BULETINUL INSTITUTULUI POLITEHNIC DIN IAȘI
Publicat de
Universitatea Tehnică „Gheorghe Asachi” din Iași
Volumul 65 (69), Numărul 3, 2019
Secția
ELECTROTEHNICĂ. ENERGETICĂ. ELECTRONICĂ

APLICATION OF INDEPENDENT COMPONENT ANALYSIS IN LOAD PROFILE STUDY

BY

DANIELA IRIMIA[*] and ELENA CRENGUŢA BOBRIC

”Ştefan cel Mare” University of Suceava
Faculty of Electrical Engineering and Computer Science

Received: December 20, 2019
Accepted for publication: March 18, 2020

Abstract. The paper aims to establish the load profiles for the consumers, in a looped network, when active and reactive power flow on the branches are known. The algorithm used is independent component analysis (ICA), a statistic computational method that allows the extraction of additive components from a mixed signal. The method requires two restrictions referring to the statistically independence of the additive components and a non Gaussian probability distribution of the sources. In the paper, ICA was used to reconstruct active and reactive power requests according to consumer load profiles considering as mixed signals power flows on branches. ICA is a blind source separation algorithm, so it does not require knowledge of network parameters or configuration. The consumer load profiles obtained by the independent component method overlapped with a good approximation over the real load graphs of consumers used in modeling.

Keywords: independent component analysis; branch power flow; electric network; consumer load profile; statistical signal processing.

1. Introduction

On April 1986, at a scientific meeting held in Utah on Neural Networks for Computing, Jeanny Herault and Christian Jutten presented a research paper

[*]Corresponding author: *e-mail*: daniela.irimia@usm.ro

about a learning algorithm capable to blindly separate mixtures of independent signals (Herault & Jutten, 1986). Beginning with this moment there have been developed a lot of researches based on independent component analysis. ICA is a blind source separation method, so it allows the extraction of component signals from a mixture of them.

During almost four decades since the first presentation of the independent components method, this has proved applicable in a multitude of different fields. As its name indicates, the purpose is to reconstruct the independent sources knowing a linear mixture of source signals. The kind of problems solved by independent component analysis algorithm are called "cocktail party" problems. As an example, we consider four people in the same room, talking at the same time. Three microphones placed in different location in the room will capture a mixture of the voices signals. The blind separation technique is able to correctly identify each voice signal, knowing only the number of people who speak and the linear mixture of their voice signal. In order to get good results, the source signals must meet two conditions: they need to be statistically independent of each other and the values for each source signal have non-Gaussian distribution. A remarkable number of researches are in medical field, the method being applied for the processing of biological signals recorded by electrocardiograms, electroencephalograms, etc. For example, in (Calhoun *et al*., 2009) is shown how to remove artifacts which are mixed in different biomedical signals such as Electroencephalogram (EEG), Magnetoencephalography (MEG) or functional magnetic resonance imaging (fMRI). The same method is used in (Pontifex et al., 2017) to separate brain signals from other signals generated by other activities or in (Deprez *et al*., 2018) to study a cochlear implant artifacts attenuation method which influences EEG recordings in case of Electric auditory steady-state responses (EASSRs) measurements. Also (Pang *et al*., 2016) described how to obtain a high-quality ECG by removing the interference respiratory signals demonstrating that ICA algorithm is more powerful and more effective to de-noising the respiratory signal from ECG. Used as a data-mining tool ICA can extract biologically relevant gene expression features from microarray data (Kong et al., 2008), or may be the basis for the analysis of neural networks in Parkinson's disease (Onu *et al*., 2015).

Another area in which ICA can be applied is the financial one or in stock market. Using the algorithm of independent components can be identified some driving mechanisms which act in time series representing currency exchange or daily returns of stocks (Back & Weigend, 1997; Kiviluoto & Oja, 1999).

Image processing is another area where the independent components method has proven useful. In Derrode *et al*., (2003), the method was used for segmenting the image for the purpose of extracting certain layers from the initial image and in (Lee & Lewicki, 2002) for removing the noise from the raw images corrupted or affected by Gaussian noise. Another interesting application of ICA in the field of image processing was to increase copyright protection by using a blind watermark (Hajisami *et al*., 2011). Experimental results prove that ICA based method has better results against different types of attacks like resizing, rotation, noise addition, grayscale reduction, compression, lowpass filtering, cropping.

The identification of discriminatory characteristics in biometrics can also be treated using independent component analysis. The applications in the biometric domain refer to face recognition (Dagher & Nachar, 2006), fingerprints (Long & Kong, 2004) or ear recognition (Zhang *et al*., 2005).

Telecommunications represent another area of great potential. (Ristaniemi & Joutsensalo, 1999) use ICA for blind separation of the user's own signal from the interfering signals of others in Code-Division Multiple Access mobile communications. An application of ICA method for noncircular signals based on second-order statistics provides a Faster convergence and errors smaller than other methods (Jia & Yang, 2016).

In audio signal processing field ICA method was widely used for removing noise (Zibulevsky & Pearlmutter, 2001), but also to design models for automatic speech recognition, using the method capabilities of feature extraction (Cho & Park, 2016). Radar identification of aerospace targets that have multiple moving parts (helicopters, miniature unmanned aerial vehicles) and which have special features in the radar return is analyzed in (Addabbo *et al*., 2017) using ICA.

