DECOMPOSITION OF LOAD COMPONENTS USING DATE MEASURED IN THE BEGINNING OF SUBTRANSMITION SUBSTATIONS

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ABSTRACT

usually, in the beginning of substations and MV feeders, the profile of loads is measured that is related to the total load of an area (or many of customers). There are various methods to decomposition of load profiles of different classes of customers. These methods need typical load profiles. Also they use simplifier assumptions that limits their application to the real data. In this paper a novel method based on independent component analysis is proposed. The basis of using this method is on the statistical independence of load components of different classes of customers. The proposed method decomposes the load components from the total measured load of a feeder. And then calculates the share of each component of the total load profile. To verify he method, 24-hour load curve of the feeders of a sample network is simulated and then the method is applied.

INTRODUCTION

In studies to obtain load characteristics, distribution load is classified in to different categories such as domestic, industrial, commercial, agricultural and so on. The aim of these studies is to understanding the amount and the time of use of each type of customers that their results is represented by typical load profiles[1]. Understanding the typical load profile of customers can be used to different areas such as load prediction at peak times, determination of coincidence coefficient, pricing and tariff classification in marketing and above all demand side management programs in various parts [2].

Nowadays, using smart metering devices and telecommunication systems provide accurate information of the amount of loads consumed. However, widespread use of these devices is not common in distribution utilities at least in Iran. Because their usage in wide distribution systems is not economical. Therefore, the load data is measured and saved just in the beginning of sub transmission substations [3]. different methods is proposed to use data in order to obtain load profile of customer classes [3]-[6].

In these methods, it is assumed that feeders' loads are mainly composed of one component. Typical load profiles are obtained by clustering. The algorithms in this method are k-means and fuzzy clustering [3], [4]. after typical load profile calculation, the type of feeders is determined by classification algorithms such as decision tree, support vector machine [5], [6]. In these methods decomposition of a feeder components is not done, but by assuming that a feeder is composed of just one load type, the load type of feeder is detected. Therefore, it is not possible to determine the contribution percent of each type of customers (load component) in a feeder. Thus coincidence coefficient cannot be accurately calculated.

Till now, various studies are done to obtain typical load types but load component decomposition is a research gap in this field[7]. Most of studies have turned load type decomposition problem in to an optimization problem. For example, [2] is used genetic algorithm to solve the problem. Knowing the type of feeder load and typical load profile is needed in this method. The proposed method in this paper is just based on principle of statistical independence. The proposed method is presented following. In section II, independent component analysis is described. Using ICA to decomposition of load component is presented in this section. Then, in section III, a sample distribution network is simulated to evaluate the proposed method and the results are showed. Load components of each feeder is separated by this method and then, total load is calculated by adding these components. The last section is dedicated to conclusion and discussion of the obtained results.

THE PROPOSED METHOD TO DECOMPOSITION OF LOAD COMPONENTS

Independent component analysis

In many problems, the measured signal (observation) is a combination of other signals (sources). Finding the sources in the absence of information about sources is difficult. source separation from observations is called Blind Source Separation (BSS). One of the special case of BSS is Independent Component Analysis (ICA) that is based on statistical independence of source signals.

ICA introduced early 1980s[8]. This technique attempts to convert observed signals in to the statistically independent signals. Therefore, statistical specification of signals is a crucial factor to estimate with ICA, since there is no further information in hand[9].

Assume that we observe M signals from N sources, the ICA linear model is expressed as [10], [11]:

$$\begin{aligned} x_1(t_i) &= a_{11}s_1(t_i) + a_{12}s_2(t_i) + \ \dots \ + a_{1N}s_N(t_i) + n_1(t_i) \\ x_2(t_i) &= a_{21}s_1(t_i) + a_{22}s_2(t_i) + \ \dots \ + a_{1N}s_N(t_i) + n_1(t_i) \\ &\vdots \\ x_M(t_i) &= a_{M1}s_1(t_i) + a_{M2}s_2(t_i) + \ \dots \ + a_{MN}s_N(t_i) + n_M(t_i) \end{aligned} \quad (1)$$

