# Hierarchical time-series approaches for photovoltaic systems performance forecasting with sparse datasets

Edris Khorani, Sophie L. Pain, Tim Niewelt, Ruy S. Bonilla, Tasmiat Rahman, Nicholas E. Grant and John D. Murphy

***Abstract*- Solar-based power generation presents challenges for system and grid operators due to the intermittent nature of power supply. Predicting the performance of photovoltaic (PV) power plants and rooftop systems can often be challenging due to difficulties in data collection and incoherencies in interconnected systems. Following the hierarchical aggregation structure from geographical and temporal similarities between PV systems, we suggest a simplified approach to predicting the performance of individual installations and evaluating the impact of these hypothetical installations on the overall grid. We use the hierarchical nature of power generation and ascertain weather datasets to predict the performance of new or existing systems for locations with unmeasured input data. We demonstrate an approach that could improve grid stability by using a hierarchical model on publicly available datasets on utility and rooftop installations. Ensemble Machine Learning algorithms are trained with 16 weeks of known hourly input training features to form a baseline model for known locations. The prediction accuracy is then directly compared for locations with known and unknown input features, both on a granular and subregion level. We observe a reduction in prediction accuracy by 6-8 % using the hierarchical approach. The accuracy of the hierarchical model can be further enhanced beyond our work by increasing the training dataset temporally as well as by augmenting nested layers of the hierarchy.**

***Index Terms*- Hierarchical time-series, machine learning, photovoltaic systems, predictive modelling, sparse datasets.**

## I. INTRODUCTION

### A. Background

As the photovoltaic (PV) industry continues to grow beyond the terawatt scale, PV market penetration increases and in-turn the impact of output fluctuation on the grid increases. Therefore, there is a growing need for efficient and unified forecasting methods for PV output. Power forecasting enables grid operators to make key pre-planned decisions for how and when to connect PV generation systems to the main grid and ultimately manage energy distribution effectively [1]–[3]. The ever-expanding integration of commercial and residential PV systems into the energy grid creates a challenge for handling uncertainty and unifying predictive modelling approaches. Without PV power forecasting, significant market penetration creates risks for grid stability. Alternative methods of grid stabilization include deploying costly solutions such as large energy storage systems and complicated approaches such as greater coordination and participation from the demand side [4]. At the current rate of PV deployment, solar power forecasting is expected to be indispensable in balancing the grid and exploiting a reliable PV power supply.

PV power forecasting methods can be grouped into three main categories, namely physical, statistical and artificial intelligence (AI) methods [5], [6].

Using physical models for PV output forecasting is an approach that uses weather parameters, such as solar irradiance and ambient temperature, as input vectors to physical equations to formulate a PV performance forecast, typically done using electrical modelling [7], [8]. This method works well in cases where (a) the location has stable weather or climate, and (b) when designed using minimal weather parameters (*e.g.*, only solar irradiance) [9]. Physical models are in essence physical equations that are used for electrical modelling of PV systems. Thermal modelling can also be done using physical models to predict PV module temperature [10], [11].

Selecting the type of physical model is primarily dependent on the forecasting horizon, *i.e.*, the time between the forecast and the present time [12]. For forecast horizons of less than 60 minutes, a common physical approach is Total Sky imagers (TSI) [13], [14]. Using TSI for solar output forecasting relies on the ability to extract cloud features or to forecast short-term global horizontal irradiance. In most cases, using this sky imaging method has been reported for forecasting horizons between 1 minute and 60 minutes [15]–[17]. Despite some reports showing cloud movement-based forecasting being accurate enough for windows up to 3 hours [18], forecasting horizons of hours or days ahead are typically done using numerical weather prediction (NWP) models [5], [12]. In general, methods like TSI or NWP are combined with PV models to predict the PV performance.

Statistical models can also be used for PV performance forecasting. These typically rely heavily on the availability of historical data. PV performance forecasting using statistical

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methods can be done directly or indirectly. A direct approach involves determining the relationship between input variables (*e.g.,* weather data) and PV power output using historical data, whereas an indirect approach involves modelling the required weather data like solar irradiance (typically using physical or AI models) before PV output power forecasting [5], [19], [20]. In other words, an indirect forecasting approach is done in two steps, whereas a direct approach is done in one. In numerous reports, the direct approach has been shown to be the preferred option as determined in simulations using widely available commercial PV power output forecasting software like PVsyst and PVSol [21]–[24]. In general, statistical models for PV performance forecasting are either probabilistic or deterministic [25]. Probabilistic approaches predict PV power output by approximating the power generated using the uncertainty in the input variables, whereas deterministic approaches do not take this into account and hence create more error prone results [26].

