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Enhancing the missing data imputation of primary substation load demand records

Cruz E. Borges, Oihane Kamara-Esteban, Tony Castillo-Calzadilla *, Cristina Martin Andonegui, Ainhoa Alonso-Vicario

Faculty of Engineering, University of Deusto, Avda. Universidades, 24, 48007, Bilbao, Spain

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ABSTRACT

The daily analysis of loads is one of the most important activities for power utilities in order to be able to meet the energy demand. This analysis not only includes short-term forecasting but it also encompasses the completion of missing load data, known as imputation. In this work we show that adding information of attached or bordering primary substation helps to improve the prediction accuracy in a single substation, since its neighbours may share common weather-related (e.g. temperature, humidity, wind direction, etc.) and human-related (e.g. work-calendar, holidays, cultural consumption patterns, etc.) data. In order to validate these approaches, we test the forecasting and imputation neighbouring methodology on a wide variety of datasets. Results confirm that, given a primary substation, the addition of information from surrounding substations does improve the forecasting and imputation errors.

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1. Introduction

Some decades have already passed since the gradual work of a number of pioneers enabled the term *smart grid* to leave the misty marsh plans of science fiction to step forth into the mainland of reality [1]. Smart grids are being progressively deployed, expanding the winning combination of IT (Information Technologies), digital communications and control systems to manage power flow [2]. The objective remains the same as it was in the classical electrical system, nowadays almost Fritz Lang's Metropolis-alike gigantic machines that Edison and Tesla bluntly struggled for and dreamt of: a more efficient, resilient, reliable and secure power grid.

Yet, either smart or not, the grid has been designed and is devoted to serve the humans; and human is resolution, as is irresolution, changeableness, inconstancy, mobility and fluctuation, just to mention a few facets of the same diamond [3]. Taming this stochastic beast has been the objective of a remarkable branch of research. Indeed, an accurate prediction has crucial consequences on day-ahead network operation plans, for the tiniest bias or error may increase operation costs, yielding losses ranging from hundreds of thousands or even millions of euros to the operator [4].

Thus, forecasting or the art of predicting the behaviour of different-scale loads (e.g. country-wide [5–8], zone-wide [9,10], building [1,11–14], etc.) plays a critical role in the real-time control and operation of the grids and it remains an essential task for the electric utilities. Forecasting is a critical role in preventing blackouts or losses of energy [15]. There are many factors that affect demand loads, such as climate changes, usage patterns, season, day of the week, time of the day, and so on. Foresee is even more important these days due to global warming, which brings to us a massive renewable microgrids integration.

Depending on the concerned building sector, forecasts can be categorized as those for the residential, commercial, or industrial sectors [15]. Additionally, forecasting can be categorized as short-term, medium-term, and long-term based on the time horizon. Short-term load forecasting (STLF) provides load forecasts at hourly or sub hourly intervals for the following one day to two weeks. A highly accurate STLF surely will help utilities and providers to address the tasks caused by renewable penetration and electricity market development with complex pricing strategies in future smart grid markets [15].

Generally, there are two types of approaches when addressing the forecasting challenge, namely Statistical methods as ARIMA [1], Multiple Linear Regression (MLR) [16], Semiparametric [6,17] or Nonparametric Regression [18] and Artificial Intelligence methods from Neural Networks (NN) [19–21], to Support Vector Machines (SVM) [22]. Each approach features its pros and cons: whereas statistical methods show poorer records than their counterparts [4,7], they do not have drawbacks such as difficult

* Corresponding author.
E-mail addresses: cruz.borges@deusto.es (C.E. Borges), oihane.esteban@deusto.es (O. Kamara-Esteban), tonycastillo@deusto.es (T. Castillo-Calzadilla), cristina.andonegui@deusto.es (C.M. Andonegui), ainhoa.alonso@deusto.es (A. Alonso-Vicario).

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Nomenclature

IT	Information Technologies
ARIMA	Autoregressive Integrated Moving Average
MLR	Multiple Linear Regression
NN	Artificial Intelligence methods based on Neural Networks
SVM	Support Vector Machines
VSTLF	Very Short Term Load Forecasting
VSTLI	Very Short Term Load Imputation
STLF	Short Term Load Forecasting
STLI	Short Term Load Imputation
MAPE	Mean Absolute Percentage Error
RW	Random Walk
PV	Photovoltaic
R_t	The real load at time t
L_t	The predicted or imputed load value at time t
GEFCom	Global Energy Forecasting Competition
TSO	Transmission System Operator

parametrization, non-obvious selection of variables and overfitting.

On one hand, statistical methods normally require much more historical data to *discover* the patterns inherent to the load studied [7,23,24]. Fortunately, nowadays, modern electricity networks provide remarkably rich sources of data at a highly disaggregated level [5,25]. Another drawback of statistical methods in STLF is they model the whole series without taking into account the type of the day [26]. On the other hand, Artificial Intelligence (AI) based techniques are known to be generally adaptative and robust to non-stationary data. Nevertheless, AI-based techniques are not always adaptative, especially to linear data [15], such as the data used in this paper.

