Forecasting Models For Ambulance Call Center

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Research Question

"how to reliably predict the call volumes on daily level and on half-hourly level for each urgency type and combination of urgency types for the Amsterdam area and its Ambulance Service Providers (ASPs) base locations?"

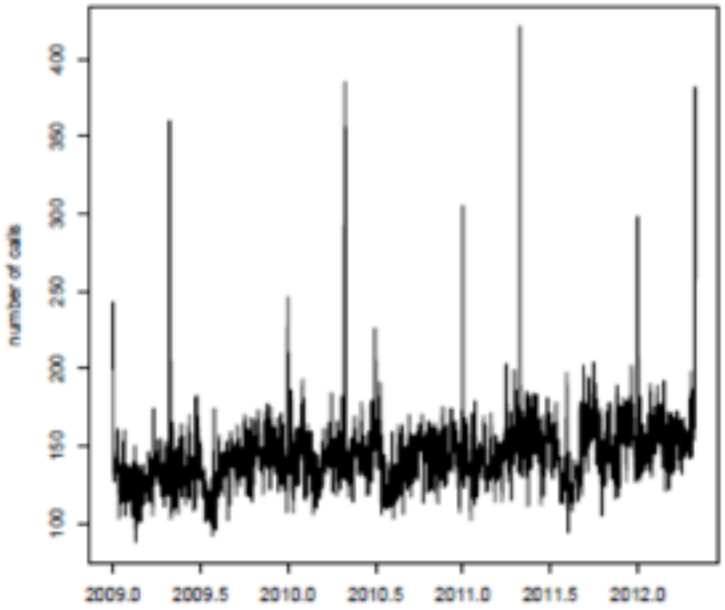
Data

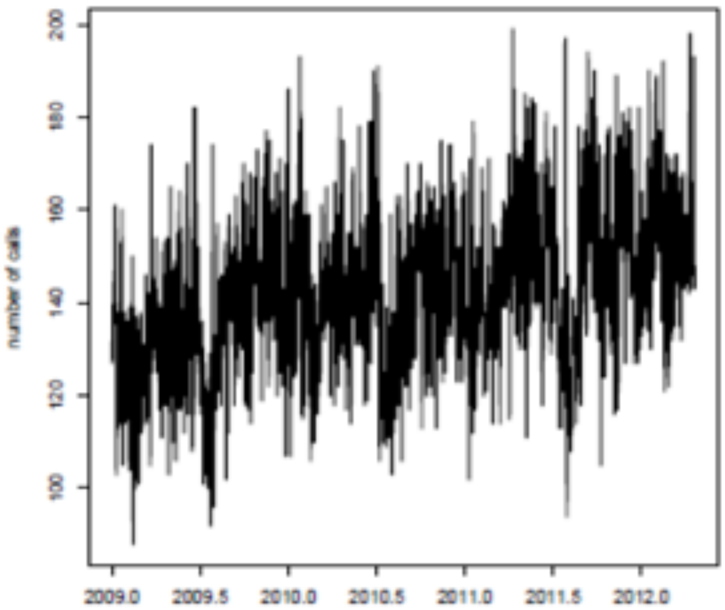
- **Source:** Meldkamer Amsterdam
- **Range:** 01-01-2009 to 30-04-2012
- **Urgency types:**
  - A1: the most urgent call with an acute threat of patient's life.
  - A2: less urgent than A1. Patient's life not under direct threat, but there might be serious injuries.
  - B: Not an A1 or A2. Are planned in advance.
- **Base locations**

Data pre-processing

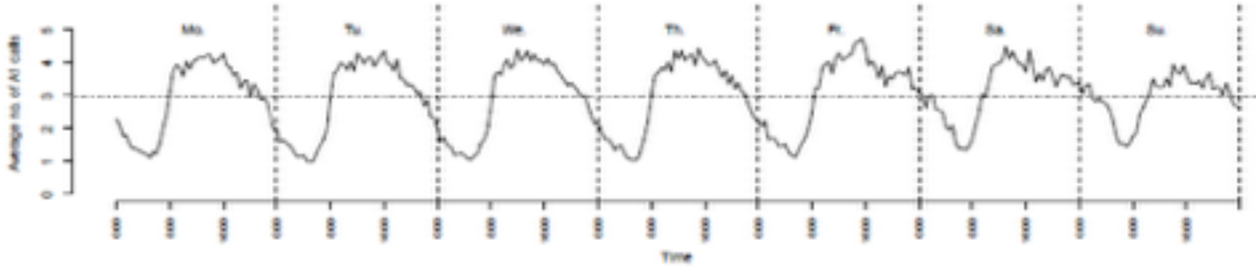
Outliers: historical average based on past data

