COMPARISON OF STRATEGIES FOR MULTI-STEP AHEAD PHOTOVOLTAIC POWER FORECASTING BASED ON HYBRID GROUP METHOD OF DATA HANDLING NETWORKS AND LEAST SQUARE SUPPORT VECTOR MACHINE

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ABSTRACT

The advancement of photovoltaic (PV) energy into electricity market requires efficient photovoltaic power prediction systems. This study is focused on the forecasting of the power output of a photovoltaic system located in Apulia - South East of Italy at several horizons up to 24h, using historical PV output power data and performed by different prediction methods: the Least Square Support Vector Machine (LSSVM), a relatively unexplored neural network known as Group Method of Data Handling (GMDH) and a hybrid algorithm (GLSSVM), based on the combination of the first two models. Furthermore three strategies for multi-step ahead forecasting (Direct, Recursive and DirRec) were applied and compared to achieve better accuracy of PV power forecast. A detail analysis of the normalized mean error is carried out to compare the different forecasting methods. The statistical distribution with the estimation of the skewness and kurtosis statistical metrics provide a better understanding of the origin of differences between the prediction and measurement data.

Highlights

- Photovoltaic forecast is performed by the historical PV power data
- LS-SVM and the GMDH models are applied to predict the PV output power at 24 hours
- Multi-step ahead forecasting strategies (Direct, Recursive and DirRec) were implemented
- A comparative analysis based on the mean error is performed to evaluate the accuracy
- A hybrid method GLSSVM has been investigated

Keywords

Photovoltaic Power Forecast, Least Square Support Vector Machine (LS-SVM), Group Method of Data Handling (GMDH), Multi-step ahead forecasting, Forecasting errors, GLSSVM, hybrid.

1. INTRODUCTION

In the last decade the energy demand is exponentially increased, hence its management is vital to defend the planet earth [1 - 3]. The renewable energy (wind, solar, wave and biomass) is one of the strategies [4], together energy savings on the demand side [5] and efficiency improvements in the energy production and management [6 -7] for a sustainable development. In the last years, various strategies have been implemented by several countries to promote the renewable energy [8 - 11].

In this context, it is of the great interest the development of energy models, for allowing efficient energy planning and management. In [12] an overview of different models has been presented regarding energy planning, energy supply–demand, renewable energy, emission reduction, focusing on forecasting models, which represent an efficient support for electricity suppliers, to plan, manage and dispatch the electrical power plants installed.

PV systems and wind turbines are clean, inexhaustible, and environment-friendly renewable energy options. However, these energy resources cannot be considered as continuous supply of energy due to the seasonal variations and the high installation cost.

Nevertheless, the large-scale integration of renewable energy into the electricity system presents some limitations, as the variability of the renewable sources. This randomness influences the efficiency of the electric grid.

The power output of PV systems is highly variable due to its dependence on meteorological conditions [RUSEN].

Hence, it becomes important the development of accurate forecasting models. In the literature, different forecasting methods were developed in various research fields. Among the different prediction methods, the Artificial Neural Networks (ANNs) were extensively used in different fields, for example to forecast the electricity load [13 - 14].

Elman neural network was implemented in F. Almonacid, C. Rus, P. Pérez-Higueras, L. Hontoria Calculation of the energy provided by a PV generator. Comparative study: Conventional methods vs. Artificial neural networks. Energy, 36 (2011), pp. 375–384

-[**16**] for the wind power forecasting and a comparison between the ANNs, ARMA (Auto Regressive Moving Average), ANFIS (Adaptive Neuro-Fuzzy Inference Systems) models was performed in [17]. Regarding the photovoltaic power, an overview of the Artificial Intelligence techniques, applied for modeling, prediction, simulation, optimization and control of the photovoltaic systems was illustrated in [18].

In [15] ANNs were applied to obtain the energy production and the V–I curve of a PV module for a pair of determined values of irradiance and cell temperature.

In [21] short-term solar energy predictions were performed and the performance of ordinary LSR (least-square regression), regularized LSR and ANN models were compared. In order to improve the generalization capability of the models, more experiments like variable segmentation, subspace feature sampling and ensembling of models were conducted. It was observed that model accuracy can be improved by proper selection of input data segments. Further improvements can be obtained by ensemble of forecasts of different models.

The PV forecasting models can be mainly classified into three types: a first type estimates the power produced by using the instantaneous value of solar irradiance and solar cell or air temperature. In a second type of ANN-based models, the current and the past values of the output power are used in order to predict the future ones. The third type of models is a combination of the first and the second kind; it can forecast indirectly the produced power based on the present and the past values of power, and meteorological parameters such as air temperature, solar irradiance and relative humidity.

Several previous works have implemented a two-stage approach. In the first stage, the solar irradiance on different time scales is forecasted, and then the forecasted irradiance and temperature data are used to estimate the PV power.

The prediction of the solar radiation has been performed with various statistical models: Artificial Neural Networks [19 - 20], ANFIS [~~**23**~~ 25], Fuzzy logic [**22**], Wavelet neural networks [25] and hybrid model ANN/ARMA [26].

In [25 MARTIN] a comparisons of different statistical models (autoregressive, neural networks and fuzzy logic models) was done in order to establish the best approach for the prediction of half daily values of global solar irradiance with a temporal horizon of 3 days. The best approach to forecast half daily values of solar irradiance was neural network models.

A solar radiation forecast technique based on fuzzy and neural networks together was developed in [23], the forecast results followed the real values very well under different sky and temperature conditions. The Mean Absolute Percentage Error (MAPE) was much smaller compared with that of the other solar radiation method.

In [27 Voyant] the hybrid ARMA/ANN model outperformed the stand alone ANN to predict hourly global radiation for five places in Mediterranean area using data issued from a numerical weather prediction model.

Instead of using a two-stage approach, another appropriate strategy could be directly forecasting the power output based on some prior information or readily accessed data.(CAMBIARE PAROLE E METTERE REF) [28 - 30].

In [22 CHEN] a simplified approach for forecasting 24-h ahead of power generation using a radial basis function network (RBFN) was proposed. Instead of using two-staged methods, a direct forecast of the power output of the PV system was performed from its historical record and the online meteorological services.

A promising and relatively unexplored sub-model of ANN is the neural network known as Group Method of Data Handling (GMDH). The GMDH is an inductive learning algorithm that allows to find a relation between input and output variables, selecting an optimal structure of the model or network, through a quadratic regression polynomials with two input variables, known as Partial Descriptions of data (PDs) [37]. This approach of the self–organizing is based on the sorting of possible variants, from which it finds the best solution, minimizing the influence of the author on the results of modeling and increasing the accuracy [38].The inductive networks have the advantages of faster model development than the neural networks. The model convergence is rapid because of the lack of the local minimums. The input variables are automatically selected and the model structure is automatically configured. The GMDH technique was applied in very different fields [39 - 44]. Xu et al. [44] implemented GMDH in forecasting electric load demand, it outperforms ARIMA for short term load forecasting. In [45] the group method of data handling neural network outperformed the traditional time-series and regression-based models in the medium-term energy demand forecast. In the field of renewable energy, this model was used in [46] for predicting the mean 1 hour ahead hourly wind speed using wind speed data at Dhahran, Saudi Arabia. The results underlined improvements with respect to several machine learning approaches reported in the literature. In [47] the abductive network was applied to predict global solar radiation in the Kingdom of Saudi Arabia (KSA) based on sunshine duration, month number, latitude, longitude, and altitude of the location. SPOSTARE

One of the main limit of ANN methods is an excessive training data approximation, aim to increase the out-of-sample forecasting errors. Hence new time series forecasting models were developed based on Learning Machines using Support Data Machines (SVMs) methods that allow to resolve the over-fitting problem and achieve high performance with lower computational cost than ANN model based on back-propagation algorithms [31]. In previous study, the SVM was used to forecast the solar radiation [32 - 33], and to evaluate the photovoltaic power production [**34**]. Reformulations to the standard SVMs are known in the literature as Least Squares Support Vector Machines (LS-

SVM) method that simplifies the complex models to solve linear system, with lower computation complexity than SVMs models [35] and performance comparable to that of the standard SVM [36].

In [48] the authors investigated the applicability of the hybrid GMDH-type algorithm (GLSSVM), using three time series data, which have different statistical characteristics: the Canadian lynx data, the airline passenger data and time series of gas furnace. The results demonstrate that the model produce more accurate forecasts than GMDH and LS-SVM. Furthermore in [49] a comparison of performances of ARIMA, ANN, GMDH, LSSVM and GLSSVM models, applied to monthly river flow estimation, demonstrates that the GLSSVM returns the lower value of the mean error. The possibility to forecast the building energy consumption implementing the GLSSVM model was considerate in [50].

Hybrid GLSSVM methods are relatively new and unexplored for the forecasting of renewable power, regardless of the advantages that it showed in other fields. In this context in the present paper a hybrid GLSSVM model is applied for the predictions of hourly PV output power and compared with stand-alone GMDH and LS-SVM methods.

In order to improve the performance of the forecasting models another aspect to be taken into account, is the choice of the forecasted strategies. Irrespective of the adopted prediction model, if the one-step-prediction gives the forecasted value at the time instant immediately following the latest data, the multistep prediction starts from the historical values of time series and apply the model step by step to predict future values [51]. Nevertheless there are various ways to combine the historical values and the predicted value. The main methods of the multistep forecasting are direct and iterative methods. In the first at different time instants, the values can be forecasted all at once. In iterative method, the predicted value at the previous time horizons is the input at the successive time horizons [52]. Furthermore different strategies have been applied in the literature [53] that are obtained as combinations of the direct and iterative methods.

