Assessment of Dynamic Measurement Intervals for State Estimation in Future Distribution Systems

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***Abstract*—The ongoing energy transition introduces new load and generation units like photovoltaic generation in the medium-voltage systems network. These generation units increase the variance of the power injections, resulting in increased stochasticity of the power flow values. For confident assessment of the system's operating condition, a measurement scheme is essential for accurate state estimation at every minute of the day. This paper presents a performance assessment of the Weighted Least Square (WLS) distribution system state estimation algorithm with respect to the measurement intervals, and proposes a measurement scheme considering the measurement locations and intervals that satisfy a required error limit. The scheme is tested on a synthetic test model of a Dutch MV network, which takes into account projected (year 2040) and highly stochastic power flow profiles. Numerical results show that the proposed algorithm for the measurement scheme determination successfully satisfies the chosen error limit.**

***Index Terms*—Active distribution systems, measurement intervals, state estimation algorithms, stochastic power flows.**

I. Introduction

A. Motivation

Electricity distribution systems are challenged to host increasing numbers of highly stochastic renewable energy sources [1]. Also, the increasing number of power electronics interfaced devices, with variable output power, have a strong influence on the voltage performance and power flow patterns of the distribution system [2], [3]. In order to avoid grid operation limit violations such as congestion and over-voltages in the network, advanced control actions at the medium-voltage (MV) network level need to be carried out by the Distribution System Operators (DSOs) [1], requiring an accurate estimate of the actual system state. State Estimation (SE) algorithms are widely applied in transmission systems and now find their way to distribution systems, processing (pseudo-)measurements and their error variances to calculate the highest likelihood values for a set of variables that uniquely represent the system state [4].

A considerable factor that influences the accuracy of the SE is the input measurement variances [5]. Traditionally, a limited number of measurements (i.e. obtained by meters at some substations) are available in MV networks [6]. The variances of the sensors, together with communication delays, among other factors, affect the accuracy of the available measurements [7]. Additionally, pseudo-measurements can be eventually used as complementary measurements [8]. Pseudo-measurements are artificially generated based on historical data, and this synthetic data can have significantly high variances compared to real measurement data [9]. A higher number of additional real measurements with a small measurement interval is ideally required to enhance the numerical accuracy of SE. Nevertheless, this may involve high capital expenditures [10] and high operational costs for data processing and transmission. This brings the need for dimensioning measurement intervals such that they will ensure that the error of the resulting SE algorithm's output meets a target accuracy requirement at every minute of the day, but does not put a high burden on processing and communication systems. Thus, by determining the number, locations and measurement intervals for additional measurements, a required level of accuracy of the SE algorithm can be achieved with an optimal number of additional measurement units in the grid.

B. State of the art and scientific gap

A measurement configuration needs to consider number of meters, locations of installation, and intervals of measurements. In recent years, many algorithms have been proposed for the identification of the optimal measurement configuration for accurate distribution system state estimation. For instance, a robust meter placement algorithm is presented in [9]. It sequentially defines the placement of new meter and the number of necessary measurements and considers the measurement uncertainties using Monte Carlo (MC) simulations. Other alternative methods are based on the formulation of of multi-objective optimization problems [5], considering of predefined bounds for capital expenditures and accurracy [5].

The impact of the size of the measurement intervals on the numerical accuracy of SE is an acknowledged issue of concern in recent research works. In [12] it is shown that the interval of measurements, i.e. the time gap between one measurement and the next one, is a considerable factor that influences the SE error especially when increased stochasticity of the load profiles is present. For increased stochasticity of the load profiles, the effect of measurement intervals becomes

important because the deviation of the values (of the measurement parameters) from the time of measurement is likely to increase as the measurement interval increases. Running the SE algorithm frequently entails computational strain. So, the time intervals should be carefully determined such that a high computational capacity requirement is avoided. Further, the meter data from different locations in the network are usually received in unsynchrozied time intervals, each meter sending data when it senses a change in the measurement value. Nevertheless, determining the dynamic measurement intervals is necessary to ensure synchronization of measurement data upon which the SE algorithm can be run.

