Smoothing Parameter Optimization Routine for High-Quality a Priori Estimates in Forecasting-Aided State Estimation

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***Abstract*—Forecasting-aided state estimation is a topic of great research interest for future intelligent power grids. Estimators in this class commonly use an exponential smoothing based forecasting model to provide *a priori* estimates of the states. This forecasting capability is advantageous to system operators in taking proper actions. In this work, authors propose a periodical or event-triggered routine to improve the quality of these estimations. This routine uses an efficient optimization scheme to obtain custom smoothing parameters for each of the state variables in the forecasting model. The authors include a case study to demonstrate the high quality of the *a priori* estimates obtained with the proposed method for different forecast horizons.**

***Index Terms*—*A priori* estimates, forecasting-aided state estimation, intelligent power grid, linear exponential smoothing.**

I. Introduction

In the seminal work of Debs and Larson [1], they proposed the very fundamental algorithm for Dynamic State Estimation (DSE). Any serious attempt to model the time behavior of the system state was avoided, assuming a simple dynamic linear model where the parameters are either identity matrices or zeros. Then, at their pioneering work, Schweppe and Masiello [2] introduced another algorithm for tracking the states. It proposes a simultaneous estimation of states and parameters, which failed to identify dynamic patterns properly. Due to the ambiguity of the word "dynamic", this type of estimation is nowadays described by the term Forecasting-aided State Estimation (FASE) [3].

FASE, which can be seen as an estimated state assisted by prediction, has gained significant research interest as the power sector is undergoing a profound change. Though Weighted Least Squares (WLS) SE is a well-established and mature technique for transmission systems and also offers some recent solutions for three-phase unbalanced distribution systems [4], FASE appears to have certain advantages for the operation, control, and protection of future Intelligent Distribution Networks (IDNs). While traditional WLS based algorithms, perform the SE process from a fixed image of the network obtained at each scan of the measurements, FASE includes the effect of past measurements in its estimation. Importantly, FASE allows an *a priori* estimation of the future state of the system for the next time steps, which is particularly useful in broadening the scope of the operators or the Energy Management System (EMS), because some functions, like economic dispatching and security assessment can be performed in advance.

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In FASE, a prediction stage anticipates future values of the state variables assuming a forecasting model of the system. Some parameters of this model need to be identified. The forecasting model used to be tedious, costly and full of uncertainties. A major progress in FASE comes from [5]. This work provides two dynamic state transition models, both capable of following system changes. The dynamic model using Linear Exponential Smoothing (LES) [6] to predict the forecasting model parameters, and consequently, the *a priori* estimates, was found better for forecasting the states. Once *a priori* estimates are available, FASE proceeds with a filtering stage using techniques such as the Iterated Extended Kalman Filter (IEKF), Unscented Kalman Filter (UKF), or Particle Filter. This work, contributes to the improvement of *a priori* estimations, i.e., the prediction stage. Many of the high-impact FASE related research works, such as [3], [7]–[9], have used LES to identify the forecasting model parameters, and thus, LES is also taken as the basis for the present proposal.

In this work, the authors propose and implement an efficient optimization routine to tune up customized parameters for LES in a particular power system. The routine can be executed in either an event-triggered or periodical basis, allowing a desirable adaptation of the forecasting parameters to topological changes or seasonal variations. FASE can benefit from high-quality *a priori* estimates in different ways. Firstly, high-quality *a priori* estimates can be useful for event-triggered Distribution System State Estimation (DSSE) or Multi-Area State Estimation (MASE) techniques, such as [10]. High-quality *a priori* estimates can also be useful for some topology identification algorithms, such as [11]. Moreover, accurate *a priori* estimates reduce the computational effort of the filtering stage, thus improving the efficiency of FASE techniques.

For the benefit of the reader, a traditional formulation of the mathematical model used in FASE [5], is presented in Section II. Section III introduces the proposed optimization method, capable of providing customized exponential smoothing pa-

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rameters for each state variable. In Section IV, a case study is presented to illustrate the benefits of the proposal. Finally, Section V summarizes the most important results of this study.

