Predictive Modeling of PV Energy Production: How to Set Up the Learning Task for a Better Prediction?

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Abstract—In this paper, we tackle the problem of power prediction of several photovoltaic (PV) plants spread over an extended geographic area and connected to a power grid. The paper is intended to be a comprehensive study of one-day ahead forecast of PV energy production along several dimensions of analysis: i) The consideration of the spatio-temporal autocorrelation, which characterizes geophysical phenomena, to obtain more accurate predictions. ii) The learning setting to be considered, i.e. using simple output prediction for each hour or structured output prediction for each day. *iii*) The learning algorithms: We compare artificial neural networks, most often used for PV prediction forecast, and regression trees for learning adaptive models. The results obtained on two PV power plant datasets show that: taking into account spatio/temporal autocorrelation is beneficial; the structured output prediction setting significantly outperforms the non-structured output prediction setting; and regression trees provide better models than artificial neural networks.

Index Terms—PV energy prediction, spatial and temporal autocorrelation, structured output, regression trees, ANNs.

I. INTRODUCTION

T HE urgent need to reduce pollution emission has made renewable energy a strategic European Union (EU) and international sector. This has resulted in an increasing presence of renewable energy sources and thus, significant distributed power generation. The main challenges faced by this new energy market are grid integration, load balancing and energy trading. First, integrating such distributed and renewable power sources into the power grid, while avoiding decreased reliance and distribution losses, is a demanding task for the smart grid effort. In fact, renewable power sources, such as photovoltaic array, are variable and intermittent in their energy output, because the energy produced may also depend on uncontrollable factors, such as weather conditions. Second, the main players

M. Ceci, R. Corizzo, F. Fumarola, D. Malerba and A. Rashkovska are with the Department of Computer Science, University of Bari Aldo Moro, via Orabona 4, 70125 - Bari, Italy (e-mail: michelangelo.ceci@uniba.it; roberto.corizzo@uniba.it; fabio.fumarola@uniba.it; donato.malerba@uniba.it). A. Rashkovska is also with the Department of Communication Systems, Jožef Stefan Institute, Jamova 39, 1000 - Ljubljana, Slovenia (e-mail: aleksandra.rashkovska@ijs.si). in the energy market – the distributors and smaller companies that act between offer (traders) and request in the supply chain – have to face uncertainty not only in the request but also in the offer, when planning the energy supply for their customers. Third, the power produced by each single source contributes in defining the final clearing price in the daily or hourly market [4], thus making the energy market very competitive and a true maze for outsiders.

In order to face these challenges, it is of paramount importance to monitor the production and consumption of energy, both at the local and global level, to store historical data and to design new, reliable prediction tools. In this work, we focus our attention on photovoltaic (PV) power plants, due to their wide distribution in Europe. During the last years, the forecast of PV energy production has received significant attention since photovoltaics are becoming a major source of renewable energy for the world. Forecast may apply to a single renewable power generation system [20], or refer to an aggregation of large numbers of systems spread over an extended geographic area [3][19]. Accordingly, different forecasting methods are used. Furthermore, forecasting methods also depend on the tools and information available. Diverse resources are used to generate solar and PV forecasts depending on the forecast horizon considered, ranging from measured weather and PV system data to satellite and sky imagery cloud observations used for very short-term forecasts (0 to 6 hours ahead), to Numerical Weather Prediction (NWP) models used for horizons beyond approximately six hours [15]. Several works clarify that the best approaches make use of both measured data and NWP [18][19].

In the literature, several data mining approaches have been proposed for renewable energy power forecasting. Researchers typically distinguish between two classes of approaches: physical and statistical. The former relies on the refinement of NWP forecasts with physical considerations (e.g. obstacles and orography) [5] or measured data (approach often referred to as Model Output Statistics or MOS) [18][19], while the latter is based on models that establish a relationship between historical values and forecasted variables. Statistical approaches may or may not take into account NWP data. Some of them are based on time series [8], while others learn adaptive models from data, like autoregressive (AR) models [3], artificial neural networks (ANNs) [20], or SVM classifiers [21]. In this respect, it has been noted that physical property behavior (e.g. wind speed and solar irradiation) exhibits a trail called concept drift, i.e., they change characteristics over time [4]: Adaptive models are generally considered to produce more reliable

Manuscript received April 20, 2016. Revised July 15, 2016. Accepted for publication August 15, 2016. This work was supported by the projects "Vi-POC: Virtual Power Operation Center" (PAC02L1_00269), funded by the Italian Ministry of University and Research, and "MAESTRA - Learning from Massive, Incompletely annotated, and Structured Data" (Grant number ICT-2013-612944), funded by the European Commission. The computational work has been carried out on the resources provided by the projects ReCaS (PONa3_00052) and PRISMA (PON04a2_A). The authors also wish to thank Lynn Rudd for her help in reading the manuscript. Copyright © 2016 IEEE. Personal use of this material is permitted. However, permission to use this material for any other purposes must be obtained from the IEEE by sending a request to pubs-permissions@ieee.org.

predictions regarding concept drift, but require a continuous training phase. Combinations of statistical (ANN and SVM) and physical (MOS) approaches for renewable energy power forecasting have also been recently investigated [7].

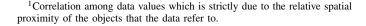
Despite the existence of such data mining algorithms applied in renewable energy power forecasting for learning adaptive models [3][4][20][21], there is no consensus about the spatio-temporal information to be taken into account, the learning setting to be considered and the learning algorithms to be used. This paper considers all these aspects as dimensions of analysis and investigates their real contribution in renewable energy power forecasting. The paper is structured as follows. Section II gives the motivation and contribution of the study. Section III formalizes the problem, how spatial and temporal autocorrelation components are considered and how the (non-)structured output learning task is defined. Section IV presents the data collection and preprocessing. The dimensions of analysis stated above are addressed in Section V, where experiments are reported and results are discussed. Finally, Section VI concludes the paper.

II. MOTIVATION AND CONTRIBUTION

The motivation for this paper comes from the different learning settings that can be found in the literature for the task at hand. Concerning the *spatio-temporal information* to be taken into account, it is noteworthy that most of the previously referenced work consider forecasting solutions for single plants and ignore the information collected from/at other plants/sites in the vicinity, even when this would be easily accessible (through spatial information). In this work, we show that this information loss may result in reduced accuracy of the forecasting models, and we advocate an approach for learning forecasting models from data related to multiple plants. Differently from the few works in the literature that consider multiple plants [3][19], our analysis also leverages the spatio-temporal auto-correlation that characterizes geophysical phenomena, such as weather conditions, to make more accurate predictions.

Indeed, site proximity of PV plants introduces *spatial* autocorrelation¹ in functional annotations and leads to the violation of the usual assumption that observations are independently and identically distributed (i.i.d.). Although the explicit consideration of these spatial dependencies brings additional complexity to the learning process, it generally leads to increased accuracy of learned models [22].

In addition, the production of PV plants is also affected by *temporal* autocorrelation, since it: *i*) tends to have similar values at a given time in close days, *ii*) has a cyclic and seasonal (over days and years) behavior, *iii*) tends to show the same trend over time. While adaptive approaches (which typically employ stream mining algorithms) deal with *i*) and *iii*), they may fail to consider *ii*), since they tend to better represent the most recently observed concepts, forgetting previously learned ones [12]. On the contrary, time series-based approaches are able to deal with *iii*), but may fail to consider *i*) and *iii*). In fact, they typically require the size of the temporal horizon as



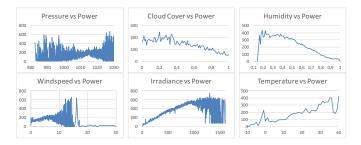


Fig. 1. Trend of pressure (hPa), cloud cover (%), humidity (%), wind speed (m/s), irradiance (W/m2), temperature ($^{\circ}$ C) (X-axis) with respect to the energy produced (KWh) (Y-axis).

input: Considering a short-term horizon (e.g. daily) excludes a long-term horizon (e.g. seasonal) and vice versa.

Although several approaches combine both the spatial and the temporal dimensions [10] from stream data, they have not been applied in the context of renewable energy power prediction. Moreover, they do not take the spatial autocorrelation phenomenon into account and, thus, do not exploit the spatial structure of the data [6]. In this paper, similarly to other approaches, we exploit NWP to benefit from uncontrollable factors, but additionally, we evaluate at which extent taking into account spatial and temporal autocorrelation is beneficial. While spatial autocorrelation is taken into account by resorting to two well known techniques in spatial statistics, temporal autocorrelation is considered by resorting to directional statistics.

Concerning the *learning setting*, in the existing work, the classical solution is to learn a predictive model which predicts the energy that will be produced at a specific hour and day in the future. This approach, however, appears to be too limiting if we consider that two consecutive hours are seen as independent examples. An alternative solution is to resort to approaches that learn predictive models for structured output (structured output prediction) [16]. In principle, this approach should be able to catch (and model) dependence between consecutive hours of the same day, just as some time-series methods do for short-term prediction.

Concerning the *data mining algorithm*, we investigate the predictive performance obtained with two different algorithms, one which learns ANNs and another one which learns regression trees. While ANNs have been extensively used for energy prediction [4], regression trees have received significantly less attention. Both algorithms are also able to deal with the non-linearity of production with respect to some of the considered features (see Fig. 1). In any case, we study and compare their performance for the problem at hand. Actually, in our framework, we can plug-in any learner which can learn models for both non-structured and structured output.

The contributions of the paper aim to provide a comprehensive analysis of the problems described before and to understand what matters if we want to achieve good and reliable predictions. In particular, the contributions include: I) The explicit consideration, with two different solutions, of the spatial autocorrelation and the investigation of its effect at different extents in predictive modeling of energy production. In this way, weather conditions (e.g. temperature,

solar radiation, wind direction and (wind) speed, quantity of rain) are appropriately exploited for forecasting purposes. 2) The explicit consideration of the temporal autocorrelation and the investigation of its effect at different extents in predictive modeling of energy production, in order to deal with non-stationary (cyclic and seasonal) data, in an adaptive model. 3) An investigation of the effect of the structured output prediction approach. 4) An investigation of the effect of the effect of the specific learning algorithm used. 5) The identification, by means of a feature selection step, of the best variables to be used for prediction. We orthogonally investigate all the aspects discussed before through an extensive experimental evaluation on two datasets for PV power plants in Italy and USA.

III. METHOD

The task we intend to perform is to predict PV power generation from *i*) historical data on power production, *ii*) weather forecast data provided by NWP systems, *iii*) weather information collected by sensors, *iv*) geographic coordinates of the plants, *v*) additional features representing spatial and temporal autocorrelation. Similarly to [8], the output is a fine-grained prediction for the next day at one hour intervals.

The learning algorithms update the prediction models every day. We use historical weather information collected by sensors as features in the training phase, whereas we use weather forecast data provided by NWP systems as features for predictions. Formally, let P_i be the *i*-th plant, we define:

- $\pi_i = \langle x, y \rangle$, the geographic coordinates of P_i ,
- α_{i,j,h}, a vector representing the sun's position at the location of P_i, on day j and at hour h,
- $p_{i,i,h}$, a vector representing properties of P_i ,
- $w_{i,j,h}$, a vector for the observed weather data of P_i ,
- $w'_{i,i,h}$ a vector that represents NWP forecast data for P_i ,
- $s_{i,j,h}$, a vector modeling spatial autocorrelation at P_i ,
- $t_{i,j,h}$, a vector modeling temporal autocorrelation at P_i ,
- $y_{i,j,h}$, a value representing the production (KWh) of P_i .

In our approach, we use π_i , $\alpha_{i,j,h}$, $p_{i,j,h}$, $w_{i,j,h}$, $s_{i,j,h}$, $t_{i,j,h}$ (independent input features) and $y_{i,j,h}$ (dependent/target variable), for training purposes and π_i , $\alpha_{i,j,h}$, $p_{i,j,h}$, $w'_{i,j,h}$, $s_{i,j,h}$ and $t_{i,j,h}$ for prediction purposes. The value of the predicted attribute – the energy production – is available only during training. It is noteworthy that $p_{i,j,h}$ is used to represent data about the plants, which are valid at a certain time-point. Examples of features used in $p_{i,j,h}$ are: age of the plant, number of working inverters and maximum plant production. These data allow the learning algorithm to directly predict the production, instead of the percentage of the production with respect to the maximum plant production.

The applied spatial and temporal autocorrelation techniques are discussed in the next two subsections. The last subsection describes the two learning settings for predicting $y_{i,j,h}$, namely structured and non-structured output prediction.

A. Spatial Autocorrelation

The proximity of sensors induces spatial autocorrelation in the data. According to [17], the inappropriate treatment of sample data with spatial dependence could obfuscate important

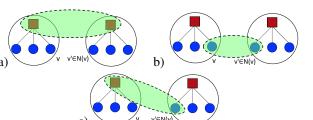


Fig. 2. Different types of autocorrelation (dashed lines): Squares and circles represent target and input features, respectively; bigger circles represent different sites; N(v) represents the neighborhood of the site v. (a): Spatial lag model. (b) and (c): Two forms of spatial cross-regressive model.

insights and observed patterns may even be inverted when spatial autocorrelation is ignored. Taking autocorrelation into account allows the models to avoid overfitting and exploit information coming from close sites. To accommodate several forms of spatial correlation, various models have been developed in the field of spatial statistics. The most known types are the spatial lag model and the spatial cross-regressive model [2]. While the former considers autocorrelation on the target variables, the latter considers cross-correlation between input features at one site and target variables at other sites, as well as cross-correlation between input features at one site and input features at other sites (see Fig. 2).

