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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:

ABM	Agent-Based Modeling
AHU	Air Handling Unit
ANFIS	Adaptive Neuro-Fuzzy Inference System
BEMS	Building Energy Management System
DSM	Demand-Side Management
HMM	Hidden Markov Model
HVAC	Heating Ventilating and Air Conditioning
MAE	Mean Average Error
MAPE	Mean Absolute Percentage Error
MAX	Maximum Error
OPC	Open Platform Communications
R^2	Coefficient of Determination
RMSE	Root Mean Squared Error
RNN	Recurrent Neural Network
SCADA	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 machine actuations in installations where multiple machines are available [12]. Furthermore, the combination of HVAC load forecasting with machinery efficiency maps, represents an underexploited avenue of improvement with a high potential for the optimization of the operation of the system. That is, the demand anticipation and the utilization of the most suitable machine for each situation would provide a positive affectation to the overall equipment's performance, which is a significant present-day problem in building management and maintenance. Indeed, the overall efficiency of the installation could be improved, since the current most common method for allocation HVAC capacity is based on setting the same water temperature thresholds on all the available machines [13].

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

1.2 Literature review

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

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

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

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

1.3 Innovative contribution

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

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

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

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

2. Proposed Methodology

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

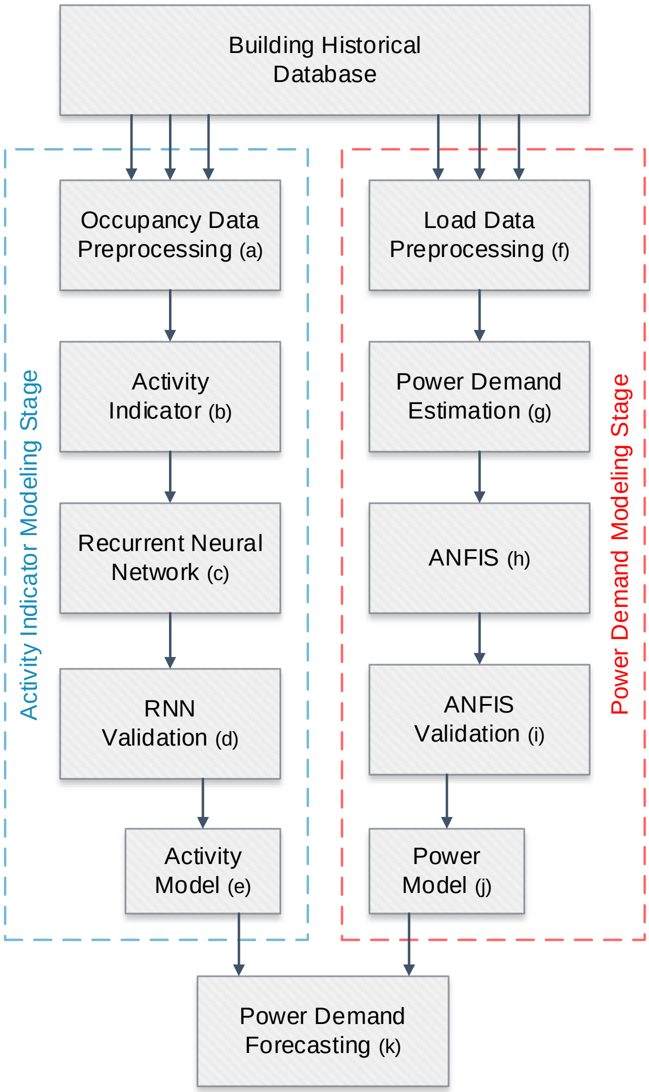

Fig 1. Steps of the proposed power demand forecasting methodology divided into activity modeling stage and power demand modeling stage.

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

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

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

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

2.1 Activity indicator modeling

In the literature, some studies use timetables as a rough estimation of occupancy, exploring the potential energy savings that could be achieved by implementing management strategies that take advantage of personalized occupancy schedules [28], schedules of the temperature settings of the building [29], or occupancy patterns derived by mining the energy consumption of appliances [30]. However, a recent review of occupancy modeling approaches concluded that schedule-based methodologies are not suitable for applications aimed at improving energy efficiency in buildings, in favor of more sophisticated methods that are able to learn and predict the behavior of occupants [21]. Accordingly, the implementation of a new model of the occupancy pattern of a building is introduced in this methodology.

