Sugestion of a neuro-genetic hybrid system as an alternative for the electric power consumption curves evaluation

Sugestão de um sistema híbrido neuro-genético como alternativa para a avaliação de curvas de consumo de energia elétrica

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Abstract

This paper presents a model based on hybridism between Artificial Neural Network (ANN) and Genetic Algorithm (GA), that can identify on load curve, acquired any point of distribution system, the portions of consumption relative to each one of main consumer sectors in that point. The initial result indicates a best performance of conventional ANN, however when the complexity training patterns increase, the hybrid system starts to present best results, showing its power. Made the necessary simulations and checked the validity of association between ANN with GA, the developed system can be consider a powerful tool to the distribution electrical network management.

Keywords

Genetic Algorithm, Artificial Neural Network, Hybrid System, Load Curve

Resumo

Este artigo apresenta um modelo baseado no hibridismo entre Rede Neural Artificial (RNA) e Algoritmo Genético (AG), capaz de identificar, na curva de carga adquirida em um ponto qualquer do sistema de distribuição, as porções de consumo relativas a cada um dos principais setores consumidores presentes naquele ponto. Os resultados iniciais indicaram uma melhor performance da RNA convencional, porém à medida que se aumentou a complexidade dos padrões de treinamento, o sistema híbrido passou a apresentar resultados cada melhores, mostrando assim sua robustez.

Palavras Chave

Algoritmo Genético, Redes Neurais Artificiais, Curva de Carga

Introduction

To improve the electrical distribution network quality it's a permanent interest of power companies. Therefore, quality services with acceptable values must be offered. In direct form this involves to manage efficiently all distribution system. Nowadays, this supervision is carried out with Geographic Information System (GIS) tools associated with calculation of transformers demand, a result of correlation curve KWh versus KVA. Simple linear regression is used to estimate this curve, which make the process not too accurate. To estimate consumer's load, the traditional methodology consider only end consumption, refusing the characteristic of different kind of consumers: residential, commercial, industrial, rural and others.

This papers presents an application an ANN type Multi-Layer Perceptron, with the purpose to compare the showing results and to verify the advantages of hybridism use. The Hybrid System proposed uses GA to the ANN training, in other words, the determination of best values to the ANN synaptic weights. Defined the work methodology, the practical valuation of the model starts, and the results presented by hybrid system are compared with those generated by ANN training by the conventional method well-known as Back Propagation Error (BP).

The practical application proposes that load curve acquired be analyzed in any point of distribution system. Known this curve, the system should identify instant consumption quantities, relative to each one of main consumer sectors: industrial, commercial and residential. Subsequently are considered oscillations about these curves, in a way to approach the real situation.

Artificial Neural Networks

They are computer models working in a similar way to the human brain. Like the human neural system structure, the artificial neural networks (ANN) are composed by processing elements in parallel operation, named neurons, interconnected by neural connections named synapses, (Rooij, Jain Johnson, 1996)

The most used ANN is known as Perceptron and was proposed by Frank Rosenblatt in 1958 in his book "Principles of Neurodynamics", (Rosenblatt,1958).

This model is a composite of entry units, processing elements and outlet unit, according the figure bellow:

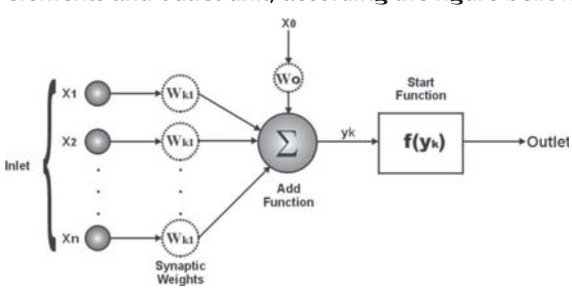

Figure 1 – Rosenblatt's Model of Artificial Neuron

To each inlet is associated a "synaptic weight", or just "weight". In the outlet we have the inlet pondered addition, expressed as follows:

$$yk=\Sigma\ (W_i * X_i) + x_0 * w_0 \qquad (1)$$

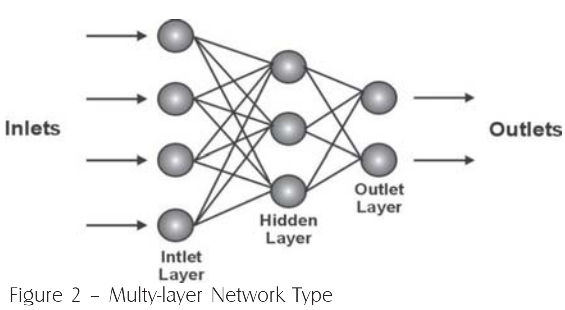

Figure 2 – Multy-layer Network Type

The activation function aims to limit the outlet signals in a known values interval. Many types of functions are used and choose is determined by the application type. Among the most used are the linear and sigmoid functions (logarithm and hyperbolic).

Regarding the topology, the most usual is the one similar to an oriented graphic, with all knots connected to the others. This is named MLP (multi-layer perceptron network), or multi-layers perceptrons network, as shown bellow:

In this topology each network neuron is connected to the others at the later and/or nearer layer. The existent signal in each inlet is conveyed to those in intermediate layer and so on up to the outlet.

To this strong tight up connected neurons set it is possible to associate some type of knowledge that will be stored at the existent connections among the adjoining neurons.

When knowledge is associated to ANN we say that the *learning* happened, and this process happen through another called *training*.