To correlate historical data to predict power output, statistical approaches through autoregression, moving average, integrated moving average, or vector autoregression have been reported [27]–[29]. Advancements in statistical methods beyond models like the autoregressive moving average (ARMA) [30] have been reached, such as the more generalized ARMA model, namely ARMAX model, which caters for exogenous input variables [31], and other reports using partial functional linear regression for PV performance forecasting [32]. Nonetheless, these statistical forecasting techniques inherently suffer in accuracy when unexpected fluctuations in solar irradiance occur [24].

AI models can be used to predict the performance of PV systems. They can be considered as sophisticated statistical approaches beyond regression analysis techniques that can offer more advanced forecasting methods. A wide variety of advanced AI techniques have been applied to tackle PV forecasting, with some cases enhancing prediction accuracy using modified versions of existing AI models [24], [33]–[35]. A very common approach found in literature for PV time-series forecasting is a form of recurrent neural network (RNN), namely long short-term memory (LSTM) [6], [20], [34], [36]. The suitability of this method for time-series forecasting in general is due to the ability to store dependencies in sequential data, allowing for better understanding of temporal dependencies [37]. In other reports in literature, artificial neural network (ANN) models are shown to be highly suitable for PV performance forecasting [24], [38], [39]. Neural networks work well for this type of time-series forecasting as they can handle variable length-sequences, *i.e.,* they can store information from more distant past time steps. This type of information is typically lost when using more traditional statistical techniques like ARMA. Beyond neural networks, other AI models like support vector regression have been successfully implemented [40]. Based on reports in literature, the choice of model varies frequently, but key considerations to take are highlighted as the forecasting horizon, computational complexity and dataset quality (*i.e.*, temporal density and variety in parameters). AI models can also be used in conjunction with physical models, forming a hybrid model, to create an enhanced forecasting method that combines multiple algorithms or modelling approaches to improve accuracy [41], [42]. However, this is typically a more complex approach and requires high computing power.

Despite the sophistication of current applications of AI to PV forecasting and the accuracies reported, in many real world cases, predicting PV performance is hindered by (a) difficulties in measuring the required data (*e.g.*, lack of nearby weather station), (b) sparse datasets (*e.g.,* new plants/domestic premises), or (c) technical faults during data collection (*e.g.*, faults in sensors for global horizontal irradiance or temperature measurements) [1], [14]. Furthermore, the ability to predict confidently the impact of new PV systems on the overall grid has not been fully established. Forecasting PV power for these types of applications is the focus of this study.

### *B. Hierarchical Time-Series Forecasting*

Time-series forecasting is a common method that exploits machine learning (ML) techniques in many predicting applications, including market demand, stock-market returns, and predictive maintenance. Often, real-world time series follow a hierarchical aggregation structure which arises from physical hierarchies such as geographical (*e.g.*, country-wide COVID-19 cases broken down by regions [43]), categorical (*e.g.*, overall sales broken down into product categories) or temporal (*e.g.*, annual data partitioned into months, weeks, days). Exploiting the hierarchical nature of data for predictive modelling can be useful when accounting for unmeasured or unexplained variables, borrowing "strength" from stronger datasets to poorer ones and using the structure in the data collection step to interpret and utilize incomplete information more effectively. In the case of PV installations, time-series forecasting can benefit from hierarchical enhancement techniques and prove extremely useful in applications including (i) aggregated power prediction from granular (individual) systems to predict overall grid power (bottom-up approach), (ii) improved grid stability, and (iii) bypassing technical faults in data collection at monitors and sensors, *e.g.,* by using a top-down approach. A schematic diagram of our proposed approach is illustrated in Fig. 1. Each level of the hierarchical tree can be weighted based on the geographical differences and energy capacity of each neighboring/overarching system. In Fig. 1, $\alpha_i$ or $\beta_j$ can be taken as the weight for the *i*-th subregion and *j*-th PV system in the hierarchy.

In this work, we focus on exploiting the hierarchical nature of such data to predict PV power generation at a subregional and granular level. The goal of this work is not to seek the most optimal predictive model for time-series forecasting of PV power generation as this has been widely reported in the literature [36], [44]–[46]. Rather, we aim to train a predictive model to assess the advantages of hierarchical approaches. For this, we use a dataset collected by the United Kingdom (UK) Power Networks [47] that collates voltage, current, power, energy and weather data for 18 weeks from multiple substations and domestic premises across the UK. We use this dataset to explore the potential ways to both answer the research questions at hand as well as providing an *Occam's Razor-esque* solution.

