ELEKTRYKA 2018
Zeszyt 1 (145) Rok LXIV

Nicusor Constantin TOMA[1], Mihai GAVRILAS[2], Bogdan Constantin NEAGU[2]
[1]Delgaz Grid S.A. Târgu Mureş, Romania
[2]Gheorghe Asachi Technical University Iasi, Romania

APPLICATION OF SMART METERING SYSTEMS FOR ENERGY LOSSES ASSESSMENT AND FORECASTING IN DISTRIBUTION SYSTEMS

Summary. This paper presents a proper methodology for assessing and forecasting the active energy losses in LV distribution networks, based on the real measurements, provided by smart meters. The proposed methodology uses a characteristic load profile estimation based on knowledge data discover (KDD) approach and daily energy. The results are comparable with the real case, that use the energy profile from smart meters.

Key words: power distribution network, power losses, characteristic load profile.

1. INTRODUCTION

The Smart Grids is an electrical network that use digital technology to monitor and control the electricity consumption between generations to end-users. In accordance with the requirements of the EU, 80% of end-users must have devices withy smart measures before 2020 [1]. This paper deals with a major interest issue to electricity suppliers and distributors: energy losses assessment in low voltage (LV) electrical networks. Currently, electrical distribution networks supply a growing number of single-phase customers with unbalanced phase distribution, which determines inefficient operating conditions for these networks.

The traditional approach computes the energy losses using two specific coefficients „time of losses" and the "maximum load". The drawback of this approach consist in a very subjective value of these coefficient and significant errors in the assessment maximum apparent power. Distinct approaches are being proposed or by different authors. In [2] the authors propose an approach for assessing and forecasting the energy losses in uncertainty conditions via regression models, by using a methodology to group networks in representative clusters and assess energy losses based on characteristic values associated to each cluster. In addition, paper [3] proposes to use real network measurements for generating typical load profiles, able to characterize the load profiles of different type of customers. This paper presents a proper methodology for assessing and forecasting the active energy losses in LV distribution networks, based on the real measurements, provided by smart meters. The proposed methodology uses a characteristic load profile estimation based on knowledge data discover (KDD) approach for detection of outlier using data provided by Smart Meters [4].

The paper has four sections. In section two, the methodology for determining the end-users "characteristic" load profiles based on the KDD principle and consumers' daily energy consumption are presented. The energy losses assessment by using repeated load flow in distribution systems is presented in Section three. Next, a study case with results from applying the proposed approach for estimating the active energy losses in a real LV distribution network was performed.

2. LOAD ESTIMATION USING SMART METERING MEASUREMENTS AND KNOWLEDGE DATA DISCOVER APPROACH

Through data mining techniques, valuable information can be extracted from large amount of big data in a distribution system. In the load profile estimation, the representative characteristics of load curves can be obtained by removing the outliers (i.e. no load) using a KDD approach. The steps for the KDD process are shown in Fig. 1 [5].

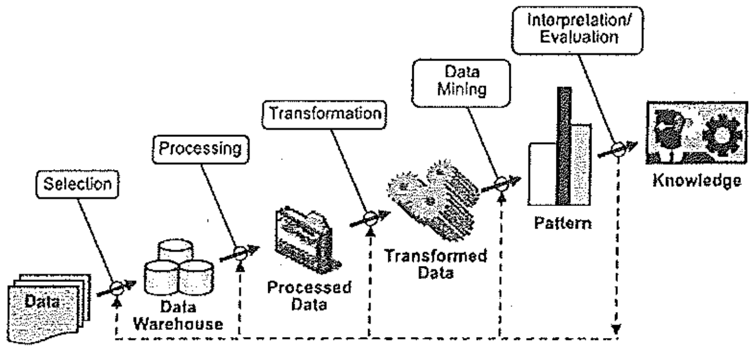

Fig. 1 – The KDD process for load profile estimation

Our methodology uses in the processing step of the KDD, all end users' energy profile extracted form Data Warehouse (Smart Meter database), as shown in Fig. 2.