To train one ANN is to find an ideal weight set in such a way that, to each inlet presented to the network, this one succeeds answering in the most desirable way. Nearer to the desired answer lower the error made, and this is chosen as performance measure.

For training evaluation, the majority of methods use values supplied by the descending gradient of error function. For practical purposes, training with high complex degrees, this tends to be multi-modal, with many peaks and sinks. This may drive the process to stop in a point of minimum place of error surface, driven to an early convergence. This way the ANN will not answer in adequate way. So, the proposal for using the Genetic Algorithms as an alternative to the gradient-based methods, is worthwhile and justifies this paper.

Genetic Algorithms

In a short way, the genetic algorithms (GA) may be understood as optimization tools able to minimize or maximize functions, based on Charles Darwin's theory combining genetics and natural selection.

In other words, the GA's are computer models able to process possible solutions for specific problems in structures similar to the biologic chromosome, and apply genetic operators into these structures in position to preserve and also to bring together random values in potential solutions.

For practical purposes, to optimize means to find out a solution corresponding to a point of maximum (or minimum) of a specific function. This is named objective function, or *aptitude function,* according GA's terminology.

The set of possible solutions for the *aptitude function* is named *population.* Each possible solution is named *individual (or chromosome, as per the GA terminology).*

Each chromosome is compounded by a set of values named *genes* and each value the gene may take is called *allele*.

The process begins with the creation of a random initial population. This initial population is compounded by a pre-determined number of individuals. These individuals are nothing but the random generated sets, considered as potential solutions for the problem. Following step is to evaluate the "aptitude" of each one of these individuals in relation to the aptitude function. To each evaluated individual is given an aptitude value according its "proximity" with regard to the problem solution. In other words, nearer the solution bigger the aptitude given to this individual and, therefore, bigger the chance of its characteristics (genotypes) be "inherited" by its descendants in future generations.

After the whole evaluation, those that will be submitted to the genetic operator application, will be chosen randomly through a process that simulates a roulette. The ones better adapted will have bigger chance to be selected. Upon these will happen the *genetic operators* action for the making of the new population. When this is already made a new generation was completed. The process is repeated in iteratively way up to finding a solution, or the number of specified generations be achieved.

Hybrid Systems

With the consolidation of Artificial Intelligence techniques and their constant applications into many areas, a new generation of intelligent systems began to be developed through the addition of two or more artificial intelligence techniques.

The techniques hybridization may result in powerful systems, where one can supply the other's deficiency, yielding but from the advantages each one of the techniques provide.

The specific proposal of this paper is the artificial neural networks training (ANN), through genetic algorithms for the detection of existent standards in electric power consumption.

When the ANN training occurs the synaptic weights are adjusted for the ANN presents a pre-determined outlet. This is not so easy and many factors may act preventing ANN to behave in the desired way. For example, the over specialization and the lack of capability in recognizing the standards generated by inconsistence of training set. Other very important causes are the early convergence because of a local minimum and also the neurons number definition into intermediate layer.

The key point in ANN training is the ANN outlet error behavior, once it is in its function that the synaptic weights are adjusted. As training goes on these are adjusted in a way to minimize the error. Algorithms that use the error function-sinking gradient make adjustment, normally. When this function is multi-modal the gradient may stop in a local minimum point, no longer reaching the minimum error in network outlet.

Suggestion for solution of this problem is the GA use, also applied to functions minimization. The advantage in the use of GA is that they do not use any type of information supplied by gradient. So, the suggest is to make the necessary training using the GA, as well as the Error Backpropagation Algorithm make possible to do a parallel comparison among the applied methods for the standards recognition.

Practical Application

At present there is a great concern of the power utility companies in supplying good quality services, which allows application of profitable tariffs. To make this possible it is necessary permanent supervision, availability of operation resources and investments in electric distribution network.

The present distribution system supervision models are based on transformers demand calculation, that is made through a correlation curve of consumption x demand (KWh x KVA). This curve is estimated through a numeric method named simple linear regression, which may presents little precision regarding the required one for the supervision of electric network distribution (Todesco, Pimentel and Bettiol, 2004).

Looking for a distribution improvement, the proposal is to submit a methodology based on Artificial Neural Networks (ANN), for the electric power distribution network management, through the analysis of characteristic load curves from the most important consumers sectors: home, commerce and industry.

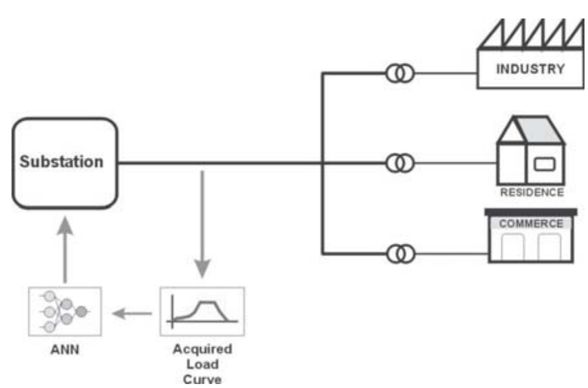

Figure 3 – Practical Application

Knowing the amount of consumed power by determined sector, allow the allocation of the non-used-parcel to the others, that is, the intelligent redistribution may mean better availability, conservation and profitability. Starting from these advantages, simulations are initiated for proving this application viability.

