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Approximation of the time alignment error for measurements in electricity grids

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***Abstract*—Measurements of parameters in electricity grids are frequently captured as average values over some time interval. In scenarios of distributed measurements such as in distribution grids, offsets of local clocks can result in misaligned averaging intervals. This paper investigates the properties of the so-called time alignment error of such measurands that is caused by shifts of the averaging interval. We extend a previously derived Markov-modulated model and provide an approximation of the variance of the time alignment error. The model accounts for slow-decaying correlation structure found in actual traces of electrical measures. We compare results of three electrical measures for 20 traces with numerical results and simulations from the the fitted Markov model.**

***Index Terms*—electrical distribution grids, measurement errors, clock synchronization**

I. Introduction

The use of digital data sources in electricity distribution grids has grown rapidly. Measurement devices such as smart meters and smart inverters at prosumer connection points or measurement devices in junction boxes and secondary substations serve as data sources that provide values of voltages, currents, and power. These measurements are typically averaged over some logging interval of duration T, where T can range from a few seconds to tens of minutes.

Since the measurement devices are geographically distributed, these time intervals may be subject to clock deviations, which present a challenge for applications in energy grids requiring that values collected from different measurement devices averaged over the *same* time interval $[t_i, t_i + T]$ be correlated. An example of such applications is the calculation of electricity losses in part of the grid, and a quantification of the effect of clock deviation can be an important element of the loss calculation. While typical clock deviation errors are in the order of few seconds [2], they can be larger in the case of infrequent clock synchronization or slow and highly variable communication delays on the communication network between master clock and measurement devices. Any offset of the clock at the measurement device will in fact lead to a shifted averaging interval. Another cause of such shifted interval can occur when there is no synchronization of clocks and the start of the averaging interval is determined by a request message from a data concentrator; the offset of the averaging interval is then determined by the selection of the request trigger at the concentrator and by the sum of the one-way communication delays and the required processing times of this request.

This paper extends earlier work [14] where we introduced a Markov-modulated model to study the impact of the timing error generated by the clock offset of the measurement interval, denoted as δ, on the value of the measured average. The model additionally provided an approximation of the standard deviation of the time alignment error, denoted as ϵ. While the previous paper provided a useful framework for analyzing this error, it is limited in capturing the correlation structure of power and voltage traces, which extends over long time periods. To account for this correlation here we introduce an extended model, referred to as MMPP-GapT, along with a new approximation of the standard deviation of ϵ. We carry out a systematic study of the accuracy of the approximation for a large selection of data sets and different measurands (voltage, active power, and reactive power). We compare the approximation to results from the traces and simulation of the fitted Markov model, using an evaluation metric that takes into account the slope of the approximately linear behavior of the standard deviation of ϵ for increasing clock offset δ. Our analysis demonstrates that our approximation is reasonable for characterizing the behavior of ϵ for the measurands considered under varying measurement settings.

The remainder of the paper is organized as follows. Section II provides a brief overview of related work. Section III provides a summary of previous results and the details of the 'MMPP-Gap$T$' model and the associated approximation of the standard deviation of ϵ. In Section IV, we describe the traces we consider, and carry out an analysis of the behavior of the standard deviation of ϵ as a function of the clock offset δ, and lastly introduce an evaluation metric that makes it possible to compare the approximation to simulated and actual traces.

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II. Related Work

The quantification of the impact of measurement errors in different application contexts in general distributed systems has received increasing attention in the last few years. As one example of relevant research, measurement errors at the sensor may propagate through the whole computation chain, see, e.g., [5] for work characterizing such errors and their impact. Specifically in energy grids, recent work has addressed how to handle heterogeneous and noisy measurements in the context of grid estimation [4], [7], [12]. Those papers focus mainly on noise on the measurands and how to include such noise characterization in grid estimation procedures. In contrast to that, this paper addresses the impact of time alignment errors for measurands that are averaged over a time interval.

The impact of timing in access to measurement information in distributed systems has earlier been analyzed in [6] and such analysis put into context of different electricity grid applications in [8], [9] and also in generalized networked control applications [10]. This paper instead focuses on the deviations of a measurand caused by time alignment deviations at the sensor. The authors in [3] present an initial analysis of this aspect of the problem, however, their focus was on an empiric evaluation of the distribution of subsequent samples in a smart meter measurement trace. In contrast, this paper provides a detailed analysis of the time alignment error based trace analysis, simulations, and a stochastic model. Lastly, time series with long-range autocorrelation characteristics are common in many domains and can be successfully modeled by Markov models, see [13] and [11] for examples.

