RE-EMPOWERED

Renewable Energy EMPOWERing
European & InDian Communities

Deliverable 3.3: Report on forecasting algorithms

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DEM Demonstrator, pilot, prototype	**CO** Confidential, only for members of the consortium (including the Commission Services)
DEC Websites, patent fillings, videos, etc.	**EU-RES** Classified Information: RESTREINT UE (Commission Decision 2005/444/EC)
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EXECUTIVE SUMMARY

The increased interest in distributed energy sources and the smart grid is associated with the necessity of forecasting renewable energy generation and load demand, to satisfy both the prosumer and consumer sides. In this regard, current studies are focusing on developing forecasting techniques to manage weather and behavior-based uncertain challenges.

The local energy systems will feature highly varying and stochastic generation and loads, which calls for accurate forecasting. This task seeks to develop such forecasting tools for solar and wind generators, as well as loads, whose available flexibility is critical to the project. Forecasts will be provided for different time horizons, both for operational aspects and for scheduling purposes. Recent advances in the field of machine learning and artificial intelligence will be leveraged.

To this end, three different machine learning approaches have been described and implemented for all demo sites, while an additional approach considering practical issues that may arise in the actual implementation of the tools at the demo sites is proposed, adopting a simpler approach. The performance of machine learning algorithms was quite good for the majority of the demo sites. The suggestion of machine learning approaches to be implemented on demo sites has also been analyzed. This task complements other tasks of this WP, particularly T3.1 and T3.2, as well as provides algorithms that will be utilized as part of the tools development in WP4 of RE-EMPOWERED.

KEYWORDS:

Renewable Energy Source Forecasting, Load Forecasting, Machine Learning, Solar PV Power, Wind Power

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Acronyms

Acronym	Description
AE	Autoencoder
ANN	Artificial Neural Networks
CNN	Convolutional Neural Network
DL	Deep Learning
EMS	Energy Management System
Gb (i)	Beam (direct) irradiance on the inclined plane (plane of the array)
GBI	Direct irradiance on the inclined plane
Gd (i)	Diffuse irradiance on the inclined plane (plane of the array)
GDI	Diffuse irradiance on the inclined plane
GFS	Global Forecast System
Gr(i)	Reflected irradiance on the inclined plane (plane of the array)
GRI	Reflected irradiance on the inclined plane
IQR	InterQuartile Range
LSTM	Long-Short Term Memory
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MARPE	Mean absolute relative percentage error
MG	Microgrid
NMAE	Normalized mean absolute error
NRMSE	Normalized root mean square error
OCSVM	One-Class Support Vector Machine
PV	Photovoltaic
RBF	Radial Basis Function
RMSE	Root mean square error
RMSRPE	Root mean square relative percentage error
RNN	Recurrent Neural network
SAPM	Sandia PV Array Performance Model
SL	Supervised Learning

1 Introduction

1.1 Purpose and scope of the document

This deliverable provides algorithms for accurate forecasting of renewable generation, i.e., solar photovoltaic (PV) power and wind power, and electric load power. Three algorithms have been developed as part of T3.5, Work Package 3 (WP3) of the RE-EMPOWERED project, titled "Forecasting algorithms". The deliverable provides the forecasting tools for solar and wind generation, as well as loads, whose available flexibility is critical to the project. The forecasts are developed for aggregated PV and wind power, as well as electric load at diverse demonstration sites for short-term operation, and longer horizons too, such as day-ahead. Moreover, the algorithms are based on machine learning and artificial intelligence. The report analyses the available data needed to perform forecasting. The main results for the uncertainties are presented while considering all RE-EMPOWERED demo sites. The document also provides suggestions regarding the ecoEMS and ecoMG tools development, as to which forecasting algorithm performs best at each demo site.

Note that an early version of this deliverable was submitted to the DST, upon request, on June 2022.

1.2 Structure of the document

This deliverable provides an overview of the forecasting algorithms. Initially, it focuses on the different data sets and demo sites that are used in the forecasting algorithms. Further on, in Section 4, four forecasting algorithms are elaborated. In addition, the details of each algorithm are presented. Section 5 provides the design of the forecasting algorithms and illustrates the data preprocessing and feature engineering for each algorithm. In Section 6, the overview of the implementation of the forecasting algorithms to each demo site is shown. Section 7 validates the prediction results that are produced by the forecasting algorithms. Finally, the conclusions and discussion are given in Sections 8 and 9, respectively, while the relevance of the forecasting algorithms to RE-EMPOWERED is provided in Section 10.

2 Introduction to forecasting algorithms

In this subsection, a brief introduction and overview of the short-term forecasting algorithms is presented. The increased interest in distributed energy resources and the smart grid has driven the necessity of forecasting renewable energy generation and load demand to satisfy both the prosumer and consumer sides. In this regard, current studies are focusing on developing forecasting techniques to manage weather and behavior-based uncertain challenges. There are already many ways to forecast these inputs in the literature [1].

A well-known method for forecasting uncertainties is the linear regression method. The linear regression method is used to forecast by creating the relationship between the response and explanatory variables, e.g., an explanatory variable such as wind speed helps to predict the response variable such as wind power. However, the linear regression method leads to three concerns. Firstly, to forecast the future wind power, the wind speed for the future is required. Thus, wind speed must be forecasted to further obtain future forecasted wind power values. By using forecasting values to forecast the future, the forecasting error is increased. Secondly, uncertain parameters can vary with time, e.g., seasonal effects. Finally, it can have a high computational burden. The forecasting algorithms can be split into two linear regression models. The first model considers simple mapping of the explanatory variable to the response variable. The second model is autoregressive. The autoregressive model is often called the online learning method, as the online learning method is based on recursivity, i.e., the new update is based on the relationship between the last and the new data point. Regarding the highlighted concerns, like computational burden and forecast error, the online learning method performs better [2].

As a step further, the machine learning approaches have gained a lot of attention in the field of forecasting algorithms. The machine learning methods have proved their higher capability in terms of having accurate solutions, even for renewable energy generation and demand forecasts, which are more complex and uncertain. In recent years, Deep Learning (DL) has stepped forward with Artificial Neural Networks (ANNs) and multiple layers to learn the main relations even if they are non-linear and complex. Even in the DL literature, there are many methods to apply. For time series forecasting, most regression problems employ supervised learning (SL). SL finds the right weight and learns the algorithm to map from the input to the output. Since the data is time-series data, recurrent neural networks (RNN) will be used to include the valuable past data [1].

RNN is especially used for Time Series Forecasting. RNNs have the potential to be effectively used in modeling, system identification, and adaptive control applications. In fact, RNN learning algorithms rely on the calculation of error gradients with respect to the network weights, while the major difference between recurrent neural networks and other static or feedforward networks, is the fact that the gradients are time-dependent or dynamic. Thus, the current error gradient does not only depend on the current input, output, and targets, but rather on its possibly infinite past. RNN can remember but ANN cannot, so that the error should be back propagated from the last time (X_t) to the starting point. RNN can be shown in Figure 1. RNN will have a loop in the hidden layer and that loop shows that the hidden layer will give feedback to itself. The time horizon in RNN is very large. Thus, in RNN there is a problem of Long Term dependency. This probelm is solved by another type of RNN generally called as Long-Short Term Memory (LSTM) [3, 4, 5, 6, 7, 8].

Additionally, there has been high importance put on increasing the performance of the forecasting algorithms [9]. The machine learning approaches have been advanced through fuzzy approaches and hybrid implementations. Indeed, the performance can be increased by using a combination of different methods, such as data clustering and supervised NN training [9].

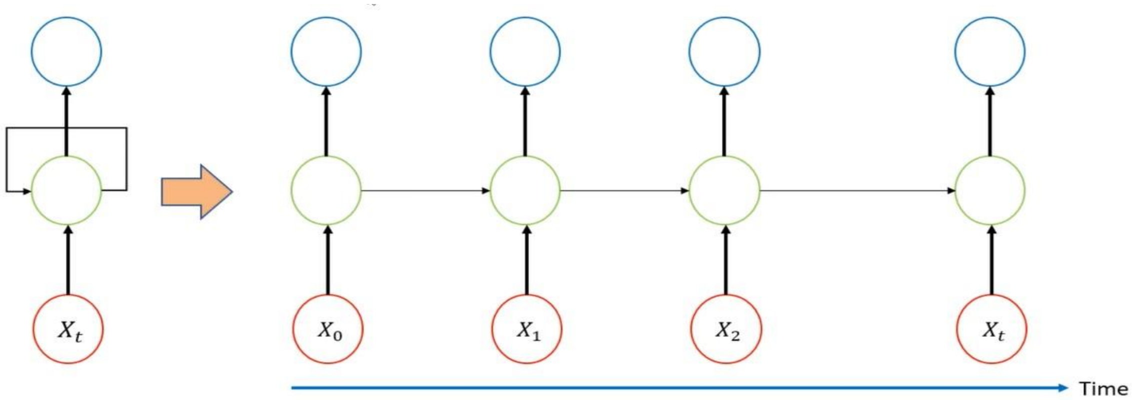


Figure 1. Recurrent Neural Network

In this deliverable, three different advanced methods will be implemented to forecast the renewable generation and demand, i.e. LSTM Auto-Encoder, hybrid LSTM-CNN and fuzzy-RBF-CNN.

However, the performance of data driven forecasting algorithms is obviously affected by the availability and accuracy of historical data. In small-scale microgrids, like the Gaidouromantra microgrid of the Kythnos demo site of RE-EMPOWERED, adequate historical data might be unavailable. Furthermore, even if they are available, the small scale of RES capacities and number of residents that use their electrical appliances can result in significant forecast errors, even while using advanced forecasting techniques. Apart from those issues, both the Gaidouromantra MG and the Indian demos have installed or are expected to install additional equipment, e.g., additional battery storage capacity and further PV power capacity. This will allow the residents to extend their use of electrical appliances. Thus, historical data currently available might be inaccurate since they depict a different state in each MG with the existing equipment and the restriction that it forces to the residents' electricity consumption. Since data driven load forecast modules performance are strongly related to the data used for their training, there might be an underperformance when applied in the demo MGs in the future, due to the aforementioned reasons. Thus, simpler forecast approaches can be applied since they have similar performance and are simpler to be applied. To address this, a fourth simplified forecasting technique for PVs and Load, which will be used by the ecoMicrogrid tool is also proposed and compared with the abovementioned more advanced methods, using historical data from the Gaidouromantra microgrid.

3 Data sets

The proposed algorithms are evaluated on the four RE-EMPOWERED demo sites, namely [10]:

- Kythnos island in Greece
    - Kythnos power system with 1100 kW rated power
    - Gaidouromantra microgrid in Kythnos with 4 kW rated power
- Bornholm island in Denmark with 25 MW rated power
- Ghoramara island in India
- Keonjhar microgrid in India

Kythnos data and the data for Gaidouromantra microgrid have been collected by NTUA, Bornholm data has been collected by DTU, and the Ghoramara and Keonjhar data sets have been collected by VNIT [1].

The main goal is to perform multi-step forecasting for each data set by considering the univariate time series or multivariate inputs sufficient data is available. The data sets are not the same with the main differences arising in terms of implementation details, which will be described within the relevant sections.

To perform forecasting for the generation side, the historical data set is required for PV and Wind power generation. In the Indian demo sites, there is no availability of such historical data. Hence, the corresponding data set is downloaded from the PVGIS [11, 12]. In this PVGIS tool, the exact location of the island needs to be mentioned. There will be pre-defined specifications while downloading the data, i.e., PV technology, installed peak power and system losses. Here, while downloading the data for Indian demo sites, PV technology as Crystalline silicon, installed peak power as 1 MW (which is considered base or rated power) and system losses as 14% are considered.

In the forecasting algorithm, for calculating metrics like MAE, RMSE, etc., the base or rated power should be taken and compared with the forecasted power. For Indian demo sites the base power is taken as 1 MW, as it was already mentioned, while downloading the data set from PVGIS. The data obtained from PVGIS is the artificial data. In practice the rated power may differ according to the electric demand.

4 Proposed forecasting algorithms

In this section, the three algorithms to forecast renewable generation and demand, i.e., LSTM, hybrid LSTM-CNN and fuzzy-RBF-CNN, are introduced and explained. In the final subsection, the simplified PV and load forecast modules, which will be used by the ecoMicrogrid are also introduced.

4.1 LSTM Auto-Encoder

LSTM is a complex version of RNN and a type of RNN with more layers inside of the cell. To overcome the drawback of vanishing or exploding gradient, RNN was introduced and has shown impressive performance, while dealing with sequential data. The presence of a memory unit in RNN ensures backward connection. Due to its high computational time and fading of inputs, LSTM, a modified version of RNN, was introduced for capturing long-term dependencies. The basic structure of the LSTM model is shown in Figure 2. In this figure, C_t and h_t are long term and short term. The operation of LSTM is handled by the three main layers, i.e., input gate layer, output gate layer and forget gate layer, which provide them with the power to selectively learn, unlearn or retain information from each of the units. The forget gate decides which information should be forgotten from the previous cell state for which it uses a sigmoid function. The input gate controls the information flow to the current cell state using a point-wise multiplication operation of 'sigmoid' and 'tanh' respectively. Lastly, the output gate decides which information should be passed on to the next hidden state.

The input X_t and h_{t-1} are fed to all the layers, i.e., f_t, i_t, C_t and O_t where C_t uses tanh as an activation unit, while others are using sigmoid. Thus, to deal with sequential data available through measurement devices, to understand the energy generation and consumption pattern, and to capture long-term dependency, forecasting is carried out using LSTM. LSTM Model has been implemented in this algorithm for all the demo sites [6].

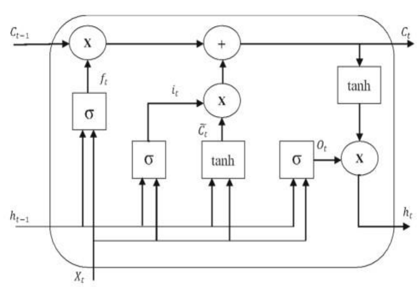


Figure 2. Structure of the LSTM cell

Autoencoder (AE) is good in dealing with both compact illustration and de-noising of input as shown in Figure 3 while a one-class support vector machine (OCSVM) is used to filter the corrupted measurements.

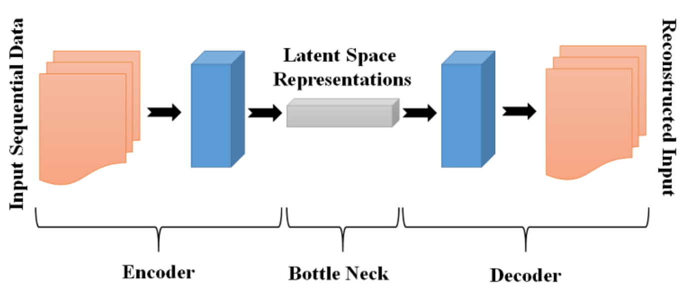


Figure 3. The architecture of Autoencoder (AE)

4.2 Fuzzy-RBF-CNN

The applied forecasting algorithm called Fuzzy-RBF-CNN consists of three layers: a fuzzy clustering, an RBF-CNN regressor and an aggregation layer. At the first layer, a clustering method groups the input data into multiple clusters. The fuzzy clustering algorithm forms clusters that have to share a portion of their space with their neighboring clusters in order for every input to be able to activate more than one cluster and an ensemble prediction to be created at the second layer. Each cluster created corresponds to a fuzzy rule of the fuzzy clustering layer.

Following the fuzzy clustering method, the inputs are distributed to the second layer where an RBF-CNN regressor is applied to each cluster. As shown in Figure 4, an RBF-CNN regressor is an innovative neural network architecture composed of three RBF, a convolutional, a pooling and two fully connected layers and receives the data subset constructed by the corresponding cluster (fuzzy rule) at the first layer.

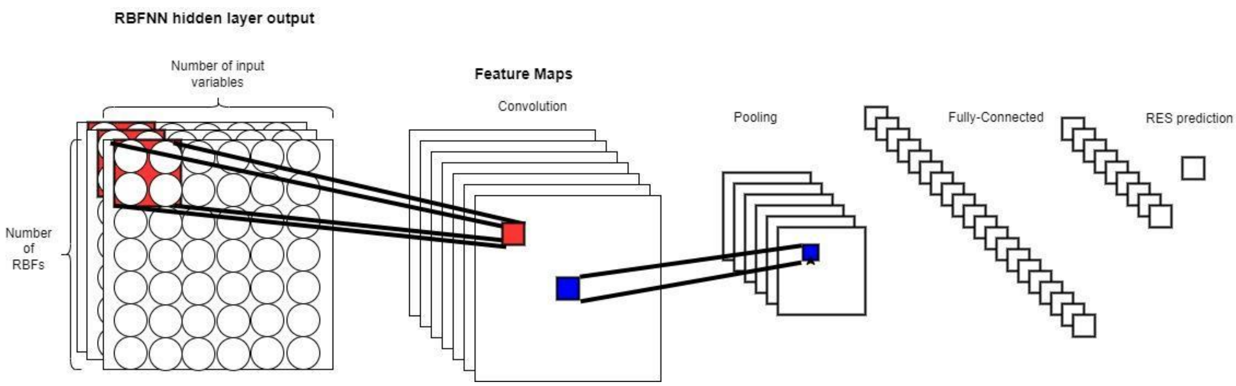


Figure 4.The RBF-CNN regressor structure.

The convolutional layer creates feature representations of the RBF kernel activations element-wise utilizing the kernel topology and reduces the impact of the non-useful information provided by each kernel. Training of an RBF-CNN regressor requires that the optimal parameters of the RBF kernels, namely the kernel number, centers and widths, are estimated through three different algorithms described in [13, 14, 15]. The optimized RBF kernels transform the input data to a higher dimensional space with their activations becoming new data representations. The CNN is trained using the transformed input data at a second stage that analyses in more detail than an RBFNN, the relations of a kernel element with its neighbors; namely with the elements that correspond to a different input variable or kernel. Following the above two stage training procedure, an RBF-CNN regressor operates as a compact neural network that consists of three RBF, a convolutional, an averaging pooling and two fully-connected layers.

The final prediction of the proposed model will be provided at the third layer by averaging the ensemble predictions of the RBF-CNN regressors that correspond to the clusters activated in the fuzzy clustering layer. Figure 5 shows the proposed model structure, where three clusters (darker shade) are activated and contribute to the final load prediction. In this example, input x_i activates fuzzy rules 2, 3 and 5 and the RBF-CNNs which are connected to these rules provide an independent prediction. The final prediction is obtained by averaging these predictions.

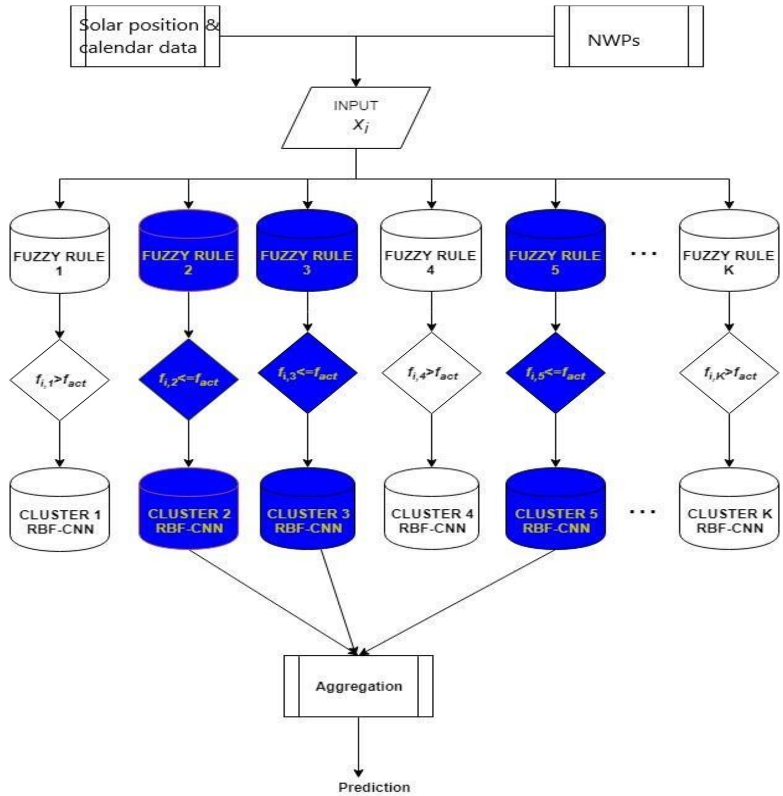


Figure 5. The forecasting algorithm architecture (colored branches signify the activated clusters).

4.3 Hybrid LSTM-CNN

In this subsection, a combination of the LSTM model and Convolutional Neural Network (CNN) is elaborated. Creating a hybrid architecture is receiving higher attention in the forecasting literature. In the hybrid model, LSTM and D-CNN networks are combined into one. The main difference between LSTM and other common DL networks is that LSTM inserts the knowledge of the temporal difference from data as an addition to the mapping input to outputs only. The use of LSTM improves the ability to store important prior data and the inclusion of 1D-CNN assists in including important features [3]. Figure 6 shows the overall LSTM model, while Figure 7 illustrates the architecture of the LSTM-CNN architecture.

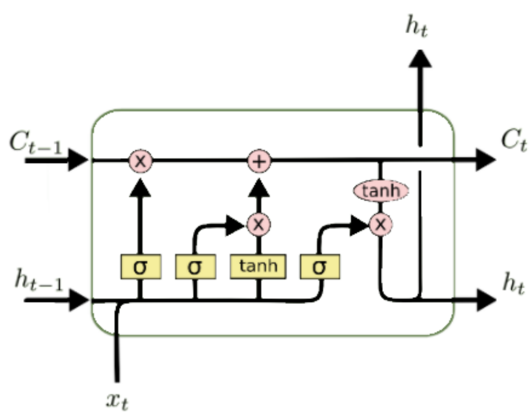


Figure 6. The representation of the LSTM model [16].

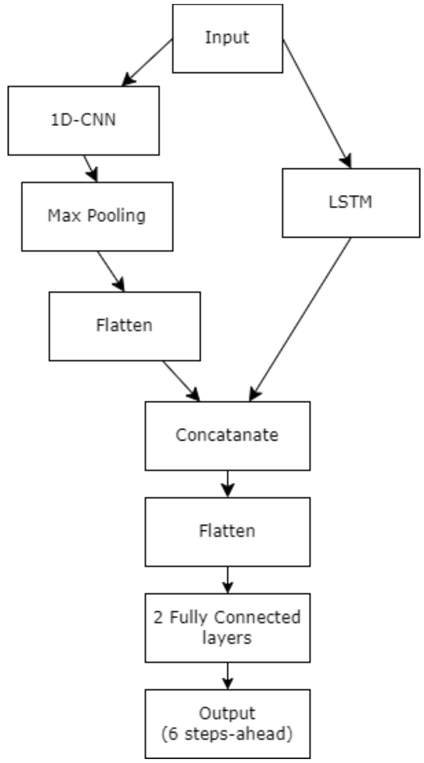


Figure 7. The CNNLSTM forecasting architecture [3].

4.4 Simple Forecast Modules

The Gaidouromantra MG and the Indian demo sites have PV production as an intermittent RES production source. For the ecoMicrogrid tool, a simplified model that uses the physical representation of the PV panels and the power converter is used to get the short term PV forecast.

To produce the PV power forecast, the physical model requires weather data predictions for the following hours. The open GFS (Global Forecast System), [17], was used, which can provide weather data predictions anywhere on earth. The GFS is updated every 6 hours. The GFS is run at two resolutions, 0.25 deg and 0.5 deg, and is available with a 3 hours' time resolution. The weather data include the ambient temperature, the wind speed, global horizontal irradiance, diffuse horizontal irradiance, direct normal irradiance and cloud coverage.

The modeling of the PV module includes the modeling of the PV system based on the equations defined in the Sandia PV Array Performance Model (SAPM). The equations and the modeling of the PV plant power output based on weather conditions (temperature, irradiance. wind speed, cloud coverage) can be found in [18].

For the load forecasting, a simplified model slightly different from the persistence model was used. The persistence model along with the measured value at time interval t considers also the forecasted value in the horizon T. This forecast approach produces the forecast on time interval t by computing the mean of the load recorded in the previous time interval (t-1dt) as well as load value recorded the previous day on the same interval (t-1day).

5 Design of forecasting framework

Data preprocessing is a process of preparing the raw data and making it suitable for a machine learning model. It is the first and crucial step while creating a machine learning model. The various steps involved in this process are as follows:

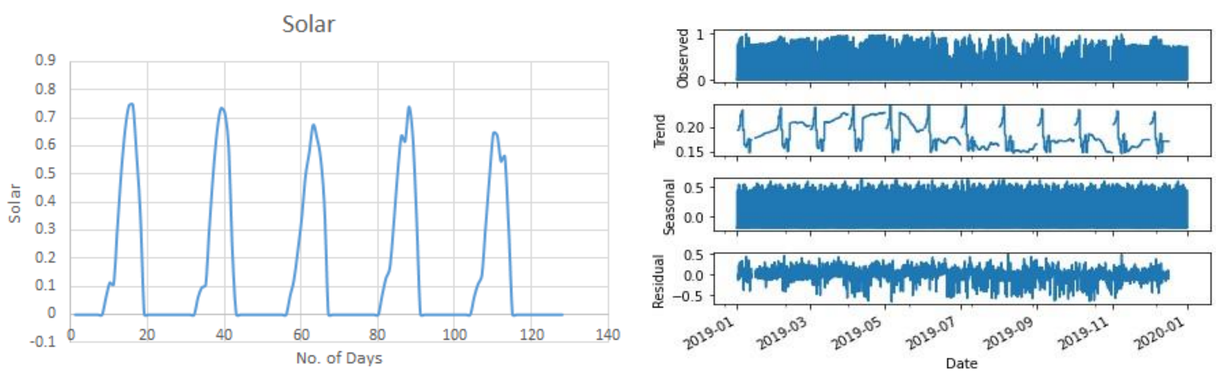
- Getting the Dataset
- Importing Libraries
- Importing Dataset
- Finding Missing Data

Data Visualization defines a graphical representation of the information of a particular data [8]. The forecasting interval is defined as one hour and 6 hours ahead [1].

