The Pharma Innovation Journal 2023; 12(2): 3376-3384

www.ThePharmaJournal.com

The Pharma Innovation

ISSN (E): 2277-7695
ISSN (P): 2349-8242
NAAS Rating: 5.23
TPI 2023; 12(2): 3376-3384

www.thepharmajournal.com
Received: 11-09-2022
Accepted: 07-11-2022

Development of hybrid time series models for forecasting autumn rice production in Assam

Borsha Neog, Bipin Gogoi, Smrita Barua, Supahi Mahanta and Kushal Sarmah

Borsha Neog
Assistant Professor, Department of Agriculture Statistics, Assam Agricultural University, Jorhat, Assam, India

Bipin Gogoi
Professor, Department of Statistics, Dibrugarh University, Dibrugarh, Assam, India

Smrita Barua
Assistant Professor, Department of Agriculture Statistics, Assam Agricultural University, Jorhat, Assam, India

Supahi Mahanta
Assistant Professor, Department of Agriculture Statistics, Assam Agricultural University, Jorhat, Assam, India

Kushal Sarmah
Assistant Professor, Department of Agriculture Meteorology, Assam Agricultural University, Jorhat, Assam, India

Corresponding Author:
Borsha Neog
Assistant Professor, Department of Agriculture Statistics, Assam Agricultural University, Jorhat, Assam, India

Abstract
The study of forecasting in time series analysis has become a powerful tool in different applications in the agricultural field. The major goal of time series models comprises forecasting into the short- and long-term period, smoothening of irregular series and causal modelling of variables moving with time. Yearly data on production of Autumn rice have been used for forecasting from the year 1951 to 2018. The data from 1951-1998 were used for model building and 1999 - 2018 were used for checking the forecasting performance of the model. In this study ARIMA, ANN, SVM time series models and hybrid of both ARIMA-ANN, ARIMA-SVM were used to analyse the past behaviour of production of Autumn rice in order to make inferences about its future behaviour. ARIMA (2,1,2) model was selected as suitable model for Autumn rice and MAE for hybrid ARIMA (2, 1, 2)-ANN was found to be 34615.361 as compare to 39637.856 of ARIMA (2, 1, 2), MAE for hybrid ARIMA (2, 1, 2)-SVM was found to be 29464.313 as compare to 39637.856 of ARIMA (2, 1, 2) and 34615.361 of hybrid ARIMA-ANN. Hence, the performances of hybrid ARIMA-ANN and ARIMA-SVM were found to be better than that of ARIMA for both under training as well as testing data sets. And from the results, we found hybrid approach gives better results for forecasting of crop production.

Keywords: Autumn rice, ARIMA-ANN, ARIMA-SVM

1. Introduction

Statistical forecasting model is used to develop accurate forecasting by using past data through identification of trends and patterns of the data. In other words, statistical forecasting is the likelihood estimation of an event to take place in future based on available data. Proper forecast is very much essential in an economic system as it would be easier to formulate the policy makers regarding allocation, price fixation, procurement, irrigation, marketing and storage. Statistical computing, modelling and forecasting data are key instruments for addressing these problems. The study of forecasting in time series analysis has become a powerful tool in different applications in the agricultural field. The major goal of time series models comprises forecasting into the short- and long-term period, smoothening of irregular series and causal modelling of variables moving with time. Dependency through time is the basis for extrapolation into the future. Another goal of time series analysis is detecting changes in structure in the series- possibly as a result of an intervention such as economic policy, pollution incident or medical treatment.

One of the major and widely used time series models is the autoregressive integrated moving average (ARIMA) model. Due to its statistical properties, ARIMA model is more popular in time series data. It is also known as Box-Jenkins methodology (Box and Jenkins 1970) in the model building process. But this model has a limitation as it assumes linearity as observed in the time series. Therefore, no nonlinear patterns can be detected by the ARIMA model. However, linearity is a useful assumption and powerful tool in many different areas. It became clearer in the early 1980s that the approximation of the linear models for complex data is not always satisfactory. The last two decades plenty of literature have emerged that deal with testing and modelling of non-linear time series data. The recent resurgence of research activities in Artificial Neural Network (ANN) as well as its successful applications suggest that it can be an important method for time series forecasting. As compared to the traditional methods, ANN is a data driven, self-adaptive, nonlinear, nonparametric method in which there are a few a priori assumptions. The major advantage of neural network (NN) is flexibility of nonlinear modelling and no need to specify a particular model form.

