Short-term Demand Forecasting For Operational Control of the Barcelona Water Transport Network

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Abstract
This paper focuses on the forecast of the hourly water demand data of distinct pressure floors of the Barcelona water transport network. Several methods to forecast the hourly water demand are studied and compared with the aim of being applied for the operational control of the Barcelona water transport network. The short-term forecast of the intraday series have a main feature: the double periodicity (daily and hourly). To address this issue several extensions of the classical time-series forecasting methods are proposed: seasonal *ARIMA*, structural models and the exponential methods without external information. The paper focuses on the daily and hourly forecasts. In the hourly forecast, the exponential smoothing method is the most accurate. On the hand, the seasonal *ARIMA* and the exponential smoothing are similar in the daily time scale.

Keywords
Short-term forecasting; exponential smoothing methods, internal model control

INTRODUCTION
In large scale infrastructures, such as the complex water transport network of Barcelona city used in this work, a telecontrol system must acquire, store and process thousands of flowmeter and other sensor data every hour to achieve an accurate monitoring of the whole network in real time. The real-time network control needs an accurate prediction of the future consumption. These future values help the operational control system to decide the new actions in the future.

There are different prediction scales: long, medium and short term. The prediction for the long-term allow to built new infrastructure and guess the possible future problems. The short-term and medium-term forecasting is basically useful for the operational control (Cembrano, 2000) of the network. These forecasts helps to manage the control elements for the next hours, days or months. This paper focus on the short-term forecast, because the optimal operational control works at hourly time scale. The selected forecast method should be easy to use and should be automatically calibrated. Moreover, this method should be adaptable, because in the network there are many demand time series to model and each floor of pressure has their own demand characteristics.

The considered forecast methods are univariate. Although it is known that the water demands are strongly influenced by the meteorological variables, they are difficult to predict in short periods. But these variables tend to change in a smooth way. This fact is important since intradays water demand captures this effect. So, the prediction has the meteorological effects included. Aside, the on-line forecast does not work well with multivariate models.

The main objective of this paper is to study several methods to predict the next twenty-four hours demand and the next seven days consumption. In particular, the ARIMA, basic structural and exponential smoothing models are considered. However, in these three approaches, there are a lot degrees of freedom to tune to build a short-term demand prediction that will be discussed along the paper. Finally, two ARIMA, one structural and one exponential smoothing models are implemented and compare with two naïve models. Finally, the model that provides best results in Barcelona network case study is selected.

METHODS

Double seasonal *ARIMA* models

The first method proposed to forecast the short-term series is the double seasonal *ARIMA* model (Box et al., 94). This method was used over the years, but in recent years this method has lost popularity.

The *ARIMA* prediction can be written as a polynomial of the past values and the past prediction errors. The characteristic of the seasonal *ARIMA* is that need one polynomial for the regular component and other for the seasonal. Moreover, the double seasonal *ARIMA* separates the seasonal polynomial in two polynomials. Each seasonal polynomial works only with one periodicity. This model is expressed as $ARIMA(p,d,q)x(P_1,D_1,Q_1)_{s1}x(P_2,D_2,Q_2)_{s2}$ where p, d, q, P_1, D_1, Q_1, P_2, D_2 and Q_2 are the degrees of the polynomials and s_1 and s_2 are the number of periods in each seasonality.

The main problem of this method is that the difference operator orders and the distinct polynomials are not easy to determine. Another problem is the identification of the model. This process can not be done in real-time. The large number of the seasons in the second seasonality, $s_2=168$, makes hard to obtain a good identification. So, an extension of the *airline model*: $ARIMA(0,1,1)x(0,1,1)_{24}x(0,1,1)_{168}$ is proposed and the three parameters are determined with the maximum likelihood method.

Daily seasonal *ARIMA* model with hourly pattern

The second method continues the works of (Quevedo et al, 2006; Blanch et al, 2009) by improving their ideas and algorithms.

The basic idea is to work in two time scales: daily and hourly. In each scale, a specific model is constructed. In the daily scale, the method works with the total day's consumption and the forecast is based on a seasonal *ARIMA* model. In the hourly scale, the method works with the hourly consumption and the forecast is based on the daily patterns.

