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Activity-Aware HVAC Power Demand Forecasting

Abstract – The forecasting of the thermal power demand is essential to support the development of advanced strategies for the management of local resources on the consumer side, such as heating ventilation and air conditioning (HVAC) equipment in buildings. In this paper, a novel hybrid methodology is presented for the short-term load forecasting of HVAC thermal power demand in smart buildings based on a data-driven approach. The methodology implements an estimation of the building’s activity in order to improve the dynamics responsiveness and context awareness of the demand prediction system, thus improving its accuracy by taking into account the usage pattern of the building. A dedicated activity prediction model supported by a recurrent neural network is built considering this specific indicator, which is then integrated with a power demand model built with an adaptive neuro-fuzzy inference system. Since the power demand is not directly available, an estimation method is proposed, which permits the indirect monitoring of the aggregated power consumption of the terminal units. The presented methodology is validated experimentally in terms of accuracy and performance using real data from a research building, showing that the accuracy of the power prediction can be improved when using a specialized modeling structure to estimate the building’s activity.

Keywords – energy management systems, load prediction, machine learning, neural networks, smart buildings.

Nomenclature:

<i>ABM</i>	Agent-Based Modeling
<i>AHU</i>	Air Handling Unit
<i>ANFIS</i>	Adaptive Neuro-Fuzzy Inference System
<i>BEMS</i>	Building Energy Management System
<i>DSM</i>	Demand-Side Management
<i>HMM</i>	Hidden Markov Model
<i>HVAC</i>	Heating Ventilating and Air Conditioning
<i>MAE</i>	Mean Average Error
<i>MAPE</i>	Mean Absolute Percentage Error
<i>MAX</i>	Maximum Error
<i>OPC</i>	Open Platform Communications
R^2	Coefficient of Determination
<i>RMSE</i>	Root Mean Squared Error
<i>RNN</i>	Recurrent Neural Network
<i>SCADA</i>	Supervisory Control and Data Acquisition

1. Introduction

1.1 Background and motivation

Recent advances in the functionalities of modern Building Energy Management Systems (BEMS) in terms of monitoring and supervision [1, 2] have paved the way in the framework of smart buildings for the introduction of Demand-Side Management (DSM) practices [3], which are one of the most important methods for achieving energy savings [4]. The increased insight derived from this progress has been instrumental in the further study of context-aware solutions that are capable of improving the energy efficiency of technical services in BEMS by building on the expanded knowledge available [5]. By accounting for up to 40% of the power consumed in buildings, heating ventilating and air conditioning (HVAC) systems, in particular, have attracted a substantial share of current research efforts [6, 7].

In modern buildings, load modeling and forecasting methodologies able to predict the future power demand of HVAC systems are an important concern of installation managers due to the useful knowledge that they provide [8], since real-time demand information plays a role in mitigating energy waste [9]. Several types of methodologies exist, being data-driven approaches the most prevalent. However, when applied to HVAC systems, these methodologies are mostly aimed at forecasting the consumption load [10]. Instead, focusing on the thermal power demand may help abstract from performance differences caused by regulation systems and to better reflect the power needs of the facility. Automation systems can benefit from this information in order to make decisions autonomously by following energy-saving optimization strategies. This is especially true for the control of HVAC equipment, where the predicted load could be used for implementing model-predictive control strategies. Multiple control approaches applied to HVAC systems that could benefit from this information can be found in the literature, such as the planning of energy storage during off-peak periods using cooling storage systems [11]. Others also include the planning of adequate startup and shutdown times for heating and cooling equipment in order to save energy by meeting the right amount of power demands, and for the orchestration of

37 machine actuations in installations where multiple machines are available [12]. Furthermore, the combination of HVAC
38 load forecasting with machinery efficiency maps, represents an underexploited avenue of improvement with a high
39 potential for the optimization of the operation of the system. That is, the demand anticipation and the utilization of the most
40 suitable machine for each situation would provide a positive affectation to the overall equipment's performance, which is a
41 significant present-day problem in building management and maintenance. Indeed, the overall efficiency of the installation
42 could be improved, since the current most common method for allocation HVAC capacity is based on setting the same
43 water temperature thresholds on all the available machines [13].

44 Even though this framework represents one of the main current research interests stated by the related scientific
45 community, the obstacles for its implementation are double-sided. First, the efficiency maps are difficult to obtain when
46 precision beyond the manufacturer's sparse figures is desired, as they would require extensive testing of the unit in each
47 installation, and would likely drift over time as the equipment deteriorates with aging. Secondly, the methodologies for
48 obtaining load predictions in HVAC systems are not mature enough and their implementation can be quite challenging due
49 to the potential complexity of energy systems [14].

50 1.2 Literature review

51 In the recent literature, considerable scientific effort has been committed to the research of load forecasting algorithms
52 and methodologies, as seen in the latest review papers [15]. A comprehensive review of more than one hundred papers on
53 electrical load forecasting defined a general taxonomy for selecting modeling algorithms from the point of view of their
54 popularity in different applications, indicating that data-driven approaches are mainly used in short-term forecasting
55 applications due to their complex dynamics [16]. In contrast, a comparative analysis studied eleven modeling algorithms
56 from the point of view of their performance when applied to the same dataset, revealing their applicability in different
57 scenarios including cases with limited data or high variability [17]. However, even though numerous general-purpose
58 approaches exist for the implementation of load forecasting, their limitations are revealed when applied to real HVAC
59 systems, which are mainly related to the difficulty of adapting the predictions to the power demand changes caused by
60 fluctuations of influencing parameters, such as the weather and the occupant's behavior during the day [8].

61 In this regard, recent studies as the one presented by M. Peña *et al.* in [18], confirm the significant correlation between
62 the occupancy of the building's spaces and the HVAC equipment's actuations and consequent operational regime changes.
63 This, as promoted by different authors, as T. Hong *et al.* in [19], indicates that the occupancy should be a key aspect in the
64 research of energy usage in buildings, because of its potential contributions to efficiency improvements. Actually, a recent
65 review of energy efficient ventilation strategies concluded that large amounts of energy are being wasted because of
66 conditioning building areas that have effectively empty periods of time, and that accounting for these may help to greatly
67 increase efficiency [20]. Indeed, most of the current load simulation and forecasting methodologies show a lack of
68 occupancy awareness, while the available studies dealing with the integration of occupancy data into load forecasting
69 systems to enhance the accuracy of power demand predictions present critical limitations and insufficient proficiency [21].

70 Similarly, a recent review of artificial intelligence methods for load forecasting in buildings suggested that the
71 integration of occupancy data has the potential for improving energy predictions [22]. Moreover, it was stated by J.
72 Massana *et al.* in a study of the application of neural networks for building energy forecasting, that occupancy-based inputs
73 should be taken into consideration in future studies because of the impact that the occupancy can have on the building's
74 thermal energy usage. This is shown in [23] and further developed in [24], where several attributes were studied,
75 concluding that it would be useful to create occupancy indicators for improving the prediction capabilities.

