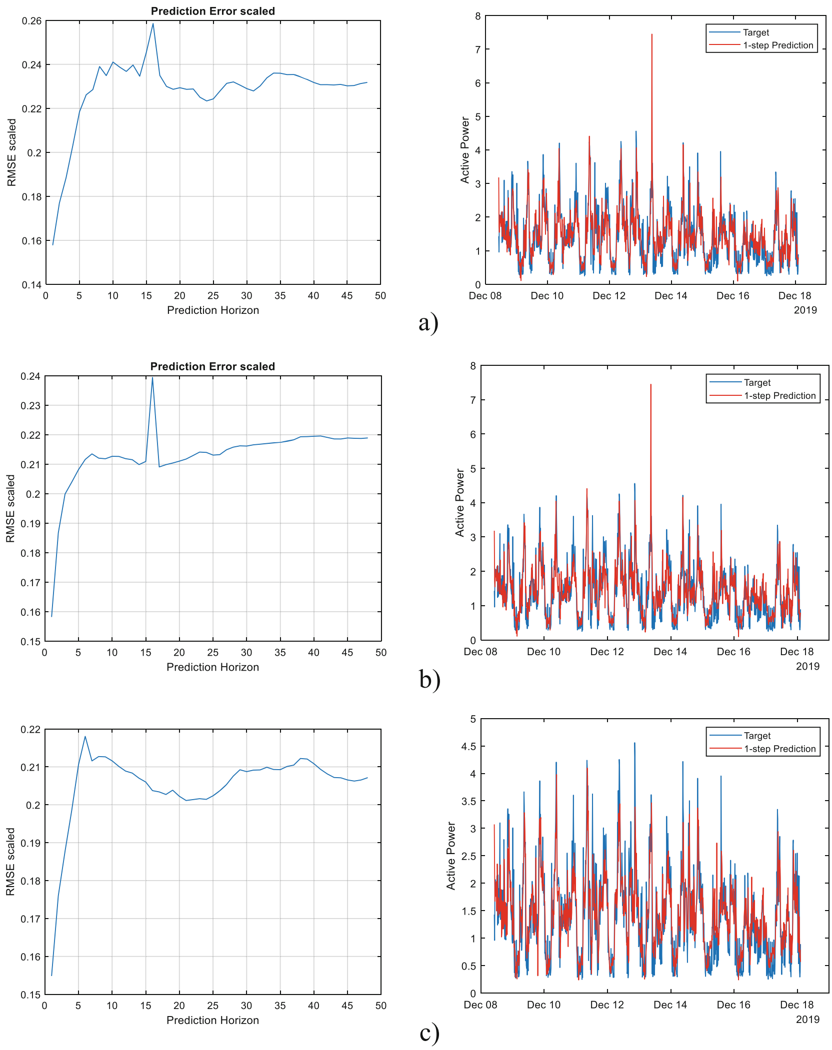

Fig. 3. Left: evolution of the RMSE over PH; right: predicted and real active power series. a) 1st MOGA execution; b) 2nd MOGA execution; c) ensemble approach

$$y(k) = f\begin{pmatrix} y(k-1), y(k-2), y(k-3), y(k-4), y(k-6), y(k-11), \\ y(k-14), y(k-92), y(k-93), y(k-97), y(k-98), \\ y(k-99), y(k-670), y(k-671), y(k-675), y(k-676) \end{pmatrix} \quad (4)$$

The performance results obtained with this model are presented in the 2nd row of Table 2. As before, the forecasting performance was assessed in the same period employed for the previous MOGA iteration. The RMSE evolution and the 1-step-ahead forecast are presented in Fig. 3b). As can be seen, slightly better results are obtained.

Finally, an ensemble approach was experimented. Making use of the preferred set, the results were obtained as the median of the values of the preferred set models. The graphs equivalent to Figs. 3a) and b) are presented in Fig. 3c). This last approach significantly improved the forecasting performance.

5 Conclusions

This paper describes the first steps of the development of a HEMS for an existing house, in the South of Portugal, under normal usage. The first step to achieve this was the development of an IoT acquisition system and platform, which was the first focus of this paper. With the small amount of data collected so far, a model to forecast the total electric consumption was also developed. Its performance will be improved, as more data become available. Notice that none of the exogenous variables considered, day code and occupation, was selected in the chosen models. Additionally, we assume that the use of weather information, mainly the air temperature, will bring an increased forecasting performance. Subsequently, models to forecast the consumption of schedulable electric appliances will be developed, as well as models for predicting the electric energy produced by the PV installation. These predictive models will be used to design a predictive control HEMS solution, which is the final goal of the current project.

