

The modelling of time-series and the evaluation of forecasts for the future: the case of the number of persons per physician in turkey between 1928 and 2010.

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Abstract

Objectives: Health professionals are very important for improving the health status of the society and maintaining a healthy life. The aim of the present study is to model the number of persons per physician via Box-Jenkins and exponential smoothing methods and trend models, to compare these models, and to make estimations for the future. ARIMA or Box-Jenkins models are the combinations of AR and MA models administered to the series differenced at degree d .

Methods: The research material consists of data regarding the number of persons per physician between 1928 and 2010. The data were obtained from STATISTICAL INDICATORS Journal published by the Turkish Statistical Institute. 1928-2010 the number of persons per physician data ARIMA, exponential smoothing, and then modeled by Moving Average methods for future studies (2020) model performance is evaluated.

Results: The goodness of fit criteria of the relevant models. It is seen that the ARIMA (0,1,0) model has the best values except for Mean Absolute Percentage Error (MAPE) and Mean Absolute Error (MAE), but it is the Holt model which has lower mean error.

Conclusion: All administrative works and functions such as planning, organization, management, and rearrangement of healthcare services should be based on the data/evidence to be provided by this institution. Likewise, the problems and effects of healthcare services should be evaluated based on the data of this institution.

Keywords: Time series, Forecasting consistency, ARIMA models, Exponential smoothing methods, Estimation trend.

Abbreviations:

ARIMA: Autoregressive Integrated Moving Average; RMSE: The Square Root of Mean Square Errors; MAPE: Mean Absolute Percentage Error; MAE: Mean Average Error; MaxAPE: Maximum Absolute Percentage Error; MaxAE: Maximum Absolute Error; Norm. BIC: Normalized Bayesian Information Criterion.

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Introduction

Health professionals are very important for improving the health status of the society and maintaining a healthy life. Therefore, the number of employees working in the field of health, their education, the place they receive education, and the units or departments where they provide service are of great importance. Effective and productive healthcare services require sufficient number of health professionals, their training in accordance with contemporary criteria, and their balanced distribution across the country through a good planning.

According to the statistical indicators (1923-2011) data published by the Turkish Statistical Institute (TUİK), a considerable progress has been made in the field of healthcare services and society's health status in Turkey from the Republic period to the present time. While there were 6437 sickbeds in 86 establishments with bed in the first year of the Republic, the number of establishments with bed rose to 1198 and that of sickbeds increased to 192685 in 2005. In other words, while there were 5.1 beds per 10000 people in 1923, there came to be 26.7 beds per 10000 people in 2005 [1].

Data regarding the number of individuals per physician, which is an important indicator of development in healthcare services, indicate that there has been a regular fall in the number of individuals per physician in Turkey (i.e. healthcare services in Turkey have been going through a positive change both quantitatively and qualitatively). The number of persons per physician across Turkey was 12,841 in 1928, 12,217 in 1930, 2799 in 1960, 1088 in 1990, 693 in 2002, 591 in 2010, and 573 in 2013 (Table 1). The quantitative distribution of physicians in Turkey on the basis of province shows that Istanbul contains the biggest number of physicians. Of 95,190 physicians in Turkey in 2002, 20.2% served in Istanbul, 12.5% in Ankara, and 9% in Izmir. The number of physicians in these three provinces was 39,684. That is to say, 41.7% of the physicians in Turkey served in these provinces. The provinces having the fewest number of physicians were Bayburt, Hakkari, Tunceli,

Ardahan, Iğdır, Şırnak, and Kilis, and the number of physicians in each one of these provinces corresponded to a very low percentage of the total number of physicians across the country like 1% [1].

The aim of the present study is to model the number of persons per physician via Box-Jenkins and exponential smoothing methods and trend models, to compare these models, and to make estimations for the future.

Material and Methods

The research material consists of data regarding the number of persons per physician between 1928 and 2010. The data were obtained from STATISTICAL INDICATORS Journal published by the Turkish Statistical Institute [2].

