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Research paper

Forecasting electricity demand of municipalities through artificial neural networks and metered supply point classification

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ABSTRACT

This study develops a methodology to characterise and forecast large consumers' electricity demand, particularly municipalities, with hundreds of different metered supply points based on the previous characterisation of facilities' consumption. Demand forecasting allows consumers to improve their participation in electricity markets and manage their electricity consumption. The method considers a classification by different types of metered supply points combined with artificial neural networks to obtain hourly forecasts using well-known parameters such as day types, hourly temperature, the last hour of electricity consumption, and sunrise and sunset time. We apply the methodology to the municipality of Valencia using over five hundred hourly load profiles for a year during 2017 and 2018. Our results present aggregated forecasts with a maximum Mean Absolute Percentage Error of 3.8% per day, outperforming the same forecast without classifying Metered Supply Points. We conclude that a correct electricity demand forecast for a consumer with different types of consumption does not need submetering, but characterising Metered Supply Points is an option with lower costs that allows for better predictions.

1. Introduction

Cities are the centre of work and social activity and where most of the resources necessary for life exist: hospitals, universities, administration centres, etc. Cities have a high population density, and by 2050, over 65% of the world's population will live in cities (UCCRN, 2018). Consequently, cities, which only occupy around 2% of the planet's surface, are energy sinks, consuming two-thirds of the world's energy and being responsible for 70% of carbon dioxide emissions (C40 cities, 2021; Wei et al., 0000). Therefore, great efforts are being made to characterise and understand urban energy consumption (Pesantez et al., 2023; Hu et al., 2013)

That high energy consumption is also present in municipalities, which own facilities like schools, offices and health centres that offer services to a vast population. Municipalities also own public lighting, traffic lights and other infrastructures that in big cities can represent a considerable share of the energy consumption in the city. This consumption constitutes an integral part of their budgets (de Barcelona, 2020; de València, 2021). For this reason, some municipalities have started to install renewable generation and procure electricity in wholesale markets to eliminate intermediary costs (Cambranos, 2019; Anon, 2018). Others had more ambitious plans and created municipal electricity retail companies to not only purchase electricity for municipal loads but also to offer this service to residential consumers (Barcelona Energía, 2021; Hamburg energie, 2021)

However, buying electricity in the wholesale markets has many associated risks (Ojanen and Minor Subject Teletraffic Theory, 2002; Boroumand and Zachmann, 2012; Bartelj et al., 2010). One of the most important is penalties due to unbalances between the electricity bought and the consumed (Cabello García, 2020; Carbajo, 2007). These imbalances can lead to significant economic losses (Hou et al., 2019; Barcos et al., 2020). Therefore, municipalities need to count on good tools to forecast their demand to avoid substantial losses and to plan demand-side strategies (Strbac, 2008; Moghaddam et al., 2011).

Multiple methods are used in electricity load forecasting, and there is an increasing interest in it (Velasquez et al., 2022). Some of the most used are the Auto-Regressive Integrated Moving Average (ARIMA) (Singh et al., 2012), the Auto-Regressive Moving Average (ARMA) (Box et al., 2015; Kuster et al., 2017), linear and multiple regression methods, Support Vector Machines (SVM) (Cortes and Vapnik, 1995) and Artificial Neural Networks (ANN). ANN is one of the methods to forecast energy and electricity demand and generation that has gained popularity in the last years (Li et al., 2015; Zhang et al., 1998; Huang and Wei, 2020; Maaouane et al., 2022; Kim et al., 2020).

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Nomenclature

Abbreviations

ANN	Artificial Neural Networks
AR	Auto-Regressive
$ARIMA$	Auto-Regressive Integrated Moving Average
$ARMA$	Auto-Regressive Moving Average
CM	Cemeteries
DOP	Day Of Prediction
EME	Energy Mean Error
LM	Libraries and Museums
MA	Moving Average model
$MAPE$	Mean Absolute Percentage Error
MSP	Metered Supply Points
PA	Analysis Period
PG	public Parks and Gardens
PL	Public Lightning
PM	Public Markets
PO	Public Offices and working buildings
SC	Schools
SVM	Support Vector Machines
TL	Traffic Lights and tunnel ventilation systems

Indices

i	Neuron index
n	Neuron layer
t	Time period (hour)

Parameters

a_i^n	Output of the ith neuron of the n layer
b_i	Bias of the ith neuron of the n layer
E_t	Energy consumed in time period t
$\hat{E}_t$	Prediction of the energy consumption for time period t
N	Number of neurons in the $n-1$ layer
$T_{Avg,t}$	Average temperature in the three time periods t
T_t	Temperature in time period t
tsr	Sunrise time for the DOP t
tss	Sunset time for the DOP t
$w_{i,i+1}$	Weight of the connection between the ith and ith+1 neurons

In this context, Li et al. present an application to forecast electricity consumption in buildings using this method (Li et al., 2015). Similarly, Kumar et al. explore the energy use of buildings by using ANN in Kumar et al. (2013). On the other side, Zhang et al. present a revision of applications of ANN based on a survey, showing their pros and cons (Zhang et al., 1998).

Besides, one strategy followed by some authors is dividing the electricity consumption by end-uses (Ghisi et al., 2007; Farinaccio and Zmeureanu, 1999; Murthy et al., 2001; Tran et al., 2021) and day types (Trull et al., 2021). In Escrivá-Escrivá et al. (2014) and Escrivá-Escrivá et al. (2011a) ANN have been used to forecast the energy behaviour of individual consumers or small groups of consumers. The authors propose a method that combines the ANN strategy with dividing consumption into end-uses applied to large buildings. Therefore, a particular set of processes is considered, including heat pumps, only chillers systems, public lighting, etc.

There are examples of demand forecasts of municipalities based on different parameters. For example, Parraga-Alava et al. (2020) present a prediction model based on socio-demographic features. Another example is presented by Andersen et al. (2019), who elaborates on a prediction model for Danish municipalities based on the projection of global national consumption by sectors. However, there are no examples in the bibliography regarding the application of ANN for predicting consumption in municipalities based on processes. This end-use decomposition presents complexities since they count on many consumption points whose end uses are broad. In practice, conducting an end-use decomposition of a whole city would result in a deep study of the end uses that every building or municipal facility has and a significant expense on measurement devices and a good data acquisition system. Hence, developing a systematic methodology to combine end-use decomposition with ANN applicable to facilities with many consumption points of different natures is essential to optimise the work. At the same time, the obtained results have satisfying accuracy.

Nevertheless, this end-use decomposition presents complexities for big consumers like municipalities since they count on many consumption points whose end uses are broad. In practice, conducting an end-use decomposition of a whole city would result in a deep study of the end uses that every building or municipal facility has and a significant expense on measurement devices and a sound data acquisition system. A review of the literature shows that there are neither studies dedicated to characterising the demand patterns of the relevant consumption processes in municipalities nor articles proposing tools or procedures that allow predicting the hourly electricity consumption of this type of consumer using the available information provided by the smart meters installed in the Metered Supply Points (MSP).

Hence, the objective of this study is twofold: on the one hand, to characterise the consumption patterns of the different types of facilities that a municipality may have and, subsequently, propose a methodology to forecast these consumption profiles on an aggregate basis to be able to predict future consumption, better understand and monitor electricity consumption and be able to participate in electricity markets actively. In this sense, we propose a method to forecast short-term municipalities' electricity demand based on the classification of MSP and the application of ANN. MSP classification is a similar approach to end-use decomposition. Still, instead of splitting consumption into end uses, we divide consumption by groups of MSP that share a similar load curve and are affected by the same variables (temperature, sunset time, etc.).

Municipalities' most common groups of MSPs are public lighting, offices, working buildings, and schools. Once municipality consumption is divided into groups of MSP, we apply ANNs to each group. We facilitate the learning process and improve the forecast results by performing the classification before the ANN application. The novelty of this paper lies in the following aspects:

- We propose a methodology to forecast municipalities' electricity consumption with hundreds of MSPs of different types of facilities and end-uses. The methodology is applied to an actual case study and has the potential to be replicated to forecast the electric consumption of other municipalities. That could lead to public administrations having a more profound knowledge of their short-term future consumption. Thus, the prediction tools facilitate demand-side strategies or even buy their electricity in the wholesale markets, get the corresponding savings, and avoid possible dependence on third parties. The methodology offers significant potential for a future with increasing consumption monitoring. The higher the data availability, the better the method performs since the classification process becomes more precise, improving ANN's training process and results.

- Additionally, we present the results of characterising the consumption processes of a municipality via a thorough analysis of actual historical data (annual load curves) provided by hundreds of smart meters installed in the MSPs. Also, we found the most relevant variables influencing the electricity consumption of the different types of facilities in municipalities. This point tries to help to fill the gap mentioned above in the literature.

In this paper, we apply the described methodology to forecast the electricity demand for a whole year of the municipality of Valencia on a day-to-day basis and with hourly granularity. We use 525 actual load curves provided by the Valencia Council that represent an entire year's consumption from 2017–2018.

The rest of the paper is organised as follows. In Section 2, we provide a description of the methodology implemented. Section 3 applies the method to the case of study, the municipality of Valencia. Section 4 presents and discusses the results of a whole-year forecast, and finally, in Section 5, we draw some conclusions.

2. Material and methods

This section presents the methodology followed to forecast the electricity consumption of a municipality.

2.1. Prediction models

As explained by Box et al. in Box et al. (2015), the basic ARMA model comprises an Auto-Regressive model (AR) and a Moving Average model (MA). The Auto-Regressive model is a linear regression of the current value based on one or more previous values. Just as an AR, the MA is a linear regression, at the difference that it regresses current values against the white noise or error of one or more past values. An interesting comparison between these two models is discussed by Kuster et al. in Kuster et al. (2017), based on over 113 different case studies reported across 41 academic papers. The model ARMA can only be accurate if they are stationary. ARIMA is used if the process is dynamic and the series transformation to the stationary form is done first. A comparison of applications between ARMA and ARIMA models is presented by Singh et al. in Singh et al. (2012).

Regression analysis is present in many forecasting processes. Other independent variables can define the dependent variable or output. Linear regression links the output to the independent variable by the simple linear model.

