Proceedings of the Seventh IASTED International Conference
POWER AND ENERGY SYSTEMS
August 29–31, 2007, Palma de Mallorca, Spain
ISBN Hardcopy: 978-0-88986-689-8 / CD: 978-0-88986-690-4

LOAD TYPE MIXTURE EXTRACTION FROM MEASURED TIME SERIES OF HAND-OVER POINT ACTIVE POWER

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ABSTRACT
Energy management systems depend on information on grid condition. In low and mean voltage level grids this information is not entirely available and thus has to be assumed at the best. Therefore knowledge about load type mixture is very useful.

In this paper a nodal load extraction algorithm is presented. It helps to determine the amount of different load types at a specific node or within a high or mean voltage level grid by only using measured time series of active power flows at hand-over points as input parameter. These time-series are superposed by potentially high variable fed powers of distributed generation sources and influenced by many other unknown variables.

With this algorithm it is possible to determine load composition of one single node as well as of a whole distribution grid segment.

KEY WORDS
Load type mixture, mean voltage level, grid condition identification, analytic load profiles, energy management systems

1. Introduction

Nowadays energy management systems are developed for mean and low voltage layer grids. Unfortunately these grids are sparsely equipped with measurement technique so grid state identification which is essential for management systems is complicated [1]. Nevertheless at least active power flows at hand-over points are measured. These time series are the sum of powers of loads and feeders so if the measurement period is long enough it is possible to derivate some information about mixture and amount of load types.

2. Analytic Load Profiles

To simplify estimation of energy consumption of costumers within one year VDEW announced eleven different analytic load profiles merged into groups of domestic, industrial and agricultural type:

- common industry
- industry on weekdays 8 am to 6 pm
- industry on weekdays (evening)
- continuous industry
- stores and barbers
- bakeries
- industry on weekends
- common domestic
- common agriculture
- milk production
- miscellaneous agriculture

Fig.1 to Fig.3 show load profiles of each group in winter (black) and summer (grey) normalized to 4 MWh / a.

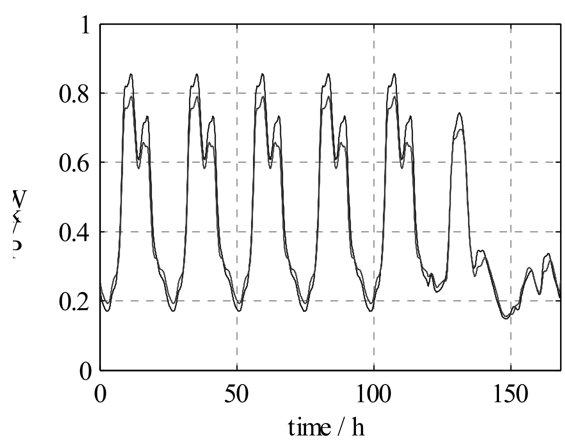

Fig. 1: Load profile industry on weekdays 8 am to 6 pm

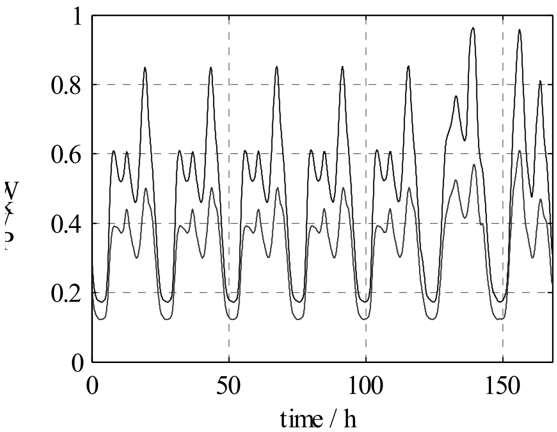

Fig. 2: Load profile common domestic

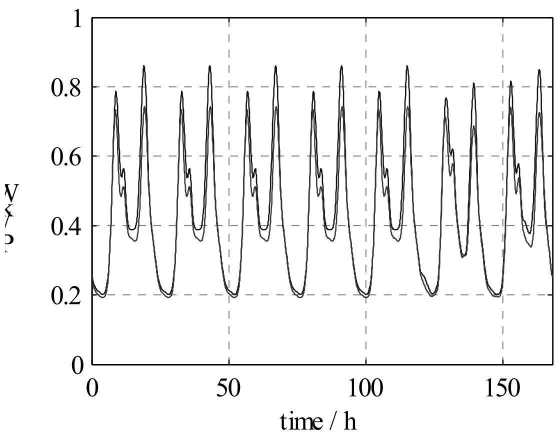

Fig. 3: Load profile common agriculture

VDEW profiles are obtained by averaging over a huge amount of customers of the same type within several years and do not represent the behaviour of one single load [2].

These eleven load profiles are supplemented by profiles describing off-peak storage heating, street lighting, heat pumps and other detachable loads as seen in Fig.4 [3].

