Preprints of the 21st IFAC World Congress (Virtual)
Berlin, Germany, July 12-17, 2020

Forecasting Electricity Demand in Households using MOGA-designed Artificial Neural Networks

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Abstract: The prediction of electricity demand plays an essential role in the building environment. It strongly contributes to making the building more energy-efficient, having the potential to increase both thermal and visual comfort of the occupants, while reducing energy consumption, by allowing the use of model predictive control. The present article focuses on the use of computational intelligence methods for prediction of the power consumption of a case study residential building, during a horizon of 12 hours. Two exogeneous variables (ambient temperature and day code) are used in the NARX model Two different time steps were considered in the simulations, as well as constrained and unconstrained model design. The study concluded that the smaller timestep and the constrained model design obtain the best power demand prediction performance. The results obtained compare very favourably with similar approaches in the literature

Keywords: Electric Power, prediction methods, neural networks, multiobjective optimization

1. INTRODUCTION

The prediction of the energy demand in buildings is important on many levels, from the household unit to the country level. It is necessary due to the essential role it plays in the electricity industry, as it provides the basis for the decision-making processes concerning power system planning and operation, as well as a basis for the demand side response through the use of model-based predictive control (MPC) and optimization of the devices´ operation. Predictions not only contribute to balancing demand and supply via on-site renewable energy sources (as the case of nearly zero energy buildings) at the household level, but also to utility planning. Traditionally, utilities apply prediction over a group of houses/buildings. However, with the improvement in technology, nowadays it is possible to predict at the household level, increasing the accuracy and providing powerful insights over the individual patterns of consumption – being able to address individually the demand response actions and increasing the flexibility of the whole energy systems.

The use of data-driven methods for energy demand forecasting has been steadily increasing over the years. The main applications of the data-driven prediction methods of energy consumption in residential buildings may be segmented in three classes: 1) use of big data in the design stage to determine the best strategies to be adopted in terms of civil and energy engineering; 2) simulation and prediction of the performance mainly to allow MPC, optimization of network configuration; 3) continuous evaluation through the building lifecycle, e.g. safety of data storage in the cloud, refilling missing data, failure prediction, and preventive maintenance.

The number of factors involved in energy consumption makes it very challenging to accurately implement its forecasting. Because of that, the research community has been giving increased focus on this topic during the last years. For reviews, please see (Daut et al., 2017, Amasyali and El-Gohary, 2018).

The present article focuses on the use of computational intelligence methods for prediction of the electricity consumption of a case study residential building, during a horizon of 12 hours, based on the endogenous variable (energy demand) and two exogenous variables (ambient temperature and day code). The work was developed in the scope of the Project "NILMforIHEAM – 01/SAICT/2018 – Non-invasive load monitoring applied to intelligent energy management of residential buildings", funded by the Operational Program CRESC Algarve 2020.

1.1 Brief literature review

This work is based on the prediction of energy consumption via computational learning methods. Computational learning methods are data-driven methods based on input and output values that can predict, in this context, the power consumption of buildings without knowing the complex internal physical relationships of the system (Ferreira and Ruano, 2011). There is no preliminary need for heat transfer equations or parameters as detailed thermal behaviour or geometry. Indeed,

[1] The authors acknowledge the support of: Programa Operacional Portugal 2020 and Operational Program CRESC Algarve 2020 grant 01/SAICT/2018, Fundação para a Ciência e Tecnologia, , through IDMEC, under LAETA, grant UIDB/50022/2020.

these models are based on the usage of a function determined using samples of data describing the behaviour of a specific system (Foucquier et al., 2013, Killian and Kozek, 2016).

Among the reviewed publications, the use of predictive models for MPC-based applications are dominant (von Grabe, 2016). The utilization of MPC for energy management in buildings has achieved substantial consideration in the last decade due to its importance to the building energy demand. The expansion in computational capabilities concerning building intelligence frameworks and the accessibility of further building information has driven its growth. Besides, the prediction of energy consumption has been decidedly connected to dynamic energy management frameworks, just as to the ideal administration of on-location sustainable power sources, such as solar energy. More details on this kind of application may be found in Serale et al. (2018).