## II. METHODS

A schematic diagram of our ML pipeline is shown in Fig. 2(a). In this approach, PV performance and weather data are initially cleaned to handle missing data, correct any structural errors present and remove any irrelevant criteria, *e.g.,* other PV performance metrics like the generated current as the predictive modelling concept for this type of output feature would be similar. The combined dataset is then transformed so that it is coherent and useful for analysis. Once exploratory data analysis has been conducted, key input features are selected and extracted, and additional features are engineered based on domain knowledge. Various ensemble models are tested, *e.g.*, *XGBoost* [48], Random Forest (RF) regressor [49], and the combination of RF and a rolling window technique. The model is selected based on comparing the various ensemble models prediction accuracies using our testing dataset. From this, RF regressor is taken as our baseline model to predict PV output for locations with known input features to then directly compare this with the hierarchical approaches for locations with unknown input features. The RF regressor model begins with a decision tree (*i.e.*, a binary tree) to find a variable-value pair from the data trained [50], [51]. The decision tree is built by recursively dividing the data into subsets using feature values that minimize the impurity measure. For regression trees, the impurity measure can be translated to variance reduction, whereby the variance in the subset, S, can be defined as

$$V(S) = \frac{1}{|S|}\Sigma_{i\epsilon S}(y_i - \bar{y})^2 \quad (1)$$

where $y_i$ is target value for the *i*-th datapoint, and $\bar{y}$ is the mean of the target value in subset S. If the subset is split into two subsets, $S_1$ and $S_2$, the variance reduction, $V_{reduction}$, is determined as

$$V_{reduction} = V(S) - (\frac{|S_1|}{|S|}V(S_1) + \frac{|S_2|}{|S|}V(S_2)) \quad (2)$$

In this model, an ensemble of regression trees is constructed, where each tree is trained on a sample of the training data and a random subset of the features is taken at each split [52]. The aggregation of all trees constructs the RF regressor prediction. In other words, if the prediction of a single tree, $T_j$, is $\hat{y}_j(i)$, the RF prediction is

$$\hat{y}_{RF}(i) = \frac{1}{J}\Sigma_{j=1}^{J}\hat{y}_j(i) \quad (3)$$

The hyperparameters in the selected ML model are tuned using *GridSearchCV*, where the data are cross-validated against various combinations of hyperparameters [49]. Other parsimonious hyperparameter tuning approaches exist and could be implemented instead in this step. The hyperparameter tuning is done using the 16 weeks training dataset and the 2 weeks testing set is excluded to avoid overfitting. The tuned model is then used to predict the testing dataset for PV output of locations with known input features (*i.e.,* locations where the model has been trained with the training set) and compared with using a weighted hierarchical approach to predict PV output for locations with unknown input features. To measure the accuracy of the predicted power output, we use $R^2$, which measures how well the variance in the actual power is defined by the predicted power as such:

$$R^2 = 1 - \frac{\Sigma(y_i - \hat{y}_i)^2}{\Sigma(y_i - \bar{y})^2} \quad (4)$$

where $y_i$ is the actual power generated, $\hat{y}_i$ is the forecasted power generated, and $\bar{y}$ is the mean of the y values. Additionally, we use the mean absolute error (MAE) to measure the error between actual and forecasted power as

$$MAE = \frac{\Sigma_{i=1}^{n}|y_i - \hat{y}_i|}{n} \quad (5)$$

where n is the total number of datapoints, $y_i$ is the actual power generated and $\hat{y}_i$ is the forecasted power generated. The total dataset used for each location of interest is 18 weeks of hourly data (energy and weather) while the testing set used is two weeks. The data splitting for this study is illustrated in Fig. 2(b).

