Machine Learning on Buildings Data for Future Energy Community Services

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***Abstract*— The decentralization of energy generation and transmission demand for the Internet of Energy with real-time peer-to-peer energy exchange. The intermittent renewable energy provides a challenge of consumption flexibility at consumer side. Buildings are significant in this new context, since they are the biggest energy consumer worldwide and can contribute to local renewable energy production as well. Therefore, proactive building services will be required in near future in order to operate energy community. This paper deals with energy flexibility obtained through PV production forecast for a community. Decision tree technique is applied on historical hourly data of 3 years for week-ahead forecast of building consumption, photovoltaic production, and for fault detection diagnostic. Feature engineering and energy expertise used to obtain good forecasting performances are discussed. The significance of these technics for prospective energy community service is also discussed in the paper.**

Keywords*— *machine learning, energy flexibility, random forest, gradient boosting, auto-consumption, building consumption, PV forecast, energy communities.

I. BUILDINGS AS A PILLAR OF THE INTERNET OF ENERGY

Environmental policies and the reduction in production cost of renewable energy are transforming the energy landscape of cities and countries worldwide. The renewable energy is decentralized and intermittent in nature and due to its constraints, it modifies the role of transmission system operator (TSO) and distribution system operator (DSO) while connected to the energy grid. In this context, the role of DSO is becoming increasingly significant to keep the balance of energy flows for avoiding local congestion. In [1], the Center on Regulation in Europe highlights different proposals for DSO-TSO interactions that allow the trade of flexible services.

With the decentralization of energy network and implementation of Internet of Energy (IoE), each node of the energy network will be able to produce, consume and store energy. These real-time peer-to-peer exchanges constitute IoE revolution, and require a real paradigm shift in technological solutions and energy regulation. Today, the operators of the electrical networks are practically blind on the scale of the districts and can only through demonstrators sketch the potential of solutions to prepare the future [2]. IoE will rely on net-metering to decide the dynamic electricity pricing; based on the available energy storage (kWh) it will also depend on the capacity (kW). Therefore, it accounts for strong time dependence. The complexity of pricing will no longer allow optimal human decision-making, rather a set of third-party players should be developed to implement advising and controlling services.

IoE is not only made up of smart grids; it is also comprised of the actors at each node of these grids. For instance, energy management at a local level should aim for a multi-objective optimum integrating economic constraints, environmental issues, and citizen choices. Self-consumption is a good way to involve consumers in energy system and to play on levers that the economic aspects could not reach. It permits to reduce transmission loss (8% on average), reduces the infrastructure investments and motivates the increase in consumption, particularly in cities. Legislation on collective self-consumption is already in place in some countries like France [3], which encourages the citizens to play an active role in IoE. They can thus collectively produce and consume their own energy. However, it is required that these solutions that are promoting the penetration of renewable energies must be complemented by the services for operators and consumers (i.e. the occupants of buildings).

Residential and commercial buildings are the biggest energy consumer worldwide; mainly for their needs related to thermal comfort. They consumed more than 37% of final energy in OECD countries in 2017 on par with transport (37%) and ahead of industry (25 %) [4]. In perspective of decentralized production in proximity of load centre, energy production could be very strongly developed on these buildings in the coming years. The French Environment and Energy Management Agency (ADEME) proposed a scenario for a 100% renewable mix across France in 2050; where 34% of the capacity would be generated by photovoltaic panels on the rooftop of the buildings [5]. According to this report, buildings flexibility will help up to 18% for managing the network balance of 100GW peak demand, essentially from heating, ventilation, air conditioning (HVAC) (14GW) and hot water tank (4GW).

Buildings are therefore essential in the energy transition [6]. However, they must be able to communicate with each other and offer services to network operators or at the level of energy communities.

II. MACHINE LEARNING FOR BUILDING ENERGY SERVICES

As mentioned above, buildings must offer flexibility to ensure optimum energy management. Two such tools that might already be implemented in buildings are as follows:

- Optimization of the energy bill: by proposing an adaptive contract, based on the analysis of past data and long-term forecasts. This helps in notifying the consumer to avoid upcoming over-consumption through load shedding and hence to avoid financial penalties.
- Fault detection diagnosis and maintenance: it allows to detect a variation in the measurement compared to a baseline, indicating a potential malfunction.