Table 1. The number of persons per physician between 1928 and 2010.

Year	Physician	Year	Physician	Year	Physician	Year	Physician	Year	Physician
1928	12,841	1946	8,746	1964	3,024	1982	1,508	2000	755
1929	12,971	1947	7,754	1965	2,859	1983	1,484	2001	718
1930	12,217	1948	7,613	1966	2,817	1984	1,435	2002	693
1931	13,133	1949	7,780	1967	2,758	1985	1,381	2003	684
1932	12,678	1950	6,890	1968	2,711	1986	1,386	2004	650
1933	12,703	1951	3,250	1969	2,266	1987	1,349	2005	643
1934	12,910	1952	3,522	1970	2,228	1988	1,253	2006	664
1935	12,909	1953	3,144	1971	2,193	1989	1,160	2007	648
1936	12,706	1954	3,357	1972	2,279	1990	1,088	2008	628
1937	11,960	1955	3,371	1973	2,057	1991	1,052	2009	607
1938	12,274	1956	3,228	1974	1,871	1992	1,000	2010	591
1939	11,512	1957	3,414	1975	1,843	1993	949	2011	593
1940	11,819	1958	3,373	1976	1,749	1994	894	2012	583
1941	11,326	1959	3,393	1977	1,746	1995	862	2013	573
1942	10,314	1960	2,799	1978	1,690	1996	855	-	-
1943	10,526	1961	3,436	1979	1,655	1997	836	-	-
1944	10,946	1962	3,215	1980	1,631	1998	808	-	-
1945	9,629	1963	2,666	1981	1,603	1999	773	-	-

Autoregressive Integrated Moving Average (ARIMA) method, which is used for forecasting time-series events, was developed by Box and Jenkins [3]. ARIMA modeling approach is limited to the assumption that there is linearity between the variables. On the other hand, researchers have developed alternative modeling perspectives for forecasting time-series events where linearity assumption is not fulfilled.

ARIMA or Box-Jenkins models are the combinations of AR and MA models administered to the series differenced at degree d. The essence of the Box-Jenkins method is the choice

of an ARIMA model that is the most suitable one among various models based on the structure of the current data but contains limited number of parameters. As a whole, these models, which are non-seasonal, are represented as ARIMA (p, d, q).

In the models [4],

p: Degree of autoregressive model,

q: Order of moving average model,

d: Degree of non-seasonal differencing.

The expression of ARIMA (p, d, q) model can be defined as indicated in equation (1):

$$Z_t = \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + \dots + \phi_p Z_{t-p} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \dots - \theta_q a_{t-q} \quad (1)$$

Here: ϕ_p : Parameter values for autoregressive operator; a_t : Error term coefficients; θ_q : Parameter values for moving average operator; Z_t : Time series of the original series differenced at degree d.

$$W_t = Y_t - Y_{t-1}, t=1, 2, \dots, t \quad (2)$$

The first differences series is defined as given in the equation (2).

W_t =The first differences series,

Y_t =The random variables subset of the original time series.

If the first differences series is not stationary, stationary is checked by differencing the first time series again. This is modeled as given in equation (3).

$$Z_t = W_t W_{t-1}, t=1, 2, \dots, t \quad (3)$$

When the degree of differencing is d=0 (that means that the original series is stationary), ARIMA model will be AR, MA, or ARMA model. Due to this feature, it can be said that ARIMA models incorporate all of the Box-Jenkins models [5].

Seasonal Box-Jenkins models are represented as ARIMA (p,q,d)(P,D,Q)s. Here, P is the degree of Seasonal Autoregressive (SAR) model; D is the number of seasonal differencing operations; Q is the order of Seasonal Moving Average (SMA) model; and s is the period. In a combined autoregressive moving average model, the future value of a variable is assumed to be a linear function of past observations and random errors [6]. Seasonal ARIMA (p,q,d) (P,D,Q)s models ARIMA (p,d,q) models relationship is represented in Equation (4). They are SARIMA models [7].

$$\Phi P(B) \phi p(B)[1-B^s]^D [1-B]^{-d} Z_t = \alpha + \Theta Q(B) \theta q(B) A_t \quad (4)$$

The model establishment process involves certain repetitive steps [3]. These steps are indicated in the flow chart given in Figure 1.