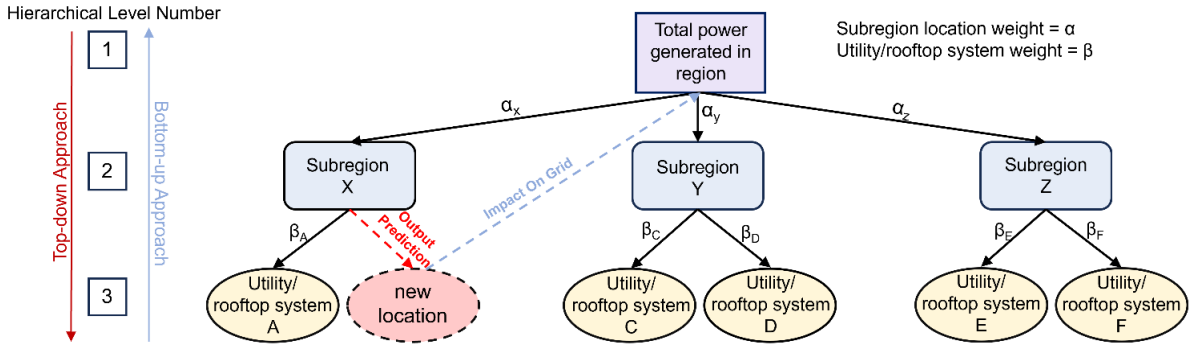


Fig. 1. Schematic diagram of interconnected systems based on hierarchy and the importance of hierarchical levels to predict performance of new systems and the consequent impact on the grid.

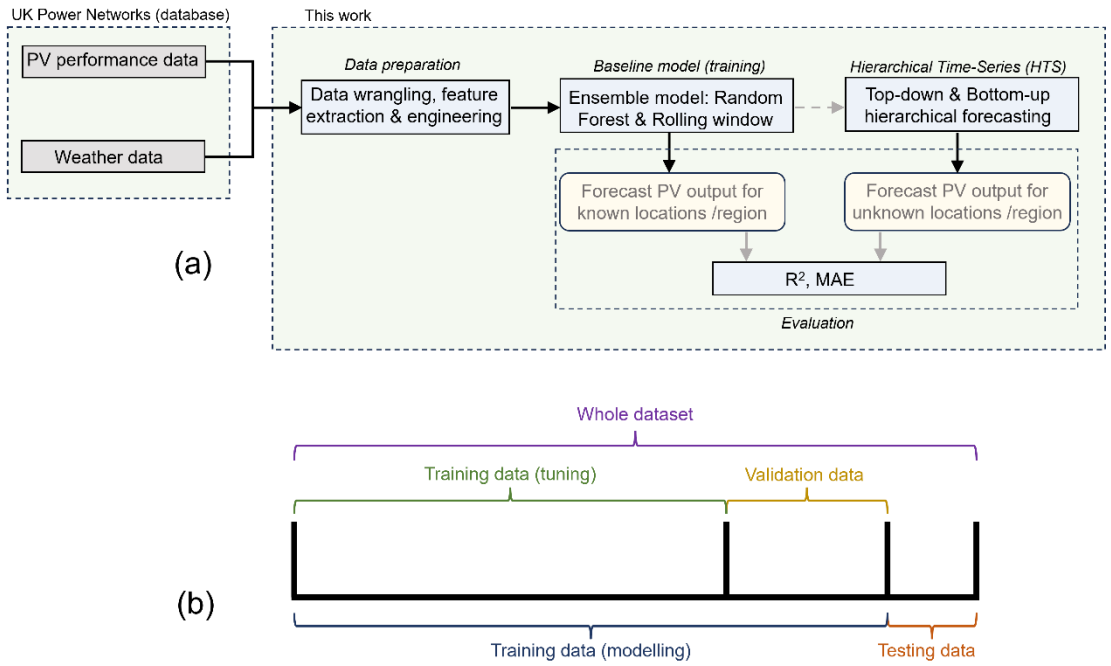


Fig. 2. (a) Schematic diagram of predictive modelling pipeline of interest and (b) illustration of data splitting used for modelling and cross-validation.

## III. Results and Discussion

### A. Feature Selection and Feature Engineering

First we identify the various parameters that could be used as input features from over 27 options in our example dataset [47]. To optimize the choice of input features for our baseline global univariate model, we begin with using a Spearman cross-correlation matrix to remove colinear variables where a strong monotonic association exists. The Spearman correlation is shown in Fig. 3, where two examples of cross-correlations are shown as a function of the power generated: outdoor temperature (*TempOut*) vs global horizontal irradiance (*SolarRad*), and outdoor humidity (*OutHum*) *vs*. outdoor temperature. Combining our exploratory data analysis steps with the cross-correlation matrix, we find that the outdoor temperature, humidity, and solar radiation (*i.e.,* global horizontal irradiance) are the most influential features to be considered. Additionally, domain knowledge in the field can be useful for selecting and engineering new features to improve model performance. We demonstrate this by introducing two sensible time coordinates as input features, namely day of the year (1-365) and total minutes (0-1440) to improve the performance of our predictive model.