76 On this subject, some methodologies for the modelling and forecasting of occupancy in buildings exist, being Agent-
77 Based Modelling (ABM), and Hidden Markov Models (HMMs) the most common. ABM approaches try to mimic the
78 behavior of occupants within a building in order to simulate either occupancy patterns or their effects at the occupant level
79 [25], hence being too fine-grained for full building applications. Alternately, HMMs are stochastic processes that naturally
80 fit the problem of modelling occupancy patterns, because they treat occupancy as a series of transitions between states and
81 attempt to estimate and simulate the probabilities of transitions among such states [26]. HMMs are useful at low
82 aggregation levels, for example for assessing the probability of a given space becoming occupied, but are not a good fit for
83 big scenarios, as the complexity grows exponentially with the number of zones [27]. Another disadvantage of HMMs at
84 high aggregation levels is that their future state is a function of their current state, not taking into consideration past states.
85 This property could neglect important features of the aggregated occupancy, such as the ratio of change. Indeed, complete
86 and viable solutions are yet to be investigated, and the proper way to monitor the occupancy, to define the indicators and to
87 integrate them into a load forecasting system remain to be established.

88 1.3 Innovative contribution

89 In this paper, an HVAC thermal power demand forecasting methodology composed by the integration of a power
90 demand model and an activity indicator model is studied. The methodology aims to extract the occupancy patterns in order
91 to determine the level of activity in the building and thus to improve the accuracy of the power demand forecasting. With
92 this objective, the building's historical database is divided into occupancy and load data for separate preprocessing. Then,
93 an activity indicator is built and a model is implemented using Recurrent Neural Networks (RNN) to enhance the
94 consideration of dynamic temporal patterns, while the power demand characterization is carried out by means of a state-of-
95 the-art Adaptive Neuro-Fuzzy Inference System (ANFIS) structure. Finally, a reliable and robust power demand
96 forecasting model is obtained by the serialized fusion of both inference systems.

97 The main contribution of this study lies in a new data-driven short-term load forecasting methodology for the prediction
98 of the thermal power demand of HVAC systems in buildings, and the introduction and verification of an activity indicator
99 estimation procedure to support the prediction of the power demand.

100 Aligned with the current research challenges in the field, the methodology takes advantage of real-time occupancy data
101 in order to predict an activity indicator, providing accurate insight regarding the thermal needs of the building in terms of
102 the volume of consumption endpoints in operation. Furthermore, due to the difficulty in directly measuring the thermal
103 power demand signal, which would involve the use of extensive instrumentation installed in consumption endpoints
104 throughout the building, an estimation method is proposed in order to calculate the actual power draw, derived from the
105 measurement of the thermal power output of the HVAC energy production equipment in the building. The novelty of this
106 work includes the implementation of a new hybrid solution that offers major advantages over traditional approaches. In
107 particular, the collaborative model structure, comprehending the separate modeling of the activity indicator's dynamics and
108 the thermal power demand characterization, differs from classical single model approaches in that it allows the selection,
109 tuning and fitting of each structure independently, increasing its adaptability to the dynamics of each signal and improving
110 the resulting accuracy through the specialization of its modeling process. It should be noted that this is the first time that
111 this methodology as well as this activity indicator modelling is used in building automation and energy management for
112 providing accurate insight regarding the thermal needs of the building, with the objective of supporting the enhancement of
113 resource management and the optimization of the operation of local equipment.

114 This paper is organized as follows. Section II presents the proposed methodology, focusing on the occupancy
115 monitoring to create an activity indicator, the thermal demand estimation of the HVAC system and the load forecasting that
116 merges this information in order to calculate predictions. Section III describes the test environment. Section IV shows the
117 experimental results obtained from the implementation and validation in a real building. Finally, the conclusions of this
118 work are drawn in Section V.

119 **2. Proposed Methodology**

120 A step-by-step diagram of the complete methodology is shown in Fig. 1, which is divided into three stages: the activity
121 indicator modeling stage, where an artificial activity indicator is defined and modelled, the power demand modeling stage,
122 where the power demand of the HVAC system is estimated and modelled separately and finally the demand forecasting
123 stage, where predictions are obtained by means of the evaluation of the models.

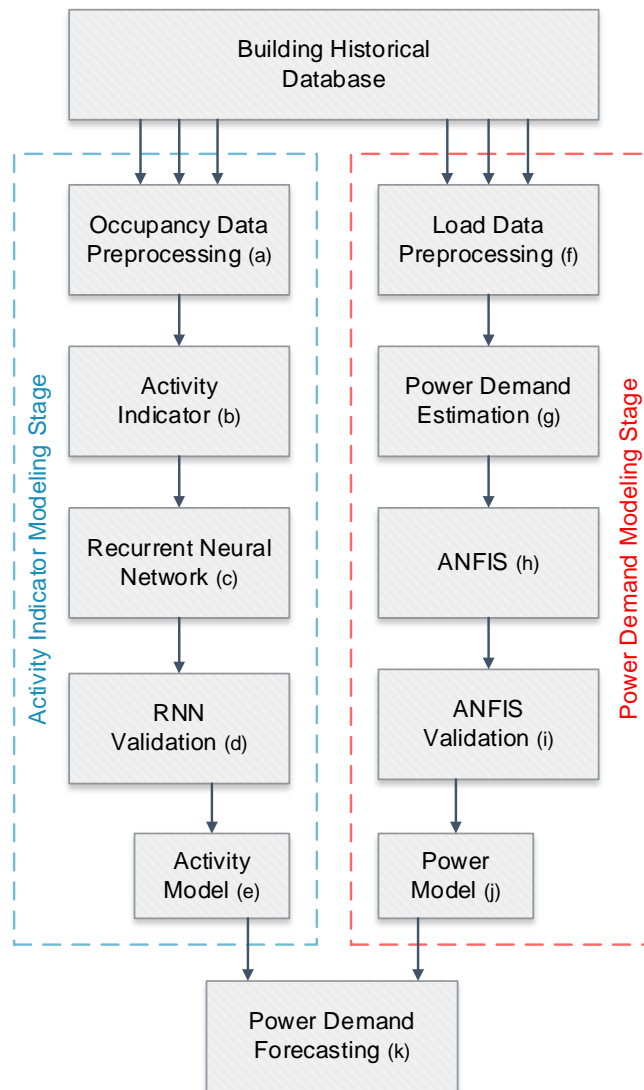


Fig 1. Steps of the proposed power demand forecasting methodology divided into activity modeling stage and power demand modeling stage.