C. Outline

Motivated by the described needs above, in this paper, a measurement configuration is proposed that heuristically assigns measurement locations and assesses the effect of dynamic measurement intervals such that the SE error complies with a predefined upperbound at all times. The contributions of this paper are: (i) performance assessment of WLS SE algorithm with respect to different measurement intervals; (ii) An algorithm to determine the locations of additional meters and the necessary dynamic measurement intervals to satisfy a chosen error threshold at every minute of the simulated future day. The implementation is carried out on a synthetic model of a 10 kV Dutch MV network, taking into account a futuristic scenario based on the projections for the year 2040 resulting from the research presented in [13].

The subsequent sections have the following purpose: Section II briefly describes the basics behind the WLS SE algorithm, the mathematical modelling of the loads in the network, and the measurements required as inputs to the SE algorithm. Section III explains the proposed performance assessment procedure for the SE algorithm with respect to different measurement intervals. Section IV overviews the proposed algorithm to determine the measurement configuration, considering placement of additional meters in light of different measurement intervals. Numerical results are presented and analysed in Section V. Concluding remarks are summarized in Section VI.

II. Mathematical modelling

A. SE algorithm

SE is a procedure that calculates the highest likelyhood values of the state variables of a system by using a set of noisy measurements. The nodal voltage WLS SE algorithm, described in [9], is used in this paper.

B. Load modelling

The loads in the network are modelled as normally distributed functions as follows:

1) The one-minute resolution daily active and reactive power consumption profiles of the households in the LV networks (which are connected as loads at the buses of the MV network) are simulated using an artificial load profile generator (ALPG) presented in [14]. The electricity profiles include PVs, CHPs, HPs (heat pumps) and EVs, which simulate 2040 scenario for the Netherlands presented in [13].
For this, first a pool of profiles is simulated using the ALPG for each LV network [15]. The matrices $\boldsymbol{P}_i$ and $\boldsymbol{Q}_i$, each containing a pool of L one-minute resolution profiles $[p_{il}(1), \cdots, p_{il}(1440)]$ and $[q_{il}(1), \cdots, q_{il}(1440)]$ generated for the active and reactive power consumption of the ith bus of the MV network, respectively. Here,

$$\boldsymbol{P}_i = [\boldsymbol{p}_{i1}, \ldots, \boldsymbol{p}_{iL}]^\intercal, \quad \boldsymbol{Q}_i = [\boldsymbol{q}_{i1}, \ldots, \boldsymbol{q}_{iL}]^\intercal, \tag{1}$$

and

$$\boldsymbol{p}_{il} = [p_{il}(1), \cdots, p_{il}(1440)], \tag{2}$$
$$\boldsymbol{q}_{il} = [q_{il}(1), \cdots, q_{il}(1440)]. \tag{3}$$

2) Arrays $\boldsymbol{f}_p(t)$ and $\boldsymbol{f}_q(t)$ are active power and reactive powers of all buses created using normal distribution fitting method on each $\boldsymbol{P}_i$ and $\boldsymbol{Q}_i$, as described in [15], for each minute:

$$\boldsymbol{f}_p(t) = N(\boldsymbol{\mu}_{p,t}, \boldsymbol{\sigma}^2_{p,t}), \tag{4}$$
$$\boldsymbol{f}_q(t) = N(\boldsymbol{\mu}_{q,t}, \boldsymbol{\sigma}^2_{q,t}). \tag{5}$$

Function $N(\cdot)$ is a Gaussian (normal) distribution function, defined by the corresponding arrays of mean and variance $\boldsymbol{\mu}_{p,t}$ and $\boldsymbol{\sigma}^2_{p,t}$ for the active power and $\boldsymbol{\mu}_{q,t}$ and $\boldsymbol{\sigma}^2_{q,t}$ for the reactive power.

