The application of the data mining in the integration of RES in the smart grid

Consumption and generation forecast in the I3RES project

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***Abstract*—Accurate models for predicting generation, demand, prices, and storage under uncertainties are essential for managing safe, sustainable and reliable electric grids. In this investigation, the use of data-mining methods for building models of electrical consumption and renewable generation aimed at integrating renewable generation for smart grid control is studied. The results presented are part of the I3RES project that aims at building future energy solutions for smart electric grids considering the typical uncertainties of the renewable generation. Our results indicate that the data-mining techniques are able to provide forecasts with reasonable accuracy in the presence of uncertainties. Furthermore, such forecasts are useful in building controllers that can perform control actions such as demand side management in smart grids.**

***Keywords*—RES;smart grid; data mining; DSM;**

I. Introduction

Spiraling fuel prices, increasing energy carbon foot-print, and energy consumption have significantly raised environmental and economic concerns. The judicious use of energy and integration of Renewable Energy Sources (RES) are seen as promising solutions in this scenario. However, intermittencies in renewable generation and issues with their integration prevent its integration into the grid. Consequently, acute utilization of the RES in grid operations, along with reducing carbon footprint has become a challenge itself.

In order to overcome the aforementioned difficulties, the EU FP7 I3RES project integrates RES in the electrical distribution grid by incorporating intelligence at three different levels: 1) in the integration of Renewable Energy Sources (RES), with the aim of minimizing the impact of such sources` intermittency, smart mechanisms for control and management are developed; 2) in the interoperation of all actors involved through a integration system and finally: 3) in the overall operation of the Smart Grid by attaining in advance predictions of parameters that allow the distribution system operator (DSO) to manage and operate the network more efficiently. The main approach followed to achieve these objectives has involved handling the raw-data obtained from the grid so as to transform it into knowledge about renewable generation and loads.

One relevant actor of the Smart Grid (SG) scenario is the Aggregator; its main role focuses on purchasing and selling electricity on behalf of a group of consumers and electricity generators. The Aggregator, along with DSO and customers, are involved in the Demand Side Management (DSM) process, which has been defined in I3RES with the focus on encouraging the insertion of renewable sources, avoiding load peaks, minimizing failure risks in the grid operation, and contributing to a more active participation of the final user.

In the I3RES framework, two scenarios model the DSM process: day-ahead and intraday. In the day-ahead scenario, DSOs and Aggregators anticipate grid conditions based on consumption and generation prediction realized by the algorithms implemented that are totally suited for the scenario at hand. Thus, the prediction algorithms allow both agents, DSO and Aggregators, to know in advance the estimated consumption or generation values; possible problems can be avoided as the DSM can apply diverse actions to influence the user consumption behavior. The types of actions that try to encourage the modification of users' consumption are mainly indirect. Conversely, in the intraday scenario, with little time scope in advance, if the DSO detects that the grid's proper operation will be destabilized (based on the predictions done by the algorithms) due to peak consumption or drops in the RES generation, the DSM strategy can only apply direct signals aiming at limiting users' consumption.

Additionally, as it has been introduced in the overall objectives of the I3RES project, particular emphasis will be put in facilitating the participation of the Aggregator in the DSM process. This task will be carried out by developing smart functionalities to analyze and predict customer consumption and generation. Hence, prediction techniques are essential to react in advance to different grid situations. Moreover, in the case of RES generation, prediction tools allow the reduction of uncertainty of this type of sources.

Therefore, the main technical objection of electrical companies to introduce more RES generation is its uncertainty and, thus, the possible grid instability that it might produce. Having a better and advanced knowledge of RES generation, thanks to prediction tools, will debunk this argument, helping RES integration.

For such purposes, in recent years, data mining has become one of the most valuable tools for extracting knowledge and establishing patterns from data in order to produce useful information for decision-making processes. Utilizing such techniques, the available information on consumption and generation will be analyzed and patterns inferred so as to model a tool capable of predicting future values.

