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Paper:

Neural Network Ensemble-Based Solar Power Generation Short-Term Forecasting

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This paper presents the applicability of artificial neural networks for 24 hour ahead solar power generation forecasting of a 20 kW photovoltaic system, the developed forecasting is suitable for a reliable Microgrid energy management. In total four neural networks were proposed, namely: multi-layred perceptron, radial basis function, recurrent and a neural network ensemble consisting in ensemble of bagged networks. Forecasting reliability of the proposed neural networks was carried out in terms forecasting error performance basing on statistical and graphical methods. The experimental results showed that all the proposed networks achieved an acceptable forecasting accuracy. In term of comparison the neural network ensemble gives the highest precision forecasting comparing to the conventional networks. In fact, each network of the ensemble over-fits to some extent and leads to a diversity which enhances the noise tolerance and the forecasting generalization performance comparing to the conventional networks.

Keywords: neural networks, solar power generation, short-term forecasting, neural network ensemble

1. Introduction

The need for more flexible electric systems, changing regularity and economic scenarios, energy saving and environmental impacts are providing impetus to the development of new power system perception. In this regard, Microgrid (MG) can be considered as one of the most promising concepts; a MG is defined as an integrated power delivery system consisting of interconnected loads, storages facilities and distributed generation sources mainly consisting in Renewable Sources (RS) such as solar and wind energy. As an integrated system, a MG can operate in grid-connected or autonomous mode (islanding mode). The optimization of the operation cost is an important challenge for MG development and competition, that is greatly depending on the management of the power generation from renewable sources where the generation capacity varies largely with weather conditions, hence the usefulness of the RS power generation forecasting.

This study focuses on the power generation forecasting of a photovoltaic system, recently Artificial Neural Network (ANN) has been applied for such purpose regarding to its approximation capability of any continuous nonlinear function with arbitrary accuracy that offer an effective alternative to more traditional statistical techniques proposed so far [1–5].

Maher and Mohsen [6] proposed a neuro-fuzzy network associated to Kalman Filter for both medium-term and short-term irradiance forecasting. The neuro-fuzzy estimator presents daily time distribution of meteorological parameters relying on climatic behavior of the previous day. Auto-Regressive Moving Average (ARMA) model of the medium-term forecasting is associated to Kalman filter for short-term forecasting. J.C. Cao and SH.Cao [7] proposed a Recurrent Back-Propagation Neural Network (RBPNN) combined to wavelet analysis to forecast solar irradiance that was beforehand sampled into time-frequency domain using wavelet transformation, each domain was associated to a RBPNN. K.S.Reddy and Manish Ranjan [1] compared a Multi-layred Perceptron Neural Network (MLPNN) to other correlation models to estimate monthly and hourly values of global radiation. Yingni Jiang [8] proposed a MLPNN to predict actual values of monthly mean daily diffuse solar radiation in Zhengzhou (China), solar radiation data was collected from nine stations in different cities. Eight stations were used for the training process while the remaining one was used to test and validate the proposed neural network. Mohandes et al. [2] proposed a Radial Basis Function Neural Network (RBFNN) to estimate the monthly mean daily values of solar radiation on horizontal surfaces, the obtained results was compared with classical regression model. Sulaiman et al. [9] presented three ANNs with different types of inputs for predicting the total AC power output of a grid-connected PV system. The authors found that the ambient temperature and the solar radiation are the most relevant factors in affecting the PV system performances. However for forecasting the output power generation of the PV system, the network inputs should be forecasted also which may seriously affect the accuracy of the results. Kawaguchi et al. [10] proposed an ANN for the prediction of the electric power generation of a PV solar cell, the network inputs are composed of experimental

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electrical and metrological parameters measured during five days only, while the output is the prediction for three hours of peak generation.

