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Forecasting of Particleboard Consumption in Iran Using Univariate Time Series Models

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The performance of the Autoregressive Integrated Moving Average (ARIMA) model and Double and Holt-winters exponential smoothing techniques for forecasting the consumption of particleboard in Iran are compared. Annual time series data from 1978 to 2009 in the modeling process, and observations from 2010 to 2012 were used to check the accuracy of the models' forecasting performance. Also, the models' performances were calculated in terms of RMSE criterion, and the consumption of particleboard in Iran was forecasted up to the year 2017 using the most appropriate model. The results of comparing different forecast models showed that the ARMA (2,1) model yielded the lowest RMSE value compared to the other two models, which makes it more appropriate for the prediction of consumption of particleboard in Iran. Results also revealed that there might be an increasing trend in the consumption of particleboard, *i.e.*, an average annual increasing rate calculated as 5% for particleboard. Thus, it was predicted that the consumption of particleboard would increase from 901,652 m^3 in 2012 to 1,178,320 m^3 in 2017.

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INTRODUCTION

Forecasts are produced in a wide range of fields, as they are important tools for decision making. In this regard, forecasting of forest products' demand is one of the key inputs for successful market planning in the forest sector (Hetemaki and Mikkola 2005). Among different forest products, wood-based panels, such as particleboard, have enjoyed an extremely wide range of applications in furniture and joinery as well as in the building and construction industries (Tajdini *et al*. 2014).

The particleboard industry in Iran is one of the oldest industries in the wood-based panels industry section. It has lasted more than 50 years, and in comparison with other wood-based panels, such as fiberboard, plywood, and veneer, it has a relatively favorable economic situation at the moment. In 2012, there were more than 19 active manufacturing factories with a total nominal capacity of 1,078,890 m^3, which produced 881,634 m^3 of particleboard (85% of the total nominal capacity). Therefore, with respect to 901,652 m^3 consumption for this product in 2012, it can be stated that 97.8% of the total consumption of the country was produced by the local manufacturers and the remainder was supplied through importation (Ministry of Industries and Mines of Iran 2013). The available data also showed that over 32,001 m^3 of particleboard, with a price of $8 million, was imported

in 2012. In the same year, the amount of export was 11,983 m^3 (Tehran Chamber of Commerce, Industries, Mines and Agriculture 2013).

The particleboard industry has the potential to use wood wastes including branches, cotton and corn surplus, flax and hemp, and other woody plants. Conversely, the particleboard industry is considered to be able to satisfy the demand of raw woody materials, which reduces the pressure on the Iranian forests. Therefore, because of the importance of this product for different purposes, such as manufacturing furniture and other applications, the prediction of particleboard future demand would be helpful from different aspects. Several methods have been applied to forecast in forest products markets in various parts of world. For instance, the lumber demand in the United States was forecasted by Alexander *et al*. (2003) using time series analysis methods. Song (2006) compared and predicated the price of softwood lumber in US using univariate forecasting methods (ARIMA, Spectral, simple Lag and simple dummy-variable models), as well as multi-equation models (VAR, 2SLS and EMC models). Bayatkashkoli *et al*. (2008) forecasted the export and import rates of wood and wooden products, such as particleboard and plywood in Iran, using forecasting techniques of trend and regression formulations. Arabatzis and Klonaris (2009) analyzed the Greek aggregate import demand for unprocessed wood (such as logs), processed wood (such as sawn wood), veneer crafts (such as veneer sheets) and wood manufactures during the period of 1969 to 2001 using the linear approximation of quadratic AIDS (QUAIDS) model. Azizi *et al*. (2009) provided projection for consumption of particleboard, fiberboard, MDF, and plywood in Iran using the exponential smoothing model until 2012. Ioannou *et al.* (2009) used the Artificial Neural Networks (ANN) model to predict the prices of conifer fuel wood in Greece. Koutroumanidis *et al*. (2009) used the ARIMA and Artificial Neural Networks (ANN) models as well as a hybrid approach (ARIMA-ANN) to predict the future selling prices of the fuel wood (from broadleaved and coniferous species) produced by Greek state forest farms. Emang *et al*. (2010) used univariate time series models, including Holt-winters-seasonal, ARAR algorithm, and seasonal ARIMA modeling to forecast the future volume of exporting wooden products (including chipboard and moulding) in Malaysia. Mohammadi Limaei *et al*. (2011) analyzed time series and an autoregressive procedure to predict the export and import of wood in Iran. Tajdini *et al*. (2014) forecasted the consumption of wood-based panels in Iran using exponential smoothing and ARIMA models until 2014.