II. Data Analytics in the Smart Grid

The deployment of the Smart Grids in Europe has opened new opportunities to the development of new applications and solutions for a more efficient management and operation of electric grids. The analysis of the data coming from the AMI (Advanced Metering Infrastructure), added to the possibility of having more granular information (meter readings every 15 minutes, for example, instead of one single measure per day), can provide companies capabilities for forecasting demand, shaping customer usage patterns, preventing outages, optimizing unit commitment, among others [1].

However, up to now not all Utilities are prepared to analyze and manage this large volume of data that come from the AMI. Assuming smart meter measurements every 15 minutes, at least 96 million new data per day for every million meters are generated. Thus, this challenge aims at extracting knowledge from the data provided by the AMI and converting it into useful information for the agents involved in the DSM process. The graph above of Figure 1 represents the load curves of one smart meter with data measured from Monday to Thursday during 6 months. As it can be easily adverted, at a first glance, it is not possible to extract any information from it.

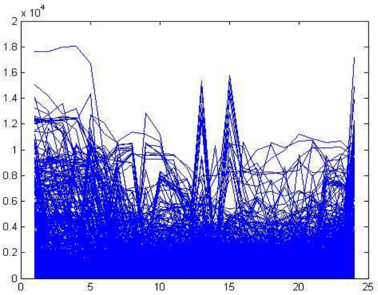

Figure 1. Users load curves representation for 6 months.

Data mining comprises the computational process of discovering patterns in large data sets involving methods that belong to artificial intelligence, machine learning, statistics, and database systems. The overall goal of the data mining process in the I3RESproyect is to inspect, clean, transform, and model data with the aim of discovering useful information, suggesting conclusions, and supporting decision-making.

When the process allows for the understanding of what happened in the past, commonly linked to diagnosis, it is called Descriptive Analytics. In other scenarios, these patterns are inferred so as to be utilized to make predictions, assuming that the future, at least the near future, will not be much different from the past. Thus, a proper analysis of historical consumption information can allow, for example, inferring the behavior of a customer in the following hours. This is called Predictive Analytics. Finally, if the intention gravitates on performing decision making processes, diagnoses made based on such predictions offer special advantages in such a way that, for example, the consumption in a specific period of time can be reduced to avoid a grid overload. In this case Optimization techniques or Prescriptive Analytics are utilized for problem solving.

However, the data analytic algorithms utilized in the I3RES project, as most of the commonly utilized ones, are non-deterministic; involving that, with the same input, not always the same output is obtained. These methods depend on the initialization, training set, cross validation scheme and some stochastic parameters which control the behavior of the algorithm during the iterative process, among other parameters that need to be ad-hoc configured and adapted for the handled scenario. Henceforth, a different methodology from the traditional used for software development should be followed: CRoss-Industry Standard Process for Data Mining (CRISP-DM [2]) is a data mining process model that describes approaches commonly used by data mining experts.

III. Energy consumption forecast

The problem tackled in this section consists of forecasting the consumption for the next 24 hours taking into account historical data attained from Steinkjer (the demonstration pilot located in Norway) and provided by NTE comprising two years of information captured from smart meters with hourly measures. This prediction will be realized, as a mandatory requirement from the DSO, at a certain secondary substation (CT). The reason behind the DSO requires such aggregated consumption is that in the DSM process, the main objective aims at adjusting the consumption and generation overall curve loads, and no user level or small variations are relevant in such task.

Basically consumption prediction in I3RES is done with two main inputs: historic energy consumption and weather forecast. The forecasting tool works inferring a function from the provided historical data so as to use such acquired knowledge for mapping new examples. First, the historical data is shaped by power consumption values captured over a period of time. The main idea is based on learning from past cases captured in the historical data from Steinkjer in order to being capable of forecasting future cases. The predictions realized are totally suited for the scenario at hand as the tools are trained with data from such particular scenario.

On the other hand, the weather information provided has the aim of helping the algorithm to infer the relation between the weather in a certain area and the energy consumption in such area. For this purpose, apart from the information related to identify the forecast (location and date time), some parameters that directly affect the consumption, such as temperature, wind speed, humidity, pressure and dew point have been included.

