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Remote Calibration of Wattmeter in a Low-Voltage AC Network

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Abstract: - This paper presents and compares several algorithms for selecting optimal averaging intervals for short-term power measurements in low-voltage AC networks. These intervals are crucial in reducing the statistical variance of power estimates, which is essential for the remote calibration of wattmeter's and the accuracy of smart sockets. The research focuses on minimizing fluctuations in power consumption data, which are influenced by various network-connected loads. By analyzing different power averaging interval selection algorithms, the study provides a methodology to enhance the reliability and accuracy of remote calibration processes for wattmeter's in dynamic power quality conditions.

The research presents results that demonstrate the effectiveness of different algorithms in minimizing power estimate variance. The findings indicate that specific algorithms are better suited for certain types of power quality conditions, leading to more accurate power measurements. These results support the feasibility of using the proposed methods for remote calibration and provide guidelines for selecting appropriate averaging intervals in practical scenarios.

Keywords: calibration, electrical grid, power measurement, smart electricity meter, watthour meters.

I. Introduction

The advent of smart electricity meters has significantly impacted energy management across Europe. With over 450.000 consumers participating in various pilot projects, smart meters have demonstrated the potential to reduce electricity consumption by 5% to 8.7%, depending on the scope of the project. Not only do these devices enable more efficient electricity use, but they also allow distribution network operators to remotely monitor and address illegal electricity consumption in real-time. This capability simplifies grid maintenance, optimizes investments, and reduces costs associated with meter maintenance and reading. Smart meters, which record electricity consumption at 15 minute intervals, also foster market competition by enabling independent suppliers to offer better services, prices, and innovative solutions. This increased competition is beneficial to both consumers and the national economy.

In the context of low-voltage alternating current (AC) networks, the concept of remote calibration of wattmeter's has gained attention. This approach allows for the verification and adjustment of meters directly at their installation sites, under dynamic power quality conditions. The term "calibration" in this paper refers to instrument gain adjustment rather than precise metrological calibration, as defined by the International Vocabulary of Metrology (VIM3). The focus is on gain adjustment of electrical watt-hour meters and smart sockets, which can also serve as a step towards remote verification of wattmeter's. This developed calibration method involves calibrating a wattmeter (CW) with a wattmeter of remote metering (WRM) [1]–[9].

This paper discusses the development and implementation of this remote calibration method, highlighting its significance in maintaining the accuracy and reliability of smart meters in today's evolving electrical distribution networks. They are spaced apart, but at the same time they can measure temporarily increased load energy consumption is shown in Fig. 1.

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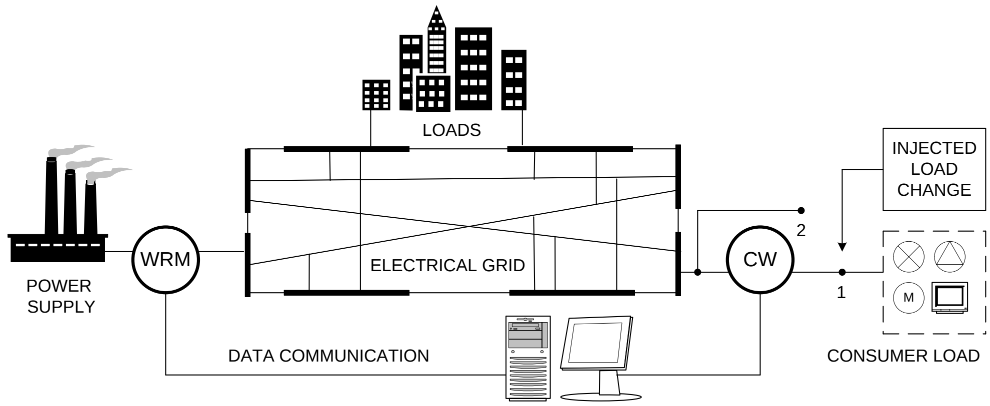


Fig. 1. Remote calibration of wattmeter.