SVM were firstly introduced in 1995 by Cortes and Vapnik (Cortes and Vapnik, 1995). The power of an SVM stems from its ability to learn data classification patterns with balanced accuracy and reproducibility. Although occasionally used to perform regression, SVM has become a widely used tool for classification, with high versatility that extends across multiple data science scenarios, including brain disorders research. An SVM decision function is more precisely an optimal "hyperplane" that serves to classify observations belonging to one class from another based on patterns of information about those observations called features. That hyperplane can then be used to determine the most probable label for unseen data, as explained by Pisner and Schnyer in Pisner and Schnyer (2020), where they explore the main characteristics of the SVM method and its applications to the medical field.

ANN are mathematical models which process information inspired by the human brain (Katal and Singh, 2022), imitating the way that biological neurons signal to one another. Indeed, ANNs are considered one of the earliest general machine learners, the reason for which they were adopted to solve data-based problems in engineering (Worden et al., 2023). The basic idea under the implementation of ANN is to develop systems able to do complex evaluations from the interaction of many simpler processes that can work in parallel (Meyer-Baese and Schmid, 2014). A specific ANN depends on the type of elements that compose the network, the connections between them (architecture), and how the connections between such elements in the network are adjusted (training) (Wu and McLarty, 2000). ANN can be trained with past input and output data and forecast future outputs given only the inputs.

2.2. Methodology

Fig. 1 summarises the methodology used in this study, which consists of three parts.

2.3. Data collection, treatment and classification

First, obtaining as much data as possible from at least one year is necessary to appreciate the seasonal behaviour of demand so that ANNs can be adequately trained. The granularity of data is also essential. A one-hour granularity is required for the method proposed in this paper, but more granular data can be used, too. Consumption data should be as specific as possible. This means having a repository of load curves from specific MSPs instead of having consumption inventories that combine data from several consumption points.

Furthermore, it is necessary to classify every load curve available of every MSP by groups. As noted above, these groups should share a similar consumption scheme and variables influencing consumption. Also, the different day types should be the same. Some of these groups are usually public lighting, offices, working buildings, and schools.

Also, collecting data from the potential inputs introduced to the model is essential. Some of these probable inputs are hourly temperatures and sunrise and sunset time for the analysis period, while others as daily average temperatures may appear. Once data is collected, anomalous data should be removed to exclude noise from the analysis that could affect the performance of the forecast. Examples of anomalous data are sudden value drops to zero or extremely high values.

After collecting and filtering the available data, aggregated consumption data of every MSP group must be classified into different day types for every group of MSP. A typical day-type classification consists of treating weekdays and weekends separately. However, depending on the MSP group, other day types might be helpful for the analysis. This classification should be done by observing and analysing the consumption patterns of every group.

2.4. Design of an ANN for every MSP group

The second part of the proposed methodology consists of the design of ANNs for every MSP group. The first step of the ANN design is the preselection of inputs. Since almost all of the MSP groups represent different types of buildings, most inputs correspond to external temperatures and previous electricity consumption, as both have a significant correlation with future consumption (Roldán-Blay et al., 2013).

Some authors also use outdoor solar radiation (Mena et al., 2014). In Akarslan and Hocaoglu (2018), the actual date, time and electricity consumption are inputs. Nevertheless, the relation between the possible inputs and electrical consumption has been analysed to check whether the selected inputs for every MSP group would introduce helpful information to the model. For example, in Fig. 2, the influence of the electrical consumption of the previous hour to the hour of prediction (t) and the temperature at t on consumption is shown for an example MSP group. We see that consumption at t and $t-1$ are linearly related.

Conversely, we can also appreciate the influence of cooling and heating systems over electrical consumption. As temperature increases or decreases above or below 20 °C, heating and cooling systems work and consumption rises. Therefore, these two inputs are part of the model for this particular MSP group.

In contrast, some inputs are unrelated to consumption, as shown in Fig. 3. In this case, the represented inputs are sunrise and sunset

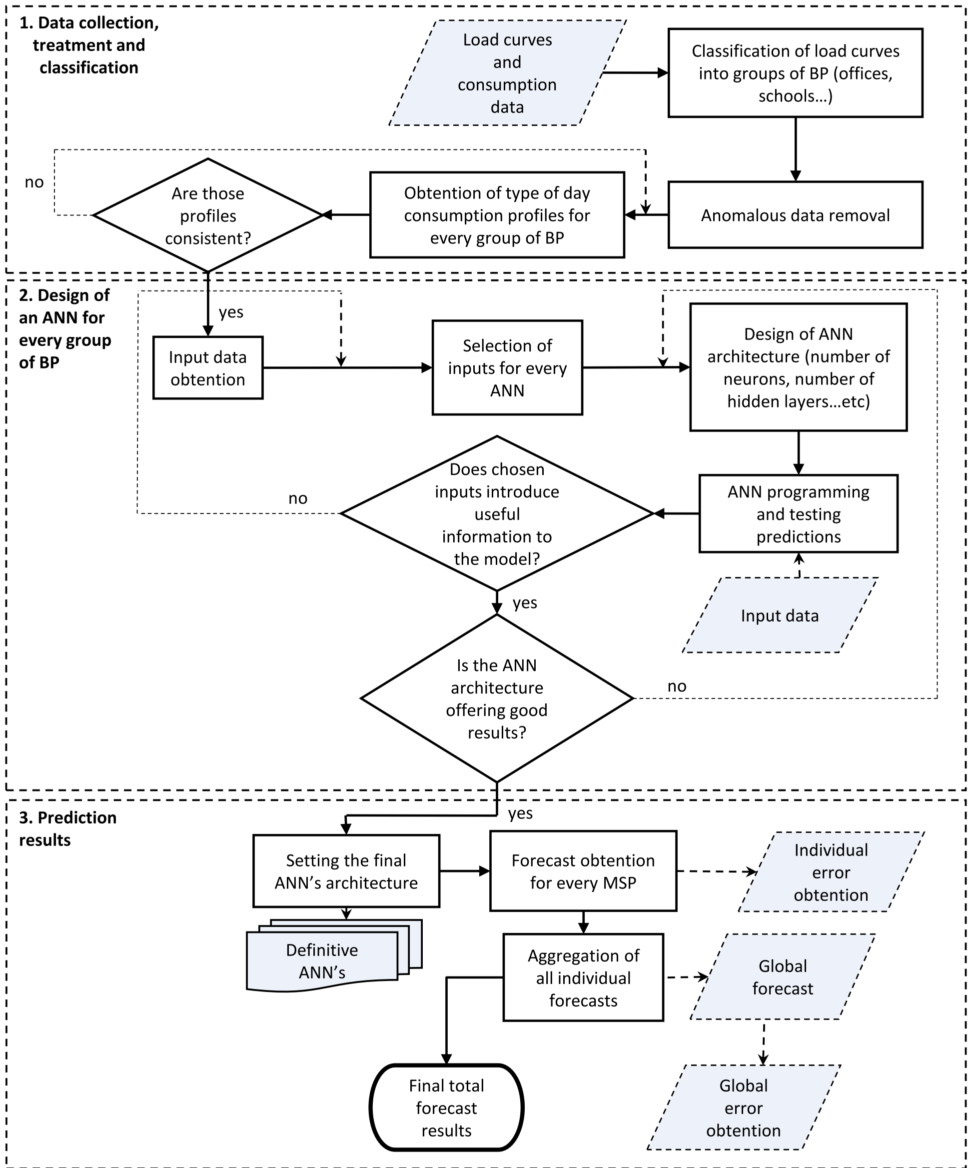


Fig. 1. Methodology block diagram.

time. For some MSP groups, like public lighting, these inputs will have an essential influence on consumption. However, for this example, the MSP group in the figure, the represented inputs and consumption are unrelated. Hence, these two inputs will not be part of the model.

Once inputs are selected, the process of defining the ANN architecture itself starts. During this phase, it is needed an initial choice of parameters such as the number of hidden layers, number of neurons, training algorithm and activation functions (Mohandes et al., 2019). These parameters are optimised after checking ANN results and behaviour since deciding ANN architecture is usually an iterative process.

After several tests and bibliography revision, the ANN architecture is presented in Table 1.

The network used is a feed-forward neural network, also called a multi-layer perceptron, in which the directed graph establishing the interconnections has no closed paths or loops (Fine, 2006). If a simplified architecture of an ANN ensemble is chosen, the parameters involved are represented:

The example presents a three-layer neural network with one input layer (see Fig. 4), one hidden layer and one output layer. Each one of them is represented by a superscript ranging from (0) for the input layer to (2) for the output layer (Zou et al., 2009). The output for layers one and two is calculated as the weighted sum of the inputs of the previous layer:

Table 1
ANN architecture.

Parameter	Value
Type of network	Feed-forward
Number of hidden layers	1
Number of neurons in hidden layers	5
Training algorithm	Levenberg–Marquardt
Activation function	Sigmoid function

$$a_i^n = f\left(\sum_{j=0}^{N} w_{i,i+1}^{n-1} \cdot a_i^{n-1} + b_i^n\right) \tag{1}$$

Where:

- a_i^n: Output of the ith neuron of the n layer
- $w_{i,i+1j}$: Weight of the connection between the ith and ith+1 neurons

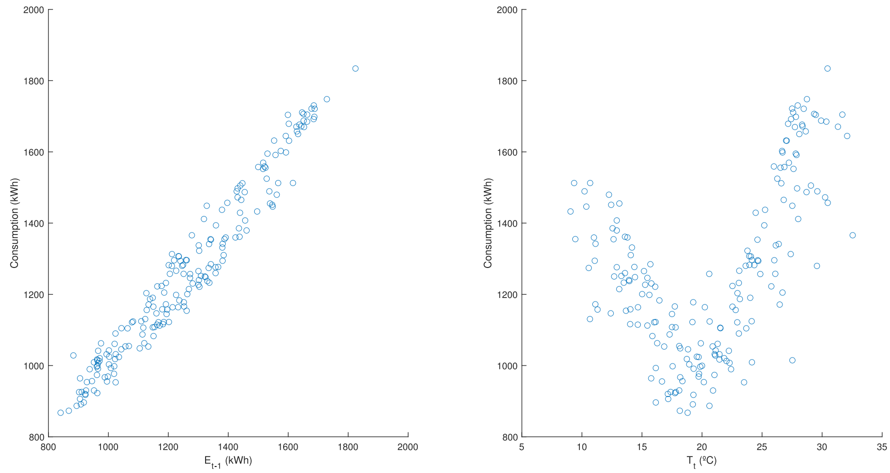


Fig. 2. Influence of variables over electrical consumption.

