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Statistical modeling to forecast the wood-based panels consumption in Iran

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Abstract

In this paper, the consumption of wood -based panels in Iran are forecasted up to the year 2014 using statistical time series exponential smoothing and ARIMA models. The models performance was calculated in term of RMSE. ADF test was applied to investigate the stationary character of the data. The results indicated that the Holt-winters exponential smoothing model with the smallest RMSE can be selected as the best forecasting model for particleboard and plywood. The ARIMA (2,1,1) model provided the smallest RMSE and it was selected as the best forecasting model for veneer. Forecasting accuracy of the Holt-Winters model is more than the double exponential smoothing model, especially in the case of plywood. It was projected that consumption levels particleboard, veneer and plywood to increase and then decrease from 2010 to 2014 respectively. The most significant increase is forecasted in the consumption of veneer and particleboard. The average annual rates of increase are calculated as 5.1% and 1.17% for veneer and particleboard respectively. For plywood, the average annual rate of decrease is 3%. Particleboard. The consumption quantity of particleboard and veneer will increase from 684790 and 115880638 m^2 in 2009 to 749428 and 206424496 in 2014 respectively. For plywood, the consumption quantity will be reduced from 32000 in 2009 to 23035 m^3 in 2014.

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Introduction

Wood-based panels have enjoyed an extremely wide range of applications in furniture and joinery as well as in building and construction industries. Similar to any other communities, the consumption of wood and wood–based panels in Iran have raised in the recent years, and over the last ten years, the consumption of particleboard, plywood and veneer showed the average annual growth of 8, 41.52 and 6% respectively (Mofrad, 2010). Tajdini *et al.,* (2011) expressed that consumption of particleboard as an one of the most important wood panels in Iran is influenced to it's price and price of MDF (as a substitute for particleboard) commodities and the first lagged quantity of GNP. Azizi *et al.,* (2008) investigated the per capita consumption of wood panels for the period of 1997 to 2007 and estimated the demand of wood panels in Iran by the year of 2012.The exponential smoothing method was also used to obtain per capita consumption pattern of wood panels in Iran to estimate the demand of wood panels by the year of 2012. Results revealed that the consumption of particleboard, fiberboard and medium density fiberboard in Iran will increase by 33%, 72 % and 107%, respectively up to the year of 2012. At the global scale, the consumption of wood –based panels during the period 1990-2005 indicated the average annual growth of 4.3 % and it is predicted that this rate will decrease as low as 3% until 2030 (FAO, 2009).

During the past decade, interest in short-term economic forecasting has increased markedly due to drastic changes in the world's economies. Developments in information technology, world trade liberalization and European integration had caused the transfer of economic fluctuations from one geographic region to another more rapidly than before. Changes in both international and domestic economic growth rates are reflected in fluctuations in the consumption of forest products (Hanninen, 2004) and the forecasting of wood-based panels consumption enables policy makers to develop long-term programs for this industrial sector and formulate appropriate strategies to meet the growing demand. Several methods have been applied to forecast the future demands of wood products. The lumber demand in the United States was forecasted by Alexander *et al.,* (2003) using time series analysis methods. Malaty *et al.,* (2007) analyzed the Nordic pine saw log regional markets and placed special emphasis on the short-run forecasting of different time series models up to April 2006. As a benchmark case, they compared the models performance in terms of root mean square forecasting errors (RMSE) of standard autoregressive moving average (ARIMA) and vector autoregressive (VAR) models to those of Harvey's (1989) structural time series model (STSM), which, unlike to the standard methods, decomposes the time series into unobservable components, such as deterministic and stochastic trend and seasonal and cyclical behavior. The results indicate that, in most cases, the STSM together with Kalman filter estimation outperform ARIMA and VAR estimation. With hindsight, stumpage markets experienced a price decrease during July-December 2005 and a turning point up in early 2006 but none of these models were able to accurately predict. Based on these results, it seems that, in real–life forecasting situations, it is quite difficult to reach precise estimates for the stumpage prices based on solely using the time series approach (irrespective of how flexible the models may be with respect to structural changes).

