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FORECASTS OF PERFORMANCE INDICATORS IN THE HEALTH SYSTEM USING THE ARIMA METHOD

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Abstract

This paper presents quarterly forecasts on several performance indicators from the Romanian health system, from a county emergency hospital. Using data from the period 2010-2022, forecasts are made for the period 2023-2025 of the average duration of hospitalization, the rate of bed utilization, the index of complexity of cases, the number of cases and the average cost of hospitalization. The method used is that of the auto-regressive integrated moving average (ARIMA) applied to time series. The Dickey-Fuller test is used to check the stationarity of the time series, as well as other tests for the validation of prediction models.

Keywords: health system, forecast, ARIMA method
JEL Classification: I12, C02, C13, C53

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1. Introduction

Health is one of the areas of great importance in a society, having an impact on economic and social results, because it is closely related to productivity, human capital and the availability of resources, thus contributing to economic growth and the sustainable development of a society. An effective health system is essential for any country to achieve its social and economic goals, to ensure that citizens have the opportunity to lead healthy and productive lives (Grossman, 1972).

The main objective of this paper is to make predictions on some health performance indicators at a county emergency hospital in Romania, in order to optimize the management and improve the quality of medical services offered to patients. These forecasts are of great importance for a more efficient planning regarding the distribution of resources according to the anticipated demand, this fact contributing to an optimal financial allocation and improving the management of the hospital.

Health management is a complex and interdisciplinary activity that involves, on the one hand, leadership skills and resource management, but also a thorough knowledge of health systems and health regulations, on the other hand. Thus, an optimal management in the health sector can lead to an improvement in the health status and quality of life of patients, but also to increasing the efficiency of health systems.

The key performance indicators in a health system are useful in measuring organizational performance, as it results from the studies of Bergeron (2017), Fuchs (1986), Leggat et al. (1998), Parmenter (2010).

Forecasting healthcare performance indicators such as the average duration of hospitalization (DMS), bed utilization rate (RUP), case complexity index (ICM), number of cases (NC) and average cost of hospitalization per day (CM) has multiple benefits and is useful in many essential aspects of health management and planning.

Thus, forecasts of indicators such as bed utilization rate and average duration of hospitalization, allow hospitals to anticipate resource requirements and adjust their care capacity based on anticipated demand. This fact is quite important in order to avoid overloading during busy periods with more patients, but also underutilizing the hospital's resources during periods with fewer patients. Forecasts of the average hospitalization cost per day can determine the optimal allocation of the hospital budget, allowing an efficient distribution of financial resources and thus contributing to an optimal management of public funds and ensuring the financial sustainability of hospitals.

Statistical analyses and forecasts can help to identify the seasonality of some performance indicators, such as, for example, the increase in the number of cases in the colder periods of the year. Also, they can help hospital managers to make decisions based on scientific arguments and trends, being able to adapt more quickly to changes in the medical environment (Chatfield, 2000).

This includes decisions related to health personnel, investments in more efficient equipment or expanding the number of beds in the hospital. Furthermore, forecasting allows for the early identification of problems or imbalances, such as increases in the average length of hospital stay or patient costs, giving managers the opportunity to intervene to solve these problems before they become difficult to solve.

If actual data deviates significantly from those predicted, this may signal the need for corrective measures or re-evaluation of management strategies. Also, by optimizing resources and anticipating needs, forecasts can help improve the quality of services offered to patients, reducing waiting times and ensuring better access to appropriate care (Duarte and Faerman, 2019).

Thus, making forecasts on performance indicators in emergency county hospitals in Romania is a powerful tool for planning and efficient management of resources, improving the quality of services and ensuring the financial sustainability of the healthcare system. These predictions help make decisions based on scientifically validated data and quickly adapt to changes in the health environment, contributing to a more robust and better prepared health system for the future.

The work is structured in four parts. In the second part, a review of the specialized literature is made regarding the statistical analysis of performance indicators in the health system. It was possible to find the use of the auto-regressive integrated moving average (ARIMA) method in making forecasts of the indicators in the health system. The third part contains the methodology of the scientific research where the stages of applying the ARIMA method and the statistical tests used to validate the models are presented. The last part contains the new elements of the work, where forecasts are presented for the performance indicators at a county emergency hospital in Romania.

The novelty of the study consists in making quarterly forecasts for the period 2023-2025 on the performance indicators at the Constanta County Emergency Clinical Hospital, using the ARIMA method. These forecasts are applied to some performance indicators in the health sector such as the bed utilization rate, the average length of hospitalization, the number of cases, the average cost per day and the index of complexity of the cases, providing in this way an approach that is scientifically validated for the optimization management of hospital resources, as well as improving the quality of medical services.

2. Literature review

Accurately forecasting the demand for medical resources, such as hospital beds and medical staff, is very important for effective planning, thus the ARIMA method can be useful in anticipating needs based on historical trends. The work of Janssen et al. (2020) used ARIMA models to forecast the need for beds in intensive care units during the COVID-19 pandemic in the Netherlands, this study being very useful for resource allocation in crisis conditions.

The ARIMA method is also used to analyze and forecast drug price trends and health spending, these forecasts being useful for developing effective health strategies and optimal budget planning. Thus, the study by Schuetz et al. (2018) investigated the price fluctuations of generic drugs in Europe using ARIMA models to assess long-term trends. The results of their study provided valuable insights into the important factors influencing drug prices.

In the work of Duarte and Faerman (2019), a prediction was made of performance indicators specific to an emergency department in a hospital, which is useful in improving the quality of the medical act and optimizing resources. This paper uses the ARIMA method for forecasting and makes a comparison with Prophet analysis, which is an autoregressive forecasting model based on recurrent neural networks.

The study by Kittipittayakorn (2024) investigated the performance of two main econometric models, the first being the ARIMA method and the second being the vector error correction (VEC) model, in predicting future life expectancy at birth in Europe. The results of the study showed that the ARIMA model better predicted future life expectancy at birth for half of the European countries investigated in the paper, while the VEC model was more accurate for the other half.

The main objective of the study by Earnest, Chen et al. (2005) was the application of type (ARIMA) models to make real-time predictions of the number of occupied beds in a hospital in Singapore. The ARIMA (1,0,3) model was found to be able to describe and predict well the number of occupied beds during the SARS outbreak.