This study investigates the predictive power of univariate time series models include: Double exponential smoothing model, Holt-winters exponential smoothing model, and Autoregressive Integrated Moving Average (ARIMA), as well as the consumption of particleboard in Iran, was forecasted for the period of 2013-2017 using the most appropriate model. Conveying information regarding the trend of coming consumption enables policy makers to develop long-term programs for the manufacturing sector and formulate appropriate strategies so as to meet the domestic demand.

EXPERIMENTAL

Methodology

Univariate time series models

The time series models frequently consider the variable's behavior in the past as the basis for forecasting. Before using these models, it is necessary to survey their

randomness, because if the data are random, it would not be possible to use forecasting models based on the past trend. To do this, the parametric test of Durbin-Watson and the non-parametric test of Runs were used. Also, to perform the Durbin-Watson test, it is necessary that the observations conform to a normal distribution. In this study, the observations' normality was investigated using the Kolmogorov-Smirnov (KS) test.

Exponential smoothing (ES) models

Exponential smoothing is a procedure used for the continuous revision of a forecast in light of more recent experience. This method is a relatively simple, yet robust approach to forecasting. It is widely used in business for forecasting demand for inventories (Gardner 1985). It has also performed surprisingly well in forecasting competitions against more sophisticated approaches (Makridakis and Hibon 2000).

Single exponential smoothing (SES) model

SES model is a procedure that repeats enumeration continually using the most recent data. This method can be used if the data is not significantly influenced by trend and seasonal factors. The single exponential smoothing model for a time series (y_t) is given by the model equation:

$$y_t = \mu_t + \varepsilon_t \tag{1}$$

The smoothing equation is:

$$F_t = \alpha y_t + (1 - \alpha)F_{t-1} \tag{2}$$

The h-step-ahead prediction equation is,

$$\hat{y}_{(t+h)} = F_t \ , \quad \text{h= 1, 2,...} \tag{3}$$

where μ_t represents the time-varying mean(level) term , ε_t is a white noise error term, and α is a smoothing constant between 0 and 1. The smoothed statistic F_t is a simple weighted average of the previous observation and the previous smoothed statistic (F_{t-1}).

Double exponential smoothing (DES) model

The DES model is a refinement of the popular single exponential smoothing model that includes another component, which takes into account any trend in the data. When, there is an increasing or decreasing trend in the data over time, single exponential smoothing forecasts tend to lag behind observations. Double exponential smoothing is designed to deal with such data by taking their trends into account. The double exponential smoothing model for a time series (y_t) is given by the model equation:

$$y_t = \mu_t + \beta_t t + \varepsilon_t \tag{4}$$

The smoothing equations are,

$$F_t = \alpha y_t + (1 - \alpha)F_{t-1} \tag{5}$$

$$F'_t = \alpha(F_t - F_{t-1}) + (1 - \alpha)F'_{t-1} \tag{6}$$

where μ_t represents the time-varying mean(level) term, β_t represents the time varying slope term (called "trend" term by exponential smoothers) , ε_t is a white noise error term, F_t is the single smoothed series, and F'_t is the double smoothed series. The symbol α stands for the

smoothing parameter, between $0 < \alpha \leq 1$. The forecasts from double smoothing are computed using the following formula.

$$\hat{y}_{(t+h)} = F_t + F'_t[(h-1) + 1/\alpha)] \tag{7}$$

Holt-Winters exponential smoothing (HWES) model

HWES model is similar to the double method, but it uses parameters that are different from the one used in the original series to smooth the trend value. The prediction of Holt-Winters exponential smoothing can be obtained by using two smoothing constants and the following three equations,

$$L_t = \alpha y_t + (1 - \alpha)(L_{t-1} + b_{t-1}) \tag{8}$$

$$b_t = \beta(L_t - L_{t-1}) + (1 - \beta)b_{t-1} \tag{9}$$

$$\hat{y}_{(t+h)} = L_t + hb_t \tag{10}$$

where y_t is the observed value at time t, L_t is the forecast at time t, b_t is the estimated slope at time t, α is the first smoothing constant used to smooth the observations, β is the second smoothing constant used to smooth the trend, and y_{t+h} is forecast value for period $t + h$. It must be mentioned that α and β are determined by minimizing the sum of squares of the forecast errors (MSE or RMSE).