The article contributes to the field of power measurement and calibration by introducing and evaluating a set of algorithms designed to optimize the averaging intervals used in power measurements. These algorithms help to minimize fluctuations in power data, which directly impacts the reliability and accuracy of remote calibration processes for wattmeter's. Additionally, the research provides a methodology that can be applied to improve the performance of smart meters and related devices, particularly in terms of energy monitoring and management in low-voltage networks. The work also lays the groundwork for future advancements in remote calibration techniques, contributing to the overall efficiency and accuracy of electrical measurement systems.

II. Analysis of Wattmeter Calibration

Several references propose methods for the remote monitoring of the calibration status of electrical energy meters, including revenue meters and smart sockets. A common aspect of these methods is the connection of the meters under calibration to the same electrical grid as a reference or summation meter. These methods are designed to facilitate the simultaneous calibration (or adjustment) of all meters connected to the network. According to these methods, the meters undergoing calibration are remotely linked to a reference instrument via the electrical distribution grid, typically on a single phase. The characteristics of the interconnecting medium, such as losses, reactive components, and power consumption fluctuations due to load activity, may vary over time [1]–[9].

This paper examines the impact of the interconnecting medium on the performance of the proposed method. The sequence diagram of the method is presented in Fig. 2. According to this diagram, a gain adjustment estimate is obtained by simultaneously collecting power samples at both the WRM and the CW wattmeter's for each power injection location: behind the CW (switch position 1 in Fig. 1) and in front of the CW (position 2 in Fig. 1).

It is crucial that the power consumption, as measured by the reference wattmeter (Fig. 1), caused by all loads (excluding the injected load) in the grid remains constant. Power fluctuations occur not only due to the switching of loads on and off but also over short time scales (on the order of seconds). The short-term fluctuations of an AC power grid have not yet been studied in detail. The widespread adoption of switching, nonlinear, and power consumption-regulating loads has led to the emergence of distorted power and current profiles in the network, introducing a wide spectral content in the measured power consumption profile (time series). The average power estimated over the time interval $[t_n, t_{n+1}]$ is expressed as:

$$P_{\mathrm{Av}} = \frac{1}{t_{n+1} - t_n} \int_{t_n}^{t_{n+1}} \left(P_0 + P_{\mathrm{inj}} + P_{\mathrm{F}}(t) + n(t) \right) dt, \tag{1}$$

where P_0 and P_{inj} are power and injected power that are constant during the acquisition time interval (T_1, T_2, T_3 in Fig. 2), $n(t)$ is Gaussian noise of measurements, and $P_{\mathrm{F}}(t)$ is fluctuating power in the interval $[t_n, t_{n+1}]$. The issue of unknown and time-varying disturbance rejection presents a significant challenge in this context. Extending the integration period can mitigate the variance caused by Gaussian noise components. However, the power fluctuation $P_{\mathrm{F}}(t)$ spectrum is dominated by harmonics, and the variance is further reduced when the integration interval is an integer multiple of the fundamental harmonic period. Since the method relies on average power calculations, it is not necessary for the time intervals T_1=T_2=T_3 to be identical.

To ensure accurate calibration of smart meters, it is essential that all loads connected to the power grid maintain a constant power consumption during the calibration period (lasting a few seconds). By understanding the nature of power fluctuations in the grid, it is possible to predict intervals of stable power consumption. This necessitates an analysis of power fluctuation behavior, which can identify and exploit favorable time intervals for data transmission and meter calibration operations [10]–[18]. For the remote wattmeter calibration method, the ability to predict short-term stable power consumption is also required. Therefore, a tracking algorithm designed to determine the optimal power integration period is essential. The necessity for online tracking arises from the vast diversity of electrical loads connected to the grid, leading to unpredictable short-term power fluctuation profiles that can not be forecasted during the design phase [19], [20]. Given that the WRM is exposed to a larger set of loads compared to the CW, the power profile acquired by the WRM is expected to exhibit more significant fluctuations. Consequently, the optimal averaging period tracking procedure should be performed at the WRM. The optimal averaging period (number of samples) determined by the WRM must then be communicated to the CW to ensure that both wattmeter's collect the same number of power samples corresponding to the same time interval.