III. Time Alignment Error: MMP-GapT Model

In this paper, we focus on the error introduced to a measurement of an average of an electrical variable, which has the true behavior $m(t)$. The measurement device determines the average value $\hat{m}(T, \delta)$ of $m(t)$ over a time interval $I = [\delta, \delta + T]$. Example scenarios, which are later analyzed are measurements of average voltage, average active power and average reactive power in a low-voltage (LV) electricity grid.

Our goal is to study the error of this measured average value that results from the shift of the measurement interval by some offset δ. Without loss of generality, we position the time interval of interest to start at $t = 0$, see Figure 1. We then define the time averaged value of the measurand starting over a shifted interval with offset δ as:

$$\hat{m}(T, \delta) := 1/T \int_{\delta}^{T+\delta} m(t)dt. \tag{1}$$

The desired true value is achieved for $\delta = 0$, but an offset $\delta > 0$ can be caused by different reasons including non-ideal clock synchronization. In order to analyze the impact of this time alignment offset, we analyze the caused error in the value domain defined as [14]:

$$\epsilon(T, \delta) := \hat{m}(T, 0) - \hat{m}(T, \delta). \tag{2}$$

We call $\epsilon(T, \delta)$ the resulting interval alignment error caused by an interval offset of δ and for an averaging period of duration T.

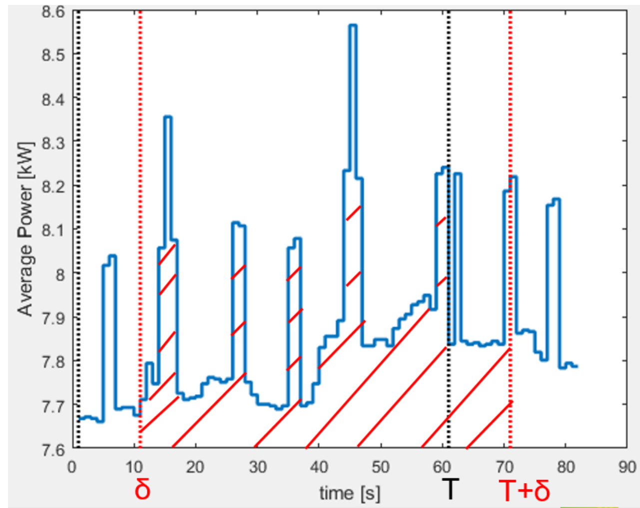

Fig. 1. Illustration of the time alignment error for a measurement of active power (data taken from [14]) that is averaged over a time interval of duration T

A. Summary of previous results

Reference [14] introduced the calculation of the expected value of the time alignment error when the true physical measurand is described by a Markov modulated process with generator matrix $\mathbf{Q}$ and the corresponding values of the measurand are represented in the diagonal of the matrix $\mathbf{E}$:

$$\mathbb{E}[\epsilon(T, \delta)] = \frac{1}{T}\boldsymbol{\pi}(0)\,[\mathbf{I} - \mathbf{G}(\delta)]\,\mathbf{H}(T)\mathbf{E}\boldsymbol{\varepsilon'}. \tag{3}$$

$\boldsymbol{\pi}(0)$ is the initial state distribution of the Markov chain, $\boldsymbol{\varepsilon'}$ is a column vector of adequate dimension with all components equal to 1. The matrix $\mathbf{G}(t)$ contains the state transition probabilities after state t and can be computed as:

$$\mathbf{G}(t) = \exp(-t\mathbf{Q}) = \boldsymbol{\varepsilon'}\boldsymbol{\pi} + \sum_{j'}^{n} e^{-t\lambda_j}\mathbf{v_j'}\,\mathbf{u_j}, \tag{4}$$

where λ_j is a non-zero eigenvalue of $\mathbf{Q}$, and $\mathbf{v_j'}$, $\mathbf{u_j}$ are its right- and left-eigenvectors. The "$'$" with j tells us that the sum excludes the eigenvalue, $\lambda_j = 0$.