Autoregressive integrated moving average (ARIMA) model

In this method, which is also called the Box-Jenkins (BJ) method, the behavior of the dependent variable (y) is explained using its values in the past and stochastic error terms (Box and Jenkins 1978). This method includes a series of four steps (Gujarati 2004): (1) Model Selection, where the order of autoregressive (p) and moving average (q) are determined after recognizing the variable's stationary degree (d). To do this, maximum lag orders of three (which have the minimum Akaike Information Criterion (AIC)), are used to select the values of p and q in the ARIMA (p, d, q) process (Pesaran and Pesaran 1997). Using this criterion in small samples requires special attention, without which the forecasting uncertainty may increase. Therefore, the RMSE criterion is also used for assessing the forecasting accuracy (Marcellinio *et al*. 2006), so that the forecasting error (in terms of RMSE) would be minimized for the minimum Akaike criterion. The following equation is used for AIC computation.

$$AIC = log\,\hat{\delta}^2 + \frac{2.k}{N} \tag{11}$$

where $\hat{\sigma}^2$ is the estimated variance of white noise (ε_t), N is the number of observations and k is the number of estimated parameters, *e.g.*, $k = p + q$.

(2) Model estimation is followed by (3) model checking. This is where normality and autocorrelation of model residuals are tested. If the residuals have a normal distribution, and their autocorrelation and partial correlation coefficients (ACFs and PACFs) are not significant among lags, it would be possible to accept the selective model as a desirable fit (Newaz 2008). Otherwise, it should be rejected and the previous stages should be repeated. (4) Forecasting, where the selected and estimated model is typically simulated forward to produce forecasts for the variable of interests at one or more relevant horizons.

The ARIMA procedure is performed on stationary data. Stationary is necessary in this method because only then one can legitimately learn from the past to predict the future

realization of a time series. Otherwise, the density of the observations estimated from the past data will not be helpful in predicting future observations. This study considers the stationary of series by two unit root tests of Augmented Dickey-Fuller (ADF) and Philips-Perron(PP). In Box and Jenkins' notation, a process is called ARIMA(p,d,q), if it yields a stationary ARMA(p,q) process after differencing it, d times. In practice, only the cases d =0,1,2 are used, where d=0 indicates a stationary ARMA process. In other words, ARIMA models get reduced to ARMA models; thus, ARIMA(p, 0, q)= ARMA(p,q), (Gujarati 2004). The general form of an ARMA model is as follows,

$$AR\ (p)\ :\ y_t = \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + ... + \alpha_p\ y_{t-p} + \varepsilon_t \tag{12}$$

$$MA\ (q):\ y_t = \beta_1 \varepsilon_{t-1} + \beta_2 \varepsilon_{t-2} + ... + \beta_q\ \varepsilon_{t-q} \tag{13}$$

$$ARMA\ (p,\ q):\ y_t = \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + ... + \alpha_p\ y_{t-p} + \varepsilon_t + \beta_1 \varepsilon_{t-1} + \beta_2 \varepsilon_{t-1} + ... + \beta_q\ \varepsilon_{t-q} \tag{14}$$

where ε_t is white noise, identically normally distributed with zero mean and variance σ^2_ε.

Evaluation Measures of Model Fitting

In this study, the demand of particleboard is determined based on an apparent consumption method (Apparent Consumption= Production + Import - Export). As a result, forecasts using consumption models reflect the apparent consumption estimate (Gupta *et al.* 2013). The complete data set must be dividing into two parts, fitting the model to the first part, but keeping back the second part, called the test set, so that predictions from the model can be compared with the observed values (Chatfield 2001). There is no principle for this dividing. In accordance with using annual data and their properties from observation limits views as well as improving forecasting performance as a result of increasing required data for model estimation, about 90% of the data (from 1978-2009) were used for estimating or fitting the forecasting models, and the remaining 10% (from 2010-2012) were used for the out-of-sample forecast performance evaluation (models validation).

Finally, forecasting was performed for the period of 2013-2017, applying the appropriate model. Also, the forecasts were evaluated by analyzing the pattern of forecasts relative to the actual values using the RMSE criterion, which is the most commonly used measure for comparing relative accuracy of forecasting models (Clements and Hendry 1998). In forecast evaluation, the use of RMSE is also justified, as it is a familiar and easily interpretable measure; the lower the RMSE, the better the forecast (Malaty 2007) and RMSE values less than 0.1 indicate good model fit (Pindyck and Rubinfeld 1998). The RMSE is found using the following equation,

$$RMSE = \sqrt{\sum(\bar{Y}_t - Y_t)^2/N} \tag{15}$$

where Y_t is the observed value, $\bar{Y}_t$ is the forecasted value, and N is the number of forecast periods.