3) For each run of the SE algorithm, by random sampling from $\boldsymbol{f}_p(t)$ and $\boldsymbol{f}_q(t)$ for each bus at every minute, a load scenario j is created, with $\boldsymbol{l}_{pj}(t)$ and $\boldsymbol{l}_{qj}(t)$ as the arrays of loads values of all buses at time t. These are obtained as follows

$$\boldsymbol{l}_{pj}(t) = \mathrm{randnorm}(\boldsymbol{f}_p(t)), \tag{6}$$
$$\boldsymbol{l}_{qj}(t) = \mathrm{randnorm}(\boldsymbol{f}_q(t)). \tag{7}$$

The function $\mathrm{randnorm}(\cdot)$ picks a random sample from a normally distributed function.

C. Measurements modelling

The SE algorithm uses real, pseudo and virtual measurements and their variances as inputs. For each run of the SE algorithm, first the true values of the parameters are modelled. The appropriate errors are incorporated to obtain the measurements. To simulate the true values of measurement parameters, a power flow is run on the system for a loading scenario j from which the true values of the system state, $\boldsymbol{V}_j(t)$ and $\boldsymbol{\delta}_j(t)$ are obtained, as well as the measurement parameters, which are the active power flow and the reactive power flow for each network's branch ($\boldsymbol{P}_{j,flow}(t)$, $\boldsymbol{Q}_{j,flow}(t)$), and the active power injection and reactive power injection at each network's bus ($\boldsymbol{P}_{j,inj}(t)$, $\boldsymbol{Q}_{j,inj}(t)$). The process of obtaining the true values, (true values model) is shown in Fig. 1.

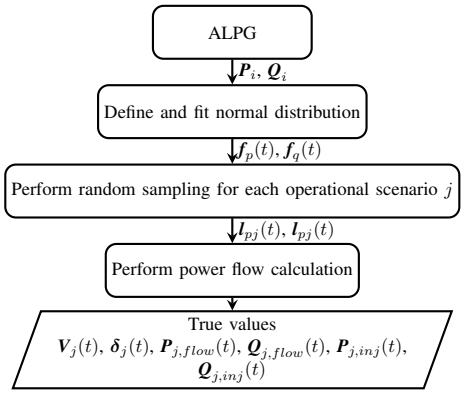

Fig. 1. Flowchart to create load scenario and true values: True value model

1) Real measurement data: It corresponds with the data acquired by each meter from different locations across the distribution system. For each measurement's point of time, the measurements' variance is assumed as 10^{-5} [12]. The following equation is adopted to model real measurements

$$\boldsymbol{z}_j(t) = \boldsymbol{z}_{j-true}(t) + \text{randnorm}(f_z(0, 10^{-5})), \tag{8}$$

where $\boldsymbol{z}_j(t)$ is the measurement vector at time t for a load scenario j, $\boldsymbol{z}_{j-true}(t)$ is the corresponding true values, which can be $\boldsymbol{V}_j(t)$, $\boldsymbol{P}_{j,flow}(t)$, $\boldsymbol{Q}_{j,flow}(t)$, $\boldsymbol{P}_{j,inj}(t)$ or $\boldsymbol{Q}_{j,inj}(t)$. 10^{-5}, and as mentioned before it is the meter variance and is applied as the variance of the zero-mean normal distribution f_z upon which random sampling is used for each bus to create a random error which is added to the true value to create real measurement data. The measurement values and variances at each point of time are defined by the actual meter measurement data and the assumed variance (10^{-5}) as in (8). This is used to generated random measurement profiles every k minutes. The variance at every minute, between the times of measurement, is defined by the random change in the measurement value from the previous minute. Interested readers are referred to [12], in which the determination of variance is fully explained based on historical profiles.

2) Pseudo measurements: At the MV buses that have no meters but do have loads connected, the pseudo measurements created for all buses are the active and reactive power injection values $\boldsymbol{P}_{j,inj-Pseudo}(t)$ and $\boldsymbol{Q}_{j,inj-Pseudo}(t)$, modelled through the profiles generated by using ALPG. Their variances are similar to the values provided in (4) and (5). They are simulated by sampling for each loading scenario j from the normal distribution functions at every minute as follows:

$$\boldsymbol{P}_{j,inj-Pseudo}(t) = -\,\text{randnorm}(\boldsymbol{f}_p(t)), \tag{9}$$

$$\boldsymbol{Q}_{j,inj-Pseudo}(t) = -\,\text{randnorm}(\boldsymbol{f}_q(t)). \tag{10}$$

3) Virtual measurement data: At the buses without loads, the bus active power injection and the bus reactive power injection are 0 W/VAR, respectively. These values are taken as accurate enough, neglecting shunt admittances in the network model. To prevent numerical computation problems, a small value of 10^{-8} is assigned to the variances.