124

125 Initially, on the activity indicator modeling stage, the occupancy data is extracted from the building's historical
 126 database and is preprocessed in order to remove gaps due to acquisition interruptions, outliers and erroneous readings (a).
 127 The activity indicator is then defined as the aggregation of the binary occupancy signals (b) and the obtained indicator is
 128 modeled by means of a recurrent neural network with global feedback (c). The trained network's performance is evaluated
 129 over a test dataset in order to validate that it has properly learned the indicator's behavior (d).

130 Afterwards, during the power demand modeling stage, power data plus auxiliary signals are loaded and preprocessed in
 131 a similar manner (f). Then, a power demand estimation method (g) allows the calculation of the total power demand
 132 corresponding to the consumption endpoints in the building, decoupling the effect of the distribution bus capacity and the
 133 control strategy. Next, an ANFIS model is built for the forecasting of the obtained thermal power consumption signal by
 134 selecting the most suitable set of input variables and training the inference structure (h). After the model is trained, it is
 135 validated (i) in a similar manner as the activity indicator model in order to ensure its accuracy.

136 Finally, the activity indicator model (e) is combined with the obtained power demand model (j) to support the
 137 calculation of power demand predictions (k). The combination is performed in series, where the output of the activity
 138 model is used as an input of the power model.

139 The following subsections describe the main stages of the methodology in detail.

140 2.1 Activity indicator modeling

141 In the literature, some studies use timetables as a rough estimation of occupancy, exploring the potential energy savings
 142 that could be achieved by implementing management strategies that take advantage of personalized occupancy schedules
 143 [28], schedules of the temperature settings of the building [29], or occupancy patterns derived by mining the energy
 144 consumption of appliances [30]. However, a recent review of occupancy modeling approaches concluded that schedule-
 145 based methodologies are not suitable for applications aimed at improving energy efficiency in buildings, in favor of more

146 sophisticated methods that are able to learn and predict the behavior of occupants [21]. Accordingly, the implementation of
147 a new model of the occupancy pattern of a building is introduced in this methodology.

148 Thus, in the proposed methodology the concept of an activity indicator is introduced with the aim of incorporating the
149 information relating to the occupancy of the building into the load forecasting system. The proposed activity indicator is
150 defined as the percentage of active spaces in a building, given that the spaces are monitored with presence detectors, which
151 are common in modern buildings for climate and lighting control purposes. The percentage of active spaces is not intended
152 to be a direct measurement of the occupation as the number of present occupants, instead it is used as a measurement of the
153 amount of activity in the building in terms of spaces where the HVAC system is in operation. The integration of this
154 indicator into the load forecasting system may lead to more accurate predictions, because the amount of rooms with an
155 operating local air handling unit (AHU) is likely to significantly affect the load of the HVAC equipment (chillers, heat
156 pumps, etc.) at the energy production stage. However, information regarding this or any other artificial activity indicator is
157 unknown beforehand, as opposed to variables such as weather conditions, which can be pulled from a local weather service
158 with reasonable accuracy. In consequence, a dedicated activity modeling system is integrated into the methodology in order
159 to independently obtain a model of the dynamics of this signal so it can be used for improving the accuracy of the
160 subsequent power demand forecasting.

161 The modeling of the activity indicator is based on a RNN, which is a data-driven technique that is well suited for cases
162 where the target signal does not present a direct correlation with other signals that could have been used as model inputs,
163 and instead depends on learning the target signal's own dynamics. This is possible because RNNs introduce the time
164 element through their internal states, which allow the network to remember information about the past and to use it for the
165 calculation of predictions, facilitating the learning of the temporal dynamics of the target, instead of relying solely on the
166 current inputs [31]. This feature of RNNs makes them suitable for modelling the activity indicator, which is not strongly
167 correlated with other signals, thus the modeling relies on accumulated state for learning its temporal dynamics, in this case
168 complemented with the time of the day and the day of the week for increased robustness. Additionally, memory units have
169 been incorporated into the network in order to provide auto-regressive behavior; this allows the network to not only take
170 into account the previous recurrent state, but past states as well.

171 The RNN is trained in open-loop form by means of backpropagation, where its coefficients are tuned with the objective
172 function corresponding to the minimization of the mean-squared error of the prediction of the state of the next iteration.
173 After the modeling process is carried out using the open-loop network, the feedback loop is closed to allow the calculation
174 of predictions taking advantage of the recurrent nature of the network. Using the closed-loop form, prediction iterations are
175 calculated based on the value of the previous state, the inputs and past states provided by the memory units,. The structure
176 of the complete closed-loop RNN is shown in Fig 2. The trained network is then validated in terms of accuracy using
177 several error metrics, evaluating its performance as more iterations are calculated. The results of the validation ascertain
178 whether the performance is sufficient at the desired prediction horizon.

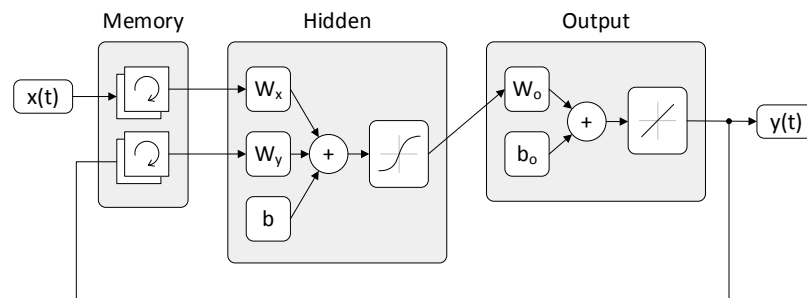


Fig 2. Structure of the closed-loop recurrent neural network, composed by an input layer with memory units, a hidden layer, and an output layer with a feedback loop.

179

180 2.2 Power demand modeling

181 The implementation of the power demand model begins with the initial step of preprocessing the signals to interpolate
182 possible gaps and filter noisy signals acquired by sensors. In addition, a final step is considered for the validation of the
183 trained model structure. However, the core of the proposed power demand modelling is composed of the following two
184 main steps: the power demand estimation, and the fitting of the ANFIS model.

185 2.2.1 Power demand estimation

186 The power consumption of HVAC systems is a form of instrumentation that is frequently found in buildings, especially
187 in modern smart buildings that incorporate BEMS, which are the main target environment of novel methodology proposals.
188 Thermal power demand, however, is not a variable that is commonly monitored directly due to the high cost of installing
189 sensors in consumption endpoints, even though it is the most useful signal to support the optimization of local resources.
190 The reasoning is based on the fact that when load forecasting systems are implemented for demand response programs or
191 other applications in the context of the smart grid, it makes sense to provide the power consumption of the complete
192 system, because these applications are focused on the optimization and planning of upstream resources. Instead, the
193 proposed method is aimed at providing a forecasting model of the thermal power demand, which can be used to optimize
194 the operation of on-site resources such as HVAC machines.