In this study, the Least Square Support Vector Machine, the Group Method of Data Handling and the hybrid GMDH type models with three multi-step ahead forecasting strategies have been compared to predict the power of a 960 kWp photovoltaic system installed in South-East of Italy, using historical data. Furthermore in order to understand how this choice can influence the performance of the multi-step ahead and to identify the method that gives the most accurate predictions, a comparison between different forecasting strategies has been performed based on a detailed error analysis ~~through the estimation of conventional metrics, as the root mean square error (RMSE), mean bias error (MBE), and mean absolute error (MAE).~~

~~An analysis of the statistical error distribution, a decomposition of the standard deviation by amplitude and phase error and the evaluation of the skewness and kurtosis statistical metrics have been also presented in order to characterize the performance of the implemented methods~~.

2. PV POWER SYSTEM AND INPUT DATA

The photovoltaic system under investigation is installed in the campus of the University of Salento, in Monteroni di Lecce (LE), Puglia (40° 19'32'''16 N, 18° 5'52'''44 E). It consists of 3.000 modules of 320 W_P, for a total nominal power of 960kW_P, mounted on a metal structure and designated to car parking, in two different tilts respectly of 3° (PV1) and 15° (PV2) and South-East oriented. A detailed analysis of the PV system performances was illustrated in [54], in which the authors investigated the power generated and photovoltaic system efficiency, considering the climatic topic of the site. To monitor the main parameters, a data acquisition system is configured, compound of the LP-PYRA02 sensors to monitor the solar irradiation on two plane, the PT100 type temperature sensors to measure the PV module temperature and the ambient temperature and three inverters to calculate the PV output power. The data were collected by a PLC Siemens with a protocols Modbus and available on web.

Linking to the web page http://supervisione.espe.it/fotovoltaicoWeb/index.htm, management of the society ESAPRO, the following data are available:

- $P_m(t)$ that is the value of the PV power measured every 1 minute (W);
- $I_3(t)$ and $I_{15}(t)$ that are the values of the solar irradiance on plain inclined at a tilt angle of 3° and 15° respectively and measured every 1 minute (W/m^2);
- $T_a(t)$ and $T_m(t)$ that are the values of the ambient temperature and module temperature, measured every 10 minutes (°C).

Taking into account that the temperature values are measured every 10 minutes, instead the solar irradiation and PV output power every 1 minute, in order to refer the values to the same samples, the measured PV power together the weather data [T_m, T_a, I_3 and I_{15}] have been defines as follows:

- P(i) is the average value of the PV power produced by the PV plant in the previous 60 minutes respect to the hour *i*:

$$P(i) = \frac{1}{60}\sum_{t=1}^{60} P_m(t) \qquad \text{i =1,…N} \qquad (1)$$

- $I_3(i)$ and $I_{15}(i)$ are the average value of the solar irradiance on plain inclined respectively at a tilt angle of 3° and 15° in the previous 60 minutes respect to the hour *i*
- $T_a(i)$ and $T_m(i)$ the hourly average value of the ambient temperature and module temperature in the previous 60 minutes respect to the hour *i*

To implement the forecast methods, in order to predict the PV power at 24-hour time frame, two series data of PV power are defined as follows:

- $\ddot{P}_b(i)$ is defined as the sum of the "b" previous values at the time instant i of the average hourly power values

$$\ddot{\mathrm{P}}_{\mathrm{b}}(\mathrm{i}) = \sum_{\mathrm{k=i-b}}^{i-1} \mathrm{P(k)} \quad \forall \text{ b} = 1, 2, 3\ldots.24 \qquad (4)$$

- $\widehat{P_h}(i)$ is defined as the sum of the next h values at the time instant i of the average hourly power values

$$\widehat{P_h}(i) = \sum_{\mathrm{i+1}}^{i+h} \mathrm{P(k)} \quad \forall \text{ h} = 1, 2, 3\ldots.24 \qquad (5)$$

The selection data of the input vector, called as forecasting factors, is most important in the implementation of the prediction models. In [55] an analysis of the impact of weather parameters in the PV power forecast is carried out.

In the present work, two different input vectors were chosen to implement the different forecasting methods, defined as follows:

- the hourly average value of the module temperature (°C), ambient temperature (°C), irradiance on plain inclined at a tilt angle of 3° and 15° (W/m2) and PV power (W) for each i records

$$\text{(IV1) Input Vector 1} \;\; \mathrm{X(i)} = [\,\mathrm{T_m(i)},\ \mathrm{T_a(i)},\ \mathrm{I_3(i)},\ \mathrm{I_{15}(i)},\ \mathrm{P(i)}] \qquad (6.a)$$

- the hourly average value of the module temperature (°C), ambient temperature (°C), irradiance on plain inclined at a tilt angle of 3° and 15° (W/m^2), PV power (W) and the hourly power values in each of the previous 24 hours, as defined by Eq.4, for each i record:

$$\text{(IV2) Input Vector 2} \;\; \mathrm{X(i)} = \left[\,\mathrm{T_m(i)},\ \mathrm{T_a(i)},\ \mathrm{I_3(i)},\ \mathrm{I_{15}(i)}, \mathrm{P(i)},\ \ddot{\mathrm{P}}_1\mathrm{(i)},\ \ddot{\mathrm{P}}_2\mathrm{(i)},\ \ddot{\mathrm{P}}_3\mathrm{(i)}, \ldots,\ \ddot{\mathrm{P}}_{23}\mathrm{(i)},\ \ddot{\mathrm{P}}_{24}\mathrm{(i)}\right] \qquad (6.b)$$

In this study, the time series data are considered from 05/03/2012 to 31/12/2013, for a hourly record's number of N=15.755. The various forecasting strategies are implemented using the 65% of records (10.264) to train the neural network and the 35% remaining of data (5.491) sets to test.

3. THE FORECASTING MODELS

In this section the PV power output prediction models, LS-SVM GMDH and GLSSVM, are described.

3.1 LEAST SQUARES SUPPORT VECTOR MACHINE

The Support Vector Machine is an alternative method to the ANN [31]. The Artificial Neural Network has the tendency for overfitting and requires the enormous computational resources for the training. The LS-SVM is computationally less expensive, since the training requires only the solution of a set of linear equations.

Given a training set of N data points $\{y_k, x_k\}_{k=1}^{N}$, where $x_k \in R^n$ is the k-th input data and $y_k \in R$ is the k-th output data, the following regression model can be constructed by using $\varphi(x_k)$, nonlinear function mapping of the input space to a higher dimensional space:

$$y_k = w\varphi(x_k) + b \quad k = 1,\dots,N \qquad (7.a)$$

where w is the weight vector and b is the bias term.

The above regression equation is transformed to a quadratic optimization problem with constraint, it means to minimize a cost function J:

$$\min_{w,\xi} J_{LS}(w,\xi) = \tfrac{1}{2} w^T w + \gamma \tfrac{1}{2} \sum_{k=1}^{n} \xi_k^2 \qquad (7.b)$$

with ξ_k is an artificial variable, γ is the regularization factor and subject to equality constrains

$$y_k[w^T \varphi(x_k) + b] = 1 - \xi_k, \quad k = 1,\dots,n \qquad (7.c)$$

In order to solve this optimization problem, Lagrange function is defined as:

$$L(w,b,\xi;\alpha) = J_{LS} - \sum_{k=1}^{n} \alpha_k \left\{ y_k [w^T \varphi(x_k) + b] - 1 + \xi_k \right\} \qquad (7.d)$$

with $\alpha_k \in R$ is the Lagrangian multiplier,

Solving these equations results into:

$$\min \hat{y} = \sum_{k=1}^{n} \alpha_k K(w, x_k) + b \qquad (7.e)$$

Where $\hat{y}$ is the approximated value of y_k and $K(w, x_k)$ is called the kernel function, in the present study the Radial Basis Function kernel RBF is used. The LS-SVM is tuned by searching the optimal regularization " kernel parameters" as well as the model order, using a 10-fold cross-validation (CV) procedure [35].

3.2 GROUP METHOD OF DATA HANDLING

GMDH are self organizing neural networks. This means that the connections between neurons in the network are not fixed but are selected during training to optimize the network. The neurons, basic components of the nervous system, are interconnected through synapses. When the neuron receives an external input, each synapse determines the contribution at the response of the neuron. In this way the neurons are called passive, they don't select the input variables. The theory of self-organization of neural networks researches the best combination of the neurons in order to improve the rule of each neuron in the neural network [56]. In the self-organization of neural networks the main input variables, the number of active neurons, number of layers, neurons in hidden layers are configured automatically, through an iterative process, in which the model structure is modified in order to find the best data prediction [57]. The method defines the model structure and the dependence of the output values on the most significant input variables.

The GMDH networks employ the regression analysis implementing a polynomial, noted as Ivakhnenko polynomial [39]

$$y = a_0 + \sum_{i=1}^{M} a_i x_i + \sum_{i=1}^{M} \sum_{j=1}^{M} a_{ij} x_i x_j + \sum_{i=1}^{M} \sum_{j=1}^{M} \sum_{k=1}^{M} a_{ijk} x_i x_j x_k \qquad (8.a)$$

where M is the numbers of input variables, (x_1, x_2 … x_M) are the input variables, (a_1, a_2 … a_M) are the coefficients.

Generally, in most application the equation (8.a) is in the quadratic form of two variables, noted as partial descriptions (PD):

$$y = a_0 + a_1 x_i + a_2 x_j + a_3 x_i x_j + a_4 {x_i}^2 + a_5 {x_j}^2 \quad (8.b)$$

Given a matrix, as the input data, containing N points of observations of M variables, it is considered two parts of it. The first part, about two thirds of points, makes up the learning subsample and the remaining the check subsample. The learning sample is used to estimate the coefficients of the polynomial, the remain samples are used to choose the structure of the optimal model that returns minimum error between the predicted value and expected output [58]. In the training step all pair (x_i, x_j) of the input variables are considered as input data and the regression polynomial is built with Eq. (8.b), obtaining a new variable that represents the new input for the next layer. The iterations, generally from 2-3 steps, continue until the errors of the test data in each layer become constant. Free software was used for this purpose

[59]. The configuration of the GMDH model, used in this work, is shown in Fig. 1.

