Determination of the Most Appropriate Statistical Method for Estimating the Production Values of Medium Density Fiberboard

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This study determines an optimum method to predict Turkish Medium Density Fiberboard (MDF) production values using ARIMA (Box-Jenkins), regression, and Artificial Neural Network (ANN). The prediction performance of these methods is also compared. A total of 14 independent variables, likely to influence MDF production, were determined, and the production values of the next 9 years (2017-2025) were predicted on the basis of these variables. The test results indicate that the best Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Deviation (MAD) prediction performance belongs to the prediction performed with ANN.

Keywords: MDF; ARIMA; Regression; ANN; Prediction

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INTRODUCTION

Modelling and other prediction methods are widely used in part due to recent developments in technology. Such increased variety of prediction methods has enabled a more thorough evaluation of analyses, thus paving the way for obtaining better results. ARIMA (Box-Jenkins), regression, and Artificial Neural Networks (ANN) are some of the commonly applied prediction methods.

In the literature, these three methods have been widely applied for prediction purposes of fields including production, marketing, finance, stock exchange, agriculture, forestry, food, energy, banking, automotive, and aviation. Many studies have used artificial neural networks (Arizmendi *et al.* 1993; Fletcher and Goss 1993; Grudnitski and Osburn 1993; Balestrino *et al.* 1994; Aiken *et al.* 1995; Kaastra and Boyd 1995; Kiartzis *et al.* 1995; Gately 1996; Zhang *et al.* 1998; Kolehmainen *et al.* 2001; Pijanowski *et al.* 2002; Huang 2004; Niska *et al.* 2004; Elminir *et al.* 2005; Huang 2007; Pindoriya *et al.* 2008; Hadavandi *et al.* 2010; Blanco *et al.* 2012; Miljanović *et al.* 2017; Bardak 2018; Sozen *et al.* 2018; Nguyen *et al.* 2018) and regression analysis (Katipamula *et al.* 1998; Ghiaus 2006; Wang and Xia 2009; Catalina *et al.* 2013; Braun *et al.* 2014; Amiri *et al.* 2015; Fumo and Rafe Biswas 2015; Sebri 2016; Walter and Sohn 2016; Libaoa *et al.* 2017).

The ARIMA method has been used in a wide variety of fields as much as the other two methods because of its ease of application (Hamed *et al.* 1995; Yayar and Karkacier 2003; Altin 2007; Katsoulis and Pnevmatikos 2009; Cenan and Gurcan 2011; Jakaša *et al.* 2011; Shukla and Jharkharia 2011; Celik 2013; Ayodele *et al.* 2014; Tavakkoli *et al.* 2015; Zhang *et al.* 2017). Also, the following papers used at least two of these methods for prediction: Goh (1998); Prybutok *et al.* (2000); Alon *et al.* (2001); Ho *et al.* (2002); Somvanshi *et al*. (2006); Zou *et al.* (2007); Koutroumanidis (2009); Sahoo *et al.* (2009);

Zhang *et al.* (2010); Adebiyi *et al.* (2014); Ozoh *et al.* (2014); Voronin and Partanen (2014); Yi *et al.* (2014); Kaytez *et al.* (2015); Ertugrul and Bekin (2016); and Hanief *et al.* (2017).

In this study, the prediction performances of the mentioned methods were compared after prediction of the Medium Density Fiberboard (MDF) production quantities of Turkey.

EXPERIMENTAL

Data

The dependent variable, used in ARIMA, Regression, and ANN models, is the variable that is the subject of the prediction, and it comprises the values related to MDF production in Turkey (Fig. 1). The independent variables to be used in the regression analysis and ANN prediction models were inquired by a team of experts, and 14 variables that were likely to affect MDF production were determined accordingly. These independent variables are: MDF export (m^3), MDF import (m^3), Furniture export ($), Furniture import($), Consumer Price Index (CPI), Producer Price Index (PPI), Gross National Product Per Capita (GDP), Exchange Rate, Economic Growth (%), Population, Log (m^3), Industrial Wood (m^3), Building Number, and Building Area (m^2). While all of these variables were used in the regression estimation, the number of variables was reduced to ten in order to provide more effective training of the network in ANN estimation. A data set involving a 26-year period (1991-2016) was used for the variables assigned for each product and model. SPSS for regression analysis, MATLAB for artificial neural networks, and MINITAB for ARIMA were used to build the most suitable models for prediction.

