On the role of lagged exogenous variables and spatio-temporal correlations in improving the accuracy of solar forecasting methods

Athanassios Zagouras, Hugo T. C. Pedro, Carlos F. M. Coimbra*

*Department of Mechanical and Aerospace Engineering, Jacobs School of Engineering
Center of Excellence in Renewable Energy Integration and Center of Energy Research
University of California San Diego, La Jolla, California, 92093, USA*

Abstract

We propose and analyze a spatio-temporal correlation method to improve forecast performance of solar irradiance using gridded satellite-derived global horizontal irradiance (GHI) data. Forecast models are developed for seven locations in California to predict 1-hour averaged GHI 1, 2 and 3 hours ahead of time. The seven locations were chosen to represent a diverse set of maritime, mediterranean, arid and semi-arid micro-climates. Ground stations from the California Irrigation Management Information System were used to obtain solar irradiance time-series from the points of interest. In this method, firstly, we define areas with the highest correlated time-series between the satellite-derived data and the ground data. Secondly, we select satellite-derived data from these regions as exogenous variables to several forecast models (linear models, Artificial Neural Networks, Support Vector Regression) to predict GHI at the seven locations. The results show that using linear forecasting models and a genetic algorithm to optimize the selection of multiple time-lagged exogenous variables results in significant forecasting improvements over other benchmark models.

Keywords: solar forecasting, time-lagged correlation, gridded data, exogenous input data, genetic algorithm

1. Introduction

Large-scale utilization of solar energy for power generation requires advanced forecasting technologies to handle the variability of this weather-dependent resource. Several research groups have developed forecast algorithms and methodologies to predict ground irradiance at different forecasting horizons, ranging from minutes out to days ahead into the future [1].

The numerical tools that ingest relevant ground telemetry, remote sensing data and numerical weather prediction results typically include simple deterministic models with complex preprocessing steps, stochastic time series models such as AR, ARMA and ARIMA, machine learning tools such as Artificial Neural Networks, K-Nearest-Neighbors, Supported Vector Regression, and many other post-processing algorithms [1–4]. Most existing operational models use only local data and are limited to observe variations in the input variables in a single point in space, and are “blind” to the motion of weather systems across the earth’s surface. A few recent studies employed spatially distributed data to cover small regions in space. Linij et al. [5] use data from a network of 80 rooftop sensors in Tucson, AZ, Yang et al. [6] use a network of 10 sensors in Singapore and Sözen et al. [7] train a neural network for 12 ground stations spread over Turkey.

In both cases the researchers reported substantially improvements to the forecast skill. The drawback for such approach is that, a network of ground sensors is costly to deploy and maintain due to required regular maintenance. When no such ground truth data is available, is it possible to find some useful approximations to irradiance measurements as Pelland et al. [8] have done by using spatially distributed irradiance forecast from the Canadian Meteorological Centre. Al-Alawi and Al-Hinai in [9] developed a neural network based forecasting model to predict the global radiation for remote locations in Oman, where ground-based measurements are not available.

*Corresponding author: ccoimbra@ucsd.edu (Carlos F. M. Coimbra)

In a similar way to these authors, we explore in this work simple forecast models that include irradiance data from locations in the vicinity of the point of interest. Here gridded data comes, not from a numerical weather prediction, but from models that ingest satellite images to estimate the solar irradiance at the ground level. Such models have grown in accuracy in recent years (see for instance [10, 11]). Moreover, such data will even be more accurate in the near future with GOES-R, the next generation of geosynchronous environmental satellites by NOAA, that will increase the frequency of full-disk imagery from 30 minutes to 5 minutes [12].

The objective of this paper is to introduce a forecasting approach that improves the prediction accuracy of ground measured irradiance data throughout the state of California through the use of exogenous satellite-derived variables. Two main aspects are explored by the proposed methodology. First is to investigate how exogenous input data obtained by difference source than a ground-based sensor at the point of interest affect the forecast of the measured observations. It is important to identify the seeking area around the vicinity of a ground location where a model can search for exogenous input data. Secondly, the time latency of both the endogenous and exogenous inputs plays a crucial role in the forecasting performance, as well as the optimization of selecting a number of exogenous variables from different time lags. Given a large dataset of gridded satellite data, we propose a time-lagged correlation analysis between the ground measured times series and the gridded data to define potential seeking regions based on the degree of correlation. We study different types of forecasting models including the persistent model, Artificial Neural Networks (ANN), Support Vector Regression (SVR), linear models using a variety of time-lagged input data and a linear model optimized by Genetic Algorithms (GA). The latter provided the best forecast accuracy for forecast horizons up to 3 hours ahead, with respect to any ground location and evaluated on different periodic partitions of an independent testing subset.

The remainder of the paper is organized in four parts: in Section §2, the case study will be presented. Section §3 is devoted to a description of the time-lagged correlation analysis and the developed models. Section §4 analyses the experimental results. The conclusion is reported in Section §5.

2. Case Study

2.1. CIMIS ground data

Ground-based hourly irradiance data used in this study were obtained from 7 weather stations operated by California Irrigation Management Information System (CIMIS). A network of 120 automated weather stations throughout the entire state of California constitute the CIMIS program managed by the Office of Water Use Efficiency (OWUE), California Department of Water Resources (DWR). Aiming to assist in the efficient management of irrigation water resources, DWR and the University of California, Davis established the CIMIS program in 1982. The CIMIS weather stations are located at key agricultural and municipal sites to either measure various meteorological data on an hourly basis or calculate them from measure values. The weather stations are equipped to measure data such as solar radiation, air and soil temperature, relative humidity, precipitation, and wind speed and wind direction. In the present study, we selected seven weather stations located at distinct sites in California, from the north to the south as well as at coastal and inland sites (Fig 1). The wide range of stations was based on the estimated solar variability that each location experiences and their geographic proximity to regions where antipodal climatic conditions occur. For instance, San Diego is exposed to the marine layer of the Pacific ocean which substantially affects solar variability, whereas Merced, located in the Central Valley of California and has hot, dry, cloudless summers and notably low solar variability.

Table .2 summarizes geographical information for the sites used. Solar radiation data were obtained for a 45-month period from January 2009 to September 2012. The total solar radiation that reaches each weather station is measured by a LI200S Li-Cor photovoltaic pyranometer. The 60 readings per minute are then averaged to hourly data and published on the CMIS portal. The error accuracy of the Li-Cor pyranometer is within $\pm 5\%$ under natural sunlight conditions.

The ground data were split into training, validation and testing sets, respectively. The training set was used for the time-lagged correlation calculations and the estimation of the model parameters, the validation set was used for the parameter optimization and the testing was applied for evaluating the generalization capacity over independent data. The three data sets were created with the following algorithm: the 1st week of every month was assigned to the validation set, the 2nd to testing and the remaining data were used for training. This resulted in a typical data partition

Figure 1: Map of California in gray with selected CIMIS weather stations marked in black and labeled.

with 50% for training and 25% for validation and testing, respectively. This splitting algorithm ensures that all the subsets share similar seasonal trends.

2.2. Satellite-derived data

In addition to the CIMIS data, we use gridded data values of GHI for the state of California provided by the *SolarAnywhere*[®] [13]. The Enhanced Resolution dataset, for the same period as the CIMIS dataset, consists of satellite-derived GHI data on an approximately 0.01° resolution grid both in latitude and longitude and a 30 min time sampling rate. *SolarAnywhere*[®] global and direct irradiance values are derived from the SUNY semi-empirical satellite-to-irradiance model, which relies on imagery collected from the GOES-W and GOES-E satellites in conjunction with other meteorological data sources [14, 15]. A number of studies validates the accuracy of SUNY model at several individual locations with a typical error of the derived global and direct irradiance estimates correspond to 5% and 10%, respectively [14–16]. Particularly for the GHI data in the state of California, Nottrott and Kleissl [10] have demonstrated that SUNY model estimates GHI with an average mean bias error of 5%, which is comparable with that of ground-based measurements.

In order to reduce the large number of grid nodes we applied a median filter to all the non-overlapping windows consisted of 5×5 nodes. The use of the median function is based on the consideration that adjacent nodes in the grid should have relatively smooth deviation of GHI values. Thus, every 25 km^2 region (i.e. 5×5 grid) is represented by the median GHI value of the node values in the window. As the window slides over the entire image, the result from the median filter is assigned to a new grid, which is composed of the coordinates of the central node in each window. In order to match the 30-minute satellite-derived GHI with the 1-hour ground data we averaged the former dataset over 1 hour intervals (± 30 -min). Finally, the preprocessed *SolarAnywhere*[®] dataset, that shares common time stamps with the CIMIS dataset (Jan 2009 - Sept 2012), was also split into the three subsets described above.

2.3. Clear-sky model and clear-sky index

The clear-sky models (CSM) are employed by several applications in the solar engineering field to compute the expected ground irradiance for sky conditions at any location and time. In recent past a number of CSM has been

presented which are associated with a variety of different climatic input parameters [17, 18]. The normalization of satellite data by the expected clear sky values constitutes an important preprocessing task where the normalized irradiance becomes independent from factors such as the geographic location, the time of year and the variability associated with deterministic solar diurnal cycle. In this study we employed the CSM proposed by Ineichen and Perez (2002) [19] which requires as the only atmospheric input the Linke turbidity factor at an airmass of 2. **In contrast to other multi-parameter CSM in the literature, the selection of this model lies in the availability of broadband input parameters and the demonstrated good performance in the state of California [20]. Current research on the accuracy of diverse CSM has shown that the particular model is among the four best-performing models out of 54 CSM in total [21].** The CSM values, GHI_{cs} , were calculated for all the nodes of the reconstructed grid domain and the hourly averaged time stamps as described in the section §2.2. The clear sky index $k_{exo/endo}$, defines the normalized $GHI_{exo/endo}$ time series, which is calculated as:

$$k_{exo/endo}(t) = \frac{GHI_{exo/endo}(t)}{GHI_{cs}(t)}, \quad (1)$$

where the subscripts *exo/endo* indicate either the satellite-derived data (the exogenous variables) or the ground measured GHI at the CIMIS stations (the endogenous variables). Both the $k_{exo/endo}$ time series values vary between 0 and 1, representing fully overcast sky or completely clear conditions, respectively.