In this paper, we will try to go further by expressing the needs for the implementation of new service tools for energy communities. The tools presented below may rely on the same technics already used for optimizing the energy bill or for diagnosis of a consumer, yet they need to be adapted for an energy community.

- Optimizing collective self-consumption: ensuring a balance between production and consumption at the community level through promoting the penetration of renewable energies.
- Energy flexibility: each building offers the means of quantifying the potential flexibility and activating negotiations for flexible actions to the community.

Predicted models must be deployed in order to make these services work. An approach is to develop physical models often resulting from specialized expertise and in-depth knowledge of the system to be modelled [7].

Another way is to model physical system using artificial intelligence (AI). AI is now a thriving technology driven by the convergence of deep learning, and planetary-scale data. Its impact on human society is expected to be on a scale comparable to electricity. During 1975-1990, artificial neural network improved its performance by two innovations: multi-layer perceptrons with soft decision surface and learning with back-propagation. However, since 2012, deep learning (DL) has been found effective to provide reliable solutions for longstanding problems [8]. Long short term memory (LSTM) is a recurrent neural network (RNN) dedicated to time series modelling which is able to catch different dynamics of the signal. This deep learning technique has been successfully applied for building hourly consumption prediction [9]. Support vector machine (SVM) is another machine-learning algorithm, which can be applied to predict building energy consumption [10]. Both of these technics are complex; notably with hyper-parameters to tune, with long time to train, and difficult to interpret. In this paper, we used a machine learning method based on decision trees, which has the advantage of being quick to calculate and easily interpretable.

The three most common barriers to AI are: (1) insufficient labeled data for learning, (2) insufficient computing power and (3) prohibitive cost of encoding domain knowledge. The barrier (2) is not addressed in this paper, but we are going to discuss on data availability and the link between domain-specific expertise which are required to build efficient AI.

To implement the proposed building services, it is required to create a forecasting model. The classical horizon for model predictive control is a day-ahead forecast, while in order to provide other kind of services for energy planning including human decision-making, we will study in the following section a week forecast modelling. Therefore, sufficient and reliable historical data is required to make a supervised learning model with the characteristics as follows.

- Data Length: it can be important to capture short term as well as long term dynamics, like the annual seasonality.
- Sampling Frequency: the choice of sampling frequency is according to the model requirement and the memory constraint of hardware. Any fine sampling which can be down-sampled for annual history is helpful in this regard.
- Data Quality: it is common to have missing data or outliers. In the case of missing data, an interpolation during the pre-treatment phase is helpful for a time series data, whereas certain technics can be used to detect and remove the outliers.
- Data Quantity and Diversity: a diverse and big data brings more choices of feature selection according to the needs of the predictive model. The features can be sorted according to the best correlations among the parameters.

To illustrate this, we are modelling consumption of the GreEn-ER building [6], a 22,000 m² service building, accommodating 2,000 occupants, and massively monitored and controlled for energy efficiency. It has around 1500 connected sensors. The consumption of the building is mainly driven by the thermal comfort of the occupants and air quality. The historical consumption of a period of 3 years (from 2017 to 2019) is used for modelling. For the purpose of training the model, we will use the data of 2 years, while the last year will be used for model validation.

III. CONSUMPTION FORECAST AND FEATURE ENGINEERING

The first task of a modelling is the definition and selection of the features from the raw data (also called feature engineering). Features are the inputs of the prediction model. There are two categories of features to be selected for making a predictive model of the consumption of GreEn-ER. The first category of features is based on the historical raw data. Specifically, these are Date Time Features, Lag Features and Windows Features. A second category of features are the exogenous variables, which are correlated to the variable to predict. We briefly discuss these features by illustrating on the building consumption prediction.

A. *Date Time Features*

The Date Time features correspond to properties linked to the instants of the observations. For instance, the time of day helps to model the daily frequency and therefore helps to model daily events such as the automatic start of heating at 6 a.m., the arrival of staff at the office at 8 a.m., the lunch break etc. The day of week makes it possible to model working days and weekends. The day of year allows to take into account the seasons and holidays.

