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System of automatic control of power usage based on a neural network

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Abstract — in this article is considered a problem of prediction amount generated energy from renewable sources with the help of a neural network. Our system can be part of some systems for tasks of managing distribution of energy. First our mission is to analyze information. We sorted all incoming data form renewable sources and divide them on four types each for the season (summer, autumn, winter, spring). The second one is that we predict future values using recurrent neural network called “Nonlinear autoregressive model process with exogenous input” (NARX) that trained on previous data from the sources and weather conditions that already been sorted by the season for more accurate values. In this paper, we will closely analyze this prediction model and give some modelling results. After we have predicted values we can analyze and compare it with estimate consumption level, then we can control distribution of electric energy over the grid by unplugging some not important systems. If we can`t equalize levels of regeneration and consumption we convert our system to general source of electric energy to buy some time to renewable source recharge the battery. The system mostly independent but it`s can be integrated in a big or small Smart Grid. Such systems often include renewable sources of energy and they need maintaining distribution. In addition, our system can save money just because the main priority of it is efficient use of electric energy. We all know that energy from renewable sources is cheaper than from general electric grid and system try to use it on 100%.

Keywords - control system; neuron network; NARX; Smart Grid; Levenberg-Marquardt optimization; Bayesian regulation.

I. INTRODUCTION

The task of energy-efficient management of electricity consumption and generation is extremely important for small and big networks. In our time usage renewable sources is more and more common, but it`s not that simple just buy solar panel and plug it into the network, at first, we need some interconnections that includes batteries and different converters, then we need control system to manage all incoming generation and maintaining all power consumption. During the development of control systems, it is necessary to predict the values of power generating of electricity. Since the volume of the generating charts database must be sufficiently large to allow prediction to be reliable, it is advisable to apply modern mathematical approaches to processing these graphs, in particular, variant of recurrent neural network “Nonlinear autoregressive model process with exogenous input” (NARX). Based on the creating of a database of daily dependencies of consumption for different seasons, it’s possible to form four various small database and apply them to train our prediction network for more reliable result. Even with all our precaution predicting value still be not perfect so our system must have feedback connection that ensure that error would be in certain limits. So, with all that predicted data we can effectively response for all rise and falls of generating energy. If total generated energy within the hour will be not enough then we must decide what to do: we can connect our network to general electric grid but it would be costlier and not effective or we can unplug some no critical systems to just level of consumption we need. Of course, the second one is more effective but system must understand what is really in our need, maybe not now, but after some time environment can change and unpredictable humans may use what we disable some time ago. In this paper we didn`t consider about it but have in mind that`s although possible situation at some point.

II. MAIN BLOCKS

To be more concrete our database consists of temperature data, power generation data and cloudiness data. All of that data must be categorized by different seasons (summer, autumn, winter, spring).

Firstly, new data from sources passing distribution between seasons so that prediction network would training only on data within short limit, of course, there would be some unique values but if we gather enough data there are so small amount of them so they can be forgotten.

After sorting, values pass to our predicting network NARX. This is a powerful class of models which has been demonstrated that they are well suited for modeling nonlinear systems and specially time series. One principal application of NARX dynamic neural networks is in control systems. Some important qualities about NARX networks with gradient-descending learning gradient algorithm have been reported: (1) learning is more effective in NARX networks than in other neural network (the gradient descent is better in NARX) and (2) these networks converge much faster and generalize better than other networks [1].

MODEL

A state space representation of recurrent NARX neural networks can be expressed as:

$$z_k(k+1) = \begin{Bmatrix} F\big(u(k), z_i(k)\big), i = 1 \\ z_i(k), \;\; i = 2,3,\dots,N \end{Bmatrix}$$

Where the output $y(k) = z_i(k)$ and $z_i, i = 1,2,\dots,N$, are state variables of recurrent neural network and *u(k)* is past observation, *k* is time instance.

The recurrent network exhibits forgetting behavior, if:

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$$\lim_{m\to\infty} \frac{\partial z_i(k)}{\partial z_j(k-m)} = 0 \ \forall k, m \in K, i \in O, j \in I,$$

Where z is state variable, m is number of steps, “I” denotes the set of input neurons, “O” denotes the set of output neurons, “K” denotes the time index set [2].

