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# Artificial Intelligence Techniques for Energy Balance Forecasting

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## Abstract

*Commercial success in photovoltaic system area depends actually on the ability to submit competitive predictions relative to energy balance trends Thus, it seems convenient to "anticipate" this parameter in order to act consequently and resort to protective actions. In this context, this paper proposes a tool for energy balance prediction based on ANFIS (Adaptive Neuro Fuzzy Inference System). This neuro- fuzzy predictor is modified in order to obtain an accurate forecasting for medium term. The solutions are illustrated on a real application and take into account the known "future": the programmed actions.*

**Key words:** *neuro- fuzzy network, ANFIS, energy, forecasting, prediction error.*

## Introduction

Nowadays there are huge ranges of energy market participants, bidding strategies are more and more complex, and a number of financial derivatives have been developed. Commercial success depends on the ability to submit competitive predictions relative to energy balance trends (difference between the electricity produced and consumed - DPcg) [1]. Thus, it seems convenient to "anticipate" a phenomenon in order to act consequently and resort to protective actions.

In particular, the different time horizons required by the electricity markets (e.g., day-ahead, hour-ahead) can be respectively associated to short term (STLF) [2], medium term (MTLF) or with long term forecasting (LTLF) [3]. For short term forecasting the information is sampled on an hourly (or half hourly) basis, or even a daily basis (for load peak prediction) so is defined as varying from a few minutes up to a few weeks ahead. This type of prediction is important because the national grid requires DPcg values at any moment in the day. Traditionally, hourly forecasts with a lead time between one hour and seven days are required for the scheduling and control of power systems. The medium term forecasting in energy field covers the horizon from one month up to a few years ahead and finally, the long term horizon considers load peaks and consumed energy, on a yearly basis, for several years ahead. For example, long-term forecasting is relevant for the planning of new electricity utilities, and inaccurate predictions have important financial costs. For these particular forecasting cases is a need for accurate prediction.

From the perspective of the system operators and regulatory agencies**,** the medium term forecasting is a source of primary information for the safe and reliable operation of the system. For producers also, these ones are a basic tool for determining the optimal utilization of generators and power stations, as some facilities are more efficient than others.

Despite the many publications and models of load forecasting that have been developed in the last few decades, few amongst those have dealt with the medium term forecasting. This paper deals with this type of forecasting. Precisely, it is based on neuro - fuzzy networks in order to estimate the DPcg evolution for a medium time horizon. This artificial intelligence tool is applied is illustrated on a data based from an experimental photovoltaic amphitheatre of average dimension (0.4 kV/10kW), located in the east-centre region of Romania, more precisely in the city of Târgoviste [4].

In this context, the paper is organized in two parts. First of all, the forecasting framework is delimited, starting with the definition, metrics, approaches and tools. In the second section the chose of a neuro-fuzzy tool is argued using the existed approaches and the results obtained by different authors. A new ANFIS (Adaptive Neuro Fuzzy Inference System) architecture is proposed, illustrated and discussed.

## Forecasting framework

Considering the benefits that forecasting may bring to the security, economics and resource management fields, the scientific community is now beginning to take some interest in this area. The control of the performance prediction represents the premise of a good global performance.

In literature, the forecasting is called also prediction or prognosis and this reveals that there is no consensual acceptation of term [5, 6, 7, 8]. Due to these facts, in this article the forecasting will be associated with the notion of prediction and will determine the future state of the analyzed system the closest possible to the future real state of the system.

Actually the systems are very complexes and the conditioning parameters that influence system functioning are significant. Often their actions induce nonlinearities in system modelling process because cannot be always precisely described. In these cases it is very difficult to determine any sort of model for prediction purposes.

Artificial Neural Networks (ANNs) are techniques use often for load forecasting. For short term forecasting horizons in particular, the neural networks have a good flexibility in capturing nonlinear interdependencies between the load and exogenous variables. However, the ANN models are complex and difficult to understand, and are often over-fitted. Indeed, their structure is sufficiently opaque that it is not clear why they should forecast as well as they do. As a result, the literature is still undecided as to their practical utility for electricity load forecasting. Articles that deal with ANN models, in particular for short term load forecasting horizon are [9, 10, 11, 12, 13, 14].

Despite all publicized successes, neural network based load forecasting models have been designed relying on time-consuming, empirical, and suboptimal procedures [15]. The potential for applying neural networks to short term load forecasting depends strongly on the extraction of appropriate input variables. This requirement has often been neglected, and many proposals for building the neural network input space still use (linear) correlation analysis. Input selection procedures with the capacity to extract high order statistical information from the input-output data must be employed to fully exploit the ANN mapping capability.