As mentioned above, most of the referred papers deal with the solar radiation parameters forecasting such as: global solar radiation, irradiance, irradiation and clearness index. Some authors reported that their results can be extended to predict solar energy conversion for a photovoltaic system. Nevertheless, the forecasting error would logically increase regarding to the necessity of forecasting the inputs [9, 10], the incertitude of the PV model and the deviation between the provided forecasting and the local solar radiation level associated to the photovoltaic dispositive. The objective of this study is to validate several ANN models that supplies an immediate and reliable 24 hour ahead of Solar Power Generation (SPG) forecasting for a 20 kW photovoltaic system located in Tokyo University of Agriculture and Technology (TUAT). In total four ANN's has been developed, consisting on a MLPNN, RBFNN, Recurrent Neural Network (RNN) and Neural Network Ensemble (NNE). Each neural network will be evaluated for different ranges of climatic conditions basing on error forecasting performance by the mean of statistical and graphical methods.

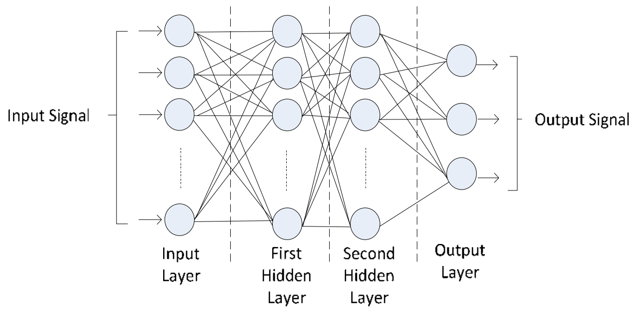

Fig. 1. Architecture graph of a MLPNN with two hidden layers.

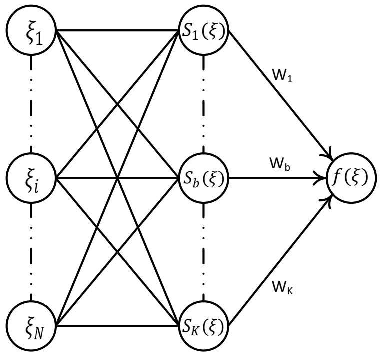

Fig. 2. Architecture graph of a RBFNN.

2. The Developed Artificial Neural Networks

2.1. Multi Layred Perceptron Neural Network

Multi-layred Perceptrons has been applied successfully to solve some difficult and diverse problems basing on a preliminary supervised training with error back propagation algorithm using an error correction learning rule. Basically, error back learning consists in two pass through the different layers of the network, a forward pass and backward pass. In the forward pass an activity pattern (input vector) is applied to the sensory nodes of the network, its effect propagates through the network layer by layer to produce an output as actual response. During the backward pass synaptic weights are adjusted in accordance to an error correction-rule. The error signal (subtracted from a desired value) is then propagated backward through the network against the direction of the synaptic connections [11]. In general MLPNN's can have several hidden layers (**Fig. 1**), however according to K.M.Hornik [12] a neural network with single hidden layer is able to approximate a function of any complexity. If we consider a MLPNN with one hidden layer, tanh as an activation function and a linear output unit, the equation describing the network structure can be expressed as:

$$o_k = v_{ok} \sum_{j=1}^{q} v_{jk} \tanh(w_{oj} + \sum_{i=1}^{p} w_{ij} x_i). \quad \ldots \quad (1)$$

Where o_k is the output of the k^{th} output unit, v_{jk} and w_{oj} are the network weights, p is the number of network inputs, and q is the number of hidden units. During the training process, weights are adjusted in such a way that the difference between the obtained outputs o_k and the desired outputs d_k is minimized, which is usually done by minimizing the following error function:

$$E = \sum_{k=1}^{r} \sum_{e=1}^{n} \left(d_{e,k} - o_{e,k}\right)^2. \quad \ldots\ldots\ldots \quad (2)$$

Where r is the number of network outputs and $n$is the number of training examples. The minimization of the error function is usually done by gradient descent methods, which have been extensively studied in the field of optimization theory [13].