The study of Barliba et al. (2012) proposed a hospital performance management model using seven performance indicators. The data were obtained from five county emergency hospitals and included indicators such as: the degree of occupancy of beds, the average duration of hospitalization and the index of complexity of cases, which are also found in our paper. Finally, the authors presented the strengths and weaknesses of the model, which resulted from testing the relevance of the studied performance indicators.

Birsan (2020) makes a presentation of the criteria according to which the performance indicators of the health system in Romania should be selected. At the end, choose a set of 5 indicators, which also includes the indicators used in this paper, for a hospital with 274 beds, in the period 2015-2019, and do an empirical analysis, without using inferential statistical methods.

The work of Cicea and Busu (2009) analysed the main indicators that characterize the health system in Romania, in order to identify its potential strengths and weaknesses, focusing on financial indicators. Also, the evolution of the number of medical personnel per 10,000 inhabitants between 1994 and 2007 in Romania is presented. A comparison is made between the number of doctors and dentists per 10,000 inhabitants, the number of beds per 1,000 inhabitants and the average duration of hospitalization in 2007, in different countries.

Paper by Freeman (2002) provides a systematic review of the empirical and theoretical writings on the use of performance indicators in the UK. The paper highlights potential issues and investigates how best to obtain, implement and use performance indicator data, presenting the results thematically.

3. Research methodology

In the paper we will use the ARIMA method to make forecasts for the period 2023-2025 on some indicators in the health system. The verification of the validity of the forecasting models will be done with the help of statistical tests.

The t-Student statistical test is used to test the null hypothesis H_0: the coefficients are not significantly different from 0, respectively the alternative hypothesis H_1: the coefficients are significantly different from 0. If the probability attached to the t-Student test is lower than the chosen significance threshold (usually 0.05), then the null hypothesis is rejected and the hypothesis H_1 is accepted, i.e. the coefficients are significantly different from zero.

The F-test (Fisher-Snedecor) verifies the null hypothesis H_0: all coefficients are not significantly different from 0, respectively the alternative hypothesis H_1: there is at least one coefficient different from 0. If the probability attached to the F-test is lower than the significance threshold chosen (usually 0.05) then the null hypothesis is rejected and the hypothesis H_1 is accepted, i.e. there is at least one coefficient different from 0.

Autocorrelation of errors occurs when the errors (residuals) of a regression model are correlated with each other, that is, the value of an error at a given time depends on the values of previous errors. This violates one of the basic assumptions of linear regression, which assumes that the residuals are independent. The Durbin-Watson test (Durbin and Watson, 1950) generates a scored test statistic (DW) based on the difference between the residuals between two consecutive points in time,

$$DW = \frac{\sum_{i=2}^{n}(\hat{\varepsilon}_i - \hat{\varepsilon}_{i-1})^2}{\sum_{i=1}^{n}(\hat{\varepsilon}_i)^2}, \tag{1}$$

The null hypothesis H_0: there is no first-order autocorrelation (errors are independent), respectively the alternative hypothesis H_1: there is first-order autocorrelation (positive or negative). For verification, the DW value is compared to the lower limit d_L and upper limit d_U from the Durbin-Watson table for a certain significance threshold, usually 5%. If DW is in the interval (d_U, 4-d_U) then the null hypothesis H0 is accepted, which means that the errors are not autocorrelated.

The Breusch-Godfrey test (Breusch, 1978 and Godfrey, 1978) is a statistical test used to check for the presence of higher-order autocorrelation (i.e., autocorrelation of errors at multiple lags) in the residuals of a regression model. An auxiliary regression is constructed in which the square of the estimated residuals is the dependent variable, and the original explanatory variables and lags of the residuals as the dependent variables.

$$\hat{\varepsilon}_i^2 = \alpha_0 + \alpha_1 X_{1i} + \alpha_2 X_{2i} + \cdots + \alpha_k X_{ki} + \rho_1 \hat{\varepsilon}_{i-1} + \rho_2 \hat{\varepsilon}_{i-2} \ldots + \rho_p \hat{\varepsilon}_{i-p} + \epsilon_i, \tag{2}$$

where

- $\hat{\varepsilon}_i$ are the estimated residuals from the original model
- $X_{1i}, X_{2i}, \ldots X_{ki}$ are the original explanatory variables
- $\hat{\varepsilon}_{i-1}, \hat{\varepsilon}_{i-2}, \ldots, \hat{\varepsilon}_{i-p}$ are the lags of the residuals
- p is the maximum lag order for which autocorrelation is checked
- ϵ_i is the error of the auxiliary model

The F (Fisher) statistic is used to test the overall significance of the lag coefficients of the residuals. The null hypothesis H_0: there is no autocorrelation at any order (all lag coefficients are zero) is checked, respectively the alternative hypothesis H_1: there is autocorrelation at least one order (at least one of the lag coefficients is different from zero). If the value of the F-test statistic is greater than the corresponding critical value for some level of significance (typically 5%), the null hypothesis is rejected, indicating the presence of higher-order autocorrelation. The Breusch-Godfrey test also generates an attached probability. If this probability is greater than 0.05, then the hypothesis H_0 is accepted, and there is no autocorrelation, at a chosen significance threshold of 5%.

The ARCH test (Engle, 1982) is a statistical test used to detect the presence of conditional heteroscedasticity in time series. Heteroscedasticity occurs when the variance (dispersion) of a regression model's errors is not constant. The ARCH test is based on estimating a regression model and analysing its residuals to check whether there is dependence in the squared errors, that is, whether the errors have an autoregressive pattern.

The test uses the R^2 statistics from the auxiliary regression to calculate a test statistic, which is then compared to a chi-square distribution to determine if there is significant conditional heteroscedasticity. The test statistic is given by $LM = T \times R^2$, where T is the number of observations and R^2 is the coefficient of determination from the auxiliary regression. The null hypothesis H_0: there is no conditional heteroscedasticity, which means that the variance of the residuals is constant over time, respectively the alternative hypothesis H_1: there is conditional heteroscedasticity, that is, the variance of the residuals depends on their previous values. If the value of the test statistic exceeds a certain critical threshold (determined by the chi-square distribution with the number of degrees of freedom equal to the number of lags), the null hypothesis of homoscedasticity is rejected (i.e., conditional heteroscedasticity is accepted). The test also generates an attached probability. If this probability is greater than 0.05 then the null hypothesis is accepted and we do not have heteroscedasticity, at a significance level of 5%.