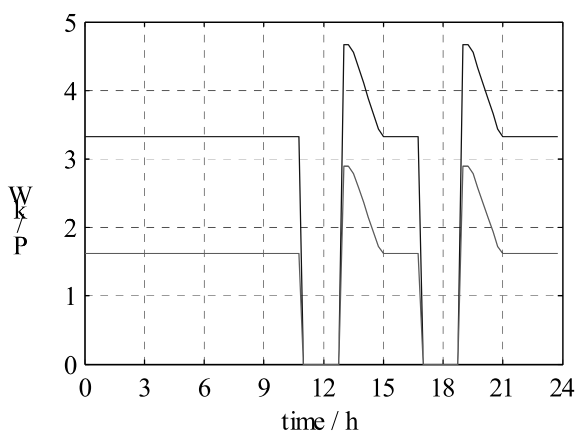

Fig. 4: Load profile of detachable 5 kW heat pump.

3. Nodal load extraction

Nodal load extraction offers the possibility of determining load composition from measured active power time series of nodes or hand-over points. Therefore a measured power time series $\boldsymbol{p}_{\text{meas}}$ of the point of interest has to be available. Furthermore the measuring time period and a set of x load profiles are known [4]. It can contain all analytic load profiles as well as off-peak heating, street lighting and other specific or detachable load profiles. Furthermore it is possible to add some series of controllable feeders to $\boldsymbol{L}$ to optimize extraction.

The algorithm tries to find a weighting vector $\boldsymbol{w}$ such that the difference between measured and calculated nodal load time series is minimized [5], [6], [7], [8], [9].

$$\begin{aligned}\Delta\boldsymbol{p} &= \boldsymbol{p}_{\text{c}} - \boldsymbol{p}_{\text{meas}} = \begin{bmatrix}\boldsymbol{p}_1 & \cdots & \boldsymbol{p}_x\end{bmatrix}\boldsymbol{w} - \boldsymbol{p}_{\text{meas}} = \boldsymbol{Lw} - \boldsymbol{p}_{\text{meas}} \\ &= \begin{bmatrix} p_1(t_{\text{start}}) & \cdots & p_x(t_{\text{start}}) \\ \vdots & & \vdots \\ p_1(t_{\text{end}}) & \cdots & p_x(t_{\text{end}})\end{bmatrix}\begin{bmatrix} w_1 \\ \vdots \\ w_x\end{bmatrix} - \begin{bmatrix} p_{\text{meas}}(t_{\text{start}}) \\ \vdots \\ p_{\text{meas}}(t_{\text{end}})\end{bmatrix}\end{aligned} \tag{1}$$

Therefore all first partial derivatives of the quadratic difference function f have to be set to zero.

$$\begin{aligned} f &= \Delta\boldsymbol{p}^{\text{T}}\Delta\boldsymbol{p} = \left(\boldsymbol{Lw} - \boldsymbol{p}_{\text{meas}}\right)^{\text{T}}\left(\boldsymbol{Lw} - \boldsymbol{p}_{\text{meas}}\right) = \\ &= \boldsymbol{w}^{\text{T}}\boldsymbol{L}^{\text{T}}\boldsymbol{Lw} - \boldsymbol{w}^{\text{T}}\boldsymbol{L}^{\text{T}}\boldsymbol{p}_{\text{meas}} - \boldsymbol{p}_{\text{meas}}^{\text{T}}\boldsymbol{Lw} + \boldsymbol{p}_{\text{meas}}^{\text{T}}\boldsymbol{p}_{\text{meas}}\end{aligned} \tag{2}$$

$$\begin{aligned}\frac{\partial f}{\partial \boldsymbol{w}} &= \frac{\partial \boldsymbol{w}^{\text{T}}}{\partial \boldsymbol{w}}\boldsymbol{L}^{\text{T}}\boldsymbol{Lw} + \boldsymbol{w}^{\text{T}}\boldsymbol{L}^{\text{T}}\boldsymbol{L}\frac{\partial \boldsymbol{w}}{\partial \boldsymbol{w}} \\ &\quad - \frac{\partial \boldsymbol{w}^{\text{T}}}{\partial \boldsymbol{w}}\boldsymbol{L}^{\text{T}}\boldsymbol{p}_{\text{meas}} - \boldsymbol{p}_{\text{meas}}^{\text{T}}\boldsymbol{L}\frac{\partial \boldsymbol{w}}{\partial \boldsymbol{w}} = \boldsymbol{0}\end{aligned} \tag{3}$$