The NARX model for approximation of a function can be implemented in many ways, but the simpler seems to be by using a feedforward neural network with the embedded memory (a first tapped delay line), as is shown in figure 1, plus a delayed connection from the output of the second layer to input (a second tapped delay line).

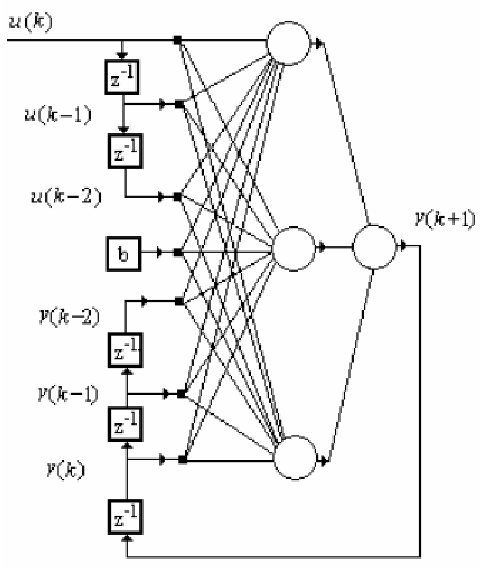

Fig. 1. NARX model.

Making the network dependent on d_u previous sequence elements is identical to using d_u input units being fed with d_u adjacent sequence elements. This input is usually referred to as a *time window* since it provides a limited viewed on part of the series. It can also be viewed as a simple way of transforming the temporal dimension into another spatial dimension [2].

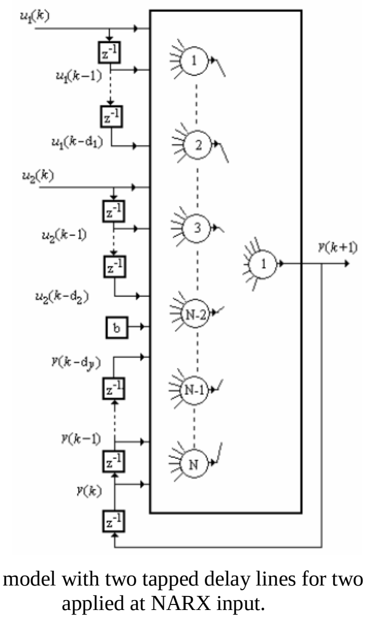

Fig. 2. NARX model with two tapped delay lines for two time series applied at NARX input.

In practice it was observed that forecasting of a time series will be enhanced by simultaneously analyzing related time series. For example, electrical power consumption for the next day will be better predicted if taken together, last p_c day consumptions and last p_t environment temperatures are simultaneously applied as inputs to the neural networks. The architectural model in figure 2 is make to test this hypothesis A generalized implementation of this model allows the input and output to be multidimensional, and thus applying to the “multivariate” type of time series.

For the architectural model in figure 1 the notation used is NN (d_u, d_y; N) to denote the NN with d_u input delays, d_y output delays and N neurons in layer 1. Similarly, for the architectural model in figure 1 the notation used is NN (d_{u1}, d_{u2}, d_y; N).

For the NN models used in this work, with two levels (level 1 surnamed *input* layer and level 2 or *output* layer), the general prediction equations for computing the next value of time series $y(k+1)$ (output) using model in figure 2, the past observation $u(k)$, $u(k-1)$, …, $u(k-d_u)$ and the past outputs $y(k)$, $y(k-1)$, …, $y(k-d_y)$ as inputs, may be written in the form:

$$y(k+1) = F_0 \left\{ w_{b0} + \sum_{h=1}^{N} w_{h0} * F_h\left(w_{h0} + \sum_{i=0}^{d_u} w_{ih} u(k-i)\right) + \sum_{j=0}^{d_y} w_{jh} y(k-j)) \right\}$$

For the model in figure 2, the prediction equations for computing the output value $y(k+1)$ using the past observations $u_1(k)$, $u_1(k-1)$, …, $u_1(k-d_u)$ for the first time series, the past observations $u_2(k)$, $u_2(k-1)$, …, $u_2(k-d_u)$ for the second time series and the past outputs $y(k)$, $y(k-1)$, …, $y(k-d_y)$ as inputs, may be written in the form [3]:

$$y(k+1) = F_0 \left\{ w_{b0} + \sum_{h=1}^{N} w_{h0} * F_h\left(w_{h0} + \sum_{i1=0}^{d_{u1}} w_{i1h} u_1(k-i_1)\right) + \sum_{i2=0}^{d_{u2}} w_{i2h} u_2(k-i_2)) + \sum_{j=0}^{d_y} w_{jh} y(k-j)) \right\}$$

