

FORECASTING THE SALES OF CONSOLE GAMES FOR THE ITALIAN MARKET

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Abstract: In videogames industry, time series analysis can be very useful in determining the general evolution and behaviour of the market dynamics. These methods are applicable to any time series forecasting problem, regardless of the application sector. This article discusses time series approaches to forecast the sales of console games for the Italian market. In particular two univariate techniques were evaluated, exponential smoothing and the SARIMA technique. The aim is to exploit the capabilities of these statistical methods in order to have a comparison of the results and to choose the most accurate model through an ex-post evaluation. Using monthly time-series data from November 2005 to September 2017, the selection of the most suitable model was indicated by the smallest value of the measures of accuracy (MAPE, sMAPE, RMSE) for the out-of-sample observations regarding the period October 2017-September 2018. The implementation of the models was done using Forecast PRO and Gretl. The time series involved is related to the sales regarding the first party manufacturers of consoles and handhelds (Microsoft, Sony and Nintendo).

Keywords: exponential smoothing, SARIMA, forecast, videogames.

1. Introduction

There is a constant need regarding the demand forecasting. Given the strong seasonal nature and the marked fluctuations due to technological innovation and pricing policy, predicting the evolution of a particular business which follows some dynamics, is a crucial aspect in order to identify the appropriate and specific model able to encompass all the features and peculiarities of the market. Furthermore, successful planning of the devices allows the manufacturers to shape more accurate production planning. In this paper two statistical models were applied, exponential smoothing and the SARIMA model, and the goal is to predict the most accurate values of console games for 12 months ahead with the use of ex-post analysis. Moreover, the market is also affected by the games genres and by the game-players

attitude, and additionally by some external conditions. This article consists of four sections:

- The methodology used and a brief description of the measures of the loss function.
- The monthly dataset.
- Results.
- Concluding remarks.

The forecasting models were developed using the first l to 12 observations, where l is the length of the series. This period is normally set by the production planning and decision-making, and another reason is due to yearly seasonality. Then, 12 forecasts values were produced for each model and their accuracy was evaluated compared to the actual values not used in developing the forecasting models. The first approach is based on the exponential smoothing methods and is derived from the work by Kalman [1960]. Exponential smoothing, or ETS, are the common methods of forecasting, mainly due to the very simple concept and minimal computation. Furthermore, ETS methods are also very flexible and they are supported by several analysis and practical applications [Hibon, Makridakis 1979]. The second approach is based on the Box Jenkins procedure, [Box et al. 1994] where it is supposed that the time series is stationary. In order to do that, Box and Jenkins recommend differentiating non-stationary time series, one or more times, to achieve stationarity. The approach is based on the combination of autoregressive and moving average parameters. The classification of this model is called ARIMA, or SARIMA if the seasonal part of the model is included. The methods are evaluated for short-term forecasting horizons.

2. Methodology

The most popular methods in the univariate modelling technique are represented by exponential smoothing and SARIMA techniques. The forecast for exponential smoothing is obtained as the weighted average of previously observed values where the weights decline exponentially, then the recent observations concur to the forecast more than the values of earlier observations [Office for National Statistics, 2008]. In particular the Holt-Winters method with damped trend was used. Damped trend is very important for forecasting properties, as confirmed by Gardner (2006) and the importance of using damped trend is recognized e.g. by Hyndman, Koehler, Ord and Snyder [2008]. The characteristics and flexibility of the model were described by Gardner and McKenzie [2011]. The assumption regarding the SARIMA model is related to the fact that the observed values depends on the linear combination of previously observed values. The advantage of the SARIMA model is due to the model building and the process used for accepting or rejecting the parameters after the diagnostic checking. Another feature is flexibility in case the representation is only for the AR part or the MA part or the combination (ARMA); for this class of

models the limitation is due to the linear hypothesis of the time series Zangh [2001]. Both the methods are used for monthly data.

