NEURAL NETWORK MIDDLE-TERM PROBABILISTIC FORECASTING OF DAILY POWER CONSUMPTION

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Summary

1. A new modelling approach for power consumption forecasting (recurrent NN). We call it NAX.
2. An application to the gefcom 2017 small data-set. Point and density forecasting.
3. A comparison between *ex post* and *ex ante* forecasting.

Literature review

1. The main successes of NN have been obtained on big data-set (see e.g. LeCun et al., 2015, and references therein).
2. Ormoneit and Neuneier (1996) apply to financial time series NN with distributional parameters as output (mixture of Gaussian). Vossen et al. (2018) use a NN to forecast the parameter of the (Gaussian) distrubtion of power consumption.
3. Hyndman and Fan (2010) introduced the idea of *ex post* and *ex ante* forecasting.

The Dataset

Gefcom 2017 dataset on New England power consumption. Daily consumption and daily average temperatures (dry and wet bulb).

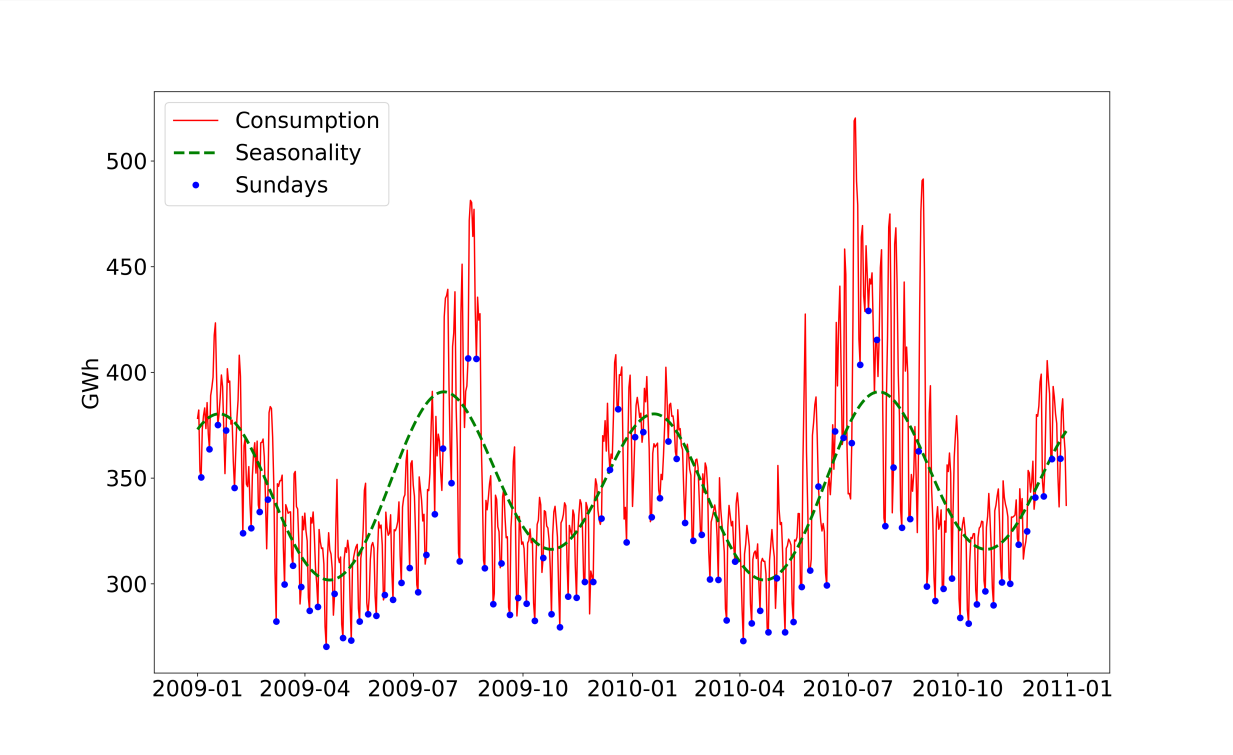

Figure: Cumulated power consumption in New England between January 2009 and December 2010 with the fitted seasonal behaviour.