Recent methodological reviews were published on the use of computational learning for the prediction of energy usage in buildings (Loyola, 2018, Wei et al., 2018), in which the use of computational learning techniques was proven very effective. These studies compare different methodologies and highlight the importance of the mentioned models for prediction. They also present a detailed review concerning the main concepts and technologies of the use of big data in building design and energy usage prediction, based on the survey of around 100 cases of applications. It is recognized that tools as MATLAB and Python are used to develop mathematical programming.

Several studies used Artificial Neural Networks (ANN) as the primary technique to evaluate and predict energy consumption (Ahmad et al., 2018, Rahman et al., 2018, Ai et al., 2019). Among the reviewed studies, it was possible to identify the main inputs used in the computational learning models. These input data may be segmented into two main categories: weather-related parameters and building pertaining parameters. Concerning the weather-related parameters, the atmospheric temperature is the parameter most used as an exogenous variable, but also solar radiation availability and relative humidity. Considering the building-related parameters, the total building energy consumption data is the most used variable, followed by parameters as occupancy, usage of devices, indoor temperatures and fenestration characteristics.

The prediction of the energy consumption may have different focus among the studies, considering the slice of total energy demand in the building under consideration. Most samples of studies reviewed in the scope of this work focus on the whole-building energy consumption (Wakui et al., 2017, Do and Cetin, 2018, Fayaz and Kim, 2018), however other studies focus only on heating demand (Ai et al., 2019, Arabzadeh et al., 2018), only on cooling demand (Moon and Jung, 2016), both on heating and cooling (Geysen et al., 2018), and also on the detailed segmentation considering devices and other uses as water heating (Babaei et al., 2015). The prediction horizon of reviewed studies was segmented in an hourly fraction, hour, day, month and year, with varying prediction time steps (most hourly for one-day as a prediction horizon, and daily for the one-month horizon). The validation methods of the prediction models also varied between the different studies reviewed: use of analytical proof, experimental analysis, model comparison, reference comparison, and simulation comparison, being analytical proof and experimental analysis the most used. An extensive review may be found in (Amasyali and El-Gohary, 2018, Mynhoff et al., 2018).

1.2. Objectives and work organization

The present study aims to discuss the prediction of energy consumption in a residential building, having as a case study the Honda Smart Home, located in Davis, United State. The objective is to develop an accurate prediction model, in order to be subsequently used in decision making and model predictive control. The design formulation (unconstrained or constrained optimization), as well as the time-step to be employed are also discussed here.

The paper is organized into five sections. Section 1 presents the scope of work, background information, and objectives. Section two presents the case study, the Honda Smart Home architecture and the dataset available by their experimental campaigns. The data used as input for the models developed by this work are also presented in this section. Section three presents the predictive model design, concerning problem formulation, the prediction horizon validation method, and design experiments. Results are shown and discussed in Section four, and Section five presents the conclusions and points out future research.

2. CASE STUDY DESCRIPTION – HONDA SMART HOME US

The Honda Smart Home (HSH) US (Honda, 2019), located on the West Village campus of the University of California, Davis, was brought to light in 2014. The building is considered to be a Net Zero Energy Building (NZEB), due to its capability to produce on-site all the electricity – by renewable energy use – to meet the electricity needs annually. The construction of the HSH was made based on sustainable materials and techniques, and it accounts also with a ground-source heat pump, efficient equipment and lighting, and a complex home energy management system to control the different systems accordingly. The building is extensively described on its website. The group responsible for the HSH makes available experimental data every six months. Based on the publicly available data, some studies were developed, focused mainly on the integration between electric vehicles and the smart home, and the home management systems of the HVAC solutions, as well as construction practices.

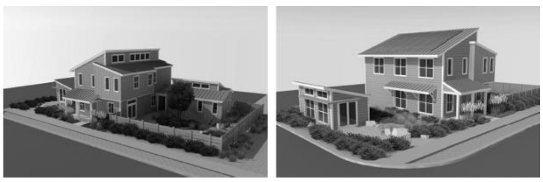

Fig. 1. Honda Smart Home US. Source: (Honda, 2019).

