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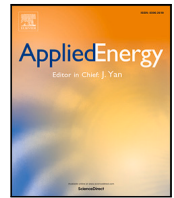
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Unsupervised separation of the thermosensitive contribution in the power consumption at a country scale

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ABSTRACT

A large part of French electricity consumption variation is due to temperature fluctuations. While HVAC (heating, ventilation and air-conditioning) systems consumption are directly affected by the temperature, other systems (refrigerator, freezer, water heater) can also be driven by weather changes making thermal contribution to overall consumption difficult to extract. This paper presents a “by-design” unsupervised data-driven method to separate the consumptions due to the weather in the overall electricity consumption. The proposed deep-learning model is based on the separation of meteorological parameters from calendar ones within the model architecture. The performances of this model, in particular its ability to split consumption mechanisms, is tested on a synthetic dataset and on the french consumption dataset. Being relatively simple and interpretable, this approach can be generalized to other countries whereas energy sobriety represents an important challenge we are facing.

1. Introduction

Accurate power consumption forecast at a country scale is essential to anticipate future needs and prevent an overload of the electric network. To provide such forecasts, an understanding of the consumption mechanisms is required. Temperature is one of the main factors influencing power consumption [1–6], and its importance is expected to increase even more with climate change [7]. Accurately estimating the part of the electrical consumption that is due to the temperature, and more generally the weather, is essential as heat and cold waves can lead to overloads and large power outages [8,9]. We refer to the portion of the consumption depending on temperature as the thermosensitive or meteorological part.

Source separation in energy data is a well studied topic. On a small scale, such as for one or a few houses, methods that separate the individual consumption of the various appliances exist and are commonly known as Non-Intrusive Load Monitoring (NILM). The term “non-intrusive” indicates a separation carried out without the addition of measuring equipment. NILM can rely on supervised or unsupervised methods. In the case of unsupervised methods, the main approaches are variants of Hidden Markov Models [10], Graph Signal Processing [11, 12], event detection based [13] and Deep Learning [14,15]. A survey on these methods is presented in [16]. These techniques have been

used to disaggregate consumptions due to meteorological effects like heating, ventilation and air-conditioning [17,18], but only at a single house scale. Even if some consumption disaggregation has been studied on low rate smart energy consumption data [12], most of the non-intrusive load monitoring is done using high frequency consumption measurements [13], few appliances [12,17,18] or both [10,14,15]. Moreover, these methods provide consumption per device. Estimating consumption due to temperature would then be an additional step.

At a larger scale, such as cities, regions or countries, it is impossible to attribute power consumption to single appliances with NILM techniques because of their high number. Literature is more focused on the impact of temperature on power consumption, rather than on the separation of the consumption mechanism. This impact has been studied and quantified in Spain [3,4], India [5], France [19], Milan (Italy) [6]. These papers show that the temperature has a direct effect on the electrical consumption. The consumption is negatively correlated with the temperature for low temperatures (effects of heating) and positively correlated for high temperatures (effects of air conditioning).

Mor et al. propose a technique to disaggregate the consumption due to different use at a district level on a region of Spain in [20]. They first reduce the dimensionality of the problem by applying a clustering on the considered districts. They compute a *base load* as Fourier series

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describing the hour and weekday cycles with few harmonics. The HVAC (heating, ventilation and air-conditioning) consumption is then considered to be the difference between the true consumption and the base consumption. This *base load* identified by this technique is limited to slow variations since only the first Fourier harmonics are used to describe the consumption. In addition, variations in consumption due to aperiodic phenomena such as public holidays and school vacations cannot be included in the *base load* and are therefore identified as part of HVAC.

The disaggregation of the consumption due to the weather is a complex single-channel source separation problem. Moreover, the consumption due to the weather is not measured, which imposes an unsupervised approach and leads to difficulties for the evaluation of our separation.

We introduce a new approach, based on a combination of two artificial neural networks, to separate the consumption due to the weather from the consumption due to other causes. The meteorological and calendar features are treated separately in an architecture that allows to assign different parts of the power consumption to the meteorological features and to other causes.

The originality of this paper is to propose a simple and interpretable fully unsupervised approach, to disentangle temperature induced consumption from other sources, going beyond limitations of the existing approaches.

This paper is focused on French consumption, based on open-source data from RTE [dataset] [21]. It is organized as follows: the methodology is presented in Section 2. In Section 3, the datasets and the feature engineering are explained. Finally, in Section 4, the validity of the model is verified by analyzing the results on different metrics.

2. Methodology

In this section, the approach proposed to model the power consumption and to extract the thermal contribution is presented.

2.1. Electricity consumption and meteorological part

Power consumption has been shown to be largely dependent on temperature. This influence has been quantified in Spain [3,4], in Italy [6] and in France [19]. This dependence is clearly visible on Fig. 1, with consumptions being higher for low and high temperatures. The part sensitive to the temperature is mainly caused by electric heating and water heaters during winter and air conditioners and refrigerators in summer. For cold temperatures, the correlation between temperature and power consumption is negative, as a decrease in temperature induces an increase in heating consumption. For hot temperatures, the correlation is positive, as one more degree means more air conditioning. The use of air conditioning is fairly limited in France, while heating is frequently electric. This explains why the consumption is more sensitive to cold temperature than to hot temperature. This share of consumption is also sensitive to cloud cover, as solar radiation has an influence on building temperature.

Another part of the power consumption is due to socio-economic causes. This consumption is independent from the temperature and follows the same daily and weekly cycles as human activity. This segment of electricity consumption is also sensitive to public holidays and school holidays, as they influence people's behavior. The daily and weekly cycles, as well as the holidays can be identified on Fig. 2.

In this paper, the assumption is made that the consumption sensitive to the temperature is independent from social and economic effects and that the consumption due to social and economical effects is independent from the temperature. Under this assumption, the meteorological consumption can be defined as the consumption share dependent on meteorological conditions and the calendar consumption can be defined as the consumption share dependent on socio-economic activity. The

total consumption can be written as the sum of these two consumptions (Eq. (1))

$$Y_t = Y_{M,t} + Y_{C,t} \quad (1)$$

where:

- Y_t is the power consumption at time t
- $Y_{C,t}$ is the calendar consumption at time t
- $Y_{M,t}$ is the meteorological consumption at time t

The problem of electrical consumption disaggregation can be written as the identification of two non-linear functions f_M and f_C , depending respectively on k_M meteorological features $\mathbf{m}_t = m_t^1, \dots, m_t^j, \dots, m_t^{k_M}$ (temperature and cloudiness in different cities) and on k_C calendar features (day, hour, etc.) $\mathbf{c}_t = c_t^1, \dots, c_t^j, \dots, m_t^{k_C}$. The total power is the sum of the calendar and meteorological parts as described above:

$$Y(\mathbf{m}_t, \mathbf{c}_t) = f_m(\mathbf{m}_t) + f_c(\mathbf{c}_t) \quad (2)$$

Available data are thus defined by two matrices:

$$M \in \mathbb{R}^{T \times k_M} = \begin{bmatrix} m_1^1 & \dots & m_1^j & \dots & m_1^{k_M} \\ \vdots & & \vdots & & \vdots \\ m_i^1 & \dots & m_i^j & \dots & m_i^{k_M} \\ \vdots & & \vdots & & \vdots \\ m_T^1 & \dots & m_T^j & \dots & m_T^{k_M} \end{bmatrix} \quad (3)$$

and

$$C \in \mathbb{R}^{T \times k_C} = \begin{bmatrix} c_1^1 & \dots & c_1^j & \dots & c_1^{k_C} \\ \vdots & & \vdots & & \vdots \\ c_i^1 & \dots & c_i^j & \dots & c_i^{k_C} \\ \vdots & & \vdots & & \vdots \\ c_T^1 & \dots & c_T^j & \dots & c_T^{k_C} \end{bmatrix} \quad (4)$$

where T is the duration of each time series. \mathbf{m}_t and \mathbf{c}_t are thus instantaneous values of the vector of meteorological and calendar features and \mathbf{m}^j and \mathbf{c}^j are time series of the j th meteorological and calendar features.