A. Data Procesing

The availability of a considerable amount of data becomes a critical aspect. In order to estimate more accurately the amount of data that could prejudge the outcome of the forecast, many aspects have to be taken into account. These parameters range from the data variation change over time seasonality, to the number of outliers detected, the absence of certain values, the need for data cleansing, among others. The influence of such parameters directly affects the expected accuracy of the algorithms prediction.

The seasonality of the data cannot be analyzed in detail, as the days are less than two years and not all seasons can be examined with more than one-year information. However, this lack of historical depth has proven not to be so decisive. The reason behind this lays on the smooth variations of the consumption loads; when training the algorithm for a determinate date, not only the data from the previous year is used, but also the previous month's information is helpful.

Closely related to the aforementioned depth in the data, the process of data cleansing, totally adapted to the algorithm that will be used, has to be determined. This basic cleansing should take into account the number of measures that are corrupted along all the collected data. In other words, among all the available data stored from the meters, some of them would have erroneous values, or even absence of them due to failures. Those values directly affect the quality of the information that will be provided to the algorithm.

Once the available data is processed, the next step in this analysis should comprise the detection of outliers within the stored data. Generally, an outlier is an observation point that is distant from other observations.

Once the data cleansing of both set of information (the consumption and the weather forecast) was done, the following step was to merge both sets of disjoint dates. In another words, it was necessary to integrate multi-magnitude incomplete weather forecast data with the "clean consumption" data, as the days when both set of data were complete and available were different.

B. Modeling

For the consumption forecast task, so far, two forecasting techniques have been implemented: Support Vector Machines (SVM) and Random Forests (RF). All schemes use the same set of feature inputs. The first technique is known to be one of the most consolidated regression one, even though it requires high computational complexity. The second option proposed, RFs, are one of the most promising regression techniques based on information theory with one of the best balances between computational burden and accuracy. So far, this second option is attaining the best results in the tests implemented with the data acquired form Steinkjer.

A random Forest regressor is composed by a set of decision trees that consist of internal nodes that represent the decisions corresponding to the hyperplanes or split points, and leaf nodes that represent regions or partitions of the data space. Those regions are labeled with the majority class and are characterized by the subset of data points that lie in that region. One of the advantages of decision trees is that they produce models that are relatively easy to interpret as the output of a decision tree is transparent, which makes it easy for users to understand. In particular, a tree can be easily read as set of decision rules, with each rule's antecedent comprising the decisions on the internal nodes along a path to a leaf, and its consequent being the label of the leaf node. Therefore, decision tree models are used in this scenario to examine data and induce the tree and its rules that will be used to make predictions. The prediction is used in this application to predict continue variables, where absolute values are required. However, decision tree techniques may suffer of scalability and efficiency problems, such as substantial decrease in performance and poor use of available system resources [3], if the scenario highly increases. However, in this case, as the consumption prediction is realized not for individual consumers, but for aggregated consumption values at substation level, it is highly improbable that these issues will affect the performance of the algorithm. Additionally, for tackling such problem, the basic implementation of random forest has not been selected; alternatively, the algorithm utilized is based on a random forest (RF) basis.

On the other hand, SVM are supervised learning classification methods based on maximum margin linear discriminants; the goal is to find the optimal hyperplane that maximizes the gap or margin between the classes. Further, the optimal nonlinear decision boundary between classes which corresponds to a hyperplane in some high-dimensional nonlinear space can be found.

The main task of such techniques is the analysis of the data and extracting patterns, even for classification or regression analysis. Given a set of training examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one category or the other, making it a non-probabilistic binary linear classifier. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on. In these cases the SVM is utilized for regression, not just for making a classification of the samples.

Still there is no technique that has been proven to outperform all classification or prediction problems [4, 5]. The selection of the classification model is critical as well as difficult, even though in this case there is a lot of prior knowledge about the problem. Furthermore, some classification processes are quite unpredictable or nondeterministic, which requires an iterative process until the feedback on the performance of the system is satisfactory. All these aspects will be tackled when further describing the validation of the algorithm, where the total customization of the algorithm to the scenario handled is depicted.

