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Wind Power Forecasting using Emotional Neural Networks

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Abstract— **Emotional neural network (ENN) is a recently developed methodology that uses simulated emotions aiding its learning process. ENN is motivated by neurophysiological knowledge of the human's emotional brain. In this paper, ENNs are developed and examined for prediction tasks. Genetic algorithm is applied for optimal tuning of crisp numerical parameters of ENN. The performance of the proposed ENN is examined using data sets for a couple of synthetic (with constant and variable noise) and real world (wind farm power generation data) case studies. A traditional artificial neural network (ANN) is also implemented for comparison purposes. Numerical results indicate the superiority of ENN over ANN in terms of accuracy and stability.**

Keywords—emotion; BEL; BELBIC; forecasting; wind power.

I. INTRODUCTION

Wind power is a renewable energy that its forecasting process is known as a problematic task. Accurate forecasts for wind power generation are vital for the management of power systems, controlling and scheduling of smart grids, and optimal integration of wind farms into energy systems [1]. In the literature, there are two general approaches for wind power forecasting. The first approach mainly includes mathematical models such as AR (autoregressive), ARMA (autoregressive integrated moving average) and ES (exponential smoothing) [1]-[4]. Artificial intelligence (AI) methods such as artificial neural networks (ANNs) [5]-[9] and adaptive neuro-fuzzy inference systems [10]-[12] are in the second approach. The distinguishing feature of AI methods with respect to the mathematical models is the excellent learning capability. AI methods learn behaviour by observing the previous values and accurately predicting the future values. Recently, it has been shown that ANN-based prediction intervals [13]-[15] are better predictor than traditional regression models for forecasting wind power [1].

This paper addresses a new class of ANNs named emotional neural networks (ENNs) [39]. ENNs have been successfully utilized for learning in complex systems such as geomagnetic activity of the earth magnetosphere which is a complex dynamical system [37-38]. They can be categorized to the brain emotional learning (BEL)-based ENNs [15]-[17] and the emotional back propagation (EmBP) based ENNs [18]-[20]. With respect to the EmBP, the BEL networks are closer to the human emotional process and show higher accuracy in learning applications. BEL networks have been created via anatomical computational model of emotional brain (EB) [39] and successfully investigated in various control and prediction applications [21]-[23]. This paper aims to apply a BEL-based ENN in wind power forecasting. To the best of our knowledge, ENNs have not yet been examined for renewable energy forecasting. They have demonstrated promising results for modeling complex systems and patterns. This justifies their application for wind power forecasting.

The organization of the paper is as follows: Neuropsychological motivation, ENNs and proposed learning method are presented in Section 2. Experimental results on wind power forecasting and synthetic data prediction are demonstrated and discussed in Section 3. Finally, conclusions are made in Section 4.

II. EMOTIONAL NEURAL NETWORKS

A. Biological features of emotional brain

The important findings of EB have been reported by LeDoux [24]-[26]. These findings characterize the signal propagation paths in EB including short projections and inhibiting connections. Due to the existence of short paths in EB, it can response to the inputs rapidly. This fast reaction has motivated the researchers to model EB and employ the resulting models in various engineering applications.