LEARNING ALGORITHM

For learning purposes, a dynamic back-propagation algorithm is required to compute the gradients, which is more computationally intensive than static back-propagation and takes more time. In addition, the error surfaces for dynamic networks can be more complex than those for static networks. Training is more likely to be trapped in local minima [4]. The selected training method in this work uses the advantage of availability at the training time of the true real output set. It is possible to use the true output instead of the estimated output to train the network which has the feedback connections network which has the feedback connections decoupled (cut). The decoupled network has a common feedforward architecture which can be trained with classical static back-propagation algorithm. In addition, during training, the inputs to the feedforward network are just the real/true ones – not estimated ones, and the training process will be more accurate. The training process has some difficulties. One is related to the number of parameters, which refers to how many connections or weights are contained in network. Usually, this number is large and there is a real danger of "overtraining" the data and producing a false fit which does not lead to better forecasts. For NARX neural network model the number is given by $p = (d_u + d_y + 2)\ N$. A solution is penalizing the parameter increase [4]. This fact motivates the use of an algorithm including the regularization technique, which involves modifying the performance function for reducing parameters value. Practically, the typical performance function used in training, MSE, is replaced by a new one, MSEreg, as follows:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(e_i)^2 = \frac{1}{N}\sum_{i=1}^{N}(t_i - y_i)^2$$

$$MSW = \frac{1}{n}\sum_{j=1}^{n} w_j^2$$

$$MSEreg = \xi MSE + (1-\xi)MSW$$

where t_i is the target and ξ is the performance ratio. The new performance function causes the network to have smaller weights and biases, and in this way forces the network response to be smoother and less likely to overfit.

The network training function that updates the weight and bias values according to Levenberg-Marquardt optimization was modified to include the regularization technique. It minimizes a combination of squared errors and weights and, then determines the correct combination so as to produce a network which generalizes well. The process is called Bayesian regulation.

In general, in function approximation problems, for networks that contain up to a few hundred weights, the Levenberg-Marquardt algorithm will have the fastest convergence. This advantage is especially noticeable if very accurate training is required. However, as the number of weights in this network increases, the advantage of this algorithm decreases [4].

POST PREDICTION SYSTEM

So, after we have our prediction and it`s close too future real values we can manage processes generation and consumption. First of all, we must check if all the generation power is enough to supply all our consumption. On this stage we sum predicted values and search for arithmetical mean and of course we know estimate future average value of consumption, so we compare this and make some decisions. If our difference is more than zero and it`s means prediction values are in appropriate level of consumption we fine to only maintain system as it`s. If difference is less we check how big this difference and plug out not important systems.

III. RESULTS OF MODELLING

Our model consists of table of data in Excel that already been sorted by seasons and some values of estimate level of consumption also sorted by seasons. Some of these values you can watch in table 1:

TABLE I. PART OF A DATABASE.

Temperature, C				**Generation, kW**				**Estimate level of consumption, MW**			
sum	***aut***	***win***	***spri***	***sum***	***aut***	***win***	***spri***	***sum***	***aut***	***win***	***spri***
25	11	-5	0	30	25	10	15	2	2,5	4,5	3,5
23	19	-3	1	28	24	9	14	Cloudness			
27	18	-1	3	31	23	11	12	0,3	0,2	0,5	0,6
30	17	-8	5	27	20	8	14	0,4	0,5	0,6	0,4
23	16	-10	6	30	24	10	13	0,3	0,4	0,3	0,3
25	15	-11	2	28	20	11	17	0,5	0,3	0,2	0,4
26	12	-15	3	29	19	13	16	0,1	0,3	0,8	0,5
27	12	-13	7	31	21	12	15	0,2	0,4	0,9	0,3
27	15	-10	8	32	22	8	15	0,5	0,2	0,6	0,6
28	14	-7	8	33	20	9	16	0,6	0,6	0,7	0,4
29	13	-9	5	30	19	10	18	0,3	0,6	0,5	0,5

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This data has needed to predict future values by using modeling platform called MATLAB. So, we use special MATLAB function to perform our NARX neuron network [5].