Model structure

We model the logarithm of the power consumption

$$Y_t = T_t + S_t + R_t \quad , \tag{1}$$

where

$$\begin{cases} T_t & = \beta_0 + \beta_1 t \\ S_t & = \sum_{k=1}^{2} \left[\beta_{1+k} \sin\left(k\omega t\right) + \beta_{2+k} \cos\left(k\omega t\right)\right] \\ & \quad + \beta_6 D_{Sat}(t) + \beta_7 D_{Sun}(t) + \beta_8 D_{Hol}(t) \end{cases} .$$

Model structure

We model the residuals R_t with a simple NN with just one hidden layer and a feedback from the output to the input.
The NN has a two dimensional output the mean μ_t and variance σ_t^2 of the residual R_t. We train the NN using a Gaussian likelihood

$$L(\mu_t, \sigma_t | R_t) = \frac{1}{\sqrt{2\pi\sigma_t^2}} \exp - \frac{(R_t - \mu_t)^2}{2\sigma_t^2} \quad .$$

Model structure

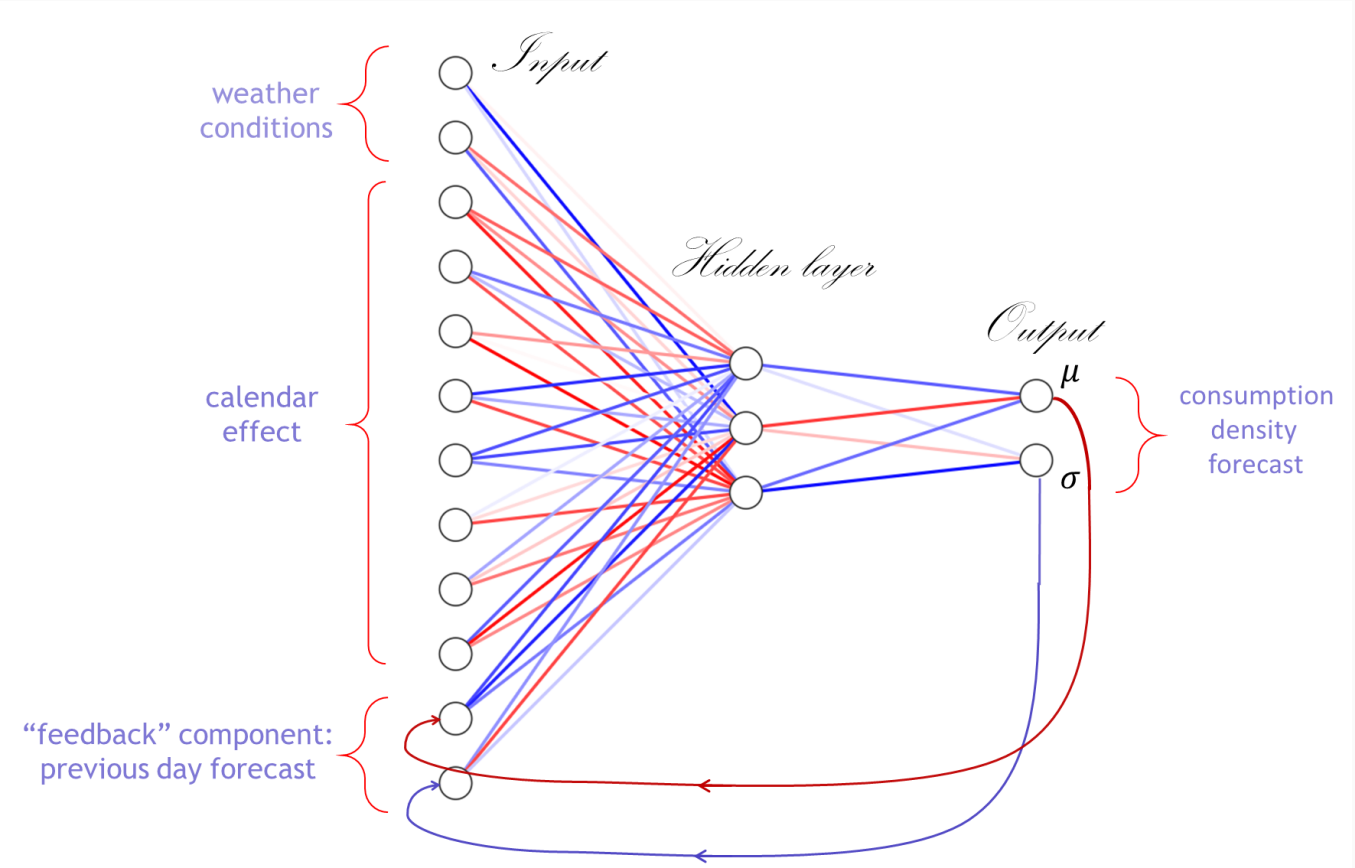

Figure: NAX model selected in the validation procedure.

Data-set segmentation

1. We train on a grid of NN hyperparameters (including the lenght of the training set) and validate on 2011.
2. We train the selected model on the year before 2012 and test on 2012.

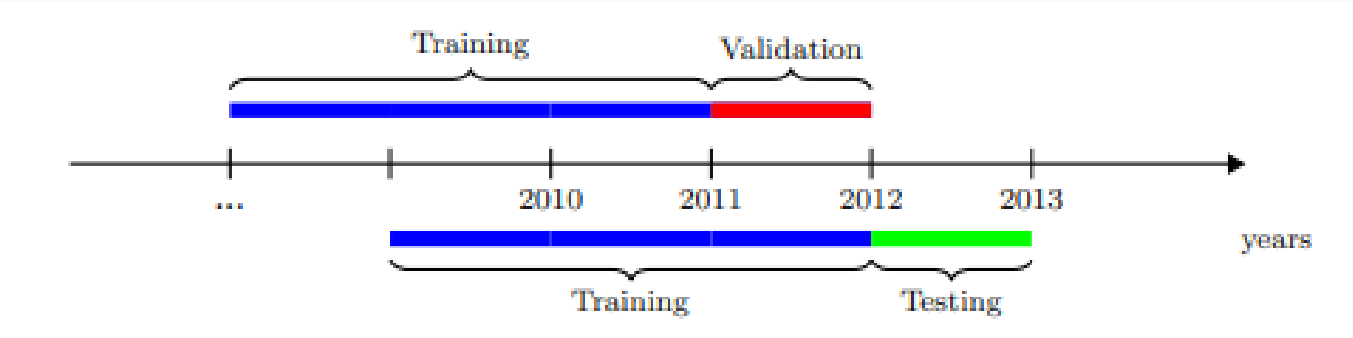

Figure: Data-set segmentation sketch.

