XIX IMEKO World Congress
Fundamental and Applied Metrology
September 6–11, 2009, Lisbon, Portugal

A NEW APPROACH TO DEMAND MEASUREMENT OVER THE ELECTRICITY DISTRIBUTION NETWORK

José Santo Guiscafré Panaro [1]

[1] UFF – Universidade Federal Fluminense, Niterói, Rio de Janeiro, Brazil,
panaro@telecom.uff.br

Abstract – This work proposes a method that allows the remote measurement of the electric power demand of clusters consisting of a small group of consumers that are connected to a line section of the distribution network and concentrated in an electricity pole.

The method is based on the detection of the electrical current and voltage changes at both ends of a distribution line section, and then computing the demand of the clusters. Due to the statistical nature of the electricity consumption, coincident demand steps of the users can cause some error that can be considered as noise perturbing the measurement signal. The measurement error characteristics are predicted through simulation.

The obtained results show that the new technique can be an efficient tool to reduce technical and non-technical losses in the electricity distribution network.

Keywords: Distribution networks, electricity demand measurement, non-technical losses.

1. INTRODUCTION

The energy distribution companies are strongly affected by technical and non-technical losses. As measurement of electric power consumption is directly related to the revenue of the companies, an important aspect is the development of new technologies and systems to reduce those losses [1]-[3].

For non-technical losses (NTL), commonly associated with irregular connections and adulteration of the characteristic of meters installed in the consumers' premises, the improvement of measurement techniques and equipment that minimize this possibility are crucial.

The affected elements and authorities have developed methods to reduce NTL, primarily based on detection by utility companies' meter reading employees and statistical analysis of customer information.

Despite the best efforts, the current results of NTL measurements are often inaccurate at best, because the figures rely heavily on the records of detected cases, rather than by actual measurement of the electrical power system. Furthermore, the majority of measurement equipment in electrical power systems does not facilitate time-varying calculations of system losses, which makes accurate determination of NTL impossible [4]. In fact, any given power system would have some loads that are not metered at all, which would affect the outcome in any calculations as NTL.

The apparent obvious solution to this is to install meters at every billed load and to use meters that sample load power or voltage values at reasonable intervals. However this solution is nearly unfeasible to implement in large service areas because of the logistical and economical costs of the meters. Small-to-medium-scale implementation remains a possibility because of the lower costs and the added application of real-time pricing [4], but always there is the possibility of some kind of meter adulteration or bypassing.

In order to deal with the pointed difficulties, we propose an alternative approach to controlling the technical and non-technical losses over the low-voltage distribution network by measuring the line voltage and current at both ends of a line section of the distribution network and computing the power demand of the groups of consumers connected to the line, which are concentrated in the electricity poles. A line section consists, typically, in the wire segment located between two line transformers.

2. SYSTEM MODEL

The system model considered in this work involves an electrical line section model and a consumer demand profile model that are specified in the following subsections.

2.1. Line section model

The model illustrated in the Fig. 1 represents basically a line section consisting of an electrical conductor with total electrical resistance *R*. The demand of the *k*-th consumer cluster connected to the line is represented by a current source whose short-term value is given by i_k. The resistance between the reference edge of the line section and the tap connecting to the *k*-th consumer cluster is defined as

$$R_k = \sum_{j=1}^{k} r_j = m_k R \qquad (1)$$

where r_j represents the ohmic resistance of each one of the *K* subsections of the line, and $0 \leq m_k \leq 1$ is the resistance ratio representing the ratio between the resistance from the reference edge until the considered cluster and the total resistance of the line section.

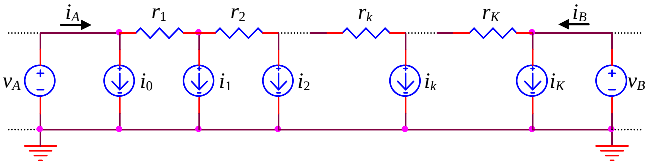

Fig. 1. Line section model.

We assume that voltages and currents at the edges of the line section are known by direct measurement. The voltage and current of the reference edge (point *A*) are denoted by v_A and i_A respectively, while the voltage and the current at the other edge (point *B*) are represented by v_B and i_B.