Analysis based on the independent components of the acoustic signals that appear in mechanical systems due to vibrations, is useful in machines condition (Cheng *et al*., 2015) or in fault diagnosis of rolling element bearings (Guo *et al*., 2014). Experimental vibration investigations on a scaled submarine show that ICA is efficient too in identification of vibratory source signals of complex structures (Lee *et al*., 2015). The detection and diagnosis of defects in the capacitors system of a power plant using ICA provided also valid and effective results (Ajami & Daneshvar, 2014). The study of vibrations that appear in buildings reveals that the vibration pattern in normal condition is affected by external sources like noise and vibration from road and rail traffic, wind, earthquakes, blasting, construction operations, and so on. As an example, (Popescu, 2010) shows how to separate the vibration produce by underground traffic from the mixture of building vibrations.

Another ICA potential and ability in extracting features is presented in (Sun *et al*., 2019). The authors show the success of ICA in assessing the performance of an electronic nose capable to analyse gas composition in complicated environments.

For detecting defects in the OLED (Organic Light Emitting Displays) panels, the first step is to establish the connection between the independent components and the background image in the case of the faultless image. Using the demixing matrix, the background image is reconstructed and then subtracted from the captured test image. Thus is obtained the image with preliminary defects from which the defects can be identified (Wang *et al*., 2012).

The ICA algorithm has also been successfully used in power systems. In order to improve the operational safety and stability of the energy system, an accurate separation of harmonics from the grid voltage is needed. This separation was realized with excellent performance by (Cai *et al*., 2017), based on ICA. Another application of the independent components method in power systems, presented in (Liao & Niebur, 2003) is the estimation of load profiles based on the active power flows on the grid branches.

The present paper uses a blind separation technique in order to estimate active and reactive load profile for consumers, without knowing the configuration or the parameters of electrical network.

In planning and management of electric networks it is important to know the forecast of all consumers' electricity loads. In this regard, it is important to know the load profiles of all networked customers. Because monitoring and remote transmission of consumption involves significant costs, estimating load profiles using statistical algorithms can be a viable alternative.

The paper shows that ICA algorithm is capable of providing correct evaluations for individual consumers load profiles, without any information about electrical network.

2. Mathematical Model of Independent Component Analysis

Independent component analysis is an important algorithm for statistical signal processing community. It is a linear transformation method, so the observed signals are linear combination of unknown independent source signals. In order to blindly estimate source signals, the inverted unknown mixing matrix must be determined.

The statistical model called independent component analysis is mathematical expressed by the equation:

$$\boldsymbol{X} = \boldsymbol{A} \cdot \boldsymbol{S}, \tag{1}$$

where: $\boldsymbol{X} \in R^{M \times P}$ is the matrix whose columns contained the mixed signals (observations vector). The number of rows corresponds to the independent source signals, and the data on each column corresponds to the number of samples of mixed signals. $\boldsymbol{S} \in R^{N \times P}$ – matrix whose columns contained the source signal vectors, $\boldsymbol{A} \in R^{M \times N}$ – mixing matrix, containing unknowing constant elements.

This model shows that the observed data (***X***) are generated by mixing ***S*** components. The only known data are the elements of ***X*** and using them, both ***A*** and ***S*** must be estimated. The most important assumption for ICA is that ***S*** components are statistically independent. Two variables are considered to be independent if the information about the values of first variable does not give any information on the second one, and vice-versa. Mathematically, if two or more variables are independent, the joint probability function of all variable is the product of probability density of each of them.

The estimation of independent components is realized based on minimization of mutual information or the estimation of maximum likelihood. The paper works with FastICA algorithm, which is based on minimizing mutual information.

First step needed in applying ICA is centering the data. This involves diminishing each element with the mean value of the signal, thus obtaining a zero value on each row of the $\boldsymbol{X}$ matrix.

$$x_{ij} \leftarrow x_{ij} - \frac{\sum_{j'} x_{ij'}}{P}, \tag{2}$$

$i = 1,\ldots,M$, $j = 1,\ldots,P$.

This way, $\boldsymbol{S}$ can be considered to be zero-mean, as well. After mixing matrix $\boldsymbol{A}$ is estimated, the mean vector of $\boldsymbol{S}$ is added back to the centered estimates.

Another preprocessing step consists in whitening the observed variable, which means that any correlation in the data is removed. Whitened is realized applying a linear transformation to $\boldsymbol{X}$ vector so that a new white vector $\tilde{\boldsymbol{X}}$ is obtained. The covariance matrix of $\tilde{\boldsymbol{X}}$ is the identity matrix:

$$\boldsymbol{E}\left\{\tilde{\boldsymbol{X}}\ \tilde{\boldsymbol{X}}^T\right\} = \boldsymbol{I}. \tag{3}$$

One of the commonly used whitening methods is based on eigenvalue decomposition on the covariance matrix of centered data.

$$\boldsymbol{E}\left\{\boldsymbol{X}\ \boldsymbol{X}^T\right\} = \boldsymbol{E}\ \boldsymbol{D}\ \boldsymbol{E}^T, \tag{4}$$

where: $\boldsymbol{E}$ is the orthogonal matrix of eigenvectors, $\boldsymbol{D}$ – diagonal matrix of eigenvalues.

