

Neuro-Fuzzy Predictive Model for PV Energy Production based on Weather Forecast

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Abstract—This paper introduces an evolutionary optimization algorithm as a tool for training an Artificial Neural Network used for production forecasting of solar energy PV plants. This optimized procedure essentially represent a bio-inspired heuristic search technique which is used to solve complex forecasting problems modeled on the concepts of biological neurons. Some simulation results are reported to highlight advantages and drawbacks of the proposed method in order to suitably apply this algorithm to a neuro-fuzzy system application in solar energy production. The weather forecast data related to the PV plants are supplied by the airport service close to the production site and relative data are pre-processed using Fuzzy Logic techniques.

Index Terms—PV energy prediction, Neural Networks.

I. INTRODUCTION

In recent years solar power is getting more and more important as an alternative and renewable energy source, especially for small autonomous electrical power systems, villages and also rural areas. Photo-voltaic (PV) plants can also be connected to the traditional grid for energy distribution, but variations in solar power can cause, in general, voltage and frequency fluctuations.

Load and energy production forecasting has always been crucial for the effectiveness of power system planning and operation. Lots of electric power companies are now forecasting power load based on traditional prediction methods [1]. However, since the relationship between power load and factors influencing power production is nonlinear, it is difficult to identify its nonlinearity by using traditional prediction methods.

Moreover, renewable energy sources have increased the complexity of this scenario, thus requiring the capability to predict the dynamics of the system and to offer an optimal management; therefore, it has been proposed the application of advanced forecasting techniques integrated with an optimization algorithm in order to create a predictive model of the physical system and to provide an efficient control of resources and information. To implement this approach, evolutionary optimization procedures adaptively and dynamically analyzing consumer profiles have been defined in the so called digital energy environment [2].

Advanced forecasting techniques provide utilities with reliable production predictions and the opportunity to plan for

additional power supply and to make proactive actions. This aspect can have an impact on the economic balance of the systems especially in an integrated smart grid solution perspective. In fact, in this way the system-plant management is capable for example to plan appropriate preventive maintenance strategies in order to minimize energy losses due to unproductive suspensions. It can be estimated in the order of million dollars per MW per year adopting predictive strategies in the renewable energy sector and just the 10% of these are due to an optimized operating efficiency [3].

Increased solar power penetration is possible if measures are taken concerning solar radiation forecasting. This procedure may also affect the energy efficiency of the conventional power stations, since it affects the operation point of the power units. Prediction of solar power is therefore of importance for efficient load management and operation of the system. It has been suggested in literature [4], [5], [6] that solar power forecast could be based on the use of Artificial Neural Networks (ANNs). They are particularly appealing because of their ability to model an unspecified nonlinear relationship between production and weather variables.

II. ARTIFICIAL NEURAL NETWORKS

Computation techniques play an important role in most engineering applications in which optimization problems have to be solved. Usually the complex nature of many practical problems involves an effective use of Artificial Neural Networks to solve them. ANNs are useful tools when it is necessary to understand the complex and nonlinear relationships among data, without any a-priori assumption concerning the nature of these correlations.

ANN is an effective computing method, in order to easily process the dynamic behavior of time-varying variable, as previously presented by the authors in [7]. It is a computational model that simulates the features and behavior of the human brain neural networks. It consists of an interconnected group of artificial neurons that suitably processes information according to the strength of connections among them. In more practical terms neural networks are non-linear statistical data modeling tools used to model complex relationships between inputs and outputs or to find patterns in data.

For the considered forecasting application, a multilayered

perceptron (MLP) has been utilized. The MLP is a well-known universal approximator and has been extensively used in engineering applications, as well as other kind of ANN.

Training algorithms are used to train the network by learning the nonlinear behavior between input and output data. Therefore the learning process should result in finding the weights configuration associated to the minimum output error, namely the optimized weights configuration.