Regarding STLF in substations, [27] proposed an interesting STLF-based approach for the detection of gain and offset errors that are introduced by the measurement equipment. The implemented system was tested against real power load data that was provided by electricity suppliers. The study mainly focused on detection of measurement errors in electronic sensors, nonetheless, the proposal did not consider the detection of random errors. Whereas [28] focused on STLF for substations implementing a time series method for forecasting next day loads the error of the French studied substation model had been reduced by about 30%. The authors of [29] propose an adaptative load forecasting methodology, which automatically selects the forecast method that fits better considering some important features such as day of the year, type and condition of the distribution network. As far as we know, there are not so many papers which simultaneously address the problem of missing data using both techniques imputation and forecasting.

The missing of data is unquestionably a struggling task when forecasting energy generation. Some researches have proposed how to cope with it depending on the baseline circumstances. In [30] they have analysed 8 different method for imputing data missing and concluded that before selecting one of them it very important to know how much data is missing? nonetheless, it seems not be as prevalent as they mention in the paper since their conclusion for data ranged of 10% to 30% the best method was always K-nearest neighbours (KNN). Whereas, in [31] the methodology is not dependent on data size, data resolution and amount of missing and incomplete data and they achieved a 3% of performance implementing the mean absolute range normalized error (MARNE). In [32] they developed a missing data treatment method oriented to electric vehicle charging values though, using only five methods namely constant-zero, mean, median, maximum likelihood, and multiple imputation methods. In the end, they concluded that median and constant (zero) imputations seem the best among constant imputation methods.

The authors of [12] explored an intuition that had already been validated in other disciplines [33–36]: adjacent zones, sharing commonalities such as similar weather, geographic location [37], may help improve the forecasting of a single substation. The results of this work were promising but lacked of generality. In this paper we present a comprehensive study on the missing data treatment. One of the main prerequisites of almost all forecasting methods is to have a complete database of historical data. However, as all practitioners know, this is hardly ever the case. The art of completing the missing information in a database is known as *imputation*. While there are a large knowledge about the imputation problem as a technique (see, for example, [38–41] and references therein) there are not many previous works on the context of electric load information. To our knowledge, the only attempt to tackle this problem in this particular context is the seminar work of Giannakis et al. [42–44].

The authors in [45] developed a missing data imputation technique based on correlation-connected clusters. This technique considers the local correlation among the measurements to estimate missing power grid data. A similar perspective is presented by [46] who proposed a convex-optimization-based method and provides its theoretical guarantee in the data identification. Using the same methods, [47] proposed a model, defined as "union and sums of sub-spaces", to characterize practical nonlinear datasets, i.e. each data point belongs to either one of a few low-dimensional sub-spaces or the sum of a subset of sub-spaces. [48] designed a model to detect the occurrence of anomalous events and abnormal conditions at both lateral and customer levels. The former papers addresses some very concerning data problems intentionally produced by human raids/attacks in order to produce information gaps.

In this paper we present a novel method to deal with missing data using models that contain information of adjacent zones. Against this background, we advance the state of the art in two main ways. First, we present a comprehensive study of the improvement that neighbouring loads bring to the forecasting problem. Second, we thoroughly test and validate the imputation problem, showing that the aforementioned intuition also applies in this case. Therefore, the working hypothesis for this paper says: The inclusion of surrounding or adjacent primary substations loads improves the accuracy of both the forecast and imputation problems. It is important to emphasize the importance of the initial data treatment to improve the load forecast, as noted by [49].

The remainder of the paper is organized as follows. Section 2 details the differences among imputation and short-term forecasting. Section 3 introduces the models used in this paper. Section 4 describes the experiments carried in order to test our hypothesis, including the datasets used. Finally, Section 5 presents and discusses the results obtained and summarizes our contributions and draws the avenues of future works.

2. Imputation as a forecasting task

In this paper we face two problems with a similar structure but that yield rather different results. On the one hand, we have the so-called *forecasting* problem, which main objective is to predict the evolution of a single variable considering its past

behaviour under similar conditions. In our case, we want to predict the energy expected to be consumed/delivered at a primary substation in the following hour. This last restriction limits the search for solutions since we are not able to use information stemming from time-points beyond the current one. For example, we cannot use weather data from 17.00 to predict the energy load at 17.00; instead we must use either *predicted* weather data from 17.00 or previous energy load data.

On the other hand, we have the *imputation* problem, which objective is to figure out the value for one variable in the near past. Imputation is a common classification that groups methods used when, for instance, the reading of a metre is missing or is incorrect. For example, suppose that the time now is 14.00 and we find that the primary substation is missing data at 12.00 due to a malfunction in the metring process. This missing data at 17.00 may be needed by the forecasting process to predict the load at 20.00. In this case, in order to estimate the missing value at 17.00, we may use both data from former time points (e.g. from 15.00 or 16.00) and from later time points (e.g. 18.00 and 19.00). Specifically for this paper, we will consider the *online* imputation problem, since the missing value is the last value of a time series.