We use two spatial statistics when building the crossregressive model between PV plants: 1) the Local Indicator of Spatial Association (LISA) for representing a local measure of spatial autocorrelation [1]; 2) the Principal Coordinates of Neighbor Matrices (PCNM) for representing the spatial structure in the data [9]. Compared to the classical STAR model [23], which combines spatial and temporal information in an autoregressive model, the advantage of the solution we adopt is that we are able to embed spatial and temporal information in new features rather than in the model (but still taking autocorrelation into account). This gives us the opportunity to plug-in any off-the-shelf learning algorithms and to separately investigate the contribution of spatial and temporal information.

To compute the LISA, the spatial neighborhood of an entity (i.e. PV plant) is expressed as a matrix, and for each spatial entity and data point observed in a time horizon, the local Moran's I index [1] is computed using the matrix. More precisely, given n PV plants, the first step is to define a neighborhood matrix δ of size $n \times n$, such that:

$$\delta[P_a, P_b] = \begin{cases} 1 & \text{if } dist(P_a, P_b) < maxDist\\ 0 & \text{otherwise,} \end{cases}$$
(1)

where P_a and P_b are two of the *n* plants. The *maxDist* threshold is a user-defined parameter that determines the effect of the autocorrelation. The elements of δ are then transformed: $\delta'[P_a, P_b] = \frac{1}{|N(P_a)|} \delta[P_a, P_b]$, where $N(P_a)$ is the set of nodes which are at a distance less than or equal to *maxDist* with respect to P_a . In this way, the sum of the elements on each row in δ' is either 0 or 1.

The subsequent step consists in computing the deviation of the variable of interest with respect to the mean according to the z-score normalization [14]. Since in our approach we are interested in identifying the contribution of the neighborhood for each feature, this computation is performed for each feature considered (e.g.: temperature, humidity, etc.). More formally, for a plant P_a at day j and hour h, we compute:

$$z_{a,j,h}^{(x)} = \frac{x_{i,j,h} - \overline{x}}{\sigma_x},\tag{2}$$

where x is a generic variable used for representing either weather condition, weather forecast or plant information (that is, a generic element of the vectors w, w' and p), \overline{x} represents the average of the variable x and σ_x represents the standard deviation of x. On the basis of $z_{a,j,h}^{(x)}$, it is possible to compute the local Moran's I for the variable x of the plant P_a for day j and hour h (according to [1]): $I_{a,j,h}^{(x)} = z_{a,j,h}^{(x)} \cdot \sum_{P_i \in N(P_a)} \delta'[P_a, P_i] \cdot z_{i,j,h}^{(x)}$. According to [25], we incorporate local spatial autocorrela-

According to [25], we incorporate local spatial autocorrelation terms as predictors in regression equations (in the vector $s_{a,j,h}$, which has one element for each possible variable x), giving place to autoregressive models.

The PCNM is used to define new features which represent the spatial structure of the data, so to exploit autocorrelation in the learning phase. Its computation has three steps:

- 1) The Euclidean (geographic) distance matrix D between plants is computed ($D = [d_{i,j}] = [dist(P_i, P_j)]$).
- 2) A threshold value t is chosen to construct a truncated distance matrix $D^* = [d_{ij}^*]$ as follows:

$$d_{ij}^* = \begin{cases} d_{ij} & \text{if } d_{ij} \le t \\ 4t & \text{otherwise} \end{cases}$$

 A principal coordinate analysis (PCoA) of the truncated distance matrix D* is performed. This analysis consists in the diagonalization of Δ, where:

$$\Delta = -\frac{1}{2} \left(\mathbf{I} - \frac{1 \cdot 1^t}{n} \right) \mathbf{D}_2^* \left(\mathbf{I} - \frac{1 \cdot 1^t}{n} \right)$$
(3)

with $\mathbf{D}_2^* = [(d_{ij}^*)^2]$, I be the identity matrix and 1 be a vector of 1s.

It has been proven (see [9]) that the eigenvectors of Δ are vectors with unit norm maximizing Moran's I under the constraint of orthogonality, whereas the eigenvalues of this matrix are equal to Moran's I coefficients of spatial autocorrelation (post-multiplied by a constant). They can also be either positive or negative (because the original Euclidean distance matrix has been truncated). Eigenvectors associated with high positive (or negative) eigenvalues have high positive (or negative) autocorrelation and describe global and local structures. Since we are interested in considering only positive spatial autocorrelation, only eigenvectors corresponding to positive eigenvalues are kept and used as spatial descriptors.

The principal coordinates of each spatial descriptor (used as features in $s_{i,j,h}$) are obtained by scaling each eigenvector u_k of Δ to the length $\sqrt{\lambda_k}$, where λ_k is the eigenvalue associated with eigenvector u_k . Finally, the value of t used in D^* is defined as the maximum distance between two PV plants ($t = \max_{i,j} d_{i,j}$), in order to guarantee that the data are all connected.

B. Temporal Autocorrelation

Weather data is inherently seasonal/cyclical. For instance, summer days are featured by an increased irradiance compared

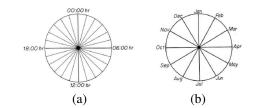


Fig. 3. (a) Daily circumference. (b) Yearly circumference.

to winter days. Moreover, if we consider an absolute time reference, the irradiance is almost equal for two (close) days at the same hour. Hence, we expect to increase the reliability of predictions if days closer to the prediction (target) day are more influential in the model.

To account for both seasonal and daily cyclicity, we use two alternative solutions. The first solution is simple and consists in considering, as input features (independent variables), the values of time and day scaled in the range [0,1] for both training and target days. The second solution is to resort to directional statistics which represent directional or circular distributions of the data by "wrapping" the probability density function around the circumference of a circle of unit radius. We follow this approach by "wrapping" information collected at a specific time-point around two circumferences, namely the daily circumference and the yearly circumference (see Fig. 3). The former catches the distribution of the production over the different hours of the day, while the latter catches the distribution of the production over the 365 days of the year.

More specifically, for each day in the training (historical) data, we compute its radial distance d_r on the circumference from the target day. Since the learning algorithm is able to consider the similarity between two values, the value 2π – d_r is incorporated as input feature in the model (in $t_{i,i,h}$). Note that this approach requires an update of the model every day, which is in line with the learning setting we consider. However, the same approach cannot be adopted to catch the distribution of the production over the different hours of the day since this would require updating the model every hour. The solution we adopt in this case is to directly include in the model the radial value of the specific hour h_r as input feature (independent variable in $t_{i,j,h}$). The disadvantage is that we can not catch similarities in the energy produced between the last and the first hours of the day when, however, PV energy is not produced.

C. The learning setting: Structured and non-structured

As previously mentioned, we also investigate the application of structured output prediction models to the specific task. In particular, we consider multi-target models where, instead of a single model that predicts the production at a single hour, we have a single model that predicts 24 output variables at the same time. In principle, learning multi-target models should present some benefits over learning a local model for predicting the production at each hour. Indeed, it is generally recognized that structured models are typically easier to interpret, perform better and overfit less than singletarget predictions [16]. In this specific application, multi-

TABLE I Correspondences between independent variables in the non-structured and structured output settings.

Non-structured	Structured	
$\alpha_{i,j,h}$	$\alpha_{i,j,h=1:24}$	
$p_{i,j,h}$	$p_{i,j,h=1:24}$	
$w_{i,j,h}$	$w_{i,j,h=1:24}$	
$w_{i,j,h}^{\prime}$	$w'_{i,j,h=1:24}$	
$s_{i,j,h}$	$s_{i,j,h=1:24}$	
$t_{i,j,h}$	$t_{i,j}$	(only daily information)

target models can also exploit the dependencies between the productions at two different hours of the same day. The main issue is the collinearity problem, since the linear dependence between attributes may negatively affect the learned model.

Formally, when a non-structured output prediction setting is used, the predicted value is $y_{i,j,h}$ (for the plant *i*, at the day j and hour h). On the contrary, if a structured output prediction setting is used, the predicted value is a vector $[y_{i,j,1}, y_{i,j,2}, \dots, y_{i,j,24}]$ (for the plant *i*, at the day *j*). Since in the structured output prediction setting, the unit of analysis is the day and in the non-structured output prediction setting the unit of analysis is the hour, the independent variables are different. In fact, in the non-structured output setting, each training instance represents a single hour, while in the structured output approach each training instance represents a single day. This means that, in order to keep the same information between the two settings, it is necessary to reserve 24 variables in the structured output setting to represent the value observed for the same property. Formally, the correspondences defined in Table I hold.

IV. DATA COLLECTION AND PREPROCESSING

Coherently with the problem definition provided in Section III, we distinguish between data locally collected by sensors installed on the PV power plants and data collected from external sources, such as weather forecast services (NWP). While locally collected data are used to initialize part of the features in $w_{i,j,h}$ and the dependent variable $y_{i,j,h}$, external sources are used to initialize remaining features in $w_{i,j,h}$ (that are not collected by sensors), as well as features in $w'_{i,j,h}$. The raw data are preprocessed and normalized before subjecting them to the data mining algorithms. In this way, we solve problems related to measurement errors, null values and outliers, as explained in the following.

A. Locally Collected Data

The first problem we consider is how to deal with missing values related to sensor failures or communication problems for the features in $w_{i,j,h}$. It is noteworthy that most of the PV plants collect data every 10 or 15 minutes, thus we can still estimate reliable hourly averages if few measurement values are missing. However, if for a feature we cannot reliably compute its average due to the presence of several <u>null</u> values, we have to substitute them with a value returned by external systems for the specific position and time. To make the values collected by sensors comparable with the values returned by external systems for the same feature (e.g. temperature), they

are both z-score normalized (see Equation (2)). If external systems provide us with no information, we replace the <u>null</u> value with the average of the feature observed for the same month of the same year at the same hour. Similarly, in the (rare) cases we are not able to reliably compute the hourly average for the independent variable $y_{i,j,h}$, we substitute it with the average value observed by the sensors in the same month at the same hour.

After replacing the missing values, we check for the presence of outliers: if the value of the feature x in $w_{i,j,h}$ observed by the sensors is outside the range $[\overline{x} - 4 \cdot \sigma_x; \overline{x} + 4 \cdot \sigma_x]$ (a relaxed 3-sigma rule), we consider it an outlier and handle it in the same way we handle null values.

B. External Data

In order to obtain external data, we query external services which provide interpolated data for past days and NWP values for the future days. Interpolated data are used either to initialize features in $w_{i,j,h}$ which are not collected by sensors, or, as previously mentioned, to correct incomplete and wrong data (in $w_{i,j,h}$) obtained by the sensors. On the contrary, NWP values are used to initialize features in $w'_{i,j,h}$.

Independently of the use of data obtained from external sources, the input parameters we use for querying data are latitude, longitude and time-stamp of interest. The obtained features are: pressure, percentage of cloud cover, type of precipitation, intensity of precipitation, temperature, dew point, ozone, wind speed, humidity, wind bearing and irradiance. Once retrieved, all the values are z-score normalized (see (2)).

Finally, in order to appropriately learn a prediction model (especially for ANNs), data must be scaled to the unit interval. Hence, we apply a min-max normalization [14] for each final feature, considering the *min* and *max* of the values observed (for $w_{i,j,h}$ and $w'_{i,j,h}$, obtained after z-score normalization). Actually, we consider the *max* increased by 30 percent, to handle future situations in which the observed values of each feature might exceed the current maximum.

V. EXPERIMENTS

A. Datasets

In our empirical evaluation, we consider two datasets: a real dataset, named PVItaly, collected by an Italian company, and a dataset concerning the PV production in USA available at the National Renewable Energy Innovation (NREL) web site (http://www.nrel.gov/), and henceforth referred to as NREL.

PVItaly data are collected at regular intervals of 15 minutes (measurements start at 2:00 and stop at 20:00 every day) by sensors located on 18 plants in Italy. The time period spans from January 1st, 2012 to May 4th, 2014. The installed peak power of the PV arrays is between 982.80 KW peak and 999.99 KW peak, and the average is 995.71 KW peak. The amount of missing values and outliers in the data is relatively small, if compared to the total amount of data: around 1% for missing values and around 3% for outliers.

The NREL dataset originally consists of simulated PV data for 6000 plants for the year 2006. We perform cluster sampling over the original dataset by first selecting 16 States with the

TABLE II INDEPENDENT VARIABLES USED IN DIFFERENT SCENARIOS. h is not USED IN THE DAILY SETTING.

	Non-temporal	Non-cyclic	Cyclic
NoSpat.	p, α, w	j, h, p, α, w	j, h, t, p, α, w
LatLon	p, α, w, π	j, h, p, α, w, π	$j, h, t, p, \alpha, w, \pi$
LISA	p, α, w, s^{lisa} p, α, w, s^{pcnm}	$j, h, p, \alpha, w, s^{lisa}$	$j, h, t, p, \alpha, w, s_{ncnm}^{lisa}$
PCNM	$p, \alpha, w, s^{perturn}$	$j, h, p, \alpha, w, s^{pcnm}$	$j, h, t, p, \alpha, w, s^{pcnm}$

highest Global Horizontal Irradiation (GHI). Then, from each State, we select 3 PV plants, resulting in PV data from 48 plants. The plant capacity is between 7 MW and 200 MW, and the average is 82.37 MW.