Hetemaki and Obersteiner, (2001) provided projections of newsprint demand for the United States (US) up to 2020. Three different approaches were used to compute the projections. First, various specifications of the standard model used in forest product demand literature, which we call the *classical model*, were estimated using annual data from 1971–2000. The results indicated that structural change in the newsprint consumption pattern took place at the end of the 1980s. The classical model fails to explain and forecast the structural change. These observations motivated the formulation of alternative models. Thus, a *Bayesian* model that allows industry experts to use prior knowledge on the future demand for newsprint to be included in the projections was estimated. Also, an *ad hoc* model, in which the newsprint demand is considered as a function of changes in newspaper circulation, was used to compute projections. Finally, the forecasts of these models are evaluated along with some of the existing projections.On the contrary to some recent projections (e.g. FAO), the results indicated that US newsprint demand is likely to decline in the long term. FAO has been publishing long-term projections since the beginning of the 1960s, and the most recent being the FAO, (1999) outlook study. This report, which is based on the PELPS model, provides projections for global forest products consumption, production, trade, and prices up to 2010. The FAO (1999) projections are based on an empirical model, in which the demand for forest products are determined by economic growth (GDP), real prices of forest products, and lagged demand. Song, (2006) showed that a combination of models have shown to be the best forecasting models for lumber prices, and a combination of univariate and multi-equation models were shown to be the best forecasting models for lumber quantities. The selected combinations of models were shown to be the best with additional observations. It was also shown that lumber quantities could be forecasted better than lumber prices. Mohammadi Limaei *et al.,* (2011) have analyzed time series and autoregressive procedure to predict the export and import of wood in Iran. The results showed that it is possible to predict the wood export via a first order autocorrelation function. The mean of the wood export in the distance future was calculated to be 2133 tons per year. Hetemaki and Mikkola, (2005) forecasted the import demand for coated printing and writing paper in Germany. A number of univariate time series models, single equation econometrics models and multivariate systems models were estimated using quarterly data from 1991:Q1-2001:Q2 and observations from 2001:Q3-2002:Q4 are used for the out of sample forecast performance evaluation. Forecasts are also computed using various weighted combinations of the individual forecasting models. The results indicated that the forecast accuracy increases when one moves from univariate time series models to econometric models. The best single forecasting model in terms of the root-mean–squared error criterion is a VARX model in differences. However, by optimally combining individual model forecasts, one is able to produce even more accurate forecasts.

In this paper, we intend to provide the forecast for the wood–based panels including particleboard, veneer and plywood (with the exception of MDF and Fiberboard, due to the lack of productions data prior to 1996 in Iran) consumption using statistical time-series modeling techniques. The results of our forecast can be considered as the representative of the countries in this region. The main goal is to present and compare the models performance in terms of root mean square forecasting errors (RMSE). Finally, we will forecast the consumption of the mentioned products for the period of 2010-2014 applying the appropriate model for each product.

Materials and methods

The model was estimated applying annual time series data for the period 1981–2006 (model fitting) and the observations for the period 2007-2009 were used for the out–of-sample forecast evaluation (validation). The series used forecasting are the quantities of wood-based panels including particleboard, veneer and plywood. In this paper, due to the lack of time series data on MDF and fiberboard consumption quantities, we could not forecast these commodities. The consumption pattern is based on the following model:

$$Co=P+(I-E)+(So-Sc) \qquad (1)$$

Where, *Co*: apparent consumption of the mentioned wood–based panels; *P*: production quantity in the specified period; *I*: import quantity; E: export quantity; *So*: inventory at the first year of period and *Sc*: inventory at the end of period. The later parenthesis is equivalent to changes in the stock. Import quantities of particleboard, plywood and veneer (expressed in m^3 and m^2 respectively) were extracted from Iran Foreign Trade Annual Book. The quantities of particleboard, plywood and veneerproduced in m^3 and m^2 were received from the

Statistical Center of Iran. The Eviews 6 package was used for the forecasting models.

To obtain new empirical evidence on the wood–based panel consumption in Iran in terms of short-term forecasting, we applied time–series models including Double and Holt-Winters Exponential Smoothing, and ARIMA and ARMA methods are which consist of two processes auto-regression and moving average.
Simple exponential smoothing Model (SES).