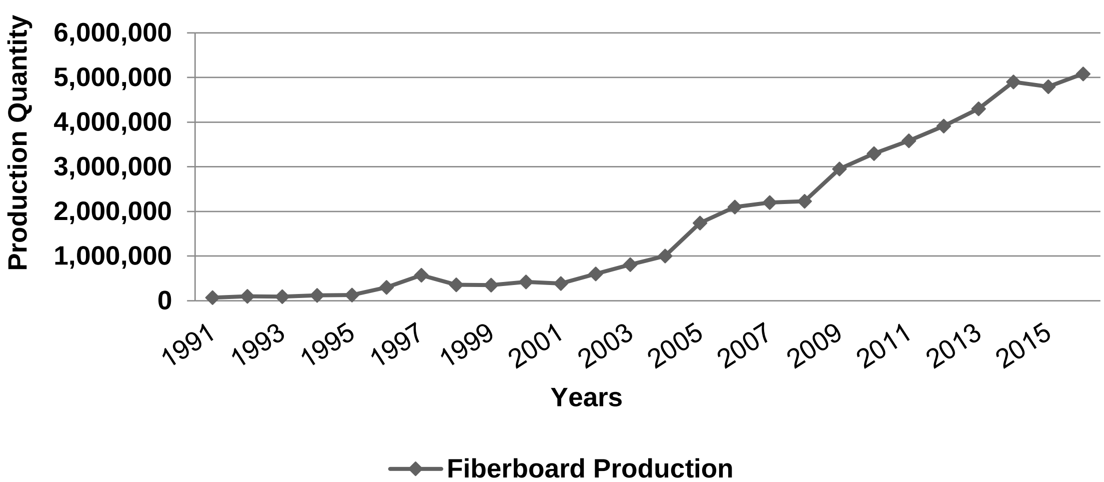


Fig. 1. The production amounts of MDF in Turkey (m^3) (FAO, 2017)

The future values of the independent variables to be used in the model should also be estimated as a means to make future predictions with regression and ANN models. The estimations for these values for the next nine years (until 2025) were found based on time series, and predictions were made on the basis of these estimated values. Initially, stationarity tests on times series were performed in prediction with ARIMA, and after ensuring stationarity, the most suitable model for prediction was determined. The prediction performances were compared after the calculation of Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Deviation (MAD) values, which are widely used in the literature.

ARIMA Method

In cases where time series were stationary, *i.e.*, the average, variance, and covariance of the process varied depending on time, ARMA (*p*,*q*) or special versions of this model (AR(*p*) and MA (*q*)) were used. However, time-dependent variations in the average and variance of time series could occur in reality. Such situations are called non-stationary states. Such time series can be used after being transformed into stationary states. Stationarizing the time series is possible through evaluating the first and second differences series. In this case, the model is referred to as ARIMA (*p,d,q*) (Hamzacebi and Kutay 2004; Topcuoglu *et al.* 2005; Ozdemir and Bahadır 2010).

Introduced by Box and Jenkins, the ARIMA model has been one of the most popular approaches for time series forecasting analysis. The ARIMA model can be used when the time series is stationary and there is no missing data within the time series (Box and Jenkins 1970; Koutroumanidis *et al.* 2009).

Generally, a nonseasonal time series can be modeled as a combination of past values and errors, which can be denoted as ARIMA (*p,d,q*) and expressed as a Eq. 1,

$$Y_t = \phi_0 + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \ldots - \theta_q \varepsilon_{t-q} \quad (1)$$

where Y_t is the actual value, ε_t is the random error at time *t*, $\phi_i (i = 1,2,3 \ldots p)$ and $\theta_j (j = 1,2,3 \ldots q)$ are model parameters, *p* and *q* integers that are often referred to as orders of autoregressive and moving average, respectively.

Regression Method

Regression analysis is a statistical procedure that uses the least squares approach in estimating the relationship between independent variables and the dependent variable in developing the estimation model (Cabuk *et al.* 2011; Cabuk *et al.* 2014).

If the regression analysis involves one dependent and one independent variable, then it is a simple linear regression. A simple linear regression model is solved with the following equation,

$$Y = \beta_0 + \beta_1 X_1 + \varepsilon \quad (2)$$

where β_0 and β_1 represent the regression coefficients of the model, ε represents the error term, *Y* represents dependent, and *X* represents independent variables.

If the regression analysis involves one dependent and two or more independent variables, then it is multiple linear regression. Multiple linear regression models are solved with the following equation,

$$Y = \beta_0 + \beta_1 X_1 + \beta_1 X_1 + \ldots + \beta_n X_n + \varepsilon_i \quad (3)$$

where Y is the dependent variable, $X_1, X_2, \ldots X_n$ are the independent variables, *n* the number of variables, $\beta_1, \beta_{1\ldots}\ \beta_n$ are the regression coefficients, and ε is an error to account for the discrepancy between predicted data and the observed data.

