

A COMPARISON OF METHODS FOR FORECASTING EMERGENCY DEPARTMENT CROWDING

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Hospital
Braga



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Outline of the talk

- Motivation and Objectives
- Emergency Department Unit (ED) – Braga's Hospital
- Data
- Forecasting Methods
- Evaluation Metrics
- Computational Tests
- Results Analysis
- Management Optimization
- Limitations & On-going Work
- References



Motivation

- Patients large influx to ED is an international and growing problem (**Overcrowding**), ED arrivals increase year after year
- Great increase in life expectancy, difficulties in access to primary care, ...



large delays, patient and staff stress, medical errors, in-hospital infection, abandonment of service, loss of profit, complaints...



Decrease health service level

Motivation and Objectives

Non-scheduled inputs

vs

needs of scheduling resources

- ED admissions represent more than **50%** of admissions in hospital wards!
- Daily, we know that **9%** of patients coming to ED will need to stay in-hospital care
- The in-hospital logistics must be adjusted to the everyday needs of new patients (number of beds, staff, medications, food etc)

Motivation

Trade-off: efficient delivery healthcare services vs optimizing costs

- It is crucial to forecast the arrivals to ED!

BUT

- large number of variables in a complex system:
 - Disease epidemiology (seasonality, ageing population,...)
 - Environmental factors (temperature, rainfall, humidity, pollution, ...)
 - Social events (academic parties, sport competitions, ...)
 - Holidays
 - Team scheduling – professionals availability, legal constraints on price of work hour

Motivation and Objectives

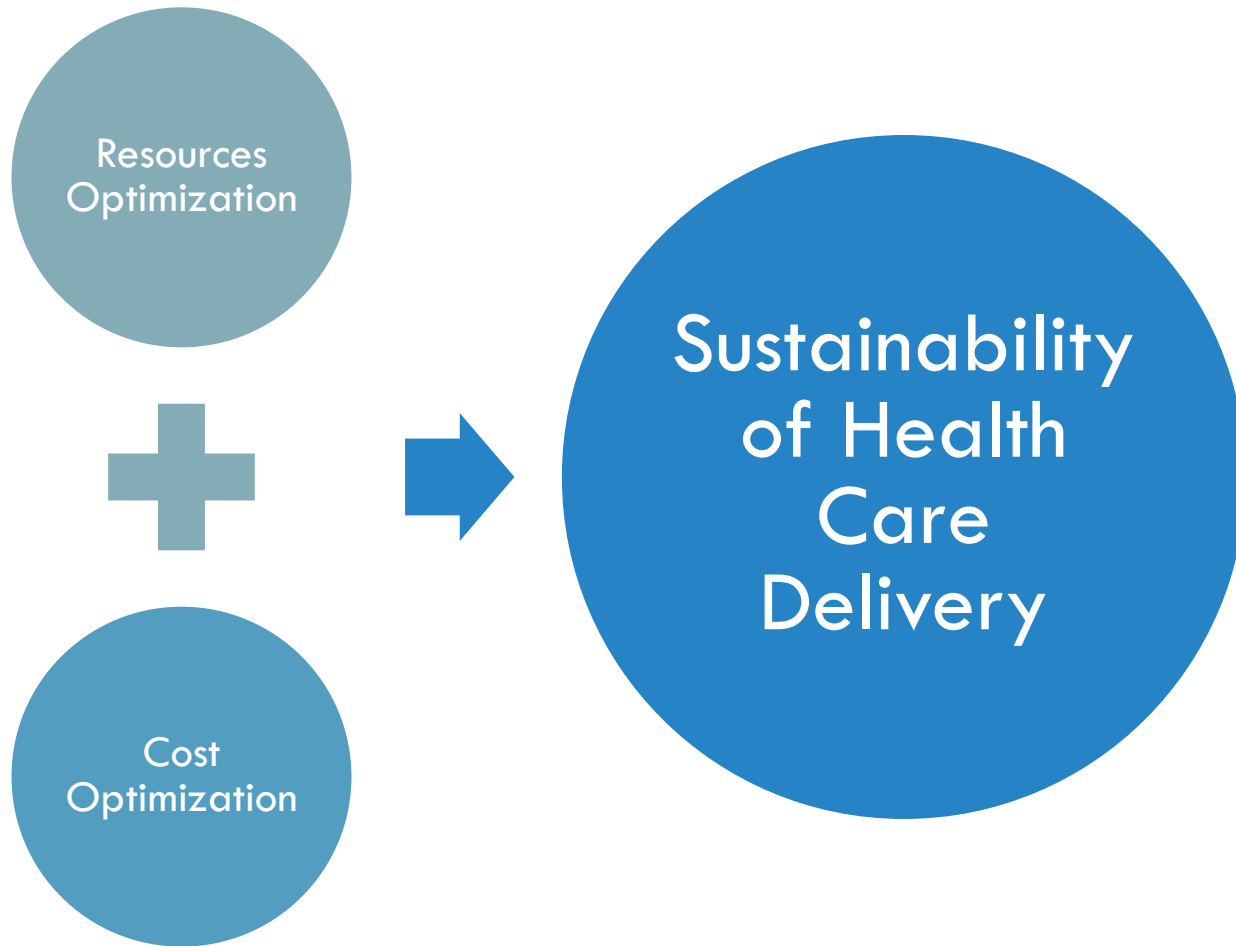
- Metrics based on empirical knowledge can not respond on time to large variation on arrivals



**Forecasting Methods and their comparison:
based on long time series**

(use statistical data about recent performance to predict current and future performance to a short-term)

Motivation and Objectives



Emergency Department (ED)