II. The Mathematical Model

Four parts can be distinguished in FASE: the measurement model, the dynamic forecasting model, the identification of forecasting parameters, and the state filtering process [5]. They are briefly described in this section, with special attention given to the forecasting stage in which this proposal is focused.

A. The Measurement Model

The measurement model is essential for the filtering stage. At an instant of time, k, the measurement vector, $\mathbf{z_k}$, of m actual observations is related with the state vector, $\mathbf{x_k}$, containing n state variables as

$$\mathbf{z_k} = \mathbf{h}(\mathbf{x_k}) + \mathbf{e_k}, \tag{1}$$

where, $\mathbf{h}$ is a vector containing nonlinear functions, based on Ohm's and Kirchhoff's laws, which transforms the state vector space to the theoretical measurement space. The measurement error vector, $\mathbf{e_k}$, contains white Gaussian noise with zero mean and a covariance matrix $\mathbf{R_k}$ for weighing inputs with their estimated precision. Equation (1) is then linearized as described in [5].

B. Dynamic Forecasting Model

It is assumed that the state vector complies with the following dynamic model:

$$\mathbf{x_{k+1}} = \mathbf{F_k}\mathbf{x_k} + \mathbf{G_k} + \mathbf{w_k}, \tag{2}$$

where $\mathbf{F_k}$ is a non-zero $(n \times n)$ diagonal matrix, $\mathbf{G_k}$ is a non-zero $(n \times 1)$ vector and $\mathbf{w_k}$ is white Gaussian noise with zero mean and covariance matrix $\mathbf{Q_k}$.

C. Identification of Forecasting Parameters

In this step, the parameters of the dynamic forecasting model, $\mathbf{F_k}$ and $\mathbf{G_k}$, are derived. The quality of this identification determines the goodness of the states' forecast. LES is traditionally used in FASE for this task. From the taxonomy of exponential smoothing methods [6], which consists of 15 models, those with additive trend and no seasonal component have been widely adopted in FASE implementations. In this work, the Damped Trend Method (DTM) is used, but the proposed methodology can be applied to other models in a straightforward manner. DTM is a damped variant of the popular Holt's method which improves its long-term forecasting features. The equations for the DTM can be formulated for each state variable, i, sample, k, and forecast horizon, h, as,

$$\text{Level:} \quad l_k^i = \alpha^i \hat{x}_k^i + (1-\alpha^i)(l_{k-1}^i + \phi^i b_{k-1}^i), \tag{3}$$

$$\text{Trend:} \quad b_k^i = \beta^i (l_k^i - l_{k-1}^i) + (1-\beta^i)\phi^i b_{k-1}^i, \tag{4}$$

$$\text{Forecast:} \quad \widetilde{x}_{k+h}^i = l_k^i + (\phi^i + {\phi^i}^2 + ... + {\phi^i}^h) b_k^i, \tag{5}$$

where α^i, β^i and ϕ^i are the smoothing parameters and dampen factor, respectively. l_k^i and b_k^i are the level and trend, $\hat{x}_k^i$ is the *a posteriori* estimate and $\widetilde{x}_{k+h}^i$ is the *a priori* estimate. The backcasting method can be used for initialization purposes.

Taking the mathematical expectation of $\mathbf{x_{k+1}}$ in (2) as the forecast value, the *a priori* estimate can be expressed as

$$\mathbf{\widetilde{x}_{k+1}} = \mathbf{F_k}\mathbf{\hat{x}_k} + \mathbf{G_k}. \tag{6}$$

Identifying terms in (6) and (3)–(5) leads to

$$F_k^{ii} = \alpha^i (1 + \phi^i \beta^i)$$
$$G_k^i = (1 + \phi^i \beta^i)(1-\alpha^i)\widetilde{x}_k^i - \phi^i \beta^i l_{k-1}^i + {\phi^i}^2 (1-\beta^i) b_{k-1}^i.$$

D. State Filtering

The objective of the filtering stage is to find an *a posteriori* estimation of the system state. This is done by minimizing together the error between theoretical and actual observations and between filtered and forecast states, for which different techniques have been proposed. State filtering is out of the scope of this contribution, however, it is worth mentioning that IEKF [5] was used in the case study shown in this work.