2.1. Simple exponential smoothing

The general form of simple exponential smoothing [Brown 1959], is given by:

$$F_t = \alpha z_t + (1 - \alpha)F_{t-1}, \quad (1)$$

$$\hat{z}_t(l) = F_t, \quad (2)$$

where z_t is the actual value in period t , F is the level at time t , α is the smoothing coefficient taking values in the interval $(0,1]$ and $\hat{z}_t(l)$ the l step ahead forecast at period t . The corresponding forecast error is given by:

$$e_t(l) = z_t(l) - \hat{z}_t(l) = z_t(l) - F_t \quad (3)$$

whereas

$$e_t = z_t - \hat{z}_{t-1} = z_t - F_{t-1}. \quad (4)$$

Then, from (1) we have:

$$F_t = F_{t-1} + \alpha e_t. \quad (5)$$

By successive substitution, this equation becomes:

$$F_t = \alpha \sum_{i=0}^{\infty} (1 - \alpha)^i z_{t-1} \quad (6)$$

which is simple exponential smoothing (SES).

2.2. Holt's method

Another contribution is given by Holt [1957] where the estimation is:

$$F_t = \alpha z_t + (1 - \alpha)(F_{t-1} - T_{t-1}), \quad (7)$$

where T_{t-1} and T_t is the Trend at time $t - 1$ and t . Then,

$$T_t = \beta(F_t - F_{t-1}) + (1 - \beta)T_{t-1}, \quad (8)$$

where α is the smoothing coefficient for the level and β is the smoothing coefficient for the trend in the interval $(0,1]$.

Then, the l step ahead forecast is given by:

$$\hat{z}_t(l) = F_t + lT_t. \quad (9)$$

As we can see, Holt's method is using different constants for local level and trend.

2.3. The Holt-Winters method

This method is based on Holt's calculation with the additional term introduced by Winters [1960] related to the seasonal evaluation. The general equation is then:

$$F_t = \alpha(z_t - I_{t-p}) + (1 - \alpha)(F_{t-1} + T_{t-1}), \quad (10)$$

$$T_t = \beta(F_t - F_{t-1}) + (1 - \beta)T_{t-1}, \quad (11)$$

$$I_t = \gamma(z_t - F_t) + (1 - \gamma)I_{t-p}, \quad (12)$$

$$\hat{z}_t(l) = F_t + lT_t + I_{t-p+m}, \quad (13)$$

where z_t is the time series in period t , F_t is the level, I_t and I_{t-p} are the seasonal indicators at time t and $t-p$; α , β and γ are the smoothing coefficients for level, trend and seasonality. Position p refers to the length of a complete seasonal cycle. $\hat{z}_t(l)$ represents the smoothed forecast from the origin to lead time.

Another version is the Holt-Winters method with damped trend: this method has been modified by Gardner and McKenzie [1985] in order to gain more controls on the trend extrapolation. The equation of damped form is written as:

$$F_t = \alpha(z_t - I_{t-p}) + (1 - \alpha)(F_{t-1} + \delta T_{t-1}), \quad (14)$$

$$T_t = \beta(F_t - F_{t-1}) + (1 - \beta)\delta T_{t-1}, \quad (15)$$

$$I_t = \gamma(z_t - F_t) + (1 - \gamma)I_{t-p}, \quad (16)$$

$$\hat{z}_t(l) = F_t + \sum_{i=1}^m \delta^i T_t + I_{t-p+m}, \quad (17)$$

where z_t is the time series in period t , F_t is the level, I_t and I_{t-p} are the seasonal indicators at time t and $t-p$ and α , β and γ are the smoothing coefficients for level, trend and seasonality and δ is the dampening coefficient. $\hat{z}_t(l)$ represents the smoothed forecast from the origin to lead time l .

2.4. The SARIMA method

Box and Jenkins proposed a complete process where the main steps are:

1. Identification. At this stage the potential model is proposed after a preliminary transformation and stationary conditions have been achieved.

2. Estimation and diagnostic. After the identification, the parameters of the SARIMA model are estimated and submitted for the diagnostic process.

3. Forecasting. The final aim of the process is to produce out-of-sample forecasted observations based on the training set. The forecast is provided with the confidence interval.