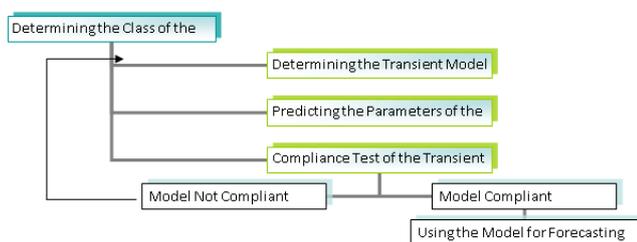


Figure 1. Model Establishment Process.

In determining the model, a model is selected from model classes such as AR, MA, ARMA, ARIMA, and SARIMA.

Then the parameters of the transient model are forecasted by use of efficient statistical techniques, and the standard errors of

coefficients are calculated to test whether or not they are significant. In the last stage, compliance of the model is checked for forecasting. To this end, the autocorrelation function of the model is examined by drawing the graph of the autocorrelation coefficients of the errors of the transient model that is assumed to be compliant. If this function displays a particular shape, it is concluded that errors are not random. This kind of a finding means that the determined transient model is not compliant. Therefore, one turns to the second step again, and this process is repeated until the compliant model is determined through a new transient model. The model passing the compliance check is now ready to be used for forecasting [8].

Forecasting methods based on exponential smoothing and moving averages are also used in forecasting. Simple exponential smoothing method was derived from moving averages and is expressed as indicated in Equation (5) [9].

$$Z'_t = \alpha Z_t + (1+\alpha)Z'_{t-1} \quad (5)$$

$$\hat{Z}_{t+1} = Z'_t$$

Here, \hat{Z}_{t+1} refers to the forecast value for the forthcoming period; α refers to smoothing coefficient (it takes a value in the range of $0 < \alpha < 1$); Z_t refers to true index value in period t or new observation; and Z'_t refers to former smoothed value. The most important point to consider at this point is the determination of α so that mean square errors are minimized. The seasonal ARIMA model or SARIMA model is an expanded form of ARIMA, which allows for seasonal factors to be reflected [10-13]. Holt's two-parameter linear exponential smoothing method equation is indicated in Equation (6) [14].

$$Z'_t = \alpha Z_t + (1-\alpha)Z'_{t-1} + T_{t-1}$$

$$\hat{Z}_{t+1} = Z'_t + IT_t$$

Here, $T = \beta(Z'_t - Z'_{t-1}) + (1-\beta)T_{t-1}$. In addition, β and $1-\beta$ are the parameters of the method and take a value between 0 and 1.

Brown's exponential smoothing method is expressed as follows:

$$S_t = \alpha(Y_t - I_{t-1}) + (1-\alpha)(S_{t-1} - b_{t-1})$$

$$b_t = \gamma(S_t - S_{t-1}) + (1-\gamma)b_{t-1}$$

$$I_t = \beta(Y_t - S_t) + (1-\beta)I_{t-L} \quad (7)$$

$$F_{t+m} = S_t + mb_t + I_{t-L+m}$$

t is a value observed at time Y_t ; t is a seasonal component; b_t is the smoothing component of the trend of t ; L is the number of periods in a season; F_{t+m} is one forecast ahead of m periods; m is the number of forecasted periods; α is parameter smoothing; β is seasonal smoothing parameter; and γ is the smoothing parameter of the trend [15].