### B. Hyperparameter tuning

We performed a systematic automated tuning of the following parameters in the baseline Random Forest Regressor model: *n_estimators*, defining the number of trees in the forest, *max_depth,* the maximum depth of the trees, *min_samples_split*, the number of samples required to split an internal node, *min_samples_leaf, the* minimum number of samples required to be at a leaf node. These were tuned together in a cross-validation grid search approach to find the combination of parameter values that maximizes the balanced accuracy score over the complete test dataset. Tuning was done using the training dataset, keeping the testing set separate. The cross-grid search was conducted using the parameter ranges given in Table 1.

TABLE I
Hyperparameter tuning parameter ranges and optimized values.

| Hyperparameter | Range | Optimal value |
|---|---|---|
| *n_estimators* | 10-200 | 76 |
| *max_depth* | 0-30 | 11 |
| *min_samples_split* | 2-20 | 13 |
| *min_samples_leaf* | 1-6 | 4 |

### C. Machine Learning Model Evaluation

To examine the performance of our baseline ML model, we identify what contribution each feature has on the model output, *i.e*., the generated PV power. This is done using a Shapely additive explanations (SHAP) plot [53], as displayed in Fig. 4. Feature values are scaled based on the size of the numerical value, *i.e.,* red corresponds to a large value and blue is used for smaller input feature values. In Fig. 4, each datapoint is represented in a violin plot for easier visualization of the distribution. The dots in Fig. 4 for the *SolarRad* feature represent outliers. For the case of the *SolarRad* feature, it is evident that large values (*i.e.,* when the global horizontal irradiance is high) force the model to predict larger power generation outputs, and *vice versa*, which is a good sanity check for verifying that the baseline model understands this feature well. For the case of *total_minutes,* very large or very small values (*i.e.,* nighttime or early morning) result in reducing the output prediction, whilst the mid-range values (*i.e.,* during peak sunlight hours) results in a larger output prediction.

SHAP plots can also be used to identify the order of importance of each input feature to the model output. In our case, the *DayOfYear* feature is signified as the least impactful input feature to our model output. This is to be expected as our temporal range is 16 weeks (June-September). If the dataset included more temporal data to cover the entire year, the seasonality would be more impactful to the model predictions, likely increasing the impact of this feature to the baseline model accuracy. In

other words, the difference in *DayOfYear* between *e.g.,* July and August is less significant than it would be when comparing *e.g.,* February and August for power output predictions. It is intuitive to see that using such an extended temporal length would also affect the prediction power of the *total_minutes* parameter. We continue using these input features for our work.

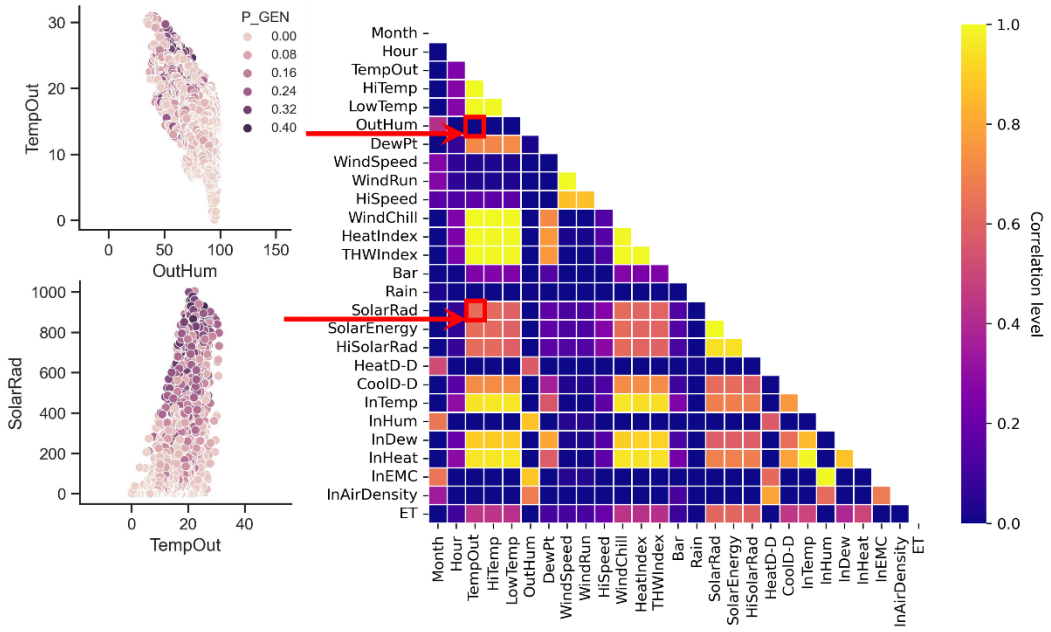


Fig. 3. Spearman cross-correlation matrix of parameters of interest for global univariate modelling. The color of each matrix location indicates the determined correlation, where yellow corresponds to high correlation, and blue corresponds to low correlation. As examples, the correlation between *TempOut* and *OutHum* as a function of *P_Gen*, and between *TempOut* and *SolarRad* as a function of *P_Gen*, are shown on the left. In these plots, darker circles correspond to greater power generation, whereas paler circles correspond to lesser power generation.