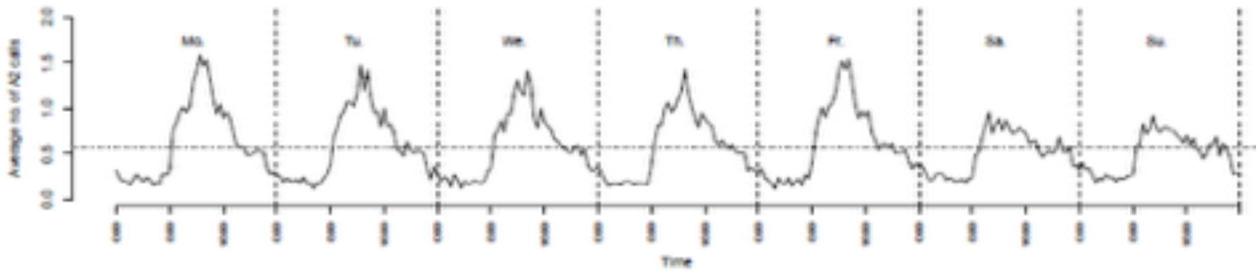
Example: A1 daily call volume of the Amsterdam region

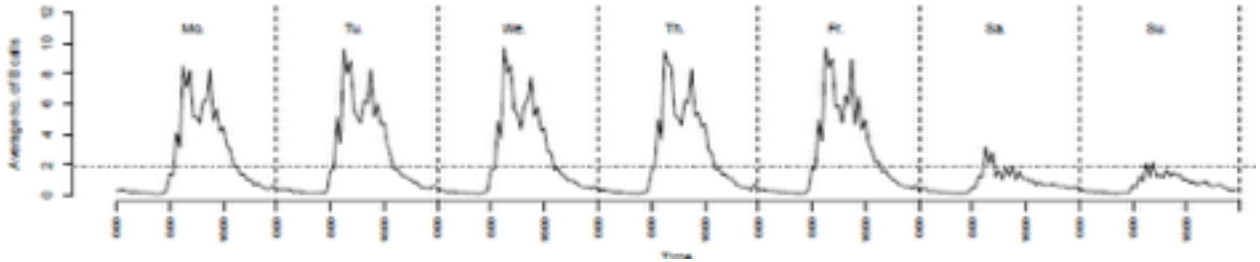




Seasonality: intra-week







Forecasting Models: daily level

- Multiplicative model
- Adjusted multiplicative model (adj.M)
- Innovation state space models (ISS)
- Trigonometric exponential smoothing models (TBATS)