Artificial Neural Network

Artificial neural networks (ANN) are based on the functioning principle of the human brain, and they have emerged as a result of integrating learning processes into computer systems. This model has found a variety of applications ranging from finance and marketing to several engineering sectors. This method has been successful in producing reliable results and effective solutions of complex non-linear problems. For these reasons, this model is commonly used. In this context, ANN are capable of revealing unknown and indiscernible relationships and enabling their effective and optimum use (Kurt *et al*. 2017).

Artificial neural networks have been proposed as an adaptive evaluation method that can operate with missing data, derive decisions even under uncertain conditions, and tolerate errors (Oztemel 2012). A typical ANN cell is comprised of input data, weights, addition function, activation function, and output (Fig. 2). The data from the outer environment is taken into the ANN through the first layer (input layer). This layer constitutes the parameters that affect the problem. The parameters in the input layer are multiplied by weight coefficients that specify their effect in the neuron, then, the net input received by the neuron is calculated with addition function. Afterwards, this calculated net input value is evaluated by an activation function to determine the corresponding output to be produced. The output value specified by the activation function is then sent to another ANN neuron as input (Kurt *et al*. 2017).

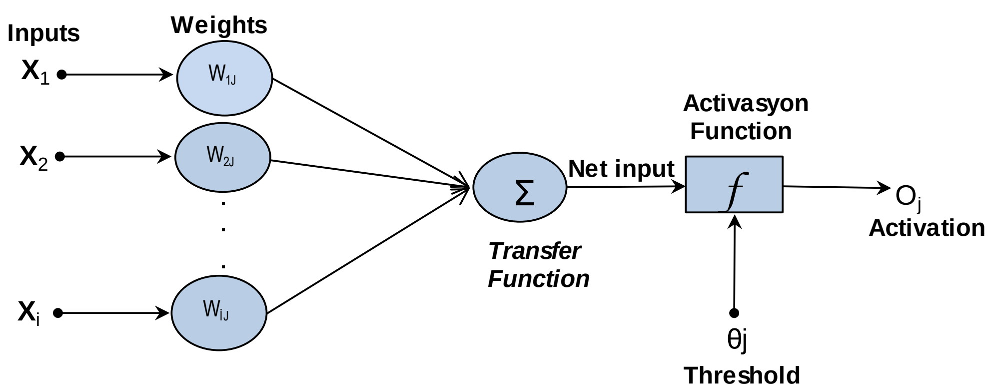


Fig. 2. A typical artificial neural network cell

The function of the network is described as follows,

$$Y_J = f\left(\sum_i w_{ij} x_{ij}\right) \tag{4}$$

where Y_j is the output of node j, f is the transfer function, W_{ij} connection weight between node j and node i in the lower layer, X_{ij} is the input signal from the node i in the lower layer node j.

RESULTS AND DISCUSSION

Data Analysis, Model Selection, and Forecast

Prior to the prediction process, the data subject to prediction were brought in compliance with each prediction method, and the model was built accordingly.

ARIMA results

The series' stationarity was checked with "Dickey-Fuller Tests" prior to the prediction process with ARIMA method. Augmented Dickey-Fuller test results are given in Table 1. As indicated by the results, the presence of a unit root is evident as the Dickey-Fuller test statistics of MDF production values exceeded the critical value of 1.836115. Also, the series is not stationary, as the significance (p) level 0.9995>0.05 (Stationarity: If p<0.05, the series is stationary).

Table 1. Augmented Dickey-Fuller Test Results

Actual Values			
		t-Statistic	**p-values**
Augmented Dickey-Fuller test statistic		1.836115	0.9995
Test critical values	**%1**	-3.724070	
	%5	-2.986225	
	%10	-2.632604	
Second Differences Series			
		t-Statistic	**p-values**
Augmented Dickey-Fuller test statistic		-4.931274	0.0008
Test critical values	**%1**	-3.788030	
	%5	-3.012363	
	%10	-2.646119	

As also indicated by the declining trend analysis graph, the series is under the effect of seasonal factor (Fig. 3). Dickey-Fuller test results, which were obtained after the evaluation of the second differences of MDF production values, show that the series is completely stationarized and the effect of the seasonal factor is eliminated (Dickey-Fuller test statistics is lower than the critical value of -4.931274, with a significance level of 0.0008<0.05).

