PREDICTING HVAC-BASED DEMAND FLEXIBILITY IN GRID-INTERACTIVE EFFICIENT BUILDINGS UTILIZING DEEP NEURAL NETWORKS

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KEYWORDS

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ABSTRACT

Grid-interactive efficient buildings (GEBs) can provide flexibility services to the grid through demand response. This paper presents a novel predictive modeling methodology to estimate the availability of electrical demand flexibility in GEBs under demand response schemes. In this context, a physics-based energy simulation model of a reference building, considering the cooling demand in the summer season as the flexible load, is utilized. Accordingly, the impact of increasing the indoor setpoint temperature by 1.5 °C (for a maximum of 3 hours per day), which enables the demand side flexibility with a reduction of the cooling equipment's electrical load, is simulated. Next, each demand response event is gathered, sorted, and then used to train the model to predict similar future events over the same time horizon in the following days. For this purpose, a deep neural network model trained using an expanding window training scheme is utilized to predict (15 minutes before the event) the load in the next 3 hours while undergoing the flexibility scenario. It is demonstrated that, with four months of training data, the model offers a promising prediction accuracy with a Mean Absolute Percentage Error (MAPE) of 3.55%.

INTRODUCTION

The energy systems in recent years have undergone fundamental changes driven by the integration of renewable energy sources (RES). By 2020, 22% of the European Union's (EU's) energy consumption was provided from renewables (European Commission 2022c), but new targets have been proposed to achieve a share of 45% by 2030 (European Commission 2022b). Traditionally, electricity production has been vertically integrated between the large power plants and end-users, with only a one-way flow from the transmission to distribution lines. Given the vertical structure of the electric grid, the Distribution System Operators (DSOs) were responsible for dealing with security issues in their network development methods. However, this configuration has been transforming lately, with expansion in decentralized production boosted by implementing renewable energy sources in the distribution nodes (Knezovic et al. 2015; EvolvDSO 2014).

The high penetration of RES, such as photovoltaics (PV) and wind generation, with their intermittent and unpredictable nature (Koltsaklis et al. 2017), has created new challenges for real-time balancing in the grid between the demand and supply side without interrupting the advancement of decarbonization and efficiency (Minniti et al. 2018).
Thus, the paradigm has changed and moved to a coordinated action between the DSOs and the Transmission System Operator (TSO) to balance and secure the system by integrating new flexibility measures.
Therefore, grid-interactive efficient buildings (Neukomm et al. 2019) under the demand response (DR) scheme are presented. Buildings consume 36% of the worldwide primary energy produced (Santamouris and Vasilakopoulou 2021), up to 38% of which is attributed to the consumption of heating, ventilation, and air conditioning (HVAC) types of equipment, regarded as Flexible Loads (FLs) (González-Torres et al. 2022). Thus, the buildings that offer demand response employing the flexibility of the corresponding HVAC load, as individual participants or aggregated with other

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entities, can become active bidders in the forthcoming flexible markets. Furthermore, the increasing penetration of smart meter readers across Europe (Bularca et al. 2018), the growing number of smart/IoT devices, and the recent notable progress in the area of artificial intelligence are permitting the application of demand response strategies and forecasting the energy flexibility in buildings (Sharda et al. 2021).

Flexibility in Energy Markets

Currently, several markets for energy balancing, such as day-ahead or ancillary markets, are provided and coordinated by market operators strictly related to the TSO (EU4Energy 2020), with different bidding periods, contracts, and payment options in different countries. The integration of demand-side flexibility into the historic markets is still a subject under investigation owing to two existing core issues: first, the minimum size for biding, which expands the necessity for aggregating the actors to be part of a reserve market such as the manual Frequency Restoration Reserve (mFRR) that is the current Swedish flexibility project Sthlmflex (Chondrogianniset al. 2022); and secondly, the need for scheduling the load dispatching or reduction to be part of day-ahead balancing markets or congestion management markets controlled by DSOs.
It is worth mentioning that the mFRR project previously mentioned allows the implementation of flexibility schemes, giving extra benefits based on the accuracy that the flexibility is delivered: a total payment of the delivered flexibility when the provider has been able to provide at least 80% of the flexibility scheduled, reducing then linearly the payment to 40%, and no payment if the provided flexibility is below 40%. Additionally, countries like the Netherlands with the GOPACS project (GOPACS 2019; Chondrogianniset al. 2022) and Germany with the Enera Flexmarkt (Chondrogianniset al. 2022) have developed other projects to integrate demand flexibility under existing or new energy markets. In both cases, they provide short-term local flexibility markets for congestion management following the intraday market gate closure time, with nominal values starting from 1 hour to 15 minutes. More regulated and rigid markets, such as the Italian ARERA, have started projects to include aggregated and non-aggregated distributed energy resources (e.g., demand side flexibility) as a part ancillary service market with the ongoing project UVAM (Unità Virtuali Abilitate Miste, i.e., virtually aggregated mixed units) (Gulotta et al.2020). Schwidtal et al. 2021 emphasized the positive effect of the involvement of decentralized flexibility in the Italian market, highlighting the need to reduce the minimum bidding size of 1[MW] to extend the potential for new flexibility resources.