III. Smoothing Parameter Optimization

Traditional works on FASE with LES use preassigned uniform values as smoothing parameters for the state variables, e.g. $\alpha^{all} = 0.6$, $\beta^{all} = 0.4$ and $\phi^{all} = 0.95$. These figures are selected based on the experience of the user or at most, after some trial and error. In this section, an efficient process for the optimization of these parameters, which provides custom values for each state variable, is proposed.

The load profile of electric networks shows clear seasonality patterns, as is the case of a daily pattern. This fact can be exploited in order to optimize the smoothing parameters of each state variable given a set of daily measurements, so as to obtain improved estimates in the future. The algorithm proposed in this section can be scheduled periodically or executed on an event-triggered basis in order to obtain a better adjustment of the estimates to long-term seasonality patterns, such as monthly pattern, or topology changes.

The accuracy of *a priori* estimates of the state variables should be assessed by comparing them with the "exact" values of that states. Unfortunately, in real applications those "exact" values are unknown, so they have to be compared with *a posteriori* estimates. Different accuracy indicators have been proposed in literature for error minimization [6]. In this work the Root Mean Squared Error (RMSE) is used, which is particularly suitable for exponential smoothing, as proportionally larger weight is put in larger errors. RMSE for a specific state variable, i, can be defined as

$$RMSE^i = \sqrt{\frac{1}{K}\sum_{k=1}^{K}(\widetilde{x}_k^i - \hat{x}_k^i)^2}, \tag{7}$$

where, K is the total number of time steps considered in the calculation.

The optimization problem to be solved can be expressed as the minimization of an aggregate of those $RMSE^i$ values. The search space for this optimization task grows exponentially with the number of state variables, which can make the problem infeasible for medium or large systems. This is caused by the fact that $RMSE^j$ depends not only on α^j, β^j and ϕ^j, but also on the parameters for the rest of the state variables, i.e. α^i, β^i and ϕ^i with $i \neq j$, through their influence in the *a posteriori* estimates. In order to get rid of this difficulty, the present proposal makes use of the low weight of this second factor of influence, which allows a decoupled calculation of the smoothing parameters of each state variable, provided that *a posteriori* estimates are iteratively corrected through an external loop (two or three iterations suffice in most cases). With this solution, which is presented in **Algorithm 1**, the optimization process can be run in a time with a linear dependency on the number of state variables, making it valid for large networks. Particle Swarm Optimization (PSO) is selected in this work as an optimization tool to probe the validity of the proposal due to its straightforward implementation and simple handling of non-linear constraints. In any case, a deterministic procedure could also be employed for the same purpose.

Algorithm 1 Optimization of smoothing parameters

Input: $\mathbf{z_k} \leftarrow$ Grid measurements, daily register.
Output: α^i, β^i, ϕ^i // Customized smoothing parameters

```
Initialization of α^i, β^i, φ^i
while max(|Δα^i|, |Δβ^i|, |Δφ^i|) > ε do
    Calculate a posteriori estimates, x̂_k, using FASE
    for i = 1 to n do // Run through state variables
        // Minimization of RMSE^i using PSO
        Random initialization of particles' speed and position
        for t = 1 to T do // Run through iterations
            for p = 1 to P do // Run through particles
                for k = 1 to K do // Run through time samples
                    Calculate a priori estimates, x̃_k
                end for
                Calculate RMSE^i
            end for
            Update particles' speed and position
        end for
    end for
    Update α^i, β^i, φ^i
end while
return α^i, β^i, φ^i
```