Therefore, the main difference between imputation and forecasting is the information that can be used to estimate the desired value at a specific point in time. In the case of prediction, our objective is to predict the value of the load L at time $t+h$ with $h \geq 1$ using information until time t. Namely, the following is a valid forecasting model for L:

$$L_{t+h} = f(L_t, \ldots, L_{t-i}, X_t, \ldots, X_{t-j}), \tag{1}$$

where i, j are two integer constants, f is some function and X is a set of exogenous variables.

On the other hand, when imputing our objective is, as before, to know the value of the load L at time $t+h$ with $h \geq 1$ but, in this case, we can also use information of the exogenous variables until time $t+h$. Namely, the following is a valid imputing model for L:

$$L_{t+h} = f(L_t, \ldots, L_{t-i}, X_{t+h}, \ldots, X_{t-j}), \tag{2}$$

where f, X, i and j are as in Eq. (1). Please note that in both cases t is measured in hours.

2.1. Short term vs very short term

Practitioners usually differentiate the previous problems also depending on h, namely, depending on the time frame of the prediction. In fact, when the prediction time frame h is between 1 and 24 h, these problems are known as *Very Short Term Load Forecasting* (VSTLF) or, similarly, *Very Short Term Load Imputation* (VSTLI). On the contrary, when the time frame h is between 24 and 168 h, the problem is then known as *Short Term Load Forecasting* (STLF) or, similarly, *Short Term Load Imputation* (STLI). Please note that, in either case, the objective is to predict the loads L from $t+1$ to $t+h$.

The previous classification is important since these problems occur in two different departments of a utility. While STLF is related to demand response or purchasing decision, VSTLF is usually related to control decision of the electrical grid.

3. Models

The authors of [16] introduced a methodological approach base on MLR to build STLF models based on benchmarking. The complete model was tested in the 2017 Global Energy Forecasting Competition (GEFCom17) [49] and topped number 1, achieving an impressive 3% MAPE error (see Section 4 for more details), 2 points better than the second best model. We have used this model as the baseline. It is worth highlighting that based on the competition results [49], no technique or methodology dominated the others.

MLR requires the input of temperature, month, hour, and day-type. Please note that in this model the day-types considered include: $\{mon, tue-thu, fri, sat, sun\}$ plus several *special* dates such as Christmas or Eastern. Moreover, square and cubic powers of the temperature are also added in order to approximate the non-lineal behaviour. In addition, the model presents an interaction effect among variables. The final model is:

$$L_{t+h} = \beta_0 + \beta_1 Tr + \beta_2 D_t + \tag{3}$$
$$+ \beta_3 H_t + \beta_4 M_t + \beta_5 D_t H_t + \tag{4}$$
$$+ \beta_6 M_t T_t + \beta_7 M_t T_t^2 + \beta_8 M_t T_t^3 + \tag{5}$$
$$+ \beta_9 H_t T_t + \beta_{10} H_t T_t^2 + \beta_{11} H_t T_t^3 + \tag{6}$$
$$+ \beta_{12} L_t + \beta_{13} L_{t-1} + \beta_{14} L_{t-2} + \tag{7}$$
$$+ \beta_{15} L_{t-24} + \beta_{16} L_{t-25} + \beta_{17} L_{t-26}, \tag{8}$$

where $L(t)$ denotes the load at hour t, Tr the trend, D_t represents the day-type at time t, H_t the hour of the day at time t, M_t the month at time t, T_t the temperature at time t and β_i are real coefficients.

As can be seen, MLR presents two main components: the Autoregressive part and Meteorological variables. The autoregressive part (lines (7) and (8) in the previous model) captures the dynamic of the load based on previous states. More accurately, this part estimates the *shape* of the load profile. On the other hand, the Meteorological variables (lines (5) and (6) in the previous model) are responsible for capturing the *height* of the load profile. Please note that the model has some *constants* terms (lines (3) and (4) in the previous model) that are difficult to associate with any of the previous parts.

The main idea in this paper is to add a third component to the previous model: the adjacent zones' loads. The objective is to check whether this amendment helped to improve the forecast accuracy. More accurately, we have included terms such as:

$$\sum_{k \in K} \gamma_1^k L_t^k + \gamma_2^k L_{t-1}^k + \gamma_3^k L_{t-2}^k + \tag{9}$$
$$+ \gamma_4^k L_{t-24}^k + \gamma_5^k L_{t-25}^k + \gamma_6^k L_{t-26}^k, \tag{10}$$

where K is the set of neighbouring zones of the load substation to model, L_t^k represents the load of the neighbouring zone k at time t and γ_i^k are the model's parameters to estimate.