To develop the present study, and based on the background information previously presented, from the data set provided by the HSH group, two parameters will be used from the HSH data set. They are the total average electric power demand and the outdoor ambient temperature. The whole dataset with minute sampling intervals may be found in (Honda, 2019). During the considered three-year period, the power hits a maximum of 8,57 kW, a minimum of 0 kW and a mean value of 0,99 kW. During the same period, the temperature achieves a maximum of 42,82 ºC, a minimum of -2,00ºC and an average value of 17ºC.

3. PREDICTIVE MODEL DESIGN

The data set is composed of 15 min averages of power consumption and outdoor temperature of the HSH, during three years (2016, 2017 and 2018). Additionally, a codification of each day, within a week, considering holidays and their position within the week, was employed (Ferreira et al., 2009). The model intends to predict the power consumption for a prediction horizon of 12 hours, in a multi-step fashion.

The problem type is one-step-ahead prediction, in a non-linear autoregressive with exogenous inputs (NARX) configuration and the delays associated with each variable (v1 – power, v2 – ambient temperature, v3 – the day code). The model design employed intends to obtain a small Root Mean Square Error (RMSE) over the prediction horizon, which is 12 hours. Two Problems (P) are simulated in this work, each one in two versions: i) P1a - hourly time steps and a multi-objective unconstrained design; ii) P1b - hourly time steps and a multi-objective constrained design; iii) P2a - 15-minutes time step and a multi-objective unconstrained design and; iv) P2b - 15-minutes time step and a multi-objective constrained design. Notice that the 15 minutes time-step is due to the technical requirements of interchanging energy-information between the prosumer and the energy supplier (Presidencia do Conselho de Ministros, 2019).

3.1 Data set construction

The data set construction aims to select data for training, testing and validation data for the artificial neural network design. This work uses the *ApproxHull* algorithm proposed by Khosravani et al. (2016). ApproxHull is a randomized approximation algorithm for determining the convex hull of the data, that treats memory and time complexity efficiently. These convex hull vertices are compulsorily introduced in the training set so that the model can be designed with data covering the whole operational range.

ApproxHull is an incremental algorithm, applicable to high dimension data efficiently; it starts with an initial convex hull and subsequently the current convex hull grows iteratively by adding the new vertices into it. A pre-processing phase is performed on the original data set before applying the convex hull. It scales the dimensions in the range of [-1,1], identifies the maximum and minimum of each dimension (as vertices of the initial convex hull). Then, it generates a population of k facets based on the initial vertices of the convex hull, with validity checked in each iteration, identify the furthest points in the current facets population as new vertices of the convex hull, updating the current convex hull by adding the newly found vertices to the current set of vertices. A detailed explanation of the convex hull method and algorithm may be found in (Khosravani et al., 2016).

For the data set construction, the whole interval of data (samples (S)) is employed for both problems. To each variable [v1, v2, v3], lags are associated for three periods: period 1 (first lags immediately before the sample), period 2 (lags centred 24h before), and period 3 (lags centred a week before). The lags are, for each variable, respectively: P1 [4, 4, 1], [1, 1, 0] ,[1, 0, 0]; P2 [20, 20, 1], [4, 4, 0], [4, 0, 0]. The number of Training Samples (S_{tr}) is 60% of the whole set, while Testing Samples (S_{te}) and Validation Samples (S_{va}) have a dimension of 20% each. All convex hull points are incorporated in the training set. The input used to MOGA (Multiobjective Genetic Algorithm) are the three data sets generated.

3.2 MOGA design

The design criteria include multiple conflicting objectives, which implies that the model identification problem must be considered as a multiobjective combinatorial optimization. Genetic algorithms are particularly well suited to address this problem because they can evolve optimized model structures that meet pre-specified design criteria in acceptable computing time. Globally, the ANN structure optimization problem can be viewed as a sequence of actions undertaken by the model designer, which should be repeated until pre-specified design goals are achieved. These actions can be grouped into three major categories: problem definition, solution(s) generation and analysis of results. For a detailed explanation of the MOGA design framework used, please consult Ferreira and Ruano (2011)).