3.3 GLSSVM HYBRID MODEL

The GLSSVM is a hybrid model, which combines the group method of data handling (GMDH) and the least squares support vector machine (LSSVM) [48]. The input data of the novel hybrid forecasting model are chosen by GMDH model and are used as input data of LSSVM model to forecast the output signal. In each layer, all combinations of two input variables (xi; xj) are considered and for each one the regression polynomial is calculated by Eq. 8.b. The output data of the GMDH model, which gives the lowest error, are used together with the input variables as input for LS SVM model. The GLSSVM algorithm is performed by 3 to 5 iteration, until the output data have the minimum value of the error [49]. In Fig. 2 the structure of the GLSSVM model for PV output power forecasting is illustrated.

4. STRATEGIES FOR MULTI-STEP-AHEAD TIME SERIES FORECASTING

In addition, the selection of the prediction strategy for multi-step-ahead forecasting has been analyzed by comparing three multi-step ahead time series forecasting strategies [53].

Direct strategy

In the Direct strategy (Dir), the forecast model has the same input vector and different models for each horizon time. Hence f_{dh} models that are independent for each time horizon h, are used to train and test as follows:

$$\bar{P}_1(i) = f_{d1}\left(T_m(i),\ T_a(i),\ I_3(i),\ I_{15}(i), P(i),\ \ddot{P}_1(i),\ \ddot{P}_2(i),\ \ddot{P}_3(i), \dots ,\ \ddot{P}_{23}(i),\ \ddot{P}_{24}(i)\right)$$

$$\bar{P}_2(i) = f_{d2}\left(T_m(i),\ T_a(i),\ I_3(i),\ I_{15}(i), P(i),\ \ddot{P}_1(i),\ \ddot{P}_2(i),\ \ddot{P}_3(i), \dots ,\ \ddot{P}_{23}(i),\ \ddot{P}_{24}(i)\right)$$

$$\bar{P}_h(i) = f_{dh}\left(T_m(i),\ T_a(i),\ I_3(i),\ I_{15}(i), P(i),\ \ddot{P}_1(i),\ \ddot{P}_2(i),\ \ddot{P}_3(i), \dots ,\ \ddot{P}_{23}(i),\ \ddot{P}_{24}(i)\right) \quad (9.a)$$

with i=1, 2 … N and h= 1, 2 …24

The use of the measured data as model inputs doesn't deteriorate the accuracy of the prediction, so there is not cumulative error but only the forecasting error as the difference between the prediction value and the measured data.

Recursive strategy

The Recursive strategy (Rec) implements the same model f_r for each horizon h, but the previous predictions are used in place of the original data set as inputs to evaluate the next prediction

$$\bar{P}_1(i) = f_r\left(T_m(i),\ T_a(i),\ I_3(i),\ I_{15}(i), P(i),\ \ddot{P}_1(i),\ \ddot{P}_2(i),\ \ddot{P}_3(i), \dots ,\ \ddot{P}_{23}(i),\ \ddot{P}_{24}(i)\right)$$

$$\bar{P}_2(i) = f_r\left(T_m(i),\ T_a(i),\ I_3(i),\ I_{15}(i), P(i),\ \bar{P}_1(i),\ \ddot{P}_2(i),\ \ddot{P}_3(i), \dots ,\ \ddot{P}_{23}(i),\ \ddot{P}_{24}(i)\right)$$

$$\bar{P}_h(i) = f_r\left(T_m(i),\ T_a(i),\ I_3(i),\ I_{15}(i), P(i),\ \bar{P}_1(i),\ \bar{P}_2(i), \dots ,\ \bar{P}_{h-1}(i),\ \ddot{P}_h(i),\ \ddot{P}_{h+1}(i), \dots , \ddot{P}_{24}(i)\ \right) \quad (9.b)$$

The number of the input data is the same of the Direct strategy. The accuracy of the prediction is degraded, aim to the use of the prediction values as inputs of model.

DirRec strategy

The Direct and Recursive approach are combined in the DirRec strategy [60]. A model f_{dr} is defined for each time horizon h and it uses the measured data and the previous predictions as inputs to obtain the values at the next step. Hence, the DirRec strategy can be written as:

$$\bar{P}_1(i) = f_{dr}\left(T_m(i),\ T_a(i),\ I_3(i),\ I_{15}(i), P(i), \ddot{P}_2(i),\ \ddot{P}_3(i), \dots ,\ \ddot{P}_{23}(i),\ \ddot{P}_{24}(i)\right)$$

$$\bar{P}_2(i) = f_{dr2}\big(\mathrm{T_m(i)},\ \mathrm{T_a(i)},\ \mathrm{I_3(i)},\ \mathrm{I_{15}(i)}, \mathrm{P(i)}, \bar{P}_1(i), \ddot{\mathrm{P}}_2(\mathrm{i}),\ \ddot{\mathrm{P}}_3(\mathrm{i}), \dots,\ \ddot{\mathrm{P}}_{23}(\mathrm{i}),\ \ddot{\mathrm{P}}_{24}(\mathrm{i})\big)$$

$$\bar{P}_h(i) = f_{drh}\left(\mathrm{T_m(i)},\ \mathrm{T_a(i)},\ \mathrm{I_3(i)},\ \mathrm{I_{15}(i)}, \mathrm{P(i)}, \bar{P}_1(i), \bar{P}_2(i), \dots, \bar{P}_{h-1}(i),\ \ddot{\mathrm{P}}_2(\mathrm{i}),\ \ddot{\mathrm{P}}_3(\mathrm{i}), \dots,\ \ddot{\mathrm{P}}_{24}(\mathrm{i})\right) \quad (9.c)$$

Differently from the previous strategies, the number of the model input increases by one at the next step. So the cumulative prediction error increases, but since the real data are used as input, it is less than the recursive strategy.

It's noted that the three strategies gives the same results at the next 1 hour.

5. THE FORECASTING PERFORMANCE EVALUATION

Several statistical metrics were introduced to evaluate the forecasting performance, as follows.

5.1 NORMALIZED ERROR

The difference between predicted and measured data is the simplest error measure. In order to evaluate the performance of the different forecasting methods, the statistical metrics were introduced as follows:

- Normalized error $$E_h(i) = T_{\mathrm{h}}(\mathrm{i}) - \bar{\bar{P}}_{\mathrm{h}}(\mathrm{i}) \quad (10.a)$$
- Normalized mean bias error (%) $$NMBE(h) = \left(\frac{1}{M}\cdot\sum_{i=1}^{M} E_h(i)\right) * 100 \quad (10.b)$$
- Normalized mean absolute error (%) $$NMAE(h) = \left(\frac{1}{M}\cdot\sum_{i=1}^{M} \left|E_h(i)\right|\right) * 100 \quad (10.c)$$
- Normalized root mean square error (%) $$NRMSE\,(h) = \sqrt{\frac{1}{M}\cdot\sum_{i=1}^{M} \left(E_h(i)\right)^2} * 100 \quad (10.d)$$

where:

i = generic hour of the predicted data from 1 to N

h = time horizon;

M = number of predicted data, equal to 5.491 (see Section 2)

$\overline{\overline{P}}_h(i) = \dfrac{\overline{P}_h(i)}{Max_{i=1}^{M}(\hat{P}_h(i))}$ is the normalized predicted power at generic istant i for the time horizon h;

$T_h(i) = \dfrac{\hat{P}_h(i)}{Max_{i=1}^{M}(\hat{P}_h(i))}$ is the normalized power value used as testing data at hour i for time horizon h;

with $\overline{P}_h(i)$ the predicted power value and $\hat{P}_h(i)$ the target defined as Eq.5.

5.2 THE AMPLITUDE AND PHASE ERROR

The decomposition of the standard deviation error SDE, as the sum of two elements, allows to recognize if the prediction method under or over-estimates the PV power:

$$SDE(h) = \sqrt{\frac{1}{M-1} \cdot \sum_{i=1}^{M} \left(E_h(i) - \hat{E}_h(i)\right)^2} \qquad (11.a)$$

$$SDE^2 = SD_{bias}^2 + DISP^2 \qquad (11.b)$$

where $\hat{E}_h(i) = \dfrac{1}{M} \cdot \sum_{i=1}^{M} E_h(i)$ is the Mean normalized error

SD_{bias} and DISP are the amplitude and the phase errors.

The amplitude error is due to an overestimation or underestimation of the measured data. The phase error is due to a timing shift of the predicted values respect to the real data.

The SD_{bias} and DISP are defined as:

- Standard deviation bias $\quad SD_{bias}(h) = \sigma_T(h) - \sigma_P(h) \qquad (11.c)$
- Dispersion $\quad DISP(h) = \sqrt{2\sigma_T(h)\sigma_P(h)(1 - R_{TP})} \qquad (11.d)$

where:

- $\sigma_T(l)$ = standard deviation of $\overline{\overline{P}}_h(i)$

- $\sigma_P(l)$ = standard deviation of T_h (i)

- R_{TP} = the cross-correlation coefficient between $\overline{\overline{P}}_h$ (i) and T_h (i)

5.3 THE STATISTICAL ERROR DISTRIBUTION

The SKEW (skewness) and KURT (Kurtosis) statistical metrics were introduced to investigate the error distributions and defined as follows:

$$SKEW(h) = \frac{M}{(M-1)(M-2)} \cdot \sum_{i=1}^{M} \left(\frac{E_h(i) - \hat{E}_h(i)}{SD_{bias}(h)} \right)^3 \tag{12.a}$$

$$KURT(h) = \left\{ \frac{M(M-1)}{(M-1)(M-2)(M-3)} \cdot \sum_{i=1}^{M} \left(\frac{E_h(i) - \hat{E}_h(i)}{SD_{bias}(h)} \right)^4 \right\} * \frac{3(M-1)^2}{(M-2)(M-3)} \tag{12.b}$$

The skewness measures the symmetry of the distribution, in particular the distribution is skewed left if the skewness is negative. Instead, the distribution curve is skewed right for positive values of skewness. The distribution is symmetric if the skewness is near zero. The Kurtosis describes the magnitude of the peak of the distribution and indicates if the data are peaked or flat relative to a normal distribution. Therefore, for high values of Kurtosis parameter, the distribution has a peak near the mean and decreases rather rapidly with heavy tails. Instead, the distribution has a flat trend near the mean rather than a sharp peak in presence of low value of Kurtosis parameters.