$$\mathbf{H}(T) := \int_0^T \mathbf{G}(t)\,dt = \boldsymbol{\varepsilon'}\,\boldsymbol{\pi}T + \sum_{j'}^{n} \frac{1}{\lambda_j}[1 - e^{-T\lambda_j}]\mathbf{v_j'}\,\mathbf{u_j}. \tag{5}$$

Reference [14] further shows that the expected value of the time alignment error in steady-state is 0. It also studies the resulting time alignment error for the measurement of active power at the connection of an office building to the low-voltage grid. The analysis of the time-series of measurements in 1-second intervals shows that the distribution of the time alignment error is approximately normal in certain parameter ranges, see Figure 2 for illustration.

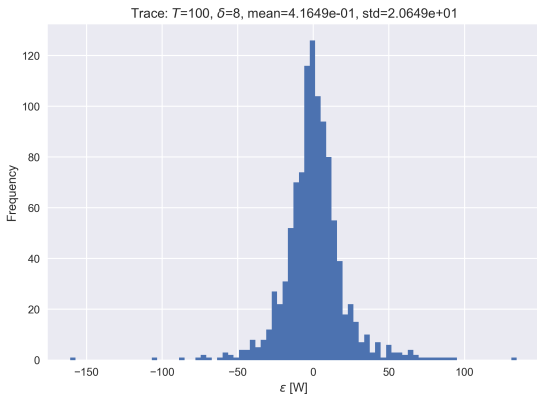

Fig. 2. Empiric distribution of ϵ from [14] for active power at the grid connection of an office building.

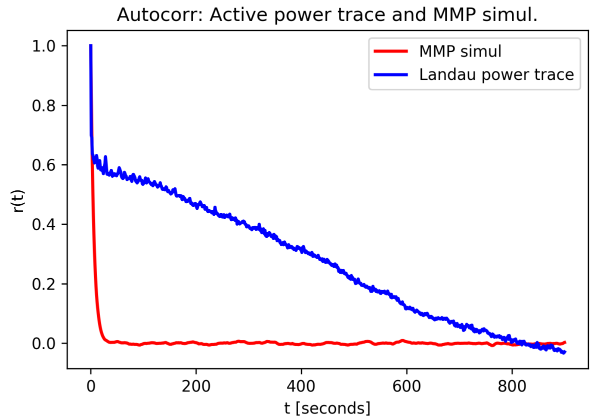

Fig. 3. Autocorrelation function of of an average active power measurement from an office building compared to that from simulation of fitted Markov model derived in [14].

As a normal distribution is characterized by mean and standard deviation, for a quantification of the error, a study of the standard deviation of the error distribution is interesting. Reference [14] provides a first approximation of this standard deviation; however, the presented estimate and already the underlying Markov modulated process has some severe drawbacks when applied to energy related data as explained in the next subsection.

B. Challenge of correlation over minute time scales

The limitation of our earlier model and approximation [14] stems from the fact that they do not account for the correlation structure inherent in electricity traces. This is illustrated in Figure 3, which shows the autocorrelation function of an average active power measurement from an office building introduced in [14]. As the figure shows, the trace is positively correlated over a long time period. This behavior is consistent across the different traces we use in this paper. In contrast, a simulation of the fitted Markov-modulated model produces a correlation structure that quickly decays, also shown in the figure. In order to better characterize the time alignment error, it is important to capture the effect the autocorrelation has on the calculation of the error. Since the latter is dependent on observations that are $T+\delta$ apart, an improved model would need to exhibit correlation at such lags. Further, correlation that is present within the averaging period T does not impact the statistics of time alignment error. This intuition is the basis for the development of the MMPP-GapT model, described next.

C. Approximation by MMP-GapT Model

We now extend the Markov modulated process in order to capture correlation properties of the measurand with time-scales of T. First we rewrite the definition of the time alignment error as follows:

$$\epsilon(T,\delta) = 1/T \left[\int_0^T m(t)dt - \int_\delta^{T+\delta} m(t)dt \right] =$$

$$1/T \left[\int_0^\delta m(t)dt - \int_T^{T+\delta} m(t)dt \right] =: 1/T\,[L-R].$$

Therefore, the time alignment error is actually fully defined by the two intervals of size δ that are marked in the illustration of Figure 1, whose integration provides the values L and R.