The seasonal *ARIMA* models works with data that presents a repeated stochastic pattern. This model only needs two polynomials and can be expressed as $ARIMA(p,d,q)x(P,D,Q)_s$. The numbers p, d, q, P, D and Q are the degree of the distinct polynomials. The best model is selected with Bayesian Information Criterion (Schwarz, 1978) considering the set of models generated by $0 \le p \le 3$, $0 \le P \le 1$, $0 \le q \le 3$ and $0 \le Q \le 1$.

Once a daily prediction for specific day is obtained that it is distributed along the day hours using a demand pattern. The demand pattern is generated such that the sum of components at the end of the day is one, because the sum of the hours predictions is the daily forecast. Previous works (Quevedo et al., 2006) show that several types of demand patterns should be used: one for weekdays, one for Saturdays and one for Sundays/holidays. Then, the hourly prediction is obtained by distributing the daily prediction using the demand pattern.

The hourly prediction is based on the pattern demand has a big problem: it does not use the new available information since the hourly prediction is computed for the whole day without reestimating it taking into account the registered demand of the daily hours already elapsed. To solve this problem a new procedure for hourly demand forecast based on the consumption of the previous hours and the daily consumption has been developed.

Basic Structural Model
Basic structural models can be used taking into account that the time series can be divided in additive independent components. These models gained popularity in the mid eighties, because the modelisation is simple and the Kalman filter helps us to optimize few parameters (Harvey, 1989).

In our case, it is assumed that the time series can be divided in three additive independent parts: level, seasonal and irregular components. Thus, the model can be written as follows

$$x(t) = L(t) + S(t) + e(t)$$

where the *L(t)* is the level component, *S(t)* is the seasonal component and *e(t)* is the irregular component. The two regular components are random walks and their best prediction is the recent past value. This model can also be written as state space model. This allows using the Kalman filter and the maximum likelihood procedure to obtain the variances.

In case that the double seasonality is considered, the two seasonal components can be included. In this case, a huge number of dummy variables appear. To alleviate this problem, one seasonal can be alternatively considered using periodic splines to characterize the intradays demands. Harvey and Koopman (Harvey et al., 1993) studied this method to forecast the hourly electrical demand.

Exponential Smoothing method
The exponential smoothing methods were proposed by Brown in the fifties. Holt and Winters improved the method to work with tendency and seasonal components. After the Winters paper their method is know as Holt-Winters method, although it is a kind of exponential smoothing method. Its main characteristic is their simplicity. So, this method does not need off-line identification phase and only an optimization with least squares or other method is required. For this reason, it is used as automatic forecasting method. Nowadays, it is a standard method in the electricity and water demand forecast.

The prominent problem of the Holt-Winters method is that it works with just one periodicity (additive or multiplicative). Taylor (Taylor, 2003) proposed a new extension with a multiplicative double seasonality.

The Holt-Winters prediction for with multiplicative one seasonal periodicity is

$$\hat{x}(t+k|t) = \big(L(t) + k \cdot T(t)\big) S(t + k - \left[\frac{k}{s} + 1\right] s)$$

where *L(t)* is the level component, *T(t)* is the trend component, *S(t)* is the seasonal component, *s* is the period and *[a]* is the integer part of *a*. These components can be modelled as follows

$$L(t) = \alpha \frac{x(t)}{S(t-s)} + (1-\alpha)\big(L(t-1) + T(t-1)\big)$$
$$T(t) = \gamma\big(L(t) - L(t-1)\big) + (1-\gamma)T(t-1)$$
$$S(t) = \delta \frac{x(t)}{L(t)} + (1-\delta)S(t-s)$$

and α, γ and δ are the parameters. The least squares parameter method provides these parameters. Often, the residuals of the model are correlated. In this case a simple *AR(1)* is added to improve the prediction residuals.

