Predicting Patient Waiting Times at an Emergency Call Line at a Dutch GP Office

Using ARIMA-family Time Series Forecasting

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Background and Case Description

- Emergency call line operated by a single **GP office in the Netherlands** during out-of-office hours for **milder urgencies**
- Currently using Discrete Event Simulation model based on empirical variable distributions of arriving calls and shifts available to obtain **waiting time predictions**
- **Relevance**: Different approaches to predict patient waiting time have not been tested in this case (yet)
- Waiting time: influenced by service side (number of shifts) and demand side (incoming calls) (Queuing theory [1])
- **Linear** and non-linear approaches in previous literature predicting waiting time and patient arrivals: ARIMA-family (Linear), LSTM (Non-linear, see J.Tian's poster) [2]
- ARIMA-based models model and predict time series by combining autoregressive components, moving average components, differencing (and seasonal components) [3]
- We adopt ARIMA-family time series forecasting expanding to a model with **external predictors** (calendar variables, incoming calls, number of shifts available*)
- Models adopted: ARIMA, SARIMA, SARIMAX

Research Question: Which one of the commonly-used methods – time series forecasting with ARIMA-family models or LSTM – predicts patient waiting times at the client's GP emergency line in the Netherlands with higher accuracy?

Sub-RQ 1: Which time series approach among the ARIMA-family predicts hourly patient waiting times in our case of the single Dutch GP emergency line with the highest accuracy?

Sub-RQ 2: Does the most accurate ARIMA-family model produce more accurate hourly predictions of patient waiting times than the current simulation-based model used the client's GP emergency line in the Netherlands?

Aim: 1. Compare the accuracy of commonly-used linear time series forecasting methods and LSTM for patient waiting time prediction for a single GP practice operating an emergency line in the Netherlands

2. Compare which ARIMA-family approach predicts hourly patient waiting times at the Dutch GP office with the highest accuracy

3. Test if time series forecasting methods improve the accuracy of waiting time predictions of the current simulation-based model

Method

Modified Box-Jenkins method [4]:

- Models tested in order: ARIMA, SARIMA, SARIMAX (parsimony recommended in the method)

1. Data preparation and investigation:

- Preprocessing: hourly format, missing data, outliers, normalization, feature engineering, creation of a shorter dataset for variable inclusion
- Seasonality and stationarity determination

2. Model identification: using differencing and seasonality suggestions from previous step, lowest AIC model configuration

3. Parameter Estimation: using parameter configuration determined in previous step

4. Assumptions checking: independence and constant variance of residuals

5. Forecasting and Validation:

- Metrics used: MAE, RMSE (the lower the better)[5]
- 3 time-frames (day, week, month)

6. Model Selection

- Among each model type (ARIMA, SARIMA, SARIMAX) *and SARIMAX with No. of Shifts trained on less data*
- Based on Forecast Accuracy

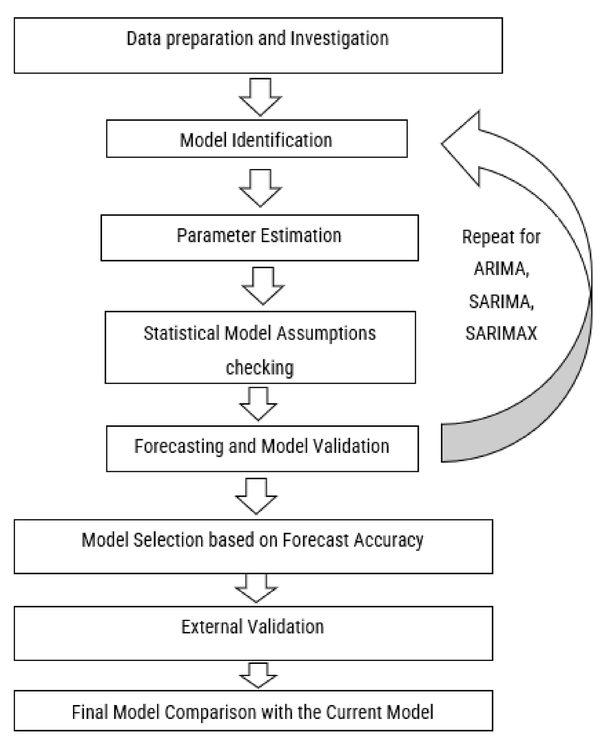
7. External Validation

- external dataset (most recent data - May)

8. Final Model Comparison

- Comparison with the current simulation model and LSTM

Schematic Representation of the Method



Data Description and Results

- Average of mean waiting time per hour: 5.67 min (SD: 8.25) - Differs based on day/ hour
- Data used: 20 January 2022 to 17 April 2023 (from 1 March for No. of Shifts), 10 873 observations (1 152 obs. For the shorter dataset No. of Shifts)
- **Hourly** intervals of observations
- **Seasonality and Stationarity:** seasonality of 24 (daily), time series relatively stationary

Best models identified for each model-type:

- ARIMA: ARIMA(1,0,1)(0,0,0)
- SARIMA: SARIMA(0,1,2) (0,0,2)24
- SARIMAX:
  - SARIMAX(0, 1, 5)(0, 0, 2)24 without calls,
  - SARIMAX (1,1,1)(2, 0, 0)24 with calls
- **Smaller training set with No. of Shifts attempted: SARIMAX (0,1,0)(0,0,0)[24] without shifts, with calls*
- **SARIMAX model** with calls **selected,**
- SARIMAX model without calls: selected as second most accurate

