Adaptive Probabilistic Forecasting of Electricity (Net-)Load
Supplementary Material

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April 20, 2023

1 Introduction

This document gathers supplementary material to accompany the article "Adaptive Probabilistic Forecasting of Electricity (Net-)Load".

2 Comparison to [1]

We present in Table 1 the results obtained on the GB data set by the method developed in [1].

3 Comparison to a Linear Model

One might wonder what is the interest of adapting a GAM instead of directly adapting a linear model. We compare the GAM Kalman to the linear Kalman on the same covariates. We choose to study the US data set because it considers daily data. Therefore, there is no time of day in the model, whereas the GAM developed for the GB application takes the time of day as input. As it is a crucial variable of very nonlinear impact, it would not be fair to compare our GAM to a linear model. The results displayed in Table 2 show that the dynamic version of the Kalman filter yields good results already in the linear setting; however it is widely outperformed by the adaptation of the GAM by the Kalman filter. That's why we assess that this Kalman adaptation of GAM reaches the right trade-off between learning complex dependence of the load to explanatory variables thanks to nonlinear GAM effects and fast reactivity thanks to the Kalman filter.

4 Computational Complexity

We give in Table 3 computational times obtained on a personal computer (Intel core i5 1.4 GHz, 4 cores) with parallelization on 4 cores.

The online methods are much faster because they do one pass on the data only, while the optimization of the GAM takes longer; in particular the estimation of the incremental offline GAM consists in around 1000 GAM estimations (each day for three years).

	2019		2020		2021	
Forecast	nRMSE	nMAE	nRMSE	nMAE	nRMSE	nMAE
Incremental offline GAM (daily)	0.338	0.307	0.370	0.344	0.377	0.365
Kalman GAM (Dynamic)	**0.324**	**0.292**	**0.328**	**0.301**	**0.332**	**0.307**
Reference [8]: APLF	0.335	0.301	0.365	0.330	0.347	0.325

Table 1: Results obtained by the method introduced in [1] on Great Britain data, compared to our results.

	2020		2021	
Forecast	nRMSE	nMAE	nRMSE	nMAE
GAM KF Static	0.206	0.195	0.204	0.178
GAM KF Dynamic	**0.194**	**0.168**	**0.198**	**0.166**
Linear: KF Static	0.365	0.336	0.379	0.332
Linear: KF Dynamic	0.216	0.197	0.234	0.197

Table 2: Comparison GAM vs linear model for the US data set.

Data set	Offline GAM	Kalman adaptation	Incr. offline GAM	Offline QR	QR OGD	BOA
GB	16 min	14 sec	12 days	6.4 min	3.7 min	17 min
US	0.84 sec	0.15 sec	6.7 min	1.34 sec	6.6 sec	7.5 sec

Table 3: Computational time of the different algorithms.

References

[1] V. Álvarez, S. Mazuelas, and J. A. Lozano, "Probabilistic load forecasting based on adaptive online learning," *IEEE Transactions on Power Systems*, vol. 36, no. 4, pp. 3668–3680, 2021.