The research methodology includes the following steps: 1. Experimental acquisition of active power consumption profiles in various types of buildings: private dwellings, offices, multi-apartment buildings, and factories. 2. Implementation of averaging interval selection algorithms using Matlab modeling. 3. Comparative evaluation of the algorithms' ability to track the optimal power averaging interval by processing the acquired power consumption data.

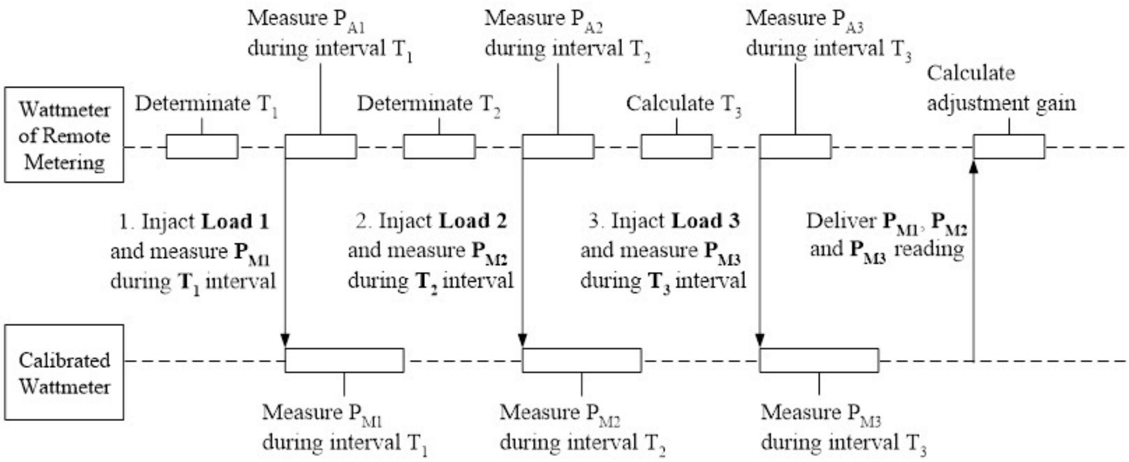


Fig. 2. Remote wattmeter calibration method implementation diagram.

Although the remote calibration procedure involves power integration over three intervals (as shown in Fig. 2), the subsequent research focuses on optimizing the averaging interval selection by minimizing the variance between two neighboring average power estimates. Experimental results indicate that the optimal interval is not significantly different whether it is determined by minimizing the squared distance between two neighboring samples or three neighboring samples.

III. Experimental Setup and Results

In the experimental setup, active power and AC were employed as primary variables. The update interval was configured to 0.1 seconds, aligning with five cycles of the AC grid's fundamental frequency. The measurement period was defined as the duration between the initial and final zero-crossings (either rising or falling) within each data update interval.

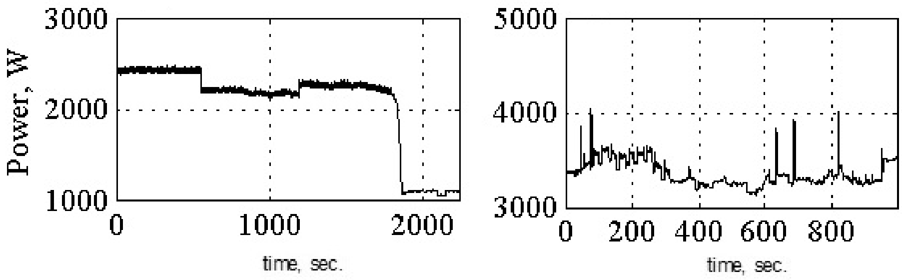
The results from the experimental measurements of active power consumption profiles were obtained for three distinct settings: 1. a private dwelling (Site No.1), 2. an office (Site No.2), and 3. a multi-apartment building (Site No.3). These results are mathematically summarized in Table I.

Table I. Active Power Consumption Profiles

Name	**Time (s)**	0	50	100	150	200	250	300	350	400	450	500
No.1	P_a **(W)**	685	533	405	507	595	695	455	403	667	538	411
No.2	P_a **(W)**	2000	2250	2465	2175	2385	2135	2205	2475	2500	2345	2485
No.3	P_a **(W)**	4050	3895	4300	4270	3745	3680	4070	3865	3605	3995	4250

Three representative, long-term power consumption patterns (up to 500 seconds) were analyzed across different buildings. Table I illustrates the active power consumption profiles recorded during the evening of a typical working day and during peak load conditions. The active power supply network analyzed is a single-phase system servicing: a private dwelling, an office, and a multi-apartment building comprising ten apartments.