III. Performance assessment methodology

The intervals at which real measurements are taken affect the SE error and so, must be considered while determining the measurement configuration such that the SE error satisfies the required limit at each simulated minute. A performance assessment is carried out as explained below, whose results show the effect of measurement intervals on the SE error.

1) The range of time interval values of real measurements for which the error profiles are calculated is set as ***range*** $= [5, 15, \cdots]$ and no pseudo measurements are considered.
2) For each run of the SE algorithm, the true values model shown in Fig. 1 is run for every minute of the day to obtain $\boldsymbol{z}_{j-true}(t)$ at all buses.
3) For each minute t, the real, virtual and pseudo measurements and their variances are created considering the measurement intervals as every k minutes. Here k is the next value in ***range*** starting from the first value. The measurements are represented by $\boldsymbol{z}_j(t)$.
4) Using the measurements $\boldsymbol{z}_j(t)$, i.e. $\boldsymbol{V}_{meas-j}(t)$, $\boldsymbol{P}_{meas-j,inj}(t)$ and $\boldsymbol{Q}_{meas-j,inj}(t)$ with their corresponding variances defined by $\boldsymbol{var}_j(t)$, the SE algorithm is executed (cf. II-A) at every minute to generate different system states $\boldsymbol{V}se_j(t)$, $\boldsymbol{\delta}se_j(t)$.
5) The system states calculated using the SE algorithm are contrasted against the actual values calculated by using the true values model shown in 1 to calculate the SE error at every minute as follows:

$$error_j(t) = \frac{|\boldsymbol{v}_{se-mn,j}(t) - \boldsymbol{v}_{mn,j}(t)|}{|\boldsymbol{v}_{se-mn,j}(t)|} \cdot 100, \tag{11}$$

where $\boldsymbol{v}_{se-mn,j}(t)$ is the value of $\boldsymbol{V}se_j(t)\angle\boldsymbol{\delta}se_j(t)$ averaged over all the buses at time t. Similarly, $\boldsymbol{v}_{mn,j}(t)$ is the average value of $\boldsymbol{V}_j(t)\angle\boldsymbol{\delta}_j(t)$. By calculating the SE error for every minute, the error profile for a scenario j is determined.

The steps 2-5 comprise one MC simulation. The error profile generated at each simulation (out of M simulations) is kept in the following matrix:

$$\boldsymbol{Er} = \begin{bmatrix} error_1(1) & \cdots & error_1(1440) \\ \vdots & & \\ error_M(1) & \cdots & error_M(1440) \end{bmatrix}. \tag{12}$$

6) The 99th percentile error $er(t)$ at every minute is calculated from ***Er*** to eliminate extreme values and get the error profile $\boldsymbol{er} = [er(1), \cdots, er(1440)]$.
7) Steps 2-6 are done consecutively for each value in ***range*** (by updating k) to generate error profiles at each time interval. These error profiles can be compared to observe the effect of increasing time intervals.

The performance assessment methodology is shown in Fig. 2.