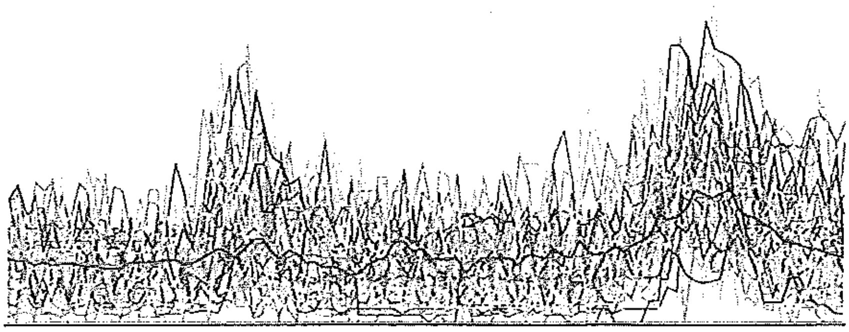

Fig. 2 – Real energy load profile to all end users

In the processing step the characteristic load profile process begin by computing the average value of active power as:

$$P^{*} = \frac{1}{n}\sum_{k=1}^{t} P_k^{*} = \frac{1}{n}\sum_{k=1}^{t} \frac{P_k}{W_k} \tag{1}$$

where P_k and W_k is the active power and energy of the consumer k; n is the maximum number of consumers; t is number of sampling from the analysed period.

By using the data mining process all the no-load curves were neglected, and the load profile estimation for the n consumers and the presented in Fig. 2 is used:

$$P_{med_i} = P^{*} \cdot W_k \tag{2}$$

where P_{medi} is the average value of estimated active power by using our methodology.

The estimated characteristic profile used subsequently for the energy losses forecasting is presented in Fig. 3.

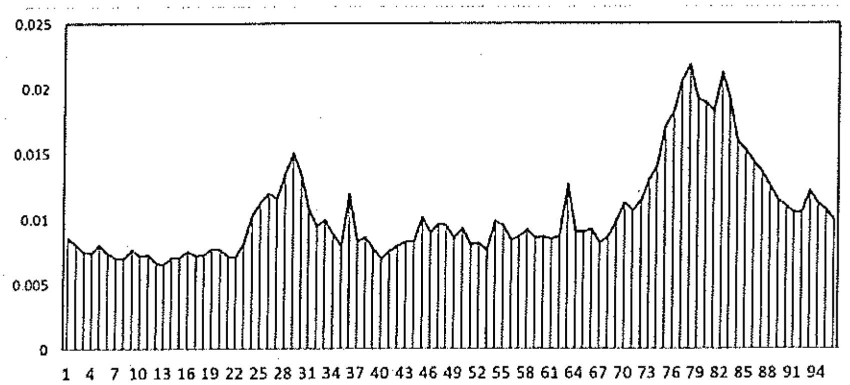

Fig. 3 – The characteristic profile resulted using our proposed approach

3. ENERGY LOSSES ASSESEMENT USING LOAD FLOW COMPUTATION

The optimal results regarding the active energy losses assessment in distribution networks can be obtained directly using some repeated load flow computation for a necessary and sufficient number of levels. For a distribution network the mathematical model leads to the solving of nonlinear algebraic equations, such as the following:

$$\begin{aligned} P_i &= G_{ii} \cdot U_i^2 + \sum_{\substack{k=1 \\ k \neq i}}^{n} U_i \cdot U_k \left[G_{ik} \cdot \cos(\delta_i - \delta_k) + B_{ik} \cdot \sin(\delta_i - \delta_k)\right], \quad i = \overline{1,n}; \ i \neq e \\ Q_i &= -B_{ii} \cdot U_i^2 - \sum_{\substack{k=1 \\ k \neq i}}^{n} U_i \cdot U_k \left[B_{ik} \cdot \cos(\delta_i - \delta_k) - G_{ik} \cdot \sin(\delta_i - \delta_k)\right], \quad i = \overline{1,n}; \ i \neq e \end{aligned} \tag{3}$$

where: P_i, Q_i – active and reactive powers injected in the network node i; G_{ii}, G_{ik}, B_{ii}, B_{ik} – real and imaginary elements of the nodal admittance matrix; U_i, U_k, δ_i, δ_k – modules and arguments of voltages in analysed network nodes i and k.

By adopting some additional simplifying hypotheses (considering elements only through reactance, estimating the voltages in the nodes through their rated values and eliminating the trigonometric functions, taking into account that the phase differences of the voltages at the terminals of the elements are low), the equations system (3) becomes linear, such as:

$$P_i = U_{n,i} \sum_{\substack{k=1 \\ k \neq i}}^{n} U_{n,k} \cdot B_{ik} \cdot (\delta_i - \delta_k); \quad i = \overline{1,n}; i \neq e \tag{4}$$

where $U_{n,i}$, $U_{n,k}$ – nominal voltages of the i and k nodes.