The embedded PSO algorithm [12] solves the following constrained objective function for each of the state variables in a decoupled way,

$$
\begin{aligned}
\text{minimize } \; & RMSE^i = f(\alpha^i, \beta^i, \phi^i) \\
\text{subject to } \; & 1 - 1/\phi^i < \alpha^i < 1 + 1/\phi^i \\
& \phi^i - 1 < \beta^i < (1 + \phi^i)(2/\alpha^i - 1) \\
& 0 < \phi^i \leq 1.
\end{aligned} \tag{8}
$$

The traditional bounds of these parameters, i.e. $0 < \alpha < 1$, $0 < \beta < \alpha$, based on an interpretation as weighted average of past values, has been superseded by a state space approach to LES, in which the limits shown in (8) are based on a stability argument [6]. Solutions out of these bounds are rejected within the PSO algorithm by adding a penalization function.

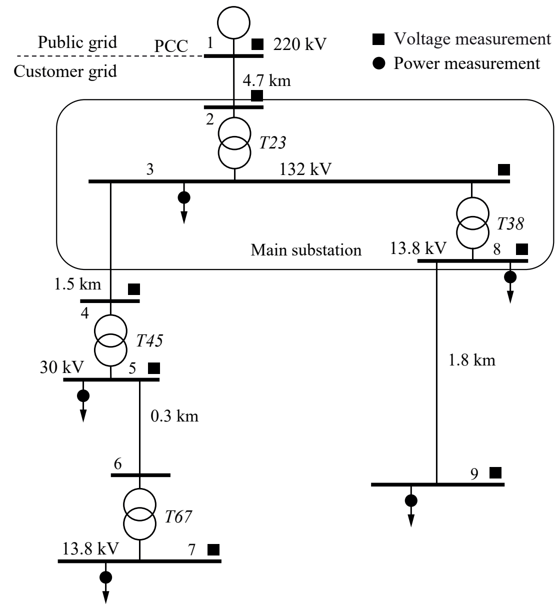

Fig. 1. 9-bus Industrial distribution grid

IV. Case Study

A well-tested industrial power system previously used in [12] has been adopted to demonstrate the usefulness of the proposal. The said system, depicted in Fig. 1, is a 9-bus simplified version of the industrial network of a steel mill in the north of Spain. The specific data of this network, together with the set points of the embedded tapped transformers, have been summarized in Table I. The implementation of the algorithms used in this case study was carried out in the MATLAB programming platform and tested in an Intel Core i5 - 6400M - CPU 2.70 GHz computer.

TABLE I
Parameters and Setup of the Distribution Grid

Lines (z) and transformers (S_n, R_{sc}, X_{sc}, tap)						
Line 12	0.025+0.240i Ω/km	T23	2×270 MVA	0.90%	12.97%	0.98
Line 34	0.161+0.151i Ω/km	T45	3×37.5 MVA	0.90%	8.95%	0.99
Line 56	0.568+0.133i Ω/km	T67	10 MVA	0.95%	4.76%	1.00
Line 89	0.161+0.112i Ω/km	T38	3×50 MVA	0.92%	7.95%	0.98

Loads (P, Q - daily peak values)			
Bus 3	64.0 MW, 56.8 Mvar	Bus 8	42.0 MW, 47.8 Mvar
Bus 5	24.0 MW, 21.9 Mvar	Bus 9	5.0 MW, 4.4 Mvar
Bus 7	7.0 MW, 6.2 Mvar		

A set of measurements, in the minimum number to make the system observable, were taken as true values in order to allow for the calculation of “exact” results for the state of the system. Notice, that this is only done with the aim of validating the accuracy of the proposed *a priori* estimates, i.e., these results are not used during the optimization process. The load profile of a winter day at the different buses of the grid, using quarter-hourly real and reactive power values, is considered. A realistic performance was obtained by making use of the ADRES-CONCEPT database [13]. Table I shows the peak values of these load profiles. The state of the system is obtained from these data using a power flow algorithm [14]. Gaussian noise was added to an augmented set of measurements, which are highlighted in Fig. 1, to obtain corrupted values valid to feed the FASE algorithm is a realistic fashion: 0.1% and 2.0% of the mean of the normal distribution was selected as the standard deviation of voltages and power injections, respectively. Thus, these standard deviations were also used for the error covariance matrix **R** in the FASE algorithm.