In order to detect stationarity and seasonality, the autocorrelation and partial autocorrelation plot are used. Once these aspects have been addressed, the next process is to identify the appropriate orders of parameters p , q and P , Q . The general equation is

$$\Phi(B^s)\nabla_s^D z_t = \Theta(B^s)\alpha_t, \quad (18)$$

where $s = 12$ and $\nabla_s = 1 - B^s$ and $\Phi(B^s)$ and $\Theta(B^s)$ are polynomials of orders P and Q . The equation that links errors α_t with equation (18), is given by

$$\phi(B)\nabla^d \alpha_t = \theta(B)a_t, \quad (19)$$

where a_t is the white process and $\phi(B)$ and $\theta(B)$ are polynomials in B of degrees p and q respectively. Substituting (19) in (18), we obtain a multiplicative model:

$$\phi_p(B)\Phi_P(B^s)\nabla^d \nabla_s^D z_t = \theta_q(B)\Theta_Q(B^s)a_t. \quad (20)$$

Then the resulting process is said to be of the order $(p, d, q) \times (P, D, Q)$.

The forecast for lead time l , is given by:

$$\hat{z}_t(l) = \psi_l^* a_t + \psi_{l+1}^* a_{t-1} + \psi_{l+2}^* a_{t-2} + \dots \quad (21)$$

where ψ_j^* are to be determined. The mean square error of the forecast is

$$E[z_{t+l} - \hat{z}_t(l)]^2 = (1 + \psi_1^2 + \psi_2^2 + \dots + \psi_{l-1}^2) \sigma_a^2 + \sum_{j=0}^{\infty} (\psi_{l+j} - \psi_{l+j}^*)^2 \sigma_a^2 \quad (22)$$

which is minimized by setting:

$$\psi_{l+j} - \psi_{l+j}^* = 0.$$

Thus we have,

$$z_{t+l} = (a_{t+l} + \psi_1 a_{t+l-1} + \dots + \psi_{l-1} a_{t+1}) + (\psi_l a_t + \psi_{l+1} a_{t-1} + \dots) = e_t(l) + \hat{z}_t(l) \quad (23)$$

and the variance of the forecast error is:

$$V(l) = \text{Var}[e_t(l)] = (1 + \psi_1^2 + \psi_2^2 + \dots + \psi_{l-1}^2) \sigma_a^2.$$

Then, from a difference equation form we have

$$\begin{aligned} [z_{t+l}] = \hat{z}_t(l) &= \varphi_1 [z_{t+l-1}] + \dots + \varphi_{p+d} [z_{t+l-p-d}] - \theta_1 [a_{t+l-1}] - \\ &\dots - \theta_q [a_{t+l-q}] + [a_{t+l}]. \end{aligned} \quad (25)$$

Then the variance is:

$$V(l) = (1 + \sum_{j=1}^{l-1} \psi_j^2) \sigma_a^2, \quad (26)$$

where the prediction interval is given by:

$$z_{t+l}(\pm) = \hat{z}_t(l) \pm u_{\frac{\alpha}{2}} \left(1 + \sum_{j=1}^{l-1} \psi_j^2\right)^{1/2} s_a \tag{27}$$

2.5. Measuring forecast error

After the model is identified and specified, its performance should be compared with the historical data. The most common indicators of loss function are MAPE (Mean Absolute Percentage Error) and sMAPE (symmetric Mean Absolute Percentage Error), according to Armstrong [1985]:

$$\text{MAPE} = \frac{1}{n} \sum_{t=1}^n \left| \frac{z_t(l) - \hat{z}_t(l)}{z_t(l)} \right| 100, \tag{28}$$

$$\text{sMAPE} = \frac{1}{n} \sum_{t=1}^n \frac{|z_t(l) - \hat{z}_t(l)|}{(|z_t(l)| + |\hat{z}_t(l)|) / 2} 100. \tag{29}$$