The datasets of temporal vectors $GHI_{exo/endo}$ and $k_{exo/endo}$ are created for the three time subsets described in the section §2.1. They consist of N time series vectors of the irradiance features (i.e., $GHI_{exo/endo}$ or $K_{exo/endo}$) for daytime periods. The number of vectors, $N = 16625$, results from the total number of nodes of the reconstructed $\sim 5 \text{ km} \times 5 \text{ km}$ grid and correspond only to land regions of California.

3. Forecasting framework

Using the datasets explained above we address a simple question: having access to gridded irradiance data (measured or modeled as in this case) can these data be used to improve irradiance forecast for a given location within the gridded data domain and how can this be done? The answer to the first part of the question is trivial: spatially distributed irradiance data should always improve the forecast accuracy. Cloud advection, for instance, cannot be detected with irradiance data from a single location but can be easily observed in gridded data. Large improvements in the forecast accuracy should be expected when such information is available.

The second part of the question has multiple possible answers and it depends on the preferences of the researcher. In the remainder of this paper we will provide our approach and assess its performance.

In general terms the forecast models here proposed are given by:

$$\begin{aligned} \hat{k}(t + \delta) = & f(k_{endo}(t), k_{endo}(t - \Delta t), \dots, k_{endo}(t - i\Delta t), \\ & k_{exo,1}(t), k_{exo,1}(t - \Delta t), \dots, k_{exo,1}(t - i\Delta t), \\ & \dots, \\ & k_{exo,j}(t), k_{exo,j}(t - \Delta t), \dots, k_{exo,j}(t - i\Delta t), \dots) \end{aligned} \quad (2)$$

where $\hat{k}(t + \delta)$ is the forecasted value at time $t + \delta$, k_{endo} is the clear-sky value at the location of interest, and k_{exo} is the clear-sky irradiance from exogenous locations obtained from the gridded data. Models were developed to forecast horizons $\delta = 1, 2, 3$ hours. The number of exogenous locations $k_{exo,j}$ is not defined beforehand nor is the number of time lags $t - i\Delta t$. The approximation function f can take various forms depending on the forecast model used. In this work we will explore the following tools: linear models, Artificial Neural Networks and Support Vector Regression. The dependent variable in these models is the clear-sky index and not the irradiance, given that contrary to GHI, the k time series is stationary. However, all the results and error analysis presented ahead will be in terms of irradiance, which can be obtained as $\hat{I}(t) = \hat{k}(t) \times I_{cs}(t)$.

The choice of exogenous locations and time-lagged variables to be included in Eq. 2 will be addressed below. The optimal set of exogenous variables and time-lagged data will be determined through a genetic algorithm. However, given that any point in the California dataset could be used as an exogenous input we propose a preprocessing technique to reduce the set of candidates to a more manageable number. This step is based on the correlation analysis between the ground data for the selected locations and the gridded GHI data.

Figure 2: Frequency distribution of the Pearson ρ correlation coefficients values between the CIMIS station at Merced and the time shifted satellite-derived K time series at CA by a) 0 h, b) 1 h, c) 2 h, d) and 3 h. The horizontal axis represents bins of correlation coefficients values, while the vertical axis refers to the number of map pixels occur at each bin.

3.1. Time-lagged correlation analysis

Time-lagged correlation analysis is a challenging approach of stochastic modeling to investigate the pairwise relationship between time shifted solar-irradiance time series, as a function of both the spatial distribution of the measurements sites and the time delays of the measured irradiance [22–24].

Before developing the forecast models in detail, it is necessary to examine two essential aspects. The first is to define the spatial area characterized by significant correlation between k_{exo} and k_{endo} time series for different locations. The exogenous inputs to Eq.2 will be selected from these areas. In general, it is expected that these areas will be formed by the grid nodes closest to the ground stations. The second aspect is to determine a criterion based on the correlation magnitude that will define these areas. In order to address these two issues, we performed a time-lagged correlation analysis between the k_{endo} time series at each of the CIMIS locations with time-lagged k_{exo} satellite-derived time series from the entire state of California. The Pearson correlation coefficient ρ is defined as:

$$\rho_{\tau,i} = \frac{cov(k_{endo}(t), k_{exo,i}(t - \tau))}{\sigma(k_{endo}(t)) \sigma(k_{exo,i}(t))}, \quad (3)$$

with $i = 1, \dots, N$, where $\tau = \{0, 1, 2, 3\}$ represents the hourly time lags applied to the k_{exo} time series, and cov and σ stand for covariance and standard deviation, respectively.

The “connection” between the k time series of selected ground points of interest with a large satellite-derived auxiliary dataset of antecedent data can now be interpreted by a lag-dependent Pearson correlation coefficient map. All the time series used for the correlation analyses were obtained from the training subset. While we aim to short-term forecast horizons, the time lags were defined to vary between 0 and 3 hours.

A preprocessing step of the correlation analysis for each reference location requires to clean the CIMIS data from any missing values or invalid measurements and perform an overlapping match with the corresponding satellite data. Specifically, all the time stamps of an entire day are removed if a missing/invalid value during that day is detected. Although the number of overlapped data among the cases of different CIMIS locations is variable, they always exceed 90% of the initial dataset size.

The group of grid points with the largest correlation to the reference point are used to form the area wherein exogenous time series can be selected as inputs to the forecast models. Once the correlation maps for the delay τ are computed and, given a threshold value $\rho_{\tau,lim}$ to define the set of nodes in the the search area S , the later is given as:

$$S_{\tau}|_{\rho_{\tau,lim}} = \{i : \rho_{\tau,i} \geq \rho_{\tau,lim}\}, \tau = \{0, 1, 2, 3\} \quad (4)$$

and the set of exogenous variables associated to these indices is

$$K_{\tau}|_{\rho_{\tau,lim}} = \{k_{exo,i} : i \in S\}, \tau = \{0, 1, 2, 3\} \quad (5)$$

Figure 2 shows the distribution of correlation values for the different lags for Merced. The figure shows a number of grid points between 100 and 200 that have the highest correlation with the CIMIS ground time series for different time lags. The highest correlations decrease with increasing time lags. We therefore define the search areas for each CIMIS reference location as the regions of top-correlated pixels with respect to different time lags.

An example of the correlation map ρ_0 for Davis is illustrated in Fig. 3a. While an extensive area of well correlated locations (i.e. $\rho > 0.5$) encloses the CIMIS station at Davis, we confine the search area to the 100 most correlated nodes, $\rho_{lim} = \rho_{100th}$. The search areas for the locations Davis, McArthur and Torrey Pines (San Diego) are shown with red in Fig. 3 (b-d), respectively. The blue areas indicate the nodes whose correlation with the ground data is smaller than the threshold. The shape of the search area is variable and depends on the threshold value and the location of reference. This evidence indicates the necessity of performing correlation analysis in order to accurately define the boundaries of the area of potential exogenous locations.

Figure 3: a) Heatmap of the correlation coefficients between the SolarAnywhere[®] K time series at the California state and the CIMIS station at Davis. The colorbar on the right indicates the magnitude of the Pearson ρ values. The seeking areas for b) Davis, c) McArthur and d) Torrey Pines (San Diego) after applying the threshold of the 100 highest correlated nodes are illustrated in red. The remaining nodes of the CA territory below the threshold values are colored in blue. At these examples no time lag was applied. The correlation analysis is referred to the training subset.

3.2. Linear models

The simplest class of forecast modes used in this work are linear models. The general expression for these models is given by

$$\begin{aligned}\hat{k}(t + \Delta t) = & A_0 + \sum_{i=1}^N A_i k_{endo}(t - (i - 1)\Delta t) \\ & + \sum_{i=1}^N \sum_{j=1}^M B_{ij} k_{exo,ij}(t - (i - 1)\Delta t)\end{aligned}\quad (6)$$

with $k_{exo,ij} \in K_i$. The coefficients A_i and B_{ij} are determined such that they minimize the error

$$e(A_i, B_{ij}) = \frac{1}{N} \sum_{i=1}^N |\hat{k}_i - k_i|, \quad (7)$$

for data points in the training data set. The minimization is done with the quasi-Newton algorithm available through the function *fminunc* implemented in MATLAB (R3013a). The forecast performance of the various models developed is assessed relatively to the persistence model which is given by Eq. 6 with $A_1 = 1$ and all other coefficients equal to 0.