3.1. The proposed models

Herewith we have achieved a comprehensive study to compare all models combining these three components. In this way, we will try to assess the contribution of every piece of the model to the forecasting and the imputation accuracy. It is noteworthy that all the presented models are extensions of Tao's Vanilla Model [50]. Table 1 summarizes the main features of the models considered in this paper, such as:

3.1.1. AUTO

Composed of lines (7) and (8) of the main model, this is the traditional autoregressive model. It is expected to behave reasonably well in the forecasting problem as this model can capture the dynamic part of the load profile. On the contrary, on imputation problems it is more important to capture the correlation with other substations so it is expected to behave worse than its counterparts.

Table 1
Models components.

Model name	Autoregressive	Meteorological	Neighbourhood
AUTO	✓	✗	✗
MET	✗	✓	✗
NBHD	✗	✗	✓
LF	✓	✓	✗
NAUTO	✗	✓	✓
NMET	✓	✗	✓
GLF	✓	✓	✓
RW	✗	✗	✗

3.1.2. MET
Composed of lines (5) and (6), this model only accounts for the meteorological part. It is expected to behave badly in all cases, as this model barely captures the dynamic part of the load profile and cannot exploit the correlation with other substations.

3.1.3. NBHD
Composed of lines (9) and (10), this model focuses just on the neighbourhood substations. The behaviour of this model will be similar to (or better than) the AUTO model as it is a sort of autoregressive model. In fact, this model not only extracts the shared dynamics of the substations, but also gathers part of the correlations between them as well.

3.1.4. LF
This is the one of the most used models to issue a STLF. In fact, this is the very same model proposed in [16] and our base model. It is expected to work very well in both problems as it can completely capture the dynamic part of the load curve.

3.1.5. NAUTO
This is a model similar to the previous one but swapping the autoregressive part with the neighbourhood part. In fact, this model is composed by lines (5), (6), (9) and (10) of the main model. This model should also obtain very good results as it can mimic both components, the dynamic of the load, by exploiting the correlation with their neighbourhoods, and the meteorological variables.

3.1.6. NMET
This model contains the autoregressive part as well as the neighbourhood part. Viz., it is composed of lines (7), (8), (9) and (10) of the main model. This model learns quite well the dynamic of the load curve but it will only infer the effect of the meteorological variables through the neighbourhood part of the model. So it should have result quite similar to AUTO in both problems.

3.1.7. GLF
This is the full model. It is composed of the three aspects discussed above, i.e., lines (7), (8), (5), (6), (9) and (10) of the main model. It is expected to outperform the rest.

Please note that all models also have the *constants* terms defined in lines (3) and (4).

3.1.8. RW
Finally, we have also tested a random-walk model *RW* defined as $L_{t+h} := L_t$. Obviously, this model does not present any of the components aforementioned and will be used as the contrast model.

3.2. Modification of the models to fit VSTLF, STLI and VSTLI

The general model was designed to satisfy the restrictions of the STLF problem. The authors of [16] adapted it to also fit the VSTLF and Long Term Load Forecasting problems [51]. The former was just a matter to define $h = 1$, whereas the latter consisted on adding socio-economics variables such as Gross domestic product (GDP), labour force, etc. In the this paper, we have applied a similar approach; indeed, we will include small modifications to have our models working in the four problems.

In the case of VSTLF, we will tailor it in the same way as the authors of [16]. For the imputation problems, we will adapt all part of the model except the autoregressive part (i.e. lines (3), (4), (5), (6), (9) and (10)) to include terms until $t + h$. In fact, this means that there will be models that will be exactly the same in more than one problem. For example, the model MET will be the same for problems STLF and VSTLF, while the problem AUTO will be the same for STLF and STLI.

4. Experiments

4.1. Experimental settings

The experiments have been carried out on two x64 workstation using Weka 3.6 [52]. More precisely, we have addressed the *LinearRegression* model (trained using Weighted Least-Mean Squares).

We have used one year training in all cases. After constructing the model, we have tested its behaviour measuring the error between the predicted data and the real one in 100 days in the Short Term problems (240 h in the Very Short Term) picket up at random. Please note that these days (respectively, hours) have not been used in the training phase. Moreover, we have used real weather data instead of predicted one in our experiments; i.e. we have issued an *ex post* forecast.

To quantify the error we address MAPE; it is a simple unit-free measure that can straightly compare the results obtained with several datasets. Moreover, it is one of the most widely-used measurement in STLF. MAPE is calculated as follows:

$$\text{MAPE} := \frac{100}{|V|} \sum_{t \in V} \frac{|R_t - L_t|}{|R_t|},$$

where V the validation set, $|V|$ its cardinality, R_t the real load at time t and L_t the predicted or imputed one.

4.2. Datasets

We have carried our experiment using six different datasets. We have covered the entire scale: from one of the biggest electricity markets in the world to a group of four buildings. Every dataset consist of several times-series of load measurements from different points in the system (typically primary substations) that are *close*. We have got the information from the websites of the Transport System Operators or directly from the metre. Please note that two of the datasets are not public. We will summary in the next sub subsections the main characteristics of all datasets.