By solving the equations system (4) the active power flows on all network elements are:

$$\begin{aligned} P_{ik} &= B_{ik} \cdot U_{n,i} \cdot U_{n,k} \cdot (\delta_i - \delta_k) \\ P_{ki} &= -P_{ki}; \quad i = \overline{1,n}; \qquad i \neq k \end{aligned} \quad , \tag{5}$$

and active power losses on the entire power network shall be determined as:

$$\Delta P = \sum_{i=1}^{n-1} \sum_{k=i+1}^{n} \frac{P_{ik}^2}{U_{n,i} \cdot U_{n,k}} R_{ik} \tag{6}$$

This determinist method using for the active energy losses evaluation through repeated load flow computation, the daily active/reactive load curves with a sufficient number of load levels were considered. The daily active energy losses are computed with the relation:

$$\Delta W_{day} = \sum_{k=1}^{N_p} \Delta P(k) \cdot \Delta t_k \tag{7}$$

where: N_p – number of levels from daily load curves; Δt_k – duration of the k level from the load curves.

4. CASE STUDY

The case study was conducted on a LV rural distribution network from East of the Romanian country. The analysed network has a total length of three kilometres and feeds 172 households (109 first feeder and 63 on the second feeder) and the public lighting. The on-line diagram is presented in Fig. 4. The line length between 2 posts was considered as 40 m, in accordance with specified Romanian standards.

The energy losses in the unbalance LV network were computed using repeated load flow computation in DigSilent Power Factory application based on the Newton-Raphson load flow algorithm [6]. As input data, the measured three phase active and reactive power and the single-phase end-user's locations (phase A, B or C) solved with a Matlab application were used. However, as input data is necessary to specify the distribution network topology and also the impedances and lengths of each overhead lines branch.

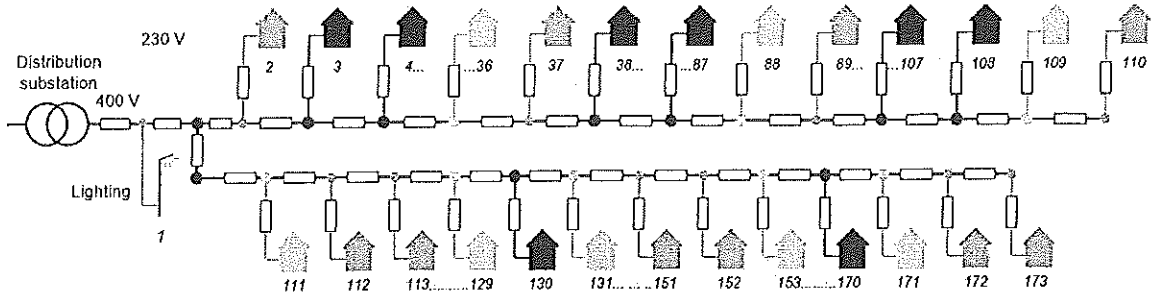

Fig. 4 – Single-line diagram of the LV distribution network

For instance, in order to assess the energy losses in the LV distribution system, the simulation was conducted for a total time interval of a day, with real measurement samples taken both at 15 and 60 minutes, which means 96 and 24 load flow calculations. Secondly, the energy losses were estimated by using the load profile forecasted with our proposed approach also in 96 and 24 load flow calculations. Because of the heavy data volumes and limited paper space, the results will be synthetically presented.

The summary result table will display in Table 1. Then, input data are real (provided by smart meters) and estimated with our proposed approach. For validate the energy losses method, it is reported to the total active energy injected in the substation (582.95 kWh).

Table 1 - Summary results for the daily energy losses in LV distribution network

Type of load flow	Imput data	Active energy losses	
		[kWh]	[%]
15 minutes	Real	100.84	17.3
	Estimated	100.46	17.2
1 hour	Real	102.23	17.5
	Estimated	97.00	16.6

Only for the firsts branches of each feeder F1 and F2 (Fig. 4) the energy losses are indicated in umbalance way in Table 2. It can be observed that by using our energy losses forecasting method (the end users consumption profiled with a characteristic load profile), the values of the three phases are different, but the error are small for the sum of them.