Power consumption spectrograms, as illustrated in Fig. 3, demonstrate that short-term power fluctuations within the frequency range of several hertz can exhibit both temporal variability and relative constancy despite significant changes in long-term power consumption (on the order of hundreds of seconds). Both long-term and short-term power consumption profiles can display considerable variability. Consequently, it is essential to determine the power averaging interval that minimizes variance between adjacent averaged estimates dynamically during operation.



a) b)

Fig. 3. Spectrogram of power consumption in: (a) office, (b) multi-apartment.

Short-term power fluctuations stay within some selected range during some selected time interval. In Table II there are presented probabilities $pr(T_w)$ (%), that standard deviation of power fluctuations in the interval of length T_w does not exceed threshold power. This means that the relative level e (%) of active power oscillation is expressed as a percentage of the average active power value in the range T_w. In Table II constant order moving averaging filtering (5'th order and 10'th order in Table II) was applied prior to the estimating histograms.

Table III. Relative Ammount of Time Intervals and Range of Power Fluctuations Defined by Threshold Value

moving averaging filter order *N*=5							
T_w (s)	0	0.5	1	1.5	2	2.5	3
A (%)	97	94.5	93	90.5	89	86.5	85
B (%)	94	91.5	90	87.5	86	83.5	82
C (%)	91	87	83	79	75	71	67
D (%)	73	67	61	55	49	43	37
moving averaging filter order *N*=10							
T_w (s)	0	0.5	1	1.5	2	2.5	3
A (%)	99	97.5	94	92.5	91	89.5	88
B (%)	98	96.5	95	93.5	90	88.5	87
C (%)	96	92	88	84	80	76	72
D (%)	90	82	76	70	64	58	52

Here A - $pr(T_w)$, when e = 1%, B - $pr(T_w)$, when e = 0.75%, C - $pr(T_w)$, when e = 0.5%, and D - $pr(T_w)$, when e = 0.25%. In the implementation of the remote active power calibration method, it is anticipated that the likelihood of observing constant power consumption will progressively increase. However, probabilistic functions alone can not identify the optimal averaging interval for power consumption at any given moment. To address this, it is necessary to enhance the probability of selecting the optimal averaging interval by determining it dynamically in real-time.

IV. Power Averaging Interval Selection Algorythms

The paper classifies power averaging period selection algorithms designed to minimize variance between neighboring averaged power estimates into the following categories:

1. Time-based Selection:
   1.1. Constant Interval (Algorithm A1): Utilizes a fixed averaging interval;
   1.2. Random Averaging Interval (Algorithm A2): Employs a randomly varying averaging interval.
2. Adaptive Selection (Tracking):

2.1. Current Interval Search (Algorithms A31 and A32): Adjusts based on an active search within current averaging intervals;

2.2. Historical Reference:

2.2.1. Standard Deviation Tracking (Algorithm A4): Monitors the standard deviation of previous averaged samples;

2.2.2. Spectral Analysis (Algorithm A5): Derives the interval from the frequency spectrum of previous samples.

The performance of each algorithm is evaluated based on criteria such as variance in averaged estimates, computational cost (related to real-time processing capabilities), and implementation complexity.

Algorithm (A1) is the simplest in terms of implementation and requires no computational resources for real-time execution. However, its effectiveness in minimizing variance is limited, especially in the presence of initially unknown power fluctuation characteristics. Algorithm (A1) serves as a baseline for evaluating the improvement potential of other methods. For calibration speed considerations and the sampling period of power consumption, the sample range for averaging in Algorithm (A1) is between 5 and 15, corresponding to a time interval of $T_{\min}$ = 0.5 s to $T_{\max}$ = 1.5 s.