Dictated by the Kirchhoff's Current Law (KCL), the total current entering in the line section has the same magnitude of the total consumer demand, that is

$$i_A + i_B = \sum_K i_k \tag{2}$$

Clearly, if only the voltages and currents at the edges of the line are known, for $K > 2$, the exact value of the current demand of each line tap is indeterminate.

2.2. Short-term demand statistical model

Most of the domestic loads are connected and disconnected from the power line abruptly as in the case of illumination devices and electrical appliances. Therefore, the resultant instantaneous electricity demand has a switched profile by nature. Based on this fact, we assume that the short-term current demand of a consumer varies essentially in the form of current steps whose amplitude and switching timing are random variables.

Unfortunately, in the literature we could find only long-term models for consumer electricity demand with time resolution of hours or at best of minutes, reflecting only an average profile. Consequently, this work will adopt a simple heuristic short-term model to the electrical current demand of a single domestic consumer. Although additional refinement can be done to improve it, the proposed model is adequate to simulate and verify the proposed concept.

We assume that there are two basic consumer demand components that should be combined: periodic and non-periodic. Periodic demand is caused by loads that are switched at quasi-regular intervals as in the case of refrigerators, electric boilers, etc. Non-periodic demand is generated by turning electrical loads on and off asynchronously. In addition, in each case, we consider the existence of an additive white Gaussian noise (AWGN) ingredient that characterizes the instantaneous demand fluctuations of the loads. Thus, the electrical current demand of each consumer can be represented by

$$i_k = i_P + i_N = \sum x_i + \sum y_i \tag{3}$$

where i_P and i_N are, respectively, the total periodic and non-periodic loads.

Each cycle of the periodic demand components can be modeled as

$$\mathbf{x} = \begin{cases} \mathbf{X}, & 0 < t \le \boldsymbol{\tau}_{\mathbf{x_{on}}} \\ 0, & \boldsymbol{\tau}_{\mathbf{x_{on}}} < t \le \boldsymbol{\tau}_{\mathbf{x_{off}}} \end{cases} \tag{4}$$

where $\boldsymbol{\tau}_{\mathbf{x_{on}}}$ and $\boldsymbol{\tau}_{\mathbf{x_{off}}}$ are vectors of n_x Gaussian random variables $\mathcal{N}(\mu_\mathrm{x}, \sigma_\mathrm{x})$ following the normal probability density function:

$$f_\mathrm{x}(\tau) = \frac{1}{\sigma_\mathrm{x}\sqrt{2\pi}}\, e^{-\frac{(\tau - \overline{\tau_\mathrm{x}})^2}{\sigma_\mathrm{x}^2}} \tag{5}$$

The mean and the standard deviation vectors for $\boldsymbol{\tau}_{\mathbf{x_{on}}}$ are given by $\overline{\boldsymbol{\tau}_{\mathbf{x_{on}}}}$ and $\boldsymbol{\sigma}_{\mathbf{x_{on}}}$ respectively. Similarly, for $\boldsymbol{\tau}_{\mathbf{x_{off}}}$ these vectors are given by $\overline{\boldsymbol{\tau}_{\mathbf{x_{off}}}}$ and $\boldsymbol{\sigma}_{\mathbf{x_{off}}}$. During the active interval the current demand of the *i*-th load is given by X_i.

In a similar manner to the previous case, each cycle of the non-periodic loads can be modeled as

$$\mathbf{y} = \begin{cases} \mathbf{Y}, & 0 < t \le \boldsymbol{\tau}_{\mathbf{y_{on}}} \\ 0, & \boldsymbol{\tau}_{\mathbf{y_{on}}} < t \le \boldsymbol{\tau}_{\mathbf{y_{off}}} \end{cases} \tag{6}$$

where $\boldsymbol{\tau}_{\mathbf{y_{on}}}$ and $\boldsymbol{\tau}_{\mathbf{y_{off}}}$ are vectors consisting of n_y exponential random variables with probability density function given by

$$f_\mathrm{y}(\tau) = \frac{1}{\tau_\mathrm{y}} e^{-\tau/\tau_\mathrm{y}} \tag{7}$$

and expected value vectors given by $\overline{\boldsymbol{\tau}_{\mathbf{y_{on}}}}$ and $\overline{\boldsymbol{\tau}_{\mathbf{y_{off}}}}$ respectively. In this case, the current demand of *i*-th periodical load during the on-interval, offers a constant demand, Y_i.