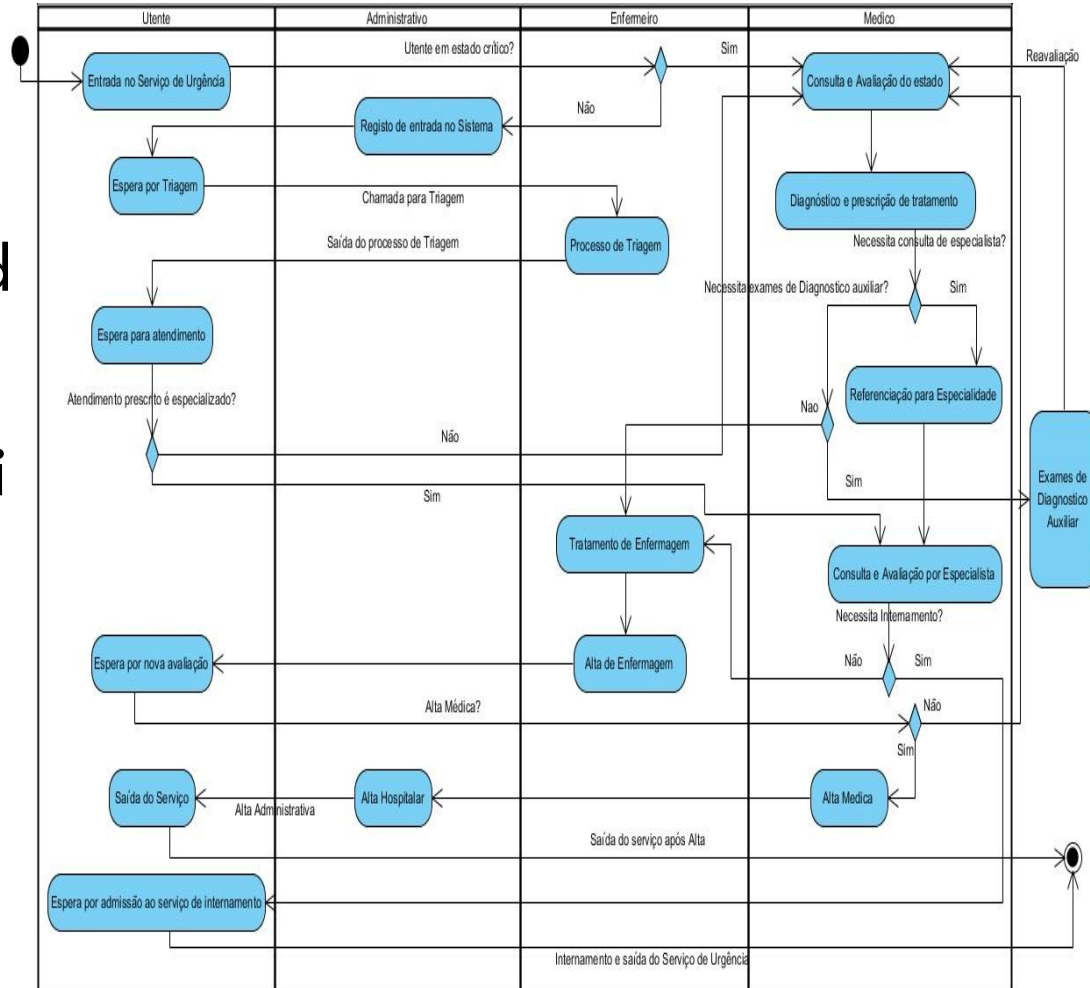
Important concepts:

- **Arrivals** – each person after being administrative processed (even if leaves before/after triage)
- **Admission** – each person admitted to an hospital ward
- **Discharge** – to be discharge you could be:
 - ❖ transferred to another hospital
 - ❖ treated and go home
 - ❖ referred to another health care facility (**admission**)
- **Analysis Unit** – the unit that is used during the study to evaluate the forecasting (month, **day**, hour)
- Max stay in ED is 24h

