ANN-based Scenario Generation Methodology for Stochastic Variables of Electric Power Systems

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Abstract

In this paper a novel scenario generation methodology based on artificial neural networks (ANNs) is proposed. The methodology is flexible and able to generate scenarios for various stochastic variables that are used as input parameters in the stochastic short-term scheduling models. Appropriate techniques for modeling the cross-correlation of the involved stochastic processes and scenario reduction techniques are also incorporated into the proposed approach. The applicability of the methodology is investigated through the creation of electric load, photovoltaic (PV) and wind production scenarios and the performance of the proposed ANN-based methodology is compared to time series-based scenario generation models. Test results on the real-world insular power system of Crete and mainland Greece present the effectiveness of the proposed ANN-based scenario generation methodology.

Keywords: Artificial neural networks, load forecasting, photovoltaic generation, scenario generation, wind production.

1. Introduction

The development of sustainable energy systems based on reduced fossil fuel emissions, improved energy efficiency and increased renewable energy sources (RES) penetration is a leading priority of the energy roadmaps in many countries worldwide [1], [2]. However, the promotion of sustainability in power systems should take into account the inherent characteristic of uncertainty, which poses difficulties in predicting the exact values of many random variables that influence the power system operation in different time scales (long-term, short-term, real-time). For instance, the electric load, the generation unit availability and the RES production (characterized by high variability and uncertainty) are stochastic variables that have a strong impact on the secure, reliable and efficient power system operation and management. The great value for predicting these variables led to the development of appropriate forecasting tools that in some cases can be very accurate (e.g. hourly load forecasting for large regions).

Popular forecasting methods include ARMA models [3] that are used for stationary time series, ARIMA models for non-stationary processes, SARIMA models that capture seasonal patterns of the time series and ARMAX models that include input terms related to exogenous parameters [4]. Another forecasting approach includes probabilistic methods based on probability density functions (PDFs) [5]. Finally, another popular approach that is able to capture both linear and non-linear dependencies and has been widely used in power systems engineering and other sciences comprises the Artificial Neural Networks (ANN). Relevant bibliography dealing with the design and use of ANNs for load, photovoltaic (PV) and wind generation forecasting can be found in references [6]-[8].

In many cases, and especially in power systems with a large share of variable RES production, typical deterministic scheduling procedures based on point forecasts are not adequate. A point forecast represents an estimation, a single summary statistics, for the examined random variable [9]. However, the probability that this event occurs in clearly close to zero, since a point forecast is always subject to an error. Therefore, stochastic approaches have been adopted lately using multiple scenarios as inputs that account for possible realizations of the random variable and not just the most likely outcome. Through the stochastic approaches more robust solutions are expected compared to the deterministic approaches based solely on the point forecast, since more information regarding the uncertainty of the random variable in incorporated in the optimization problem. However, the challenge of creating reliable scenario sets it is not an easy task. The effects of stochastic wind and load on the unit commitment and economic dispatch problems with high levels of wind power are investigated in [9], where it is shown that stochastic optimization results in better performing schedules than the deterministic optimization. A two-stage stochastic programming model for committing reserves in systems with large amounts of wind power is presented in [11], where the proposed model outperforms common deterministic rules for reserve quantification. Finally, the solution of the unit commitment problem under a two-stage stochastic programming formulation is investigated in [12] considering the effects of generation availability and load uncertainty.

For these approaches that require the presence of a scenario set, various methodologies have been proposed in the literature for the generation of a representative set of scenarios for random variables. A popular scenario generation technique is the moment matching method that was used in [13] to generate a limited number of scenarios that satisfy specified statistical properties. The basic idea is to minimize some measure of distance between the statistical properties of the generated outcomes and the specified properties. The same authors in [14] presented an algorithm that produces a discrete joint distribution consistent with specified values of the first four marginal moments and correlations. The joint distribution is constructed by decomposing the multivariate problem into univariate ones and using an iterative procedure to achieve the correct correlations without changing the marginal moments. An approach that relies on the moment-matching technique was proposed in [15].

The approach was based on the idea of integrating simulation and optimization techniques. In particular, simulation is used to generate outcomes associated with the nodes of the scenario tree, which, in turn, provide the input variables for an optimization model that aims at determining the scenarios' probabilities matching some prescribed targets. An algorithm based on heteroskedastic models and a moment matching approach to construct a scenario tree that is a calibrated representation of the randomness in risky asset returns was presented in [16].

Another widely used scenario generation technique is the path-based method [17]. This method evolves the stochastic process to generate complete paths in a 'fan' structure, which is transformed into a scenario tree using "clustering", also called "bucketing".

An optimization-based method to generate moment matching scenarios for numerical integration and how it can be used in stochastic programming has been proposed in [18]. The main advantage of the method is its flexibility: it can generate scenarios matching any prescribed set of moments of the underlying distribution rather than matching all moments up to a certain order, and the distribution can be defined over an arbitrary set. In the same framework, three approaches for generating scenario trees for financial portfolio problems have been presented in [19]. These are based on simulation, optimization and hybrid simulation/optimization. Finally, an optimal discretization method that seeks to find an approximation of the initial scenario set that minimizes an error based on the objective function was described in [20].

Other scenario generation methods can be found in papers that deal with wind power uncertainty. A method that allows for the generation of statistical scenarios from non-parametric probabilistic forecasts is described in [9], while a first-order autoregressive time-series model with an increasing noise to approximate the behavior of wind speed forecast errors is presented in [21]. This model allows for the creation of a large number of wind speed scenarios using Monte Carlo simulations, which are then transformed into wind power scenarios with the use of an aggregated power curve model. In addition, simple scenarios around point forecasts are generated in [22] for the optimal scheduling of the generators in a wind integrated power system considering the demand and wind power production uncertainty. Finally, a new scenario generation methodology that adopts the empirical distributions of a number of forecast bins to model the forecast error of wind power, which are used as inputs to scenario generation, is proposed in [23].

This paper proposes a novel scenario generation methodology suitable to account for various stochastic variables commonly used in power system studies (e.g. electric load, PV and wind production). The proposed technique combines ANNs that are able to capture the linear or non-linear dependencies of the time series under consideration with its historical values, as well as with exogenous variables (e.g. ambient temperature, wind speed, solar radiation, etc.), with an iterative process based on the assimilation of randomly generated uncorrelated error terms with specific statistical properties to the ANN outputs. Actually, the methodology presented in this paper is an extension of the methodology proposed in [25] that includes time series analysis to create scenarios. The extension of the methodology takes advantage of the easy modeling of time stamping, which generally presents correlations with the underlying variables, and the easy incorporation of exogenous inputs in the ANN-based scenario generation application. These features are very useful in creating more representative and well-defined sets of scenarios, further analyzed in the following through the comparison of the proposed approach with two relevant scenario generation approaches.

The remainder of the paper is organized as follows: Section 2 describes in detail the proposed scenario generation methodology, which is extended to account for cross-correlated stochastic processes and scenario reduction techniques. Section 3 presents results from the application of the proposed methodology for the creation of scenarios of electric load, PV and wind production. In Section 4 the performance of the proposed methodology is compared with two relevant scenario generation approaches, while in Section 5 the value of the proposed method for the optimal participation of a PV agent in day-ahead electricity market with respect to the other two scenario generation approaches is investigated. Finally, valuable conclusions are drawn in Section 6.