Algorithm (A2) introduces variability by altering the averaging interval according to a predefined random sequence generated by a reference instrument. This method, inspired by spread spectrum techniques in communication theory, aims to reduce variance in averaged estimates by increasing resistance to constant but unknown disturbances. The use of a broad spectrum of averaging intervals allows for better rejection of the unknown and slowly varying primary harmonic of short-term fluctuations compared to a fixed interval determined at design time. To ensure comparability with Algorithm (A1), the random averaging interval in Algorithm (A2) is also constrained within the range of 0.5 to 1.5 seconds.

V. Adaptive Averaging Size Tracking Procedures

1. Based on Search in Current Averaging Intervals: According to this procedure, the selected and equal number of active power samples are acquired for both averaging intervals correspondingly from t_m to $t_m+T_{\max}$ (first interval) and from $t_m+T_{\max}$ to $t_m+2T_{\max}$ (second interval). Then the first and the second optimal averaging time intervals: $[t_m+s_{1\text{opt}}(t_m)T_s,\ t_m+(s_{1\text{opt}}(t_m)+n_{\text{opt}}(t_m))T_s]$ and $[t_m+T_{\max}+s_{2\text{opt}}(t_m)T_s,\ t_m+T_{\max}+(s_{2\text{opt}}(t_m)+n_{\text{opt}}(t_m))T_s]$ are determined by solving the optimization problem is:

$$\min_{n,s_1,s_2}\left(P_{\text{Av}}\left(t_m,n,s_1\right)-P_{\text{Av}}(t_m+T_{\max},n,s_2)\right), \tag{2}$$

subject to: $n_{\min} \le n \le n_{\max}$; $0 \le s_1 \le s_{\max}$; $0 \le s_2 \le s_{\max}$; where $(n_{\max} = T_{\max}) / T_s$ and $(n_{\min} = T_{\min}) / T_s$ are correspondingly the largest and the least accepted number of samples to average, $s_{\max} = (T_{\max} - T_{\min}) / T_s$ and T_s is power sampling period. In the following modeling $n_{\min}$ = 5 and $n_{\max}$ = 15 samples were accepted. Averaged power is expressed as:

$$P_{\text{Av}}\left(t_m,n,s\right)=\frac{1}{n}\sum_{k=1}^{n}p(t_m+(k-s-1)T_s), \tag{3}$$

A less computationally demanding version (lite version) of the procedure assumes that $s_{1\text{opt}}$ = 0 and $s_{2\text{opt}}$ = 0 solving optimization problem (2) only for the variable n.

2. Referring to Previous (historic) Averaged Samples:

a) Standard deviation feature tracking: The problem of tracking of optimal number of measured power samples to average at a discrete time moment t_m and $n_{\text{opt}}(t_m)$ is defined as:

$$\min_{n_i}(\omega_i\cdot\sigma_p^2(t_m,n_i)), \tag{4}$$

$i=\overline{1,K}$ subject to: $n_i = (n_1, n_2, ..., n_K)$. Standard deviation of averaged power estimate is:

$$\sigma_p^2(t_m,n_i)=\frac{1}{N}\sum_{j=1}^{N}(P_{\text{Av}}(n_i,t_m-T_s\cdot n_i\cdot(j-1))--M(P_{\text{Av}}(n_i,t_m)))^2, \tag{5}$$

where averaged power sample at the discrete time moment t_m is:

$$P_{\text{Av}}\left(t_m,n_i\right)=\frac{1}{n_i}\sum_{k=1}^{n_i}p(t_m-(k-1)T_s), \tag{6}$$

and average of previous N averaged power samples is:

$$M(P_{\mathrm{Av}}(n_i,t_m)) = \frac{1}{N}\sum_{j=1}^{N}(P_{\mathrm{Av}}(n_i,t_m - T_{\mathrm{s}}\cdot n_i\cdot(j-1)), \quad (7)$$

where N is number of averaged power estimates that are used to calculate standard deviation according to (5). Weights w_i in (4) are intended to assign some priority levels to averaging over n_i samples. Therefore, two cases were investigated first, when weights are equal to 1, and second, when they are linearly increasing for larger n_i values. Results of sampled and averaged power calculated according from (4) to (7) are shown in Table III.