5.1 LSTM Auto-Encoder

5.1.1 Data preprocessing

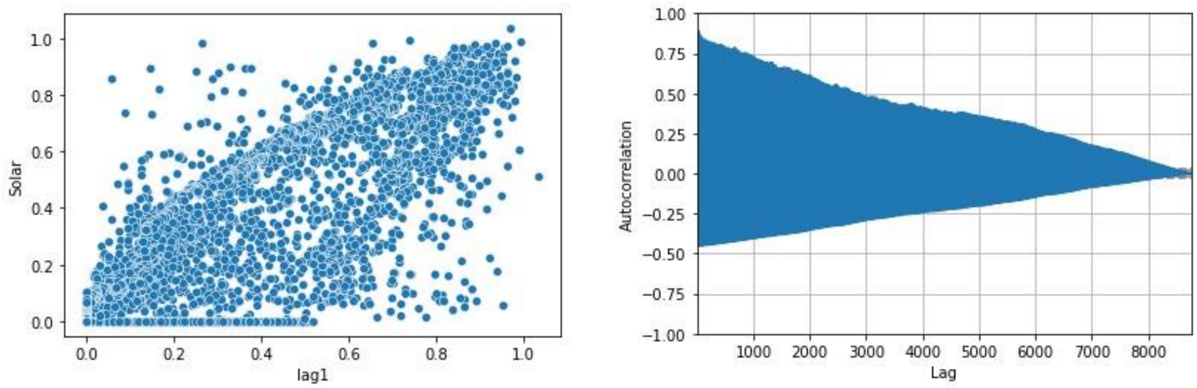
The data preprocessing is presented based on the example of the Ghoramara Island demo site. The variation of solar insolation with respect to time is shown in Figure 8a). The seasonal variation and mentioning trends are shown in Figure 8b).



a) b)

Figure 8. a) Data Visualization Plot for PV b) Seasonal Decompose Plot for PV

A lag plot checks whether a data set or time series is random or not. A lag plot is a special type of scatter plot with two variables. One set of observations in a time series is plotted (lagged) against a second, later set of data. The lag plot for the given Indian demo site (Ghoramara Island) is shown in Figure 9a). Autocorrelation plots are a commonly used tool for checking randomness in a data set. This randomness is ascertained by computing autocorrelations for data values at varying time lags. The autocorrelation plot for the observed values in the dataset is shown in Figure 9b).



a) b)

Figure 9. a) Lag Plot for PV for Ghoramara Island b) Autocorrelation Plot for PV for Ghoramara Island

5.1.2 Feature Engineering and Feature Selection

Feature scaling is a method used to normalize the range of independent variables or features of data. It can be normally done with Normalization or Standardization, so that all the values will be in the range of 0-1. In python, it can be directly called from the function MinMaxScaler. The basic formula for Normalization and Standardization are given below respectively.

$$X_{new} = \frac{X_i - \min(X)}{\max(x) - \min(X)}$$

$$X_{new} = \frac{X_i - X_{mean}}{Standard\ Deviation}$$

Outlier detection is an essential role while data is being pre-processed. Outliers are individual values that fall outside of the overall pattern of a data set. The interquartile range rule is useful in detecting the presence of outliers. In this algorithm, InterQuartile Range (IQR) is implemented which uses the difference between the third and the first quartile of a distribution (or the 75th percentile minus the 25th percentile).

- The first quartile Q_1, which represents a quarter of the way through the list of all data
- The median of the data set, which represents the midpoint of the whole list of data
- The third quartile Q_3, which represents three-quarters of the way through the list of all data

Otherwise, extrapolating the range would be tough. The interquartile range is similar to the range but less sensitive to outliers. The interquartile range is computed similarly to the range. Simply subtract the first quartile from the third quartile to find it as shown below.

$$IQR = Q3 – Q1$$

5.2 Fuzzy-RBF-CNN

5.2.1 Data clustering

The first Fuzzy-RBF-CNN layer is designed to cluster the input dataset according to the variables containing the most useful information, so that each input vector will belong to more than two groups. Thus, the most highly-correlated to the output variables define the shape and number of the first layer clusters. In solar power forecasting the most valuable input variables to a model are the latest solar power observation, the direct irradiance on the inclined plane (GBI) and the hour of the prediction time. The training process of the

Fuzzy-RBF-CNN first layer requires those variables to be represented with fuzzy membership functions. The value range of each variable is divided into fuzzy sets having common characteristics. Each fuzzy set has a linguistic representation and is described by a membership function. For example, regarding the 'hour' variable multiple fuzzy sets are used during daylight hours, while night hours - when the solar power time series has zero variance - belong to one fuzzy set.

5.2.2 Feature Engineering and Feature Selection

Before the RBF-CNN training procedure begins, the input variables that do not contain useful information need to be removed from the data subset of a cluster by applying the permutation importance technique [19] using a random forest. Initially, a random forest is trained and its performance defines the baseline. Then, a randomly chosen variable is permuted from the dataset and the random forest performance is calculated again. The variable importance is calculated as the difference between the baseline performance and the performance on the permuted dataset. The input variables with positive importance are kept for the RBF-CNN training

5.3 Hybrid LSTM-CNN model

The data preprocessing, feature engineering and data division are elaborated on the example of the Bornholm demo site.

5.3.1 Data preprocessing

The Bornholm demo site has historical PV power, wind power, load, temperature, wind speed, radiation, and day-ahead prices. While meteorological data is in 5 minutes intervals, the rest has a 1-hour resolution. As mentioned, the forecasting interval is defined as one hour and 6 hours ahead. Therefore, we arrange the meteorological features as 1 hour by taking the average. There are many systematic NaN values on PV, wind, and load data. Since there are many NaN values, interpolation might be not the best approach for this case. Instead, the NaN values are fulfilled by using the same hour on the previous day. The outliers are replaced with NaNs and the other rare NaN values which are not systematic are fulfilled with the backward method. The representations of the missing data sets on the measured PV power, wind power and load data are shown in Figure 10 for Bornholm demo site. A similar approach is followed for the other demo sites.

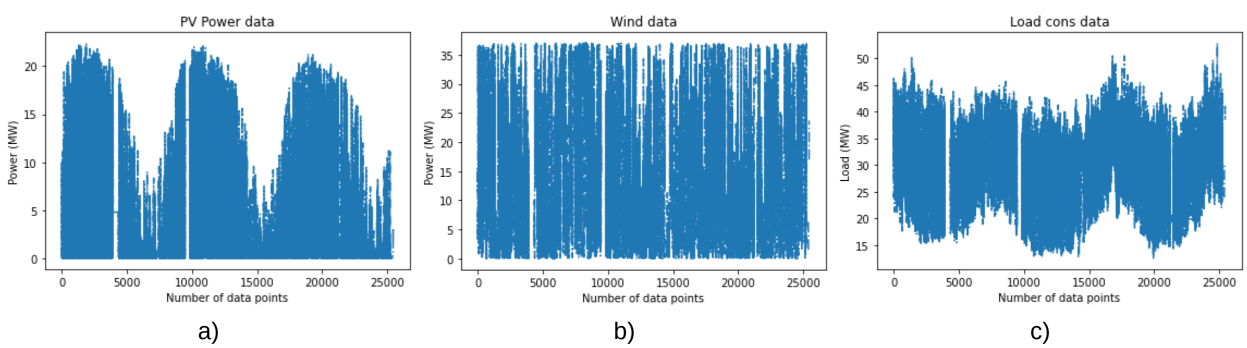


Figure 10. Representation of the missing data set at Bornholm demo site on the measured a) PV power b) wind power c) load data.

5.3.2 Feature Engineering and Feature Selection

After the data has been processed, new external features such as day and year information are added to feed into the heat map which is one of the most common ways to investigate the relations between inputs and output. Since it is not a classification problem, it is slightly challenging. The correlation heat map for PV is shown in Figure 11 for Bornholm data set.

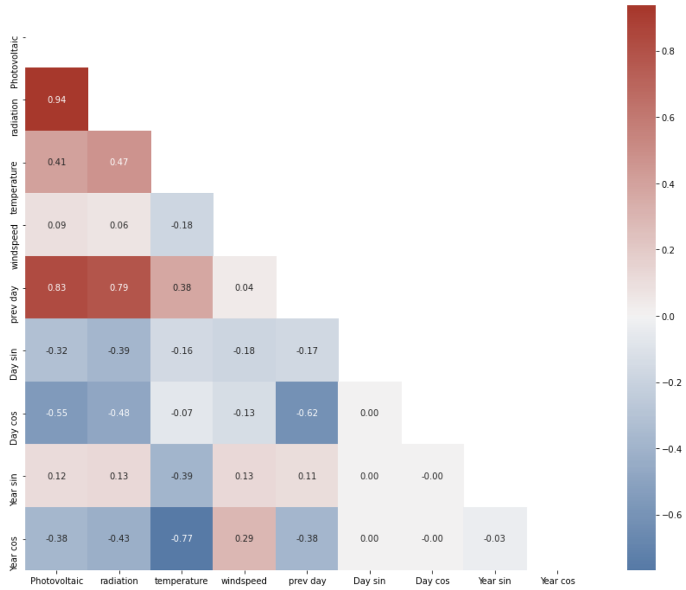


Figure 11. The correlation of the Bornholm data for PV forecasting.

Here, it can be directly seen that wind speed does not seem relevant in addition to year info. Solar radiation and the previous day's power output are the most relevant features. To use any SL model, the time series data should be transformed into a special format based on the DL model. All the processing is completed for each data set in the same way.

5.3.3 Data Division with 5-fold Cross-Validation

The data is split into the training, validation, and test datasets by 80%, 10% and 10%, respectively. The data set is not randomly shuffled before this division because of two main reasons:

1. It ensures that chopping the data into windows of consecutive samples is still possible.
2. The validation/test results will be more realistic since we do not change the nature of the data, while through the cross-validation, the data can be equally tested and evaluated on the data collected after the model is trained.

Here, cross-validation is not applied to finish forecasting by considering the training time (and given a higher percentage for the test set), it can be applied if it will be necessary.

Then, the data is normalized with the following equation to adjust all features in a similar scale.

$$z = \frac{x - \mu}{\sigma},$$

where μ is the mean and σ is the standard deviation.

Figure 12 shows the selected and normalized features to forecast PV for Bornholm demo site. Radiation has quite a similar shape with PV in addition to the previous day vector.

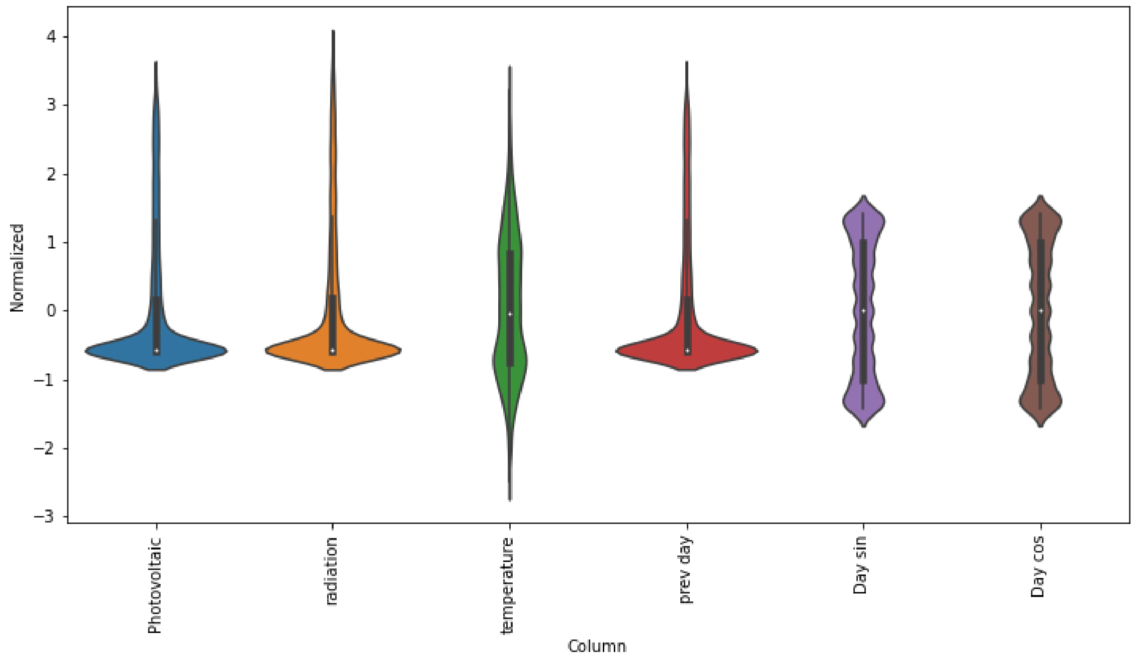


Figure 12. The visualization of the Bornholm data after the normalization

6 Implementation of the proposed algorithms

In this section, the implementation of the proposed algorithms for each demo site is elaborated. Table 1 provides an overview of the uncertainties forecasted at each demo site. As the wind power is currently not measured in Indian demo sites, wind speed is forecasted in addition to PV.

Table 1. The power data forecasted at each demo site

Demo site	Uncertainty	Forecasting
Kythnos	Wind	-
	PV	✓
	Load	✓
Gaidouromantra	Wind	-
	PV	✓
	Load	✓
Bornholm	Wind	✓
	PV	✓
	Load	✓
Ghoramara	Wind	-
	PV	✓
	Load	-
Keonjhar	Wind	-
	PV	✓
	Load	-

6.1 LSTM Auto-Encoder

A basic LSTM Model has been developed as discussed above. This algorithm is applied to all the four demo sites i.e Ghoramara island, Keonjhar, Bornholm island, Kythnos power system and Gaidouromantra microgrid in Kythnos (the last two commonly forming the Kythnos demo site). As there is no historical data available for the Indian demo site, load forecasting for Indian demo sites is quite difficult. The weather data for both the Indian demo sites were obtained from PVGIS. The various parameters considered in the model from the dataset are mentioned below:

- Gb(i): Beam (direct) irradiance on the inclined plane (plane of the array) (W/m^2)
- Gd(i): Diffuse irradiance on the inclined plane (plane of the array) (W/m^2)
- Gr(i): Reflected irradiance on the inclined plane (plane of the array) (W/m^2)
- G(i): Total Insolation or irradiance (W/m2) – Targeted Value
- P: PV Power Output
- Sun Height (m)
- Wind Speed (m/s^2)
- Temperature (°C)

When it comes to Bornholm demo site, the LSTM Model has been implemented for wind power forecasting, solar PV forecasting and load forecasting. For load forecasting, input parameters considered are wind speed and temperature and output parameter is power consumption in MW. Similarly, the wind power and PV power forecasting are also performed. The wind power generation and PV power generation data is available along with input parameter as wind speed, total insolation and temperature for Bornholm Island [15]. For the Gaidouromantra microgrid and Kythnos power system, in addition to load data, the dataset for weather parameters is downloaded from PVGIS [12]. When it comes to Indian demo sites, the weather data downloaded for Ghoramara and Keonjhar for PVGIS has wind speed and temperature. No historical data for weather and load is available for both islands. As a result, load forecasting is not performed. Wind forecasting is done using wind speed as the target parameter and input parameters as temperature and sun height (a slight correlation is there between them). Similarly, PV power forecast is done, considering input parameters as wind speed, total insolation, temperature and sun height.

For all the demo sites, the dataset is considered for 1 year and that dataset is split into training and testing sets. This splitting is done using 90-10%. The training set is 90% of the whole dataset and the remaining 10% is given to the testing set.

10% of the dataset given to the testing set and Forecasted results have been plotted for 2 weeks (15 days), considering dates from 15 days of November.

In the algorithm, the LSTM model is built as follows.

- Dense layer: 100
- Dropout: 70
- RepeatVector (For Encoding)
- TimeDistribution (For Decoding)
- Batch size: 70
- No. of Epochs: 100
- Optimizer: Adam
- Loss function: Mean Squared error

6.2 Fuzzy-RBF-CNN

For all demo sites, weather predictions obtained by PVGIS [11] were applied. The proposed model was evaluated to solar power forecasting with both short-term and day-ahead horizons. Especially, for short-term predictions where the forecasting horizon was 6 hour-ahead, the proposed model applied to the following case studies:

- Gaidouromadra microgrid located on Kythnos island of Greece with 1100W rated power
- Kythnos power system in Greece with 240 kW rated power
- Bornholm island of Denmark with 25 MW rated power
- Ghoramara island of India with 1 MW rated power
- Keonjhar island of India with 1 MW rated power,

while it utilized for day-ahead horizons at the first three case studies.

For the case studies regarding Gaidouromadra, Bornholm, Ghoramara and Keonjhar, weather predictions obtained by PVGIS [11] were applied. Namely,

- the direct irradiance on the inclined plane (GBI),
- the reflected irradiance on the inclined plane (GRI),

- the diffuse irradiance on the inclined plane (GDI)
- and the sun height,

while for the Kythnos case-study, numerical weather predictions obtained by GFS [17] were used. In specific:

- the percentage of cloud coverage
- the downward short-wave flux
- the temperature
- the sun zenith and azimuth.

Also, calendar data of prediction hour as hour and month were used as inputs, while for the short-term forecasting cases, the three most recent observation were added to the dataset.

It should be noted that for the Gaidouromadra, Kythnos and Bornholm case studies, real solar power observation time-series were available, while artificial power data from PVGIS were used at the Ghoramara and Keonjhar case studies. Table 2 contains information about the training and testing period defined at each demo site.

Table 2. Training and testing periods used on each demo site

Demo site	Training period	Testing period
Gaidouromantra	25/02/2015 10:00 - 14/10/2016 23:00	15/10/2016 00:00 - 15/12/2016 14:00
Kythnos	01/01/2019 00:00 - 30/11/2019 23:00	01/12/2019 00:00 - 31/12/2019 23:00
Bornholm	12/03/2019 01:00 - 14/10/2020 23:00	15/10/2020 00:00 - 31/12/2020 23:00
Ghoramara	01/01/2015 00:00 - 14/10/2016 23:00	15/10/2016 00:00 - 31/12/2016 23:00
Keonjhar	01/01/2015 00:00 - 14/10/2016 23:00	15/10/2016 00:00 - 31/12/2016 23:00

The proposed model was also evaluated for the load forecasting of Kythnos and Bornholm islands and for the wind power forecasting of Bornholm island. Numerical weather predictions (NWPs) from GFS are used here. In specific, the input of the proposed model on load forecasting contains the averaged prediction values of temperature, wind speed and cloud coverage obtained by GFS NWPs and the past load values which are recorded during the most recent week of the prediction time. At the case of Kythnos island, the training period was from 2019-01-01 to 2019-11-30 and the testing period was from 2019-12-01 to 2019-12-31, while at the case of Bornholm island the training period was from 2019-03-12 to 2021-10-21 and the testing period was from 2021-10-22 to 2022-02-04.

Finally, the proposed model was tested on Bornholm's wind power production case study. GFS NWPs were used for this application. Specifically, the proposed model input comprises of the wind speed and the wind direction forecasts together with the three most recent wind power observations. The proposed model was trained with the data recorded on the period from 2019-03-12 to 2021-10-21 and was tested on the period from 2021-10-22 to 2022-02-04.

6.3 Hybrid LSTM-CNN model

The proposed Hybrid LSTM-CNN algorithm is also compared with LSTM and naïve method which is used as a baseline. Comparing the baseline and DL models, the baseline model is quite simpler and will work faster but struggle to catch more complex results. On the other hand, DL models can outperform but takes more time for training and finding the right parameters. There is also a comparison between CNNLSTM hybrid model and regular LSTM model.

Time series data is transferred into a three-dimensional structure since the CNNLSTM hybrid architecture requires it like any regular CNN or LSTM network instead of two dimensions.

Regarding the Bornholm demo site, based on the analysis there are 6 features for this data set; radiation, temperature, previous day power generation, sin component for the day and cos component for the day. The number of prior time steps, called as lag, to predict both next step and 6 steps ahead is taken as 12. The number of epochs is 100, batch size is 64, optimizer is Adam, LSTM layer has 64 neurons and fully connected layer has 32 neurons.

Regarding the Indian demo sites, the feature set for Ghoramara is Gb, Gd, Gr, H_sun, sin component for the day and cos component for the day.

Regarding the Kythnos power system demo site, meteorological data set is similar to data of the Indian demo sites. The main difference is having a historical PV output since this system is already built and it is measuring the power output. Thus, based on this information and analysis, the feature list will be like the one for Indian demo sites.

When it comes to LSTM-CNN algorithm and its implementation to each demo site, only the selection of features is different between the data sets. The main difference about the data set for Indian demo sites is that generation data is not available and we cannot use it for training (there is no historical generation information) and both the training and testing are completed based on the calculated generation of PV.

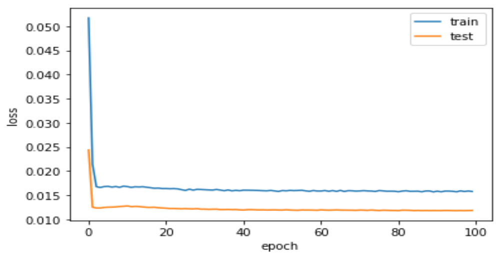
7 Validation and results

In this section, the validation of the proposed algorithms is performed and the main results for each demo site, subjected to different forecasting algorithms, are presented. As given in subsection 6, each forecasting algorithm performs the preprocessing of the data, which might result in different horizons when splitting the datasets into training and testing.

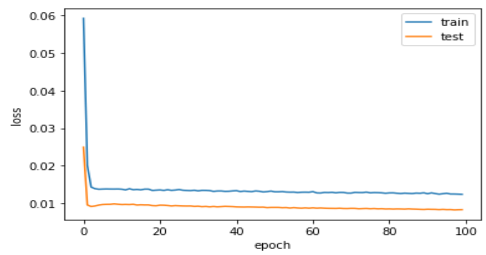
7.1 LSTM Auto-Encoder

7.1.1 One step ahead forecasting for PV

In Figure 13, losses and the number of epochs are shown for Ghoramara and Keonjhar demo sites.



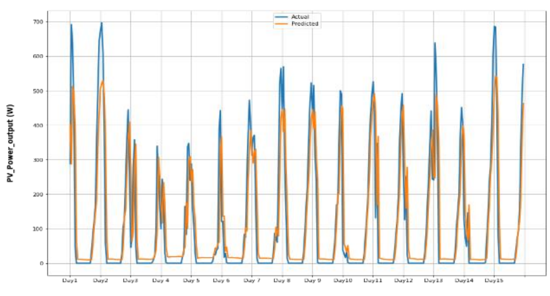
a)



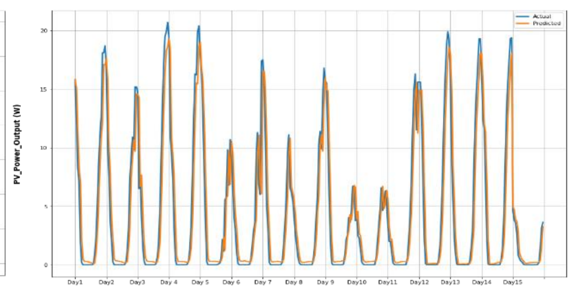
b)

Figure 13. Loss vs No.of Epochs for the test set for PV power at a) Ghoramara demo site b) Keonjhar demo site

Figure 14a) and Figure 14b) present the solar PV forecasting results at Ghoramara and Keonjhar demo sites respectively.



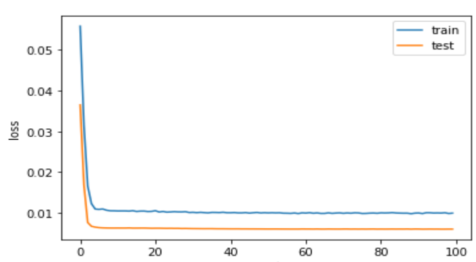
a)



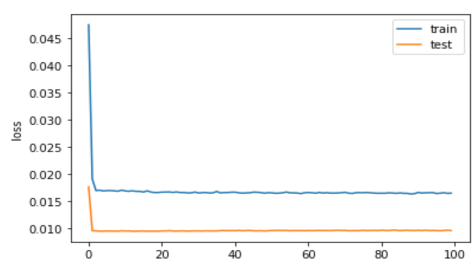
b)

Figure 14. Solar PV Power Forecasting (Actual and Prediction) at a) Ghoramara demo site b) Keonjhar demo site.

In Figure 15a), loss and number of epochs are shown for Bornholm demo site, while in Figure 15b), loss and number of epochs are shown for Gaidouromantra demo site are shown.



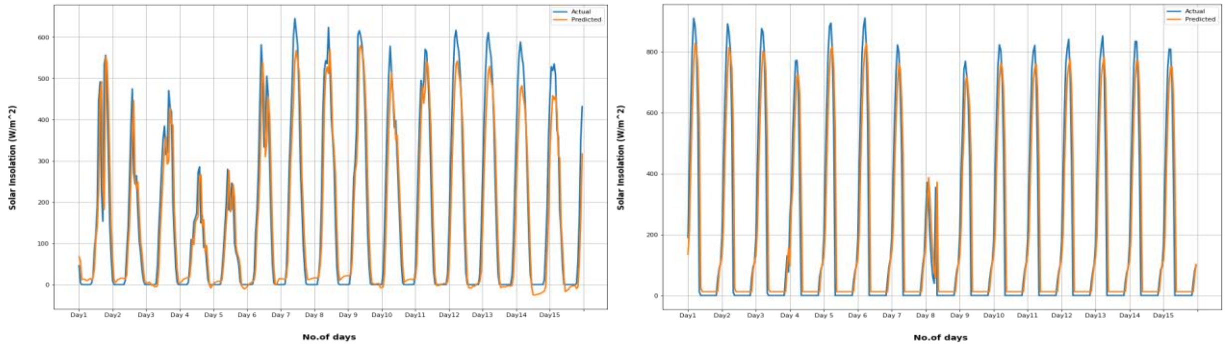
a)



b)

Figure 15. Loss vs No.of Epochs for the test set for PV power at a) Bornholm demo site b) Gaidouromantra demo site

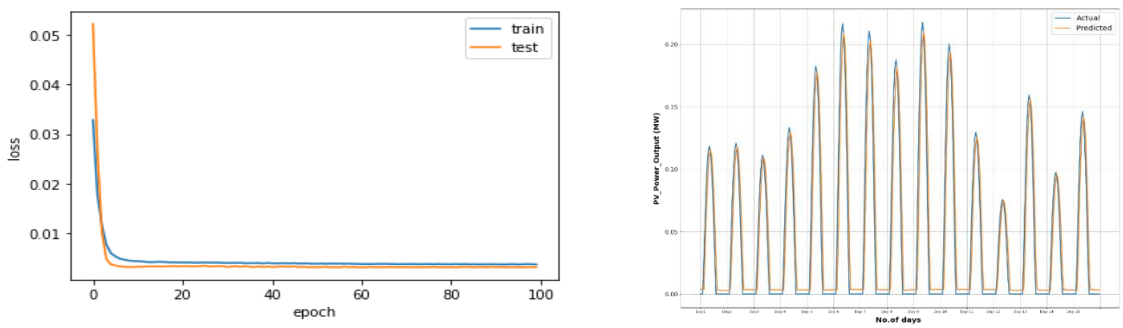
Figure 16a) presents the solar PV forecasting results at Bornholm demo site and Figure 16b) presents the solar PV forecasting results at Gaidouromantra demo site.



a) b)

Figure 16. Solar PV Power Forecasting Plots (Actual and Prediction) at a) Bornholm demo site b) Gaidouromantra demo site.

Figure 17 shows the loss and number of epochs, as well as the predictions for PV power on Kythnos power system.