195 Since directly measuring the thermal power consumption of the building in real-time is not a commonly affordable
 196 option, which would limit the applicability and impact of the methodology, an indirect solution is proposed. The method
 197 follows a grey-box approach to allow the estimation of the power demand observed in the thermal distribution bus of the
 198 building, implemented as described next.

199 The energy balance of the bus (1) is calculated for each time sample, where Q_{in} is the thermal power produced by the
 200 HVAC equipment, measured using an ultrasonic flow meter plus a differential temperature sensor, and Q_{out} is the power
 201 drawn from the bus, which is not known. The energy accumulated in the bus Q_{bus} during each cycle is described by (2)
 202 where C_p is the specific heat of the fluid in the bus, ΔT_{bus} is the increment of the temperature of the bus, and m is the total
 203 mass of the fluid.

$$204 \quad \Delta Q_{bus} = Q_{in}(t) - Q_{out}(t) \quad (1)$$

$$205 \quad Q_{bus} = C_p \cdot m \cdot \Delta T_{bus} \quad (2)$$

206
 207
 208 Once the energy balance is defined by the input energy flow Q_{in} and the energy accumulated in the bus Q_{bus} , the
 209 resulting power flow being drawn by the consumption endpoints Q_{out} can be calculated by subtraction.

210 2.2.2 Power demand model fitting

211 After the thermal power demand is obtained, a forecasting model is built for this new signal. The method used in this
 212 study for the implementation of the load forecasting is the Adaptive Neuro-Fuzzy Inference System (ANFIS). Even though
 213 neural networks are the most popular data-driven methods, mainly due to their accuracy and non-linear mapping
 214 capabilities [32], they present drawbacks such as falling on local minima and requiring large datasets [33]. Instead, ANFIS
 215 combines the advantages of neural networks with fuzzy systems to better handle complex and adaptive systems, having
 216 been validated in multiple load forecasting studies [34].

217 For the implementation of the ANFIS model, several input signal candidates are considered besides the previously built
 218 activity indicator, including weather parameters and other variables commonly available in BEMS, as described in the test
 219 environment section. In order to select the a set of signals that allows the proper characterization of the power demand, an
 220 input selection process is carried out, which is based on the cross-correlation analysis between each of the input candidates
 221 and the target signal to rule out uncorrelated signals, and the study of their dynamics by means of the frequency analysis of
 222 each variable. Having considered the candidate inputs and obtained the final selection, an ANFIS model is trained and then
 223 evaluated using common performance indicators: the Root Mean Squared Error (RMSE), the Mean Absolute Percentage
 224 Error (MAPE), the Mean Absolute Error (MAE), the Determination Coefficient (R^2) and the Maximum Error (MAX).

225 2.3 Power demand forecasting

226 Finally, the power demand of the HVAC system of the building can be predicted using the combination of the trained
 227 models obtained following the previous steps. The activity indicator model provides a measure of the future occupancy
 228 level, which drives the HVAC power. Then, the expected power demand is calculated to obtain the final prediction,
 229 corresponding to this activity and the other influencing variables. In summary, the obtained models are combined in series,
 230 with the activity indicator forecast being fed to the power demand model to calculate the final prediction.

231 Besides the activity indicator estimation procedure, the hybrid solution adopted in this study offers several advantages
 232 over traditional approaches. Namely, instead of fitting a single model using a general-purpose tool, a collaborative and
 233 modular structure is proposed based on specialized models built for the activity and for the power demand. Such solution
 234 allows to fit and tune each method independently, adapting it to the dynamics of each signal and allowing to separately
 235 train the models with the use of different datasets.

236 3. Test Environment

237 For the validation of the proposed methodology, the complete system has been implemented in a real building in Spain.
 238 The building is a research ecosystem of the Universitat Politècnica de Catalunya – BarcelonaTech, which consists of
 239 offices and laboratories with a surface of 2.400m². The environment accommodates several research groups that specialize
 240 in the fields of energy efficiency, electronics, automatics, and biotechnology, among others. In this regard, the nature of the
 241 tasks carried out by the staff adds a degree of additional variability to the usage patterns of the building, thus increasing the
 242 complexity of the forecasting.

243 The building has several HVAC machines to be able to maintain appropriate comfort levels, including energy
 244 production equipment such as chillers and heat pumps, and distribution AHUs for pre-conditioning and air renewal.
 245 Additionally, the installation includes terminal AHUs that service each of the spaces in the building, with spaces having
 246 multiple AHUs depending on their surface. The characteristics of these machines are shown in Table I.

247 TABLE I SUMMARY OF HVAC MACHINES IN THE TEST BUILDING.

Id	Type	P _{elec} [kW]	P _{thermal} [kW]
----	------	------------------------	---------------------------

R1	Electrical Chiller	56.6	150
R2	Electrical Chiller	56.6	150
BC1	Heat pump	56.7	130
BC2	Heat pump	66.2	150
CAL1	Natural Gas Boiler	2	430
CL1	Global AHU	5.5	n/a
CL2	Global AHU	7.5	n/a

248

249 In order to operate the equipment, a Modbus communication bus reads status variables such as temperatures and
 250 operation modes and delivers control signals to the HVAC installation, including the production and distribution
 251 equipment. Additionally, the building has an OPC server with a SCADA that centralized other sensors, including a local
 252 weather station and sensors from each of the rooms and spaces in the building. The control of the HVAC system is
 253 performed through the SCADA, which supports manually setting up priorities and schedules for the machines as well as
 254 supervising their state in real time.

255 The test building includes a total of 130 terminal AHUs, 60 of those installed in offices, meeting rooms and
 256 laboratories, and the rest in common areas. These units are wired to passive infrared presence detectors and use their
 257 feedback for the regulation of the temperature in each space, which allows the fine-grained control of the internal
 258 temperatures in the building. Each space is allowed to define its own comfort range, within global constraints.

259 Two separate datasets are used for the experimental validation of the proposed methodology. For the activity indicator
 260 model, the available dataset comprises 8 months of data, sampled with an acquisition period of 4 minutes, from March to
 261 October of 2016, including the individual occupancy signal of each of the spaces of the building. Separately, the dataset for
 262 the power demand model comprises 11 weeks of data, sampled with an acquisition period of 4 minutes, from late June to
 263 early September of 2016, as the dataset corresponds to the cooling power demand, which is only relevant during summer.
 264 The power demand dataset contains the power output of the energy production equipment, the bus impulsion and return
 265 temperatures, and the external temperature and solar irradiation, measured by the weather station. The comprehensive list
 266 of available signals is shown in the following table.

267

TABLE II SUMMARY OF SIGNALS AVAILABLE IN THIS STUDY.

Name	Description
P_{th}	Aggregate thermal power from the energy meter.
T_{imp}	Bus impulsion temperature.
T_{ret}	Bus return temperature.
T_{ext}	Outdoor temperature.
Sol	Solar irradiation.
Occ_x	Presence detector signals (x: 1, 2, 3, etc).
Act	Artificial activity indicator.

