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APPLICATION OF NEURAL NETWORKS TO FORECAST PHOTOVOLTAIC POWER IN THE FRAMEWORK OF THE VALORISATION OF RENEWABLE ENERGIES IN BENIN REPUBLIC

Agbokpanzo Richard Gilles[1], Didavi Audace[2], Houngan Aristide and Espanet Christophe
[1]Department of Sciences and Industrial Technics, ENSET Lokossa, UNSTIM, Benin
[2]Department of Electrical Engineering, EPAC, University of Abomey-Calavi, Benin
E-Mail: richgille@gmail.com

ABSTRACT

This paper aims at applying neural networks to the prediction of the output power of a photovoltaic installation in the framework of the valorisation of renewable energies in the Benin Republic. This prediction was made by using a hybrid neural network (NARX network and feedforward neural network) that we trained with MATLAB's Neural Network Start (NNS) tool where we used 12 years (01-01-2005 to 12-31-2016) meteorological data uploaded in the PVGIS database and Levenberg-Marquardt's algorithm. We used the NARX network (Nonlinear Auto-Regressive with eXogenous Input) network for the prediction of meteorological data such as the beam radiation (direct) on the inclined plane, the diffuse irradiance on the inclined plane, the position of the sun, the air temperature at 2m from the ground and the total wind speed at 10m from the ground at a 3-hour horizon. The feedforward network was then used to forecast PV power from the predicted meteorological data at a 72-hour horizon. At the end of the prediction, we were able to obtain a mean square error of 0.46 and a regression coefficient of 0.99.

Keywords: PV power, prediction, NARX network, feedforward neural network, weather data, benin.

INTRODUCTION

Like many other parts of the world, West Africa faces huge energy challenges. In particular, there is an urgent need to expand access to energy and redesign energy matrices in line with the 2015 Paris Accord, which calls for rapid decarbonization in order to reduce the impact of climate change. The Sustainable Development Goals, adopted by the United Nations to guide social development processes, also call for a transition to new energy systems, largely based on renewable energy. These global climate and sustainability imperatives have reinforced the West African region's own motivation to establish realistic long-term energy plans (IRENA, 2018, PANER, 2015). In 2013, the International Renewable Energy Agency (IRENA) conducted its first assessment of the future prospects for renewable energy in the continental countries of the Economic Community of West African States (ECOWAS). This assessment, presented in the 2013 report entitled "West African Power Pool: Planning and Prospects for Renewable Energy", followed two major regional policy developments: the formal adoption of the 2011-2012 Master Plan of the West Africa Power Pool (WAPP) and the ECOWAS Renewable Energy Policy (PERC), which aims at increasing the share of renewable energy in the overall mix of power generation options in the region to 23% in 2020 and 31% in 2030 (ECREEE, 2013).

Since this analysis, the energy landscape in West Africa has maintained its dynamism. Ambitious efforts have continued to be made at national and regional levels to further develop and harmonize policy objectives and frameworks to capitalize on the region's vast renewable energy potential, enhance energy access and meet rapidly growing demand (PANER, 2015).

In Benin, the National Renewable Energy Action Plan (PANER) indicates that, in the framework of the implementation of the ECOWAS Renewable Energy Policy (PERC), Benin has set itself the objective of reaching 150 MW in 2020 and 456 MW in 2030 (PANER, 2015) in terms of installed capacity of renewable energy power plants (PANER, 2015). Good integration of renewable energies is therefore essential in order to achieve the various objectives within the timeframe. In this respect, several modes of development are possible:

- the development and installation of renewable energy production plants for populations isolated from the network and whose connection would generate an unprofitable investment;
- the development and installation of power plants connected to the grid to reduce the amount of energy consumed by the population, the country's dependence on the outside world for its energy supply;
- the development of low-power installations at the scale of housing for landing to power failure situations;
- the release of public utility charges (traffic lights, pubic lighting of the roads, markets) from the grid by installing off-grid solar or solar-powered solutions, or wind turbine.

The perfect solution would therefore be to take full advantage of all the renewable energy sources available on the Beninese territory in order to firstly satisfy the needs of the population in terms of electrical energy and secondly to achieve the objectives that the country has set itself in the framework of the development of renewable energies. Hybrid systems for the production of renewable energy are therefore a perfect solution.