Fig. 2 shows an example of the resultant demand profile for the proposed model, relative to the combination of two loads, being one periodic component with parameters $X_1 = 2$ A, $\overline{\tau_{\mathrm{x}_{\mathrm{on}}}} = 10$ min and $\overline{\tau_{\mathrm{x}_{\mathrm{off}}}} = 60$ min and the other a non-periodic component with parameters $Y_1 = 1$ A, , $\overline{\tau_{\mathrm{y}_{\mathrm{on}}}} = 30$ min and $\overline{\tau_{\mathrm{y}_{\mathrm{off}}}} = 60$ min.

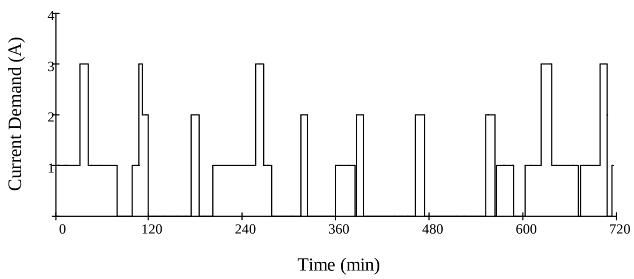

Fig. 2. Demand profile due to the combination of a periodic load and a non-periodic load with the following parameters: $X_1 = 2$ A, $\overline{\tau_{\mathrm{x}_{\mathrm{on}}}} = 10$ min, $\overline{\tau_{\mathrm{x}_{\mathrm{off}}}} = 60$ min; $Y_1 = 1$ A, $\overline{\tau_{\mathrm{y}_{\mathrm{on}}}} = 30$ min, $\overline{\tau_{\mathrm{y}_{\mathrm{off}}}} = 60$ min.

3. SYSTEM ANALYSIS AND DESIGN

We consider that the short-term voltages and currents at the edges of the line section of Fig. 1 are sampled regularly at a sufficient high rate f_s (e.g., at each power line cycle or so). Thus, the probability that two or more loads are switched in the same instant can be obtained by

$$P_m = 1 - \prod_K (1 - p_k) \tag{8}$$

where p_k is the k-th line tap switching average probability in any sample interval given by

$$p_k = \frac{\sum_{n_x} \left(\overline{\tau_{x\text{on}}} + \overline{\tau_{x\text{off}}} \right)^{-1} + \sum_{n_y} \left(\overline{\tau_{y\text{on}}} + \overline{\tau_{y\text{off}}} \right)^{-1}}{f_s/2} \tag{9}$$

As mentioned before, it is not possible to determine the exact value of the current demand of each line tap of the system by merely measuring the voltage and current signals of the line section edges. However, we can get an estimate by detecting the voltage and current variation signals of the line section edges and submitting them to a reasonably simple signal processing.

3.1. Basic Demand Measuring Process

Supposing that in a considered sample interval the current demand changes are due to a single consumer cluster, then the circuit illustrated in Fig. 3 is valid and, in this case, the cluster current variation is given by

$$\Delta \hat{\imath}_k = \Delta i_A + \Delta i_B \tag{10}$$

Furthermore, we can determine which cluster has caused the demand change, first writing that

$$\Delta v_A - m_k R \Delta i_A = \Delta v_B - (1 - m_k) R \Delta i_B \tag{11}$$

and, then determining the resistance ratio value from the tap that caused the current variation:

$$\widehat{m}_k = \frac{\dfrac{\Delta v_A - \Delta v_B}{R} + \Delta i_B}{\Delta i_A + \Delta i_B} \tag{12}$$

As we assume that the topology of the line section is identified, i.e., the resistance values $R_k = m_k R$ of the subsections are known, the estimate of the resistance ratio $\widehat{m}_k$ uniquely identify the consumer cluster that caused the demand variation.

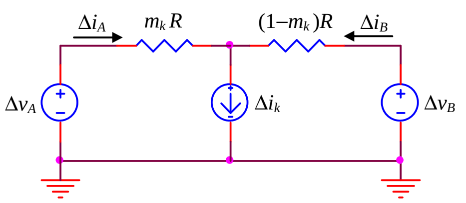

Fig. 3. Model for current demand variation in a single line tap.