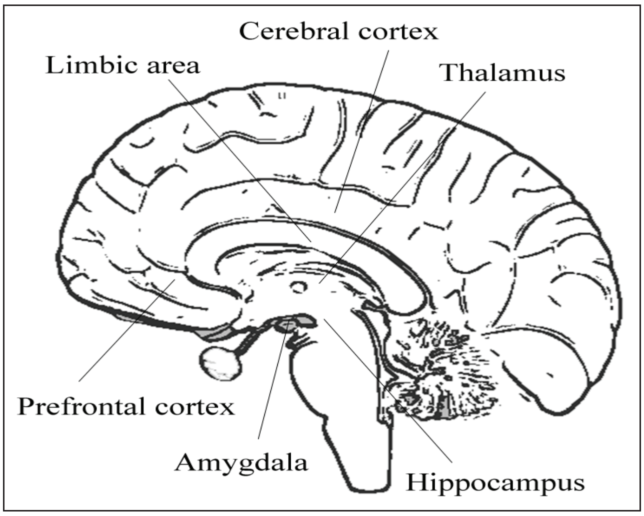

Fig. 1. The LS in the brain

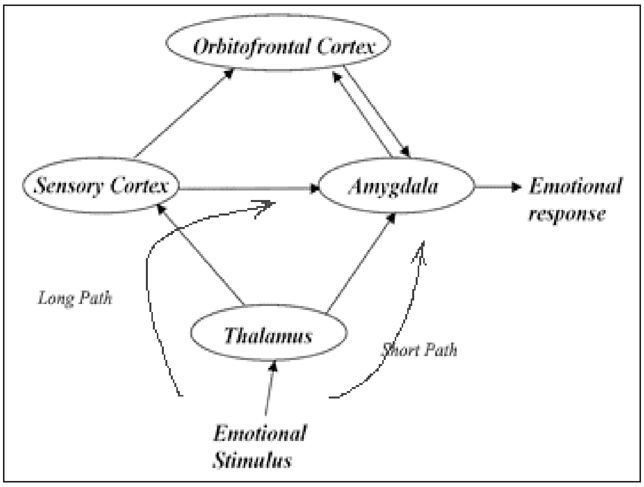

Fig. 2. The routes of sensory information for emotional modeling

An anatomical model of EB includes the limbic system (LS) theory of emotion [27]. Fig. 1 shows some main components of LS including amygdala (AMYG), orbitofrontal cortex (OFC), thalamus, and sensory cortex. In EB, there are two different ways that external stimulus can reach the AMYG (Fig. 2). The first which is short and fast, but imprecise, comes directly from the thalamus. The second is long and slow but precise and comes from the sensory cortex. These paths are presented in Fig. 2. AMYG based on these paths can provide imprecise but rapid response. EB also is equipped by a mechanism that controls this imprecise response. This mechanism lies on the AMYG-OFC interaction. OFC is involved in the process of decision making in uncertain and unpredictable situations and can estimate uncertainty [28-29]. According to the AMYG-OFC interaction, OFC then tries to inhibit the imprecise AMYG's answers [30-31]. In other words, EB provides the utilities that in addition to ability to make quick imprecise response, it can inhibit them i.e. innately the uncertainty can be produced and can be inhibited in emotional brain. In order to survival-keeping, this mechanism is optimal and feasible whenever a quick reaction is necessary in emergencies e.g. facing to danger and whenever a precise response should be made.

B. Practical models of emotion

It is not unlikely that the artificial NNs inspired from EB can show these important characteristics in the real word applications. ENNs have been produced through computational models of emotion [32], [39]. There are two important approaches of emotional modeling including: appraisal approach and anatomical approach [32], [39]. In appraisal approach, the emotional process of brain is described linguistically and by using IF-THEN rules [39]. These rules are frequently extracted according to the appraisable psychological situations. In contrast, anatomical view is based on LeDoux's findings.

A BEL-based ENN is presented in Fig. 3 which is based on AMYG-OFC interconnection. Model consists of two main subsystems. Each subsystem consists of a number of nodes which are related to the dimension of input pattern. At first, the input pattern enters the thalamus part of the model to calculate the imprecise input and submits it to AMYG as one of the inputs. The OFC does not receive any input from thalamus. Instead, it receives AMYG output in order to inhibit the final output.

The input pattern is illustrated by vector $\boldsymbol{P}=[p_1, p_2, p_3 \ldots, p_{n+1}]$ beginning the data flow and feed forward computing. T is the target value beginning the learning flow as well as backward learning computing.