In order to set up these hybrid systems for the production of renewable energy, they therefore face problems of feasibility, efficiency, optimization and profitability. For the feasibility, several works have been done and several models of hybrid systems have been developed, so the big problem lies in the efficiency, optimization and profitability of the system. Production fluctuations, dictated by meteorological hazards, are independent of consumption for wind and solar renewable energies, which occupy a large part of the renewable energies often used (L. Stoyanov, 2011). New situations must therefore be managed: overproduction of electricity in off-peak periods, random means of production in peak periods. This intermittency of these energies (wind and solar) is therefore a very important factor in the stability of the network and thus influences the efficiency, profitability and optimization of the production system (A. Jurado *et al*., 2017).

Several methods have been developed to compensate for these intermittencies. Among others we can mention: demand management (D. Grand *et al*.), international exchanges (https://www.banquemondiale.org/fr/news/feature/2018/04/20/regional-power-trade-west-africa-offers-promise-affordable-reliable-electricity), energy storage (B. Multon and al 2003; G. Robin and al. 2004; L.-M. Jacquelin and al. 2013; C. Kerzreho, 2002; J. Klaimi, 2017), forecasting of renewable energies (P. Zhang and al. 2010; V. C. Gungor *et al., 2011;* A. Henriot and al., 2014; http://www.smartgrids-cre.fr/index.php?p=integrationenr-smart-grids). It is this last point that is highlighted in this article. This paper aims at applying neural networks in the prediction of photovoltaic power from meteorological data of the city of Natitingou (Benin) downloaded in the PVGIS database.

MATERIALS AND METHODS

Overview of the Exploited Data

The data used were obtained from the PVGIS meteorological database (https://re.jrc.ec.europa.eu/pvg_tools/fr/tools.html#TMY (accessed Jun. 01, 2020)). The main characteristics are presented below:

- Location of the site: Natitingou (Benin)
- Geographical position of the site: Latitude: 10.2983; Longitude: 1.3782
- Period: 01-01-2005 to 31-12-2016
- Exploited meteorological data:
  - Output power for an installed peak PV power of 1 kWp (W);
  - Beam irradiation (direct) on the inclined plane (grid plane) (W/m2)
  - Diffuse irradiance on the inclined plane (plane of the network) (W/m2)
  - Position of the sun in degrees;
  - Air temperature at 2m (°C);
  - Total wind speed at 10m (m/s).

All the data can be downloaded at: https://drive.google.com/file/d/163G-EOeJIqQ9u5H-DhlBlwAo_N8v1Ul/view?usp=sharing

FORECASTING WITH MATLAB

Preparation of Data

Data is at the heart of statistical learning (SL). They are crucial for learning, testing, validation and monitoring of the system. One of the reasons why AI (Artificial intelligence) has seen a resurgence in popularity is largely due to the triple combination of the massive processing capabilities of the cloud, the availability of large amounts of data, and the evolution of algorithms (especially with Deep Learning). The last two of these three reasons have a lot to do with "datas". In fact, the more data available to feed algorithms, the better. However, having a lot of data is not enough. It also needs to be of good quality, otherwise AI systems are chess. Problems almost always come from this quality. So that the models and that they provide the expected results, the statistics are properly trained and that they provide the data used must be clean, accurate, complete and well labeled. Preparation of this data is therefore a crucial step, which today is creating a new and growing demand for tools and services in this area (https://www.lemagit.fr/conseil/Machine-Learning-lindispensable-preparation-des-donnees-requiert-encore-beaucoup-dhumain)

Forecasting

The output power prediction based on meteorological data (sun position, temperature at 2m from the ground, total wind speed at 10m from the ground, beam radiation (direct) on the inclined plane (network plane)) is made using a hybrid neural network composed of a Feedforward Neural Network (FNN) and a Nonlinear Autoregressive Exogenous Model (NARX) network. The NARX network allowed us to predict the weather data being used based on previous weather data at the one-hour horizon and the FNN network to predict PV output power based on forecasted weather data. Figure-1 illustrates the organization of the hybrid network.