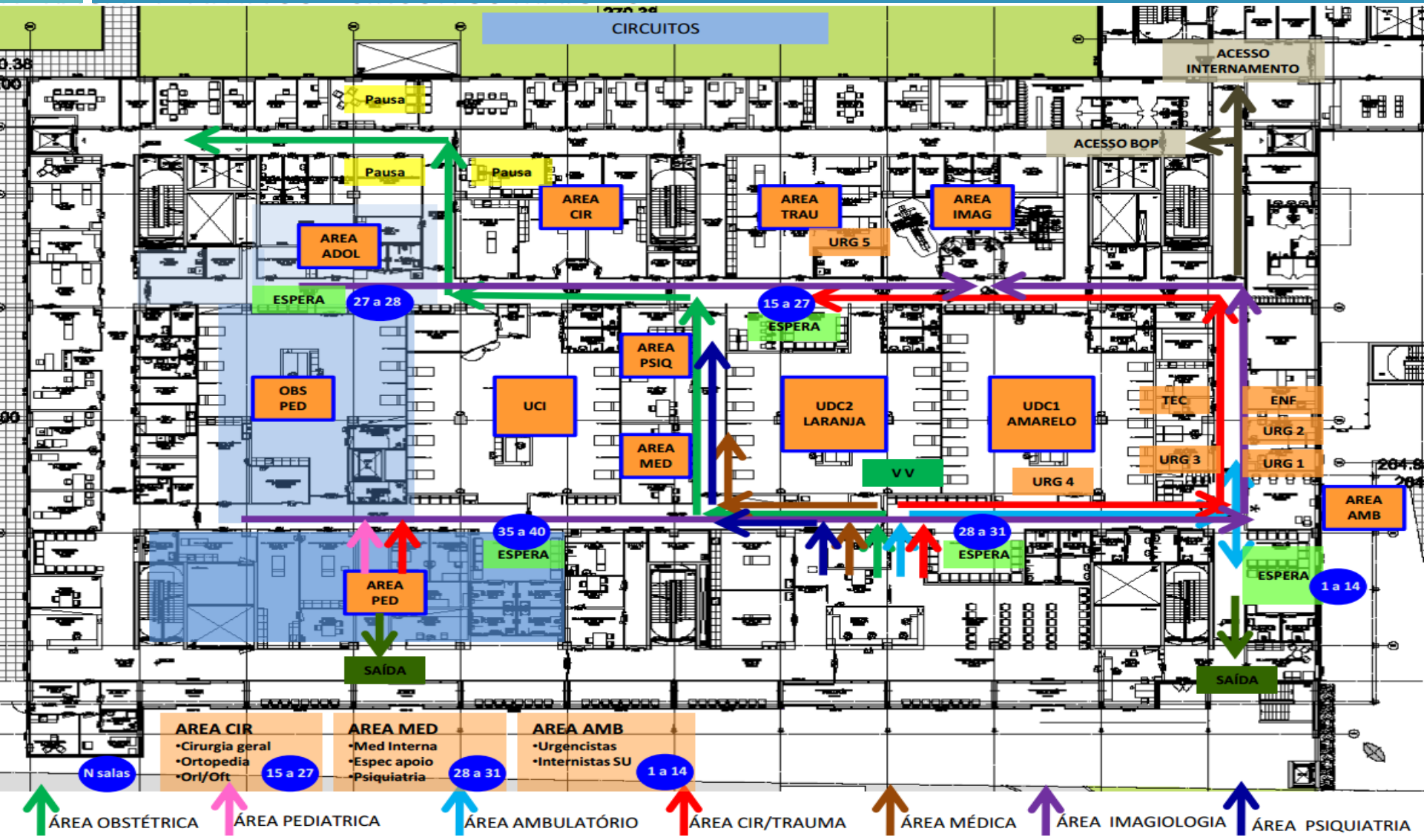
Emergency Department (ED)

Braga's Hospital ED

- 1.100.000 inhabitants referred to Braga Hospital
- Complex organization
 - ▣ More than 250 professionals
 - ▣ More than 450 patients/day and their relatives

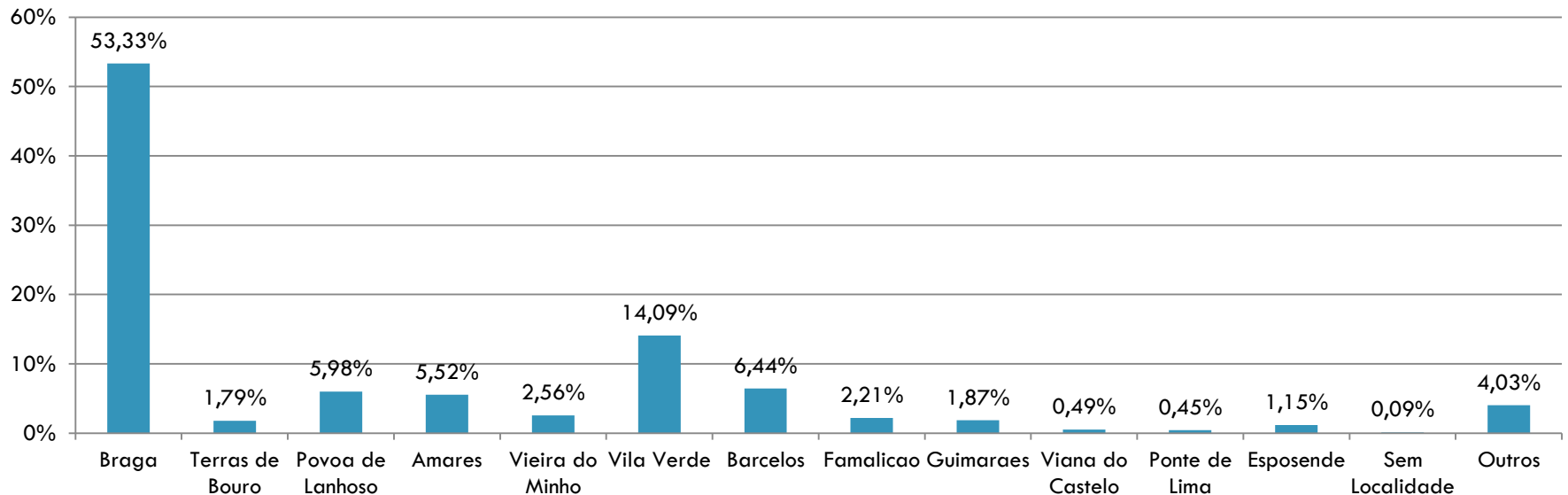


Emergency Department (ED)