The advantages and the drawbacks of AI forecasting techniques, precisely of ANN, leaded us to the choosing of nonlinear network (neuro-fuzzy systems- NFs) approximators as reference tool for our approach of medium term energy balance forecasting.

Neuro- fuzzy systems are a combination of ANNs and fuzzy sets and represent a powerful tool to model systems behavior. The ANN is used to define the clustering in the solution space, which results in creation of fuzzy sets [17].

A particular architecture of neuro-fuzzy systems is represented by the adaptive neuro-fuzzy inference system (ANFIS) [18]. ANFIS is a Sugeno-type fuzzy inference system in which the parameters associated with specific membership functions are computed using either a backpropagation gradient descent algorithm alone or in combination with a least squares method. Precisely, the ANFIS architecture is equivalent with a two-input first-order Sugeno fuzzy model with nine rules, where each input is assumed to have three associated membership functions. It has been widely applied to random data sequences with highly irregular dynamics [19] e.g. forecasting non-periodic short-term stock prices [20].

The success of ANFIS is given by aspects like: the designated distributive inferences stored in the rule base, the effective learning algorithm for adapting the system's parameters or by the own learning ability to fit irregular or non-periodic time series. On the other hand, used in application alone to non-periodic short-term forecasting, ANFIS predictions make large residual errors due to high residual variance, consequently degrading prediction accuracy [21]. It is very difficult to interpret for a non expert the fuzzy rules generated by ANFIS because of the form of consequents (linear combination of inputs).

## Neuro fuzzy energy balance forecasting

The actual challenges consist in controlling the performance of the future state of the system for medium term. Most of the papers that use ANFIS for prediction consider the inputs as they exist in the benchmarks. In this paper ANFIS use a data base with 290 data points {y(t),u(t)}, from t=1 to t=296. From the monitored plant, the Solar Amphitheatre [4], the DPcg is considered as output of the model- y(t) and the exterior temperature as input- u(t). ANFIS is a data-driven approach relies on the assumption that the statistical characteristics of data are relatively unchanged unless a malfunctioning even occurs. It hasn't a close relation with the system mathematical model and it is used when is difficult even impossible to catch the system behavior.

The proposed framework consider forecasting process as a aggregate function of past, present and future states. Thus, the ANFIS inputs are modified (Fig. 1) and a third variable (a schedule action) is added. It appears in prediction function definition and is the results of the necessity of taken into account of "known future" actions dues of precise moments in the week or in the year and changes the initial objective profile. For example, it is expected a modification of the consumers behaviors due summer, winter holydays or week-end time.

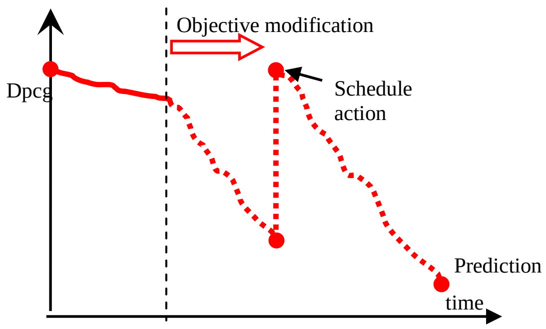


**Fig 1.** Future states that influence prediction process.

The error distribution is usually expected to be normal white noise in a forecasting problem, but it will probably not be so in a complex problem like load forecasting. No single error measure could possibly be enough to summarize it. The shape of the distribution should be suggested. Keeping the total error low, therefore, means keeping the model simple.

It is well known that goodness-of-fit statistics are not enough to predict the actual performance of a method. The implications and consequences of the choices made in design, implementation and validation of neuro- fuzzy architecture are very important. Often appears problems of overfitting or overparametrization [22].

Considering the metrics described above, we have observed that the ANFIS architecture, for two and three selected inputs, has satisfactory results for a short term prediction. For medium and long term, the obtained errors became bigger and bigger and this affects the forecasting in terms of accuracy and confidence (Fig. 2)

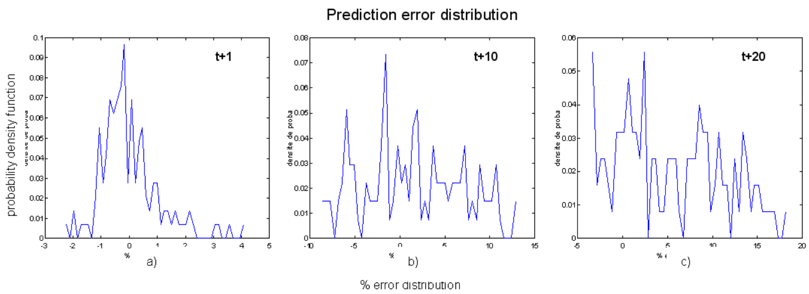


**Fig. 2.** Error prediction distributions for two inputs ANFIS.

The prediction results from Fig. 2 are obtained for an ANFIS with two selected inputs, for a time horizon equal with 1 (Fig. 2 (a)), 10 (Fig. 2 (b)) and 20 (Fig. 2 (c)).