2. Methodology

2.1 Forecasting with ANNs

Neural Networks (NNs) may be seen as multivariate, nonlinear and nonparametric methods, and they could be expected to model complex nonlinear relationships much better than the traditional linear models [24]. Given a proper set of explanatory variables for a single stochastic variable, the NN is trained in order to capture the nonlinear dependency between the inputs and the respective output. Therefore, NNs can be seen as a "black-box", however a good engineering judgment is necessary for a successful NN setup (layers and neurons selection, explanatory variable selection, etc.). In contrast to traditional linear models, NNs are very flexible in integrating time stamping inputs, such as the hour-of-day, day-of-year, etc. Many stochastic processes are highly related to time stamping information and this is a valuable advantage of NNs.

A detailed analysis on ANN training properties and parameterization practices can be found in [24]. The ANN structure used in this paper includes a multi-input/single output design (one step-ahead forecasting) with three layers (one input, one output and one hidden layer) and feed-forward design (i.e. the outputs of one layer are used as inputs to the following layer). In general, the estimation of parameters (weights) is performed by minimizing a loss function (usually a quadratic function of the output error is used). For the parameters estimation, a back-propagation algorithm which uses a steepest-descent technique based on the computation of the gradient of the loss function with respect to the network parameters is used in this paper. Finally, the hyperbolic sigmoid function in the interval [-1 1] is used as the activation function.

The ANN inputs selection is based on experience and engineering judgment. For the stochastic variables under study in this paper, there is considerable experience on the selection of appropriate explanatory variables. In the examined case study we have selected the explanatory variables and historical values based on both engineering judgment and trial and error in order to achieve uncorrelated error time series during the training process, further analyzed in the following. In detail, the ANN inputs are: a) historical values of the time series of interest, b) one or more exogenous input parameters correlated to the time series of interest and c) appropriate time indices. Time indexing inputs are introduced in the ANN as a pair of variables, $\sin\left(2\pi k/T\right)$, $\cos\left(2\pi k/T\right)$, where T is the period of the respective time index, k (e.g. $T = 24$ for Hour-Of-the-Day (HOD), $T = 7$ for Day-Of-the-Week (DOW) or $T = 365$ for Day-Of-the-Year (DOY)) [6]. Time indexing inputs are important to model seasonality effects related to HOD, DOY and DOW. A generic description of the ANN inputs and output is given in Table 1.

During the training stage the ANN is presented with a sequence of historical input - desired output pairs. Its internal parameters (weights) are adjusted so that the "training error" is minimized.

Once the training stage is completed and the ANN weights have been adjusted, the recall stage begins, in which the trained ANN is used for actual forecasting. For one step-ahead forecasting the ANN runs only once. For two or more steps-ahead forecasting, an iterative application of the one step-ahead forecasting ANN is necessary. In each new iteration the time indexing inputs are updated accordingly and non-available input variables (related to either the time series being forecasted or the exogenous parameters) are replaced by the corresponding forecasts obtained so far. With the iterative application of the one step-ahead forecasting ANN (rolling update of the ANN inputs) the forecast horizon can be extended to any desired number of time steps in the future.

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2.2 Scenario Generation with ANNs

The scenario generation methodology using ANN is illustrated in Fig. 1 for three time steps ahead.

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Once the training of the ANN is completed, the time series of the residuals (errors) of the training phase is calculated as the difference between the forecasted values (using the trained ANN) and the historical values (real measurements). A statistical analysis of the time series of the residuals investigates whether the time series could be considered a Gaussian white noise signal, i.e. it has almost zero autocorrelation coefficients for all time delays other than zero and the error distribution can be approximated by a normal distribution with zero mean and standard deviation σ (i.e. $N(0,\sigma)$).

As already mentioned, the procedure to generate a set of scenarios for a stochastic process $\boldsymbol{Y}$ (e.g. electric load, PV or wind production) comprises an iterative process based on random generation of Gaussian white noise. These error terms follow the approximated distribution of the time series of the residuals derived during the training phase. Based on this logic [25], an appropriate algorithm is proposed to generate a set of scenarios using ANNs, described as follows:

As illustrated in Fig. 1, time indexing (HOD, DOW, DOY) is specified as an input to the ANN in each stage, exactly as described in the training and the recall phase. For the first step ahead forecast (t), the input vector comprises of: the previous n recorded (real) values of the time series $\{x_{t-1}, x_{t-n}\}$ (dark blue color), the forecast value of any exogenous input $\hat{y}_t$ for the first step ahead (orange color) and possibly previous m recorded (real) values of the same exogenous inputs $\{y_{t-1}, y_{t-m}\}$ (green color). The first step ahead ANN output ($\hat{x}_t$) is distorted by the normal distributed error term and yields an input for the two steps ahead forecast $t+1$ ($\tilde{x}_t$) (light blue color), along with the $n-1$ previous recorded values of the time series $\{x_{t-1}, x_{(t+1)-n}\}$ (dark blue color), the forecasted values of any exogenous inputs $\{\hat{y}_t, \hat{y}_{t+1}\}$ (orange color) for the first two steps and possibly previous $m-1$ recorded values of the same exogenous inputs $\{y_{t-1}, y_{(t+1)-m}\}$ (green color).

In each iteration (time step), the total number of inputs remains intact. However, as the algorithm moves forward in time, the recorded (real) values used as input in the first steps are gradually replaced by the outputs of the ANN of the previous steps (distorted forecasted values) and the forecasted values of the exogenous inputs accordingly. The input shifting is illustrated in Fig. 1.

The above process is repeated until the desired scenario generation horizon is reached. The entire process is also repeated as many times as the desired number of scenarios. Due to the random generation of error values, a different path is created in each iteration. However, all paths follow the statistical properties of the initial error time series.

The algorithm is also presented step-by-step in Fig. 2, where N_T denotes the desired number of forecast periods (steps) and N_Ω denotes the desired number of scenarios.

2.3 Scenario Generation for Cross-Correlated Stochastic Processes

The management of the power systems with high renewable penetration involves many stochastic processes that are statistically dependent. For instance, the energy injection from adjacent wind farms or PV stations frequently follows similar patterns. Modeling this statistical correlation is crucial for the System Operator who is responsible for the scheduling and the real-time operation of the power system. In this paper, the procedure presented in [25] is embedded in the proposed ANN-based scenario generation methodology for the creation of spatially and temporally cross-correlated scenarios regarding the energy injection from neighboring RES plants.

In this context, in case that two stochastic processes $\boldsymbol{Y_a}$ and $\boldsymbol{Y_b}$ are statistically dependent, the dependency is transferred to the series of residuals $\boldsymbol{\varepsilon_a}$ and $\boldsymbol{\varepsilon_b}$ and, therefore, $\boldsymbol{\varepsilon_a}$ and $\boldsymbol{\varepsilon_b}$ should be cross-correlated.

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In order to determine the degree of dependency of the series of the residuals, a cross-correlogram that represents the cross-correlation coefficients for different time lags can be derived [1]. According to the shape of the residual cross-correlogram, three different types of dependent stochastic processes can be distinguished, namely contemporaneous, quasi-contemporaneous and non-contemporaneous stochastic processes. For further details on the distinction and the features of cross-correlated stochastic processes the interested reader can refer to [25].