In a real environment, as result of the system noise, the values obtained are approximated. Based on the Detection Theory, if we assume that the process noise is Gaussian then the optimal detection is maximum likelihood detection [5][6]. This implies that we should choose the nearest valid m_k of the obtained value in (6).

The estimate for the current demand of each consumer cluster can be achieved by totalizing the demand changes, that is, for each cluster we can compute

$$\hat{\imath}_k = \sum_K \Delta \hat{\imath}_k \tag{13}$$

3.2. Advanced Demand Measuring Process

The technique developed in the previous subsection is flawless while demand variations do not occur simultaneously in multiple taps. However, in the event of multiple tap switching (MTS), if a process adjustment is not made, the accumulation process defined in (13) can be permanently disturbed.

For consumer energy demand control purposes, we consider a catastrophic event when a negative demand step is lost permanently. The reason is that in this situation the consumer demand can become overestimated for a large period of time as illustrated by Fig. 4. Therefore, we assume that some amount of underestimate error in the demand measurement can be tolerated, but not overestimate errors.

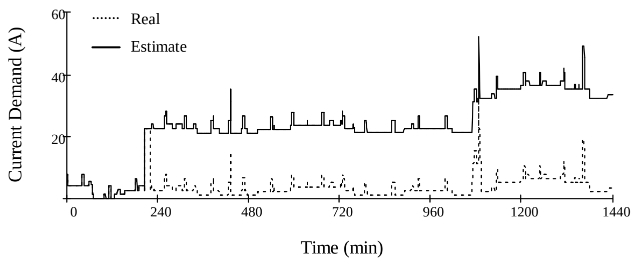

Fig. 4. Example of demand overestimates: - catastrophic events at t_1 = 220 min and t_2 = 1092 min.

Fortunately, MTS events can be detected. To examine this question more briefly, we consider a simplified model for the line section of the Fig. 1, assuming ideal voltage sources and equidistant line taps, i.e., $r_k = R/K$. Taking these conditions into account, result that $\Delta v_A = \Delta v_B = 0$ and $m_k = k/K$. Thus, for this simplified model, we conclude that the source of each single tap demand change can be determined by

$$\hat{k} = \widehat{m}_k K = \frac{K \Delta i_B}{\Delta i_A + \Delta i_B} \tag{14}$$

If the demand change is due to a single tap, the result obtained from (14) should be an integer in the range [0, K]. However, in the case of MTS, the relationship in (10) is not valid anymore and the resultant value from (14) will be a real number in the range (-∞, ∞). Therefore, single and multiple tap switching can be distinguished by examining the result furnished by (14). To mitigate the incident noise, the output $\hat{k}$ can be compared with its nearest integer $r(\hat{k})$, where $r(\cdot)$ represents the rounding function. A single tap event can be declared if the measured distance given by

$$\delta = \left| r(\hat{k}) - \hat{k} \right| \tag{15}$$

is smaller than an arbitrary threshold value ε, that is, if $\delta < \varepsilon$.

As MTS is detectable, the next step is to control the accumulating process in (13) in order to avoid overestimates like those illustrated in Fig. 4. As tap switching probabilities are relatively small, i.e., $p_k \ll 1$, we consider that the vast majority of the MTS events occur by the demand variation of only two taps, Δi_{k_1} and Δi_{k_2}, as illustrated in Fig.5.

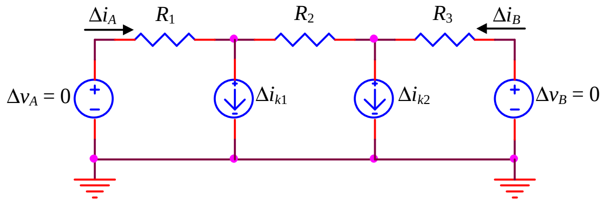

Fig. 5. Model for current demand variation in two line taps.

In the event of MTS, there are four specific conditions related to the polarities of Δi_A and Δi_B. Case 1 occurs when both are positive and if we consider that multiple taps are submitted to increasing demands, one good strategy in this case is do not add anything to the demand estimates $\hat{\imath}_k$, i.e, $\Delta\hat{\imath}_k = 0$. In this way, overestimating the demand of wrong consumer clusters is avoided.