In order to apply the ARIMA method we will use the Dickey-Fuller test to determine the stationarity of the time series. The Dickey-Fuller test (Dickey and Fuller, 1979) is a statistical test used to determine whether a time series is stationary or not. Stationarity is an important characteristic of a time series, meaning that the statistical properties of the series, such as mean and variance, do not change over time. The Dickey-Fuller test checks for the existence of a unit root in the autoregressive (AR) model, which indicates the non-stationarity of the time series. If there is a unit root, then the time series tends to move over time, increasing or decreasing, without returning to a constant mean.

The Augmented Dickey-Fuller (ADF) test is based on the fact that the series can have a deterministic trend or a constant (intercept) and allows the addition of lag terms to correct for autocorrelation of the residuals. This test is more used in practice because adding lags solves the problem of autocorrelation of residuals, which can lead to erroneous results in the case of the simple Dickey-Fuller test. The basic mathematical model of the augmented Dickey-Fuller test can be expressed as follows:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + \epsilon_t, \tag{3}$$

where

- y_t is the *analyzed* time series
- Δy_t is the first-order differentiation, i.e. $y_t - y_{t-1}$
- α is the *constant* term (intercept)
- βt is the linear trend term
- γy_{t-1} is the *autoregressive* coefficient for the first-order lag
- $\delta_1, \delta_2 \dots, \delta_p$ are the *coefficients* for the additional lag terms
- ϵ_t is the error, called *white* noise.

The Dickey-Fuller test verifies the null hypothesis H_0: the time series has a unit root (is non-stationary), respectively the alternative hypothesis H_1: the time series does not have a unit root (is stationary). The interpretation of the test results is done by comparing the value of the test statistic (attached probability) with predefined critical values (at significance levels of 1%, 5%, 10%). If the value of the test statistic is less than the critical value, the null hypothesis is rejected, indicating that the time series is stationary. The test also generates an attached probability and if this is less than 0.05 then the series is stationary at a 5% significance level.

The ARIMA method (Box and Jenkins, 1976) is one of the most widely used time series modelling and forecasting techniques. This method is useful in modeling and forecasting the values of a time series in which we have autocorrelation, that is, there are dependent relationships between the past and future values of a variable. The ARIMA model consists of three main parts:

- the autoregressive (AR) part of the model, which assumes that the values in the series depend linearly on the previous values, and in an AR(p) model, "p" represents the number of previous terms that are used to predict the current value.
- the integrated (I) part refers to the number of differentiations required to transform a non-stationary time series into a stationary one.
- the moving average (MA) part, which assumes that the current value of the time series can be expressed as a sum of past random error terms, and in an MA(q) model, "q" represents the number of past errors included in the model.

The ARIMA model combines these three components into a general model that can be written as:

$$X_t = c + \phi_1 X_{t-1} + \phi_1 X_{t-1} + \cdots + \phi_p X_{t-p} + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_q X_{t-q}, \qquad (4)$$

where the series X_t was differentiated d times to make it stationary and $\phi_1, \phi_1, \ldots, \phi_p$ are the autoregressive coefficients, c is a constant, ϵ_t is the random error at time t, and $\theta_1, \theta_2, \ldots, \theta_q$ are the coefficients of the moving average.

An ARIMA (p, d, q) model is defined by three parameters:

- p: the order of the autoregressive component (AR),
- d: differentiation order (I),
- q: the order of the moving average component (MA).

For the construction of an ARIMA model, the following steps are followed (Maddala, 2001 and Wooldridge, 1999):

Identification:

- stationarity: it is checked if the series is stationary and if so, an ARMA(p,q) model results. Otherwise, differencing is performed to make it stationary, and an ARIMA(p,d,q) model is obtained.
- autocorrelation: autocorrelation functions (ACF) and partial autocorrelation functions (PACF) are analysed using the correlogram of the stationary series to identify possible values corresponding to p and q. Autocorrelation determines the MA(q) component and partial correlation determines the AR(p) component)

Estimation:

- estimation of the parameters p, d and q can be done by the least squares method or the maximum likelihood method. Among several possible and validated models, the one for which the values of the Akaike and Schwartz criteria are the lowest is chosen. The coefficient of determination R^2 is also taken into account, to have a higher value.

Diagnostics:

- evaluate the model to check if the residuals (errors) are white noise (random series without autocorrelation). This can be done by checking the correlogram of the residuals. Attached probabilities (p-values) greater than 0.05 mean that the residuals are not autocorrelated, at a 5% significance level (they are not white noise). This hypothesis can also be verified by applying the Breusch-Godfrey test or the Ljung-Box test.
- it is checked if the estimated ARIMA process is stationary: the roots of the AR component are inside the unit circle.
- check if the estimated ARIMA process is invertible: the roots of the MA component are inside the unit circle.

If all the previous conditions are satisfied, you can move on to forecasting. Otherwise, another ARIMA model is estimated and conditions are checked.

Forecast:

- after the model has been validated, it can be used to forecast future values of the time series.

4. Forecast of performance indicators at SCJU Constanța

4.1. Average length of hospitalization

In Figure no. 1 we have a graphical representation of the average duration of hospitalization per quarter, from the period 2010-2022. We will make a forecast for the period 2023-2025. The prediction method is ARIMA.

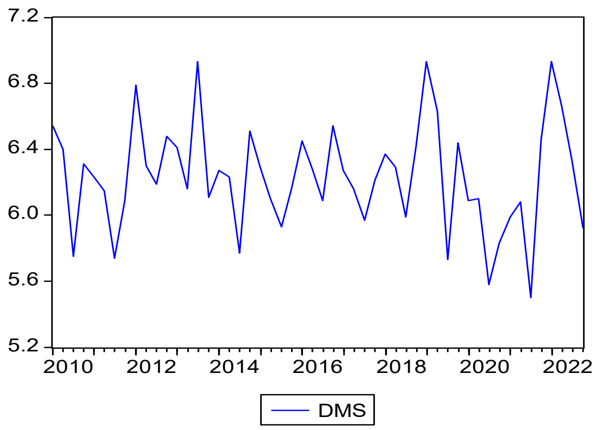

Figure no. 1: Average length of quarterly hospitalization at SCJU Constanța

Source: Made by the authors with Eviews software

We check whether the original series is stationary by applying the Dickey-Fuller test for a constant, non-trending model. Since the probability attached to the test is 0.00 which is less than 0.05 it follows that the null hypothesis is rejected and the alternative hypothesis is accepted i.e. the original series is stationary (Table no. 1).