Data

Percentage of arrivals distributed by county

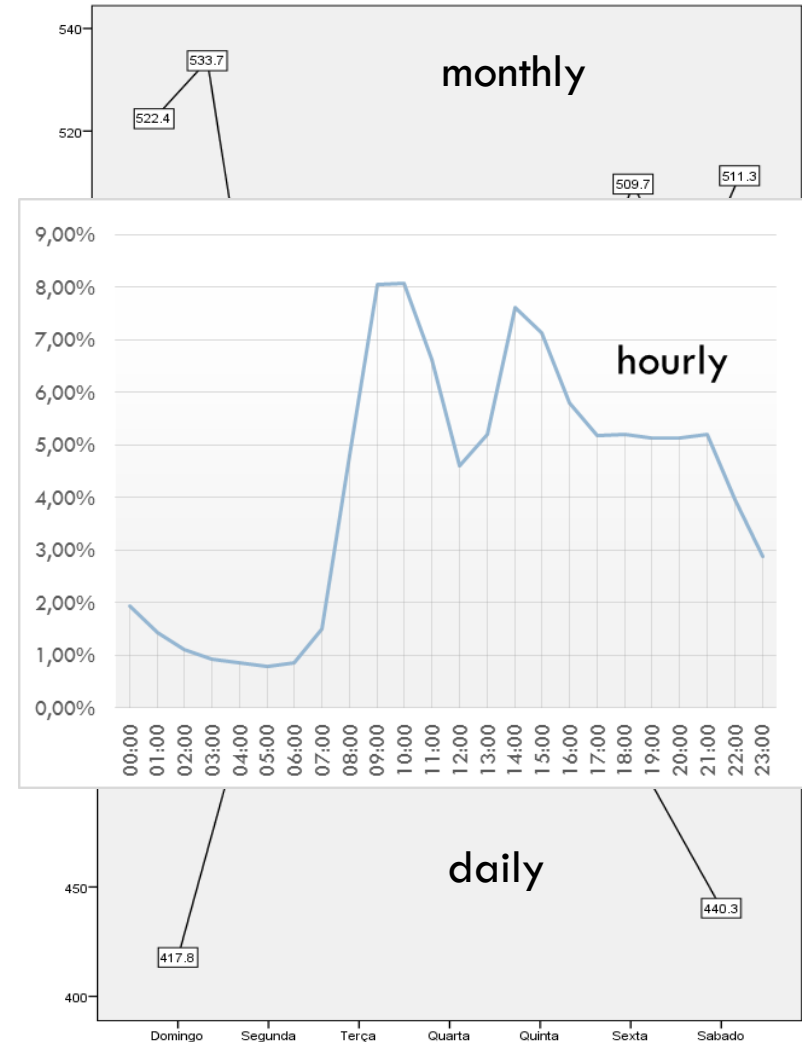


Data

- Data collected for users arrivals **Jan 2012 - Dec 2014**
 - 2012 and 2013 will be used as Test Data
 - **177 769 arrivals in 2012**
 - **185 132 arrivals in 2013**
- Study more than 40 scientific articles: selection the best methodological choices to the collection and data analysis
- Data collected:
 - Hour of arrival, triage color, triage destiny, age, sex, data of arrival, Times between stages inside the ED department, discharge hour, ...

Statistical Tests

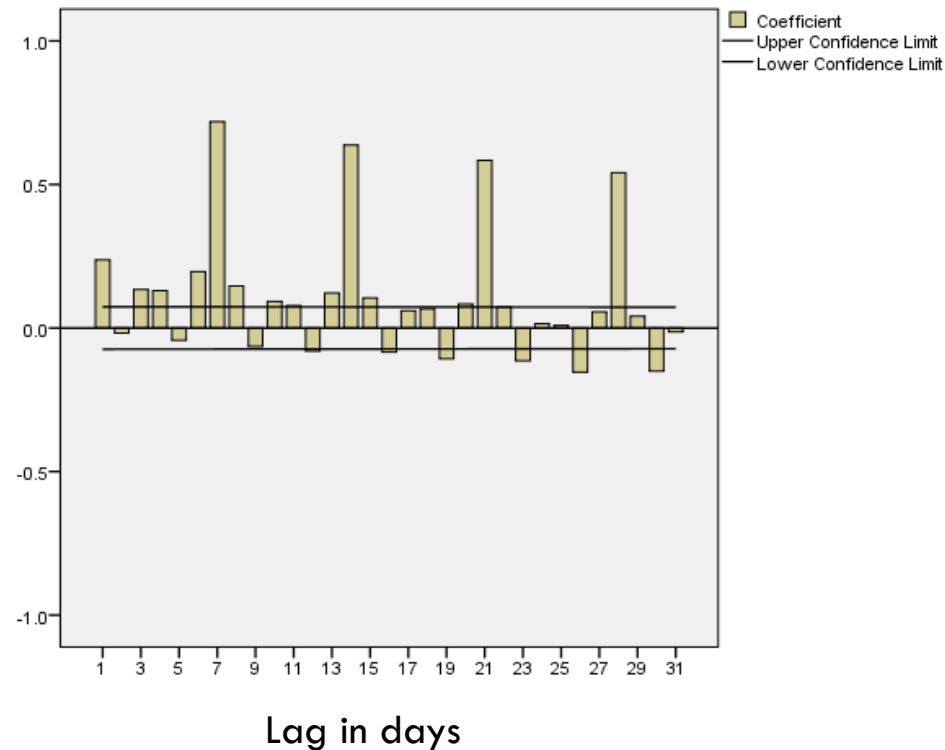
- Statistic analysis for monthly, daily and hourly arrival from more than 350 000 arrivals
- Highs of 705 persons a day with mean of almost 500
- Population characteristics were also analysed for the period of study
- Looking for patterns, seasonality and trends on data for the daily arrival



Statistical Tests

The autocorrelation is a linear dependence of one variable to itself at two different points in time in the same time series

Long Series Correlation (in SPSS)



- Autocorrelation Function (ACF) shows a strong correlation between the data each **7day period**