As a basic structural model, the classical Holt-Winters method only has a one seasonal component. To handle the both seasonal periodicities present in the hourly water demand, the double seasonal Holt-Winters method introduced by Taylor (Taylo, 2003) will be used. This extended model has the following form

$$\hat{x}(t+k|t) = \big(L(t) + k \cdot T(t)\big) \cdot S_1\left(t + k - \left[\frac{k}{s_1} + 1\right] s_1\right) \cdot S_2\left(t + k - \left[\frac{k}{s_2} + 1\right] s_2\right)$$

where *L(t)* is the level component, *T(t)* is the trend component, $S_1(t)$ is the first seasonal component, $S_2(t)$ is the second seasonal component, s_1 and s_2 are the number of seasons of each period. These components can be modelled as

$$L(t) = \alpha \frac{x(t)}{S_1(t-s_1)S_2(t-s_2)} + (1-\alpha)(L(t-1) + T(t-1)$$
$$T(t) = \gamma\big(L(t) - L(t-1)\big) + (1-\gamma)T(t-1)$$
$$S_1(t) = \delta_1 \frac{x(t)}{L(t)S_2(t-s_2)} + (1-\delta_1)S_1(t-s_1)$$
$$S_2(t) = \delta_2 \frac{x(t)}{L(t)S_1(t-s_1)} + (1-\delta_2)S_2(t-s_2)$$

and α, γ, δ_1 and δ_2 are the parameters that should be estimated with least squares method. Usually, the model residuals are correlated. To address this issue the model should include an error model. In particular, the residuals are modelled with $AR(1)xAR_{s1}(1)$. The new forecasting method is better than former without the correction residuals.

Naïve methods

All the proposed forecasting methods will be compared against two naive methods. These methods are applied as benchmark method. If the method is worse than they, it can not able to capture the variability of the data.

The first naïve method is the random walk. The random walk is widely used as benchmark method. The random walk prediction is a constant forecast with the last real value. The second method is a seasonal version of the random walk. This method is used when the time series contain seasonality. Their prediction is the *t*-s value where *t* is the predicted time and *s* is the number of periods: for the weekly period, $s=7$ or $s=168$ depending on the considered time scale (daily or hourly).

RESULTS

The Barcelona water transport network is composed of about 100 pressure floors. At present, the information system receives, in real time, data from 100 control points, mainly flow meters and a few pressure sensors. Its worth to notice that only few floor of pressure concentrate almost 75% of the water consumption. So, we concentrate in these floors, because the improving prediction in these floors could lead a major economical benefits. The paper just presents the results for pressure floors of biggest demand The other major floors have a similar behaviour than those that are presented in this paper.

To compare the distinct forecasts methods, a set of comparative indicators are used. These indicators help to decide which forecast model is the best. Since the best model will presumably depend on the time scale considered. We expected that the best model for the daily prediction will not give the best hourly forecast. The repeatability of historical data also influence on the prediction quality of each model.

The set of indicators are

- *Explained variance* measures the not modelled variance, $EV = 1 - \frac{Var\,(e_k)}{Var\,(x_k)}$. If the EV=1, the model capture the whole process variance.
- *Mean absolute errors* measures the deviation absolute errors means in the units of the

process, $MAE = \frac{1}{n}\sum_{i=1}^{n} |e_k(i)|$.

- *Mean squares error* can be expressed as $MSE = \frac{1}{n}\sum_{i=1}^{n} e_k(i)^2$.
- *Mean absolute percentage error* has $MAPE = \frac{100}{n}\sum_{i=1}^{n} |\frac{e_k(i)}{\mu}|$. This indicator rescales the errors respect the process mean, so it allows working without units.