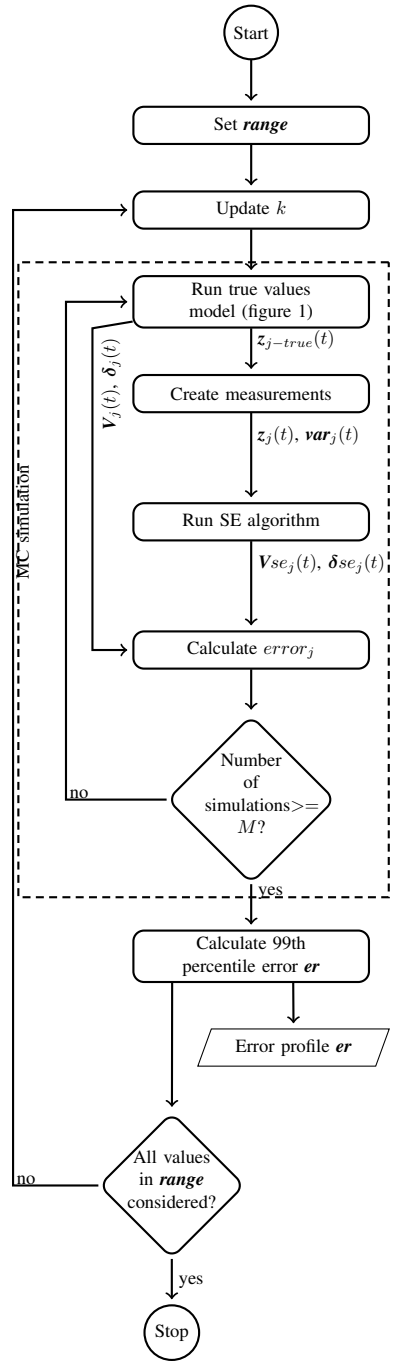

Fig. 2. Performance assessment methodology

IV. Algorithm to determine Measurement Configuration

Higher stochasticity in the measurement parameters would mean frequent triggering of the SE algorithm to satisfy the error requirement. This indicates a considerable computational burden in order to keep the SE error below a chosen limit at every minute of the day. To reduce the computational capacity needed to monitor the system, the proposed algorithm determines a dynamic measurement interval scheme as a part of the measurement configuration to ensure that higher computational capacity can be dynamically allocated for the time duration with higher stochasticity and less capacity can be allocated for the time duration with lower stochasticity in the measurement parameters. This way, the proposed algorithm aims to maintain the SE error below a required threshold at every minute of the day. The algorithm first determines the meter placement locations in the grid and then determines the dynamic intervals at which the measurements need to be taken such that the error requirement is satisfied for every minute.

A. Meter placement locations

The MV buses that have more than two adjacent buses connected are selected for meter placement because they influence more buses. Then, in accordance with the practical application of DSO Stedin, every 4th MV bus, excluding the MV buses where meters already exist, is chosen as a basic meter location scheme. Five real measurements are taken from each metered MV bus, i.e. magnitudes of the bus voltages, incoming active power flow and reactive power flow, outgoing active power flow and reactive power flow. In order to achieve full observability, additional low-cost meters are placed at the LV bus connected through an MV/LV transformer to every second MV bus in the MV network. Three real measurements are obtained from each of these buses, which are bus voltage magnitudes and the outgoing active power flows and reactive power flows from the LV bus towards the MV/LV transformer. Apart from this, fully accurate virtual measurements can be used for the MV buses to which the metered LV buses are connected, since those MV buses have zero power injection values. So, for every 4 MV buses, there is a metered LV bus and virtual measurements at the corresponding MV bus. This provides 10 measurements for every 5 buses at every minute, which are, 5 real measurements from one MV bus, 3 real measurements from one LV bus and 2 virtual measurements from one MV bus. Hence this placement scheme ensures the minimum of $2{\cdot}n$ measurements for every n buses in the grid, which is a necessary condition for system observability. An example of this placement scheme is illustrated in the Fig. 3.