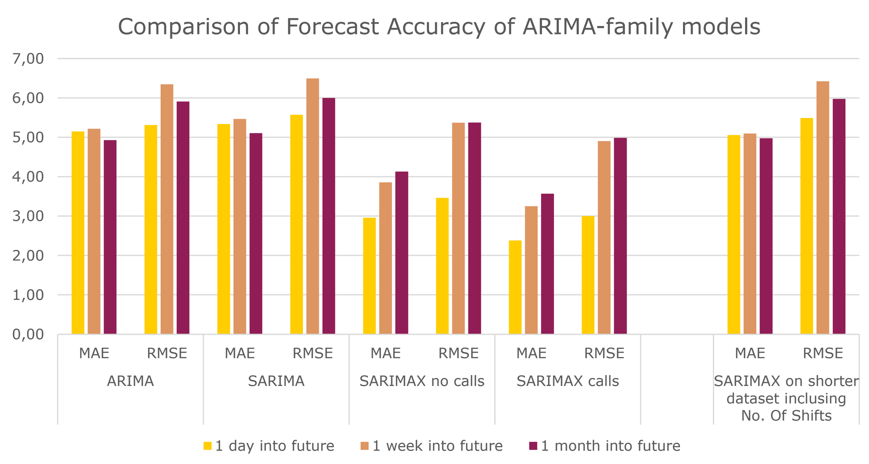


Figure 1:
Comparison of Forecast Accuracy of ARIMA-family models (all were tested on the same dataset, used for step 6: model selection)

External validation and Model Comparison with the Current Simulation Model

SARIMAX model with calls

- Better short-range predictions
- Mid-range predictions worse
- Better long-range predictions (much lower RMSE)

Table 1
Selected SARIMAX Model Performance, external validation dataset

	MAE	RMSE
1 day into future	1.5969	1.8025
1 week into future	3.2285	4.5014
1 month into future	3.4401	5.0827

Table 2
Current Model Performance, external validation dataset

	MAE	RMSE
1 day into future	2.4239	4.3992
1 week into future	2.6004	4.6021
1 month into future	4.9893	9.7346

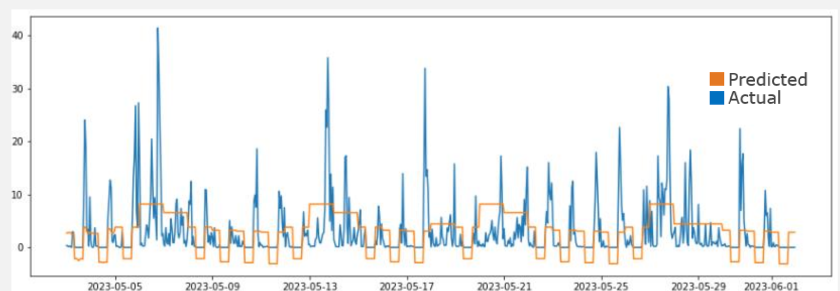


Figure 2:
Prediction visualization SARIMAX model without calls, external validation dataset

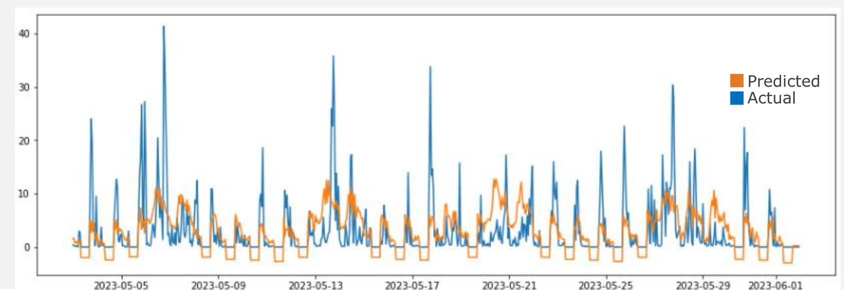


Figure 3:
Prediction visualization SARIMAX model with calls, external validation dataset

Discussion and Conclusion

- **Seasonality found** similarly to other studies that used hourly interval [6,7]
- **Best performance among ARIMA-family models: SARIMAX with calls**
  - Exogenous predictors improve forecast accuracy [6]
  - Inclusion of calls increases accuracy on all time-horizons
  - Accuracy of ARIMA-family models is the worst for weekly predictions
- **Best model comparison to the Current model**:
  - SARIMAX with calls better performance on short- and long-range predictions
  - SARIMAX with calls has smaller errors than the current model
- **LSTM vs SARIMAX** model: LSTM better performance on all time-ranges (see J. Tian's poster). Similar to previous research [8]

Limitations

- Generalizability to only a single GP office
- Sensitivity
- Number of Shifts – small dataset
- Short time span (problematic to test yearly seasonality)

Conclusion

- LSTM even better performance, trained on less data
- LSTM implementation recommended
- From ARIMA-family models: SARIMAX using number of calls recommended as first options, SARIMAX without number of calls as second option

References

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