Table no. 1: Dickey-Fuller test at DMS for SCJU Constanța

Null Hypothesis: DMS has a unit root			
		t-Statistic	**Prob.**
Augmented Dickey-Fuller test statistic		-6.071940	0.0000
Test critical values:	1% level	-3.565430	
	5% level	-2.919952	
	10% level	-2.597905	

Source: Made by the authors with Eviews software

Using the DMS correlogram we checked several possible ARMA models of type (p,q). Several valid models resulted, but we chose the ARMA (2,2) model, having the lowest values of the Akaike and Schwarz criteria. It is found that in the selected model the estimated coefficients are significant, having the probabilities attached to the t-Statistic test lower than 0.05. The F-test with value 6.03 and attached probability 0.004 confirms the overall validity of the model. Also, the residuals of the model are not autocorrelated, a fact confirmed by the Durbin-Watson tests with the value 1.60 and Breusch-Godfrey with the attached probability 0.32. These results suggest that the model correctly captures the dynamics of the time series, with no significant autocorrelation between the residuals.

The ARCH test confirms the lack of heteroscedasticity, the probability attached to the test being 0.93, greater than 0.05 (Table no. 2). This indicates that the variability of the errors does not change over time. Also, the ARIMA process is stationary and reversible, according to the values of the inverted AR and MA roots.

Table no. 2: ARMA (2,2) model at DMS for SCJU Constanța

Dependent variable: DMS			
Variable	Coefficient	t-Statistic	Prob.
C	6.227542	152.5701	0.0000
AR(2)	-0.988841	-23.21563	0.0000
MA(2)	0.932608	20.67659	0.0000
		Akaike info criterion	0.465627
R-squared	0.204343	Schwarz criterion	0.580348
Adjusted R-squared	0.170486	F-statistic	6.035355
Durbin-Watson stat.	1.609480	Prob(F-statistic)	0.004646
		F-statistic	Prob.
Breusch-Godfrey Serial Correlation LM Test:		1.166572	0.320672
ARCH Test:		0.006832	0.934476

Source: Made by the authors with Eviews software

The forecast is given and is represented graphically, with the confidence interval, in Figure no. 2. Forecasts show relative stability in values, with small seasonal fluctuations throughout each year. In conclusion, the ARMA (2,2) model is adequate to model and forecast the average length of hospitalization at SCJU Constanța, providing solid forecasts for the period 2023-2025.

Year: quarter	Forecast
2023:1	6.439
2023:2	6.255
2023:3	6.018
2023:4	6.200
2024:1	6.434
2024:2	6.254
2024:3	6.022
2024:4	6.200
2025:1	6.429
2025:2	6.253
2025:3	6.027
2025:4	6.201

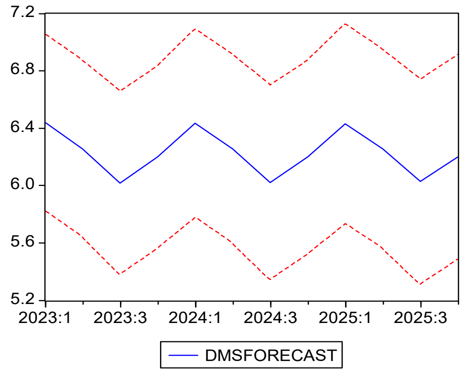

Figure no. 2: Quarterly DMS forecast at SCJU Constanța

Source: Made by the authors with Eviews software

4.2.Bed utilization rate

Analyzing Figure no. 3, where we have the graphic representation of the bed utilization rate per quarter from 2010-2022, a massive decrease is noted in the second quarter of 2020 due to the restrictions imposed by the Covid pandemic. Starting from 2022, it returns to values recorded before the pandemic.

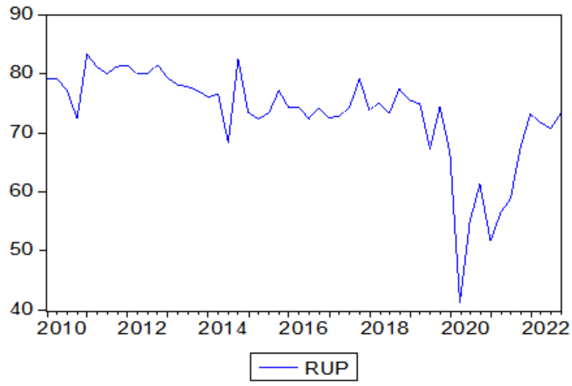

Figure no. 3: Quarterly bed utilization rate at SCJU Constanța

Source: Made by the authors with Eviews software

We check whether the original series is stationary by applying the Dickey-Fuller test for a constant and trend model. Since the probability attached to the test is 0.029, which is less than 0.05, it follows that the alternative hypothesis is accepted and the null hypothesis is rejected, that is, the original series is stationary (Table no. 4).

This suggests that the RUP time series does not show long-term upward or downward trends. Using the DMS correlogram we check several possible ARMA models of type (p,q). Several valid models resulted, but we chose the ARMA (1,3) model, which has the lowest Akaike and Schwarz criteria values.

Table no. 4: Dickey-Fuller test at RUP for SCJU Constanța

Null Hypothesis: RUP has a unit root			
		t-Statistic	**Prob.**
Augmented Dickey-Fuller test statistic		-3.719962	0.0299
Test critical values:	1% level	-4.148465	
	5% level	-3.500495	
	10% level	-3.179617	

Source: Made by the authors with Eviews software

It is found that in the selected model the estimated coefficients are significant, having the probabilities attached to the t-Statistic test lower than 0.05. The overall validity of the model is given by the F-test with a value of 32.3 and an attached probability of zero. It is found that the residuals of the model are not autocorrelated, a fact confirmed by the Durbin-Watson tests with the value 2.21 and Breusch-Godfrey with the attached probability 0.36. This indicates that the model is well fitted to the data. The ARCH test confirms the lack of heteroscedasticity, the probability attached to the test being 0.93 (Table no. 5).