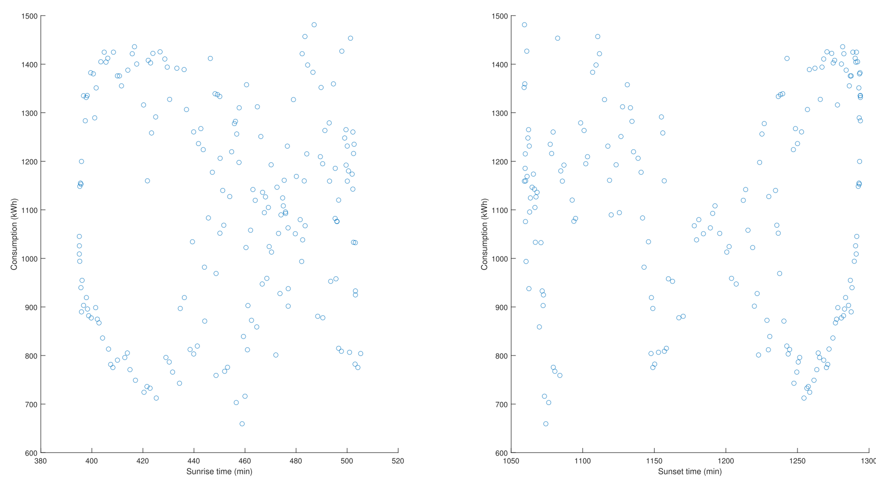


Fig. 3. Influence of variables over electrical consumption.

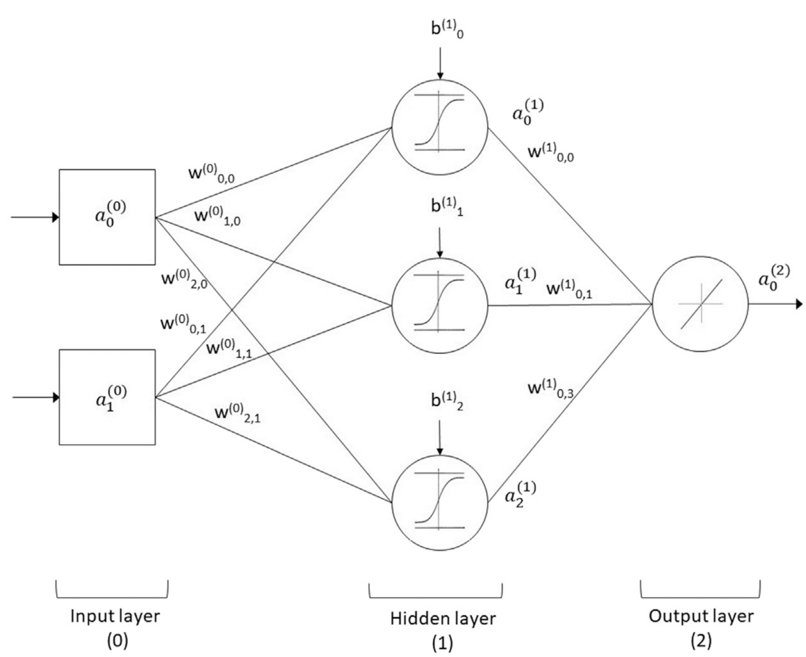


Fig. 4. Scheme of a three-layer neural network with three neurons in the hidden layer.

– b_i: Bias of the ith neuron of the n layer
– N: number of neurons in the $n-1$ layer

Eq. (1) can also be written in matrix form:

$$\begin{bmatrix} a_0^{(n)} \\ a_1^{(n)} \\ \vdots \\ a_k^{(n)} \end{bmatrix} = f\left(\begin{bmatrix} w_{0,0} & w_{0,1} & \cdots & w_{0,N} \\ w_{1,0} & w_{1,1} & \cdots & w_{1,N} \\ \vdots & \vdots & \vdots & \vdots \\ w_{k,0} & w_{k,1} & \cdots & w_{k,N} \end{bmatrix} \cdot \begin{bmatrix} a_0^{(n-1)} \\ a_1^{(n-1)} \\ \vdots \\ a_N^{(n-1)} \end{bmatrix} + \begin{bmatrix} b_0 \\ b_1 \\ \vdots \\ b_K \end{bmatrix}\right) \tag{2}$$

Which also can be expressed as:

$$\boldsymbol{a^n} = f\left(\boldsymbol{W} \cdot \boldsymbol{a^{n-1}} + \boldsymbol{b}\right) \tag{3}$$

Where k is the number of neurons in the n layer.

The activation function used within the neurons in the hidden layer is the sigmoid function. The weighted sum of inputs is passed through the activation function, and this output serves as an input to the next layer.

Since the range of the sigmoid function is [0,1], using it guarantees that the output of this unit will always be between 0 and 1. Also, as the sigmoid function is non-linear, the result of this unit would be a non-linear function of the weighted sum of inputs (Saeed, 2021).

However, the function used in the output layer is a linear function defined by ($y = m \cdot x$). That means that the activation function has no impact on the output, which is calculated directly as the weighted sum of the outcomes of the previous layer.

The network is trained with the Levenberg–Marquardt back propagation algorithm (Marquardt, 1963; Moré, 1978; Hagan and Menhaj, 1994; Waseem et al., 2019). In a very simplified form, this algorithm initialises the weights and biases of the network randomly and obtains the first output. Then, it compares this output with the actual value provided during the training phase and adjusts all the internal parameters to reduce the error between the obtained and actual production. This process is repeated several times until the error reaches a minimum. Then, when the network is fed with new inputs, it can forecast a unique output.

After deciding on the architecture, the different ANNs are programmed. The most important factors of these ANNs are the following:

- A single ANN is programmed for every hour of the day of prediction (DOP). That means that the forecast of one day comprises the results of 24 single ANNs. Every ANN is trained only with data from the same hour of the selected previous days.
- Every ANN is trained only with days of the same type explained in Section 2 and behaves similarly to the DOP.
- Every hourly network is trained only with the 15 previous days of the same type.

2.5. Prediction results and error calculation

Once the training phase is completed, the method feeds the hourly networks with new input data corresponding with the DOP data. Then, it aggregates the hourly results to obtain full-day or several-day predictions. It uses the Mean Absolute Percentage Error (MAPE) (Armstrong and Collopy, 1992) and the Energy Mean Error (EME) (Escrivá-Escrivá et al., 2011b) to check the network performance.

$$MAPE = \frac{\sum_{t=1}^{N} \frac{\left|\hat{E}_t - E_t\right|}{\left|E_t\right|}}{N} \tag{4}$$

$$EME = \sum_{t=1}^{N} \frac{\left|\hat{E}_t - E_t\right|}{\sum_{t=1}^{N} E_t} \times 100 \tag{5}$$

Where:

– N is the total number of hours within the period that wants to be predicted.
– $\hat{E}_t$ is the predicted consumption at t.
– E_t is the actual consumption at t.

At that point, we observe the results graphically and analytically. If the prediction is not working correctly, we check whether the architecture of the ANN or the input selection could be optimised. Finally, annual consumption for the different MSP groups is forecast. Then, all these individual yearly predictions are added to obtain the global prediction of the municipality. Yearly forecast performance is evaluated through Eqs. (4) and (5).

3. Case study

This section presents the methodology explained in Section 2 applied to the municipality of Valencia. It considers the data availability, the final classification of MSPs, the explanation of the anomalous data removal, the day type identification, and the selection of inputs and ANN programming.

3.1. Data availability

First, we obtain data on electricity consumption registered by the installed smart meters through interviews with the council's electricity supply managers. Available data consists of a list of the power meters, location, type of consumption point and tariff, contracted power, yearly consumption, and other data. Some of the load curves for this power meter. Five hundred twenty-five hourly load curves are available for the study from September 2017 to September 2018, which is the analysis period (PA) and represents a total consumption for the PA of 49 GWh.

3.2. MSP classification

One of the first tasks is grouping the load curves of every MSP. Initially, in the Excel data sheet mentioned above, MSPs were classified into 15 groups. However, we reduced this number to 8 by grouping the MSPs according to their characteristics, scheduled energy uses, and most important variables affecting consumption. Finally, the groups established are public lightning (PL), schools (SC), public parks and gardens (PG), public offices and working buildings (PO), cemeteries (CM), public markets (PM), libraries and museums (LM) and traffic lights and tunnel ventilation systems (TL). The number of load curves available for each different MSP group is presented in Table 2:

3.3. Anomalous data removal

We eliminate data considered anomalous by two methods:

- Simple observation of load curves: First, the consumption of every MSP group is calculated daily. When representing daily consumption for the whole PA for every MSP group, we identify and remove anomalous data, like zero consumption days or extremely high consumption days.
- Average and thresholds approach. As in the previous step, daily consumption is calculated. Then, a script is programmed in Matlab. This script analyses each day individually and calculates the average consumption of the seven previous of the same type of day. A threshold is established above and below the calculated average. If the day's consumption is greater or lower than the thresholds, we consider that day's consumption anomalous. The threshold is calculated as a percentage of the seven previous days' average. This depends on the variance of the consumption type analysed.