3.3. ANN

Another class of models tested here are based on ANNs. These are useful tools for approximating complicated mapping functions for problems in classification and regression [25], and have been used extensively in solar radiation modeling and forecasting (see e.g., [26, 27]). An ANN is a particular representation of an output y in terms of some input variables x . This representation is based on signals being sent through elements called neurons in such a way that the processing of the input signals produces an output, $\hat{k}$, that is sufficiently close to the desired target value of k . Neurons are arranged in layers, where the first layer contains the set of inputs, the last layer contains the output, and the layers in between, referred to as hidden layers, contain hidden neurons. This work uses feedforward neural network with N_{inp} inputs and N_{hid} neurons in one hidden layer with a linear output activation. The ANN forecast model can be expressed as,

$$\hat{k} = \sum_{i=1}^{N_{hid}} w_i f_i^{hidden} \left(\sum_{j=1}^{N_{inp}} w_{ji} x_j + w_{0i} \right) + w_0, \quad (8)$$

where f_i^{hidden} are sigmoidal functions, such as the hyperbolic tangent function. The weights, w_{ji} and w_i in the network were determined with the Levenberg-Marquardt numerical optimization algorithm that minimizes the mean squared error (MSE)

$$e(w_i, w_{ij}) = \frac{1}{N} \sum_{i=1}^N (\hat{k}_i - k_i)^2, \quad (9)$$

3.4. Support Vector Regression

In order to assess the performance of another family of predictors, we use an attractive approach for time series forecasting, the SVR model based on Vapnik's concepts of support vector machines (SVM) [28]. SVR method relies its popularity on characteristics such as the robust and sparse regressions, good generalization performance, unique solution compared to ANN due to the absence of local minima. The basic idea behind SVR is to transform the data $\mathbf{x}$ from an initial input space into a higher dimensional feature space as a means of a nonlinear mapping function Φ to account for nonlinearity. The transformed feature space maximizes the geometrical margins between the objects allowing the better separation. The hyperplane at the feature space is computed by the linear equation:

$$f(x) = \langle w, \Phi(x) \rangle + b, \quad (10)$$

where $\langle \cdot, \cdot \rangle$ denotes the inner product, with $w \in R^n$, $b \in R$ and $\Phi : R^n \rightarrow D$. Initial data $\mathbf{x}$ lay on the R^n dimensional space, D is the target feature space, w defines a set of coefficients to be determined and b is the intercept.

The regression problem is equivalent to the optimization problem stated in [28] of finding the parameter vector w and intercept b by requiring the minimization of the equation:

Table 1: List of possible exogenous variables to include into the forecast models.

$k_1(t)$	$k_2(t)$	$\dots$	$k_{N_{exo}}(t)$
$k_1(t - \Delta t)$	$k_2(t - \Delta t)$	$\dots$	$k_{N_{exo}}(t - \Delta t)$
$\vdots$	$\vdots$	$\ddots$	$\vdots$
$k_1(t - (N_{lag} - 1)\Delta t)$	$k_2(t - (N_{lag} - 1)\Delta t)$	$\dots$	$k_{N_{exo}}(t - (N_{lag} - 1)\Delta t)$

$$\min_{\mathbf{w}, b, \xi, \xi^*} \frac{1}{2} \|\mathbf{w}\|^2 + C \sum_{i=1}^n (\xi_i + \xi_i^*), \quad (11)$$

subject to

$$\begin{aligned} f(x_i) - y_i &\leq \varepsilon + \xi_i, \quad \xi_i \geq 0, \quad \forall i, \\ f(x_i) - y_i &\geq -\varepsilon - \xi_i^*, \quad \xi_i^* \geq 0, \quad \forall i, \\ i &\geq 1, 2, \dots, N \end{aligned} \quad (12)$$

where the regularization parameter C determines the trade-off between the 'flatness' of f and amount up to which deviations larger than the regression margin ε are tolerated. The slack constrains ξ, ξ^* are introduced to measure the distance between the input data and outside the ε -tube [29]. The solution to the regression problem requires computations of only the above mentioned inner product, which can be presented in the feature space as a *kernel* function:

$$f(x) = \sum_{i=1}^N \alpha_i K(x, x_i) + b, \quad (13)$$

where α_i are Lagrange multipliers associated with the constrains and $K(x, x_i)$ is the introduced kernel function. The Gaussian radial basis function (RBF) is selected among basic kernel choices, defined as:

$$K(x, x_i) = G(\|x - x_i\|; \gamma) = e^{-\gamma \|x - x_i\|}, \quad (14)$$

where γ is an user defined parameter that defines the kernel behavior, while x is the center of the Gaussian distribution. Here, the parameters γ and C are set equal to 16 and 0.25, respectively.

3.5. Selecting exogenous variables

The models explained in the previous sections receive as inputs the clear-sky index from the ground data and the clear-sky index from the satellite gridded data. After applying the correlation analysis procedure outlined in section 3.1 there are still hundreds of possible inputs to consider at the different time-lags with significant correlation $\rho_{\tau, i} \geq 0.5$. The first approach used to include exogenous variables in the forecast models was an brute force method in which, for each lag correlation map $\rho_{\tau, i}$, all the exogenous variables in the set $K_{\tau} \big|_{\rho_{\tau, lim}}$ with $\rho_{\tau, lim} = \{\rho_{\tau, 1st}, \rho_{\tau, 2nd}, \dots, \rho_{\tau, 50th}\}$. The possible inputs, for those cases, are summarized by Table 1 that list the available inputs for the 4 time lags considered (the table rows) and the N_{exo} exogenos locations in the set $K_{\tau} \big|_{\rho_{\tau, lim}}$ (the table columns). In other words, exogenous locations with the highest 1, 2, $\dots$, 50 correlations within the seeking area, as it is defined in §3.1, for each lag were included in to the forecast models, the free parameters computed using the validation dataset and the error metrics computed for the testing set. This approach returned the best forecast models that use all the highest correlated (up to 50) nodes for a single time lag.

In order to involve all the time lags in the same model we used a simple search algorithm:

1. find the best number of highly correlated exogenous data, at lag 0-hours, to add to the forecast algorithm
2. sequentially add highly correlated exogenous data from lag 1-hour to the set found in the previous step and determined the number of exogenous variables (if any) that minimize the forecast error
3. repeat step 2 for the exogenous data at lags 2- and 3-hours.

3.6. Genetic algorithms

The previous section explained a brute force method to include exogenous variables in the forecast. In this section we explain a more general approach to the problem of finding the best set of exogenous inputs based on the heuristic search tool, the genetic algorithm [30]. The GA is especially useful for problems such as this where it is not possible to map the search space analytically. In this work, the GA starts with an initial population of individuals generated randomly, each of which representing a different set of exogenous inputs. Each individual in the population is described by a binary vector with length $N_{Lag} \times N_{Exo}$. The element $i = (j - 1)N_{Lag} + k$ in the one of these vectors, where j and k are the row index and column index from Table 1, respectively, dictates the inclusion (if equal to 1) or the exclusion (if equal to 0) of the jk input into the forecast model.

All the individuals are then evaluated using the linear forecast explained above. The individuals with the lowest MSE when applied to the optimization dataset are selected as parents for the following generation. Eighty percent of offspring generation is created through crossover (bit-wise random recombination from two parents). The remainder 20% are created through mutation of randomly selected parents. In this case mutation operates by flipping a bit at some randomly chosen sites. The new generation is again classified in terms of forecast MSE and the process is repeated until there is no more improvement in the best individual or a prescribed number of generations is achieved, 100 in this case.

Due to the stochastic nature of the GA, multiple runs were performed to ensure that the final solutions do not vary significantly depending on the GA run. Figure 4 illustrates the evolution of multiple GA runs for the location of Windsor for the 1 hour forecast horizon. Each of the 10 GA runs start with a random initial population for a fixed number of 100 generations. It is notable in Fig. 4 that the short range of the generated fitness scores is mainly found within the first two standard deviations of the mean, and the upper and lower quartiles are almost included within one standard deviation. Consequently, a single run of the GAs can be used to provide a reliable and fast solution.

Figure 4: Genetic algorithm performance graphs for 1h forecast horizon at Windsor station: a) Summer (Biannual), b) Annual. Statistical measures (mean, standard deviations, upper and lower quartiles, max/min data range) of the fitness score (%) are presented for 10 runs with a random initial population against a learning time of 100 generations.

4. Forecasting results

4.1. Preprocessing and forecast models

As explained in section §2, we focus on performing our forecasting models to GHI data selected from ground locations throughout CA referred to as endogenous variables, while satellited-derived GHI data are considered as exogenous variables. A preprocessing step for only daylight timestamps includes the removal of missing values, calculation of the CSM values, normalization to clear sky index $k_{exo/endo}$ and division of the entire data period into training, validation and testing sets. Subsequently, all of the previously described forecasting methods are applied to predict future values of normalized GHI for 1h, 2h and 3h ahead forecast horizons. The inputs were either time-lagged or synchronous endogenous ground-measured k time-series with/without exogenous variables obtained from the satellite gridded data.

The experiments in this study were conducted in a three-step procedure. In the first step we conduct a correlation analysis between the selected CIMIS location and the time-lagged satellite-derived k time-series from the training subset to investigate the spatial area of the highest correlated locations. A threshold value of the 100 most well-correlated locations around a CIMIS station has previously identified to define the seeking area for each lag.