By following the method described in Section III, optimum values of α^i, β^i and ϕ^i were calculated for the 17 state variables of the grid. These values are shown in Table II. The good adjustment of these parameters to the optimization data set can be observed in Table III. Here, the $RMSE$ value is calculated for the *a priori* estimates in three different cases: (a) the naïve case, in which the state of every variable is forecast using the value of the preceding state, i.e $\widetilde{x}^i_{k+1} = \hat{x}^i_k$, (b) a case with non-optimized parameters, taken identically for all the state variables, and (c) the proposed improvement, which uses custom optimized parameters. This last case, clearly beats (a) and (b). In Table III, $RMSE$ was calculated considering the error between the *a priori* estimates and the "exact" results, not to let *a posteriori* estimates hide any estimation error.

TABLE II
OPTIMUM α^i, β^i AND ϕ^i FOR STATE FORECASTING ($h = 1$)

Voltage	α^i	β^i	ϕ^i	Phase	α^i	β^i	ϕ^i
V_1	0.003	0.871	0.000	θ_1	–	–	–
V_2	0.567	1.995	0.027	θ_2	1.130	1.099	0.429
V_3	1.183	1.000	0.447	θ_3	1.114	1.151	0.445
V_4	1.184	1.000	0.451	θ_4	1.121	1.131	0.443
V_5	1.228	0.962	0.531	θ_5	1.191	0.989	0.456
V_6	1.233	0.953	0.531	θ_6	1.203	0.959	0.447
V_7	1.305	0.839	0.575	θ_7	1.409	0.123	0.868
V_8	1.357	0.730	0.540	θ_8	0.999	1.406	0.404
V_9	1.361	0.735	0.567	θ_9	1.133	1.035	0.354

TABLE III
$RMSE$ (IN THOUSANDS) FOR A PRIORI ESTIMATES OF STATE VARIABLES APPLIED TO THE OPTIMIZATION DATA SET ($h = 1$)

Voltage	(a)	(b)	(c)	Phase	(a)	(b)	(c)
V_1	0.390	0.369	0.021	θ_1	—	—	—
V_2	0.419	0.434	0.349	θ_2	0.107	0.125	0.087
V_3	1.862	2.293	1.482	θ_3	1.230	1.438	0.986
V_4	1.889	2.325	1.499	θ_4	1.235	1.445	0.993
V_5	3.031	3.739	2.222	θ_5	2.085	2.451	1.641
V_6	3.077	3.791	2.253	θ_6	2.063	2.425	1.636
V_7	4.723	5.880	3.305	θ_7	3.230	3.696	2.680
V_8	3.514	4.427	2.566	θ_8	2.155	2.489	1.799
V_9	3.945	4.962	2.820	θ_9	2.268	2.604	1.941

However, the applicability of the method is not still demonstrated until this point, as the optimization process is based in past values from an *optimization data set*. To probe the real benefit of the proposal, a *test data set* of power injections from a summer day was extracted from the ADRES-CONCEPT database. This set is built with data from the same aggregated loads used in the optimization data set, but corresponding to days from different seasons. The risk of overfitting is avoided due to clearly diverse profiles, as can be seen in Fig. 2, where the measurements for real and reactive power at bus 8 have been depicted for both the optimization and test data sets. The FASE algorithm was run again on this new data for the three cases described above, but using the previously optimized α^i, β^i and ϕ^i values in case (c). Table IV clearly shows that the daily seasonality of the data leads to improved *a priori* estimates also for future values, to an extent that, even when compared with the best alternative method, the average error is reduced over 17%. In order to further illustrate the interest of the proposed method, Fig. 3 shows the daily profile for the voltage at bus 9 and for the phase angle at bus 6. In this figure, the true values of these state variable are depicted together with the *a priori* estimates from cases (a), (b) and (c). The *a posteriori* estimates of the different cases are not shown in the figure for the sake of clarity.