The ANN structure used in the present work uses as model type Radial Basis Function (RBF). In this particular application, MOGA determines the optimal number of neutrons in a range from 2 to 10 and selects the most important input features within a range from 2 to 20. Topology and feature selection are performed by the genetic part of MOGA. Each model in the current population is a specific RBF, whose parameters are estimated (trained) using a modified version of the Levenberg-Marquardt algorithm, which exploits the linear-nonlinear parameter separation.

At the first iteration of the training algorithm the model parameters have to be initialised. This particular application uses clustering to spread the centers in distinct regions of the input feature space. As the ANN training algorithm is iterative, an early-stopping criterion is used as a termination criterion. As the model is nonlinear, the final result depends on the initial values of its parameters. As such, five training trials are executed for each RBF, and the best compromise trial over all the objectives, is selected among the five.

Considering the actions briefly detailed, the objectives to minimize are the RMSEs of the training set (ε_{tr}), of the testing set (ε_{te}), the model complexity ($O(\mu)$) and the forecasting error (ε_p). This last criterion is obtained as:

$$\varepsilon_p\left(D,PH\right)=\sum_{i=1}^{PH} RMSE\left(E\left(D,PH\right),i\right) \quad (1)$$

where D is an additional simulation set, with p data points, and E is an error matrix:

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

where $e[i,j]$ is the model prediction error taken from the instant i of D at step j of PH. This is an unconstrained multi-objective optimization problem. Sometimes some of the objectives are setup as goals that must be met, and the objective problem becomes constrained.

MOGA is executed with 80 generations, a population size of 100, the proportion of random emigrants of 0.10 and a crossover rate of 0.70 is employed. When MOGA stops its execution, the non-dominated or preferable (with restrictions) set of models is evaluated on a third data set, the validation data set (ε_{va}), in order to avoid any tendency that may have arisen during the MOGA optimization. The final selection of one model is then performed based on the objective values obtained and the RMSE obtained over the validation data set. After the first unconstrained design of each problem, the second design is performed, with constraints on some of the objectives, taking into consideration the unconstrained results. The restrictions considered for both P_{1b} and P_{2b} were RMSE(ε_{tr}) = 0,21, RMSE(ε_{te}) = 0,20 and $O(\mu)$ = 210 (P_{1b}) and 200 (P_{2b}).

4. RESULTS AND DISCUSSION

4.1 ApproxHull output

The results obtained by the Approxhull algorithm, are presented in Table *2*.

Table 2. ApproxHull results

P	S	Features	Vertices	S_{tr}	S_{te}	S_{va}
P1	26111	21	1199	15666	5222	5223
P2	104519	69	1711	62711	20903	20905

4.2 Non-dominated sets

The minimum results for the non-dominated sets (using data scaled in the interval [-1,+1]) are presented in Table 3. It is possible to conclude that smaller RMSE errors for training, testing, and validation belong to P_2 (with 15 minutes time steps). Notice also that, in terms of ε_p the summation for P_2 extends to 4 times the number of terms of P_1.

Table 3. Minimum values for non-dominated or preferable sets

P	P_{1a}	P_{1b}	P_{2a}	P_{2b}
ε_{tr}	0,18	0,17	0,12	0,12
ε_{te}	0,16	0,16	0,14	0,11
ε_{va}	0,16	0,16	0,14	0,11
ε_p	3,92	3,94	9,24	9,26

4.3 Selected models

Eqs (3) to (6) present the lags used in the selected models for P_{1a}, P_{1b}, P_{2a}, and P_{2b}, respectively. Further details and performance obtained with the selected models are presented in Table 4.

$$v_1[k]=f\begin{pmatrix} v_1[k-1],v_1[k-2],v_1[k-3],v_1[k-24], \\ v_1[k-25],v_1[k-167],v_1[k-168],\ v_1[k-169], \\ v_2[k-1],v_2[k-3],v_2[k-24],v_3[k-1] \end{pmatrix} \quad (3)$$

$$v_1[k]=f\begin{pmatrix} v_1[k-1],v_1[k-3],v_1[k-4],v_1[k-25], \\ v_1[k-167],v_1[k-168],v_2[k-3],v_3[k-1] \end{pmatrix} \quad (4)$$