Another measure of accuracy is given by RMSE (Root Mean Squared Error)

$$\text{RMSE} = \sqrt{\frac{(z_t(l) - \hat{z}_t(l))^2}{N}} \tag{30}$$

3. Empirical analysis

3.1. The Dataset

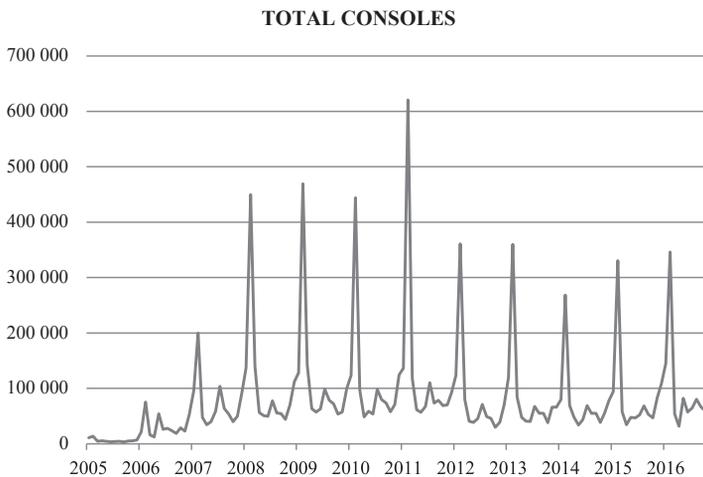


Fig. 1. Dataset for consoles between November 2005 and September 2017

Source: Ubisoft Italy.

The dataset consists of 143 observations between November 2005 and September 2017. No specification by manufacturer or breakdown by platform game has been included. The data is related to the aggregation of the console games and handhelds provided by the three main producers (Microsoft, Sony and Nintendo) in the above mentioned period. The graphic representation, (Figure 1) shows a remarkable seasonality corresponding to the month of December in each year.

4. Results

4.1. Holt-Winters exponential smoothing with damped trend

Following the method with damped trend, the parameters were: $\alpha = 0.1029$, $\beta = 0.0253$, $\gamma = 0.8981$ and $\delta = 0.9818$. It is clear that parameter α can assume values between 0 and 1. If α is zero, a constant unchanging seasonal component is used to generate the one-step-ahead forecasts. If the α parameter is equal to 1, then the seasonal component is modified “maximally” at every step of the forecast procedure. The outcome using this process is reported in Table 1 and in Figure 2.

Table 1. Comparison between the actual data and the exponential smoothing forecast with additive damped trend.

Period	Actual	Forecast (Exp. Smoothing Damped Trend)
Oct-17	78.319	111.203
Nov-17	196.358	140.886
Dec-17	309.692	343.317
Jan-18	58.297	55.237
Feb-18	43.646	34.614
Mar-18	48.974	78.477
Apr-18	54.708	56.246
May-18	62.360	64.133
Jun-18	81.477	79.367
Jul-18	59.154	65.761
Aug-18	50.182	57.672
Sep-18	80.697	68.650

Source: Actual Data: Ubisoft Italy; Forecast Exp Smooth. Damp. Trend: Forecast Pro Soft.

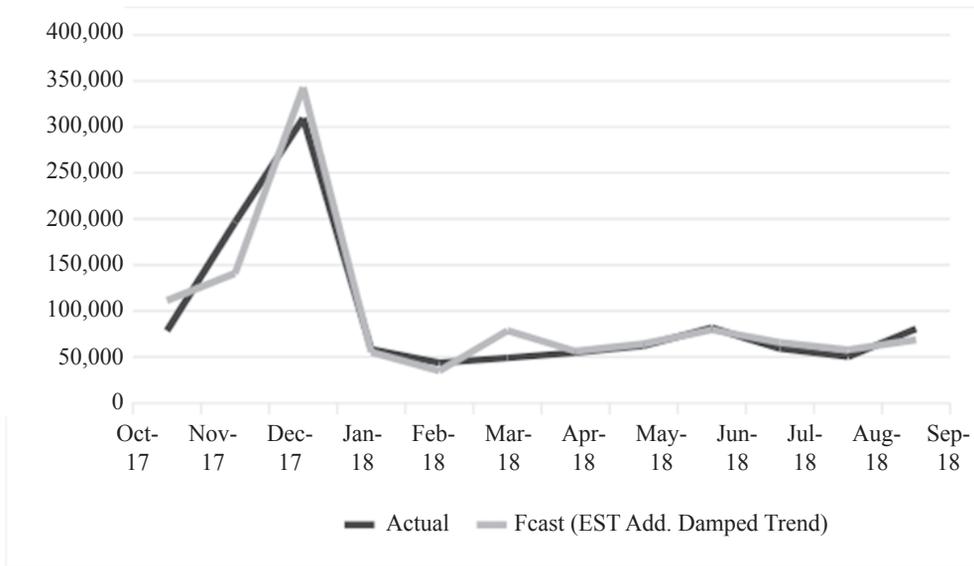


Fig. 2. Comparison between actual data and forecast line using exponential smoothing with damped trend parameter