Forecasting Methods

- **Exponential smoothing** -> is a common procedure based on giving a weight average of past values of the time series, reducing this burden over time. The adjust is made by a constant.
- **ARIMA and Seasonal ARIMA:**
(AR)-AutoRegressive, (I)- Integrated, (MA)- Moving Average
ARIMA (p,d,q)
 - p is the number of autoregressive terms
 - d is the number of no seasonal differences for stationary
 - q is the number of lagged forecast errors in the prediction equation
- **Multiplicative Holt-Winters** -> 3 coefficients
 - 1 for Seasonality other for Trend and the last one for the Level
- **Holt-Winters** -> 2 coefficients
 - 1 for Trend and another for Level
- **Moving Average**

Forecasting Methods

Important concepts:

□ Test Period vs Evaluation Period

Test period is the data period used for the model to learn

Evaluation period is the period used to evaluate the forecast given by the model using the appropriate metrics

Evaluation Metrics

Evaluation Metrics: to measure and validate the model forecasting

- AIC -> Akaike Information Criteria
- BIC -> Bayesian Information Criteria
 - Based on percentage error:
 - MAPE -> Mean Absolute Percentage Error
 - MAD -> Mean Absolute Error
 - Dependent on the scale
 - RMSE -> Root Mean Square Error

Evaluation Metrics

MAPE (Mean Absolute Percentage Error)

- ❑ Based on percentage error
- ❑ Is independent of the scale
- ❑ Facilitates direct comparison of a forecasting model over multiple time series

$$MAPE = \left(\frac{1}{n} \sum_{t=1}^n \left| \frac{y_t - \hat{y}_t}{y_t} \right| \right) * 100$$

And Now... How to decide!?

- **Which one is the best model for this ED???**

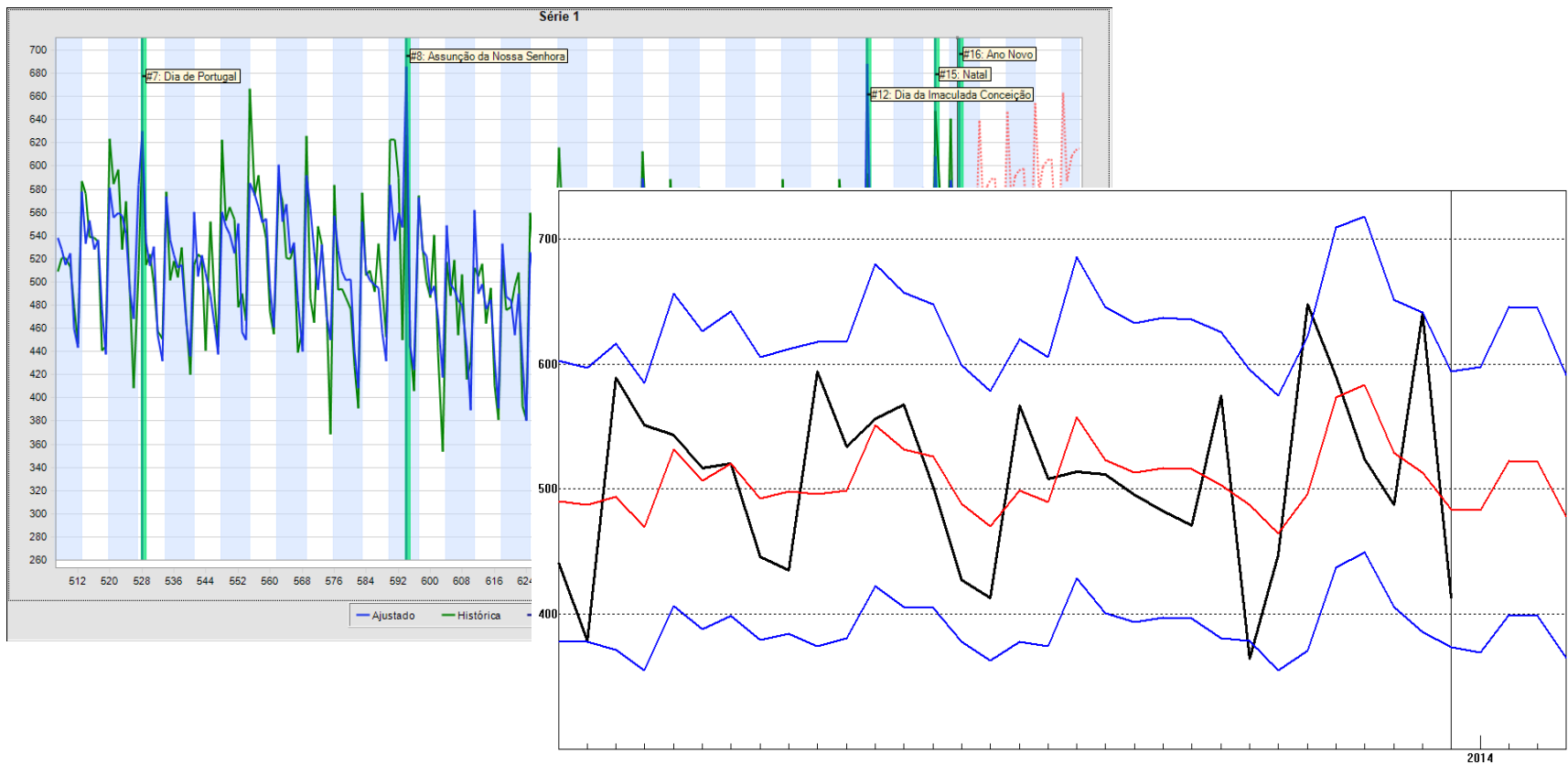
After comparing the different forecasting methods we came to the best model.

The MAPE for the test period was compared between each model as well as the MAPE for the first month of evaluation.