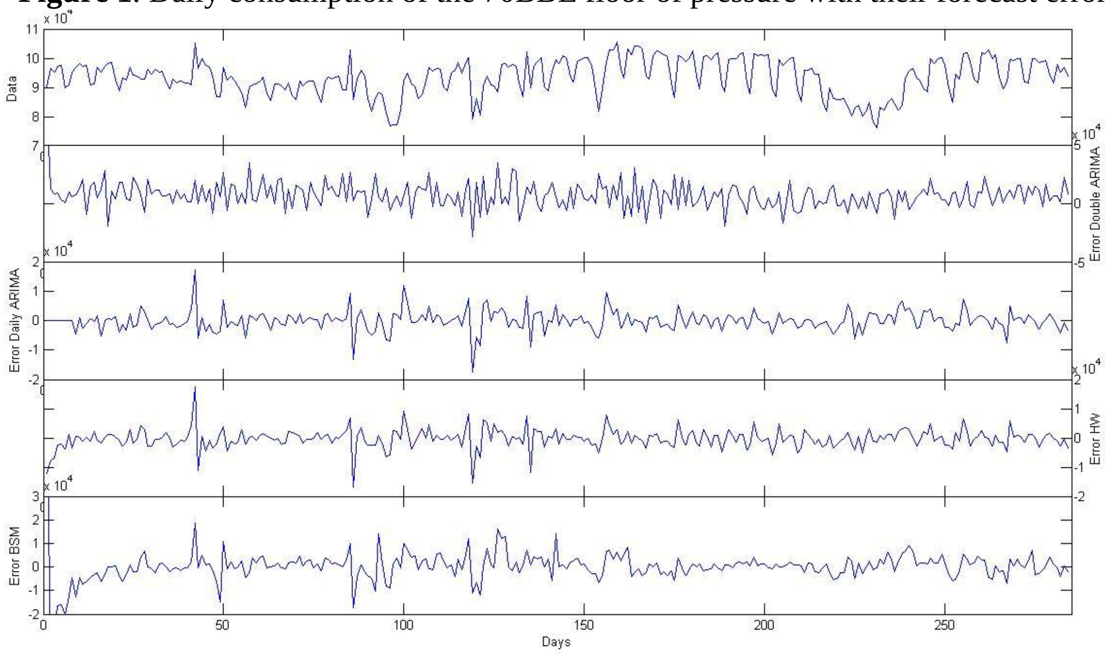
where $e_k(i)$ is the k-steps prediction error from time i, x_k is the time series and μ is the mean of the time series. We want that *EV≈1*, *MAPE≈0%* and that *MAE*, *MSE* will be small. The *MAPE* is widely used in many industry comparisons and their interpretations are similar to *MAE* and *MSE*. The advantage of *MAPE* is that it is not dimensional.

The results presented for 70BBE pressure floor are representative of the results obtained in most of the pressure floor.

70BBE pressure floor

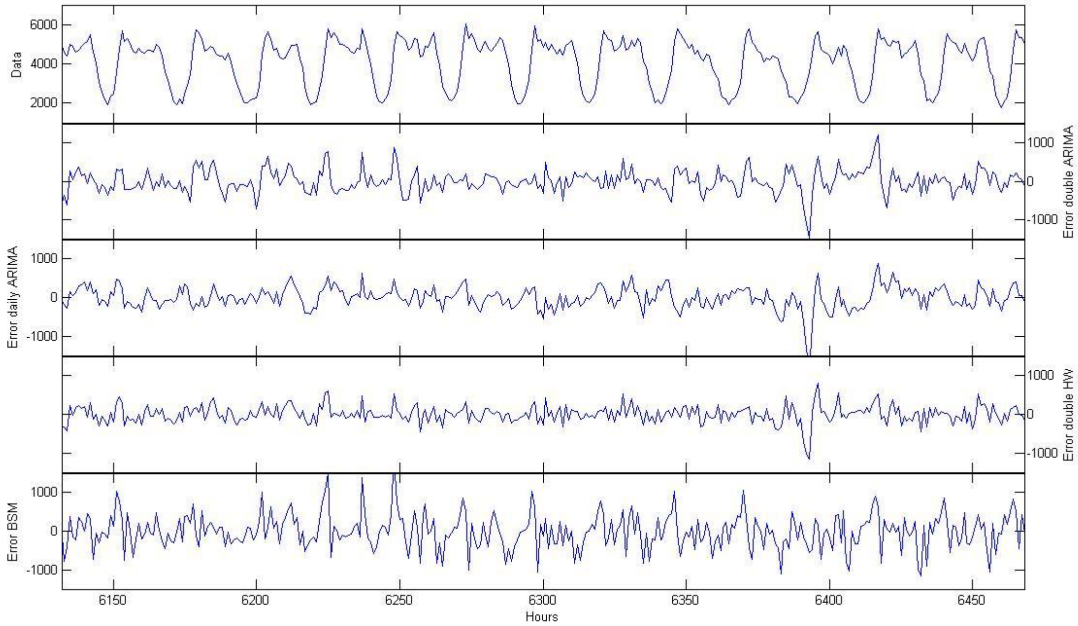
The 70BBE pressure floor is selected, because it represents the *25%* of the total consumption in the city. The other major pressures floors have similar characteristics as *70BBE*. Figure 1 presents the daily consumption and one-step forecast errors of the considered methods. The first graph presents the real data. The daily forecast for the hourly model is the sum of the forecast from one to twenty-four step. The second graph presents the double *ARIMA* forecast error for the daily consumption. The third graph presents the daily *ARIMA* error. In this example, the selected model structure is $ARIMA(0,1,1)x(0,1,1)_7$. The forth graph presents the Holt-Winters forecast error. The fifth graph presents the basic structural model. From these graphs, it can be observed that the double *ARIMA* has the biggest error. The basic structural model has heteroscedasticity error, which is error with a non-constant variance. The daily *ARIMA* and double Holt-Winters errors are similar and the errors peaks are caused for the special events. In the future works, the selected procedure should be improved to take into account the influence of these events.