The consumption data is available over all different regions and is defined by the matrix

$$Y \in \mathbb{R}^{T \times k_R} = \begin{bmatrix} y_1^1 & \dots & y_1^j & \dots & y_1^{k_R} \\ \vdots & & \vdots & & \vdots \\ y_i^1 & \dots & y_i^j & \dots & y_i^{k_R} \\ \vdots & & \vdots & & \vdots \\ y_T^1 & \dots & y_T^j & \dots & y_T^{k_R} \end{bmatrix} \quad (5)$$

where k_R is the number of french regions considered in this paper. The learning task associated with this problem is thus to find two components \hat{Y}_M and \hat{Y}_C , respectively referred to as the ‘‘meteorological consumption’’ and ‘‘calendar consumption’’ of Y by minimizing the loss function given in Eq. (6):

$$L(Y, \hat{Y}_M, \hat{Y}_C) = \|Y - \hat{Y}_M - \hat{Y}_C\| = \|Y - f_M(M) - f_C(C)\| \quad (6)$$

2.2. Disaggregation model

The proposed model consists in defining f_M and f_C as multi-layer perceptrons.

$$\forall t \in \llbracket 1, T \rrbracket, \hat{y}_{M_t} = f_M(\mathbf{m}_t), \hat{y}_{C_t} = f_C(\mathbf{c}_t) \quad (7)$$

Multi-layer perceptrons (MLP) are known to be a universal function approximator [22]. They are a type of feed-forward artificial neural network with multiple layers, each one consisting in a parameterized linear function followed by a non-linear activation function. The parameters of the linear functions are optimized during the learning process in order to minimize an error between the outputs of the MLP and the targets. The main hyperparameters are the number of layers,

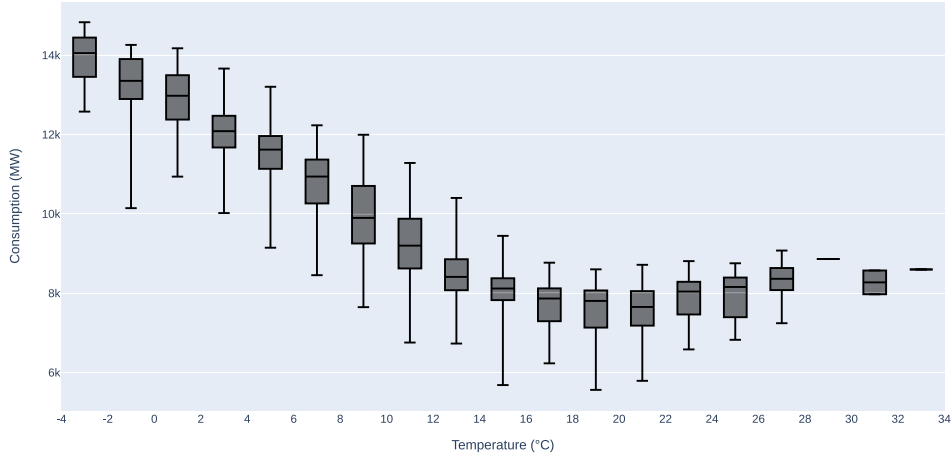


Fig. 1. Weekday consumption in the most populated french region at 12 am versus last 24 h averaged temperature. The correlation between temperature and consumption is clearly visible on low and high temperatures. At low temperatures, electric heating causes the correlation to be negative, while air conditioning causes the correlation to be positive at higher temperatures.

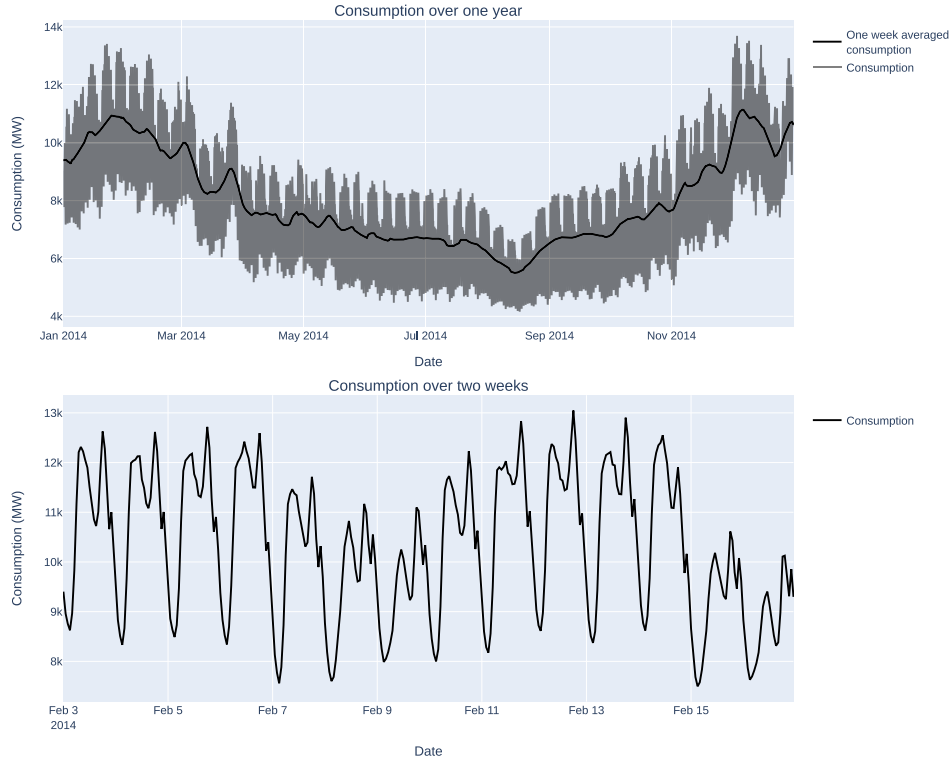


Fig. 2. French power consumption over one year and over two weeks. The socio-economic effects are visible on the graphs since power consumption follows human activity. On the first graph, the impact of school holiday can be observed during august and for christmas, as well as the impact of the 14th july public holiday. The effect of other holidays is not as easily identifiable since they occur at times when consumption variability is greater due to heating. The second graph shows that consumption follows daily and weekly cycles, reflecting human activity.

the number of neurons on each layer, the choice of activation function, the loss function, the optimizer and the learning rate.

Following the approximation $Y = \hat{Y}_C + \hat{Y}_M$, we define the architecture of the model to represent this separation. To do so, two parallel MLPs with different input, one with meteorological features and the second with calendar ones, have been combined to predict the overall consumption as described in Fig. 3. Doing so, one can train the network on the error involving the total consumption instead of individual predictions for \hat{Y}_M and \hat{Y}_C that are not accessible. This model is shown on Fig. 3. The loss function l_t is thus defined by:

$$l_t = MSE(y_t - \hat{y}_t) = MSE(y_t - y_{\hat{M}t} - y_{\hat{C}t}) \quad (8)$$

Where MSE is the mean square error, a loss function commonly used in deep learning for regression problems. The consumptions are reconstructed for each region separately in order to help the network to learn the relation between the regional features (temperature, nebulosity, school holiday) and the meteorological and calendar consumptions in the given region. There is a compromise to be made regarding the choice of consumption granularity. A finer division of consumption (“département” or city) would provide weather features that are more representative of the area under consideration, but would increase the number of features and thus the risk of overfitting. Fine granularity data may also be difficult to obtain.

