Forecasting Uncertainty in Electricity Demand

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ÉCOLE POLYTECHNIQUE FÉDÉRALE DE LAUSANNE

Forecasting uncertainty in electricity demand

- Forecast electricity demand
  - expected value (“point” forecast)
  - distribution
- Requirements
  - ✓ understandable/interpretable
  - ✓ computationally efficient

use Generalized Additive Models

build the prediction intervals directly by estimating the (time-varying) conditional mean and variance

Our general model of electricity demand

$$Y_t = \mu(x_t) + \sigma(x_t)\epsilon_t$$

y_t = the demand at time t
x_t = vector of covariates
ϵ_t = the error at time t

$$\mathbb{E}[Y_t] = \mu(x_t)$$
$$\text{Var}(Y_t) = \sigma^2(x_t)$$

In practice, $\underline{\mu(\cdot)}$ and $\underline{\sigma^2(\cdot)}$ are unknown!
conditional mean — conditional variance

➡ Estimate $\mu(\cdot)$ and $\sigma^2(\cdot)$ from empirical data

❶ Estimating the conditional mean $\mu(\cdot)$

Use Generalized Additive Model (GAM)

$$F(\mu(x_t)) = \sum_{i=1}^{I} f_i(x_t)$$

link function, e.g., identity or logarithm

transfer function

basis functions

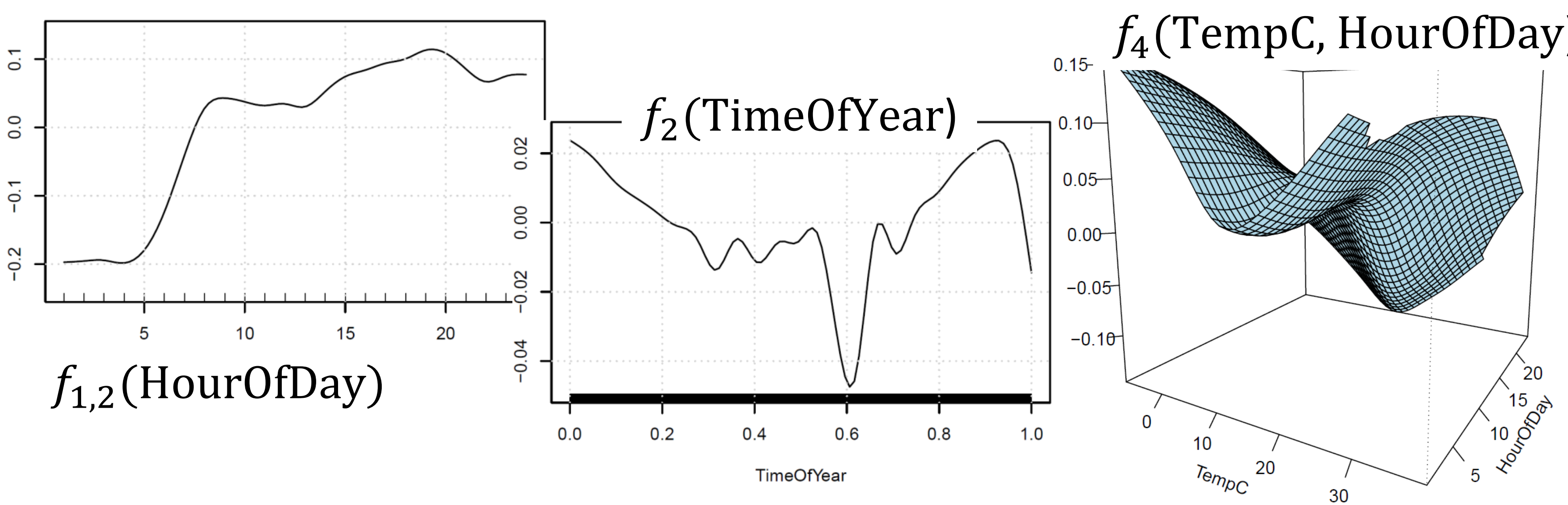
$$f_i(x_t) = \mathbf{1}_{(x_t \in A_i)} \, \beta_i^T \, b_i(x_t)$$

Example:

$$\begin{aligned}\log(\mathbb{E}[Y_t]) = \beta_0 + \beta_1 \mathtt{tmrwDayType}_t + \\ \textstyle\sum_{j=1}^{8} \mathbf{1}_{(\mathtt{DayType}_t = j)} f_{1,j}(\mathtt{HourOfDay}_t) + \\ f_2(\mathtt{TimeOfYear}_t) + f_3(\mathtt{TempC}_t, \mathtt{Humidity}_t) + \\ f_4(\mathtt{TempC}_t, \mathtt{HourOfDay}_t) + f_5(\mathtt{LagNSameDTLoad}_t) + \\ \textstyle\sum_{j=1}^{8} \mathbf{1}_{(\mathtt{DayType}_t = j)} f_{6,j}(\mathtt{LagLoad}_t)\end{aligned}$$