The well-known objective of machine learning is to adjust the bias-variance compromise in order to have a model which generalizes well the behaviour of the data, and which therefore leads to a robust prediction. For this, we need a model that reduces the bias but without leading to over-fitting (i.e. decision tree), and at the same time it ensures the smallest possible variance in the data without leading to under-fitting. To solve the problem of bias-variance, we can adopt an ensemble approach, that cuts training data into a set of smaller data sets (bootstrapping), performs several learnings and returns the average. This technique is known as Random Forest (RF) [12]. RF has been compared in [13] with neural network for HVAC hourly consumption forecast, and the authors claim that for comparable performance, RF is easier to use. It has been used for automated measurement and verification before and after a retrofit (pre-retrofit and post-retrofit data) and to predict how much energy the retrofit saved [14]. RF has been also used for building consumption anomaly detection [15].

Comparing to conventional time series prediction methods such as SARIMA (Seasonal Auto-Regressive Integral Moving Average), learning methods based on RF show better performance if features are well studied [16].

The regression model defined with 100 estimators, takes only 4 seconds to be trained on a desktop computer for a historical data of 2 years at 1 hour sampling time, with 5 features. This makes a total of 87,600 entries in the historical data.

Fig. 1 shows the actual and predicted load curves for the building. The hourly mean error calculated for the whole year 2019 is 90kWh, which renders the model appropriate. Fig. 2 shows the features importance obtained after model training. The Day of Year feature explains half of the behaviour of the consumption, while Hour of Day is second important feature with 30% importance.

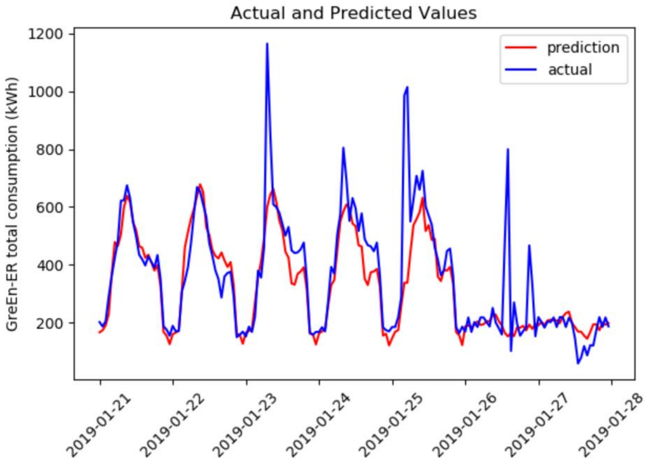

Fig. 1. One-week prediction using Random Forest, based on Date Time Features

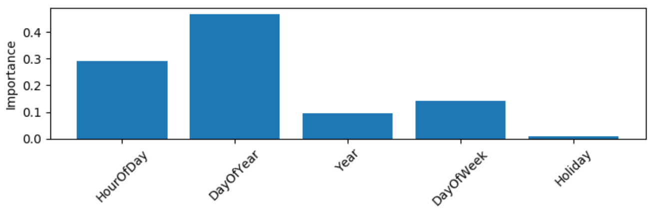

Fig. 2. Date Time Features importance for consumption forecast

B. Lag Features

Lag features appear particularly for time series. They introduce the dependence of the current value on the past values. The downside of this feature is that it cannot be predicted, so the model prediction horizon becomes limited very quickly. If a 1 step lag shift is made and a model is trained on that feature, the model will be able to forecast 1 step ahead having observed current state of the series. So, during the initial lag selection, a balance between the optimal prediction quality and the length of forecasting horizon has to be found.

It can be observed by looking at the autocorrelation of the consumption data (Fig. 3) that a consumption value at a certain hour has a strong dependence on the previous hour (h-1) or the previous few hours (h-n, where n is number of hours), then a dependence on the consumption of the previous day at the same time (h-24). The consumption value at a certain hour also has a strong dependence on consumption at the same time in the previous week (h-168).