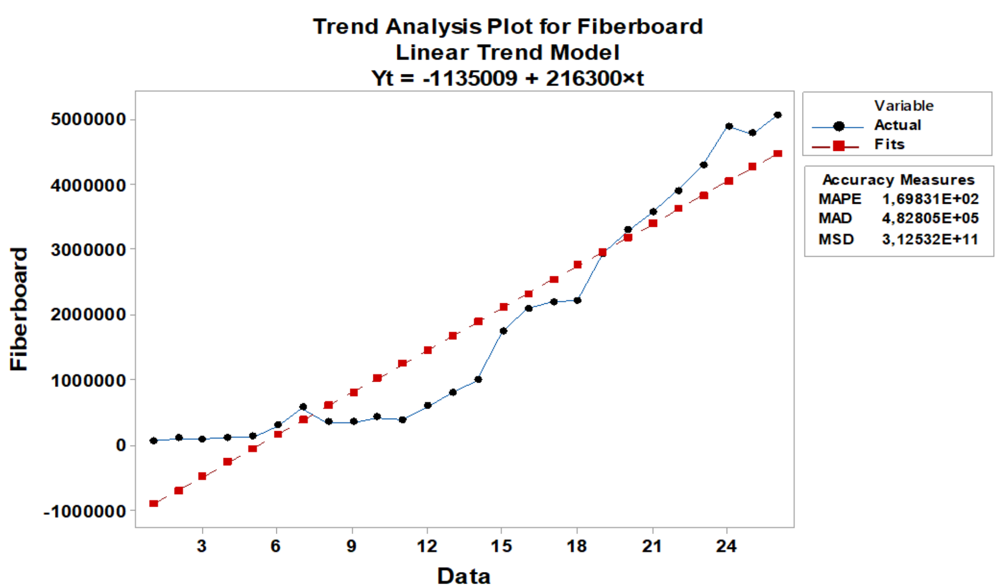


Fig. 3a. Trend analysis graphs for MDF production values

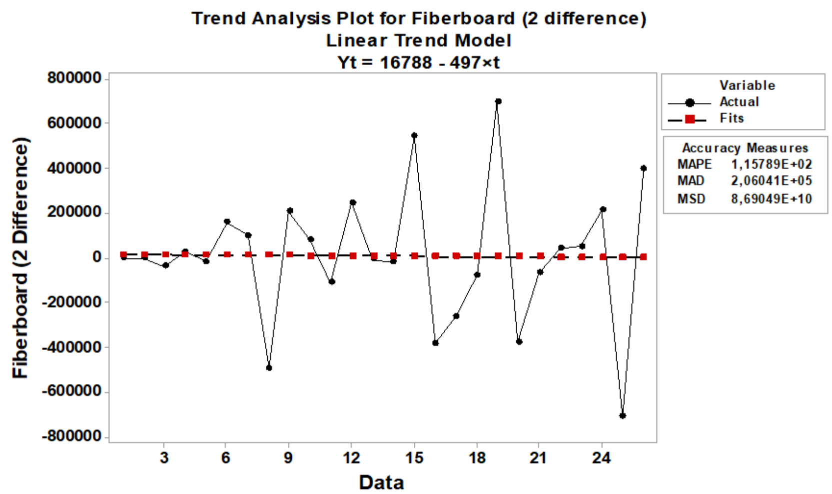
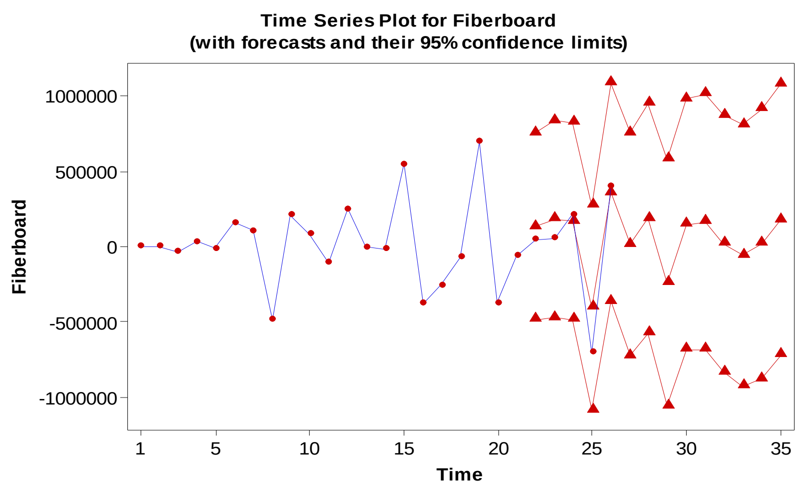