The input signal P enters to the thalamus and then goes to the sensory cortex. The AMYG receives the input pattern including: $p_1, p_2, \ldots, p_n$ from sensory cortex, and p_{n+1} from the thalamus. The p_{n+1} is the imprecise output of thalamus and one of AMYG inputs. It is calculated as:

$$p_{n+1} = mean_{j=1\ldots n}(p_j) \tag{1}$$

As illustrated in Fig. 2, v_{n+1} is related weight. The mean operator simulates the uncertain information coming from thalamus. Furthermore the OFC receives the input pattern including $p_1, p_2, \ldots, p_n$ from the sensory cortex. Final output is calculated by following formulas,

$$E = E_a - E_o \tag{2}$$

where E_a and E_o are the outputs of AMYG and OFC respectively,

$$E_a = \sum_{j=1}^{n+1} (v_j \times p_j) \tag{3}$$

$$E_o = \sum_{j=1}^{n} (w_j \times p_j) + b \tag{4}$$

where v s are AMYG weights, w s are OFC weights, b is OFC bias, and p s are the elements of input pattern. The final output Eq. (2) includes OFC inhibitory task on AMYG output (E_a).

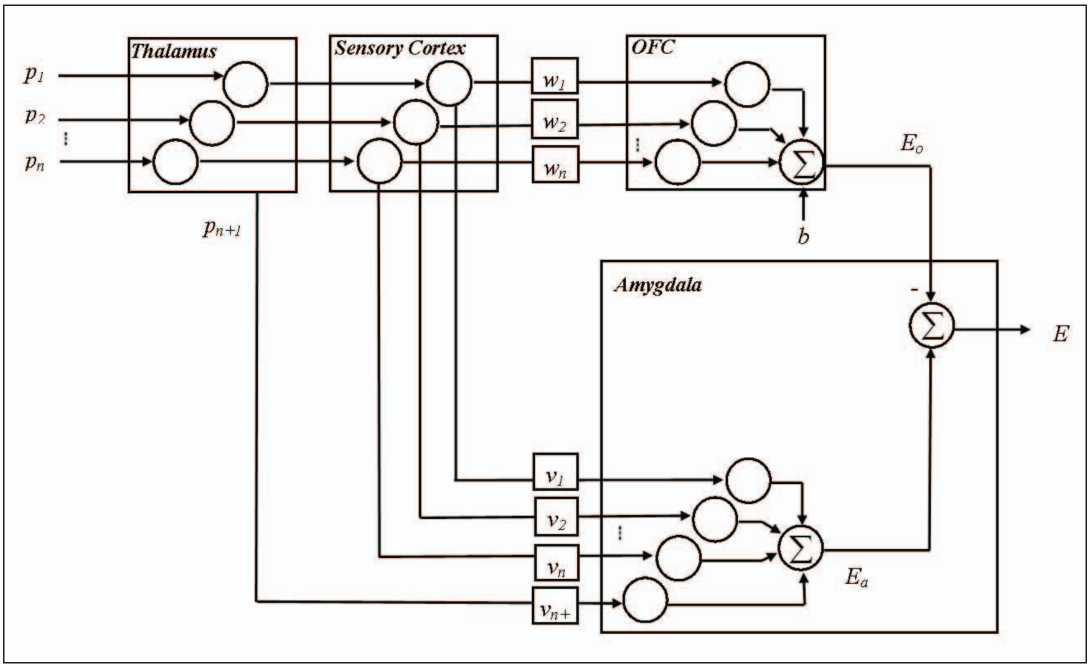

Fig. 3. An ENN inspired from amygdala-OFC interactions

Researchers in artificial intelligence have successfully utilized this model and its modified version in various control applications and prediction problems. Examples can be found in [21]-[23].

C. Learning

Here we apply genetic algorithm (GA) to optimize crisp numerical weights of ENN. GA is an optimization algorithm that minimizes a cost function (fitness) to find the best solution (best chromosome) for a problem. At the first step, chromosomes are initialized. A chromosome is formed and represented as follows;

$$Chorom_i = [\mathrm{v}_1, \mathrm{v}_2, \ldots, \mathrm{v}_n, \mathrm{v}_{n+1}, \mathrm{w}_1, \mathrm{w}_2, \ldots, \mathrm{w}_n, \mathrm{b}] \quad (5)$$