The independence of the time alignment error from the behavior of the measurand in the time period $[\delta, T]$ is used to construct an improved model, referred to as MMPP-GapT. The model uses the Markov modulated process from [14] only within the two intervals $[0,\delta]$ and $[T, T+\delta]$. The matrices $\mathbf{Q}$ and $\mathbf{E}$ from the previous model provide the corresponding behavior. An additional matrix $\mathbf{P_{0,T}}$ is provided in addition to represent the state transition behavior between time 0 and time T. The use of this matrix allows to represent correlation of the measurand on these time scales.

The variance of $\epsilon(T,\delta)$ then follows as:

$$Var(\epsilon(T,\delta)) = 1/T^2\,[Var(L) + Var(R) - 2\,COV(L,R)]\,. \tag{6}$$

The easiest approximation for this variance results under the assumption that the Markov chain does not change state during the two intervals of duration δ that contribute the integrated values L and R. Under this assumption, all three summands on the right-hand side in 6 grow linearly with δ. The calculation of $Var(L)$, $Var(R)$ and $COV(L,R)$ follows then straightforward by the definition of the variance and $COV(L,R) = E\,(L-E(L))\cdot(R-E(R))$ from the initial state probability $\boldsymbol{\pi}(0)$, from the values in the diagonal of $\mathbf{E}$, and from the state probabilities at time T, $\boldsymbol{\pi}(0)\cdot\mathbf{P_{0,T}}$. Note that the actual Markov transition rates in $\mathbf{Q}$ are not even used in this approximation.

IV. Accuracy Study

We now investigate the accuracy of the proposed MMP-GapT Model in comparison to the previously proposed MMP model from [14]. The latter reference had shown example results for a single measurement of active power of one-second resolution taken at the grid connection of an office building. We now investigate the new model and the derived approximation of the standard deviation of the time alignment error for different measurands, active power, reactive power, and voltage, for a set of household connections.

A. *Overview of Customer Measurements*

The measurement data we use for the accuracy evaluation of the extended model and its derived approximation formula 6 was taken by the ADRES project [1]. The entire data contains one-second measurements on each phase of the three-phase connections of 30 households in upper Austrian taken during 2011. We use for the analysis the following subset of the data:

- One week of data (604800 samples each) for Phase A of the first 10 household measurements during winter.
- One week of data for the same phase and households during summer.
- Voltage to neutral at that phase, active power at that phase, and reactive power at that phase.

This adds up to 10 households, times 2 seasons, times 3 measurands, so in total 60 sets of one-week measurements.

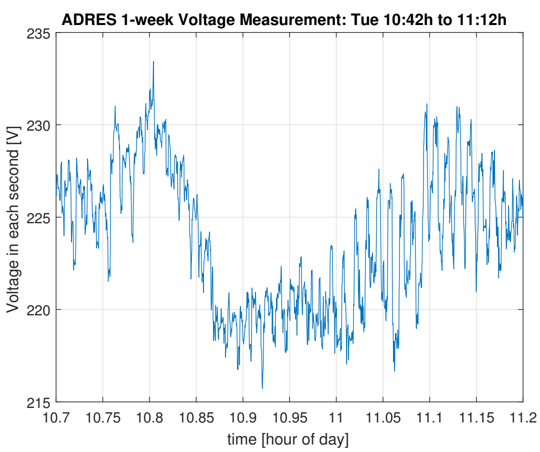

Fig. 4. Example measurements of voltage in one-second intervals (half an hour shown from the one-week trace)

Figure 4 illustrates one voltage trace that is used in the analysis; for better visibility, the figure only shows half an hour from that one-week trace. Figure 5 shows the corresponding empiric distribution of the voltage values of the full one-week trace. The dotted vertical lines mark the boundaries that are used for discretization of the voltage values for the MMP model. The MMP-GapT model uses the same discretization.