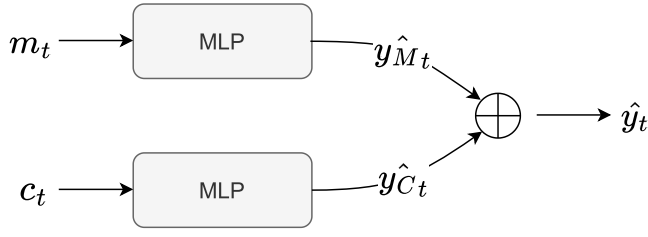


Fig. 3. Illustration of the disaggregation model: the weather features m_t and the calendar features c_t are the respective inputs of 2 distinct multi-layer perceptrons in order to produce two intermediary consumptions $y_{\hat{M}t}$ and $y_{\hat{C}t}$. The optimization of the networks is done by minimizing the difference between the sum of the 2 outputs $\hat{y}_t = y_{\hat{M}t} + y_{\hat{C}t}$ and the real electrical consumption y_t at time t .

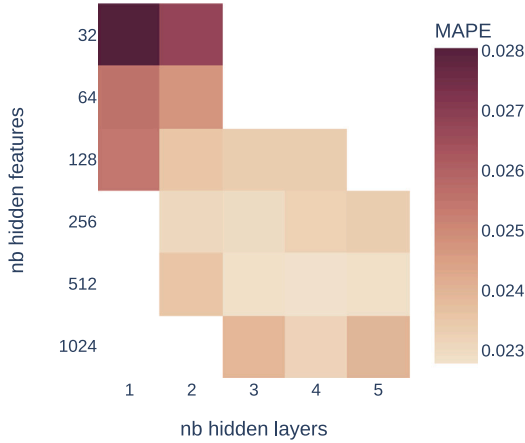


Fig. 4. Consumption reconstruction error for varying number of layers and number of nodes in the models multilayer perceptrons. The model is trained on the training set and the results are obtained with the validation set. The best results are obtained for 4 layers of 512 nodes.

Through the backpropagation process, this approach enables the training of both networks by calculating the gradient of the cost function with respect to the parameters of the multi-layer perceptrons, arising from the differentiation of the loss function and the application of the chain rule.

2.3. Implementation

The proposed models are implemented in pytorch-lightning [23], a pytorch [24] overlay which makes the coding of artificial neural network workflows lighter. Each submodel has 2 hidden layers with 256 nodes each. The activation functions on the hidden layers are ReLU ($f(x) = 0$ if $x < 0$, else x), the final activation is a Softplus function ($f(x) = \log(1 + \exp(x))$). A batch size of 32 and an Adam's optimizer with a learning rate of 0.0001 are considered. An L2 regularization is used to limit overfitting. The choice of the number of hidden layers and the number of nodes has been done by extensively testing various configurations. For separation to be reliable, reconstruction must be reliable. This is why the selected model is the one that minimizes the reconstruction error. This is not an ideal metric, as it gives no indication of the quality of the separation, but it remains relevant in the absence of annotations. The results of these tests are shown on Fig. 4. The best results are obtained for 4 layers of 512 nodes.

3. Datasets description and feature engineering

The performances of the proposed approach has been tested on two dedicated datasets. While the unsupervised approaches described above allow for the unraveling of electrical charge without the need for a real-world example to compare against, the direct drawback

is the inability to evaluate the performance of such a separation. In order to overcome this issue, the models were evaluated on a synthetic dataset for the disaggregation, while the overall total consumption performances were evaluated on both synthetic and real french power consumption dataset.

3.1. French power consumption dataset

The dataset is an aggregation of data from different sources. The French power consumption is obtained from the national electricity transmission system operator *Réseau de Transport d'Electricité* RTE [dataset] [21]. The weather conditions comes from the French national meteorological service *Météo France* [dataset] [25]. Calendar information such as school vacations and public holiday come from French government open data source [dataset] [26,27]. The dataset involves data over seven years from 2013 to 2019, all features are region scale with one-hour frequency. For each region, the power consumption is a sum of all the user's consumption coming from every sector. The weather features are the temperature and the nebulosity. The original weather data is sampled at 3 h, it is resampled at 1 h with a linear interpolation. The research of the best hyperparameters has been done using the 2013 to 2016 data for training and the 2017 to 2018 data for evaluation. The final evaluation has been done using the 2013 to 2018 data for training and the 2019 data for evaluation.

3.2. Synthetic dataset

The synthetic dataset aims to evaluate the ability of the proposed architectures to separate consumptions when the thermal and calendar effects are perfectly separated and fully known. This dataset is composed of 4 calendar consumptions and 4 meteorological consumptions, in order to simulate different regions. The calendar and meteorological consumptions are created separately and added together in order to create the total consumption.

The calendar consumption is defined by three functions f_h , f_d and f_w :

$$Y_{C, \text{synth}} = f_h(\text{hour}) \times f_w(\text{weekday}) + f_d(\text{day of year}) \quad (9)$$

where f_h is an hourly consumption profile based on the mean consumption for the given hour in a french region, f_w is a linear coefficient depending on the weekday allowing to weight higher consumption during working days than during weekend and f_d is a seasonal component (cosine) with a minimum on June, 21, representing consumption due to artificial lighting.

The model of the meteorological consumption considers only the temperature effect. A piece wise linear model, similar to the model proposed by Pagliarini et al. [6], is considered and tuned using the actual temperature of 4 french regions. Three linear segments are considered: consumption decreases at low temperatures, remains constant in the intermediate range, and then increases at high temperatures (see Fig. 5). The temperature considered $T_{\text{applied}, t}$ for each region for this consumption is a weighted average of T_{t-24} to T_t , with T_t being the temperature at time t . The temperature considered is $T_t^* = \frac{\sum_{i=0}^{23} T_{t-i} \times (24-i)}{\sum_{i=0}^{23} (24-i)}$. This averaging was chosen to take into account thermal inertia in consumption, while giving greater importance to the most recent temperatures.

The meteorological consumption is therefore a function of a feature not given as input to f_M . This allows to check the robustness of the models. The piecewise linear functions are distinct for each of the 4 regions, to present different responses to the temperature according to the climate.

Gaussian noise is added to the two consumption in order to evaluate the robustness of the proposed models. The standard deviation of the noise is arbitrarily fixed to 2% of the mean value for the calendar and meteorological consumption.

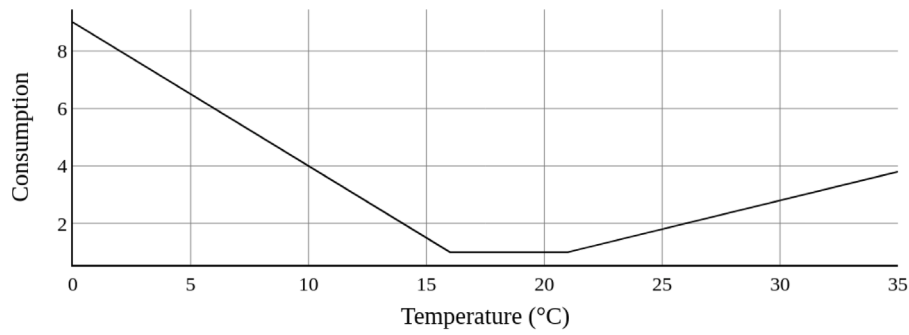


Fig. 5. Synthetic meteorological consumption versus temperature used to create the synthetic dataset. The temperature considered to create the consumption is a weighted average of the temperatures over the last 24 h.