Table 2 - Summary results of energy losses for unbalanced state for firsts branch F1 and F2

Imput data	Phase	15 minutes		1 hour		15 minutes	1 hour
		F1, [kWh]	F2, [kWh]	F1, [kWh]	F2, [kWh]	F1+F2, [kWh]	F1+F2, [kWh
real	A	2.23	0.24	2.2	0.24	2.47	2.44
	B	1.51	0.73	1.6	0.72	2.24	2.32
	C	0.51	0.17	0.52	0.16	0.68	0.68
	N	0.54	0.28	0.56	0.24	0.82	0.8
	total	**4.78**	**1.42**	**4.88**	**1.36**	**6.2**	**6.24**
Estimated	A	0.24	1.49	0.24	1.48	1.73	1.72
	B	0.71	2.38	0.72	2.28	3.09	3
	C	0.16	0.51	0.16	0.52	0.67	0.68
	N	0.20	0.49	0.2	0.48	0.69	0.68
	total	**1.31**	**4.88**	**1.28**	**4.72**	**6.19**	**6**

The errors of values regarding the active energy losses assessed with real information provided from smart meters and those estimated using the daily energy and a characteristic profile are presented in Fig. 5. Regarding the unbalanced steady state, for the two first branch of the LV distribution network proposed for analysis, the errors between the energy losses estimation by using different measurement intervals, with both real and forecasting approach was indicated in Fig. 6. In the two aforementioned cases the average value of the energy losses is 1.81% for real, respectively 1.61 for our approach.

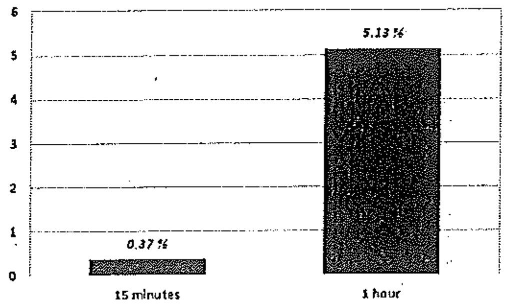

Fig. 5 – The errors between the two methods, for both measurement intervals

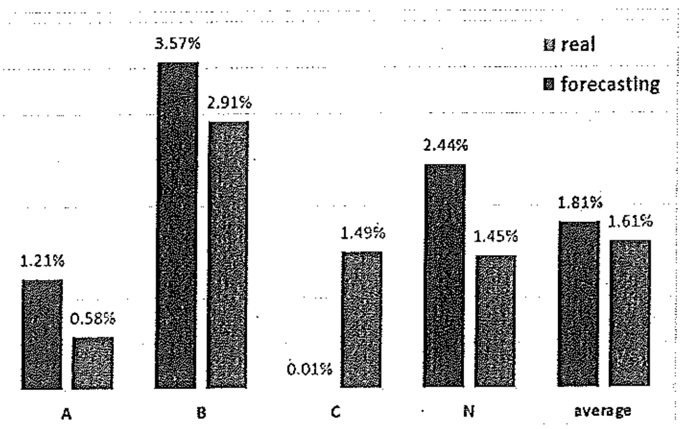

Fig. 6 – The errors between the two methods, for both measurement intervals on the first branch of the two LV network feeders

In conclusion, if the measurement interval is 1 hour the error is maximum 5.2%, but in the 15 minutes' intervals, our proposed methodology has small errors, between (0.2% and 0.4 %) and can be used with success for assessing and forecasting the active energy losses for all LV distribution network which have traditional meters.

BIBLIOGRAFIA

1. Levenda, A., Mahmoudi, D., Sussman, G., "The Neoliberal Politics of "Smart": Electricity Consumption, Household Monitoring, and the Enterprise Form", Canadian Journal of Communication, v. 40, n. 4, nov. 2015, pp. 615-636.

2. Queiroz L., Cavellucci C., Lyra C., "Evaluation Of Technical Losses Estimation In LV Power Distribution Systems", Cired, Prague, 2009.
3. Fidalgo J. N., Matos M., Marques M., "Estimation and Allocation of Losses in Distribution Networks", http://www.aedie.org/9CHLIE-paper-send/350-FIDALGO.pdf.
4. Neagu B.C., Grigoras G., Toma N.C,"Detection of Irregular Consumption to Load Monitoring in Smart Grids Environment", 22nd IMEKOTC4 International Symposium&20th International Workshop on ADC Modelling and Testing, Iasi, Romania, September 14-15, 2017.
5. Gilchrist, M., Mooers, D., Skrubbeltrang, G., Vachon, F., "Knowledge discovery in databases for competitive advantage", Journal of Management & Strategy, 3(2), 2010, pp. 2-15.
6. https://www.digsilent.de/en/powerfactory.html

PhD. Student Nicusor Constantin Toma
Prof. Mihai Gavrilas
Gheorghe Asachi Technical University
Faculty of Electrical Engineering
21-23 D. Mangeron Bivd.
Iasi, Romania
e-mail: ovidiuivanov@tuiasi.ro
mgavril@tuiasi.ro