Fig. 3b. Trend analysis graphs for MDF production values



Period	Forecast (2. Differences)	Lower	Upper	Forecast (Actual)
2012	132889	-490982	756760	4002889
2013	182995	-473460	839449	4603773
2014	169053	-487518	825624	5373710
2015	-409534	-1089798	270730	5734113
2016	359486	-366438	1085410	6454002
2017	12522	-729150	754193	7186413
2018	185245	-581261	951750	8104069
2019	-242429	-1065585	580727	8779296
2020	147196	-688138	982529	9601719
2021	163472	-688316	1015260	10587614
2022	18696	-837304	874695	11592205
2023	-60715	-933306	811875	12536081
2024	16486	-883064	916036	13496443
2025	178724	-724567	1082015	14635529

Fig. 4. ARIMA prediction results for 2012-2025 (m^3)

After the series was stationarized, different models were applied and as a result of the trials, the ARIMA (5,2,2) model was determined to be the most suitable model for prediction. Upon determination of the best model and statistical validation, the prediction stage was initiated. The prediction results for 2012-2025 period are given in Fig. 4.

Regression results

Dependent and independent variables were entered into the system to determine the most suitable model for prediction, and the best regression model for MDF production was sought accordingly. The regression results, related to the built models are given in Table 2. As shown in the summarized table, all of the regression models built with one variable (Furniture Export), two variables (Furniture Export, Building Areas) and three variables (Furniture Export, Building Areas, CPI) are valid and significant, *i.e.*, they are applicable to the prediction process. In all regression models, coefficients of determination (R^2) were found to be significantly high, and the validity of the models were also verified with F statistical values and α=0.05 significance level between dependent and independent variables. In this research, the prediction process was performed with the regression model using three independent variables (Furniture Export, Building Areas, CPI), as the R^2 =0.989 value represented by three independent variables is a significantly high coefficient of determination. This value indicates that the chosen independent variables predict the MDF production with 98% reliability, thus verifying the suitability of the built linear model.

Table 2. Model Summary and Coefficients

Model Summary						
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Sig. F Change	Durbin Watson
1	.990[a]	.979	.978	2.57476E5	.000	2.073
2	.992[b]	.983	.982	2.37102E5	.031	
3	.995[c]	.989	.988	1.92685E5	.002	
Predictors: [a](Constant), Furniture Export; [b] (Constant), Furniture Export, Building Areas; [c](Constant), Furniture Export, Building Areas, CPI						

Coefficients						
Model	Predictors	Unstandardized Coefficients		Standardized Coefficients	t	Significance
		B	Std. Error	Beta		
1	Constant	74282.789	71680.767		1.036	.310
	Furniture Export	.002	.000	.990	33.626	.000
2	Constant	-230863.56	148053.441		-1.559	.133
	Furniture Export	.002	.000	.855	13.302	.000
	Building Areas	.005	.002	.148	2.303	.031
3	Constant	-499120.49	141728.757		-3.522	.002
	Furniture Export	.001	.000	.409	3.022	.006
	Building Areas	.008	.002	.228	4.011	.001
	CPI	82.955	23.163	.384	3.581	.002

Accordingly, the most suitable regression model for prediction of MDF production can be given with the following expression:

$$Y_{fproduction} = -499120.492 + 0.001_{Furnexport} + 0.008_{Buildareas} + 82.955_{CPI} \quad \text{(model 3)}$$

The t and F statistical test results of the hypotheses that apply for the independent variables and the overall model are given in Table 3.

Table 3. T and F test Results of Independent Variables

Variables	$T_{calculation}$	T_{table}	Result	H_0	Significance
Furniture Export	3.022	2.074	$T_{calculation} > T_{table}$	reject	Significant
Building Areas	4.011	2.074	$T_{calculation} > T_{table}$	reject	Significant
CPI	3.381	2.074	$T_{calculation} > T_{table}$	reject	Significant
Model	**$F_{calculation}$**	**F_{table}**	**Result**	**H_0**	**Significance**
Model 3	679.939	3.05	$F_{calculation} > F_{table}$	reject	Significant

Prior to the prediction of MDF production values with the Regression model, the projection of the independent variables for the next nine years were found with ANN with relation to the time series (years) and the projection values were calculated on the basis of these obtained values. The models which were used to predict the independent variables were significant at a level of $p<0.05$ (Table 4).