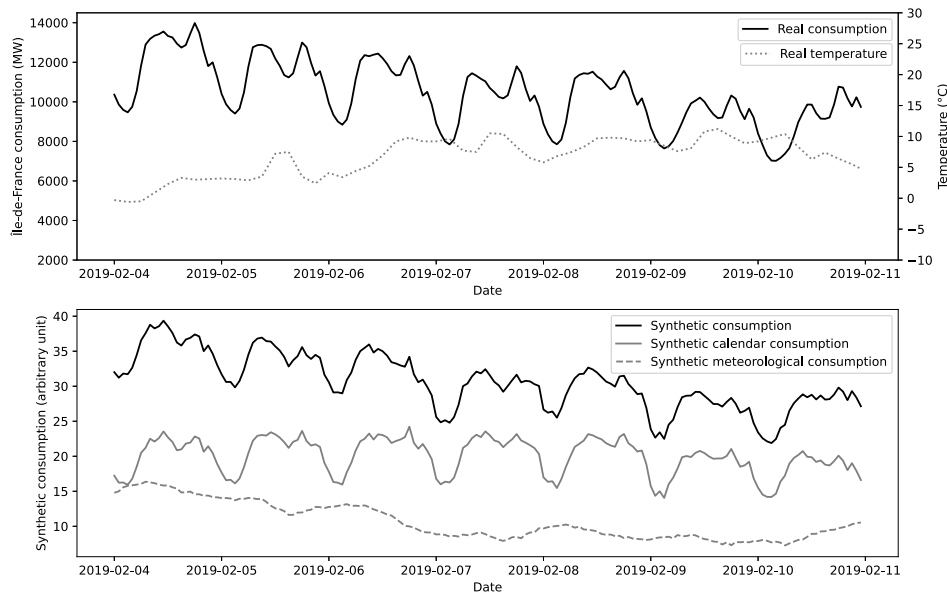


Fig. 6. Synthetic consumption versus real consumption over a week for a single region. The temperatures used for the synthetic consumption creation are the temperatures of the region displayed on the upper chart (Île-de-France). The synthetic consumption qualitatively follows the same variations as the real consumption, over the daily and weekly cycles and over the temperature evolution.

The total consumption is obtained by adding the meteorological consumption and the calendar consumption, as shown in Eq. (10). This total consumption does not aim to be a model of the french consumption, but aims to involve the same phenomena over the calendar and temperature features than the actual french consumption.

$$Y_{\text{synth}} = Y_{M,\text{synth}} + Y_{C,\text{synth}} \quad (10)$$

As shown is Fig. 6, the synthetic consumption's variations are representative from real consumption variations.

3.3. Feature engineering

Classical cosine and sinus functions (Eqs. (11)–(12)) are used to transform the cyclic features and avoid the discontinuity at the end of a cycle (23:00 to 00:00, sunday to monday, december to january, etc.):

$$x_{\text{cos}} = \cos\left(2\pi \frac{x}{x_{\text{max}}}\right) \quad (11)$$

$$x_{\text{sin}} = \sin\left(2\pi \frac{x}{x_{\text{max}}}\right) \quad (12)$$

where x is the feature considered and x_{max} its maximum value.

The calendar features are shown in Table 1.

The year is not provided in order to limit the overfitting on training data. This choice is equivalent to assume that the consumption mechanisms do not vary from a year to another. The performance

Table 1

Calendar features supplied to the model. The cyclic features (hour, weekday, week of the year) are encoded with cosine and sinus in order to avoid the discontinuities.

Feature	Encoding
Hour of the day	cyclic encoded
Day of the week	cyclic encoded
Week of the year	cyclic encoded
Sunset duration	percentage of the day
Public holiday	boolean
School holiday	booleans for each region

obtained by the model leads us to believe that this hypothesis is valid for periods of a few years, since changes in consumption patterns are a slow phenomenon.

The meteorological features are shown in Table 2.

The nebulosity has effects on the thermal radiation received by the buildings and therefore on the HVAC power consumption.

The HVAC power consumption does not only depend on the instantaneously meteorological conditions. Various effects can cause a delay before a consumption variation. For instance, effects of the outside temperature are slowed down due to the buildings thermal isolation and the incoming water temperature (which has influence on water heater consumption) has a slower dynamic than air temperature. In order to

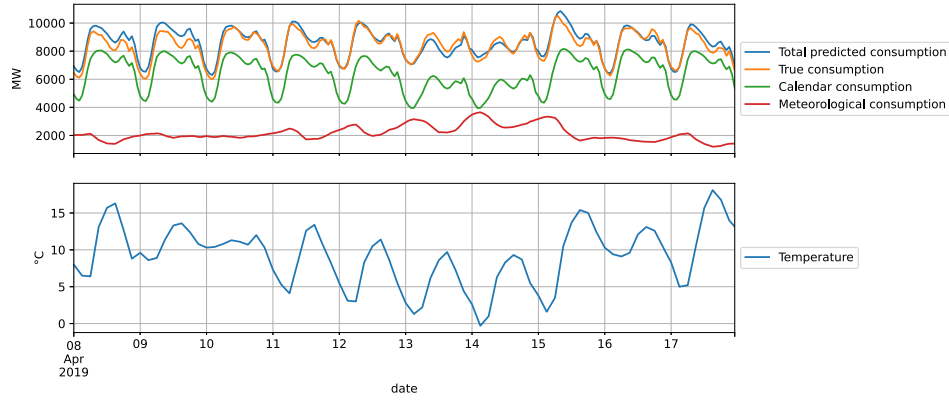


Fig. 7. Consumption separation for a region over an unseen time period. The daily and weekly cycles are visible on the calendar consumption, and a negative correlation can be seen between the temperature and the meteorological consumption.

Table 2

Meteorological features supplied to the model. Moving averages are used to create new temperature and nebulosity features in order to take into account longer-term effect of the weather on the power consumption.

Feature	Encoding
Instantaneous temperature of each region	scaled between -1 and 1
Instantaneous nebulosity of each region	scaled between -1 and 1
Last 6 h average temperature of each region	scaled between -1 and 1
Last 6 h average nebulosity of each region	scaled between -1 and 1
Last 12 h average temperature of each region	scaled between -1 and 1
Last 12 h average nebulosity of each region	scaled between -1 and 1
Last 24 h average temperature of each region	scaled between -1 and 1
Last 24 h average nebulosity of each region	scaled between -1 and 1

capture the consumptions due effects with various dynamics, features corresponding to the moving average temperature and nebulosity over different time periods are used in addition to instantaneous values.

The overall consumption of each region are normalized between 0 and 1 (MaxAbsScaler).

4. Results

In this section, we discuss the results obtained by the model on the two datasets. First, the predicted consumptions are compared to the real value. As explained in Section 3, while this is not a problem for the synthetic dataset, the unsupervised approach makes it impossible to monitor the performances of the meteorological consumption and calendar consumption independently on the real-world dataset. The sum of these two consumptions are therefore compared to the real consumption. Secondly, two scores are created to measure the influence of the temperature on the meteorological and calendar consumptions. Finally, we discuss the effect of compensatory bias in the models.

4.1. Qualitative observations

Fig. 7 shows the separation of consumptions over the period from April 8 to April 17, 2019 for the region Île-de-France. As part of the test dataset, these data were not used in the training of the model. This example illustrates the different variables that influence consumption. Daily and weekly (weekend is 13/04 and 14/04) cycles are well represented in the calendar consumption, with day/night cycles and consumption reduction over the weekend. The meteorological consumption is influenced differently by the temperature depending on the range considered. A change in temperature has a greater effect on meteorological consumption at low temperatures (13/04–14/04) than at mild temperatures (8/04–9/04). The decrease in temperature causes an increase in meteorological consumption.

Table 3

Mean Absolute Percentage Error (MAPE) between the predicted meteorological consumption and calendar consumption and their ground truth values on the synthetic dataset. The very low reconstruction error (particularly on the data without noise) shows that the proposed model performs an accurate separation when the consumption are due to distinct mechanisms.