Table no. 5: ARMA (1,3) model at RUP for SCJU Constanța

Dependent variable: RUP			
Variable	Coefficient	t-Statistic	Prob.
C	72.77524	26.80018	0.0000
AR(1)	0.616494	5.357697	0.0000
MA(3)	0.361119	2.589689	0.0127
		Akaike info criterion	6.311838
R-squared	0.574285	Schwarz criterion	6.425475
Adjusted R-squared	0.556547	F-statistic	32.37579
Durbin-Watson stat.	2.211757	Prob(F-statistic)	0.000000
		F-statistic	Prob.
Breusch-Godfrey Serial Correlation LM Test:		1.022866	0.367595
ARCH Test:		0.077089	0.782475

Source: Made by the authors with Eviews software

This shows that the variability of the errors is constant over time. The ARMA (1,3) process is stationary and invertible, fact confirmed by the values of the inverted AR and MA roots, which are subunit. The forecast can be found with its graphical representation in Figure no. 4.

Year: quarter	Forecast
2023:1	73.368%
2023:2	71.946%
2023:3	72.334%
2023:4	72.503%
2024:1	72.607%
2024:2	72.671%
2024:3	72.711%
2024:4	72.735%
2025:1	72.751%
2025:2	72.760%
2025:3	72.766%
2025:4	72.769%

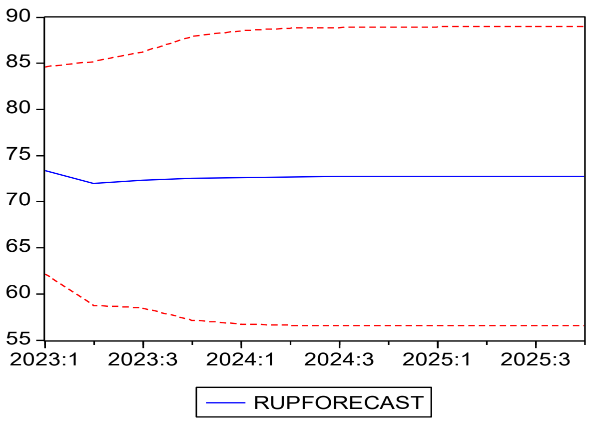

Figure no. 4: Quarterly RUP forecast at SCJU Constanța

Source: Made by the authors with Eviews software

Forecasts for the bed utilization rate show a stabilization of values around 72-73% between 2023 and 2025, with small seasonal fluctuations. In conclusion, the ARMA (1,3) model provides a good fit for the time series of the bed utilization rate at SCJU Constanța and stable forecasts for the next period, indicating a return to pre-pandemic values.

4.3. Case complexity index

It can be seen in in Figure no. 5, where we have the graphic representation of the complexity index of cases per quarter from 2010-2022, that there are fluctuations in this indicator, but in general it has a moderate upward trend.

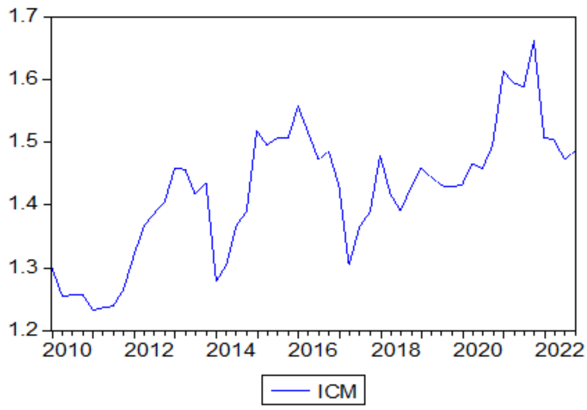

Figure no. 5: Quarterly case complexity index at SCJU Constanța

Source: Made by the authors with Eviews software

We check whether the original series is stationary by applying the Dickey-Fuller test for a model with constant and trend, but because the probability attached to the test is 0.2026, which is greater than 0.05, it follows that the null hypothesis is accepted, the original series does not is stationary (Table no. 6) and presents trend.

Table no. 6: Dickey-Fuller test at ICM for SCJU Constanța

Null Hypothesis: ICM has a unit root			
		t-Statistic	**Prob.**
Augmented Dickey-Fuller test statistic		-2.804033	0.2026
Test critical values:	1% level	-4.148465	
	5% level	-3.500495	
	10% level	-3.179617	

Source: Made by the authors with Eviews software

The first difference is calculated and a new series denoted D(ICM) is obtained, which is stationary, because the probability attached to the Dickey-Fuller test is 0.00 and the null hypothesis is rejected (Table no. 7).

Table no. 7: Dickey-Fuller test at D(ICM) for SCJU Constanța

Null Hypothesis: D(ICM) has a unit root			
		t-Statistic	**Prob.**
Augmented Dickey-Fuller test statistic		-7.598780	0.0000
Test critical values:	1% level	-3.568308	
	5% level	-2.921175	
	10% level	-2.598551	

Source: Made by the authors with Eviews software

Using the correlogram of the D(ICM) series, we checked several possible ARIMA models of type (p,1,q), resulting in several valid models. The ARIMA (1,1,1) model was chosen, where the values of the Akaike and Schwarz criteria were the lowest. It is found that in the selected model (Table no. 8), the estimated coefficients are representative at a significance level of 5%, having the probabilities attached to the t-Statistic test lower than 0.05. Also, the model is generally valid, as confirmed by the F-test with a value of 3.57 and an attached probability of 0.03. The residuals of the model are not autocorrelated, a fact confirmed by the Durbin-Watson tests with a value of 2.00 and Breusch-Godfrey with an attached probability of 0.39. The ARCH test confirms the presence of homoscedasticity, the probability attached to the test being 0.53, which indicates a constant variation of the residuals throughout the analyzed period Also, the process is stationary and reversible, according to the inverted AR and MA roots, which indicates a stable and predictable behavior of the process.

Table no. 8: ARIMA (1,1,1) model for D(ICM) at SCJU Constanța

Dependent variable: D(ICM)			
Variable	Coefficient	t-Statistic	Prob.
C	0.004464	2.890090	0.0058
AR(1)	0.774805	5.972228	0.0000
MA(1)	-0.997141	-18.22595	0.0000
		Akaike info criterion	-2.988931
R-squared	0.132093	Schwarz criterion	-2.874209
Adjusted R-squared	0.095161	F-statistic	3.576640
Durbin-Watson stat.	2.003508	Prob(F-statistic)	0.035819
		F-statistic	Prob.
Breusch-Godfrey Serial Correlation LM Test:		0.938533	0.398724
ARCH Test:		0.393190	0.533661

Source: Made by the authors with Eviews software

The forecast and its graphical representation are found in Figure no. 6.

The ARIMA (1,1,1) model provides a robust fit for analyzing and forecasting the case complexity index at SCJU Constanța. The complexity of the cases shows a slightly increasing trend, reflecting a constant evolution in terms of the complexity and nature of the conditions treated in the institution.