Table 4. Regression Equations Used for the Prediction of the Independent Variables

MDF Export	*Industrial Wood*
$Y_{fexport}$= -62019640.348+31083.517.*x*	Y_{Inwood}= -934200.017+472.586.*x*
MDF Import	*Log*
$Y_{fimport}$= -51391381.786+25799.940.*x*	Y_{Log}= -516147.911+266.988.*x*
CPI	*Population*
Y_{CPI}= -2069704.563+1037.561.*x*	$Y_{Population}$ = -1643089.749+854.574.*x*
PPI	*Building Number*
Y_{PPI}= -22861.948+11.462.*x*	$Y_{Buildnumber}$ =760222.936-324.275.*x*
GDP	*Foreign Exchange*
Y_{GDP}= -73401.630+36.872.*x*	$Y_{Fexchange}$= -70.333+0.036.*x*
Permit Area	*Furniture Export*
$Y_{Buildareas}$ = -10598040543.3+5342855.76.*x*	$Y_{Furnexport}$=198097192665.99+99272459.3.*x*
Economic Growth	*Furniture Import*
$Y_{Egrowth}$= -11.989+0.008.*x*	$Y_{Furnimport}$= -70609098615.6+35426127.5.*x*

Table 5. Regression Prediction Results for 2012-2025 (m^3)

Years	Regression Forecasts	Years	Regression Forecasts
2012	4084214.843	2019	5433014.197
2013	4643969.223	2020	5661100.375
2014	5333765.582	2021	5889186.553
2015	5058546.385	2022	6117272.731
2016	5300825.889	2023	6345358.91
2017	4976841.841	2024	6573445.088
2018	5204928.019	2025	6801531.266

After the determination of independent variables with the best suitable model, the MDF production values for years 2016-2025 were predicted (Table 5).

Artificial neural network results

Ten variables, likely to be effective on the MDF production, constituted the input variables of the ANN model. The feedforward backpropagation ANN was used by the use of input and output neurons. The number of hidden layers was set as 1, and the number of neurons in the hidden layer was set as 8 after a number of trials between 1 and 10. Sigmoid activation function, commonly used for ANN, was used as the activation function. The number of neurons in the output layer was specified as 1, as this value can be equal to the number of dependent variables for cause-and-effect-relation based predictions. The structure of the ANN model, built for MDF production, is given in Fig. 5.

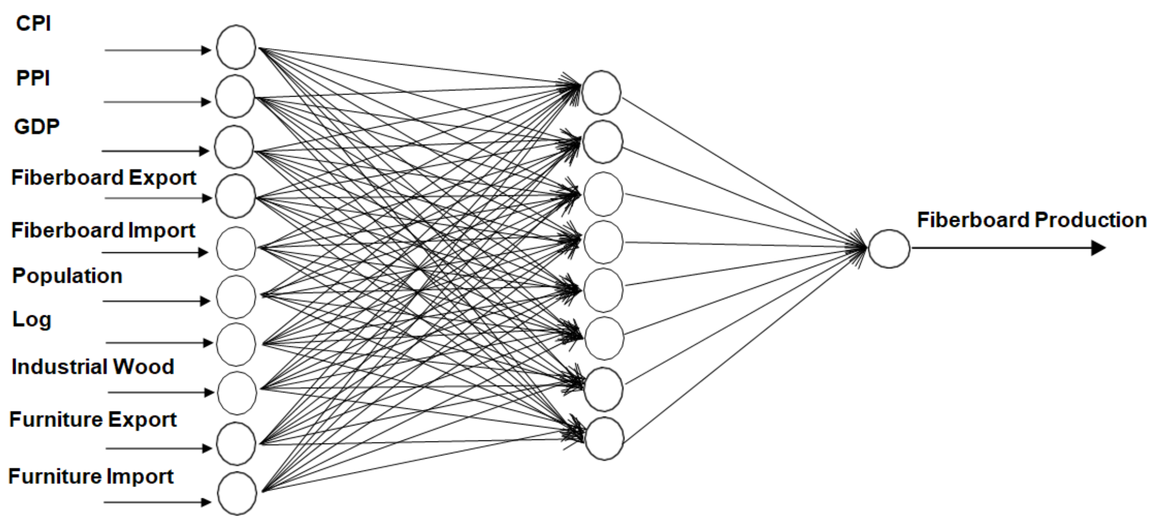


Fig. 5. The structure of the ANN model

Following the determination of the number of input and output neurons for ANN model, independent and dependent variables were subjected to the logarithmic transformation, for ensuring their usability in the system. Twenty-six data sets for each year within the period from 1991-2016 were evaluated, and 70% of these data were used for training, 15% were used for validation, and 15% were used for testing purposes.