The new white vector $\tilde{\boldsymbol{X}}$ will be:

$$\tilde{\boldsymbol{X}} = \boldsymbol{E}\boldsymbol{D}^{-1/2}\boldsymbol{E}^T\boldsymbol{X} = \boldsymbol{E}\boldsymbol{D}^{-1/2}\boldsymbol{E}^T\boldsymbol{A}\boldsymbol{S} = \tilde{\boldsymbol{A}}\boldsymbol{S}. \tag{5}$$

By performing the whitening, the number of parameters to be estimated is reduced by almost half.

Performing these two steps together is referred to as sphering, and is important to speed up the algorithm of ICA. These consist of setting to zero the mean and covariance, and equalized the variance.

After the two preprocessing steps were performed, an iterative algorithm is applied in order to find a matrix $\boldsymbol{W}$, which is the inverse of mixing matrix, also called un-mixing matrix:

$$\boldsymbol{Y} = \boldsymbol{W}\boldsymbol{X}, \tag{6}$$

$\boldsymbol{Y}$ extracted signals matrix ($N \times P$),
$\boldsymbol{W}$ unmixig matrix ($N \times M$),
$\boldsymbol{X}$ mixture signals matrix ($M \times P$).

When the number of sources is equal with the number of mixture signals, matrix $\boldsymbol{A}$ is invertible and $\boldsymbol{W} = \boldsymbol{A}^{-1}$. When the number of source signals is (higher) larger than the number of mixture ($n > m$), $\boldsymbol{A}$ is not invertible, and the problem is called over-complete. When the number of source signals is less than the number of mixture ($n < m$), the problem is called under-complete and can be solved by deleting some mixture.

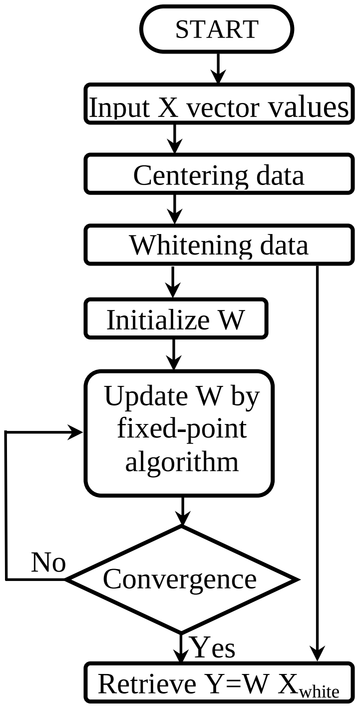

Fig. 1 – FastICA method flow chart.

The steps to be followed in applying the FastICA algorithm are shown in Fig. 1.

The independent component method has two ambiguities. The first one is about the sign and it is not important for most of the problem. The second ambiguity referred to the order of independent component, which is freely changed.

The paper used FastICA algorithm implemented in Matlab and available free of charge on World Wide Web.

Multidimensional variable vectors of power flow on network branches were considered as mixed signals, both for active and reactive power. These are linear combinations of consumers' active and reactive power demands. The multidimensional variable vectors representing consumers load profiles are independent, so they can be estimated using the statistical technique called independent component analysis (ICA).

3. Case Study

The study was conducted on a 5-node looped network (Fig. 2), which feeds 4 consumers with different load profiles. The voltage level of the analyzed network is 220 kV. Consumer load profiles were chosen so that they were statistically independent, because these will be the source signals to be determined. Consumer load profiles are known and will be compared to those resulting from the application of the ICA algorithm.

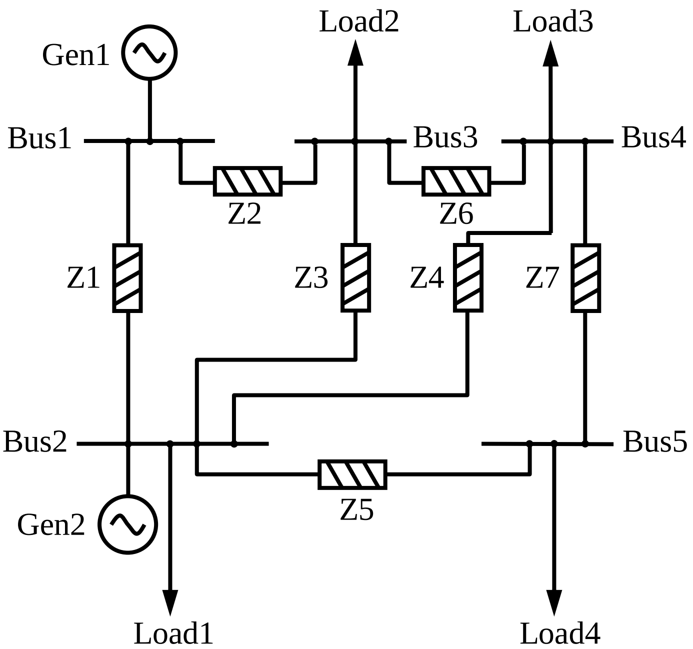

Fig. 2 − Electrical network.

Knowing the topology and network parameters, there have been calculated power flows through each branch. The calculations were performed over a 24 hours period using ETAP18.1. The active and reactive power flows provided by ETAP in watts are shown in Table 1.