B. *Metric for accuracy analysis*

We seek to evaluate the accuracy of the MMP-GapT model and associated approximation, first with respect of an individual trace, and more generally across different traces. In order to mimic averaging intervals that are commonly used by modern smart meter systems, we use an interval duration of $T = 15min = 900s$ in our analysis. In the first case, we consider the behavior of the standard deviation of the time alignment error ϵ as a function of δ in the range 0 to 60 seconds, to cover a sufficient range for the magnitude of the clock deviation that can be expected in practice. Since the measurands are expressed using different units, we normalize the standard deviation by the mean of the trace, yielding a scale-invariant statistic that enables a more meaningful comparison. We call this normalized standard deviation here time-alignment induced relative error. In the second case, the metric for comparison we adopt is based on the relative deviation from the slope of $std(\epsilon)$ of the trace across the same range of δ. More precisely, we use the slope of the line from a linear regression fit as the basis for comparison to the slope resulting from the simulation of the fitted MMP-GapT model and the derived approximation. The slope of the regression line can be argued to be an appropriate metric for two reasons: 1) it suppresses the statistical variability of the measurement and 2) $std(\epsilon)$ grows approximately linearly for the range of δ considered. We next present an evaluation of the accuracy of the MMP-GapT model and approximation based on these metrics.

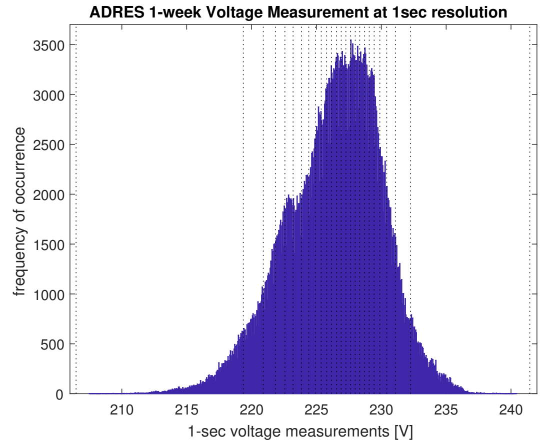

Fig. 5. Histogram of the voltage measurements and visualization of the boundaries for discretization in Markov model.

C. *Result for std(ϵ)*

First we compare the normalized $std(\epsilon)$ metric for different traces to that obtained from the MMP model, MMP-GapT and the approximation presented earlier. Figure 6 shows the result for an active power measurement collected in the summer, while Figure 7 shows the result for a measurement of reactive power collected during the winter. In the first figure, both models and the approximation provide a good match for the result from the trace for $\delta \leq 10$. For $\delta > 10$, the MMP and MMP-GapT models appear to provide a slight overestimate and underestimate of $std(\epsilon)$ of the trace, respectively, while the approximation more closely matches the trace. When looking at the plotted values for a clock deviation of $\delta = 10s$, the standard deviation of the time alignment error is approximately 5% of the measurand and for each additional second of

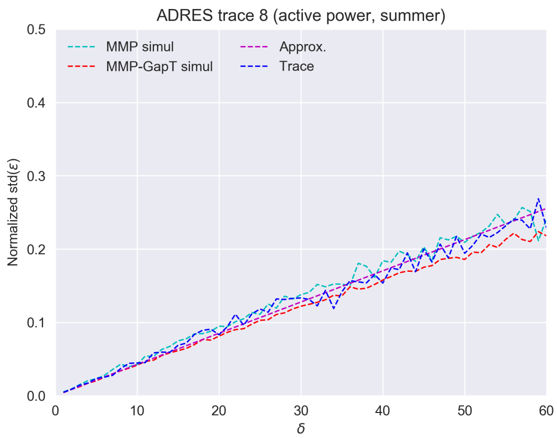

Fig. 6. Comparison of normalized $std(\epsilon)$ for an active power measurement.

misalignment of the averaging interval, an additional 0.40% of relative error of the average active power results.

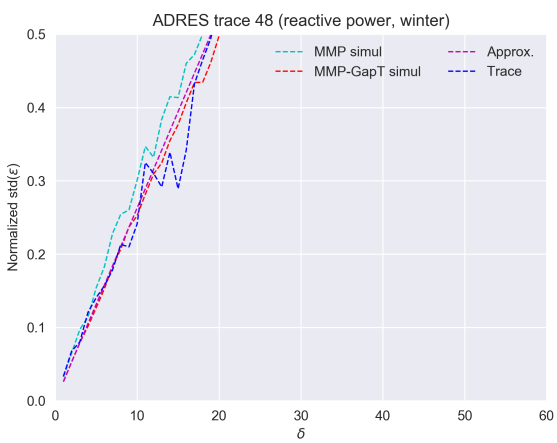

Fig. 7. Comparison of normalized $std(\epsilon)$ for an reactive power measurement.