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

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

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

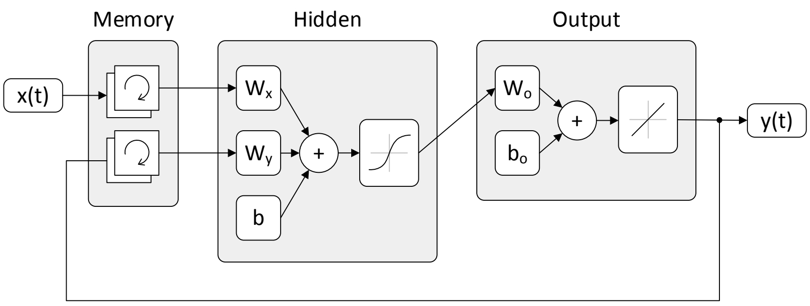

Fig 2. Structure of the closed-loop recurrent neural network, composed by an input layer with memory units, a hidden layer, and an output layer with a feedback loop.

2.2 Power demand modeling

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

2.2.1 Power demand estimation

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

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

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

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

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

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

2.2.2 Power demand model fitting

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

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

2.3 Power demand forecasting

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

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

3. Test Environment

For the validation of the proposed methodology, the complete system has been implemented in a real building in Spain. The building is a research ecosystem of the Universitat Politècnica de Catalunya – BarcelonaTech, which consists of offices and laboratories with a surface of 2.400m^2. The environment accommodates several research groups that specialize in the fields of energy efficiency, electronics, automatics, and biotechnology, among others. In this regard, the nature of the tasks carried out by the staff adds a degree of additional variability to the usage patterns of the building, thus increasing the complexity of the forecasting.

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

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

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

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

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

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.
$T_{re}t$	Bus return temperature.
T_{ext}	Outdoor temperature.
Sol	Solar irradiation.
Occ_x	Presence detector signals (x: 1, 2, 3, etc).
Act	Artificial activity indicator.

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

4. Experimental Results

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

4.1 Activity indicator modeling

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

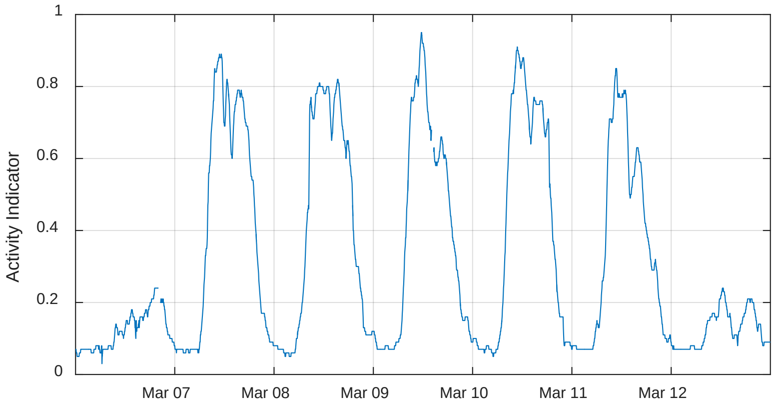

Fig 3. Activity indicator estimated from the aggregate of the individual occupancy signals during a week in March of 2016.

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

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

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

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

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

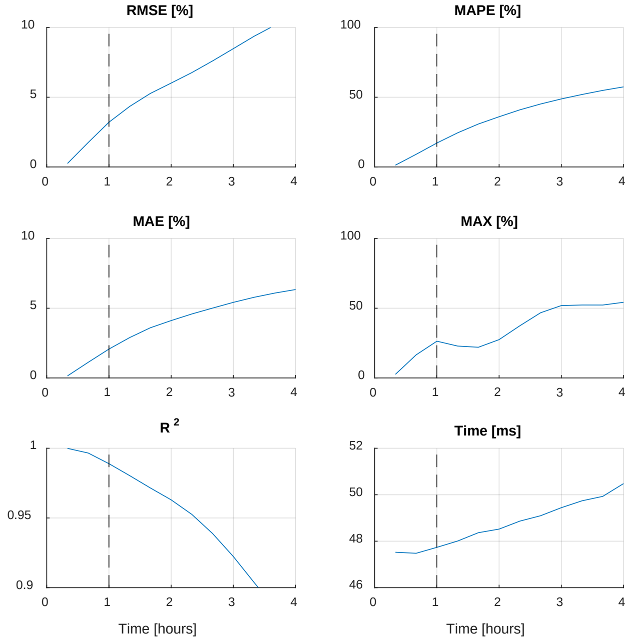

Fig 4. Performance of the activity indicator model when used for multi-iteration predictions using the validation set. Root mean squared error, RMSE. Mean absolute percentage error, MAPE. Mean absolute error, MAE. Maximum error, MAX. Determination coefficient, R^2. Evaluation time.