268

269 The forecasting horizon is set to one hour in this case, as a shorter horizon would limit the applicability of the load
 270 forecasting methodology, and would not allow optimization systems to plan actions with sufficient foresight. Furthermore,
 271 a one-hour forecast horizon is sufficient to adapt the predictions to the significant dynamics observed in the building's
 272 datasets, which are in the range of two to three hours.

273 4. Experimental Results

274 This section shows the implementation of the proposed methodology and discusses the obtained experimental results in
 275 the described test environment.

276 4.1 Activity indicator modeling

277 After the preprocessing of the dataset's signals to remove gaps and to filter out erroneous out-of-range samples, the
 278 activity indicator is built using the sum of the individual occupancy signals obtained from the presence detector associated
 279 to each space. The resulting activity indicator is shown in Fig 3. The pattern presented by the resulting signal follows an
 280 expected trend, the indicator rises in the morning as more spaces in the building become occupied and their presence
 281 detector is triggered, some drops are observed at midday as people leave for lunch, and finally most people leave during the
 282 evening. However, being a research facility, some remnant occupation can routinely be observed in the building, even
 283 during nighttime.

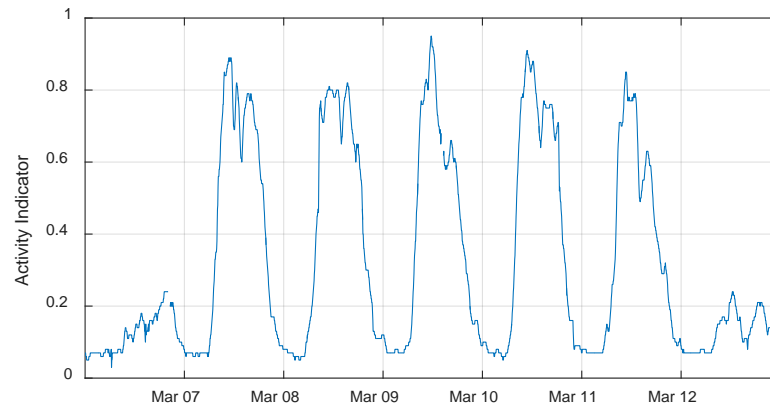


Fig 3. Activity indicator estimated from the aggregate of the individual occupancy signals during a week in March of 2016.

284

285 Next, the activity indicator model is built using a RNN, which must be configured before the training. The parameters
 286 to be configured are the time step between the recurrent iterations, the number of memory units on the inputs and on the
 287 output feedback loop, and finally the number of neurons in the hidden layer.

288 Considering the temporal aspect of RNNs, it is necessary to properly configure the iteration time step according to the
 289 dynamics present in the signal and the desired prediction horizon. Thus, a small time step value in the range of minutes is
 290 required in order to capture the dynamics for the next hour horizon. Further experimentation was performed in order to
 291 characterize the effect of increasing the iteration time step value. This improves the performance of the network when
 292 predicting the activity indicator several hours ahead. In fact, it was possible to predict the activity of the next 8 hours with
 293 slightly over 10% RMSE. However, even though increasing the time step lead to expanding the forecasting horizon where
 294 the model was still usable, the performance decreased in the short-term, which is precisely when maximum performance is
 295 required in order to feed the power demand model. Thus, the value of the iteration time step of the RNN was configured at
 296 4 minutes, which is the minimum acquisition-step available in this case.

297 Regarding the number of memory units, this amount is set to zero for the inputs, since the dynamics of the input signals
 298 of the activity indicator model, which are the day of the week and the time of the day, are not relevant. Instead, the number
 299 of memory units in the output feedback loop is set to 15, which at 4 minutes per iteration step matches the one hour
 300 forecasting horizon desired. Therefore, the past states in the last hour are used when forecasting the next hour. Additional
 301 experiments were conducted, confirming that including too few units resulted in poor performance, while including too
 302 many units did not improve the prediction accuracy, but severely increased the training time due to the added parameters.

303 Concerning the amount of neurons in the hidden layer, related studies recommend using a number of neurons bigger
 304 than the number of inputs in order to contribute to an information expansion prior to the output convergence. Subsequently,
 305 further empirical experiments were carried out in order to select an optimal configuration. An amount of 16 neurons is
 306 finally selected for the hidden layer, as fewer neurons were not able to fully estimate the dynamics of the signal, and more
 307 neurons increased the training time while actually decreasing performance.

308 After the training of the network with the selected configuration, the performance of the resulting model was evaluated
 309 over a reserved validation dataset, which accounted for 30% of the available data. The selected performance indicators are
 310 the defined for the power demand model: the root-mean-square error (RMSE), the mean absolute percentage error
 311 (MAPE), the mean average error (MAE), the maximum error (MAX) and the coefficient of determination (R^2). Because of
 312 the iterative nature of the evaluation of the recurrent network, where each prediction is fed back into the model to generate
 313 the next state, it is not enough to evaluate the forecasting performance of a single step, as the error is accumulated at each
 314 iteration. Thus, the multi-iteration performance must be evaluated to find out if the model is suitable. Fig. 4 shows the
 315 progression of the selected performance indicators as the prediction horizon is expanded. As it can be observed, all of the
 316 considered error indicators exhibit a performance decrease as more iterations are applied to the RNN. At 1-hour prediction
 317 horizon the mean absolute error is 2.3%, which is a very accurate response taking into account the apparent random
 318 behavior of the occupancy in buildings, therefore the model is deemed acceptable for the further implementation of the
 319 methodology. It is also observed that the evaluation time increases in a linear trend as more feedback loops are applied in
 320 order to increase the prediction horizon.

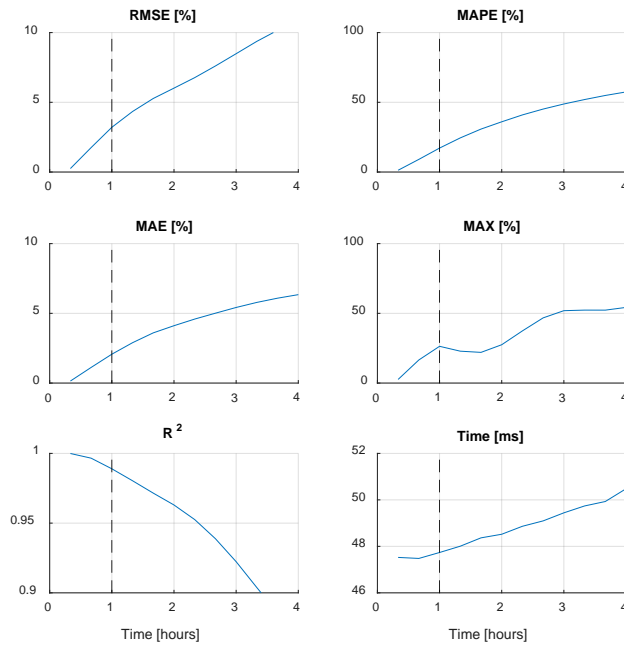


Fig 4. Performance of the activity indicator model when used for multi-iteration predictions using the validation set. Root mean squared error, RMSE. Mean absolute percentage error, MAPE. Mean absolute error, MAE. Maximum error, MAX. Determination coefficient, R^2 . Evaluation time.