Source: Actual Data: Ubisoft Italy; Forecast EST Damp. Trend: Forecast Pro Soft.

4.2. The SARIMA model

From the data presented in Figure 1, a logarithm transformation is appropriated in order to obtain a more homogenous variance of the series. Each value in the series is substituted with its natural logarithm, and then a reverse of the logarithms of the single values is applied at the end of the process. At the identification stage, the goal is to detect seasonality and the order of the autoregressive and moving average parameters. The AR and MA parameters were identified by the autocorrelation and partial autocorrelation function. The diagnostic check for the model is given by the traditional measures of accuracy such as the Akaike Information Criteria [Akaike 1974], BIC [Schwarz 1978], and HQC [Hannan, Quinn 1979], while the prediction performance was provided by the loss function such as MAPE, sMAPE and RMSE. In this case SARIMA 2,1,0 (1,1,0)₁₂ was chosen. Table 2 and Figure 3 report and summarize the result of the application.

Table 2. Comparison between the actual data and the SARIMA 2,1,0 (1,1,0)₁₂ forecast

Period	Actual	Forecast SARIMA (2,1,0) (1,1,0) ₁₂
Oct-17	78.319	96.096
Nov-17	196.358	132.815
Dec-17	309.692	345.977
Jan-18	58.297	55.582
Feb-18	43.646	33.444
Mar-18	48.974	64.486
Apr-18	54.708	51.244
May-18	62.360	57.271
Jun-18	81.477	71.849
Jul-18	59.154	57.290
Aug-18	50.182	49.733
Sep-18	80.697	66.882

Source: Actual Data: Ubisoft Italy; Forecast SARIMA (2,1,0) (1,1,0)₁₂: GRETLL Soft.

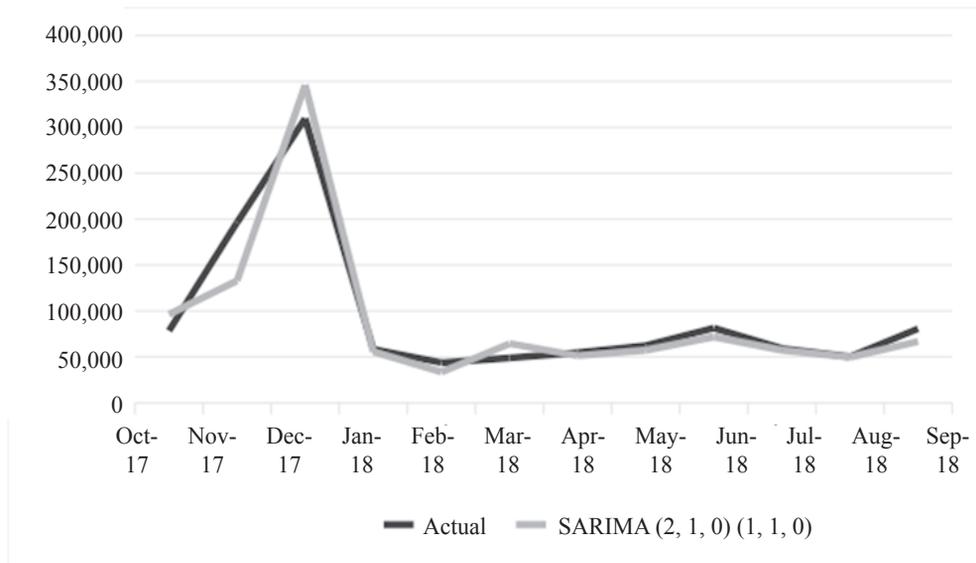


Fig. 3. Comparison between actual data and forecast line using the SARIMA model (2,1,0) (1,1,0)₁₂

Source: Actual Data: Ubisoft Italy; Forecast SARIMA: GRETLL Soft.