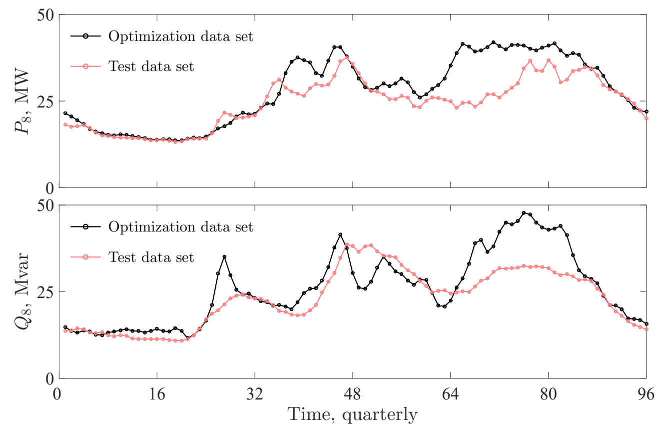

Fig. 2. Daily load profile at bus 8: optimization and test data sets

TABLE IV
$RMSE$ (IN THOUSANDS) FOR A PRIORI ESTIMATES OF STATE VARIABLES APPLIED TO THE TEST DATA SET ($h = 1$)

Voltage	(a)	(b)	(c)	Phase	(a)	(b)	(c)
V_1	0.379	0.358	0.020	θ_1	—	—	—
V_2	0.373	0.354	0.282	θ_2	0.113	0.136	0.101
V_3	1.169	1.261	0.983	θ_3	1.281	1.534	1.135
V_4	1.186	1.281	0.993	θ_4	1.290	1.547	1.143
V_5	1.890	2.141	1.435	θ_5	2.127	2.607	1.833
V_6	1.922	2.182	1.454	θ_6	2.127	2.609	1.839
V_7	2.929	3.424	2.199	θ_7	3.301	4.186	2.916
V_8	1.995	2.085	1.538	θ_8	2.143	2.525	1.973
V_9	2.351	2.464	1.745	θ_9	2.298	2.747	2.081

The method presented in this contribution is not limited to provide *a priori* estimates for the next time step (i.e. $h = 1$). In fact, giving h in (5) a higher value allows to formulate, simultaneously, estimations for a larger horizon. Table V shows the optimized smoothing parameters for $h = 2$ (i.e., two samples ahead) for the present case study, and Table VI and Table VII show the corresponding $RMSE$ values. Though, as expected, the error grows significantly for larger horizons, the usefulness of the optimization proposal is still important. Thus, the average error is reduced over 4% when compared with the best alternative.

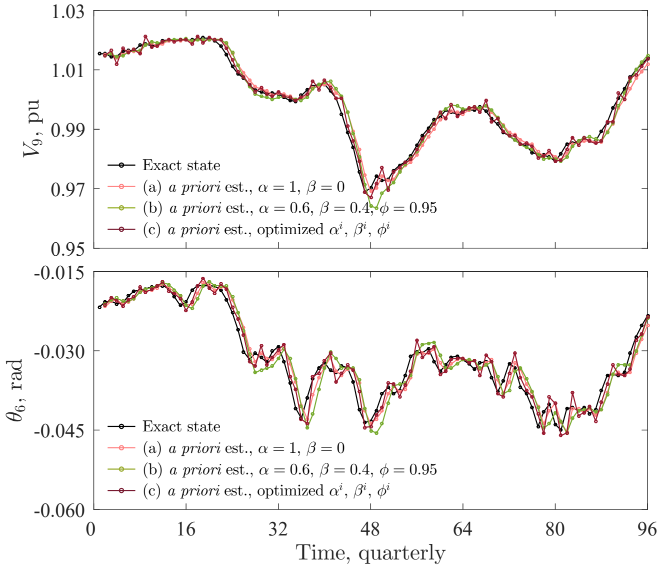

Fig. 3. *A priori* estimates for voltage at bus 9 and phase angle at bus 6. Exact state, (a) naïve case, (b) uniform values, (c) optimized parameters