4.2 Power demand modeling

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

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

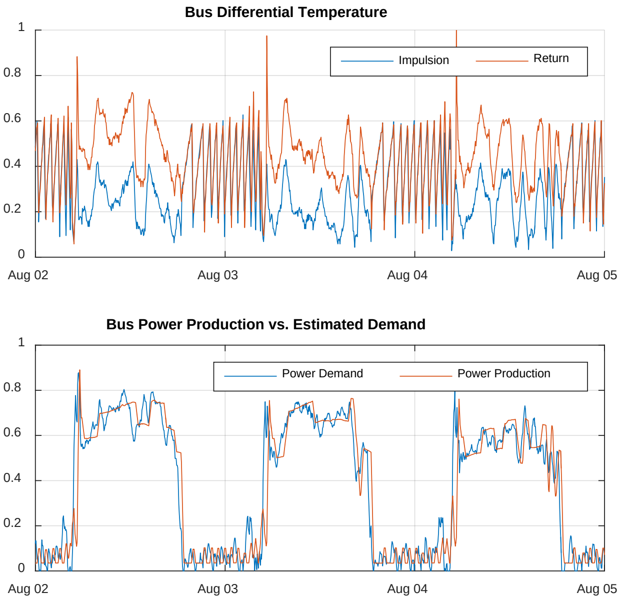

Fig 5. Normalized power demand signal drivers. a) Bus impulsion and return temperatures. b) Bus power production and estimated demand.

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

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

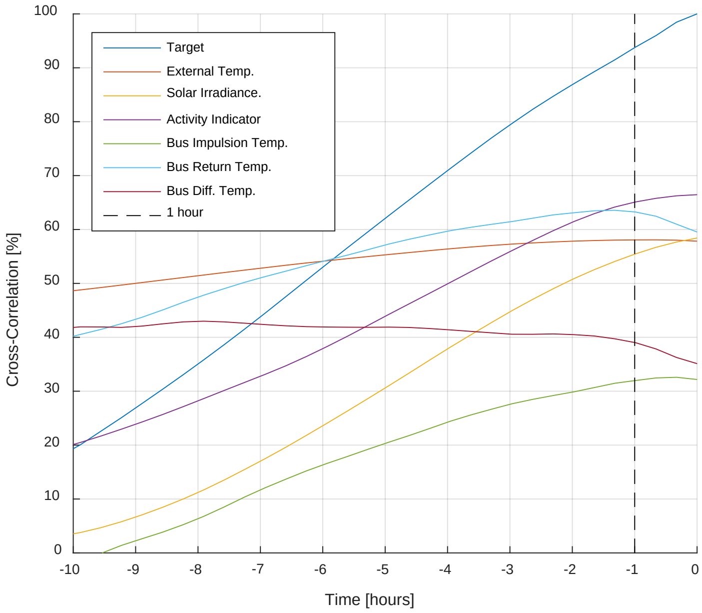

Fig 6. Cross-correlation between each model input candidate and the forecasting target.

The different cross-correlation pairs are shown in Fig. 6, where each series shows the correlation between an input candidate and the thermal power demand as a time shift is applied between the two signals. It is desirable that the selected 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 be observed, the most strongly correlated input candidates when the offset between each pair is 1 hour are the external temperature, the solar irradiance, the activity indicator and the bus return temperature. On the other hand, the bus impulsion temperature and the bus temperature differential present low correlation with the target. Finally, it is noticeable that the target shows a strong correlation with itself when a 1 hour offset is applied, therefore the current power demand value was also considered as an input for the model. A sample of the preselected input variables is shown in Fig. 7.