Ex post prediction

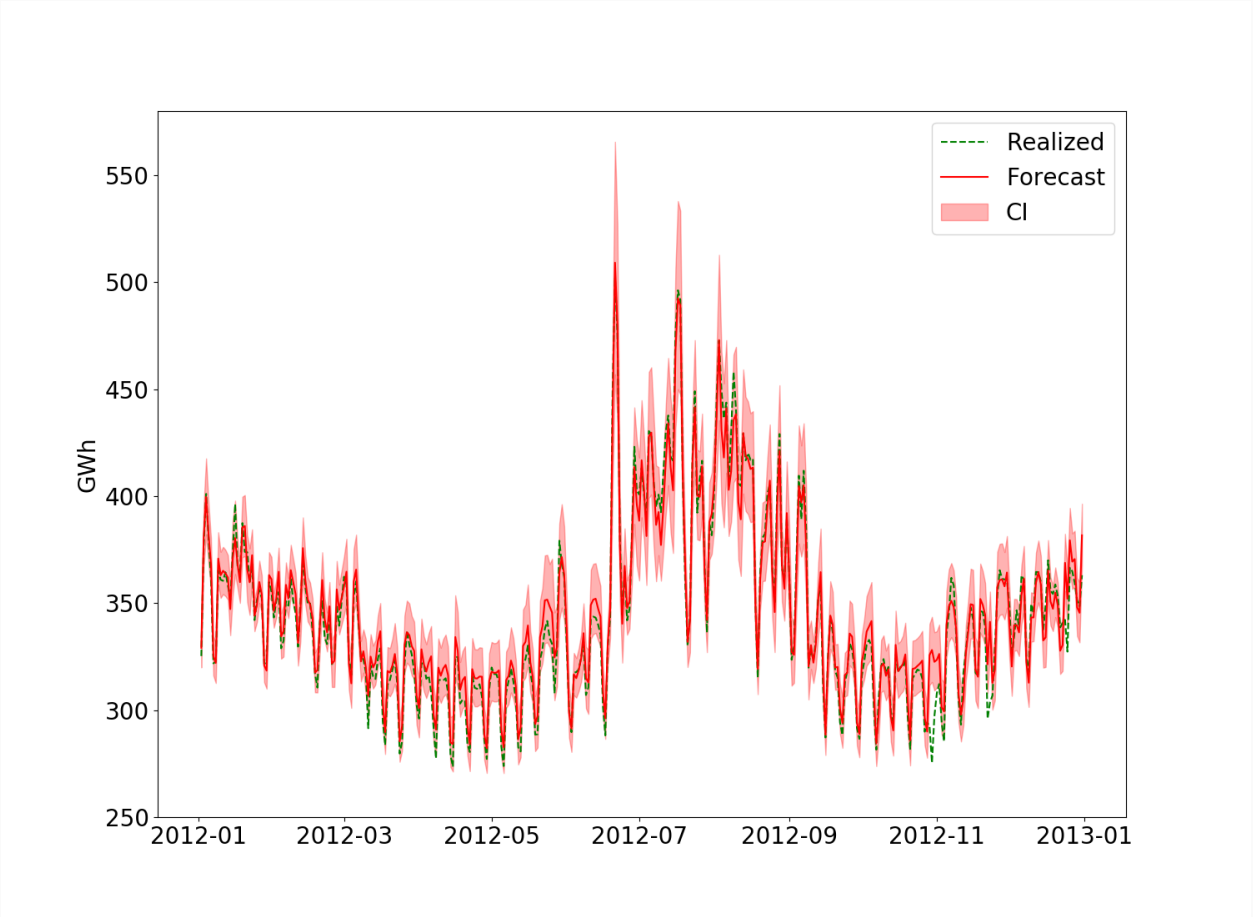

Figure: NAX power consumption middle-term density prediction. *Ex post* prediction use realized temperature data.

Ex post prediction

We compare the NAX performances with the ones of a General Linear Model (GLM) an ARX model and the gaussian process (GPX) of Baviera and Messuti, 2019.

	GLM	ARX	GPX	**NAX**
RMSE [GWh]	26.69	26.13	10.74	**8.10**
MAPE (%)	6.00	5.80	2.50	**1.74**
APL [GWh]	7.43	7.24	3.04	**2.15**

Table: RMSE MAPE and APL (a measure of the density forecasting error) for the four models considered on the test set (2012).

Ex ante prediction

We simulate temperatures on the testing set (Hyndman and Fan, 2010).