Year: quarter	Forecast
2023:1	1.499
2023:2	1.510
2023:3	1.519
2023:4	1.527
2024:1	1.535
2024:2	1.542
2024:3	1.548
2024:4	1.554
2025:1	1.559
2025:2	1.564
2025:3	1.570
2025:4	1.575

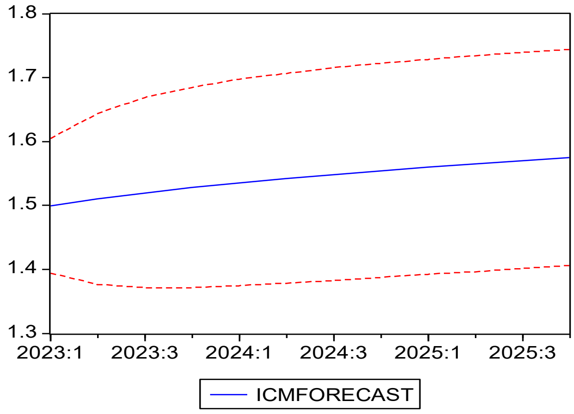

Figure no. 6: Quarterly ICM forecast at SCJU Constanța

Source: Made by the authors with Eviews software

4.4. Number of cases

From the analysis of the data in Figure no. 7, which represents the number of cases treated at SCJU Constanța per quarter in the period 2010-2022, a sharp decrease can be seen in the second quarter of 2020 due to the restrictions imposed by the Covid pandemic. This significant reduction reflects the immediate impact of the restrictive measures on hospital activity. Starting with the second half of 2022, a return to values recorded before the pandemic is observed.

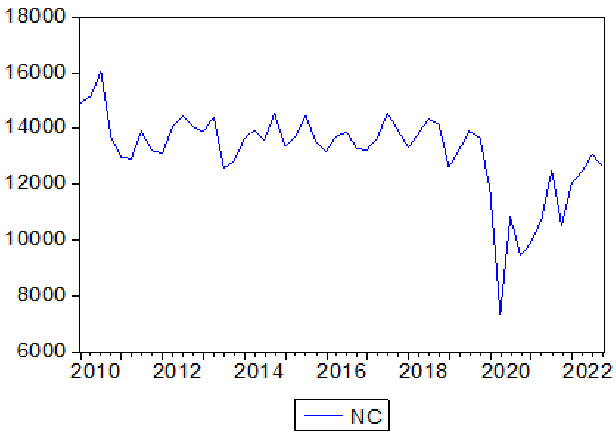

Figure no. 7: Quarterly number of cases at SCJU Constanța

Source: Made by the authors with Eviews software

To be able to apply the ARIMA method for forecasting, we check whether the initial series is stationary by applying the Dickey-Fuller test for a constant, non-trending model. Since the probability attached to the test is 0.029, the alternative hypothesis is accepted and the null hypothesis is rejected, that is, the original series is stationary (Table no. 9), being suitable for ARIMA modeling.

Table no. 9: Dickey-Fuller test at NC for SCJU Constanța

Null Hypothesis: NC has a unit root			
		t-Statistic	**Prob.**
Augmented Dickey-Fuller test statistic		-3.147112	0.0293
Test critical values:	1% level	-3.565430	
	5% level	-2.919952	
	10% level	-2.597905	

Source: Made by the authors with Eviews software

Using the NC correlogram, by checking several possible ARMA models of type (p,q), the ARMA(1,4) model was selected, which has the lowest Akaike and Schwarz criteria values. It is observed that in the selected model the estimated coefficients are significant, having the probabilities attached to the t-Statistic test lower than 0.05. The overall validity of the model is confirmed by the F-test with a value of 25.7 and zero attached probability. Also, the residuals of the model are not autocorrelated, a fact that results from the Durbin-Watson tests with the value 2.10 and Breusch-Godfrey with the attached probability 0.68. The ARCH test confirms the lack of heteroscedasticity, the probability attached to the test being 0.65 (Table no. 10), which confirms a constant variation of the residuals and the stability of the model. Also, the ARMA (1,4) process is stationary and invertible, as shown by the inverted AR and MA roots, suggesting that the process is stable and suitable for forecasting.

Table no. 10: ARMA (1,4) model for NC at SCJU Constanța

Dependent variable: NC			
Variable	Coefficient	t-Statistic	Prob.
C	13080.37	24.29963	0.0000
AR(1)	0.634741	5.674606	0.0000
MA(4)	0.334868	2.375941	0.0215
		Akaike info criterion	16.83779
R-squared	0.517539	Schwarz criterion	16.95143
Adjusted R-squared	0.497437	F-statistic	25.74497
Durbin-Watson stat.	2.101732	Prob(F-statistic)	0.000000
		F-statistic	Prob.
Breusch-Godfrey Serial Correlation LM Test:		0.376640	0.688260
ARCH Test:		0.207889	0.650483

Source: Made by the authors with Eviews software

Projections of the number of cases indicate a stabilization of values around 13,000 cases per quarter between 2023 and 2025 (Figure no. 8). The graph in Figure no. 8 illustrates this steady evolution, along with the associated confidence intervals.

The ARMA (1,4) model provides a robust estimate for forecasting the number of cases treated at SCJU Constanța, reflecting a post-pandemic stabilization of hospital activity. After the shock of the pandemic restrictions, the number of cases is expected to remain constant in the coming years.

Year: quarter	Forecast
2023:1	13.077
2023:2	12.933
2023:3	13.058
2023:4	13.095
2024:1	13.090
2024:2	13.086
2024:3	13.084
2024:4	13.083
2025:1	13.082
2025:2	13.081
2025:3	13.080
2025:4	13.081

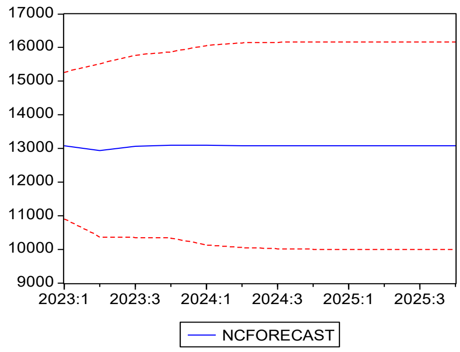

Figure no. 8: Quarterly NC forecast at SCJU Constanța

Source: Made by the authors with Eviews software

4.5.Average cost of hospitalization

Analyzing Figure no. 9, where we have the graphic representation of the average cost of hospitalization per quarter from 2010-2022, it can be seen that we have an increasing trend. However, significant fluctuations are observed during the Covid-19 pandemic, which reflects its impact on hospitalization costs.