Case 2 occurs when both Δi_A and Δi_B are negative. In this case, the worst situation is when one of the conflicting taps is responsible for almost the totality of the demand change. Thus, the most conservative decision in this case, is to deduct the demand variation integrally for all taps, i.e., $\Delta\hat{\imath}_k = \Delta i_A + \Delta i_B$.

For the remaining cases, the polarities of the demand changes have opposite signs. In this case, this implies that the variations Δi_{k_1} and $\Delta i_{k_2}$are also in opposite directions. An analysis in the circuit shown in Fig.5 reveals that

$$\begin{bmatrix}\Delta i_{k_1}\\ \Delta i_{k_2}\end{bmatrix} = \begin{bmatrix}1 + R_1/R_2 & -R_3/R_2\\ -R_1/R_2 & 1 + R_3/R_2\end{bmatrix} \cdot \begin{bmatrix}\Delta i_A\\ \Delta i_B\end{bmatrix} \tag{16}$$

Case 3 is for $\Delta i_A < 0$ and $\Delta i_B > 0$, resulting that $\Delta i_{k_1} < 0$ and $\Delta i_{k_2} > 0$. In this case, the most negative value for Δi_{k_1} occurs for the minimum value of R_2, which corresponds to the situation in which the active taps are adjacent, that is, for $k_2 = k_1 + 1$. The same conclusion is also valid for the case 4, when $\Delta i_A > 0$ and $\Delta i_B < 0$. Thus, rewriting (16) for $R_1 = kR/K$, $R_2 = R/K$ and $R_3 = (K - k - 1)R/K$, we obtain that

$$\Delta\hat{\imath}_{k_1} = \begin{cases}(1 + k)\Delta i_A - (K - k - 1)\Delta i_B, & 0 \le k < K\\ 0, & k = K\end{cases} \tag{17}$$

and

$$\Delta\hat{\imath}_{k_2} = \begin{cases}(K - k + 1)\Delta i_B - (k - 1)\Delta i_A, & 0 < k \le K\\ 0, & k = 0\end{cases} \tag{18}$$

For estimation purposes, the result in (17) can used to estimate $\Delta\hat{\imath}_k$ for case 3 and case 4 can be handled by (18).

As we choose the detection process to avoid overestimates, the output of the accumulation process (13) is often underestimated and, eventually, reaches the zero baseline and an important question is how to handle these events. As current demand is non-negative, the basic action in those circumstances is to limit the value of $\hat{\imath}_k$ to zero. Moreover, in those occasions that the baseline is reached due to the detection of a single tap switching event, there is the opportunity to correct the baseline since the last occurrence of cases 2, 3 or 4 at time t_0. This can be done by subtracting the negative output $\hat{\imath}_k(t_1)$ provided by (13) for the entire time range $[t_0, t_1]$, that is

$$\hat{\imath}_k(t) = \hat{\imath}_k(t) - \hat{\imath}_k(t_1), \qquad t = t_0, \cdots, t_1 \tag{19}$$

Summarizing the above discussion, we propose the following demand measuring process, computed at every sample interval:

- *Step 1:* Verify if the line tap estimate $\hat{k}$ is close enough to a integer in the range $[0, K]$, that is, using (15) compare δ and ε. If $\delta > \varepsilon$, a MTS event was detected and go to step 2. Otherwise, an single tap event was recognized for the tap $\hat{k}$. Compute the demand variation estimate for this tap, $\Delta\hat{\imath}_{\hat{k}}$, using (10) and set the estimates for all other taps to zero. Jump to step 5.
- *Step 2:* As a MTS event was detected, then compare the values of Δi_A and Δi_B. If the polarities are opposite, go to step 3. Else, if both values are positive, do nothing and jump to step 4. Otherwise, if both values are negative, then deduct integrally the demand variation for all taps, computing (10) for $k = 0, 1, \cdots, K$ and store the current time t_0. Jump to step 4.
- *Step 3:* If $\Delta i_A < 0$ and $\Delta i_B > 0$, then compute $\Delta\hat{\imath}_k = \Delta\hat{\imath}_{k_1}$ using (17) for each line tap. Otherwise, evaluate $\Delta\hat{\imath}_k = \Delta\hat{\imath}_{k_2}$ by means of (18), for $k = 0, 1, \cdots, K$. In both cases, store the present time t_0.
- *Step4:* Compute the demand estimates $\hat{\imath}_k$ for all taps using (13). If any value results to be negative, set this value to zero. Wait for next time interval.
- *Step 5:* Compute the demand estimates $\hat{\imath}_k$ for all taps using (13). If, for any k, the value results to be negative, correct the baseline for this line tap recalculating $\hat{\imath}_k$ via (19). Wait for the next time interval.