Score	$MAPE^{meteo}$	$MAPE^{cal}$
Performance without noise	1.07% ($\sigma = 0.07\%$)	0.20% ($\sigma = 0.02\%$)
Performance with noise	1.97% ($\sigma = 0.09\%$)	0.91% ($\sigma = 0.01\%$)

4.2. Reconstruction error

4.2.1. Component-wise reconstruction error

The synthetic dataset allows to compare the predicted meteorological consumption and calendar consumption with their ground truth value. The optimization is done on the sum of the meteorological and calendar consumption, a compensatory bias can appear between the two consumptions (this drawback is discussed in part 4.4). The bias can be offset on the calendar (respectively meteorological) consumption by subtracting the mean of the calendar (respectively meteorological) prediction and adding the mean of the calendar (respectively meteorological) consumption to the predictions, as expressed in Eqs. (13)–(14).

$$y_{M_t}^* = y_{\hat{M}_t} - \frac{1}{T} \sum_{i=1}^T y_{\hat{M}_i} + \frac{1}{T} \sum_{i=1}^T y_{M_i} \quad (13)$$

$$y_{C_t}^* = y_{\hat{C}_t} - \frac{1}{T} \sum_{i=1}^T y_{\hat{C}_i} + \frac{1}{T} \sum_{i=1}^T y_{C_i} \quad (14)$$

The accuracy of the reconstruction is measured using the mean average percentage error (MAPE):

$$MAPE(X_1, X_2) = \frac{1}{T} \sum_{t=1}^T \left| \frac{x_{1t} - x_{2t}}{x_{1t}} \right| \quad (15)$$

where X_1 and X_2 are two time series of length T .

The MAPE of the meteorological and calendar consumption are thus defined by

$$MAPE^{meteo} = MAPE(Y_M, Y_M^*) \quad (16)$$

and

$$MAPE^{cal} = MAPE(Y_C, Y_C^*). \quad (17)$$

The $MAPE^{meteo}$ and $MAPE^{cal}$ evaluated on the synthetic dataset with and without noise are presented Table 3. The performance is measured by averaging the results over 10 training to limit sensitivity to initialization.

Table 4

MAPE between the predicted total consumption and the actual consumption. The low error on the French dataset shows that the network can accurately model the consumption phenomena. Therefore, our assumption of 2 consumptions created by separated mechanisms seems to be respected.

Metric	$MAPE^{TOT}$	$MAPE^{TOT}$	$MAPE^{TOT}$
	French dataset	synthetic dataset with noise	synthetic dataset no noise
Separation model	2.09%($\sigma = 0.1\%$)	0.76%($\sigma = 0.01\%$)	0.17%($\sigma = 0.01\%$)
Comparative model	2.30%($\sigma = 0.2\%$)	0.76%($\sigma = 0.01\%$)	0.15%($\sigma = 0.02\%$)

The error on the data without noise is very low, which shows the ability of the proposed model to accurately separate the calendar and meteorological effect. The reconstruction error increases for noisy data, but this increase is quite marginal, which illustrates the robustness of the model.

The weather features given to the models are different from the one used to create the synthetic dataset (T_t^*). The reconstruction obtained by applying this artificial restriction confirms that the models have a generalization capacity in the absence of the precise data used during the generative process. This result is particularly important for the application to real data, because the features that generate them are by nature not accessible to us.

4.2.2. Total reconstruction error

While the disaggregation of the electrical consumption between calendar and meteorological part is the main goal of this paper, the comparison between the real consumption and the sum of the estimated calendar consumption and meteorological consumption is an important metric. It allows us to ensure that the overall consumption is well reconstructed. A well reconstructed consumption has two meanings. Firstly, it means that the inputs provided to the model are sufficient to model consumption. Secondly, it provides confidence in the quality of the separation of the two consumptions. The score used to measure the reconstruction is again the MAPE.

In order to assess the effects of the consumption separation hypothesis on the overall reconstruction, a comparative model was created. This comparative model is a simple multilayer perceptron that reconstructs the overall consumption using all the features available to the separation model. Doing so, the comparative model is not constrained by the hypothesis of two separated consumption mechanisms. The hyperparameters of the comparative model are chosen in the same manner than for the disaggregation model. The selected architecture is composed of 3 hidden layers of 256 nodes.

The performance is measured by averaging the results over 10 training to limit sensitivity to initialization.

$$MAPE^{TOT} = MAPE(Y, \hat{Y}) \quad (18)$$

The total reconstruction error of the proposed models according to the MAPE metric evaluated on the french dataset and on the synthetic dataset is presented Table 4.

With an error of 2.09% as shown in Table 4, the presented approach allows a correct modeling of the consumption phenomena. As we can see in Fig. 8, the reconstruction is precise both on a daily scale and on a yearly scale. The accurate reconstruction performed by the separation model shows that the provided features are sufficient to predict the consumption.

The comparative model does not perform as well as the separation model on the real data due to overfitting. It achieved the same MAPE of 1.4% on the training data that the separation model. This overfitting occurred with a L2 regularization. A regularization through dropout was also considered but lowered the performances. This drop of performance shows that the separation of the meteorological and calendar features in the architecture helps the generalization capability of the model.

The fact that the comparative model does not perform better than the separation model provides confidence that the hypothesis of two separate consumption mechanisms is respected on real data. Indeed, consumption depending simultaneously on calendar and weather features cannot be modeled by the separation model and would increase the reconstruction error.

In comparison to the obtained scores, Pagliarini et al. achieve 1.3% MAPE on their best consumption approximation in [6]. They reconstruct the daily consumption, fit their model on the same data that they use to measure the MAPE and do not separate the consumptions. Behm et al. achieve 2.8% MAPE on their load profiles in [28], without separating calendar and meteorological effects. The data of these authors are not available, and their approaches are too different from the one proposed in this article to rigorously compare the performances. These scores are given as an indication in order to better situate the modeling abilities of the proposed models.

Two causes limiting the performance achievable with the models can be identified:

- The features given to the model are not sufficient to explain all consumption phenomena. For instance, the weather data is given for only 12 locations for the entire country, and the different public holidays and school holidays might not have the same influence on people's behavior but have the same encoding. This choice was made to limit overfitting.
- The model only considers the temperature with few different averaging (instant, 6, 12 and 24 h), while the temperature can have effects on the consumption at different time scales. Adding more temperature features does not improve the performances since this pushes the models to overfit. However, an optimization of the temperature averaging choice could improve the performances. This will be the object of further work.

The total consumption reconstruction error is higher for mild temperatures than for low or high temperatures (Fig. 9, upper left). An explanation of this difference of performance could be that the meteorological and calendar consumptions are more intricated at mild temperature than on temperatures where heating or cooling are constantly used. The weekday has also an impact on the accuracy of the reconstructed consumption (Fig. 9, lower left). Consumption is more predictable during the weekend than during the working days. Reconstruction quality varies from month to month. The model has a greater reconstruction error on April, September and October (Fig. 9, lower right). This could be due to an overestimation of the heating consumption since some heaters are completely off. However, this should not be overinterpreted since the test dataset consists of only one year of consumption data. Finally, consumption over public holidays is well reconstructed (Fig. 9, upper right). Even if public holidays are less represented in the data, and if the specificity of the holidays are not integrated in the data, the reconstruction error is just slightly greater for public holiday than for regular days (1.95% versus 1.60% for the daily power consumption).

4.3. Correlation based scores

4.3.1. Definition of the scores

Another performance indicator of the model is the correlation between the consumption and the temperatures. We are looking for two different behaviors for these correlations.

- The meteorological consumption has to be highly correlated to the temperature. The correlation has to be negative for cold temperatures (1 °C more means less heating), and positive for hot temperatures (1 °C more means more air conditioning consumption).
- The calendar consumption is wanted to be independent from the temperature. The daily calendar consumption and the average daily temperature should be decorrelated

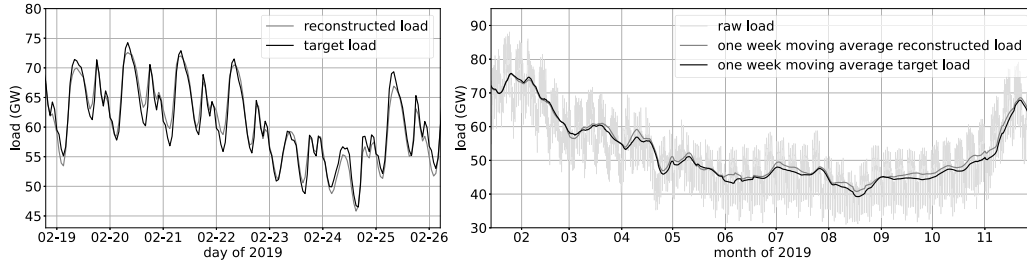


Fig. 8. One week (left) and averaged one year (right) sample of the actual french power consumption of 2019 compared to the model's prediction. The consumption modeling is precise both on a daily scale and on a yearly scale.