Eq. (3) can be reformed into

$$\begin{aligned}&\frac{\partial \boldsymbol{w}^{\text{T}}}{\partial \boldsymbol{w}}\boldsymbol{L}^{\text{T}}\boldsymbol{Lw} + \frac{\partial \boldsymbol{w}^{\text{T}}}{\partial \boldsymbol{w}}\boldsymbol{L}^{\text{T}}\boldsymbol{Lw} \\ &- \frac{\partial \boldsymbol{w}^{\text{T}}}{\partial \boldsymbol{w}}\boldsymbol{L}^{\text{T}}\boldsymbol{p}_{\text{meas}} - \frac{\partial \boldsymbol{w}^{\text{T}}}{\partial \boldsymbol{w}}\boldsymbol{L}^{\text{T}}\boldsymbol{p}_{\text{meas}} = \boldsymbol{0} \\ &\Rightarrow 2\left(\frac{\partial \boldsymbol{w}^{\text{T}}}{\partial \boldsymbol{w}}\left(\boldsymbol{L}^{\text{T}}\boldsymbol{Lw} - \boldsymbol{L}^{\text{T}}\boldsymbol{p}_{\text{gem}}\right) - \boldsymbol{0}\right) = \\ &\quad = 2\,\boldsymbol{E}\left(\boldsymbol{L}^{\text{T}}\boldsymbol{Lw} - \boldsymbol{L}^{\text{T}}\boldsymbol{p}_{\text{gem}}\right) = \boldsymbol{0}\end{aligned} \tag{4}$$

which results into the weighting vector $\boldsymbol{w}$ [9]:

$$\boldsymbol{w} = \left(\boldsymbol{L}^{\text{T}}\boldsymbol{L}\right)^{-1}\boldsymbol{L}^{\text{T}}\boldsymbol{p}_{\text{meas}} \tag{5}$$

such that a measured nodal load time series is best assumed by

$$\boldsymbol{p}_{\text{ass}} = \boldsymbol{L}\,\boldsymbol{w} \tag{6}$$

Extraction quality decreases with increasing amount of fluctuating feeders hardly to forecast. It can be improved by out-counting weather-dependent feeders like wind turbines before load extraction which mostly is possible due to data availability. Alternatively measuring period should be extended or average time series of several years should be used [9].

Besides weighting shifts among agricultural load profiles might be possible due to similarity to themselves. For the same reason this shifting is almost negligible [9].

4. Example

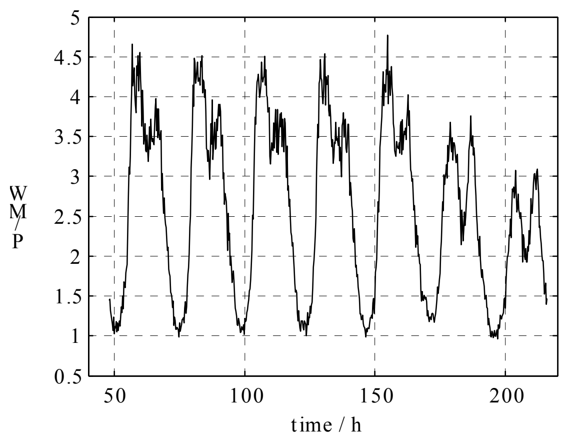

Fig. 5: measured time series

Fig.5 shows a measured time series of nodal active power within one week containing an unknown composition of loads and different feeders. Load type mixture now has to be figured out.

The load extraction algorithm returns the following (rounded) load mixture provided that each load consummates 4 MWh / a.

Table 1: Load type mixture

H0	G0	G1	G2	G3	G4
1193	490	597	491	868	672
G5	G6	L0	L1	L2	Rest
252	330	784	24	0	0

5. Conclusion

Load type mixture extraction is a quick and simple way to determine load composition. The gained information is useful for grid condition identification, development of energy management systems and load forecasting. Quality of extraction can be improved by out-counting time series of feeders.

References

[1] M. Wolter, Power flow simulation of autonomous MicroGrids fed by renewable sources, *WSEAS Transactions on Power Systems, I(11),* 2006, 1911-1917.

[2] H. Meier, C. Fünfgeld, T. Adam, B. Schieferdecker, *Repräsentative VDEW-Lastprofile* (Frankfurt (Main), D: VDEW, 1999).

[3] T. Hartmann, T. Mühlhaus, H. Neumann, H. Reuter, H. Röschmann, *Praxisleitfaden Lastprofile für unterbrechbare Verbrauchseinrichtungen* (Berlin, D: Verband der Netzbetreiber - VDN - e.V. beim VDEW, 2002).

[4] C. Daniel, F. S. Wood, *Fitting Equations to Data* (New York, NY: John Wiley & Sons, 1980).

[5] J. J. Grainger, W. D. Stevenson, *Power system analysis* (New York, NY: McGraw-Hill, 1994).

[6] A. Abur, A. G. Expósito, *Power system state estimation: theory and implementation* (New York, NY: Dekker, 2004).

[7] B. R. Oswald, *State Estimation* (Hannover, D: IEH, 2005).

[8] A. Monticelli, *State Estimation in electric power systems: a generalized approach* (Boston, TX: Kluver Academic Publishers, 1999).

[9] M. Wolter, *Entwicklung eines MicroGrid Simulators* (Hannover, D: IEH, 2006).

[10] P. S. Kundur, N. J. Balu, *Power system stability and control* (New York, NY: McGraw-Hill, 1994).

[11] N. R. Draper, H. Smith, *Applied regression analysis, 3rd edition* (New York, NY: John Wiley & Sons, 1998).