2.2. Radial Basis Function Neural Network

RBFNN's have been successfully employed in many real world tasks in which they have proved to be a valuable alternative to MLPNN's since it requires less computing power and time. These tasks include chaotic time-series prediction, speech recognition, and data classification [14]. Furthermore, given a sufficient number of hidden units a RBFNN is considered as a universal approximator for any continuous functions [15]. The construction of a RBFNN in its most basic structure (**Fig. 2**) involves three layers with entirely different roles. The input Layer is made up of a source node that connects the network to its external environment, the second layer which is the only hidden layer in the network, applies a non linear transformation from the input space to the hidden space. In most applications the hidden space is of high dimensionality, which is directly related to the network capacity to approximate a smooth input-output mapping. The output layer is linear, supplying the response of the network to the pattern applied to the input layer [11].

If we consider a RBFNN with a single output node that computes a linear combination of the hidden units outputs, parameterized by the weights w between hidden and output layers, the function computed by the network is therefore expressed as:

$$f(\xi, w) = \sum_{b=1}^{k} W_b S_b. \quad \ldots\ldots\ldots \quad (3)$$

Where ξ is the vector applied to the input units and S_b denotes the basis function b, each of the N components of the input vector ξ feeds forward to k basis functions whose outputs are linearly combined with weights $\{W_b\}_{b=1}^{k}$ into the network output $f(\xi, w)$. The most common choice for the basis functions is the Gaussian, in this case the function computed becomes:

$$f(\xi, w) = \sum_{b=1}^{k} W_b \left(\frac{-\|\xi - m_b\|^2}{2\sigma_B^2} \right). \quad \ldots \quad (4)$$

Where each hidden node is parameterized by two quantities: the center m in input space, that corresponds to the vector defined by the weights between the node and the input nodes, and the width σ_B.

2.3. Recurrent Neural Network

Recurrent networks are neural networks with one or more feedback loops, the feedback could be of a local or global type. Starting from a MLPNN as a basic building structure, the global feedback can take various forms: like a feedback from the output neurons to the input layer or from the hidden neurons of the network to the input layer or even booth (when the MLPNN has two or more hidden layers, the possible forms of feedback are expanded). The application of feedback enables RNN to acquire state representations, which make it a suitable device for nonlinear prediction and modeling [11].

In this paper we used a subclass of RNN known as Elman recurrent neural network introduced by Elman in 1990 [16]. The particularity of such network consists of a set of context units added to a multi-layer perceptron network (**Fig. 3**). The context units are connected to the hidden layer with a fixed weight of value $+1$. The computation layer of a recurrent multilayer perceptron has feedback to the context unit that presents it inputs for the next computation, the learning process is proceeded as follow:

1. Set the context to 0; t=1;
2. Pattern x^t is clamped, the forward calculation are performed once;
3. The back-propagation learning rule is applied;
4. $t \leftarrow t+1$; go to 2.

2.4. Neural Network Ensemble

Although an ANN is providing a relevant methodology for solving several types of nonlinear problems, it is still considered as an unstable learning model [17]. In fact, the changes on training data and the architecture of the network which incorporate: the number of hidden layer, the number of neurons and the initial connections weights has an effect on the network training and predicting performance. Moreover the fitting to the regularities of the data and the fitting to the noise part of the data during the training of a single neural network constraint the training model to be trapped in a local optimum solution with low forecasting accuracy. On the other hand, there are no systematic investigation for those issues, mostly researchers has adopted trial and error methodology to deal with these inconsistencies [18]. In this study a robust network ensemble is proposed to enhance the learning model performance by improving the generalization ability and reducing the variance and the performances instability with a relative simple implementation. Indeed, the major feature of a NNE is redundancy; basing on combination of different learning machines each one could perform the task on its own leading to better generalization performance.

When building bagged neural network ensemble (**Fig. 4**), each network $\psi_b(x)$ is associated to a training set D_b that belongs to the original training set D, so that a network ensemble $\{\psi(x)\}_{b=1}^{B}$ is obtained. Each network among the ensemble will constitute a base predictor, the forecasting result of the networks ensemble is aggregated basing on their average values to get the grand total predictor ensemble $\psi_{Bag}(x)$. As the noise is varying among the ensemble networks, the averaging ensemble tends to mitigate it by retraining the fitting to the regularities of the data.