4.2.1. Global energy forecasting competition
This dataset belongs to an unknown Transmission system operator (TSO) from the USA [49]. This dataset was used in the GEFCom17 competition. It contains twenty (labelled from 1 to 20) zones with data from January 2004 to the June 2008. Most of them have a quite similar profile but there are several zones that have poisonous data. In fact, zones 3 and 7 are almost identical, zone 2 is just zone 6 scaling down (and are quite similar to zones

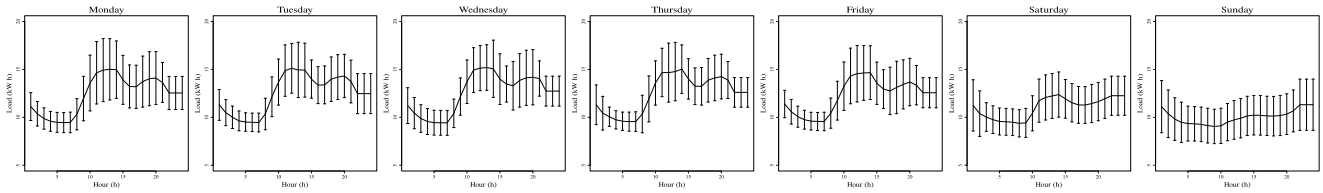

Fig. 1. Average daily load for zone PDT of dataset Ciudad Real. Error bars denotes $\pm\sigma$.

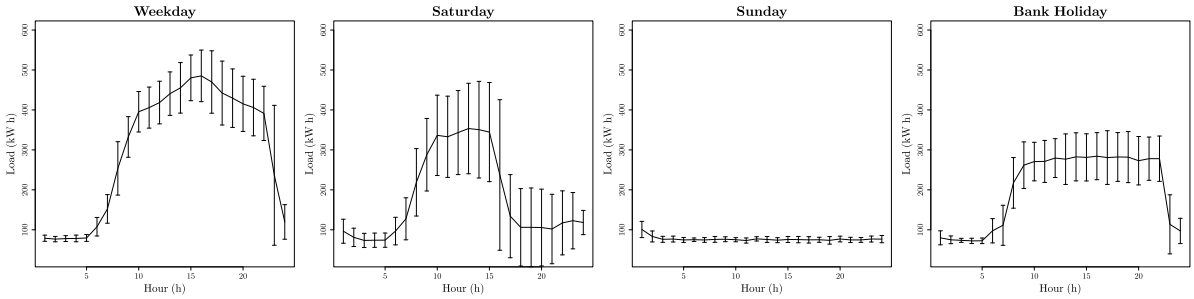

Fig. 2. Typical load for CRAI building. Error bars denotes $\pm\sigma$.

3 and 7) and, finally, zone 9 seems to be unrelated to the rest of the data (particularly to the weather variables provided).

We have used data from 01/01/2004 to 30/12/2004 to train our models. In this dataset, the first year is complete and afterwards data from eight weeks was deliberately subtracted. The aim of the competition was to fill these gaps as well as to predict one week after the end of the dataset for both, the twenty zones and the aggregated load. Obviously, we have extracted from the validation set these weeks.

4.2.2. Pennsylvania, Jersey, and Maryland interconnection

This dataset belongs to the PJM [53] Interconnection that comprises the states of Delaware, Illinois, Indiana, Kentucky, Maryland, Michigan, New Jersey, North Carolina, Ohio, Pennsylvania, Tennessee, Virginia, West Virginia and the District of Columbia. PJM is one of the biggest electrical market systems in the world. Similar to the previous case, the data was recorded from five primary substations (AEP, COMED, DAY, DOM, DUQ) since January 2006 until December 2010. In this case we have used data from 01/01/2006 to 31/12/2006 in the train set. Please note that we have selected these zones as they are the ones with data in the selected time period. Moreover, all zones in this dataset present quite a regular profile.

4.2.3. New York independent system operator

This dataset contains the primary substation records of New York City [54]. The records of this dataset were collected from June 2007 to October 2010. This data detail the hourly consumption of eleven primary substations (CAPITL, CENTRL, DUNWOD, GENESE, HUDVL, LONGIL, MHKVL, MILLWD, NYC, NORTH and WEST). It is important to note that the NORTH zone has a quite *flat* load curve quite different from the rest of the zones. We suspect that NORTH may be a substation supplying an industrial area and this fact could explain its distinct curve. In this case the train set consists on the measures from 01/01/2007 to 31/12/2007.

4.2.4. Canary islands

This dataset has been obtained from the Canary Islands [55], which form a Spanish archipelago located just off the northwest coast of mainland Africa. The data was collected from the primary substations (HIERRO, FUERTEVENTURA, GCANARIA, GOMERA, PALMA, LANZAROTE and TENERIFE) of the seven island from the Spanish TSO since March 2012 until May 2013. In this dataset, all zones show quite a homogeneous profile although each island records a separated load. The training set is composed of the records from 12/03/2012 to 11/03/2013.