321

322 4.2 Power demand modeling

323 Having accomplished the activity indicator modeling stage and having obtained an activity model suitable for use, the
 324 next step is to carry out the power demand modeling stage, where the activity forecasting is integrated with ANFIS in order
 325 to model the power demand of the HVAC system.

326 A dataset was extracted from the building's historical database, comprising the variables defined in the test
 327 environment section. After the preprocessing of these signals, the first step was to calculate the power demand signal from
 328 the measured power output of the machines and the bus temperatures by means of the estimation of the bus dynamic
 329 behavior. The bus temperature signals and the estimated power demand compared to the measured power production are
 330 shown in Fig 5 for a period of three days in August.

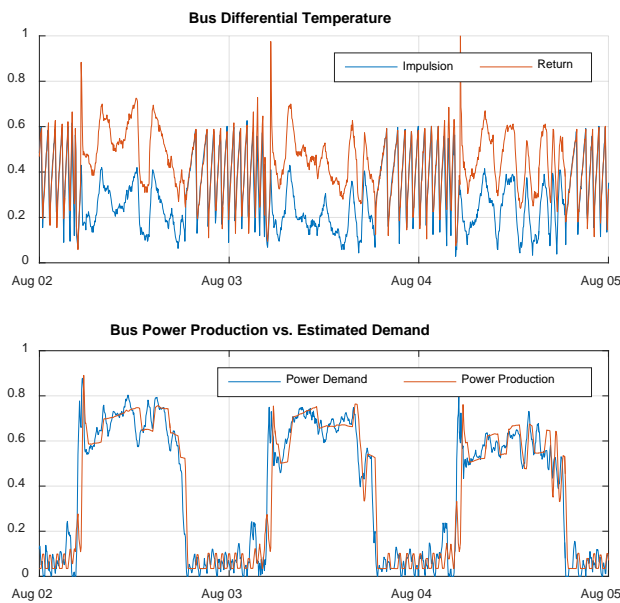


Fig 5. Normalized power demand signal drivers. a) Bus impulsion and return temperatures. b) Bus power production and estimated demand.

331

332 As it can be observed in Fig. 5(b), the power demand signal, corresponding to the aggregated power drawn by the
 333 consumption endpoints in the building, presents higher dynamics than the power production, corresponding to the
 334 aggregated power generated by the production equipment, while having the same integral value, as the consumed energy
 335 must be equal to the production. It is worth mentioning that there is a delay between the risings and fallings of the power
 336 demand compared to the power production. This is due to the control scheme implemented in this HVAC system, which
 337 does not take into account power demand, and instead focuses on maintaining the bus temperature between thresholds. The
 338 difference between the power production and the power demand at the end of each workday is energy that is wasted and
 339 will not be consumed by the HVAC system. This energy remains in the distribution bus until it is dissipated because of
 340 insulation losses. Having a power demand forecast, this could be improved by producing the minimal energy that is
 341 required to match the power demand.

342 In order to build the power demand model, a set of variables are selected as the inputs for the model from the available
 343 signals in order to facilitate the work of the training algorithm. The following signals were considered as inputs: external
 344 temperature, solar irradiation, bus impulsion temperature, bus return temperature, bus differential temperature and finally
 345 the estimated activity indicator. To select the model's inputs, the cross-correlation between the target signal and each of the
 346 input candidates is calculated in order to rule out uncorrelated signals.

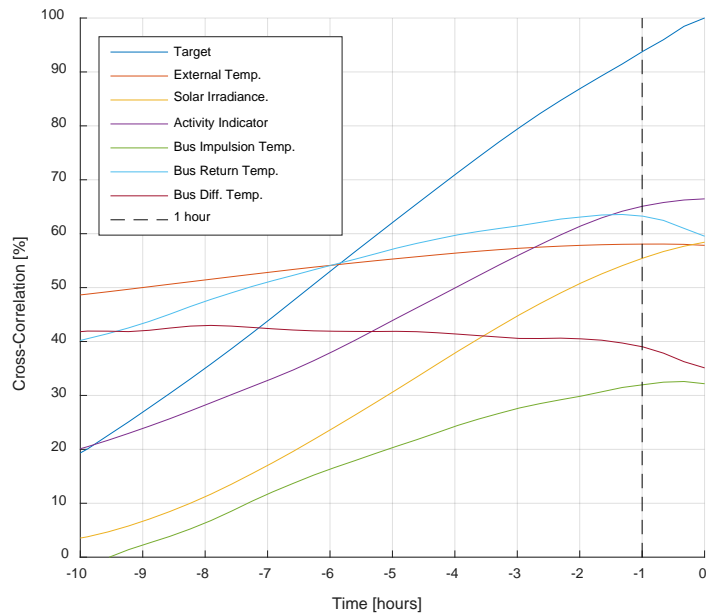


Fig. 6. Cross-correlation between each model input candidate and the forecasting target.

347
 348 The different cross-correlation pairs are shown in Fig. 6, where each series shows the correlation between an input
 349 candidate and the thermal power demand as a time shift is applied between the two signals. It is desirable that the selected
 350 inputs show a high correlation with the target signal at the forecasting horizon, which is set to 1 hour in this case. As it can
 351 be observed, the most strongly correlated input candidates when the offset between each pair is 1 hour are the external
 352 temperature, the solar irradiance, the activity indicator and the bus return temperature. On the other hand, the bus impulsion
 353 temperature and the bus temperature differential present low correlation with the target. Finally, it is noticeable that the
 354 target shows a strong correlation with itself when a 1 hour offset is applied, therefore the current power demand value was
 355 also considered as an input for the model. A sample of the preselected input variables is shown in Fig. 7.