$$v_1[k]=f\begin{pmatrix} v_1[k-1],v_1[k-12],v_1[k-13],v_1[k-17],v_1[k-18], \\ v_1[k-92],v_1[k-96],v_1[k-97],v_1[k-672],v_1[k-673], \\ v_1[k-675],v_2[k-2],v_2[k-5],v_2[k-11], \\ v_2[k-12],v_2[k-16],v_2[k-20],v_2[k-99] \end{pmatrix} \quad (5)$$

$$v_1[k]=f\begin{pmatrix} v_1[k-2],v_1[k-4],v_1[k-19],v_1[k-92],v_1[k-94], \\ v_1[k-100],v_1[k-673],v_1[k-675],v_2[k-2],v_2[k-4], \\ v_2[k-11],v_2[k-13],v_2[k-17],v_2[k-18],v_2[k-19], \\ v_2[k-93],v_2[k-94],v_2[k-100],v_3[k-1] \end{pmatrix} \quad (6)$$

Table 4. Selected model results

P	P_{1a}	P_{1b}	P_{2a}	P_{2b}
Features	12	8	18	19
Neurons	9	2	8	9
$O(\mu)$	117	18	152	180
$\|\|w^2\|\|$	795	11,9	56,8	29,5
ε_{tr}	0,18	0,19	0,16	0,12
ε_{te}	0,16	0,16	0,15	0,11
ε_{va}	0,16	0,17	0,15	0,11
ε_p	4,19	3,94	9,46	9,34

As if can be seen, the considerations done for Table 3 are valid for Table 4.

To analyze the prediction results a one-week period, from 23 February to 1 March 2016, was employed. A prediction horizon of 12 hours was considered, which means that for Problems P_1 12 prediction steps were used, while for P_2 48 steps-ahead were employed. The forecasting error for this period and for each one of the four problems is shown in the last line of Table 4. As it can be seen, P_1 problems (with 1-hour step) performance is worse than using a 15-min prediction step, in P_2 problems. Analyzing now the model design formulation, the constrained one (b) obtains better results than the unconstrained one (a). Overall, P_{1a} obtains the worst forecasting results, while P_{2b} achieves the best ones. Figure 2 presents the target values (real building power demand) and one-step prediction values for these two extreme cases.

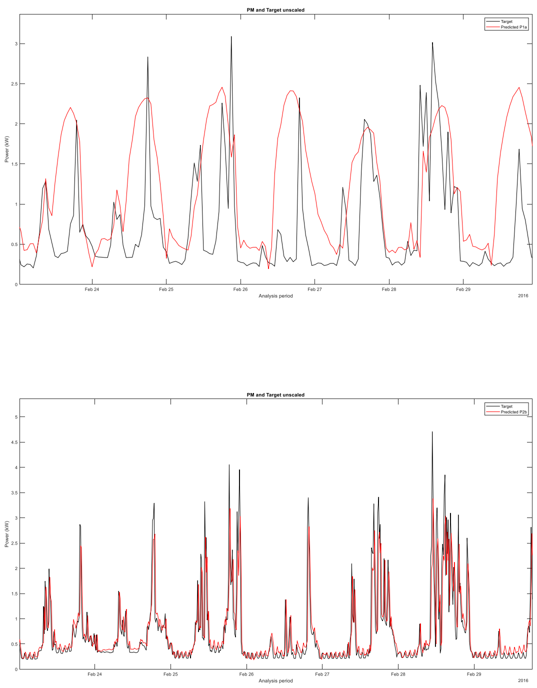

Fig. 2. Target values and one-step-ahead predicted values obtained with model (3) - top and model (6) - bottom.

Another important prediction indicator is how the forecasting error evolves throughout the prediction horizon. For P_1 problems, the RMSE along PH ranged between 0,67 and 0,85 kW (please note that the original scale is now used), for P1a, and for P1b, between 0,71 and 0,89. For P2, the RMSEs varied between 0,55 and 1,10 for P2a, and for P2b, between 0,67 and 0,83. It is interesting to verify that, although in P_2 problems 48 steps are considered, and in P_1 only 12, the former models obtain a better RMSE evolution. Figure 3 illustrates the evolution of the RMSE over PH of model (6).

