

# Long-term forecasting of daily electricity consumption for individual meters

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## Introduction

With the increasing use of smart meters there is a huge potential to increase awareness among residential electricity consumers on how they are using electricity. To do this, models which can handle the huge diversity in electricity consumption observed in residences [1] are needed. For this we have applied a Recursive Least squares (RLS) scheme with forgetting, and model selection tools to chose exogenous variables. This scheme is now used in the mobile app Watts, which now has over 24.000 user.

## Data

- ▶ The output data consists of hourly electricity purchase aggregated to daily values Figure (1).
- ▶ Input data consists of:
  - ▶ The length of the night, calculated from household location.
  - ▶ Average ambient temperature of the day.
    - ▶ Temperature difference for fixed indoor temperature (22°C).
    - ▶ Low pass filtered temperature difference [2].

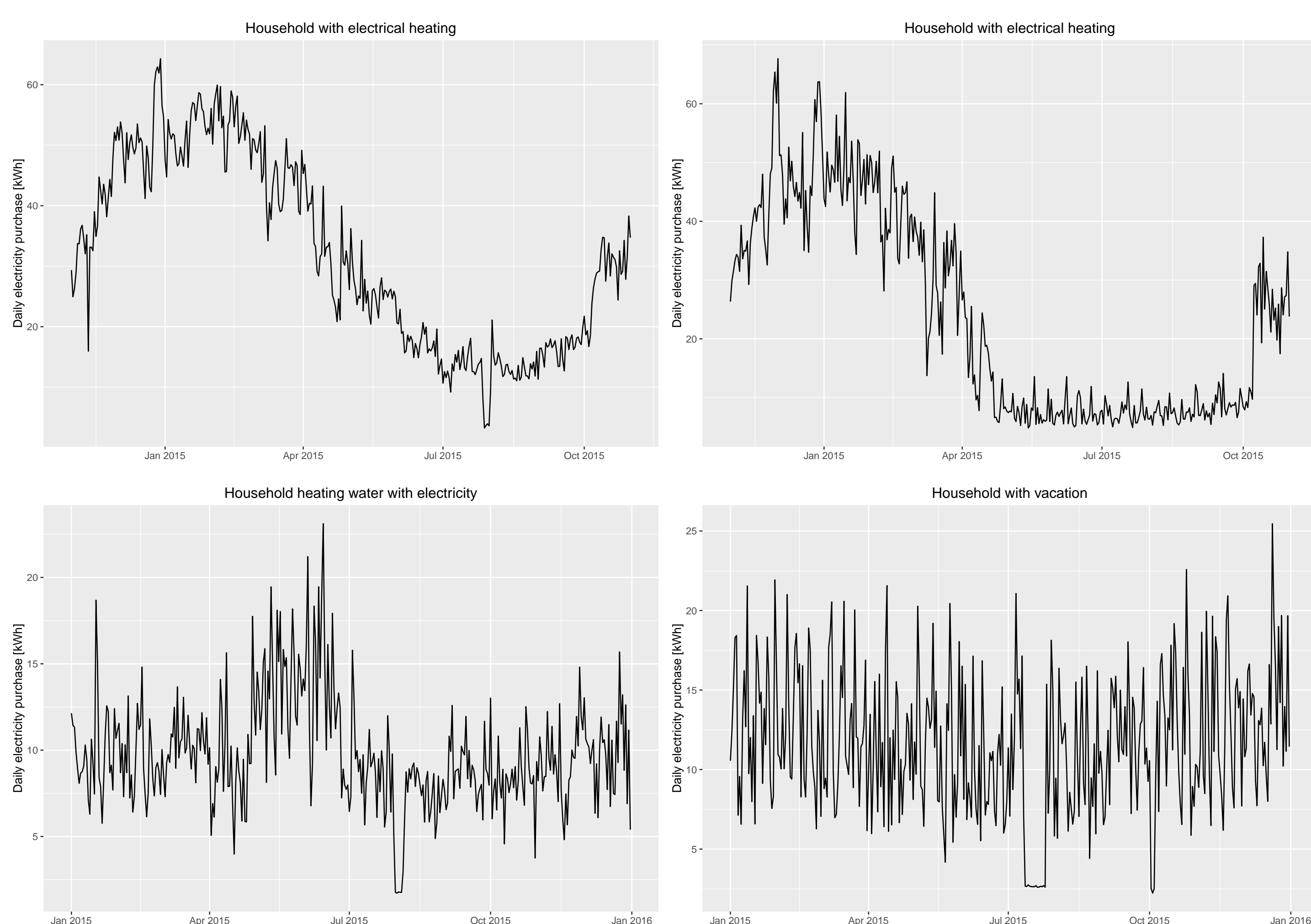


Figure 1 : Examples of electricity use time-series

## Methods, Recursive Least Squares

RLS with forgetting is a parametric model where the implementation is based on [3]. To briefly give an idea of the RLS algorithm it is shown for horizon  $k$  below:

Update step:

$$\mathbf{R}_t = \lambda \mathbf{R}_{t-1} + \mathbf{X}_t \mathbf{X}_t^T$$

$$\hat{\boldsymbol{\theta}}_t = \hat{\boldsymbol{\theta}}_{t-1} + \mathbf{R}_t^{-1} \mathbf{X}_t (Y_t - \mathbf{X}_t^T \hat{\boldsymbol{\theta}}_{t-1})$$

Prediction step

$$Y_{t+k} = \mathbf{X}_{t+k}^T \hat{\boldsymbol{\theta}}_t$$

Here  $\hat{\boldsymbol{\theta}}_t$  is the parameter vector  $Y_t$  is the observation at time  $t$  and  $\mathbf{X}_t$  is the vector of variables at time  $t$ ,  $\mathbf{R}_t$  is the inverse sample covariance matrix and  $\lambda$  is the forgetting factor. One model for each horizon  $k$  is fitted, hence for a quarterly forecast we need 92 models.