4.2.5. Ciudad real

This dataset belongs to the province of Ciudad Real. It is a province in the south-western part of the autonomous community of Castilla-La Mancha, Spain. The dataset contains records from 10 substations (CIU, CTV, DA2, DAI, MAL, PDP PDT, PEM, PLM, SOL and VPE). They were collected from the primary substations from January 2009 until December 2012 by the Distribution System Operator. The training set is composed by data from 01/01/2009 to 31/12/2009. The zones in this dataset present an uniform behaviour, distinguishing among weekdays, Saturdays and Sundays (as portrayed in Fig. 1). Each substation, still, supplies to a different mix of consumer types.

4.2.6. Bilbao campus of the University of Deusto

This dataset consist on the measured the electrical consumptions from four different buildings in the Bilbao Campus of the University of Deusto (UD) different buildings located in the same campus of an university in Spain (CEN, CRAI, GEO and LIT) from September 2012 to December 2013. Three of them, gather the records from standard university buildings (*i.e.* classrooms and offices), while one contains the data of the campus main library. The load profile present a quite different behaviour depending on the day. Fig. 2 shows the typical behaviour of the main library. As can be seen it presents a more hectic activity until late at night as well as during Saturdays and this fact is reflected on the load profile.

4.3. Weather data

Since all the models demand weather information, we have obtained it from Wunderground[1]; similarly, the weather related to Spanish zones has been procured from AEMET.[2] Please note that we have used in each case the weather information belonging to the nearest station of every zone (i.e. in datasets PJM, NYISO, CR, CAN and UD). On the contrary, the dataset of the GEFCom17 competition already provided weather information but it

[1] http://www.wunderground.com/.

[2] http://www.aemet.es/.

Table 2
Weather Station Selection Results for GEFCom17 (MAPE %). In bold the selected weather station for every substation.

Zone	WS_1	WS_2	WS_3	WS_4	WS_5	WS_6	WS_7	WS_8	WS_9	WS_{10}	WS_{11}
1	7.94	8.13	7.75	7.95	**7.69**	7.86	8.13	8.14	7.77	8.18	8.10
2	8.17	8.06	7.90	8.12	8.09	**7.58**	7.60	7.72	7.99	8.06	7.96
3	7.79	**7.39**	8.17	7.89	8.14	7.97	7.89	7.94	8.16	8.16	8.13
4	7.67	7.85	7.82	7.91	7.94	8.12	**6.69**	8.11	7.28	8.11	7.70
5	7.90	7.95	8.10	7.99	8.10	7.98	8.02	8.13	8.07	**7.53**	8.11
6	7.88	7.78	7.92	7.86	7.86	**6.80**	7.93	7.92	8.12	7.89	8.10
7	7.64	**6.21**	8.15	8.06	7.99	6.32	8.08	8.09	7.91	7.89	8
8	7.78	8.14	7.87	8.05	7.90	**6.54**	7.95	7.83	7.95	8.08	8.14
9	7.97	8.11	8.14	8.17	8.10	**7.87**	8.03	8	7.98	7.99	8.02
10	8.19	7.93	8.13	8.02	8.15	8.12	**7.70**	8.02	8.17	8.19	8.09
11	7.92	8	7.91	7.90	7.54	8.01	7.98	7.96	8.15	7.96	**7.35**
12	7.86	7.92	7.96	**6.87**	8.11	8.18	7.96	7.55	7.93	8.11	7.96
13	7.49	6.96	8.11	8.16	7.56	7.99	7.88	8.16	7.95	**6.59**	7.92
14	7.88	7.73	7.39	8.17	8.11	7.93	8.12	**6.96**	7.95	7.94	8.10
15	7.93	7.56	7.82	8.12	**6.54**	7.83	8.17	8.08	8	8.04	8.15
16	7.76	**7.13**	8.04	8.17	7.78	7.67	8.12	7.97	8.10	8.16	7.94
17	**7.84**	8.16	7.95	8.11	8.12	7.91	8.05	7.99	8.08	8.17	8.16
18	7.98	7.95	8.05	7.87	8.10	7.94	8.08	7.88	**7.86**	8.11	7.90
19	8.01	7.90	7.89	**7.85**	7.95	7.97	8.12	8.13	8.05	8.14	8.06
20	8.15	7.84	8.04	7.86	8.08	**7.63**	8.04	7.90	7.86	7.95	7.96

Table 3
Summary of the results. Mean MAPE $\pm\sigma$ (%).

Problem	*VSTLF*	*VSTLI*	*STLF*	*STLI*
RW	6.98 ± 2.78	6.98 ± 2.78	13.41 ± 7.57	13.41 ± 7.57
AUTO	5.07 ± 3.11	5.07 ± 3.11	12.23 ± 10.36	12.23 ± 10.36
MET	8.48 ± 6.85	8.48 ± 6.85	8.38 ± 7.16	8.38 ± 7.16
NHBD	6.31 ± 6.91	5.69 ± 7.16	9.69 ± 7.42	6.1 ± 8.05
NMET	2.76 ± 2.02	2.74 ± 2.42	8.91 ± 6.31	5.41 ± 6.74
NAUTO	4.85 ± 5.83	5.19 ± 6.58	7.85 ± 7.37	5.68 ± 7.72
LF	2.78 ± 2.11	2.78 ± 2.11	7.37 ± 6.45	7.37 ± 6.45
GF	**2.63 ± 2.11**	**2.67 ± 2.49**	**7.25 ± 6.57**	**5.25 ± 6.88**

Table 4
P-values of the Friedman test for the comparison of the models.