To forecast the consumption, in the first step the single exponential smoothing procedure is applied. This model assumes that the series is stationary, and without a trend. Simple exponential smoothing is used for short-range forecasting, usually for one month into the future. The relationship which characterizes the single exponential smoothing procedure is: $Y_n = a + \varepsilon_n$ (2)

a: represents the constant, and ε_n stands for the residuals. To forecast the n+1 moment in the moment n, the following series is computed recursively:
$\hat{Y}_{n+1} = \alpha . Y_n + (1-\alpha). \hat{Y}_n$, where n=1,t+K; (3)

The number of available observations is shown by *t*, and *k* stands for the time horizon for which the forecast is made. α is the smoothing factor, which can take values between 0 and 1, a value close to 0 means that the expected values for *n+1* are equal to the prior forecast, and a value close to 1 suggests that the forecasts are equal to the previous observation. The value of α is usually determined by minimizing the sum of squares of the forecast errors:

$$\frac{1}{n}\sum_{i=o}^{n-1}(Y_{n+1} - \hat{Y}_{n+1})^2 = \frac{1}{n}\sum_{i=0}^{n-1} e_{n+1}^2 \quad (4)$$

The relationship no. 3 is applied recursively for each observation from the series, and then the new smoothed value $\hat{Y}_{n+1}$ is computed as the weighted average of the current observation, Y_n and the previous smoothed observation, $\hat{Y}_n$. Thus each smoothed value $\hat{Y}_{n+1}$ is the weighted average of the previous n observations, whose weights decrease exponentially in the past. Therefore, Y_1 takes the weight of $\alpha.(1-\alpha)^{n-1,}$ Y_2 a weight of $\alpha.(1-\alpha)^{n-2,}$ and Y_{n-1} being weighted with α.(1-α). Equation 3 can be written as:

$$\hat{Y}_{n+1} = \alpha . \sum_{i=1}^{n}(1-\alpha)^i . \hat{Y}_{n+1-s} \quad (5)$$

The initial value of $\hat{Y}_1$ is usually equal to Y_1, or with the average of the initial values of the series.
Double Exponential Smoothing Model (MNED)
This method applies two equations recursively for Y_n, as follow:

$S_n = \alpha . Y_n + (1-\alpha). S_{n-1}$ (6)

$D_n = \alpha . S_n + (1-\alpha). D_{n-1}$ (7)

S_n is the single smoothed series and *D_n* is the double smoothed series and a stands for the smoothing parameter, between 0 <α ≤1. This method is appropriate for any series with a linear trend. The forecasts from the double smoothing are computed as follow:

$$\hat{Y}_{n+h} = \left(2 + \frac{\alpha . k}{1-\alpha}\right). S_n - \left(1 + \frac{\alpha . k}{1-\alpha}\right). D_n = \left(2S_n - D_n + \frac{\alpha}{1-\alpha}.(S_n - D_n)\right). k \quad (8)$$

Expression (8) can be interpreted as an equation with intercept $2S_n - D_n$ and slope $\frac{\alpha}{1-\alpha}.(S_n - D_n)$.The initial values for S_1, respectively D_1 are usually set to be equal with Y_1, or with the average of the initial values of the series.

Holt –Winters Simple Exponential Smoothing Model (HWESM).
This method is appropriate for any series with a linear trend without seasonal variations. This technique is using two recursions, the forecasted series being:

$Y_{n+k} = a + b.k$ (9)

a is the intercept, and *b* stands for the slope which are computed recursively:

$a_n = \alpha . Y_n + (1-\alpha).(a_{n-1} + b_{n-1})$ (10)

$b_n = \beta .(a_n - a_{n-1}) + (1-\beta). b_{n-1}$ (11)

α and β are smoothing factors, and can be found within the interval $\alpha, \beta\ \varepsilon[0,1]$, determined by minimizing the sum of squares of the forecast errors. Each prediction is computed based on the previous one. The slope b_n of the series is multiplied by the forecast horizon, *k*, and will be added with the intercept of the series. a_n the estimated values of the series is determined by the relationship 12:

$$\hat{Y}_{n+k} = \hat{a}_n + \hat{b}_n . k \quad (12)$$

The initial value of a_1, is usually Y_1, and b_1 is general set to be equal with 0, or the average of the initial values of the series, or the difference of the initial observations.