The first step is the typical load curves definition that represents the behavior of the three main consumer sectors. To each one of these curves we associate a behavior taken as standard for that sector. The following graphics present these standards that will be used in simulations.

Home Sector **Comercial Sector** **Industry Sector**

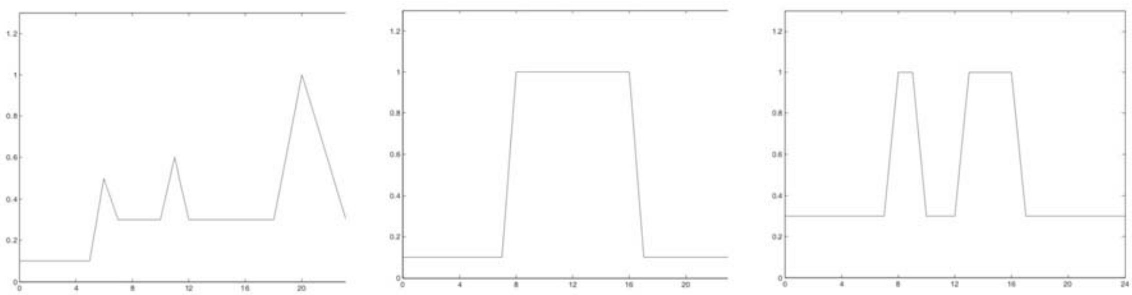

Figure 4: Curves used as reference for Home, Commerce and Industry Sectors

The training sets are composed by samples of these standards, as well as some compounds made among them. Including some compounds into training set means "teaching" the ANN to recognize them.

The idea of compounding standards is justifiable because the aim is evaluate an acquired load curve in any point of the power distribution network, and this is the compounding of present consumers sector curves in that system point.

The first simulation comprises curves regarding the home and commerce sectors, as well as their compounds. The data regarding this simulation are as follows:

Training Set

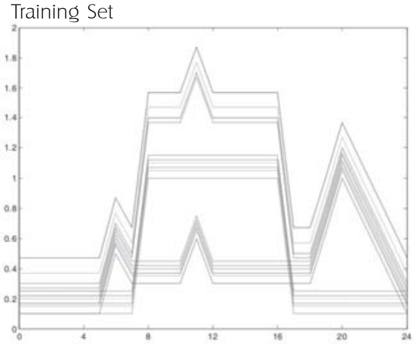

Figure 5: Training set made with representative curves from home and commerce sectors, the same their compositions

Validation Set

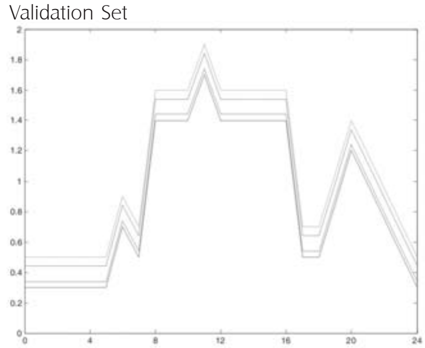

Figure 6: Validity set made up by composition of representative curves from home and commerce sectors

Used Standards:	
Training	*Validity*
Beginning Amplitudes from Home Sector: 0,17 | 0,20 | 0,15 | 0,1 | 0,25 | 0,22	Composition of curves referred to Home and Commerce Sectors, with following Amplitude starting values:
Beginning Amplitudes from Commerce Sector: 0,10 | 0,17 | 0,20 | 0,25 | 0,22 | 0,15	0,15 (R) + 0,15 (C); 0,17 (R) + 0,17 (C); 0,22 (R) + 0,22 (C); 0,25 (R) + 0,25 (C)
Composition of preceding: 0,10 (R) + 0,20 (C) | 0,15 (R) + 0,10 (C); 0,17 (R) + 0,10 (C) | 0,22 (R) + 0,25 (C); 0,25 (R) + 0,22 (C) | 0,20 (R) + 0,17 (C)	*Where:* 0,10 (R) + 0,20 (C) is the composition of Home Sector curve with starting amplitude equal to 0,10 added to the one from commerce sector with starting amplitude of 0,20

It is important to detach that in training set, twelve simple standard samples and six compositions with them are used, enough for the ANN learning.

Table 1: Results of simulation made with home and commerce standards

Expected Results		Obtained Results			
		BACKPROPAGATION		GA	
Outlet 1 *Home*	**Outlet 2** *Commerce*	**Outlet 1** *Home*	**Outlet 2** *Commerce*	**Outlet 1** *Home*	**Outlet 2** *Commerce*
0,15	0,15	0,1502	0,1501	0,1514	0,1503
0,17	0,17	0,1709	0,1708	0,1629	0,1583
0,22	0,22	0,2204	0,2205	0,2092	0,1908
0,25	0,25	0,2484	0,2488	0,2590	0,2251
Error		***6,0e-006***		***0,0019***	

According the above results, the first simulation was well succeeded in both cases. The difference between errors proves the former statement.

Though the training made via GA takes more time to find out the ideal weights set, its use may be a good alternative for the cases where the training with the conventional methods do not yield satisfactory results.

In the next simulation were used, like training standards, the curve samples regarding the industrial and home sectors, as well as their compositions.

The data referred to this simulation is shown as follows.