6. RESULTS AND DISCUSSION

First of all, the LS-SVM and GMDH forecast methods, in combination with the Dir strategy, were trained using two different input vectors as described by eqs.6.a-b in section 2. To compare the results obtained by the different models and inputs, the normalized error and its statistic distribution were considered. The error distributions allow to quantify the frequency of occurrence of errors below or above a certain level. The GMDH model outperforms the LS-SVM for all investigated look-ahead times. Furthermore the models trained taking into account the historical power values related to the previous 24 hours outperform the forecast system, based only on the previous 1h value of the measured photovoltaic power. Fig. 3 plots the NMAE values in the day-ahead time frame. It's evident that the highest normalized error values were obtained in the case of the training based on the input vector 1. The NMAE increases when the time horizon increases until to 12 hours, then for higher time horizons it slightly decreases due to the periodicity of PV power data. This decrease is less noticeable for the models trained with the second input vector IV2, where the highest value has been reached at the horizon of 18 hours. The statistical distributions of the power prediction error for the same cases were reported in

Fig. **4**. It is observed that the error distributions are concentrated between -20% and +30% for both the models trained with the input vector IV1 and between -10% and +20% for the training with the input vector IV2. For a 1-hour look-ahead time, the errors are mainly in the range [0% – 10%], whereas the error never exceeds the 20% boundary. For this horizon the training with the input vector IV1 leads to the highest probability of lowest errors with a probability of 64%. For look-ahead times of 6h, 12h and 24h the training with the input vector IV2 outperforms the one with IV1. For time horizon up to 12h, the normalized error has the highest probability still in the range [0% -10%], with a probability value of 44%. Furthermore the error distributions are shifted on the right at 24h, it means that the normalized error has a high probability to assume value in the range [10% - 20%], in which a probability of 40% is observed for the training with the input vector IV2. Besides the statistical distribution of the normalized error for both the models trained with the input vector IV1 is generally more flat than with input vector IV2.

Regarding the multistep approach the Direct, Recursive and DirRec strategies were applied at the LS-SVM and GMDH models to predict the PV power at next 24 hours through the training on the IV2. In Fig. 5 the predicted $\overline{P}_{\text{h}}$ and the target $\hat{P}_h(i)$ power data of three day of June 2013 are plotted at 1h and 12h. The predicted values are in agreement with the real power at 1h, but when the time horizon increases at 12h, all the forecasting models underestimate the PV power peaks and slightly overestimate the PV power when it is close to zero, in agreement with the trend of NMBE, plotted in Fig. 7. For a 1-hour look-ahead time positive values of the Ei are observed when the PV power increases and negative values if the PV power decreases or is zero, with similar values for the three strategies. For long prediction time horizons large prediction errors mainly occur when the PV power drastically changes.

The NMBE, NMAE and RMSE are plotted in a daily time frame in Fig. 7. The negative values assumed by NMBE for all the forecasting models underline that the models underestimate the PV power data for all the investigated time horizons. Nevertheless, the smallest NMBE values are observed at the short time horizon in the case of the GMDH method, instead at long time horizon for the LS-SVM model. Concerning the multistep strategies, the Recursive strategy, returns the highest NMBE values, with a greater underestimation of the predicted PV power. Focusing on the NMAE, it changes in the range 3% – 11% and increases if the time horizon rises until 20h, after that it slightly decreases. The comparisons between the different multistep strategies show that at short time horizons (up to 6 h) the errors are quite similar for both the methods (LS-SVM and GMDH), then increasing the time horizon the DirRec strategy improves the predictions, leading to lowest NMAE values, in particular in combination with the GMDH model. The Recursive strategy gives the worst results at long time horizons, in according with the NMBE analysis.

In the Recursive strategy, to evaluate the next prediction, the forecast at previous time step are used together with the measured historical data as input that means apply one-step-ahead prediction many times. This entails a higher strategy prediction error, because of the cumulative error introduced through the inputs, which includes the approximation of future values. In the Direct strategy, only the measured data and not the prediction data at previous step, as for the Recursive strategy, are used as input of different models for each time step. It means that there is not cumulative error, but only the forecast error. The DirRec strategy is the combination of the Direct and Recursive strategies, in other words it uses different models at every time step and the prediction data at previous step as input. This approach increases linearly the complexity of the model and the prediction error, because of the cumulative error, but since the measured data continue to be as input, the cumulative error is always less than in the Recursive strategy. Another analyzed statistical metrics is the NRMSE. This metric considers squared errors giving more weight to large errors. Its trend is similar to the one of the NMAE, increasing with the prediction time length. It confirms that the GMDH model with the DirRec strategy outperforms the other prediction methods.

The standard deviation error SDE, the amplitude error SD_{bias} and the phase error DISP, which have been defined in Eq. (11.a-c-d) were evaluated to analyze the fluctuations of the error around the mean value, as reported in Table 1. Large prediction errors have the largest effects on the standard deviation error SDE. When the time horizon increases the SDE rises, the amplitude and phase error also increase for long time prediction horizons. All the models under-estimate the PV power, as shown by the negative values of SD_{bias}. They introduce the phase errors that increase when prediction time horizon increases, as underlined by the values of the dispersion DISP. The results of the decomposition of the SDE, as defined Eq. 13.b, are illustrated in Fig. 8. The values of SDE^2, SD^2_{bias} and $DISP^2$ are plotted for each method. The results show that the main contribution at the standard deviation error is given by the phase error. The SD_{bias} is less than 0.5%. Actually, this means that the models have low systematic errors. This is a nice property that is wanted when using a prediction model. The lowest values of SD_{bias} and DISP are still recorded for GMDH model with DirRec strategies.

In Fig. 9 the error statistical distributions, obtained from the predictions of the LS-SVM and GMDH models implementing Dir, Rec and DirRec strategies, were plotted at five time horizons. Focusing on the LS-SVM model, at short time prediction horizons, the error distributions of all strategies are quite similar. The values of the probability in the range [0% - 10 %] are between 43%-49% at 1h up to 12h. For long time horizon, as at 24h, the histograms are shifted on the right and the normalized error has the highest probability in the range [10% - 20%], with a probability value of 40%. Furthermore in the short time horizons the LS-SVM and GMDH are almost equivalent, while the benefits due to the GMDH are more evident in the longer prediction lengths. The best results are given by the LS-SVM model for very short time horizon (1h) by the GMDH models for long time horizons. For the most of the horizons, the DirRec strategy outperforms the Dir and Rec. Regarding the GMDH model, the highest probability values are recorded in the range [0% - 10 %] until 6h with greatest probability values for the DirRec strategy, respect to Dir and Rec strategies. The probability peak decreases at about 40% at 12 h and it is shifted in the range [10% - 20%] at 24h. Focusing on the strategies, using the direct strategy (Dir) the probability that the normalized error assumes a value in the range [0% - 10%] is between 40% and 50% until 12h. At 24h the probability is less than 40%, with the maximum value in the range [10% - 20%]. Implementing the Recursive strategy the probability distribution changes from 42% to 49% until 12h with the highest values for GMDH model, except at 1h, in which it assumes more high values for the LS-SVM model. At 24h the histograms are shifted on the right, this means that it's more probable to find normalized errors in the range [10% - 20%] and a value of 38% is recorded implementing the LS-SVM. Analogous considerations, made to the Recursive strategies, are valid for the DirRec strategy.

The skewness and kurtosis statistics allow to characterize the forecast error distributions. Fig. 10.a-b shows the SKEW and KURT values, evaluated for the LS-SVM and GMDH prediction methods and the different strategies. Focusing on LS-SVM, the skewness is always negative for very short (less than 3h) and long time horizons (longer than 18 h), hence the error distribution was generally left-skewed until 3h and later 18h and right-skewed for time horizons in the range 3h-18 h. Focusing on the kurtosis values, as expected the hour-ahead forecasts have much higher kurtosis values than those at the day-ahead timescale, with the trend of decreasing the value of the kurtosis parameter when the forecasting horizon increases. As attempt, the forecast in the day-ahead time frame increases the uncertainty compared to the single hour ahead. It means that the error distribution is narrow with high peak value at short time horizon, and then it becomes flat for long time step. At the same time horizon the highest kurtosis values are recorded for the DirRec strategy implemented with the GMDH model, it means that its error distribution is closer to a normal distribution, consequently the forecasts based on this method are more accurate.

A final analysis was carried out regarding a novel hybrid forecasting model which combines the group method of data handling (GMDH) and the least squares support vector machine (LS-SVM), known as GLSSVM. The output variable of the GMDH model is combined with the input variables and used as input for the LSSVM model.

The GLSSVM model is implemented only for the Direct with IV2 and DirRec strategies, considering that the results of the previous analysis underline the worst performance of the Recursive strategy. The GLSSVM algorithm is carried out by three iteration steps. The NMAE of two strategies applied to the GLLSVM model is plotted in Fig. 11 and compared with the original model GMDH and LS-SVM. It increases when the horizon time increases and it assumes values in the range 2,9% - 9,5%. The implementation of the Dir and DirRec strategies with the GLSSVM model allows to obtain a decrease of the NMAE of 0,6% and 0,2% with respect to the simple LS SVM and GMDH methods.

In Fig. 12.a-b the error statistical distributions of three forecast models were compared at five time horizons and taken into account the different strategies Dir and DirRec. Focusing on the GLSSVM method and both strategies, the probability to found a normalized error in the range [0% - 10%] increases until 6h, where it's assumes the highest values of 57% and 55% respectively for Dir and DirRec strategies. At long time horizons it's noted that the histograms are shifted on the right and the curves are more large and flat. It means that normalized error is mainly in the range [10% - 20%] with a probability value of 42,3% at 24h, implementing the DirRec strategy.