4.3. Evaluation of the two approaches

The primary aim and the purpose of this paper was to evaluate, for this market, the use and capabilities of two univariate techniques, exponential smoothing and the SARIMA technique. Based on the chosen models, the performance of the two

models was evaluated in terms of accuracy. The accuracy of time series is a crucial aspect for many decision-making problems and the measures of accuracy are expressed by MAPE, sMAPE and RMSE related to an ex-post analysis on the last 12 months. Below in Table 3, the performances for these methods based on the measures are proposed.

Table 3. Proposed measures of accuracy of the methods

	MAPE	sMAPE	RMSE
ETS	0.180	0.110	23.283
SARIMA	0.145	0.101	22.999

Source: ETS: Forecast Pro Soft. SARIMA (2,1,0) (1,1,0)₁₂: GRETL Soft.

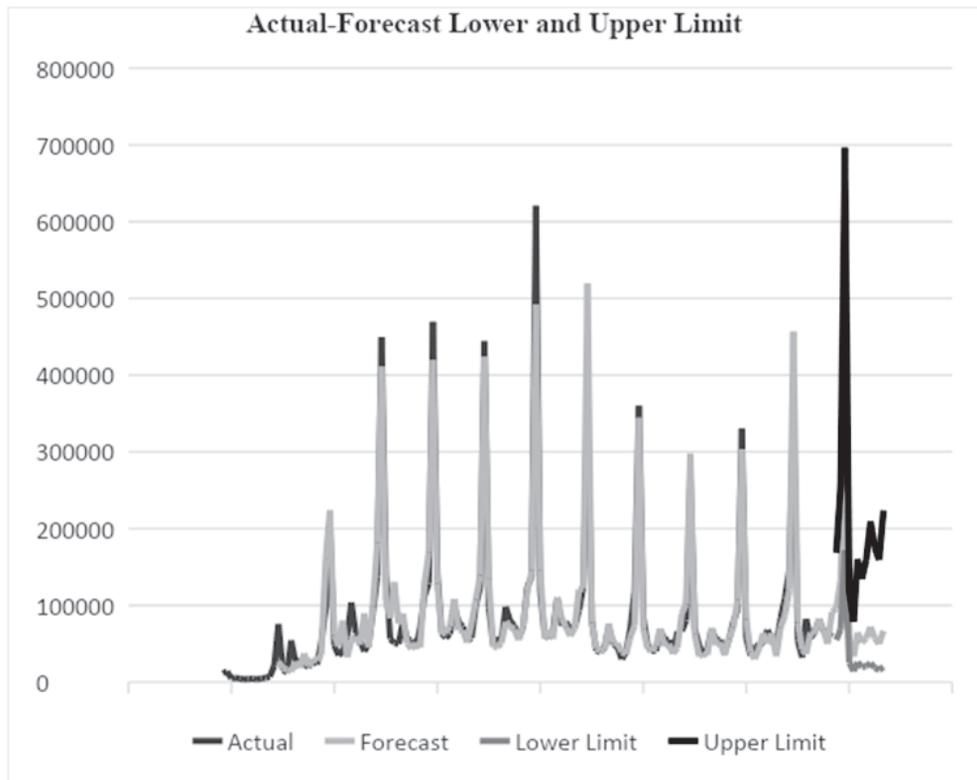


Fig. 4. Actual data and forecast line using the SARIMA model (2,1,0) (1,1,0)₁₂

Source: Actual Data: Ubisoft Italy; Forecast SARIMA (2,1,0) (1,1,0)₁₂: GRETL Soft.