Computational Tests

Way the model adapt itself to the historical data (**Best model**)

$SARIMA(1,1,1)(1,0,1)_7$ – Oracle Crystal Ball



Way the model adapt itself to the historical data (**Second model**)

$ARIMA(0,0,1)(1,0,0)$ – Forecast Pro

Result Analysis

□ SARIMA(1,1,1)(1,0,1)₇

MAPE 5.78%	RMSE 38
MAD 28	U de Theil 0.4334
Durbin-Watson 1.97	Ljung-Box 10.707,98
Lambda de transformação 1	AIC 7,27
BIC 7,27	AICc 7,27

□ ARIMA(0,0,1)(1,0,0)

Within-Sample Statistics	
Sample size 731	Number of parameters 2
Mean 42.48	Standard deviation 2.954
R-square 0.3052	Adjusted R-square 0.3043
Durbin-Watson 1.879	** Ljung-Box(18)=714.1 P=1
Forecast error 2.464	BIC 55.09
MAPE 8.282%	RMSE 54.68
MAD 40.5	

□ Moving Average

MAPE 9.82%	RMSE 59
MAD 47	U de Theil 0.7477
Durbin-Watson 1.87	Ljung-Box 11.227,51
Ordenar 8	Sazonalidade 7

Result Analysis

□ Multiplicative Winters

Within-Sample Statistics	
Sample size 731	Number of parameters 3
Mean 496.7	Standard deviation 65.36
R-square 0.1865	Adjusted R-square 0.1843
Durbin-Watson 1.752	** Ljung-Box(18)=1434 P=1
Forecast error 59.03	BIC 59.71
MAPE 10.09%	RMSE 59.71
MAD 48.79	

□ Holt-Winters

Within-Sample Statistics	
Sample size 731	Number of parameters 2
Mean 496.7	Standard deviation 65.36
R-square 0.08391	Adjusted R-square 0.08265
Durbin-Watson 1.806	** Ljung-Box(18)=829.6 P=1
Forecast error 62.6	BIC 63.08
MAPE 10.63%	RMSE 62.52
MAD 51.19	

□ Exponential Smoothing

MAPE 10.23%	RMSE 61
MAD 49	U de Theil 0.7703
Durbin-Watson 1.78	Ljung-Box 11.227,51
Alfa 0.1119	Sazonalidade 7

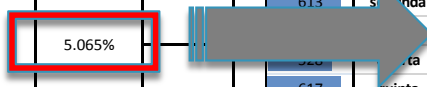
Results Analysis

Best Model – MAPE – January 2014

valor observado	Janeiro 2014	5%	valor previsto	95%	MAPE Semana	MAPE 2 semanas	MAPE 3 semanas	MAPE 4 semanas	Semana
456	quarta	445	507	569					1ª Semana
554	quinta	476	541	606					
571	sexta	461	528	594					
475	sabado	400	467	535	6.002%				
462	domingo	379	447	516					
588	segunda	522	591	660		6.753%			
593	terça	431	501	571					
584	quarta	451	523	596					
585	quinta	471	545	619					
648	sexta	454	529	605					
471	sabado	393	469	545	7.503%		5.670%		2ª Semana
440	domingo	372	449	527					
613	segunda	513	591	670					
564	terça	423	503	582					
528	quarta	443	525	606					
617	quinta	463	546	629					
545	sexta	446	531	615					
453	sabado	385	471	557	3.505%				3ª Semana
448	domingo	364	451	538					
611	segunda	504	592	680					
515	terça	415	504	593					
567	quarta	434	526	618					
541	quinta	454	547	640					
561	sexta	437	532	626					
485	sabado	377	472	568	3.249%				4ª Semana
452	domingo	356	453	550					
624	segunda	494	593	691					
512	terça	406	505	605					
574	quarta	425	527	629					
546	quinta	444	548	652					
558	sexta	427	533	638					

