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Sonic log analysis in oil wells through Box and Jenkins methodology

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The sonic profile is used, mainly in exploration wells, which receive greater investment in data acquisition because these wells serve as a reference for analyzing the petroleum potential of the area. The sonic profile was introduced in the 50s, with the goal of providing support for seismic exploration, and subsequently became extensively used for studies on total porosity of the rocks traversed by the well. This paper aims to apply the use of Box-Jenkins methodology to analyze the sonic profile in the process of profiling an oil well. The data were provided by PETROBRAS/UO-SEAL, the analyzes were performed using the variable DT (delay time). The statistical software was used to meet the best ARIMA model fit, and was observed as the stationarity before and after modeling through the autocorrelation function and the partial autocorrelation function. The criterion for validation of the model was the MAPE (Mean Absolute Percentage Error). Several models were tested and found for the best model - the ARIMA (3, 1, 2) with MAPE of 4.68%.

Key words: Synthetic sonic log, time series, Box and Jenkins.

INTRODUCTION

Oil is used in various segments of the industry, as raw material, fuel and with the rising price of oil exploration companies were forced to make the most of the deposits already known for the lowest possible cost. Thus, the optimization of reservoir development has become critical to the success of the oil industry, and seismic, which until then was not used in a systematic way in the development of oil fields, now seen as a potential tool for this purpose (Lima, 2005; Gardner, 1974).

The sonic profile was introduced in the 50s, with the goal of providing support for seismic exploration; subsequently became extensively used for studies of total porosity (t) of the rocks traversed by the well. The sonic tool consists basically in record time that elapsed between the moment a compression sound pulse is emitted by a transmitter, mounted on a mandrel inside the pit, until his arrival in two distinct receptors on the same mandrel. The difference between the two arrival times (transmitter - receiver near T-RP and transmitter - receiver away T-RL) is called transit time or *delay time* (DT) (Lima, 2005).

With this, the paper aims to use the Box and Jenkins methodology to find models of autoregressive integrated moving average, ARIMA (p, d, q) that best fits the data

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set variable of the sonic log (DT) wells analyzed.

THEORY PROFILING

After the drilling phase of the well, various tools are generally lowered in order to measure some properties of rocks, fundamental for characterization and economic evaluation. This process is known as profiling.

The profiling provides important information about the formations traversed by the well, such as lithology (rock type), thickness, porosity, pore likely exist in fluids and their saturations. The major limitation of the profiling is the small extent of its radius of investigation side, so that only the vicinity of the well is analyzed by profiling (Thomas, 2001).

According to Cunha (2012), the profiling can reveal the existence of oil and gas sufficient to justify the expense of the well logging. This operation is usually done by subcontractors. On land rigs contracted, the company sends a logging unit mounted on a truck, while at sea the unit is fixed in the probe, installed in a small shelter. The profiling unit is equipped with computers, winches and controls that perform the operation.

The logging tool is lowered into the well on a conductor cable to the desired depth. The unit pulls the tool that goes well by detecting certain aspects of the formation through which it passes. The information is sent to the surface by the cable conductor and recorded by computers. The log is printed for later analysis (Cunha, 2012).

Types of profile

There are several types of profiles used for many different applications, all with the aim to better assess the geological formations for the occurrence of a commercial hydrocarbon deposit. The most common profiles are: Spontaneous Potential, Gamma Ray, Neutron, Induction, Sonic, Density and Caliper (Doventon, 2004).

FORMULATION AND ARIMA EQUATIONS

The steps of the methodology Box and Jenkins are the identification, estimation and verification of diagnosis by analyzing the number of waste from the adjustment, if the model is accepted as good, going to the prediction phase, otherwise the analysis waste must indicate the tentative new model.

To validate the choice of the best model, we use the MAPE (Mean Absolute Percentage Error). The MAPE is calculated from a step ahead forecasts generated by each model estimated (Russo, 2002; Box and Cox 1964).