For this analysis on ETS methodology, a dampening coefficient has been used, which means that although trend damping is more complex than other ETS methods, the forecast result is efficient avoiding any kind of overshooting problem [Gardner,

McKenzie 1988]. Whereas the Holt-Winters method tends to overestimate the forecast line, Gardner and McKenzie [1985] demonstrated that δ gives more control on trend extrapolation. In fact if $0 < \delta < 1$ it is normally distributed with a mean of 0 and a variance of $\sigma^2/(1 - \delta^2)$. The process for the SARIMA model's identification was performed using traditional criteria such as AIC [Akaike 1974], BIC [Schwarz 1978], and HQC [Hannan, Quinn 1979] together with the loss functions MAPE, sMAPE and RMSE. For this specific case, two models were compared, SARIMA (0, 1, 1) (0, 1, 1)₁₂ and SARIMA (2, 1, 0) (1, 1, 0)₁₂. The model used for the prediction was SARIMA (2, 1, 0) (1, 1, 0)₁₂, where in spite of a very small increase in the above mentioned criteria, the measure of loss functions are better than SARIMA (0, 1, 1) (0, 1, 1)₁₂. Furthermore, the result for annual data as an out-of-sample forecast is showing a remarkable improvement using the seasonal ARIMA model compared with exponential smoothing with damped trend. Based on the analysis, the SARIMA (2, 1, 0) (1, 1, 0)₁₂ model is the most suitable model for forecasting the console games, see Figure 4.

5. Concluding remarks

The complexity of this market is mainly due to manufacturer's decision. For this article, the forecast estimation is based on the physical consoles, including handhelds. The estimation process is absolutely crucial and once the estimation is completed, the manufacturer could use the estimation to accept or reject the financial risk. Additionally, the forecast demand could use this value to predict several items such as accessories, sequel games and other complements. Furthermore, consoles and handhelds are embracing both the physical and digital markets, giving a greater continuity for the software manufacturers. In this scenario, a good forecast representation is fundamental for various reasons, especially for consumer needs. Moreover, the demand forecast is also affected by the games genres and by the game-players attitude, and additionally, by some external conditions. This is confirmed by the survey led by ESA (Entertainment Software Association) where the average age of players in 2017 is 35 years old and in subsequent years is reducing year over year, in the meantime the percentage of female gamers is increasing year on year. Exponential smoothing and the SARIMA model are just a part of several techniques like hybrid models, the non-linear artificial neural network and others. They are still solid, reliable and very user-friendly due to many software applications for PCs. In this article two models were compared, exponential smoothing with damped trend and the SARIMA model. The criteria of evaluating these models was the loss function represented by MAPE, sMAPE and RMSE in Table 3. In terms of performance, the smallest values concerning these measures represent the best choice between the models studied, and the preferred option for this time series is SARIMA (2, 1, 0) (1, 1, 0)₁₂. Therefore the SARIMA model is the most reliable and relevant model for this analysis.

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PROGNOZOWANIE SPRZEDAŻY GIER KONSOLOWYCH NA RYNEK WŁOSKI

Streszczenie: Analiza szeregów czasowych może być bardzo przydatna w określaniu ogólnej ewolucji i zachowania dynamiki rynku gier wideo. Metody mogą być stosowane do poszukiwania rozwiązań problemów związanych z prognozowaniem szeregów czasowych, niezależnie od sektora aplikacji. W prezentowanym artykule omówiono aplikacyjne aspekty zastosowania szeregów czasowych do prognozowania sprzedaży gier konsolowych na rynek włoski. Zastosowano i oceniono użyteczność dwóch technik jednoczynnikowych, takich jak wygładzanie wykładnicze i technika SARIMA. Celem badania było wykorzystanie możliwości tych metod statystycznych do porównania wyników i wybrania najdokładniejszego modelu na podstawie oceny *ex post*. Na podstawie danych miesięcznych (od listopada 2005 r. do września 2017 r.) wskazano najbardziej odpowiedni model o najmniejszej wartości miar dokładności (MAPE, sMAPE, RMSE) dla obserwacji poza próbą dotyczących okresu październik 2017 r. – wrzesień 2018 r. Implementację modeli przeprowadzono z wykorzystaniem Forecast PRO i Gretl. Szeregi czasowe dotyczyły wielkości sprzedaży pierwszych producentów konsol i urządzeń przenośnych (Microsoft, Sony i Nintendo).

Słowa kluczowe: wygładzanie wykładnicze, SARIMA, prognoza, gry wideo.