Goodness of fit criteria of the obtained models is evaluated through comparison with one another. R^2 is a commonly known criterion. It is the goodness of fit criterion of the linear model. It is also known as coefficient of determination. It is in the range of 0-1 and smaller values indicate that the model does not have a good fit for the data. Stationary R^2 is a

criterion that compares the stationary part of the model and the basic model. It is preferred when there is a trend or seasonal pattern. RMSE is the square root of mean square errors. It is used for indicating how different dependent series are from the level forecasted by the model. Smaller values show that model forecasting is better. MAPE refers to mean absolute percentage error, is independent of the units of the series, and thus can be used in the comparison of different series. MAE refers to mean average error and is expressed with the series' own units. MaxAPE is the maximum absolute percentage error measure. It indicates the highest error occurring among the forecasted

values, is expressed in percentage, and thus unit independent. It is a measure that can be used for the worst scenarios among the forecasts. MaxAE is the maximum absolute error and is expressed in the same unit as the dependent series. Norm. BIC (Normalized Bayesian Information Criterion) is the general measure of the total fit of the model. This measure is used for making a comparison between different models when the series are the same, and smaller values indicate a better model [16-18].

Results

Table 2. Exponential smoothing methods forecasts about the number of persons per physician between 2011 and 2020.

Years	The Observed Number of Patients	Simple Exponential Smoothing	Holt Model	Brown Model	Linear Trend	Quadratic Trend	Exponential Trend	S curve
2011	593	595	569.09	583.6	-2374	1651.7	459	536.03
2012	583	598	548.04	572.62	-2534	1778.6	440	518.31
2013	573	602	527.76	562.89	-2695	1912.4	422	501.2
2014	-	605	508.24	554.54	-2855	2052.9	405	484.68
2015	-	608	489.44	547.72	-3016	2200.2	388	468.72
2016	-	612	471.33	542.55	-3177	2354.2	373	453.31
2017	-	615	453.89	539.19	-3337	2515	357	438.42
2018	-	619	437.1	537.79	-3498	2682.6	343	424.04
2019	-	622	420.93	538.52	-3658	2856.9	329	410.14
2020	-	626	405.36	541.59	-3819	3038	315	396.72

Table 3. The comparison of exponential smoothing and trend models.

Model	Simple Exponential Smoothing	Holt Model	Brown Model	Linear Trend	Quadratic Trend	Exponential Trend	S curve
MAPE	6.332	5.252	5.716	89	31	14	12

MAPE values in the Tables 2 and 3 show that the best forecasting model is the Holt model among exponential smoothing and trend methods [19].

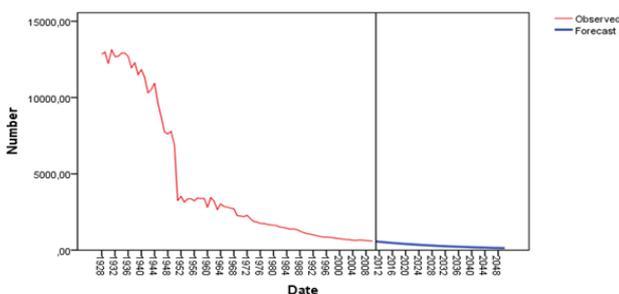


Figure 2. The logarithm of the number of persons per physician by year and the Holt model forecasting graph of the values differenced at the first degree.

Box Jenkins (ARIMA) model

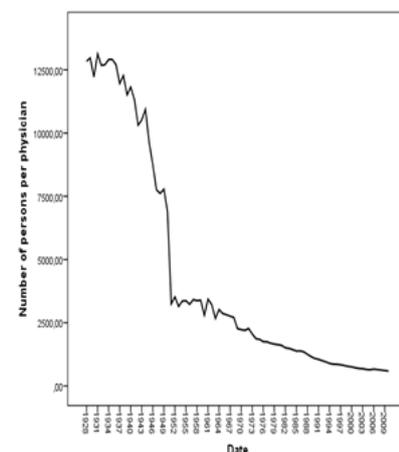


Figure 3. The pilot graph of the number of persons per physician by year.

The Table 2, Table 3 and Figure 2 demonstrates that forecasting values based on the simple exponential smoothing method are appropriate for the period between 2010 and 2015, but reliability of forecasts falls for the period between 2016 and 2020.