The weather data is queried from Forecast.io (http://forecast. io/), while the irradiance for the PVItaly dataset is queried from PVGIS (http://re.jrc.ec.europa.eu/pvgis/apps4/pvest.php). Forecast.io data comes from a wide range of data sources, which are statistically aggregated to provide the most accurate forecast possible for a given location. PVGIS data makes use of monthly averages of daily sums of global and diffuse irradiation. The averages represent the period 1981-1990. We queried the PVGIS database for each day and plant separately by using a custom-made wrapper, specifying the date and the coordinates of the plants of interest (latitude and longitude).

More formally, for the defined vectors in Section III, the following input features are considered:

- π_i : latitude, longitude;
- *j*, *h*: day and hour, respectively;
- α_{i,j,h}: altitude and azimuth, queried from SunPosition (http://www.susdesign.com/sunposition/index.php);
- p_i : site ID, brand ID, model ID, age in months;
- $w_{i,j,h}$ and $w'_{i,j,h}$: ambient temperature, irradiance, pressure, wind speed, wind bearing, humidity, dew point, cloud cover, descriptive weather summary;
- $s_{i,j,h}^{lisa}$: LISA indexes $I_{i,j,h}^{(x)}$ for each variable x from $w_{i,j,h}$ (or $w_{i,j,h}$) and $\alpha_{i,j,h}$;
- s_i^{pcnm} : *n* PCNM coordinates (*n* = 15 for the PVItaly dataset, *n* = 30 for the NREL dataset),
- $t_{i,j,h}$: radial day distance d_r and radial representation of the hour h_r .

All datasets, the results and the system are available at: http://www.di.uniba.it/~ceci/energyprediction/.

B. Experimental Settings

We distinguish between hourly and daily settings. In the hourly setting, we investigate non-structured models with single output - the production $y_{i,j,h}$ of the plant P_i at a specified day j and specified hour h. In the daily setting, we investigate structured models with 24 outputs - the productions $y_{i,j}$ of the plant P_i for the hours from 1:00 to 24:00 on a specified day j (actually, we only consider the interval 2:00-20:00, because of the available data). For both settings, we investigate several scenarios with increasing spatio/temporal complexity (see Table II). Moreover, in the daily scenarios, we consider the representation summarized in Table I. The number of attributes and the number of examples considered for each scenario for the both datasets are given in Table III.

For the evaluation, the datasets are randomly split into training days (85%) and testing days (15%). The learning

TABLE III NUMBER OF ATTRIBUTES PER SCENARIO. N: NUMBER OF EXAMPLES.

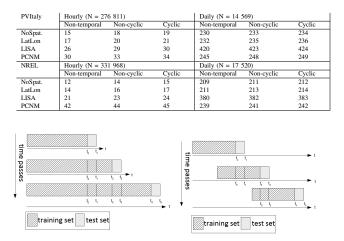


Fig. 4. Evaluation (training and testing) procedure with landmark window model (left) and count-based sliding window model (right).

strategy is iterative - for each testing day, the model is learned on all the previous days and tested on the considered day (example(s) unseen by the trained model). After testing, the testing day becomes part of the training set. This testingretraining procedure is repeated for each testing day and the error contributes to the reported result. The evaluation procedure is based on the "landmark window model" and on the "count-based sliding window model" [11]. While the first model takes into account all the historical data, the second only takes into account the most recent window of a given number of instances. We performed experiments with the count-based sliding window model for window lengths 1000, 2000 and 4000 examples (see Fig. 4). We also investigate different values for the maxDist threshold for the LISA method. Experiments are run three times with different random splits into training and testing sets, and the average error on the test set is reported.

For ANNs, we use the *encog* implementation of the Resilient Propagation (RPROP+) algorithm for training neural networks (http://www.heatonresearch.com/wiki/Resilient Propagation#Implementing_RPROP.2B). RPROP+ is one of the best general-purpose neural network training methods implementing the back-propagation technique. It performs a direct adaptation of the weight step based on local gradient information. The basic principle is to eliminate the harmful influence of the size of the partial derivative on the weight step - it considers only the sign of the derivative to indicate the direction of the weight update. We use RPROP+ since it has been proven effective for renewable energy prediction [4]. Furthermore, RPROP+ does not require typical ANN parameters, such as learning rate and momentum, since they are automatically tuned during the training phase. The ANN topology has 1 hidden layer with the number of hidden neurons equal to 2/3 of the sum of the number of inputs and outputs.

For regression trees, we use the system CLUS that views a tree as a hierarchy of clusters (Predictive Clustering Trees - PCTs): the top-node corresponds to one cluster containing all

the data, which is recursively partitioned into smaller clusters while moving down the tree. CLUS, including PCTs for multitarget regression [16], is available at clus.sourceforge.net.

For the evaluation of the results, we consider three indicators of the predictive performance, namely, the Root Mean Squared Error (RMSE), the Mean Absolute Error (MAE) (MAE results are available at www.di.uniba.it/~ceci/energyprediction/) and the improvement with respect to the persistence model (i.e., the model that forecasts the same production observed 24 hours before). For an analysis at a disaggregated level, we also perform feature selection with the aim of automatically identifying the most relevant input features for the task at hand. According to [13], the feature selection step has been performed as a best-first search in backward mode: starting from the complete feature set, the worth of each subset of attributes is evaluated by considering the individual predictive ability of each feature along with their degree of redundancy.

C. Results and Discussion

The results on the PVItaly and NREL datasets for the investigated hourly and daily scenarios are reported in Table IV for RPROP+ and CLUS. Negative percentages of improvement mean that the investigated model does not outperform the persistence model. The improvement of the best performing results are highlighted in bold. The results show that the best results for the PVItaly dataset are obtained in the setting LISA, Non-cyclic, CLUS, Daily; while for the NREL dataset the best results are obtained in the setting PCNM, Cyclic, CLUS, Daily. Moreover, from the results, it is clear that the landmark model outperforms the count-based sliding window model. This is confirmed also statistically (see Table V, sections "TRAINING WINDOW"). Finally, although there is no statistical evidence, LISA with small values of maxDist show the best performances for PVItaly. This is not confirmed in NREL, where distances between plants are larger and behaviors at coarsegrained granularity are caught by the models.

In addition to the results reported in the tables, we also perform a more systematic analysis in order to understand what matters if we want to achieve good and reliable predictions. According to the contributions stated in the introduction, we compare the results across four dimensions:

- 1) Spatial: NoSpat. vs. LatLon vs. LISA vs. PCNM;
- 2) Temporal: Non-temporal vs. Non-cyclic vs. Cyclic;
- 3) Structural: Hourly vs. Daily;
- 4) Algorithmic: RPROP+ vs. CLUS.

All the above comparisons are orthogonally performed on both real-world datasets. The different dimensions of analysis for the landmark window model are graphically presented in Fig. 5. Additionally, the analysis is complemented with statistical (Wilcoxon signed rank) tests (see Table V). The considered LISA results are for maxDist of 15 km for the PVItaly dataset and 600 km for the NREL dataset.

1) Spatial: The comparison in Fig. 5 (a) shows that, by varying the spatial complexity, there is no single spatial configuration which outperforms all the others. However, by considering the statistical tests for spatial autocorrelation, we can see that PCNM is the best performing method. The

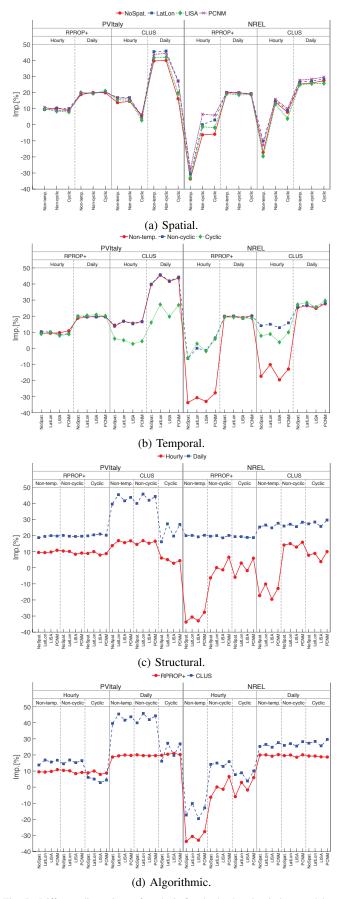


Fig. 5. Different dimensions of analysis for the landmark window model.

TABLE IV

RPROP+ AND CLUS AVERAGE PERFORMANCE (3 RUNS) ON THE PVITALY AND NREL DATASETS. FOR LISA, A,B AND C INDICATE DIFFERENT VALUES OF maxDist: 15 km, 30 km and 45 km for PVITALY, and 300 km, 600 km and 900 km for NREL. S1000, S2000 and S4000 indicate the sliding count-based model with different window lengths.