Matrix model of (1) can be written as (2):

$$X(t_i) = AS(t_i) + N(t_i) \quad (2)$$

Where $S(t_i) = [s_1(t_i),..., s_N(t_i)]$ is N-dimensional vector of sources, $X(t_i) = [x_1(t_i),..., x_M(t_i)]$ is the M-dimensional vector of observation signals, $N(t_i) = [n_1(t_i),..., n_M(t_i)]$ is the M-dimensional vector of measured noises, $A = [a_{ij}]$ is the unknown matrix named combination matrix, t_i time index and $i = 1,2,..., T$. in most of problems, the noise can be ignored, thus (2) is expressed by (3) as :

$$X = AS \quad (3)$$

Where S and X are $M \times T$ and $N \times$T dimensional matrices, respectively. In fact, in ICA, the goal is to find vector S and combination matrix A of observation X. by finding pseudo inverse matrix A, sources vector can be expressed by:

$$S = WX \quad (4)$$

W is pseudo inverse matrix of matrix A that is named isolation matrix. In (4), matrix W can be calculated if the following 3 conditions are met:

1-source signals must be statistically independent.

2-probability distribution function should be non-Gaussian

3-the number of observation vectors should be greater than or equal the number of sources signals : $M \geq N$.

To do this, objective function is defined based on different criterion that minimization and maximization of them is determined by special algorithms that leads to the estimation of matrix W. among these algorithms FastICA is used frequently because of its calculation efficiency. In this paper, FastICA is used for decomposition of load components of measured data of substations.

Non-Gaussian calculation

As said before, the first step to calculate sources is finding a proper objective function. Many of ICA based algorithms uses non-Gaussian value of independent sources as objective function. Therefore, the first step is to select a criterion for non-Gaussian measurement of a signal. Kurtosis is a conventional quantity for determining non-Gaussian value that is defined as:

$$kurt(y) = \frac{\kappa_4}{\kappa_2^2} - 3 \quad (5)$$

Where κ_4 and κ_2 are second and fourth order of culmulants. The kurtosis is zero for a Gaussian random variable, for sub-Gaussian and super Gaussian ariables this value is less or more than zero, respectively. Simple calculation is one of the kurtosis advantages, but this technique is very sensitive to noises and outliers. Thus negentropy is a common approach because of its robustness. Negentropy is defined as the differential between the entropy of a random variable and the entropy of a Gaussian variable with the same average and variance. In (6) and (7), N(S) is the negentropy of random variable S, y_G is Gaussian variable with the same average and variance with S, H(.) is the entropy function and f(.) the is probability distribution function.

$$N(S) = H(y_G) - H(S) \quad (6)$$

$$H(S) = -\sum f(S)\log(f(S)) \quad (7)$$

Calculation of negentropy by (6) is difficult, because it needs probability density function that is not usually in hand. Therefore, the approximation is used for calculations, practically.

$$N(S) \approx k[E\{G(S)\} - E\{G(y_G)\}]^2 \quad (8)$$

K is a constant value and G(.) is a desired function. S and yG have zero average and variance, as well. G(.) of any function can be non-second order. Functions in (9) are proposed for G(.) that make more stability and simplicity in algorithm [12]:

$$G_1(S) = \frac{1}{a_1}\log\cosh(a_1 S)$$
$$G_2(S) = \frac{1}{a_2}\exp(-a_2 S^2/2) \quad (9)$$
$$G_3(S) = \frac{1}{4}S^4$$

Where a_1 and a_2 are constants.

Constant point algorithm or FastICA

FastICA algorithm is based on fixed point theorem. This algorithm is an iterative process based on optimization function. Optimization function of this algorithm can be based on different criteria such as negentropy, kurtosis , among these algorithms, using negentropy has desired accuracy and speed. In this paper this criterion is used as a tool for determining the objective function of algorithm.

Load component decomposition

Measured loads at the beginning feeders can be modeled as (10) with ignoring measured noises.

$$I_{fk}(t_i) = c_{k1}I_{s1}(t_i) + c_{k2}I_{s2}(t_i) + ... + c_{kN}I_{sN}(t_i) \quad (10)$$

Where $I_{fk}(t_i)$ denotes the beginning current of feeder k at t_i, $I_{sj}(t_i)$ denotes the component j current in the network. This component can be domestic, commercial, official or street lighting. c_{kj} is the contribution coefficient of component j current and N denotes the number of load components, as well.

Matrix form of (10) for all substation feeders is as (11). The goal is to calculate the contribution matrix C and the current vector of load component Is according to the measured current in the beginning of the feeder.

$$I_f = CI_s \quad (11)$$

By comparing (3) and (11), it can be concluded that by

substituting parameters of measured current of feeders in ICA model load components can be estimated by ICA. It should be noted that since the current is composed of real and imaginary components, ICA model is used for both components.