Figure 1. Daily consumption of the 70BBE floor of pressure with their forecast errors.



In Figure 2, a piece of the hourly time series with their one-step forecast errors is presented. The first graph is the hourly data. The second graph corresponds to double *ARIMA* errors. The third graph is the error forecast using the adaptable demands patterns. The forth graph presents the double Holt-Winters forecast errors. The last graph presents the basic structural model errors. It can be observed that the basic structural model error have the biggest variance. The patterns distribution of the daily consumption and double Holt-Winters are similar. The double *ARIMA* have a lot of large error peaks that suggest us that the model is not correct.

Figure 2. A piece of hourly consumption of the 70Bbe with their forecast errors.



It can also be noticed that the double *ARIMA* and the basic structural models are worst than the others two. The daily *ARIMA* and the double Holt-Winters are similar and visually can not be decided which is the best. In Figure 3 and Figure 4, the *EV* and *MAPE* indicators for each model are presented in the daily and hourly scales. In Table 1 and Table 2, there are *MAPE* indicators for calibration phase in both scales.

Figure 3. The *EV and MAPE* indicators for each method in the daily scale for the 70BBE.

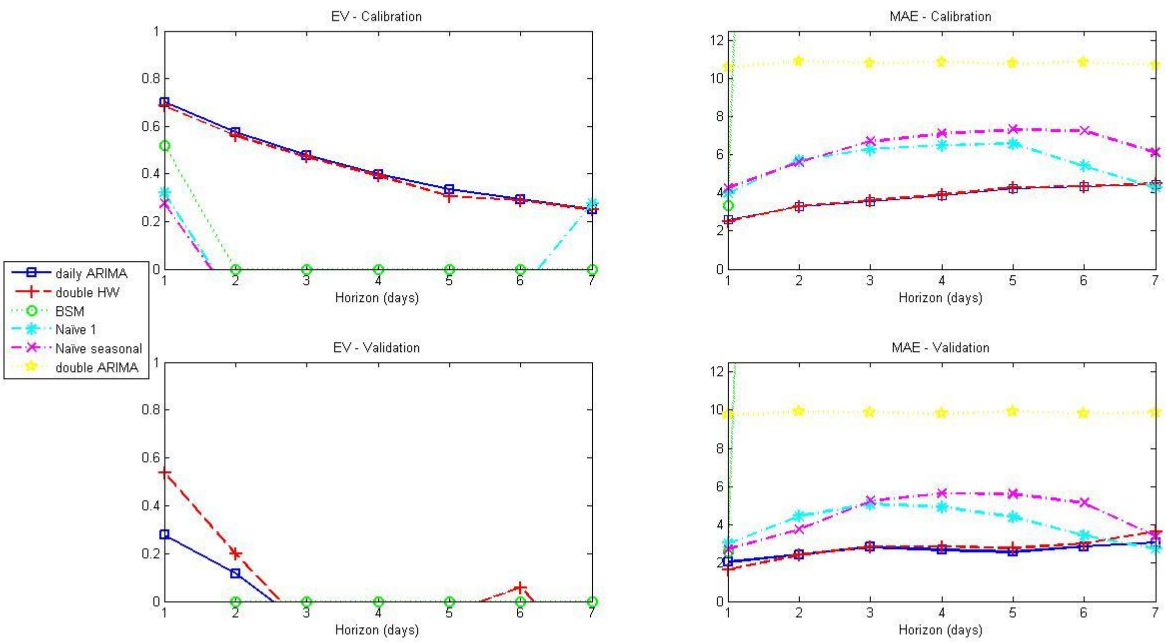


Table 1. *MAPE* indicator for each method for the daily time series of the 70BBE.