Problem	VSTLF	STLF	VSTLI	STLI
p-value	$1.09 \cdot 10^{-10}$	$1.62 \cdot 10^{-10}$	$1.06 \cdot 10^{-10}$	$1.21 \cdot 10^{-10}$

was anonymized (i.e. in the documentation of the competition there is no information about the relation between the meteorological information and the zone it corresponds). In this latter case, we have carried out a brute-force test training with only one year of training data and six months of forecasting, pairing every weather station with every zone in order to highlight pairs with the best results. This outcome is summarized in Table 2.

5. Results and discussion

Table 3 lists a summary of the experimental results: each row shows the mean and the standard deviation of the MAPE achieved by the proposed models in all datasets for the four problems described before. Fig. 3 shows the real versus the forecasted data for two days on one of the test zones and Tables A.6 to A.9 displays the results in full detail.

As expected, the RW model has presented the worst results, however, these results obtained by RW were better than the Multilayer perceptron model. The former result confirmed the results obtained in [12], where we have not been able to achieve errors of less than 20%. On the other hand, the proposed model (GLF) has achieved better results than the base model (LF) in all problems. In between, the picture is blurry and seems to be problem-dependent. In the next paragraphs, we will discuss problem by problem the behaviour of the models.

Obviously, the errors of the models in both version of the Very Short Term problems are tinier than their corresponding Short Term versions. This phenomenon occurs due to the fact that we are issuing a prediction (or, respectively, an imputation) of the very near future and these processes do not fluctuate much over time. More interesting conclusions came when comparing the output of the best models between the Imputation and Forecasting variants. When considering Very Short Term version of the problems, the differences are small as there are little improvement margin but, when assessing the Short Term version, we found quite huge differences in favour of the Imputation version of the models. This results is quite obvious if we consider that when we include the information of the neighbourhood zones for imputation we are issuing something that is very close to the Very Short Term version of the problem.

In order to ascertain whether the differences between the models are statistically significant, we have carried out a Friedman rank test with Bergmann *post hoc* (see [56] for an in depth explanation of this method). We have set the significance level α at 0.05.

As can be seen in Table 4 we have detected statistical differences between the models in all cases as the p-values are way below the significance level. The results of the Bergmann procedure are summarized in Figs. 4 and 5. In these figures we have ranked the models according to the results in terms of MAPE in the vertical axis. Models that are marked by a line are the ones in which we have **not** found differences using the Bergmann procedure. Please note that the placement of the models in the horizontal axis has exclusively been an aesthetic issue.

As can it be seen in these figures, we usually have three groups: the group that contains the RW model (worst group), the group that contains the GLF model (best group) and a group with the rest of the models (middle group).

More accurately, in Very Short Term problems, the groups are quite homogeneous; the worst group is composed of the MET and RW models. The behaviour of the MET model is remarkable as it has performed worse than the RW model. It was expected to behave badly, but not so much. The middle group is composed of NBHD, AUTO and NAUTO. Finally, the best group is composed of GLF and NMET. Please note that in VSTLI, LF forms its own group, while in VSTLF it is included in the best group.

On the contrary, on Short Term, the groups are quite different. The worst group is also composed by the RW and AUTO models in both cases, but the similarities finish here. While in STLF the best group is composed by LF and GLF in STLI the best group is composed by GLF and NMET (but NAUTO and NBHD are also quite close in terms of MAPE). All these models have information about

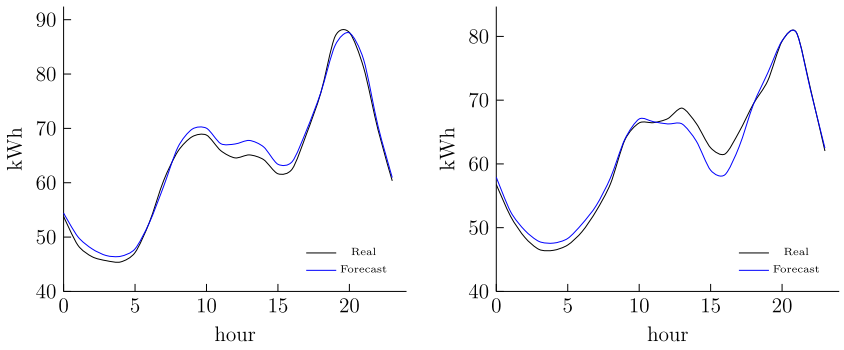

Fig. 3. Real versus forecast using GLF method of a Monday (left) and a Sunday (right) for Fuerteventura dataset.