Demand Flexibility in Grid-Interactive Efficient Buildings (GEBs) and the Need for Penalty-Aware Demand Prediction

Grid-interactive efficient buildings (GEBs) are a category of energy-efficient buildings that provide demand flexibility by optimizing energy costs, network services, and occupants' needs and preferences with the integration of smart devices (Neukomm et al. 2019). GEBs can manage their demand and generation based on external grid signals such as price, CO_2 emissions, or grid congestion (Jensen et al. 2017; Reynders et al. 2018). To allow this, the building should be capable of reducing/increasing its consumption following the requirements of the signal in a given period, which can be in the order of seconds (e.g., ancillary services, power control, or frequency containment) or for more extended periods that can go from 15 minutes to 1 hour to dispatch energy flexibility.

Junker et al. 2018 named the load under a demand response scheme or penalty-aware demand as a *flexibility function (FF)*, described in the following equation:

$$FF = \sum_{t=0}^{T} (E_{baseline,t} - E_{penalty-aware,t}) \quad (1)$$

Where, in period T of signal-aware demand, the energy that the building can provide is the difference between the estimated baseline energy demand of the building and the penalty-aware demand.

Figure 1 illustrates the flexibility function, showing that in the period of unaware-signal demand, the function follows the typical baseline consumption, but when the building is aware of the signal, the load is reduced for an established period. Then a rebound effect is created when penalty-aware equipment returns to its normal behavior.

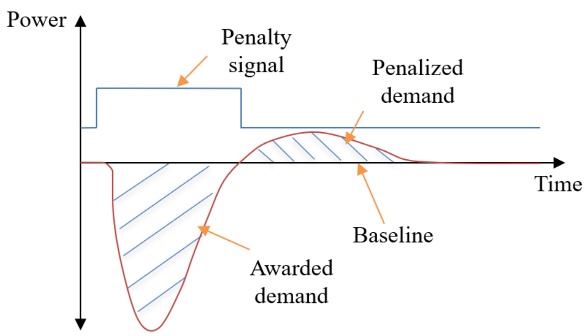

Figure 1: The representation of the Flexibility Curve (FF) (Junker et al. 2018) shows the expected load behavior of buildings when flexibility is implemented in response to grid signals.

Hence, if we consider one or more grouped buildings as active participants in energy-flexible markets, it is necessary to establish the amount of flexibility in terms of energy and time that this building/s can provide. For that, it is essential to develop predictive models for the baseline consumption and penalty-aware demand; the latter one is the focus of this work.

CASE STUDY

This work presents a novel approach for predicting demand response events in GEB, aiming to provide new sources of flexibility (upward and downward) for congestion management, tertiary services, or balancing of the grid. Therefore, a physics-based energy simulation is performed considering setpoint management to simulate the grid's penalty signal, creating a demand response event that involves a reduction in the energy consumption of the legacy HVAC equipment in the selected building. Accordingly, this general approach proposes load-shifting based on setpoint modifications as demand –side flexibility strategy, which is applicable from grid balancing markets (as an active participant in the bidding process) till voluntary energy/price efficient schemes for building management.

Next, the local time series associated with the demand response scenario is utilized for training a deep neural network that can predict 15 minutes prior to the signal application (1 timestep of base electrical consumption) and the demand response scenarios for up to 3 hours (12 timesteps of 15 minutes each), allowing the forecasting of the flexibility event from 15 minutes before it could happen. The training is based on the time-dependent values of solely three features: electrical consumption, solar radiation, and outdoor temperature of the previous 20 hours before the DR event happens, which are considered as inputs for the neural network.

DEEP LEARNING CONCEPTS

The current section will present the basic theory used in the development of deep learning (DL) models for the prediction of the flexibility curve.