Multiplicative Model

- Assumption: constant probabilities over time

$$y_t = L_t \cdot \Pi_{i_t, j_t} + e_t$$

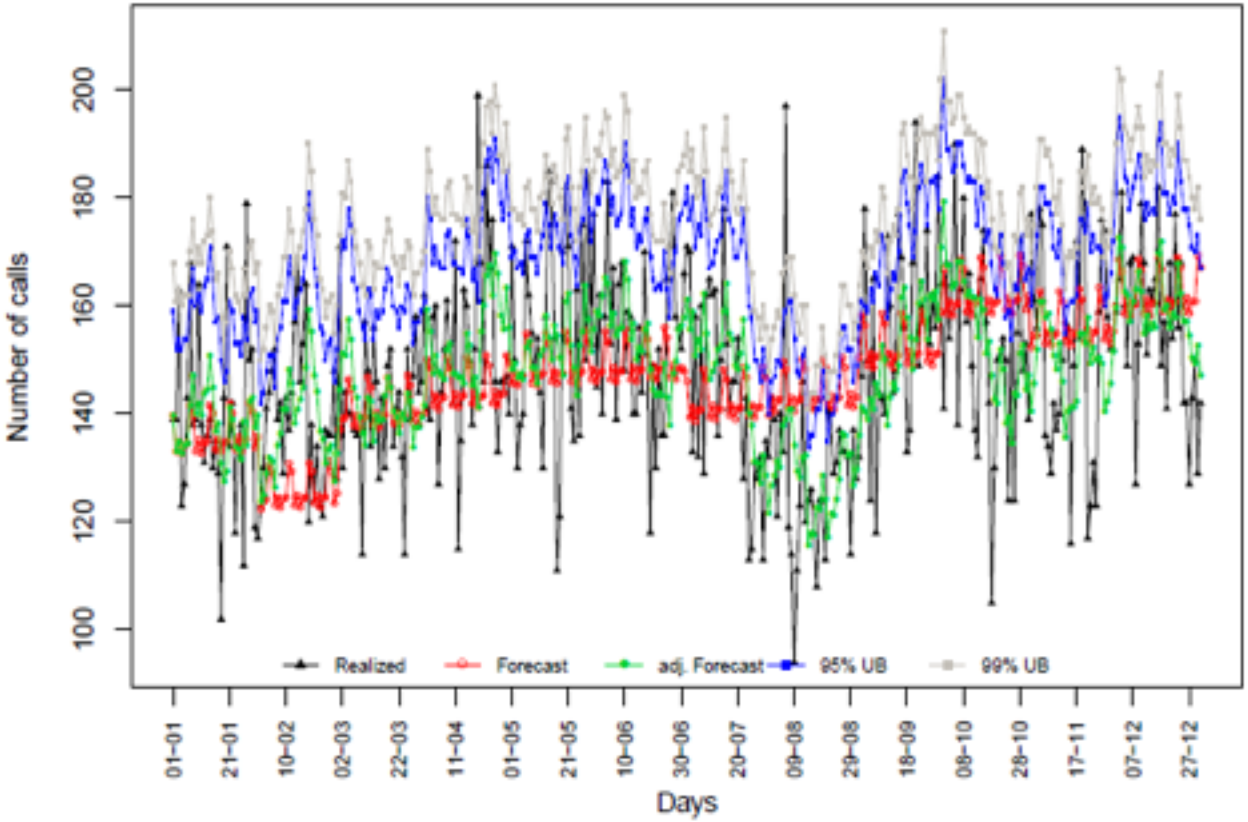
Adjusted Multiplicative Model

- Adj-M: the forecast from the multiplicative model was improved by adding an average percentage difference between the realised and the old forecast using different adjustment horizons

$$\hat{x}_{t,adj} = \hat{x}_t \cdot (1 + \alpha_t)$$

Adjusted Multiplicative

Example: A1 of the Amsterdam region (1week)



Innovations State Space Models

- Assumption: the development of the time series over time is determined by an unobserved series of vectors with which are associated a series of observations (Koopman et al., 2002)
- The innovations of the unobserved state component as well as the observation are driven by the same disturbance
- Hyndman et al. (2002) derived the ISS formulation for different exponential smoothing methods and implement these methods in the “Forecast” package

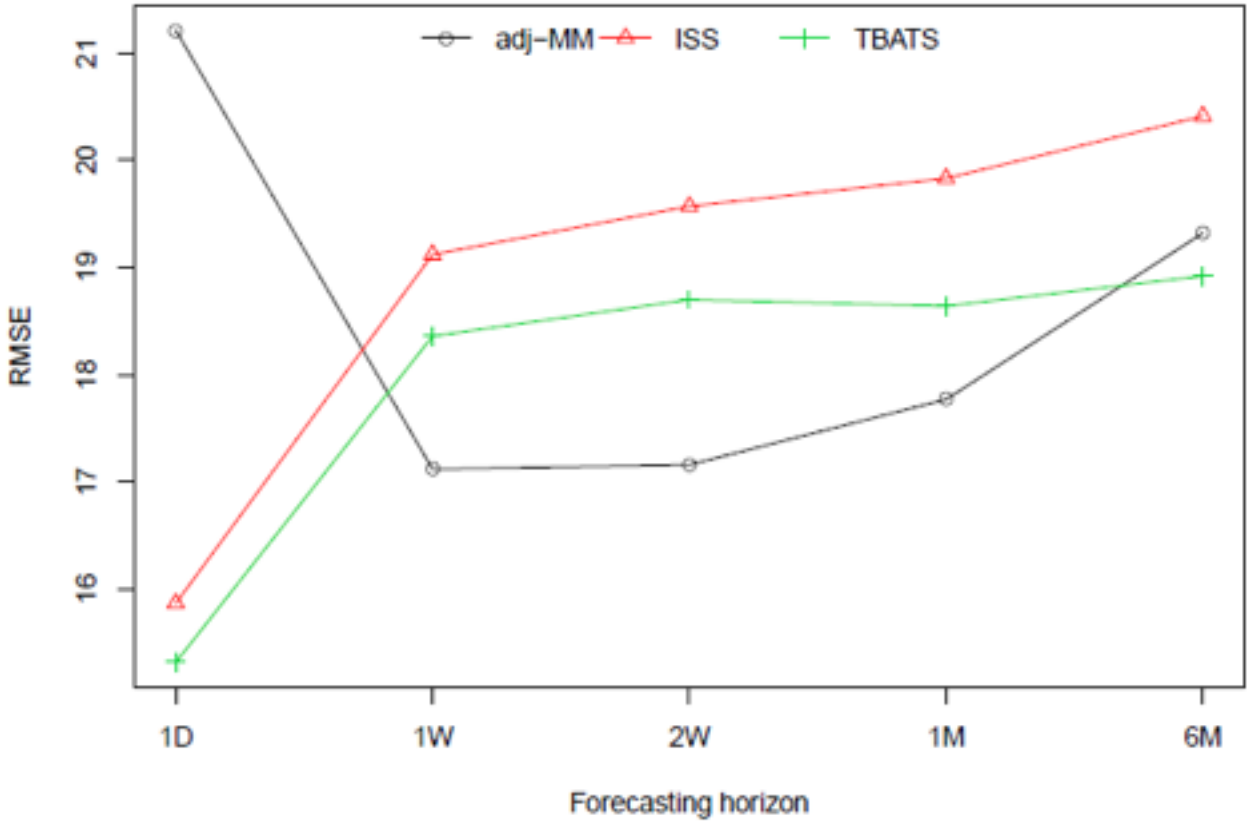
Trigonometric Exponential Smoothing Models (TBATS)