In general, a variance-covariance matrix $\boldsymbol{G}$ can be used to identify the cross-correlations between $\boldsymbol{\varepsilon_a}$ and $\boldsymbol{\varepsilon_b}$. This matrix is symmetric by definition, and, therefore, can always be diagonalized. In other words, an orthogonal transformation can be used to model such series of errors, as follows:

$$\boldsymbol{\varepsilon} = \begin{pmatrix} \boldsymbol{\varepsilon}^{\boldsymbol{\alpha}} \\ \boldsymbol{\varepsilon}^{\boldsymbol{b}} \end{pmatrix} = \boldsymbol{B} \cdot \boldsymbol{\xi} = \boldsymbol{B} \cdot \begin{pmatrix} \boldsymbol{\xi}^{\boldsymbol{\alpha}} \\ \boldsymbol{\xi}^{\boldsymbol{b}} \end{pmatrix} \qquad (1)$$

In this context, white noise (independent standard normal errors ξ) can be generated, and then, cross-correlated according to the variance-covariance matrix $\boldsymbol{G}$ using the orthogonal transformation. In most engineering applications, matrix $\boldsymbol{G}$ besides being symmetric is also positive definite and as such can be decomposed through the computationally advantageous Cholesky decomposition, which avoids the calculation of eigenvalues and eigenvectors. The Cholesky decomposition can be stated as:

$$\boldsymbol{G} = \boldsymbol{B} \cdot \boldsymbol{B}^{\boldsymbol{T}} \qquad (2)$$

where $\boldsymbol{B}$ is an inferior triangular matrix that turns out to be the orthogonal matrix required for transformation (1).

The analytical description of the scenario generation methodology for cross-correlated stochastic processes is outside the scope of this paper and the interested reader can refer to [25] for further details. Indicative results from the incorporation of the aforementioned methodology into the proposed ANN-based scenario generation algorithm presented in Section 2.2 are given in Section 3.

2.4 Scenario Reduction Technique

More than often, the computational performance of stochastic programming optimization models is highly dependent on the size of the scenario set. For this reason, a compromise between the necessary number of scenarios and the computational burden of the associated stochastic programming model needs to be made, so that the problem can be solved using acceptable computational resources. For this purpose, scenario reduction techniques are usually applied. Various scenario reduction techniques have been reported in the literature so far.

The scenario reduction methodology adopted in this paper is based on the concept of the probability distance [25]. In general, the probability distance allows for quantifying how "close" two different sets of scenarios representing the same stochastic process are. In this context, if a large scenario set is close enough to a reduced one in terms of the probability distance, the optimal solution of the simpler problem (which is formulated and solved using the reduced set of scenarios) is expected to be close to the optimal value of the original problem (which is formulated and solved with the extended set of scenarios). An overview of the theoretical background underlying the concept of probability distance is thoroughly presented in [26], while its application to scenario reduction is discussed in detail in [27]. In this paper, the scenario reduction methodology based on the probability distance criterion is used to effectively reduce the initially extended number of scenarios created by the proposed ANN-based scenario generation methodology.

3. Case Study

In this section, the application of the ANN-based scenario generation methodology for three distinct stochastic variables, namely electric load, PV and wind production, is analytically presented. The implementation took place for the system load of the real-world insular power system of Crete, Greece, for spatially close real-life wind farms located in Crete and for adjacent PV plants located in mainland Greece. In each one of the three cases, different number of scenarios and scenario reduction techniques (cross-correlated or not) are applied on purpose, in order to highlight the flexibility of the proposed methodology. It is noted that, when used below, the application of the cross-correlated scenario generation algorithm is limited for scenarios of the same stochastic variable. The method can be extended to create cross-correlated scenarios for the three stochastic variables simultaneously; however, this extension is not included in the paper since it does not actually affect the philosophy of the proposed method.

3.1 Scenario Generation for System Load

In order to create scenarios for the system load of Crete, the ANN was trained with: a) the hourly load time series and b) the maximum and minimum daily temperature of the insular power system of Crete, Greece, of the years 2011 and 2012. The recall stage took place for the year 2013. The hourly load time series (real measurements) for the three-year period (2011-2013) is presented in Fig. 3.

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There are many combinations of time lags that can lead to a successful training. After extensive testing, 29 time lags were chosen, extended back to one week prior to the forecast hour. All ANN inputs are presented in Table 2. The maximum and minimum daily temperatures in Heraklion Crete were also used as ANN exogenous inputs. The time series of the residuals derived from the 1-hour ahead training for the years 2011-2012 is presented in Fig. 4, while the autocorrelation diagram of the same time series is presented in Fig. 5.

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It is obvious that the autocorrelation coefficients beyond the zero lag are negligible. In Fig.

6 the histogram of the residual time series is illustrated, which is approximated by a normal distribution with zero mean and standard deviation $\sigma = 4.83$ MW.

As described above, the scenario generation methodology can be extended up to many steps ahead, provided that forecasts of the exogenous inputs are available up to the desired horizon. In Fig.7, the proposed methodology is used to create 100 scenarios for five days ahead with hourly discretization, beginning on Friday, 10th of May 2013. The real and forecasted system load values are also presented. In addition, 1000 scenarios for 24-hours ahead are created for the 18th of July 2013 and shown in Fig. 8. The 1000 initially created equiprobable scenarios are then reduced to 5 scenarios (reduced set) using the scenario reduction methodology outlined in Section 2. The final set of scenarios along with their correspondent probabilities is presented in Fig. 9.

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3.2 Scenario Generation for PV production

The proposed ANN-based scenario generation methodology is also used to create scenarios for PV production. In general, PV production is usually highly correlated between adjacent PV stations. Therefore, the proposed methodology was applied for the creation of cross-correlated scenarios for the electricity production of two PV stations located in the adjacent prefectures of Attica and Viotia in central mainland Greece. The installed capacity of the PV stations is 0.15 MW and 1 MW, respectively. After numerous tests, 11 time lags were chosen. In addition, exogenous factors were also used to improve both the ANN training and the scenario generation procedure. During the training phase, irradiation measurements were used and during the scenario generation, irradiation forecasts were used as exogenous inputs. All inputs of the related ANN are presented in Table 3.

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The training phase includes the period Jan-2011 to Jul-2012. Results are presented for a single day of August 2012. The scenario generation procedure comprises the generation of an initial set of 50 cross-correlated scenarios (original set) that was finally reduced to a set of 20 scenarios per PV station (reduced set). For the reader's convenience, in all figures the PV production is normalized with the installed capacity of each PV station and, therefore, per unit (p.u.) values are used.

Fig. 10 illustrates the original sets of 50 cross-correlated scenarios for each PV station. Both sets were created according to the methodology described in Section 2 It is noted that the initial 50 scenarios are equiprobable, and therefore, each pair of cross-correlated scenarios of the two PV stations is assigned a probability of 1/50=0.02.