Neural Networks

Artificial neural networks (ANN) consist of fully interconnected neural networks under a parallel scheme (see Figure 2), where the first layer represents the inputs with which our model will be trained; the last layer corresponds to the output layer, which can have one or more neurons if multiple predictions are needed; and finally, it can include a set of intermediate hidden layers that increase the complexity of the model (Jain et al. 1996). Each subsequent layer calculates the previous layer's output, passing them to the next one until the last layer is reached.

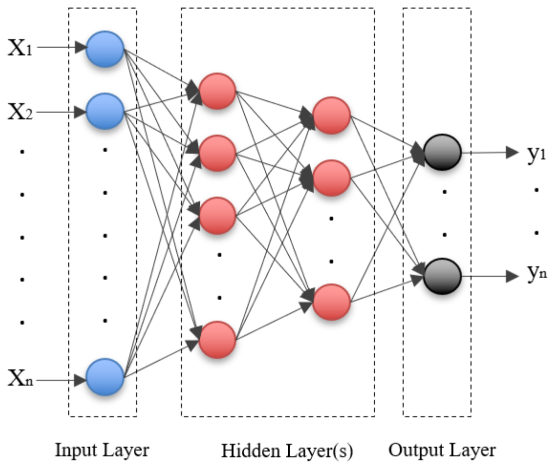

Figure 2: Typical structure of two hidden layers feed forward neural network.

In the frame of this work, *Multi-Layer Perceptron (MLP)* (Murtagh 1991), a feedforward neural network commonly employed when sequential data needs to be processed (e.g., time series), is used. The workflow involved in the MLP training consists of calculating the associated weights with forward propagation and optimizing the model using the *Stochastic Gradient Descent (SGD)* with backward propagation. The loss gradient concerning the model's weights is recalculated multiple times to minimize the loss and improve the model's accuracy.

Expanding Window Multi-Step Forecasting

The training procedures utilized in this work correspond to an *Expanding Window* (Bergmeir and Benítez 2012) with multi-step forecasting. Here the forecast horizon is extended with each new data point becoming available, training the model gradually over time, emulating the online learning process.

Multi-step forecasting is used when long-term forecasting is required to forecast long periods (Masum et al. 2018; Abedi and Kwon 2023). The application of multi-step forecasting is exemplified in Equation 2, where at a current time t, a model M trained with the data of the earlier n time steps to forecast τ time steps forward.

$$F_{t+\tau} = M(t, t-1, \dots, t-n+1) \qquad (2)$$

It is important to consider that the case of expanding windows corresponds to a modification of time-series cross-validation; thus, the process of online training using expanding windows is equivalent to the validation process.

METHODOLOGY

The current section presents the methodology for generating the demand response scenario and the predictive model development.

Physics-based Simulation

For the development of this work, first, a physics-based co-simulation has been carried out using EnergyPlus V9.4 (Crawley et al. 2001) and its Python API (U.S. Department of Energy 2021) to exemplify the electrical consumption of a small office building (see Fig. 3) under a penalty-aware demand response scheme. The simulation consists of a sub-hourly frequency simulation of 4 timesteps per hour (every 15 minutes) and only in the summer season, from June to September. The frequency of the energy simulation's timesteps has been chosen per the information provided by the European Commission 2022a., where it is established that a minimum sampling frequency of 15 minutes is expected to be provided by the smart electric meter.

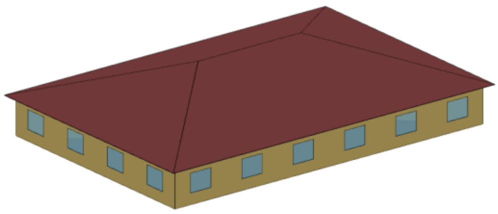

Figure 3: Sample office building used on physical-based simulations in *EnergyPlus*.

The model is a reference building model developed under the ANSI/ASHRAE/IES Standard 90.1 (ASHRAE 2010) representing small office buildings and provided by a study conducted by Deru et al. 2011. The complete specifications of the building are presented in Table 1.

Table 1: Description of the building used in the physics-based simulations in *EnergyPlus*.

