Implementing ICA in consumers load profile estimation

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Abstract: - This paper aims to use independent components analysis for consumer load profile study. The paper points out some general notions about the method of analyzing independent components - a statistical method that is receiving more and more attention from the research community. The method is a blind source separation one and it is used especially for signal processing. The paper show how ICA can be used in order to identify typically consumer load profiles.

Key-Words: - ICA – independent component analysis, load profile, power system,

1 Introduction

The Independent Components Method is part of the blind separation methods. It has received increasing attention over the last decade, mainly from the research community in the field of signal processing. The aspects of the method are multidisciplinary, at the intersection of statistical mathematical methods, neural networks, form recognition, theory of information and / or identification systems. The study of bibliographic references for the development of this paper has identified the application of the independent component method in areas such as: signal processing, process monitoring, electroencephalogram or electrocardiogram analysis, image recognition, topographic representation, financial time series forecasting, load type profiles.

The purpose of ICA is to decompose an arbitrary mixture of signals into source signals, assuming they are statistically independent. This concept is basically a fine tuning of the principal component analysis (PCA), where decomposition of the mixed signal into the uncorrelated components is sought.

This paper aims to apply the independent component algorithm for electrical network in order to identify consumer load profiles. Obtaining the consumers load profiles across an electrical network can be achieved by knowing either the power flows on the branches or the variation in time of the generated power, especially when using the distributed sources (solar, wind, biomass, micro hydro power plants, etc.). Given the fact that consumer loads are statistically independent, they can be extracted from the mixed signals on the basis of a statistical-mathematical method known as ICA. This is possible without having to know the network topology or its parameters.

2 Consumer load profile

The characteristics of the electrical loads are basic elements for solving complex technical and economic problems based on the design of power supply installations of different categories of consumers.

Load profiles (or load curve or load diagram) are the curves that indicate the change in time of the electrical load of a receiver (consumer) - individual graph or group of receivers (consumers) - group graphs. The load profile of a consumer or plant is therefore a graphical representation of the evolution of the load over time and is characterized by certain non-dimensional indicators; it reproduces the timing of the receivers and is a characteristic of every consumer.

The importance of load curves for the power system is particularly due to the very rigid correlation of production with electricity consumption in the absence of adequate storage facilities. From the elevated load curves for a certain amount of time, it can be seen that each consumer has a maximum power (or peak load) that can occur once in the chosen range (on a given day and at a specific time hour) or that can be repeated with the same value several times during the considered period. This load peak is an important dimension for the sizing of a consumer's power supply. Load profiles are being drawn up at different levels within the energy system: for an aggregate, section, economic unit, system node, or the entire energy system. Load profiles can be categorized by consumer type, duration of load variation monitoring, season, working day / weekend, etc.

The shape of the load profiles is generally random, depending strongly on the peculiarities of consumers. For power consumption, the most common types of load curves are: the daily load curve, the yearly curve, and the maximum monthly power curve.

3 Load profiles study using ICA

The ICA method can be applied in several areas involving the processing of signals or data. The method was designed to identify source signals knowing a linear mixture of them. The most common example of the ICA method is cocktail party problem. It is considered that in a room there are a number of microphones, placed in different positions, which record the sounds in the room. Depending on their position, the recorded signals will be different. But all will be mixes obtained by overlapping the same sources. The difference between the mixed signals recorded by the microphones is due to the different locations of the microphones. Mixed signals recorded by microphones represent linear combinations of source signals. The independent component method allows the identification of source signals, knowing only their linear combinations, ie microphone recordings. Mixed (known) signals can be expressed in matrix form

$$\boldsymbol{X} = \boldsymbol{A} \cdot \boldsymbol{S} \quad (1)$$

X-matrix of mixed signals
S-matrix of source signals
A-mixing matrix.

The purpose of the problem of determining the ***S***-matrix of the source signals is actually reduced to the matrix ***B*** estimate, so that:

$$\boldsymbol{S} = \boldsymbol{B} \cdot \boldsymbol{X} \quad (2)$$

B – demixation matrix.

A necessary condition for applying the ICA algorithm is that the source signals are statistically independent.

In the following, we apply the ICA method to identify consumer types when we have a composite load profile. In order to make this study, we have the load profiles for the following categories of consumers: slaughterhouse (C1); commerce (C2); saw (C3); hotel (C4); a shoe factory (C5); a woodworking plant (C6), represented in fig.1.