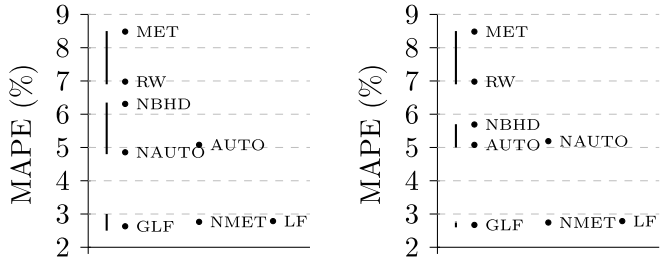

Fig. 4. Summary of the results in graphical form for the Very Short Term problems. Left figure display the results for VSTLF while right table display VSTLI.

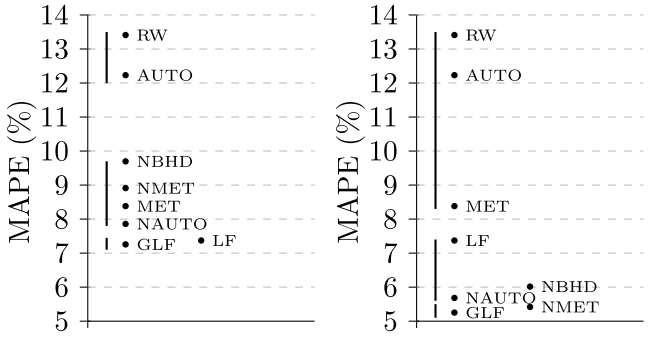

Fig. 5. Summary of the results in graphical form for Short Term problems. Left figure display the results for STLF while right table display STLI.

the neighbourhood, so it seems that the neighbourhood part of the model accomplishes quite a difference in this problem.

It is worth mentioning that the inclusion of the third component in line (9) outperformed all forecasting and imputation tests.

Finally, it is worth noting that we have also made a preliminary test of the methodology used with non-linear models. In particular, we have extended the Neural Network (NN) models proposed in [57] to include information about the load consumption in adjacent areas to test if the same improvements in day ahead short term forecasting accuracy are found in non-linear models.

To this end, first we have tuned the parameters using a grid search methodology. The best results were obtained using the back-propagation algorithm with learning rate $L = 0.3$, momentum rate $M = 0.2$, percentage size of validation set $V = 0$, threshold for number of consecutive errors $E = 20$, 1000 train epochs and 24 hidden layers. Table 5 compare the results on a selection of data sets with the previous ones. *NN LF* denotes the vanilla NN model while *NN GLF* the extended one. As can be seen, the behaviour in this case is completely different; not only

Table 5
MAPE results in **day-ahead** forecasting for NN model (%).

Model	*AEP*	*COMED*	*DAY*	*DOM*	*DUQ*
MLR LF	3.03	2.67	3.1	3.43	4.05
MLR GLF	**2.65**	**2.52**	**2.99**	**3.29**	**3.93**
NN LF	5.7	9.54	5.73	8.24	6.61
NN GLF	7.93	8.72	4.84	8.43	6.02

the neighbourhood information has only improved the forecast in half of the dataset but also the overall results are very far from the MLR models.

Even though NN are able to produce very good results on the STLF problem (see [58] for example) it seems that it is not so easy to transfer the same approach to the imputation problem. In future research we plan to perform an holistic assessment performing a comparison with several non-linear algorithm in both approaches (forecasting and imputation) to try to understand when the neighbourhood information would help these models.

6. Conclusion and future work

This work continues and completes a previous research in which we empirically tested an intuition already proven in other more perceptible fields: that data sources with common global factors show complementaries that may help enhance the forecast on each of the compounding sources.

In this way, we have extended the work of [12] by thoroughly testing a cutting-edge STLF algorithm in four different situations, ranging from classical STLF and VSTLF to STLI and VSTLI. The objective of this integral validation was on the one hand to check whether adding surrounding data enhances the results of imputation (as it does with STLF), and to refine the conclusions roughly pointed in [12]. Both objectives have been achieved and our results show that adding adjacent substation data ameliorates the quality of either forecasting and imputation but in the latter it is fundamental to include this information.

In any case, though the assessment may be considered basic, it covers a large amount of the real cases that are presented in actual measurements. Moreover, we believe that the paper is already quite complex to present a rather lengthy assessment about imputation that will not have a mirror formulation in the forecasting task and would not allow a proper comparison between them, which is the actual objective of the paper

Future works will concentrate in this promising area. As one may expect, some substations bring more (or higher) enhancement than others. We will further research this logical phenomenon in order to design an algorithm that selects the best surrounding substation cluster that tops both the forecasting and the imputation ability.

CRediT authorship contribution statement

Cruz E. Borges: Conceptualization, Methodology, Funding acquisition. **Oihane Kamara-Esteban:** Methodology, Software, Data curation. **Tony Castillo-Calzadilla:** Validation, Investigation. **Cristina Martin Andonegui:** Writing - review & editing, Visualization. **Ainhoa Alonso-Vicario:** Supervision, Project administration.

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.

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Appendix A. Supplementary data

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