Training Set

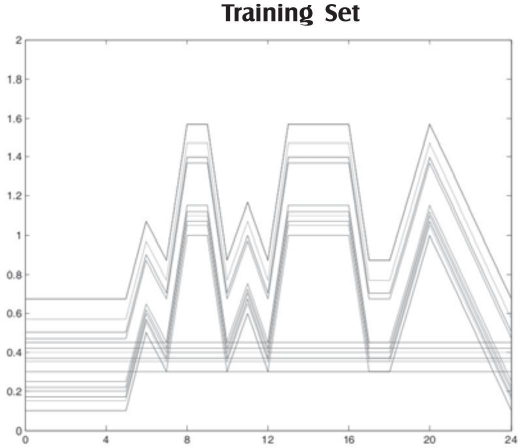

Figure 7: Training set made with curves representing home and industry sectors, as well as with their compositions

Validation Set

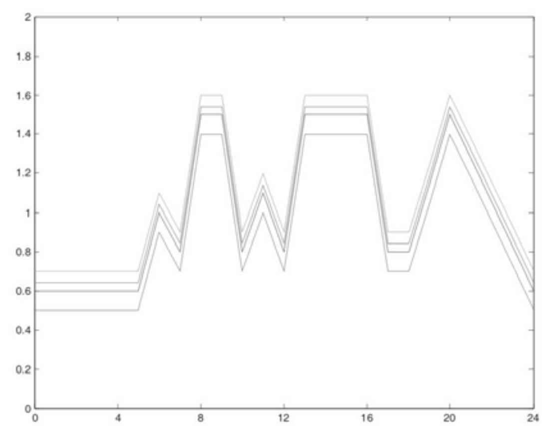

Figure 8: Validation set made with composed curves representing the home and industry sectors

Used Standards:

Training

Starting Amplitudes from Home Sector:

0,17	0,20	0,15	0,1	0,25	0,22

Starting Amplitudes from Industry Sector:

0,30	0,37	0,40	0,45	0,42	0,35

Composition with following amplitudes:

0,10 (R) + 0,40 (I)	0,15 (R) + 0,40 (I)
0,17 (R) + 0,30 (I)	0,22 (R) + 0,45 (I)
0,25 (R) + 0,42 (I)	0,20 (R) + 0,37 (I)

Validation

Composition of curves referred to Home and Industry Sector with the following starting values of Amplitude:

0,20 (R) + 0,40 (I)
0,22 (R) + 0,42 (I)
0,15 (R) + 0,35 (I)
0,25 (R) + 0,45 (I)

Table 2: Results from simulation made with home and industry standards

Expected Results		Obtained Results			
		BACKPROPAGATION		GA	
Outlet 1 *Home*	Outlet 2 *Industry*	Outlet 1 *Home*	Outlet 2 *Industry*	Outlet 1 *Home*	Outlet 2 *Industry*
0,20	0,40	0,2020	0,4084	0,2066	0,3973
0,22	0,42	0,2209	0,4237	0,2145	0,4182
0,15	0,35	0,1496	0,3524	0,1854	0,3413
0,25	0,45	0,2460	0,4410	0,2258	0,4476
Error:		***0.00019038***		***0.0020***	

Results above show again the viability of using GA as an alternative to backpropagation. The difference between error values is 0,0018, that means in general the results in both cases are nearer the desired ones. For the next simulation were chosen the industry and commerce sectors.

The training set is made according the chosen criteria in former cases. The validation set is made by samples not used for training, that shows the learning capacity of ANN.

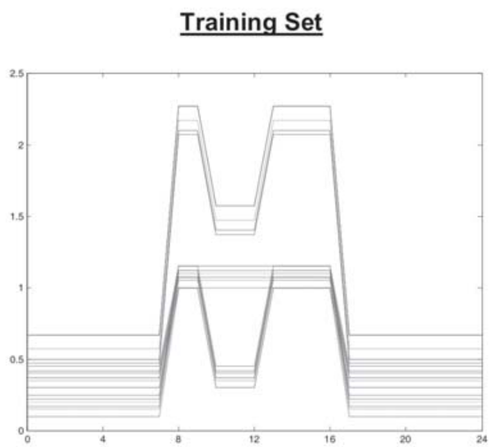

Figure 9 - Training set made by representative curves from industry and commerce sectors, as well as their compositions

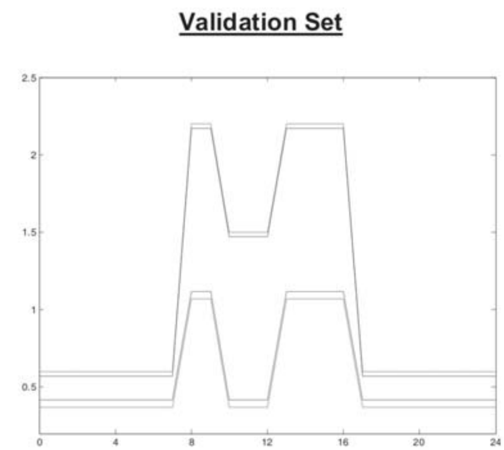

Figure 10 - Validation set made by composition of curves representing industry and commerce sectors

Used Standards:

Training

Starting Amplitudes from Industry Sector:

0,30	0,37	0,40	0,45	0,42	0,35

Starting Amplitudes from Commerce Sector

0,17	0,20	0,15	0,1	0,25	0,22

Composition of former:

0,30 (I) + 0,20 (C)	0,35 (I) + 0,15 (C)
0,37 (I) + 0,10 (C)	0,42 (I) + 0,25 (C)
0,45 (I) + 0,22 (C)	0,45 (I) + 0,17 (C)