### *D. Direct Machine Learning Modelling vs Hierarchical Approach*

The optimized ensemble regressor model is taken as our baseline predictive modelling method. Our key interest is implementing a sufficiently accurate model to compare direct predictive modelling against the proposed hierarchical approach. In the latter, we use the directly modelled PV output of location(s) with known input features to predict the output of locations where the input features of interest are unknown. Our goal therefore is to simplify the predictive modelling approach when input datasets are sparse or unknown, and not to just fine-tune baseline models for time-series forecasting. This is where the top-down approach becomes useful, as directly predicting the PV performance for new systems with unknown datasets or existing systems with sparse datasets can be otherwise challenging. In our work, we only use 16 weeks of hourly data for the model training, which partly restricts the accuracy of the baseline model due to temporality limitations. Additionally, predicting the subregional or regional PV power generation is difficult without the bottom-up approach, *i.e.*, the granular PV predictions must be combined to provide an overall combined forecast within a selected subregion or region. This is why we are interested in both the top-down and bottom-up approaches and hence explore the hierarchical time series method in this study.

After training our model using three locations with known input features (specifically Maidstone, Gravesend, and Colchester in the UK), we predict the power output using two weeks of testing data for each location of interest. This is a top-down prediction approach, using known input feature locations, where each location tag is encoded and included as an input feature. The normalized actual vs predicted power for these locations are shown in Fig. 5 (a)-(c). By aggregating the prediction for each location, we can also predict the total power generated within that subregion. Without this bottom-up approach, it would be difficult to predict subregional power generation as the input features are location specific. This is a considerable benefit of the hierarchical approach. The normalized actual vs. predicted power for the bottom-up approach for three locations with known input features is shown in Fig. 5 (d). We also include locations with unknown input features (*i.e.,* the model is not trained for these PV systems and has not seen any input data related to these locations). The combination of a system with unknown input features in Crawley, UK, and the three known locations to form a bottom-up prediction is conducted. The actual vs predicted total power generated in this subregion is shown in Fig. 5 (e). This is done by scaling the model to include the energy capacity of the system in Crawley. Additionally, the top-down approach is tested for the PV system in Crawley, with the actual vs. predicted power for this system shown in Fig. 5 (f).

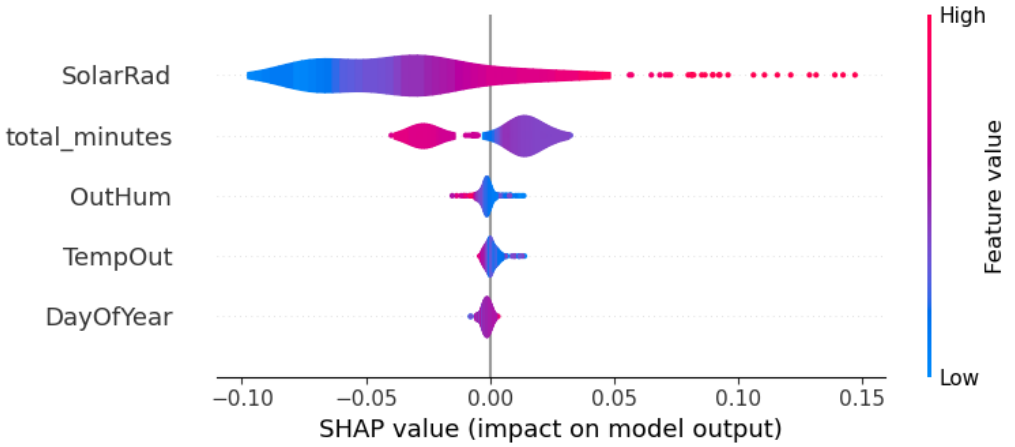


Fig. 4. SHAP plot displaying the contributions of each feature to the baseline ML model.