The power flows on the network branches, for 24 hours, provided by ETAP will be the mixed signals used as input data in the independent component method.

As a method of determining the independent components, the FastICA algorithm developed at the Faculty of Science of the University of Helsinki was used.

As mentioned in the previous paragraph, multidimensional variables represented by active and reactive power flows on the branches are subjected to a preprocessing step. First, a data centering, consisting of lowering the average value of each component of the multivariable vectors is achieved, thus bringing the mean to zero.

Table 1
Active and Reactive Power Flow on Branches

P_{Z1} [p.u.]	Q_{Z1} [p.u.]	P_{Z2} [p.u.]	Q_{Z2} [p.u.]	P_{Z3} [p.u.]	Q_{Z3} [p.u.]	P_{Z4} [p.u.]	Q_{Z4} [p.u.]	P_{Z5} [p.u.]	Q_{Z5} [p.u.]	P_{Z6} [p.u.]	Q_{Z6} [p.u.]	P_{Z7} [p.u.]	Q_{Z7} [p.u.]
0.261	0.257	0.129	0.122	0.085	0.077	0.070	0.063	0.056	0.046	0.090	0.082	0.024	0.024
0.265	0.260	0.132	0.124	0.088	0.078	0.072	0.064	0.056	0.047	0.095	0.083	0.026	0.025
0.256	0.249	0.129	0.121	0.087	0.078	0.071	0.064	0.056	0.047	0.093	0.082	0.025	0.025
0.246	0.249	0.124	0.119	0.083	0.076	0.068	0.063	0.055	0.047	0.088	0.079	0.024	0.024
0.255	0.264	0.128	0.121	0.085	0.074	0.070	0.061	0.056	0.045	0.091	0.078	0.025	0.023
0.444	0.348	0.225	0.164	0.152	0.102	0.124	0.084	0.088	0.074	0.168	0.104	0.049	0.026
0.651	0.472	0.351	0.239	0.251	0.160	0.203	0.130	0.127	0.091	0.287	0.178	0.089	0.051
0.819	0.752	0.393	0.299	0.251	0.146	0.211	0.135	0.252	0.341	0.238	0.063	0.032	-0.069
0.869	0.835	0.400	0.324	0.244	0.153	0.208	0.144	0.276	0.392	0.218	0.051	0.017	-0.088
0.883	0.788	0.396	0.294	0.234	0.127	0.199	0.121	0.263	0.355	0.211	0.032	0.017	-0.087
0.905	0.822	0.404	0.308	0.237	0.135	0.200	0.128	0.257	0.355	0.217	0.042	0.022	-0.082
0.870	0.764	0.404	0.308	0.248	0.154	0.206	0.137	0.206	0.264	0.252	0.104	0.052	-0.030
0.960	0.964	0.430	0.382	0.253	0.186	0.214	0.172	0.279	0.424	0.230	0.085	0.021	-0.083
1.000	1.000	0.450	0.385	0.267	0.178	0.226	0.165	0.282	0.409	0.246	0.079	0.028	-0.081
0.976	0.976	0.436	0.387	0.256	0.188	0.217	0.170	0.265	0.374	0.235	0.108	0.030	-0.059
0.819	0.688	0.387	0.288	0.243	0.153	0.200	0.130	0.165	0.170	0.260	0.137	0.067	0.012
0.749	0.492	0.359	0.228	0.229	0.139	0.185	0.112	0.110	0.066	0.262	0.160	0.084	0.051
0.697	0.488	0.346	0.229	0.229	0.141	0.185	0.114	0.109	0.067	0.264	0.162	0.084	0.052
0.709	0.495	0.352	0.241	0.233	0.155	0.188	0.125	0.111	0.073	0.269	0.179	0.086	0.057
0.721	0.487	0.358	0.237	0.236	0.151	0.191	0.122	0.112	0.074	0.273	0.174	0.087	0.055
0.731	0.454	0.370	0.227	0.250	0.149	0.202	0.121	0.118	0.071	0.287	0.171	0.093	0.055
0.720	0.474	0.367	0.235	0.249	0.153	0.201	0.124	0.119	0.075	0.285	0.172	0.091	0.055
0.430	0.332	0.212	0.151	0.140	0.090	0.114	0.074	0.079	0.051	0.152	0.097	0.046	0.030
0.262	0.291	0.129	0.126	0.085	0.070	0.069	0.058	0.056	0.042	0.090	0.074	0.024	0.022

A second step of preprocessing consists in whitening. By whitening the variance is normalized in all directions. Whitening ensures all the source signals are treated equally before the algorithm begin. The whitening active power flows on branches are shown in Fig. 3.

The same preprocessing steps are applied to consumers load profiles. These steps are necessary in order to compare the real load profiles with those calculated based on ICA. The 24 hours load profile shape is shown in Fig. 4.

After the preprocessing steps are done FastICA algorithm is running. The only data to be entered is the profiles for active and reactive power flow and the number of consumers feed by electrical network. The FastICA toolbox allows you to perform analyzes for multiple computational modes and more ways to treat nonlinearities. The algorithm has been applied twice: for the active and reactive load.