	PVItaly Dataset						NREL Dataset						
RPROP+		Hourl	·			Daily			Hourly	-		Daily	
01000	Non-temp	Non-cyc		Cyclic	Non-temp.	Non-cyclic		Non-temp.	Non-cyclic	Cyclic	Non-temp.	Non-cyclic	Cyclic
S1000	RMSE Imp.		-	-		-	% RMSE Imp.	-	1	RMSE Imp.%	RMSE Imp.%		RMSE Imp.%
	0.139 -9.2 0.137 -7.8	0.141 -1		.140 -9.6 .141 -10.9	0.114 10.67 0.112 11.91	0.112 12.0 0.113 11.13		0.172 -42.4 0.168 -38.3	0.139 -14.6 0.131 -8.4	0.148 -21.9 0.140 -15.8	0.123 -1.8 0.127 -5.0	0.129 -6.6 0.126 -3.7	0.130 -7.1 0.147 -21.4
	0.137 -7.8				0.112 11.91 0.114 10.47	0.112 12.00			0.131 -8.4	0.140 -13.8	0.127 -5.0	0.120 -3.7	0.147 -21.4
	0.139 -9.5	0.140 -9		.140 -10.3	0.124 2.76	0.124 2.61	0.128 -0.4	0.131 -8.0	0.121 0.39	0.121 0.27	0.105 13.60	0.101 16.47	0.107 11.89
	0.144 -12.9				0.126 0.65	0.126 1.12	0.131 -2.7	0.172 -42.3	0.135 -11.5	0.149 -23.1	0.116 4.51	0.123 -1.2	0.129 -6.5
LISA C	0.144 -12.7	0.143 -1	2.7 0.	.124 2.55	0.125 1.57	0.143 -12.6	0.126 0.74	0.130 -7.1	0.121 -0.2	0.118 2.32	0.102 15.55	0.105 13.17	0.101 17.02
S2000	RMSE Imp.	% RMSE In	p.% R	MSE Imp.%	RMSE Imp.%	RMSE Imp.	% RMSE Imp.	% RMSE Imp.%	RMSE Imp.%	RMSE Imp.%	RMSE Imp.%	RMSE Imp.%	RMSE Imp.%
NoSpatia	0.136 -7.0	0.137 -7	•	.138 -8.7	0.114 10.22	0.113 11.54		0.166 -37.3	0.132 -8.9	0.127 -4.9	0.130 -7.2	0.128 -5.9	0.128 -6.0
LatLon	0.137 -7.3	0.140 -9	6 0.	.139 -9.0	0.115 9.49	0.112 12.22	2 0.114 10.2	0.163 -34.6	0.123 -1.4	0.123 -1.5	0.128 -5.8	0.131 -7.9	0.124 -2.2
	0.144 -13.4				0.114 10.52	0.115 9.58	0.116 9.17	0.163 -34.4	0.128 -6.0	0.127 -5.1	0.120 1.11	0.120 0.63	0.117 3.36
	0.135 -6.4	0.137 -8		.138 -8.2	0.124 2.84	0.123 3.35	0.126 0.99	0.120 1.16	0.116 3.84	0.120 1.30	0.114 5.59	0.113 6.94	0.128 -5.3
	0.136 -7.1	0.139 -9		.140 -9.8	0.128 -0.2	0.128 -0.7	0.128 -0.6	0.166 -36.8	0.130 -7.3	0.129 -6.4	0.134 -10.7	0.126 -4.0	0.132 -9.2
	0.139 -8.9	0.137 -7			0.126 1.35	0.125 1.83	0.126 1.09	0.125 -3.1	0.114 5.78	0.116 4.24	0.111 8.27	0.112 7.67	0.119 1.77
	RMSE Imp.		•	1			% RMSE Imp.	-	RMSE Imp.%		RMSE Imp.%		RMSE Imp.%
-	0.130 -1.7	0.133 -4		.134 -5.0	0.108 14.91	0.109 14.03			0.125 -3.5	0.127 -5.1	0.124 -2.6	0.126 -4.0	0.126 -3.9
	0.135 -6.1 0.145 -13.7	0.133 -4		.135 -6.2 .142 -11.4	0.110 13.69 0.110 13.88	0.110 13.43			0.119 1.48 0.120 1.19	0.123 -1.5 0.129 -6.3	0.125 -3.4 0.115 5.10	0.124 -2.6 0.117 3.08	0.137 -13.1 0.123 -1.3
	0.143 -13.	0.145 -1		.142 -11.4	0.116 8.85	0.112 12.40	0.117 8.30	0.137 -29.2	0.120 1.19	0.129 -0.3	0.113 5.10	0.117 5.08	0.125 -1.5
	0.135 -5.7	0.135 -7		.138 -8.2	0.124 2.28	0.123 3.00	0.121 5.23	0.158 -30.7	0.123 -1.8	0.130 -7.3	0.129 -6.4	0.132 -8.6	0.135 -11.1
	0.138 -8.6	0.137 -7		.138 -8.6	0.115 9.56	0.123 3.78	0.117 8.33	0.115 4.74	0.114 5.85	0.109 9.67	0.115 4.89	0.115 4.98	0.109 10.07
	RMSE Imp.						% RMSE Imp.		RMSE Imp. %		RMSE Imp.%	RMSE Imp. %	RMSE Imp.%
	0.115 9.50	0.114 10	•	.116 8.94	0.103 18.73	0.102 20.02		-	0.129 -6.3	0.128 -5.8	0.097 19.65	0.097 19.58	0.098 19.29
LatLon	0.115 9.37	0.114 10			0.102 19.51	0.102 19.63			0.121 0.10	0.118 2.98	0.097 20.07	0.097 19.91	0.098 19.32
PCNM	0.113 10.8	6 0.116 9.	13 0.	.116 8.77	0.102 19.77	0.102 19.63	3 0.102 20.2	0.155 -27.7	0.113 6.55	0.112 7.34	0.097 20.24	0.097 20.14	0.098 19.49
	0.115 9.71	0.117 8.4		.117 7.93	0.102 19.91	0.103 19.44			0.105 13.24	0.106 12.78	0.099 18.39	0.107 11.44	0.11 10.14
	0.125 1.67	0.128 -0		.126 1.27	0.113 11.19	0.117 8.26	0.117 8.28	0.161 -32.9	0.123 -1.3	0.122 -1.1	0.098 19.26	0.099 18.54	0.097 19.95
LISA C	0.125 1.91	0.128 -0	7 10	.126 0.70	0.115 9.89	0.113 10.80							
			, 0.			0.115 10.00	0.118 7.71	0.113 6.34	0.110 9.55	0.118 2.65	0.122 -0.3	0.103 15.15	0.11 9.44
CLUS				PVItaly			5 0.118 7.71	0.115 0.54	1	0.118 2.65 NREL			0.11 9.44
CLUS	Non-temp	Hourl	γ			Daily Non-cyclic		Non-temp.	Hourly Non-cyclic	1		Daily Non-cyclic	0.11 9.44 Cyclic
CLUS		Hourl	v lic	PVItaly Cyclic	Dataset Non-temp.	Daily Non-cyclic		Non-temp.	Hourly	NREL Cyclic	Dataset Non-temp.	Daily Non-cyclic	
S1000		Hourl Non-cyc % RMSE Im 5 0.110 13	v lic .p.% Rl .93 0.	PVItaly Cyclic MSE Imp.% 133 -4.6	Dataset Non-temp. RMSE Imp.% 0.074 42.17	Daily Non-cyclic RMSE Imp. 0.073 42.32	Cyclic 76 RMSE Imp. 2 0.103 19.49	Non-temp.	Hourly Non-cyclic	NREL Cyclic	Dataset Non-temp. RMSE Imp.% 0.098 19.36	Daily Non-cyclic RMSE Imp.% 0.090 25.91	Cyclic RMSE Imp.% 0.089 26.36
S1000 NoSpatia LatLon	RMSE Imp. 0.111 12.8 0.108 15.4	Hourl Non-cyc RMSE Im 5 0.110 13 5 0.107 16	lic p.% Rl .93 0. .11 0.	PVItaly Cyclic MSE Imp.% 133 -4.6 131 -3.0	Non-temp. RMSE Imp.% 0.074 42.17 0.066 47.85	Daily Non-cyclic RMSE Imp. 0.073 42.32 0.066 47.99	Cyclic % RMSE Imp. 2 0.103 19.49 9 0.099 22.50	Non-temp. 6 RMSE Imp.% 0.157 -29.9 0.145 -19.7	Hourly Non-cyclic RMSE Imp.% 0.114 5.76 0.113 6.76	Cyclic RMSE Imp.% 0.137 -13.1 0.133 -10.2	Dataset Non-temp. RMSE Imp.% 0.098 19.36 0.096 20.68	Daily Non-cyclic RMSE Imp.% 0.090 25.91 0.088 27.02	Cyclic RMSE Imp.% 0.089 26.36 0.089 26.66
S1000 NoSpatial LatLon PCNM	RMSE Imp. 0.111 12.8 0.108 15.4 0.108 15.2	Hourl Non-cyc RMSE Im 5 0.110 13 5 0.107 16 7 0.108 15	lic p.% RI .93 0. .11 0. .36 0.	PVItaly Cyclic MSE Imp.% 133 -4.6 131 -3.0 130 -2.1	Non-temp. RMSE Imp.% 0.074 42.17 0.066 47.85 0.068 46.61	Daily Non-cyclic RMSE Imp. 0.073 42.32 0.066 47.99 0.068 46.86	Cyclic % RMSE Imp. 2 0.103 19.4' 0 0.099 22.5' 5 0.098 23.1'	Non-temp. 6 RMSE Imp.% 0.157 -29.9 0.145 -19.7 0.149 -23.0	Hourly Non-cyclic RMSE Imp.% 0.114 5.76 0.113 6.76 0.112 7.63	Cyclic RMSE Imp.% 0.137 -13.1 0.133 -10.2 0.136 -12.4	Non-temp. RMSE Imp.% 0.098 19.36 0.096 20.68 0.089 26.82	Daily Non-cyclic RMSE Imp.% 0.090 25.91 0.088 27.02 0.087 28.29	Cyclic RMSE Imp.% 0.089 26.36 0.089 26.66 0.086 28.92
S1000 NoSpatia LatLon PCNM LISA A	RMSE Imp. 0.111 12.8 0.108 15.4 0.108 15.2 0.109 14.5	Hourl Non-cyc RMSE Im 5 0.110 13 5 0.107 16 7 0.108 15 9 0.109 14	lic p.% Rl .93 0. .11 0. .36 0. .77 0.	PVItaly Cyclic MSE Imp.% 133 -4.6 131 -3.0 130 -2.1 133 -4.3	Non-temp. RMSE Imp.% 0.074 42.17 0.066 47.85 0.068 46.61 0.071 44.17	Daily Non-cyclic RMSE Imp. 0.073 42.32 0.066 47.99 0.068 46.86 0.071 44.52	Cyclic % RMSE Imp. 2 0.103 19.4' 0 0.099 22.50 5 0.098 23.1' 2 0.102 19.8'	Non-temp. % RMSE Imp.% 0.157 -29.9 0.145 -19.7 0.149 -23.0 0.174 -43.3	Hourly Non-cyclic RMSE Imp.% 0.114 5.76 0.113 6.76 0.112 7.63 0.139 -14.4	Cyclic RMSE Imp.% 0.137 -13.1 0.133 -10.2 0.136 -12.4 0.168 -39.0	Dataset Non-temp. RMSE Imp.% 0.098 19.36 0.096 20.68 0.089 26.82 0.109 9.92	Daily Non-cyclic RMSE Imp.% 0.090 25.91 0.088 27.02 0.087 28.29 0.111 8.15	Cyclic RMSE Imp.% 0.089 26.36 0.089 26.66 0.086 28.92 0.112 7.41
S1000 NoSpatial LatLon PCNM LISA A LISA B	RMSE Imp. 0.111 12.8: 0.108 15.4: 0.108 15.2: 0.109 14.5: 0.105 17.5:	Hourl Non-cyc RMSE Im 5 0.110 13 5 0.107 16 7 0.108 15 0 0.109 14 4 0.104 18	Iic p.% RI .93 0. .11 0. .36 0. .77 0. .00 0.	PVItaly Cyclic MSE Imp.% 133 -4.6 131 -3.0 130 -2.1 133 -4.3 130 -2.0	Non-temp. RMSE Imp.% 0.074 42.17 0.066 47.85 0.068 46.61 0.071 44.17 0.063 50.36	Daily Non-cyclic RMSE Imp. 0.073 42.32 0.066 47.99 0.068 46.86 0.071 44.52 0.063 50.62	Cyclic % RMSE Imp. 2 0.103 19.4' 0 0.099 22.50 5 0.098 23.1' 2 0.102 19.8' 2 0.098 22.8' 2 0.098 22.8'	Non-temp. % RMSE Imp.% 0.157 - 29.9 0.145 - 19.7 0.145 - 19.7 0.149 - 23.0 0.174 - 43.3 0.160 - 32.3	Hourly Non-cyclic RMSE Imp.% 0.114 5.76 0.113 6.76 0.112 7.63 0.139 -14.4 0.116 4.34	Cyclic RMSE Imp.% 0.137 -13.1 0.133 -10.2 0.136 -12.4 0.168 -39.0 0.144 -19.0	Dataset Non-temp. RMSE Imp.% 0.098 19.36 0.096 20.68 0.089 26.82 0.109 9.92 0.093 23.26	Daily Non-cyclic RMSE Imp.% 0.090 25.91 0.088 27.02 0.087 28.29 0.111 8.15 0.090 25.51	Cyclic RMSE Imp.% 0.089 26.36 0.089 26.66 0.086 28.92 0.112 7.41 0.090 25.98
S1000 NoSpatial LatLon PCNM LISA A LISA B LISA C	RMSE Imp. 0.111 12.8: 0.108 15.4: 0.108 15.2: 0.109 14.5: 0.105 17.5: 0.105 17.7:	Hourly Non-cyc RMSE Im 5 0.110 13 5 0.107 16 7 0.108 15 0 0.109 14 4 0.104 18 3 0.104 17	Iic p.% Rl .93 0. .11 0. .36 0. .77 0. .00 0. .98 0.	PVItaly Cyclic MSE Imp.% 133 -4.6 131 -3.0 130 -2.1 133 -4.3 130 -2.0 132 -3.9	Non-temp. RMSE Imp.% 0.074 42.17 0.066 47.85 0.0071 44.17 0.063 50.36 0.064 49.94	Daily Non-cyclic RMSE Imp. 0.073 42.32 0.066 47.99 0.068 46.88 0.071 44.52 0.063 50.62	Cyclic % RMSE Imp. 2 0.103 19.4* 0 0.099 22.5* 5 0.098 23.1' 2 0.102 19.8* 2 0.102 19.8* 2 0.098 22.8* 2 0.101 20.7*	Non-temp. % RMSE Imp.% 0.157 -29.9 0.145 -19.7 0.149 -23.0 0.174 -43.3 0.160 -32.3 0.175 -44.7	Hourly Non-cyclic RMSE Imp.% 0.114 5.76 0.113 6.76 0.112 7.63 0.139 -14.4 0.116 4.34 0.138 -13.9	Cyclic RMSE Imp.% 0.137 -13.1 0.133 -10.2 0.168 -39.0 0.144 -19.0 0.157 -29.3	Non-temp. RMSE Imp.% 0.096 20.68 0.089 26.82 0.109 9.92 0.093 23.26 0.114 6.08	Daily Non-cyclic RMSE Imp.% 0.090 25.91 0.088 27.02 0.087 28.29 0.111 8.15 0.090 25.51 0.111 8.00	Cyclic RMSE Imp.% 0.089 26.36 0.089 26.66 0.086 28.92 0.112 7.41 0.090 25.98 0.111 8.08