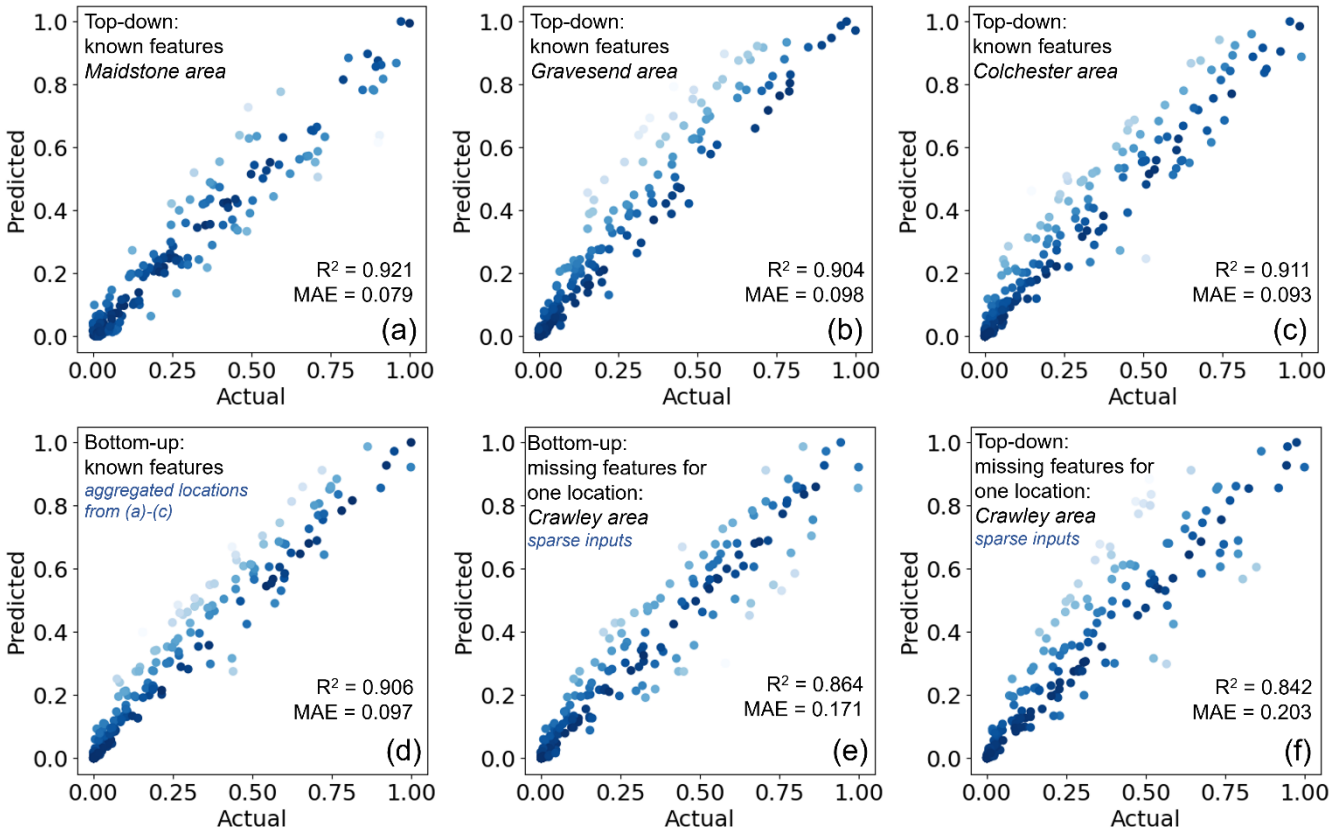


Fig. 5. Normalized actual vs predicted power output using top-down model for locations with known input features, namely (a) Maidstone, (b) Gravesend, (c) Colchester, and (d) bottom-up approach for locations with known input features, (e) bottom-up with locations with known features and one additional location (Crawley) with unknown input features, and (f) top-down for Crawley location with unknown features.

To measure the accuracy of the predictions for each case in Fig. 5, the $R^2$ values and mean absolute error (MAE) are calculated and shown in Fig. 6. This is useful as $R^2$ determines the proportion of variance between the actual and predicted power output, where $R^2 = 1$ would suggest a "perfect" prediction. MAE is also useful for determining the absolute error in forecasts and is used in this work as an additional metric for comparing model prediction results. We only state $R^2$ values in the main text hereon as the metric for comparison, but the same information can be translated using MAE. We include top-down and bottom-up predictions for two additional locations in Haywards Heath and Polegate, UK, with unknown input features in Fig. 6.