The second step follows with the application of all the forecasting models to the validation subset for each location of interest. In this step each model goes through a parameter optimization step to ensure the accuracy of the prediction process. All the terms of 1h-to-3h time-lagged or synchronous (zero time lag) endogenous/exogenous data inputs were examined with respect to the configuration of each model, as described by the Eq. 2. In particular, the linear model was applied either to only endogenous variables or to both endogenous and exogenous input data for the various time lags and forecast horizons. It is worth noting that the seeking area for exogenous variables varies for different locations and at each implementation the models use a different number of exogenous variables within the predefined area of interest, varying gradually from 1 to 50. The upper limit of 50 exogenous variables was selected based on a realistic scenario of choosing a reasonable number of locations that can be potentially used for hosting ancillary ground stations. In brief, we can distinguish five basic variations of the used linear models. First, the simple persistence model, second, the linear model using only endogenous variables and the linear model that uses a combination of endogenous variables accompanied by exogenous variables from a single lag separately. Furthermore, we select to add together the number of exogenous variables that perform best for each lag in order to investigate the effect of applying simultaneously different but also best performing time-lags to the prediction of future values. In this model type, exogenous variables from previous lags are added only if they improve the forecast. Another essential point of using exogenous variables to improve the performance of the linear models, is the type of linear models that uses the GA to determine the optimal set of exogenous variables for each time lag. The heuristic search by the GA applies always within the seeking area derived from the correlation analysis at each time lag and the selected number of variables is independent from a time lag to another. In our case study, experiments with various GA population sizes showed that there is no significant improvement to select more than 50. Finally, the SVR and ANN non-linear forecast models, using only multiple time-lagged endogenous inputs, are used to provide more advanced reference models than the linear ones.

Upon the completion of each model's parameters optimization, the third step of the experimentation is to apply the trained forecasting models to the testing subset. Once the model parameters are determined, we evaluate the models on the testing set in terms of measuring their efficiency to an independent period of input data. Results generated by all the forecast models to both the validation and testing subsets with reference to each CIMIS location. The following subsection provide an overview of the performance metrics.

4.2. Performance measures

To evaluate the performance of the developed prediction models, we use the naive persistence model as the reference model. The output of the forecasting models are the predicted $\hat{k}$ time-series for each ground point of interest, which are transformed to predicted GHI values, as defined by the Eq.1. Both for the validation and the testing subsets, the predicted results for each case are compared with the measured observations by calculating the Root Mean Square Error (RMSE) as follows:

$$RMSE = \sqrt{\sum_{t=1}^{n_s} \frac{(\mathcal{P}(t) - \hat{\mathcal{P}}(t))^2}{n_s}}, \quad (15)$$

where $\mathcal{P}$ stands for the measured GHI observations (W/m^2) at each ground CIMIS location at time t , $\hat{\mathcal{P}}$ denotes the predicted GHI values at the same location and n_s is the length of data set.

In order to examine the relative improvement of the different prediction methods over the baseline persistence model, we calculate the model quality skill s defined by:

$$skill(\%) = (1 - \frac{RMSE_{mod}}{RMSE_{pers}}) \times 100, \quad (16)$$

where $RMSE_{mod}$ means the RMSE of each model forecast, while $RMSE_{pers}$ stands for the RMSE of the persistence forecast model on either the validation or the testing subset. The higher the value of s , the better the forecasting model

against the persistence model performs. Negative values of s indicate that the forecasting model fails to outperform the persistence model, while s equal to 1 denotes a perfect forecast with zero $RMS E_{mod}$.

In addition, the Coefficient of Determination (R^2) statistical measure is calculated as follows:

$$R^2 = 1 - \frac{\sum_{t=1}^{n_s} (\mathcal{P}(t) - \hat{\mathcal{P}}(t))^2}{\sum_{t=1}^{n_s} (\mathcal{P}(t) - \bar{\mathcal{P}})^2}, \quad (17)$$

where $\bar{\mathcal{P}}$ is the mean of the measured values $\mathcal{P}$ for the period of each subset. Complementary to the comparative advantage of a forecasting model against a simple reference model as this is calculated by s , the Coefficient of Determination scores between 0 and 1 indicate the extent to which the predicted $\hat{\mathcal{P}}$ variables are predictable from the measured values $\mathcal{P}$. In other words, the R^2 values show how accurately the predicted points fall on a simple regression line (See Fig 7). This metric evaluates the performance of each model independently of the reference model's performance and provides insight into the reliability of the model itself.

4.3. Seasonal-dependent optimization

In the initial experiments the models were developed using the entire dataset as explained above. This results that the free parameters in the different models are optimized for data belonging to the whole year and all types of weather conditions. It is then possible, that if the models are retrained for smaller sets of more coherent data the performance may increase. To study this effect the original data sets are divided with respect to seasons in a very simple way:

- quarterly, the sets are divided into four meteorological seasons defined as i) Winter (Dec-Jan-Feb), ii) Spring (Mar-Apr-May), iii) Summer (Jun-Jul-Aug) and iv) Autumn (Sep-Oct-Nov).
- biannual, the sets are divide into two major subsets i) Nov-Mar and ii) Apr-Oct. This selection is contingent on empirical regional conditions.
- annual, data from the entire year forms either the validation or the testing set.

4.4. Forecasting performance

Tables 3-11 present the performance results in terms of forecast skill s and $RMSE$ with respect to the three seasonal-dependent types for partitioning the evaluation period of time (i.e. validation and testing subsets) as well as the forecast horizon. As the Tables show, each row indicates a different model, while each column corresponds to a different CIMIS ground station. Metric values are given for both the validation and the testing subsets. Whereas the experiments are conducted on a seasonal basis taking into consideration the aforementioned division scenarios, the performance metrics are calculated accordingly. In order to simplify the presentation of the results, we thereafter merge the forecasts into an annual basis while ensuring that the merged timestamps are distinct. Consequently, the following figures and tables display the merged results obtained by different forecast methods and partition of the evaluation subsets.

For better visualization of the results at Tables 3-11, we plot the content of each table in a radial plot in Fig. 5. The measured s -skill scores for the testing subset for each forecasting model can be read by tracing an axis from the center outwards, each axis corresponds to one of the 7 CIMIS ground locations. Therefore, values obtained from the same method across different ground stations can be connected by a joined line and the corresponding area is shaded by different colors to increase the distinction. We label the axes in the prescribed geographical orientation of the ground stations, starting clockwise with McArthur (northern) to Torrey Pines (southern).

Figure 6 shows the bar plots of s -skill values for the best performing forecasting method, the linear model optimized by the GA, both at each quarter of the four-seasonal division of the evaluation subsets and also the merged scheme. In these plots, each set of bars corresponds either to the seasonal or the merged results, while the color of each bar stands for different prediction horizon and evaluation subset. From this figure it can be seen that the forecasting performance varies from a season to another, depending also on different factors such as the location of the CIMIS stations and the evaluation subset in use.

By plotting the pairs of forecasted $\hat{\mathcal{P}}$ values and measured $\mathcal{P}$ observations of the testing subset for specific ground stations, we produced the scatter plots at Fig. 7. As can be seen from the scatter plots, the Coefficient of Determination

(R^2) values are calculated to quantify the degree of dispersion of the forecasted values about the 1:1 reference line. The highest values of R^2 , the better performance of the forecasting method. The upper half set of scatter plots outlines the performance of the ground station with the best results (i.e. De Laveaga) and the bottom half plots refer to the less well performing station (i.e. Parlier). As the key aspect of using the R^2 metric is to measure the accuracy of a forecasting model autonomously rather than comparatively to a reference model, the scatter plots correspond to the best performing and the reference model, as these are derived from our experiments. Hence, the left column of the 7 corresponds to the linear model optimized by GA and the right column corresponds to the persistence reference model. The rows show examples for 1 and 3 hours ahead forecastings. We also indicate the quality of the forecast in terms of RMSE above each scatter plot. From this figure it can be seen that the depicted performance of each case is relevant to the corresponding s -skill metric; the linear model optimized by the GA performs always better than the persistence model. It is obvious that both the location of the point of interest and the forecasting horizon affect the forecasting quality.

5. Conclusions

This study shows that the forecasting accuracy for GHI in the state of California can be substantially increased through exogenous, satellite-derived data (such as the data provided by the gridded *SolarAnywhere*[®] dataset). Given the costs associated with ground-based station networks, the proposed methodology leverages the availability of low-cost satellite data in such way that the forecasts can be improved at any point of interest. To this end, we: i) propose a time-lagged correlation analysis to define precisely the seeking area of the exogenous satellite inputs, and ii) demonstrate that the linear model optimized by GA outperforms any other method tested here. As for the forecasting improvements by means of s -skill, the GA optimized model outperforms the persistent model by 8.458 to 40.419% on the quarterly basis, 8.185 to 41.180% on the biannual basis and 8.969 to 39.196% on the annual basis, depending on the forecast horizon and station location. Summing up the results, we conclude that a combination of hourly-shifted inputs (up to 3h) before the current time t is critical for forecast improvements. We also determine the optimum number of exogenous variables per lag.

The seasonal partition of the evaluation subsets shows that there are periodic tendencies of the irradiance input for all the models except the best performing model, which performs fairly unbiased for all seasons. The results shown in the Fig. 5 indicate that the shape of the patterns are significantly altered in season-dependent divisions, in contrast to that of the best model, which remains robust for certain forecast horizons.

An optimal spatial distribution for sensor networks can be determined through direct application of the top performing forecasting model. Points of interest located near the coastline (e.g. De Laveaga, Windsor, Torrey Pines) exhibit better accuracy compared to the forecast improvements of mostly dry, cloudless inland locations such as Merced, Davis, Parlier. With respect to the quarterly seasonal results (Fig. 6), the coastal locations perform considerably better during summer and autumn as compared to the most dynamic periods in winter and spring. The negative s -skill result for the summer quarter at Davis can be explained as input data discrepancies from different sources. Our findings also reveal the weakness of the reference model to perform well as the forecast horizon progresses. It is apparent that the well performing locations exhibit a more distinct forecast improvement against the reference model at larger forecast horizons (see Fig. 7).