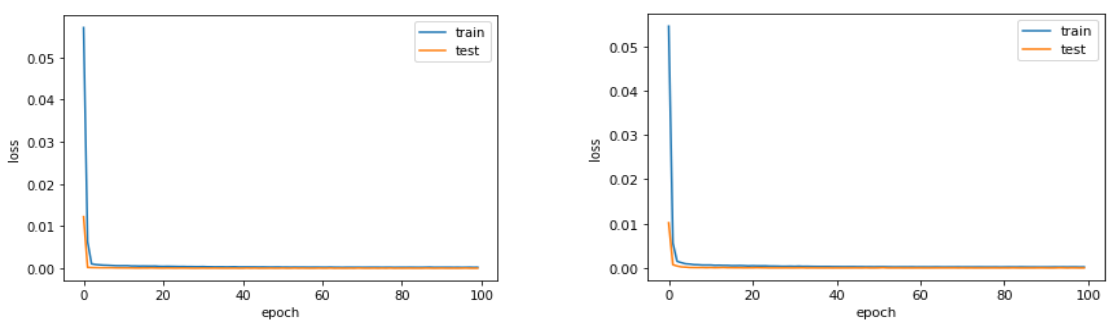


a) b)

Figure 17. Demo site of Kythnos power system a) Loss vs No.of Epochs for the test set for PV power at b) Solar PV Power Forecasting Plots (Actual and Prediction)

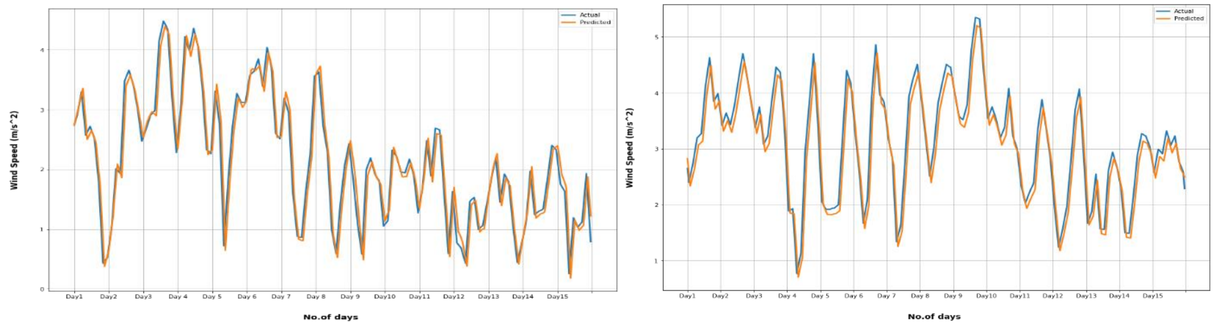
7.1.2 One step ahead forecasting for wind speed

In Figure 18, losses and the number of epochs are shown for Ghoramara and Keonjhar demo sites, while Figure 19a) and Figure 19b) present the wind speed forecasting results at Ghoramara and Keonjhar demo sites respectively.



a) b)

Figure 18. Loss vs No.of Epochs for the test set for wind speed at a) Ghoramara demo site b) Keonjhar demo site

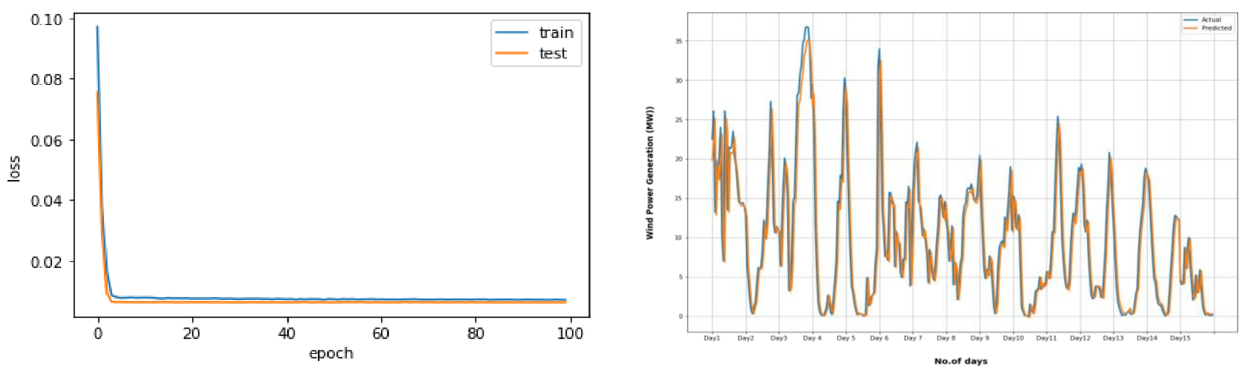


a) b)

Figure 19. Wind speed Forecasting (Actual and Prediction) at a) Ghoramara demo site b) Keonjhar demo site.

7.1.3 One step ahead forecasting for wind power

In Figure 20a), losses and the number of epochs are shown for Bornholm demo site, while Figure 20b) presents the wind power forecasting results at Bornholm demo sites.

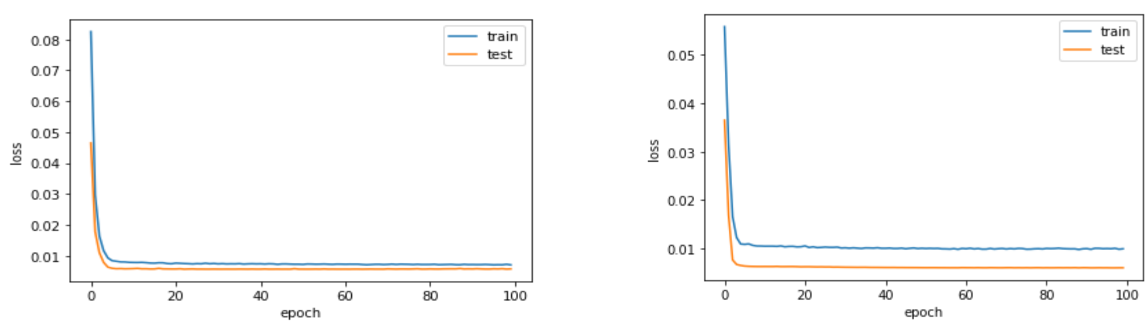


a) b)

Figure 20. Bornholm demo site: a) Loss vs No.of Epochs for the test set for wind power b) Wind power forecasting (Actual and Prediction)

7.1.4 One step ahead forecasting for electric load

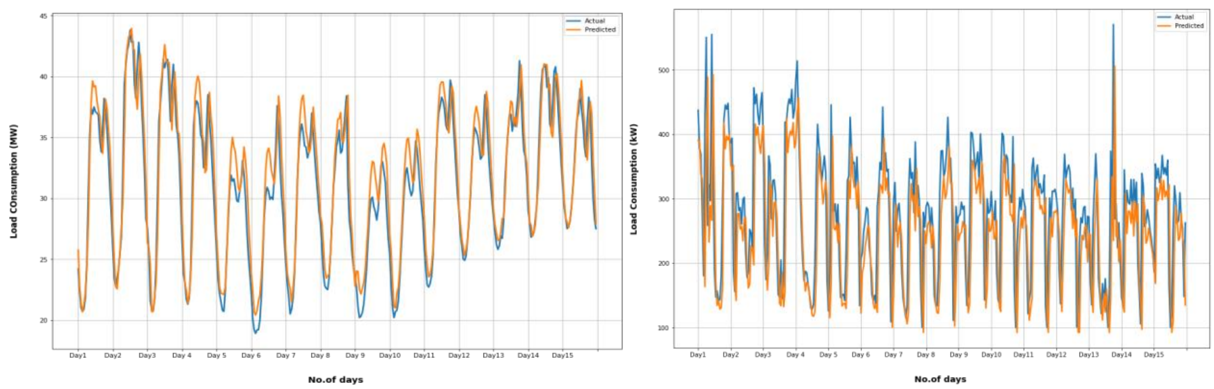
In Figure 21, loss and number of epochs when forecasting electric load are shown for Bornholm and Gaidouromantra demo sites.



a) b)

Figure 21. Loss vs No.of Epochs for the test set electric load at a) Bornholm demo site b) Gaidouromantra demo site

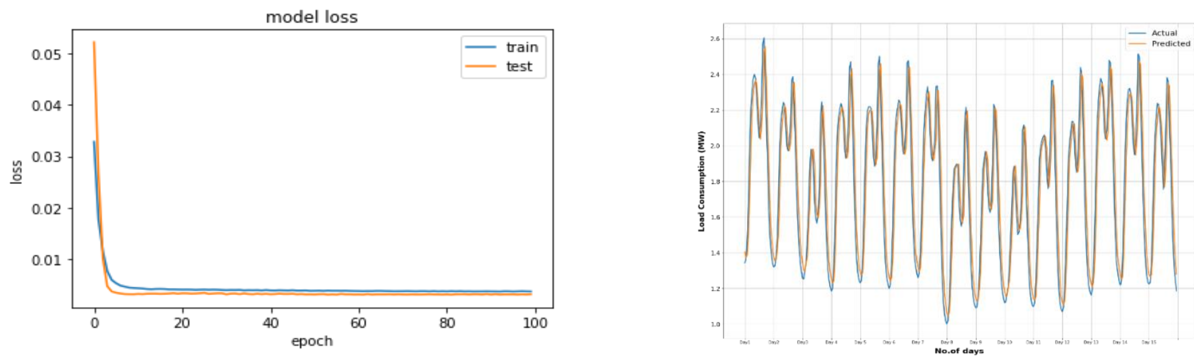
Figure 22a) and Figure 22b) present the electric load forecasting results at Bornholm and Gaidouromantra demo sites respectively.



a) b)

Figure 22. Electric load Forecasting (Actual and Prediction) at a) Bornholm demo site b) Gaidouromantra demo site.

Loss and number of epochs for forecasting electric load on Kythnos power system, as well as the forecasted values are shown in Figure 23.

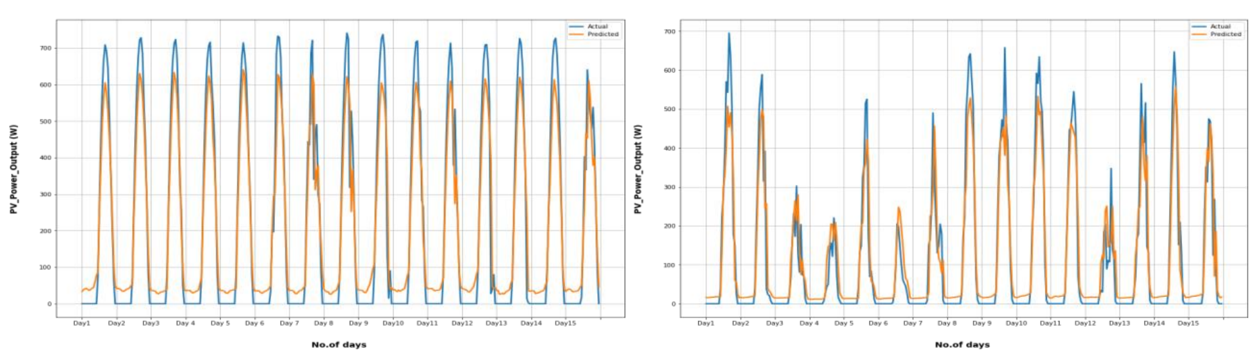


a) b)

Figure 23. Demo site of Kythnos power system a) Loss vs No.of Epochs for the test set electric load at b) Electric load Forecasting (Actual and Prediction).

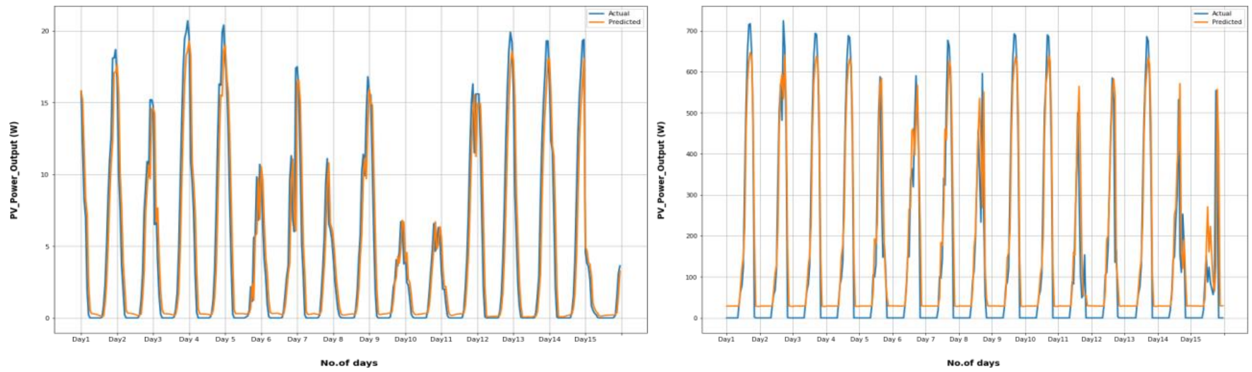
7.1.5 Six steps ahead forecasting for PV

In Figure 24a) and Figure 24b), six hours ahead predictions for solar PV power at Ghoramara and Keonjhar demo sites respectively are presented. Figure 25a) and Figure 25b) present the six hours ahead predictions for Bornholm and Gaidouromantra demo sites respectively. Figure 26 presents the six hours ahead predictions for PV on Kythnos power system.



a) b)

Figure 24. 6 steps ahead forecasting for PV power at a) Ghoramara demo site b) Keonjhar demo site



a) b)

Figure 25. 6 steps ahead forecasting for PV power at a) Bornholm demo site b) Gaidouromantra demo site

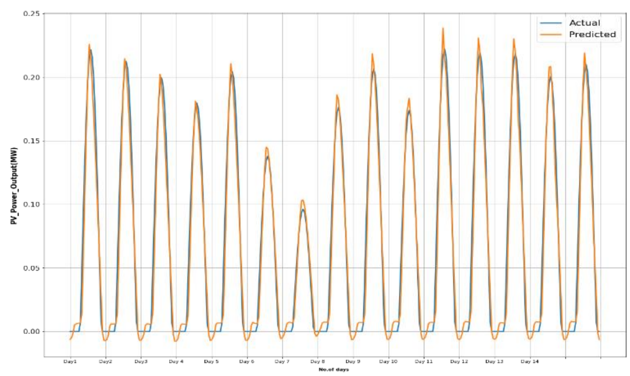
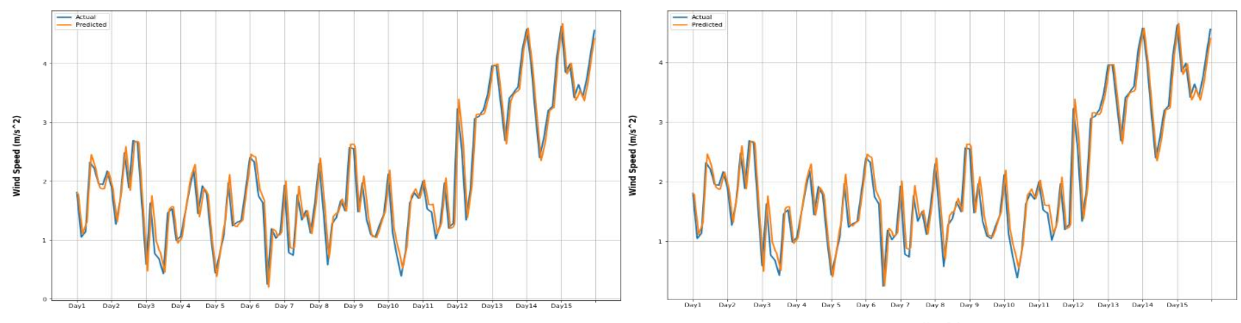


Figure 26. 6 steps ahead forecasting for PV power at demo site of Kythnos power system

7.1.6 Six steps ahead forecasting for wind speed

In Figure 27a) and Figure 27b), six hours ahead predictions for wind speed at Ghoramara and Keonjhar demo sites respectively are presented.



a) b)

Figure 27. 6 steps ahead forecasting for wind speed at a) Ghoramara demo site b) Keonjhar demo site

7.1.7 Six steps ahead forecasting for wind power

Figure 28 presents the six hours ahead predictions for wind power at Bornholm demo sites.

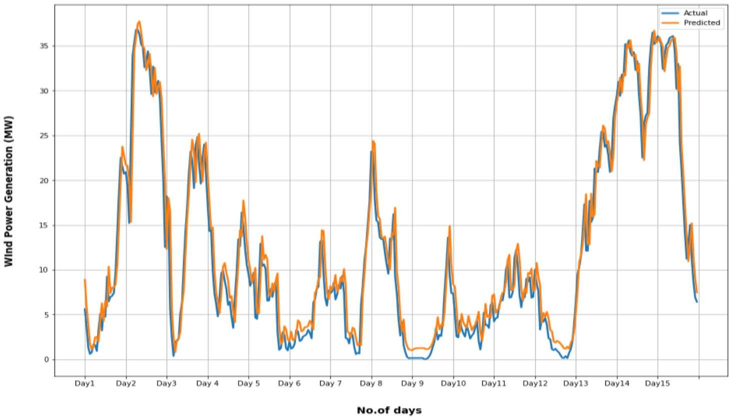
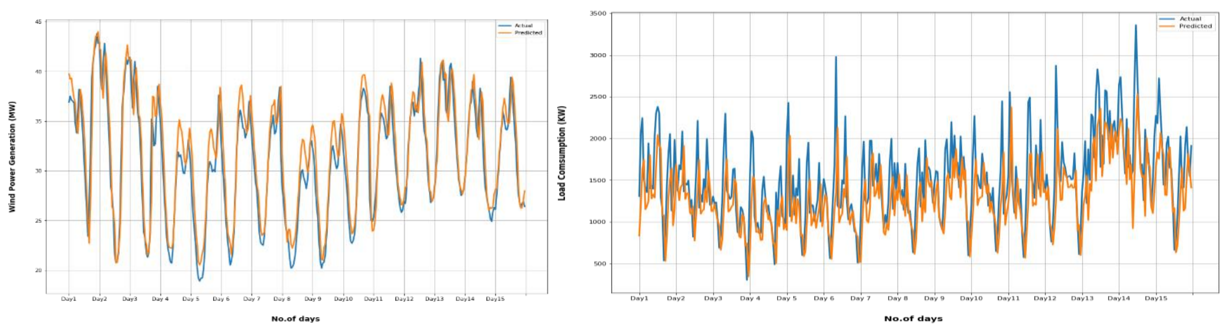


Figure 28. 6 steps ahead forecasting for wind power at Bornholm demo site

7.1.8 Six steps ahead forecasting for electric load

In Figure 29a) and Figure 29b), six hours ahead predictions for electric load at Bornholm and Gaidouromantra demo sites respectively are presented. Figure 30 presents six hours ahead predictions for electric load at Kythnos power system.



a) b)

Figure 29. 6 steps ahead forecasting for electric load at a) Bornholm demo site b) Gaidouromantra demo site

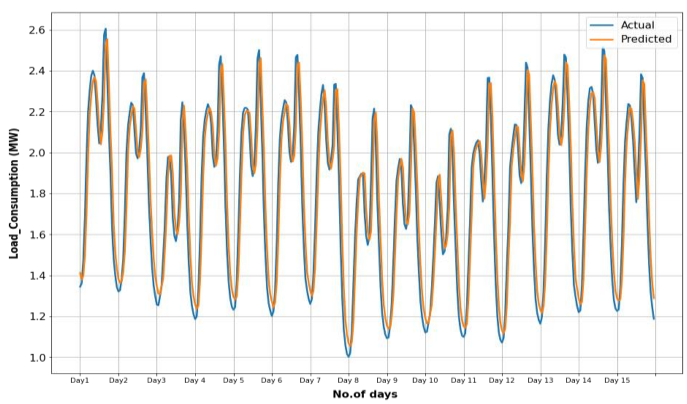
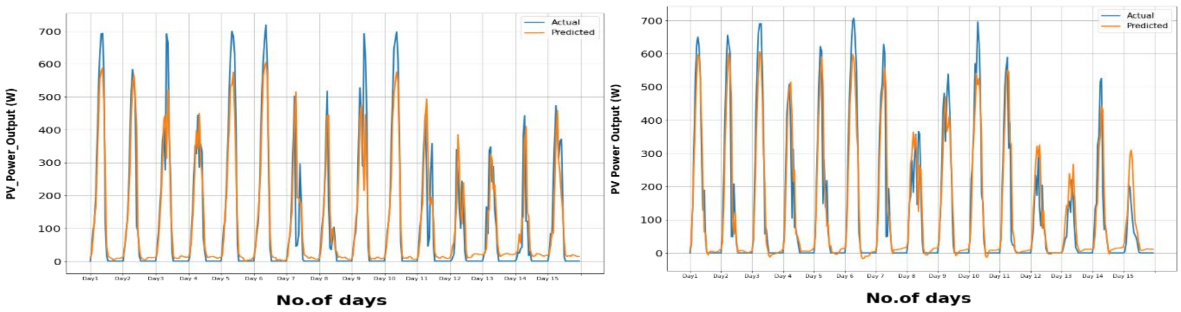


Figure 30. 6 steps ahead forecasting for electric load at demo site of Kythnos power system

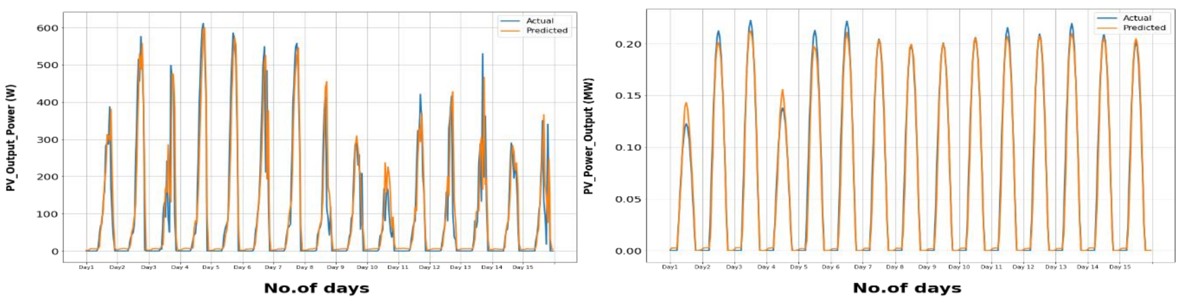
7.1.9 Day-ahead forecasting for PV

Figure 31 and Figure 32 present the day ahead forecasts for PV at Indian demo sites, Bornholm and Kythnos power systems, while Figure 33 presents the day ahead forecasts for PV at Gaidouromantra demo site.



a) b)

Figure 31. Day-ahead forecasting for PV power at a) Ghoramara demo site b) Keonjhar demo site



a) b)

Figure 32. Day-ahead forecasting for PV power at a) Bornholm demo site b) Kythnos power system

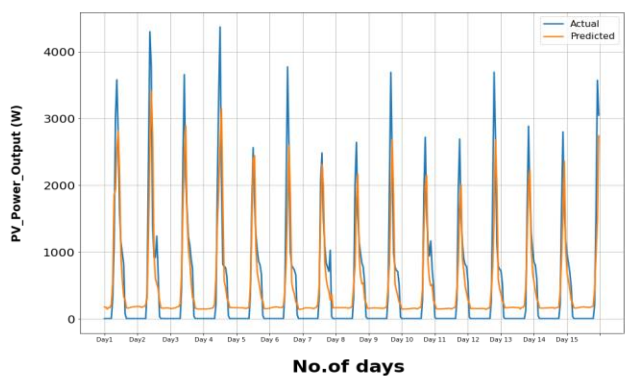
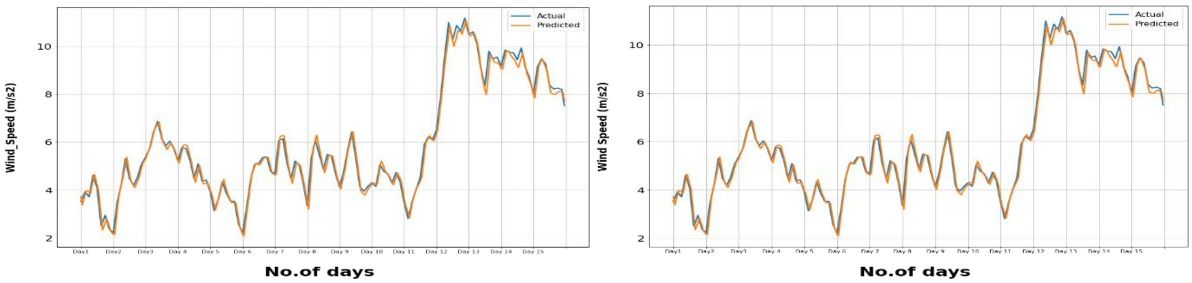


Figure 33. Day-ahead forecasting for PV power at Gaidouromantra demo site

7.1.10 Day-ahead forecasting for wind speed

Figure 34 provides the day-ahead forecasts for wind speed for Ghoramara and Keonjhar.



a) b)

Figure 34. Day-ahead forecasting for wind speed at a) Ghoramara demo site b) Keonjhar demo site

7.1.11 Day-ahead forecasting for wind power

Figure 35 provides the day-ahead forecasts for wind power for Bornholm.

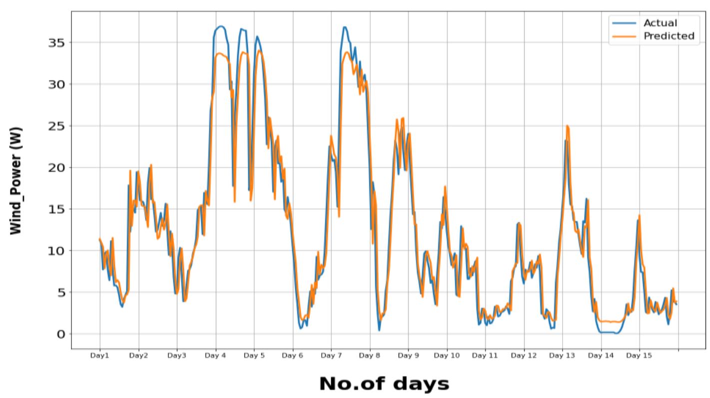
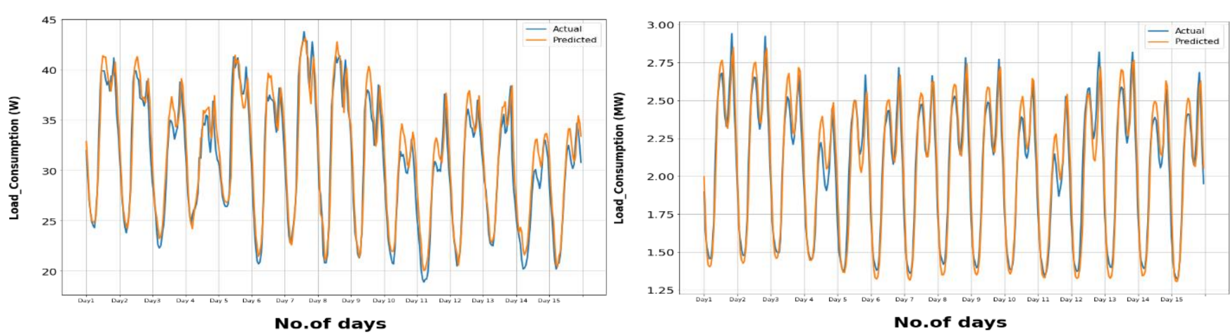


Figure 35. Day-ahead forecasting for wind power at Bornholm demo site

7.1.12 Day-ahead forecasting for load

Figure 36 and Figure 37 provide the day-ahead forecasts for electric load for Bornholm, Kythnos and Gaidouromantra.



a) b)

Figure 36. Day-ahead forecasting for electric load at a) Bornholm demo site b) Kythnos power system

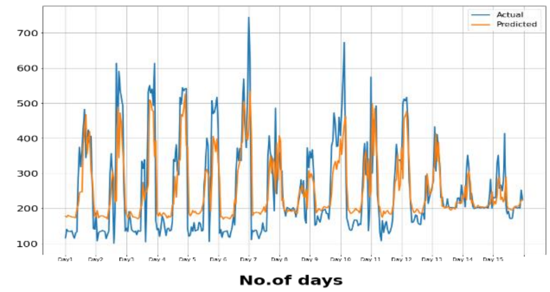
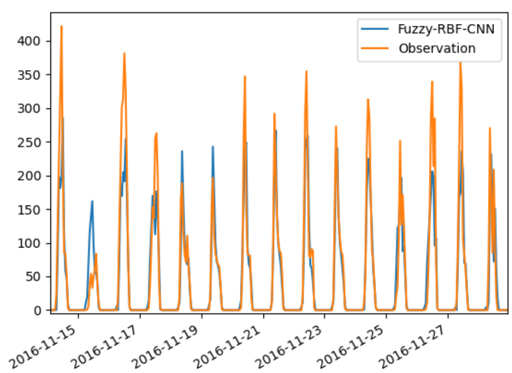


Figure 37. Day-ahead forecasting for electric load at Gaidouromantra demo site

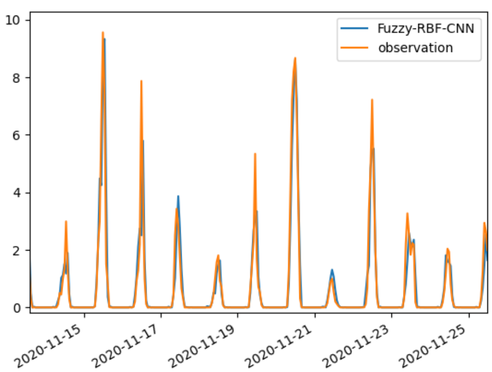
7.2 Fuzzy-RBF-CNN

7.2.1 One step ahead forecasting for PV

In Figure 38a) and Figure 38b), snapshots for 1 hour-ahead predictions for PV power at Gaidouromantra and Bornholm demo sites respectively are presented. Figure 40 provides the one hour ahead forecasts for PV at Kythnos power system.