TABLE V
OPTIMUM α^i, β^i AND ϕ^i FOR STATE FORECASTING ($h = 2$)

Voltage	α^i	β^i	ϕ^i	Phase	α^i	β^i	ϕ^i
V_1	0.002	0.343	0.000	θ_1	–	–	–
V_2	0.485	1.948	0.057	θ_2	1.461	0.156	0.826
V_3	1.343	0.682	0.394	θ_3	1.447	0.187	0.811
V_4	1.342	0.685	0.398	θ_4	1.453	0.179	0.816
V_5	1.392	0.641	0.468	θ_5	1.521	0.147	0.841
V_6	1.392	0.643	0.472	θ_6	1.523	0.138	0.847
V_7	1.441	0.590	0.521	θ_7	1.448	0.116	0.871
V_8	1.540	0.430	0.437	θ_8	1.406	0.137	0.853
V_9	1.536	0.442	0.462	θ_9	1.430	0.102	0.856

V. CONCLUSIONS

This work presents a straightforward method to formulate improved *a priori* estimates in FASE. The proposed methodology uses PSO as a tool to optimize LES parameters. This contribution clearly demonstrates that the use of custom optimized parameters for each of the state variables overcomes the traditional use of uniform parameters in FASE applications. Reductions in the average error of *a priori* estimates for the next time step greater than 17% are achieved in the presented case study. The method shows also an interest in the forecasting of state variables with larger horizons, when non-optimized formulations may become useless. This type of optimization can successfully exploit the seasonality pattern of load profiles on daily basis. The execution time of the proposed optimization method grows linearly with the number of state variables, thus making it suitable to be applied to large grids.

TABLE VI
$RMSE$ (IN THOUSANDS) FOR A PRIORI ESTIMATES OF STATE VARIABLES APPLIED TO THE OPTIMIZATION DATA SET ($h = 2$)

Voltage	(a)	(b)	(c)	Phase	(a)	(b)	(c)
V_1	0.547	0.596	0.389	θ_1	—	—	—
V_2	0.641	0.721	0.607	θ_2	0.186	0.201	0.167
V_3	3.324	3.801	3.030	θ_3	2.155	2.312	1.915
V_4	3.373	3.854	3.070	θ_4	2.161	2.320	1.923
V_5	5.442	6.222	4.822	θ_5	3.644	3.930	3.237
V_6	5.532	6.311	4.895	θ_6	3.597	3.882	3.209
V_7	8.607	9.836	7.479	θ_7	5.664	5.942	5.177
V_8	6.290	7.327	5.645	θ_8	3.678	3.932	3.333
V_9	7.069	8.207	6.298	θ_9	3.790	4.042	3.513

TABLE VII
$RMSE$ (IN THOUSANDS) FOR A PRIORI ESTIMATES OF STATE VARIABLES APPLIED TO THE TEST DATA SET ($h = 2$)

Voltage	(a)	(b)	(c)	Phase	(a)	(b)	(c)
V_1	0.533	0.581	1.211	θ_1	—	—	—
V_2	0.542	0.577	1.185	θ_2	0.188	0.216	0.192
V_3	2.128	2.108	1.954	θ_3	2.146	2.450	2.158
V_4	2.161	2.143	1.976	θ_4	2.158	2.468	2.175
V_5	3.484	3.611	2.957	θ_5	3.551	4.154	3.514
V_6	3.549	3.687	3.004	θ_6	3.543	4.152	3.520
V_7	5.465	5.829	4.563	θ_7	5.599	6.776	5.570
V_8	3.672	3.523	3.079	θ_8	3.611	4.088	3.735
V_9	4.324	4.167	3.592	θ_9	3.864	4.458	4.019

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