Finally, in parallel to the aforementioned methods, as it has been introduced in previous section, it is very important to make a good feature selection to assure that the input data to feed the algorithm provides the best results. For example, the information to predict the consumption, in a tertiary building at 7 a.m. is not the same than at 11 a.m. Indeed, at 7 a.m. there is a big difference of the consumption related with the previous and following hours and probably the slope will depend on the output temperature. However, the consumption during the hill zone (midday) is very similar, which means that the consumption of the previous hour is enough for the prediction.

The process followed with Steinkjer data was to discard those features with less influence in the results obtained in a set of test cases. The features that were analyzed are the following: different time windows for consumption variables, additional weather variables, and even the linear dependencies between the combinations of more than one single feature.

C. Steinkjer Validation

TABLE I. DATA SET

Historic depth	Not consecutive days are available
Starting date	03-12-2011 at 0:00
Finishing date	05-10-2014 at 23:00
Seasons	Summer and Winter
Frequency	24h forecast specifying the amount of energy hourly
Quality	Several data cleansing processes required. Discarding process for days with missing values
Input data	Consumed active energy at substation level: aggregation of individual accumulative measurements (data provided by NTE) and extracting differential measurements. Weather forecast information: temperature, wind speed, humidity, pressure and drew point.

The forecast is executed for all days of the dataset and the analysis has been done comparing the prediction value of each 24 hours with the real data registered for that day. In order to obtain statistical results, 10 Monte Carlo interactions are done for each test case.

Error = (Forecasted Value (t)-Real Value (t))/(Real Value(t))

TABLE II. ENERGY CONSUMPTION FORECAST RESULTS

N	Energy consumption forecast results		
	Test Case	Accumulative error (min/mean/max/std)	Differential error (min/mean/max/std)
1	Consumption	0.04/0.14/0.49/0.08	2.84/6.28/16.25/2.25
2	Consumption + Weather	0.04/0.16/1.56/0.15	2.39/6.89/16.28/2.40
3	Working days (Consumption)	0.05/0.49/5.11/0.57	2.23/7.13/26.34/3.17
4	Working days (Consumption + Weather	0.05/0.49/5.14/0.57	2.11/7.12/26.46/3.16

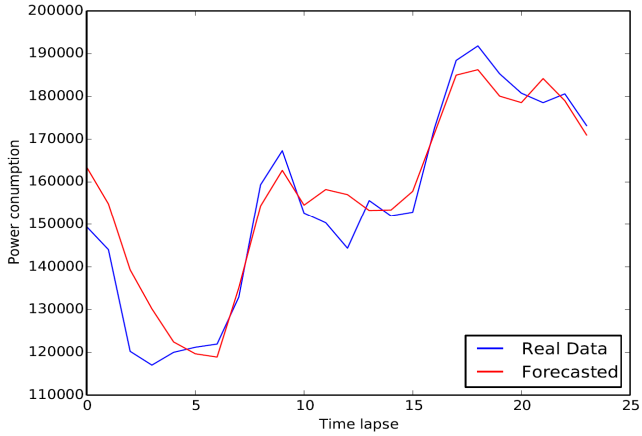

Figure 2. Consumption forecast for accumulative and differential values.

IV. WIND GENERATION FORECAST

Wind power is a renewable clean green energy which is following upward tendencies and hence, becoming one of the world's fastest growing ones. Nowadays, it covers a significant percentage of electrical demand worldwide [5-11]. However, the energy source's extreme uncertainty makes the wind power have shortcomings of intermittency and volatility. Thus, wind power fluctuations need to be balanced through: 1) the regulation of standby generators and, 2) by energy storage system. Wind power forecasting (WPF) is an instrument to help efficiently address this challenge, and significant efforts have been invested in developing more accurate wind power forecasts.

Dependence on the discontinuity of the wind is one of the largest problems of wind power [11-21]. Wind generation forecast is also strongly affected by a correct topographical analysis of the site where the farm is. Additionally, plant information must be taken into account in a wind generation model; in particular, plant power curves are highly non-linear and small errors in wind speed lead to big errors in power generation.

