New Particle Swarm Neural Networks Model Based Long Term Electrical Load Forecasting in Slovakia

S.H. OUDJANA[1], A. HELLAL[2]
[1, 2] University of Laghouat, Department of Electrical Engineering, Laboratory of Analysis and Control of Energy Systems and Electrical Systems, LACoSERE, Laghouat 03000, ALGERIA
samirehamid@yahoo.fr

Abstract: - Long-term load forecasting accuracy is very important for electrical power systems. This paper explores the application of new model using neural networks (NN) and Particle Swarm Optimization (PSO) to study the design of load forecasting systems for many years ahead using historical loads databases of Slovakia power systems. In this study, instead of the method of back-propagation of the gradient, the optimization technique by swarms of particles is well tested for training neural network that optimizes the forecast error. Simulations were run and the results are discussed showing that New Hybrid Technique (PSO-NN) is capable to decrease the load forecasting error.

Key-Words: - Load Forecasting, Neural Networks, Particle Swarm Optimization

1 Introduction

The load forecasting is an important constituent for the management power system utility. It helps the electricity producer to make the right decision to unit commitment and reduce the use of reserves. Thus it plays a key role in reducing the cost of electric generation and remains essential for the reliability of the power system. It is therefore extremely important for the generation transmission and distribution of electric energy and the energy market [1].

Since the profile of energy production of the next day must be intended for every day, the Load Forecasting of the next day is a daily task dispatching center. The forecast error affects a lot of economic operations and the profitability of the power system. For example, an increase of prediction error of 1% in Britain causes the increased cost of 10 million pounds per year [2].

The results obtained from load forecasting process are used in planning and operation. Long-term load forecasting, one to ten years ahead monthly and yearly values, is applied in expansion planning, inter-tie tariff setting and long-term capital investment return problems [3].

Electricity consumption varies depending on several parameters, the main ones is seasonality climate and electricity prices. Other explanatory variables are: exceptional events can disrupt the pattern of consumption (eg. winter storms, final world cup of football), but their impact is impossible to predict.

The methods used to solve the load forecasting problem can be mainly divided into two categories: statistical methods and artificial intelligence methods. The artificial intelligence methods are flexible in finding the relationship between the load and its related factors, particularly for load forecasting of anomalous days. The artificial neural networks (ANN) do not require human experience and are not intended to establish a relationship between the input and output observed. The principle of NNs is to establish the load profile from the training based on historical data, among the different methods of training. The most widely used for the load forecasting is the method of back-propagation of error based on the gradient method [4.8], except that sometimes the back propagation method falls into the local minima of the squared errors. It is therefore necessary to find an optimization technique capable of reaching the global minimum of the forecast error, instead of the back-propagation method. The technique of particle swarm optimization (PSO) is tested for training the neural network that optimizes the forecast error [1,2] [9,10].

Our paper contribution is applied and validates the performance of hybrid technique PSO-NN of new models using historical data of yearly electricity consumption from Slovakia power systems utility, these data provided by European Network of Transmission System Operators for Electricity (ENTSOE) [11].

2 Neural Networks

From the beginning of nineties, new techniques appear to study the electrical load forecasting such as artificial neural networks. These recent techniques quickly became widely used in short-term load forecasting. The mathematical model of an artificial neuron (Fig.1) consists essentially of an integrator that performs a weighted sum of its inputs. The result n of this sum is then transformed by a transfer function f which produces the output of a neuron. The R input neurons correspond to the vector $P = [p_1.\ p_2.\dots.\ p_R]^T$. Whereas $W = [w_{11}.\ w_{12}.\dots.\ w_{1R}]^T$ represents the vector of the weights of the neuron, and b is a bias. The output n of the integrator is given by the following equation:

$$n = \sum_{j=1}^{R} w_{1,j} p_j - b \tag{1}$$

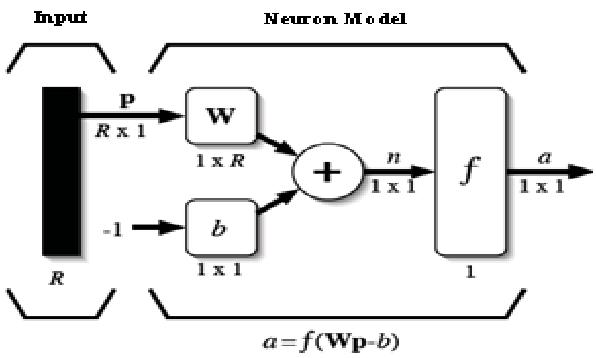

Fig. 1 Model of an artificial neuron

3 Particle Swarm Optimization

Particle swarm optimization is a metaheuristic based on the model developed by C. REYNOLDS in the late 1980's to simulate the movements of a group of bird indeed in some animal groups like group of fish. We can observe the dynamics of relatively complex movements while the individual themselves have access to only limited information, such as position and velocity from their nearest neighbors, we can observe such a group of fish is able to avoid a predator. A swarm is composed of many particles. The size can be dynamic: if no particle of the swarm improves the solution. We can generate other and can also remove them. Each particle i is characterized by its position x_i and a velocity vector v_i. At each iteration. The particle moves as following:

$$x_i(t) = x_i(t-1) + v_i(t-1) \tag{2}$$

To formalize this movement in more detail, we can put it that way for each particle:

$$v_i^{k+1} = wv_i^k + c_1 rand_1\left(pbest - x_i^k\right) + c_2 rand_2\left(gbest - x_i^k\right) \tag{3}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{4}$$

K: Number of iteration
x : Particle position
v : Particle velocity
pbest: Best position of the particle
gbest: Global best of all the particles of Swarm
w: Weighting function
$c_1.c_2$: Weighting factor
rand : Random numbers. uniform distribution on [0. 1]

Weighting function is given by:

$$w = w_{max} - \frac{w_{max} - w_{min}}{k_{max}} k \tag{5}$$

w_{min} : Initial weight
w_{max} : Final weight
k_{max} : Maximum number of iterations

4 Load Forecasting by Using PSO-NN

The training of artificial neural networks is an important phase which is used to adjust the bias and the synaptic weights so that the square error between the desired value (target) and forecasting value is minimum as possible. Among the different methods of training, the most widely used for the load forecasting is the method of back-propagation based on the gradient method, except that sometimes the back-propagation method falls in local minima of squared errors.

It is therefore necessary to find an optimization technique capable of reaching the global minimum of the forecast error. Instead of the method of back-propagation of the gradient, the optimization technique by swarms of particles is well tested for training neural network that optimizes the forecast error.

The database of this model depends on historical load data frome 1998 until 2005, so the load of the previous year is used to forecast the actuel load, this model can be used to forecast six yearly loads ahead.

4.1 Algorithm of the method

The procedure of the technique is presented as follows:

initialize swarm with random v and position x

initialize $w.c_1.c_2$

k : number of iteration

begin

x_i^k: Position of a particle

$pbest_i$: Personal best position of i^{th} particle

v_i^k: velocity of i^{th} particle

gbest: global best of all the particles of swarm

Calculate the value of the load

Calculate the mean square error *MSE* for each particle in the swarm as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(L_i^d - \widehat{L_i})^2 \quad (6)$$

Where n is the number of examples of the training set. L_i^d is the desired load. and $\widehat{L_i}$ is the expected load

For each particle i in the swarm:

If ($x_i^k < pbest_i$) Then

$$pbest_i = x_i^k$$

If ($pbest_i <$ gbest) Then

$$gbest = pbest_i$$

Position and velocity are then updated as per the following equations:

$$v_i^{k+1} = wv_i^k + c_1 rand_1(pbest - x_i^k) + c_2 rand_2(gbest - x_i^k)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1}$$

best individual from swarm is chosen as the output

End

Parameters chosen for the PSO optimization technique:

MSE: Objective function

wmax = 0.9: Initial weight.

wmin = 0.4: Final weight.

imax = 100: Maximum number of iterations

c1 = c2 = 2: Weighting factor.

nind = 10: Swarm size.