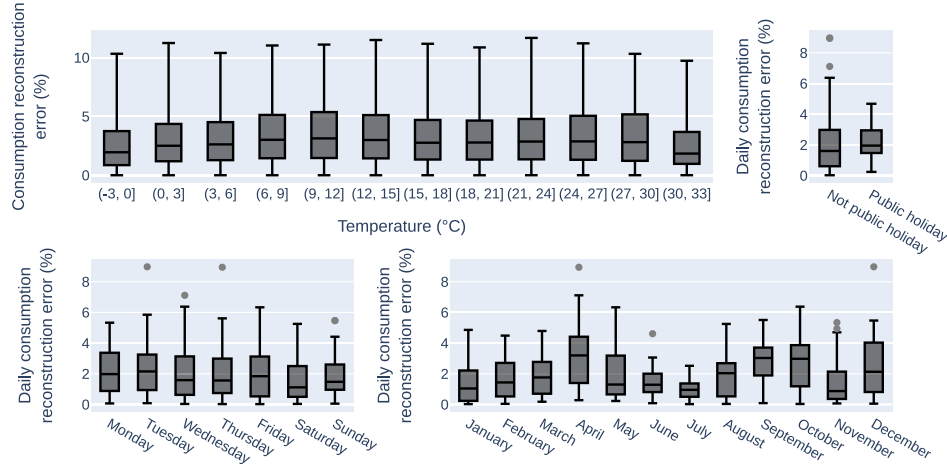


Fig. 9. Consumption reconstruction error versus different calendar features. The total reconstructed consumption ($\hat{Y} = \hat{Y}_M + \hat{Y}_C$) is compared to the true consumption on the French dataset.

Consumption increases during working hours due to human activity, while at the same time the temperature increases. In order to avoid that the scores are influenced by this correlation, the data used are total daily consumptions and average daily temperature.

In order to measure these two effects, we have created adequate scores.

The meteorological consumption has to be correlated in absolute value with the temperature. The chosen score is the mean absolute correlation between daily consumption and daily average temperature. The correlations between daily meteorological consumption and daily average temperature are computed over 14 days. The score is then computed by taking the mean of the absolute value of the correlations.

$$\text{CORR}^{\text{meteo}} = \frac{1}{N} \sum_{i=1}^N |\text{corr}((y_{M_i}^{24}, \dots, y_{M_{i+13}}^{24}), (T_i^{24}, \dots, T_{i+13}^{24}))| \quad (19)$$

Where $y_{M_i}^{24} = \sum_{t=24*j}^{24*j+23} y_{M_t}$ is the daily meteorological consumption of the i th day and T_i^{24} is the average temperature of the i th day.

The correlation used is Spearman's correlation because the relation between the temperature and the consumption is not necessary meant to be linear. Spearman's correlation uses the ranks of the value instead of the values itself, allowing to conclude on the existence of monotonic relationship between two variables rather than the existence of linear relationship in the case of Pearson's correlation.

This score is better when being high, but cannot reach 1 because the consumption and temperatures are almost independent when the temperature is mild, about 17 °C/19 °C. This effect can be observed on Fig. 10, and has been identified in Refs. [2,3].

Another score is defined for the calendar consumption. Since the calendar consumption and the temperature should be independent, their correlation should be near to 0, but even independent variables can have a non-zero correlation, and the variance of the correlation

can be high given the small size of the samples. For instance, there is a 10% chance of getting a Spearman correlation greater than 0.46 with an uncorrelated sample of 14 data points [29]. To avoid misinterpretation of these correlations, the correlation coefficients are averaged on temperature windows. We made this choice rather than the choice of increasing the size of the samples because longer periods can contain various temperature on which the temperature has different effects on the consumption. The average on temperature windows is to make sure that there are no effects that compensate from a temperature to another (positive correlations for low temperature and negative correlations for high temperatures for instance). Fig. 12 presents the correlation between daily calendar consumption and daily temperature versus mean temperature during the period. This figure shows that the correlations are centered on 0. The score is computed by averaging the correlations by temperature bins, as described by the following equation:

$$\text{CORR}^{\text{calendar}} = \frac{1}{N_{\text{bins}}} \sum_{i=1}^{N_{\text{bins}}} \left| \frac{1}{N_{\text{corr},i}} \sum_{j \in \text{bin}_i} \text{corr}((y_{C_j}^{24}, \dots, y_{C_{j+13}}^{24}), (T_j^{24}, \dots, T_{j+13}^{24})) \right| \quad (20)$$

where N_{bins} is the number of temperature bins, arbitrary chosen to be 20, $N_{\text{corr},i}$ is the number of correlations computed for the i th bin. As in the meteorological correlation score, $y_{C_j}^{24} = \sum_{t=24*j}^{24*j+23} y_{C_t}$ is the daily calendar consumption during the j th day, T_j^{24} is the average temperature on the j th day and the correlation used is Spearman's correlation. Fig. 12 provides a more visual understanding of the averaging by temperature bins used in the computation of the score.

We want our calendar consumption to be as independent as possible from the temperatures, so a better score is a score with a value near to 0.

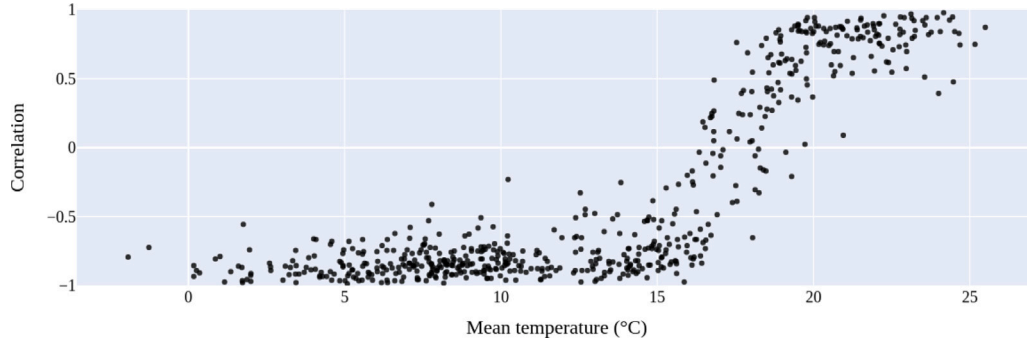


Fig. 10. Correlation between daily meteorological consumption and daily temperature versus mean temperature on the period. The correlation used is Spearman's correlation. The correlation are computed on periods of 14 days in order to limit the overlap of cold days and warm days in a single period. The meteorological consumption and the temperature are highly correlated: negatively during the cold temperatures and positively during hot temperatures. The intermediate zone, from 16 °C to 19 °C does not have a clearly visible correlation.