Box-Jenkins Forecasting Model

Box-Jenkins method is the most widely used model for stationary time series modeling. To be able to implement Box- Jenkins method, the time series must be stationary (Gujarati, 2004). Stationary means that the mean and autocovariances of the series do not depend on time and therefore are constant. Standard estimation procedures cannot be applied to the model that contains a non stationary respondent variable or explanatory variables (Hamilton, 1994). If the series is not stationary, it should be made stationary by taking the difference of a few times. Box-Jenkins method is based on the principle that each time series is a function of past values and may only be explained by their means. Assumptions cannot be applied based on the econometric models, but there is not any restrictive assumption for Box-Jenkins method. This method is in contrast to the regression models that explains Y_t with a *k* number of explanatory variables of $x_1, x_2, x_3,..., x_k$, The dependent variable Y_t can be explained by its own past or lagged values and stochastic error terms. The most important stage of the Box-Jenkins method is the selection of the appropriate ARMA (p, q) model. Autoregressive moving average models are recommended to be based on stationary series, in the form of equation 13:

$$Y_t = \phi_0 + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + \varepsilon_t - \Theta_1\varepsilon_{t-1} - \Theta_2\varepsilon_{t-2} - \ldots - \Theta_q\varepsilon_{t-q} \quad (13)$$

Y_t is dependent variable at time t, $Y_{t-1}, Y_{t-2,...}, Y_{t-p}$ are response variable at time lags t-1,t-2,....t-p, respectively. $\phi_0, \phi_1, \phi_{2,...}, \phi_p$ are coefficients to be estimated. ε_t is error term at time t and $\varepsilon_{t-1}, \varepsilon_{t-2}, ..., \varepsilon_{t-q}$ are errors in previous time periods that are incorporated in the response Y_t . $\Theta_1, \Theta_{2,...}, \Theta_q$ are coefficients to be estimated. In ARMA model, p and q are the order of the autoregressive and the order of the moving average parts respectively. The ARMA models, as stated can only be used on stationary series. So for non-stationary series, the ARIMA (p,q,d) models will be used, namely the autoregressive integrated moving average models, where d is the order of differentiation for the series to become stationary. If the original series is stationary, d=0 and the ARIMA models reduce to the ARMA models.

ARIMA (p,q,d) has the general form of equation 14:

$$\phi_p(B)(1-B)^d Y_t = \mu + \Theta_q(B)\varepsilon_t \quad \text{or} \quad \phi_p(B)\ W_t = \mu + \Theta_q\ (B)\varepsilon_t \quad (14)$$

μ is constant mean of the process, B is the lag operator and the order of differentiation is equal to: $W_t = \Delta^d Y_t = (1-B)^d\ Y_t$.

In this research, we will use Augmented Dickey fuller test (ADF) to determine the order of differentiation of variables (d) to determine whether the time series are stationary or not. The test was run with an intercept and a trend, against intercept but not a trend. In this test the lag length of variables will be determined by Schwarz Bayesian (SBC) and Akaike (AIC) information criterions. If in the specified lag length, the Mackinnon critical values (MCV) exceeded the Dickey-Fuller absolute critical value, then the hypothesis that the given time series is non-stationary was rejected. On the other hand, if it is less than the absolute Mackinnon critical value, then the time series was found to be non-stationary. If the series was non-stationary, it was transformed by taking the first differentiation over one year. The above procedure was repeated until a stationary series was reached.

The next step in the identification process is to find the initial values for the orders of non-seasonal parameters p and q, which is based on the approach specified by Pesaran and Pesaran, (1997) and is obtained using Schwarz Bayesian (SBC) and Akaike (AIC) information criterions. These criterions are often used in ARIMA model selection and identification. The SBC imposes greater penalty for additional coefficients than the AIC, but generally the model with the lowest AIC and SBC values should be chosen. After the model identification, we must estimate the parameters by Ordinary Least Square method (OLS). In the diagnostic step, the model must be checked for adequacy by considering the properties of the residuals whether the residuals from ARIMA model must take the normal distribution and should be random, At the end and in the last step, we should forecast the fitted model.