Neural networks and traditional time series models have been compared in several studies.

Kohzadi *et al*. revealed that the neural networks are superior to ARIMA methods for forecasting of commodity price. Hervai *et al*. examined linear and ANN models for forecasting seasonally unadjusted monthly data on European industrial production series and conclude that linear models generally produce more accurate post sample forecast than neural network models at horizons of up to a year, in terms of root mean sq. error.

Generally, agricultural data known to be multifaceted and often nonlinear in nature, so in this study ARIMA, ANN, SVM time series models and hybrid of both ARIMA-ANN, ARIMA-SVM were used to analyse the past behaviour of production of agricultural crop in order to make inferences about its future behaviour. It has been observed that hybrid methods (Zhang 2003, Jha and Sinha 2014) [13,]10 are more effective and efficient ways to improve forecast ability of the model.

2. Data and methodology

Yearly data on production of Autumn rice have been used for forecasting from the year 1951 to 2018. The data from 1951-1998 were used for model building and 1999 - 2018 were used for checking the forecasting performance of the model. The statistical software *viz*., SPSS, R; were used for modelling and forecasting of production of agricultural crops in Assam. SPSS software was used to build the suitable ARIMA model nonlinearity test for residuals obtained from ARIMA models using Ljung-Box test. R software package 'Forecast' was used for modelling and forecasting using NN and package 'e 1071' was used for modelling and forecasting using SVM.

ARIMA models represent different kinds of time series as AR, MA, and ARMA series [Zhang 2003]. ARIMA models are flexible in nature and have more powerful and efficient than other structural models to generate short run prediction.

2.1 Time series forecasting models

2.1.1 The ARIMA model

In an ARIMA model, time series variable is assumed to be a linear function of past actual values and random shocks. An ARIMA (p, d, q) model is defined by the following equation

$$\phi(B)(1-B)d\ yt=\Theta(B)\ \varepsilon t \qquad [1]$$

Where,

$\phi(B)= 1- \phi 1B-\phi 2B2-\ldots-\phi pBP$ (Autoregressive parameter)
$\Theta(B)= 1- \Theta 1B-\Theta 2B2-\ldots-\Theta pBP$
(Moving average parameter)

εt = White noise or Error term
d= Differencing term
B= Backshift operator i.e., $BaYt=Yt-a$

ARIMA methodology is carried out in three stages, *Viz*., Identification, estimation and diagnostic checking. Identification of d is necessary to make the non-stationary time series to stationary. A formal statistical test to check the stationarity, known as the test of unit root hypothesis or Augmented Dickey Fuller test. ADF test was utilized to check the stationarity. A good account on ADF test can be found in Makridakis *et al*. (1998) [11]. At the stage of estimation, parameters are estimated for the ARIMA model tentatively chosen at the early identification stage. Parameters estimation for ARIMA model is generally done through iterative least squares method. The adequacy of selected model is tested at the stage of diagnostic checking. At this stage, testing is done to see if the estimated model is statistically adequate i.e., whether the error terms are white noise which means error terms are uncorrelated with mean zero and constant variance. For this purpose, Ljung-Box test is applied to the original series or to the residuals after fitting a model. A good account on Ljung-Box test can be found in Box *et al*. (1994) [5]. If the model is found to be inadequate, the three stages are repeated until satisfactory ARIMA model is selected for the time series under consideration.

2.1.2 Ljung-Box test

The Ljung-Box test, named after statisticians Greta M. Ljung and George E.P. Box, is a statistical test that checks if autocorrelation exists in a time series. It is sometimes called Box-Pierce test. The test identifies whether or not errors are iid (i.e., white noise). The null hypothesis of Ljung-Box test is

H_0: The residuals are independently distributed and the alternative hypothesis is

H_1: The residuals are not independently distributed; they exhibit serial correlation.