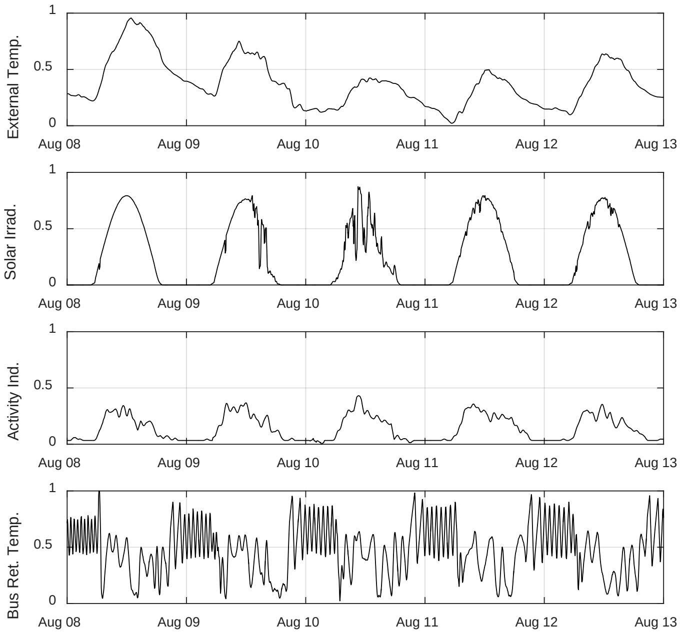

Fig 7. Selected input variables during a period of 5 days in August.

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

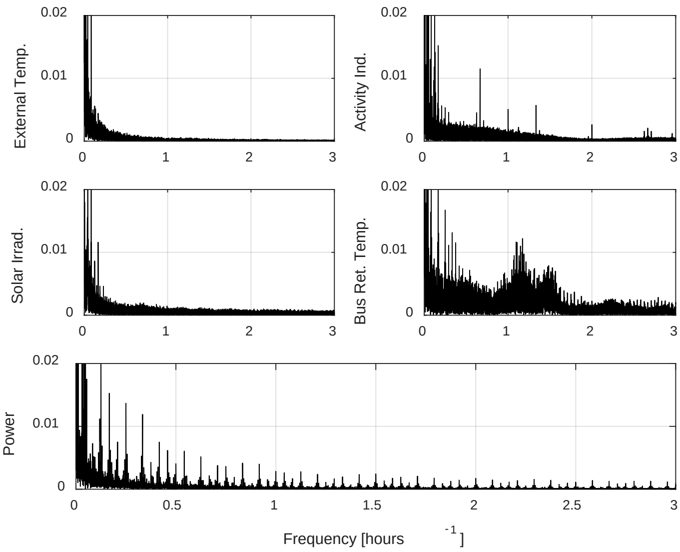

Fig 8. Frequency spectrum comparison between the power demand model input candidates and the power demand target signal.

Additional empirical analyses carried out with the available signals, reveal that the use of both the external temperature and the solar irradiance do not improve the modeling performance, as these two signals present correlation between them and introduce redundant information into the model. As the external temperature presents a smoother behavior than the solar irradiance, which has very steep peaks due to passing clouds, and a forecast of the external temperature is readily available through a local weather service provider, but not for the case of the irradiance, the latter was discarded and only the former was used. Regarding the current value of the target, it was noticed that it improved the forecasting accuracy when included, as it provided a reference point to calculate the next values. Concerning the bus temperature signals, only the return temperature was used, as it provides feedback about the state of the production/demand match. The bus differential temperature was considered, even though it presented low correlation with the target, in an attempt to increase the accuracy of the model during rapid changes, as the bus differential presents high dynamics. This helps the model perform better in some cases, but overall introduces noise and is finally discarded. Finally, another considered variable is the day of the week, which was included as it helps the ANFIS rule inference step to properly characterize the behavior of the power demand during weekends. In summary, the study revealed that the most appropriate set of signals to characterize the power demand of the building is: the external temperature, the activity indicator, the bus return temperature, the current power demand value and the day of the week.

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

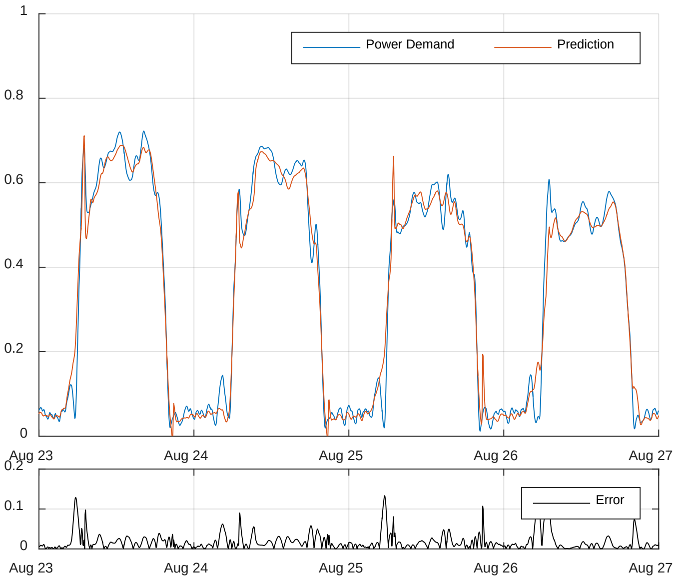

Fig 9. Comparison between the power demand signal and a prediction obtained using the trained power demand model.