The performances of different approaches have been evaluated on the basis of Root Mean Square Error (RMSE). RMSE is the most commonly used measure comparing relative accuracy of forecasting models (Clements and Henry 1998). In forecast evaluation, the use of RMSE is also justified, because it is a familiar and easily interpretable measure: the lower the RMSE, the better the forecast (Malaty *et al.*2007). Following equation is the respective formula used in computing the RMSE.

$$\text{RMSE}=\sqrt{\frac{\sum_{i=1}^{n}(Y_i-\widehat{Y})^2}{n}} \tag{15}$$

y_i and $\hat{y}_i$ are the actual observed values and the predicted values respectively and n is the number of the predicted values. The accuracy of forecast is evaluated based on the estimation of error. Thus the smaller the value of RMSE, the better will be the forecast. Finally, based on the selected models, we will forecast for the period 2010 to 2014.

Results

The results of the unit root test indicated that all of the variables are non-stationary at 5 % level (the null hypothesis of non-stationarity of the time series are not rejected), but after the first differentiation, the data is stationary. Therefore, variables are designated as I(1) or integrated of the order 1. Table 1 summarized the results of Augmented Dickey–Fuller test. In order to calculate test statistics for the OLS regression, we have assumed that the residuals are normally distributed. A useful test for normality is the Jarque-Bera test, under the null hypothesis of normality, the result indicates that they are normally distributed.

Table 1. Augmented Dickey–Fuller tests for the consumption quantities of wood-based panels.

Variable	Intercept		Trend and Intercept		Results
	ADF-Statistics	Critical value*	ADF-Statistics	Critical value*	
Particleboard	-0.10(0)	-2.98	-2.39(0)	-3.60	Non-stationary
	-6.18(0)	-2.99	-4.46(1)	-3.62	Stationary
Plywood	-2.32(0)	-2.98	-2.49(0)	-3.60	Non-stationary
	-4.37(0)	-2.99	-4.61(0)	-3.61	Stationary
Veneer	-2.32(0)	-2.98	-2.47(0)	-3.60	Non-stationary
	-5.78(0)	-2.99	-5.87(0)	-3.61	Stationary

Table 2. Estimated root mean square errors and α and β coefficients of different exponential smoothing methods.

Variable	RMSE				The fitted model
	Double	Holt-Winters	α	β	
Particleboard	42557.02		0.24	-	Holt-Winters
		41297.90	0.71	0.02	
Plywood	20116.37		0.24	-	Holt-Winters
		19154.29	0.78	0.10	
Veneer	23669105		0.26	-	Holt-Winters

The results of estimated Holt-Winters and Double exponential smoothing models for particleboard, plywood and veneer consumption and forecasting quantities for the period of 2007-2010 are summarize in Tables 2, 3, and 4.It is evident from the observation listed in table 2, for smoothing of the data, Holt-Winters exponential smoothing model was the most appreciate model, because for the time series, it revealed the smaller RMSE.Tables 3 and 4 show the results of forecasting wood –based panel consumption quantities using different exponential smoothing models. Both double exponential and Holt-Winters models for the time series estimated that the forecast values are smaller than actual quantities in the period of 2007 to 2009 except in the case of the consumption quantity of plywood that the double exponential smoothing model has estimated the forecast to be greater than its actual quantities. Also, the calculated RMSEs given in the tables 3 and 4 showed that forecasting accuracy of the Holt-Winters exponential smoothing model better than the double exponential smoothing model, especially in the case of time series of plywood consumption. As seen from the tables, the forecast quantities are close to their actual quantities.

Table 3. Forecast results of wood-based panels consumption quantities by applying Double exponential smoothing models.

	RMSE	2007		2008		2009	
		Actual	Forecast	Actual	forecast	Actual	Forecast
Particleboard (m^3)	42557	723417	643637	771631	669482	793362	695327
Plywood (m^3)	20116	31532	42260	29701	43156	32000	44053
Veneer (m^2)	23669105	178561705	93625701	111959000	97722759	115880638	101819816

Table 4. Forecast results of wood-based panels consumption quantities by applying Holt-Winters exponential smoothing models.