4. SIMULATION RESULTS

All simulations conducted in this work employ the line section model and the short term demand models described in Section 2. Additional conditions include: a) equidistant line sections, i.e, $r_k = R/K$; b) ideal voltage sources, i.e., $\Delta v_A = \Delta v_B = 0$; and c) identical demand profile in all line taps. For the last condition, although the number and type of loads connected to the line taps could vary, the same arrange was used in all taps. The basic loads that can be combined and employed in the simulations are listed in Table 1.

Table 1. Basic load types used in simulations.

Type	Amplitude (A)	τ_{on} (min)	τ_{off} (min)
Periodic	4 ~ 6	5	60
Non-periodic, high current	20 ~ 22	10	360
Non-periodic, medium current	10 ~ 12	30	720
Non-periodic, long-lasting	3 ~ 5	240	720
Non-periodic, low current 1	1 ~ 3	10	60
Non-periodic, low current 2	1 ~ 3	180	720

Fig. 6 illustrates the typical total current demand profile $i_T = i_A + i_B$, resultant for a 50-tap line section, with each tap submitted to all the six different types of loads listed in Table 1.

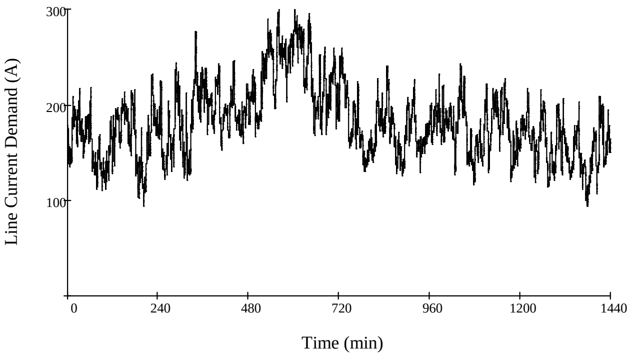

Fig. 6. Typical total current demand profile for a 50-tap line section. Each tap submitted to all the six load types of the Table 1.

Fig. 7 illustrates the fundamental distinction between the basic and advanced demand measurement processes. Fig. 7(a) shows how the first strategy fails to deal with a catastrophic event around t = 530 min, while Fig. 7(b) exhibits the capacity of the refined process in managing the situation successfully.

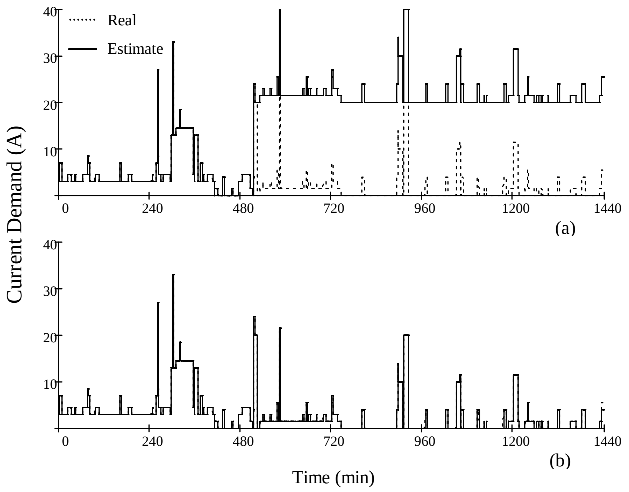

Fig. 7. (a) Basic demand measurement process failure dealing with a catastrophic event at t = 530 min. (b) Advanced demand measurement process deals with the same event successfully.

Fig. 8 illustrates how basic and advanced strategies deal with MTS events. Fig. 8(a) confirms that basic process is predisposed to overestimate the demand, while Fig. 8(b) shows that errors in the advanced process tend to underestimate it.