Type	Office
Location	Rome, Italy
Total Floor Area	510 [m^2]
Window Fraction	24.4% for South and 19.8% others
Heating type	Air-source heat pump with gas furnace as backup
Cooling type	Air-source heat pump
Thermostat Setpoint	24°C Cooling/18°C Heating
Thermostat Setback	30°C Cooling/15°C Heating

The demand response scenario is generated by modifying the cooling setpoints' thermostats in the different thermal zones of the building, with an increase of up to 1.5°C in a limited period. Therefore, a decrease in the electrical consumption related to the cooling system is produced with a posteriori rebound effect by the return to the typical setpoint temperature values in the zones. In the scope of this research, the penalty signal is triggered every weekday at 3 p.m.; thus, the prediction horizon of three hours will include 12 timesteps between 3 p.m. and 6 p.m. There is one extra timestep between 2:45 p.m. and 3 p.m., considering that the goal of the simulation is to allow the prediction of the possibility of providing flexibility 15 minutes before it occurs.

Demand Response Prediction

The second part of the work contains the data gathering obtained from the simulation and the development of predictive pipelines with *Deep Neural Network* models using *Python* and *TensorFlow* (Abadi et al. 2016) for predicting the time window in which the demand response is generated.

Consequently, the predictive model is trained using the sequential data of electrical consumption, outdoor temperature, and solar radiation from 18:30 (the day before) to 14:30 (the current day), summing 80 triplets for a sampling frequency of 15 minutes, equivalent to an input of 240 features. The testing scenario considered an expanding window training with an online learning approach, emulating a real-time model deployment. Thus, the model is retrained each time a new flexibility event occurs, expecting an improvement in the model's overall accuracy with the sequential addition of data.

The novelty of this approach lies in predicting each timestep when the demand side response is generated, avoiding the error propagation that multiple predictive models can have when calculating the possible available energy flexibility. To accomplish this, a neural network is modeled with 240 perceptrons in the input layer, two hidden dense layers with 128 perceptrons with RELU activation, and a final layer with 13 outputs corresponding to each time step of the demand response event with linear activation. Additionally, the Adam optimizer, a variation of stochastic gradient descent, is employed to minimize the error in the training of the network.

Mean Absolute Percentage Error (MAPE), presented in Equation 3, is implemented for calculating the training and test performance in each time window, considering 350 epochs for the optimization. In the equation, y and $\hat{y}$ refers to the real and predicted values, respectively, while n represents the total number of data included in the evaluation.

$$MAPE = \frac{100\%}{n} \sum \left| \frac{y - \hat{y}}{y} \right| \qquad (3)$$

RESULTS AND DISCUSSION

This section presents and discusses the results of the proposed deep learning model for forecasting energy consumption under penalty-aware events. The results are shown using Mean Absolute Percentage Error (MAPE), considering the accumulative results of only the first hour, the first two hours, and the overall three hours of

prediction for the testing set to demonstrate the impact of increasing the prediction horizon.
Table 2 shows the statistical results in terms of average MAPE for the training and testing of the DL model. The training of the considered model consists of 75 different window lengths, starting with only two flexibility events for the first training and then finishing the last training with 77 events, increasing one by one over time, simulating online learning. Figure 4 displays the distribution of MAPE obtained for different horizons of predictions and the training error.

Table 2: Statistical information for test and training error, considering the forecasting horizon from 1 to 3 hours ahead. all the results are in percentage [%].

Metrics	Test [%]			Training [%]
	1 hour	2 hours	3 hours	
Mean	2.75	2.46	3.55	2.66
Std	2.75	1.87	1.95	0.45
Min	0.15	0.50	0.63	1.7
Max	14.72	10.19	11.01	3.92

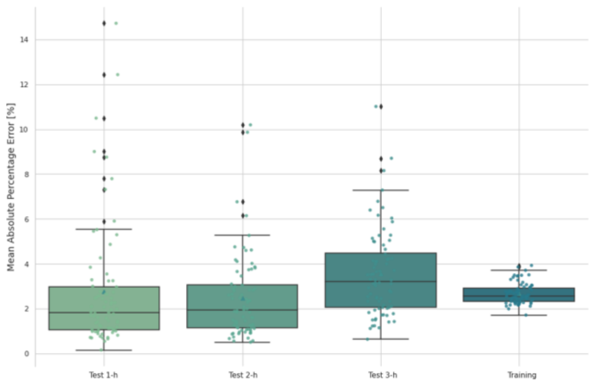

Figure 4: Boxplot representing the mean absolute percentage error obtained in training and testing one hour ahead, two hours ahead, and three hours ahead of the forecasting model.