The proposed methodology can be readily adapted to existing networks of ground stations or to a single ground station that is covered by high-resolution satellite imagery. Although several studies have indicated the use of exogenous variables derived by neighboring stations of an existing station, the innovation of this study is in the exploitation of satellite-derived inputs within a gridded domain to generate accuracy and robustness in the forecasts. Hence, the ultimate proximity that can be reached between the point of interest and the potential exogenous variables, together with the localization of the seeking area and the optimization of time-lagged exogenous variables, suggests a reliable approach towards the development of more accurate and robust solar forecasts.

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References

- [1] R. H. Inman, H. T. C. Pedro, C. F. M. Coimbra, Solar forecasting methods for renewable energy integration, *Progress in Energy and Combustion Science* 39 (6) (2013) 535–576.
- [2] R. Marquez, V. G. Gueorguiev, C. F. M. Coimbra, Forecasting of global horizontal irradiance using sky cover indices, *Journal of Solar Energy Engineering* 135 (1) (2012) 011017–011017.
- [3] Y. Chu, H. T. C. Pedro, C. F. M. Coimbra, Hybrid intra-hour DNI forecasts with sky image processing enhanced by stochastic learning, *Solar Energy* 98, Part C (2013) 592–603.
- [4] R. Marquez, H. T. C. Pedro, C. F. M. Coimbra, Hybrid solar forecasting method uses satellite imaging and ground telemetry as inputs to ANNs, *Solar Energy* 92 (2013) 176–188.
- [5] V. P. A. Lonij, A. E. Brooks, A. D. Cronin, M. Leuthold, K. Koch, Intra-hour forecasts of solar power production using measurements from a network of irradiance sensors, *Solar Energy* 97 (2013) 58–66.
- [6] D. Yang, C. Gu, Z. Dong, P. Jirutitijaroen, N. Chen, W. M. Walsh, Solar irradiance forecasting using spatial-temporal covariance structures and time-forward kriging, *Renewable Energy* 60 (2013) 235 – 245.
- [7] A. Sözen, E. Arcaklıoğlu, M. Özalp, N. Çağlar, Forecasting based on neural network approach of solar potential in Turkey, *Renewable Energy* 30 (7) (2005) 1075 – 1090.
- [8] S. Pelland, G. Galanis, G. Kallos, Solar and photovoltaic forecasting through post-processing of the Global Environmental Multiscale numerical weather prediction model, *Progress in Photovoltaics: Research and Applications* 21 (3) (2013) 284–296.
- [9] S. Al-Alawi, H. Al-Hinai, An ANN-based approach for predicting global radiation in locations with no direct measurement instrumentation, *Renewable Energy* 14 (14) (1998) 199 – 204.
- [10] A. Nottrott, J. Kleissl, Validation of the NSRDB-SUNY global horizontal irradiance in california, *Solar Energy* 84 (10) (2010) 1816–1827.
- [11] L. Nonnenmacher, A. Kaur, C. F. M. Coimbra, Verification of the SUNY direct normal irradiance model with ground measurements, *Solar Energy* 99 (2014) 246–258.
- [12] Geostationary Operational Environmental Satellite R-Series, User Systems: GOES-R Rebroadcast (2014).
URL <http://www.goes-r.gov/users/grb.html>
- [13] Solar Anywhere, SolarAnywhere data, Clean Power Research 2012 (2012).
URL <http://www.solaranywhere.com>
- [14] R. Perez, P. Ineichen, K. Moore, M. Kmiecik, C. Chain, R. George, F. Vignola, A new operational model for satellite-derived irradiances: description and validation, *Solar Energy* 73 (5) (2002) 307–317.
- [15] R. Perez, P. Ineichen, M. Kmiecik, K. Moore, D. Renne, R. George, Producing satellite-derived irradiances in complex arid terrain, *Solar Energy* 77 (4) (2004) 367 – 371.
- [16] F. Vignola, P. Harlan, R. Perez, M. Kmiecik, Analysis of satellite derived beam and global solar radiation data, *Solar Energy* 81 (6) (2007) 768 – 772.
- [17] P. Ineichen, Comparison of eight clear sky broadband models against 16 independent data banks, *Solar Energy* 80 (4) (2006) 468–478.
- [18] R. H. Inman, H. T. C. Pedro, C. F. M. Coimbra, Solar forecasting methods for renewable energy integration, *Prog. Energy Combust. Sci.* 39 (2013) 535 – 576.
- [19] P. Ineichen, R. Perez, A new airmass independent formulation for the linke turbidity coefficient, *Solar Energy* 73 (3) (2002) 151–157.
- [20] A. Zagouras, R. H. Inman, C. F. M. Coimbra, On the determination of coherent solar microclimates for utility planning and operations, *Solar Energy* 102 (2014) 173–188.
- [21] V. Badescu, C. A. Gueymard, S. Cheval, C. Oprea, M. Baci, A. Dumitrescu, F. Iacobescu, I. Milos, C. Rada, Accuracy analysis for fifty-four clear-sky solar radiation models using routine hourly global irradiance measurements in romania, *Renewable Energy* 55 (2013) 85 – 103.
- [22] C. N. Long, T. P. Ackerman, Surface measurements of solar irradiance: a study of the spatial correlation between simultaneous measurements at separated sites, *J. Appl. Meteor.* 34 (1995) 1039–1046.
- [23] C. Glasbey, R. Graham, A. Hunter, Spatio-temporal variability of solar energy across a region: a statistical modelling approach, *Solar Energy* 70 (4) (2001) 373 – 381.
- [24] A. Mellit, Artificial intelligence technique for modelling and forecasting of solar radiation data: a review, *Int. J. Artif. Intell. Soft Comput.* 1 (1) (2008) 52–76.
- [25] C. Bishop, Neural networks and their applications, *Review of Scientific Instruments* 65 (1994) 1803–1832.
- [26] H. T. C. Pedro, C. F. M. Coimbra, Assessment of forecasting techniques for solar power production with no exogenous inputs, *Solar energy* 86 (7) (2012) 2017–2028.
- [27] A. Mellit, M. Bengharoun, S. Kalogirou, Modeling and simulation of a stand-alone photovoltaic system using an adaptive artificial neural network: Proposition for a new sizing procedure, *Renewable Energy* 32 (2) (2007) 285–313.
- [28] V. N. Vapnik, *The Nature of Statistical Learning Theory*, Springer-Verlag New York, Inc., New York, NY, USA, 1995.
- [29] B. Scholkopf, A. J. Smola, *Learning with Kernels: Support Vector Machines, Regularization, Optimization, and Beyond*, MIT Press, Cambridge, MA, USA, 2001.
- [30] J. H. Holland, *Adaptation in natural and artificial systems*, Ann Arbor MI, University of Michigan Press, 1975.

Figure 6: Quarterly seasonal and merged s -skill results for the linear model optimized by GA. The color of the bars indicate the time horizon used, as well as the evaluation subset (validation or testing).

Figure 7: Scatter plots of measured and predicted measurements of the testing subset as they divided into a quarterly seasonal basis. The predicted measurements are relating to the merged results for the following Location - Forecast Horizon - Model: a) De Laveaga - 1h - GA, b) De Laveaga - 1h - Persistence, c) De Laveaga - 3h - GA, d) De Laveaga - 3h - Persistence, e) Parlier - 1h - GA, f) Parlier - 1h - Persistence, g) Parlier - 3h - GA, h) Parlier - 3h - Persistence. The s -skill (%) values for each row are 19.950, 40.149, 11.027, 8.458, respectively. The coefficient of determination (R-square) and the RMSE are also shown above each plot. Solid red lines are referred to the 1:1 reference lines.

Table .2: Characteristics of CIMIS Weather Stations (sorted by North to South).

No.	CIMIS ID	Station name	Latitude (°)	Longitude (°)	Elevation (ft)	Irrigation region	County
1	43	McArthur	41°3'53"	-121°27'16"	3310	Northeast Plateau	Shasta
2	6	Davis	38°32'9"	-121°46'32"	60	Sacramento Valley	Yolo
3	103	Windsor	38°31'35"	-122°49'42"	85	North Coast Valleys	Sonoma
4	148	Merced	37°18'49"	-120°23'11"	200	San Joaquin Valley	Merced
5	104	De Laveaga	36°59'52"	-121°59'45"	300	Monterey Bay	Santa Cruz
6	39	Parlier	36°35'51"	-119°30'15"	337	San Joaquin Valley	Fresno
7	173	Torrey Pines	32°54'4"	-117°15'0"	335	South Coast Valleys	San Diego

Table .3: Summary of the forecast skill and the RMSE statistical error merged results for 1h-ahead horizon on a quarterly basis. The acronyms PERS, ENDO, ANN, SVR, EXO.1 to EXO.4, EXO.best and GA stand for the persistence, the linear model using only endogenous variables (CIMIS locations), the ANN, the SVR, the linear models using exogenous variables from a single lag (0h,1h,2h and 3h time shifts, respectively), the linear model that uses the best exogenous variables from each of the time lags, and the linear model optimized by the GA, respectively. The column labels ‘Val’ and ‘Test’ indicate the validation and testing subsets.