In order to obtain a good performances as result of implementing neuro-fuzzy tools in forecasting approaches, this article propose a novel architecture for ANFIS as an alternative for medium time error stabilization. This one links the ANFIS modules in series to penalize the growth tendency of error in time. The performance measured in terms of error became satisfactory a medium term (Fig. 3).

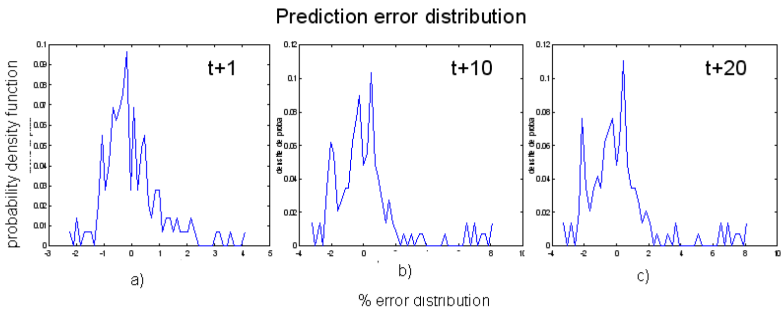


**Fig. 3.** Error prediction distributions for two inputs series link ANFIS.

The effect of taking into account the "future" for prediction, in other words the modification of the mission profile due to some extern intervention has also influence over error (Fig. 4, on the next page).

## Conclusions and work in progress

Controls of the performance prediction represent the premise of a good global forecasting performance. The existing approaches, methods, metrics and tools for load forecasting are discussed from different points of view. The identified problems and advantages create the context for proposing a new ANFIS architecture capable to ensure for the prediction a stability in terms of errors magnitude for a medium term horizon. Also, the preplanned actions require the availability of assets under consideration for a specified time. The obtained confidence level at this point of time is a satisfactory one from the industrials point of view.

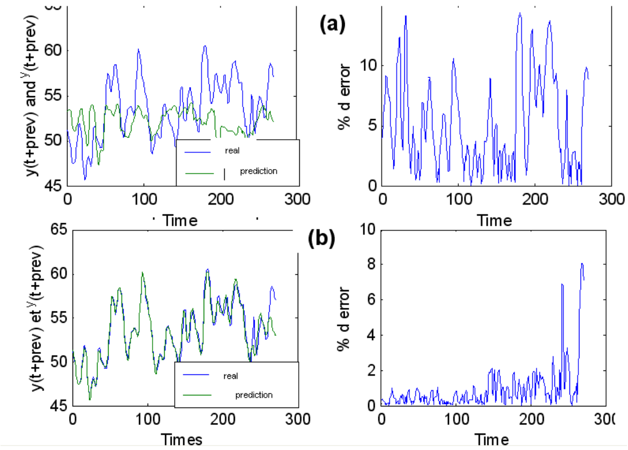


**Fig. 4.** Error prediction distributions for ANFIS without (a) and with (b) external interventions.

The work is still in progress and the developments are at present extended in three principal ways. First, the definition of new loss functions capable to penalize the errors above an acceptable tolerance level. Secondly, the application of other tools as techniques for a global forecasting has to be investigated and, finally, an amelioration of obtained predictive system in terms of interpretability.

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# Reţelele neuro fuzzy în predicţia pe termen mediu a bilanţului de putere dintre generare şi consum

## Rezumat

*În prezent succesul implementării sistemelor fotovoltaice depinde în mare măsură de abilitatea de a predicţiona evoluţia bilanţului de putere dintre generare şi consum. Aşadar este de dorit a se estima valoarea acestui parametru pentru a putea adopta măsurile corespunzătoare. În acest context, structura de predicţie bazată pe ANFIS (Sistem de Inferenţă Neuro-Fuzzy) este modificată prin considerarea "viitorului" cunoscut: acţiuni programate. Propunerea de îmbunătăţire a acurateţei predicţiei pe termen mediu este ilustrată cu ajutorul datelor monitorizate de la o aplicaţie reală.*