In order to validate the methodology and to evaluate its performance and generalization capabilities, a cross-validation strategy was followed. The cross-validation implementation removes one week of data at a time from the dataset, builds a model using the remaining data and validates the model against the removed subset. Thus an 11-fold cross-validation is considered. The results of the cross-validation are shown in Fig. 10, where several performance indicators were calculated when the model is applied over the training set and separately over the validation set. As it can be observed, the error indicators are quite low, with the mean absolute error being the most compelling at an average value of 2% during training and 3% during validation. The maximum error shows an average of 13%, which is acceptable due to the occasional rapid 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 error indicators are also noticeably higher when week 3 is used as validation and is excluded from the training. This observation indicates that week 3 presents a behavior that differs from the rest of the data, as the resulting model achieves worse prediction performance when learning from the other cases.

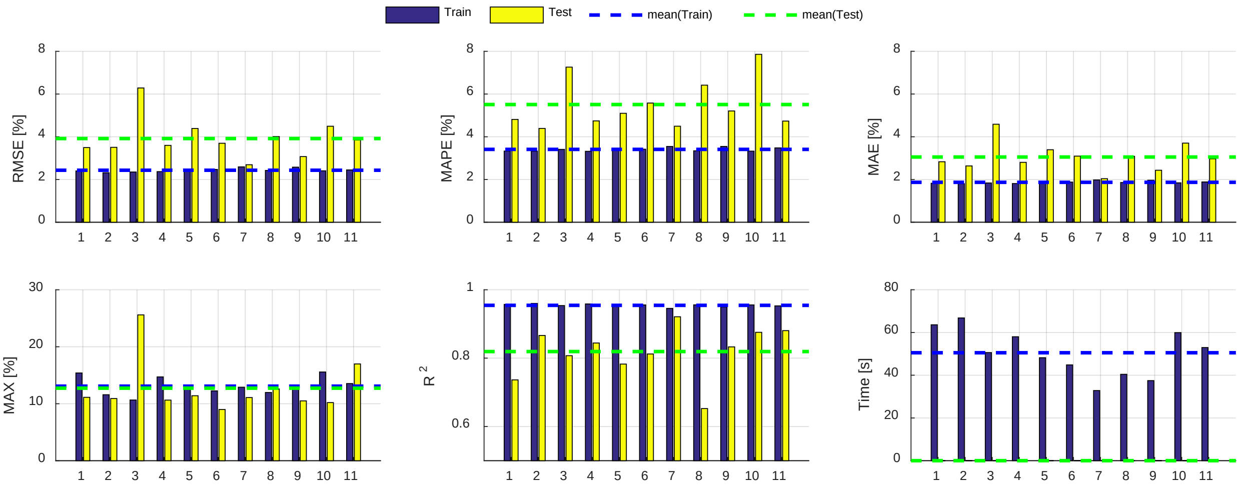

Fig 10. Results of the cross-validation process when splitting the data into 11 subsets, corresponding to the weeks in the dataset.

Finally, in order to quantify the increase of performance provided by the application of the proposed methodology, the obtained results have been compared with a classical load forecasting implementation based on ANFIS [35]. The evaluation of the power demand modeling stage using the proposed methodology resulted in decreased error metrics. The following table shows the performance change when comparing the average performance metrics of the proposed methodology to the ones obtained from the cross-validation of the classical approach both including and withholding the 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	Δ%	Value	Δ%
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
R^2	0.821	0.775	+5.58	0.704	+14.25
TIME	51.21	51.57	-0.70	30.260	+40.91

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

5. Conclusions

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

The integration of the activity assessment into the modeling process, through the definition of an indicator that reflects the occupancy state of the whole building, has been shown to increase the accuracy of the power demand forecasting. The error metrics are significantly decreased when the activity is used as an additional input for the power demand forecasting, but they are further diminished when the neural network is included as a dedicated means to learn the activity's dynamics, providing an estimation of the use that the building shall receive in the following hour. To this end, the implementation of the activity modeling with a recurrent neural network is validated as suitable approach in order to consider the temporal patterns of the building's activity, as the proposed activity modeling process exhibits an important performance increase compared with state-of-the-art approaches, achieving a mean absolute error below 10%.

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

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

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

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