Power demand of a load is not constant during a year, weak or even a day. These changes are composed of slow and fast parts. Slow part is represented by hour-hour changes. At any moment there are also some fast changes on this process. These fast fluctuations show fast changes of the load in seconds or minutes and considered as random variables [13]. Therefore, it could be possible to represent load component current as a set of variable and determined components. Variable component relates to fast changes (dependent component) and determined component denotes the slow changes(independent component)[14]. Thus, it is not possible to apply ICA on load profiles, directly. The solution is to use a filter to decompose these changes (or components).

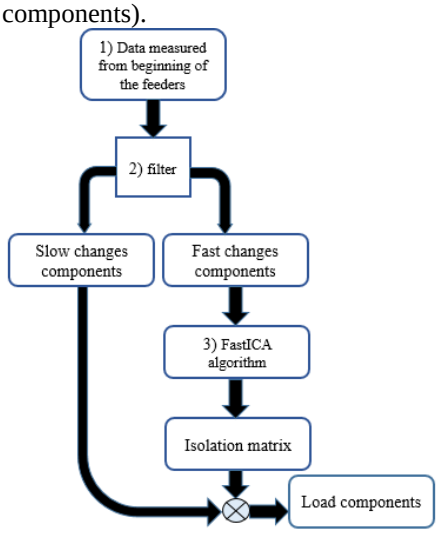

Fig. 1. Flowchart of the proposed method to decomposition of load components

This filter permits the independent parts to pass. Then, ICA is applied to filter output[13]. If ϕ denotes the function of filter, of the load components can write:

$$I_{f-slow} = I_f \phi = CI_s \phi = CI_{s-slow}$$
$$I_{f-fast} = I_f \phi = CI_s \phi = CI_{s-fast} \quad (12)$$

As (12) shows, it is possible to apply ICA on the fast changes data and then the isolation matrix W would be calculated. Also, slow changes isolation matrix can be estimated by using this matrix.

Fig. 1 shows the flowchart of proposed method to decomposition of the load of the feeder using ICA. In step 1, the profile of the selected feeder current has been saved. This profile is divided in to the slow and fast partition in step 2. Then, FastICA algorithm is applied on the fast component of the current of step 2, in the next step. The result in this step is matrix W. step 4 is dedicated to the multiply of matrix W in to the slow component of load current in order to calculate load component.

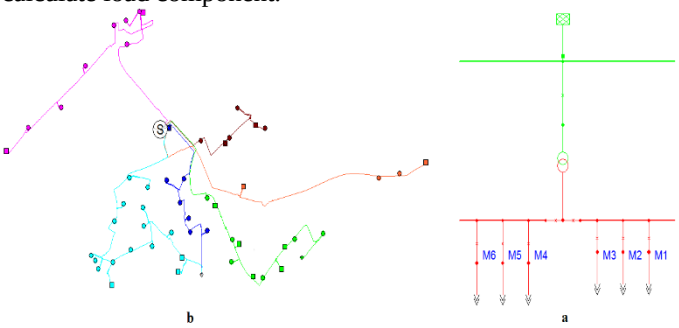

Fig. 2. Sample network simulated in software Power factory, (a) indoor substation, (b) network feeders and load points

Table 1. the peak value of each load components of the feeders

Feeder name	domestic	commercial	official	street lighting	total
Feeder 1	2720.2	3521	761.6	123.2	7126
Feeder 2	1518.6	460.6	243.6	241.2	2437
Feeder 3	1676.6	140	225.4	131.6	2173.6
Feeder 4	2158.6	0	0	162.4	2321
Feeder 5	417.2	492.8	446.6	117.6	1474.2
Feeder 6	3463.6	0	200.2	130.2	3792

CASE STUDY

To verify the proposed method, it is tested on a sample distribution grid. This network has 4866 customers and the load peak is 19.3 MW. It is assumed that loads are classified in to 4 classes: domestic, commercial, official and street lighting. the loads are supplied from 6 feeders and one substation. the data of each feeder load is tabulated in Table I. the network is simulated in Power factory v. 15.7 (Fig. 2). To modeling slow changes of different load class, it is used load profile in [15].