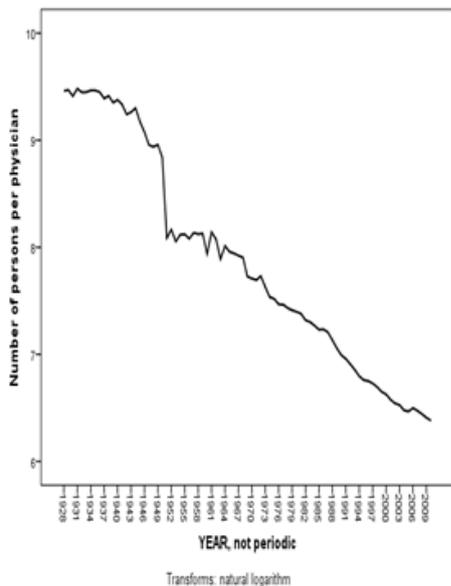


Figure 4. The pilot graph of the values whose logarithm was taken for the number of persons.

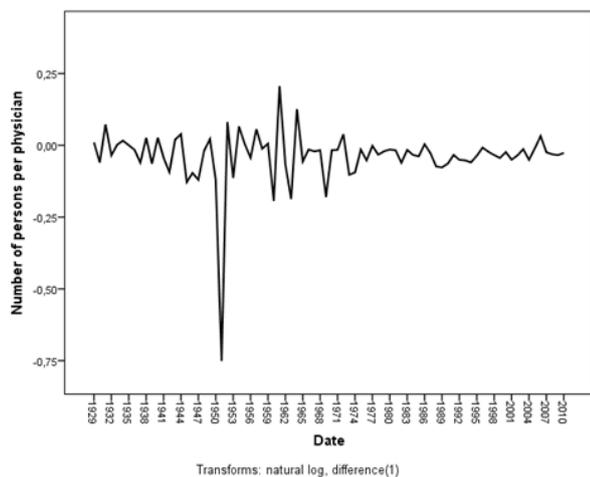


Figure 5. The logarithm of the number of persons per physician by year and the pilot graph of the values differenced at the first degree.

The Figure 3 presents a non-stationary display both in the variance and in the average. The Figure 4 takes the logarithm of the data but fails to achieve stationarity both in the variance and in the average. The Figure 5 differences at the first degree and takes the logarithm of the data and presents a stationary display both in the average and in the variance, though partly.

In this instance, the autocorrelation (acf) graph (Figure 6) forecasts the coefficient of the MA model while the partial autocorrelation (pacf) graph (Figure 7) forecasts the coefficient of the AR model.

Table 4. ARIMA (0,1,0) Model fit statistics.

Model	Stationary R ²	R ²	RMSE	MAPE	MAE	MaxAPE	MaxAE	Norm.BIC
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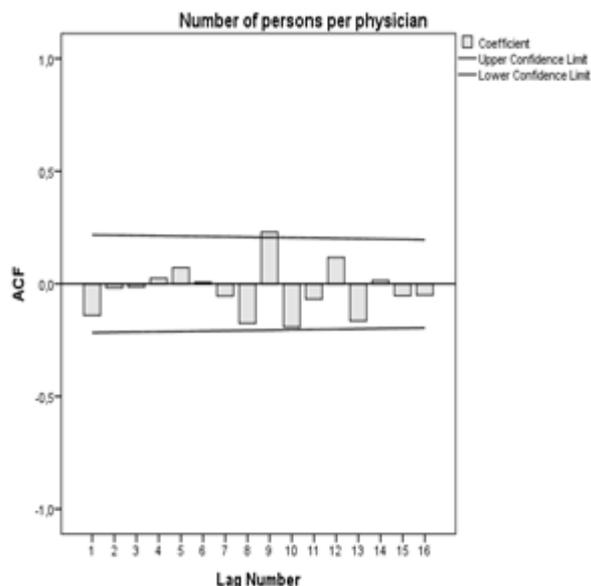


Figure 6. The autocorrelation (acf) graph of the values differenced at the first degree and the logarithm of the number of persons per physician by year.