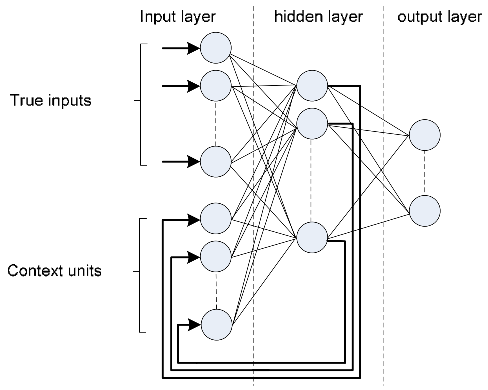

Fig. 3. Schematic diagram of a three layered Elman recurrent neural network.

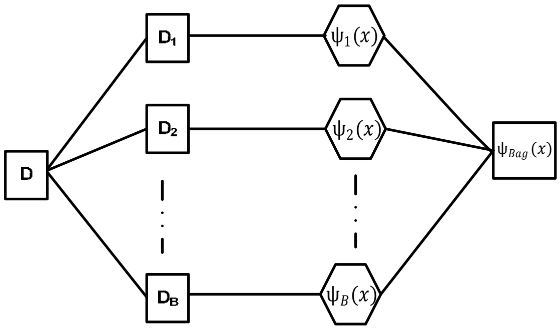

Fig. 4. Framework of a Bagged Neural Network Ensemble.

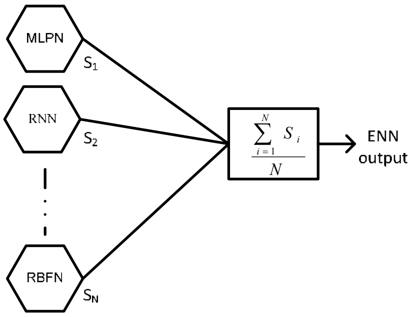

Fig. 5. Architecture of the proposed neural network ensemble.

Fig. 6. The studied photovoltaic field in Tokyo University of Agriculture and Technology.

Neural Network Ensemble bagging algorithm
(Bootstrap Aggregation learning)

1. Let B be the final number of predictors required.
2. Take a training set $D = \{(x_1, d_1), \ldots, (x_N, d_N)\}$.
3. For $b = 1$ to B do:
   - Make a new training set D_b by sampling M items uniformly at random with replacement from D.
   - Train an estimator ψ_b with this set D_b and add it to the ensemble.

In the present study, an ensemble of bagged neural networks consisting in: MLPNN, RBFNN and RNN is proposed. The NNE provides a forecasting based on the average of the ensemble network outputs (**Fig. 5**). The ensemble could be also composed of similar types of neural networks, where the framework and training data set related to each network would be coherently different from network to another.

2.5. Methodology

The experimental system used in this research is a Grid-connected photovoltaic field (**Fig. 6**) installed in Tokyo University of Agriculture and Technology. The PV system consists of 14 parallel panels connected to 12 panels in series (the module manufacturer specifications are provided in the Appendix).

Input training data are composed of hourly and daily weather parameters recorded during 2007 and 2008. Vapor pressure, humidity, cloud coverage and sunshine duration were collected by Japan Meteorological Agency in the local area of TUAT, while the maximum, minimum and average temperature, solar radiation and the SPG output was recorded in TUAT (**Fig. 7**). It should be noted that some of the daily recorded data was cut-off during the data processing due to the presence of erroneous measures.

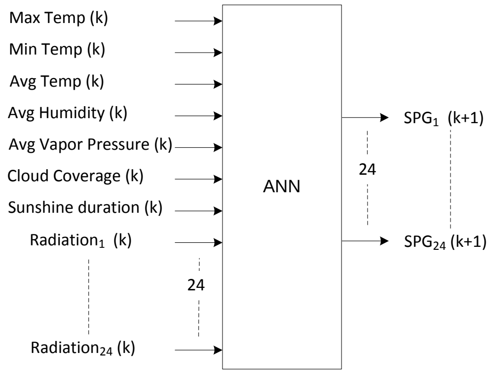

Fig. 7. Inputs and outputs for the proposed ANN's.