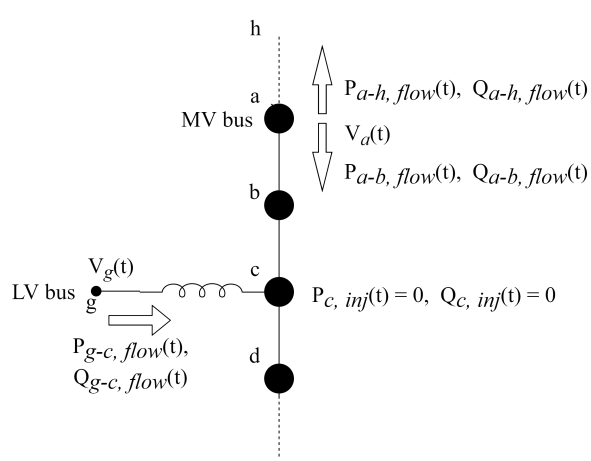

Fig. 3. Meter placement scheme

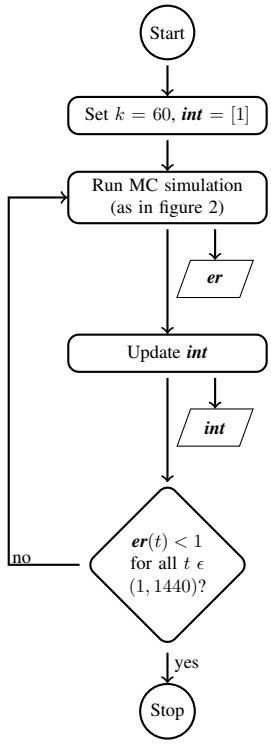

Fig. 4. Measurement Configuration

The following steps explain the iterative calculation of dynamic measurement intervals using MC simulations that ensures every minute satisfaction of the error requirements:

1) The first iteration starts with the measurement intervals of 1-hour ($k = 60$). The array of measurement instants (in minutes) is created with initial values every 60th minute, ***int*** $= [1, 61, \cdots, 1381]$.
2) An MC simulation is performed as in section III to obtain the 99th percentile error profile **er** for the 60-minute measurement intervals. The measurement vector $\boldsymbol{z}_j(t)$ here represents the real measurements $\boldsymbol{V}_{meas-j}(t)$, $\boldsymbol{P}_{meas-j,flow}(t)$ and $\boldsymbol{Q}_{meas-j,flow}(t)$ at the metered buses and virtual measurements $\boldsymbol{P}_{meas-j,inj}(t)$ and $\boldsymbol{Q}_{meas-j,inj}(t)$ at buses with no loads, for every minute.
3) In each hour, ***int*** is updated with the time instants t when the ***er***$(t) > 1$ (the error threshold chosen in this paper is 1%). By comparing the error profile to the threshold for every hour, the algorithm is able to produce dynamic measurement intervals. The density of the resulting measurements varies according to the amount of stochasticity of the measurement parameters throughout the day, which can be observed in section V.
4) Steps 2 and 3 are repeated until ***er***$(t) < 1$ for every minute $t \epsilon (1, 1440)$. This ensures that the error requirements are satisfied for every minute.

The proposed algorithm for determining the measurement scheme is shown in Fig. 4.

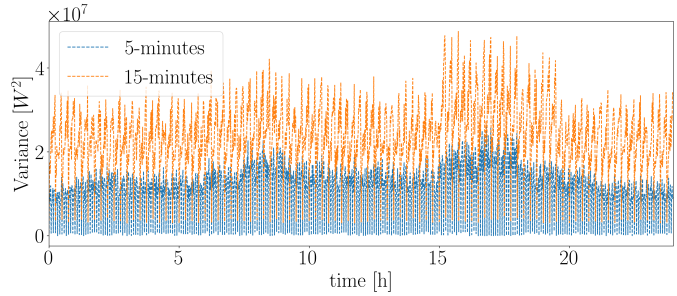

Fig. 5. The variance profiles for 5-minute and 15-minute measurement intervals

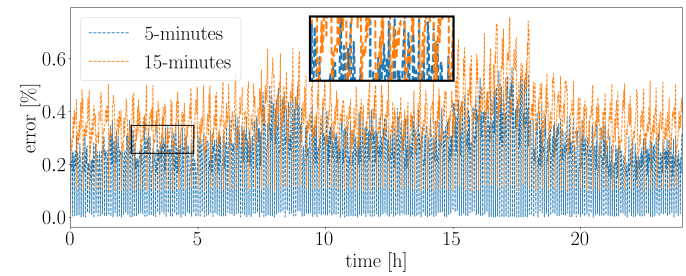

Fig. 6. Error profiles for 5-minute and 15-minute measurement intervals

V. Results

A. Performance Assessment

After running the performance assessment described in section III for measurement intervals of every 5-minutes and every 15-minutes, the resulting measurement variance profiles and their corresponding SE error profiles are shown in Fig. 5. Note from Fig. 6 that the error increases when the number of minutes past the previous time of measurement also increases. The inset magnified image of the error profiles in Fig. 6 shows the decrease in error at the measured intervals for both cases. This shows the dependence of the SE error on the measurement variance, since the measurement variance increases as the number of minutes since the previous time of measurement increases, which can be seen in the Fig. 5. Thus, the error values are higher for the 15-minute measurement intervals than for the 5-minute intervals.