Table IIIII. Averaged Power Profiles

Time (s)	1	2	3	4	5	6	7	8	9	10
$\boldsymbol{P_a}$ **(W)**	2145	2143	2141	2142	2146	2155	2210	2190	2170	2145
Time (s)	11	12	13	14	15	16	17	18	19	20
$\boldsymbol{P_a}$ **(W)**	2151	2159	2163	2265	2268	2270	2271	2265	2270	2275

Weights w_i and number or N of averaged power samples must be selected before its solution (2). This optimization method involves calculating all possible values and then choosing the smallest one.

b) Spectrum analysis-based tracking:

In this approach, optimal averaging period $n_{\mathrm{opt}}(t_m)$ is selected according to the equation:

$$n_{\mathrm{opt}}(t_m) = round(\left(\frac{1}{T_{\mathrm{S}}\cdot f_{\mathrm{spmax}}}\right), \quad (8)$$

restricted by condition:

$$\frac{T_{\min}}{T_{\mathrm{S}} \leq n_{\mathrm{opt}}(t_m)} \leq \frac{T_{\max}}{T_{\mathrm{S}}}, \quad (9)$$

where f_{spmax} is frequency corresponding to the peak of power consumption profile spectrum in the range from $1/T_{\max}$ to $1/T_{\min}$.

VI. Testing of Averaging Interval Selection Algorythms

Mean of squared differences between neighboring averaged samples $M(\Delta P_{\mathrm{Av}}(n_{\mathrm{opt}},\ t_m))^2$ is chosen as a performance criteria (PC) of optimal averaging interval tracking procedure:

$$M(\Delta P_{\mathrm{Av}}(n_{\mathrm{opt}},t_m))^2 = \frac{1}{L}\sum_{m=1}^{L-1}(P_{\mathrm{Av}}(n_{\mathrm{opt}}(t_m),t_m) - -P_{\mathrm{Av}}(n_{\mathrm{opt}}(t_{m-1}),t_{m-1}))^2, \quad (10)$$

where L is the total number of power estimates obtained by tracking and averaging procedure. Average power estimate at the time moment t_m is calculated by averaging $n_{\mathrm{opt}}(t_m)$ previous raw power samples.

The worst and the best improvement of performance criteria in percentage are defined correspondingly:

$$G_{\min} = \frac{\min(M(\Delta P_{\mathrm{Av}}(n_i,t_m))^2 - M(\Delta P_{\mathrm{Av}}(n_{\mathrm{opt}},t_m))^2)}{\min(M(\Delta P_{\mathrm{Av}}(n_i,t_m))^2)}\cdot 100\%, \quad (11)$$

$$G_{\max} = \frac{\max(M(\Delta P_{\mathrm{Av}}(n_i,t_m))^2 - M(\Delta P_{\mathrm{Av}}(n_{\mathrm{opt}},t_m))^2)}{\max(M(\Delta P_{\mathrm{Av}}(n_i,t_m))^2)}\cdot 100\% \quad (12)$$

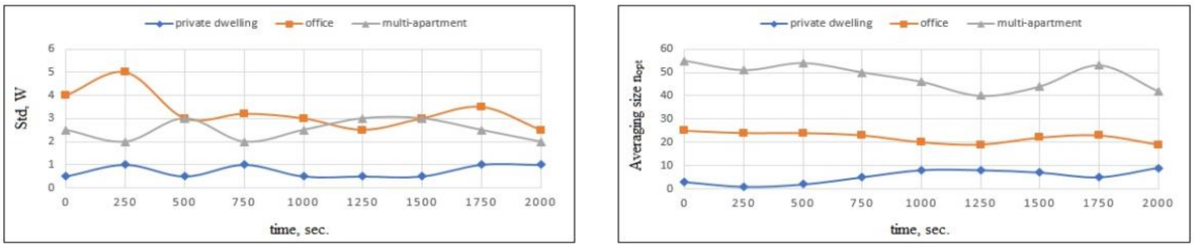
where

$$M(\Delta P_{\mathrm{Av}}(n_i,t_m))^2 = \frac{1}{L_i}\sum_{j=1}^{L_i}(P_{\mathrm{Av}}(n_i,t_m) - P_{\mathrm{Av}}(n_i,t_{m-1}))^2, \quad (13)$$

where $i = \overline{1,K}$ and L_i is the total number of power estimates obtained by averaging procedure that utilizes fixed n_i to calculate each averaged power estimate $P_{\mathrm{Av}}(n_i,\ t_m)$. Negative value of $G_{\min}$ indicates not an improvement but downgrading of the performance criteria.