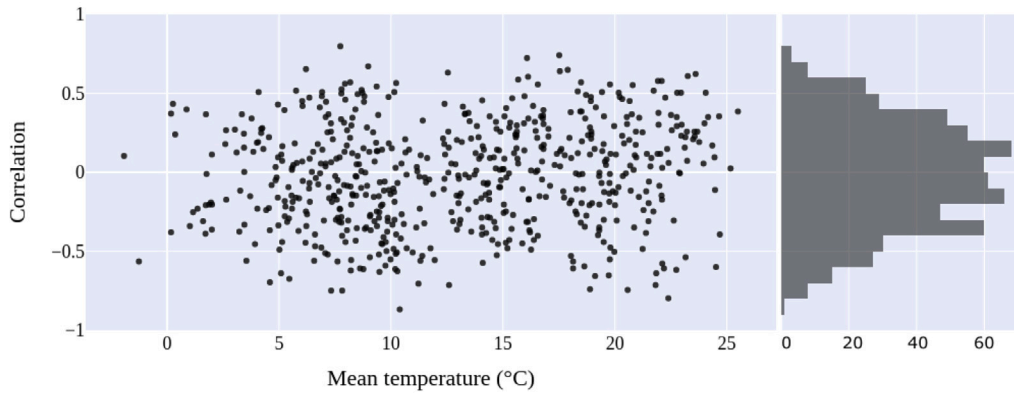


Fig. 11. Correlation between daily calendar consumption and daily temperature versus mean temperature on the period. The correlations are computed the exact same way than for Fig. 10. The small number of sample per correlation calculation makes it likely to have high correlations even for independent samples, and therefore makes the correlation noisy.

Table 5

Correlation scores on our model. The high $CORR^{meteo}$ score indicates that the meteorological prediction is highly correlated to the temperature. The low $CORR^{calendar}$ indicates that the calendar consumption is nearly independent to the temperature.

Dataset	$CORR^{meteo}$	$CORR^{calendar}$
Real french data	0.74($\sigma = 0.006$)	0.14($\sigma = 0.004$)
Synthetic data no noise	0.818($\sigma = 0.003$)	0.112($\sigma = 0.002$)
Synthetic data with noise	0.818($\sigma = 0.003$)	0.112($\sigma = 0.002$)

4.3.2. Results

Figures 10 and 12 show the correlations on which the scores are computed. The results obtained for the different models are presented in Table 5.

The meteorological consumption is highly correlated with the temperature as illustrated on Fig. 10 and with the $CORR^{meteo}$ score of 0.74. It can be noticed that the absolute correlation is higher in the low temperatures than in the hot temperatures. One explanation to the reduced correlation on high temperatures is that the air conditioners are less implanted than electric heaters, particularly in the northern regions which are colder.

The high correlation between the meteorological consumption and the temperature indicates that the meteorological consumption predicted by the model indeed captures consumption that is temperature sensitive. In the same way, the low correlation between the calendar consumption and the temperature indicates that this consumption is mainly composed of temperature insensitive phenomena.

4.4. Compensatory bias of the models

The regression conducted by the proposed models is performed on the sum of the meteorological and calendar consumption. A compensatory bias, added to f_C and subtracted to f_M would not have any influence on the loss and would not influence the model's training. The meteorological and calendar consumptions are therefore learned to an additive bias. To compensate these two biases, we add a constant to f_C and subtract the same constant to f_M .

RTE Provides a definition of the meteorological consumption and sets its minimum value to 0 W [30]. The meteorological consumption could thus be offset using this minimum value. The offsetted meteorological model defined by

$$f_M^*(\mathbf{m}_t) = f_M(\mathbf{m}_t) - \min_i f_M(\mathbf{m}_i). \quad (21)$$

The same offset is also used to define the offsetted calendar consumption model

$$f_C^*(\mathbf{c}_t) = f_C(\mathbf{c}_t) + \min_i f_M(\mathbf{m}_i). \quad (22)$$

This offsetting of the two models does not change the scores presented in this section, since the correlation is not affected by an offset, and the sum of the two consumptions stays the same.

5. Discussion

An unsupervised deep learning approach has been proposed to separate the consumption due to the weather from the consumption due

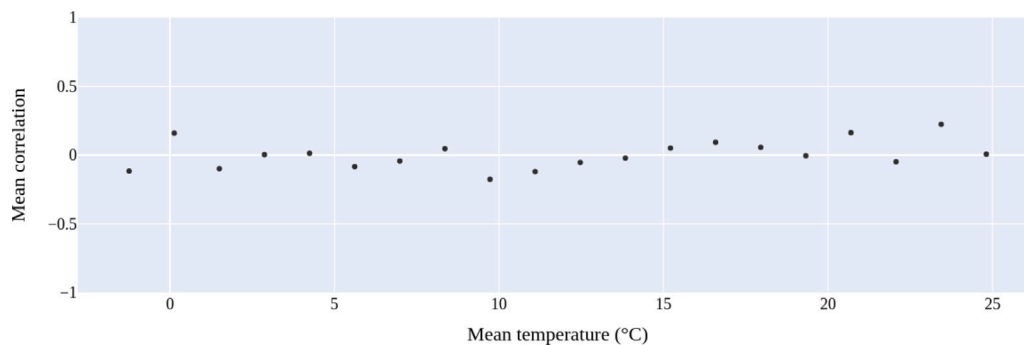


Fig. 12. Correlation between daily calendar consumption and daily temperature versus mean temperature on the period, averaged on temperature windows. The correlations are computed the exact same way than for Figs. 10 and 11. The averaging reduces the variance of the correlations. The calendar correlation score is computed by averaging the ordinates of the points. We can see on the figure that there is no significant correlation between the calendar consumption and the temperature.

to other causes. It is non-intrusive, since it requires no measurements other than total consumption and meteorological information. Our results show that the model performs an accurate reconstruction of the consumption at a country scale, with a MAPE of 2.09% on real data. In the framework of this paper, the proposed approach has been applied to French electricity consumption. Application to other countries is straightforward once the consumption and meteorological data have been collected and the variables impacting consumption have been identified. The low complexity of the model makes it easy to use on other data, with training possible on a desktop PC without GPU/TPU in less than an hour. The comparison with a simple multilayer perceptron model showed that the proposed approach helps in avoiding overfitting.

The hypothesis underlying this model, stipulating that weather consumption is separated from the rest of consumption, cannot be formally verified. It can be thought that this hypothesis is close to reality for french data, since the model reconstructs the total consumption accurately. This assumption may be too simplistic for data from other countries. It is possible, for example, that there are countries in which the HVAC systems in the home are very different from those in the workplace. In this case, consumption due to temperature would not be totally separated from that due to socio-economic factors, and the proposed model would no longer be relevant. The overestimation of consumption during the cold spells of April, September and October could be due to lower thermosensitivity, as heaters were switched off during this period. Nevertheless, consumption reconstruction remains correct during this period, with an average error of 3.1%. Moreover, the comparative model does not reconstruct consumption any better, even though it is not constrained by this hypothesis. Another limiting hypothesis of the model is that the consumption mechanisms do not change from one year to another. The reconstruction performance leads one to believe that these changes are indeed slow. If this model was being considered for a use over a longer period, it should be retrained periodically on recent data. In the event of a sudden change of the consumption mechanisms (like during COVID19 lockdowns for instance), the model would not adapt. This is not specific to the proposed model but would also apply to other methods.

The presence of gas heating reduces thermosensitivity because the presence of electric heating is reduced. However, this should not affect the model's performance as long as the distribution of heating types remains constant, since the use of gas heating does not alter electricity consumption. It would be possible to run a similar model to identify the gas consumption due to temperature. To do this, it would be necessary to identify the calendar variables specific to gas consumption. Distributed generation, such as customer owned solar panels or small wind turbines may have an impact on the model by reducing the observed consumption. In the case of our data, the impact is limited, as self-consumption represents only 0.2% of the energy produced in

France in 2022 [31]. If this share were to increase significantly, the model would have to be re-trained regularly to adapt to changes in consumption. This would also mean reconsidering the features used by the model, so that the drop in consumption due to self-consumption can be predicted correctly. The wind at different locations, for example, could provide useful information for the model.