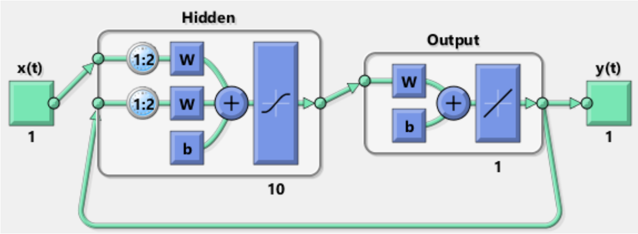

Fig. 3. Model of NARX in MATLAB function.

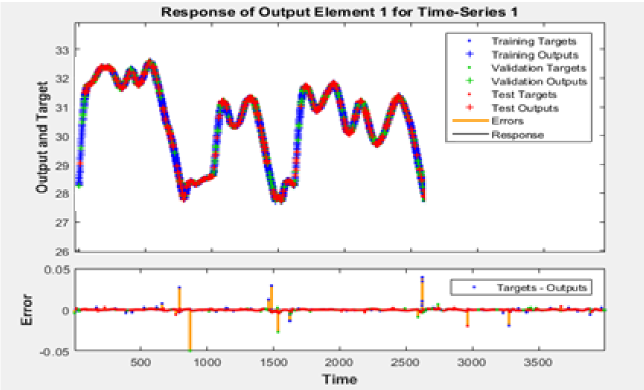

Fig. 4. Plot of predicted generation values (in summer) of solar panel

This data has could be transferred to the block of decision making so all we have to do is summarize predicted values and compare it with estimates values.

IV. Conclusion

Our system solves some problems of controlling in complex systems such as Smart Grid. It can manage distribution of energy across the network and unplug some parts of it to prevent the situation when power is not enough or can use some external sources of the energy. This system is only on stage of theoretical modeling and needed more time to fully be appropriate to development. As we said before system need more thorough algorithm to decide what to do in different circumstances it will be more likely as real virtual intelligent that can make decisions based on previous experience and estimate predictions. Of course, we need a lot of data to perform such a difficult system and strong computational apparat. Neuron network will be more and more our salvation for the future.

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Система автоматического контроля энергопотребления на основе нейронной сети

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У цій статті розглядається проблема прогнозування кількості виробленої енергії з поновлюваних джерел за допомогою нейронної мережі. Наша система може бути частиною деяких систем для завдань управління розподілом енергії. Перша наша місія - це аналіз інформації. Ми відсортували всі вхідні дані з поновлюваних джерел і розділили їх на чотири типи за сезоном (літо, осінь, зима, весна). Друга полягає в тому, що ми прогнозуємо майбутні значення, використовуючи періодичну нейронну мережу під назвою «Нелінійний процес авторегресивної моделі з екзогенним входом» (NARX), який тренувався за попередніми даними з джерел та погодних умов, які вже були відсортовані за сезоном для більш точних значень. У цій роботі ми детально проаналізуємо цю модель прогнозування та дамо деякі результати моделювання. Після того, як ми передбачили величини, ми зможемо проаналізувати та порівняти їх із оціночним рівнем споживання, тоді ми можемо контролювати розподіл електричної енергії по електромережі, відключивши кілька не важливих систем. Якщо ми не можемо зрівняти рівень регенерації та споживання, ми перетворимо нашу систему на загальне джерело електричної енергії, щоб виграти деякий час для відновлювального джерела, щоб зарядити акумулятор. Система здебільшого незалежна, але вона може бути інтегрована у велику чи малу Smart Grid. Такі системи часто включають відновлювані джерела енергії, і вони потребують постійного розподілу. Крім того, наша система може економити гроші лише тому, що головним її пріоритетом є ефективне використання електричної енергії. Всі ми знаємо, що енергія з відновлюваних джерел дешевша, ніж із загальної електричної мережі, і система намагається використовувати її на 100%.

Ключові слова- система управління; мережа нейронів; NARX; Smart Grid; оптимізація Левенберга-Маркарда; Байєсівське регулювання.