Thus if the number of input features is n then the number of learning weights e.g. the number of genes in each chromosome is $2n+2$. Let Y^k be output of model with $Chorom_i$'s weights in response to k th input pattern $\boldsymbol{P}^k$;

$$Y^k = E(P^k; Chorom_i) \quad (6)$$

$E(\boldsymbol{P}^k; Chorom_i)$ denotes the output of model calculated by Eq. (2) for the kth pattern and with given weights in $Chorom_i$. Thus fitness function of this chromosome is calculated as follows;

$$fitness_{train}(Chorom_i) = \frac{1}{m}\left(\sum_{k=1}^{m}(Y^k - T^k)^2\right)^{0.5} \quad (7)$$

where Y_k is the response to the kth input pattern ($\boldsymbol{P}^k$), T^k is the related target, and m is number of pattern-targets. So minimizing the fitness function means minimizing the total error for all training samples. The proposed supervised GA-based learning algorithm for ENN architecture is as follows:

GA-based Learning algorithm of ENN

Input: matrix $P_{c\times n}$ including c patterns with n features and array $T_{c\times 1}$ including target of c patterns

Output: array $W_{m\times(2n+2)}$ including($2n+2$) weights for single output

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1) Initial a population with real 2n+2 genes for each chromosome. (Eq. 5)

2) Calculate fitness of each individual by using Eq. (7)

3) Select the individuals

4) Mating

5) Mutations

6) Replace the poor individuals with power offspring and create next generation.

7) If stop criterion is not satisfied goto step 3 else W(i) = best chromosome

8) End

Table 1. Datasets information

Dataset Name	*Type of Dataset*	*# of Inputs*	*# of instances*	*# of learning samples*
Captl_WF [1]	Real	16	8712	4296
5d-function [33], [34]	Synthetic with constant noise	5	500	350
5d-function [35], [36]	Synthetic with nonconstant noise	5	500	350

Actually, GA applies chromosome Eq. (5) with fitness function Eq. (7) in order to find optimized network crisp weights.

III. NUMERICAL RESULTS

The proposed ENN and GA learning method have been written and tested on Matlab R2010b. The source code is accessible from www.bitools.ir/projects.html. Root mean square error (RMSE) is the performance measure for evaluation of results. Table 1 shows the information related to the data sets. This includes the number of attributes, instances, and classes. The hourly wind power dataset (named Captl_WF) is from Capital wind farm located in New South Wales, Australia [1]. The wind farm data includes normalized pattern-targets for 2010. All data samples are normalized to [-1,1]. The first six months of 2010 are used for training and developing models. The second half of data is used for validation and testing purpose (3 months for each case). We use this dataset to do some experiments to examine performance of ENNs and compare them with performance of a feedforward neural network model. We consider Levenberg-Marque (LM) learning based NNs with at least five different structures (single layer with 5, 10, 15, 20, and 25 neurons in the hidden layer). For each network, experiments are repeated 10 times. The results are presented in Table 2 and compared using RMSE. The obtained RMSE for 5, 10, 15, 20, and 25 hidden neurons are 0.5718±0.004, 0.5813±0.004, 0.5912±0.007, 0.5888±0.004 and 0.5888±0.007 respectively. Additionally the correlation analysis is used to determine the quality of inputs for wind farm forecasting [1]. Thus the best MLP architecture for Captl_WF forecasting is 16-5-1 (16 input features, 5 hidden neurons and 1 output.)

In terms of assessment, we consider two things: accuracy (measured by RMSE) and repeatability (measured by std of accuracy index). Fig. 4 shows the comparative results and Table 3 reports percentage of improvement over traditional modeling techniques. As illustrated in the Fig. 4 and Table3, ENN improves RMSE about 1% and decreases std more than 85%. Thus ENN is more accurate and more stable than traditional models in wind power forecasting.