6. Conclusion

A model is proposed to separate consumption due to the weather from consumption due to other causes under the hypothesis of separation of the consumption mechanisms. The performance achieved on synthetic data shows that the separation is accurate when this hypothesis is verified. The low reconstruction error and the comparison with a model not constrained by the hypothesis leads one to believe that the assumption of separated consumptions is close to reality. An analysis of the correlations between consumption and temperature shows that, as expected, weather consumption is highly correlated to temperature (positively for hot temperatures, negatively for low temperatures) and calendar consumption is uncorrelated with temperature.

Further investigation will focus on the identification of consumption due to mixed causes, i.e. meteorological consumption influenced by the time and the day and calendar consumption influenced by the temperature. Relationships can indeed be observed between meteorological phenomena and temporal human behavior. The choice of the averaging windows for the creating of the meteorological features may have an impact on the model's performances, which could be evaluated in future work.

CRediT authorship contribution statement

Charles Dampeyrou: Writing – original draft, Software, Methodology, Investigation, Conceptualization. **Antoine Goichon:** Software, Investigation, Formal analysis. **Martin Ghiene:** Writing – review & editing, Supervision, Methodology. **Valentin Tschannen:** Writing – review & editing, Methodology, Formal analysis. **Sofiane Schaack:** Writing – review & editing, Supervision, Methodology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The link to the data source is provided in the references.

References

- [1] Jovanović Saša, Savić Slobodan, Bojić Milorad, Djordjević Zorica, Nikolić Danijela. The impact of the mean daily air temperature change on electricity consumption. *Energy* 2015;88:604–9.
- [2] Hor Ching-Lai, Watson Simon, Majithia Shanti. Analyzing the impact of weather variables on monthly electricity demand. *IEEE Trans Power Syst* 2005;20:2078–85.
- [3] Valor Enric, Meneu Vicente, Caselles Vicente. Daily air temperature and electricity load in Spain. *J Appl Meteorol* 2001;40(8):1413–21.
- [4] Pardo Angel, Meneu Vicente, Valor Enric. Temperature and seasonality influences on Spanish electricity load. *Energy Econ* 2002;24(1):55–70.
- [5] Harish Santosh, Singh Nishmeet, Tongia Rahul. Impact of temperature on electricity demand: Evidence from Delhi and Indian states. *Energy Policy* 2020;140:111445.
- [6] Pagliarini Giorgio, Bonfiglio Carlotta, Vocale Pamela. Outdoor temperature sensitivity of electricity consumption for space heating and cooling: An application to the city of Milan, North of Italy. *Energy Build* 2019;204:109512.
- [7] Burillo Daniel, Chester Mikhail V, Ruddell Benjamin, Johnson Nathan. Electricity demand planning forecasts should consider climate non-stationarity to maintain reserve margins during heat waves. *Appl Energy* 2017;206:267–77.
- [8] Hines Paul, Balasubramaniam Karthikeyan, Sanchez Eduardo Cotilla. Cascading failures in power grids. *IEEE Potentials* 2009;28(5):24–30.
- [9] Añel Juan A, Fernández-González Manuel, Labandeira Xavier, López-Otero Xiral, De la Torre Laura. Impact of cold waves and heat waves on the energy production sector. *Atmosphere* 2017;8(11).
- [10] Mauch Lukas, Yang Bin. A novel DNN-HMM-based approach for extracting single loads from aggregate power signals. In: 2016 IEEE international conference on acoustics, speech and signal processing. 2016, p. 2384–8.
- [11] Zhao Bochao, He Kanghang, Stankovic Lina, Stankovic Vladimir. Improving event-based non-intrusive load monitoring using graph signal processing. *IEEE Access* 2018;6:53944–59.
- [12] Zhao Bochao, Ye Minxiang, Stankovic Lina, Stankovic Vladimir. Non-intrusive load disaggregation solutions for very low-rate smart meter data. *Appl Energy* 2020;268:114949.
- [13] Anderson Kyle D, Bergés Mario E, Ocneanu Adrian, Benitez Diego, Moura José MF. Event detection for non intrusive load monitoring. In: IECON 2012 - 38th annual conference on IEEE industrial electronics society. 2012, p. 3312–7.
- [14] Kelly Jack, Knottenbelt William. Neural NILM: Deep neural networks applied to energy disaggregation. In: Proceedings of the 2nd ACM international conference on embedded systems for energy-efficient built environments. New York, NY, USA: Association for Computing Machinery; 2015, p. 55–64.
- [15] Devlin Michael, Hayes Barry P. Non-intrusive load monitoring using electricity smart meter data: A deep learning approach. In: 2019 IEEE power & energy society general meeting. 2019, p. 1–5.
- [16] Faustine Anthony, Mvungi Nerey Henry, Kaijage Shubi, Michael Kisangiri. A survey on non-intrusive load monitoring methodologies and techniques for energy disaggregation problem. 2017, arXiv.
- [17] Liang Ming, Meng Yao, Lu Ning, Lubkeman David, Kling Andrew. HVAC load disaggregation using low-resolution smart meter data. In: 2019 IEEE power & energy society innovative smart grid technologies conference. ISGT, 2019, p. 1–5.
- [18] Hobby John, Shoshitaishvili Alexander, Tucci Gabriel. Analysis and methodology to segregate residential electricity consumption in different taxonomies. *IEEE Trans Smart Grid* 2012;3:217–24.
- [19] Özkizilkaya Özlem. Thermosensibilité de la demande électrique : identification de la part non linéaire par couplage d'une modélisation bottom-up et de l'approche bayésienne [Ph.D. thesis], Ecole Nationale Supérieure des Mines de Paris; 2014.
- [20] Mor Gerard, Cipriano Jordi, Martirano Giacomo, Pignatelli Francesco, Lodi Chiara, Lazzari Florencia, et al. A data-driven method for unsupervised electricity consumption characterisation at the district level and beyond. *Energy Rep* 2021;7:5667–84.
- [21] Réseau de Transport d'Electricité (RTE). 2023, <https://odre.opendatasoft.com/explore/dataset/eco2mix-regional-cons-def>. [Accessed 11 August 2023].
- [22] Hornik Kurt. Approximation capabilities of multilayer feedforward networks. *Neural Netw* 1991;4(2):251–7.
- [23] Falcon William, Borovec Jirka, Wälchli Adrian, Eggert Nic, Schock Justus, Jordan Jeremy, et al. PyTorchLightning/pytorch-lightning: 0.7.6 release. Zenodo; 2020.
- [24] Paszke Adam, Gross Sam, Massa Francisco, Lerer Adam, Bradbury James, Chanan Gregory, et al. PyTorch: An imperative style, high-performance deep learning library. In: Wallach H, Larochelle H, Beygelzimer A, d'Alché Buc F, Fox E, Garnett R, editors. Advances in neural information processing systems 32. Curran Associates, Inc.; 2019, p. 8024–35.
- [25] Météo France open data. 2023, <https://public.opendatasoft.com/explore/dataset/donnees-synop-essentielles-omm/table/?sort=date>. [Accessed 11 August 2023].
- [26] School holidays dates. 2023, <https://data.education.gouv.fr/explore/dataset/fr-en-calendrier-scolaire/>. [Accessed 11 August 2023].
- [27] Public holiday dates. 2023, https://etalab.github.io/jours-feries-france-data/csv/jours_feries.csv. [Accessed 11 August 2023].
- [28] Behm Christian, Nolting Lars, Praktiknjo Aaron. How to model European electricity load profiles using artificial neural networks. *Appl Energy* 2020;277:115564.
- [29] Ramsey Philip H. Critical values for spearman's rank order correlation. *J Educ Stat* 1989;14(3):245–53.
- [30] RTE thermosensitivity description. 2023, <https://bilan-electrique-2020.rte-france.com/sensitivity-to-temperatures-and-end-uses/?lang=en#>. [Accessed 11 August 2023].
- [31] Distributed generation of electricity in France. 2024, <https://www.rte-france.com/wiki-energie/electricite-autoconsommation-remede-crise-energie>. [Accessed 3 October 2024].