To verify the performance of this forecasting technique, we can calculate the mean absolute percentage error:

$$MAPE = \frac{100}{n}\sum_{t=1}^{n}\frac{|L_t - \widehat{L_t}|}{L_t} \quad (7)$$

L_t : Desired load

$\widehat{L_t}$: Forecast load

n : Number of patterns

5 Simulations

To validate the hybrid technique PSO-NN in terms of the mean relative error, we must test multiple databases and techniques. To do this, we used databases based on historical data of yearly electricity consumption from 1998, then we compare between NN technique, and proposed hybrid technique PSO-NN. The performance of technique is verified by the mean absolute relative error MAPE. Table 1 and 2 represent the desired and forecast load, and the values of the mean absolute relative error, using two different techniques. Fig. 2 illustrate the annual load profile of Slovakia electrical power system. The NN and PSO-NN models are presented in Fig. 3 and 4 respectively.

Due to the industriel development, and economic growth in Slovakia, the request energy is increased. We get forecasting error less than 10%, witch be acceptable in long-term load forecasting. The PSO-NN model is better than NN model, in term of forecastig error, the forecasting error using PSO-NN model is 5,04% (Table 2). So the correlation between the current and previous yearly loads is strength , and the perfermances of hybridation technique PSO-NN are satisfaisant.

The hybrid technique of the neural network with particle swarm optimization applied to long-term load forecasting give the acceptable values of forecasting error. These values influenced by the impact factor on load such as temperature and the historic loads, furthermore the parameters of the PSO technique and the activation function of neural network can be change the forecasting error.

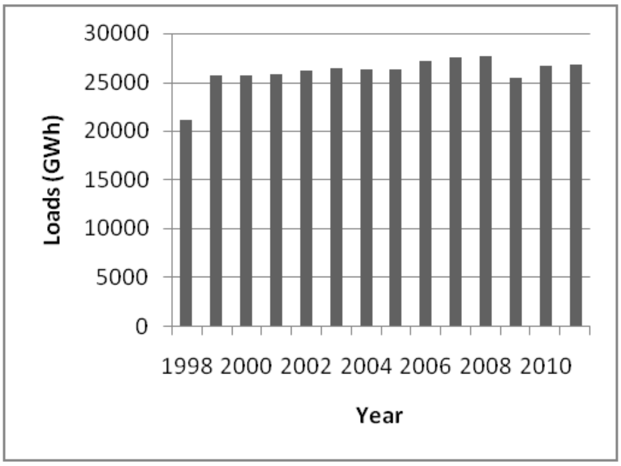

Fig. 2 Slovakia Annual Load Curve

Table 1. Load forecasting using NN

Year	Actual (GWh)	Forecast (GWh)
2006	27208	25445
2007	27581	25449
2008	27635	27280
2009	25436	27391
2010	26636	25445
2011	26780	25445
MAPE (%)	5,43	

Table 2. Load forecasting using PSO-NN

Year	Actual (GWh)	Forecast (GWh)
2006	27208	25129
2007	27581	26594
2008	27635	26757
2009	25436	26765
2010	26636	24964
2011	26780	25604
MAPE (%)	5,04	