Autoregressive models AR (p)

The model AR (p) assumes that the observation of this variable can be explained by a weighted sum of the previous variables of the same variable and a current error a_t (Russo et al., 2006).

$$\tilde{Z}_t = \pi_1 \tilde{Z}_{t-1} + \pi_2 \tilde{Z}_{t-2} + \cdots + a_t \quad (1)$$

$$\tilde{Z}_t = \phi_1 \tilde{Z}_{t-1} + \phi_2 \tilde{Z}_{t-2} + \cdots + \phi_p \tilde{Z}_{t-p} + a_t \quad (2)$$

If we define the operator stationary autoregressive of order p;

$$\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p \quad (3)$$

Then we can write; $\phi(B)\tilde{Z} = a_t$.

Models moving average MA (q)

Models MA (q) resulting from the linear combination of random shocks occurring in the current period and past periods (Box and Cox, 1964; Russo et al., 2006). A model Mobile Averages (MA (q)) is defined according to the equation:

$$\tilde{Z}_t = \mu + a_t - \theta_1 a_{t-1} - \cdots - \theta_q a_{t-q} \quad (4)$$

And being: $\tilde{Z}_t = Z_t - \mu$, we:

$$\tilde{Z}_t = \left(1 - \theta_1 B - \cdots - \theta_q B^q\right) a_t = \theta(B) a_t \quad (5)$$

were, $\theta(B)$ is the average mobile operator of order q (Moretin and Toloi, 2006).

Autoregressive models and moving average ARMA (p, q)

By combining the templates AR (p) and MA (q), it is expected that the ARMA (p, q) be extremely parsimonious model using few coefficients to explain the same sequence (Box and Cox, 1964; Russo et al., 2006).

Here, then the ARMA (p, q) of the form:

$$\tilde{Z}_t = \phi \tilde{Z}_{t-1} + \cdots + \phi_p \tilde{Z}_{t-p} + a_t - \theta a_{t-1} - \cdots - \theta_q a_{t-q} \quad (6)$$

Models autoregressive integrated moving average ARIMA (p, d, q)

The class of ARIMA (p, q, d) to an integrator d is defined by the equation.

If: $W_t = Z_t - Z_{t-1} = (1 - B)Z_t = \Delta Z_t \quad (7)$

If: $W_t = \Delta^d Z_t$ is stationary, can represent W_t by an ARMA model (p, q), in other words:

$\phi(B)\Delta^{d}Z_t = \theta(B)a_t$. (Moretim, 2006) (8)

After varying the series d times to make it stationary, the ARIMA model (p, d, q) can be adjusted via the ARMA model (p, q) cited in d above. The number of differences needed to make the series is called stationary order of integration (Box and Cox, 1964).

METHODOLOGY

The analyzed data set is about information on the variables of profiles of wells that measure properties of the rocks crossed for the well, that it is located in a field of oil of the Basin Sedimentary Sergipe Alagoas. Some of these wells make use of a complete set of profiles, also the sonic one. The possible stratifications of the samples will be identified as: lithologics depth, types (compositions), stratigraphics levels, etc.

According to Russo (2011), to guarantee the quality of the results specific tests were carried through parallel to the analysis statistics of the results, such as: test for the parameters, test of significance of the relation between the variable, the verification of the determination coefficient, the significance of the correlation and regression, as well as the occurrence of aberrant points and crossed validation.

Characterization of the variable of profile

Sonic – DT (delay time)

A sonorous wave measures the time necessary to cover a rock foot - this time is called transit time. This time is inversely proportional to the sonic speed of the rock. It is used for estimation of the porosity, correlation of wells, estimations of the degree of compaction of the rocks, estimations of the elastic constants of the rock, detention of breakings and support to the seismic one (synthetic seismogram). It is measured in microseconds for foot (Russo et al., 2011).

Characterization of the geologic variable

Stratigraphics Levels - L_st

This variable indicates the different geologic levels crossed by the wells. They can differentiate one from the other in function of different attributes as geologic ages of the rocks, origins in different sedimentary environments that in last analysis go to express themselves as rocks with different mineralogy's compositions causing variations of the physical and chemical aspects of these rocks. Most importantly, these stratigraphic levels can be tracked laterally, well to well on the basis of its signatures of the profile.

RESULTS AND DISCUSSION

Analysis of well

Data are from the Sergipe Alagoas sedimentary basin. The variable analyzed is DT (sonic profile). The set of variable data sonic profile is represented by Table 1 which describes the characteristics of the cases in numerical terms. The number of observations of the variable DT for well B was 10.809, with mean transit time of 83.075 and 382.767 variance. The coefficient of variation is 23.55% indicating a homogeneous distribution.