	RMSE	2007		2008		2009	
		Actual	Forecast	Actual	forecast	Actual	Forecast
Particleboard (m^3)	41298	7234117	636312	771631	652471	793362	668631
Plywood (m^3)	19154	31532	30174	29701	29154	32000	28134
Veneer (m^2)	23628842	178561705	92597749	111959000	95961870	115880638	99325992

Table 5. AIC values based on different orders of p and p for consumption quantity of particleboard.

		q			
		0	1	2	3
P	0	-	23.91	24.03	24.15
	1	24.33	23.54	23.65	23.75
	2	24.37	23.64	23.77	24.24
	3	24.42	24.48	24.17	23.96

ARIMA model

The time series for the consumption quantities of wood-based panels were stationary after the first differentiation (Table1). Therefore, the ARIMA model is used to forecast where d or the order of differentiation of variables is equal to 1. Also, as was stated earlier in this paper, the approach given by Pesaran and Pesaran, (1997) is used to determine the autoregressive (p) and moving average (q) orders. Thus, first we estimated the models by applying different orders of p and q and using the maximum lag length of three and then the optimal ARIMA model was selected based on the lowest Akaike Information Criteria (AIC). According to minimum value of AIC, for particleboard,plywood and veneer, the ARIMA (1,1,1), ARIMA (3,1,1) and ARIMA (2,1,1) models were chosen respectively(Tables 5,6 and 7).

The results of ARIMA models for the consumption quantities of wood-based panels and forecasted quantity for each panel in the period of 2007 to 2009 are given in the table 8.The results revealed that the forecast for particleboard is close to its actual quantities in the period of 2007 to 2009. For the time series of plywood the forecast value is larger than its actual quantities. Also, for veneer the ARIMA (2,1,1) is estimated the forecast quantity to be smaller and greater than its actual for 2007 and 2008-2009 respectively.

Table 6. AIC values based on different orders of p and p for consumption quantity of plywood.

		q			
		0	1	2	3
P	0	-	22.73	22.13	22.20
	1	22.78	22.09	22.20	22.24
	2	22.85	22.67	22.70	22.31
	3	22.93	22.08	22.23	22.25

Table 7. AIC values based on different orders of p and p for consumption quantity of veneer.

		q			
		0	1	2	3
P	0	-	36.79	36.43	36.59
	1	37.22	36.38	36.53	36.70
	2	37.24	36.34	36.54	36.67
	3	37.37	37.43	37.36	37.22

Table 8. Forecast results of wood-based panels consumption quantities by applying the ARIMA (p,d,q) model.

			2007		2008		2009	
	ARIMA(p,d,q)	RMSE	actual	forecast	actual	forecast	actual	forecast
Particleboard (m^3)	ARIMA (1 ,1 ,1)	51326.3	723417	731766	771631	771145	793362	811891
Plywood (m^3)	ARIMA (3 ,1 ,1)	19436.8	31532	38102	29701	40956	32000	44132
veneer (m^2)	ARIMA (2 ,1 ,1)	201180518	178561705	110427719	111959000	121784747	115880638	133927758

Table 9. Evaluation of the different forecast models for particleboard consumption (m^3).

		2007		2008		2009	
	RMSE	actual	forecast	Actual	Forecast	actual	forecast
Double smoothing	42557	723417	643637	771631	669482	793362	695327
Holt-Winters smoothing	41298	723417	636312	771631	652471	793362	668631
ARIMA(1 ,1 ,1)	51326	723417	731766	771631	771145	793362	811891

Forecast evaluation

The results of evaluation and comparing different forecast models for particleboard, plywood and veneer consumption quantities are given in the tables of 9, 10 and 11 respectively.