s (%)	Torrey Pines		De Laveaga		Windsor		McArthur		Davis		Merced		Parlier	
	Val	Test	Val	Test	Val	Test	Val	Test	Val	Test	Val	Test	Val	Test
ENDO	1.922	2.288	6.394	6.435	5.686	5.051	2.074	2.484	0.671	1.145	2.498	2.078	1.840	1.119
ANN	7.183	5.656	9.267	10.768	11.117	14.502	1.876	4.644	-3.734	1.996	2.254	2.167	1.318	2.915
SVR	6.346	3.162	8.963	9.539	10.134	14.704	2.129	3.700	0.537	1.777	-3.650	4.636	1.809	2.130
EXO.1	6.835	7.106	9.036	9.763	16.026	13.214	8.878	7.650	8.088	6.502	11.712	11.983	8.671	3.491
EXO.2	5.691	5.786	9.374	10.180	14.405	10.951	7.123	4.889	4.629	3.075	7.136	7.122	7.135	1.188
EXO.3	5.274	4.208	9.168	8.334	10.891	7.124	4.758	5.194	2.932	2.428	4.596	5.285	4.361	1.271
EXO.4	5.130	4.018	8.692	7.455	7.847	6.343	3.382	3.375	1.692	0.896	3.408	3.475	2.504	1.008
EXO.best	15.172	11.893	16.009	16.535	23.054	22.345	11.997	10.398	10.616	9.383	14.445	14.518	12.461	6.857
GA	22.318	13.413	23.070	19.950	29.258	24.699	19.398	12.041	17.309	11.953	20.004	15.984	20.480	11.027
RMSE														
(W/m²)														
PERS	82.695	82.680	80.997	85.960	77.045	72.112	81.603	78.115	66.283	57.200	68.124	72.160	58.727	56.299
ENDO	81.105	80.788	75.818	80.429	72.664	68.469	79.911	76.175	65.838	56.546	66.422	70.661	57.647	55.668
ANN	76.755	78.003	73.491	76.704	68.480	61.654	80.072	74.488	68.758	56.059	66.589	70.596	57.953	54.657
SVR	77.447	80.065	73.737	77.761	69.238	61.508	79.865	75.226	65.927	56.184	70.611	68.815	57.665	55.100
EXO.1	77.042	76.804	73.678	77.568	64.698	62.583	74.358	72.140	60.922	53.481	60.146	63.513	53.635	54.333
EXO.2	77.989	77.896	73.404	77.209	65.947	64.214	75.790	74.296	63.215	55.442	63.263	67.021	54.537	55.630
EXO.3	78.334	79.200	73.571	78.796	68.654	66.974	77.720	74.058	64.339	55.811	64.993	68.347	56.167	55.583
EXO.4	78.452	79.357	73.957	79.552	70.999	67.537	78.843	75.479	65.161	56.688	65.803	69.652	57.257	55.731
EXO.best	70.149	72.846	68.030	71.747	59.283	55.998	71.813	69.993	59.246	51.833	58.284	61.684	51.409	52.438
GA	64.239	71.590	62.311	68.811	54.503	54.301	65.774	68.710	54.810	50.363	54.496	60.626	46.700	50.091

Table .4: Same as in Table .3, but for 2h-ahead horizon on a quarterly basis.

s (%)	Torrey Pines		De Laveaga		Windsor		McArthur		Davis		Merced		Parlier	
	Val	Test	Val	Test	Val	Test	Val	Test	Val	Test	Val	Test	Val	Test
ENDO	6.820	7.873	16.070	20.443	12.615	13.131	4.093	4.286	1.785	2.950	4.449	3.918	4.700	2.337
ANN	10.936	10.774	16.776	20.512	17.157	23.895	5.515	6.634	-2.981	2.879	-0.547	7.465	5.166	1.703
SVR	11.539	11.135	17.206	22.835	14.739	21.678	3.693	5.556	3.444	2.157	1.385	6.232	3.587	3.104
EXO.1	13.347	13.178	28.014	26.390	31.394	25.868	13.365	10.602	12.078	9.640	16.137	14.492	14.911	5.445
EXO.2	12.348	11.253	25.627	25.122	24.928	21.971	9.784	7.423	9.349	8.003	13.738	12.764	13.057	3.689
EXO.3	11.941	10.284	21.015	24.752	17.498	16.573	8.331	7.698	5.227	5.623	9.205	9.127	9.342	3.261
EXO.4	10.421	10.148	17.531	21.004	14.580	14.641	6.153	5.862	4.389	2.812	6.169	6.284	6.482	3.495
EXO.best	19.636	17.852	30.683	27.028	33.530	26.460	15.213	9.817	15.922	12.443	19.722	16.114	17.192	6.255
GA	29.185	20.312	38.299	30.884	41.913	30.169	24.284	15.284	22.740	12.220	27.261	17.593	24.741	10.495
RMSE														
(W/m²)														
PERS	116.385	120.273	121.470	128.025	111.829	101.584	105.982	98.573	85.274	70.816	87.340	85.355	75.313	72.459
ENDO	108.447	110.804	101.950	101.853	97.722	88.244	101.644	94.348	83.752	68.727	83.454	82.010	71.773	70.766
ANN	103.657	107.315	101.092	101.765	92.643	77.311	100.138	92.034	87.815	68.777	87.818	78.983	71.423	71.225
SVR	102.955	106.880	100.570	98.790	95.346	79.563	102.068	93.096	82.337	69.289	86.130	80.035	72.612	70.210
EXO.1	100.851	104.423	87.442	94.240	76.722	75.306	91.817	88.123	74.974	63.989	73.246	72.985	64.083	68.514
EXO.2	102.014	106.738	90.341	95.862	83.953	79.264	95.613	91.256	77.301	65.149	75.341	74.460	65.479	69.786
EXO.3	102.487	107.903	95.944	96.336	92.262	84.749	97.153	90.985	80.816	66.834	79.301	77.565	68.277	70.097
EXO.4	104.256	108.067	100.175	101.135	95.524	86.711	99.461	92.794	81.531	68.825	81.952	79.991	70.432	69.927
EXO.best	93.532	98.802	84.200	93.422	74.333	74.705	89.859	88.896	71.696	62.004	70.115	71.601	62.366	67.927
GA	82.418	95.843	74.949	88.486	64.958	70.937	80.246	83.507	65.882	62.162	63.530	70.339	56.680	64.855

Table .5: Same as in Table .3, but for 3h-ahead horizon on a quarterly basis.

s (%)	Torrey Pines		De Laveaga		Windsor		McArthur		Davis		Merced		Parlier	
	Val	Test	Val	Test	Val	Test	Val	Test	Val	Test	Val	Test	Val	Test
ENDO	10.992	13.264	20.011	31.019	10.550	22.793	5.768	5.311	3.086	4.510	6.451	4.769	6.187	3.305
ANN	14.850	17.172	23.853	31.068	24.424	27.787	6.207	6.284	1.933	5.173	6.349	8.498	5.361	5.242
SVR	15.039	15.903	26.657	33.762	24.162	29.671	4.473	3.580	4.679	7.690	3.236	7.581	3.949	5.687
EXO.1	16.583	19.171	37.954	39.639	38.823	34.087	13.126	11.920	12.566	13.431	19.175	15.424	18.136	6.325
EXO.2	18.541	16.731	31.613	37.592	32.809	27.916	10.890	9.408	10.547	10.146	15.252	14.263	14.011	6.604
EXO.3	16.941	16.975	25.398	35.276	18.794	24.157	9.794	6.702	7.770	9.223	10.475	11.567	11.966	5.594
EXO.4	14.612	16.090	23.161	32.635	11.784	23.458	7.496	6.932	4.757	4.998	8.450	7.893	9.377	6.030
EXO_best	23.499	19.061	39.327	38.975	40.047	35.913	16.611	12.153	13.425	13.474	21.762	15.062	20.886	5.315
GA	31.674	23.375	45.669	40.149	48.228	34.372	22.477	12.788	23.612	14.104	30.875	16.530	28.322	8.458
RMSE (W/m ²)														
PERS	133.729	139.035	146.940	153.054	130.277	116.329	117.653	104.111	94.307	77.827	96.818	86.155	81.182	78.188
ENDO	119.030	120.593	117.536	105.578	116.533	89.814	110.867	98.582	91.397	74.318	90.573	82.046	76.159	75.603
ANN	113.870	115.160	111.891	105.503	98.458	84.004	110.351	97.569	92.484	73.801	90.672	78.833	76.830	74.089
SVR	113.618	116.925	107.771	101.380	98.800	81.814	112.391	100.384	89.895	71.843	93.685	79.623	77.976	73.741
EXO.1	111.553	112.381	91.170	92.385	79.700	76.676	102.210	91.701	82.456	67.375	78.254	72.866	66.459	73.242
EXO.2	108.935	115.773	100.487	95.518	87.535	83.855	104.842	94.316	84.360	69.931	82.051	73.866	69.807	73.024
EXO.3	111.075	115.434	109.621	99.063	105.794	88.228	106.130	97.134	86.979	70.650	86.677	76.189	71.467	73.814
EXO.4	114.189	116.664	112.907	103.105	114.926	89.041	108.834	96.894	89.821	73.938	88.638	79.355	73.570	73.473
EXO_best	102.304	112.534	89.153	93.401	78.105	74.552	98.110	91.459	81.646	67.341	75.748	73.178	64.226	74.032
GA	91.372	106.536	79.834	91.605	67.447	76.345	91.209	90.797	72.039	66.850	66.926	71.913	58.189	71.575

Table .6: Same as in Table .3, but for 1h-ahead horizon on a biannual basis.