Table 1. Descriptive analysis of DT.

Summary	DT
Number of cases	10809
Average	83.075
Median	77.017
Minimum	50.415
Maximum	190.385
Variance	382.767
Standard deviation	19.564
Standard error	0.188
CV%	23.550

Identification of the model structure

Initially, a plot was made to understand the behavior of the variable. As the depth increases DT (delay time) tends to be low, although there are some peaks. These can be explained according to Lima (2005), which states that high times DT may represent fractures, landslides or even the presence of gas. It is observed in Figure 1, that the series is not stationary on average and variance, as it used the difference (*d=1*).

The autocorrelation function and partial autocorrelation function are shown outside the confidence limits.

The Figure 2 shows a typical correlogram a series of non-stationarity: the autocorrelation coefficient starts with a high value very slowly and tends to zero as the delay increases, and the partial autocorrelation coefficients function also appear outside the confidence limits.

Estimation of model parameters

After many attempts the model that best fit the series was ARIMA (3, 1, 2). Figure 2 shows the behavior of the series after shaping. Mean 83.075 DT thus revealed that after shaping the series is stationary on average and variance. More importantly, to employ the Box-Jenkins methodology, you need to have at hand a stationary series or it may become stationary. This estimated model is used to make predictions; we must assume that the characteristics of this model are constant over time and especially in future periods (Box and Cox, 1964). Several models were tested with Table 2 showing a comparison between some models.

For the ARIMA (3, 1, 2) a MAPE of 4.68% was recorded; for ARIMA (1, 0, 3) the MAPE was 8.61%, thus calculating the MAPE with the analysis of autocorrelations possible to establish the ARIMA (3, 1, 2) as the best model found.

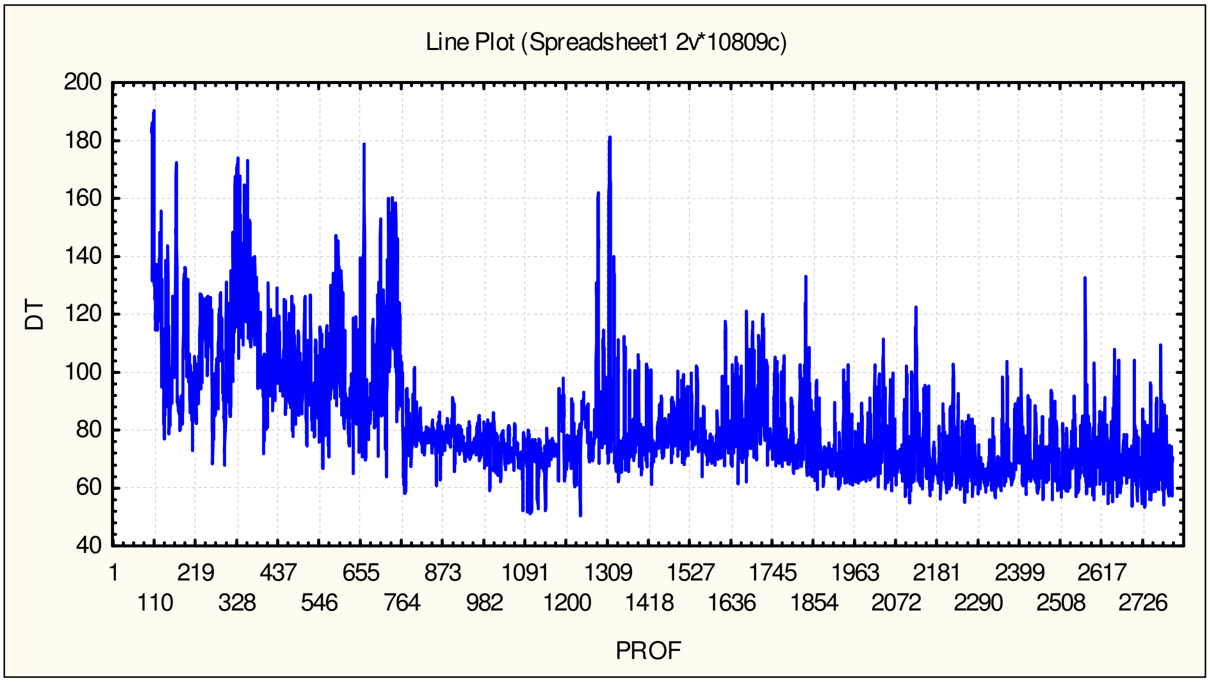

Figure 1. Series DT.