At the time of measurement the variance values are not higher for 15-minute interval profile because the measurement variances only depend on the meter accuracy, which are the same in both cases. The resulting error profiles evidence that higher error values would be obtained when an increase of the measurement interval occurs. Note also that the error values (at the time of measurement) have comparable magnitude for both 5-minute and 15-minute intervals.

B. Measurement configuration

Fig. 7 shows the number of measurements required for each hour of the day in order to satisfy the SE error requirements at every minute of the day. The number of measurements required varies for every hour throughout the day. A relatively higher number of measurements are required during the morning and evening hours which coincide with the hours of higher stochasticity in the network loads.

Fig. 8 illustrates the percentage error with the 1-minute resolution profile, obtained with the new measurement configuration. This includes the meter locations and the updated measurement intervals determined by the proposed algorithm in section IV. It is shown that the new error profile will not be above assumed threshold of 1%. It is worth recalling that the algorithm stops when this target is reached. In this way, the locations of the meter and the dynamic measurement intervals are determined using the proposed algorithm.

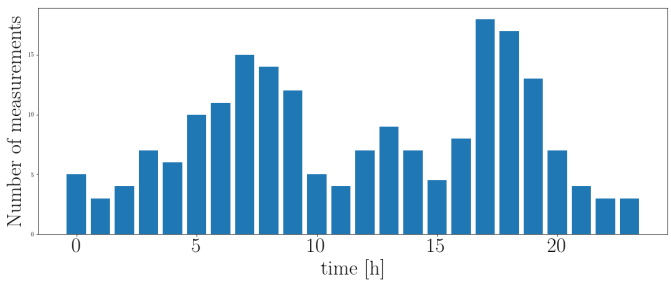

Fig. 7. Measurements' number per hour (obtained when the algorithm ends)

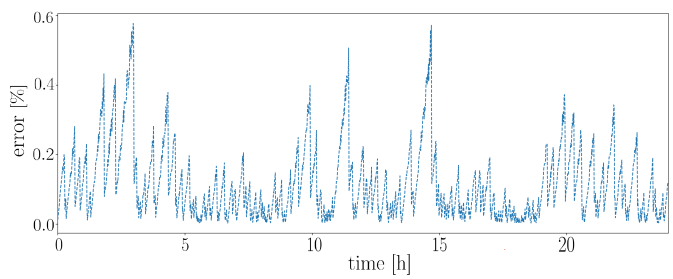

Fig. 8. Error profile ***er*** (obtained when the algorithm ends)

VI. Conclusions

The WLS SE algorithm's performance is evaluated with respect to the measurement intervals. Two measurement intervals were compared to observe the effect of the measurement intervals on the SE error. It is observed that the variance of the measurements increases with the increase of of minutes after previous measurement. Since the SE error depends on the measurement variance, the SE error increases with an increasing number of minutes after previous measurement. This eventually leads to higher error values for the 15-minute measurement interval case, when compared to the 5-minute measurement interval case. In order to satisfy a chosen SE error requirement, a new algorithm is suggested to define the locations for additional meters and the suitable measurement intervals. This reduces the use of pseudo measurements, thereby decreasing the total variance. Numerical results also suggest that the measurement intervals should be dynamically depending on the time of the day, since the stochasticity of the network loading varies throughout the day. The measurement intervals are iteratively determined such that a higher number of measurements are used in hours with highly variable power flow profiles. This is ensured by updating the measurement intervals for every hour, by comparing the error profiles to the chosen error threshold. The results show that the measurement configuration determined by the proposed algorithm satisfies the chosen error requirement at every minute of the day. Future work should assess the effect of different test cases with load profiles characterize by different time correlations.

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