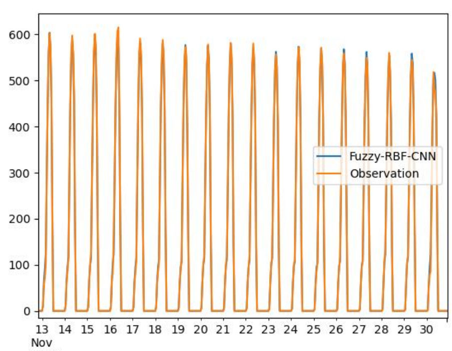
a)



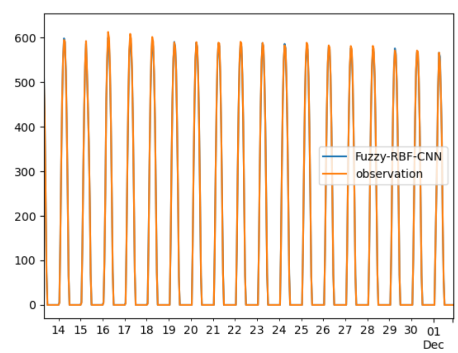
b)

Figure 38. The 1 hour-ahead predictions of proposed model for PV power at a) Gaidouromantra demo site during 15 days of November 2016. b) Bornholm demo site during 12 days of November 2020

Figure 39a) and Figure 39b) present the snapshots for 1 hour-ahead predictions for PV power at Ghoramara and Keonjhar demo sites respectively.



a)



b)

Figure 39. The 1 hour-ahead predictions of proposed model for PV power at a) Ghoramara demo site during 17 days of November 2016. b) Keonjhar demo site during 15 days of November 2016

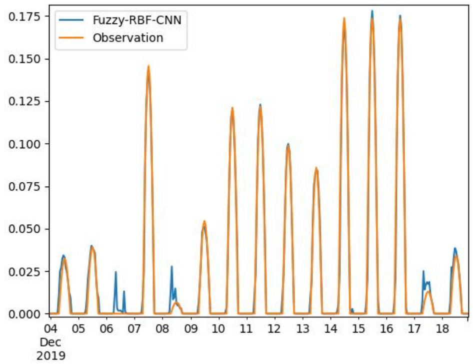


Figure 40. The 1 hour-ahead predictions of proposed model for PV power at demo site of Kythnos power system during 15 days of November

7.2.2 One step ahead forecasting for wind power

Figure 41 presents snapshots for 1 hour ahead wind power predictions from Bornholm demo site.

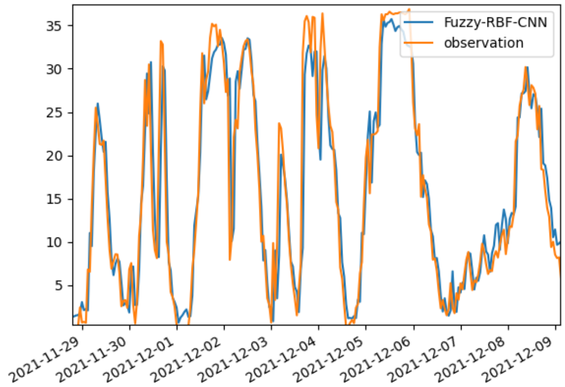
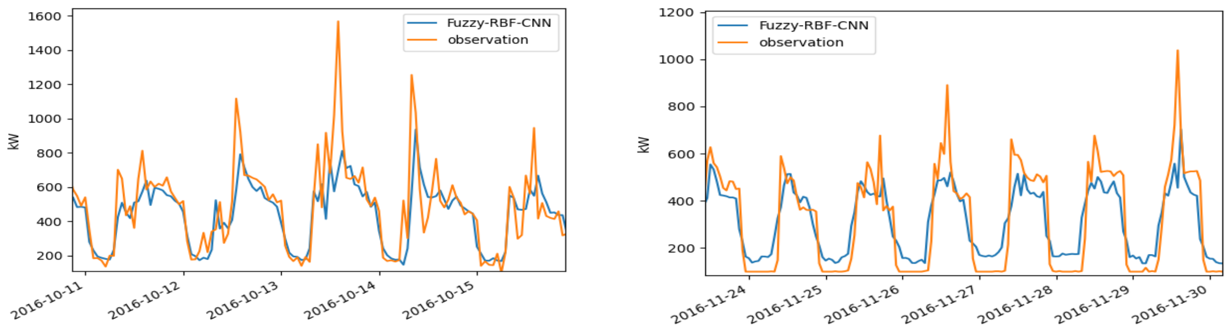


Figure 41. The 1 hour-ahead load predictions of proposed model on Bornholm case-study during 2 days of November and 8 days of December

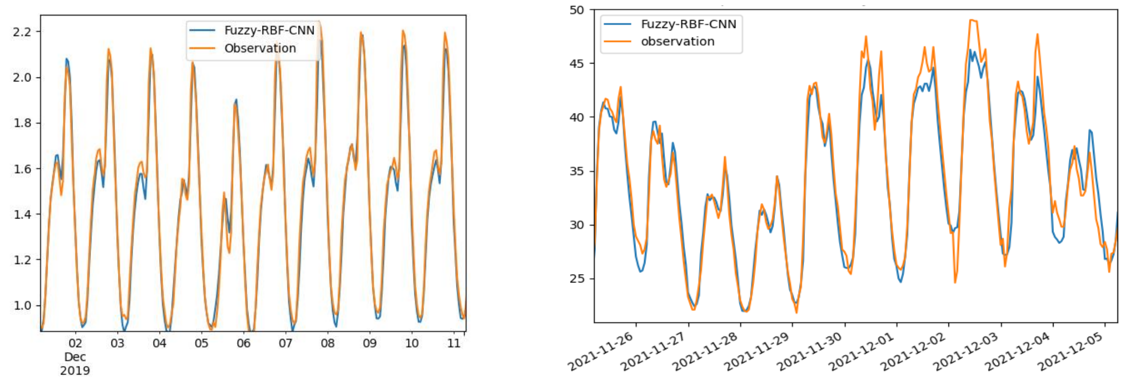
7.2.3 One step ahead forecasting for electric load

In Figure 42, snapshots for 1 hour-ahead predictions for electric load at Gaidouromantra demo sites during different periods are presented. Figure 43 presents snapshots for 1 hour ahead load predictions from Kythnos power system and Bornholm demo sites.



a) b)

Figure 42. The 1 hour-ahead predictions of proposed model for electric load at Gaidouromantra demo site during a) 5 days of October 2016. b) 7 days of November 2016

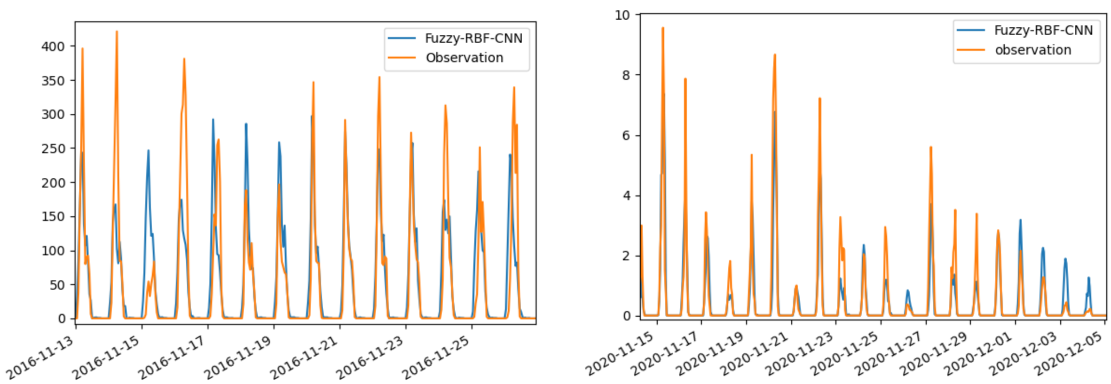


a) b)

Figure 43. The 1 hour-ahead predictions of proposed model for electric load at a) Kythnos power system during 10 days of December 2019 b) Bornholm case-study during 5 days of November and 5 days of December

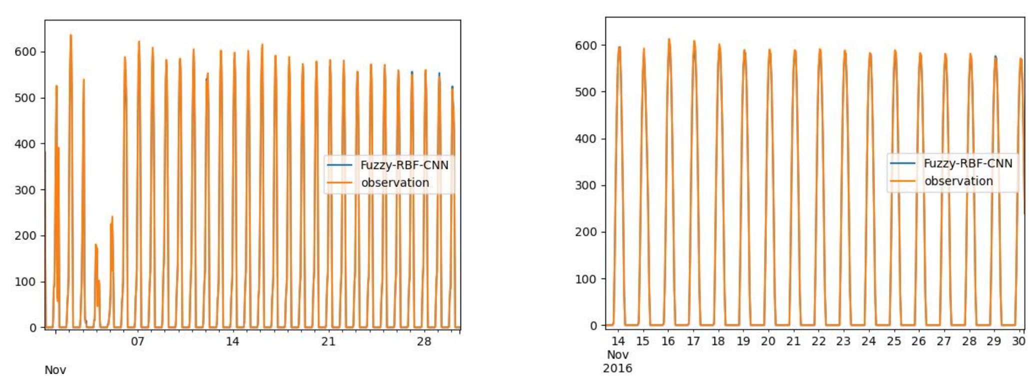
7.2.4 Six steps ahead forecasting for PV

In Figure 44a) and Figure 44b), six hours ahead predictions for Gaidouromantra and Bornholm respectively are presented. Figure 45a) and Figure 45b) present the six hours ahead predictions for PV power at Ghoramara and Keonjhar respectively. Figure 46 provides the six steps ahead forecasts for PV power at Kythnos power system.



a) b)

Figure 44. The 6 hour-ahead PV power predictions of proposed model at a) Gaidouromantra demo site during 15 days of November 2016. b) Bornholm demo site during 20 days of November and December 2020



a) b)

Figure 45. The 6 hour-ahead PV power predictions of proposed model at a) Ghoramara demo site during November 2016. b) Keonjhar demo site during the last 15 days of November 2016

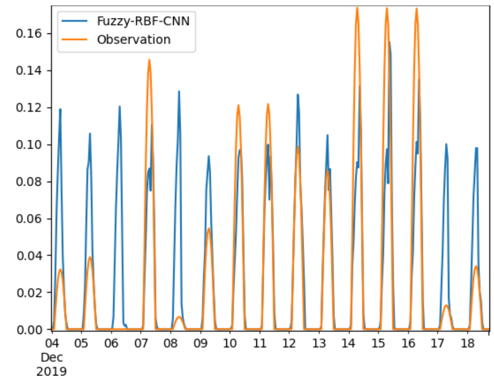


Figure 46. The 6 hour-ahead PV power predictions of proposed model at Kythnos power system during 15 days of November 2016

7.2.5 Six steps ahead forecasting for wind power

Figure 47 presents snapshots for 6 hours ahead wind power predictions from Bornholm demo site.

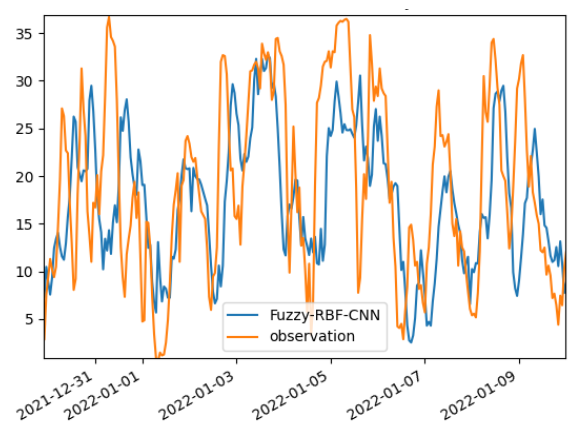
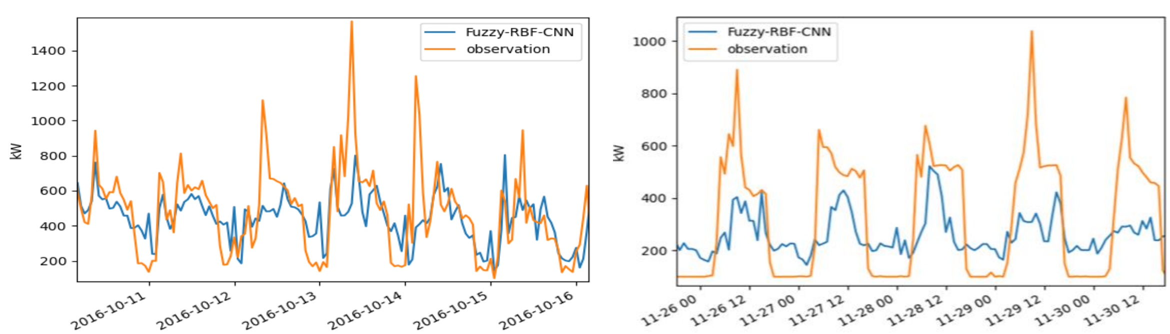


Figure 47. 6 hour-ahead load predictions of proposed model on Bornholm case-study during 2 days of December and 8 days of January

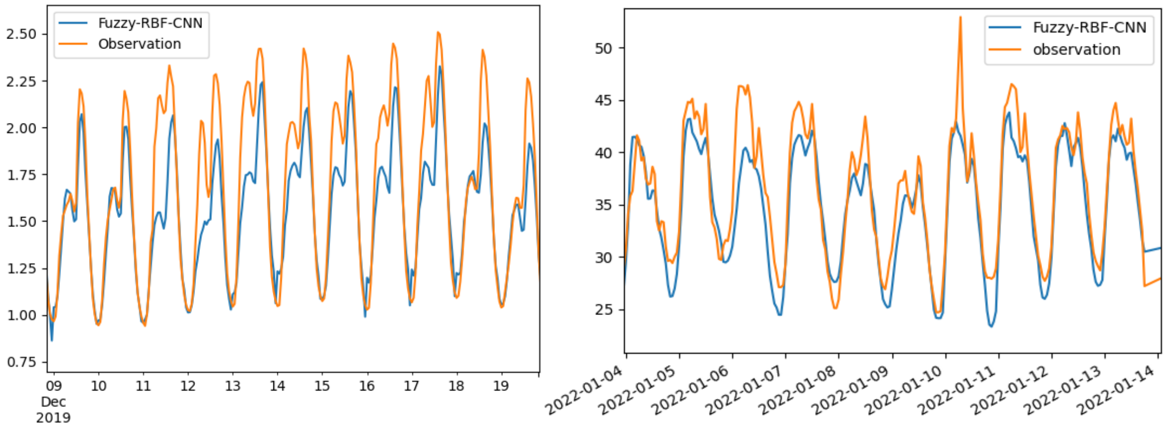
7.2.6 Six steps ahead forecasting for electric load

In Figure 48, six hours ahead predictions for electric load at Gaidouromantra demo sites during different periods are presented, while Figure 49 provides the six hours ahead forecasts for electric load at Kythnos power system and Bornholm demo sites.



a) b)

Figure 48. The 6 hour-ahead predictions of proposed model for electric load at Gaidouromantra demo site during a) 6 days of October 2016. b) 5 days of November 2016

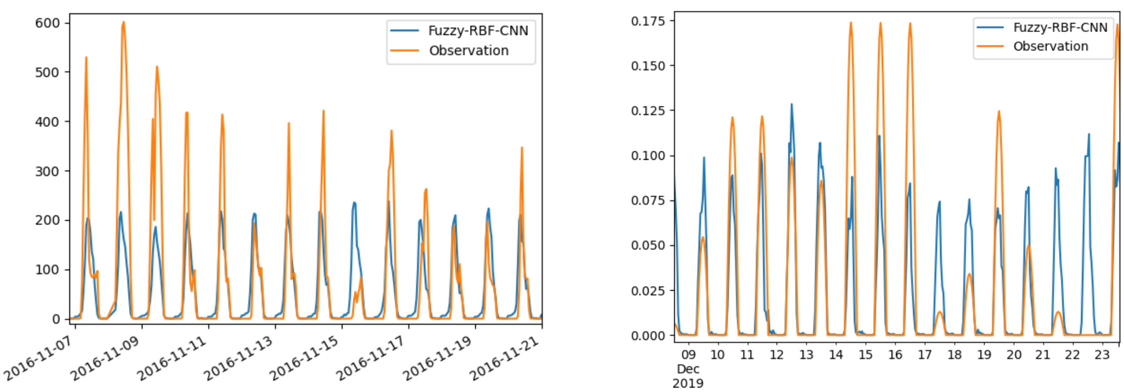


a) b)

Figure 49. The 6 hour-ahead predictions of proposed model for electric load at a) Kythnos power system during 11 days of December 2019 b) Bornholm case-study during 10 days of January

7.2.7 Day-ahead forecasting for PV

Figure 50 provides the day-ahead forecasts for PV power at Gaidouromantra and Kythnos power system, while Figure 51 provides the day-ahead forecasts for PV power at Bornholm demo site. Figure 52 provides the day-ahead forecasts for PV power at Ghoramara and Keonjhar.



a) b)

Figure 50. The day-ahead predictions of proposed model for PV at a) Gaidouromantra demo site during 15 days of November 2016 b) Kythnos power system during 15 days of December 2019

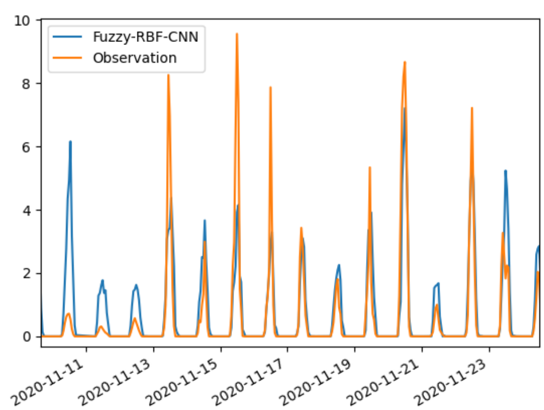
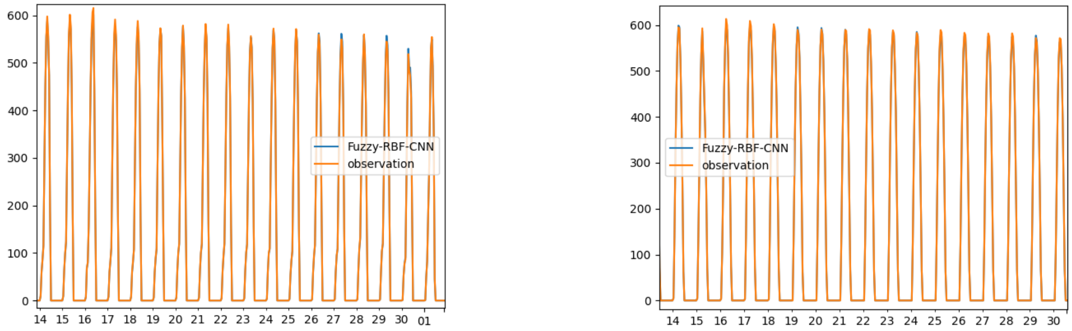


Figure 51. The day-ahead predictions of proposed model for PV at Bornholm demo site during 14 days of November 2020



a) b)

Figure 52. The day-ahead predictions of proposed model for PV at a) Ghoramara case-study during 16 days of November 2020 b) Keonjhar case-study during 16 days of November 2020

7.2.8 Day-ahead forecasting for wind power

Figure 53 presents a snapshot for day-ahead wind power predictions for Bornholm demo site.

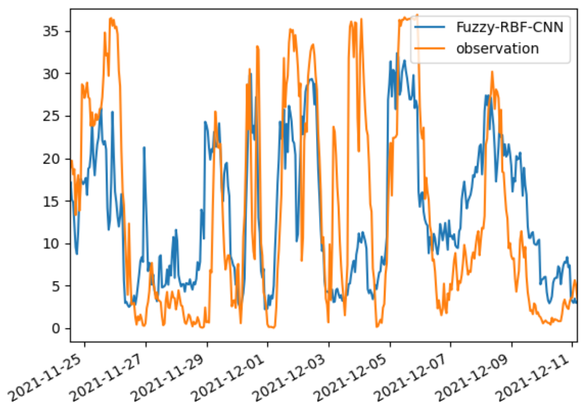
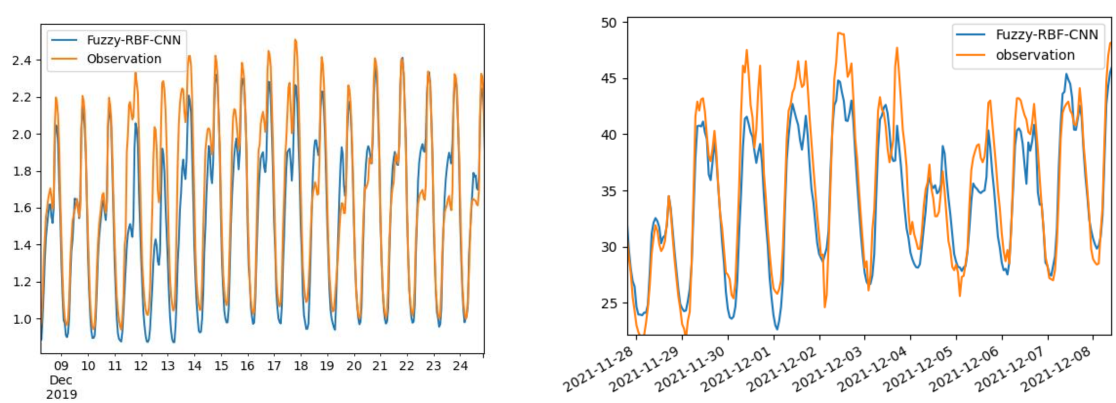


Figure 53. The day-ahead predictions of proposed model for wind power at Bornholm demo site during 5 days of November and during 10 days of December

7.2.9 Day-ahead forecasting for electric load

Figure 54 presents snapshots for day-ahead wind power predictions for Kythnos power system and Bornholm demo sites.



a) b)

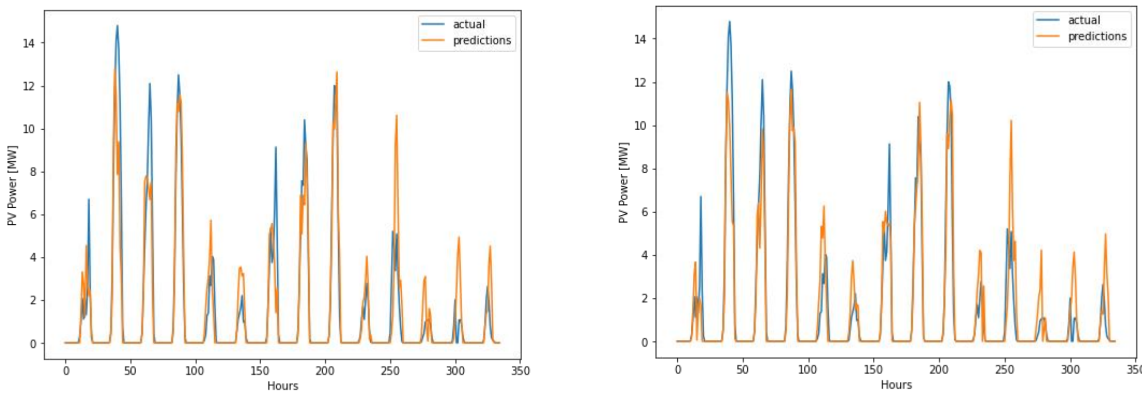
Figure 54. The day-ahead predictions of proposed model for electric load at a) Kythnos power system during 15 days of December b) Bornholm case-study during 2 days of November and during 8 days of December

7.3 Hybrid LSTM-CNN model

The following results, in this subsection, belong to the first two weeks of the test set.