Table 2
MSP groups.

n	MSP group		Available load curves
1	Public lightning	PL	144
2	Schools	SC	18
3	Parks and gardens	PG	56
4	Public offices and working buildings	PO	78
5	Cemeteries	CM	3
6	Public markets	PM	5
7	Libraries and museums	LM	3
8	Traffic lights and tunnel ventilation systems	TL	218
TOTAL			525

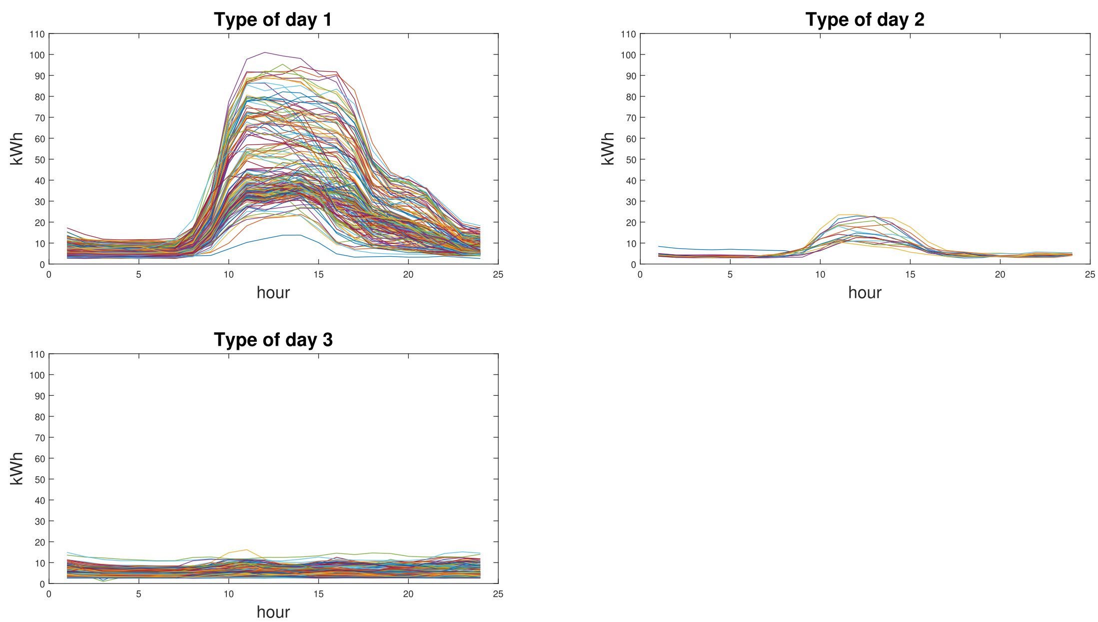


Fig. 5. Daily consumption profiles for the SC group.

3.4. Identification of type of day profile

To make accessible the ANN learning process, we establish a type of day classification for each of the groups of MSP in Table 2. We follow a cyclic process: First, we observe the load curves individually to see the weekly consumption profile. Then, we make an initial type of day classification according to those profiles. If, after this classification, we find non-coherent profiles, we rethink the type of day separation until we reach the minimum day types that fairly represent the consumption behaviour.

The following figure shows the different consumption profiles for the SC MSP group, which have different behaviour depending on the type of day. The consumption of the rest of the MSP groups, except the PO MSP group shown on 5, is relatively constant and does not allow the creation of day-type profiles significantly different from others. In the PM group's case, the day classification type is not helpful since only five load curves are available, and each one follows different consumption patterns. Fortunately, the consumption of this group is low compared with the rest. Thus, the error introduced by this MSP group will not significantly change the precision of the total forecast.

3.5. Selection of ANN inputs

As stated in Section 2, most of the inputs correspond to external temperatures and previous electricity consumption. Also, for certain groups like PL, it is necessary to know when the sunrise and sunset occur for the DOP since it will indicate when electricity consumption rises or drops.

Temperature data is obtained from the Polytechnic University of Valencia weather station. However, there were some gaps in the collected data during specific periods. Hence, we used the method presented in Roldán-Blay et al. (2013) to forecast the missing temperatures. Sunset and sunrise time data were obtained from Manatechs (2017). The council's electricity supply managers directly provided the load curves.

Finally, the inputs used for SC, PO, CM, PM and LM are the energy consumed at $t-1$ (E_{t-1}), the average temperature of the three previous hours ($T_{Avg,t-3}$) and the temperature at t (T_t). PG and TL groups only receive the previous consumption input since their daily consumption profile remains constant, having a slight variation depending on the day type. Finally, PL receives the previous consumption and the day's minute when the sunrise and sunset occur for the DOP (tsr and tss). A summary of the inputs and day type classification for every ANN is presented in Table 3.

3.6. ANN programming

After deciding on the architecture, we program the different ANNs. To do so, we use Matlab's Deep Learning Toolbox. We program a general script for every single ANN. These scripts work as follows:

First, the script receives the corresponding ANN inputs for all the analysis periods (PA). The granularity of the prediction is one hour, so the ANN receives 8760 values for each input. The script is also fed with actual hourly consumption for the PA, which will be ANN's output during the training phase. Secondly, we select only the days of the same type of DOP. Then, we train a single ANN for every hour of the DOP (see Fig. 6).

Table 3
ANN parameters.

MSP group	n	Type of day	Input 1	Input 2	Input 3
LM	1 2	Working days Weekends, holidays and August	E_{t-1}	T_t	$T_{Avg,t-3}$
SC	1 2 3	School days Working Weekends, August	E_{t-1}	T_t	$T_{Avg,t-3}$
PO	1 2 3	Working days except Tuesdays Tuesday working days Weekends and holidays	E_{t-1}	T_t	$T_{Avg,t-3}$
PM	1 2	Working days (including Saturdays) Sundays and holidays	E_{t-1}	T_t	$T_{Avg,t-3}$
PG	1 2	Working days Sundays and holidays	E_{t-1}	–	–
PL	1	All	E_{t-1}	tsr	tss
TL	1	All	E_{t-1}	–	–
CM	1	All	E_{t-1}	T_t	$T_{Avg,t-3}$

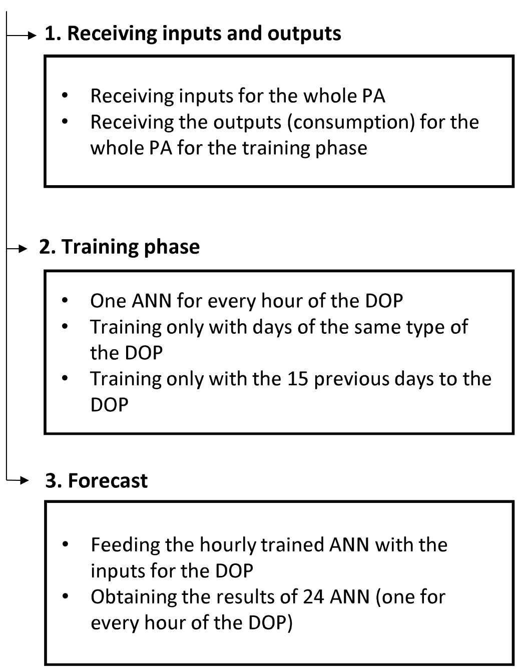


Fig. 6. Daily consumption profiles for the LM TOC.

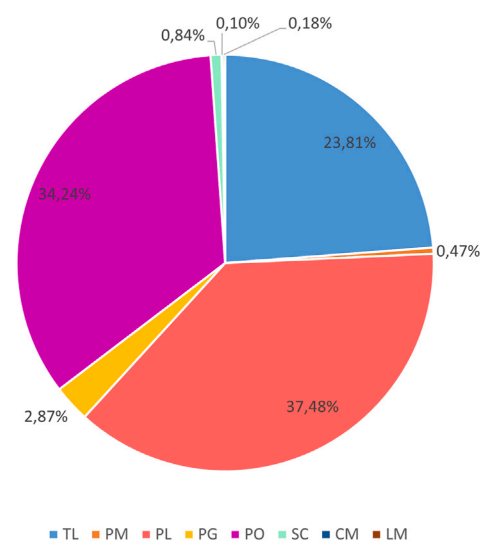


Fig. 7. Annual energy consumption distribution of every MSP group.

Therefore, the prediction of a whole day will be the group of the results of 24 ANN. Every hourly network is trained only with data from the moment t of the 15 previous days, adopting a sliding time window strategy (Yang et al., 2005). If we train the ANN during hour 15, ANN will only train with data from hour 15 of the 15 previous days to the DOP. If many measures are used in the training phase, random and uncontrolled training data may be introduced (Escrivá-Escrivá et al., 2011a).

To train the networks, data has to be split into three sets: training, validation, and testing. The division is randomly made between the 15 selected days, establishing only the percentages of data dedicated to each group. We use 70% for training, 15% for validation and 15% for testing, which means that 12 days are used for training, 2 for validating and 1 for testing. The training set is used in parallel with the validation set. During the training phase, outputs obtained with the ANN are compared with those given, and weights and biases are adjusted to match inputs with outputs. The validation set continuously checks the ANN's performance by calculating the prediction error. When that error reaches a minimum, the training phase is finished, and an error is obtained through the testing set. The testing set is not strictly necessary since the prediction will be a test, but Matlab does not allow setting the testing set percentage to 0, so a minimum rate of 5% has been considered.

Once the training phase is completed, we feed the hourly networks with new input data corresponding to the DOP input data. Then, we aggregate the hourly results to obtain full-day or several-day predictions. To check the network performance, we use Eqs. (4) and (5).

4. Results and discussion

This section presents the different forecast results obtained through the MSP classification and the ANN application. First, we calculate the results of every individual MSP group. Then, we aggregate the individual forecasts to obtain a complete forecast for all the Valencia municipality consumption. For the individual forecasts, only the results of the most influential groups in annual energy consumption are presented.

As it can be seen in Fig. 7, the MSP groups that represent the highest annual electricity consumption are PL (37,48%), PO (34,24%) and TL (23,81%). Hence, achieving a good forecast on these groups is vital to obtaining a good total forecast of the Valencia municipality's electricity consumption.

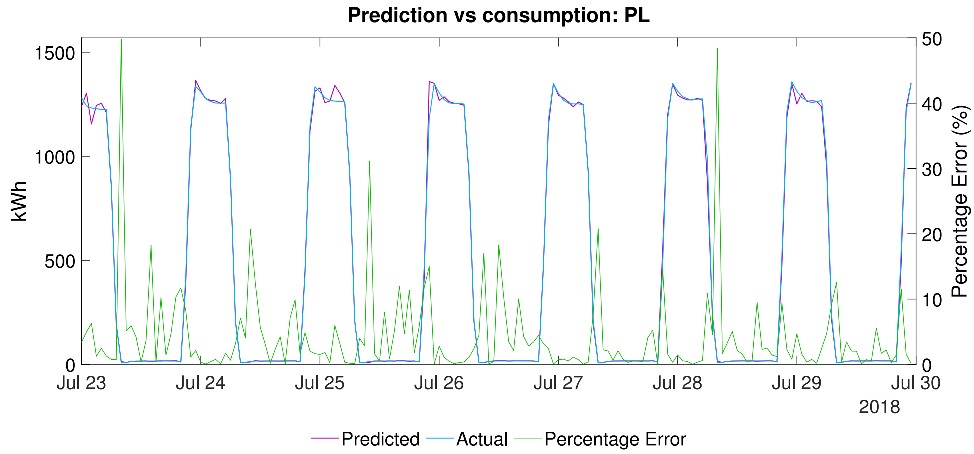


Fig. 8. Aggregated prediction for an example week for PL.