In other words, since ANN wish to infer the mapping implied by the data, the weights of the network have to be optimized in order to reach a good and accurate desired output: usually these tasks are associated to an objective function to be optimized. This function, called cost or energy function, provides the interface between the physical problems and the optimization algorithm itself. The cost function, in particular, is related to the mismatch between the proposed mapping and the data and for this reason it must contains prior knowledge about the problem domain.

A commonly used cost is the mean-squared error which tries to minimize the average squared error between the network's output, $f(x)$, and the target value y over all the example pairs.

There are often many problems related to this task: generally finding a solution in an optimization process means to reach a balance among different and often conflicting goals; as a consequence such a search could be extremely difficult. The huge number of variables is the first difficulty when dealing with one of these optimizing issues. Secondly, there are lots of weights configurations with different values of the cost function which are quite similar each other and very close to the global optimum case, even if these configurations are sub-optimal.

In particular, the approaches used to optimize and train a MLP may be divided into two main categories: the ones that need to calculate derivatives in order to optimize the objective function, such as gradient descent based strategies, e.g. the Error Back-Propagation (EBP) algorithm, and those that, starting from an initial position in the solution space, explore iteratively this space without requiring any derivatives calculation, e.g. evolutionary methods, like Genetic Algorithm (GA) or Particle Swarm Optimization (PSO) [7].

Error Back Propagation algorithm is a well known analytical algorithm used for neural networks training. In literature, there are several forms of back-propagation, all of them requiring different levels of computational efforts; the conventional back-propagation method is, however, the one based on the gradient descent algorithm.

One of the drawbacks of this method is the strong dependence upon the initial guess. A bad choice of the starting point may result in the possibility to get stuck in a local minimum and consequently to find a solution that is not the best one. Besides, most of the typical problems requiring optimization often have non-differentiable or/and discontinuous regions in the solution domain and this fact introduces difficulties in the application of these traditional methods based on derivatives calculations. These aspects are often overcome by evolutionary methods, like the one chosen by the authors, the Genetical

Swarm Optimization (GSO) algorithm [8].

GSO essentially represent a bio-inspired heuristic search technique, which can be used to solve combinatorial optimization problems, modeled on the concepts of natural selection and evolution (GA), but also based on cultural and social behaviours derived from the analysis of the swarm intelligence and interaction among particles (PSO) [9]. Previously performed analyses highlighted some advantages of the proposed technique in order to suitably apply this algorithm to neural network applications in engineering problems [10].

III. IMPLEMENTATION

As shown in Figure 1, weather forecasts are a key input when the ANN is used for forecasting. Nevertheless in case of rapid changes in solar radiation or temperature at the forecast day, produced power changes greatly and forecast error would sensibly increase. In traditional prediction methods the ANN uses all similar days data to learn the trend of similarity. However, learning all similar days' data is quite complex, and it does not help if weather conditions change suddenly during the same day. Therefore, it is necessary to integrate into the neuro-fuzzy system real time information coming from local meteorological stations and, in particular, from surrounding regions and cities, where the weather change has already occurred.

In this paper a real-world case study with a proposed approach of fuzzy filtering is suitable for dealing with the complexity of inputs involved in the available weather forecast data. Over the last decades fuzzy models have been used to replace conventional methods for engineering applications, especially in control systems, making easier the solution to many problems by introducing an unconventional set of rules. System analysis and control design for nonlinear systems based on fuzzy system approaches have been very active in the scientific community [11], [12], [13]. In this context fuzzy models, due to their intrinsic capability of approximating nonlinear data mappings, could be exploited for the preprocessing of a subset of weather data in order to filter the inputs for the ANN. As shown in detail in Figure 1 a fuzzy preprocessing toolbox is introduced into the neural system to find data correlation between UV index, cloud cover and specific time/season with irradiance value useful to perform production forecast.