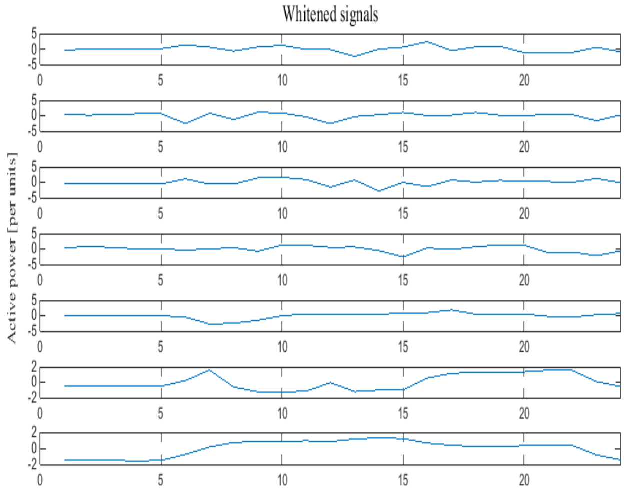

Fig. 3 − Mixed signals representing active power flows on branches after preprocessing.

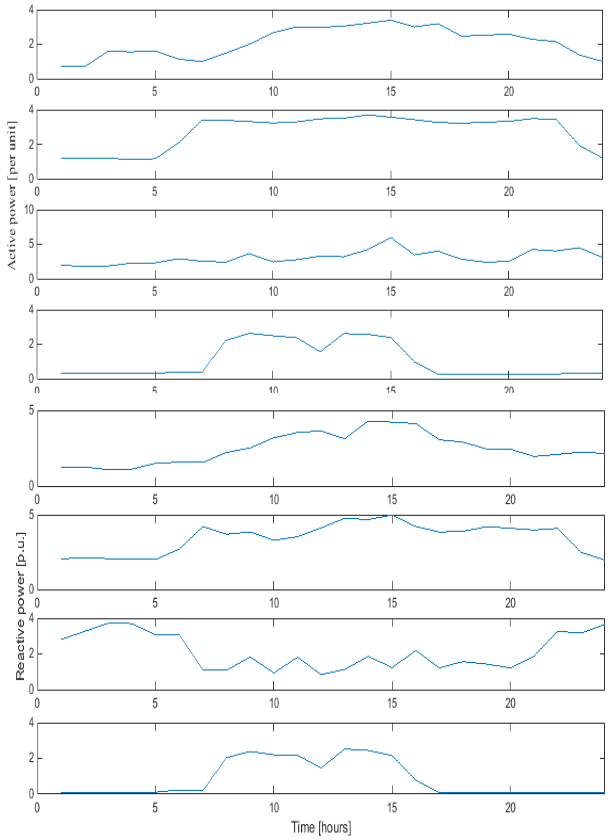

Fig. 4 − 24 hours consumers load profile.

The visual analysis of the signals provided by FastICA highlights the previously mentioned ambiguities of the algorithm. The first one is about the order of the load graphs which is arbitrary. Different aspects of the consumer load profiles allow an easy determination of the correspondence between the load profiles determined by demixing process and the real load profiles. Thus, the first real consumer corresponds, in Fig. 5, to the 3rd profile, the consumer 2, to the first profile, the third consumer has the profile 4 and the 4th consumer has the profile corresponds to the second consumer.

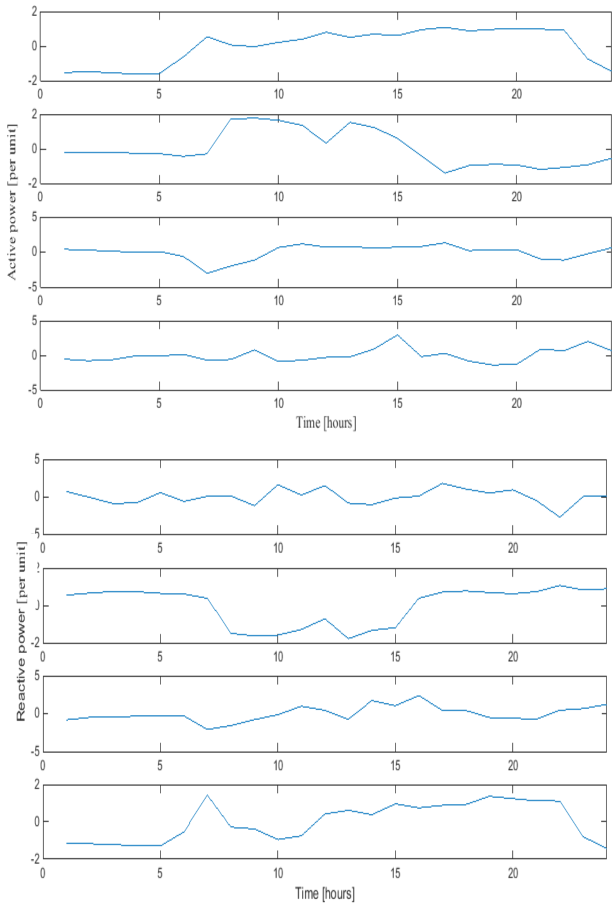

Fig. 5 − 24 hours consumer active and reactive load profile determined with FastICA.