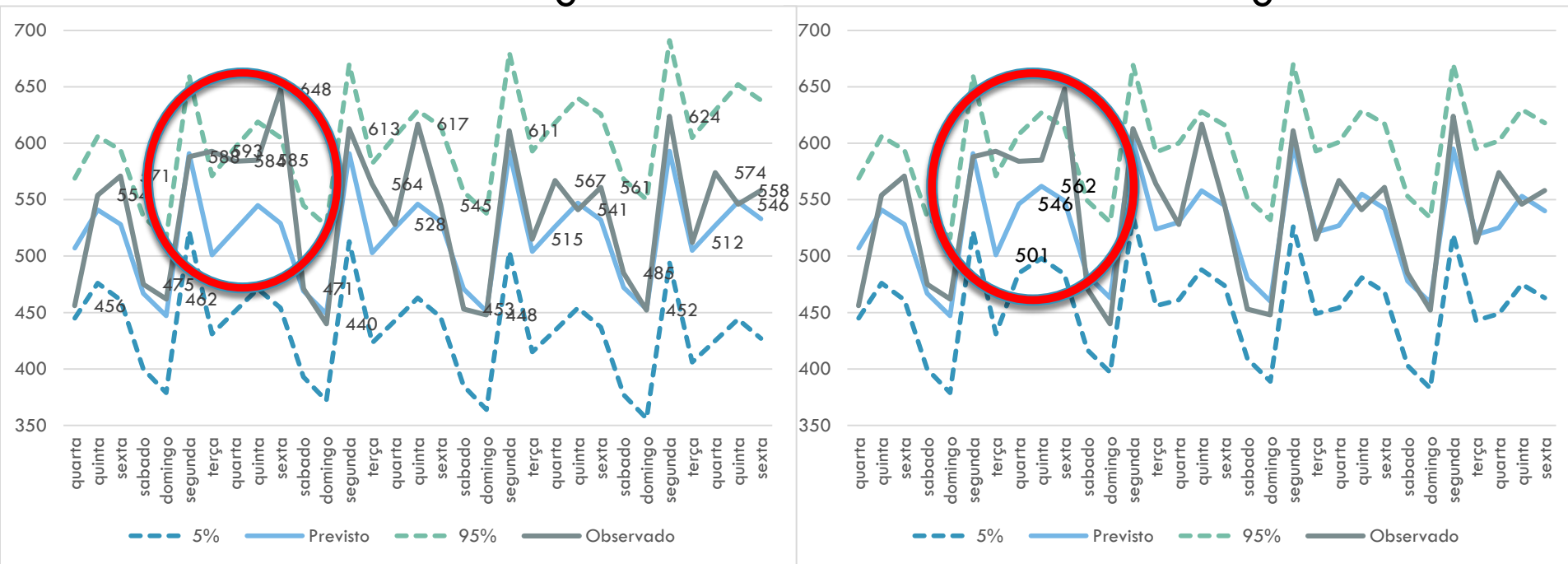
Second Model – MAPE – January 2014

valor observado	Janeiro 2014	5%	valor previsto	95%	MAPE Semana	MAPE 2 semanas	MAPE 3 semanas	MAPE 4 semanas	Semana
456	quarta	305.19	395.26	496.96					1ª Semana
554	quinta	336.74	433.6	542.68					
571	sexta	322.27	417.16	524.27					
475	sabado	406.54	512.36	630.4	20.169%				
462	domingo	455.68	567.35	691.25					
588	segunda	346.34	444.48	554.85		18.086%			
593	terça	351.24	450.03	561.05					
584	quarta	344.52	442.42	552.54					
585	quinta	418.98	526.31	645.87					
648	sexta	410.16	516.42	634.9					
471	sabado	319.45	413.95	520.67	16.003%				2ª Semana
440	domingo	330.88	426.94	535.23					
613	segunda	410.16	516.42	634.9					
564	terça	319.45	413.95	520.67					
528	quarta	330.88	426.94	535.23					
617	quinta	392.42	496.49	612.79					
545	sexta	358.72	458.49	570.49					
453	sabado	382.18	484.96	599.97	15.025%				3ª Semana
448	domingo	424.23	523.19	652.30					
611	segunda	466.49	579.19	704.55					
515	terça	310.59	403.85	509.33					
567	quarta	379.49	481.94	596.61					
541	quinta	358.72	458.49	570.49					
561	sexta	347.56	445.86	556.30					
485	sabado	359.35	459.21	571.20	14.724%				4ª Semana
452	domingo	405.1	510.74	628.61					
624	segunda	424.98	533.04	653.32					
512	terça	318.33	412.67	519.24					
574	quarta	330.88	426.94	535.23					
546	quinta	330.88	426.94	535.23					
558	sexta	346.34	444.48	554.85					



Results Analysis

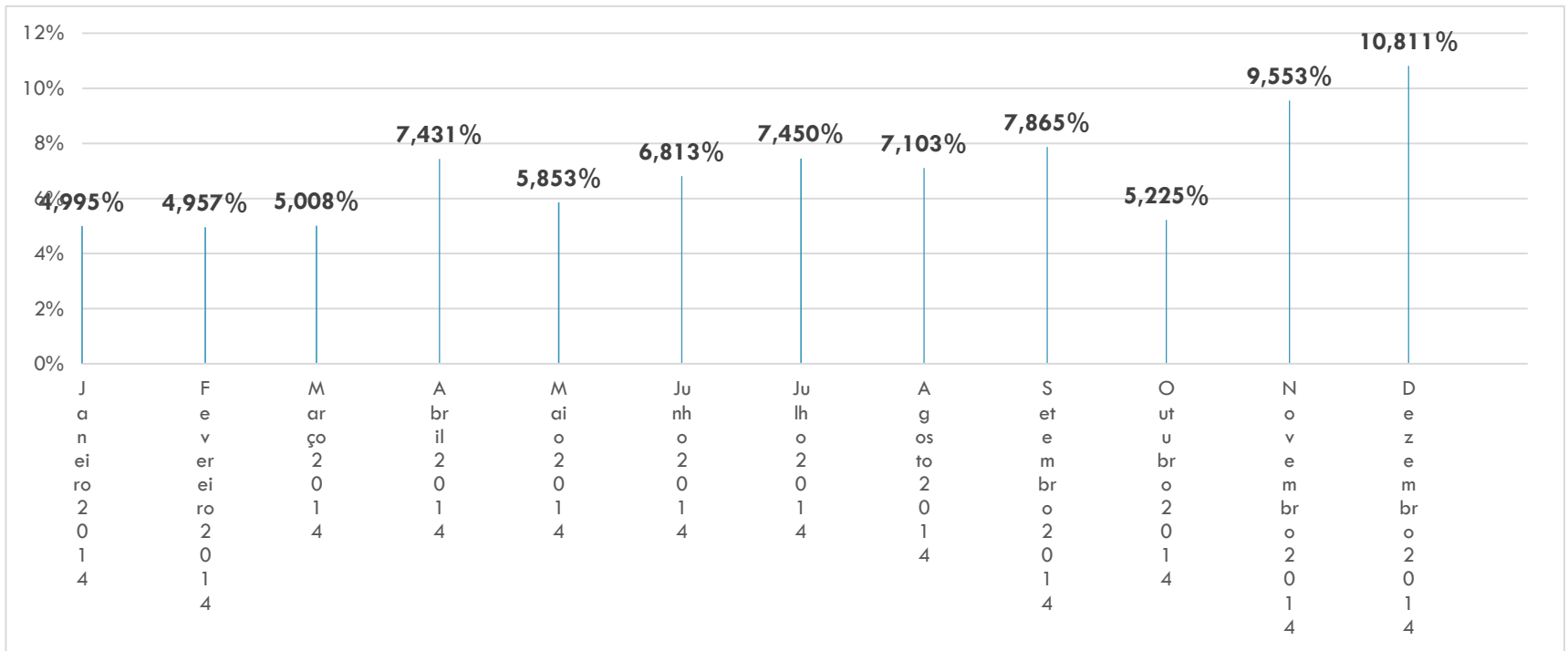
One month forecasting vs model reaction to first week of given data



- The best model was tested, for the evaluation period, by providing observed data for the first week and comparing the MAPE for the forecast on the third and fourth weeks.