Throughout all the forecasting procedures, the data in Napier logarithm scale were used in the models and thus the predicted values were in logarithmic form as well. After performing all the calculations, these variables were returned into their first condition for the purpose of comparing and interpreting the results. The Eviews 7 and SPSS software packages were utilized for all necessary data processing and calculations.

RESULTS AND DISCUSSION

Univariate Time Series Models

In these models, it is necessary to check the stationarity of series. Stationary means that the mean and variance of the series are constant and also the covariance is time-invariant (Gujarati 2004). The results obtained from the stationary of particleboard consumption are displayed in Table 1.

Table 1. Results of the ADF and PP Unit Root Tests

Variable(Logarithmic)	ADF test(with intercept and trend)			PP test(with intercept and trend)			Result
	Lag	ADF stat	MCV	Bandwidth	PP stat	MCV	
Particleboard consumption	3	-3.60*	-3.58	0	-3.76*	-3.56	I(0)
* Indicates coefficient estimate is significant at 5% level							
Notes: MCV is MacKinnon critical values for rejection of hypothesis of a unit root							

The results of the unit root tests indicated that the null hypothesis, the unit root is in series, is rejected using the ADF and PP tests at 5% critical value. Therefore, the particleboard consumption series is integrated of order zero, or $I(0)$. Also, the results of the normality and randomness tests of series, which are necessary for forecasting with time series models, are presented in Tables 2, 3, and 4.

Table 2. Results of the Kolmogorov-Smirnov Normality Test

Variable(Logarithmic)	N	Normal parameters		Z	Asymp. sig.(2-tailed)
		Mean	Std. Error		
Particleboard consumption	35	12.72	0.594	0.623	0.833

Table 3. Results of the Parametric Durbin-Watson Test

Variable(Logarithmic)	N	d*	Critical values (5%)		Result
			d_L	d_U	
Particleboard consumption	35	0.0076	1.402	1.519	The series is non-random
* d statistic is Durbin-Watson static					

Table 4. Results of the Non-Parametric Runs Test

Variable(Logarithmic)	N	Number of runs	Z	Asymp. sig. (2-tailed)	Result
Particleboard consumption	35	2	-5.490	0.000	The series is non-random

The results of the series normality test indicate that the p-value of the series is not significant at the 5% level (Table 2). As a result, the null hypothesis that the time series have a normal distribution cannot be rejected. Therefore, the particleboard consumption series can be assumed to have a normal distribution, meaning that it is possible to use the

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parametric test of Durbin-Watson for investigating the series randomness. As shown in Table 3, the results of this test indicate that the null hypothesis, based on the lack of positive autocorrelation for particleboard consumption series, is rejected ($0 < d < d_L$). Therefore, the variable is non-random and predictable. Also, the results of the Runs test severely reject the null hypothesis, showing that the variable is random at 5% level. It also emphasizes the non-random and predictable nature of this series (Table 4).

Exponential smoothing (ES) models

The results of particleboard consumption forecasting using Double and Holt-Winters exponential smoothing techniques are displayed in Table 5.

Table 5. Results of Particleboard Consumption Forecasting (in m^3) Using Exponential Smoothing (ES) Models, 2010-2012

Model	α	β	RMSE	2010		2011		2012	
				Predicted	Actual	Predicted	Actual	Predicted	Actual
DES	0.001	N/A	0.062	736165	747534	776949	816621	819992	901652
HWES	0.660	0.000	0.058	729438		777485		828697	

The final values of the smoothing coefficients for Double and Holt exponential smoothing models are shown in Table 5. The parameters with the smallest RMSE were used to forecast. As shown in the Table 5, the values predicted using both models are lower than the actual (observed) values for 2010 to 2012. Also, the value of RMSE for the Holt-Winters exponential smoothing model (0.058) is less than the one for the Double exponential smoothing model (0.062). This indicates that the model fitting degree for both Double and Holt-Winters exponential smoothing models is good (Pindyck and Rubinfeld 1998), but, the forecasting accuracy of the Holt-Winters exponential smoothing model is higher than the Double exponential smoothing model; thus, it is more desirable for forecasting.