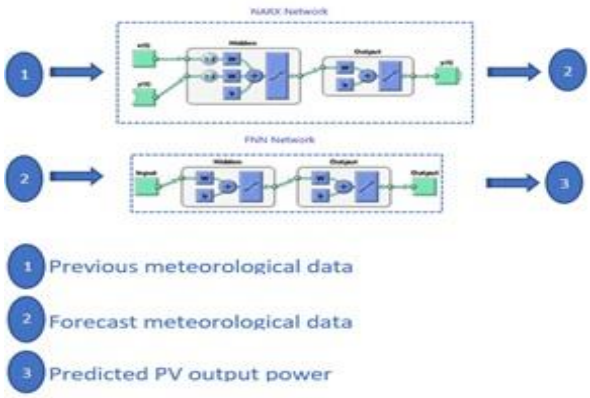

Figure-1. Organization of the hybrid network used.

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Weather Data Forecasting with NARX Network

The Nonlinear Autoregressive Exogenous Input Autoregressive Network is a dynamic recurrent network, with feedback connections surrounding several layers of the network. The NARX model is based on the linear ARX model, which is commonly used in time series modelling. The equation that defines the NARX model is as follows:

$$y(t) = f(y(t-1), .., y(t-n_y), u(t-1), .., u(t-n_u))$$

Here the MATLAB Neural Network Time Series (NNTS) tool is used. This tool allows us to solve nonlinear time series problems. To train the machine, hourly weather data from January 1, 2006 to December 30, 2016 are used. Hourly data from December 31, 2016 was used to test network performance.

Forecasting with an FNN

Feedforward neural networks are artificial neural networks in which the connections between units do not form a cycle. Direct-acting neural networks were the first type of artificial neural network invented and are simpler than their recurrent counterparts. They are called feedforward because information only flows forward (no loops), first through the input nodes, then through the hidden nodes (if they exist) and finally through the output nodes.

Here the MATLAB Neural Network Fitting (NNF) tool is used. This tool guides in the resolution of a data fitting problem, solving it through a two-layer feed-forward network trained with the Levenberg-Marquardt algorithm.

To train the machine, data from January 1, 2006 to December 28, 2016 are used. Daily data from December 29, 30 and 31, 2016 were used to test the performance of the network. 55% of the data were used to drive the machine, 30% for validation and 15% for testing.

RESULTS AND DISCUSSIONS

Weather Forecasting Results

In this section, the results of forecasts of hourly weather data at the horizon of one hour are presented. Here we have used data such as the speed of the wind at 10m from the ground, air temperature at 2m from the ground, position of the sun, the radiation direct on an inclined plane and diffuse radiation on an inclined plane at the entrance at an hour h given to predict the same data for one hour later. Figure-2 shows a summary of the performance of the NARX network.

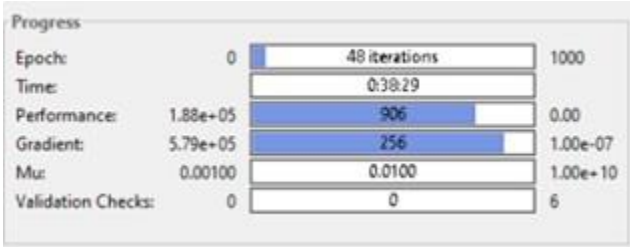

Figure-2. NARX network performance summary.

It can be noted that the best result was obtained after 48 iterations. Figure-3 shows that the mean square error (MSE) is 942, obtained at the 48th iteration.

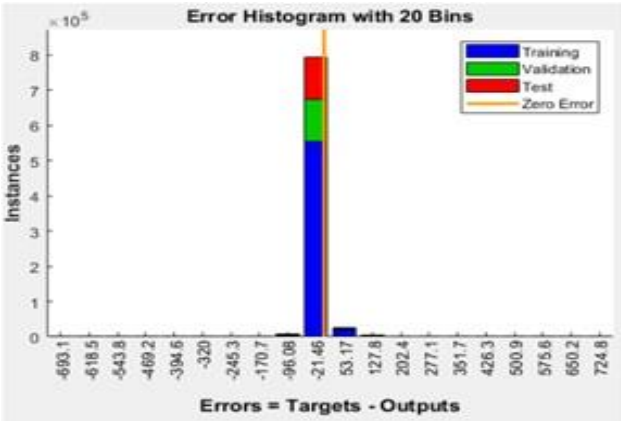

Figure-3. MSE evolution during NARX network training.