The results summarized in table 9 indicate that the Holt-winters exponential smoothing model with the smallest RMSE was selected as the best forecasting model for the consumption quantity of particleboard. The ARIMA (1,1,1,) model estimated the forecast quantities close to the actual quantities, while according to the double and Holt-Winters exponential smoothing models the estimated quantities are smaller than the actual quantities for the period of 2007 to 2009.The results revealed in the table 10 show that for the time series of plywood consumption, the Holt-Winters exponential smoothing model is the appropriate forecasting model, because it has the smallest RMSE. The ARIMA (3,1,1) and Double exponential smoothing models estimated the forecast quantities greater than and the Holt-Winters smaller than the actual quantities. The results showed that the best forecasting model for veneer consumption quantity is different (table 11). This means that, the ARIMA (2, 1, 1,) model compared to the exponential models has the smallest RMSE and therefore, it was selected as best forecasting model. The double and Holt-winters exponential smoothing models estimated the forecast to be smaller than the actual quantities in the period of 2007 to 2009, but the ARIMA (2, 1, 1) estimated the forecast to be smaller and greater than its actual quantity for 2007 and 2008-2009 respectively. The forecasts in the period of out of sample (from 2010 to 2014) were obtained using the selected best models (with the smallest RMSE) for each panel. The results are given in the Table 12.As seen from the table 12, particleboard, veneer and plywood consumption levels are projected to increase and the decrease from 2010 to 2014 respectively. The most significant forecasted increase in consumption will be for veneer and particleboard. The average annual growth rate will be 5.1% for veneer and 1.17 % for particleboard. For plywood the average annual reduction rate will be 3%. It is projected that particleboard will enjoy a rising trend, but the forecasted consumption in 2010 (684790 m^3) is less than its actual consumption quantities in 2009 (793362 m^3). Consumption quantity of particleboard and veneer from 684790 m^3 and115880638 m^2 in the year 2009 will increase to 749428 m^3 and 206424496 m^2 in the year 2014 respectively. For plywood, the initial quantity of 32000 m^3 in year 2009 will decrease to 23035 m^3 in the year 2014.

Table 10. Evaluation of the different forecast models for plywood consumption (m^3).

	RMSE	2007		2008		2009	
		actual	forecast	actual	Forecast	actual	forecast
Double smoothing	201116	31352	42260	29701	43156	32000	44053
Holt-Winters smoothing	19154	31532	30174	29701	29154	32000	28134
ARIMA (3 ,1 ,1)	19437	31532	38102	29701	40956	32000	44133

Table 11. Evaluation of the different forecast models for veneer consumption (m^2).

	RMSE	2007		2008		2009	
		actual	forecast	actual	Forecast	actual	Forecast
Double smoothing	236691005	178561705	93625701	111959000	97722759	115880638	101819816
Holt-Winters smoothing	23628842	178561705	92597749	111959000	95961870	115880638	99325992
ARIMA (2 ,1 ,1)	20180518	178561705	110427179	111959000	121784747	115880638	133927758

Discussion

The double and Holt-Winters exponential smoothing and ARIMA forecasting models were used for out-of-sample to forecast the consumption quantities of wood-based panels including particleboard, plywood and veneer. The accuracy of the forecast was measured by the RMSE criteria. The model with the smallest RMSE was selected as the best forecasting model. The results showed that, the best models for each panel are not the same. The appropriate model for the consumption quantities of particleboard, plywood is Holt-winters exponential smoothing model, and for veneer, the ARIMA forecasting model is better than exponential smoothing models. Compared with Double exponential smoothing model, Holt-Winters is the best model for the time series, because it has the smaller RMSE for the period of 2007-2009. Two exponential smoothing models estimated the forecast to be smaller than actual quantities in the period of 2007 to 2009 except in the case of consumption quantity of plywood and Double exponential smoothing model. Forecasting accuracy of the Holt-Winters exponential smoothing model is better than the double exponential smoothing model, especially in the case of time series of plywood consumption. The ARIMA models could not forecast the time series close to the actual quantities except in the case of consumption quantity of particleboard in the period of 2007-2009. The forecasts up to the year of 2014 were obtained with the selected best models. Considering the priority ranking of the different forecasting model based on the RMSE, it was seen that the share of Holt-Winters model is more than two other models in the forecasting horizon. This issue will be more in relation to forecast plywood consumption quantities. So, this model forecasts the quantities for the period of 2007-2009 closer to its quantities. Also, the results based on the selected models indicated that consumption of particleboard, veneer and plywood will increase and decrease in the future respectively.

Table 12. Forecasted quantities for wood-based panels consumption from 2010 to 2014.

	The best model	2010	2011	2012	2013	2014
Particleboard (m^3)	Holt-Winters exponential	684790	700950	717109	733269	749428
Plywood (m^3)	Double exponential	27114	26095	25075	24055	23035
Veneer (m^2)	ARIMA(2 ,1 ,1)	146856216	160570118	175069466	190354258	206424496

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