## Methods, Model Selection

For the input data forward selection is used to determine which of these should enter the model for all horizons.

To describe the weekly variation we use Fourier series where the number of sin- cosine pairs are determined by optimization over RMSE. This is done for each horizon.

In this setting the forgetting factor  $\lambda$  is fixed for all horizons.

## Results

For 23.000 households we made daily forecast on quarterly basis for one year (Figure 2) and determined the relative error from the cumulated purchase for each quarter.

In this setting positive relative error means overestimation of cumulated purchase.

Based on prior knowledge of these households and the knowledge of the exogenous variables which entered the models the errors where investigated.

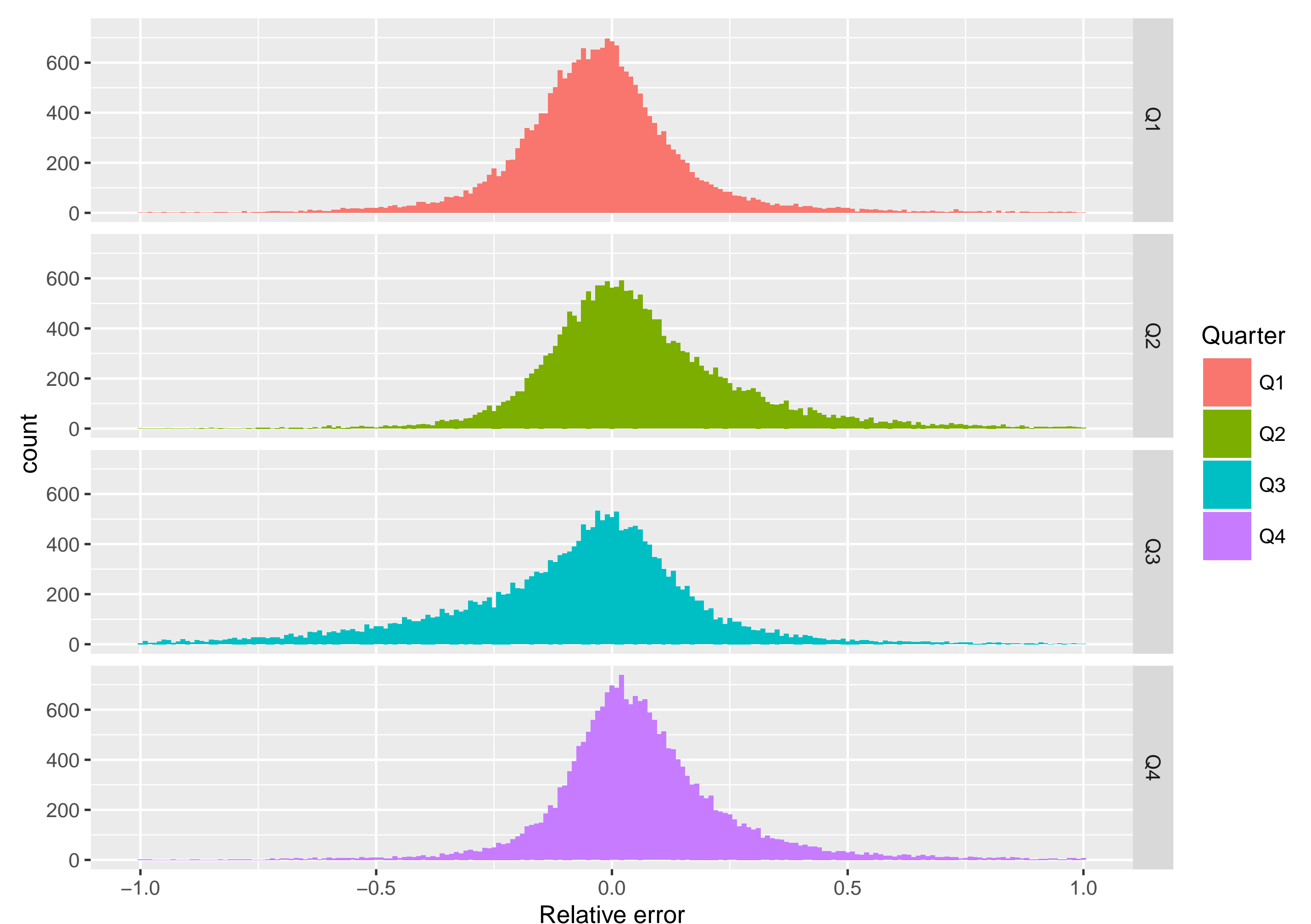


Figure 2 : Relative quarterly error of the cumulated purchase

## Discussion/Conclusion

When no weather dependence was found, the relative error seems to be distributed around zero. Weather dependence seems to introduce varying bias dependent on season. In general shock in the time series introduce bias (see Figure 1 for examples).

Suggested improvements to the model framework are to investigate different approaches of self tuning control, individual indoor temperature or regime models to cope with shocks, unknown heating periods and slow adaptation.

In general the relative error is mainly distributed within  $\pm 25\%$  which is satisfactory.

## References

- [1] Rune Korsholm Andersen. The influence of occupants' behaviour on energy consumption investigated in 290 identical dwellings and in 35 apartments. In *10th International conference on healthy buildings*, 2012.
- [2] Peder Bacher, Henrik Madsen, Henrik Aalborg Nielsen, and Bengt Perers. Short-term heat load forecasting for single family houses. *Energy and buildings*, 65:101–112, 2013.
- [3] Henrik Madsen. *Time series analysis*. CRC Press, 2007.