Horizon	Double ARIMA	Daily ARIMA	Holt-Winters	BSM	Naïve 1	Naïve 7
1	10.5612	2.6005	2.4900	3.3478	3.9869	4.2656
2	10.9078	3.2740	3.2855	100.0000	5.6993	5.6183
3	10.8099	3.5517	3.6025	100.0000	6.2783	6.6960
4	10.8586	3.8584	3.9056	100.0000	6.5002	7.1116
5	10.7913	4.2101	4.2880	100.0000	6.5699	7.3217
6	10.8718	4.3275	4.3482	100.0000	5.4119	7.2524
7	10.7100	4.4230	4.4744	100.0000	4.2656	6.1098

It can only be noticed that in the calibration phase, the daily *ARIMA* and the daily forecast of the double Holt-Winters have a good performance according to EV indication. But, in the validation phase, the *EV* indicator shows that any model is unable to capture the variance of this validation phase. In the calibration phase, the daily *ARIMA* and the daily forecast of the double Holt-Winters are able to explain the *70%* of the variance with one-step forecast but they only explain the *20%* with the seven-step forecast. This is a typical result because the seven-step forecast uses intermediate predictions while the single-step one does not. Considering the *MAPE* indicator, the behaviour in the two phases is similar. The daily *ARIMA* and the daily forecast of the double Holt-Winters have the best *MAPE* indicators. It can also be observed that the *MAPE* of the Daily *ARIMA* and the daily prediction of the Holt-Winters are smaller than *5%*. For the other methods, their *MAPE* is larger than *5%*. So, in the daily scale, the Daily *ARIMA* and the Holt-Winters have a similar behaviour.

Figure 4. The *EV* and *MAPE* indicators for each method in the hourly scale for the 70BBE floor of pressure.