It can be noted in Figure-4 that the error on the predicted outputs is the lowest (21.46) for the majority of the outputs (about 800,000 values out of 841328).

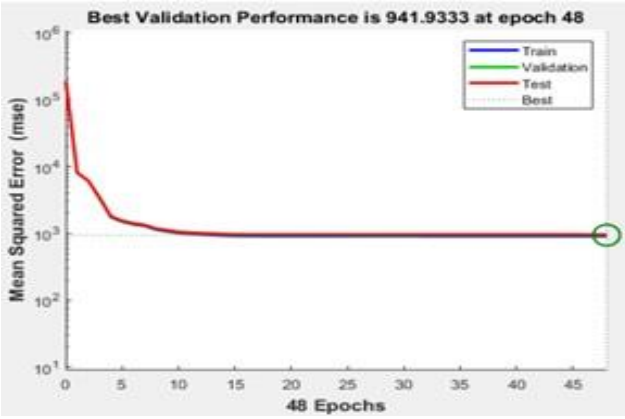

Figure-4. Histogram of errors after NARX network training.

Figure-5 shows the regression results. This allows us to validate the performance of the network. The regression graphs show the outputs of the network in relation to the training, validation and test data. A regression value R of 0.97 is shown.

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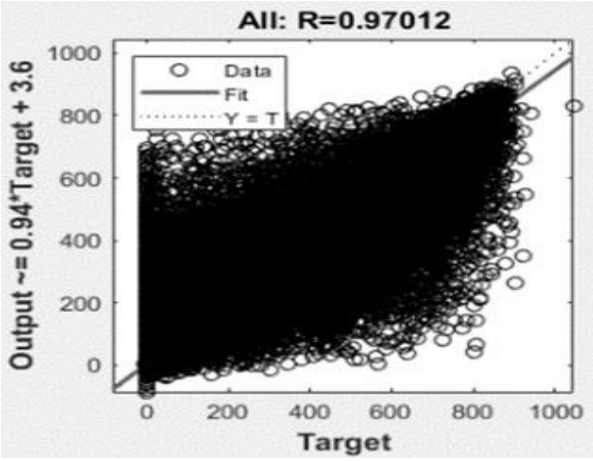

Figure-5. Regression plots after NARX network training.

Output Power Prediction Results

In this section, the results of the trained Feedforward network are presented. For a number of hidden layers of 50, the following data are used as input: wind speed at 10m, air temperature at 2m, position of the sun, direct radiation on an inclined plane and diffuse radiation on an inclined plane. Figure 6 shows a summary of the performance of FNN Network. It can already be noted that the best result was obtained after 1000 iterations.

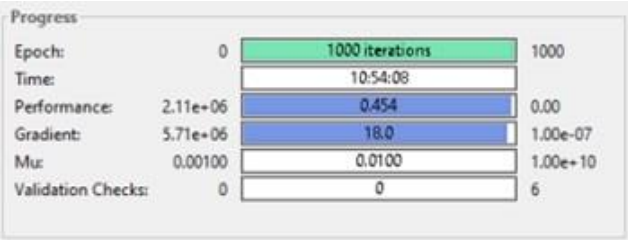

Figure-6. FNN network performance summary.

Figure-7 specifies that the mean square error (MSE) is 0.46, obtained at the 1000th iteration.

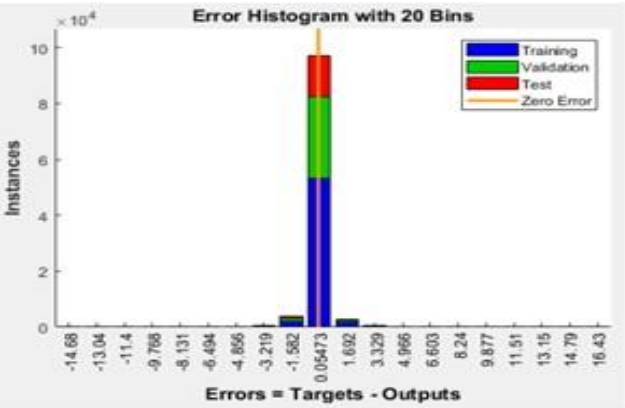

Figure-7. Evolution of MSE during FNN training.