4. Discussion

A first assessment of the accuracy of the ICA algorithm precision can be highlighted by comparing the real load graphs of the consumers with those provided by the statistical method. This comparison is shown in Fig. 6. It highlights the observance of the variation trend of active load for all four consumers. With two exceptions, observable in the case of the first consumer of Fig. 6, the gap between the load profile pairs is small.

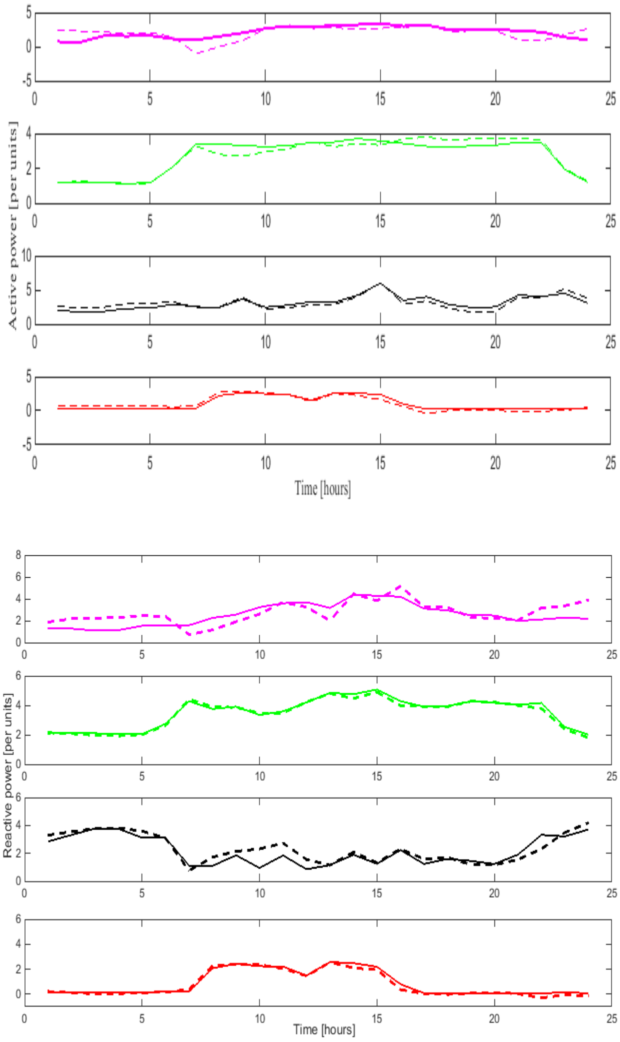

Fig. 6 − Comparison between estimated load profile provided by ICA and real consumer load profile.

A more accurate evaluation requires the calculation of errors. In Table 2 the mean and maximum relative errors for each of the four consumers are calculated.

Table 2
Mean Error for Each Consumer

	Mean error for active power, [%]	Mean error for reactive power, [%]
Cons.1	7.80	16.62
Cons.2	1.76	1.69
Cons.3	2.21	3.28
Cons.4	0.35	0.33

Calculated values for the relative mean error indicate a satisfactory accuracy of load profiles calculated with ICA. Unexpectedly, the smallest average error is in the case of the first consumer, although the difference between actual and estimated loads, highlighted on the graphs in Fig. 5, is the highest. This result is due to the fact that absolute hourly errors are both positive and negative. For a more precise assessment of the accuracy of the results obtained by the ICA method, the maximum relative errors presented in Table 2 were calculated. These indicate, as can be seen in the comparative graphs of Fig. 5, that the estimation of the first consumers load profile has the lowest precision.

On the whole, the ICA algorithm can be considered to provide good results when estimating the load profiles of consumers, knowing only the power flows on the network branches and the number of consumers.

5. Conclusion

The present paper illustrated that the consumers load profiles can be estimated using a blind separation technique. The FASTICA algorithm has been used to identify the load profiles of consumers in a network knowing the power flows on the branches. These can be considered as linear combinations of consumer loads that meet the requirement of being statistically independent.

An important advantage of applying this statistical technique is that it is not necessary to know the parameters and the network topology, but only the power flows on the branches and the number of consumers.

Acknowledgements. The authors acknowledge financial support from the project Integrated Center for Research, Development and Innovation in Advanced Materials, Nanotechnologies, and Distributed Systems for Fabrication and Control, Contract No. 671/09.04.2015, Sectoral Operational Program for Increase of the Economic Competitiveness co-funded from the European Regional Development Fund.

Part of research from this article was presented at the 12th International Conference and Exhibition on Electromechanical and Energy Systems, Sielmen 2019, event co-organized by Faculty of Electrical Engineering, “Gheorghe Asachi” Technical University of Iaşi.

REFERENCES

Addabbo P., Clemente C., Ullo S.L., *Fourier Independent Component Analysis of Radar micro-Doppler Feature*, 4th IEEE International Workshop on Metrology for AeroSpace, MetroAeroSpace 2017 - Proceedings. IEEE, ITA, 45-49.

Ajami A., Daneshvar M., *Independent component analysis approach for fault diagnosis of condenser system in thermal power plant*, Journal of Central South University volume 21, 242–251 (2014).

Ariff M.A.M., Pal B.C., *Coherency Identification in Interconnected Power System – An Independent Component Analysis Approach*, IEEE Transactions on Power Systems, **2**8, *2*, 1747-1755 (2012).