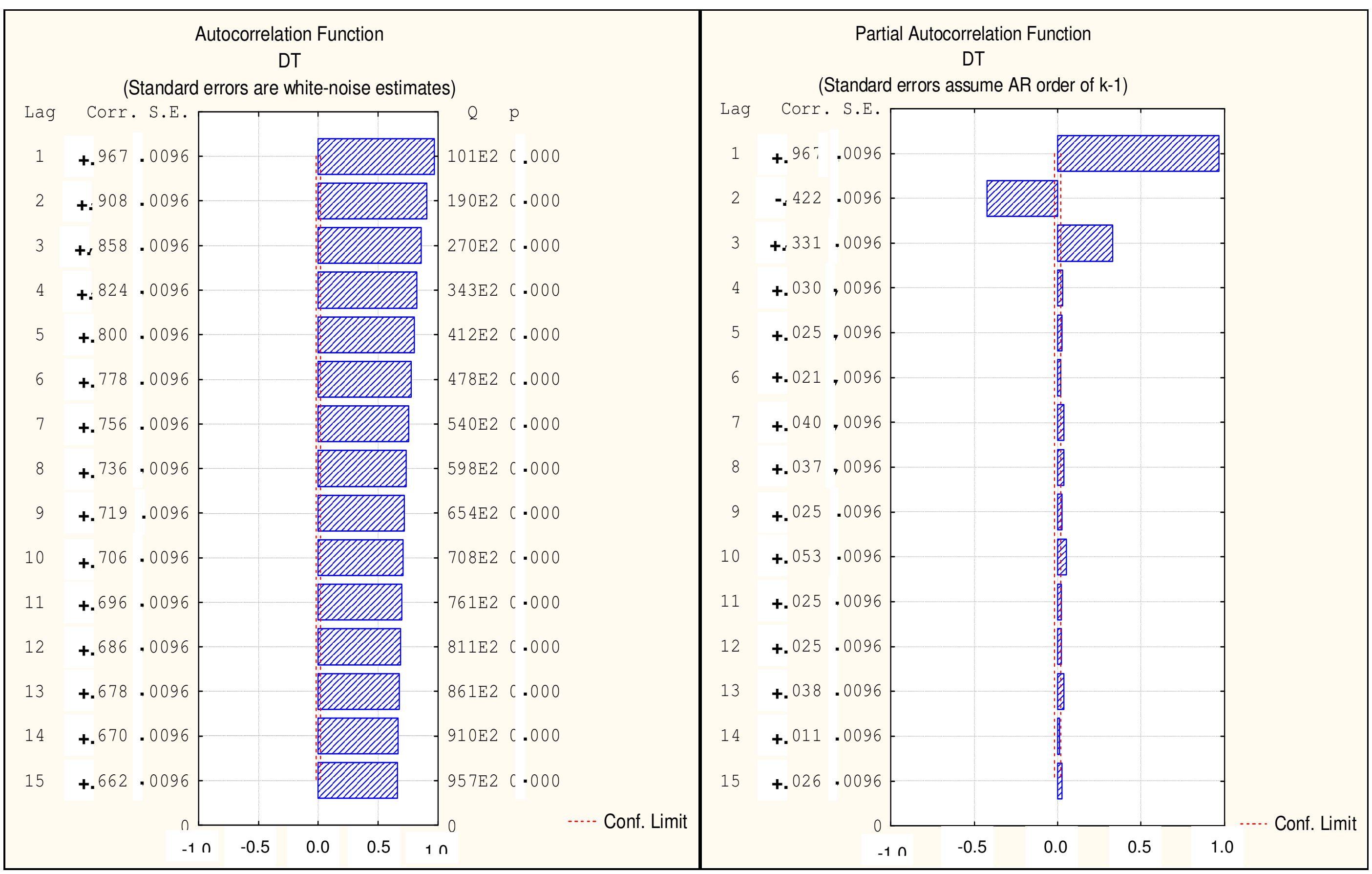

Figure 2. Autocorrelation Coefficients Function and Partial Autocorrelation Coefficients Function for real data.