4.1. MSP groups forecast results

The results of the three most important MSP groups regarding energy consumption are shown. The most critical MSP group is PL. PL is the main area of consumption in any municipality. In this case, it represents almost 40% of the total consumption, as shown on 7.

Fig. 8 shows that the forecast of the PL group is almost perfect (see Table 4). As can be seen, there is a moment in which consumption is residual. These hours correspond to the day hours, in which no lightning is needed. However, during the night hours, electricity consumption reaches its maximum. Lightning is a type of consumption that is easy to predict since the installed equipment has a constant consumption profile during the hours of use. A simpler method could have been used to predict this MSP group. However, the implementation of ANN makes the model more robust since they can adapt the results to changes like schedules of use and efficiency measures that lead to less installed power and less electricity consumption... ANNs react to these changes and learn how they affect results without redesigning the model. One of the most significant variations that this type of consumption can have is caused by the minute of the day in which the sun rises or sets, which varies throughout the year. Because of that, the time of sunrise and sunset is given as input to the ANNs of this MSP group. That way, the model can adapt to the changing switch-on times throughout the year, which a simpler model cannot.

Table 4
MAPE and EME (%) of the PL forecast for the week shown in Fig. 8.

Error	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
MAPE	6,60	3,91	5,41	3,97	2,83	4,63	2,91
EME	2,96	1,12	3,47	1,14	1,40	2,11	2,34

Even though the forecast is almost perfect, the MAPE is relatively high. This is due to how MAPE is calculated. MAPE does not consider the total volume of energy of the calculation period. Hence, during day hours in which consumption is almost zero, we can find high MAPE values even though the difference in consumption is low. This may cause the daily MAPE to be higher than expected. However, EME error is also reliable and represents better forecast behaviour.

The second MSP group in consumption is Public offices (PO). As seen in Fig. 7, public offices represent 35% of the total electricity consumption of the Valencia municipality. Consumption in offices comes from different sources. The main ones are climate equipment, which can constitute up to 40% of the total electricity consumption depending on the season, lightning, power and other equipment such as computers and servers. Since air conditioning is one of the uses that consume more energy, the external temperature is a significant variable. By feeding the ANN with the average temperature of the three previous hours and the temperature at t, the model can learn in which proportion temperature affects electricity consumption and then predict consumption given the temperature as input. Fig. 9 summarises the PO results

Table 5
MAPE and EME (%) of the PO forecast for the week shown in Fig. 9.

Error	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
MAPE	3,06	2,88	5,08	3,12	4,72	14,75	8,31
EME	2,04	2,94	3,54	2,78	4,80	12,34	8,29

Table 6
MAPE and EME (%) of the TL forecast for the week shown in Fig. 12.

Error	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
MAPE	1,016	1,179	0,549	2,572	0,962	0,499	1,079
EME	1	1,17	0,54	2,52	0,95	0,50	1,07

The forecast is precise during weekdays, as shown in Fig. 9 and Table 5. Consumption on these days starts to rise at 7:00, as people begin entering the workplace, and it starts to decrease at 17:00 as workers leave. The rest of the day is the residual consumption (some lightning, equipment like some PCs). If changes in the working schedules happen, ANNs can adapt to these changes and predict consumption accordingly after a few days of training with the new scheme. The following figure shows the results of the prediction for a single example day:

On the weekends, the forecast is poorer. During these day types, consumption is very changeable. As ANNs train with the 15 previous days of the same kind, the DOP of a weekend is trained with days from some weeks ago, in which conditions can be different from those of the DOP, introducing a higher error. However, as seen in Fig. 9, weekend consumption represents approximately 20% of the consumption during working hours. Winter weekend predictions perform better than summer weekends as seen in Figs. 9, 11 and 15 due to more predictable consumption in contrast to Summer demand correlated to air conditioning in Summer months (see Figs. 9, 10 and 14).

Finally, the TL group is the third MSP group in terms of annual electricity consumption. The results obtained can be seen in the following figure:

As seen in Fig. 12, TL consumption is relatively stable, varying between 350 and 400 kWh. Consumption in the TL MSP group is higher at night when more lights are on.

Predictions for the TL MSP group work fine, except for some unexpected peaks on days 1 and 4 of the displayed week. This might be caused by the anomalous data removal method used, explained in Section 3.3. This method takes into account daily consumption to determine whether a particular day is anomalous or not. Some consumption

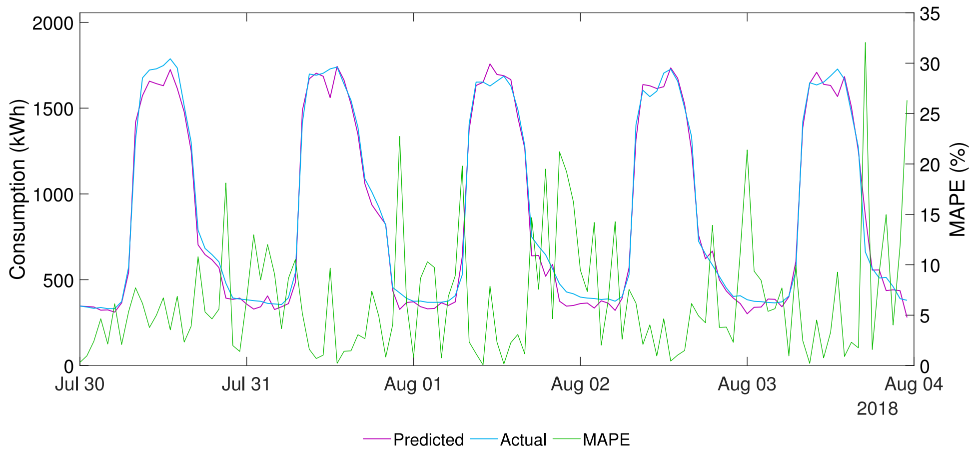


Fig. 9. Aggregated prediction for an example week for PO.

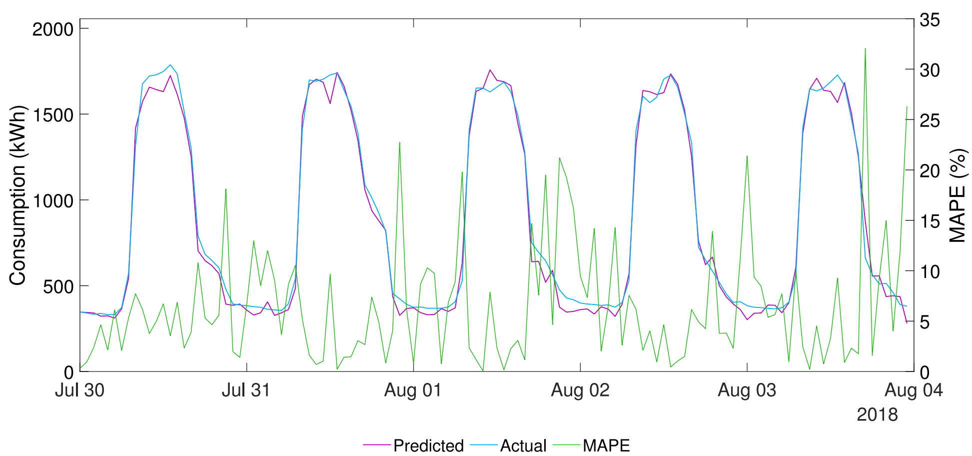


Fig. 10. Prediction vs consumption for a single day for the PO MSP group.

Table 7
MAPE and EME (%) of the total forecast for the week shown in Fig. 13.

Error	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
MAPE	2,474	3,770	1,587	1,871	1,876	4,113	3,179
EME	2,455	3,709	1,572	1,860	1,863	3,273	2,566

Table 8
MAPE and EME (%) of the total forecast for the week shown in Fig. 14.

Error	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
MAPE	1,407	2,045	2,013	2,545	1,521	5,074	3,360
EME	1,270	1,867	1,570	2,181	1,216	3,551	2,603

peaks that are not classified as anomalous might appear at certain hours. Hence, these peaks are also used to train the ANN, introducing a little error in the forecast. Even though the error introduced is insignificant, the data removal procedure could be improved to avoid these peaks in the forecast. However, MAPE and EME errors in Table 6 are very low since peaks happen only in two hours of the week.

4.2. Aggregated prediction

Once the forecast of every individual MSP group is done, they are added to achieve the forecast of the total consumption of the Valencia municipality. To appreciate the effect of seasonality on the consumption profile, we show results for one week of winter (Fig. 13 and Table 7) and another of summer (Fig. 14 and Table 8). As can be seen, the forecast is very accurate, and error measures do not surpass 4% with most of the days with MAPE and EME errors below 3% (see Table 8).

In the summer week, forecast results are better, except for some moments on the 28th and 29th of July. As seen in Figs. 13 and 14, consumption patterns for winter and summer are quite different. This can be appreciated better by plotting one weekday of winter and summer:

The differences between the two profiles are due to the following factors:

- In winter, PL must be on longer at night. That way, in the summer profile, a decrease in consumption can be appreciated at 6:00 AM, which cannot be seen in the winter profile. This is because, in summer, lights are turned off earlier. The same happens in summer since there are more sun hours, a delay in increasing electricity consumption can be seen in the afternoon. Winter consumption increases start at approximately 18:00, while summer increases start at 20:00.
- In Valencia, cooling electricity demand is higher during summer because the cooling needs in buildings are higher than the heating needs to stay within the comfort zone, plus the better COP of heating mode in heat pumps. That is why a higher consumption can be seen during summer across the working hours. However, the difference could be more noticeable.