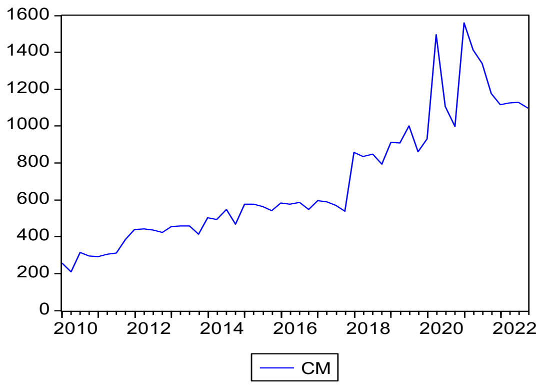

Figure no. 9: Average quarterly cost at SCJU Constanța

Source: Made by the authors with Eviews software

We check whether the original series is stationary by applying the Dickey-Fuller test for a constant and trend model, and the probability attached to the test is 0.8386. It follows that the null hypothesis is accepted, the initial series is not stationary (Table no. 11).

Table no. 11: Dickey-Fuller test at CM for SCJU Constanța

Null Hypothesis: CM has a unit root			
		t-Statistic	**Prob.**
Augmented Dickey-Fuller test statistic		-0.693579	0.8387
Test critical values:	1% level	-3.565430	
	5% level	-2.919952	
	10% level	-2.597905	

Source: Made by the authors with Eviews software

The first difference is calculated and a new series denoted D(CM) is obtained, which is stationary, because the probability attached to the Dickey-Fuller test is 0.00 and the null hypothesis is rejected (Table no. 12).

Table no. 12: Dickey-Fuller test at D(CM) for SCJU Constanța

Null Hypothesis: D(CM) has a unit root			
		t-Statistic	**Prob.**
Augmented Dickey-Fuller test statistic		-9.566859	0.0000
Test critical values:	1% level	-3.565430	
	5% level	-2.919952	
	10% level	-2.597905	

Source: Made by the authors with Eviews software

Using the correlogram of the D(CM) series and checking several possible ARIMA models of type (p,1,q) resulted in the ARIMA (1,1,2) model, which has the lowest Akaike and Schwarz criterion values. It is found for the selected model (Table no. 16) that the estimated coefficients are representative at a significance level of 5%, having the probabilities attached to the t-Statistic test lower than 0.05. Also, the overall validity of the model is ensured by the F-test with the value 9.42 and the attached probability less than 0.05. The residuals of the model are not autocorrelated, a fact confirmed by the Durbin-Watson tests with a value of 2.05 and Breusch-Godfrey tests with an attached probability of 0.53. The ARCH test confirms the lack of heteroscedasticity, the probability attached to the test being 0.92, which indicates that the variances of the residuals are constant and that the model is stable.

Table no. 13: ARIMA (1,1,2) model at D(CM) for SCJU Constanța

Dependent variable: D(CM)			
Variable	Coefficient	t-Statistic	Prob.
C	18.83459	2.857006	0.0064
AR(1)	-0.429935	-3.004544	0.0043
MA(2)	-0.500102	-3.484988	0.0011
		Akaike info criterion	12.57410
R-squared	0.286363	Schwarz criterion	12.68883
Adjusted R-squared	0.255995	F-statistic	9.429903
Durbin-Watson stat.	2.053381	Prob(F-statistic)	0.000360
		F-statistic	Prob.
Breusch-Godfrey Serial Correlation LM Test:		0.630389	0.537020
ARCH Test:		0.009832	0.921438

Source: Made by the authors with Eviews software

The ARIMA (1,1,2) process is found to be stationary and invertible, which makes it suitable for forecasting average hospitalization costs. The forecast can be observed in Figure no. 10.

Year: quarter	Forecast
2023:1	1,181.58
2023:2	1,237.27
2023:3	1,240.26
2023:4	1,265.90
2024:1	1,281.81
2024:2	1,301,90
2024:3	1,320.20
2024:4	1,339.26
2025:1	1,358.20
2025:2	1,376.88
2025:3	1,395.69
2025:4	1,414.54

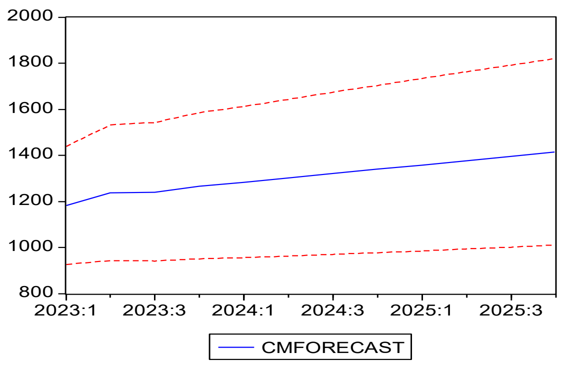

Figure no. 10: Quarterly CM forecast at SCJU Constanța

Source: Made by the authors with Eviews software

The ARIMA (1,1,2) model provides a robust forecast for the average hospitalization cost at SCJU Constanța, indicating a gradual and constant increase in the coming years, also due to inflation. After the fluctuations caused by the Covid-19 pandemic, costs are stabilizing and following an upward trend, suggesting an increase in spending in the long term.

5. Conclusions

The paper presents the quarterly forecasts with the ARIMA method from 2023-2025 at SCJU Constanța for the average duration of hospitalization, the bed utilization rate, the case complexity index, the number of cases and the average cost of hospitalization.

The statistical series of average length of hospitalization, bed utilization rate and number of cases were found to be stationary, which facilitates more accurate forecasting. In contrast, the case complexity index and average hospitalization cost are non-stationary, indicating an increasing trend and requiring the application of differences to obtain stationary series.

Seasonal fluctuations were observed in average length of hospitalization, bed utilization rate and number of cases, with lower values in quarters 2 and 3 (spring–summer) and higher values in quarters 1 and 4 (autumn–winter). This pattern was accentuated by the Covid-19 pandemic, which generated massive declines in the second quarter of 2020, followed by rebounds starting in the 4th quarter of 2022.