7.3.1 One step ahead forecasting for PV

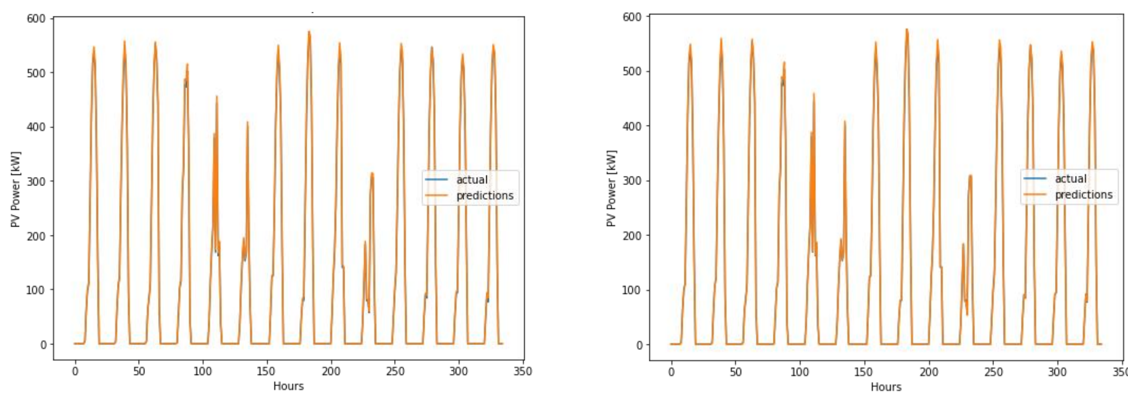
Figure 55a) and Figure 55b) present the results for the 1 hour-ahead forecasts of the LSTM and proposed hybrid LSTM-CNN models respectively for PV power at Bornholm demo site for 14 days.



a) b)

Figure 55. The 1 hour-ahead forecasts for PV power at Bornholm demo site for 14 days using a) the LSTM model b) the proposed hybrid LSTM-CNN model

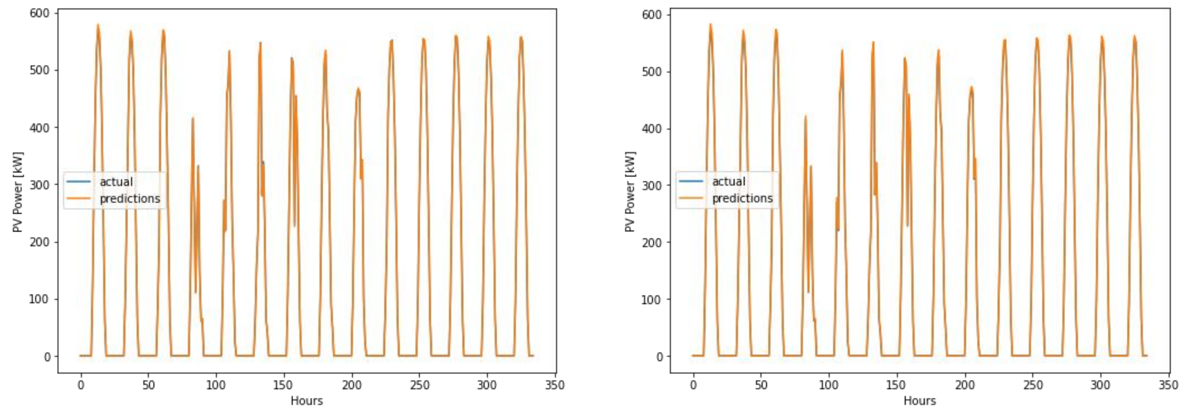
Figure 56a) and Figure 56b) present the results for the 1 hour-ahead forecasts of the LSTM and proposed hybrid LSTM-CNN models respectively for PV power at Ghoramara demo site for 14 days.



a) b)

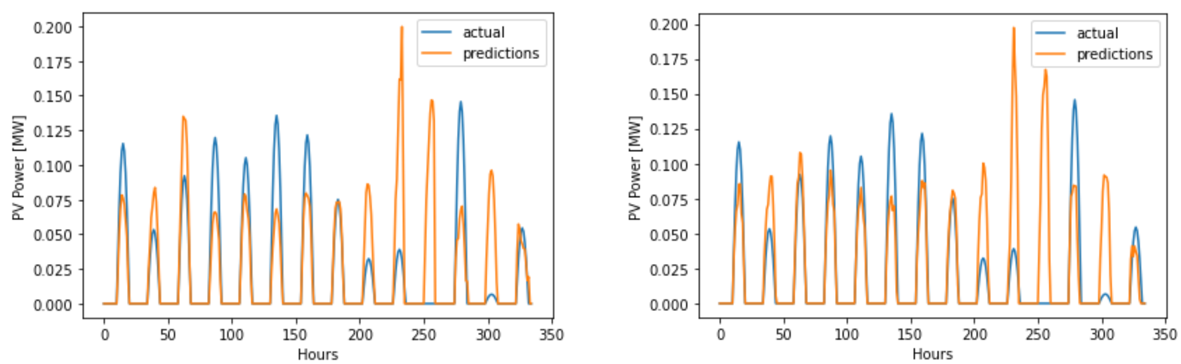
Figure 56. The 1 hour-ahead forecasts for PV power at Ghoramara demo site for 14 days using a) the LSTM model b) the proposed hybrid LSTM-CNN model

Figure 57a) and Figure 57b) present the results for the 1 hour-ahead forecasts of the LSTM and proposed hybrid LSTM-CNN models respectively for PV power at Keonjhar demo site for 14 days. Figure 58 provides one step ahead forecasts for PV power at Kythnos power system, while Figure 59 provides one step ahead forecasts for PV power at Gaidouromadra demo site.



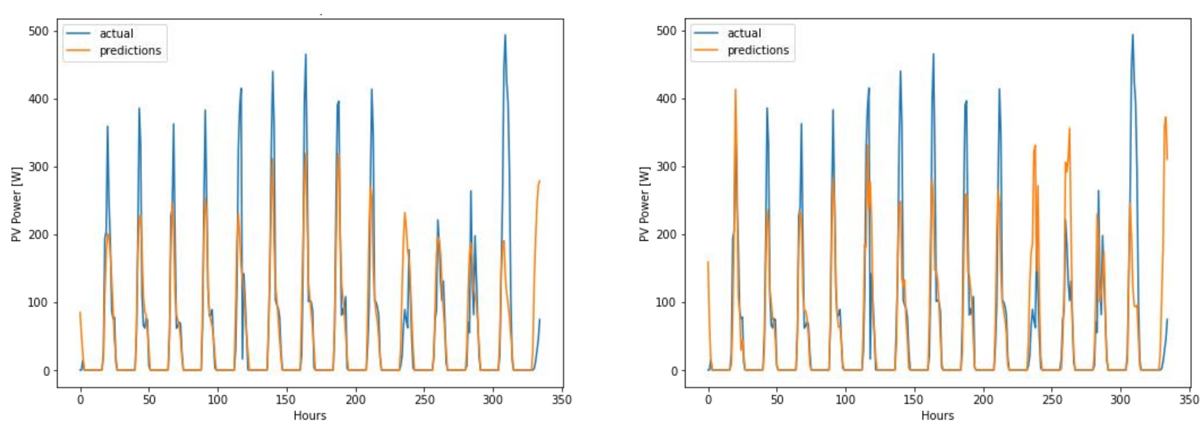
a) b)

Figure 57. The 1 hour-ahead forecasts for PV power at Keonjhar demo site for 14 days using a) the LSTM model. b) the proposed hybrid LSTM-CNN model



a) b)

Figure 58. The 1 hour-ahead forecasts for PV power at Kythnos power system for 14 days using a) the LSTM model. b) the proposed hybrid LSTM-CNN model.

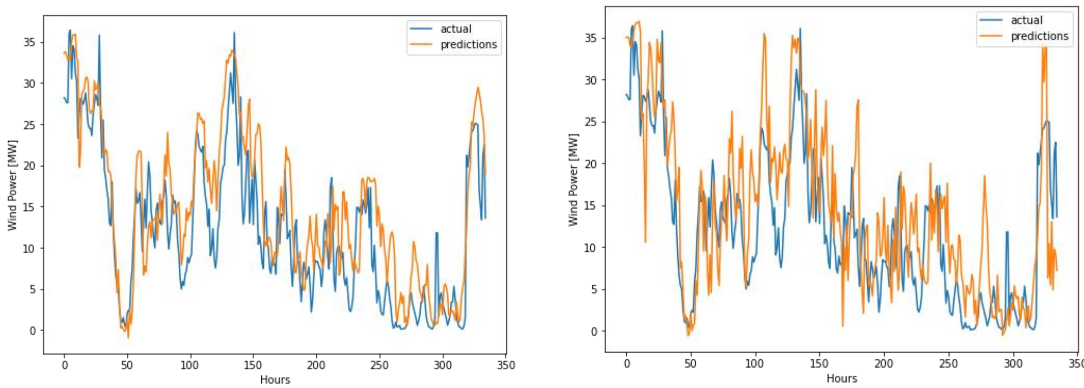


a) b)

Figure 59. The 1 hour-ahead forecasts for PV power at Gaidouromadra demo site for 14 days using a) the LSTM model. b) the proposed hybrid LSTM-CNN model.

7.3.2 One step ahead forecasting for wind power

As mentioned, the results belong to the first two weeks of the test set. Figure 60a) and Figure 60b) present the results for the 1 hour-ahead forecasts of the LSTM and proposed hybrid LSTM-CNN models respectively for wind power at Bornholm demo site for 14 days.

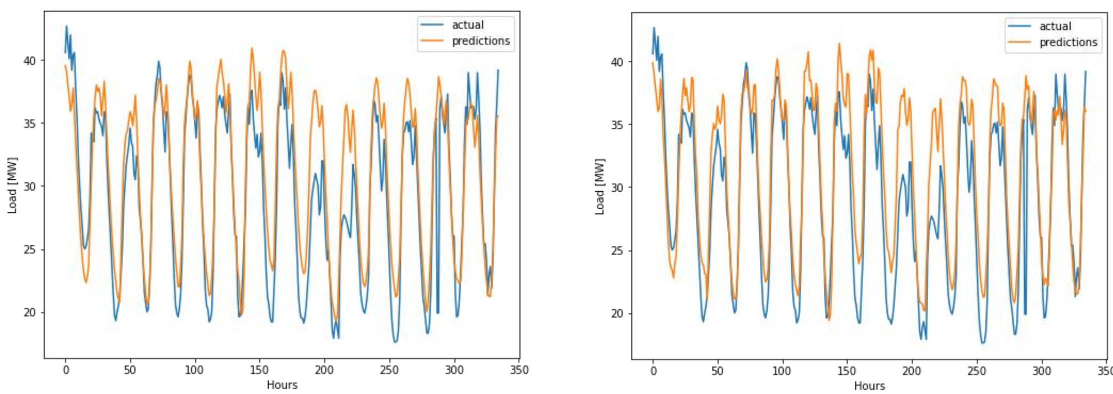


a) b)

Figure 60. The 1 hour-ahead forecasts for wind power at Bornholm demo site for 14 days using a) the LSTM model b) the proposed hybrid LSTM-CNN model

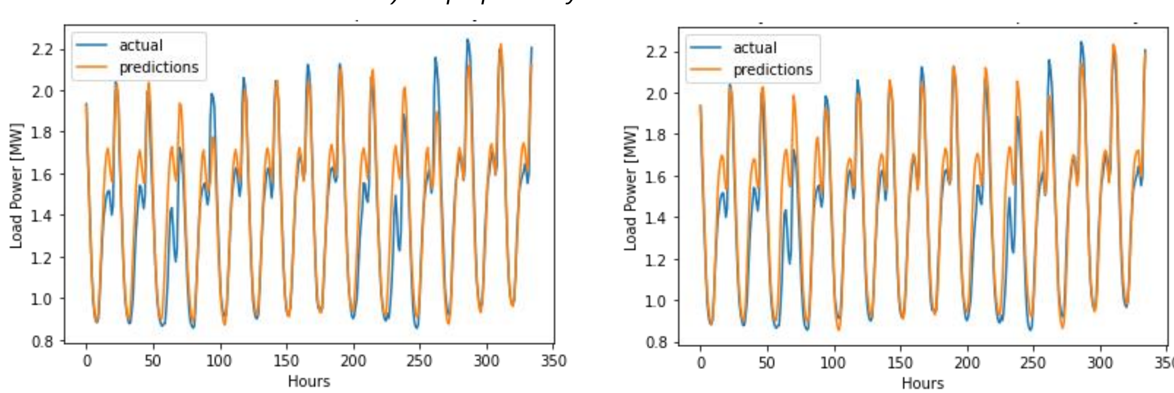
7.3.3 One step ahead forecasting for electric load

Figure 61a) and Figure 61b) present the results for the 1 hour-ahead forecasts for electric load using the LSTM and proposed hybrid LSTM-CNN models respectively at Bornholm demo site for 14 days. Figure 62 provides one step ahead forecasts for electric load at Kythnos power system, while Figure 63 provides one step ahead forecasts for electric load at Gaidouromatra demo site.



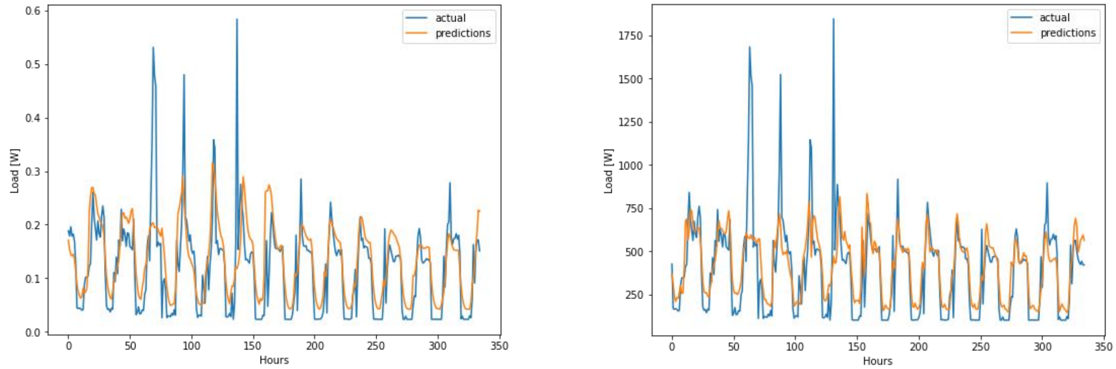
a) b)

Figure 61. The 1 hour-ahead forecasts for electric load at Bornholm demo site for 14 days using a) the LSTM model b) the proposed hybrid LSTM-CNN model



a) b)

Figure 62. The 1 hour-ahead forecasts for electric load at Kythnos power system for 14 days using a) the LSTM model b) the proposed hybrid LSTM-CNN model

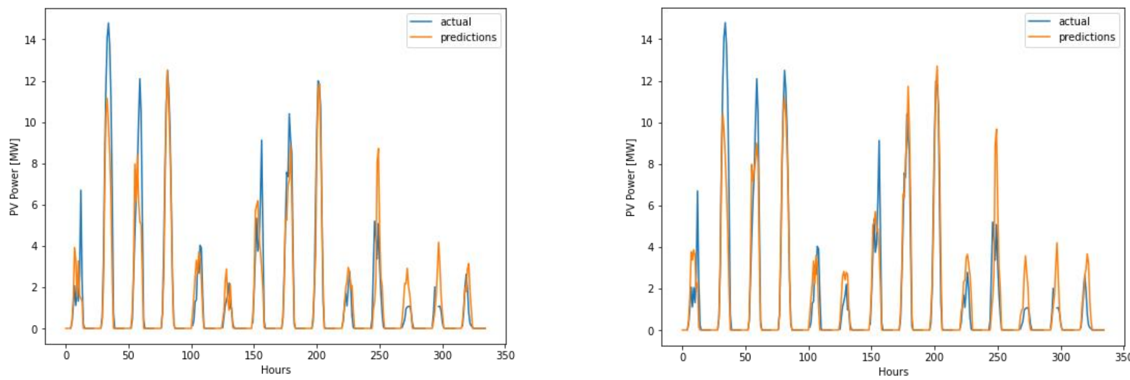


a) b)

Figure 63. The 1 hour-ahead forecasts for electric load at Gaidouromatra demo site for 14 days using a) the LSTM model b) the proposed hybrid LSTM-CNN model

7.3.4 Six steps ahead forecasting for PV

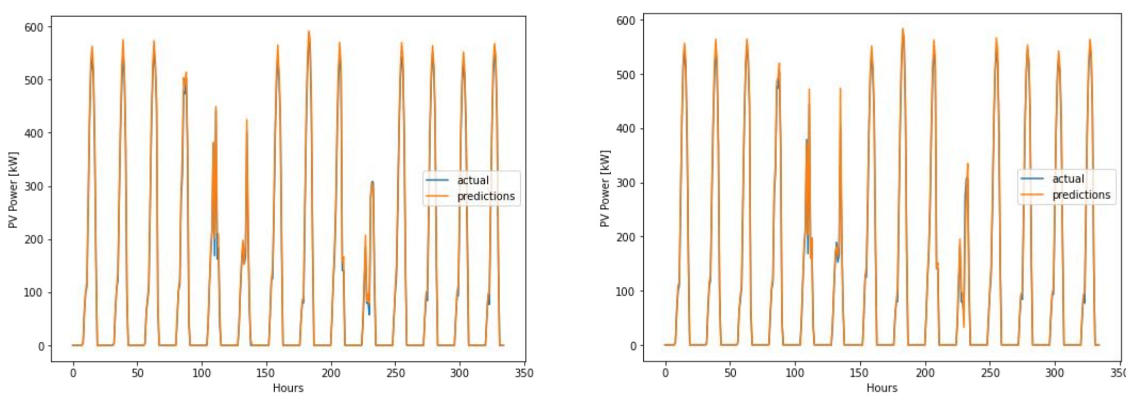
Figure 64a) and Figure 64b) present the results for the 6 hours-ahead forecasts of the LSTM and proposed hybrid LSTM-CNN models respectively for PV power at Bornholm demo site for 14 days.



a) b)

Figure 64. The 6 hours-ahead forecasts for PV power at Bornholm demo site for 14 days using a) the LSTM model b) the proposed hybrid LSTM-CNN model

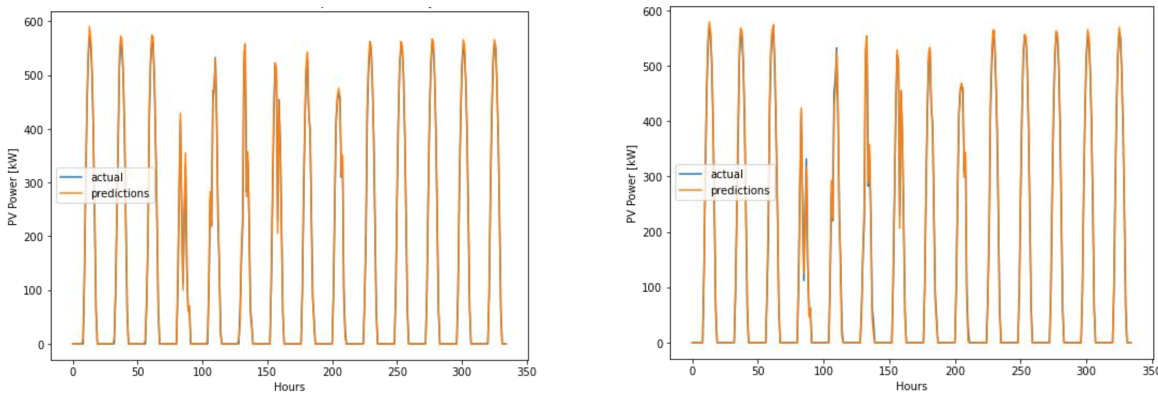
Figure 65a) and Figure 65b) present the results for the 6 hours-ahead forecasts of the LSTM and proposed hybrid LSTM-CNN models respectively for PV power at Ghoramara demo site for 14 days.



a) b)

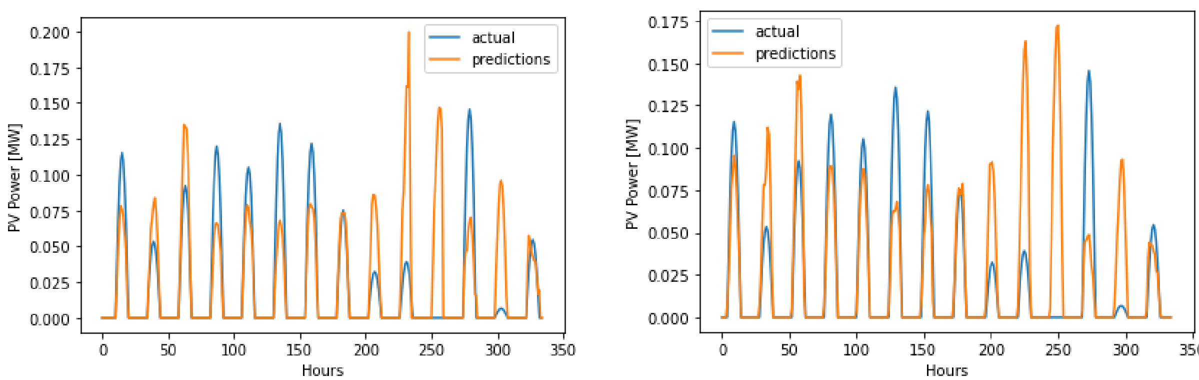
Figure 65. The 6 hours-ahead forecasts for PV power at Ghoramara demo site for 14 days using a) the LSTM model b) the proposed hybrid LSTM-CNN model.

Figure 66a) and Figure 66b) present the results for the 6 hours-ahead forecasts of the LSTM and proposed hybrid LSTM-CNN models respectively for PV power at Keonjhar demo site for 14 days. Figure 67 provides six steps ahead forecasts for PV power at Kythnos power system demo site, while Figure 68 presents six steps ahead forecasts for PV power Gaidouromatra demo site.



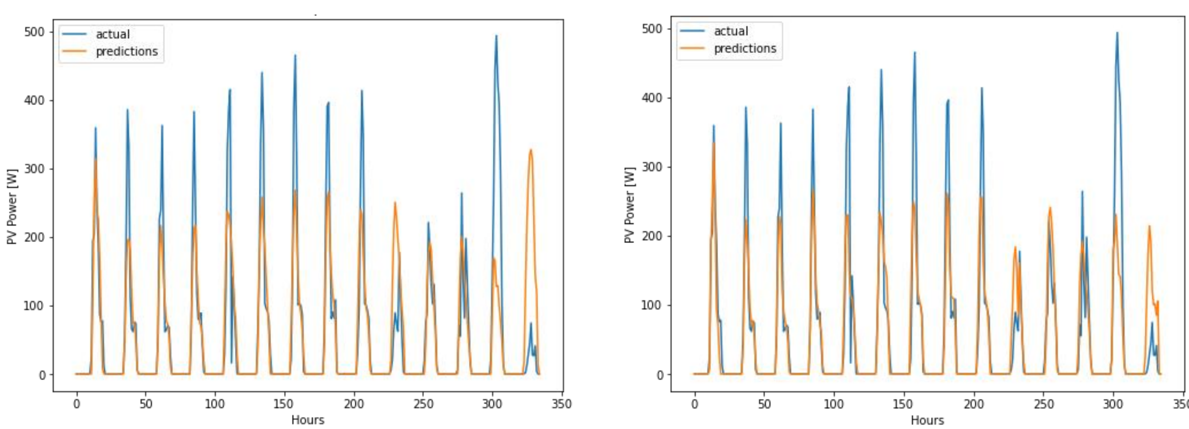
a) b)

Figure 66. The 6 hours-ahead forecasts for PV power at Keonjhar demo site for 14 days using a) the LSTM model b) the proposed hybrid LSTM-CNN model



a) b)

Figure 67. The 6 hours-ahead forecasts for PV power at Kythnos power system for 14 days using a) the LSTM model b) the proposed hybrid LSTM-CNN model

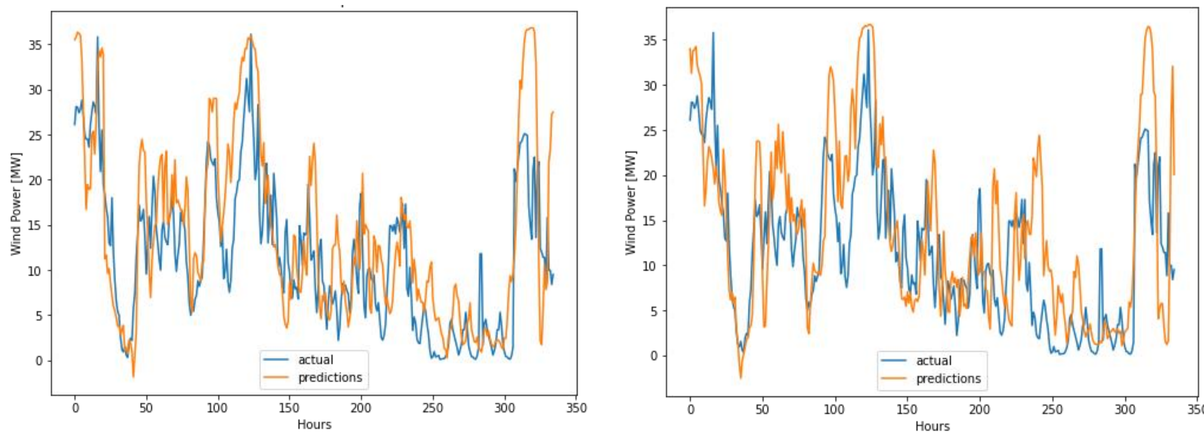


a) b)

Figure 68. The 6 hours-ahead forecasts for PV power at Gaidouromatra demo site for 14 days using a) the LSTM model b) the proposed hybrid LSTM-CNN model

7.3.5 Six steps ahead forecasting for wind power

Figure 69a) and Figure 69b) present the results for the 6 hours-ahead forecasts of the LSTM and proposed hybrid LSTM-CNN models respectively for wind power at Bornholm demo site for 14 days.