Once the initial sets of scenarios are generated, the scenario reduction technique already described in Section 2 is applied, keeping the stochastic information contained in the extreme scenarios of each PV station intact. The extreme scenarios are defined as those scenarios where the maximum daily production has the maximum and the minimum value, respectively, among all scenarios. These scenarios, despite their low probability of occurrence, can have a significant impact on the short-term scheduling of the power system. In order to maintain this information, the extreme scenarios of each PV station are excluded from the scenario reduction procedure that follows. In Fig. 10 the extreme scenarios of each PV station are illustrated in bold line along with an associated marker (Red: Attica, Blue: Viotia).

Given that the scenarios for the two PV stations have been generated with the aforementioned cross-correlation procedure, for each scenario that is selected for each PV station, the corresponding cross-correlated scenario of the other PV station is also selected, in order to be excluded from the scenario reduction procedure. In Fig. 11, the four scenarios that have been selected as extreme ones and are excluded from the scenario reduction process are presented. In this way, the modified initial set of scenarios, in which the scenario reduction process applies, is determined and presented in Fig. 12. These sets include 50 – 4 = 46 scenarios each.

The implementation of the scenario reduction algorithm on the modified initial sets of scenarios results in the reduced scenario sets that comprise 16 scenarios for each PV station. The reduced scenario sets are presented in Fig. 13, where a color scale from red to yellow is used to denote scenarios with higher to lower probability, accordingly. The final sets of scenarios comprising 20 scenarios per PV station are illustrated in Fig. 14. It is evident that the final sets result from the composition of the reduced sets (16 scenarios per PV station) and the 4 extreme scenarios initially selected.

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3.3 Scenario Generation for Wind Power Production

Following the same logic with the PV scenario generation, indicative results from the process of creating cross-correlated scenarios for the electricity production of four wind farms, namely Aiolos, Rokas, Honos Iweco and Rokas-Modi, located in the prefecture of Lasithi, Crete, are presented next. Their installed capacity is 10 MW, 12.90 MW, 4.50 MW and 4.80 MW, respectively. The related ANN inputs are presented in Table 4.

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The scenario generation process follows the same steps with the previous case. Once the initial sets of 50 scenarios are generated, the extreme scenarios are extracted, which now are defined as those scenarios where the maximum daily wind power production (in MWh) has the maximum and the minimum value, respectively, among all scenarios. The modified initial sets of scenarios, in which the scenario reduction process applies, is determined and presented in Fig. 15. These sets include 50 (initial scenarios) - 8 (extreme scenarios) = 42 scenarios each. The implementation of the scenario reduction algorithm on the modified initial sets of scenarios results in the reduced scenario sets that comprise 12 scenarios for each wind farm. The final sets of 20 scenarios composed of the reduced sets and the extreme scenarios initially selected are presented in Fig. 16.

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4. Performance Evaluation

To evaluate the performance of the proposed ANN-based scenario generation approach against previous approaches, a fair comparison between the proposed model and two other time series-based scenario generation models is performed. The comparison is carried out for the photovoltaic generation case. The first rival approach adopts the methodology presented in [25] and is based on a SARIMA time series model. The second rival approach, entitled adjusted SARIMA, is primarily based on the SARIMA time series model, but is further adjusted by a scaling factor that expresses an estimated modification on the results of the initial model, based on the information of the short-term solar irradiation forecast. Since the adjusted SARIMA approach takes into consideration an important exogenous factor, it is expected to perform better than the pure SARIMA model. The scaling factor, by which the forecasts created by the SARIMA model are adjusted, is presented in [28]. In the present work, the same scaling factor is used to adjust the scenarios created by the SARIMA model.

The three models were trained with the same photovoltaic generation data from the Attiki PV plant from 1/1/2011 to 31/6/2012. The lag terms for the SARIMA and the adjusted SARIMA models are those presented in [28]. The trained models are then tested for the entire February 2013. To this context, 28 executions are carried out, one for each day, starting at 00:00 for the 24 hours-ahead horizon. For each of the three models and for each daily execution, three distinct data sets are created: a) the 24-hour ahead forecast time series, b) 1000 equiprobable 24 hours-ahead scenarios and c) 5 final 24 hours-ahead scenarios, which are created by applying the scenario reduction algorithm on the extended scenario set. In particular, the 1000 equiprobable scenarios are reduced to 5 scenarios with their associated probabilities, which also calculated based on the algorithm briefly explained in this paper and thoroughly described in [25].

Three metrics are then used to evaluate the performance of the three scenario generation approaches. All metrics are based on the Normalized-Root-Mean-Square-Error (NRMSE) metric, and are as follows:

A) Monthly NRMSE calculation between the photovoltaic generation forecast and the photovoltaic generation measurement. This metric is suitable to compare the forecasting performance of the three approaches.

B) Monthly NRMSE calculation between each one of the 1000 initially created scenarios and the photovoltaic generation measurement. Subsequently, the mean and standard deviation of the 1000 monthly NRMSEs is calculated in order to compare the performance of the three scenario generation approaches using the different models.

C) Monthly NRMSE calculation between the dominant scenario (scenario with the highest probability) after the scenario reduction application and the photovoltaic generation measurement. This metric is suitable to compare the scenario reduction performance of the three approaches.

In all cases the NRMSE calculation considers only the daylight hours. The results are presented in Tables 5-7.

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The above detailed comparison tests clearly demonstrate that in all cases: a) the ANN model is superior in terms of forecasting and scenario generation accuracy with respect to the other two models and b) the adjusted SARIMA model performs better than the pure SARIMA model.

5. Applicability of scenario generation methodologies

In this section the practical applicability of the proposed ANN-based scenario generation methodology is evaluated and compared to the two time series-based scenario generation methodologies already described in the previous section. A simple stochastic optimization model is formulated for the development of the optimal bidding strategy of a PV agent, who is assumed to participate in a day-ahead electricity market aiming at the maximization of his profit. In this context, the added value of using the three scenario generation methodologies is compared and discussed.

It is assumed that the PV plant described in the previous section participates in the day-ahead electricity market through a market agent, named "PV agent". Although most of current electricity markets have fixed regulated tariffs for the remuneration of RES energy injection, there is a long debate among stakeholders and authorities whether RES should actively participate in the electricity market auctions, as conventional generating units do. In this case study, it is considered that RES agents participate in the day-ahead electricity market by submitting injection offers, for each hour of the next day, in the form of quantity (MWh) – price (€/MWh) pairs. In this framework, the PV agent focuses on the development of an optimal bidding strategy aiming at the maximization of his profits. Due to the small size of the PV plant, the PV agent is assumed to act as price-taker that cannot affect the energy market clearing prices, and therefore, he submits energy quantity offers (MWh) at zero price. Once the submission period closes, the Market Operator clears the market and announces the hourly energy prices for the next day (day-ahead clearing prices).

During the real-time operation the generating entities must buy (sell) any shortfall (excess) of energy with respect to the day-ahead cleared quantities from (to) the balancing market. This market comprises the activation of balancing energy from Balancing Service Providers

(BSPs), which are nominated to offer balancing services, in order to offset the energy imbalances of the Balancing Responsible Parties (BRPs). In this case the PV agent is considered as a BRP, who is charged for any negative imbalance (real-time production lower than the day-ahead cleared quantity) and is remunerated for any positive imbalance (real-time production greater than the day-ahead quantity) during the RT operation. The payment or remuneration mechanism is dependent on the specific imbalance settlement. There are various imbalance settlement rules in different real-world electricity markets [29]. However, in this paper the market settlement is kept simple on purpose, in order to focus on the comparison between the different scenario generation approaches. Two price trajectories are considered, one for positive BRP imbalances and one for negative BRP imbalances.