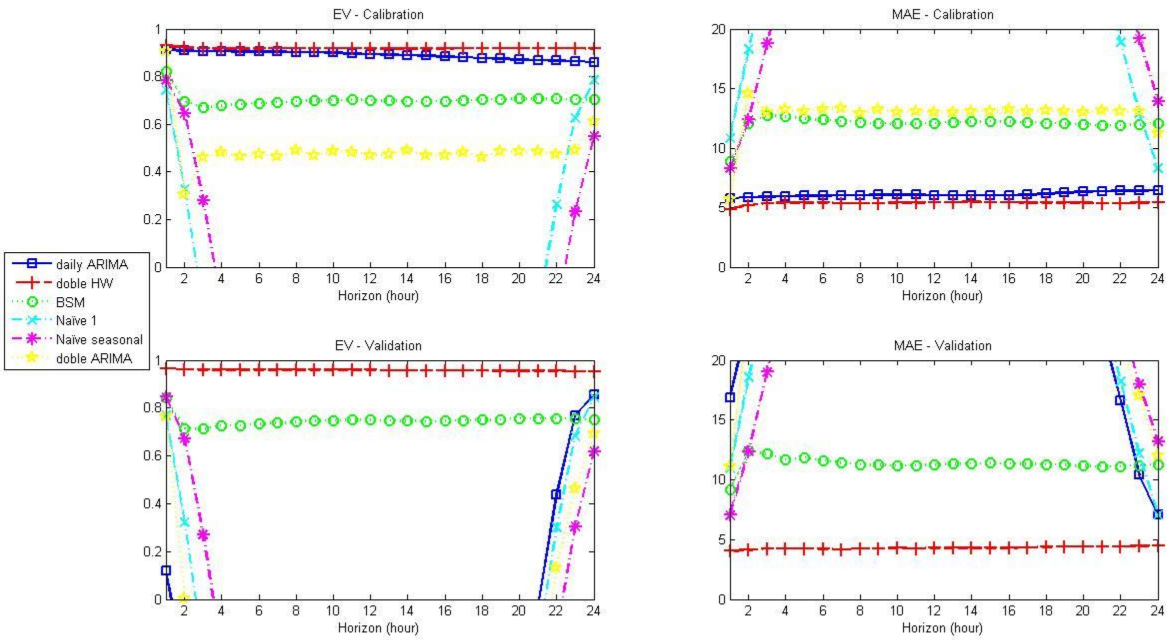


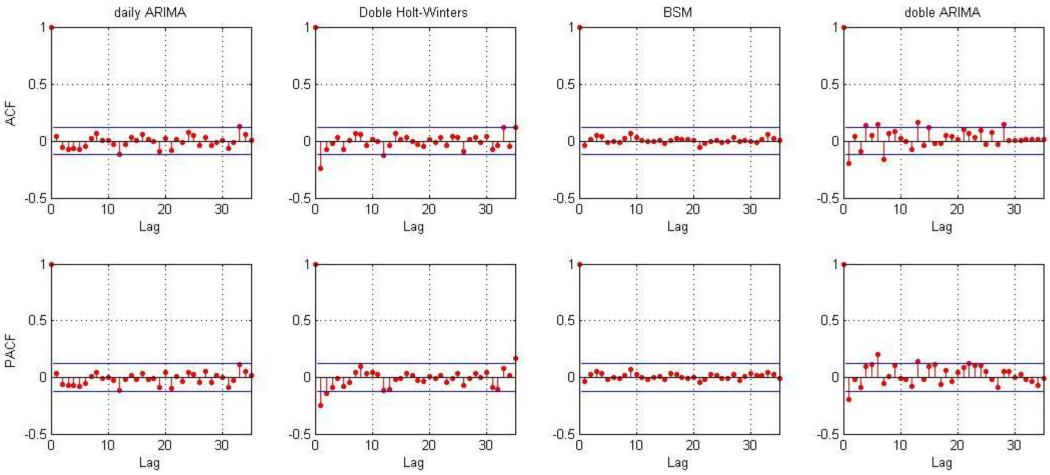
Table 2. *MAPE* indicator for each method for the hourly time series of 70BBE.

Horizon	Double ARIMA	Pattern	Holt-Winters	BSM	Naïve 1	Naïve 7
1	5.6846	5.7577	4.8709	8.8440	10.8495	8.2799
2	14.5969	5.8433	5.1908	12.0605	18.2944	12.3703
3	12.9981	5.9047	5.3459	12.7374	24.6421	18.7919
4	13.1956	5.9508	5.4046	12.6250	30.0094	24.9268
5	13.1033	5.9863	5.4201	12.4775	34.3851	30.2886
6	13.2732	6.0045	5.3957	12.3761	37.5536	34.6361
12	13.0239	6.0373	5.4401	12.0890	42.9569	43.8022
24	11.1971	6.4395	5.4437	12.0379	8.2938	13.9054

Focusing on the hourly scale, the most surprising fact is the change in behaviour between the calibration and validation phase when using the daily *ARIMA* with demand pattern distribution. In calibration phase, the indicators for this method are close to the double Holt-Winters indicators. But in the validation phase, the *ARIMA* with pattern distribution indicators are significantly worse. In the other cases, the double Holt-Winters are similar in both phases. The worsening in the daily *ARIMA* forecast may be due to the change in the patterns. So, the behaviour is different during the two phases and the pattern model is unable to forecast these changes. The rest of the methods have worse indicators than Holt-Winters.

Finally, the last check involves verifying if the daily errors were correlated or not. In case the residuals were correlated, the method will not capture all the time series information. The daily error is considered, because it provides information about future events. Figure 5 presents the autocorrelation (ACF) and partial autocorrelation (PACF) for each method. It can be noticed that the daily *ARIMA* and the basic structural model are not correlated. The double Holt-Winters presents a correlation for few lags. Finally, the double *ARIMA* presents the lags autocorrelated because the residuals are not white noise.