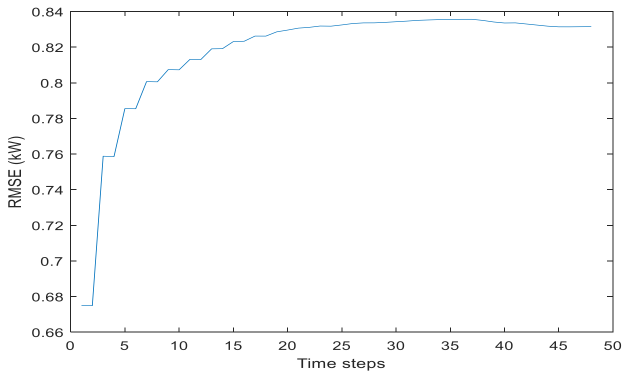

Fig. 3. RMSE evolution of the selected model for P_{2b}.

4.4 Performance Comparison

The reliability of these techniques is highly dependent on the quality and amount of available data, as the physical approaches were dependent on the complexity of the underlying model. The availability of data is recognized by many authors as a challenging factor that may be either an opportunity or an obstacle, according to the case. It is however quite tricky to perform a qualitative and comparative assessment of the various techniques devised in this field, since – again – their performances will depend on the training data used as input (Foucquier et al., 2013).

Bearing in mind that a performance comparison should be considered mainly qualitatively than quantitatively, it is nevertheless important to compare the obtained results with the performance of related studies. In Mynhoff et al. (2018), different prediction models (AN-NNAR, Hidden Markov Models, Support Vector Machines (SVM), MultiLayer Perceptrons and Deep Belief Networks) were designed for one-step daily and weekly forecasts. 8 weeks of 1-hour data were extracted from Pecan Street database, in 4 different scenarios. For daily forecasts, the RMSEs varied between 4.02 (ANN-NAR) to 1.48 (DBN) kW. Much better results were obtained in the present work, using three years of data, although a ceiling of a half day is considered.

The authors of (Yildiz et al., 2018) compared the forecasting performance of ANNs, SVMs and Least-Squares SVMs, with different data resolutions and forecasting horizons, for different load profiles, obtained by a clustering process. In the same way as in the previous work, these are one-step-ahead forecasts, although with different forecasting horizons. The best results obtained for a house with similar load profile, RMSEs within the range of 0.8 to 1.6 kW are obtained for a time resolution of 30 minutes and a 12-hours forecast. Again, the results presented in this paper compare very favorably with these values.

5. CONCLUSIONS

This work focuses on improving the accuracy of predictive models for the energy demand in buildings, using the Honda Smart Home US data as an example. It used an ANN-RBF based model with MOGA optimization, exploring two problems: three years data with hourly time steps between samples and the same data with 15-minute time steps between samples, each one analyzed using unconstrained and constrained optimization. It was shown that the smaller timesteps in a constrained model presented better prediction results.

Future work will employ these consumption forecasting models, as well as electricity production predictive models for model predictive scheduling of a real household in the South of Portugal, with PV energy production and storage.

REFERENCES

Ahmad, T., Chen, H., Guo, Y. and Wang, J. (2018) 'A comprehensive overview on the data driven and large scale based approaches for forecasting of building energy demand: A review', *Energy and Buildings,* 165, pp. 301-320.

Ai, S., Chakravorty, A. and Rong, C. (2019) 'Household Power Demand Prediction Using Evolutionary Ensemble Neural Network Pool with Multiple Network Structures', *Sensors,* 19(3), pp. 721.

Amasyali, K. and El-Gohary, N. M. (2018) 'A review of data-driven building energy consumption prediction studies', *Renewable and Sustainable Energy Reviews,* 81, pp. 1192-1205.

Arabzadeh, V., Alimohammadisagvand, B., Jokisalo, J. and Siren, K. 'A novel cost-optimizing demand response control for a heat pump heated residential building'. *Building Simulation*: Springer, 533-547.

Babaei, T., Abdi, H., Lim, C. P. and Nahavandi, S. (2015) 'A study and a directory of energy consumption data sets of buildings', *Energy and Buildings,* 94, pp. 91-99.