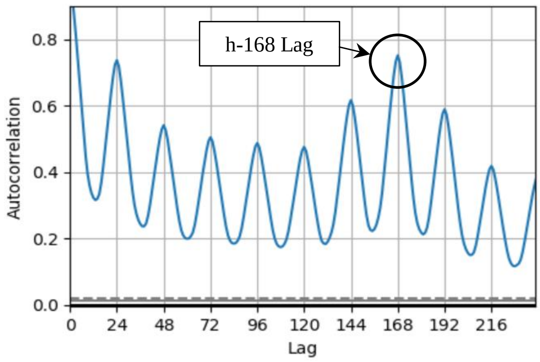

Fig. 3. Autocorrelation function of consumption time serie, hourly steps

The lag feature is very significant for the training of the model. It explains 65% of the prediction and then considerably reduces the dependency on the others. It implicitly includes information already present such as the Hour of Day or Day of Week. The result of the model is over-fitting, which leads to a poorer generalization of the model. Nevertheless, the integrated result for the year 2019 is improved by 16% with an average error of 75kWh compared to 90kWh previously.

C. Windows Features and Exogeneous Variables

Windows feature is a summary of values over a fixed window of prior time steps. It can be for example the energy consumed the day before or the previous week (sum or average value), or the minimum and maximum values. The question that often arises concerns the optimal size of the sliding window. We can apply this technique to the series to be predicted directly, but for a week-ahead forecast, we must therefore look for statistical quantities of the week before.

We can also introduce exogenous features, i.e. signals correlated to the consumption, in particular the outdoor temperature. We can therefore apply window feature on this variable to obtain the average daily temperature. The prediction of this variable is relatively easy to access by weather forecast APIs like OpenWeather[1]. Fig. 4 shows temperature and consumption for the 4 seasons (spring, summer, autumn and winter).

[1] https://openweathermap.org

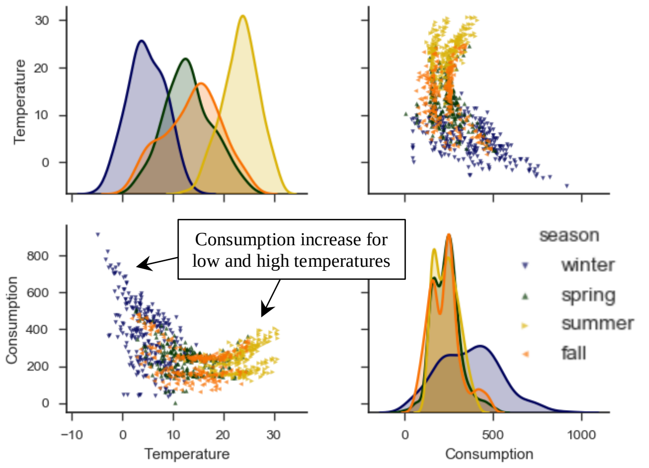

Fig. 4. Pair plot and density distribution of consumption and temperature.

After training a model with windows features, the new feature explains more than 25% of the prediction. The improvement compared to the reference is 12% with an average error of 79kWh compared to 90kWh for the reference.

Finally, if we use the two previous features (Lag h-168 and outdoor mean temperature) in combination with the windows feature, the total improvement is 39% with an average error of 65kWh integrated over the year 2019. The weekly energy calculated from this last model, is integrated over the year and gives a value of 2215 MWh, compared to 2071 MWh in reality, which is 7% error.

In this model, the lag feature (h-168) has the highest importance with 60%, while with mean outdoor temperature, it is 16%, with Day of Year, it is 11%, with Hour of Day it is 8%, with Day of Week it is 3%, with Year it is 1% and with Holiday it is nearly 0% for the whole year. Though the last feature is insignificant, it is still important for some days like in Fig. 5 (8th May: Holiday in commemoration of 2nd world war armistice in 1945).

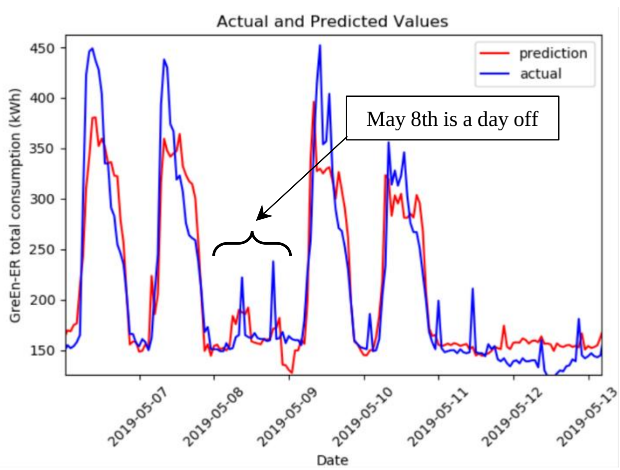

Fig. 5. Week prediction where a holiday is well forecasted even with nearly zero importance for holidays features.