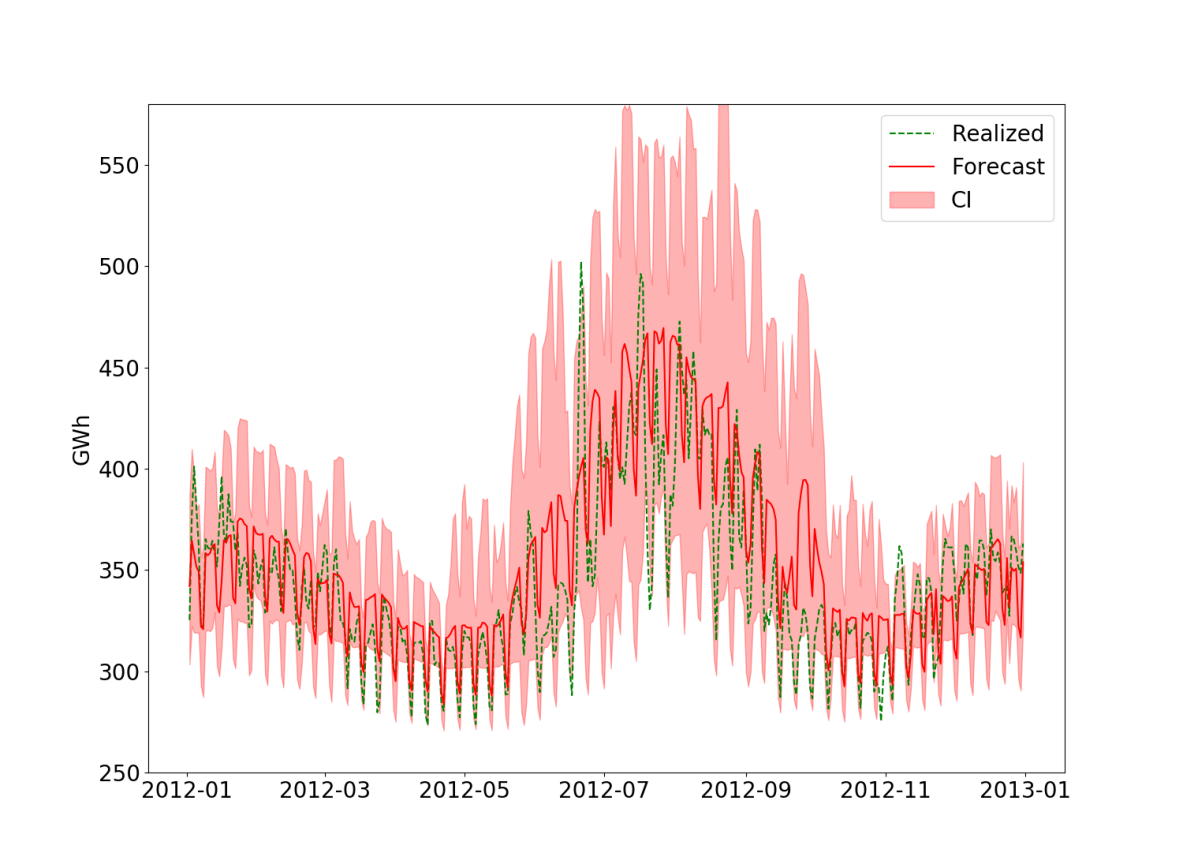

Figure: NAX power consumption ex-ante middle-term density prediction.

Conclusion

1. New NN architecture for power consumption forecasting.
2. Excellent results on Gefcom2017 (application to small dataset) both point and density *ex post* forecasting.
3. Good results in terms of *ex ante* density forecasting (simulated testing year temperatures).

References I

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- LeCun, Yann, Yoshua Bengio, and Geoffrey Hinton (2015). "Deep learning". In: *Nature* 521.7553, pp. 436–444.
- Ormoneit, Dirk and Ralph Neuneier (1996). "Experiments in predicting the German stock index DAX with density estimating neural networks". In: *IEEE/IAFE 1996 Conference on Computational Intelligence for Financial Engineering (CIFEr)*. IEEE, pp. 66–71.

References II

Vossen, Julian, Baptiste Feron, and Antonello Monti (2018). "Probabilistic forecasting of household electrical load using artificial neural networks". In: *2018 IEEE International Conference on Probabilistic Methods Applied to Power Systems (PMAPS)*, pp. 1–6.