A. Wind turbine model

In I3RES project, wind power forecasting is done using multi-layer perceptron with back propagation training (BP). The BPNN consists of three layers: input, output and hidden. The number of neurons in hidden layer is arbitrarily selected to reduce the error and, within this forecasting algorithm, 50 neurons have been utilized. As regards the activation function, the hyperbolic tangent function has been used.

The reference to the output layer is the wind-speed data, while the measurements are used in the output layer. The difference between current measurements and forecasted values is used in the feedback path of the BPNN. The forecasting procedure is shown in Figure 3.

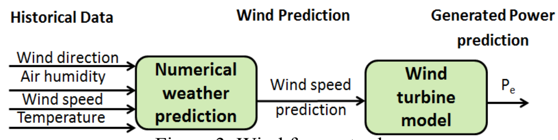

Figure 3. Wind forecast scheme.

B. Rome validation

Following the scheme proposed in previous section, Figure 4 depicts real and predicted values of the forecast obtained through the BPNN. The data obtained from the Rome meteorological centre have been used to train the network and the errors were recorded during a testing phase of 24 hours. During the training phase 5000 samples were used and the first 24 forecast values were utilized to compute the Mean Absolute Error (MAE). Results indicate that the error with BPNN is low (MAE of 23%) compared to other neural network models available in literature [14-15].

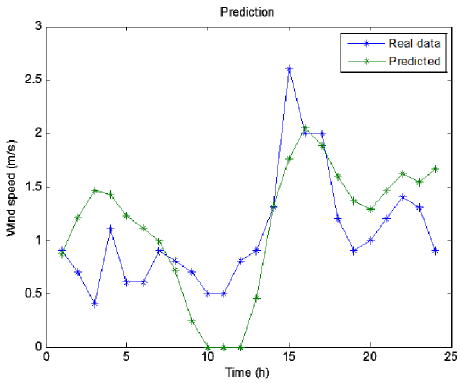

Figure 4. Wind speed forecast.

V. SOLAR GENERATION FORECAST

A. Data Procesing

Solar generation forecast stands for the use of historical measurements of weather, sun direction, scattering process, and photovoltaic (PV) cells to predict the future generation from the units. Solar forecasting methods are classified into three broad categories [22-27]: (i) now-casting, (ii) short-term forecasting and (iii) long-term forecasting. Now-casting stands for forecasting few hours ahead (3-6 hours in advance) and used in SG for control actions such as demand side management, peak-shaving, load balancing, optimal power flow and fault location, isolation and service restoration, among others. Short-term forecasting gives values of generation ranging from the next few days to one week and are used for generation planning, unit commitment, energy costs and in trading energy. Long-term forecasting refers to forecasts available for duration of months, or years and are used for long-term planning operations such as expansion planning, reactive power planning and planning future installations.

Solar generation forecast works in two steps: weather forecasting and PV power computation or estimation, as shown in Figure 4. Numerical weather prediction is not a trivial task and it is mostly used for estimating direction normal radiation [W/m^2], while the estimate of the solar radiation is used in PV panel simulators to estimate the energy generated [kWh].

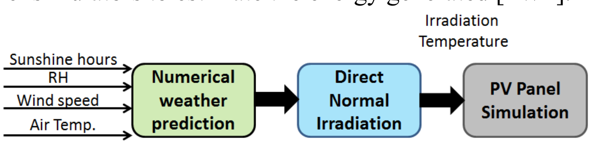

Figure 4. Solar forecast scheme.

B. Modeling

Three approaches for PV generation forecasting within I3RES have been implemented. Forecasting of PV generation is performed using:

1. Direct simulation using GHI forecast. In this method, the GHI data is obtained from the meteorological website such as the RENES [22] and then the PV model is used for simulation. Forecast obtained using this approach strongly depends on the GHI data. It can be concluded that when the provided information is precise, this method can generate good forecasts.

2. Model fitting time-series data. A time-series model can be fitted using the obtained data from the website and the PV panel generation information. This model can represent the PV generation based on different conditions. However, it is suitable only for small forecasts. Time-series change depending on the radiation, snow-cover, dust deposition, etc.