Table 2. Model parameters.

Well B	Estimate	Standard Error	T test	p-value	MAPE%
(1,0,3)	0.998	0.001	1639.428	0.000	8.61
	-0.429	0.010	-42.826	0.000	
	0.102	0.013	8.001	0.000	
	0.181	0.010	17.777	0.000	
(3,1,2)	1.414	0,030	47.518	0.000	4.68
	-0.788	0.041	-19.304	0.000	
	0.269	0.017	15.646	0.000	
	0.891	0.031	29.054	0.000	
	0.085	0.030	2.878	0.004	

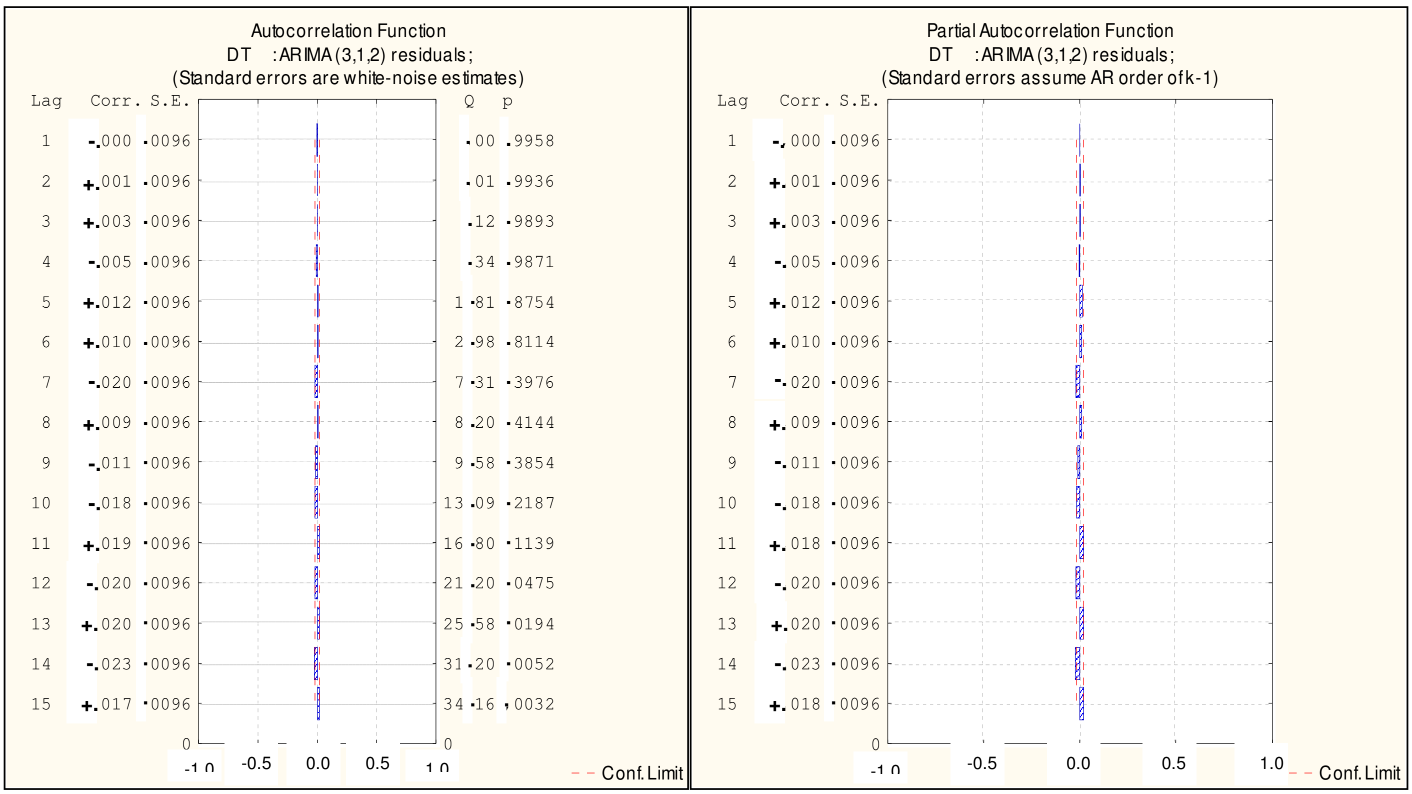

Figure 3. Autocorrelation Coefficients Function and Partial Autocorrelation Coefficients Function for transform data.