In Figure 7, a measurement of reactive power for a different household during winter time is shown. The relative error of this reactive power trace grows more rapidly with increasing time offset δ, namely by 2.12% for each additional second of interval misalignment. In this case, the MMP model provides an overestimate, while MMP-GapT and the approximation more closely match the trace. While these figures illustrate that the models and approximation can adequately capture the slope behavior, they do not provide much insight about the magnitude of the slope metric for different measurement periods and measurands. The latter is illustrated in Figure 8, which shows the variability in the slope for 40 traces, aggregated by measurand and measurement period. Each of the bars represents the mean slope for the group, and the interval endpoints correspond to the minimum and maximum slope. As the figure shows, the variability in the measurements of reactive power during the winter is most pronounced among all groupings. Generally, the relative error caused by time alignment is in the range of 0.03% and 2.12% for each second of clock deviation in this set of measurements. A closer examination of the differences between measurands and other factors that contribute to the differences between absolute slope ranges will be the subject of future work.

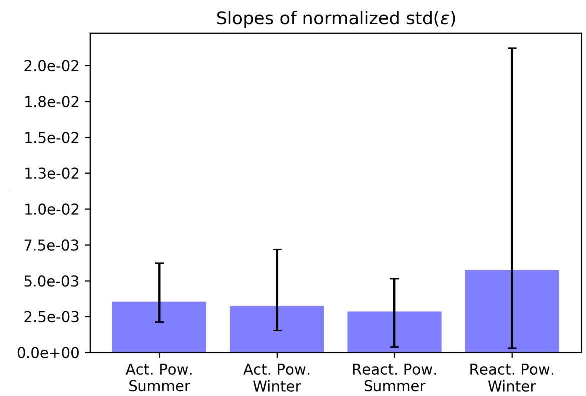

Fig. 8. Slopes of normalized $std(\epsilon)$ for trace groups.

D. Comparison of Model Accuracy

In this subsection we quantify the accuracy of the models and approximation relative to the measurements as expressed in terms of the slope metric described earlier. We aggregate the 60 traces by measurand (active power, reactive power, and voltage) and by season (Summer and winter), producing six groupings. For each grouping, we compute the mean, minimum and maximum relative error for the ten traces in the grouping based on the slope calculation for the same range of δ values considered in the previous figures, namely 1–60 seconds. We carry out this calculation on simulated traces for each of the MMP, MMP-GapT models and the analytic approximation. These results are shown in Figure 9. The solid colored bars represent the mean relative error and the lower and upper endpoints of the lines represent the minimum and maximum deviation, respectively. As can be seen in the figure, with the exception of the active power dataset for the summer, the MMP-GapT model and the approximation provide a significant improvement in relative deviation of the slope metric, both in terms of the mean and maximum. When comparing the MMP-GapT model and the approximation, the latter yields a lower relative error across all traces. For the case of active power during the summer, the MMP model provides a better fit than the MMP-GapT model. This can result for traces with a more rapidly decaying correlation structure, where the MMP-GapT model does not offer an advantage. A closer examination of the correlation structure of the traces can lead to more insights on the limitations of the MMP-GapT model and will be the subject of future work. In summary, these results indicate that the MMP-GapT model and the approximation are reasonably robust and accurate descriptors of the time alignment error under different measurement scenarios and measurands.

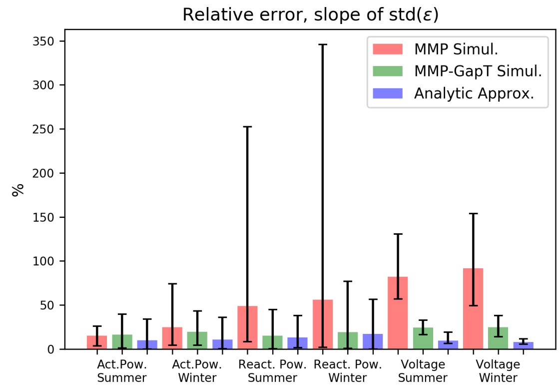

Fig. 9. Comparison of the relative deviation of the slope metric from the actual slope of $\epsilon(\delta)$ obtained from the trace: The bars show the average of the 10 analyzed traces, the marked interval shows min and max of the relative deviation of the slopes.