3. Computational intelligence based methods. Historical information on climate and GHI can be used to train an artificial neural network that can produce estimates based on current climate. In related literature, Radial Basis Function Networks have been commonly utilized for modelling solar generation. However, online estimation with RBF is not trivial. Moreover, the memory requirement is high due to higher number of hidden layer neurons.

The back propagation neural network (BPNN) was tested for solar forecasting with the given inputs. MSE of 7-8% was observed in estimating GSR with BPNN.

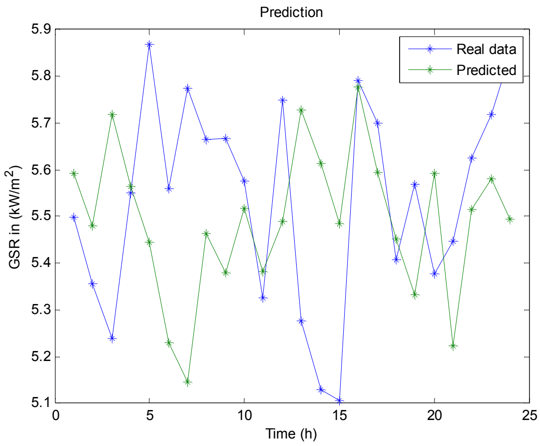

Figure 5. Real and Predicted data with BPNN

C. PV Panel Simulation

The second step in the PV generation forecast aims at simulating the energy generated from the PV panel. The single diode model shown in Figure 5 is the mostly prevalent model discussed in the literature and it has been used successfully also in this study.

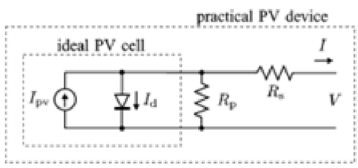

Figure 6. Single diode model of PV panel..

VI. CONCLUSIONS

DSM process has been carried out in I3RES among DSOs, Aggregators and customers in order to increase the introduction of RES sources in the grid, avoiding load peaks -minimizing failure risk in the grid operation- and contributing to a more active participation of the final user in the grid management. Prediction techniques and user classification are essential to react in advance to different grid situations. Furthermore, in the case of RES generation, prediction tools allow the reduction of uncertainty of this type of sources.

Regarding consumption forecast tasks comprised in the I3RES project, the tool has been designed to predict aggregated consumption at substation level in the grid of Demo Steinkjer (Norway). The feature selection process improved the prediction results, which means that a better understanding of the consumption patterns could be beneficial for the prediction. Thus, the regression methods implemented, totally tailored for the proposed scenario, in combination with the feature selection and data cleansing process, showed being able to obtain accurate energy consumptions 24 hour-ahead predictions.

As far as RES forecast is concerned, the prediction is conditioned by the error of the weather forecast provided by a meteorological agent, and by the orography of the RES location. The only way to improve it is by the use of a machine learning approach (e.g., neural networks) which can adapt the coarser prediction to the local conditions where the RES is installed. This also facilitates the generalization of the prediction tool without adapting the algorithm to the specific conditions of the RES unit.

The validation process demonstrated that the obtained results fulfill the purpose of the project. However, these tools should be completely installed and further validated in both real environments: the industrial one in Demo Steinkjer (Norway) and the lab one in Tecnalia Microgrid Laboratory.

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REFERENCES

[1] Managing big data for smart grids and smart meters. IBM white paper. http://www935.ibm.com/services/multimedia/Managing_big_data_for_smart_grids_and_smart_meters, May 2012.

[2] CRISP- DM methodology. http://the-modeling-agency.com/crisp-dm

[3] Phua, C. Alhakoon, D. and Lee, V (2004). Minority report in fraud detection: classification of skewed data. ACM SIGKDD Explorations Newsletter. Vol. 6 . p150 - 159

[4] Duda, R.O., Hart, P.E., and Stork D.G (2001) Pattern classification. John Wiley and Sons, New York, NY.