IV. SIMULATION RESULTS

In order to compare the different optimization approaches for training the ANN, a production forecasting problem has been considered with a different perspective compared to [1]. The focus is to highlight how fast and accurate the methods are in determining and optimizing the neural networks weights associated to the considered problem.

After a trial campaign, the network architecture which have provided better results present two hidden layers, as shown in Figure 1. In particular, the number of neurons in the input layer is 16, as reported in Table I, which describes the meteorological parameter provided from the weather forecast service.

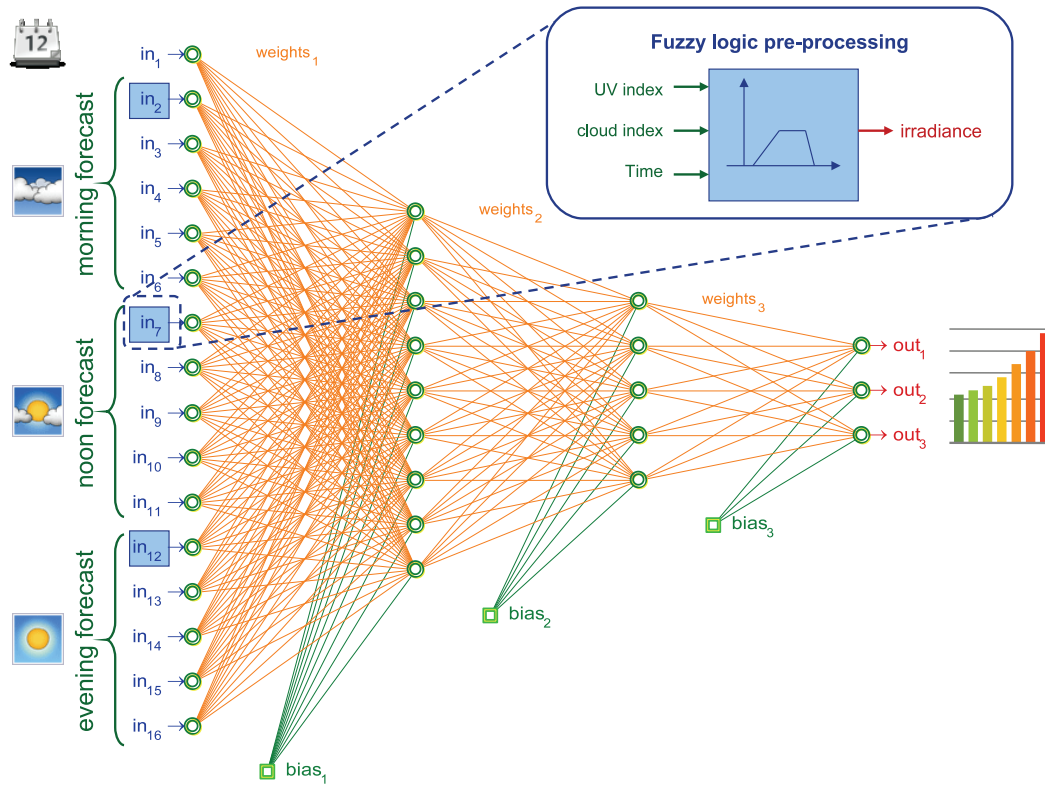


Fig. 1. Simplified view of the implemented feed-forward ANN with Fuzzy pre-processing.

TABLE I
STRUCTURE OF INPUT LAYER

Neuron	Variable name	Time	Range
i_1	Day		(1–366)
i_2	Irradiance	at 6:00	(0–1350) W/m ²
i_3	Air temperature	"	(0–30) °C
i_4	Wind speed	"	(0–20) km/h
i_5	Air humidity	"	(0–100) %
i_6	Air pressure	"	(1000–1040) mbar
i_7	Irradiance	at 12:00	(0–1350) W/m ²
i_8	Air temperature	"	(0–30) °C
i_9	Wind speed	"	(0–20) km/h
i_{10}	Air humidity	"	(0–100) %
i_{11}	Air pressure	"	(1000–1040) mbar
i_{12}	Irradiance	at 18:00	(0–1350) W/m ²
i_{13}	Air temperature	"	(0–30) °C
i_{14}	Wind speed	"	(0–20) km/h
i_{15}	Air humidity	"	(0–100) %
i_{16}	Air pressure	"	(1000–1040) mbar