The basic problem of the PV agent is to calculate the optimal offer quantities (MWh) to submit in the day-ahead market. A two-stage stochastic linear optimization problem is solved for this purpose. The PV agent creates scenarios for the estimated real-time PV production and based on these scenarios, along with the expected day-ahead and positive and negative BRP's imbalance prices, the optimal day-ahead hourly offers are calculated. The hourly day-ahead clearing prices and the hourly imbalance prices have been obtained from the EPEXSPOT website for France [30], and the RTE France website [31], respectively. Perfect knowledge is considered for all day-ahead and imbalance clearing prices, in order to focus solely on the photovoltaic generation uncertainty and the performance of the scenario generation methods. Since EPEXSPOT offer submission period for the reference day (day D) closes near 12:00 AM of the previous day (day D-1), in this study the scenarios were created at 12:00 for 36 hours-ahead (12 hours of day D-1 and 24 hours of day D). It is noted that only the PV production values for the 24 hours of day D are used as input to the PV plant optimal offering strategy problem.

The optimal offering strategy of the PV agent is formulated as a two-stage stochastic linear optimization problem, as follows:

Maximize

$$\sum_t e_t^{DA} \cdot P_t^{DA} + \sum_{t,s} p_s \cdot de_{t,s}^{pos} \cdot P_t^{Imb,pos} - \sum_{t,s} p_s \cdot de_{t,s}^{neg} \cdot P_t^{Imb,neg} \qquad (3)$$

Subject to:

$$de_{t,s} = E_{t,s}^{RT} - e_t^{DA} \qquad \forall t,s \qquad (4)$$

$$de_{t,s} = de_{t,s}^{pos} - de_{t,s}^{neg} \qquad \forall t,s \qquad (5)$$

$$e_t^{DA} \le PV^{rtd} \qquad \forall t \qquad (6)$$

where the symbols used are defined in the following:

Indices

t index of hourly time intervals

s index of scenarios

Parameters

P_t^{DA} day-ahead energy price, in €/MWh

$P_t^{Imb,pos}$ imbalance price for positive BRP imbalances, in €/MWh

$P_t^{Imb,neg}$ imbalance price for negative BRP imbalances, in €/MWh

$E_{t,s}^{RT}$ real-time photovoltaic generation for time t and scenario s, in MWh

p_s probability of scenario s

PV^{rtd} rated power of the photovoltaic park, in MWp

E_t^{Meas} measured photovoltaic generation, in MWh

Variables

e_t^{DA} day-ahead energy offer, in MWh

$de_{t,s}$ BRP energy imbalance, in MWh

$de_{t,s}^{pos}$ BRP positive energy imbalance, in MWh, positive variable

$de_{t,s}^{neg}$ BRP negative energy imbalance, in MWh, positive variable

In the above problem, the main decision variables are the first-stage variables, e_t^{DA}. Once the day-ahead quantities e_t^{DA} are calculated, the actual PV agent profit can then be calculated, based on the real PV production measurements. For the calculation of the hourly energy imbalances a new hourly parameter DE_t is defined, further distinguished in DE_t^{pos} for actual positive imbalances and DE_t^{neg} for actual negative imbalances. The three hourly parameters are defined by constraints (7)-(9), as follows:

$$DE_t = E_t^{Meas} - e_t^{DA} \qquad \forall t \qquad (7)$$

$$\text{If } DE_t \geq 0 \text{ then } DE_t^{pos} = DE_t \qquad \forall t \qquad (8)$$

$$\text{If } DE_t \leq 0 \text{ then } DE_t^{neg} = -DE_t \qquad \forall t \qquad (9)$$

Finally, the actual PV agent profit, including the actual hourly imbalances is calculated by (10):

$$Profit = \sum_t e_t^{DA} \cdot P_t^{DA} + \sum_t DE_t^{pos} \cdot P_t^{Imb,pos} - \sum_t DE_t^{neg} \cdot P_t^{Imb,neg} \qquad (10)$$

Three models, namely the proposed ANN-based model, the SARIMA-based and the adjusted SARIMA-based model, already described in the previous section, are used to create three data sets, namely as follows: a) a 36 hour-ahead forecast time series, b) 1000 equiprobable 36 hour-ahead scenarios and c) 5 final 36 hour-ahead scenarios which are created by applying the scenario reduction algorithm on the extended scenario set.

The three data sets are used as scenario sets modeling the real-time PV production uncertainty, $E_{t,s}^{RT}$ which is the input to the two-stage stochastic optimization problem. After the solution of optimal PV plant offering strategy problem, the actual profit (10) is calculated for the three data sets and the three models. A perfect forecast case, where the PV production scenario set values are substituted by a single scenario comprising the real PV generation measurement time series, is also considered as base case and comparison results with respect to the aforementioned nine cases are obtained. Each model is executed for all days of February 2013 and the respective simulation results for all nine cases in terms of the PV agent monthly profit obtained are presented in Table 8.

<INSERT TABLE 8, Color only for WEB, black-and-white in print>

The above simulation results show that, for the specific case study, the ANN-based scenario generation approach performs better than the SARIMA and the adjusted SARIMA-based approaches. These results are in line with the comparison results of the previous section. Additionally, it is obvious that the stochastic approach leads to much better results, i.e. higher PV agent profits, than the deterministic approach using the point forecasts only. Finally, the PV profits obtained using the reduced scenario set are close enough to the initial scenario set, thus justifying the efficiency of the implemented scenario reduction algorithm.

6. Conclusion

This paper proposed a novel scenario generation methodology that combines the flexible operation of ANNs with an iterative process based on the assimilation of randomly generated Gaussian white noise to the ANN outputs. A single ANN for one step-ahead forecasting was employed and a continuous rolling update of the inputs of the ANN allows the scenario generation procedure to be extended up to the desired horizon. The application of the proposed algorithm on real-life systems in combination with appropriate techniques for the creation of spatially and temporally cross-correlated scenarios regarding the energy injection from neighboring RES plants proves its effectiveness. In fact, the proposed methodology constitutes a useful tool for power system related studies, where the creation of large sets of scenarios to account for the inherent uncertainty of various stochastic variables is required.