Validation

Composition of curves regarding Industry and Commerce Sector with following Amplitude starting values:

0,42 (I)
0,37 (I)
0,40 (I) + 0,20 (C)
0,40 (I) + 0,17 (C)

Table 3: Results from simulation made with industry and commerce standards

Expected Results		Obtained Results			
		BACKPROPAGATION		**GA**	
Outlet 1 *Industry*	**Outlet 2** *Commerce*	**Outlet 1** *Industry*	**Outlet 2** *Commerce*	**Outlet 1** *Industry*	**Outlet 2** *Commerce*
0,42	0	0,4204	0,0002	0,3784	0,0396
0,37	0	0,3701	0,0002	0,3650	0,0274
0,40	0,20	0,4015	0,2011	0,4025	0,1963
0,40	0,17	0,3866	0,1860	0,3915	0,1896
Error:		***0.00043915***		***0.0045***	

This situation like the former, shown good results in both cases. Besides the differences between errors were a little higher than in former cases (0.0041), it is possible to consider as a good GA performance in acknowledging combined standards.

Comments about oscillations

The electric power consumption is something quite variable time wise, depending from a great number of factors. In a given moment the simple shut-off or re-starting of a big company's machinery will result in changes in substation load curve that is supplying power to the network branch. So, they should be taken as oscillations, and the ANN behaviour will be evaluated in these situations.

An important point regarding the consumption oscillations is about ANN, that may take a filter behaviour and not to take into consideration these variations, considering them as a noise.

Following simulations use the same criteria as the one used for the former ANN training, that is, in case we want the network identifying oscillations in standards, we should incorporate into the training set some type of related information. For this purpose we use samples from typical curves of sectors taken with some amplitude random changes. The validation sets also will have standards with oscillations changing from 1 up to 10% over the curves amplitude values.

In this first case the industry and commerce sectors will be evaluated.

Training Set

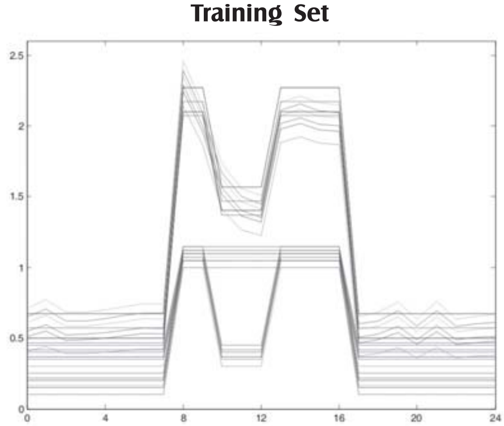

Figure 11 - Training set made by curves representing industry and comerce sectors, as well as compositions of same subject to oscillations

<u>*Used Standards:*</u>

Starting Amplitudes from Industry Sector

0,30	0,37	0,40	0,45	0,42	0,35

Starting Amplitudes from Commerce Sector:

0,17	0,20	0,15	0,1	0,25	0,22

Composition from formers with following starting amplitudes:

0,30 (I) + 0,20 (C)	0,35 (I) + 0,15 (C)
0,37 (I) + 0,10 (C)	0,42 (I) + 0,25 (C)
0,45 (I) + 0,22 (C)	0,45 (I) + 0,17 (C)

* A random variation of 0 to 10% over these amplitudes values were considered

Validation Set

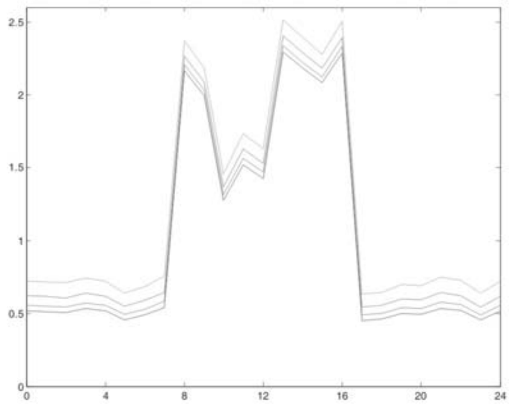

Figure 12 - Validation set made by curve compositions representing industry and commerce sectors subject to oscillations

Used Standards:

Compositions of curves referred to Industry and Commerce Sector with following starting Amplitude values:

0,30 ± 10% (I) + 0,20 ± 10% (C)
0,37 ± 10% (I) + 0,17 ± 10% (C)
0,40 ± 10% (I) + 0,20 ± 10% (C)
0,40 ± 10% (I) + 0,14 ± 10% (C)

Table 4: Results from simulation made with 10% of oscillations over amplitudes from industry and commerce standards

Expected Results		Obtained Results			
		BACKPROPAGATION		**GA**	
Outlet 1 *Industry*	**Outlet 2** *Commerce*	**Outlet 1** *Industry*	**Outlet 2** *Commerce*	**Outlet 1** *Industry*	**Outlet 2** *Commerce*
0,30 ± 10%	0,20 ± 10%	0,3443	0,2146	0,3278	0,1399
0,37 ± 10%	0,17 ± 10%	0,3640	0,2329	0,3614	0,1648
0,40 ± 10%	0,20 ± 10%	0,3953	0,2568	0,3932	0,1967
0,40 ± 10%	0,14 ± 10%	0,4554	0,2896	0,4158	0,2303
Error:		***0.0349***		***0.0129***	

According above results, it is possible to notice the viability in using GA in cases where the conventional training does not find an optimum weight set for ANN. This is one of the justifications for using hybrid systems in specific cases. According Azevedo (1999) "the tests made with simple problems for recognizing standards, generated non-conclusive results". This shows each system specificity, and the person responsible for the project should choose the best training algorithm. Next simulation will be made with representative curves from home and industry sectors. Details are given as follows.