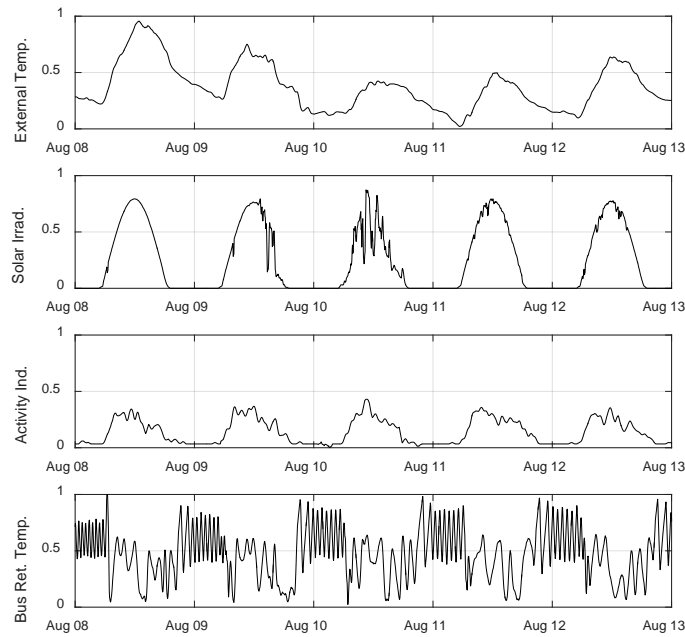


Fig 7. Selected input variables during a period of 5 days in August.

356

357 The study of the signal's frequency components, shown in Fig. 8 as the frequency spectrum analysis, revealed the
 358 magnitude of the signal's dynamics. As it can be observed, the solar irradiation and the external temperature present rather
 359 slower dynamics than the power demand, which is expected as they mostly follow a daily pattern. Instead, the activity
 360 indicator presents significant dynamics up to sub-hour period frequencies, which is more aligned with those observed in the
 361 power demand, as is the case of the bus return temperature, which presents even higher frequency components. Thus, the
 362 inclusion of the activity indicator and the bus return temperature may help the model to better adapt to the power demand's
 363 dynamics, as these signals present more similar frequency components.

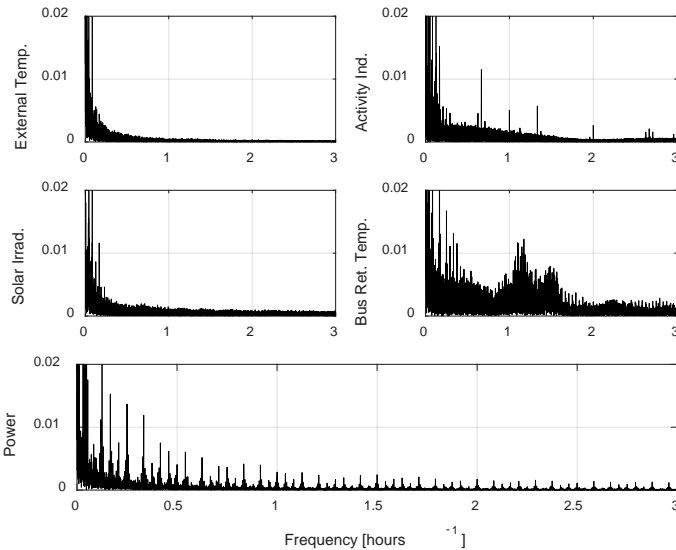


Fig 8. Frequency spectrum comparison between the power demand model input candidates and the power demand target signal.

364

365 Additional empirical analyses carried out with the available signals, reveal that the use of both the external temperature and
 366 the solar irradiance do not improve the modeling performance, as these two signals present correlation between them
 367 and introduce redundant information into the model. As the external temperature presents a smoother behavior than the
 368 solar irradiance, which has very steep peaks due to passing clouds, and a forecast of the external temperature is readily
 369 available through a local weather service provider, but not for the case of the irradiance, the latter was discarded and only
 370 the former was used. Regarding the current value of the target, it was noticed that it improved the forecasting accuracy
 371 when included, as it provided a reference point to calculate the next values. Concerning the bus temperature signals, only
 372 the return temperature was used, as it provides feedback about the state of the production/demand match. The bus
 373 differential temperature was considered, even though it presented low correlation with the target, in an attempt to increase

374 the accuracy of the model during rapid changes, as the bus differential presents high dynamics. This helps the model
375 perform better in some cases, but overall introduces noise and is finally discarded. Finally, another considered variable is
376 the day of the week, which was included as it helps the ANFIS rule inference step to properly characterize the behavior of
377 the power demand during weekends. In summary, the study revealed that the most appropriate set of signals to characterize
378 the power demand of the building is: the external temperature, the activity indicator, the bus return temperature, the current
379 power demand value and the day of the week.

380 The result of the model training is shown in Fig. 9, where it can be observed that the model closely matches the target
381 on most of the signal, presenting low average error. However, there are also error peaks that occur when the target signal
382 presents the fastest dynamics, causing error spikes due to steep changes, but having very short duration.

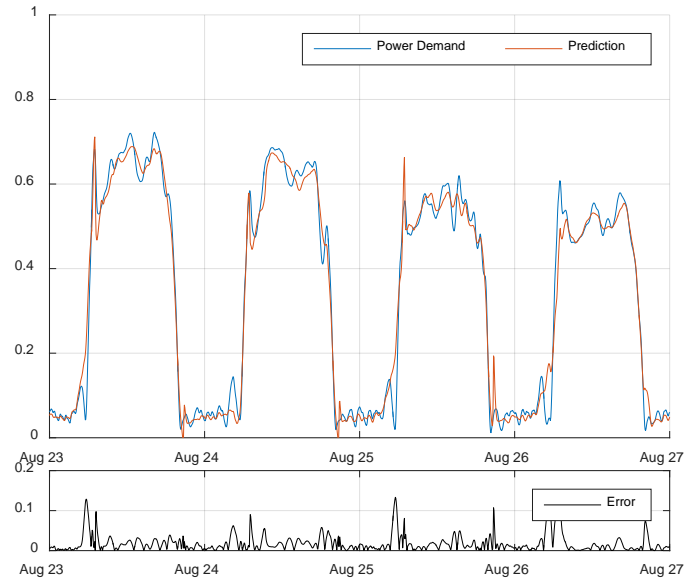
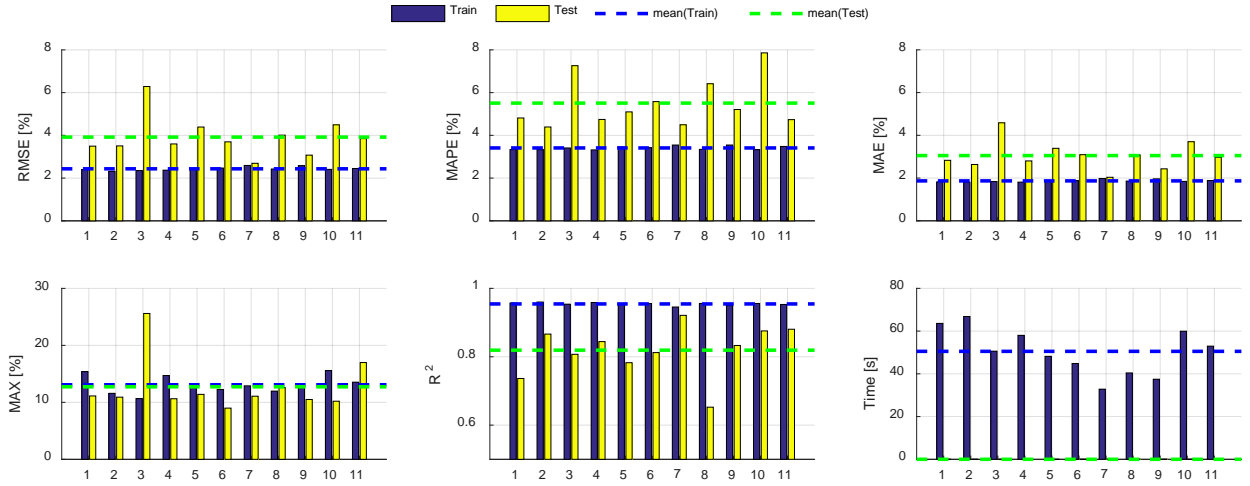


Fig 9. Comparison between the power demand signal and a prediction obtained using the trained power demand model.