S1000 NoSpatia LatLon PCNM LISA A LISA B LISA C S2000	RMSE Imp. 0.111 12.8: 0.108 15.4: 0.108 15.2: 0.109 14.59: 0.105 17.5: 0.105 17.7: RMSE Imp.	Hourly Non-cyc RMSE Im 5 0.110 13 5 0.107 16 7 0.108 15 9 0.109 14 4 0.104 18 3 0.104 17 % RMSE Im	lic p.% Rl .93 0. .11 0. .36 0. .77 0. .00 0. .98 0. p.% Rl	PVItaly Cyclic MSE Imp.% 133 -4.6 131 -3.0 130 -2.1 133 -4.3 130 -2.0 132 -3.9 MSE Imp.%	Non-temp. RMSE Imp.% 0.074 42.17 0.066 47.85 0.068 46.61 0.071 44.17 0.063 50.36 0.064 49.94 RMSE Imp.%	Daily Non-cyclic RMSE Imp. 0.073 42.32 0.066 47.99 0.068 46.88 0.071 44.52 0.063 50.62 0.063 50.22 RMSE Imp. Imp.	Cyclic RMSE Imp. 2 0.103 19.44 0 0.099 22.51 5 0.098 23.1' 2 0.102 19.8* 2 0.098 22.8* 0.101 20.76 % RMSE Imp. RMSE Imp.	Non-temp. RMSE Imp.% 0.157 -29.9 0.145 -19.7 0.149 -23.0 0.174 -43.3 0.160 -32.3 0.175 -44.7 % RMSE Imp.%	Hourly Non-cyclic RMSE Imp.% 0.114 5.76 0.113 6.76 0.112 7.63 0.139 -14.4 0.116 4.34 0.138 -13.9 RMSE Imp.%	Cyclic RMSE Imp.% 0.137 -13.1 0.133 -10.2 0.136 -12.4 0.168 -39.0 0.144 -19.0 0.157 -29.3 RMSE Imp.%	Dataset Non-temp. RMSE Imp.% 0.098 19.36 0.096 20.68 0.089 26.82 0.109 9.92 0.093 23.26 0.114 6.08 RMSE Imp.%	Daily Non-cyclic RMSE Imp.% 0.090 25.91 0.088 27.02 0.087 28.29 0.111 8.15 0.090 25.51 0.111 8.00 RMSE Imp.%	Cyclic RMSE Imp.% 0.089 26.36 0.086 28.92 0.112 7.41 0.090 25.98 0.111 8.08 RMSE Imp.% RMSE Imp.%
S1000 NoSpatial LatLon PCNM LISA A LISA B LISA C S2000 NoSpatia	RMSE Imp. 0.111 12.8: 0.108 15.4: 0.108 15.2: 0.109 14.5: 0.105 17.5: 0.105 17.7: RMSE Imp. 0.111 0.111 12.8:	Houri Non-cyc % RMSE Im 5 0.110 5 0.107 7 0.108 9 0.109 4 0.104 8 0.104 9 0.104 17 7 7 RMSE Im 3 0.104 17 7 7 RMSE Im 3 0.110 13 0.110	lic Rl p.% Rl .93 0. .11 0. .36 0. .77 0. .00 0. .98 0. p.% Rl .38 0.	PVItaly MSE Imp.% 133 -4.6 131 -3.0 130 -2.1 133 -4.3 130 -2.0 132 -3.9 MSE Imp.% MSE Imp.% 132 -3.5	Non-temp. RMSE Imp.% 0.074 42.17 0.066 47.85 0.068 46.61 0.071 44.17 0.063 50.36 0.064 49.94 RMSE Imp.% 0.075	Daily Non-cyclic RMSE Imp. 0.073 42.33 0.066 47.99 0.068 46.86 0.071 44.53 0.063 50.22 RMSE Imp. 0.0674 41.58	Cyclic % RMSE Imp. 2 0.103 19.4' 0 0.099 22.50 5 0.098 23.1' 2 0.102 19.8* 2 0.103 19.4' 0 0.098 23.1' 2 0.102 19.8* 2 0.010 20.7* % RMSE Imp. 0.103 18.8*	Non-temp. % RMSE Imp.% 0.157 -29.9 0.145 -19.7 0.149 -23.0 0.174 -43.3 0.160 -32.3 0.175 -44.7 % RMSE Imp.% 0.157 -29.9	Hourly Non-cyclic RMSE Imp.% 0.114 5.76 0.113 6.76 0.113 6.76 0.113 0.76 0.139 -14.4 0.138 -13.9 RMSE Imp.% 0.114 5.76	Cyclic RMSE Imp.% 0.137 - 13.1 0.133 -10.2 0.136 -12.4 0.168 -39.0 0.144 -19.0 0.157 -29.3 RMSE Imp.% 0.129 -6.7	Dataset Non-temp. RMSE Imp.% 0.098 0.098 0.098 0.098 20.68 0.099 23.26 0.114 0.08 RMSE Imp.% 0.093 23.26 0.114 0.08 19.36	Daily Non-cyclic RMSE Imp.% 0.090 25.91 0.088 27.02 0.087 28.29 0.111 8.15 0.090 25.51 0.111 8.00 RMSE Imp.% 0.090 0.090 25.91	Cyclic RMSE Imp.% 0.089 26.36 0.089 26.66 0.086 28.92 0.112 7.41 0.090 25.98 0.111 8.08 PRMSE Imp.% 0.088
S1000 NoSpatial LatLon PCNM LISA A LISA B LISA C S2000 NoSpatial LatLon	RMSE Imp. 0.111 12.8: 0.108 15.4: 0.109 14.5: 0.105 17.5: 0.105 17.7: RMSE Imp. 0.111 0.101 12.8: 0.107 15.60	Hourl Non-cyc % RMSE Im 5 0.110 13 5 0.107 16 7 0.108 15 9 0.109 14 4 0.104 17 5 0.104 17 6 0.104 13 6 0.104 13 5 0.107 15	lic Rl p.% Rl .93 0. .11 0. .36 0. .77 0. .00 0. .98 0. .98 0. .38 0. .58 0.	PVItaly Cyclic MSE Imp.% 133 -4.6 131 -3.0 130 -2.1 133 -4.3 130 -2.0 132 -3.9 MSE Imp.% 132 -3.5 129 -1.4	Non-temp. RMSE Imp.% 0.074 42.17 0.066 47.85 0.068 46.61 0.071 44.17 0.063 50.36 0.064 49.94 RMSE Imp.% 0.075 0.075 41.22 0.068 46.66	Daily Non-cyclic RMSE Imp. 0.073 42.32 0.066 47.99 0.068 46.80 0.071 44.52 0.063 50.62 0.063 50.62 50.22 RMSE Imp. 0.074 41.55 0.067 47.21	Cyclic RMSE Imp. 2 0.103 19.4' 0.009 22.5' 5 0.098 23.1' 2 0.102 19.8* 2 0.098 22.8* 2 0.101 20.7* 0.101 20.7* 8 8 0.103 18.8* 0.098 22.93* 1	Non-temp. 6 RMSE Imp.% 0.157 -29.9 0.145 -19.7 0.149 -23.0 0.174 -43.3 0.160 -32.3 0.175 -44.7 6 RMSE Imp.% 0.157 -29.9 0.157 -29.9 0.145 -19.7	Hourly Non-cyclic RMSE Imp.% 0.114 5.76 0.113 6.76 0.139 -14.4 0.138 -13.9 RMSE Imp.% 0.138 -13.9 RMSE Imp.% 0.113 5.76 0.114 5.76	Cyclic RMSE Imp.% 0.137 -13.1 0.133 -10.2 0.136 -12.4 0.168 -39.0 0.157 -29.3 RMSE Imp.% 0.129 -0.127 -4.5	Non-temp. RMSE Imp.% 0.098 19.36 0.098 20.68 0.099 26.82 0.109 9.92 0.093 23.26 0.114 6.08 RMSE Imp.% 0.098 0.098 19.36 0.098 19.36 0.098 20.68	Daily Non-cyclic RMSE Imp.% 0.090 25.91 0.088 27.02 0.087 28.29 0.111 8.15 0.0111 8.00 RMSE Imp.% 0.000 0.092 25.91 0.111 8.00 0.090 25.91 0.098 27.02	Cyclic RMSE Imp.% 0.089 26.36 0.089 26.66 0.086 28.92 0.112 7.41 0.090 25.98 0.111 8.08 RMSE Imp.% 0.088 0.088 27.11 0.087 28.08
S1000 NoSpatial LatLon PCNM LISA A LISA C S2000 NoSpatial LatLon PCNM	RMSE Imp. 0.111 12.8: 0.108 15.4: 0.108 15.2: 0.109 14.5: 0.105 17.5: 0.105 17.7: RMSE Imp. 0.111 0.107 15.6: 0.108 15.2:	Hourt Non-cyc % RMSE Im 0 1010 13 5 0.110 13 5 0.107 16 7 0.108 15 9 0.109 14 4 0.104 17 % RMSE Im 3 5 0.1010 13 5 0.107 15 9 0.108 15	Iic p.% Rl .93 0. .11 0. .36 0. .77 0. .00 0. .98 0. .98 0. .58 0. .14 0.	PVItaly Cyclic MSE Imp.% 133 -4.6 131 -3.0 130 -2.1 133 -4.3 130 -2.0 132 -3.9 MSE Imp.% 132 -3.5 129 -1.4 129 -1.2	Non-temp. RMSE Imp.% 0.074 42.17 0.066 47.85 0.068 46.61 0.071 44.17 0.063 50.36 0.064 49.94 RMSE Imp.% 0.075	Daily Non-cyclic RMSE Imp. 0.073 42.33 0.066 47.99 0.068 46.86 0.071 44.53 0.063 50.22 RMSE Imp. 0.0674 41.58	Cyclic % RMSE Imp. 2 0.103 19.4' 0 0.099 22.5' 5 0.098 23.1' 2 0.102 19.8' 2 0.101 20.7' % RMSE Imp. 2 0.101 20.7' % RMSE Imp. 8 0.103 18.8' 1 0.098 22.9' 1 0.098 23.2'	Non-temp. 6 RMSE Imp.% 0.157 -29.9 0.145 -19.7 0.149 -23.0 0.174 -43.3 0.160 -32.3 0.175 -44.7 6 RMSE Imp.% 0.157 -29.9 0.157 -29.9 0.145 -19.7	Hourly Non-cyclic RMSE Imp.% 0.114 5.76 0.113 6.76 0.113 6.76 0.113 0.76 0.139 -14.4 0.138 -13.9 RMSE Imp.% 0.114 5.76	Cyclic RMSE Imp.% 0.137 -13.1 0.133 -10.2 0.136 -12.4 0.168 0.157 -29.3 RMSE Imp.% 0.129 -6.7 0.127 -5.2	Dataset RMSE Imp.% 0.098 19.36 0.096 20.68 0.097 23.26 0.114 6.08 RMSE Imp.% 0.098 0.098 19.36 0.019 9.92 0.114 6.08 0.098 19.36 0.098 19.36 0.098 19.36 0.098 20.68 0.096 20.68 0.096 20.68 0.098 26.82	Daily Non-cyclic RMSE Imp.% 0.090 25.91 0.082 27.02 0.087 28.29 0.111 8.15 0.0111 8.00 0.111 8.00 0.111 8.00 0.090 25.91 0.090 25.91 0.090 25.91 0.088 27.02 0.087 28.29	Cyclic RMSE Imp.% 0.089 26.36 0.089 26.66 0.086 28.92 0.112 7.41 0.090 25.98 0.111 8.08 PRMSE Imp.% 0.088
S1000 NoSpatial LatLon PCNM LISA A LISA B LISA C S2000 NoSpatial LatLon PCNM LISA A	RMSE Imp. 0.111 12.8: 0.108 15.4: 0.108 15.2: 0.109 14.5: 0.105 17.5: 0.105 17.7: RMSE Imp. 0.111 0.107 15.6: 0.108 15.2:	Hourt Non-cyc % RMSE Im 5 0.100 7 0.108 15 0.109 14 0.104 18 0.104 3 0.1010 3 0.104 3 0.1010 3 0.1010 3 0.1010 3 0.1010 3 0.1010 3 0.1010 3 0.102 15 0.104 16 0.104 17 15 0.108 14	Iic p.% Rl .93 0. .11 0. .36 0. .77 0. .00 0. .98 0. .98 0. .58 0. .14 0. .12 0.	PVItaly Cyclic MSE Imp.% 133 -4.6 131 -3.0 130 -2.1 133 -4.3 130 -2.0 132 -3.9 MSE Imp.% 132 -3.5 129 -1.4 129 -1.2 131 -2.6	Non-temp. RMSE Imp.% 0.074 42.17 0.066 47.85 0.068 46.61 0.071 44.17 0.063 50.36 0.064 49.94 RMSE Imp.% 0.075 0.075 41.22 0.068 46.66 0.070 45.32	Daily Non-cyclic RMSE Imp. 0.073 42.32 0.066 47.99 0.068 46.80 0.071 44.52 0.063 50.62 0.063 50.22 7 RMSE Imp. 0.074 41.55 0.067 47.21 0.067 47.22 0.069 46.00	Cyclic % RMSE Imp. 0 0.103 19.4* 0 0.099 22.5* 5 0.098 23.1' 2 0.102 19.8* 2 0.102 19.8* 2 0.101 20.70 % RMSE Imp. 3 3 0.103 18.8* 1 0.098 22.9* 0.0098 23.2' 2 0.103 19.4*	Non-temp. 6 RMSE Imp.% 0.157 -29.9 0.145 -19.7 0.149 -23.0 0.174 -43.3 0.160 -32.3 0.175 -44.7 % RMSE Imp.% % RMSE Imp.% 0.157 -29.9 0.145 -19.7 0.157 -29.9 0.157 -29.9 0.157 -29.9 0.145 -19.7 0.149 -23.0 0.182 -49.9	Hourly Non-cyclic RMSE Imp.% 0.114 5.76 0.112 7.63 0.139 -14.4 0.138 -13.9 RMSE Imp.% 0.114 0.118 6.76 0.127 7.63 0.138 -13.9 RMSE Imp.% 0.114 0.112 7.63	Cyclic RMSE Imp.% 0.137 -13.1 0.133 -10.2 0.136 -12.4 0.168 -39.0 0.157 -29.3 RMSE Imp.% 0.129 -0.127 -4.5	Non-temp. RMSE Imp.% 0.098 19.36 0.096 20.68 0.109 9.92 0.093 23.26 0.114 6.08 RMSE Imp.% 0.098 0.098 19.36 0.093 23.26 0.114 6.08 0.098 19.36 0.098 19.36 0.098 20.68 0.096 20.68 0.098 26.82 0.112 7.36	Daily Non-cyclic RMSE Imp.% 0.090 25.91 0.082 27.02 0.087 28.29 0.111 8.15 0.0111 8.00 0.111 8.00 0.111 8.00 0.090 25.91 0.090 25.91 0.090 25.91 0.088 27.02 0.087 28.29	Cyclic RMSE Imp.% 0.089 26.36 0.089 26.66 0.086 28.92 0.112 7.41 0.090 25.98 0.111 8.08 PRMSE Imp.% 0.088 0.088 27.11 0.087 28.08 0.085 29.90