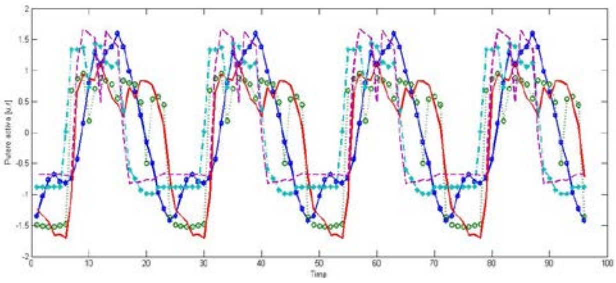

Fig.1 Real power load profiles

To exemplify how to use the independent component analysis method, four of the six load profiles were used, being considered for four consecutive days (96 h). The hourly real power values for the proposed consumers, normalized in relation to the maximum power in the system, are shown in Table 1.

Table 1 Normalized real power of the consumers for 24 hours

C1	C2	C3	C4	C5	C6
0.0520	0.5248	0.0055	0.0987	0.0225	0.0331
0.0705	0.5241	0.0051	0.0958	0.0228	0.0331
0.0852	0.5446	0.0050	0.0929	0.0228	0.0327
0.0902	0.5419	0.0050	0.0872	0.0229	0.0317
0.0835	0.6302	0.0053	0.0875	0.0231	0.0333
0.0823	0.7983	0.0057	0.0857	0.1320	0.0315
0.0867	0.9122	0.0432	0.1042	0.2942	0.0321
0.1044	0.9256	0.0465	0.1507	0.2939	0.1563
0.1375	0.9269	0.0480	0.1587	0.2988	0.1954
0.1750	0.9293	0.0347	0.1563	0.2194	0.1905
0.2028	0.9565	0.0438	0.1560	0.3062	0.1858
0.1921	0.9599	0.0467	0.1638	0.3000	0.1139
0.2032	0.9753	0.0461	0.1558	0.2690	0.1938
0.2085	0.9777	0.0449	0.1479	0.2602	0.1834
0.2206	1.0000	0.0410	0.1452	0.2677	0.1765
0.2082	0.9917	0.0461	0.1395	0.1751	0.0738
0.1861	0.9942	0.0453	0.1528	0.0578	0.0227
0.1670	0.9888	0.0450	0.1479	0.0390	0.0239
0.1448	0.9924	0.0399	0.1556	0.0172	0.0244
0.1204	0.9846	0.0228	0.1555	0.0099	0.0265
0.1007	0.9995	0.0408	0.1538	0.0094	0.0260
0.0738	0.9814	0.0416	0.1452	0.0217	0.0304
0.0585	0.6926	0.0392	0.1358	0.0223	0.0339
0.0479	0.5521	0.0077	0.1131	0.0224	0.0331

The following operations were performed on the load profiles:

• load graphs have been normalized according to the maximum power in the system;

• divided into standard deviation for data scaling;

• for data centering, average values of variables have been removed.

The resulting load profiles obtained after these operations are shown in fig.2.

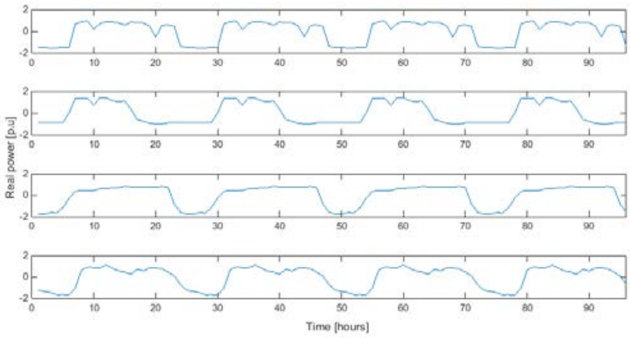

Fig.2 Centered load profiles of the consumers

Next, we will mix these signals with the "rand" function that returns a square array of random generated elements. Also, the independent component method involves a "whitening" phase of the initial signals. After mixing and whitening the signals, their new shape is shown in fig. 3.