 ARIMA model

When modeling with ARIMA, it is necessary to have a stationary time series (Gujarati 2004; Kunst 2011). According to the results shown in Table 1, this goal is achieved at the 5% level. Therefore, in ARIMA (p, d, q), $d = 0$, and the ARMA (p, q) model can be used for forecasting (Gujarati 2004). In this study, the trend (in addition to the constant) was taken into consideration in the model. If the trend was significant in the model, its effect will be omitted from the model, otherwise, modeling will be performed without it. The results of model selection are displayed in Tables 6 and 7.

Table 6. RMSE and AIC Values Based on Different Orders of p and q

q	0		1		2		3	
P	AIC	RMSE	AIC	RMSE	AIC	RMSE	AIC	RMSE
0	N/A	N/A	-0.868	0.032	-0.807	0.032	-0.789	0.102
1	-0.882	0.055	-0.906	0.046	-0.768	0.050	-1.071	0.108
2	-0.790	0.052	-1.020	**0.016**	-1.399	0.073	-1.562	0.122
3	-0.711	0.057	-1.012	0.080	-0.958	0.083	**-1.600**	0.112

Table 7. Comparison of ARMA(2,1) and ARMA(3,3) Models

ARMA(p,q)	AIC	RMSE	2010		2011		2012	
			Predicted	Actual	Predicted	Actual	Predicted	Actual
ARMA(2,1)	-1.020	0.016	727260	747534	820148	816621	900954	901652
ARMA(3,3)	-1.600	0.112	818256		952181		973478	

In this study, the approaches given by Pesaran and Pesaran (1997) and Marcellino *et al*. (2006) are used to determine the autoregressive (*p*) and moving average (*q*) orders. As shown in Table 6, the results of recognizing an ARMA (*p*, *q*) model indicated that ARMA (3,3), based on the minimum AIC, and ARMA (2,1), based on the minimum RMSE, are the best models for forecasting particleboard consumption in Iran. Therefore, both models were estimated and the series' forecasted values were compared with the actual ones. Finally, ARMA (2,1) was selected as the final model, because the difference between the Predicted and the actual values was lower for 2010- 2012, as shown in Table 7. The results of estimation using this model and the NLS method, as well as the results of checking the adequacy of the ARMA (2,1) model, are indicated in Tables 8 and 9.
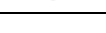
Table 8. Estimation Results of ARMA (2,1) Model with Constant and Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	11.727	0.038	306.209	0.0000
Trend	0.058	0.002	30.020	0.0000
AR(1)	1.127	0.187	6.036	0.0000
AR(2)	-0.478	0.172	-2.783	0.0101
MA(1)	-0.943	0.102	-9.252	0.0000
R^2= 0.94 ; Adjusted R^2= 0.93 ; AIC= -1.020 ; BIC= -0.786 ; F-Statistic= 93.856 (0.0000) ; Jarque-Bera= 1.596 (0.4501)				
Note: number in parenthese represent the p-value				

Table 9. Correlogram Results for the Residual of the ARMA (2,1) Model

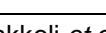| Autocorrelation	Partial Correlation	Lags	AC	PAC	Q-Stat	Prob.
		1	-0.203	-0.203	1.3664	0.242
		2	-0.024	-0.068	1.3868	0.500
		3	0.104	0.089	1.7699	0.622
		4	-0.269	-0.243	4.4400	0.350
		5	-0.161	-0.286	5.4386	0.365
		6	0.247	0.153	7.8876	0.246
		7	-0.204	-0.115	9.6168	0.211
		8	0.028	-0.099	9.6519	0.290
		9	0.148	0.007	10.649	0.301
		10	-0.205	-0.125	12.670	0.243
		11	0.052	-0.020	12.808	0.306
		12	0.079	-0.040	13.139	0.359
		13	-0.161	-0.085	14.597	0.333
		14	0.057	-0.063	14.795	0.392
		15	-0.056	-0.194	14.995	0.452
		16	-0.079	-0.060	15.429	0.493

As shown in Table 8, all of the model's parameters are statistically significant at the 5% level (p-value < 0.05). The coefficient of determination (0.94) and the F-statistic (93.9) indicate that the model is valid. Also, to investigate the residuals' normality, the Jarque-Bera test was performed, which indicates that they are normally distributed. As shown in the correlogram in Table 9, none of the autocorrelation (ACFs) and partial correlation (PACFs) coefficients of the residuals were found to be statistically significant at the 5% level. Overall, the residuals of the ARMA (2,1) model are completely random and follow a white noise process (Newaz 2008).Therefore, the chosen model is desirable for forecasting, and there is no need to search for another one. The results of particleboard consumption forecasting using the ARMA (2,1) model is displayed in Table 10.