As the results show, the forecast of the electricity consumption of the Valencia municipality is quite accurate. As was commented

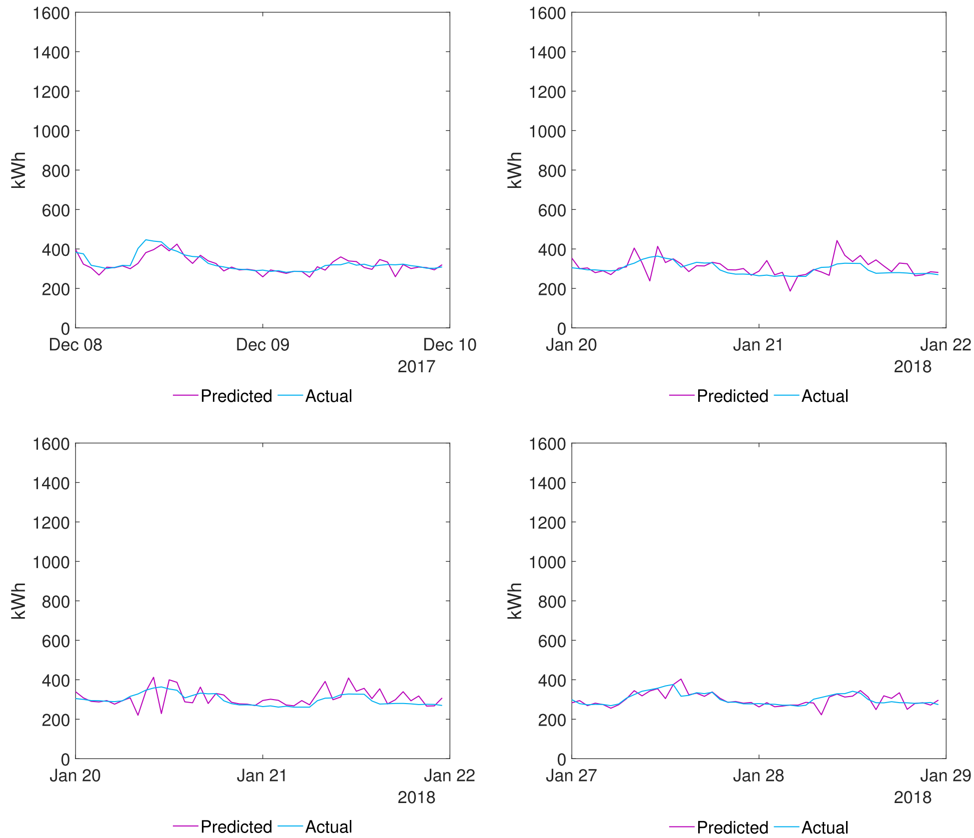


Fig. 11. Consumption vs prediction for winter weekends (PO MSP).

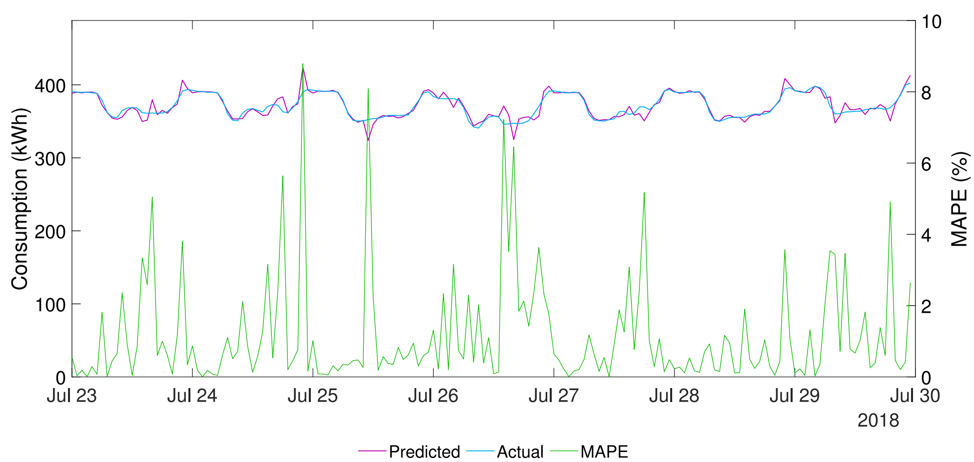


Fig. 12. Prediction vs consumption for the TL MSP group.

before, adding the individual MSP groups considerably reduces the forecast results errors. That way, by plotting the MAPE and EME errors for a sample week of every MSP, it is possible to appreciate the improvement:

As Fig. 16 shows, errors decrease significantly when performing the total forecast by adding the results of the different MSP groups. The only MSP group with a lower error by itself than the total forecast is the TL MSP group, although the difference is negligible.

EME errors also decrease when performing the total forecast of Valencia's electricity consumption. Both Figs. 16 and 17 show that MSP groups with a greater number of load curves analysed are the ones with lower EME and MAPE values. An idea widely supported in the literature (Burg et al., 2021; Sevlian and Rajagopal, 2018). However, even though the forecast of some of the MSP groups is poor, it does not affect the total forecast. This is because these MSP groups do not represent a significant level of electricity consumption compared to MSP groups like PL, PO or TL.

4.3. Justification of the MSP classification

A comparison between the results with and without classifying the MSP is made to justify the MSP classification in groups that share a similar consumption scheme and variables influencing consumption. Again, to appreciate the effects of seasonality, we analyse one week of

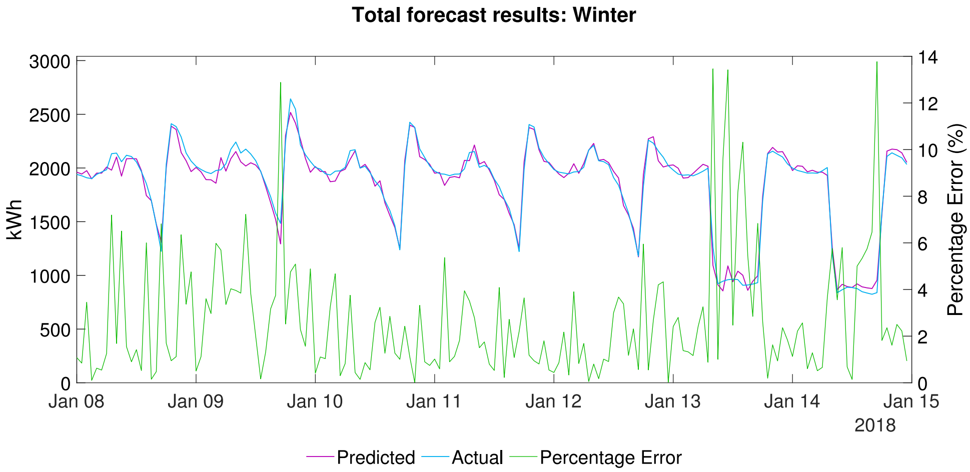


Fig. 13. Aggregated prediction for a winter week.

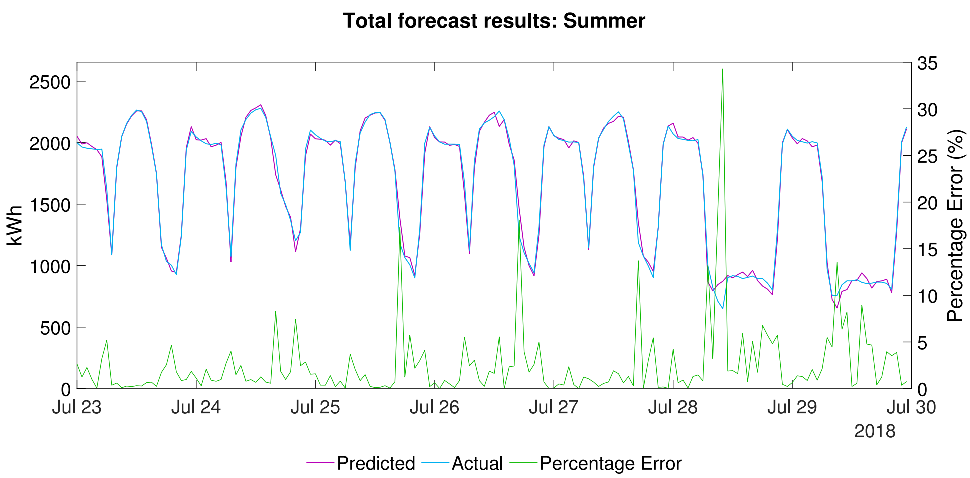


Fig. 14. Aggregated prediction for a summer week.

winter and summer. We include in the forecast as inputs all the variables on Table 3 and the total consumption of Valencia Municipality without classifying MSP. The E_{t-1} variable takes the total consumption of the previous hour. The same goes to $T_{Avg,t-3}$. Day type classification is also done; days have been classified in all the different days specified in Table 3. The day types finally used are the following ones in Table 9:

Table 9
Types of day used on the non-classified ANNs.

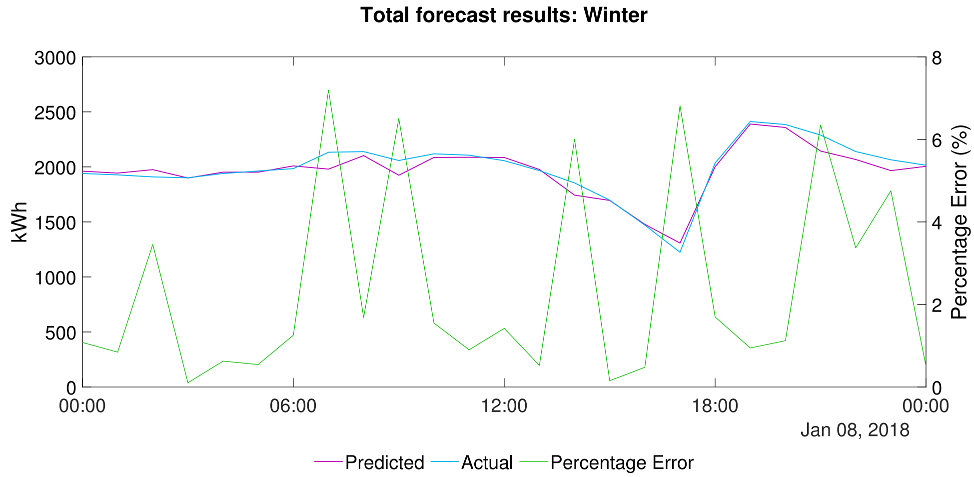
n	Type of day
Type 1	Working days except Tuesdays
Type 2	Tuesday working days
Type 3	Saturdays
Type 4	Sundays, August and general holidays
Type 5	Working days that are not school days

The ANN's architecture and training methodology are explained in Section 2 but without previously classifying MSP and using as inputs all the variables on Table 3 and types of day adapted. The next figure shows the results for a winter week without classifying consumption into MSP groups:

A forecast without classifying in the winter week is inaccurate, especially during maximum consumption when many peaks appear. The peak on January 9 is very high. It introduces an error in energy of more than 1500 kWh, which can have severe consequences if the forecast methodology is used to buy electricity in the wholesale market, for example. When performing the MSP groups' classification, results change considerably. The improvement when classifying consumption is noticeable. In Fig. 19, the errors are much more moderate. The same comparison is made in Fig. 20, but this time for the summer season.