Table 3. Predicted values for DT.

Predicted (*P*)	**Observed (*O*)**	$\left\lvert \frac{P-O}{O} \right\rvert$
59.21403	58.41020	0.013762
61.98322	62.99610	0.016078
63.45142	66.70570	0.048786
63.85260	68.16580	0.063275
64.00903	70.49220	0.09197

After finding the ARIMA model, correlation coefficients for the series patterned were obtained (Figure 3). It is observed that the values are within the confidence limits and close to zero, demonstrating the absence of correlation.

Forecast

In Table 3, the last five predictions for the variable with the DT model ARIMA (3, 1, 2) compared with their

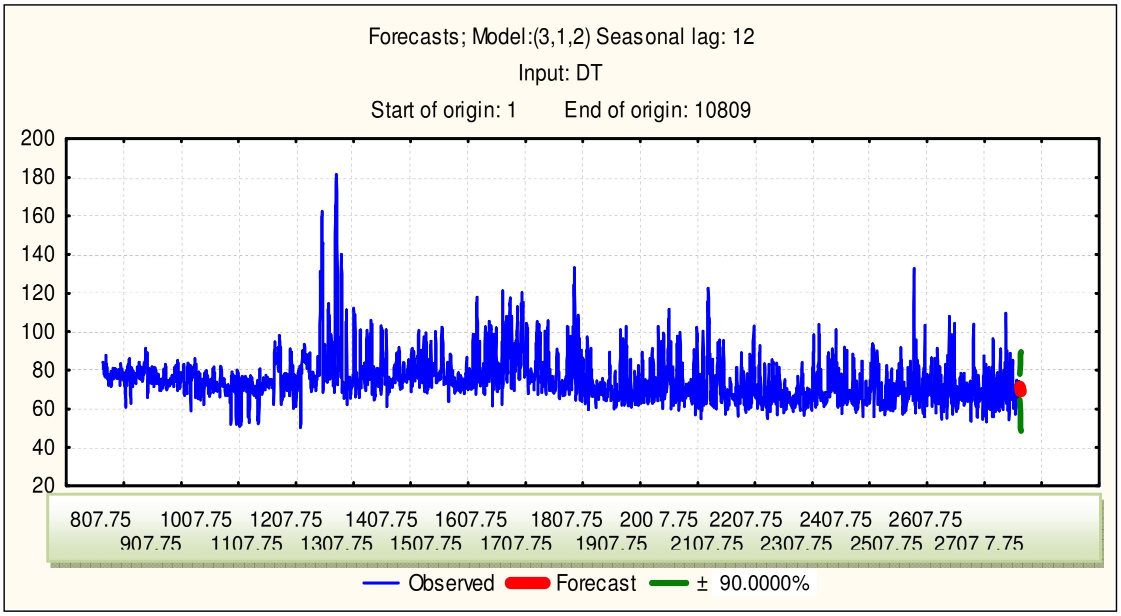

Figure 4. Forecast.

observed values, and the Figure 4 shows the Graph of the Forecast of the model.

Conclusion

This study examined the construction of models generated from synthetic sonic log in petroleum wells drilled in geological units belonging to Sergipe Alagoas sedimentary basin. These models allow geologists and geophysicists to obtain information that will improve the quality and reliability of synthetic sonic profiles generated, providing subsidies from the point of view of their suitability to be used as geological data, geophysical processing and interpretation in the areas whose wells have no sonic profile registered.

ARIMA models were applied to find a prediction equation, and several tests were performed and the model that best fit the sonic profile (variable DT, delay time) was the ARIMA (3, 1, 2). This achieved a MAPE of 4.68% and correlation coefficients within the confidence limits, thus being the most suitable to represent the data set. The predictions can be improved, still found with other analyzes which reduce even more the influence of outliers in the series.

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