The $R^2$ values for the top-down prediction of locations with known input features, namely Maidstone, Gravesend, and Colchester, are 0.921, 0.904 and 0.911, respectively. The bottom-up prediction for determining the subregional power with these locations results in an $R^2$ of 0.906. The accuracy of these predictions can be seen as acceptable for the purpose of our study, especially when considering the temporal limitations to our dataset. The bottom-up predictions when known locations are combined with locations with unknown input features result in $R^2$ values of 0.864, 0.851 and 0.850. The top-down predictions when the combined power of known locations is used to predict the power generated in locations with unknown input features (*i.e.,* Crawley, Polegate and Haywards Heath) result in $R^2$ values of 0.824, 0.829 and 0.842.

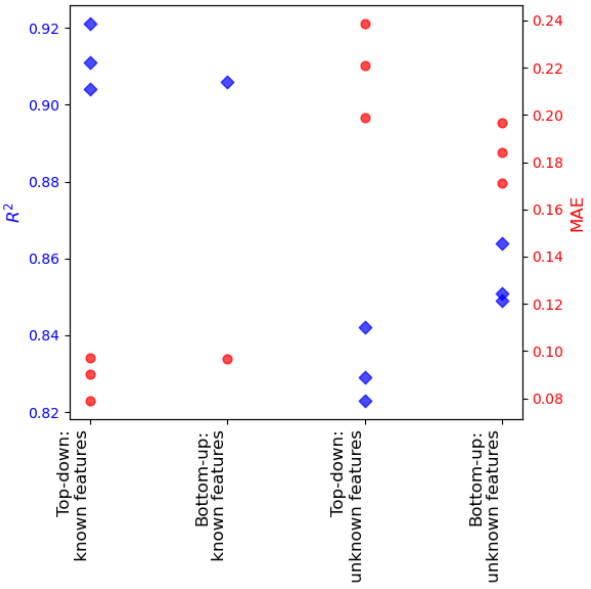


Fig. 6. $R^2$ and Mean Absolute Error (MAE) for top-down and bottom-up approaches for locations with known and unknown input features. $R^2$ value indicates accuracy of prediction, where $R^2 = 1$ means 100% of the variation in the PV power output can be explained by the prediction. $R^2$ datapoints are diamond-shaped, MAE datapoints are circles.

When considering the accuracy of the trained baseline model, the resulting accuracy of the top-down and bottom-up approaches can be considered reasonable. To improve the model predictions, a larger, nested hierarchy, and a lot more temporal training data for locations with known input features will undoubtedly increase both the baseline and in-turn the hierarchical prediction accuracy. Also, once the hierarchical nest becomes large, the latitude and longitude difference between various locations of interest can be used as well as the energy capacity of systems in locations with unknown input features. This will improve the accuracy of the hierarchical approach.

Using the hierarchical aggregation structure of this type of data is highly useful for cases where the input data of interest is unknown or scarce. This is not only for new PV systems but also when a fault occurs in data collection monitors/sensors. Undoubtedly, the accuracy of the hierarchical approach ought to be lower than direct predictive modelling as the hierarchical model has less information (*i.e.*, no input features) which reduces its predictive capabilities, but the latter is only an option when the input features are known. If there is a new PV system installed with no pre-existing data or data collection is not a possibility, the hierarchical top-down approach is provided as a useful alternative. In addition, using the hierarchical bottom-up approach is highly useful for predicting subregional and regional power generated through PV systems to enable easier decision-making for balancing grid load and energy distribution. Without the bottom-up approach, predicting the subregional or regional PV power can be challenging as the granular PV systems performance must be combined to provide insight on the total generated power within a specific area of interest.

## IV. Conclusion

This study explored the use of the hierarchical aggregation of PV performance data to predict the power generation at both a granular system and subregional level. Hierarchical performance forecasting for PV systems can be useful for cases where the input data for a location of interest is unknown, *i.e.*, when there are faults in data collection monitors or for new/existing systems with scarce datasets, and to predict the overall subregional and regional power to improve grid stability. Using an ensemble ML model, we compare direct predictive modelling with using either a hierarchical top-down or bottom-up approach to predict granular and subregional PV power. The hierarchical approaches achieve accuracies lower ($R^2$ between 0.84 - 0.82) than the direct modelling cases ($R^2$ between 0.92 - 0.90) but prove sufficiently accurate to serve as an alternative for cases where direct modelling is not an option. With a larger, nested, hierarchical system and larger temporal data, we expect the accuracy of the hierarchical top-down and bottom-up approaches to increase. This work serves as a proof of concept for exploiting the hierarchical nature of interconnected PV systems rather than a predictor optimization study.

## Data Access Statement

Data underpinning figures in this article can be downloaded from https://wrap.warwick.ac.uk/188055/. Requests for additional data should be made directly to the corresponding author.

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