7. Acknowledgements

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FIGURE CAPTIONS

Fig. 1. ANN-based scenario generation methodology for three time steps ahead
Fig. 2. ANN-based scenario generation algorithm
Fig. 3. Hourly load of the insular power system of Crete for the years 2011-2013
Fig. 4. 1-hour ahead residuals (errors) time series of the Crete system load yielded by the training stage of the years 2011-2012
Fig. 5. Autocorrelation function of the residual time series of the Crete system load yielded by the training stage of the years 2011-2012
Fig. 6. Histogram of the residual time series of the Crete system load yielded by the training

stage of the years 2011-2012
Fig. 7. Creation of 100 load scenarios for five days ahead with ANN-based scenario generation methodology

Fig. 8. Creation of 1000 load scenarios for 24 hours ahead with ANN-based scenario generation methodology
Fig. 9. Reduced set of 5 final scenarios with their correspondent probabilities by applying the scenario reduction algorithm on the extended scenario set
Fig. 10. Initial set of cross-correlated scenarios (50 scenarios per PV stations) with ANN-based scenario generation methodology
Fig. 11. Sets of the extreme scenarios (4 scenarios per PV station), (Red: Attica, Blue: Viotia)
Fig. 12. Modified initial sets of scenarios to be reduced after extracting the extreme scenarios (46 scenarios per PV station)
Fig. 13. Reduced sets of scenarios (16 scenarios per PV station) by applying the scenario reduction algorithm on the extended scenario set
Fig. 14. Final sets of scenarios including the reduced and the extreme scenarios set (20 scenarios per PV station)
Fig. 15. Modified initial sets of scenarios to be reduced after extracting the extreme scenarios (42 scenarios per wind farm)
Fig. 16. Final sets of scenarios including the reduced and the extreme scenarios set (20 scenarios per wind farm)

TABLE CAPTIONS

Table 1. Generic Input and Output Structure of the ANN
Table 2. ANN Inputs - One Hour-Ahead Electric Load Forecasting
Table 3. ANN Inputs - One Hour-Ahead PV Production Forecasting
Table 4. ANN Inputs - One Hour-Ahead Wind Production Forecasting
Table 5. Monthly NRMSE between PV generation forecasts and PV measurements
Table 6. Mean and standard deviation of the monthly NRMSE between the 1000 PV generation scenarios and PV measurements
Table 7. Monthly NRMSE between the dominant PV generation scenario after scenario reduction and PV measurements
Table 8. Absolute PV agent profits for all cases and percentage difference (in brackets) with respect to perfect forecast.

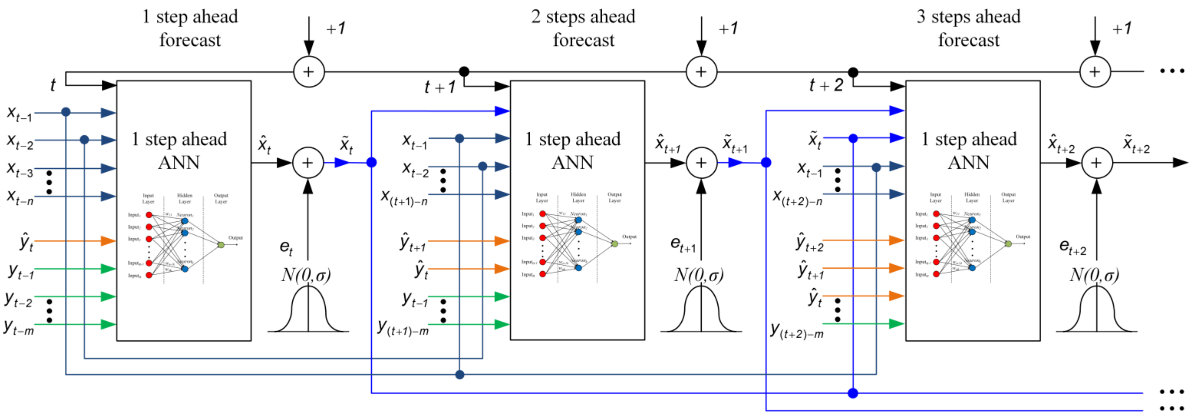

Fig.1. ANN-based scenario generation methodology for three time steps ahead

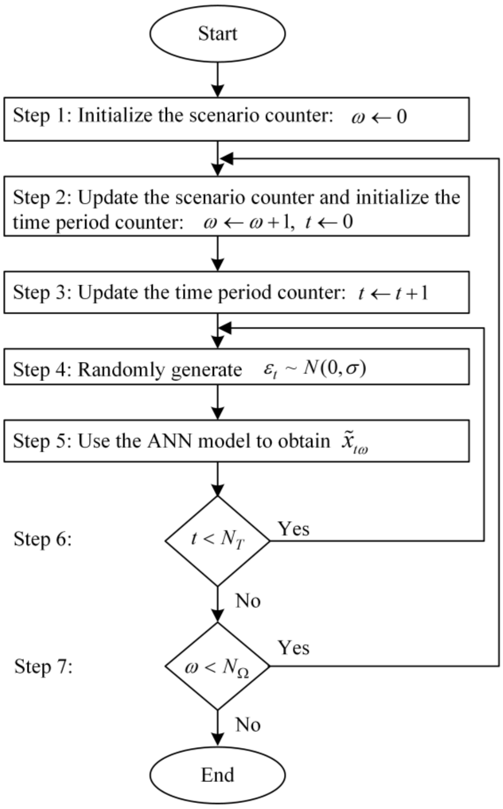

Fig.2. ANN-based scenario generation algorithm

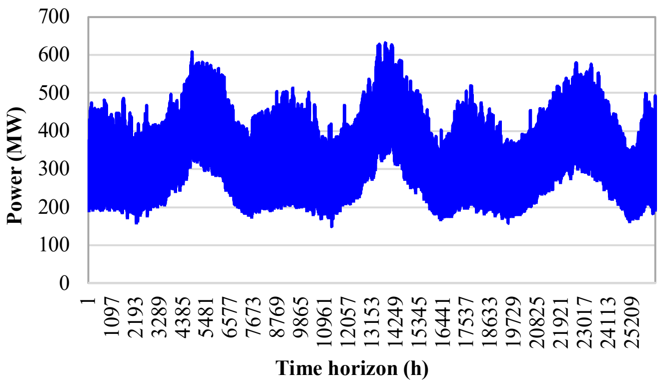

Fig.3. Hourly load of the insular power system of Crete for the years 2011-2013

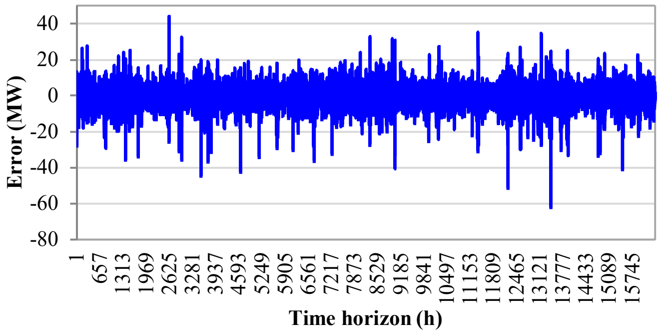

Fig.4. 1-hour ahead residuals (errors) time series of the Crete system load yielded by the training stage of the years 2011-2012

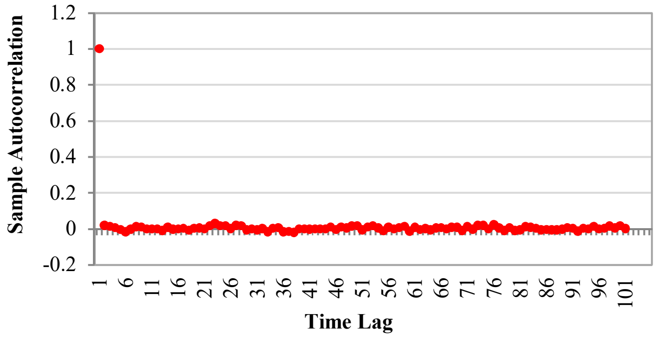

Fig. 5. Autocorrelation function of the residual time series of the Crete system load yielded by the training stage of the years 2011-2012