TABLE I. SUMMARY OF FEATURE SELECTION IMPROVEMENTS

	Reference	*Lag (h-168)*	*Outdoor mean Temperature*	*Both*
MAE (kWh)	90	75	79	65
Improvement (%)	-	16	12	39

a. Mean Absolute Error of Energy per hour

Other important features can be directly found by physical expertise of the system. In addition to the outdoor temperature forecast, it would be interesting to provide the indoor set-point temperature as a feature for forecasting. This may, varies according to the modes programmed in the BMS (Building Management System). Additional heat gain (through the occupation of the building and the radiative contributions by the glazing) is also very important in modern well-insulated buildings, so it is desirable to have a prediction.

IV. PHOTOVOLTAIC PRODUCTION FORECAST AND HYBRID DATA/PHYISCAL MODELLING

New energy services for energy management and flexibility in the local energy community require energy production forecast.

There are many photovoltaic production prediction models, owing to the different prediction horizons: ultra-short-term forecasting (a few minutes to 1 hour ahead), short-term forecasting (1 hour to several hours ahead), medium-term forecasting (several hours to 1 week ahead), and long-term forecasting (1 week to 1 year or more ahead), but also for different spatial scales (local or regional). For example, methods for micro-grids control using cameras will be on a local scale, in order to produce ultra-short-term forecasting [17]. A quite common time scale concerns day-ahead photovoltaic forecasting. A. Nespoli present in its recent paper [18] a comparison of most effective technics.

For larger horizons, we often face a strong uncertainty that local weather models seek to resolve. In [20], we developed a heuristic approach based on a prediction of nebulosity to obtain Direct Normal Irradiance (DNI) and Global Horizontal Irradiance (GHI) which are necessary for PV model. We propose here to use two specific features to train DNI, a physical model providing clear sky DNI as well as nebulosity prediction data provided by the APIs from Météo-France (AROME open data [19]). Then the same can be done for GHI in order to obtain PV production forecast.

We proceed as for consumption to a learning by RF with 200 estimators, which takes 3 seconds to train. Fig. 6 is showing DNI for a week. RF prediction has an average error of 83.4 W/m², compared to 88.5 W/m^2 for the empirical model developed in [20]. Fig. 7 shows that the clear-sky model is the most important feature (34%), then Day of Year, Cloudiness and finally Hour of Day. This complementarity between data and physical model is one of the new challenges of cyber-physical modeling in the coming years.

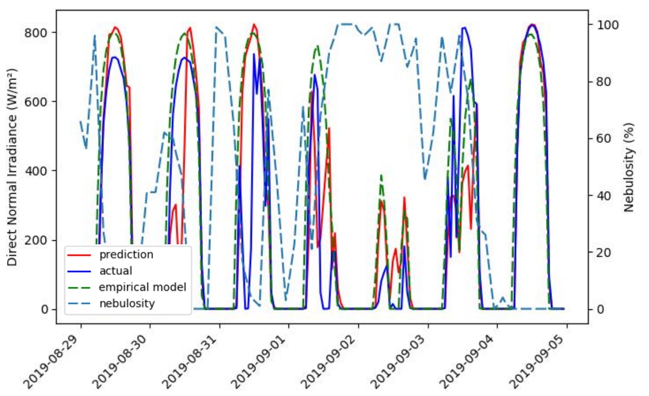

Fig. 6. Random Forest DNI forecast based on nebulosity forecast and clear sky physical model.

Fig. 7. Significance of Random Forest for Direct Normal Irradiance model

To conclude this part, powerful predictive models are easily achievable. The challenges are therefore now the development of services such as self-consumption at the scale of an energy community by exploiting these production and consumption forecasts.