The forecast without classifying is much better in the summer week than in the winter one. However, some peaks still appear. Even though they happen just at some particular hours, they could have severe consequences depending on the use of the forecast methodology. Fig. 21 shows the results by performing the MSP classification. Again, the improvement is noticeable. It is mainly observed that the forecast is smoother when the classification is done, instead of having a more saw-shape like the one observed in Figs. 18 and 20.

The improvement in the forecast when groups classify MSP can be observed visually and easily by comparing Figs. 18, 19, 20 and 21 and Table 10. When not performing the previous MSP classification, the model inputs some variables that, for most of the types of consumption of the Valencia Municipality, can act as noise in the training process. That would be the case of the t_{sr} and t_{ss} variables that would only be necessary for public lightning but not other MSPs. The same goes the other way around: variables related to temperature are unnecessary to study the consumption of public lightning, causing the ANN training process to be more erratic and, as a consequence, obtaining worse results:



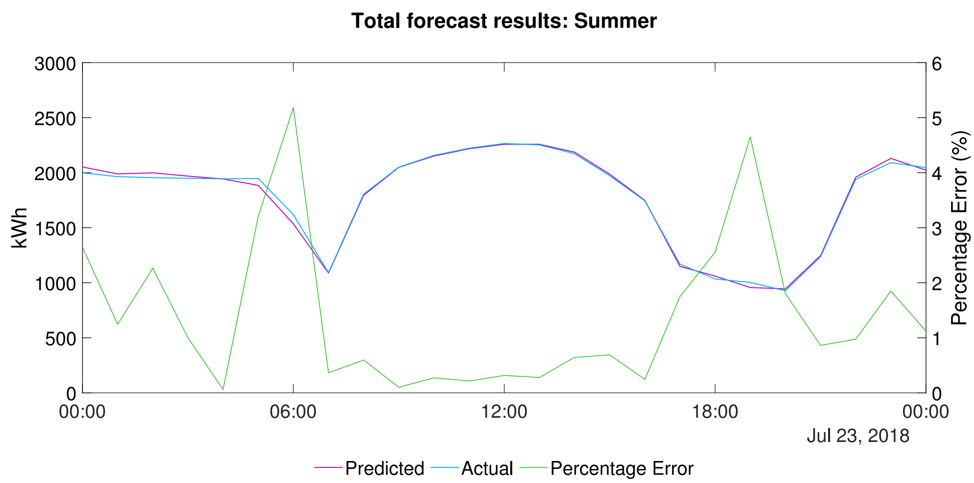


Fig. 15. Comparison between one weekday in winter and summer.

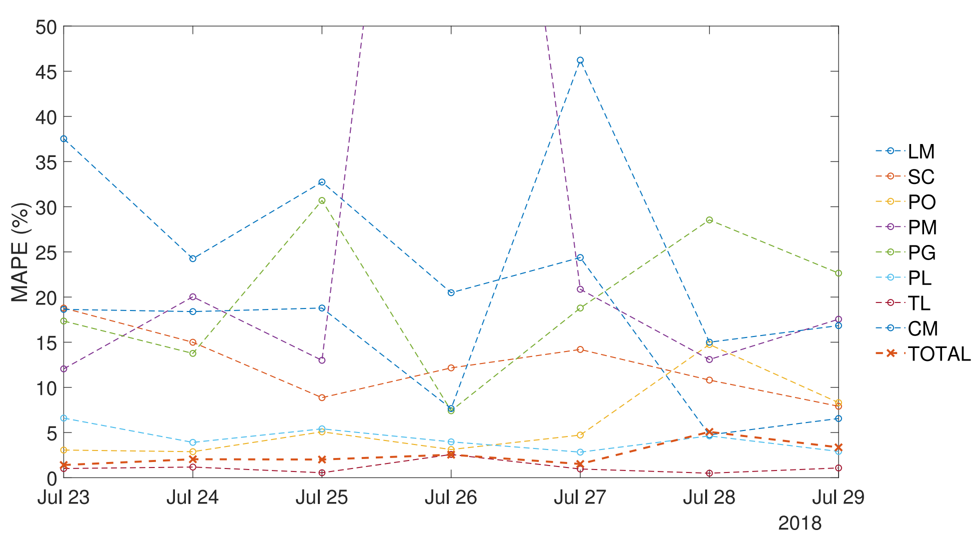


Fig. 16. MAPE error for the different MSP groups.

Figs. 22 and 23 show the increase in error measures when the forecast is not classified into MSP groups. The difference is especially noticeable in the displayed winter week, when the maximum EME error is reduced from 8% to 4% for January 9. Therefore, it proves that performing an MSP classification improves the results significantly.

5. Conclusions

This study presents the forecast of electricity consumption in large consumers, in particular the municipality of Valencia. We do so through Artificial Neural Networks (ANN) and a prior classification of Metered

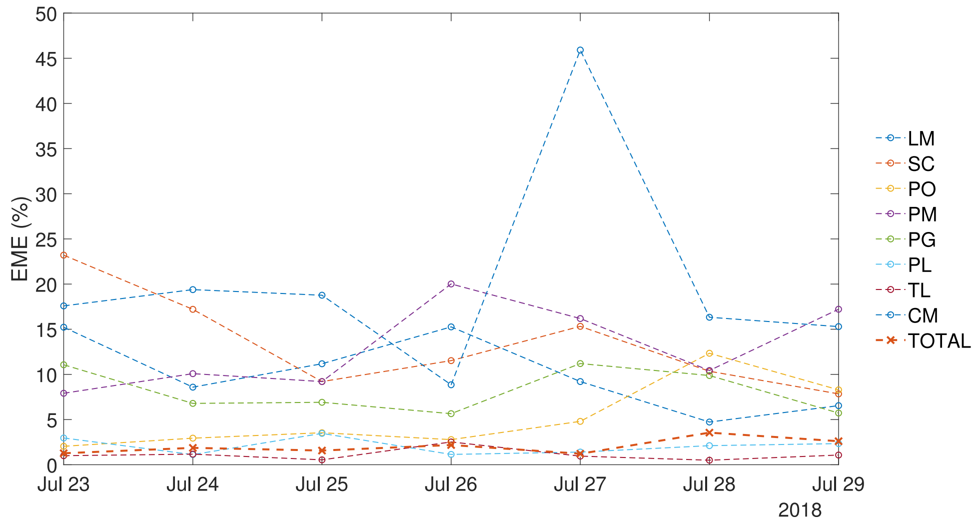


Fig. 17. EME error for the different MSP groups.

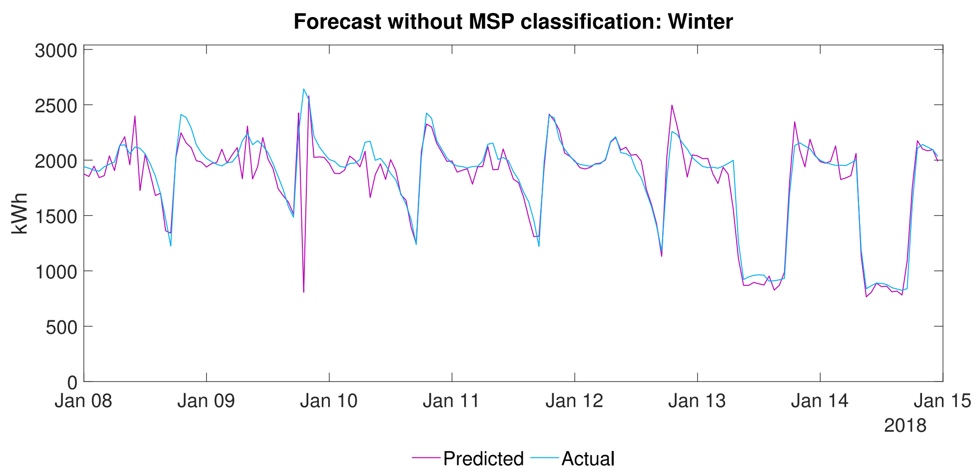


Fig. 18. Total forecast results for a winter week without classifying consumption into MSP groups.

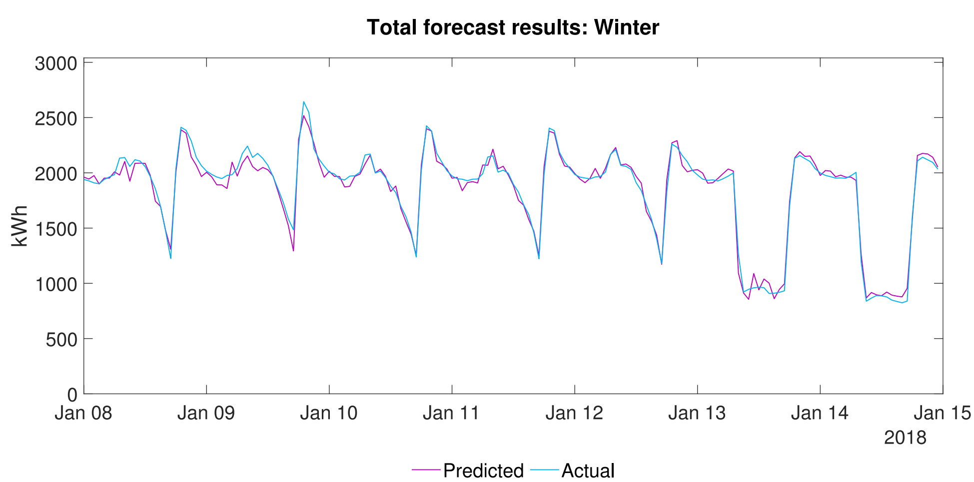


Fig. 19. Total forecast results for a winter week classifying consumption into MSP groups.