Implementing the Direct strategy, the GLSSVM method allows always to obtain the highest probability that the normalized error is in the range [0% - 10%] compared to the LS-SVM and GMDH methods until 12h. For a 24-hour look-ahead time, the GLSSVM model leads to the highest probability of lowest errors with a probability of 40% in the range [10% - 20%]. The lower error probability values are supplied by the LS-SVM model for short time horizon until to 12h, but at 24h the results are comparable to one of the GLSSVM models. Focusing on the DirRec strategy, the error distributions trend of all methods is similar with a small difference especially for LS-SVM method. The probability for GMDH and GLSSVM increases until 6h with a value of 55%. At 24h it is shifted in the range [10% - 20%] for all models and the highest probability is 42% for the GLSSVM model.

In Table 2 the performance of the GMDH, LSSVM and GLSSVM methods are compared with the results related to the predictions given by a traditional Elman ANN that the authors have implemented in [30]. The NMAE values of the different models are examined at five time horizons. The lower values of NMAE are obtained for the studied models at all time horizons. The results show that investigated models, trained taking into account the historical power values related to the previous 24 hours (Input Vector 2) and combined with the DirRec strategy, outperform the ANN forecast system [30] that was trained on the previous 1h value of the measured photovoltaic power and implemented the Dir strategy. So, the LS-SVM, GMDH and GLSVM models offer an improvement of the performance respect the ANN system.

7. CONCLUSION

The innovative short-term forecasting system based on Group Method of Data Handling (GMDH) is presented in this paper and it is compared with the Least Square Support Vector Machines (LS-SVMs). The methods are applied to forecast photovoltaic power of system, located in South East of Italy. The historical data, such as PV power, solar radiation, ambient temperature and module temperature, added to previous values of measured and/or predicted PV power were used to train the models. Three multi-step ahead time series forecasting strategies (Direct, Recursive and DirRec) are applied to the different forecasting methods. An analysis of the normalized mean error and the statistical distribution was carried out in order to compare the methods and the strategies and to identify the combination that gives the best forecasting accuracy.

A first analysis of the normalized error was carried out by using the simple GMDH, LS-SVM and Direct strategy with two different input vectors, based on the measured data. It's observed that if the PV power data, measured in the previous 24 hours, are considered together to the measured data of solar radiation, ambient temperature and module temperature, the prediction error decreases with respect to the input that uses only data measured in the instant at which the prediction is done.

To evaluate the prediction models performance, the conventional metrics, as the root mean square error (RMSE), mean bias error (MBE) and mean absolute error (MAE) were calculated comparing the simple LS-SVM and GMDH. It means that all models underestimate the PV power data and the lower values of the error are recorded for the GMDH model. Regarding the three multistep strategies, the results underline that the DirRec strategy leads to more accurate predictions, while the Rec strategy returns the worst results.

To better understand the difference between the predicted data and the real data, the standard deviation has been decomposed into two components, deviation bias and dispersion. The GMDH model reduces the dispersion error at long time horizons. So the accuracy of the prediction models in the day-ahead time frame improves if the GMDH method was implemented rather than LS-SVM models.

Further the statistical distributions of normalized error were performed at five horizons, calculating the probability that the error itself takes in values of the ranges [0% - 10%]. This probability is between 40% - 50% for time horizons from 1h to 12h. It means that the highest values of the error distribution probability are with the GMDH model combined with the DirRec strategy.

Finally, a hybrid algorithm (GLSSVM) that combines GMDH and LS-SVM models, has been considered. The highest values of probability that the normalized error is in the range [0% - 10%] can be obtained implementing the GLSSVM model with the Dir strategy for a 12-hour look-ahead time. An analysis of the NMAE shows that the hybrid model has better performance than the GMDH and LS-SVM model, in particular if the DirRec strategy has been applied.

Furthermore, a comparative analysis of the performances with the results related to the predictions given by a traditional Elman ANN demonstrates that the investigated models improves the forecasting accuracy and the hybrid model GLSSVM gives the best performances. The improvement given by the implementation of the hybrid method, which is computationally more expensive, is particularly evident with respect to the LS-SVM, while it is negligible in comparison with the GMDH model

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Table 1 Trend of SDE, DISP and SD_{bias}

	Dir		***Rec***		***DirRec***	
Horizon	***LS-SVM***	***GMDH***	***LS-SVM***	***GMDH***	***LS-SVM***	***GMDH***
			SDE			
1	0,068	0,064	0,068	0,064	0,068	0,064
6	0,102	0,101	0,101	0,097	0,100	0,095
12	0,128	0,126	0,126	0,124	0,125	0,122
18	0,147	0,144	0,148	0,149	0,143	0,140
24	0,129	0,127	0,128	0,132	0,126	0,125
			SD_{bias}			
1	-0,011	-0,008	-0,011	-0,008	-0,011	-0,008
6	-0,026	-0,019	-0,025	-0,018	-0,024	-0,018
12	-0,038	-0,031	-0,035	-0,029	-0,035	-0,026
18	-0,056	-0,051	-0,059	-0,057	-0,051	-0,043
24	-0,052	-0,050	-0,052	-0,054	-0,049	-0,042
			DISP			
1	0,067	0,063	0,067	0,063	0,067	0,063
6	0,098	0,099	0,098	0,095	0,097	0,093
12	0,122	0,122	0,121	0,120	0,120	0,119
18	0,135	0,135	0,136	0,138	0,134	0,134
24	0,118	0,117	0,117	0,120	0,116	0,118

Table 2 Comparison of performance of the GMDH, LSSVM and GLSSVM models with those of ANN model [30]

	1h	*3h*	*6h*	*12h*	*24h*
ANN [30]	6,5%	10,86%	13,79%	14,38%	19,49%
LS-SVM DirRec	3,43%	4,87%	5,71%	7,48%	8,58%
GMDH DirRec	2,90%	4,24%	5,13%	6,98%	8,33%
GLSSVM DirRec	2,92%	4,05%	5,05%	6,92%	8,17%

Fig. 1 The GMDH structure

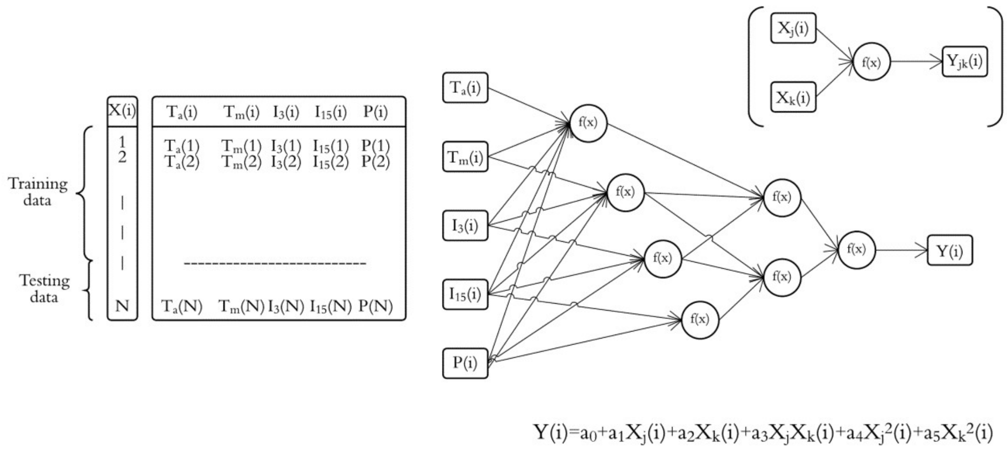


Fig. 2 Structure of the GLSSVM model for time series forecasting

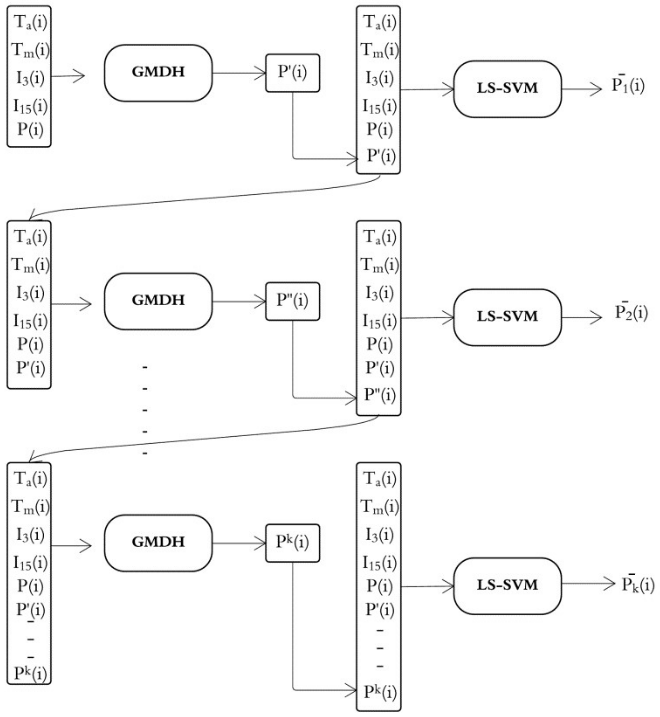


Fig. 3 NMAE, implementing two different input vectors for LS-SVM and GMDH models

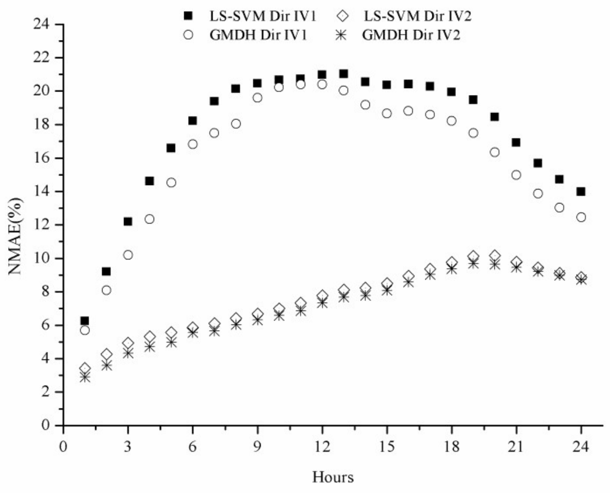


Fig. 4 Probability distributions of normalized mean bias error for the LS-SVM and GMDH models, trained with the input vector 1 and 2 at a different time horizons