Training Set

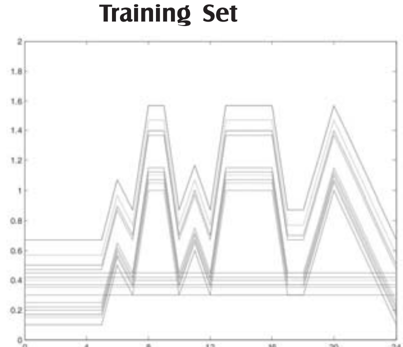

Figure 7 - Training set made with curves representing home and industry sectors, as well as with their compositions

Validation Set

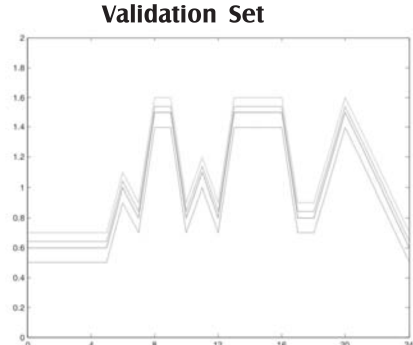

Figure8 - Validation set made with composed curves representing the home and industry sectors

Used Standards:

<u>Training</u>	<u>Validation</u>
Starting Amplitudes from Home Sector:	Composition of curves referred to Home and Industry Sector with the following starting values of Amplitude:

Starting Amplitudes from Home Sector:

0,17	0,20	0,15	0,1	0,25	0,22

Starting Amplitudes from Industry Sector:

0,30	0,37	0,40	0,45	0,42	0,35

Composition with following amplitudes:

0,10 (R) + 0,40 (I)	0,15 (R) + 0,40 (I)
0,17 (R) + 0,30 (I)	0,22 (R) + 0,45 (I)
0,25 (R) + 0,42 (I)	0,20 (R) + 0,37 (I)

Validation:

0,20 (R) + 0,40 (I)
0,22 (R) + 0,42 (I)
0,15 (R) + 0,35 (I)
0,25 (R) + 0,45 (I)

Table 2: Results from simulation made with home and industry standards

Expected Results		Obtained Results			
		BACKPROPAGATION		**GA**	
<u>Outlet 1</u> *Home*	**<u>Outlet 2</u>** *Industry*	**<u>Outlet 1</u>** *Home*	**<u>Outlet 2</u>** *Industry*	**<u>Outlet 1</u>** *Home*	**<u>Outlet 2</u>** *Industry*
0,20	0,40	0,2020	0,4084	0,2066	0,3973
0,22	0,42	0,2209	0,4237	0,2145	0,4182
0,15	0,35	0,1496	0,3524	0,1854	0,3413
0,25	0,45	0,2460	0,4410	0,2258	0,4476
Error:		***0.00019038***		***0.0020***	

Results above show again the viability of using GA as an alternative to backpropagation. The difference between error values is 0,0018, that means in general the results in both cases are nearer the desired ones. For the next simulation were chosen the industry and commerce sectors.

The training set is made according the chosen criteria in former cases. The validation set is made by samples not used for training, that shows the learning capacity of ANN.

<u>Training Set</u>

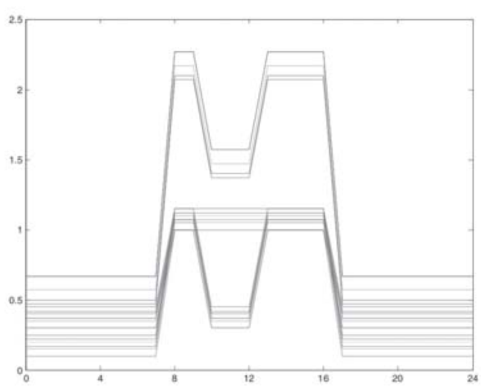

Figure 9 - Training set made by representative curves from industry and commerce sectors, as well as their compositions

<u>Validation Set</u>

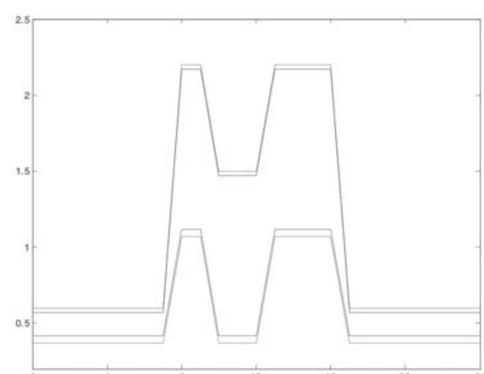

Figure 10 - Validation set made by composition of curves representing industry and commerce sectors

Used Standards:

Training	*Validation*
Starting Amplitudes from Industry Sector:	Composition of curves regarding Industry and Commerce Sector with following Amplitude starting values:

Training – Starting Amplitudes from Industry Sector:

0,30	0,37	0,40	0,45	0,42	0,35

Training – Starting Amplitudes from Commerce Sector

0,17	0,20	0,15	0,1	0,25	0,22

Training – Composition of former:

0,30 (I) + 0,20 (C)	0,35 (I) + 0,15 (C)
0,37 (I) + 0,10 (C)	0,42 (I) + 0,25 (C)
0,45 (I) + 0,22 (C)	0,45 (I) + 0,17 (C)

Validation:

0,42 (I)
0,37 (I)
0,40 (I) + 0,20 (C)
0,40 (I) + 0,17 (C)

Table 3: Results from simulation made with industry and commerce standards

Expected Results		Obtained Results			
		BACKPROPAGATION		**GA**	
Outlet 1 *Industry*	**Outlet 2** *Commerce*	**Outlet 1** *Industry*	**Outlet 2** *Commerce*	**Outlet 1** *Industry*	**Outlet 2** *Commerce*
0,42	0	0,4204	0,0002	0,3784	0,0396
0,37	0	0,3701	0,0002	0,3650	0,0274
0,40	0,20	0,4015	0,2011	0,4025	0,1963
0,40	0,17	0,3866	0,1860	0,3915	0,1896
Error:		***0.00043915***		***0.0045***	

This situation like the former, shown good results in both cases. Besides the differences between errors were a little higher than in former cases (0.0041), it is possible to consider as a good GA performance in acknowledging combined standards.

Comments About Oscillations

The electric power consumption is something quite variable time wise, depending from a great number of factors. In a given moment the simple shut-off or re-starting of a big company's machinery will result in changes in substation load curve that is supplying power to the network branch. So, they should be taken as oscillations, and the ANN behaviour will be evaluated in these situations.

An important point regarding the consumption oscillations is about ANN, that may take a filter behaviour and not to take into consideration these variations, considering them as a noise.

Following simulations use the same criteria as the one used for the former ANN training, that is, in case we want the network identifying oscillations in standards, we should incorporate into the training set some type of related information. For this purpose we use samples from typical curves of sectors taken with some amplitude random changes. The validation sets also will have standards with oscillations changing from 1 up to 10% over the curves amplitude values.

In this first case the industry and commerce sectors will be evaluated.

Training Set

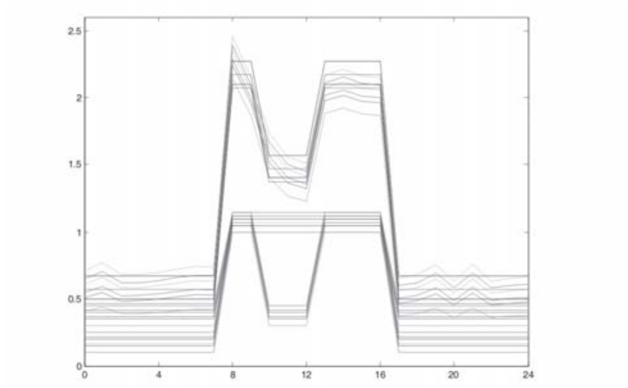

Figure 11 - Training set made by curves representing industry and commerce sectors, as well as compositions of same subject to oscillations

Used Standards:

Starting Amplitudes from Industry Sector

0,30	0,37	0,40	0,45	0,42	0,35

Starting Amplitudes from Commerce Sector:

0,17	0,20	0,15	0,1	0,25	0,22

Composition from formers with following starting amplitudes:

0,30 (I) + 0,20 (C)	0,35 (I) + 0,15 (C)
0,37 (I) + 0,10 (C)	0,42 (I) + 0,25 (C)
0,45 (I) + 0,22 (C)	0,45 (I) + 0,17 (C)

* A random variation of 0 to 10% over these amplitudes values were considered

Validation Set

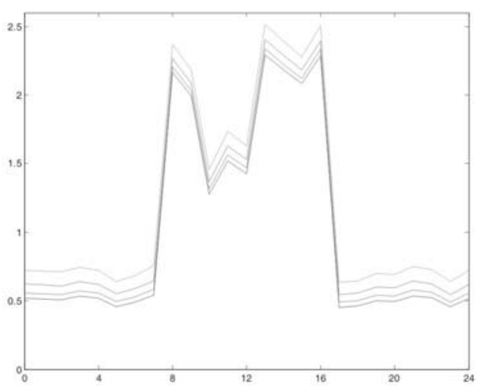

Figure 12 - Validation set made by curve compositions representing industry and commerce sectors subject to oscillations

Used Standards:

Compositions of curves referred to Industry and Commerce Sector with following starting Amplitude values:

0,30 ± 10% (I) + 0,20 ± 10% (C)
0,37 ± 10% (I) + 0,17 ± 10% (C)
0,40 ± 10% (I) + 0,20 ± 10% (C)
0,40 ± 10% (I) + 0,14 ± 10% (C)

Table 4: Results from simulation made with 10% of oscillations over amplitudes from industry and commerce standards

Expected Results		Obtained Results			
		BACKPROPAGATION		GA	
Outlet 1 *Industry*	Outlet 2 *Commerce*	Outlet 1 *Industry*	Outlet 2 *Commerce*	Outlet 1 *Industry*	Outlet 2 *Commerce*
0,30 ± 10%	0,20 ± 10%	0,3443	0,2146	0,3278	0,1399
0,37 ± 10%	0,17 ± 10%	0,3640	0,2329	0,3614	0,1648
0,40 ± 10%	0,20 ± 10%	0,3953	0,2568	0,3932	0,1967
0,40 ± 10%	0,14 ± 10%	0,4554	0,2896	0,4158	0,2303
Error:		*0.0349*		*0.0129*	

According above results, it is possible to notice the viability in using GA in cases where the conventional training does not find an optimum weight set for ANN. This is one of the justifications for using hybrid systems in specific cases. According Azevedo (1999) "the tests made with simple problems for recognizing standards, generated non-conclusive results". This shows each system specificity, and the person responsible for the project should choose the best training algorithm. Next simulation will be made with representative curves from home and industry sectors. Details are given as follows.