To model the fast changes of the loads it is used the method in [13]. To obtain load current of the feeders it is necessary to apply load flow from a sample network and the current of feeders is saved after each load flow. The proposed method is implemented in MATLAB version α2015. The result of using the method is represented in the following.

Slow and fast component decomposition

As said before, it needs to separate fast and slow changes of the load current of the feeders. Here, the method is moving average. The component with slow and fast changes of the load current is shown in Fig. 3. Red color indicates slow

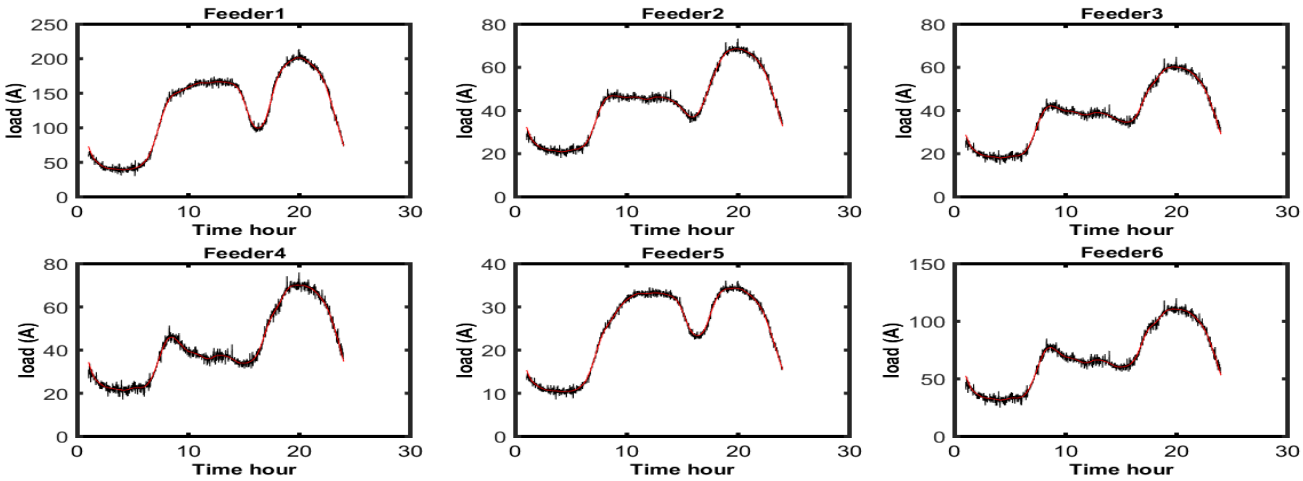

Fig. 3. Using filter on the feeders' currents. Red: slow components and black: fast parts

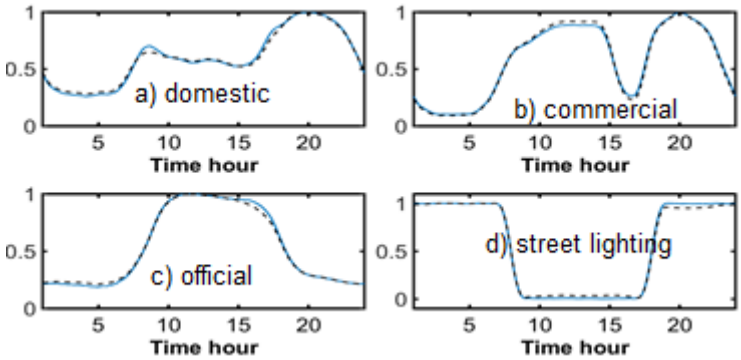

Fig. 4. Real and decomposed load components. Black: estimated values and blue : real values

changes of the load and black denoted fast changes. The extracted currents which have fast changes are used to obtain load components.

Load component separation

Applying FastICA on the fast part of load current, two isolation matrix for real and imaginary part of the load currents is obtained. As said before, the load components are obtained by multiplying these two matrix by real and imaginary part of the load slow current. Then, after calculation of real and imaginary part of the load currents, the whole profile of the currents can be calculated. The profiles of load components current are illustrated in Fig. 4.

These profiles are depicted for calculated and real currents. The values are normalized, as well. The results appear to fit the real data quite well.

Total load calculation from load components

For each feeder, the calculated load components are summed to estimate the total load profile. Total load of calculated load component and total real load of each feeder is compared in Fig. 5. As Fig. 5 illustrates, the estimated total load is close to the real load. For clarity, the difference between total calculated and real load profile is tabulated in table 2. As it shows, maximum error is for feeder 3 and equal to 10.6%.