383
384 In order to validate the methodology and to evaluate its performance and generalization capabilities, a cross-validation
385 strategy was followed. The cross-validation implementation removes one week of data at a time from the dataset, builds a
386 model using the remaining data and validates the model against the removed subset. Thus an 11-fold cross-validation is
387 considered. The results of the cross-validation are shown in Fig. 10, where several performance indicators were calculated
388 when the model is applied over the training set and separately over the validation set. As it can be observed, the error
389 indicators are quite low, with the mean absolute error being the most compelling at an average value of 2% during training
390 and 3% during validation. The maximum error shows an average of 13%, which is acceptable due to the occasional rapid
391 changes observed in the signal, but reaches a value of 26% when week 3 is not present in the training set. In fact, the other
392 error indicators are also noticeably higher when week 3 is used as validation and is excluded from the training. This
393 observation indicates that week 3 presents a behavior that differs from the rest of the data, as the resulting model achieves
394 worse prediction performance when learning from the other cases.



395 Fig 10. Results of the cross-validation process when splitting the data into 11 subsets, corresponding to the weeks in the dataset.

396 Finally, in order to quantify the increase of performance provided by the application of the proposed methodology, the
 397 obtained results have been compared with a classical load forecasting implementation based on ANFIS [35]. The
 398 evaluation of the power demand modeling stage using the proposed methodology resulted in decreased error metrics. The
 399 following table shows the performance change when comparing the average performance metrics of the proposed
 400 methodology to the ones obtained from the cross-validation of the classical approach both including and withholding the
 401 activity information.

TABLE III. PERFORMANCE COMPARISON BETWEEN THE PROPOSED METHOD (A), AND THE CLASSICAL SINGLE ANFIS APPROACH WITH THE ACTIVITY INDICATOR (B), AND THE CLASSICAL SINGLE ANFIS APPROACH WITHOUT THE ACTIVITY INDICATOR (C).

	A		B		C	
	Value	Value	$\Delta\%$	Value	$\Delta\%$	
RMSE	3.932	4.239	-7.81	5.196	-32.15	
MAPE	5.571	6.205	-11.38	7.745	-39.02	
MAE	3.055	3.384	-10.77	4.198	-37.41	
MAX	13.200	12.941	+1.96	13.352	-1.14	
R²	0.821	0.775	+5.58	0.704	+14.25	
TIME	51.21	51.57	-0.70	30.260	+40.91	

402
 403 As it can be observed, the introduction of the activity indicator causes a significant improvement in most of the
 404 performance metrics over a classical ANFIS approach that does not take into account occupancy data, except for the
 405 training time, which is almost halved. This reduction in the duration of the training time is likely due to the reduction in the
 406 size of the data and the loss of one dimension in the input space by not considering the activity indicator, which allowed the
 407 modeling to speed up convergence at the cost of increased error. Additionally, the integration of the occupancy forecasting
 408 in the proposed methodology in order to provide more updated activity values helped to further increase the performance
 409 metrics over a classical approach that used the activity indicator.

410 5. Conclusions

411 A short-term activity-aware thermal power demand forecasting methodology is studied in this paper, aligned with the
 412 state of the art on load forecasting in buildings for energy management applications. The proposed methodology consists in
 413 a hybrid modeling process where a dedicated recurrent neural network learns the dynamics present in an activity indicator
 414 developed for this study, and an adaptive neuro-fuzzy inference system correlates activity predictions obtained in this
 415 manner with the outdoor temperature and the bus return temperature in order to characterize the thermal power demand of
 416 the building's HVAC system.

417 The integration of the activity assessment into the modeling process, through the definition of an indicator that reflects
 418 the occupancy state of the whole building, has been shown to increase the accuracy of the power demand forecasting. The
 419 error metrics are significantly decreased when the activity is used as an additional input for the power demand forecasting,
 420 but they are further diminished when the neural network is included as a dedicated means to learn the activity's dynamics,
 421 providing an estimation of the use that the building shall receive in the following hour. To this end, the implementation of

422 the activity modeling with a recurrent neural network is validated as suitable approach in order to consider the temporal
423 patterns of the building's activity, as the proposed activity modeling process exhibits an important performance increase
424 compared with state-of-the-art approaches, achieving a mean absolute error below 10%.

425 The proposed thermal power demand estimation procedure allows the modelling of the total power being drawn by the
426 consumption endpoints in the building, instead of modelling the consumption of the entire installation as is done in most
427 related studies. The estimation is achieved by means of an energy meter that monitors the aggregate output of the
428 production stage equipment and the simulation of the bus capacity in order to calculate the difference. The main benefit of
429 this change is to allow the decoupling of the effect of the capacity of the distribution bus and the effect of the management
430 strategy followed by the HVAC energy production equipment. Therefore, future studies may build on this methodology for
431 implementing production management strategies that optimize the operation of the equipment according to the forecasted
432 power demand in order to increase the energy efficiency.

433 A study of the available input candidates for implementing the power demand model was carried out in order to obtain
434 a set of variables that allows the accurate modelling of the target signal. This study helped identify the set that achieves the
435 best results: the current power demand, the activity indicator, the external temperature, the bus return temperature and the
436 day of the week. The developed methodology can be generalized to other cases, extending its applicability.

437 Besides increased accuracy, the proposed methodology presents other advantages, such as the possibility of using
438 separate datasets of potentially different sizes for the activity indicator model and for the power demand model, which
439 allowed the selection of representative datasets for each case. Additionally, this decoupling allowed the separation of
440 concerns, promoting the specialization during the selection of the best modeling algorithm for each signal and the
441 independent tuning of the configuration of each model, including the use of different inputs and dynamics to match each
442 target signal's behavior. The proposed structure also decouples the model tuning process, allowing to update a model
443 independently of the other when necessary, since the activity model may need to be updated more often due to the
444 changing behavior of the activity of the building.

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