❶ Estimating the conditional mean $\mu(\cdot)$

Fit a GAM to y_t to get an estimate $\hat{\mu}(\cdot)$ of $\mu(\cdot)$



Forecasting the conditional mean $\hat{y}_t = \hat{\mu}(x_t)$

❷ Estimating the conditional variance $\sigma^2(\cdot)$

We use another GAM: $$G(\sigma^2(x_t)) = \sum_{j=1}^{J} g_i(x_t)$$

Let $z_t = \sigma(x_t)\epsilon_t$

$\hat{z}_t = \hat{y}_t - y_t$

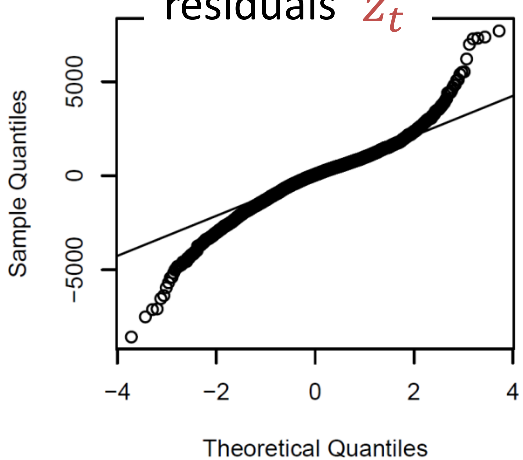
(residuals)

$$Y_t = \mu(x_t) + \sigma(x_t)\epsilon_t$$

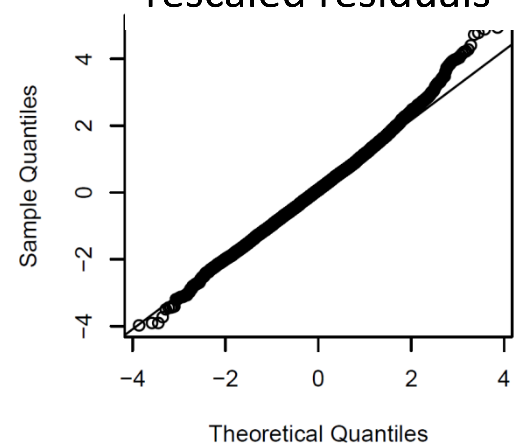
Fit a GAM to $\hat{z}_t^2$ to get an estimate $\hat{\sigma}^2(\cdot)$ of $\sigma^2(\cdot)$

Normal Q-Q Plot

residuals $\hat{z}_t$



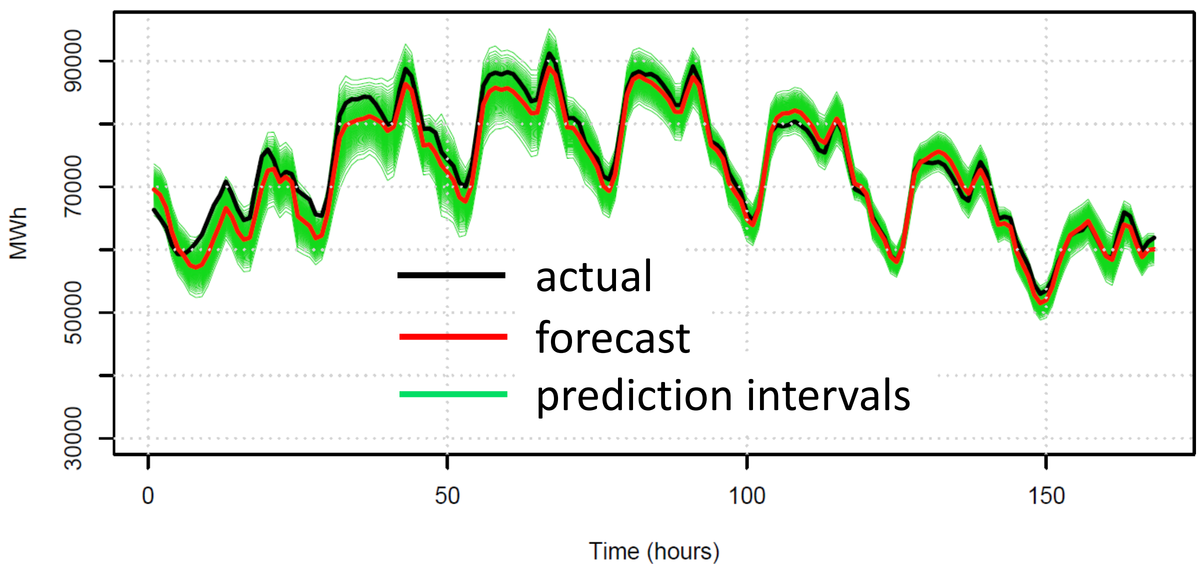
rescaled residuals $\hat{\epsilon}_t = \frac{\hat{z}_t}{\hat{\sigma}(x_t)}$