The neurons in the two hidden layers are, respectively, 9 and 5, while the output layer is composed of 3 neurons, since 3 different produced-power forecasts are considered: in fact, the authors performed simulations for three different photovoltaic power plants in order to test their method at various scale, since they have different productive capacity, as shown in Table II. To compare the numerical results it is important to underline that the three plant locations present exactly the same GPS reference points. Therefore the weather conditions can be assumed identical for the three PV plants at each time.

Different time horizons was considered in load forecasting: short term (day and several days), medium term (week and several weeks), long term (year and several years), and forecasts for different lead time can potentially be used for different aims. We finally chose a short term time base for this specific application. The neuro-fuzzy system optimized by GSO exhibit good predictive performances in all the operative conditions, in a complete sunny day, a partly cloudy one and even a plant

TABLE II
STRUCTURE OF OUTPUT LAYER

Neuron	Variable name	Range
o_1	SM 4200S-2 Produced power	(0–4) kW
o_2	SM 4200S-3 Produced power	(0–4) kW
o_3	SM 35C-4 Produced power	(0–35) kW

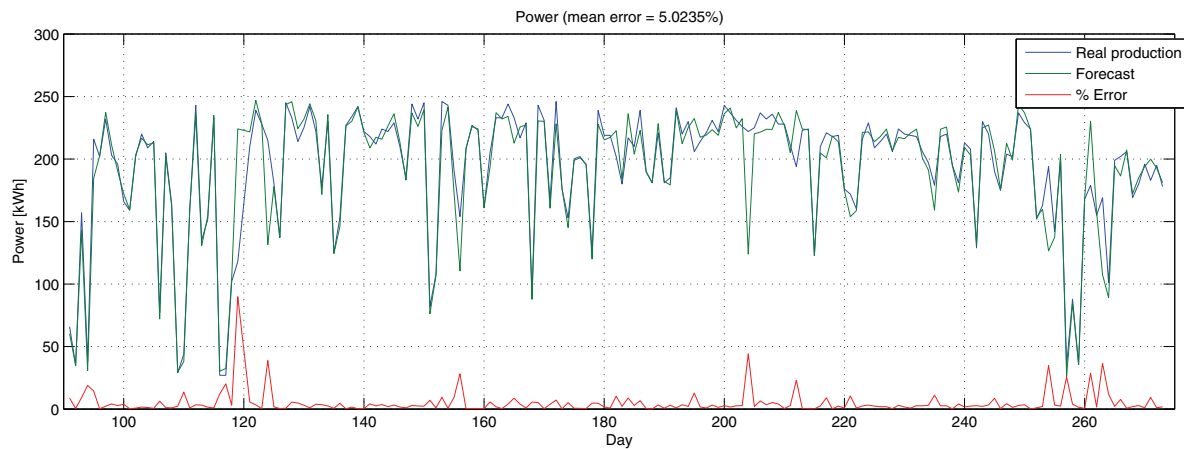


Fig. 2. Results of the forecasting over a six-months time frame and comparison with actual data.

maintenance day.

Figure 2 shows the complete data set simulations around six months and the average error is around 5%. The considered ANN behaviour does not change with respect to the plant power size.

V. CONCLUSIONS

Energy plant prediction is very important in industrial applications. An accurate prediction enables to mitigate the price risk associated with the power exchange, for instance signing more bilateral contracts. Besides, a good estimate of the load profile results in avoiding economic penalties on the balancing market. In this work the authors presented an effective and robust implementation of an Neuro-fuzzy model for forecasting of photo-voltaic energy production.

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