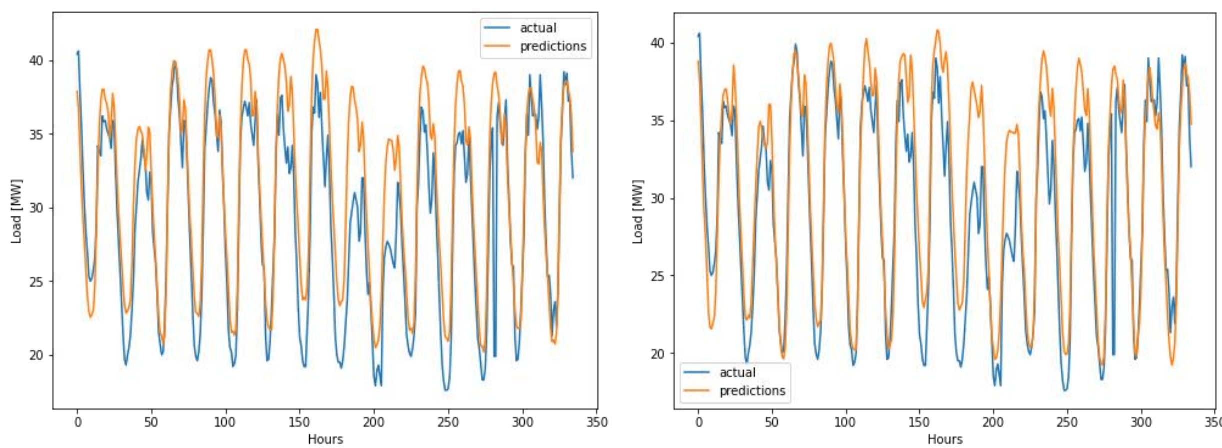


a) b)

Figure 69. The 6 hours-ahead forecasts for wind power at Bornholm demo site for 14 days using a) the LSTM model b) the proposed hybrid LSTM-CNN model

7.3.6 Six steps ahead forecasting for electric load

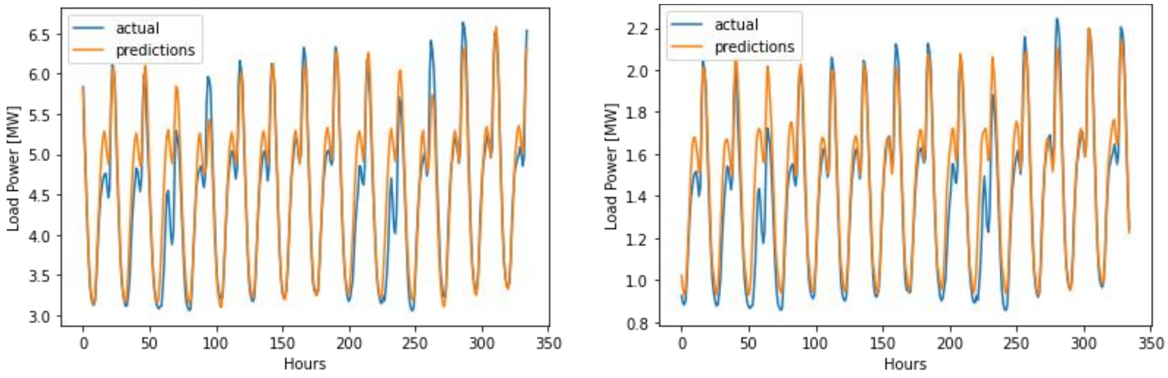
Figure 70a) and Figure 70b) present the results for the 6 hours-ahead forecasts for electric load using the LSTM and proposed hybrid LSTM-CNN models respectively at Bornholm demo site for 14 days.



a) b)

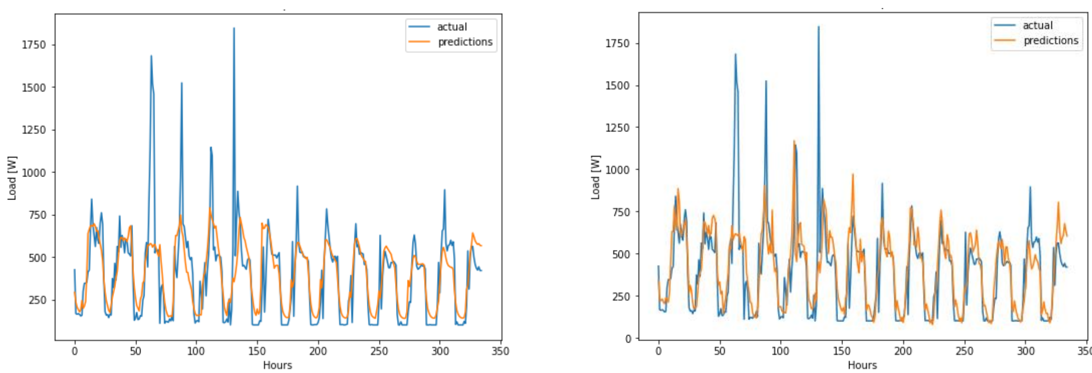
Figure 70. The 6 hours-ahead forecasts for electric load at Bornholm demo site for 14 days using a) the LSTM model b) the proposed hybrid LSTM-CNN model

Figure 71 presents six steps ahead forecasts for electric load at Kythnos power system demo site, while Figure 72 provides six steps ahead forecasts for PV power Gaidouromatra demo site.



a) b)

Figure 71. The 6 hours-ahead forecasts for electric load at Kythnos power system for 14 days using a) the LSTM model b) the proposed hybrid LSTM-CNN model

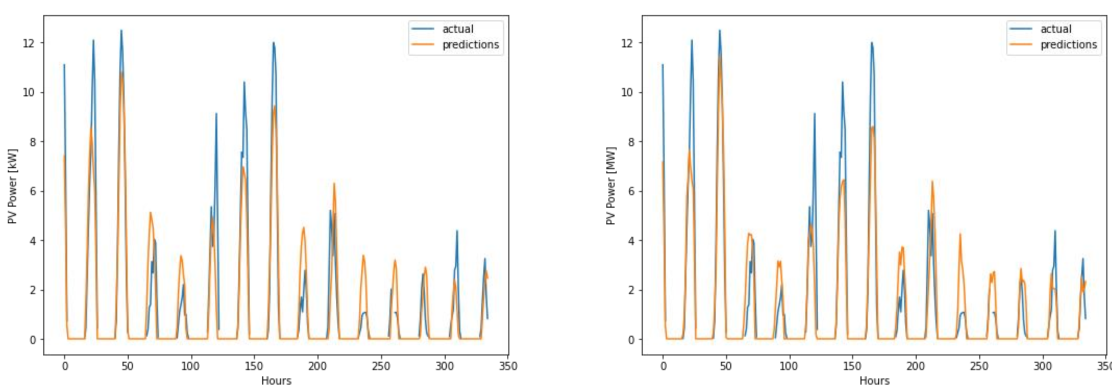


a) b)

Figure 72. The 6 hours-ahead forecasts for electric load at Gaidouromatra demo site for 14 days using a) the LSTM model b) the proposed hybrid LSTM-CNN model

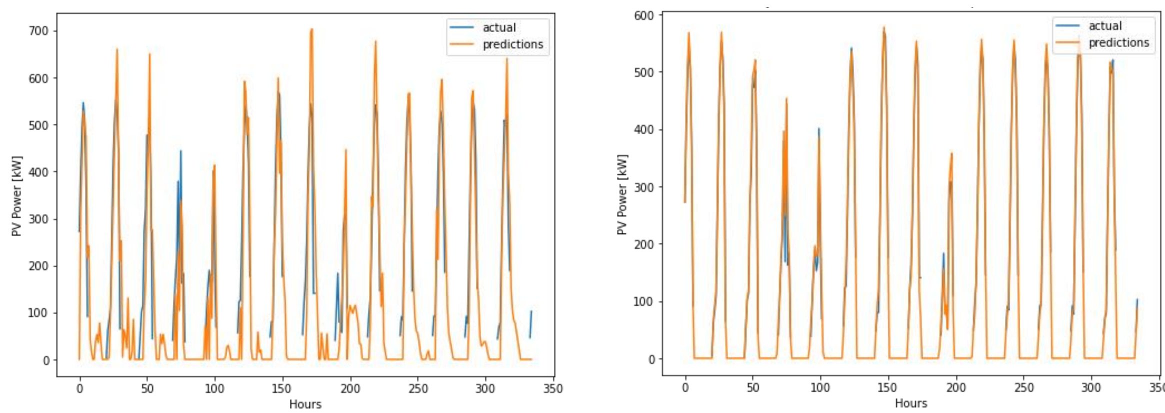
7.3.7 Day-ahead forecasting for PV

The day-ahead forecasting results for PV belong to the first two weeks of each site's test set. Figure 73 provides day ahead forecasts for PV power at Bornholm demo site. Figure 74 provides day ahead forecasts for PV power at Ghoramara demo site. Figure 75 provides day ahead forecasts for PV power at Keonjhar demo site.



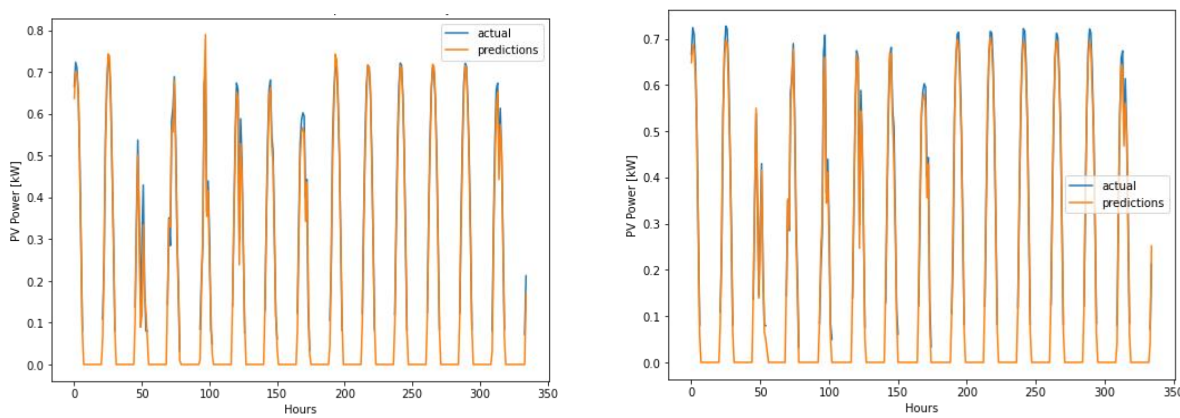
a) b)

Figure 73. The day-ahead forecasts for PV at Bornholm demo site for 14 days using a) the LSTM model b) the proposed hybrid LSTM-CNN model



a) b)

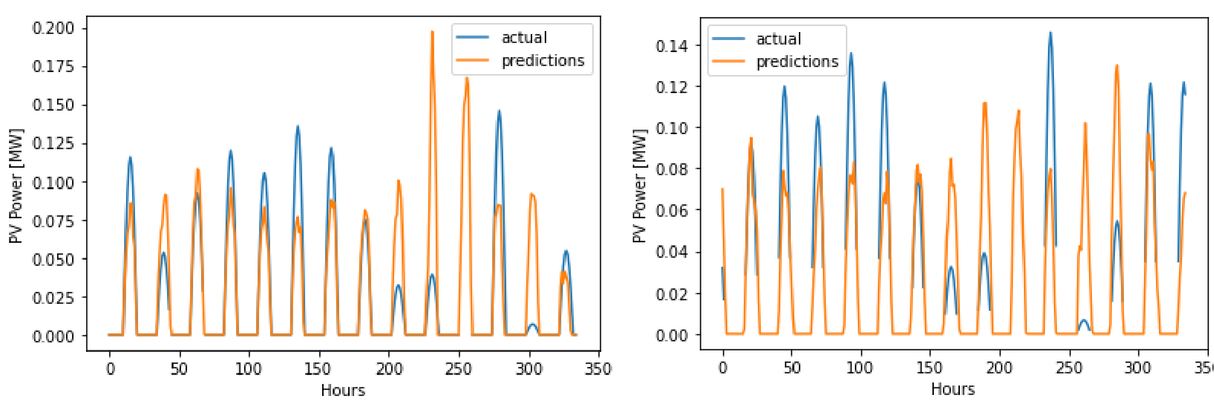
Figure 74. The day-ahead forecasts for PV at Ghoramara demo site for 14 days using a) the LSTM model b) the proposed hybrid LSTM-CNN model



a) b)

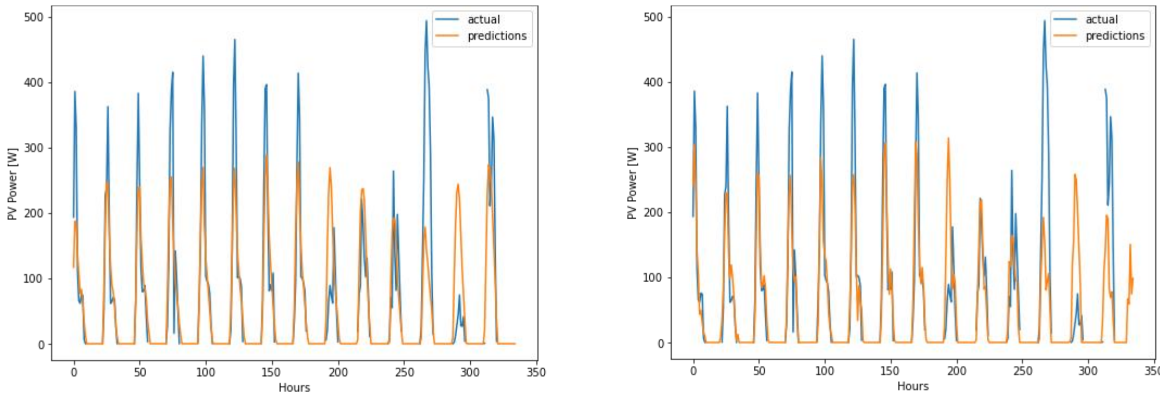
Figure 75. The day-ahead forecasts for PV at Keonjhar demo site for 14 days using a) the LSTM model b) the proposed hybrid LSTM-CNN model

Figure 76 presents day ahead forecasts for PV power Kythnos power system demo site, while Figure 77 provides day ahead forecasts for PV power at Gaidouromatra demo site. The prediction errors at Kythnos and Gaidouromatra demo sites are higher which might be due to the missing values in the datasets or not having sufficient data.



a) b)

Figure 76. The day-ahead forecasts for PV at Kythnos power system for 14 days using a) the LSTM model b) the proposed hybrid LSTM-CNN model

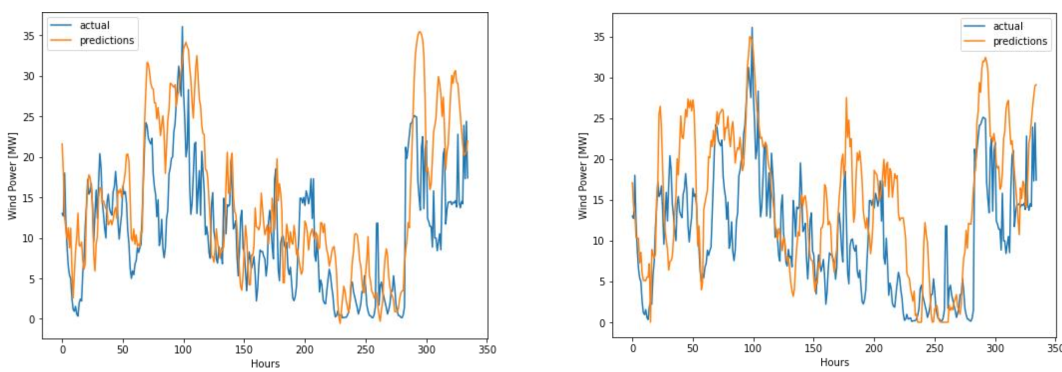


a) b)

Figure 77. The day-ahead forecasts for PV at Gaidouromatra demo site for 14 days using a) the LSTM model b) the proposed hybrid LSTM-CNN model

7.3.8 Day-ahead forecasting for wind power

The day-ahead forecasting results for wind power belong to the first two weeks of each site's test set. Figure 78 provides day ahead forecasts for wind power at Bornholm demo site.

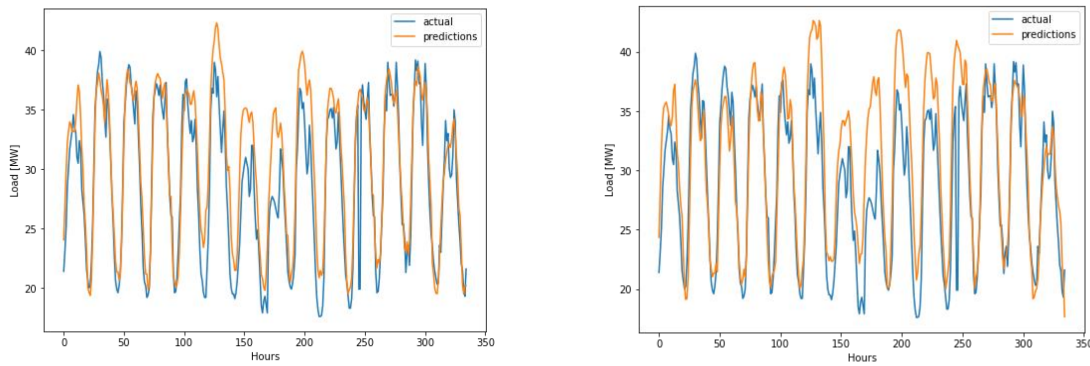


a) b)

Figure 78. The day-ahead forecasts for wind power at Bornholm demo site for 14 days using a) the LSTM model b) the proposed hybrid LSTM-CNN model

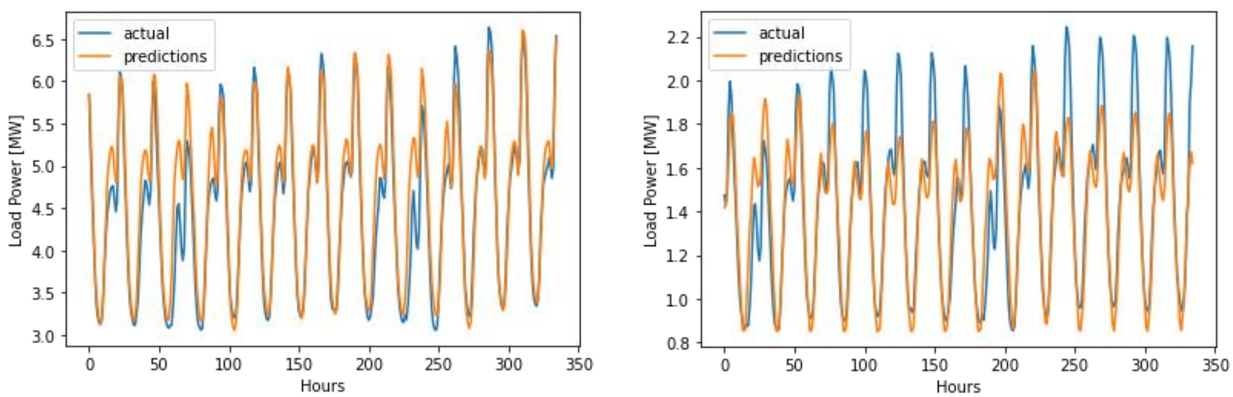
7.3.9 Day-ahead forecasting for electric load

The day-ahead forecasting results for electric load belong to the first two weeks of each site's test set. Figure 79 provides day ahead forecasts for electric load at Bornholm demo site. Figure 80 provides day ahead forecasts for electric load at Kythnos demo site, and Figure 81 provides day ahead forecasts for electric load at Gaidouromatra demo site.



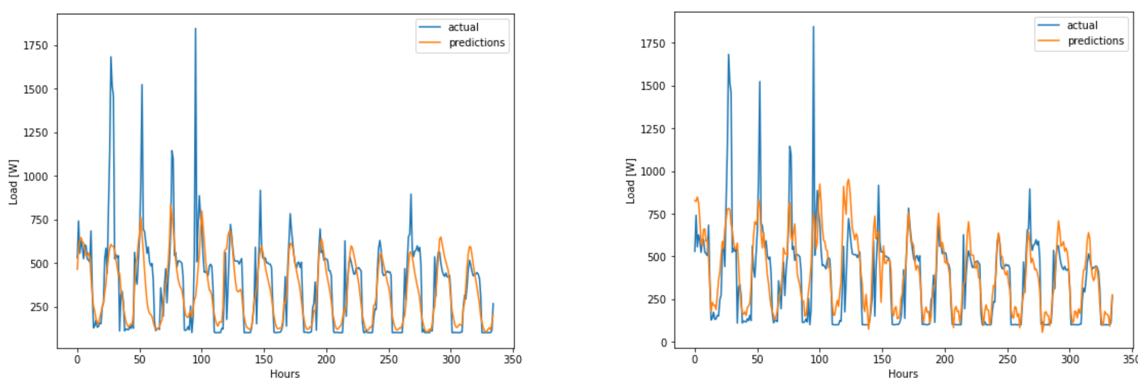
a) b)

Figure 79. The day-ahead forecasts for electric load at Bornholm demo site for 14 days using a) the LSTM model b) the proposed hybrid LSTM-CNN model



a) b)

Figure 80. The day-ahead forecasts for electric load at Kythnos power system for 14 days using a) the LSTM model b) the proposed hybrid LSTM-CNN model



a) b)

Figure 81. The day-ahead forecasts for electric load at Gaidouromatra demo site for 14 days using a) the LSTM model b) the proposed hybrid LSTM-CNN model

7.4 Overall performance of forecasting algorithms

The simplified PV and Load forecast modules implemented by the ecoMG produce a short-term prediction of 6 hours horizon. The key performance indicators used are the Root Mean Square Error (RMSE), the Mean Average Error (MAE) and Mean Absolute Percentage Error (MAPE). Different testing period was considered using the load and PV production data from August 2019 in order to have a testing period variate from the training data used for the data driven forecast tools.

The formulas for the computation are presented below with $\widehat{y_n}$ the forecasted value and y_n the actual recorded value.

$$RMSE = \frac{\sqrt{\sum_{n\in N}(\widehat{y_n} - y_n)^2}}{N}$$

$$MAE = \frac{\sum_{n\in N}|\widehat{y_n} - y_n|}{N}$$

$$MAPE = \frac{\sum_{n\in N}\frac{|\widehat{y_n} - y_n|}{y_n}}{N}$$

The day ahead weather data forecast, required by the PV physical model, was available for the same period through the Skiron database [20], since GFS historical data are not available. Both the simple PV forecast and load forecast are compared with the Fuzzy-RBF-CNN forecast module. The input data for the advanced forecast module of the PV forecast are the PV production in the 6 previous hours and NWP. The load forecast module receives as input, the load time-series of the last week and temperature time series from a NWP provider. The load forecast model combines attributes from ensemble forecasting, artificial neural networks and deep learning architectures. All the available data from the 2015-2016 period from Gaidouromantra MG were used to train the data driven method. The historical data for the test set cover the August of 2019 since during this month the houses of the MG are mainly inhabited.

The main error metrics for machine learning algorithm and their formula are given to clarify what is referred to in the given tables.

$$MSE = \frac{1}{N}\sum_{s=1}^{L}(x_s - \hat{x}_s)^2$$

$$MAE = \frac{1}{N}\sum_{s=1}^{L}|x_s - \hat{x}_s|$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{s=1}^{L}(x_s - \hat{x}_s)^2}$$

$$MAPE = \frac{1}{N}\sum_{s=1}^{L}\frac{|x_s - \hat{x}_s|}{|x_s|}x100$$

$$NMAE = \frac{\mathrm{MAE}}{\frac{1}{N}\sum_{s=1}^{L}|x_s|}$$

$$NRMSE = \frac{\mathrm{RMSE}}{\frac{1}{N}\sum_{s=1}^{L}|x_s|}$$

7.4.1 Test performance of LSTM Auto-Encoder

Table 3, Table 4, Table 5, Table 6 and Table 7 provide the solar forecasting results for Kythnos power system, Gaidouromantra, Bornholm Ghoramara and Keonjhar demo sites respectively.

Table 3. The solar forecasting results for Kythnos power system

Approach	NMAE	NRMSE	R^2
1 step ahead LSTM	0.05951	0.07036	0.8810
1 step ahead LSTM Auto-encoder	0.04746	0.0673	0.8900
6 steps ahead LSTM	0.0498	0.07021	0.9150
6 steps ahead LSTM Auto-encoder	0.0458	0.0625	0.9543
24 step ahead LSTM	0.3054	0.0587	0.9601
24 step ahead LSTM-AE	0.02402	0.0414	0.9731

Table 4. The solar forecasting results for Gaidouromantra demo site

Approach	NMAE	NRMSE	R^2
1 step ahead LSTM	0.0516	0.0778	0.8681
1 step ahead LSTM Auto-encoder	0.050	0.0687	0.8845
6 steps ahead LSTM	0.0573	0.084	0.9188
6 steps ahead LSTM Auto-encoder	0.044	0.0728	0.9205
24 step ahead LSTM	0.01068	0.0236	0.6824
24 step ahead LSTM-AE	0.00915	0.0151	0.6915

Table 5. The solar forecasting results for Bornholm demo site

Approach	NMAE	NRMSE	R^2
1 step ahead LSTM	0.0516	0.0778	0.8681
1 step ahead LSTM Auto-encoder	0.0456	0.0628	0.8905
6 steps ahead LSTM	0.0733	0.862	0.8620
6 steps ahead LSTM Auto-encoder	0.065	0.0857	0.8790
24 step ahead LSTM	0.0395	0.0632	0.7129
24 step ahead LSTM-AE	0.0253	0.0539	0.7655

Table 6. The solar forecasting results for Ghoramara demo site

Approach	NMAE	NRMSE	R^2
1 step ahead LSTM	0.0305	0.0748	0.9763
1 step ahead LSTM Auto-encoder	0.0295	0.070	0.980
6 steps ahead LSTM	0.05	0.9388	0.8460
6 steps ahead LSTM Auto-encoder	0.04817	0.079	0.90
24 step ahead LSTM	0.0451	0.0895	0.9054
24 step ahead LSTM-AE	0.03866	0.0704	0.9163

Table 7. The solar forecasting results for Keonjhar demo site

Approach	NMAE	NRMSE	R^2
1 step ahead LSTM	0.0657	0.9132	0.8865
1 step ahead LSTM Auto-encoder	0.0505	0.0815	0.9065
6 steps ahead LSTM	0.0432	0.0621	0.9475
6 steps ahead LSTM Auto-encoder	0.0401	0.06	0.9521
24 step ahead LSTM	0.0474	0.07023	0.9325
24 step ahead LSTM-AE	0.0379	0.0656	0.9451

LSTM AutoEncoder Model is implemented for solar insolation forecasting to all demo sites. The introduction of basic LSTM and LSTM Autoencoder is explained in subsection 4.1. Dataset is obtained from PVGIS for both the Indian demo sites. Data preprocessing steps involved in the algorithm are clearly mentioned in Subsection 5.1. Splitting of the dataset into training and testing is done by 90-10%. The input and output parameters that are considered for this algorithm are also mentioned in Section 3. A multivariate model is considered for solar insolation having some input parameters and forecasted using basic LSTM and LSTM AE. A comparison is made between these two models. LSTM AE is giving slightly better results than basic LSTM. It has been forecasted for one step ahead and six steps ahead forecasting.

Hence, the results for all the demo sites using LSTM AutoEncoder for six steps ahead forecasting can be summarized as follows. For Indian demo site Ghoramara, MAE is 0.04817 with the accuracy of 90%, while for Khenojhar MAE is found to be 0.0401 with the accuracy of 95.21%. For European demo site Bornholm, MAE is found to be 0.065 with the accuracy of 87.90%, while for Gaidouromandra microgrid, MAE is found to be 0.044 with the accuracy of 92.05%.

Table 8, Table 9, Table 10, Table 11, Table 12 and Table 13 are showing the wind speed and wind power forecasting results for Bornholm, Ghoramara, Keonjhar and Kythnos power system demo sites.

Table 8. The wind power forecasting results for Bornholm demo site

Approach	MAE	RMSE	R^2
1 step ahead LSTM	0.05279	0.07882	0.94688
1 step ahead LSTM Auto-encoder	0.04589	0.06958	0.9500
6 steps ahead LSTM	0.05640	0.07856	0.9479
6 steps ahead LSTM Auto-encoder	0.0469	0.06841	0.9520

Table 9. Metrics Calculation of wind power day-ahead forecast for Bornholm

Demo site	NMAE	NRMSE	R^2
24 step ahead LSTM	0.0781	0.0983	0.9312
24 step ahead LSTM-AE	0.0605	0.0804	0.9458

Table 10. The wind speed forecasting results for Ghoramara demo site

Approach	MAE	RMSE	R^2
1 step ahead LSTM	0.202	0.2522	0.9465
1 step ahead LSTM Auto-encoder	0.095	0.1026	0.9560
6 steps ahead LSTM	0.0288	0.0356	0.9501
6 steps ahead LSTM Auto-encoder	0.0165	0.0212	0.9645

Table 11. Metrics Calculation for wind speed forecast for Ghoramara

Demo site	NMAE	NRMSE	R^2
24 step ahead LSTM	0.02013	0.01945	0.9724
24 step ahead LSTM-AE	0.01130	0.01460	0.9890

Table 12. The wind speed forecasting results for Keonjhar demo site

Approach	MAE	RMSE	R^2
1 step ahead LSTM	0.2067	0.2574	0.9443
1 step ahead LSTM Auto-encoder	0.0965	0.134	0.9503
6 steps ahead LSTM	0.1754	0.1532	0.952
6 steps ahead LSTM Auto-encoder	0.0194	0.02135	0.9643

Table 13. Metrics Calculation for wind speed day-ahead forecast for Keonjhar

Demo site	NMAE	NRMSE	R^2
24 step ahead LSTM	0.0264	0.0203	0.9705
24 step ahead LSTM-AE	0.0112	0.0144	0.9829

Table 14, Table 15, Table 16 and Table 17 are showing the electric load forecasting results for Kythnos power system, Bornholm and Gaidouromantra demo sites respectively.