For obtaining the optimum results from the model to be built, the number of epochs was kept constant to find the most suitable values for momentum coefficients and learning rate. Trials between 0.1 and 0.9 were made to find the optimum learning rate and momentum coefficients and the most suitable learning rate and momentum coefficients were found as 0.3 and 0.5, respectively.

After the training of the network was completed, testing and validation procedures were performed. For the test of the model, data between 2012 and 2016, which the system has never seen before, were used. Figure 6 shows the change in the error values for the training, validation, and testing sets at each iteration for the MDF production, as well as training status of the network, and regression values. As shown in the figure, regression values are reliable at a rate of about 99% at training, validation, and testing stages.

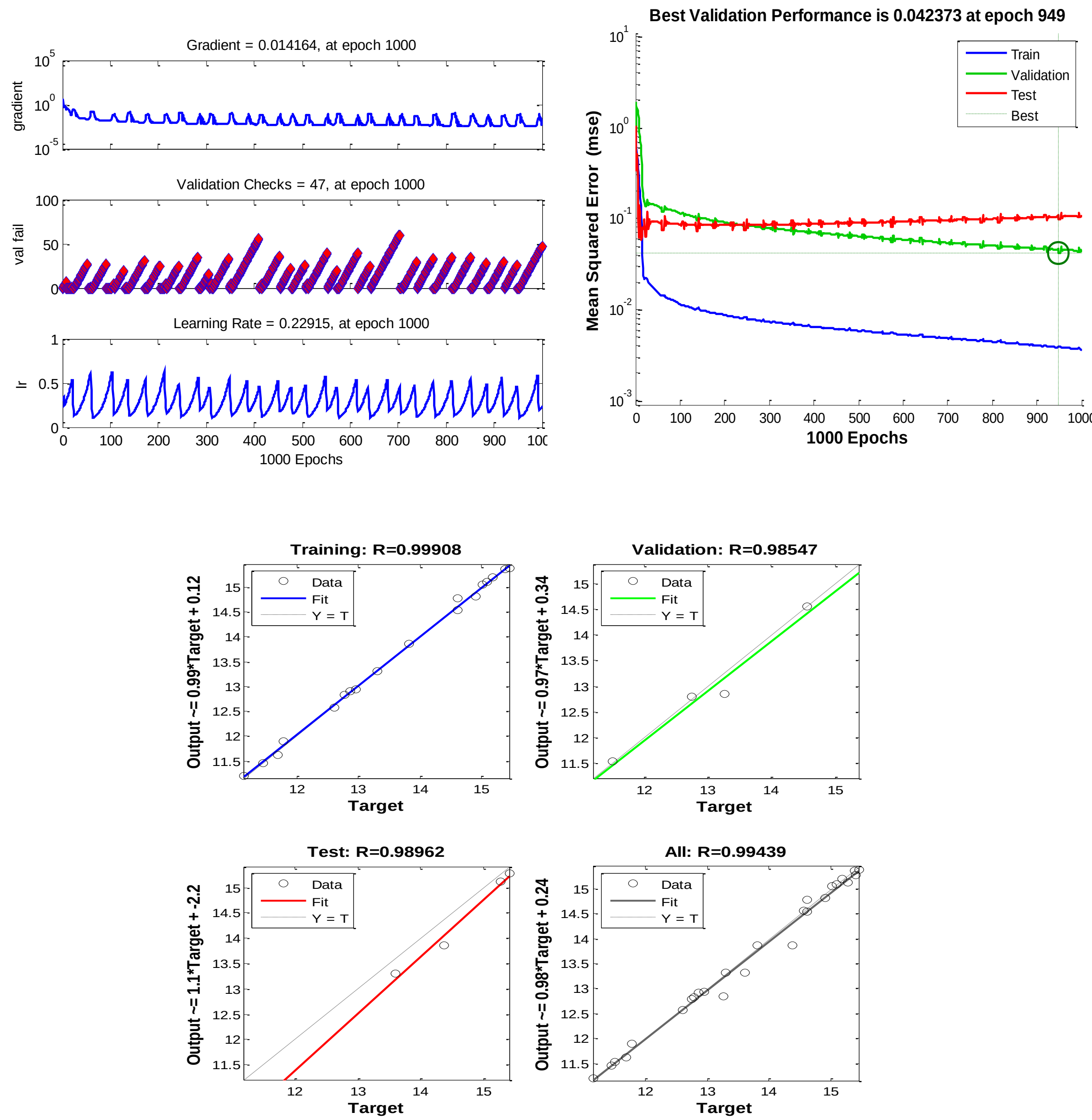


Fig. 6. Training validation and test results for ANN

After determination of the most suitable coefficients and accomplishing the training of the network, the prediction stage was initialized. Independent variables were predicted and the data were entered into the ANN model to predict the 2016-2025 MDF production values (Table 6).