Figure 5. ACF and PACF for the distinct methods.



Thus, it can be concluded that the double Holt-Winters provides the best daily and hourly forecast. These methods are better than the naive methods in every time scale and phase.

CONCLUSIONS

In this paedr, four methods to predict a future demand values in two time scales (hourly and daily) are studied and compared. These methods are tested in Barcelona water transport network in a set of representative pressure floor.

The first conclusion is that the basic structural method is the slowest, because the model contains a matrix with large dimension. This fact leads to slow the prediction. The second is that the double *ARIMA* produces bad predictions, because it can be easily influenced. The third method is based on the combination of daily *ARIMA* with pattern distribution. This method presents distinct behaviour depending on time scale and phase. In the daily scale, forecasting is good. In the hourly scale, the prediction goodness depends on the phase. In the calibration phase forecasting is good but in the validation phase it is not. Finally, the double Holt-Winters method seems to be the most robust forecasting method and it is easy to implement too.

The main daily *ARIMA* problem is in the calibration phase since while computation time is high, the selected method has better prediction. Another problem is the sensitivity to outliers. To reduce the outliers effect, an outlier detection algorithm could implement for the daily scale. This method is only good for daily forecasting because the pattern does not provide an accurate forecast in the larger time scale.

The double Holt-Winters is a deterministic method. So, in typical pressure floors, where seasonal periodicity changes smoothly, it provides good forecasting. If it is assumed that the residuals follow an *ARIMA* model, the forecast improves. The best residual *ARIMA* model is $AR(1)xAR_{24}(1)$. The parameters are estimated using the least squares method.

Since majority of pressure floors change their periodicities smoothly, it can concluded that the best method is the double Holt-Winters in both time scales.

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REFERENCES

J., Abraham B. and Ledolter. «Forecast functions implied by autoregressive integrated moving average and other related.» *International Statistical Review, 54,* 1986: 51-66.

Box G., Jenkins G. M. and Reinsel G. C. *Time Series Analysis: Forecasting and Control. 3rd edn.* Englewood Cliffs: Prentice Hall, 1994.

Cembrano G; Wells, G; Quevedo, J; Pérez R; Argelaguet R., “Optimal Control of a water distribution network in a supervisory control system”,Control Engineering Practice Journal, ISSN 0967-0661, Vol.8, pp. 1177-1188, 2000.

J., Durbin J. and Koopman S. *Time series analysis by state space methods.* New York: Oxford University Press, 2001.

A., Harvey. *Forecasting, structural time series models and the Kalman filter.* Cambridge: Univesity Press, 1989.

Harvey A. and Koopman S. «Forecasting Hourly Electricity Demand Using Time-Varying Splines.» *Journal of the American Statistical Association, 88 (424)*, 1993: 1228-1236.

D., Peña. *Análisis de series temporales.* Madrid: Alianza Editorial, 2005.
J., Poirier D. «Piecewise regression using cubic splines.» *Journal of the American Statistical Association, vol. 68,* 1973: 515-524.

Quevedo J., Puig V., Cembrano G., Aguilar J., Isaza C., Saporta D., Benito G., Hedo M. and Molina A. «Estimating Missing and False Data in Flow Meters of a Water Distribution Network.» *6th IFAC Symposium on Fault Detection, Supervision and Safety of Technical Processes.* 2006.

Schwarz, G. E. "Estimating the dimension of a model." *Annals of Statistics 6 (2)*, 1978: 461-464.

E., Taylor J. W. and McSharry P. «Short-Term Load Forecasting Methods: An Evaluation Based on European Data.» *IEEE Transactions on power systems, 22 (4)*, 2007.

Taylor J. W., de Menezes L. M. and P. E. McSharry P. E. «A comparison of univariate methods for forecasting electricity demand up to a day ahead.» *International Journal of Forecasting, 22,* 2006.

W., Taylor J. «Short-Term Electricity Demand Forecasting Using Double Seasonal Exponential Smoothing.» *Journal of Operational Research Society, 54,* 2003: 799-805.

P., Winters. «Forecasting sales by exponentially weighted moving averages.» *Management Science, 6*, 1960: 324-342.