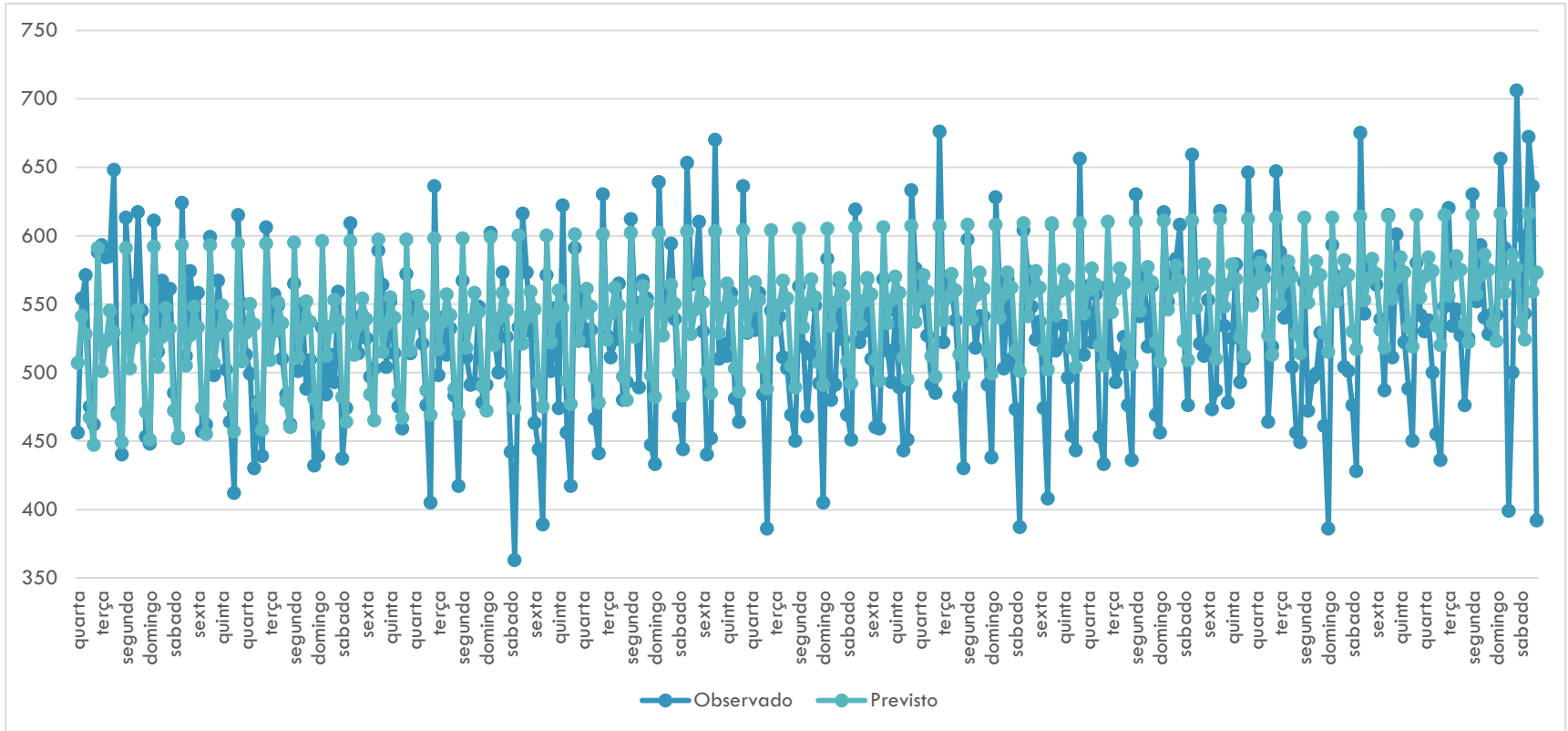
Results Analysis

- 3 month forecasting with less than 5% error
- Mean MAPE annual error of **6.922%**



MAPE for 2014 for the Best Model

Results Analysis



- The way that the model forecasts the data for all year of 2014
- Because the coefficients for the SARIMA model were calculated for the 2012 and 2013 with more weight for the final weeks of 2013 the positive trend is quite visible

Resources Optimization

- And if we could know, with a 5% error, the number of people that will arrive tomorrow on the ED?

- **Benefits that will be added**
 - Manage flexible professional scales to the flow and severity of pathologies
 - Bed allocation management - scheduled in-hospital admissions adjusted to the needs of unscheduled admissions

- Identify guidelines to help the management workflow

Limitations & On-going Work

Limitations



- Only tested for one hospital
- Tested for one year
- Not tested for all possible methods
- Metrics used could be different

On-going Work



- Relation between environment variables and ED arrivals
- Study the different arrival flows and patterns
- Correlation study between arrivals and bank holidays
- Correlation between peak temperatures with the arrival of patients to ED

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