The performance of the proposed method is also tested for synthetic datasets. This is done particularly to investigate the ability of the method in dealing with noisy datasets. The synthetic data samples are produced using the following pseudocodes:

Producer of 5d-function with constant noise

Input: no input
Output: matrix $x_{500\times5}$ including *500* patterns with *5* features and array $t_{500\times1}$ including target of *500* patterns

1) *for i = 1 to 500*
2) x_i= *five random values.*
3) *error = a normal random value.*
4) $t_i = 10*sin(pi*x_{i,1}*x_{i,2}) + 20*(x_{i,3}-0.5)^2+10*x_{i,4}+5*x_{i,5}+error$
5) *end*

Table 2. NNs architecture comparison

Hidden neurons	*Accuracy*
5	0.5718±0.004
10	0.5813±0.004
15	0.5912±0.007
20	0.5888±0.004
25	0.5888±0.007

Producer of 5d-function with nonconstant noise
Input: no input Output: matrix $x_{500\times 5}$ including *500* patterns with *5* features and array $t_{500\times 1}$ including target of *500* patterns
1) for i = 1 to 500 *2) x_i= five random values.* *3) error* = std(x_i)* *(a normal random value)* *4)* $t_i = 10*sin(pi*x_{i,1}*x_{i,2}) + 20*(x_{i,3}-0.5)\hat{}2+10*x_{i,4}+5*x_{i,5}+error$ *5) end*

Table 3. Percentage improvement of ENN in wind power forecasting

DataSet	RMSE improvement	STD improvement
Captl_WF	1%	85%

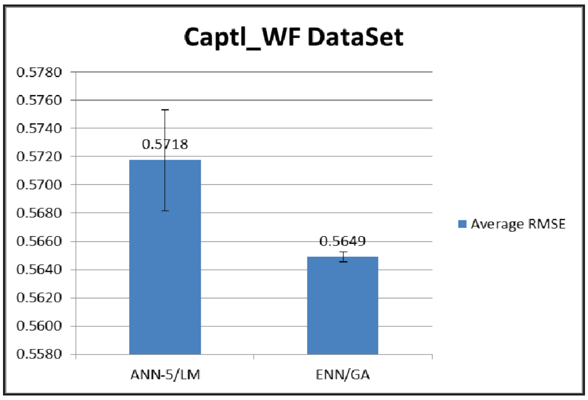

Fig. 4 RMSE comparison between NN (with LM lerning algorithm) and ENN (with GA learning) for wind power dataset.

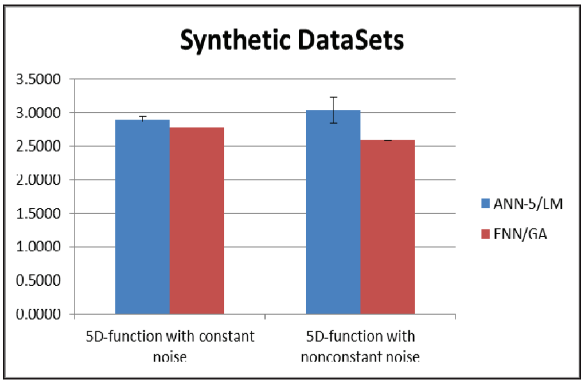

Fig. 5 RMSE comparison between NN (with LM lerning algorithm) and ENN (with GA learning) for two synthetic noisy datasets.

In the algorithms, *Std(x)* returns the standard deviation of array *x* and matrices *x* and *t* are used to evaluate performance of the proposed method. The results for the synthetic datasets are presented in the Fig. 5. It shows RMSE values for the 5d-function with constant and nonconstant noise. It also includes the results obtained using the proposed ENN with GA learning algorithm and NN with LM lerning algorithm. According to Fig. 5, the lower RMSE values are obtained from proposed method. Table 3, Fig. 4 and Fig. 5 present consistent results for all these datasets. These results are statistically significant based on 95% confidence.

IV. Conclusion

In this paper, we propose an ENN for prediction tasks. The biologically motivated emotional architecture of ENN is trained by genetic algorithm (GA) and can be used for identifying nonlinear relationships in complex systems. In the numerical studies, ENN is utilized to predict real world wind power generation and synthetic noisy data. The comparisons between an optimally developed neural network and proposed method lead to the following conclusions. Firstly, the performance of ENN is higher than conventional NN methods based on the statistics of RMSE. Secondly, ENN is more stable than traditional models for wind power forecasting.

Therefore, it can be confidently used in real world applications for forecasting and decision-making.

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