It can be noted in Figure-8 that the error on the predicted outputs is the lowest (0.05473W) for the majority of the outputs (about 95000 values out of 105120).

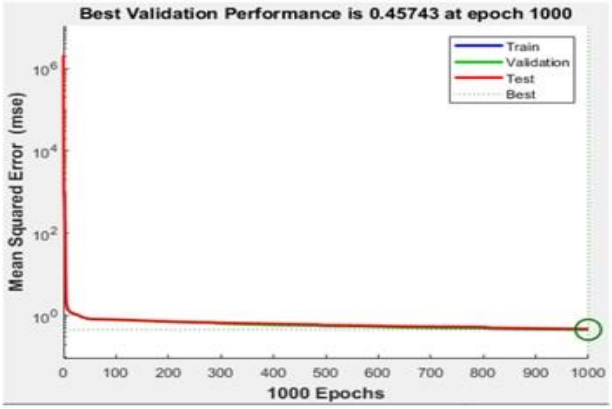

Figure-8. Histogram of errors after FNN training.

Figure-9 shows the regression results. The regression graphs show the network outputs compared to the training, validation and test data. We notice an R value of 0.999996.

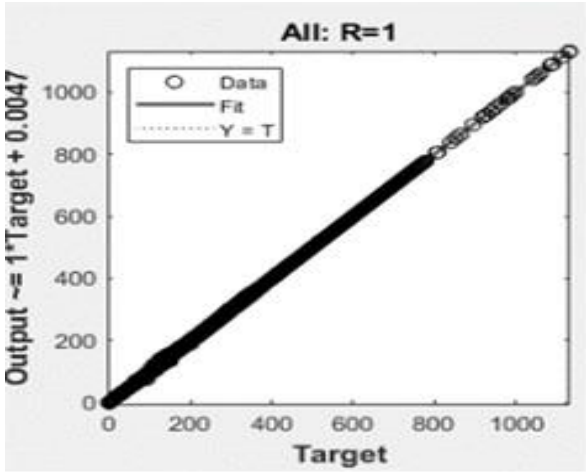

Figure-9. Regression plots after FNN training.

To evaluate the performance of network 3, we used the data from December 29, 30 and 31, 2016 to the network input. Figure-10 shows a summary of the evaluation results. MSE and R values of 0.164 and 0.999996 respectively can be noted.

Figure-10. Summary of FNN network evaluation results.

Figure-11 shows the changes in measured and predicted power.

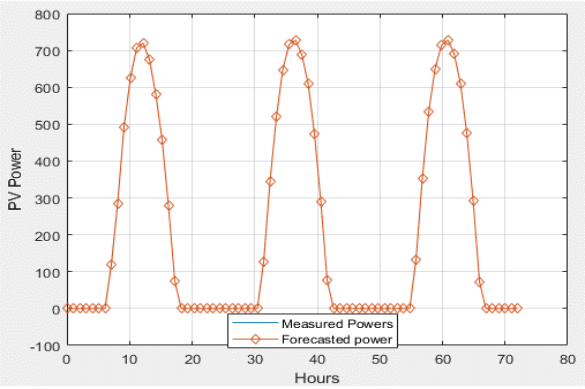

Figure-11. Measured and predicted power changes in the FNN.

Exploitation of Results

We recall that the present work aims at improving the policy of injecting PV power into an electrical grid as part of the MCA II program. For this purpose, a 2.11 MW photovoltaic installation has been dimensioned in [33]. By using the hybrid grid involved in this work, it will be possible to predict the output power of the installation within one hour from meteorological data and measurements made on the installation. Thus, with a well-controlled demand curve, it would be easy to know whether the energy produced by the installation will be in excess and to store it for any useful purpose.

CONCLUSIONS

In this paper an application of neural networks was made for the prediction of the output power of a 1kW peak power panel installed in Natitingou within the framework of the MCA II program in Benin Republic. At the end of this prediction, we were able to obtain a mean square error of 0.46 and a regression value of 0.999. This forecast will allow us to inject the necessary energy into the network and to store the excess or, in case of deficit, to plan a compensation policy in advance. Added to the developed forecast, a PV installation with dynamic production could be set up. This would allow the predicted power to be produced with a certain margin and could increase the lifetime of the installation.

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