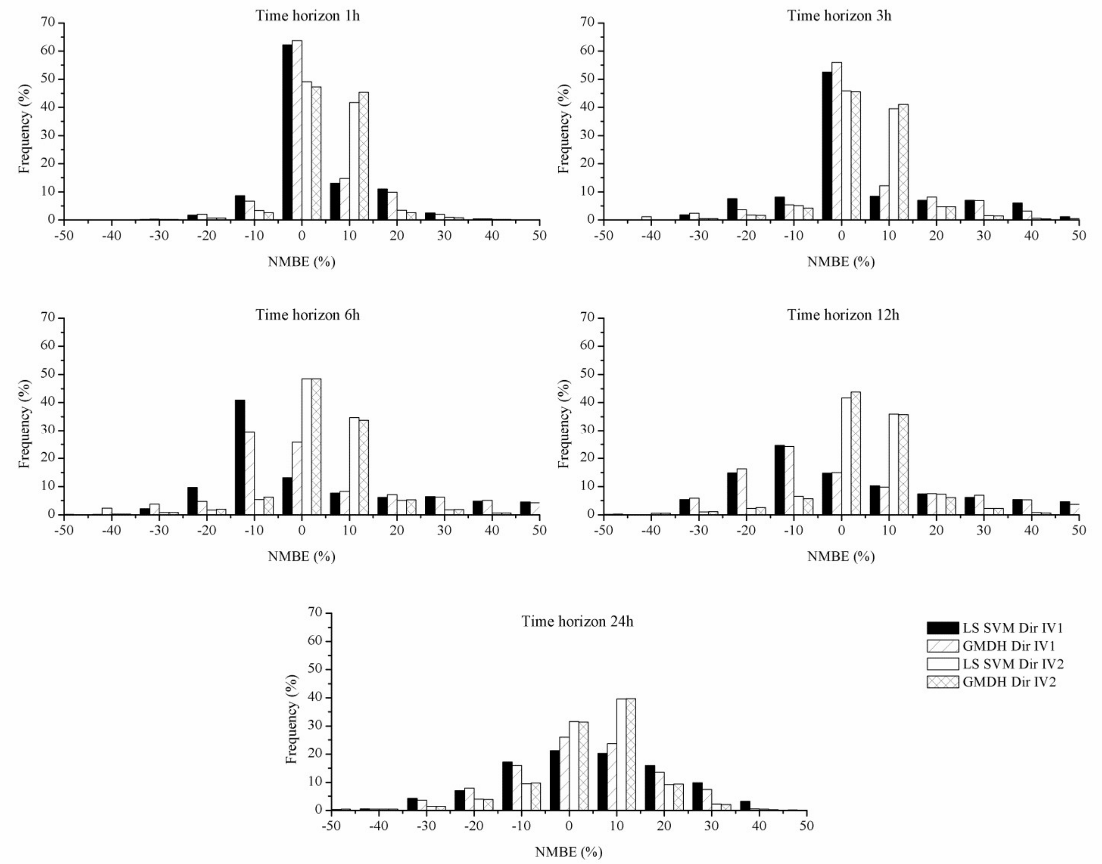


Fig. 5 Target $\hat{P}(t)$ vs predicted $\bar{P}(t)$ power of three day of June at the time horizon 1h and 12h

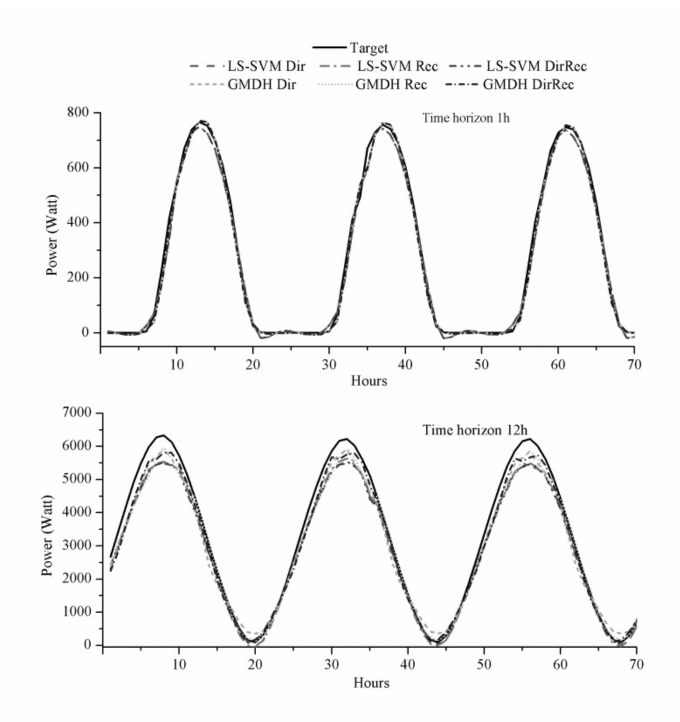


Fig. 6 Comparison of the normalized error at time horizon of 1h and 12h using three strategies for three day of June