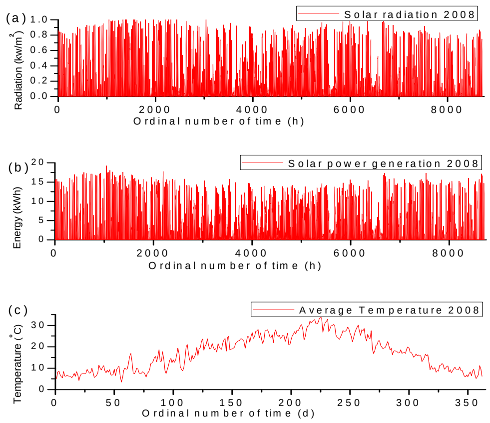

Fig. 8. Main relevant data: (a) Solar radiation 2008, (b) Solar power generation 2008 (c) Average temperature 2008.

Figure 8 shows the main relevant experimental data used for both training and testing process such as: the solar radiation used as 24 hour block input, while the solar power generation is a 24 hour output block (target) and the modules average temperature. Validation samples were used to avoid over fitting problems by setting up stopping points for the training process. In order to evaluate the reliability of the developed ANN's for different ranges of climatic conditions, the testing data set were split into 4 seasons namely: Winter (December, January and February), Spring (March, April, May), Summer (June, July and August) and Fall (September, October and November). To evaluate the forecasting performance of the proposed ANNs, five days was picked up randomly from each month in the year 2008 while the remaining data was used for the training process, **Table 1** shows in detail the number of training and testing days devoted for each season.

The rescaling (normalization) of the input training data is important to improve the training convergence of an ANN [19–21], mean 0 and standard deviation 1 based across channel normalization [22] was used for the input

Table 1. Training and testing data distribution.

	Winter [days]	Spring [days]	Summer [days]	Fall [days]
Training	164	169	165	167
Testing	15	15	15	15

training set rescaling, basing on the following relation:

$$S_i = \frac{x_i - mean}{\sqrt{\frac{\sum_{i=1}^{N}(x_i - mean)^2}{N-1}}} \quad \text{. . . . . (5)}$$

where

$$mean = \frac{\sum_{i-1}^{N} x_i}{N}$$

x_i is the raw input variable X in the i^{th}training case
S_i is the standardized value corresponding to x_i
N is the number of training case.

The target variables were linearly normalized in order to force the network values to be within the range of output activation functions using upper (Y_{max}) and lower bounds (Y_{min}) for the values:

$$Z_i = \frac{Y_i - \frac{Y_{\max} - Y_{\min}}{2}}{\frac{Y_{\max} - Y_{\min}}{2}} \quad \text{. . . . . (6)}$$

where

Y_i is the raw target variable Y for the i^{th} training case.
$Z_i$is the standardized value corresponding to Y_i.

The network framework of the MLPNN, RNN was set out basing on trial and error approach. In fact, the networks were trained for a fixed number of epochs, performance of the MLPNN and the RNN was evaluated by changing the number of the hidden nodes, while no significant decrease of the error was noticed above 27 hidden nodes and as referred previously, only one single hidden layer was sufficient for the proposed forecasting task. On the other hand, RBFNN was evolved to get round over fitting problem in relation to the choice of the network framework, the proposed RBFNN was build up of 300 hidden neurons. In fact, unlike the MLPNN and the RNN, the number of hidden nodes of a RBFNN is determined during the training and might get a big number as a couple of hundred [23]. Reducing the number of hidden neurons requested for the RBFNN training convergence is subject to several researches mainly based on optimization algorithms that allow pruning of superfluous neurons inserted for outlier, noisy and overlapping data [23–25].