V. Summary and Outlook

Due to the use of inexpensive measurement devices, the assumption of highly synchronized clocks is not realistic for distribution grid measurements. Such measurements in electrical distribution grids are often average values over some time interval, e.g. in many smart meter systems 15min intervals are used. When jointly processing measurements from different grid locations for an intended averaging interval, the impact of the clock offsets has to be considered in addition to measurement errors. As this time alignment measurement error is depending on the behavior of the measurand, the study of its behavior requires a model of the underlying measurand.

This paper enhanced the Markov modulated model originally proposed in [14] in a way that correlation properties of data over time scales of the duration of the averaging interval are modeled. The enhanced model, MMP-GapT, is then used to derive an approximation of the standard deviation of the time alignment error. The accuracy of the model and the standard deviation approximation is investigated for a set of 60 measurement traces from household connections. The results show that the proposed approximation is practically useful.

Future work will investigate the following directions: (1) investigate how the introduced slope metric (relative error per each second of clock deviation) depends on measurand, measurement season, phases, and other factors in larger sets of measurements. (2) investigate the physical reasons for differences between the electrical measurands with respect to the time alignment error and its slope; (3) analyze how to use the MMP-GapT model and and online calculations of the time alignment error for quantification of total measurement errors in observability applications for distribution grids.

References

[1] Adres-concept: Autonomous decentralised renewable energy systems, https://www.ea.tuwien.ac.at/projects/adres_concept/en/.

[2] European norm 50470: Electricity metering equipment (a.c.), 2006.

[3] A. Alimardani, F. Therrien, D. Atanackovic, J. Jatskevich, and E. Vaahedi. Distribution system state estimation based on nonsynchronized smart meters. *IEEE Transactions on Smart Grids*, 6:2919–2928, 2015.

[4] S. Bhela, V. Kekatos, and S. Veeramachaneni. Enhancing observability in distribution grids using smart meter data. *IEEE Transactions on Smart Grid*, 2016.

[5] T. Brade, S. Zug, and J. Kaiser. Validity-based failure algebra for distributed sensor systems. In *32nd International Symposium on Reliable Distributed Systems (SRDS)*, pages 143–152. IEEE, 2013.

[6] M. Bgsted, R. L. Olsen, and H.-P. Schwefel. Probabilistic models for access strategies to dynamic information elements. *Performance Evaluation*, 67(1):43 – 60, 2010.

[7] J.-C. Chen, H.-M. Chung, C.-K. Wen, W.-T. Li, and J.-H. Teng. State estimation in smart distribution system with low-precision measurements. *IEEE Transactions on Smart Grid*, 5:22713–22723, September 2017.

[8] T. le Fevre Kristensen, R. L. Olsen, H. P. Schwefel, and J. G. Rasmussen. Information access for event-driven smart grid controllers. *Sustainable Energy, Grids and Networks*, 13:78–92, March 2018.

[9] J. Madsen, M. Findrik, T. Madsen, and H.-P. Schwefel. Optimizing data access for wind farm control over hierarchical communication networks. *International Journal of Distributed Sensor Networks*, 12(5), 2016.

[10] R. Olsen, J. T. Madsen, J. G. Rasmussen, and H.-P.Schwefel. On the use of information quality in stochastic networked control systems. *Computer Networks*, 124:157–169, Sept. 2017.

[11] T. Pesch, S. Schrders, H. J. Allelein, and J. F. Hake. A new markov-chain-related statistical approach for modelling synthetic wind power time series. *New Journal of Physics*, 17(5):055001, may 2015.

[12] M. Rans. *Smart grid state estimation and its applications to grid stabilization*. PhD thesis, University of Technology Sydney, 2017.

[13] H.-P. Schwefel, I. Antonios, and L. Lipsky. Understanding the relationship between network traffic correlation and queueing behavior: A review based on the n-burst on/off model. *Performance Evaluation*, 115:68 – 91, 2017.

[14] H.-P. Schwefel, I. Antonios, and L. Lipsky. Impact of time interval alignment on data qualitiy in electricity grids. In *IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm)*. IEEE, 2018.