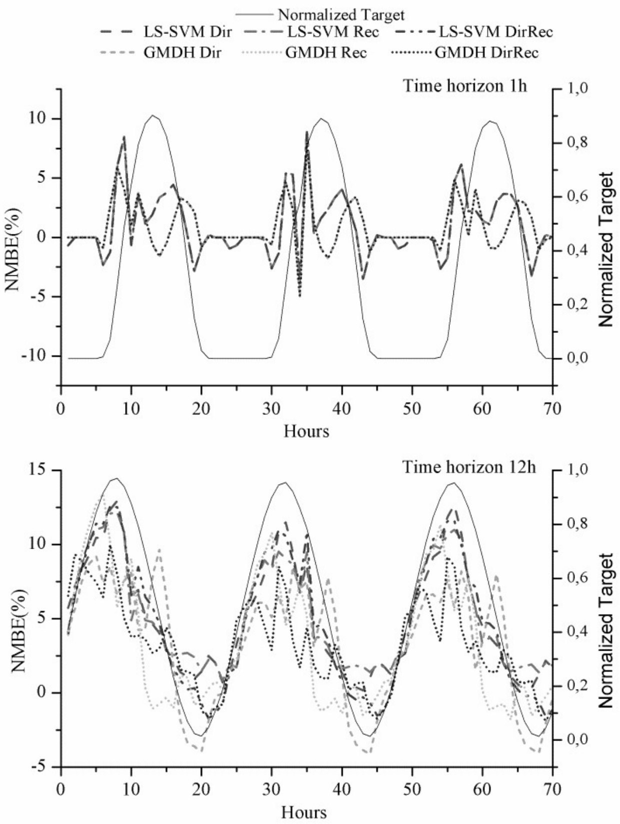


Fig. 7 NMBE, NMAE and NRMSE

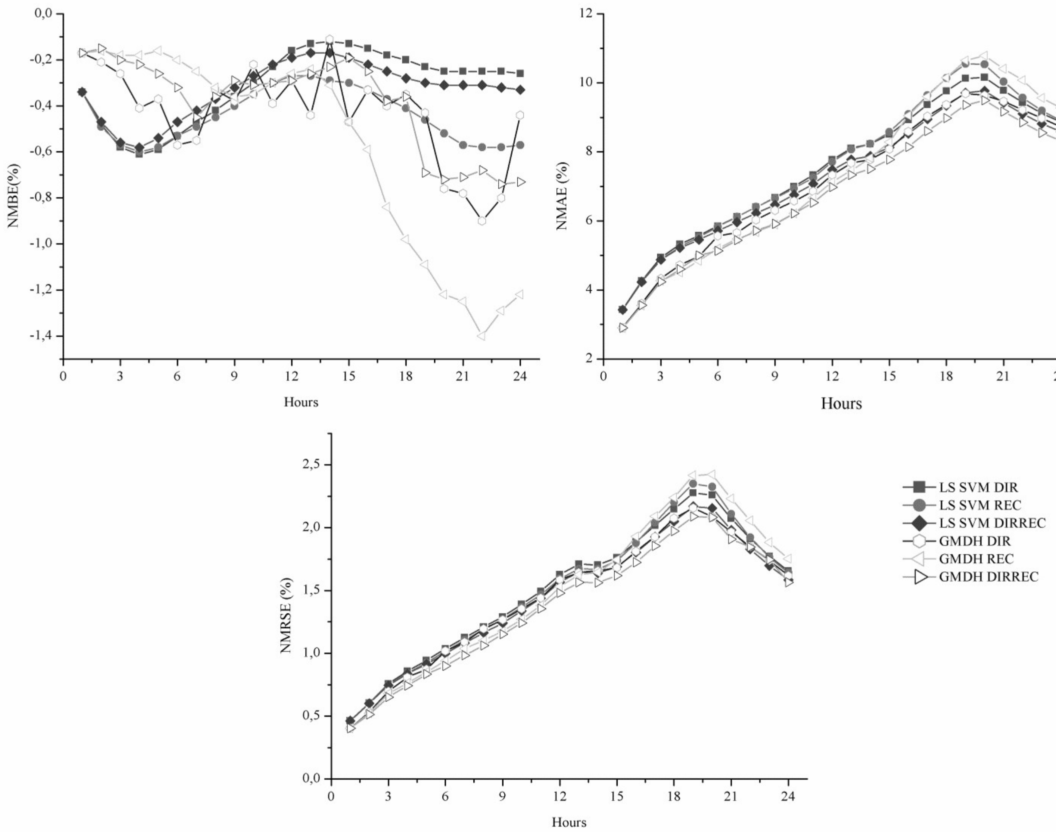


Fig. 8 Trend of SDE^2, $DISP^2$ and SD_{bias}^2 for LS-SVM and GMDH models

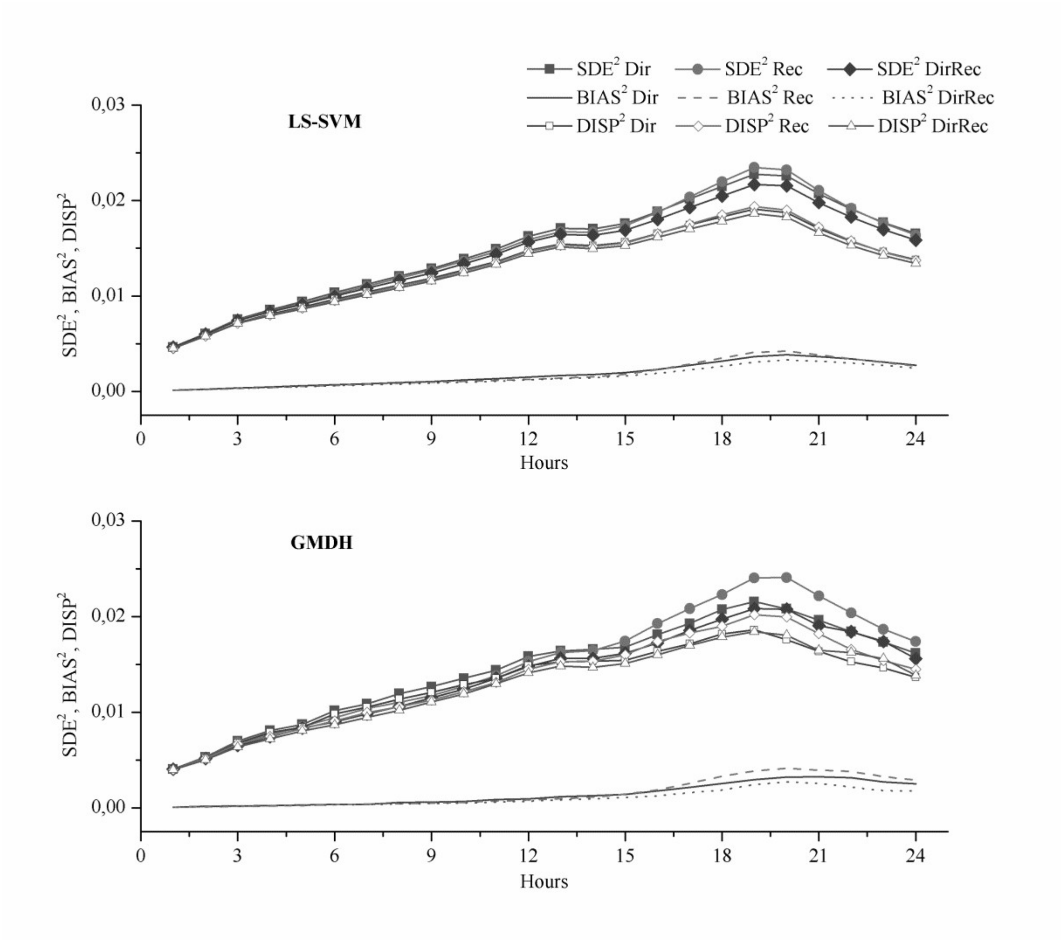
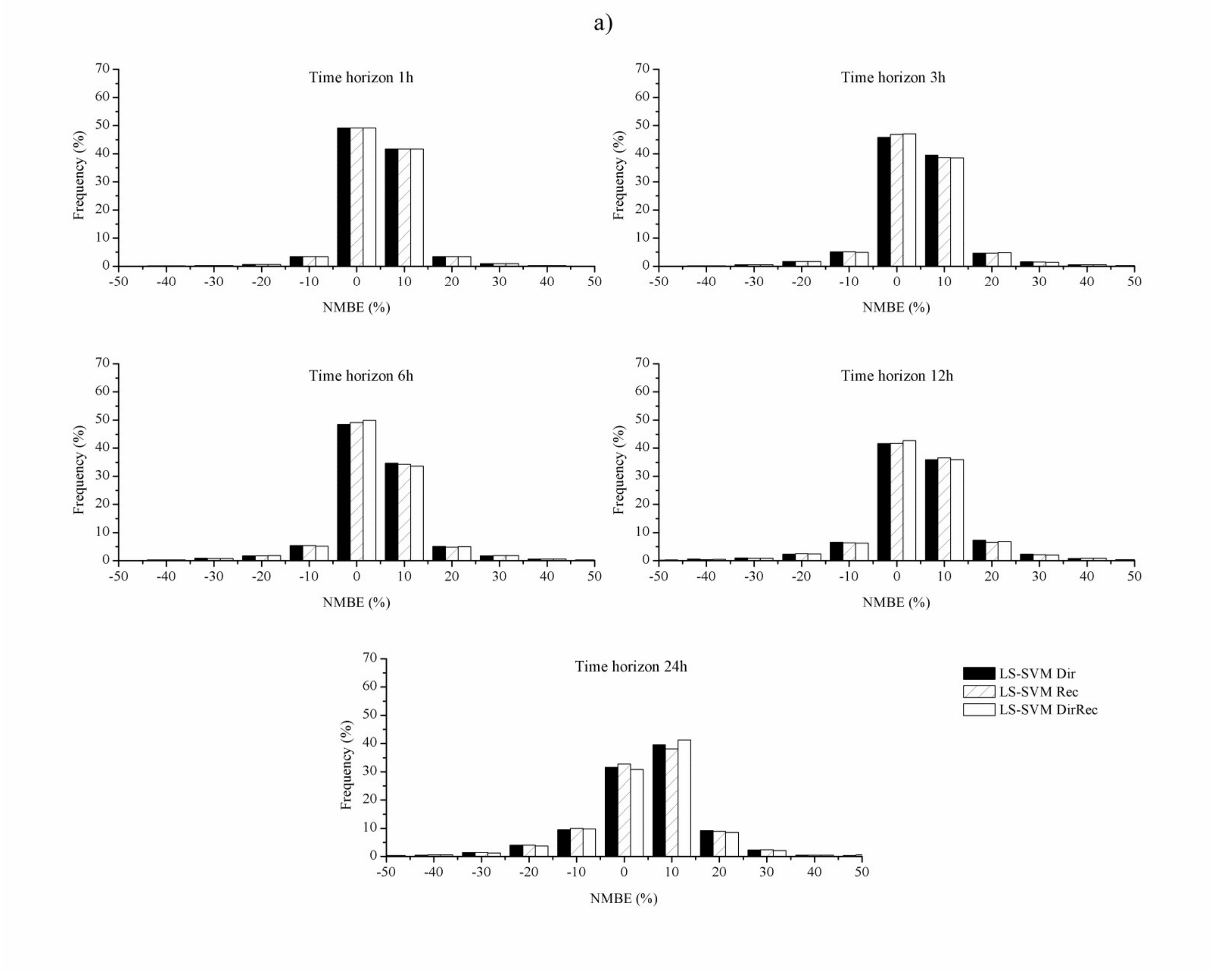
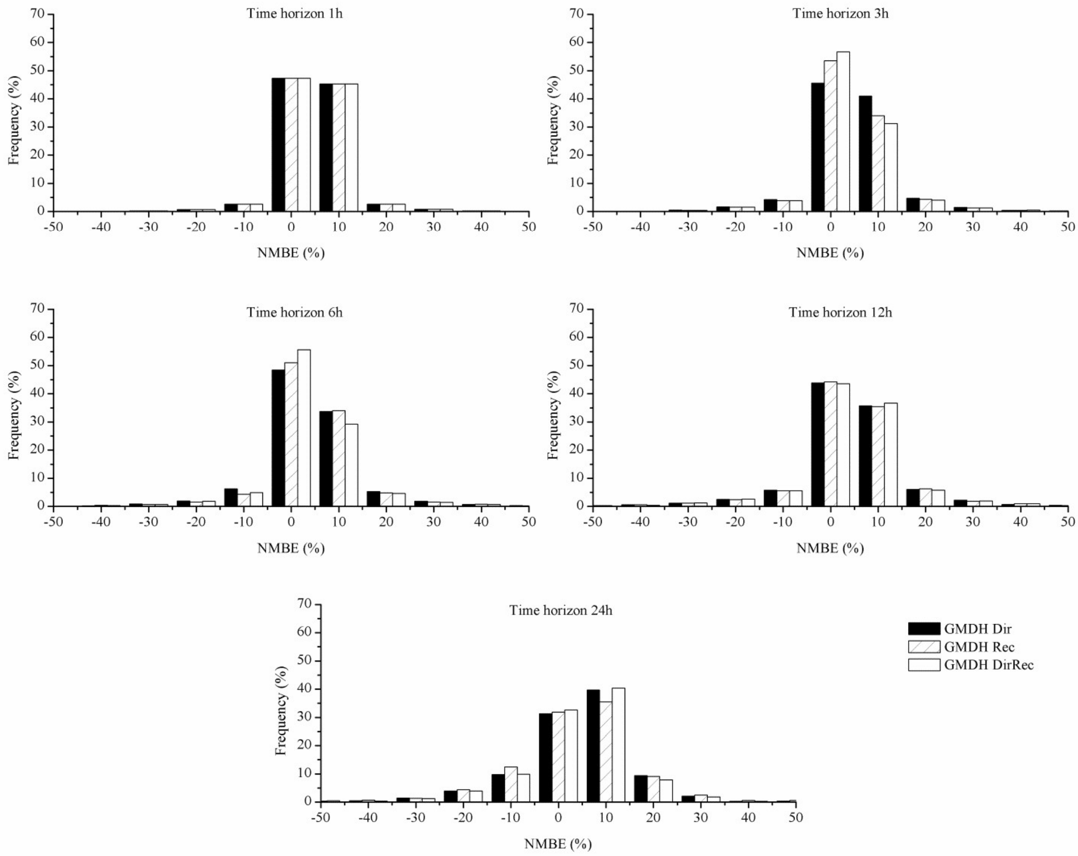