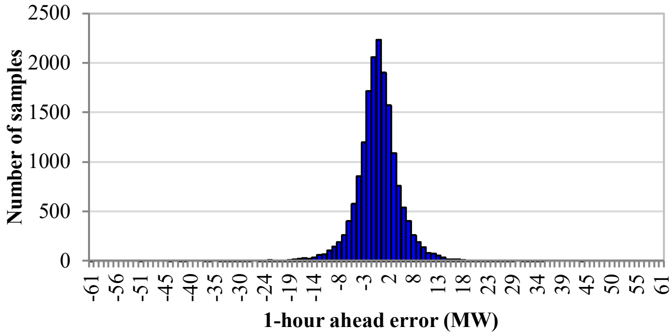

Fig.6. Histogram of the residual time series of the Crete system load yielded by the training stage of the years 2011-2012

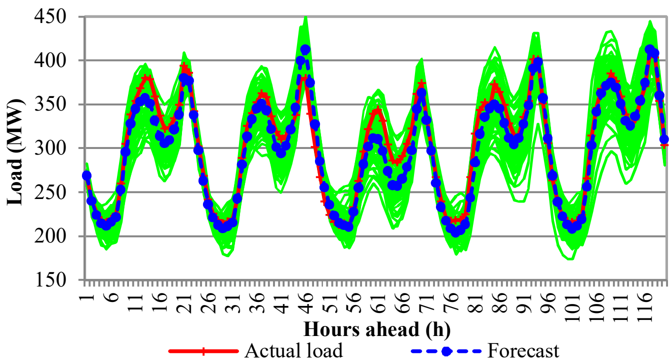

Fig.7. Creation of 100 load scenarios for five days ahead with ANN-based scenario generation methodology

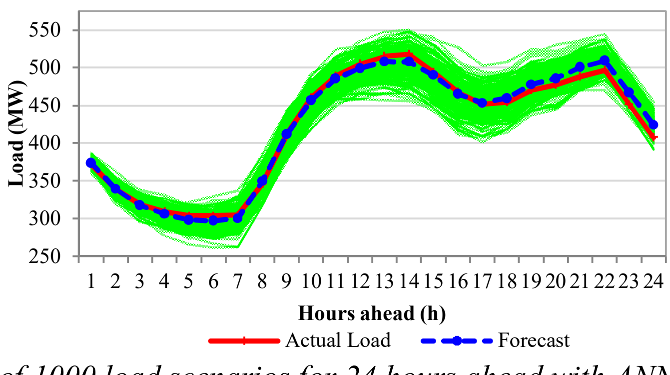

Fig.8. Creation of 1000 load scenarios for 24 hours ahead with ANN-based scenario generation methodology

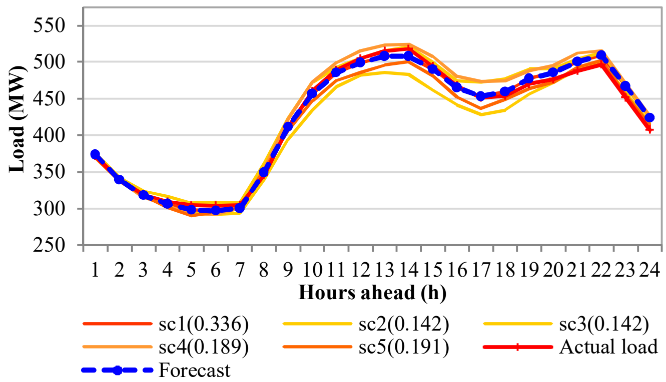

Fig.9. Reduced set of 5 final scenarios with their correspondent probabilities by applying the scenario reduction algorithm on the extended scenario set

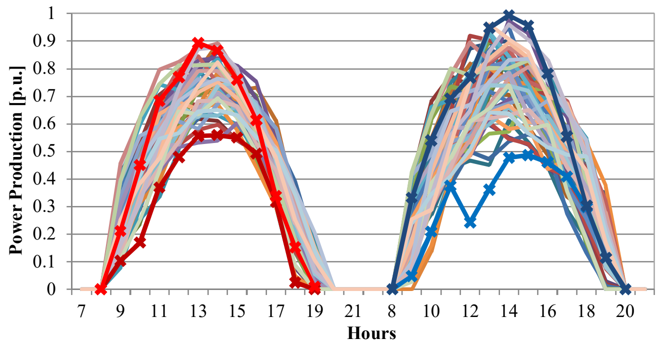

Fig.10. Initial set of cross-correlated scenarios (50 scenarios per PV stations) with ANN-based scenario generation methodology

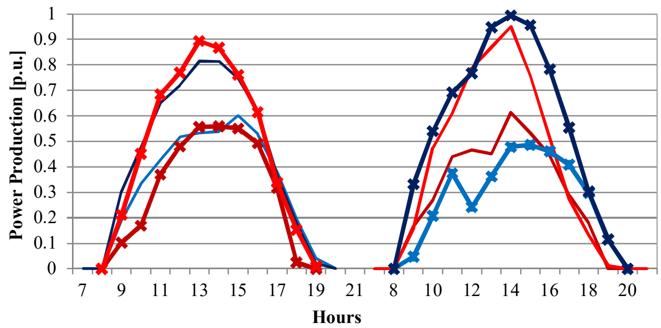

Fig.11. Sets of the extreme scenarios (4 scenarios per PV station), (Red: Attica, Blue: Viotia)

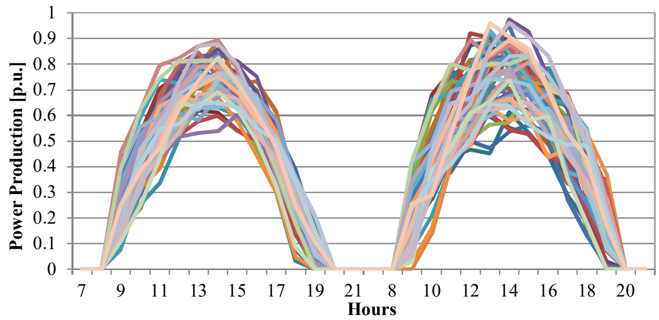

Fig.12. Modified initial sets of scenarios to be reduced after extracting the extreme scenarios (46 scenarios per PV station)

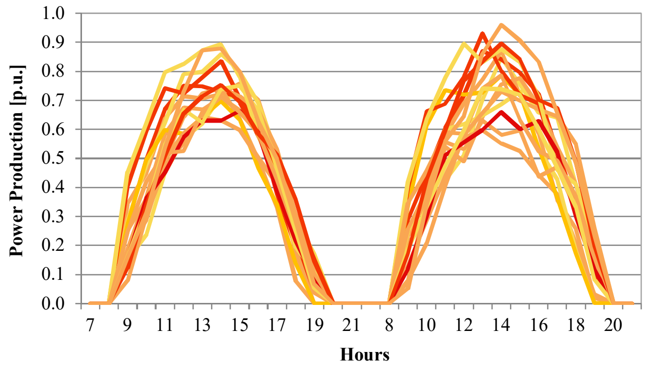

Fig.13. Reduced sets of scenarios (16 scenarios per PV station) by applying the scenario reduction algorithm on the extended scenario set