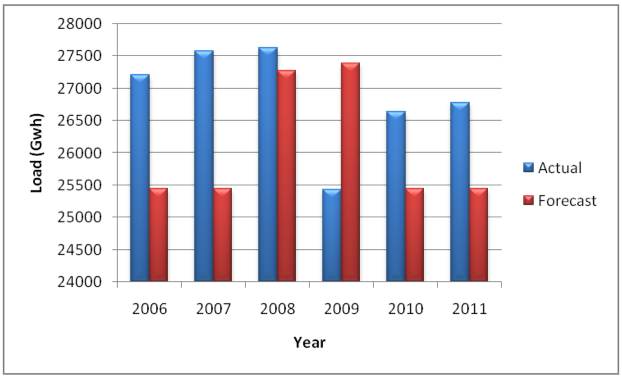

Fig. 3 Actual and forecast load using NN model

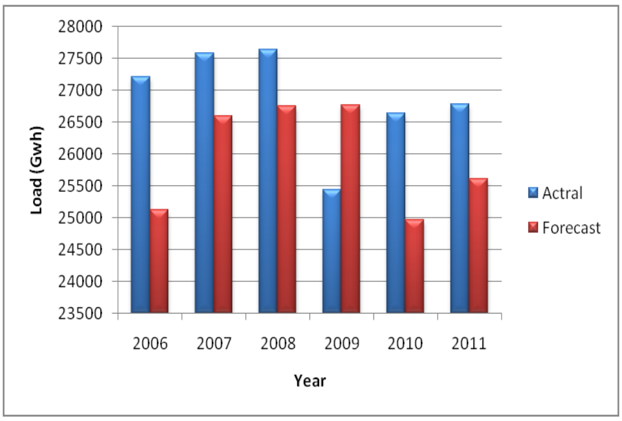

Fig. 4 Actual and forecast load using PSO-NN model

6 Conclusion

The load forecasting in electrical power system is an essential task for decision making by the dispatch center that is concerned to ensure network security by meeting the balance between supply and demand of electricity while having a management reliable and cost effective production system.

Before validating the performance of any model, the neural network must be trained by the learning phase. Among the methods of training, the method of back-propagation of error based on the gradient method, which adapts the weights and biases so that the square error between the desired and expected output must be small, except that this method fall in the local minimum of error, and to this raison, we replaced this method by the technique of particle swarm optimization PSO able to find the global minimum error during the training phase.

The work initiated in this article aimed to apply the hybridization method of neural network technique with the technique of particle swarm optimization PSO-NN to many years ahead prediction of electricity consumption in Slovakia. The PSO-NN forecasting model depend only on prévious loads and it is better and more accurately than NN model, so the electricity consumption is not only affected by the temperature,
but also it change by historical loads. This technique is useful for solving the problem of load forecasting.

References:

[1] Sandjib, M. *Short term load forecasting using computational intelligence methods*, Master Thesis. National Institute of Technology of Rourkela, 2008.

[2] Vincent , L. *Modèles semi-paramétriques appliqués à la prévision des séries temporelles Cas de la consommation d'électricité*, PhD Thesis, Université Rennes 2, 2007.

[3] AlRashidi, M.R.- EL-Naggar, K.M. Long term electric load forecasting based on particle swarm optimization, *Applied Energy*, 87, No. 1, 2010, pp.320-326.

[4] Park, D.C - El-Sharkawi, M.A. Marks, R.J.- Atlas, L.E- Damborg, M.J. Electric load forecasting using an artificial neural network, *IEEE Trans. on Power Systems,* Vol. 6, 1991, pp. 442-449.

[5] Lee, K..Y.- Tae, C. - Chao, C.K. – June, H.P. Neural network architectures for short-term

load forecasting, Neural Networks. *IEEE World Congress on Computational Intelligence*, Vol. 7, 27 June -2 July,1994, pp.4724-4729.

[6] Bakirtzis, A.G. - Petridis, V. - Kiartzis, S.J. - Alexiadis, M.C. - Maissis, A.H. - A neural network short term load forecasting model for the Greek power system., *IEEE Trans. on Power Systems,* Vol. 11. No. 2, 2012, pp. 858-863.

[7] Hongbin, W. - Wei, l.C. Load Forecasting for Electrical Power System Based on BP Neural Network, *First International Workshop on Education Technology and Computer Science*, 2009, pp. 702 - 705.

[8] Manoj, K. *Short-term load forecasting using artificial neural network techniques*, Bachelor of technology, National Institute of Technology of Rourkela, 2009.

[9] Zhang, C. – Lin, M. – Tang, M. BP Neural Network Optimized with PSO Algorithm for Daily Load Forecasting, *International Conference on Information Management, Innovation Management and Industrial Engineering*. Vol. 3, (19-21Dec 2008), pp.82-85.

[10] Vincent, G. *Optimisation par Essaim Particulaire, Mémoire Adaptative et Recherche Tabou*. PhD Thesis, Université Rennes 2, 2008

[11] https://www.entsoe.eu/.