Back A.D, Weigend A.S., *A First Application of Independent Component Analysis to Extracting Structure from Stock Returns*, Int. J. Neural System, *8*, 473-484 (1997).

Bartlett M.S., Movellan J.R., Sejnowski T.J., *Face Recognition by Independent Component Analysis*, IEEE Transactions on neural networks, **13**, *6*, 1450-1464 (2002).

Cai K., Wang Z., Li G., He D., Song J., *Harmonic Separation from Grid Voltage Using Ensemble Empirical-Mode Decomposition and Independent Component Analysis*, International Transactions on Electrical Energy Systems, **27**, *11*, (2017).

Calhoun V.D., Liu J., Adal T., *A Review of Group ICA for FMRA Data and ICA for Joint Inference of Imaging, Genetic, and ERP Data*, Neuroimage, **45**, *1*, S163-S172 (2009).

Cârţină G., Grigoraş G., Bobric E.C., Comănescu D., *Improved Fuzzy Load Models by Clustering Techniques in Optimal Planning of Distribution Networks*, 2009 IEEE Bucharest PowerTech, Bucharest, 2009, 1-6.

Cheng W., Zhang Z., Zhang J., Lu J., *Acoustical Source Tracing Using Independent Component Analysis and Correlation Analysis*, Shock and Vibration Journal, Issue Structural Dynamical Monitoring and Fault Diagnosis (2015).

Cho J.-W., Park H.-M., *Independent Vector Analysis Followed by hmm-Based Feature Enhancement for Robust Speech Recognition*, Sig. Process., **120**,200-208 (2016).

Dagher I., Nachar R., *Face Recognition Using IPCA-ICA Algorithm*, IEEE Trans. Pattern Anal. Machine Intell., **28**, *6*, 996-1000 (2006).

Deprez H., Gransier R., Hofmann M., van Wieringen A., Wouters J., Moonen M., *Independent Component Analysis for Cochlear Implant Artifacts Attenuation from Electrically Evoked Auditory Steady-State Response Measurements*, J. Neural Eng., 15(1):016006 (2018).

Derrode S., Mercier G., Pieczynski W., *Unsupervised Multicomponent Image Segmentation Combining a Vectorial HMC Model and ICA*, Proceedings of International Conference on Image Processing ICIP 2003, II-407.

Esmalifalak M., Nguyen H., Zheng R., Han Z., *Stealth False Data Injection Using Independent Component Analysis in Smart Grid*, 2011 IEEE International Conference on Smart Grid Communications, SmartGridComm, 2011, 244-248.

Ferreira D.D., Seixas J., Cerqueira A., *ICA-Based Method for Power Quality Disturbance Analysis*, 15th International conference on Intelligent System Applications to power systems, 2009.

Gavrilaş M., Neagu B.C., Pentiuc R.D., Hopulele E., *Overview on Distributed Generation Integration in Distribution Systems*, 2018 International Conference and Exposition on Electrical And Power Engineering, EPE 2018, Iaşi, 1063-1069.

Grigoraş G., Cârţină G., Bobric E.C., Barbulescu C., *Missing Data Treatment of the Load Profiles in Distribution Networks*, 2009 IEEE Bucharest PowerTech 2009, Bucharest, 1-5.

Grigoraş G., Ivanov O., Gavrilaş M., *Customer Classification and Load Profiling Using Data from Smart Meters*, 12th Symposium on Neural Network Applications in Electrical Engineering, NEUREL 2014, Belgrade, 73-78.

Guo Y., Na J., Li B., Fung R., *Envelope Extraction Based Dimension Reduction for Independent Component Analysis in Fault Diagnosis of Rolling Element Bearing*, Journal of Sound and Vibration, **333**, *13*, 2983-2994 (2014).

Gursoy E., Niebur D., *Harmonic Load Identification Using Complex Independent Component Analysis*, IEEE Transactions on power delivery, **241**, 285-292, (2008).

Hajisami A., Rahmati A., Babaie-Zadeh M., *Watermarking Based on Independent Component Analysis In Spatial Domain*, 13th International Conference on Modelling and Simulation, UKSim, 2011.

Herault J. and Jutten C., *Space or Time Adaptive Signal Processing by Neural Network Models*, AIP Conference Proceedings, **151**, 206, 1986.

Hussain M.M., Zakaria Z.H., Serwan S., *FastICA Techniques for Load Profiles Estimation*, 2012 IEEE Symposium on Industrial Electronics and Applications, ISIEA2012, Bandung, Indonesia.

Hyvärinen A., Hoyer P. O., Inki M., *Topographic Independent Component Analysis*, Neural computation, **13**, *7*, 1527-1558 (2001).

Hyvärinen A., Karhunen J., Oja E., *Independent Component Analysis*, John Wiley & Sons, **46** (2004).

Jia Y., Yang X., *Adaptive Complex-Valued Independent Component Analysis Based on Second-Order Statistics*, Journal of Electrical and Computer Engineering (2016).

Kiviluoto K, Oja E, *Independent Component Analysis for Parallel Financial Time Series*, Fifth International Conference on Neural Information. Kitakyushu, Japan: MIT Press, 1999, 895-898.

Kong W., Vanderburg C.R., Gunshin H., Rogers J.T., Huang X., *A Review of Independent Component Analysis Application to Microarray Gene Expression Data*, Biotechniques, **45**, *5*, 501-520 (2008).