Daut, M. A. M., Hassan, M. Y., Abdullah, H., Rahman, H. A., Abdullah, M. P. and Hussin, F. (2017) 'Building electrical energy consumption forecasting analysis using conventional and artificial intelligence methods: A review', *Renewable and Sustainable Energy Reviews,* 70, pp. 1108-1118.

Do, H. and Cetin, K. S. (2018) 'Evaluation of the causes and impact of outliers on residential building energy use prediction using inverse modeling', *Building and Environment,* 138, pp. 194-206.

Fayaz, M. and Kim, D. (2018) 'A prediction methodology of energy consumption based on deep extreme learning machine and comparative analysis in residential buildings', *Electronics,* 7(10), pp. 222.

Ferreira, P. M. and Ruano, A. E. (2011) 'Evolutionary multiobjective neural network models identification: evolving task-optimised models', *New Advances in Intelligent Signal Processing*: Springer, pp. 21-53.

Ferreira, P. M., Ruano, A. E., Pestana, R. and Kóczy, L. T. (2009) 'Evolving rbf predictive models to forecast the portuguese electricity consumption', *IFAC Proceedings Volumes,* 42(19), pp. 414-419.

Foucquier, A., Robert, S., Suard, F., Stéphan, L. and Jay, A. (2013) 'State of the art in building modelling and energy performances prediction: A review', *Renewable and Sustainable Energy Reviews,* 23, pp. 272-288.

Geysen, D., De Somer, O., Johansson, C., Brage, J. and Vanhoudt, D. (2018) 'Operational thermal load forecasting in district heating networks using machine learning and expert advice', *Energy and Buildings,* 162, pp. 144-153.

Honda (2019) *Honda Smart Home US*. Available at: https://www.hondasmarthome.com (Accessed: 14/10/2019).

Khosravani, H. R., Ruano, A. E. and Ferreira, P. M. (2016) 'A convex hull-based data selection method for data driven models', *Applied Soft Computing,* 47, pp. 515-533.

Killian, M. and Kozek, M. (2016) 'Ten questions concerning model predictive control for energy efficient buildings', *Building and Environment,* 105, pp. 403-412.

Loyola, M. (2018) 'Big data in building design: a review', *ITcon,* 23, pp. 259-284.

Moon, J. W. and Jung, S. K. (2016) 'Development of a thermal control algorithm using artificial neural network models for improved thermal comfort and energy efficiency in accommodation buildings', *Applied Thermal Engineering,* 103, pp. 1135-1144.

Mynhoff, P. A., Mocanu, E. and Gibescu, M. 'Statistical Learning versus Deep Learning: Performance Comparison for Building Energy Prediction Methods'. *8th IEEE PES Innovative Smart Grid Technology Conference (ISGT), October*.

Portugal, *Decreto-Lei n.º 162/2019 de 25 de outubro* (2019).

Rahman, A., Srikumar, V. and Smith, A. D. (2018) 'Predicting electricity consumption for commercial and residential buildings using deep recurrent neural networks', *Applied energy,* 212, pp. 372-385.

Serale, G., Fiorentini, M., Capozzoli, A., Bernardini, D. and Bemporad, A. (2018) 'Model predictive control (MPC) for enhancing building and HVAC system energy efficiency: Problem formulation, applications and opportunities', *Energies,* 11(3), pp. 631.

von Grabe, J. (2016) 'Potential of artificial neural networks to predict thermal sensation votes', *Applied energy,* 161, pp. 412-424.

Wakui, T., Sawada, K., Kawayoshi, H., Yokoyama, R., Iitaka, H. and Aki, H. (2017) 'Optimal operations management of residential energy supply networks with power and heat interchanges', *Energy and Buildings,* 151, pp. 167-186.

Wei, Y., Zhang, X., Shi, Y., Xia, L., Pan, S., Wu, J., Han, M. and Zhao, X. (2018) 'A review of data-driven approaches for prediction and classification of building energy consumption', *Renewable and Sustainable Energy Reviews,* 82, pp. 1027-1047.

Yildiz, B., Bilbao, J. I., Dore, J. and Sproul, A. B. (2018) 'Short-term forecasting of individual household electricity loads with investigating impact of data resolution and forecast horizon', *Renew. Energy Environ. Sustain.,* 3, pp. 3.