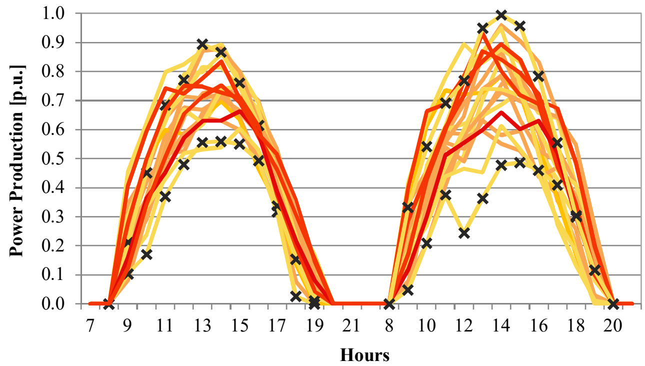

Fig.14. Final sets of scenarios including the reduced and the extreme scenarios set (20 scenarios per PV station)

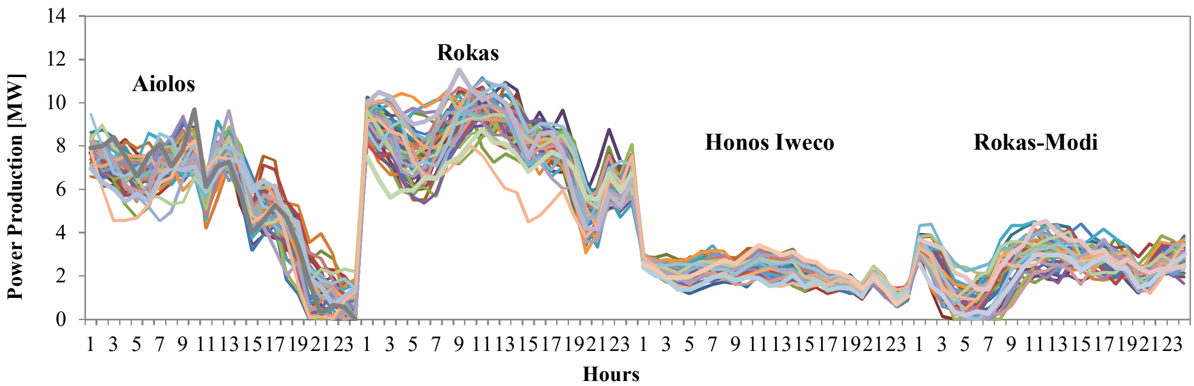

Fig.15. Modified initial sets of scenarios to be reduced after extracting the extreme scenarios (42 scenarios per wind farm)

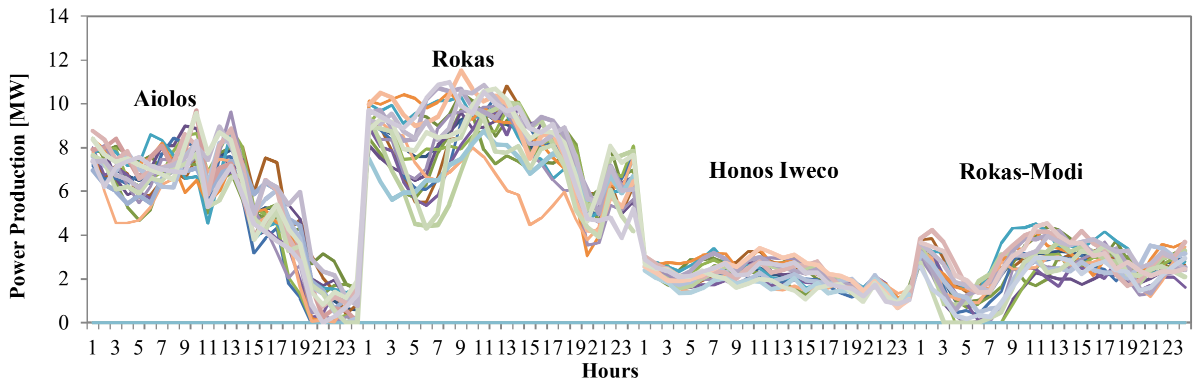

Fig.16. Final sets of scenarios including the reduced and the extreme scenarios set (20 scenarios per wind farm)

ANN Inputs	ANN Output
Historical values of the stochastic variable	One step-ahead forecasted value of the stochastic process
Forecasted and historical values of exogenous	
Time indexing: (e.g. HOD, DOW, DOY) pair of $\sin\left(2\pi k/T\right), \cos\left(2\pi k/T\right)$	

Table 1. Generic Input and Output Structure of the ANN

Historical values	$t-k$; $k=1,..,7, 23,..,26, 48,..,50, 72,..,74, 96, .., 98, 120,..,122, 144,..,146, 168,..,170$
Exogenous Inputs	• Maximum and Minimum Daily Temperature ✓ Previous day *d-1* (Historical data) ✓ Next day (Forecast data)
Time indices	HOD, DOW, DOY

Table 2. ANN Inputs - One Hour-Ahead Electric Load Forecasting

Historical values	$t-k$; $k=1,..,5, 24,..,26, 48,..,50$
Exogenous inputs	• Total Daily Solar Irradiation ✓ Previous day *d-1* (Historical data) ✓ Next day (Forecast data) • Hourly Solar Irradiation ✓ Previous hour *t -1* (Historical data) ✓ Next hour (Forecast data)
Time indices	HOD, DOY

Table 3. ANN Inputs - One Hour-Ahead PV Production Forecasting

Historical values	$t-k$; $k=1,..,5, 23,..,25$
Exogenous inputs	• Hourly Wind Speed ✓ Previous hours *t (-1, -2,-3)* (Historical data) ✓ Next hour (Forecast data)
Time indices	HOD, DOY

Table 4. ANN Inputs - One Hour-Ahead Wind Production Forecasting

ANN-based model	SARIMA model	Adjusted SARIMA model
14.3%	22.8%	15.5%

Table 5. Monthly NRMSE between PV generation forecasts and PV measurements

	ANN-based model	SARIMA model	Adjusted SARIMA model
Mean	17.3%	24.9%	20.6%
Standard deviation	1.02%	1.30%	1.88%

Table 6. Mean and standard deviation of the monthly NRMSE of the 1000 scenarios. NRMSE calculation of each scenario is based on the error between the PV generation scenario and PV measurements

ANN-based model	SARIMA model	Adjusted SARIMA model
13.9%	25.6%	17.1%

Table 7. Monthly NRMSE between the dominant PV generation scenario after the scenario reduction application and PV measurements

Case	PV agent Profits		
Perfect forecast	718.29		
	1000 scenarios	**5 scenarios**	**Forecast**
ANN-based model	712.70 (-0.78%)	706.49 (-1.64%)	686.18 (-4.47%)
SARIMA model	709.15 (-1.27%)	705.31 (-1.81%)	670.79 (-6.61%)
Adjusted SARIMA model	706.42 (-1.65%)	703.38 (-2.08%)	667.51 (-7.07%)

Table 8. Absolute PV agent profits and percentage difference (in brackets) with respect to perfect forecast.