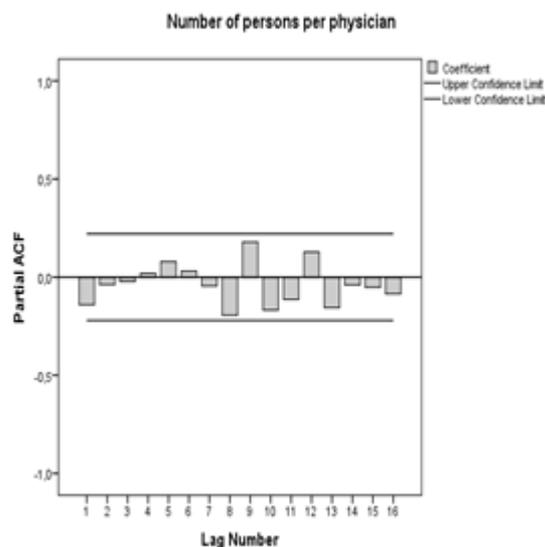


Figure 7. The partial autocorrelation (pacf) graph of the values differenced at the first degree and the logarithm of the number of persons per physician by year.

Since the acf and pacf graphs of the models do not involve any diagram outside confidence limits, AR and MA models may be taken as 0.

ARIMA (0,1,0)	-0.00044	0.986	512.436	5.395	248.814	105.224	3419.539	12.532
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Table 5. Forecast values regarding the number of persons per physician by year for the Box-Jenkins model.

Years	The number of observed patients	The number of persons per physician	Lower limit	Upper limit
2011	593	572.5	466.6	695.2
2012	583	554.1	413.8	727.3
2013	573	536.4	374.1	746.3
2014	-	519.2	341.6	758.2
2015	-	502.6	313.9	765.5
2016	-	486.6	289.7	769.3
2017	-	471	268.3	770.6
2018	-	455.9	249.2	769.7
2019	-	441.3	232	767.2
2020	-	427.2	216.3	763.2

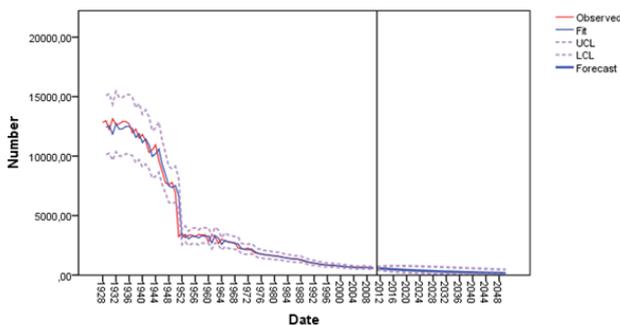


Figure 8. The Box-Jenkins model (ARIMA (0,1,0)) forecast graph of the values differenced at the first degree and the logarithm of the persons per physician by year.

The Table 4, Table 5 and Figure 8 indicates that the Box-Jenkins model method suggests that forecast values are appropriate for the years 2010 to 2016, but confidence interval gets some wider for the years 2017 to 2020, thereby leading to a fall in the reliability of forecasts.

Table 6. The Goodness of fit criteria of the exponential smoothing and ARIMA (0,1,0) models.

Model	R ²	RMSE	MAPE	MAE	MaxAPE	MaxAE
HOLT MODEL	0.986	515.088	5.252	245.017	105.934	3442.613
ARIMA (0,1,0)	0.986	512.436	5.395	248.814	105.224	3419.539

The Table 6 illustrates, in summary, the goodness of fit criteria of the relevant models. It is seen that the ARIMA (0,1,0) model has the best values except for mean absolute percentage error

(MAPE) and mean absolute error (MAE), but it is the Holt model which has lower mean error.