The prediction 3 hours ahead presents an average MAPE accuracy error of 3.55% for the total tested data, with a standard deviation of 1.95%. The average error is low considering, for example, the Sthlmflex project, where they have set a full payment if the flexibility source can dispatch at least 80% of the scheduled flexibility. Nevertheless, the error in some cases reached a minimum of 0.63% and a maximum of 11.01%.

Next, for the prediction of one hour ahead and two hours ahead, we obtain similar average values of 2.76% and 2.46%, respectively. But in the first case, the standard deviation is around 0.9 points higher since there exists a larger number of outliers in the predictions, with seven predictions having between 6% to 14.72% error. Thus, the error increases because the penalty signal induces a sudden change in behavioral patterns of the load time series, which has a non-linear dependency on the outdoor variables when part of the load is given by the cooling equipment. Therefore, accuracy improves once the model is retrained with the new flexibility event.

In Figure 5, the error variation as the training window expands is observable. Initially, it is expected to have poor accuracy since the training data is not abundant. But given that the flexibility has been triggered at the same hour every day, it is probable that the weather conditions are similar for the first data; thus, the error in all the predictions is reduced. Then, in the northern hemisphere, the temperatures increase from June to August, then decrease towards September, corresponding to the last trained data in the model. Therefore, an increase in the testing error and the dispersion of the forecasted data is expected, given that the cyclical behavior of the weather is not totally generalized by the model, which also can be observed in the training values, where the error increases up to 3.92%.

Figure 5: Mean absolute percentage error represented in the training process, considering the predictions 1-hour ahead (top), 2-hours ahead (middle), and 3-hours ahead with training score (bottom).

Additionally, as expected, the average accuracy of the result is higher when the forecasting horizon increases, while having a higher error when three hours are predicted and the lowest error for the forecasting two hours ahead. In the case of a one-hour ahead prediction, as already mentioned, the error is highly influenced by the sudden drop in the electrical load.

Finally, Figure 6 shows an example of the predicted versus actual demand response event for three hours. Between time steps 0 and 2, the load reduction is observable, with a rebound until timestep 6, when the system returns to its normal baseline load.

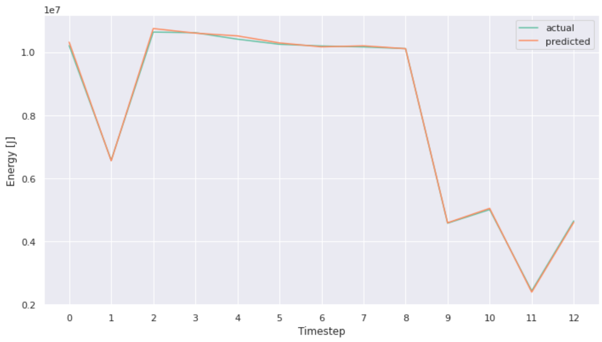

Figure 6: Example of the predicted period for a penalty-aware demand event.

CONCLUSION

This work presented a novel methodology for predicting the electrical consumption of a single office building under a demand response scenario triggered by a simulated penalty-aware signal from the grid. For this purpose, a physics-based simulation was conducted to emulate the load dispatching associated with the legacy cooling equipment of the building. The penalty signal is applied as a setpoint modification, allowing an increase of 1.5 °C for a maximum duration of three hours. Next, the demand response events are gathered and used to train a deep learning model based on a Multi-Layer Perceptron structure and an expanding window training. The study demonstrated promising results for all prediction horizons, which is 1, 2, and 3 hours ahead into the event, with a maximum average Mean Absolute Percentage Error of 3.55% for the testing in the whole period and 2.66% in the training process. There was no indication of significant overfitting of the model, even when the expanding window approach does not simply allow the hyper parametrization of the model.

The sudden load reduction in response to the signal had an expectable effect on the predictions, where the predicted values in that period (one hour ahead) showed a higher average error and higher dispersion of the predictions than when the forecasting two hours ahead was considered. The error's dispersion increased towards the September training period, when the temperature and radiation started to decrease, making the model unable to generalize as accurately as before. Thus, it is essential to consider new features that can complement the model's generalization toward cyclical data in future works.

Finally, forecasting demand response events can be further expanded to consider its application in different moments of the day, making the deep learning model more generalized. Additionally, scenarios can be considered when the heating equipment load is considered flexible, spreading this work application in different weather conditions. Demand response forecasting, together with the baseline prediction, is required for accurate accountability of the flexibility that a building can provide, which can open further options to be part of the future of local flexibility markets.

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