S1000 NoSpatia LatLon PCNM LISA A LISA B LISA C S2000 NoSpatia LatLon PCNM LISA A LISA B	RMSE Imp. 0.111 12.8: 0.108 15.4: 0.108 15.2: 0.109 14.5: 0.105 17.5: 0.105 17.7: RMSE Imp. 0.111 0.111 12.8: 0.107 15.6: 0.108 15.2' 0.108 15.2'	Hourl Non-cyc % RMSE In 5 0.107 16 7 0.108 15 0.107 16 10 5 0.107 16 7 0.108 15 0.109 14 0.104 18 0.104 18 0.104 13 5 0.107 15 0.108 15 0.108 15 0.108 15 0.108 15 0 0.105 17 0.105 17	Iic p.% RI .93 0. .11 0. .36 0. .77 0. .00 0. .98 0. p.% RI .38 0. .58 0. .14 0. .12 0. .88 0.	PVItaly Cyclic MSE Imp.% 133 -4.6 131 -3.0 130 -2.1 133 -4.3 130 -2.0 132 -3.9 MSE Imp.% 132 -3.5 129 -1.4 129 -1.2 131 -2.6 134 -5.1	Non-temp. RMSE Imp.% 0.074 42.17 0.066 47.85 0.068 46.61 0.071 44.17 0.063 50.36 0.064 49.94 RMSE Imp.% 0.075 41.22 0.068 46.62 0.076 45.32 0.072 43.42	Daily Non-cyclic RMSE Imp. 0.073 42.33 0.066 47.99 0.068 46.88 0.071 44.53 0.063 50.62 PMSE Imp. 0.067 47.21 0.067 47.22 0.067 47.21 0.063 50.19	Cyclic % RMSE Imp. 0 0.103 19.4* 0 0.099 22.5* 5 0.098 23.1' 2 0.102 19.8* 2 0.102 19.8* 2 0.101 20.70 % RMSE Imp. 3 3 0.103 18.8* 0.098 22.9* 0.003 0.098 23.2' 2 0.103 19.4*	Non-temp. % RMSE Imp.% 0.157 -29.9 0.145 -19.7 0.145 -19.7 0.149 -23.0 0.174 -43.3 0.160 -32.3 0.175 -44.7 % RMSE Imp.% 0.157 -29.9 0.145 -19.7 0.145 -19.7 0.157 -29.9 0.145 -19.7 0.145 -19.7 0.148 -19.7 0.148 -23.0 0.160 -32.3	Hourly Non-cyclic RMSE Imp.% 0.114 5.76 0.112 7.63 0.139 -14.4 0.16 4.34 0.138 -13.9 RMSE Imp.% 0.114 5.76 0.113 6.76 0.113 6.76 0.113 6.76 0.113 9.763	Cyclic RMSE Imp.% 0.137 -13.1 0.133 -10.2 0.136 -12.4 0.168 -39.0 0.157 -29.3 RMSE Imp.% 0.127 0.127 -4.5 0.127 -5.2 0.158 -30.6	Non-temp. RMSE Imp.% 0.098 19.36 0.096 20.68 0.109 9.92 0.093 23.26 0.114 6.08 RMSE Imp.% 0.098 0.098 19.36 0.093 23.26 0.114 6.08 0.098 19.36 0.098 19.36 0.098 20.68 0.096 20.68 0.098 26.82 0.112 7.36	Daily Non-cyclic RMSE Imp.% 0.090 25.91 0.082 27.02 0.087 28.29 0.111 8.15 0.090 25.51 0.111 8.00 RMSE Imp.% 0.098 27.02 0.087 28.29 0.111 8.15	Cyclic RMSE Imp.% 0.089 26.36 0.089 26.66 0.080 28.92 0.112 7.41 0.090 25.98 0.111 8.08 PRMSE Imp.% 0.088 0.088 27.11 0.085 29.90 0.0104 14.18
S1000 NoSpatia LatLon PCNM LISA A LISA B LISA C S2000 NoSpatia LatLon PCNM LISA A LISA A LISA C	RMSE Imp. 0.111 12.8: 0.108 15.4: 0.108 15.4: 0.109 14.5: 0.105 17.5: 0.105 17.7: RMSE Imp. 0.111 0.111 12.8: 0.107 15.6: 0.108 15.2: 0.105 17.6:	Hourl: Non-cyc % RMSE In 5 0.110 13 5 0.107 16 7 0.108 15 0.1017 16 17 8 0.104 18 0.104 18 0.104 3 0.110 13 5 0.107 15 0 0.108 15 0 0.108 15 0 0.108 15 0 0.108 15 0 0.108 15 0 0.108 15 0 0.108 15 0 0.108 15 0 0.105 17 5 0.105 17	Iic p.% Rl .93 0. .11 0. .36 0. .77 0. .00 0. .98 0. p.% Rl .38 .38 0. .58 0. .14 0. .12 0. .88 0. .31 0.	PVItaly Cyclic MSE Imp.% 133 -4.6 131 -3.0 130 -2.1 133 -4.3 130 -2.0 132 -3.9 MSE Imp.% 132 132 -3.5 129 -1.2 131 -2.6 134 -5.1 130 -1.8	Dataset Non-temp. RMSE Imp.% 0.074 42.17 0.066 47.85 0.063 50.36 0.064 49.94 RMSE Imp.% 0.075 0.064 49.94 RMSE Imp.% 0.075 0.064 49.94 RMSE Imp.% 0.075 0.072 43.42 0.064 49.76 0.072 43.42 0.064 49.61	Daily Non-cyclic RMSE Imp. 0.073 42.33 0.066 47.99 0.068 46.88 0.071 44.52 0.063 50.62 RMSE Imp. 0.067 47.21 0.067 47.21 0.063 50.19 0.063 50.19 0.063 50.19	Cyclic % RMSE Imp. 0 0.03 10 0.099 2 0.103 10 0.099 2 0.102 2 0.0102 2 0.0102 2 0.098 2 0.098 2 0.0103 0.0098 22.99 0 0.098 0 0.098 2 0.103 0 0.098 2 0.103 0 0.98 2 0.103 0 0.98 2 0.103 2 0.103 2 0.103 2 0.103 2 0.109 14.50	Non-temp. RMSE Imp.% 0.157 -29.9 0.145 -19.7 0.149 -23.0 0.174 -43.3 0.160 -32.3 0.175 -44.7 % RMSE Imp.% 0.157 -29.9 0.145 -19.7 0.157 -29.9 0.145 -19.7 0.145 -19.7 0.145 -19.7 0.145 -23.0 0.157 -29.9 0.145 -19.7 0.145 -19.7 0.182 -49.9 0.160 -32.3 0.175 -44.7	Hourly Non-cyclic RMSE Imp.% 0.114 5.76 0.113 6.76 0.112 7.63 0.113 6.76 0.114 5.76 0.113 6.76 0.114 5.76 0.114 5.76 0.112 7.63 0.120 7.63 0.139 -14.4 0.116 4.34 0.138 -13.9	NREL Cyclic RMSE Imp.% 0.137 - 13.1 0.133 -10.2 0.136 -12.4 0.168 -39.0 0.144 -19.0 0.157 -29.3 RMSE Imp.% 0.129 -6.7 0.127 -4.5 0.127 -5.2 0.158 -30.6 0.116 4.34	Dataset Non-temp. RMSE Imp.% 0.098 19.36 0.096 20.68 0.090 20.68 0.090 20.68 0.090 23.26 0.114 6.08 RMSE Imp.% 0.098 0.098 19.36 0.099 26.82 0.0112 7.36 0.0112 7.36 0.0114 5.88	Daily Non-cyclic RMSE Imp.% 0.090 25.91 0.088 27.02 0.087 28.29 0.111 8.15 0.090 25.51 0.111 8.00 RMSE Imp.% 0.090 0.090 25.91 0.087 28.29 0.087 28.29 0.111 8.15 0.090 25.51 0.111 8.01	Cyclic RMSE Imp.% 0.089 26.36 0.080 28.92 0.112 7.41 0.090 25.98 0.111 8.08 RMSE Imp.% 0.085 0.085 27.11 0.087 28.08 0.104 14.18 0.090 25.51 0.111 8.08
S1000 NoSpatia LatLon PCNM LISA A LISA B LISA C S2000 NoSpatia LatLon PCNM LISA A LISA B LISA C S4000	RMSE Imp. 0.111 12.8: 0.108 15.4: 0.109 14.5: 0.105 17.5: 0.105 17.7: RMSE Imp. 0.111 0.108 15.2: 0.107 17.6: 0.108 15.2: 0.108 15.2: 0.108 15.2: 0.105 17.6: 0.105 17.6: 0.105 17.6:	Hourl Non-cyc % RMSE In 0 107 16 0 107 16 0 107 16 0 107 16 0 104 18 0 104 18 0 104 13 0 0.107 15 0 0.108 15 0 108 15 0 0.108 15 0 0.108 15 0 0.108 15 0 108 15 0 0.108 15 0 0.105 17 % RMSE In % RMSE In	lic Rl .93 0. .93 0. .11 0. .36 0. .77 0. .00 0. .98 0. .98 0. .98 0. .11 0. .38 0. .12 0. .88 0. .31 0. .31 0.	PVItaly Cyclic MSE Imp.% 133 -4.6 131 -3.0 130 -2.1 133 -4.3 130 -2.0 132 -3.9 MSE Imp.% 132 -3.5 129 -1.4 129 -1.2 131 -2.6 134 -5.1 130 -1.8 MSE Imp.% MSE Imp.%	Non-temp. RMSE Imp.% 0.074 42.17 0.066 47.85 0.068 46.61 0.071 44.17 0.063 50.36 0.064 49.94 RMSE Imp.% 0.075 0.072 41.22 0.068 46.66 0.070 45.32 0.064 49.61 RMSE Imp.% 0.064 0.064 49.61 RMSE Imp.% 0.064	Daily Non-cyclic RMSE Imp. 0.073 42.33 0.066 47.99 0.068 46.88 0.071 44.52 0.063 50.62 RMSE Imp. 0.067 47.21 0.067 47.21 0.063 50.19 0.063 50.19 0.063 50.19	Cyclic % RMSE Imp. 0.103 19.4' 0.099 22.50 5 0.098 23.1' 2 0.102 19.8% 2 0.103 18.4' 0.098 22.8' 2 0.103 18.8' 0.098 22.9' 0 0.098 23.2' 0.0098 23.2' 0 0.098 23.2' 0 0.098 23.2' 0 0.103 19.4' 0 0.103 19.4' 0 0.104 14.5' 8 0.101 20.8' % RMSE Imp.	Non-temp. 6 RMSE Imp.% 0.157 -29.9 0.145 -19.7 0.145 -19.7 0.140 -23.0 0.174 -43.3 0.160 -32.3 0.175 -44.7 7 RMSE Imp.% 0.157 -29.9 0.145 -19.7 0.182 -49.9 0.160 -32.3 0.175 -44.7 % RMSE Imp.%	Hourly Non-cyclic RMSE Imp.% 0.114 5.76 0.113 6.76 0.113 - 1.4.4 0.116 4.34 0.113 6.76 0.113 6.76 0.114 5.76 0.113 6.76 0.114 5.76 0.113 6.76 0.114 5.76 0.113 6.76 0.114 5.76 0.138 -13.9 RMSE Imp.% 0.184 5.76	NREL Cyclic RMSE Imp.% 0.137 -13.1 0.133 -10.2 0.136 -12.4 0.168 -39.0 0.144 -19.0 0.157 -29.3 RMSE Imp.% 0.129 -6.7 0.127 -4.5 0.127 -5.2 0.158 -30.6 0.116 4.34 0.157 -29.3	Dataset Non-temp. RMSE Imp.% 0.098 19.36 0.096 20.68 0.099 26.82 0.099 23.26 0.114 6.08 RMSE Imp.% 0.093 0.093 23.26 0.094 20.68 0.095 26.82 0.096 26.82 0.0112 7.36 0.012 7.36 0.114 5.88	Daily Non-cyclic RMSE Imp.% 0.090 25.91 0.088 27.02 0.087 28.29 0.111 8.15 0.090 25.51 0.111 8.00 RMSE Imp.% 0.090 0.090 25.91 0.087 28.29 0.087 28.29 0.111 8.15 0.090 25.51 0.111 8.01	Cyclic RMSE Imp.% 0.089 26.36 0.089 26.66 0.086 28.92 0.112 7.41 0.090 25.98 0.111 8.08 RMSE Imp.% 0.085 29.90 0.104 14.18 0.090 25.51 0.111 8.08 RMSE Imp.% 0.885 29.90 0.104 14.18 0.090 25.51 0.111 8.08