Introduced by The Livera et al. (2001):

- Allow forecasting time series with complex seasonal pattern (e.g: multiple seasonal patterns, non integer seasonality)
- Consider only linear homoskedastic models
- Allow non-linearity's using Box-Cox transformation
- Permits the seasonal components to be approximated by the sum of sine and cosine functions

Model Comparison

- Performance on different forecasting horizons



Conclusions

- **Preliminary analysis:**
  - Extreme observations on Queen’s day, New year’s Eve, days with extreme weather conditions, and special events (national football team plays)
  - No extreme observations on other special days that are defined by the MKA like Christmas
  - Strong intra-day and intra-week seasonality

Conclusions (cont.)

- **Modelling:**
  - Adj-M:
    - Good performance on different forecasting horizons (1W, 2W, 1M)
    - Similar performance to TBATS on the forecasting horiz. of 6M
    - Well specified models
    - Conservative on half-hourly level
    - Provides good forecasts for special days except Queen’s day and New Year Eve

Suggestions for further research

- Compute confidence levels instead of upper bounds for the adj-M model
- Explain call volume data using weather data
- Investigate the causes of misspecification of the TBATS models as they provide competitive results to the adj_M model
- Using spatio-temporal models that take time and space into account

Questions

Multiplicative Model

$$y_t = L_t \cdot \Pi_{i_t, j_t} + e_t$$

Where:

$$\hat{\Pi}_{i,j} = \frac{l_{i,j} \times \hat{p}_i \times \hat{q}_j}{\sum_{j=1}^{12} \sum_{i=1}^{7} l_{i,j} \times \hat{p}_i \times \hat{q}_j}$$

Adjusted Multiplicative Model

$$\hat{x}_{t,adj} = \hat{x}_t \cdot (1 + \alpha_t)$$

$$\alpha_{t,k} = \frac{\sum_{i=1}^{k} a_{t-i}}{k}$$

$$a_i = \frac{x_i - \hat{x}_i}{\hat{x}_i}$$

Innovations State Space Models

$$y_t = Z(x_{t-1}) + G(x_{t-1}) \cdot \varepsilon_t$$

$$x_t = T(x_{t-1}) + R(x_{t-1}) \cdot \varepsilon_t$$

Trigonometric Exponential Smoothing Models (TBATS)

$$y_t^{(\omega)} = \ell_{t-1} + \varphi b_{t-1} + \sum_{i=1}^{T} s_{t-1}^{(i)} + d_t,$$