V. INTERVAL PREDICTION FOR FLEXIBILITY CAPACITY

Beside auto-consumption, flexibiliy is another challenge for the energy communities. One of them can be the real time evaluation of flexible capacity. It corresponds to the power that can be shedded or over-consumed when the grid requires it to improve the auto-consumption ratio. The capacity of evaluation of flexibility is difficult, as it strongly depends on variation of normal comfort level among the occupants. In [21], [22] we have used physical based models in order to evaluate flexibility potential of district buildings that are heated and cooled by heat pumps. Here we are questioning machine learning technics in order to provide the same kind of information.

In addition, Fault Detection Diagnosis (FDD) allows real-time detection of inconsistent behaviour by identifying measures that would go beyond a standard range of variation. For instance, FDD has been already developed by [23] using Gaussian process regression.

We are applying on GreEn-ER consumption another regression technique, which is close to Random Forest (RF). Where RF manages the variance problem thanks to bootstrapping, it does not manage at best the bias introduced by the depth of the regression trees. A variant of RF called Gradient Boosting (GB) helps to better manage the bias. While RF generates random and independent trees in parallel, GB works sequentially to create new trees depending on the performance of the previous ones. In addition, optimization uses the gradient to accelerate convergence.

In order to create the prediction boundaries, two models are built. The first one uses 10% of the smallest data, and the second one 10% of the largest data (90% quantile). To train these models, we are using the same features as part III, with the outdoor temperature, but without the historical values (h-168). The models use 200 estimators and a maximum tree depth of 10. The 2 models are trained in 46 seconds.

To illustrate the FDD, Fig. 8 presents a measured consumption (black) that goes out of limits (min: blue, max: yellow) during the first week. Maintenance on the system is then carried out and the data returns to a normal state for the 2nd week. An important remark can then be raised here, if the model takes too much account of the last measured values, like with Lag features, this kind of deviation is more difficult to identify. Indeed, the model will consider the anomalies as normal values with time.

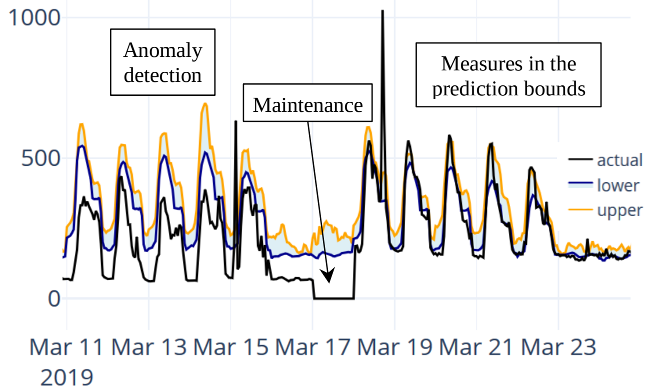

Fig. 8. Fault Detection Diagnosis (FDD) using Gradient Boosting.

Does these intervals can help to evaluate the flexibility capacity by giving possible variations of consumption while keeping the building in a “normal” state ? To go further it will be required to study indoor comfort such as temperature modeling, but also put enough information on the data in order to be able to simulate with machine learning model, the heating or ventilation switch off consequences on the comfort.

CONCLUSIONS

In this work, we implemented different machine learning technics for predicting the consumption of a building, predicting photovoltaic production or even detecting faults.

We exploited the Random Forest (RF) and Gradient Boosting (GB) technics that are based on a set of decision trees offering good prediction performance in a short time and compatible with a hardware implementation. In addition, they offer good interpretability of results due to the possibility of exploring the decision tree, and due to information regarding the importance of feature. The feature engineering work was more particularly highlighted, and shown the need to introduce more exogenous features to implement richer correlations. An expertise in the functioning of the system is then necessary, as well as the provision of the richest possible data history with allowing to make the best choices according to the needs.

We have also shown on photovoltaic production, that it can be interesting to provide data from physical models (clear sky model), and therefore that the approach by data is not contradictory with a physical approach. Again, physical expertise is needed to define the features. These consumption and production prediction services must be the basis of future services developed for the energy community in order, for instance, to optimize the rate of self-consumption.

Finally, the prediction of intervals that can be used in FDD is rich information on potential deviations in consumption and gives a first approximation of the buildings flexibility capacities.

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