[5] Safewind project: http://www.safewind.eu/

[6] Use of time-series analysis to model and forecast wind speed; *Z. Huang, Z.S. Chalab.*

[7] Improvements in wind speed forecasts for wind power prediction purposes using Kalman filtering; P. Loukaa, b, G. Galanisa, c, N. Siebertd, G. Kariniotakisd, P. Katsafadosa, I. Pytharoulisa, b, G. Kallosa.

[8] Short Term Wind Speed Predictions by Using the Grey Prediction Model Based Forecast Method; *Chi-Yo Huang, Yu-Wei Liu ; Wei-Chang Tzeng , Po-Yen Wang;* Green Technologies Conference (IEEE-Green), 2011 IEEE.

[9] Exploiting maximum energy from variable speed wind power generation systems by using an adaptive Takagi–Sugeno–Kang fuzzy model; *V. Galdi , A. Piccolo , P. Siano.*

[10] Hilbert Transform-Based Bearing Failure Detection in DFIG-Based Wind Turbines; *Yassine Amirat , Vincent Choqueuse , Mohamed Benbouzid , Sylvie Turri.*

[11] Adaptive modelling and forecasting of offshore wind power fluctuations with Markov-switching autoregressive models; *Pierre Pinson,Henrik Madsen.*

[12] ARIMA-Based Time Series Model of Stochastic Wind Power Generation; Peiyuan Chen ; Dept. of Energy Technol., Aalborg Univ., Aalborg, Denmark ; Pedersen, T. ; Bak-Jensen, B. ; Zhe Chen.

[13] Wind Power Forecasting Based on Time Series and Neural Network; *Lingling Li, Minghui Wang , Fenfen Zhu, Chengshan Wang.*

[14] Wind Power Plant Prediction by Using Neural Networks; Ziqiao Liu, Student Member, IEEE, Wenzhong Gao, Senior Member, IEEE, Yih-Huei Wan, Senior Member, IEEE, Eduard Muljadi, Fellow, IEEE.

[15] ANNSTLF-Artificial Neural Network Short-Term Load Forecaster generation three; *Khotanzad, A. Afkhami-Rohani, R. ; Maratukulam, D. ;* Power Systems, IEEE Transactions on (Volume:13 , Issue: 4)

[16] Wind power forecasting using advanced neural networks models; *Kariniotakis, G.N. , Stavrakakis, G.S. , Nogaret, E.F.;* Energy Conversion, IEEE Transactions on (Volume:11 , Issue: 4)

[17] Wind Farm Power Prediction: A Data-Mining Approach; *A. Kusiak, H.-Y. Zheng, and Z. Song* ; Wind Energy, vol. 12, no. 3, pp. 275–293, 2009;

[18] Short-Term Prediction of Wind Farm Power: A Data Mining Approach; *Kusiak, A. , Haiyang Zheng ; Zhe Song*; Energy Conversion, IEEE Transactions on (Volume:24 , Issue: 1).

[19] A comparison of various forecasting techniques applied to mean hourly wind speed time series, *Thanasis Sfetsos.*

[20] Bayesian adaptive combination of short-term wind speed forecasts from neural network models; *Gong Li, Jing Shi, , Junyi Zhou.*

[21] DELIVERABLE D-1.2 The State-Of-The-Art in Short-Term Prediction of Wind Power, *ANEMOS.plus project.*

[22] http://www.intelligence.tuc.gr/renes/

[23] Villalva, M. G., & Gazoli, J. R. (2009). Comprehensive approach to modeling and simulation of photovoltaic arrays. Power Electronics, IEEE Transactions on,24(5), 1198-1208.

[24] Yingwei, L., Sundararajan, N., & Saratchandran, P. (1997). A sequential learning scheme for function approximation using minimal radial basis function neural networks. Neural computation, 9(2), 461-478.

[25] Platt, John. "A resource-allocating network for function interpolation." Neural computation 3.2 (1991), pp. 213-225.

Kadirkamanathan, Visakan, and Mahesan Niranjan. "A function estimation approach to sequential learning with neural networks." Neural Computation 5.6 (1993), pp. 954-975.