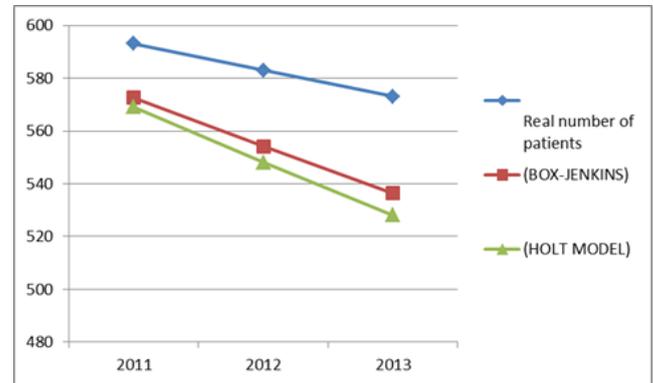


Figure 9. The Graph of the Holt Exponential Smoothing Model, the ARIMA (0,1,0) Model, and the Number of Observed Patients.

The Figure 9 illustrates the graph of observed number of patients in three years and forecasts about the number of persons per physician in three years for the Holt model of the exponential smoothing method and the ARIMA (0,1,0) model of the Box-Jenkins method.

The Figure 9 indicates that the forecasts by the ARIMA (0,1,0) model of the Box-Jenkins method are closer to the observed number of patients in comparison to the forecasts by the Holt model of the exponential smoothing method. However, since the difference is not too big, it can be said that the forecasts of both methods are good.

Discussion

This study aims to forecast the number of persons per physician in the future through predictive analysis by producing different models and determining the best models in this matter. Among the exponential smoothing models, the best predictive one was seen to be the Holt model. Among the Box Jenkins models, the best predictive one was seen to be the ARIMA (0,1,0) model.

The comparison of the above-mentioned best predictive models with one another was made based on the comparison of the forecast values of the models and the observed number of persons per physician in the first 3 years (2011, 2012, and 2013) and goodness of fit criteria. The Holt exponential smoothing model was found to be the best predictive model in terms of goodness of fit criteria in that it had a lower mean error in comparison to the other model. On the other hand, the ARIMA (0,1,0) model was seen to be the best predictive model in terms of the closeness of the forecasts regarding the first 3 years to the reality. The fact that the forecasts are quite close to the observed number of patients shows that these techniques can be used for forecasting the patient volume of hospitals and the sufficiency of staff. In this regard, more right and reliable

policies may be developed for the health care industry through forecasts for the future.

According to the activity report data of the Ministry of Health for the year 2012, 124,219 physicians worked in Turkey at the end of 2012. Of these physicians, 68,262 were specialist physicians; 35,739 were practicing physicians; and 20,218 were physician assistants. The Health Transformation Programme has facilitated the access of the patients to the doctor. The number of cases of consulting a physician per person was 3.2 in 2002 but had risen to 8.3 by 2012. The total number of physicians in Turkey was 124,219 in 2012 when the number of physicians per one hundred thousand people was 165; that of practicing physicians was 48; that of specialist physicians was 90; that of dentists was 27; that of pharmacists was 34; and that of midwives and nurses was 232. Medical faculties have 45,732 registered students and 10,440 faculty members. The number of students per faculty member is 4.3. While the number of physicians per 1000 people is 3.3 in average in Europe, this figure is around 1.6 in Turkey. It implies a considerable physician shortage. On the other hand, the quotes of medical faculties in Turkey have been increasing rapidly. The total quote was 6492 in 2008, but went up to 8453 in 2012. Proper steps should be taken for a correct planning of the quantity and quality of physicians in Turkey.

Another important recommendation is that an independent institution should be responsible for the country-wide organization of the health information system. All public and private institutions, organizations, and people operating or working in the field of health should ensure data flow to this institution. Officials should be appointed and units should be set up to ensure such data flow in institutions and organizations of a size bigger than a specific size. Legislative regulations should be introduced to accelerate bureaucratic processes in this matter. All administrative works and functions such as planning, organization, management, and rearrangement of healthcare services should be based on the data/evidence to be provided by this institution. Likewise, the problems and effects of healthcare services should be evaluated based on the data of this institution.

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