s (%)	Torrey Pines		De Laveaga		Windsor		McArthur		Davis		Merced		Parlier	
	Val	Test	Val	Test	Val	Test	Val	Test	Val	Test	Val	Test	Val	Test
ENDO	1.551	1.780	4.780	5.277	4.295	4.479	2.001	2.419	1.017	1.156	2.189	1.785	1.695	1.186
ANN	7.154	5.526	8.324	9.263	13.832	14.262	3.045	4.460	1.794	1.422	3.781	4.610	2.639	-0.484
SVR	7.188	5.255	8.911	9.385	12.157	14.610	2.996	3.223	1.590	1.115	2.954	2.814	2.370	1.298
EXO-Lag(1)	5.885	4.730	8.854	9.540	15.565	12.186	9.333	9.169	7.475	2.980	9.170	8.769	6.004	1.608
EXO-Lag(2)	4.571	5.832	10.625	10.443	14.593	10.464	5.141	5.535	2.875	2.410	5.803	5.561	4.783	1.804
EXO-Lag(3)	4.834	5.105	8.996	8.126	10.868	6.646	4.257	5.105	2.317	1.784	3.972	3.512	4.102	2.009
EXO-Lag(4)	5.000	4.059	6.642	5.783	8.245	7.135	3.280	4.000	1.103	1.186	2.895	2.568	2.313	1.914
EXO-BestLag	14.638	12.485	17.429	17.258	22.412	19.333	11.862	12.836	8.940	5.446	12.683	12.389	9.342	3.849
GA	18.804	15.908	22.414	20.968	27.598	24.595	17.414	15.471	17.784	11.238	16.969	13.408	16.261	11.301
RMSE (W/m ²)														
PERS	82.695	82.680	80.997	85.960	77.045	72.112	81.603	78.115	66.283	57.200	68.124	72.160	58.727	56.299
ENDO	81.412	81.208	77.125	81.424	73.736	68.882	79.970	76.226	65.609	56.539	66.633	70.872	57.732	55.631
ANN	76.779	78.111	74.255	77.998	66.388	61.827	79.118	74.632	65.093	56.387	65.548	68.834	57.178	56.571
SVR	76.751	78.335	73.779	77.893	67.679	61.576	79.158	75.598	65.229	56.563	66.112	70.130	57.336	55.568
EXO-Lag(1)	77.828	78.769	73.825	77.759	65.053	63.324	73.986	70.953	61.328	55.496	61.877	65.832	55.201	55.393
EXO-Lag(2)	78.915	77.858	72.391	76.983	65.802	64.566	77.408	73.792	64.377	55.822	64.171	68.147	55.919	55.283
EXO-Lag(3)	78.697	78.459	73.710	78.975	68.671	67.319	78.129	74.128	64.747	56.180	65.418	69.626	56.318	55.167
EXO-Lag(4)	78.561	79.323	75.617	80.989	70.692	66.966	78.926	74.991	65.552	56.522	66.152	70.307	57.369	55.221
EXO-BestLag	70.590	72.357	66.880	71.125	59.778	58.170	71.923	68.089	60.357	54.085	59.484	63.220	53.241	54.131
GA	67.145	69.527	62.842	67.936	55.782	54.376	67.393	66.030	54.495	50.772	56.564	62.485	49.178	49.936

Table .7: Same as in Table .3, but for 2h-ahead horizon on a biannual basis.

s (%)	Torrey Pines		De Laveaga		Windsor		McArthur		Davis		Merced		Parlier	
	Val	Test	Val	Test	Val	Test	Val	Test	Val	Test	Val	Test	Val	Test
ENDO	5.509	6.281	15.357	17.872	9.116	9.188	3.693	4.421	2.078	2.441	3.976	2.526	4.167	2.419
ANN	11.318	11.126	17.283	20.589	21.353	23.975	6.200	8.176	3.964	4.664	7.220	5.769	7.677	2.564
SVR	11.673	12.539	18.061	20.635	21.175	24.749	4.448	5.898	4.175	2.124	5.826	2.606	4.859	1.586
EXO-Lag(1)	11.278	11.023	27.295	25.640	28.761	23.166	12.137	10.862	8.097	6.751	14.295	13.520	10.806	4.147
EXO-Lag(2)	10.357	12.144	23.491	23.089	23.250	17.592	9.033	8.954	6.591	4.726	10.693	10.654	11.602	6.112
EXO-Lag(3)	11.416	11.176	21.044	21.743	17.779	12.272	7.918	8.821	3.604	3.351	7.483	5.649	6.320	4.403
EXO-Lag(4)	10.079	9.744	18.385	20.308	11.558	11.074	5.322	5.431	2.339	2.575	5.166	3.840	5.465	2.627
EXO-BestLag	20.634	17.734	28.076	26.136	32.408	27.671	15.408	16.029	11.785	9.141	16.942	15.051	15.065	6.687
GA	26.253	18.825	33.054	30.193	38.931	32.675	22.579	16.079	21.150	14.694	21.875	16.082	20.712	8.185
RMSE (W/m ²)														
PERS	116.385	120.273	121.470	128.025	111.829	101.584	105.982	98.573	85.274	70.816	87.340	85.355	75.313	72.459
ENDO	109.973	112.718	102.817	105.145	101.635	92.250	102.068	94.215	83.502	69.087	83.867	83.199	72.175	70.707
ANN	103.212	106.891	100.477	101.666	87.951	77.229	99.411	90.514	81.893	67.514	81.034	80.431	69.531	70.601
SVR	102.799	105.192	99.531	101.607	88.150	76.443	101.268	92.759	81.714	69.312	82.252	83.130	71.654	71.310
EXO-Lag(1)	103.259	107.015	88.315	95.199	79.666	78.050	93.119	87.866	78.369	66.035	74.855	73.815	67.175	69.454
EXO-Lag(2)	104.331	105.667	92.936	98.465	85.829	83.713	96.409	89.747	79.653	67.469	78.001	76.261	66.575	68.031
EXO-Lag(3)	103.098	106.831	95.908	100.189	91.947	89.117	97.590	89.878	82.200	68.443	80.804	80.533	70.553	69.269
EXO-Lag(4)	104.654	108.553	99.138	102.025	98.905	90.334	100.342	93.219	83.279	68.993	82.827	82.078	71.198	70.556
EXO-BestLag	92.370	98.943	87.366	94.564	75.588	73.475	89.652	82.772	75.224	64.343	72.543	72.508	63.968	67.614
GA	85.830	97.631	81.320	89.371	68.293	68.391	82.052	82.723	67.238	60.410	68.234	71.628	59.714	66.528

Table .8: Same as in Table .3, but for 3h-ahead horizon on a biannual basis.

s (%)	Torrey Pines		De Laveaga		Windsor		McArthur		Davis		Merced		Parlier	
	Val	Test	Val	Test	Val	Test	Val	Test	Val	Test	Val	Test	Val	Test
ENDO	9.566	10.914	24.253	31.262	17.582	18.458	5.079	5.893	3.220	3.684	5.368	1.675	6.136	3.183
ANN	14.514	16.332	24.620	28.689	27.301	27.294	8.400	7.940	6.028	5.599	8.277	2.070	7.295	2.334
SVR	13.923	15.354	28.018	31.902	26.573	30.475	5.549	7.104	5.603	6.375	8.558	-1.929	6.586	0.369
EXO-Lag(1)	14.636	16.288	36.925	35.821	37.830	30.298	12.750	12.344	9.929	6.137	17.939	15.391	15.670	9.520
EXO-Lag(2)	15.285	16.066	33.380	37.782	32.104	27.412	12.585	11.964	6.209	6.005	16.218	11.479	12.339	5.038
EXO-Lag(3)	15.066	15.335	31.403	35.864	25.792	24.022	10.361	8.426	4.284	5.068	11.872	8.497	8.937	6.297
EXO-Lag(4)	14.325	15.206	25.703	31.276	19.547	20.705	6.146	5.654	2.774	3.216	6.559	3.993	7.784	4.477
EXO-BestLag	20.693	19.276	36.697	35.806	39.953	35.403	15.177	12.868	11.350	7.216	20.907	16.169	18.396	9.023
GA	30.222	24.760	42.148	41.180	45.478	37.607	22.659	17.417	21.450	12.823	24.078	16.045	25.452	9.879
RMSE (W/m ²)														
PERS	133.729	139.035	146.940	153.054	130.277	116.329	117.653	104.111	94.307	77.827	96.818	86.155	81.182	78.188
ENDO	120.937	123.860	111.303	105.206	107.371	94.858	111.678	97.976	91.270	74.960	91.621	84.712	76.201	75.699
ANN	114.320	116.328	110.763	109.144	94.710	84.578	107.771	95.845	88.622	73.470	88.804	84.371	75.260	76.362
SVR	115.111	117.688	105.771	104.227	95.659	80.878	111.125	96.716	89.022	72.866	88.533	87.816	75.835	77.899
EXO-Lag(1)	114.157	116.389	92.683	98.228	80.994	81.084	102.653	91.260	84.943	73.051	79.450	72.894	68.461	70.745
EXO-Lag(2)	113.289	116.698	97.891	95.227	88.453	84.441	102.847	91.656	88.451	73.154	81.116	76.265	71.165	74.249
EXO-Lag(3)	113.582	117.715	100.796	98.162	96.676	88.384	105.464	95.339	90.266	73.883	85.324	78.834	73.927	73.264
EXO-Lag(4)	114.573	117.894	109.172	105.184	104.812	92.243	110.422	98.224	91.691	75.324	90.468	82.715	74.862	74.687
EXO-BestLag	106.056	112.235	93.017	98.252	78.228	75.146	99.798	90.715	83.603	72.212	76.577	72.225	66.248	71.133
GA	93.313	104.609	85.008	90.027	71.029	72.581	90.994	85.978	74.078	67.847	73.506	72.331	60.520	70.464

Table .9: Same as in Table .3, but for 1h-ahead horizon on an annual basis.