By examining the typical time series of the optimal averaging size, denoted as $n_{\mathrm{opt}}(t_m)$, in Fig. 4, it can be observed that the value of n_{opt} changes frequently due to its heightened sensitivity to the random fluctuations within the raw power profile. However, this frequent adjustment does not contribute significantly to reducing the standard deviation of the averaged power estimates. To mitigate the fluctuations in the n_{opt} series, the parameter K could be reduced (as illustrated in Fig. 4). The choice of the parameter N also influences the tracking speed; specifically, a larger N introduces a greater delay between the moment of a change in power profile characteristics and the determination of a new adapted averaging size (refer to Fig. 4).

The improvement factor G quantifies the effectiveness of the averaging size tracking procedure in enhancing the performance criteria defined in (6). For the results presented in Table IV, the tracking procedure was employed to select the optimal averaging size from the set n_i = (5, 10, 15), as indicated in the first column of Table IV. A larger number K of n_i options increases the computational cost of the tracking procedure. Therefore, selecting the set n_i, $i = \overline{1, K}$, requires careful consideration to balance computational load against the reduction in variance of averaged power estimates.



a) b)

Fig. 4. Characteristics of buildings, when $\omega_i = 0.05 \cdot n_i$, N = 30, n_i = (5, 10, 15, 20, 25, 30): (a) $S_{td}(t)$ and (b) $n_{opt}(t)$.

As seen in Table IV, the random averaging interval selection method (A2) did not demonstrate a reduction in the variance of neighboring averaged power estimates compared to all constant averaging interval options. While random interval selection improved the performance criteria described by (10) for the least suitable averaging interval (see G_{max}), it degraded the performance for the most suitable averaging interval among those preselected for testing (see G_{min}). This indicates that random period selection adds complexity without guaranteeing an improvement in the targeted criteria, thus lacking justification. Similarly, methods denoted as (A31) and (A32) yield comparable results.

Adaptive tracking methods (A4) and (A5) are more likely to achieve significant variance reduction for the least suitable constant averaging interval while only slightly increasing the average variance for the most suitable interval. Therefore, these two methods are preferred over the other methods considered. Nonetheless, method (A4) faces challenges related to the optimal selection of history buffer length N and weighting factors.

To differentiate between (A4) and (A5) computational demands are of consideration. According to (4)–(7), method (A4) requires $2K(N-1) + N\sum_{i=1}^{K}(n_i - 1)$ sum, and $K(N+2)$ division and $K(N+1)$ multiply operations to select the next averaging interval at any discrete time t_m. In total (A4) demands arithmetic operations (AO) to complete:

$$AO_{A4} = K(4N + 1) + N\sum_{i=1}^{K}(n_i - 1). \quad (14)$$

Assuming the parameter set for Method (A4) as N = 50, K = 3 and n_i = (5, 10, 15), the method requires approximately $AO_{A4} = 1953 \approx 2000$ arithmetic operations. Without applying compiler optimization techniques, each arithmetic operation involves two memory read operations for the operands and one memory write operation for storing the result. Consequently, the total number of instructions to be executed is approximately $4AO_{A4} \approx 8000$. To compute the averaging interval according to (4)–(8), and assuming a power sampling interval of T_s = 0.1 seconds, an embedded microcontroller must operate at a clock speed exceeding 80 kHz. Modern embedded microcontrollers typically operate at clock speeds greater than 10 MHz.

It is well known that the traditional Fast Fourier Transform requires $(N_{sp}/2)log_2N_{sp}$ multiplications and $(N_{sp})log_2N_{sp}$ additions. As shown in Table IV, and assuming N_{sp} = 512, the total number of arithmetic instructions required for Method (A5) is AO_{A5} = 9612, which is significantly higher than the computational demands of Method (A4). Here, No.1 represents the power consumption PC (W^2) of a house, No.2 corresponds to the power consumption of an office, and No.3 refers to the power consumption of an apartment.