$$\ell_t = \ell_{t-1} + \varphi b_{t-1} + \alpha d_t,$$

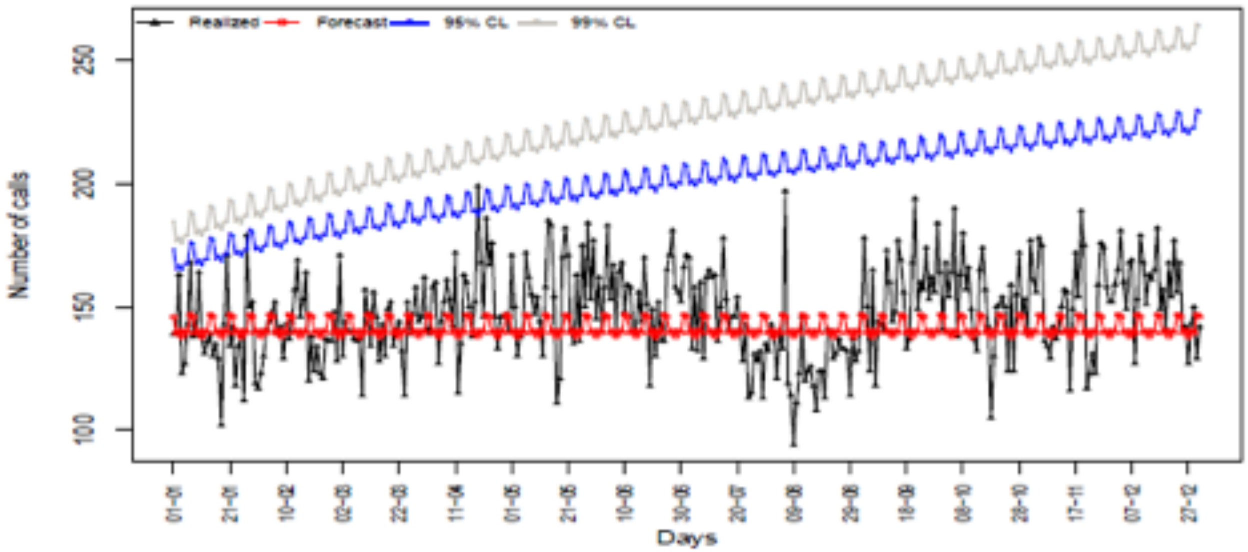
$$b_t = (1-\varphi)b + \varphi b_{t-1} + \beta d_t,$$

$$s_t^{(i)} = \sum_{j=1}^{k_i} s_{j,t}^{(i)},$$

$$d_t = \sum_{i=1}^{p} \varphi_i d_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t,$$

Innovations State Space Models

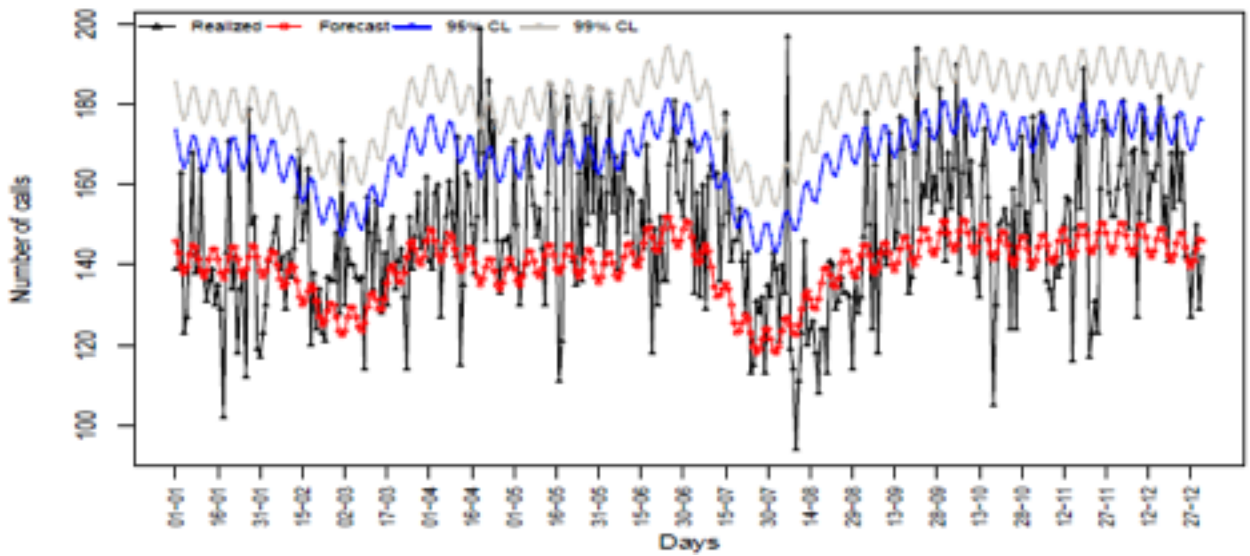
Example: A1 of the Amsterdam region (MNA)



- **Results:**
  - In general, similar performance as the adj-M model on workdays data
  - Perform poorly on weekends data
  - Most selected models were not well specified

TBATS

- Example: A1 of the Amsterdam region



- Results:
  - In general, similar performance as the adj-M
  - Not well specified models
  - Underestimate the call volume