S1000 NoSpatial LatLon PCNM LISA A LISA C S000 NoSpatial LatLon PCNM LISA A LISA A LISA C S4000 NoSpatial LatLon	RMSE Imp. 0.111 12.8: 0.108 15.4: 0.109 14.5: 0.105 17.5: 0.105 17.7: RMSE Imp. 0.101 0.107 15.6: 0.108 15.2: 0.108 15.2: 0.108 15.2: 0.108 15.1: 0.108 15.1: 0.105 17.6: 0.108 15.1: 0.105 17.6: 0.108 15.1: 0.105 17.6: 0.105 17.6: 0.105 17.6: 0.105 17.6: 0.105 17.2: 0.105 17.2: 0.105 15.3:	Hourt Non-cyc % RMSE Im 5 0.107 16 7 0.108 15 0 0.107 16 7 0.109 14 4 0.104 17 5 0.104 17 6 0.104 13 5 0.104 15 0 0.104 15 0 0.108 15 0 0.105 17 6 0.105 17 6 0.105 17 6 0.105 17 6 0.106 13 6 0.105 17 6 0.107 15 0 0.101 13 6 0.107 15	lic pp.% Rl .93 0. .11 0. .36 0. .77 0. .00 0. .93 0. .77 0. .00 0. .98 0. .14 0. .12 0. .88 0. .31 0. .31 0. .357 0. .70 0.	PVItaly Cyclic MSE Imp.% 133 -4.6 131 -3.0 130 -2.1 133 -4.3 130 -2.0 132 -3.9 MSE Imp.% 132 -3.5 129 -1.4 129 -1.2 131 -2.6 134 -5.1 130 -2.4 130 -2.4 128 -0.9	Non-temp. RMSE Imp.% 0.074 42.17 0.066 47.85 0.068 46.61 0.071 44.17 0.064 49.94 0.075 41.22 0.068 46.66 0.070 45.32 0.072 43.42 0.064 49.76 RMSE Imp.% 0.064 0.072 43.42 0.064 49.61 RMSE Imp.% 0.064 0.064 49.61 RMSE Imp.% 0.064 0.064 49.61 RMSE Imp.% 0.076 0.068 46.37	Daily Daily Non-cyclic RMSE Imp. 0.064 47.99 0.068 46.80 0.071 44.52 0.063 50.62 0.063 50.22 0.063 50.22 0.064 41.55 0.067 47.21 0.069 46.00 0.072 43.77 0.063 50.12 0.064 49.55 RMSE Imp. 0.075 0.075 40.92 0.058 46.60	Cyclic	Non-temp. RMSE Imp.% RMSE Imp.% 0.157 -29.9 0.145 -19.7 0.149 -23.0 0.174 -43.3 0.160 -32.3 0.160 -32.3 0.175 -44.7 % RMSE Imp.% 0.157 -29.9 0.145 -19.7 0.182 -49.9 0.160 -32.3 0.175 -44.7 % RMSE Imp.% 0.160 -32.3 0.175 -44.7 % RMSE Imp.% 0.157 -29.9 0.160 -32.3 0.175 -44.7 % RMSE Imp.% 0.157 -29.9 0.160 -32.3 0.157 -29.9 0.157 -29.9 0.145 -19.7	Hourly Non-cyclic RMSE Imp.% 0.114 5.76 0.139 0.139 -14.4 0.138 0.139 -14.4 0.138 0.139 -14.4 0.138 0.139 -14.4 0.139 0.139 0.114 5.76 0.113 6.76 0.112 7.63 0.139 -14.4 0.113 6.76 0.113 0.138 0.138 -13.9 RMSE Imp.% 0.114 0.113 0.76	Cyclic RMSE Imp.% 0.137 -13.1 0.133 -10.2 0.136 -12.4 0.168 0.177 -29.3 RMSE Imp.% 0.127 -4.5 0.127 0.127 -5.2 0.158 0.157 -29.3 RMSE Imp.% 0.122 0.6 0.121 0.34	Non-temp. RMSE Imp.% 0.098 19.36 0.098 26.82 0.109 9.92 0.093 23.26 0.114 6.08 RMSE Imp.% 0.098 0.098 19.36 0.098 26.82 0.114 6.08 0.098 26.82 0.112 7.36 0.033 23.26 0.114 5.88 RMSE Imp.% 0.098 0.114 5.88 RMSE Imp.% 0.098 0.098 19.36 0.098 19.36 0.098 19.36 0.098 20.68	Daily Non-cyclic RMSE Imp.% 0.090 25.91 0.082 27.02 0.087 28.29 0.111 8.15 0.090 25.51 0.111 8.00 RMSE Imp.% 0.090 0.090 25.91 0.088 27.02 0.087 28.29 0.111 8.15 0.090 25.91 0.111 8.15 0.111 8.15 0.111 8.01 RMSE Imp.% 0.090 0.092 25.91 0.092 25.91 0.092 25.91 0.092 25.91 0.092 25.91 0.092 25.91 0.094 25.91 0.098 27.02	Cyclic RMSE Imp.% 0.089 26.36 0.089 26.66 0.080 28.92 0.112 7.41 0.090 25.98 0.111 8.08 PRMSE Imp.% 0.088 0.085 29.90 0.104 14.18 0.090 25.51 0.111 8.08 PRMSE Imp.% 0.088 0.88 27.11 0.090 25.51 0.111 8.08 PRMSE Imp.% 0.088 0.088 27.29 0.087 28.25
S1000 NoSpatial LatLon PCNM LISA A LISA C S2000 NoSpatial LatLon PCNM LISA A LISA A LISA C S4000 NoSpatial LatLon PCNM	RMSE Imp. 0.111 12.8: 0.108 15.4: 0.109 14.5: 0.105 17.5: 0.105 17.5: 0.105 17.7: RMSE Imp. 0.111 0.107 15.6: 0.108 15.2: 0.108 15.2: 0.108 15.2: 0.108 15.2: 0.108 15.2: 0.111 12.8: 0.111 12.8: 0.108 15.2: 0.111 12.8: 0.111 12.3:	Hourt: Non-cyc RMSE In 5 0.110 5 0.107 6 0.107 7 0.108 8 0.104 8 0.104 8 0.104 8 0.104 9 0.108 9 0.104 10 0.104 10 0.104 10 0.104 10 0.104 10 0.104 10 0.104 10 0.104 10 0.104 10 0.104 13 0.104 13 0.107 16 0.105 17 0.105 17 0.105 18 0.110 10 0.110 10 0.107 15 0.108	Iic p.% RI .93 0. .11 0. .36 0. .77 0. .000 0. .98 0. .98 0. .98 0. .38 0. .58 0. .12 0. .88 0. .31 0. .57 0. .70 0. .20 0.	PVItaly MSE Imp.% 133 -4.6 131 -3.0 130 -2.1 133 -4.3 130 -2.0 132 -3.9 MSE Imp.% 132 131 -2.0 132 -3.5 129 -1.4 130 -2.6 134 -5.1 130 -1.8 MSE Imp.% 130 131 -2.6 134 -5.1 130 -1.8 MSE Imp.% 130 130 -2.4 128 -0.9 129 -1.2	Dataset Non-temp. RMSE Imp.% 0.074 42.17 0.066 47.85 0.068 46.61 0.071 44.17 0.063 50.36 0.064 49.94 RMSE Imp.% 0.075 0.075 41.22 0.064 49.94 RMSE Imp.% 0.075 0.072 43.42 0.064 49.76 0.072 43.42 0.064 49.61 RMSE Imp.% 0.076 0.064 49.61 RMSE Imp.% 0.064 0.064 45.01	Daily Non-cyclic RMSE Imp. 0.073 42.33 0.066 47.99 0.068 46.82 0.071 44.53 0.063 50.62 0.063 50.62 2 RMSE Imp. 0.067 47.21 0.0663 50.19 46.00 0.063 50.19 40.005 0.063 50.19 40.005 0.063 50.19 0.005 0.063 50.19 0.005 0.063 40.49.55 50.825 RMSE Imp. 0.005 40.92 0.068 46.66 0.069 45.42	Cyclic % RMSE Imp. 0 0.03 10 0.099 2 0.103 10 0.099 2 0.102 10 0.098 2 0.102 2 0.098 2 0.0102 2 0.098 2 0.0103 10 0.0098 2 0.103 18.86 0.0098 0 0.098 2 0.103 19.4 0.109 4.50 0.101 2 0.101 2 0.101 2 0.101 2 0.101 2 0.101 2 0.101 2 0.0095 2 0.0095 0 0.025 0 0.025 0.025 25.2'	Non-temp. RMSE Imp.% RMSE Imp.% 0.157 -29.9 0.145 -19.7 0.145 -23.0 0.174 -43.3 0.160 -32.3 0.175 -44.7 RMSE Imp.% 0.157 -29.9 0.145 -19.7 0.145 -19.7 0.145 -23.0 0.157 -29.9 0.145 -19.7 0.182 -49.9 0.160 -32.3 0.175 -44.7 RMSE Imp.% 0.157 -29.9 0.160 -32.3 0.175 -44.7 RMSE Imp.% 0.157 -29.9 0.145 -19.7 0.145 -19.7 0.145 -19.7 0.145 -19.7 0.149 -23.0	Hourly Non-cyclic RMSE Imp.% 0.114 5.76 0.113 6.76 0.112 7.63 0.113 6.76 0.114 5.76 0.113 6.76 0.114 5.76 0.113 6.76 0.114 5.76 0.112 7.63 0.139 -14.4 0.138 -13.9 RMSE Imp.% 0.114 0.138 -13.9 RMSE Imp.% 0.114 0.138 -13.9 RMSE Imp.% 0.114 0.138 -13.9	NREL Cyclic RMSE Imp.% 0.137 -13.1 0.133 -10.2 0.136 -12.4 0.168 -39.0 0.144 -19.0 0.157 -29.3 RMSE Imp.% 0.129 -6.7 0.127 -4.5 0.127 -5.2 0.158 -30.6 0.116 4.34 0.157 -29.3 RMSE Imp.% 0.122 -0.6 0.121 0.34 0.191 1.46	Dataset Non-temp. RMSE Imp.% 0.098 19.36 0.096 20.68 0.109 20.68 0.109 20.68 0.109 9.92 0.003 23.26 0.114 6.08 RMSE Imp.% 0.098 0.089 26.82 0.112 7.36 0.093 23.26 0.112 7.36 0.093 23.26 0.114 5.88 RMSE Imp.% 0.098 0.098 19.36 0.098 19.36 0.098 19.36 0.098 19.36 0.098 19.36 0.098 20.68 0.098 20.68	Daily Non-cyclic RMSE Imp.% 0.090 25.91 0.088 27.02 0.011 8.15 0.090 25.91 0.090 25.91 0.090 25.91 0.090 25.91 0.087 28.29 0.111 8.15 0.090 25.51 0.111 8.01 RMSE Imp.% 0.090 0.090 25.51 0.111 8.01 RMSE Imp.% 0.090 0.090 25.91 0.090 25.91 0.090 25.91 0.090 25.91 0.090 25.91 0.088 27.02 0.088 27.02 0.087 28.29	Cyclic RMSE Imp.% 0.089 26.36 0.080 28.92 0.112 7.41 0.090 25.98 0.111 8.08 RMSE Imp.% 0.088 0.080 27.11 0.087 28.08 0.085 29.90 0.104 14.18 0.090 25.51 0.111 8.08 RMSE Imp.% 0.088 0.084 27.99 0.104 14.18 0.090 25.51 0.111 8.08 RMSE Imp.% 0.088 0.085 29.90 0.087 28.25 0.087 28.25 0.085 29.73
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S1000 NoSpatial LatLon PCNM LISA A LISA C S2000 NoSpatial LatLon PCNM LISA A LISA C S4000 NoSpatial LatLon PCNM LISA A LISA A LISA B LISA C	RMSE Imp. 0.111 12.8: 0.108 15.4: 0.109 14.5: 0.105 17.5: 0.105 17.7: RMSE Imp. 0.111 0.107 15.6: 0.108 15.2' 0.108 15.2' 0.108 15.2' 0.108 15.1' 0.108 15.1' 0.105 17.6' 0.108 15.2' 0.108 15.3' 0.108 15.2' 0.108 15.2' 0.108 15.2' 0.108 15.2' 0.108 15.2' 0.108 15.2' 0.108 15.2' 0.108 15.2' 0.108 15.2' 0.108 15.2' 0.108 15.2' 0.109 14.4' 0.112 11.9' 0.105 17.5' RMSE Imp. 1.5'	Hourt: Non-cyc % RMSE In 0 0.107 16 7 0.108 15 0 0.107 16 7 0.108 15 0 0.104 18 8 0.104 17 % RMSE In 3 3 0.107 15 0 0.108 15 7 0.108 15 0 0.105 17 5 0.105 17 5 0.108 15 6 0.107 15 0 0.105 17 5 0.108 15 6 0.107 15 6 0.108 15 7 0.108 15 6 0.109 14 8 0.112 12 8 0.104 17 % RMSE In 7	y lic p.% RI p.30 0. 11 0. .36 0. 77 0. .000 0. 0. 99 .011 0. 0. 0. .000 0. 0. 0. .000 0. 0. 0. .000 0. 0. 0. .000 0. 0. 0. .0112 0. 0. 0. .0112 0. 0. 0. .0112 0. 0. 0. .0112 0. 0. 0. .020 0. 0. 0. .020 0. 0. 0. .027 0. 0. 0. .027 0. 0. 0. .027 0. 0. 0. .027 0. 0. 0.	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PVItaly Cyclic MSE Imp.% 133 -4.6 131 -3.0 130 -2.1 133 -4.3 130 -2.0 132 -3.9 MSE Imp.% 132 -3.5 129 -1.4 129 -1.2 131 -2.6 134 -5.1 130 -2.4 128 -0.9 129 -1.2 129 -1.4 130 -2.4 130 -2.4 130 -2.4 130 -1.8 MSE Imp.% 130 -2.4 130 -1.8 MSE Imp.% 130 -2.4 130 -3.8 MSE Imp.% 130 -3.8 MSE Imp.% 136 -7.2 138 -8.6 MSE Imp.% MSE Imp.% 120 -6.05	Non-temp. 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S1000 NoSpatial LatLon PCNM LISA A LISA C S2000 NoSpatial LatLon PCNM LISA A LISA A LISA C S4000 NoSpatial LatLon PCNM LISA A LISA A LISA A LISA C LISA C	RMSE Imp. 0.111 12.8: 0.108 15.4: 0.109 14.5: 0.105 17.5: 0.105 17.5: 0.105 17.5: 0.105 17.7: RMSE Imp. 0.101 0.107 15.6: 0.108 15.2: 0.108 15.2: 0.108 15.2: 0.108 15.2: 0.108 15.2: 0.108 15.2: 0.108 15.2: 0.109 14.4: 0.108 15.2: 0.109 14.4: 0.110 17.5: RMSE Imp. 0.102 0.105 17.5: RMSE Imp. 0.105 0.105 17.5: RMSE Imp. 0.101 0.102 13.7: 0.106 16.8:	Hourt: Non-cyc © Non-cyc % RMSE In 5 0.107 16 7 0.108 15 0.107 16 7 0.108 15 0.109 14 0.104 18 8 0.104 18 0.104 18 0 0.104 18 0.104 18 5 0.104 15 0.107 15 0 0.108 15 0.107 15 0 0.105 17 5 0.105 17 5 0.105 17 5 0.108 15 0 0.105 17 5 0.108 15 0 0.108 15 0.108 15 0.108 15 0 0.108 15 0.108 15 0.108 15 5 0.108 15 0.108 15 0.108	y lic p.% p.93 0. .11 0. .36 0. .77 0. .98 0. .98 0. .98 0. .98 0. .11 10. .98 0. .98 0. .112 0. .88 0. .31 0. .97 0. .20 0. .39 0. .20 0. .39 0. .20 0. .39 0. .20 0. .39 0. .20 0. .39 0. .27 0. .97 0. .85 0.	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PCNM method outperforms all other spatial configurations (significantly outperforming NoSpat. and LISA). The LISA method is not able to even outperform the simple LatLon configuration. This means that modeling autocorrelation by considering the spatial structure of the data (as PCNM does) is, in the application at hand, much more important than directly considering auto-regressive information (as LISA does). Finally, what is clear from the results is that considering spatial