Training Set

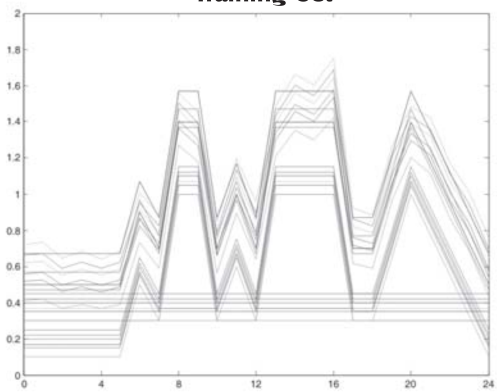

Figure 13 - Training Set made with representative curves from home and industry sectors, as well as compositions of same subject to oscillations

Used Standards:

Starting Amplitudes from Home Sector:

0,17	0,20	0,15	0,1	0,25	0,22

Starting Amplitudes from Industry Sector:

0,30	0,37	0,40	0,45	0,42	0,35

Compositions of former with following starting amplitudes:

0,10 (R) + 0,40 (I)	0,15 (R) + 0,40 (I)
0,17 (R) + 0,30 (I)	0,22 (R) + 0,45 (I)
0,25 (R) + 0,42 (I)	0,20 (R) + 0,37 (I)

* A random variation of 0 to 10% over these values was considered.

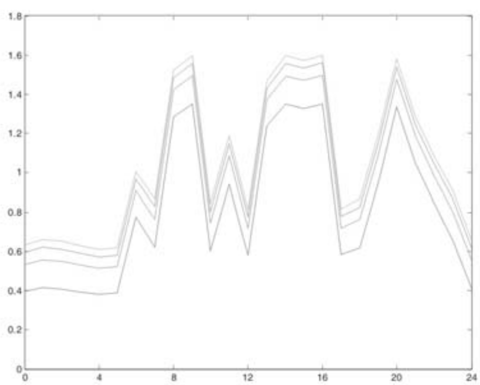

Figure 14 - Validation set made with compositions of representative curves from home and industry sectors subject to oscillations

Used Standards:

Compositions of curves regarding the Home and Industry Sectors with the following starting Amplitude values:

0,10 ± 10% (R) + 0,30 ± 10% (I)
0,17 ± 10% (R) + 0,37 ± 10% (I)
0,20 ± 10% (R) + 0,40 ± 10% (I)
0,22 ± 10% (R) + 0,42 ± 10% (I)

Table 5: Simulation results made with 10% of oscillations over amplitudes from home and industry standards

Expected Results		Obtained Results			
		BACKPROPAGATION		**GA**	
Outlet 1 *Home*	**Outlet 2** *Industry*	**Outlet 1** *Home*	**Outlet 2** *Industry*	**Outlet 1** *Home*	**Outlet 2** *Industry*
0,10 ± 10%	0,30 ± 10%	0,1528	0,2596	0,1110	0,3384
0,17 ± 10%	0,37 ± 10%	0,1862	0,3574	0,1920	0,3768
0,20 ± 10%	0,40 ± 10%	0,2121	0,3893	0,2110	0,3864
0,22 ± 10%	0,42 ± 10%	0,2307	0,4097	0,2204	0,3910
Error:		***0.0053***		***0.0033***	

Through this last simulation it is possible to restate the GA performance in ANN training. It is possible to notice also that, as long as increases the training set complexity, increases in the same proportion the backpropagation difficulties in finding the weight of ANN optimum set. This confirm the viability in using the GA in ANN training, as an alternative to the backpropagation in applications for recognition of standard compositions.

CONCLUSIONS

This work allows specific conclusions regarding to each technique and practical application.

With respect to ANN specifically it is possible to assert its efficiency in recognizing standards, immunity to noises and implementation facility. In all cases were used fourteen neurons in the first layer and eight in intermediate layer. Any change in these quantities did a significant loss in results quality, independent of the used method for training and of the ANN parameters adjustments.

Another very important point is the definition of the training set. When we want to associate some specific type of knowledge into ANN, samples of these should be part of the training set. The quantity of information used for ANN training should not be high, once this generate a super specialization, as well as cannot be small, which would prevent the learning.

Regarding the GA's, points like high cost of computing and high number of adjustments on algorithm parameters were noticed, and small variations may result in high modifications of the end result.

The way the initial population is generated, as well as the individuals number and the search space limitation, are essential questions for the algorithm success.

Each chromosome length determines the space dimensions, and this should be as limited as possible, what help very much in making easy the GA convergence.

Regarding the techniques hybridisation, in the specific case of recognizing the composed standards, it was noticed that the increase of complexity in training has produced a reduction in the quality of results generated by ANN trained by backpropagation, while the hybrid system presents a fair steady behaviour. This allows checking the consistency of a system based in cooperation between NAA and GA, and to state that in the cases where the training is complex it is advisable the use of hybrid techniques.

The results gained through numberless simulations made, as shown above, are enough for prove that the proposed aim for this work was achieved.

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