Five techniques, both design-time and adaptive, were modeled to select the optimal power profile averaging interval, and their effectiveness in minimizing the variance between neighboring averaged power estimates was compared. Based on the results obtained from processing several typical power consumption profiles acquired from an office, a multi-apartment building, and a private residential building, it was determined that adaptive optimal interval tracking procedures utilizing buffered historical power samples provided the most significant improvement in reducing variance between neighboring averaged estimates. The application of these online tracking procedures shows promise for the remote adjustment of watt-hour meter gain, particularly in terms of statistically predicting intervals of stable power consumption within the electrical grid.

Table IVV. Performance Estimation of Averaging Procedures

n_i; $i = \overline{1, K}$	No.1	G_{min}=G_{max} (%)	No.2	G_{min}=G_{max} (%)	No.3	G_{min}=G_{max} (%)
A1: Constant averaging period (n_i; $i = \overline{1, K}$)						
n=5	1016	-32/+17	119	-7/+7	7838	-18/+12
n=10	1582	-19/+19	52	-29/+15	13125	-17/+17
n=15	1608	-52/+4	75	-38/+18	19820	-23/+12
A2: Random period						
N=rand (5, 15)	1351±42	-33/+15	54.5±0.2	-6/+54	11995±50	-53/+40
A3: Two neighbors optimal interval search						
A31 Lite version	1072	-6/+33	100	-96/+16	17476	-123/+12
A32 Full version	229	+77/+86	32.8	+36/+72	13691	-74/+31
A4: Tracking procedure						
N=15 w_i=1	862	+15/+46	45.1	+11/+62	8490	-8/+57
N=15 w_i=0.05	1046	-3/+35	50.5	+1/+58	8207	-5/+59
N=30 w_i=1	759	+25/+52	45.9	+10/+61	8336	-6/+57
N=30 w_i=0.05	1037	-2/+35	50	+2/+58	7883	-1/+60
N=50 w_i=1	754	+26/+53	48.9	+4/+59	8039	-3/+59
N=50 w_i=0.05	1046	-3/+35	46.8	+8/+61	7696	+2/+61
A5: Prediction from spectrum						
N_{sp}=256	1223	-20/+23	47	+8/+60	6269	+20/+68
N_{sp}=512	1041	-2/+35	47.9	+6/+60	5919	+24/+70

Considering the computational demands, the tracking technique (A4), which minimizes the standard deviation of previously averaged power samples, was identified as the most preferable method. It has also been demonstrated that real-time implementation of this procedure is feasible using modern embedded microcontrollers. When compared to fixed averaging intervals determined at design time, the (A4) procedure either enhanced the defined performance criteria or, at worst, did not significantly degrade it for the most optimal design-time-selected interval. Given that the characteristics of the power consumption profile can not be known in advance during design time, it is recommended that the adaptive tracking procedure (A4) be implemented.

VII. Conclusions

This study has successfully developed and evaluated algorithms for optimizing averaging intervals in short-term power measurements within low-voltage AC networks. The primary objective was to reduce the statistical variance in power estimates, a critical factor for the remote calibration of wattmeter's and enhancing the performance of smart sockets. The findings indicate that specific algorithms can effectively minimize fluctuations in power consumption data, thereby improving the accuracy and reliability of power measurements in dynamic electrical environments.

The research also explored the potential for remote calibration of wattmeter's, demonstrating that gain adjustments can be effectively performed even under varying power quality conditions. However, certain limitations were identified, including the variability in load conditions that may not be fully addressed by the proposed algorithms and the potential impact of remote calibration accuracy due to distance and communication infrastructure.

Despite these limitations, the study provides a significant contribution to the field by offering a methodology that enhances the precision of power measurements and lays the groundwork for future advancements in remote calibration techniques. Future work should aim to broaden the scope of load conditions analyzed, refine remote calibration methods, and test the proposed solutions in real-world settings to ensure their robustness and applicability.

In conclusion, the methodologies presented in this research have the potential to greatly improve the accuracy and efficiency of power measurement and calibration processes in low-voltage AC networks, contributing to more reliable energy management and smarter grid technologies.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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