Finally, Fig. 9 shows the performance of the advanced demand measurement process for an increasing number of line taps. The total load of each line tap consisted of the combination of all load types listed on Table 1. As expected, the measuring error increases with the number of line taps and decrease with the sample frequency.

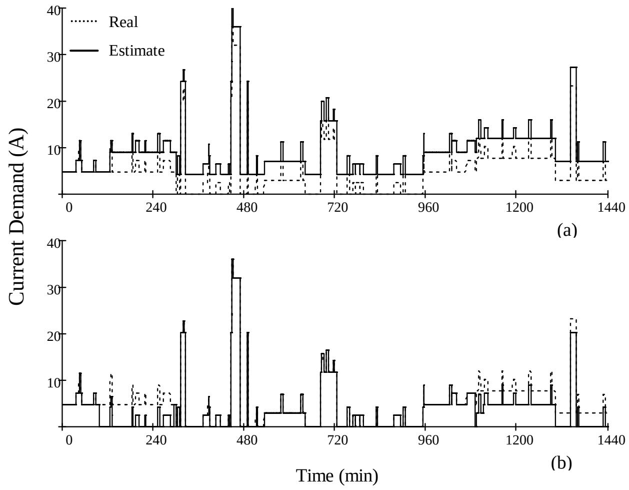

Fig. 8. (a) Basic measurement process overestimates the demand. (b) Advanced measurement process underestimates the demand.

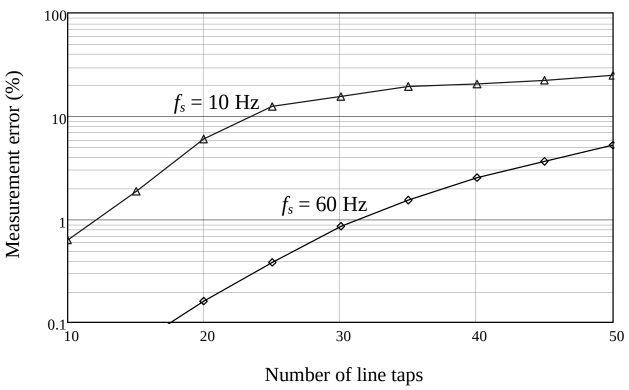

Fig. 9. Advanced demand measurement process error in function of the number of line taps, for two sample rates 10 Hz and 60 Hz.

5. CONCLUSIONS

This work proposed a method that allows measuring the electric power demand of consumer clusters remotely, that is adequate to applications for controlling technical and non-technical losses over the low-voltage distribution network.

The method is based on the detection of the electrical current and voltage changes at both ends of a distribution line section, and then computing the demand of the clusters.

The measuring process avoids overestimating the demand by detecting multiple tap switching (MTS) and taking corrective actions in the demand measurement accumulation process.

Simulations performed show that if the incidence of MTS events is kept sufficiently low, either by increasing the sample rate or, in last instance, limiting the number of taps of the line section, then long-term demand measurement process can be accurate enough to be successfully employed in applications combating technical and non-technical losses in the electricity distribution network.

REFERENCES

[1] A. C. M. de Araujo and C. A. Siqueira. “Considerações sobre as perdas na distribuição de energia elétrica no Brasil”. Seminário Nacional de Distribuição de Energia Elétrica, 17., CEMIG, Belo Horizonte, Brasil. 2006.

[2] E. A. Neto, J. Coelho, A. L. Bettiol, S. M. Barcelos. “Combate às perdas não-técnicas no Brasil”. Congreso Latinoamericano de Distribucion Electrica, Mar Del Plata, Argentina. Sep. 2008.

[3] “Reduction of Non-Technical Losses by Modernization and Updating of Measurement Systems”. Transmission & Distribution Conference and Exposition: Latin America, 2006. TDC '06. IEEE/PES, pp. 1-5, Aug. 2006.

[4] D. Suriyamongkol, *Non-Technical Losses in Electrical Power Systems*, M. Sc. Thesis, Ohio University, 2002.

[5] J. Marcum. “A statistical theory of target detection by pulsed radar”, IEEE Trans. Info. Theory, Apr. 1960.

[6] S. M. Kay. *Fundamentals of Statistical Signal Processing: Estimation Theory*. Prentice Hall. 1993.