s (%)	Torrey Pines		De Laveaga		Windsor		McArthur		Davis		Merced		Parlier	
	Val	Test	Val	Test	Val	Test	Val	Test	Val	Test	Val	Test	Val	Test
ENDO	1.535	1.734	2.121	1.896	2.337	2.480	1.754	1.800	0.731	0.804	1.415	1.289	1.006	0.904
ANN	5.748	6.387	8.423	10.223	12.556	12.833	5.346	4.658	3.035	3.596	3.675	4.265	3.912	3.097
SVR	6.064	5.355	8.240	12.067	13.175	12.722	3.396	3.767	2.942	1.222	2.584	0.667	2.160	2.272
EXO-Lag(1)	4.545	4.738	10.006	9.586	15.659	14.451	8.725	9.147	7.495	6.056	9.439	9.865	5.977	3.823
EXO-Lag(2)	3.703	5.672	10.552	11.612	12.815	11.518	5.025	4.621	2.942	4.446	4.857	4.666	3.412	3.516
EXO-Lag(3)	3.746	4.442	8.917	8.909	7.957	5.721	3.408	3.308	1.127	1.475	3.567	2.609	2.521	2.004
EXO-Lag(4)	4.106	3.791	6.292	6.058	6.386	4.997	2.774	3.096	0.889	1.217	1.850	1.423	1.140	0.627
EXO-BestLag	12.394	9.611	14.064	16.127	21.782	23.949	11.860	14.042	13.587	9.063	12.376	14.155	8.559	6.187
GA	18.028	16.044	20.900	21.495	25.045	25.161	16.175	14.752	16.398	10.434	16.144	15.641	15.699	14.302
RMSE (W/m^2)														
PERS	82.695	82.680	80.997	85.960	77.045	72.112	81.603	78.115	66.283	57.200	68.124	72.160	58.727	56.299
ENDO	81.426	81.246	79.279	84.330	75.244	70.323	80.171	76.709	65.798	56.740	67.161	71.230	58.136	55.790
ANN	77.942	77.398	74.174	77.173	67.371	62.857	77.240	74.477	64.271	55.143	65.621	69.083	56.430	54.555
SVR	77.680	78.252	74.323	75.587	66.895	62.937	78.832	75.173	64.333	56.501	66.364	71.678	57.459	55.019
EXO-Lag(1)	78.936	78.762	72.892	77.720	64.980	61.691	74.483	70.970	61.315	53.736	61.694	65.041	55.217	54.146
EXO-Lag(2)	79.633	77.990	72.450	75.979	67.172	63.806	77.502	74.506	64.332	54.657	64.816	68.793	56.724	54.319
EXO-Lag(3)	79.597	79.007	73.774	78.302	70.915	67.986	78.821	75.531	65.536	56.357	65.695	70.277	57.247	55.170
EXO-Lag(4)	79.300	79.545	75.901	80.753	72.125	68.508	79.339	75.697	65.694	56.504	66.864	71.133	58.058	55.946
EXO-BestLag	72.445	74.733	69.605	72.097	60.263	54.842	71.925	67.147	57.277	52.016	59.693	61.946	53.701	52.815
GA	67.787	69.415	64.068	67.483	57.749	53.968	68.404	66.592	55.414	51.232	57.127	60.874	49.508	48.247

Table .10: Same as in Table .3, but for 2h-ahead horizon on an annual basis.

s (%)	Torrey Pines		De Laveaga		Windsor		McArthur		Davis		Merced		Parlier	
	Val	Test	Val	Test	Val	Test	Val	Test	Val	Test	Val	Test	Val	Test
ENDO	5.093	5.918	8.770	8.682	4.468	4.634	3.284	3.129	1.668	1.884	2.903	2.275	2.659	2.087
ANN	10.546	12.161	15.205	18.371	21.160	20.312	8.302	7.004	6.532	5.322	6.551	6.012	6.773	4.022
SVR	10.780	12.415	19.158	20.858	21.253	20.045	5.544	5.122	4.655	1.471	4.406	5.257	3.929	1.456
EXO-Lag(1)	8.600	10.413	26.981	27.535	26.075	24.836	11.738	10.337	9.808	12.069	12.835	12.131	10.772	8.491
EXO-Lag(2)	7.857	9.314	24.238	24.211	20.317	15.545	7.867	7.227	5.291	7.001	9.796	8.129	8.570	6.198
EXO-Lag(3)	10.046	9.805	17.052	19.984	16.199	12.538	8.507	7.632	1.889	2.084	5.407	5.414	5.767	2.103
EXO-Lag(4)	9.113	8.973	11.869	12.457	8.728	7.526	4.058	5.063	2.482	1.664	3.012	2.267	3.835	2.391
EXO-BestLag	18.035	15.902	29.117	29.796	31.335	29.762	13.472	12.206	12.709	13.218	15.074	12.199	13.167	8.918
GA	24.448	20.084	31.402	31.259	35.322	32.455	19.343	14.778	17.374	13.532	18.594	15.408	17.469	10.428
RMSE (W/m^2)														
PERS	116.385	120.273	121.470	128.025	111.829	101.584	105.982	98.573	85.274	70.816	87.340	85.355	75.313	72.459
ENDO	110.457	113.155	110.817	116.910	106.833	96.876	102.502	95.488	83.851	69.482	84.804	83.413	73.311	70.947
ANN	104.111	105.646	103.001	104.505	88.166	80.950	97.184	91.669	79.704	67.047	81.618	80.224	70.212	69.545
SVR	103.839	105.341	98.200	101.322	88.062	81.222	100.107	93.524	81.304	69.774	83.491	80.868	72.354	71.404
EXO-Lag(1)	106.375	107.748	88.696	92.773	82.670	76.355	93.542	88.384	76.910	62.269	76.130	75.000	67.200	66.307
EXO-Lag(2)	107.240	109.071	92.028	97.029	89.109	85.792	97.644	91.449	80.762	65.858	78.784	78.417	68.859	67.968
EXO-Lag(3)	104.693	108.479	100.757	102.440	93.714	88.847	96.967	91.049	83.663	69.341	82.617	80.734	70.970	70.935
EXO-Lag(4)	105.778	109.481	107.054	112.077	102.069	93.939	101.682	93.582	83.157	69.638	84.709	83.420	72.425	70.727
EXO-BestLag	95.395	101.146	86.102	89.879	76.788	71.350	91.704	86.541	74.436	61.456	74.174	74.942	65.397	65.998
GA	87.931	96.117	83.326	88.005	72.329	68.615	85.482	84.006	70.458	61.233	71.100	72.204	62.157	64.903

Table .11: Same as in Table .3, but for 3h-ahead horizon on an annual basis.

s (%)	Torrey Pines		De Laveaga		Windsor		McArthur		Davis		Merced		Parlier	
	Val	Test	Val	Test	Val	Test	Val	Test	Val	Test	Val	Test	Val	Test
ENDO	9.013	10.508	16.477	17.148	7.633	7.853	4.469	4.125	2.740	2.997	4.312	2.590	4.424	3.020
ANN	13.095	15.540	23.136	26.614	26.421	24.349	9.689	4.704	6.659	7.645	7.568	6.063	8.414	7.061
SVR	13.432	15.841	25.757	29.908	26.199	23.968	7.251	3.044	6.212	5.104	5.271	2.333	4.631	4.148
EXO-Lag(1)	11.773	14.306	36.331	36.840	32.886	28.422	12.752	12.231	10.342	11.884	16.083	12.601	14.673	9.128
EXO-Lag(2)	13.324	14.258	33.324	36.188	28.133	21.488	11.937	9.825	5.862	7.210	12.761	10.350	11.063	7.098
EXO-Lag(3)	14.100	14.704	30.314	31.284	20.348	17.700	10.647	7.526	4.724	4.708	9.402	7.350	9.446	5.894
EXO-Lag(4)	12.215	14.168	20.560	20.827	12.869	14.236	6.144	5.481	3.270	2.526	5.794	3.152	5.346	4.121
EXO-BestLag	21.057	19.766	37.059	37.847	37.200	33.876	15.016	13.261	11.601	13.234	18.302	12.990	15.034	6.032
GA	27.471	22.442	39.897	39.196	40.747	37.312	19.012	15.749	15.992	12.871	23.010	14.494	22.758	8.969
RMSE														
(W/m²)														
PERS	133.729	139.035	146.940	153.054	130.277	116.329	117.653	104.111	94.307	77.827	96.818	86.155	81.182	78.188
ENDO	121.676	124.425	122.729	126.808	120.334	107.194	112.396	99.816	91.723	75.495	92.643	83.923	77.590	75.827
ANN	116.217	117.430	112.943	112.320	95.857	88.004	106.254	99.214	88.027	71.878	89.491	80.931	74.352	72.667
SVR	115.767	117.010	109.093	107.278	96.145	88.447	109.123	100.942	88.449	73.855	91.715	84.144	77.422	74.944
EXO-Lag(1)	117.986	119.145	93.554	96.669	87.434	83.267	102.651	91.377	84.554	68.578	81.247	75.298	69.270	71.051
EXO-Lag(2)	115.912	119.212	97.973	97.666	93.627	91.333	103.609	93.883	88.778	72.216	84.463	77.238	72.201	72.638
EXO-Lag(3)	114.874	118.592	102.396	105.173	103.768	95.739	105.127	96.276	89.851	74.163	87.715	79.822	73.513	73.579
EXO-Lag(4)	117.394	119.337	116.729	121.177	113.511	99.769	110.424	98.405	91.223	75.861	91.209	83.439	76.842	74.965
EXO-BestLag	105.571	111.553	92.485	95.128	81.814	76.922	99.986	90.305	83.366	67.527	79.099	74.963	68.977	73.471
GA	96.993	107.833	88.315	93.063	77.193	72.925	95.285	87.715	79.226	67.810	74.541	73.667	62.706	71.175