Table 6. ANN Prediction Results for 2012-2025 (m^3)

Years	ANN Forecasts	Years	ANN Forecasts
2012	4016513.581	2019	5311081.603
2013	3958080.082	2020	5464196.603
2014	4762045.691	2021	5501016.742
2015	4942232.901	2022	5664337.676
2016	4825152.927	2023	5773045.050
2017	5163605.484	2024	5990308.202
2018	5235069.407	2025	6087112.709

Comparison of the Prediction Performance

MAD, MAPE, and MSE performance results for MDF production values show that the best performance results were achieved with ANN prediction, which was closely followed by the performance results of the regression prediction results (Table 7).

Table 7. MAD, MAPE, and MSE Performance Results

Years	MDF (actual values)	ARIMA (Projected)	MAD	MAPE	MSE
2012	3915000	4002889	87889	2.24493	7.72E+09
2013	4300000	4603773	303773	7.064488	9.23E+10
2014	4900000	5373710	473710	9.667551	2.24E+11
2015	4792000	5734113	942113	19.66012	8.88E+11
2016	5084000	6454002	1370002	26.94732	1.88E+12
Average			635497.4	13.11688	6.18E+11
Years	**MDF (actual values)**	**REGRESSION (Projected)**	**MAD**	**MAPE**	**MSE**
2012	3915000	4084215	169214.8	4.322218	2.86E+10
2013	4300000	4643969	343969.2	7.999284	1.18E+11
2014	4900000	5333766	433765.6	8.852359	1.88E+11
2015	4792000	5058546	266546.4	5.56232	7.1E+10
2016	5084000	5300826	216825.9	4.264868	4.7E+10
Average			286064.4	6.20021	9.06E+10
Years	**MDF (actual values)**	**ANN (Projected)**	**MAD**	**MAPE**	**MSE**
2012	3915000	4016514	101513.6	2.592939	1.031E+10
2013	4300000	3958081	341919.9	7.951626	1.169E+11
2014	4900000	4762046	137954.3	2.815394	1.903E+10
2015	4792000	4942233	150232.9	3.135077	2.257E+10
2016	5084000	4825153	258847.1	5.091406	6.7E+10
Average			198094	4.31729	4.7E+10

As indicated by the table, the highest increase in the future MDF production is predicted by ARIMA method, whereas the lowest increase was predicted by ANN. The real and predicted values for all three methods were significantly close for the 2012-2015 period.

CONCLUSIONS

1. A comparative investigation of the prediction performances of ANN, ARIMA, and regression models was performed in the present research. MDF production values until year 2025 were predicted using the 25-year data set for the 1991-2016 period. MSE, MAPE, and MAD performance results for the test data show that the best performance results were achieved by use of the ANN model. The performance of ANN was followed by the Regression and ARIMA models.
2. Considering that some rows in the ANN data set are kept separate for validation and test operations and do not participate in the training, it is seen that they give more accurate results with less data than other estimation methods. Furthermore, the method provided a significant advantage for forecasting as it did not require any preconditions and had a flexible modeling structure.
3. The use of ANN is favored among others especially when the independent values are known. However, the ANN predictions performed with unknown independent variables in the presence of seasonality have been reported to yield low prediction performances. In this regard, independent variables should be chosen to represent the dependent variables in the best possible way, for obtaining the highest prediction performance and precision in future predictions.
4. The regression model, on the other hand, exhibited a close prediction performance to that of ANN, and yielded reasonable results, and thus proved to be an effective method for future predictions. ARIMA method can be an alternative to others, in terms of ease of application time.
5. This study reveals the advantages and disadvantages of three methods (ANN, Regression, and ARIMA) used for future predictions. In this respect, before embarking on a prediction process, a decision maker should take into consideration that the model being built should represent the main case in the best possible way without compromising on time and cost factors. The most suitable model for representation of the existing structure can be achieved, and the best prediction results can be obtained accordingly.
6. The results also will be useful for showing the opportunities and bottlenecks in the forest products sector as well as for the employees and the entrepreneurs in terms of planning, strategy, investment, marketing, raw materials, capacity and demand. The models installed in the project will be updated and used in the production projection calculations of the product mentioned in the following years.

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