Lee D.-S., Cho D.-S., Kim K., Jeon J.-J., Jung W.-J., Kang M.-H., Kim J-H., *A Simple Iterative Independent Component Analysis Algorithm for Vibration Source Signal Identification of Complex Structures*, International Journal of Naval Architecture and Ocean Engineering, **7**, *1*, 128-140 (2015).

Lee T.-W., Lewicki M.S., *Unsupervised Image Classification, Segmentation, and Enhancement Using Ica Mixture Models*, IEEE Trans. Image Process., **11**, *3*, 270-279 (2002).

Liao H., Niebur D., *Exploring Independent Component Analysis for Electric Load Profiling*, 2002 International Joint Conference on Neural Networks, IJCNN'02, **3**, 2144-2149 (2002).

Liao H., Niebur D., *Load Profile Estimation in Electric Transmission Networks Using Independent Component Analysis*, IEEE Transactions on Power Systems, **18**, *2*, 707-715 (2003).

Long F., Kong B., *Independent Component Analysis and its application in the Fingerprint Image Preprocessing*, International Conference on Information Acquisition, 2004, 365-368.

Luo W. H., Sun Y.L., *Application of Independent Component Analysis in Monitoring and Analysis of Power Quality*, Power System Technology, **15** (2006).

Neagu B.C., Grigoraş G., Scarlatache F., *Effects of Outliers on Calculation of Load Profile Factors*, 2017 International Conference on Modern Power Systems MPS 2017, Cluj-Napoca, 1-4.

Onu M., Badea L., Roceanu A., Tivăruş M., Bajenaru O., *Increased Connectivity Between Sensorimotor and Attentional Areas in Parkinson's Disease*, Neuroradiology, **57**, *9*, 957-968 (2015).

Comon P., *Independent Component Analysis, a New Concept*? Signal processing, **36**, *3*, 287-314 (1994).

Pang X. L., Ge M., Li C., *Apply ICA (Independent Component Analysis) to Removing Respiratory Interference from ECG*, Electrical and Control Engineering & Materials Science and Manufacturing, 2016.

Pontifex M.B., Gwizdala K.L., Parks A.C., Billinger M., Brunner C., *Variability of ICA Decomposition May Impact EEG Signals when used to Remove Eyeblink Artifacts*, Psychophysiology, **54**, *3*, 386-398 (2017).

Popescu Th.D., *Analysis of Traffic-Induced Vibrations by Blind Source Separation with Application in Building Monitoring*, Mathematics and Computers in Simulation, **8**0, 2374-2385 (2010).

Ristaniemi, T., Joutsensalo, J., *Independent Component Analysis with Code Information Utilization in DS-CDMA Signal Separation*, Global Telecommunications Conference - Globecom´99, Rio de Janeiro, Brazil, 320-324.

Sun R., Du H., Zheng Y., *Discriminative Power of Independent Component Analysis Applied to an Electronic Nose*, Measurement Science and Technology, **31**, *3*, (2019)

Tharwat A., *Applied Computing and Informatics*, doi.org/10.1016/j.aci.2018.08.006.

Ungureanu C., Bobric C., Irimia D., *Fuzzy Logic Control of a New Type of Electromagnetic Converter with Rolling Rotor*, 2014 International Conference on Applied and Theoretical Electricity, ICATE 2014, Craiova, 1-4.

Wang Z., Gao J., Jian C., Cen Yu, Chen Xin, *OLED Defect Inspection System Development through Independent Component Analysis*, Indonesian Journal of Electrical Engineering and Computer Science, **10**, *8*, 2309-2319 (2012).

Zhang H.-J., Mu Z.-C., Qu W., Liu L.-M., Zhang C.-Y., *A Novel Approach for Ear Recognition Based on ICA and rbf Network*, Proceedings of International Conference on Machine Learning and Cybernetics, **7**, 4511-4515 (2005).

Zibulevsky M., Pearlmutter B.A., *Blind Source Separation by Sparse Decomposition in a Signal Dictionary*, Neural Computat., **13**, *4*, 863-882 (2001).

* * * http://www.cis.hut.fi/projects/ica/Fastica/

APLICAŢII ALE METODEI COMPONENTELOR INDEPENDENTE PENTRU STUDIUL PROFILELOR DE SARCINĂ

(Rezumat)

Lucrarea îşi propune să stabilească profilele de sarcină din nodurile unei reţele buclate, atunci când se cunosc circulaţiile de putere activă şi reactivă pe laturi. Se utilizează o metodă statistică, analiza componentelor independente (ICA), care permite

extragerea componentelor sursă din amestecuri ale acestora. Metoda necesită două restricţii care se referă la independenţa statistică şi la distribuţia non-gaussiană a semnalelor sursă. În lucrare, ICA a fost utilizată pentru a extrage profilurile de sarcină activă şi reactivă din circulaţiile de putere de pe laturile reţelei. ICA este un algoritm de separare în orb a surselor, care nu necesită cunoaşterea parametrilor reţelei sau a configuraţiei acesteia. Profilele de sarcină ale consumatorilor obţinute prin metoda componentelor independente s-au suprapus cu o bună aproximaţie peste graficele reale ale sarcinilor din noduri.