Fig. 9. a-b Probability distributions of normalized error for the LS-SVM and GMDH models, implementing Dir, Rec and DirRec strategies at a different time horizons

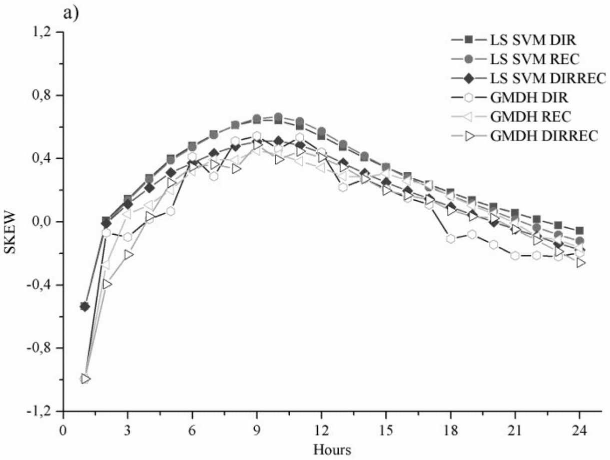


b)



Time horizon 1h
Time horizon 3h
Time horizon 6h
Time horizon 12h
Time horizon 24h
Frequency (%)
NMBE (%)
GMDH Dir
GMDH Rec
GMDH DirRec

Fig. 10.a-b Measures of Skewness and Kurtosis



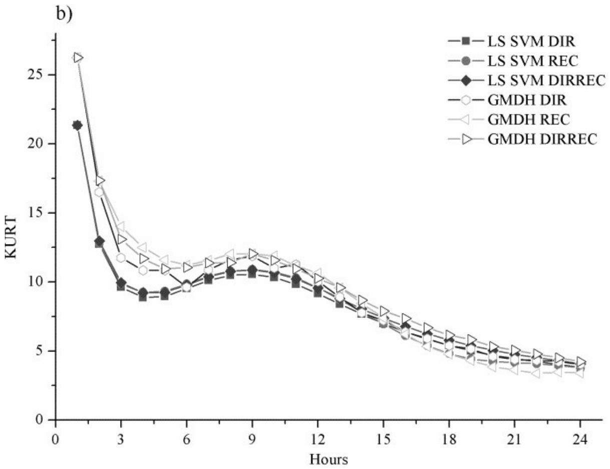


Fig. 11 Comparison between NMAE for the GMDH, LSSVM and GLSSVM models

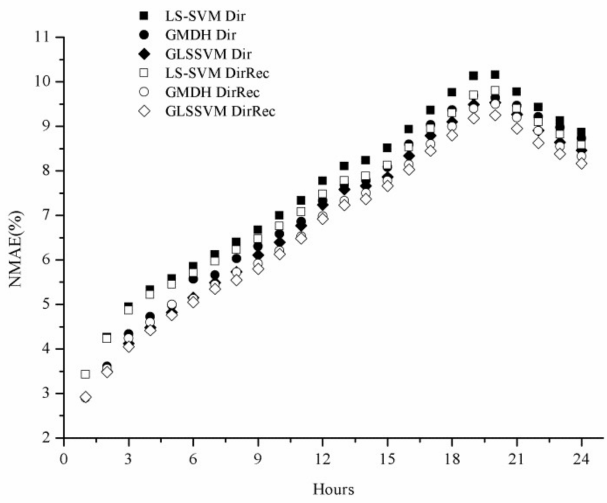
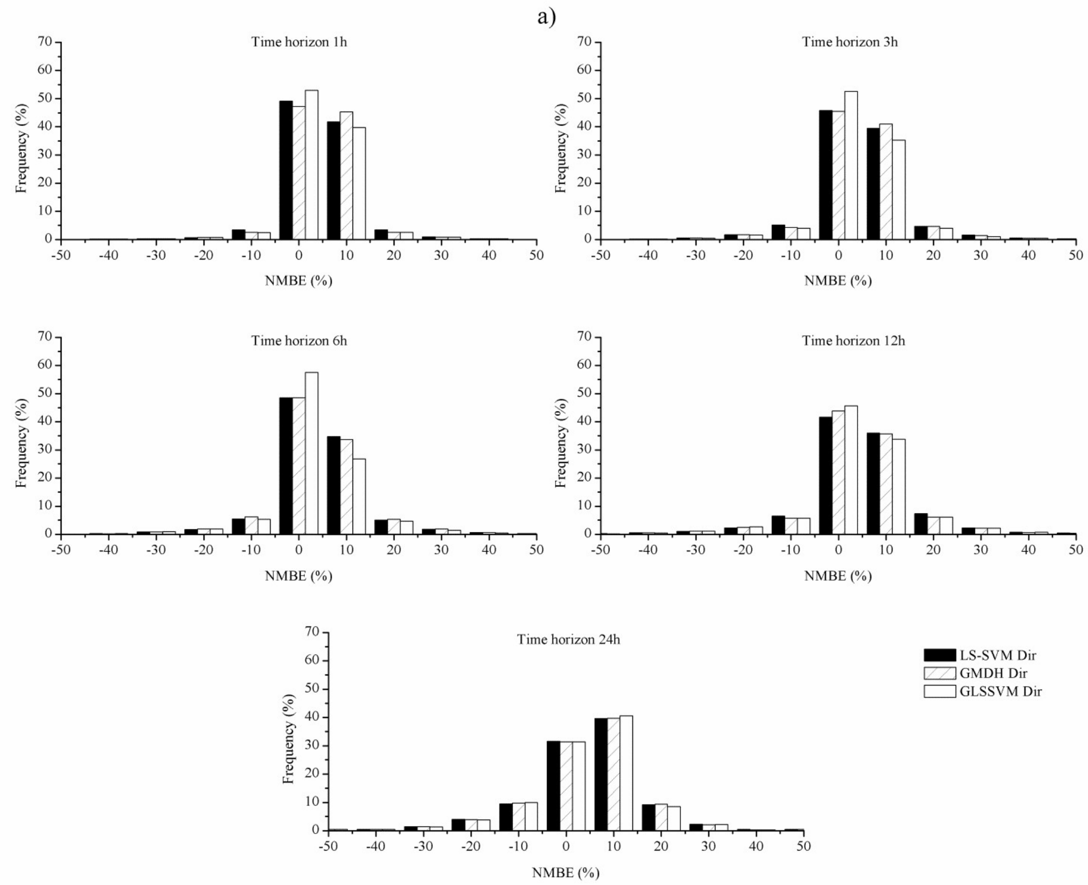
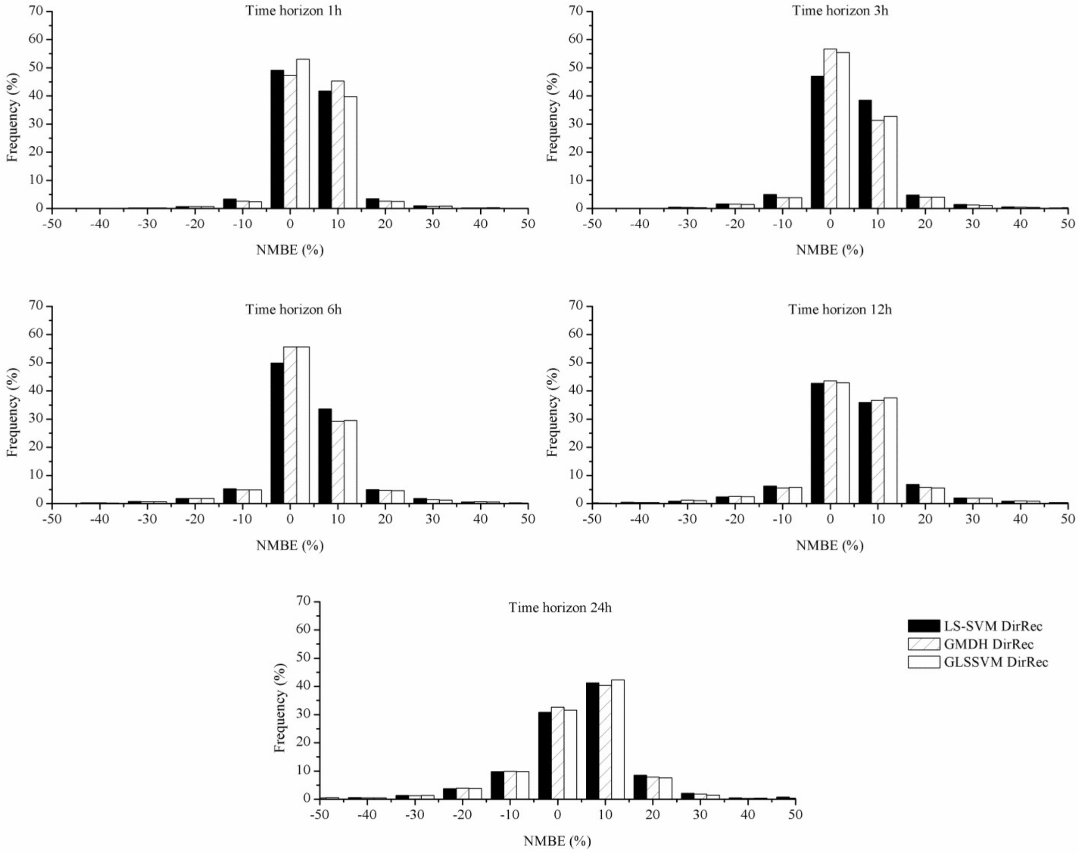


Fig. 12.a-b Probability distributions of normalized error for the LS-SVM, GMDH and GLSSVM models, implementing Dir and DirRec strategies at a different time horizons



b)



Time horizon 1h
Time horizon 3h
Time horizon 6h
Time horizon 12h
Time horizon 24h
Frequency (%)
NMBE (%)
LS-SVM DirRec
GMDH DirRec
GLSSVM DirRec

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