References

1. Pau, G., Collotta, M., Ruano, A., Qin, J.: Smart home energy management. Energies **10**, 382 (2017)
2. Ruano, A., Hernandez, A., Ureña, J., Ruano, M., Garcia, J.: NILM techniques for intelligent home energy management and ambient assisted living: a review. Energies **12**, 2203 (2019)
3. Wang, J., Li, S., Chen, H., Yuan, Y., Huang, Y.: Data-driven model predictive control for building climate control: three case studies on different buildings. Build. Environ. **160**, 106204 (2019)
4. Guo, X., Bao, Z., Yan, W.: Stochastic model predictive control based scheduling optimization of multi-energy system considering hybrid CHPs and EVs. Appl. Sci. **9**, 356 (2019)
5. Schmidt, M., Åhlund, C.: Smart buildings as cyber-physical systems: data-driven predictive control strategies for energy efficiency. Renew. Sustain. Energy Rev. **90**, 742–756 (2018)
6. Europe Solar-Store: Sharp NU-AK300. https://www.europe-solarstore.com/sharp-nu-ak300.html. Accessed 03 May 2020
7. Kostal: Plenticore Plus. https://www.kostal-solar-electric.com/en-gb/products/hybrid-inverters/plenticore-plus. Accessed 03 May 2020

8. Eft-Systems: Battery Box HV. https://www.eft-systems.de/en/TheB-BOX/product/BatteryBoxHV/3. Accessed 03 May 2020
9. Kelly, J., Batra, N., Parson, O., Dutta, H., Knottenbelt, W., Rogers, A., Singh, A., Srivastava, M.: Nilmtk v0. 2: a non-intrusive load monitoring toolkit for large scale data sets: demo abstract. In: Proceedings of the 1st ACM Conference on Embedded Systems for Energy-efficient Buildings, pp. 182–183 (2014)
10. Tp-link: Wi-Fi Smart Plug. https://www.tp-link.com/pt/home-networking/smart-plug/hs100/. Accessed 03 May 2020
11. Mestre, G., Ruano, A., Duarte, H., Silva, S., Khosravani, H., Pesteh, S., Ferreira, P.M., Horta, R.: An intelligent weather station. Sensors **15**, 31005–31022 (2015)
12. Ruano, A., Silva, S., Duarte, H., Ferreira, P.M.: Wireless sensors and IoT platform for intelligent HVAC control. Appl. Sci. **8**, 370 (2018)
13. Carlo Gavazzi Automation Company: EM340 utilises touchscreen technology. https://www.carlogavazzi.co.uk/blog/carlo-gavazzi-energy-solutions/em340-utilises-touchscreen-technology. Accessed 03 May 2020
14. Circutor: Consumption analyzers. http://circutor.com/en/products/measurement-and-control/fixed-power-analyzers/consumption-analyzers. Accessed 03 May 2020
15. Kostal: Kostal Smart Energy Meter. https://shop.kostal-solar-electric.com/en/kostal-smart-energy-meter.html. Accessed 03 May 2020
16. Ruano, A.E., Pesteh, S., Silva, S., Duarte, H., Mestre, G., Ferreira, P.M., Khosravani, H.R., Horta, R.: The IMBPC HVAC system: a complete MBPC solution for existing HVAC systems. Energy Build. **120**, 145–158 (2016)
17. Presidência do Conselho de Ministros: Decreto-Lei n.º 162/2019 de 25 de outubro (2019)
18. Ferreira, P.M., Ruano, A.E., Pestana, R., Kóczy, L.T.: Evolving RBF predictive models to forecast the Portuguese electricity consumption. IFAC Proc. Vol. **2** (2009). https://doi.org/10.3182/20090921-3-TR-3005.00073
19. Khosravani, H.R., Ruano, A.E., Ferreira, P.M.: A convex hull-based data selection method for data driven models. Appl. Soft Comput. **47**, 515–533 (2016)
20. Ferreira, P.M., Ruano, E.: Evolutionary Multiobjective neural network models identification: evolving task-optimised models. In: New Advances in Intelligent Signal Processing, pp. 21–53 (2011)