Table 14. The metrics for electric load forecasting results for Kythnos power system demo site

Approach	MARPE	RMSRPE	R^2
1 step ahead LSTM	5.03	6.98	0.8521
1 step ahead LSTM Auto-encoder	4.64	5.92	0.8755
6 steps ahead LSTM	4.87	5.90	0.9125
6 steps ahead LSTM Auto-encoder	4.56	5.84	0.9381

Table 15. Metrics Calculation of electric load day-ahead forecast for Kythnos

Demo site	NMAE	RMSE	MARPE	RMSRPE	R^2
24 step ahead LSTM	0.0468	0.0503	4.68	5.03	0.9374
24 step ahead LSTM-AE	0.0325	0.04711	3.25	4.711	0.9467

Table 16. The electric load forecasting results for Gaidouromantra demo site

Approach	MAE	RMSE	MARPE	RMSRPE	R^2
1 step ahead LSTM	0.0199	0.0301	1.99	3.01	0.5474
1 step ahead LSTM Auto-encoder	0.0103	0.02897	1.03	2.897	0.5569
6 steps ahead LSTM	0.042	0.06504	4.20	6.504	0.7741
6 steps ahead LSTM Auto-encoder	0.05	0.07521	5.00	7.521	0.7833
24 step ahead LSTM	0.02468	0.3096	2.468	3.096	0.6210
24 step ahead LSTM-AE	0.0187	0.0257	1.87	2.57	0.6494

Table 17. The electric load forecasting results for Bornholm demo site

Approach	MAE	RMSE	MARPE	RMSRPE	R^2
1 step ahead LSTM	0.0456	0.05931	4.56	5.931	0.8785
1 step ahead LSTM Auto-encoder	0.0302	0.04529	3.02	4.529	0.8854
6 steps ahead LSTM	0.06847	0.07824	6.847	7.824	0.8921
6 steps ahead LSTM Auto-encoder	0.04131	0.05154	4.131	5.154	0.90987
24 step ahead LSTM	0.0381	0.0406	3.81	4.06	0.8914
24 step ahead LSTM-AE	0.0279	0.0362	2.79	3.62	0.9178

7.4.2 Test performance of Fuzzy-RBF-CNN

In Table 18, the normalized mean absolute error is illustrated for all demo sites, and in Table 19, the cumulative and aggregated results for all demo sites are presented.

Table 18. The normalized mean absolute error for each hour-ahead for PV power for each demo site

Demo site	1 hour-ahead	2 hour-ahead	3 hour-ahead	4 hour-ahead	5 hour-ahead	6 hour-ahead	AVERAGE
Gaidouromantra	1,71%	2,46%	2,74%	2,83%	2,79%	2,77%	2,55%
Kythnos	0.91%	1.54%	2.37%	3.37%	4.35%	5.36%	2.98%
Bornholm	0,73%	0,91%	0,92%	0,96%	0,96%	0,97%	0,91%
Ghoramara	0.17%	0.19%	0.19%	0.196%	0.2%	0.203%	0.19%
Keonjhar	0.188%	0.197%	0.21%	0.226%	0.2%	0.213%	0.206%

Table 19. Cumulative results for PV power at all demo sites

Demo site	NMAE	NRMSE	R^2
Gaidouromantra	2,55%	5.49%	0.63
Kythnos	2.98%	6.73%	0.79
Bornholm	0,91%	2.40%	0.85
Ghoramara	0.19%	0.40%	0.999
Keonjhar	0.21%	0.47%	0.999

The normalized mean absolute error, root mean squared error and R^2 of the day-ahead solar power predictions are presented for Gaidouromatra, Kythnos, Bornholm, Ghoramara and Keonjhar in Table 20. The performance of the proposed model to load forecasting of Kythnos island was 8.33% w.r.t. mean absolute percentage error criterion.

Table 20. The normalized mean absolute error of day-ahead solar power predictions

Demo site	NMAE	NRMSE	R^2
Gaidouromatra	3.28%	7.07%	0.5
Kythnos	7.21%	13.64%	0.29
Bornholm	1.71%	4.28%	0.61
Ghoramara	0.18%	0.4%	0.999
Keonjhar	0.2%	0.42%	0.999

The mean absolute percentage error (MAPE) for each look-ahead hour is presented in Table 21 from the evaluation of the electric load forecasting at Gaidouromantra demo site. From the evaluation of the load forecasting from the Kythnos case-study, the mean absolute percentage error (MAPE) for each look-ahead hour is presented in Table 22. The results from the evaluation of the proposed model on short-term wind power forecasting at Bornholm island is presented in Table 23.

Table 21. The MAPE of the electric load forecasting error at Gaidouromantra demo site

	1 hour-ahead	2 hour-ahead	3 hour-ahead	4 hour-ahead	5 hour-ahead	6 hour-ahead	AVERAGE
MAPE	36.85%	34.38%	37.83%	40.81%	39.75%	53.75%	40.56%

Table 22. *The MAPE of the electric load forecasting error at Kythnos power system*

	1 hour-ahead	2 hour-ahead	3 hour-ahead	4 hour-ahead	5 hour-ahead	6 hour-ahead	AVERAGE
MAPE (%)	4.19%	4.53%	5.54%	6.50%	7.40%	8.04%	6.03%

Table 23. The results for wind power forecasting at Bornholm demo site

	1 hour-ahead	2 hour-ahead	3 hour-ahead	4 hour-ahead	5 hour-ahead	6 hour-ahead	AVERAGE
MARPE (%)	5.93%	8.51%	10.21%	11.57%	12.80%	13.62%	10.44%
RMSRPE (%)	8.53%	12.00%	14.21%	15.90%	17.35%	18.33%	14.39%
R^2	0.92	0.84	0.77	0.71	0.66	0.62	0.75

In Table 24, the error metrics obtained by the wind power predictions of the proposed model at the case study of Bornholm are shown. From the evaluation of the load forecasting on both Kythnos and Bornholm case-study, the mean absolute relative percentage error (MARPE), the root mean squared relative percentage error (RMSRPE) and R^2 for each look-ahead hour are presented in Table 25 and Table 26.

Table 24. The errors of day-ahead wind power predictions at Bornholm demo site

Demo site	NMAE	NRMSE	R^2
Bornholm	15.9%	20.81%	0.51

Table 25. The results for electric load forecasting error at Kythnos power system

Demo site	1 hour-ahead	2 hour-ahead	3 hour-ahead	4 hour-ahead	5 hour-ahead	6 hour-ahead	AVERAGE
MARPE (%)	4.27%	4.72%	5.84%	7.06%	8.02%	8.65%	6.42%
RMSRPE (%)	5.91%	6.84%	8.31%	10.32%	11.42%	12.08%	9.15%
R^2	0.95	0.94	0.91	0.86	0.83	0.81	0.88

Table 26. The results for electric load forecasting error at Bornholm demo site

Demo site	1 hour-ahead	2 hour-ahead	3 hour-ahead	4 hour-ahead	5 hour-ahead	6 hour-ahead	AVERAGE
MARPE (%)	3.08%	3.72%	4.02%	4.47%	5.02%	5.36%	4.28%
RMSRPE (%)	4.07%	4.91%	5.30%	5.79%	6.53%	6.95%	5.59%
R^2	0.96	0.94	0.93	0.92	0.90	0.90	0.93

The performances of the proposed model to day-ahead load forecasting at Kythnos and Bornholm islands are presented in Table 27.

Table 27. The performances of day-ahead load predictions at Kythnos and Bornholm demo sites

Demo site	MARPE (%)	RMSRPE (%)	R^2
Kythnos	9.35	12.67	0.81
Bornholm	5.56	7.04	0.89

7.4.3 Test performance of Hybrid LSTM-CNN

Following results present the test performance (10%) based on each site for PV, wind and load data and it can be seen the real scale (not normalized; after the forecasting the forecasted results are denormalized to understand the performance physically) of each demo site for Bornholm, Ghoramara, Kenjhar, Kythnos and Gaidouromantra respectively. In this way we can also compare the overall performance between the various fields. Before we give the results, the main error metrics are normalized Mean Absolute Error (%), normalized Root Mean Squared Error and R^2 for PV and wind power generation forecast. Also, Mean Absolute Relative Percentage Error, Root Mean Squared Relative Percentage Error, and R^2 for load demand forecast. MAPE is one of the challenging metrics if there is 0 in the x_s actual data set. Since the PV generation shows 0 kW during the nights, MAPE results are not preferred for the solar generation forecasting.

Table 28 and Table 29 provide the metrics for the forecasting of PV at Kythnos power system demo site.

Table 28. The forecasting results of the Kythnos power system for the PV test data

Approach	MAE	MSE	R^2	RMSE	NMAE	NRMSE
1 step ahead LSTM	0.0171	0.0013	0.1837	0.0355	0.0009	0.0019
1 step ahead CNNLSTM	0.0154	0.0011	0.3110	0.0327	0.0008	0.0018
6 steps ahead LSTM	0.0171	0.0012	0.1837	0.0356	0.0009	0.0019
6 steps ahead CNNLSTM	0.0163	0.0011	0.3082	0.0163	0.0009	0.0018
24 steps ahead LSTM	0.0154	0.0011	0.3110	0.0326	0.0008	0.0018
24 steps ahead CNNLSTM	0.0192	0.0015	0.0039	0.0397	0.0011	0.0023

Table 29. The additional metrics of forecasting results of the Kythnos power system for the PV test data

Approach	NMAE %	NRMSE %	R^2
Persistance	5.9875	14.0065	0.2660
1 step ahead LSTM	7.1208	14.7917	0.1837
1 step ahead CNNLSTM	6.4208	13.6208	0.3110
6 steps ahead LSTM	7.1208	14.8275	0.1837
6 steps ahead CNNLSTM	6.7833	6.7833	0.3082
24 steps ahead LSTM	6.4167	13.5833	0.3110
24 steps ahead CNNLSTM	8.0125	16.5417	0.0039

Table 30, Table 31 and Table 32 provide the metrics for the forecasting of PV power at Gaidouromantra and Bornholm demo sites.

Table 30. The metrics of forecasting results of the Gaidouromatra demo site for the PV test data

Approach	NMAE %	NRMSE %	R^2
Persistance	2.9530	23.5653	0.3897
1 step ahead LSTM	2.5657	18.7287	0.6146
1 step ahead CNNLSTM	2.6188	20.5205	0.5373
6 steps ahead LSTM	2.5337	18.8215	0.6127
6 steps ahead CNNLSTM	2.4256	17.9431	0.6480
24 steps ahead LSTM	nan	nan	0.5447
24 steps ahead CNNLSTM	nan	nan	0.5968

Table 31. The forecasting results of the Bornholm demo site for the PV test data

Approach	MAE	MSE	R^2
1 step ahead LSTM	0.0216	0.0038	0.4376
1 step ahead CNNLSTM	0.0203	0.0035	0.4754
6 steps ahead LSTM	0.0246	0.0048	0.2897
6 steps ahead CNNLSTM	0.0271	0.0047	0.3076
24 steps ahead LSTM	0.0237	0.0045	0.2709
24 steps ahead CNNLSTM	0.0275	0.0045	0.2654

Table 32. The additional metrics of forecasting results of the Bornholm demo site for the PV test data

Approach	NMAE %	NRMSE %	R^2
Persistance	1.9962	6.2511	0.2825
1 step ahead LSTM	6.0749	5.5194	0.4376
1 step ahead CNNLSTM	1.8180	5.3312	0.4754
6 steps ahead LSTM	2.2042	6.2093	0.2897
6 steps ahead CNNLSTM	2.4308	6.1286	0.3076
24 steps ahead LSTM	2.1217	6.0041	0.2709
24 steps ahead CNNLSTM	2.4671	6.0274	0.2654

Table 33, Table 34, Table 35 and Table 36 provide the metrics for the forecasting of PV power at Ghoramara and Keonjhar demo sites.

Table 33. The forecasting results of the Ghoramara demo site for the PV test data

Approach	MAE	MSE	R^2
1 step ahead LSTM	0.0021	0.0000	0.9996
1 step ahead CNNLSTM	0.00210	0.0000	0.9996
6 steps ahead LSTM	0.0535	0.0213	0.6789
6 steps ahead CNNLSTM	0.0333	0.0077	0.8836
24 steps ahead LSTM	0.13907	0.0611	0.0779
24 steps ahead CNNLSTM	0.0438	0.0121	0.8172

Table 34. The additional metrics of forecasting results of the Ghoramara demo site for the PV test data

Approach	NMAE %	NRMSE %	R^2
Persistance	3.7849	10.3019	0.7419
1 step ahead LSTM	0.1647	0.3862	0.9996
1 step ahead CNNLSTM	0.1655	0.3751	0.9996
6 steps ahead LSTM	4.2164	11.4908	0.6789
6 steps ahead CNNLSTM	2.6226	6.9184	0.8836
24 steps ahead LSTM	10.9604	19.4823	0.0779
24 steps ahead CNNLSTM	3.4480	8.6733	0.8172

Table 35. The forecasting results of the Keonjhar demo site for the PV test data

Approach	MAE	MSE	R^2
1 step ahead LSTM	0.0032	0.0000	0.9995
1 step ahead CNNLSTM	0.0019	0.0000	0.9998
6 steps ahead LSTM	0.0348	0.0070	0.9166
6 steps ahead CNNLSTM	0.0353	0.0073	0.9130
24 steps ahead LSTM	0.0578	0.0204	0.7579
24 steps ahead CNNLSTM	0.0486	0.0131	0.8443

Table 36. The additional metrics of forecasting results of the Keonjhar demo site for the PV test data

Approach	NMAE %	NRMSE %	R^2
Persistance	3.4998	9.0937	0.8355
1 step ahead LSTM	0.2496	0.5018	0.9995
1 step ahead CNNLSTM	0.1499	0.3468	0.9998
6 steps ahead LSTM	2.6915	6.4770	0.9166
6 steps ahead CNNLSTM	2.7257	6.6114	0.9130
24 steps ahead LSTM	4.4612	11.0363	0.7579
24 steps ahead CNNLSTM	3.7560	8.8512	0.8443

In general, the performance of the LSTM and hybrid LSTM-CNN models is very close. However, for one step-ahead prediction, LSTM-CNN may perform slightly better than LSTM. As expected, all the models, in any circumstances, outperform the naive model. It seems with the implementation of cross-validation, the comments can be generalized more, but it is not expected to see something quite different. Another point is that even though both the LSTM and CNNLSTM networks can be improved more, in this situation they perform quite well. Different and challenging cases might be increasing the forecasting horizon. The decision on the lag should be updated and improved based on these kinds of changes. Further discussions and results can help more in making more solid commands. Table 37, Table 38, Table 39 and Table 40 present the test performance (10%) at Bornholm demo site for wind power and electric load.

Table 37. The forecasting results of the Bornholm demo site for the wind test data

Approach	MAE	MSE	R^2
1 step ahead LSTM	0.1893	0.0688	0.3108
1 step ahead CNNLSTM	0.2104	0.0829	0.1696
6 steps ahead LSTM	0.2374	0.0003	-0.0023
6 steps ahead CNNLSTM	0.2346	0.0972	0.0238
24 steps ahead LSTM	0.3012	0.1444	-0.4472
24 steps ahead CNNLSTM	0.3033	0.1441	0.4445

Table 38. The additional metrics of forecasting results of the Bornholm demo site for the wind test data

Approach	NMAE %	NRMSE %	R^2
Persistance	37.0938	52.1651	0.2482
1 step ahead LSTM	17.5121	24.2628	0.3108
1 step ahead CNNLSTM	19.4623	26.6335	0.1696
6 steps ahead LSTM	21.9595	29.2171	0.0023
6 steps ahead CNNLSTM	21.7005	28.8323	0.0238
24 steps ahead LSTM	27.8604	35.1500	0.4472
24 steps ahead CNNLSTM	28.0528	35.1130	0.4445

Table 39. The forecasting results of the Bornholm demo site for the electric load test data

Approach	MAE	MSE	R^2	RMSE	NMAE	NRMSE	MAPE (%)
1 step ahead LSTM	0.0678	0.0074	0.7446	0.0864	0.0001	0.0001	14.1998
1 step ahead CNNLSTM	0.0681	0.0074	0.7462	0.0862	0.0001	0.0001	14.5619
6 steps ahead LSTM	0.0675	0.0073	0.7485	0.0858	0.0001	0.0001	14.2111
6 steps ahead CNNLSTM	0.0675	0.0073	0.7495	0.0856	0.0001	0.0001	14.3172
24 steps ahead LSTM	0.0997	0.0227	0.2275	0.1506	0.0001	0.0001	20.4210
24 steps ahead CNNLSTM	0.1013	0.0230	0.2174	0.1515	0.0001	0.0001	21.5828

Table 40. The additional metrics of forecasting results of the Bornholm demo site for the electric load test data

Approach	MARPE	RMSRPE	R^2
Persistance	10.4607	72.9472	0.5977
1 step ahead LSTM	8.7681	62.6660	0.7171
1 step ahead CNNLSTM	8.6554	61.8547	0.7288
6 steps ahead LSTM	8.2999	59.5170	0.7467
6 steps ahead CNNLSTM	8.3910	60.4290	0.7387
24 steps ahead LSTM	9.5641	68.9893	0.6577
24 steps ahead CNNLSTM	10.3396	73.9392	0.6088

Table 41 and Table 42 present the test performance (10%) at Kythnos power system demo site for electric load.

Table 41. The forecasting results of the Kythnos power system for the electric load test data

Approach	MAE	MSE	R^2	RMSE	NMAE	NRMSE	MAPE (%)
1 step ahead LSTM	0.0426	0.0037	0.8649	0.0615	0.0002	0.0003	44.2737
1 step ahead CNNLSTM	0.0409	0.0033	0.8808	0.0577	0.0002	0.0002	46.4187
6 steps ahead LSTM	0.1098	0.0251	0.8649	0.1584	0.0001	0.0001	43.6848
6 steps ahead CNNLSTM	0.0495	0.0048	0.8274	0.0693	0.0002	0.0003	42.0585
24 steps ahead LSTM	0.1055	0.0221	0.8808	0.1488	0.0001	0.0001	47.1979
24 steps ahead CNNLSTM	0.0685	0.0109	0.6080	0.1044	0.0003	0.0005	47.6500

Table 42. The additional metrics of forecasting results of the Kythnos power system for the electric load test data

Approach	MARPE	RMSRPE	R^2
Persistance	5.0513	8.7376	0.9286
1 step ahead LSTM	6.2577	11.8083	0.8849
1 step ahead CNNLSTM	5.4134	17.5383	0.8810
6 steps ahead LSTM	5.0897	17.1062	0.8848
6 steps ahead CNNLSTM	8.2869	14.2018	0.8240
24 steps ahead LSTM	5.4134	17.5383	0.8809
24 steps ahead CNNLSTM	13.2384	25.5841	0.3632

Table 43 presents the test performance (10%) at Gaidouromatra demo site for electric load.

Table 43. The additional metrics of forecasting results of the Gaidouromatra demo site for the electric load test data

Approach	MARPE	RMSRPE	R^2
Persistance	20.1132	503.9663	0.6850
1 step ahead LSTM	51.1772	863.4729	0.5753
1 step ahead CNNLSTM	46.9635	772.0200	0.6365
6 steps ahead LSTM	67.9269	1163.0947	0.4025
6 steps ahead CNNLSTM	74.2494	1351.5229	0.2816
24 steps ahead LSTM	46.1273	851.8494	0.4682
24 steps ahead CNNLSTM	48.5373	909.2230	0.5234

One of the interesting points is the R^2 performance at the Ghoramara and Keonjhar. These demos show high R^2 results since they use the calculated power output instead of an unavailable real measurement. Naturally, as the forecasting horizon grows longer, so do the errors. However, the MARPE and NMAE results show that as a common sign of all tables for almost every site, the trend has not drastically changed with the horizon extension. In general, the CNNLSTM hybrid frame outperforms the LSTM; however, this is not a significant improvement, and this is not for every case. The quality and capability of a better forecast depends highly on the well-measured output data and precise weather data. Both LSTM and CNNLSTM networks could not reach an average performance for the test set even though the plots that we are checking seem normal, all the error metrics go extremely high numbers which shows that the forecast was quite unsuccessful, and we see eventually NaN as an output of our error metrics. It seems that is a problem regarding the gradient, but the main problem could not be found.

The wind power and load forecasts have bigger errors than PV forecasting. R^2 explains why the error is higher. Based on these results of error metrics, it can be said that it is necessary to add more features to improve point forecast performance to keep the quality of forecast during the longer forecast horizons. In addition, other methods such as Support Vector Regression and Support Vector Machine can complement the machine learning algorithms.

7.5 Performance of simple forecast modules in ecoMicrogrid

The performance of the physics-based model presented in Chapter 4 is depicted in Table 44. The day ahead irradiance forecast is available for the same period through the Skiron database [17].

Table 44. Forecast Results from the ecoMG PV forecast

Method	RMSE (W)	MAE (W)	MAPE (%)
ecoMG PV forecast	61.89	51.47349	14.21

ecoMG forecast is executed every 3 hours while the advanced forecast every hour using real time data. Thus, since the ecoMG forecast produces the forecast based on fixed daily forecasted weather data, it has the same forecast throughout the day, while the advanced module modifies its forecast every hour. Table 45 depicts a comparison between an advanced forecast (selected as the Fuzzy-RBF-CNN method) on between prediction at different horizons with the physics induced model of the ecoMG. The absence of accurate training data and the small scale of the PV generation installed yields similar results between the advanced module and the ecoMG PV forecast.

Table 45. Comparison of the forecast modules

Method	RMSE (W)	MAE (W)	MAPE (%)
ecoMG PV forecast	61.89	51.47349	14.21
Advanced Module (Horizon)			
6 Hour ahead	122.23	91.45	20.79
5 Hour ahead	120.71	90.92	20.81
4 Hour ahead	121.02	90.03	20.62
3 Hour ahead	106.84	82.28	19.08
2 Hour ahead	99.39	77.01	18.15
1 Hour ahead	83.69	65.82	16.02

For the load forecast the advanced model was tested with a persistence model as well as a persistence model that uses the previous day data to compute the forecast. The advanced module is outperformed by a slightly different simple model. All the approaches have considerable errors in the forecast of the load in Gaidouromantra MG due to the absence of accurate load data and the small scale of the MG with only a small number of residents with limited electrical appliances.

Table 46. Comparison of in RMSE in load forecast modules in Watts

Method	ecoMicrogrid Module	Advanced
1 Hour ahead	328.96	419.94
2 Hour ahead	405.45	453.84
3 Hour ahead	419.06	463.34
4 Hour ahead	430.5	467.33
5 Hour ahead	433.82	475.20
6 Hour ahead	433.83	481.20

Table 47. Comparison of in MAE in load forecast modules in Watts

Method	ecoMicrogrid Module	Advanced
1 Hour ahead	222.96	273.63
2 Hour ahead	286.04	301.96
3 Hour ahead	304.8	312.073
4 Hour ahead	312.31	319.51
5 Hour ahead	319.07	329.64
6 Hour ahead	333.42	335.27

Table 48. Comparison of in MAPE in load forecast modules

Method	ecoMicrogrid Module	Advanced
6 Hour ahead	19.44	26.43
5 Hour ahead	26.15	28.76
4 Hour ahead	27.79	30.11
3 Hour ahead	28.32	31.21
2 Hour ahead	29.24	32.56
1 Hour ahead	31.37	33.52

The PV forecast based on the physics model for a period of a day is presented alongside with the metered values. The load forecast is also presented in Figure 17 for a period of 30 hours.

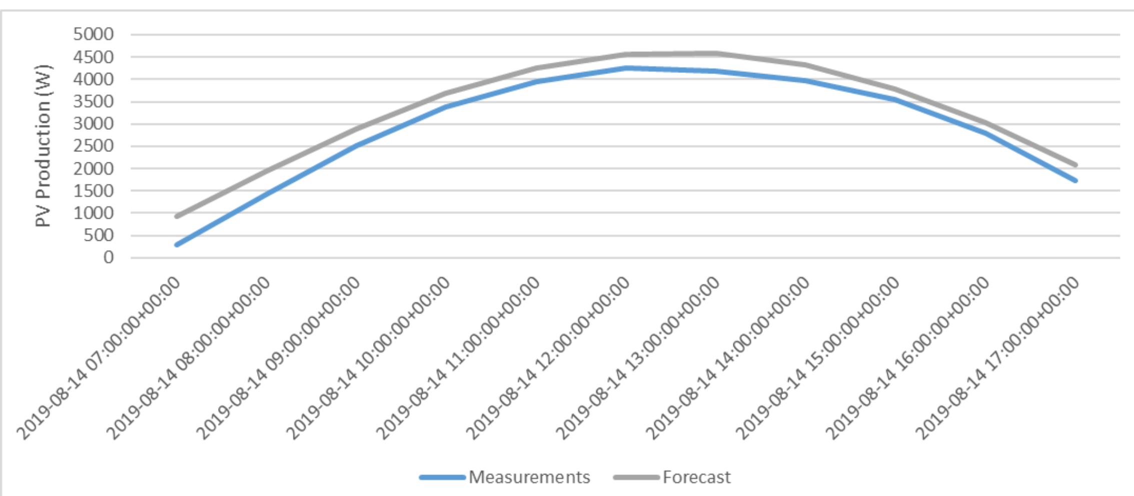


Figure 82. Comparison of measured PV generation and forecast

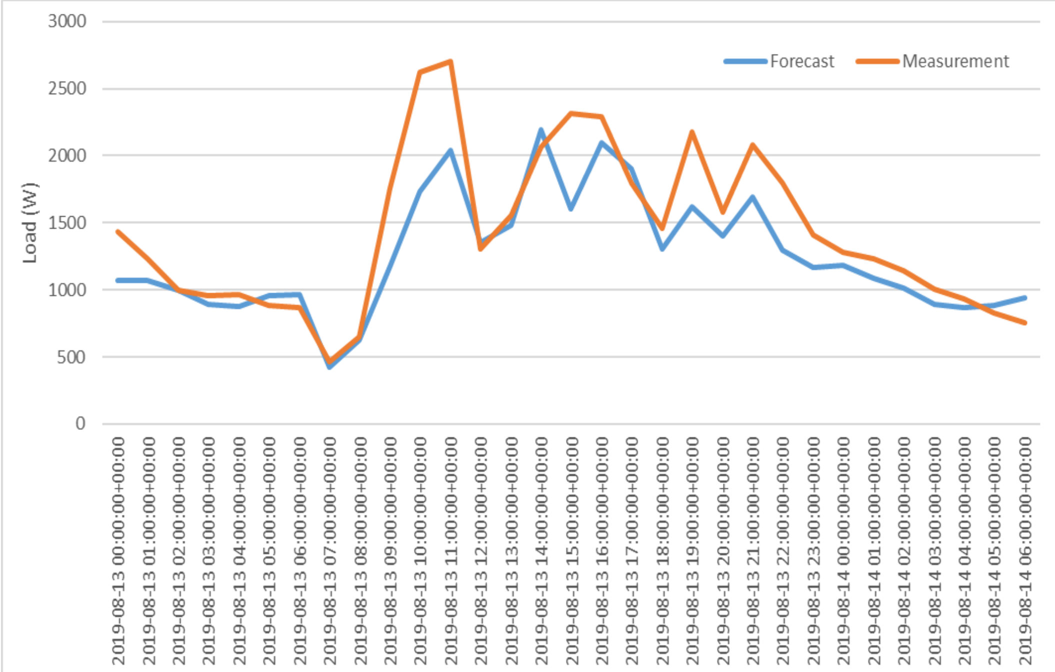


Figure 83. Comparison of load metered value and forecast

The results presented show that an advanced forecast module in a small scale MG, like the residential MG of Gaidouromantra does not provide significant benefits compared to other simplified versions of the forecast. The small number of electrical appliances and users, and the limited installations and capacities of PV modules inevitably result in large load forecast errors. Furthermore, in small residential MGs, like Gaidouromantra, the absence of accurate historical data could limit the performance of machine learning algorithms, making their performance comparable with simplified approaches.