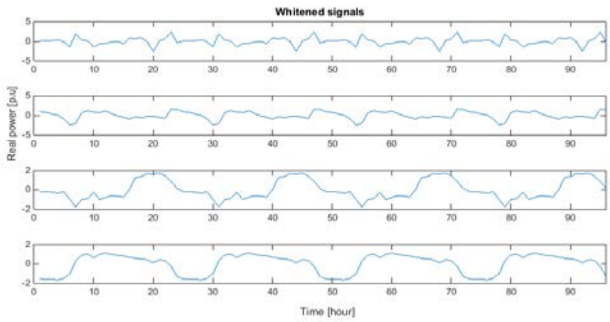

Fig.3 Mixed and bleached load profiles

The FastICA algorithm developed by ICA Group-University of Helsinki will be applied to the signals presented in fig.3. First, it is necessary to determine the number of source signals to be extracted. This can be equal to the number of mixed signals, in which case the mixing matrix is reversible and $\boldsymbol{B} = \boldsymbol{A}^{-1}$, but it can also have different values, either higher or lower The FastICA Toolbox allows you to perform analysis for multiple computational modes and more ways to treat nonlinearities. The types of nonlinearities implemented can be square, cubic, tanh or gauss functions. To avoid locking the algorithm in a local minimum, the method allows you to choose the stabilized version by changing the calculation step value. FastICA is based on a fixed point algorithm. It allows the choice of the type of estimation of the independent components based on two approaches: symmetrical (in parallel) or deflation (one by one).

The load profiles provided by FastICA are shown in fig. 4.

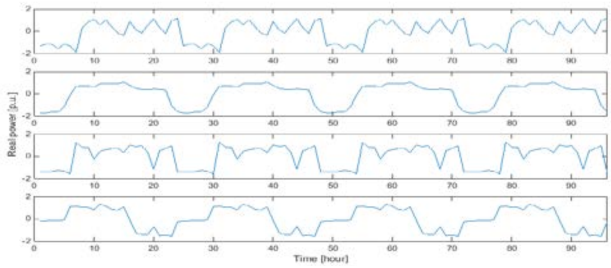

Fig.4 Load profiles resulting from ICA algorithm

A comparison between the actual load profiles of the consumers (fig. 2) and those extracted by the FastICA algorithm (fig. 4) highlights the random order of the signals provided by the applied method. The different shape of the load profiles allows the identification of each consumer profile. Another ambiguity of the applied algorithm refers to the sign of real load vector components. The results obtained for the example analyzed did not reveal this aspect.

In addition to the graphical representation of source signals, the algorithm also allows extraction of the demixing matrix, ***B***, and the source signal matrix. The last one can be used to calculate errors provided by the algorithm in estimating source signals. In case of periodic signals, the total value of the error may be affected by the number of periods considered.

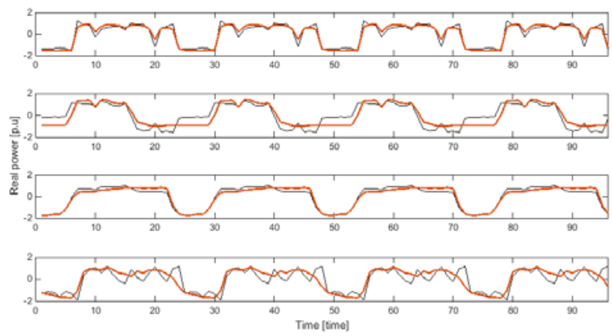

Fig.5 Comparison between actual load profiles and those resulting from FastICA algorithm

For graphical error visualization, in Figure 5, the centered customer profiles (using a thick full line) and load profiles extracted by ICA method are represented.

4 Conclusion

Independent component analysis can be a useful tool for signal processing in general, but also for studying consumer load profiles, as shown in this paper.

Due to the impossibility of storing electricity, meeting consumer energy needs requires the consumer to know the consumption in advance, which usually varies over time. An accurate estimation of the consumers' loads is important under the conditions of establishing the price of electricity through the energy market mechanism. The proposed method allows a sufficiently accurate estimation of the consumer load profiles.

A major advantage is that it is not necessary to know the topology and network parameters, but only the mixed signals that can be the power flows on the sides, the generated power, etc.

Application of the ICA method can be extended to estimate consumer loads for characteristic days (summer / winter, workday / weekend). Based on these estimates, the load type profiles can be determined for all consumers in analyzed network.

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