❸ Computing prediction intervals

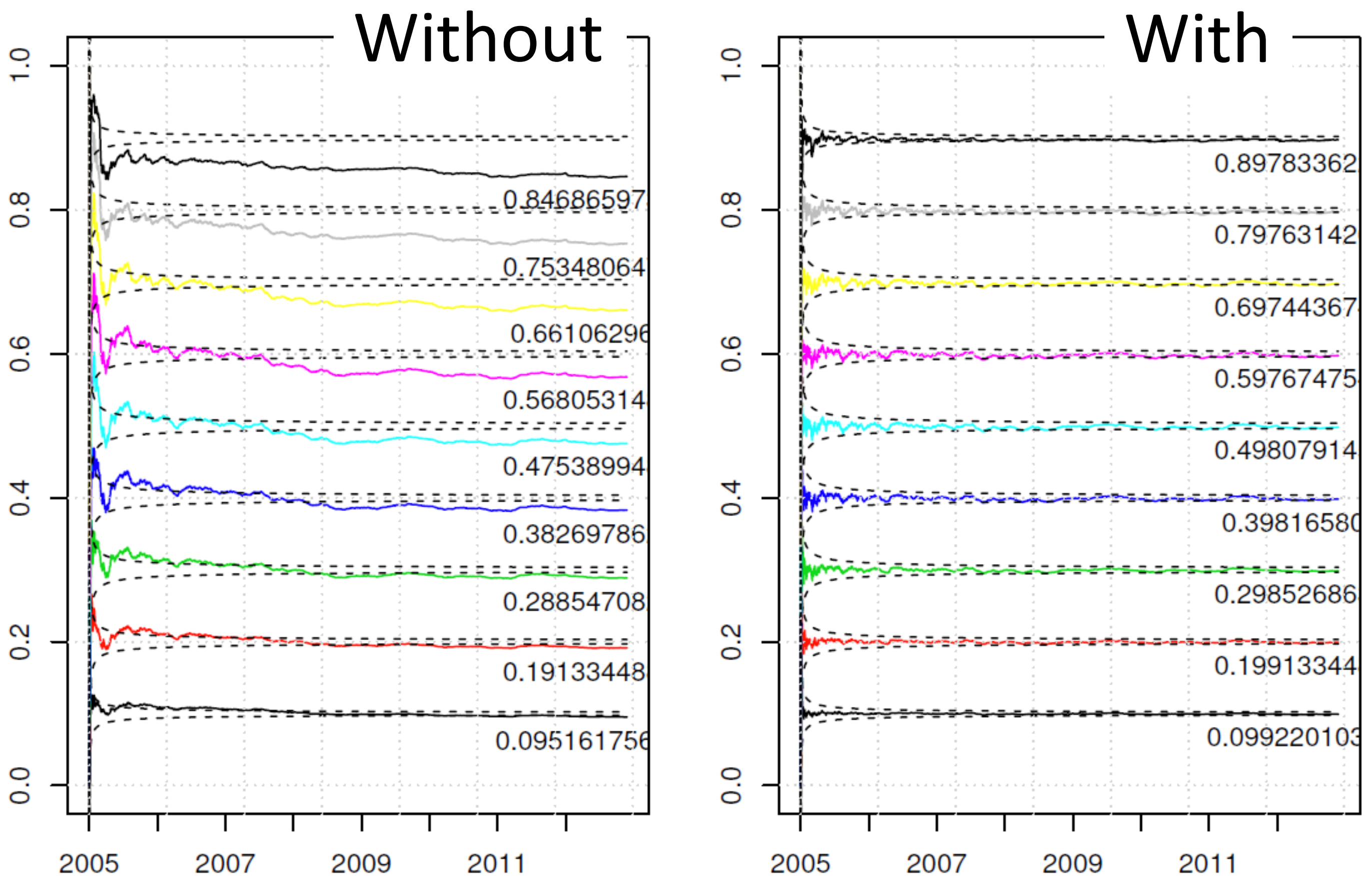
Let $q(\cdot)$ = the quantile function of the standard normal dist.

- Two-sided intervals at the $p \cdot 100$ percentile: $$\phi_t^2(p) = \hat{\mu}(x_t) \pm \left| q\left(\frac{1-p}{2}\right) \right| \cdot \hat{\sigma}(x_t)$$
- One-sided intervals at the $p \cdot 100$ percentile: $$\phi_t^1(p) = \hat{\mu}(x_t) + q(p) \cdot \hat{\sigma}(x_t)$$



❹ Online learning

- Adaptive learning for smoothing functions (Ba et al. 2012)
- Adaptive constructions of prediction intervals



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