According to the forecast, the average length of hospitalization will fluctuate slightly around 6.2 days, indicating a stabilization of this indicator in the coming years. A stabilization of the bed utilization rate is expected, with values slightly above 72%, suggesting a constant use of hospital resources. While a study carried out at the level of several county hospitals in Romania between 2008-2018 carried out by the National Institute of Public Health (2019) showed a gradual reduction in the average length of hospitalization, the study from SCJU Constanța suggests a stabilization after the pandemic period. This can be explained by the changes generated by the pandemic, which affected patient flows and the way hospitals are organized.

The same report from 2019 shows us that the bed utilization rate in Romanian hospitals was between 67% and 74%. Compared to previous studies, SCJU Constanța's forecast indicates a post-pandemic stabilization of this indicator, which is similar to the pre-pandemic values, thus confirming that hospitals are gradually adapting to new patient flows and treatment capacities. Regarding the the case complexity index, it will continue to increase slightly, reaching values of around 1.575 by the end of 2025. The number of cases treated will remain stable with slight seasonal fluctuations, but around 13,000 cases per quarter. The average cost of hospitalization has an increasing trend, amplified after 2020 by inflation and the pandemic. Fluctuations in this indicator were more pronounced during the pandemic, between 2020 and 2022. Obviously, these forecasts can be compared with the real data from 2023, when they are available, in order to see the accuracy of the forecasts.

The forecasted increase in the case complexity index and the average cost of hospitalization in Constanța is comparable to the increasing trends noted in studies analyzing healthcare resources and costs. For example, a forecasting study involving hospital management during the COVID-19 pandemic (Duarte, Walshaw and Ramesh, 2021) identified rising costs and complexity due to factors like inflation and pandemic-related resource strain. This is consistent with the forecast in Constanța, where the impact of inflation and the pandemic significantly contributed to an upward trend in hospitalization costs.

In conclusion, the analysis confirms the validity of the ARIMA models selected for forecasting the main performance indicators of SCJU Constanța. Based on forecasts, hospital performance indicators such as average length of stay, bed utilization rate, case complexity index and number of cases treated will stabilize or slightly increase by 2025. This suggests a capacity constant and balanced capacity of the hospital to manage the treated cases, with a full return to pre-pandemic values.

The study carried out at SCJU Constanța, using the ARIMA method, largely reflects the trends observed in previous studies. It provides an updated perspective on the evolution of performance indicators after the Covid-19 pandemic and suggests a stabilization of these indicators in the medium term. Previous studies provide important context for understanding the observed changes, particularly in length of hospital stay, bed utilization and hospital costs, indicating that recent trends are largely aligned with international developments

The limits of the research consisted mainly in the difficulty of obtaining the analyzed data, which are only from the period 2010-2022. The introduction of data from 2023, when most indicators have returned to pre-pandemic values, can lead to more accurate forecasts.

Regarding the proposals and further developments, a comparative statistical study can be done between several county hospitals in the country, but also in Bucharest, using updated data after the Covid pandemic. Comparative analyzes of performance indicators from these hospitals can be done as well as a panel analysis. The similarities and differences between these hospitals can be highlighted and good practices in health management can be identified.

Another direction of research could be to expand the comparative analysis of performance indicators at an international level to see how Romania stands in relation to other countries in the European Union or with similar health systems, as well as investigating how practices and policies from other countries could be adapted and implemented in Romania.

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Annex 1. Performance indicators at SCJU Constanta

Years, quarter	DMS	RUP	NC	ICM	CM
2010, I	6.54	79.18	14923	1.2989	256
2010, II	6.40	79.22	15163	1.2539	210
2010, III	5.75	77.25	16058	1.2567	314
2010, IV	6.31	72.45	13722	1.2571	297
2011, I	6.23	83.40	12962	1.2328	293
2011, II	6.15	81.21	12925	1.2365	304
2011, III	5.74	80.11	13904	1.2389	311
2011, IV	6.09	81.30	13197	1.2653	384
2012, I	6.79	81.45	13125	1.3219	438
2012, II	6.30	79.97	14041	1.3673	441
2012, III	6.19	80.09	14456	1.3872	436
2012, IV	6.48	81.54	14077	1.4056	423
2013, I	6.41	79.26	13876	1.4587	456
2013, II	6.16	78.16	14407	1.4572	458
2013, III	6.93	77.85	12591	1.4169	459
2013, IV	6.11	77.07	12830	1.4364	414
2014, I	6.27	76.08	13618	1.2783	503
2014, II	6.23	76.56	13953	1.3046	495
2014, III	5.77	68.35	13591	1.3678	548
2014, IV	6.51	82.55	14542	1.3907	469
2015, I	6.29	73.53	13364	1.5188	576
2015, II	6.10	72.47	13730	1.4958	578
2015, III	5.93	73.43	14477	1.5078	564
2015, IV	6.17	77.18	13541	1.5062	541
2016, I	6.45	74.31	13172	1.5575	584
2016, II	6.28	74.45	13707	1.5150	576
2016, III	6.09	72.44	13887	1.4724	586
2016, IV	6.54	74.33	13270	1.4856	549
2017, I	6.27	72.61	13249	1.4326	596
2017, II	6.16	72.84	13675	1.3048	588
2017, III	5.97	74.31	14543	1.3666	570
2017, IV	6.21	79.15	13991	1.3894	539
2018, I	6.37	73.96	13321	1.4787	858
2018, II	6.29	75.08	13841	1.4182	836
2018, III	5.99	73.29	14341	1.3916	847
2018, IV	6.42	77.49	14151	1.4261	795
2019, I	6.93	75.62	12626	1.4602	911
2019, II	6.63	74.93	13211	1.4439	909
2019, III	5.73	67.38	13905	1.4315	1000
2019, IV	6.44	74.52	13673	1.4293	860
2020, I	6.09	66.67	11748	1.4321	932
2020, II	6.10	41.31	7353	1.4672	1497
2020, III	5.58	54.98	10822	1.4582	1106
2020, IV	5.83	61.39	9448	1.4950	998
2021, I	5.99	51.74	9865	1.6128	1559
2021, II	6.08	56.44	10732	1.5953	1414
2021, III	5.50	58.84	12506	1.5877	1341
2021, IV	6.46	67.60	10530	1.6616	1177
2022, I	6.93	73.19	12067	1.5078	1117
2022, II	6.66	71.80	12456	1.5038	1126
2022, III	6.33	70.77	13071	1.4725	1130
2022, IV	5.92	73.46	12676	1.4866	1097

Source: SCJU Constanta