3. Results and Discussion

Several performance criteria are reported in the ANN literature as: the training time, the modeling time and the forecasting error. In the present study, as the training process is in offline mode, the first two criteria are not considered to be relevant. Thereby, the forecasting performance will be evaluated only in term of forecasting error, defined

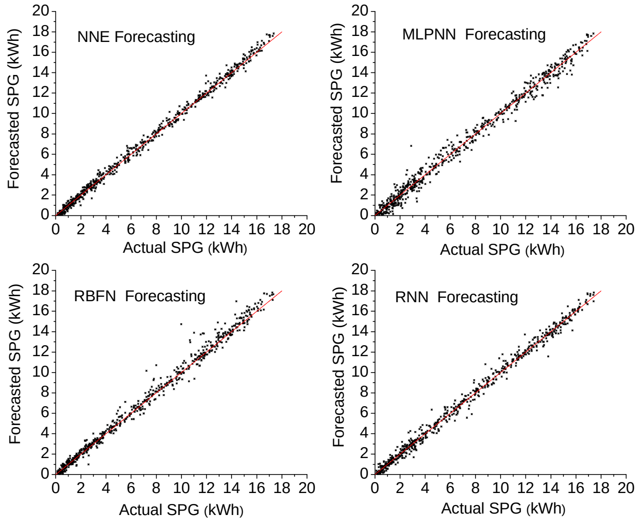

Fig. 9. Correlation between the actual and the forecasted SPG.

as the difference between the actual and the forecasted values basing on statistical and graphical approaches.

$$MAD = \frac{1}{N}\sum_{1}^{N}\left|S_{d,i} - S_{f,i}\right| \quad \text{. . . . . (7)}$$

$$MAPE = \frac{1}{N}\sum_{1}^{N}\left|\frac{S_{d,i} - S_{f,i}}{S_{d,i}}\right| * 100. \quad \text{. . . . (8)}$$

Where

$S_{d,i}$ is the i^{th} desired value (actual).
$S_{f,i}$ is the i^{th} forecasted value
N is the total number of observations.

Mean Average Deviation (MAD) and Mean Absolute Percentage Error (MAPE) defined respectively in Eqs. (7) and (8), were applied as statistical error test criteria. While a correlation graph between the forecasted and the actual values (**Fig. 9**), a 2-D error prediction form (**Fig. 10**), and 24 hour SPG comparative forecasting (**Fig. 11**) were presented as graphical error performance criteria.

Figure 9 presents a correlation analysis for the testing data set, so as to the four ANN's it is clear that the proposed NNE gives the best forecasting matching with the actual data along the diagonal axis. In fact, the SPG forecasting error performance differs from network to network in relation to the current meteorological conditions (power generation). The RBFNN seems to have a narrower scatter along the matching diagonal axis then the MLPNN or RNN for low SPG levels. However for higher SPG levels, the RNN have the best accuracy. Thereby, for a larger interval of SPG level, the NNE has logically the lowest error forecasting since it is a combination based on the average forecasting provided by the conventional ANN's. Indeed, the scatter along the whole matching diagonal line of the NNE correlation curve is the narrowest and the most stable comparing to the other ANN's.

Figure 10 represents a daily 2-D prediction error graph in kWh for the proposed ANN's during sixty days, where it can be observed that the NNE has the highest predic-

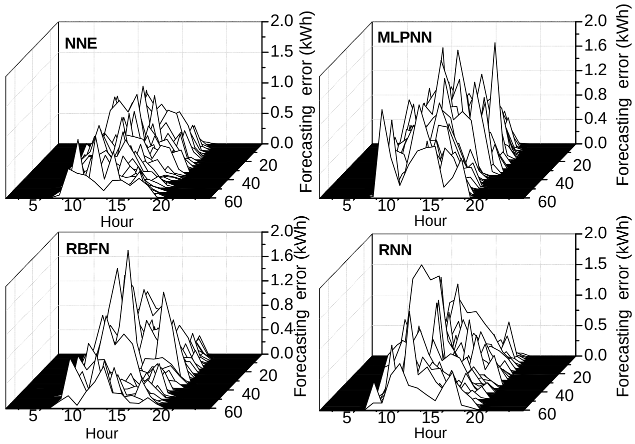

Fig. 10. Prediction error for testing data set.