autocorrelation (in any form) is generally beneficial (LatLon, LISA and PCNM outperform NoSpat.).

2) Temporal: By analyzing the contribution of temporal autocorrelation, we can see that results are not uniform in the sense that there is no single temporal configuration which outperforms the others over the two learning settings, the two learning algorithms, and the two datasets. However, the statistical tests show that the two configurations which exploit

TABLE V

p-values of the signed Wilcoxon rank tests for different dimensions of analysis. In bold statistically significant values (confidence=0.05, unless specified otherwise).

SPATIAL NoSpat. VS LatLon 0.0002 LatLon (with Bonferroni NoSpat. VS LISA 0.954 LISA correction < 0.05/6) NoSpat. VS PCNM 0.0008 PCNM LatLon VS LISA 3.43E-05 LatLon LatLon VS PCNM 0.775 PCNM LatLon VS PCNM 0.775 PCNM TEMPORAL Non-temp. VS Non-cyclic 0.005 Non-cyclic (with Bonferroni Non-temp. VS Cyclic 0.007 Non-cyclic STRUCTURAL Hourly VS Daily 5.22E-09 Daily ALGORITHMIC RPROP+ VS CLUS 4.39E-08 CLUS TRAINING Sliding 1000 vs Landmark 8.68E-10 Landmark (with B. corr. < 0.05/3 Sliding 4000 vs Landmark 4.63E-09 Landmark TRAINING Sliding 1000 vs Landmark 1.96E-04 Landmark WINDOW (CLUS) Sliding 2000 vs Landmark 1.96E-04 Landmark			p-value	winner
correction < 0.05/6) NoSpat. VS PCNM 0.0008 PCNM LatLon VS LISA 3.43E-05 LatLon LatLon VS PCNM 0.775 PCNM LISA VS PCNM 0.775 PCNM TEMPORAL Non-temp. VS Non-cyclic 0.0005 Non-cyclic (with Bonferroni Non-tyclic VS Cyclic 0.594 Cyclic STRUCTURAL Hourly VS Daily 5.22E-09 Daily ALGORITHMIC RPROP+ VS CLUS 4.39E-08 CLUS TRAINING Sliding 1000 vs Landmark 8.15E-10 Landmark (with B. corr. < 0.05/3	SPATIAL	NoSpat. VS LatLon	0.0002	LatLon
LatLon VS LISA LatLon VS PCNM 3.43E-05 0.775 LatLon PCNM LISA VS PCNM 0.775 PCNM TEMPORAL Non-temp. VS Non-cyclic 0.005 Non-cyclic (with Bonferroni Non-temp. VS Cyclic 0.594 Cyclic correction < 0.05/3)	(with Bonferroni	NoSpat. VS LISA	0.954	LISA
LatLon VS PCNM 0.775 PCNM LISA VS PCNM 4.67E-05 PCNM TEMPORAL Non-temp. VS Non-cyclic 0.005 Non-cyclic (with Bonferroni Non-temp. VS Cyclic 0.0594 Cyclic correction < 0.05/3)	correction $< 0.05/6$)	NoSpat. VS PCNM	0.0008	PCNM
LISA VS PCNM 4.67E-05 PCNM TEMPORAL Non-temp. VS Non-cyclic 0.005 Non-cyclic (with Bonferroni Non-temp. VS Cyclic 0.594 Cyclic correction < 0.05/3)		LatLon VS LISA	3.43E-05	LatLon
TEMPORAL Non-temp. VS Non-cyclic 0.005 Non-cyclic (with Bonferroni Non-temp. VS Cyclic 0.594 Cyclic correction < 0.05/3)		LatLon VS PCNM	0.775	PCNM
(with Bonferroni correction < 0.05/3) Non-temp. VS Cyclic 0.594 Cyclic STRUCTURAL Hourly VS Daily 5.22E-09 Daily ALGORITHMIC RPROP+ VS CLUS 4.39E-08 CLUS TRAINING Sliding 1000 vs Landmark 8.15E-10 Landmark WINDOW (RPROP+) Sliding 2000 vs Landmark 8.68E-10 Landmark TRAINING Sliding 1000 vs Landmark 4.63E-09 Landmark TRAINING Sliding 1000 vs Landmark 1.96E-04 Landmark		LISA VS PCNM	4.67E-05	PCNM
correction < 0.05/3) Non-cyclic VS Cyclic 0.007 Non-cyclic STRUCTURAL Hourly VS Daily 5.22E-09 Daily ALGORITHMIC RPROP+ VS CLUS 4.39E-08 CLUS TRAINING Sliding 1000 vs Landmark 8.15E-10 Landmark WINDOW (RPROP+) Sliding 2000 vs Landmark 4.63E-09 Landmark TRAINING Sliding 1000 vs Landmark 1.96E-04 Landmark	TEMPORAL	Non-temp. VS Non-cyclic	0.005	Non-cyclic
STRUCTURAL Hourly VS Daily 5.22E-09 Daily ALGORITHMIC RPROP+ VS CLUS 4.39E-08 CLUS TRAINING Sliding 1000 vs Landmark 8.15E-10 Landmark WINDOW (RPROP+) Sliding 2000 vs Landmark 8.68E-10 Landmark (with B. corr. < 0.05/3	(with Bonferroni	Non-temp. VS Cyclic	0.594	Cyclic
ALGORITHMIC RPROP+ VS CLUS 4.39E-08 CLUS TRAINING Sliding 1000 vs Landmark 8.15E-10 Landmark WINDOW (RPROP+) Sliding 2000 vs Landmark 8.68E-10 Landmark (with B. corr. < 0.05/3	correction $< 0.05/3$)	Non-cyclic VS Cyclic	0.007	Non-cyclic
TRAINING Sliding 1000 vs Landmark 8.15E-10 Landmark WINDOW (RPROP+) Sliding 2000 vs Landmark 8.68E-10 Landmark (with B. corr. < 0.05/3	STRUCTURAL	Hourly VS Daily	5.22E-09	Daily
WINDOW (RPROP+) Sliding 2000 vs Landmark 8.68E-10 Landmark (with B. corr. < 0.05/3	ALGORITHMIC	RPROP+ VS CLUS	4.39E-08	CLUS
(with B. corr. < 0.05/3 Sliding 4000 vs Landmark 4.63E-09 Landmark TRAINING Sliding 1000 vs Landmark 1.96E-04 Landmark	TRAINING	Sliding 1000 vs Landmark	8.15E-10	Landmark
TRAINING Sliding 1000 vs Landmark 1.96E-04 Landmark	WINDOW (RPROP+)	Sliding 2000 vs Landmark	8.68E-10	Landmark
	(with B. corr. $< 0.05/3$	Sliding 4000 vs Landmark	4.63E-09	Landmark
WINDOW (CLUS) Sliding 2000 vs Landmark 2.44E-04 Landmark	TRAINING	Sliding 1000 vs Landmark	1.96E-04	Landmark
Shame 2000 vs Eandmark 2.44E-04 Eandmark	WINDOW (CLUS)	Sliding 2000 vs Landmark	2.44E-04	Landmark
(with B. corr. $< 0.05/3$) Sliding 4000 vs Landmark 9.83E-05 Landmark	(with B. corr. $< 0.05/3$)	Sliding 4000 vs Landmark	9.83E-05	Landmark

temporal autocorrelation (Non-cyclic and Cyclic) significantly outperform the configuration that does not (Non-temporal), with the cyclic configuration not outperforming the non-cyclic one. This can be due to collinearity problems because of high correlation between cyclic temporal features and non-cyclic ones. Moreover, since in two out of four daily settings, the best improvement is obtained with cyclic configuration, we conclude that temporal autocorrelation is properly exploited in the case of structured output prediction, where dependencies between the productions at two different hours of the same day provide a sort of "contiguity" with respect to the temporal autocorrelation captured by the directional statistics.

3) Structural: By comparing the non-structured output prediction setting with structured output prediction, we can clearly see that the comparison is significantly in favor of the structured output prediction setting, confirming that dependence between the predictions obtained at different hours of the same day is of fundamental importance for improving predictions.

4) Algorithmic: CLUS outperforms RPROP+ with a great margin, especially for the structured output prediction setting, where it is able to improve the predictions of the persistent model for more than 45% in the case of PVItaly (with the combination Non-cyclic - LatLon) and of almost 30% in the case of NREL (with the combination Cyclic - PCNM).

Concerning feature selection, the results reported in Table VI show that it does not lead to improved performances. This means that many and distinct features contribute to provide information for better predictions. However, from the application of the feature selection algorithm, we can still have additional insights. In fact, the selected features confirm that the added spatial and temporal features are considered important for the prediction. For PVItaly, the selected features are: day, date, hour (hourly setting), irradiance, humidity, irradianceLISA, azimuthLISA, while for NREL they are: date, day, hour (hourly setting), longitude, windspeed, altitude, azimuth, cloudcoverLISA, azimuthLISA, PCNM27, PCNM28.

A different, better marked perspective of the results is provided in Fig.6 where we compare the actual and predicted curves of the production for 3 consecutive winter and summer days for both datasets for the landmark window model. For the

TABLE VI

AVERAGE RMSE (OVER 3 RUNS) WITH AND WITHOUT FEATURE SELECTION (FS). RESULTS WITHOUT FEATURE SELECTION ARE OBTAINED WITH THE CONFIGURATION PCNM - NON-CYCLIC.

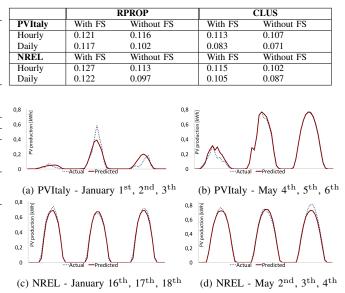


Fig. 6. Predicted (solid line) vs. actual (dotted line) production for three consecutive days (in January and May) of a single plant of PVItaly and NREL. Results for PVItaly are obtained with the CLUS-Daily-LatLon-Non-cyclic configuration, while for NREL are obtained with the CLUS-Daily-PCNM-Non-cyclic configuration. The time intervals considered are 2:00 AM - 8:00 PM. The considered plant for PVItaly is located in Sannicandro di Bari, Italy at latitude: 40.984261, longitude: 16.831031; the considered plant for NREL is located in Riverside, California at latitude: 33.671418, longitude: -115.558126.

PVItaly dataset example, a decrease in predictive performances can be observed under cloudy and rainy weather conditions (typical for winter days) compared to sunny weather conditions (typical for summer days). Moreover, the PVItaly dataset has shown to be more challenging than NREL. Namely, the PVItaly is real-world dataset, while the NREL dataset is simulated. Therefore, it is not surprising for PVItaly to exhibit greater oscillations than NREL.

VI. CONCLUSIONS

This paper studies the problem of PV energy prediction by considering different dimensions of analysis: spatio/temporal autocorrelation, the learning setting (structured output vs. non-structured output) and the learning algorithm (ANNs vs. regression trees), aiming to investigate the relevant aspects for the problem at hand. Results clearly show that structured output prediction models are much more accurate than models that predict single outputs because structured output prediction models can capture dependencies between different hours of the same day. Moreover, experimental results confirm that both forms of autocorrelation should be taken into account in this specific application: While PCNM is the best way to consider spatial autocorrelation, the simple consideration of hour and day information is enough to properly catch temporal autocorrelation. Finally, regression trees produce significantly better predictions than ANNs, indicating that also in PV energy prediction, hierarchical models are better than

flat regression functions (this was also observed in [24] for predicting electricity energy consumption).

As future work, we intend to directly consider autocorrelation in the cost function (heuristic) used to learn the ANN. We also plan to investigate more sophisticated learning methods based on ensemble techniques.

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