Table 10. Results of Particleboard Consumption Forecasting Using ARMA (2,1) Model (in m^3)

Model	MAPE (%)	RMSE	2010		2011		2012	
			Predicted	Actual	Predicted	Actual	Predicted	Actual
ARMA(2,1)	0.080	0.016	727260	747534	820148	816621	900954	901652

According to the results of forecasting accuracy evaluation of the ARMA (2,1) model for 2010 to 2012, which are shown in Table 10, the forecasted values for particleboard consumption series are almost equal to the actual (observed) values for 2010 to 2012. Also, the RMSE is 0.016 and the percentage of prediction error (MAPE) is less than 1%. This indicates that, the model fitting degree is good (Pindyck and Rubinfeld 1998), Thus, this prediction is excellent.

Forecast Comparison and Evaluation

The results of comparing different forecast models are displayed in Table 11.

Table 11. Results of Accuracy Evaluation of the Different Forecast Models for Particleboard Consumption (in m^3)

Models	RMSE	2010		2011		2012		Priority
		Predicted	Actual	Predicted	Actual	Predicted	Actual	
DES	0.062	736165		776949		819992		3
HWES	0.058	729438	747534	777485	816621	828697	901652	2
ARMA(2,1)	0.016	727260		820148		900954		1

As shown in Table 11, the ARMA (2,1) model has the lowest RMSE (0.016) and, since the RMSE value is less than 0.1, this indicates that the model fitting is good (Pindyck and Rubinfeld 1998). Also, the forecasted values for particleboard consumption series are almost equal to the actual (observed) values for the period of 2010 to 2012, as the ARMA(2,1) model forecasting range was estimated from 727,260 m^3 in 2010 to 900,954 m^3 in 2012, while its actual values were in the range of 747,534 m^3 to 901,652 m^3. Therefore, in terms of prediction accuracy, it is proposed that ARMA is the best among these models and the Holt-Winters and Double exponential smoothing models stand in the second and third positions, respectively. Therefore, the following ARMA model is used to forecast particleboard consumption in 2013-2017 as displayed in Table 8.

$$y_t = 11.73 + 0.06\text{Trend} + 1.13y_{t-1} - 0.48y_{t-2} - 0.94\varepsilon_{t-1} \qquad (16)$$

The above model was specified by the highest R^2 and adjusted R^2 values (0.94 and 0.93, respectively), and the smallest RMSE value (0.016). The arithmetic coefficients were significant (p-value < 0.05), there was normality of residuals, and residuals of the model could be regarded as white noise (there is no significant in the ACFs and PACFs of the residuals) (Newas 2008).

Table 12. Forecasted Values of Particleboard Consumption in Iran over the Period 2013-2017

ARMA(2,1) (Best model)	Year				
	2013	2014	2015	2016	2017
Forecasted values (m^3)	958888	1009767	1060626	1116088	1178320

According to the study of Azizi *et al.* (2009) and Tajdini *et al*. (2014), there is an increasing trend in the consumption of particleboard in Iran and it can be expected to have an average annual growth rate of 5% over the forecast period. This means that it is can increase by 30.7% from 901,652 m^3 in 2012 to 1,178,320 m^3 in 2017 (Table 12).

CONCLUSIONS

1. The results of both the parametric test of Durbin-Watson and non-parametric test of Runs for investigating the series randomness indicate that the randomness hypothesis of series can be rejected, meaning that particleboard consumption series is non-random and predictable and it is possible to use forecasting models based on the past trend.

2. In this study the accuracies of univariate time series models were compared for forecasting the consumption of particleboard in Iran. Results showed that all univariate time series models (DES, HWES, and ARMA models) are fully suitable models for forecasting of particleboard consumption in Iran (they have the RMSE value less than 0.1), but, since the ARMA model has higher forecasting accuracy than the exponential smoothing models, therefore, it is more appropriate for the five years forecast of particleboard consumption in Iran.

3. The results of forecasting by using ARMA model revealed that the consumption of particleboard in Iran, despite strong substitutes such as MDF, is forecasted to increase by an average of 5% per year, from 901,652 m^3 in 2012 to 1,178,320 m^3 in 2017.

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