Table 2. Maximum error and error of total decomposed load

Feeder name	Maximum error	Error (%)
Feeder 1	17.8	8.8
Feeder 2	6.5	9.3
Feeder 3	6.4	10.6
Feeder 4	3.6	5.2
Feeder 5	1.8	5.3
Feeder 6	9.2	8.3

CONCLUSION

In this paper, an approach to decomposition of measured load of substation feeders is presented that is based on independent component analysis(ICA). This method doesn't need typical load profile, unlike other methods. The methods necessitate equality of the number of measured data and load components at least. To use ICA, load component profiles must be independent from each other. But the load profiles of different components are composed of fast and slow changes

Slow parts are dependent to each other although fast parts are independent. Therefore, in this paper load components are separated by the decomposition of fast and slow part

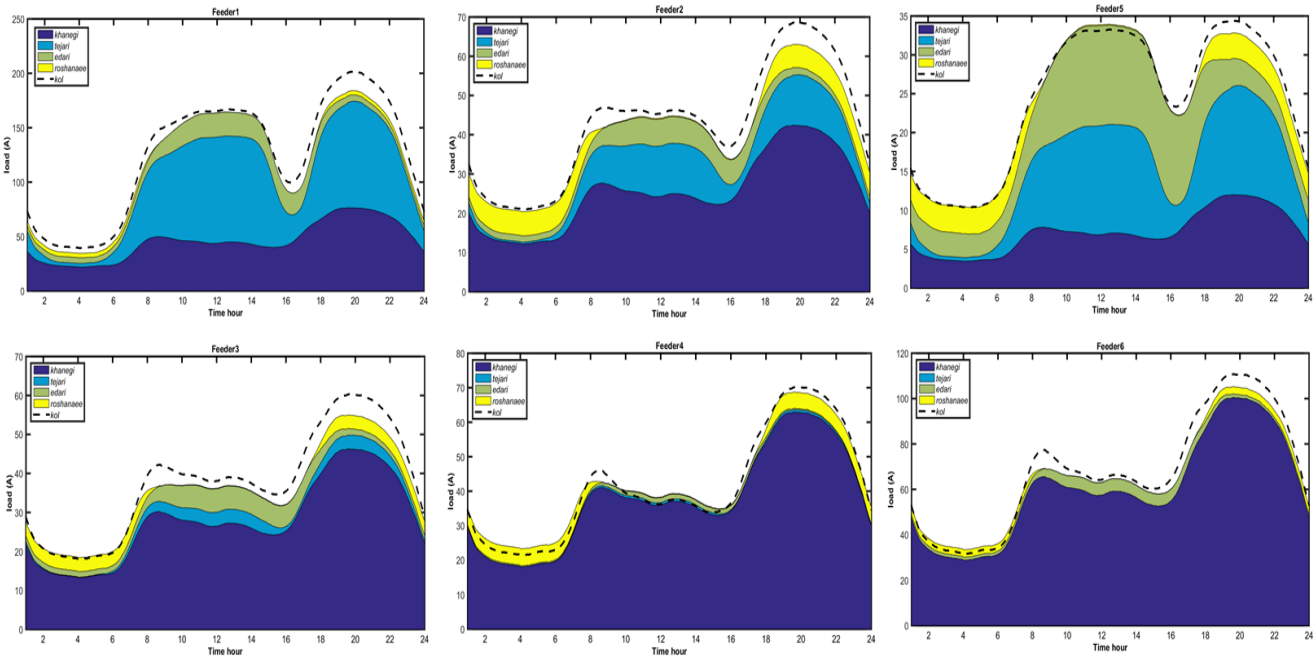

Fig. 5. Comparison between real load of feeders and total load of superposition of decomposed load component. Dark blue: domestic component, light blue: commercial component, green: official component, yellow: street lighting component and black cutline: total real load.

and then applying ICA on the fast parts. To verify the proposed method, load data of a sample network is simulated. After decomposition of load components, total load of each feeder is calculated by adding load components of each feeder. This decomposed (calculated) load profile and real data of a feeder load is compared. The results show accepted errors that verify the proposed method. Also, since the data used is close to the reel data of a feeder, this method is applicable to distribution companies.

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