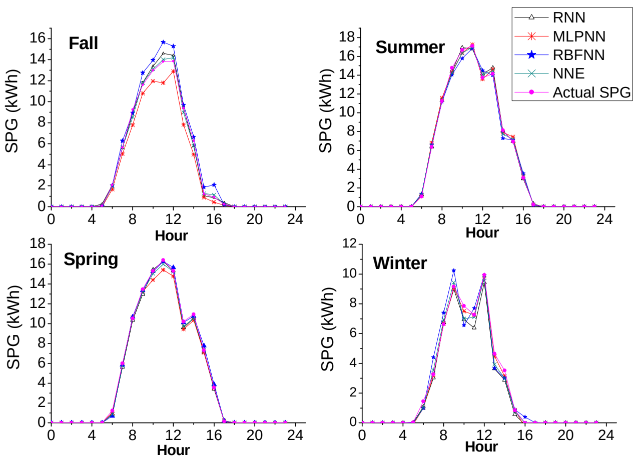

Fig. 11. Comparison of the SPG for the different proposed ANN's.

tion success with the smallest forecasting error. **Fig. 11** shows 24 hour SPG forecasting projected by the four developed ANN's, the forecasted days were selected randomly among each season data sample, comparing to the actual SPG, the NNE have the most accurate forecasting.

The same conclusion was also carried out basing on statistical error forecasting performances shown in **Table 2**. In fact, referring to the MAD and MAPE criteria, we can observe that the proposed NNE has the lowest forecasting error including different testing data sets of winter, spring, summer and fall. On the other hand RBFNN, RNN and MLPNN achieved also a reasonable forecasting accuracy, among the previous conventional neural networks the RBFNN presented the best overall results, while the MLPNN achieved the lowest forecasting accuracy. In fact the RBFNN can overcome several limitations of MLPNN and RNN such as a highly non-linear weights update and the slow convergence rate.

4. Conclusion

In this study, four neural networks were developed and applied to a 24 hour ahead forecasting of solar power generation for a 20 kW photovoltaic field. The forecasting

Table 2. Statistical errors of the developed ANN's.

		RNN	RBFNN	MLPNN	NNE
Winter	MAPE	3.9344	3.5127	3.9832	2.7867
	MAD	0.2485	0.1844	0.2127	0.168
Spring	MAPE	5.2498	5.1788	6.2676	4.1313
	MAD	0.4273	0.4557	0.384	0.3055
Summer	MAPE	6.6321	5.7643	7.2161	4.6816
	MAD	0.4473	0.3705	0.4011	0.287
Fall	MAPE	5.9481	4.0373	5.8278	3.6387
	MAD	0.2694	0.173	0.2395	0.1572

reliability was evaluated in term of forecasting error basing on graphical and statistical approaches. The experimental results showed that the NNE achieved a higher forecasting accuracy than conventional MLPNN, RBFNN and RNN. In fact, the NNE can improve the generalization and noise tolerance of learning systems effectively through aggregating numbers of neural networks with different models and diverse training data from the original source data set. The conventional neural networks fulfilled also an acceptable forecasting accuracy: in comparison, the RBFNN performed better than RNN and MLPNN while the MLPNN achieved the lowest forecasting accuracy.

Further application of the proposed ensemble will include distributed intelligent management system for the cost optimization of a MG. In fact, the knowledge of future available SPG let the system to store energy in advance or inject into the main grid, offering more flexibility to take advantage of real time electricity pricing.

Appendix A.

PV panel manufacture specifications

Manufacture	SHARP	**Weight**	12.5 Kg
Type	NE-Lo1A	**Maximum power**	120 W
Maximum voltage	600 V	**V_{oc} open circuit Voltage**	31.9 V
		I_{sc} Short circuit current	5.31 A

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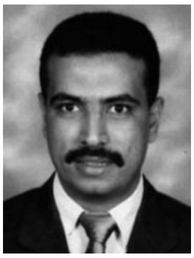
- System Control Engineering
- Renewable Energies
- Micro Grid Development



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- International Neural Networks Society (INNS)