In the PV production forecast a physics-based model slightly outperforms the advanced module in that specific testing period. This method does not need any training. Both the advanced module and the physics model require input from NWP providers. Open-source databases exist, e.g. GFS that can be used in a MG for a physics based forecast module.

In load forecast, the advanced module outperforms the persistence model, but not the model that uses historical data too. The load forecast errors for the case of Gaidouromantra is considerable, since a limited amount of users (4-5) are present in the MG during high season period, thus it is impossible to predict the electric appliance usage with greater accuracy. At the same time, those simplified modules are more easily integrated in a tool like ecoMG compared to data driven forecast modules and their operation is more easily apprehended by the MG operator.

8 Comparison of the forecasting algorithms at each demo site

In this section, an overview of the results for each demo site is presented.

8.1 Kythnos

8.1.1 Kythnos power system

Table 49 provides the inputs for each of the forecasting algorithm applied at the Kythnos power system. Table 50 and Table 51 present the overall metrics for PV power and electric load.

Table 49. The input data to proposed algorithms at Kythnos power system

Demo site: Kythnos	Uncertainty	Input data	Model
LSTM Auto-encoder	PV	Historical PV Power Output Data	Univariate input
	Load	Historical Load Data	Univariate input
Fuzzy-RBF-CNN	PV	Percentage of cloud coverage, downward short-wave flux, temperature, sun zenith and azimuth, cyclical features (calendar data of prediction hour as hour and month), three most recent observations	Multivariate inputs
	Load	Historical Load Data, temperature from GFS, cyclical features (calendar data of prediction hour as hour, week day, special day index and month)	Multivariate inputs
Hybrid LSTM-CNN	PV	Previous day output, PV system power, Gb(i), Gd(i), Gr(i), cyclical features (daysin and daycos)	Multivariate inputs
	Load	Previous day load, cyclical features (daysin and daycos)	Multivariate inputs

Table 50. The comparison of proposed algorithms for results of PV power forecasting at Kythnos power system

Demo site: Kythnos	Horizon	NMAE (%)	NRMSE (%)	R^2
LSTM Auto-encoder	1 step ahead	4.746	6.73	0.8900
	6 steps ahead	4.58	6.25	0.9543
	Day-ahead	2.402	4.14	0.9731
Fuzzy-RBF-CNN	1 step ahead	0.91	1.97	0.98
	6 steps ahead	5.36	11.2	0.51
	Day-ahead	7.21	13.64	0.29
Hybrid LSTM-CNN	1 step ahead	6.4208	13.6208	0.3110
	6 steps ahead	6.7833	6.7833	0.3082
	Day-ahead	8.0125	16.5417	0.0039

Table 51. The comparison of proposed algorithms for results of electric load forecasting at Kythnos power system

Demo site: Kythnos	Horizon	MARPE	RMSRPE	R^2
LSTM Auto-encoder	1 step ahead	4.64	5.92	0.8755
	6 steps ahead	4.56	5.84	0.9381
	Day-ahead	3.25	4.711	0.9467
Fuzzy-RBF-CNN	1 step ahead	4.27	5.91	0.95
	6 steps ahead	8.65	12.08	0.81
	Day-ahead	9.35	12.67	0.81
Hybrid LSTM-CNN	1 step ahead	5.4134	17.5383	0.8810
	6 steps ahead	8.2869	14.2018	0.8240
	Day-ahead	13.2384	25.5841	0.3632

At Kythnos power system, the forecasting was performed for PV and electric load, and the suggested algorithms are provided in Table 52. When it comes to 1 step ahead forecasting of PV power, the best performance was shown by applying Fuzzy-RBF-CNN. Fuzzy-RBF-CNN overcame LSTM Auto-encoder and Hybrid LSTM-CNN by comparing NMAE, NRMSE and R^2. For the forecasting of 6 steps ahead of PV, LSTM Auto-encoder overperformed Fuzzy-RBF-CNN and Hybrid LSTM-CNN. In regards to day-ahead forecasting of PV, LSTM Auto-encoder overperformed Fuzzy-RBF-CNN and Hybrid LSTM-CNN by comparing NMAE, NRMSE and R^2. When it comes to 1 step ahead forecasting of electric load, all three algorithm performed well. Fuzzy-RBF-CNN and LSTM Auto-encoder slightly overcame the performance of Hybrid LSTM-CNN by comparing RMSRPE. However, Hybrid LSTM-CNN overperformed LSTM Auto-encoder by comparing R^2. For the forecasting of 6 steps ahead of electric load at Kythnos power system, LSTM Auto-encoder slightly overperformed Fuzzy-RBF-CNN and Hybrid LSTM-CNN by comparing MARPE, RMSRPE and R^2. Hybrid LSTM-CNN overperformed Fuzzy-RBF-CNN by comparing MARPE and R^2, while Fuzzy-RBF-CNN slightly overperformed Hybrid LSTM-CNN in regards to RMSRPE. In regards to day-ahead forecasting of electric load, LSTM Auto-encoder overperformed both Fuzzy-RBF-CNN and Hybrid LSTM-CNN by comparing MARPE, RMSRPE and R^2 while Fuzzy-RBF-CNN performed better compared to Hybrid LSTM-CNN.

Table 52. The suggested forecasting algorithms to be applied at Kythnos power system

Kythnos	Forecasting horizon	Forecasting algorithm
PV	1 step ahead	Fuzzy-RBF-CNN
	6 steps ahead	LSTM Auto-encoder
	Day-ahead	LSTM Auto-encoder
Load	1 step ahead	Fuzzy-RBF-CNN / Hybrid LSTM-CNN / LSTM Auto-encoder
	6 steps ahead	LSTM Auto-encoder
	Day-ahead	LSTM Auto-encoder

8.1.2 Gaidouromantra microgrid

Table 53 provides the inputs for each of the forecasting algorithm applied at the Gaidouromantra demo site.

Table 53. The input data to proposed algorithms at Gaidouromantra demo site

Demo site: Gaidouromantra	Uncertainty	Input data	Model
LSTM Auto-encoder	PV	Historical PV Power Output Data	Univariate input
	Load	Historical Load Data	Univariate input
Fuzzy-RBF-CNN	PV	GBI, GRI, GDI, sun height	Multivariate inputs
	Load	Historical Load Data, temperature from GFS, cyclical features (calendar data of prediction hour as hour, week day, special day index and month	Multivariate inputs
Hybrid LSTM-CNN	PV	Previous day output, Gb(i), cyclical features (daysin and daycos)	Multivariate inputs
	Load	Previous day output	Univariate input

Table 54 and Table 55 present the overall metrics of the forecasting algorithm applied at the Gaidouromantra demo site for PV power and electric load.

Table 54. The comparison of proposed algorithms for results of PV power forecasting at Gaidouromantra demo site

Demo site: Gaidouromantra	Horizon	NMAE (%)	NRMSE (%)	R^2
LSTM Auto-encoder	1 step ahead	5.0	6.87	0.8845
	6 steps ahead	4.4	7.28	0.9205
	Day-ahead	0.915	1.51	0.6915
Fuzzy-RBF-CNN	1 step ahead	1.71	3.87	0.80
	6 steps ahead	2.77	5.82	0.56
	Day-ahead	3.28	7.07	0.5
Hybrid LSTM-CNN	1 step ahead	2.6188	20.5205	0.5373
	6 steps ahead	2.4256	17.9431	0.6480
	Day-ahead	nan	nan	nan

Table 55. The comparison of proposed algorithms for results of electric load forecasting at Gaidouromantra demo site

Demo site: Gaidouromantra	Horizon	MARPE	RMSRPE	R^2
LSTM Auto-encoder	1 step ahead	1.03	2.897	0.5569
	6 steps ahead	5.00	7.521	0.7833
	Day-ahead	1.87	2.57	0.6494
Fuzzy-RBF-CNN	1 step ahead	4.4	6.28	0.95
	6 steps ahead	7.87	10.61	0.81
	Day-ahead	8.33	10.8	0.81
Hybrid LSTM-CNN	1 step ahead	46.9635	772.0200	0.6365
	6 steps ahead	74.2494	1351.5229	0.2816
	Day-ahead	48.5373	909.2230	0.5234

At Gaidouromantra demo site, the forecasting was performed for PV and electric load, and the suggested algorithms are provided in Table 56. When it comes to 1 step ahead forecasting of PV power, all three algorithms performed well. Fuzzy-RBF-CNN overcame LSTM Auto-encoder by comparing NMAE and NRMSE, while LSTM Auto-encoder performed best in regards to R^2. Hybrid LSTM-CNN performed better than LSTM Auto-encoder by comparing NMAE, while LSTM Auto-encoder performed better in NRMSE and R^2.For the forecasting of 6 steps ahead of PV, Hybrid LSTM-CNN overperformed Fuzzy-RBF-CNN and LSTM Auto-encoder by comparing NMAE. Fuzzy-RBF-CNN outperformed LSTM Auto-encoder in NRMSE. LSTM Auto-encoder outperformed Fuzzy-RBF-CNN and Hybrid LSTM-CNN by comparing R^2, while Hybrid LSTM-CNN outperformed Fuzzy-RBF-CNN in R^2. In regards to day-ahead forecasting of PV, LSTM Auto-encoder overperformed Fuzzy-RBF-CNN and Hybrid LSTM-CNN by comparing NMAE, NRMSE and R^2. When it comes to 1 step ahead forecasting of electric load, LSTM Auto-encoder outperformed Fuzzy-RBF-CNN and Hybrid LSTM-CNN by comparing MARPE and RMSRPE. Fuzzy-RBF-CNN outperformed Hybrid LSTM-CNN and LSTM Auto-encoder by comparing R^2. For the forecasting of 6 steps ahead and day ahead forecasting results of electric load at Gaidouromantra demo site, LSTM Auto-encoder outperformed Fuzzy-RBF-CNN and Hybrid LSTM-CNN by comparing MARPE and RMSRPE. Fuzzy-RBF-CNN outperformed Hybrid LSTM-CNN and LSTM Auto-encoder by comparing R^2.

Table 56. The suggested forecasting algorithms to be applied at Gaidouromantra demo site

Gaidouromantra	Forecasting horizon	Forecasting algorithm
PV	1 step ahead	Fuzzy-RBF-CNN / Hybrid LSTM-CNN / LSTM Auto-encoder
	6 steps ahead	Fuzzy-RBF-CNN / Hybrid LSTM-CNN / LSTM Auto-encoder
	Day-ahead	LSTM Auto-encoder
Load	1 step ahead	Fuzzy-RBF-CNN / LSTM Auto-encoder
	6 steps ahead	Fuzzy-RBF-CNN / LSTM Auto-encoder
	Day-ahead	Fuzzy-RBF-CNN / LSTM Auto-encoder

However, performance of machine learning forecasting algorithms is obviously affected by the historical data available, and in subsection 7.5 it has been shown that the machine learning approaches have poorer performance in the smaller microgrids.

In small scale microgrids, such as Gaidouromantra and the Indian demo sites, adequate historical data might be unavailable, as it has been already mentioned before. Currently, historical data might be inaccurate since it depicts a different state in each MG with the existing equipment. Since the performance of the data driven load forecast modules is strongly related to the data used for the training, there might be an underperformance when applied in the small microgrids in the future. Furthermore, simplified forecasting modules are easier to integrate in a tool like ecoMG compared to data driven forecast modules and their operation is more easily apprehended by the MG operator. Thus, simple forecast module, presented in Section 4.4, is suggested to be applied since it has similar or better performance and is simpler to be applied.

8.2 Bornholm

Table 57 provides the inputs for each of the forecasting algorithm applied at the Bornholm demo site. Table 58, Table 59 and Table 60 present the overall metrics of the forecasting algorithm applied at the Bornholm demo site for PV power, wind power and electric load.

Table 57. The input data to proposed algorithms at Bornholm demo site

Demo site: Bornholm	Uncertainty	Input data	Model
LSTM Auto-encoder	PV	Temperature, Wind Speed. Solar Insolation, PV power output	Multivariate inputs
	Wind	Wind speed, Temperature, Insolation, Wind power generation	Multivariate inputs
	Load	Temperature, Wind Speed. Solar Insolation, Historical Load data	Multivariate inputs
Fuzzy-RBF-CNN	PV	GBI, GRI, GDI, sun height	Multivariate inputs
	Wind	Wind speed, wind direction from GFS	Multivariate inputs
	Load	Historical Load Data, temperature) from GFS, cyclical features (calendar data of prediction hour as hour, week day, special day index and month)	Multivariate inputs
Hybrid LSTM-CNN	PV	Radiation, temperature, Previous day output, cyclical features (daysin and daycos)	Multivariate inputs
	Wind	Wind speed, Previous day output	Multivariate inputs
	Load	Previous week load, cyclical features (daysin and daycos)	Multivariate inputs

Table 58. The comparison of proposed algorithms for results of PV power forecasting at Bornholm demo site

Demo site: Bornholm	Horizon	NMAE (%)	NRMSE (%)	R^2
LSTM Auto-encoder	1 step ahead	4.56	6.28	0.8905
	6 steps ahead	6.5	8.57	0.8790
	Day-ahead	2.53	5.39	0.7655
Fuzzy-RBF-CNN	1 step ahead	0.73	2.01	0.90
	6 steps ahead	0.97	2.54	0.84
	Day-ahead	1.71	4.28	0.61
Hybrid LSTM-CNN	1 step ahead	1.8180	5.3312	0.4754
	6 steps ahead	2.4308	6.1286	0.3076
	Day-ahead	2.4671	6.0274	0.2654

Table 59. The comparison of proposed algorithms for results of wind power forecasting at Bornholm demo site

Demo site: Bornholm	Horizon	NMAE (%)	NRMSE (%)	R^2
LSTM Auto-encoder	1 step ahead	4.589	6.958	0.9500
	6 steps ahead	4.69	6.841	0.9520
	Day-ahead	6.05	8.04	0.9458
Fuzzy-RBF-CNN	1 step ahead	5.93	8.53	0.92
	6 steps ahead	13.62	18.33	0.62
	Day-ahead	15.9	20.81	0.51
Hybrid LSTM-CNN	1 step ahead	19.4623	26.6335	0.1696
	6 steps ahead	21.7005	28.8323	0.0238
	Day-ahead	28.0528	35.1130	0.4445

Table 60. The comparison of proposed algorithms for results of electric load forecasting at Bornholm demo site

Demo site: Bornholm	Horizon	MARPE	RMSRPE	R^2
LSTM Auto-encoder	1 step ahead	3.02	4.529	0.8854
	6 steps ahead	4.131	5.154	0.90987
	Day-ahead	2.79	3.62	0.9178
Fuzzy-RBF-CNN	1 step ahead	3.08	4.07	0.96
	6 steps ahead	5.36	6.95	0.90
	Day-ahead	5.56	7.04	0.89
Hybrid LSTM-CNN	1 step ahead	8.6554	61.8547	0.7288
	6 steps ahead	8.3910	60.4290	0.7387
	Day-ahead	10.3396	73.9392	0.6088

At Bornholm demo site, the forecasting was performed for PV, wind power and electric load, and the suggested algorithms are provided in Table 61. When it comes to 1 step ahead forecasting of PV power, all three algorithms performed well. Fuzzy-RBF-CNN slightly outperformed LSTM Auto-encoder and Hybrid LSTM-CNN by comparing NMAE, NRMSE and R^2. For the forecasting of 6 steps ahead of PV, all three algorithms performed well. Fuzzy-RBF-CNN slightly outperformed LSTM Auto-encoder and Hybrid LSTM-CNN by comparing NMAE, NRMSE, while R^2 was best by applying LSTM Auto-encoder. In regards to day-ahead forecasting of PV, all three algorithms performed well. However, LSTM Auto-encoder overperformed Fuzzy-RBF-CNN and Hybrid LSTM-CNN by comparing R^2, while Fuzzy-RBF-CNN was slightly better when comparing NMAE and NRMSE. For 1 step ahead,6 steps ahead and day-ahead forecasting of wind power, LSTM Auto-encoder performed best in regards to the calculated metrics. When it comes to 1 step ahead forecasting of electric load, LSTM Auto-encoder and Fuzzy-RBF-CNN outperformed Hybrid LSTM-CNN by comparing MARPE, RMSRPE and R^2. For the forecasting of 6 steps ahead and day-ahead forecasting results of electric load at Bornholm demo site, the performance of all three algorithms was good, while LSTM Auto-encoder slightly outperformed Fuzzy-RBF-CNN and Hybrid LSTM-CNN.

Table 61. The suggested forecasting algorithms to be applied at Bornholm demo site

Bornholm	Forecasting horizon	Forecasting algorithm
PV	1 step ahead	Fuzzy-RBF-CNN / LSTM Auto-encoder
	6 steps ahead	Fuzzy-RBF-CNN / LSTM Auto-encoder
	Day-ahead	Fuzzy-RBF-CNN / LSTM Auto-encoder
Wind	1 step ahead	LSTM Auto-encoder
	6 steps ahead	LSTM Auto-encoder
	Day-ahead	LSTM Auto-encoder
Load	1 step ahead	Fuzzy-RBF-CNN / LSTM Auto-encoder
	6 steps ahead	LSTM Auto-encoder
	Day-ahead	LSTM Auto-encoder

8.3 Ghoramara

Table 62 provides the inputs for each of the forecasting algorithm applied at the Ghoramara demo site.

Table 62. The input data to proposed algorithms at Ghoramara demo site

Demo site: Ghoramara	Uncertainty	Input data	Model
LSTM Auto-encoder	PV	Total global radiation/Solar insolation, temperature, wind speed and sun height	Multivariate inputs
Fuzzy-RBF-CNN	PV	GBI, GRI, GDI, sun height	Multivariate inputs
Hybrid LSTM-CNN	PV	Gb(i),Gd(i), Gr(i), Sun height (degree) ,Int (Int: 1 means solar radiation values are reconstructed), cyclical features (daysin and daycos)	Multivariate inputs

Table 63 present the overall metrics of the forecasting algorithm applied at the Ghoramara demo site for PV power.

Table 63. The comparison of proposed algorithms for results of PV power forecasting at Ghoramara demo site

Demo site: Ghoramara	Horizon	NMAE (%)	NRMSE (%)	R^2
LSTM Auto-encoder	1 step ahead	2.95	7.0	0.980
	6 steps ahead	4.817	7.9	0.90
	Day-ahead	3.866	7.04	0.9163
Fuzzy-RBF-CNN	1 step ahead	0.17	0.4	0.999
	6 steps ahead	0.203	0.4	0.999
	Day-ahead	0.18	0.4	0.999
Hybrid LSTM-CNN	1 step ahead	0.1655	0.3751	0.9996
	6 steps ahead	2.6226	6.9184	0.8836
	Day-ahead	3.4480	8.6733	0.8172

At Ghoramara demo site, the forecasting was performed for PV, and the suggested algorithms are provided in Table 64. When it comes to 1 step ahead forecasting of PV power, all three algorithms performed well. However, Hybrid LSTM-CNN outperformed Fuzzy-RBF-CNN and LSTM Auto-encoder by comparing NMAE, NRMSE and R^2. For the forecasting of 6 steps ahead and day-ahead of PV power, all the algorithm performed well. However, the slightly better performance was evident by applying Fuzzy-RBF-CNN.

Table 64. The suggested forecasting algorithms to be applied at Ghoramara demo site

Ghoramara	Forecasting horizon	Forecasting algorithm
PV	1 step ahead	Hybrid LSTM-CNN
	6 steps ahead	Fuzzy-RBF-CNN
	Day-ahead	Fuzzy-RBF-CNN

Note that as it has been shown in subsection 7.5, machine learning approaches have poorer performance in the smaller microgrids. In addition, it is expected that there will be increase in the installed capacity of battery energy storage system or PV and wind turbines at Ghoramara demo site. With such changes, historical data at the moment might be inaccurate (if not inexistent) since it depicts a different state in the MG. Therefore, at Ghoramara, instead of machine learning algorithms, another feasible option would be to apply simple forecast modules, presented in Section 4.4, as described in this deliverable.

8.4 Keonjhar

Table 65 provides the inputs for each of the forecasting algorithm applied at the Keonjhar demo site.

Table 65. The input data to proposed algorithms at Keonjhar demo site

Demo site: Keonjhar	Uncertainty	Input data	Model
LSTM Auto-encoder	PV	Total global radiation/Solar insolation, temperature, wind speed and sun height	Multivariate inputs
Fuzzy-RBF-CNN	PV	GBI, GRI, GDI, sun height	Multivariate inputs
Hybrid LSTM-CNN	PV	Gb(i), Gd(i), Gr(i), Sun height (degree), air temperature (degree Celsius), cyclical features (daysin and daycos)	Multivariate inputs

Table 66 present the overall metrics of the forecasting algorithm applied at the Keonjhar demo site for PV power.

Table 66. The comparison of proposed algorithms for results of PV power forecasting at Keonjhar demo site

Demo site: Keonjhar	Horizon	NMAE (%)	NRMSE (%)	R^2
LSTM Auto-encoder	1 step ahead	5.05	8.15	0.9065
	6 steps ahead	4.01	6.0	0.9521
	Day-ahead	3.79	6.56	0.9451
Fuzzy-RBF-CNN	1 step ahead	0.188	0.41	0.999
	6 steps ahead	0.213	0.43	0.999
	Day-ahead	0.2	0.42	0.999
Hybrid LSTM-CNN	1 step ahead	0.1499	0.3468	0.9998
	6 steps ahead	2.7257	6.6114	0.9130
	Day-ahead	3.7560	8.8512	0.8443

At Keonjhar demo site, the forecasting was performed for PV, and the suggested algorithms are provided in Table 67. When it comes to 1 step ahead forecasting of PV power, all three algorithms performed well. However, Hybrid LSTM-CNN outperformed Fuzzy-RBF-CNN and LSTM Auto-encoder by comparing NMAE, NRMSE and R^2. For the forecasting of 6 steps ahead and day-ahead of PV power, all the algorithm performed well. However, the slightly better performance was evident by applying Fuzzy-RBF-CNN.

Table 67. The suggested forecasting algorithms to be applied at Keonjhar demo site

Keonjhar	Forecasting horizon	Forecasting algorithm
PV	1 step ahead	Hybrid LSTM-CNN
	6 steps ahead	Fuzzy-RBF-CNN
	Day-ahead	Fuzzy-RBF-CNN

Again, as it has been shown in subsection 7.5, machine learning approaches have poorer performance in the smaller microgrids. In addition, it is expected that there will be increase in the installed capacity of battery energy storage system or PV and wind turbines at Keonjhar demo site. With such changes, historical data at the moment might be inaccurate since it depicts a different state in the MG. Therefore, at Keonjhar, instead of machine learning algorithms, another feasible option to apply would be simple forecast modules, described in Section 4.4, as described in this deliverable.

9 Discussion

This deliverable has provided algorithms and an overview of the forecasting algorithms for accurate predictions of renewable generation, i.e. solar photovoltaic power and wind power, and electric load. The forecasts are developed for short-term and longer term operations. The algorithms are based on machine learning and artificial intelligence or simplified PV and load forecast modules for the case of ecoMG that will be applied in small scale microgrids. The report analyzed the available data needed to perform forecasting. Further on, the overviews of the implementation of the forecasting algorithms to each demo site have been presented and the prediction results that are produced by forecasting algorithms have been validated.

Three different machine learning approaches have been described and implemented for all demo sites. The performance of machine learning algorithms was quite good for the majority of demo sites. The suggestion of machine learning approaches to be implemented on demo sites are as follows. At demo site of Kythnos power system, it is suggested to apply LSTM Auto-encoder as it outperformed the Fuzzy-RBF-CNN and Hybrid LSTM-CNN. For Gaidouromantra demo site, the best performance was shown by LSTM Auto-encoder and Fuzzy-RBF-CNN, and both these approaches are suggested to be considered in order to forecast the uncertainties in situation where the data is available. When it comes to Bornholm demo site, the best performance was shown by LSTM Auto-encoder. In regards to Indian demo sites, Ghoramara and Keonjhar, the best performance was shown by Fuzzy-RBF-CNN. However, all the aforementioned algorithms have considered a specific data sets, and the availability of the data at each demo site. In a situation that larger portion of data is available, the forecasting algorithms should be applied again, which might affect the suggestions made.

However, performance of machine learning forecasting algorithms is obviously affected by the historical data available. In small scale microgrids, like the pilot site of Gaidouromantra, adequate historical data might be unavailable. Even if the data is available, the small scale capacity of RES and number of residents that use electrical appliances can result in significant forecast errors even in advanced forecast techniques. Furthermore, Gaidouromantra MG and the Indian demo sites are expected to install additional equipment, such as battery energy storage system or PV and wind turbines. Such increased capacity of the renewable installations will allow the residents to extend the usage of electrical appliances. Thus, historical data available at the moment might be inaccurate since they depict a different state in each MG with the existing equipment. Since the performance of the data driven load forecast modules is strongly related to the data used for the training, there might be an underperformance when applied in the small microgrids in the future due to the aforementioned reasons. The results have shown that advanced forecast modules based on machine learning in a small scale MG do not provide significant benefits compared to simplified versions of forecast that was described in this deliverable. In addition, simplified forecasting modules are easier to integrate in a tool like ecoMG compared to data driven forecast modules and their operation is more easily apprehended by the MG operator. Thus, simpler forecast approaches can be applied since they have similar performance and are simpler to be applied.

10 Relevance to RE-EMPOWERED

The forecasting algorithms developed in T3.5 as a part of WP3 can complement other tasks across the project. Firstly, developed forecasting algorithms can be used in T3.1 as a part of WP3. T3.1 is developing a framework that will co-optimize different energy vectors and conversion technologies. As input for such co-optimization, the forecasts of the uncertainties, such as wind power, PV power and load, play an important role in the energy-efficient and cost-efficient scheduling of different technologies. For the purposes of forecasting the demand loads, forecasting of thermal demand can be a crucial component. In multi-vector energy systems that involve heating or cooling, the thermal demand will be conditional on several covariates, e.g., meteorological conditions such as temperature, wind direction and strength, cloud cover, etc., and temporal factors such as the time of day, the day of week, the occurrence of holidays, etc. A forecast model that accounts for these factors could predict thermal demand load with some precision. Such a forecast model could, in turn, be used, e.g., in conjunction with PV production forecast models for the co-optimization developed for ecoEMS through T3.1. This could allow for better scheduling of production units, and for better leveraging DSM as well as other sources of flexibility in the energy system to reduce load peaks and ensure energy- and cost-efficient operations. Finally, forecast models for PV production with even greater temporal fidelity (down to sub-minute resolution) would enable even more intelligent control and co-optimization. For instance, it would allow for operating quickly reacting production units (e.g., electrical boilers) in “opposition” with the PV output, thereby providing a cost-effective means of balancing renewable electricity production and generating emissions-free heating, through sector coupling of electrical and thermal energy systems.

Moreover, forecasting algorithms are expected to correspond to a major part of the ecoEMS. The simplified PV and Load forecast modules that will be applied by ecoMG tool in the MG demo sites are analyzed too and compared with more advanced modules, presenting that they have similar performance in small scale MGs, can be easily apprehended by a MG operator and can be easily implemented in an ecoTool.

Further on, this task implemented forecasting algorithms for all the demo sites involved in RE-EMPOWERED project and it is useful to predict future requirements as per the load demand. Therefore, the forecasting algorithm can play a major role in demand side management (DSM) mechanisms. The demand side management mechanisms are being developed in T3.2 as a part of WP3. The main focus of DSM is on developing an algorithm for time slots for non-critical loads that have time-shifting potential and developing a dynamic pricing mechanism.

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