Supply Points (MSP) according to the factors influencing their daily load profiles. ANNs allow an hourly forecast of future consumption by selecting a set of inputs. We consider the hourly temperature, the last hour of electricity consumption, sunrise and sunset time, and the previous hour's average temperature, data whose forecast can be easily obtained from other sources. The classification of the MSPs leads to a critical improvement of the ANN's design and final forecast.

The methodology is applied to the Valencia Municipality. We use consumption data from 525 supply points from 2017–2018, adding a total yearly consumption of 49 GWh. After a detailed analysis, we found

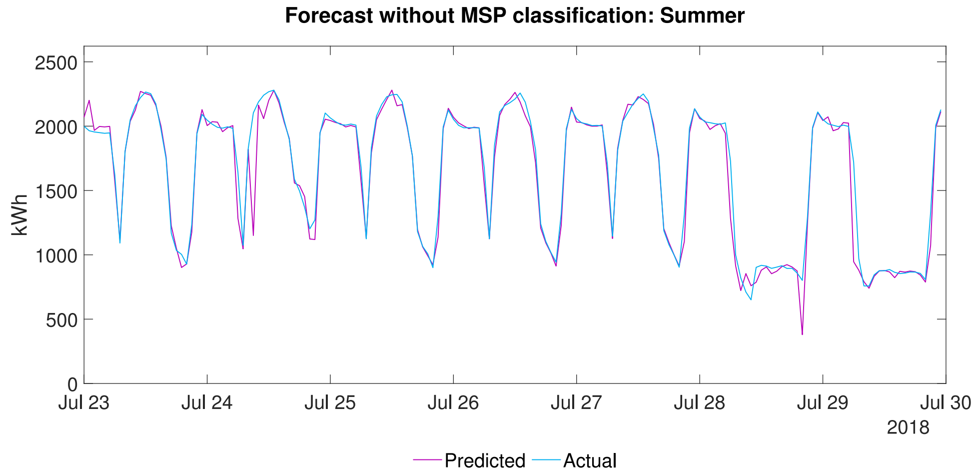


Fig. 20. Total forecast results for a summer week without classifying consumption into MSP groups.

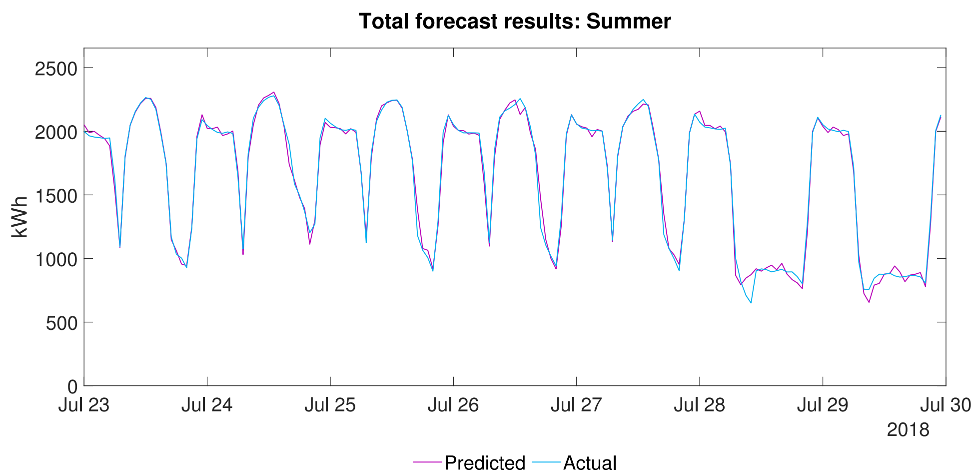


Fig. 21. Total forecast results for a summer week classifying consumption into MSP groups.

Table 10
Comparison between the results performing or not an MSP classification.

Season	MSP classification	Error	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
Summer	NO	MAPE	2,540	5,179	1,823	2,177	1,748	7,573	4,479
		EME	2,342	5,057	1,672	2,111	1,555	5,844	4,878
	YES	MAPE	1,407	2,045	2,013	2,545	1,521	5,074	3,360
		EME	1,270	1,867	1,570	2,181	1,216	3,551	2,603
Winter	NO	MAPE	5,457	7,485	4,010	3,466	3,123	6,553	4,890
		EME	5,489	8,379	4,132	3,265	3,144	6,338	4,212
	YES	MAPE	2,474	3,770	1,587	1,871	1,876	4,113	3,179
		EME	2,455	3,709	1,572	1,860	1,863	3,273	2,566

eight different groups of MSP, which are the most significant in terms of consumption: Public Lighting, Traffic Lights, and Public Offices. Also, we divided the classified MSPs into different day types to better predict future consumption.

Despite lacking a submetering system for end-uses in the MSPs, the results demonstrate that the proposed forecast methodology performs accurately, mainly when calculating a forecast for all consumption. The most precise forecasts are those of the MSP groups with more data availability (representing a more significant share of the total consumption) since they are trained with a larger sample size. Their consumption is more aggregated, limiting the variance in the consumption patterns and facilitating predicting future behaviours. The results generally show a daily MAPE between 1.4% and 3.8% and an EME between 1.27% and 3.7% during the week. We observed extreme values near 5% on Saturdays due to the high variance of the consumption profiles of some MSPs. Moreover, the results show how classifying MSPs into types outperforms the overall prediction without a classification.

The presented forecast can improve the understanding of consumption and help consumers adapt their energy demand to the future needs of the power system. Helping them to buy electricity in wholesale electricity markets with lower risks and better information. This will make consumers reduce their overall energy costs. Furthermore, in a moment of increasing digitalisation, smart meter penetration, and consumer participation in the power system, new features such as demand flexibility arise as sources of income. Future work should explore treating larger data sets, real-time implementation, and market participation potential and comparing alternative methods or adjustments to the ANN's structure with additional hidden layers.

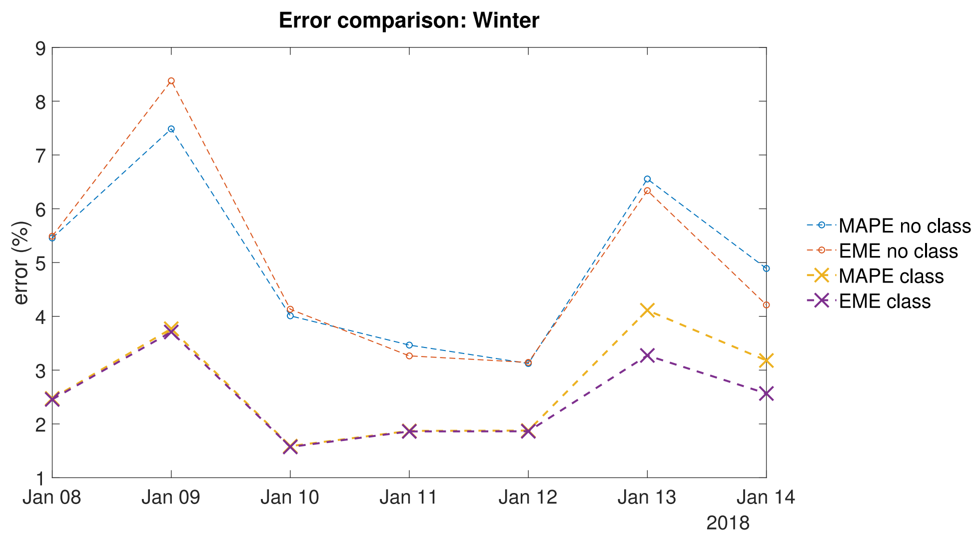


Fig. 22. Comparison between the results performing or not an MSP classification in winter.

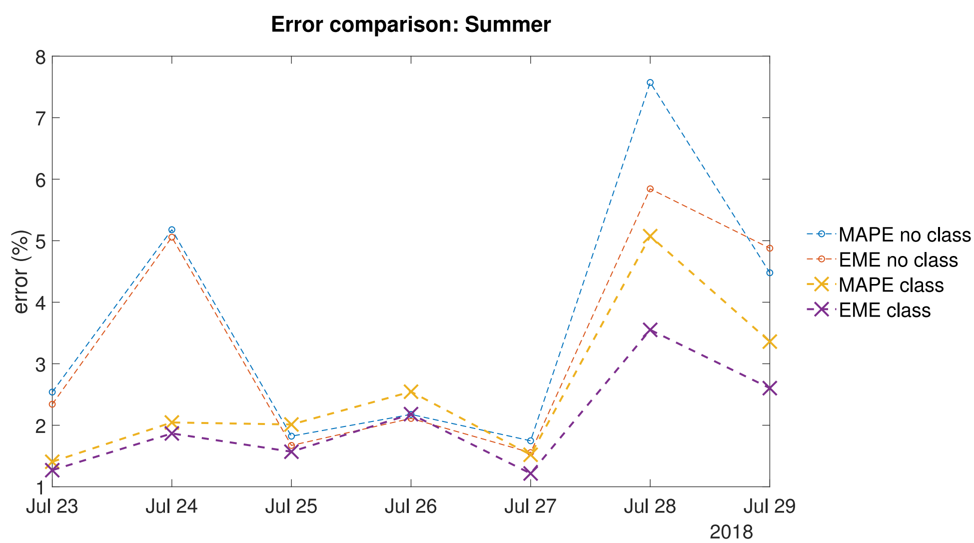


Fig. 23. Comparison between the results performing or not an MSP classification in summer.

CRediT authorship contribution statement

S. Mateo-Barcos: Data curation, Software, Visualization, Writing – original draft. **D. Ribó-Pérez:** Conceptualization, Investigation, Methodology, Supervision. **J. Rodríguez-García:** Conceptualization, Methodology, Supervision, Writing – review & editing. **M. Alcázar-Ortega:** Conceptualization, Supervision, Writing – review & editing.

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 authors do not have permission to share data.

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Appendix A

All case studies, data treatment and ANN have been solved using Matlab. We have used an Intel (R) Core (TM) i7 computer at 1.99 GHz and 16 GB of RAM.

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