The test statistic for the Ljung-Box test is as follows:

$$Q = n(n+2)\ \Sigma p_k^2 / (n-k)$$

Where
n = sample size
pk = sample autocorrelation at lag k

The test statistic Q follows a chi-square distribution with h degrees of freedom; that is,

$$Q \sim \chi 2(h).$$

We reject the null hypothesis and say that the residuals of the model are not independently distributed if $Q > \chi 2_{1-\alpha,\ h}$

2.1.3 Artificial Neural Network (ANN) model

ANN(s) models are set of nonlinear models that are able to capture different nonlinear structures present in the data set. The specification of ANN model does not require any prior assumption of the data generating process, instead it is largely depended on characteristics of the data known as data-driven approach. Single hidden layer feed forward network is the most widely used model for time series modelling and forecasting. This model is constructed by a network of three layers of simple processing units, and thus termed as multilayer ANNs. The first layer is input layer, the middle layer is the hidden layer and the last layer is output layer.

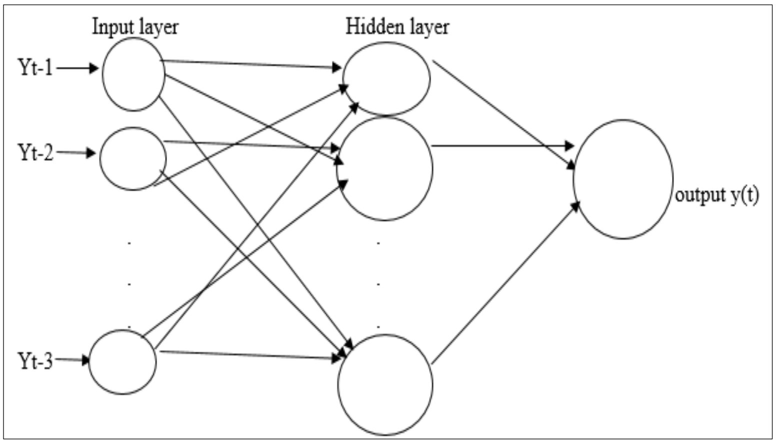


Fig 1: Neural Network architecture

The relationship between the output (yt) and the inputs (yt-1,yt-2, …, yt-p) can be mathematically represented as follows:

$$Yt= f\,(\textstyle\sum_{j=0}^{q} w_j g\,(\sum_{i==0}^{q} w_{ij}\ y_{t-i})) \qquad (1)$$

Where wj(j=0,1,2,…,q) and wij(i=0,1,2,…,p; j=0,1,2,…,q) are the model parameters often called the connection weights; p is the number of input nodes and q is the number of hidden nodes, g and f denote the activation function at hidden and output layer respectively.

2.1.4 Support Vector Machine

Support vector machine proposed by Vapnik (1998) is a nonlinear algorithm used in supervised learning framework for data classification, pattern recognition and regression analysis. The model has been built in two steps: i.e., training and testing. In the training and testing. In the training step, the largest part of the dataset has been used for the estimation of the function. In the testing step, the generalization ability of the model has been evaluated by checking the model performance in the small subset.

It has been used in a wide range of applications such as in data mining, classification, regression and time series forecasting (Cao and Tay, 2001; Flake and Lawrence, 2002; Zhao *et al*. 2006) [7-8, 14]. The ability of SVM is to solve nonlinear regression estimati8, on problems and it makes SVM successful in time series forecasting.

The SVM architecture is shown in the following Figure.

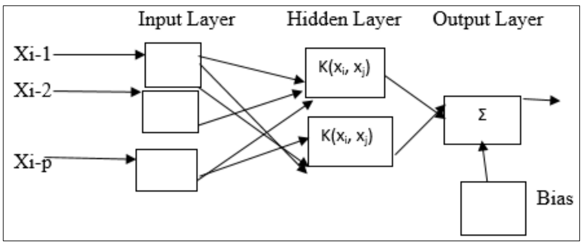


Fig 2: SVM Architecture

Evaluation Criteria

The most common error function in neural networks is the sum of squared errors. Other error functions offered by different software include least absolute deviations, least fourth powers, asymmetric least squares and percentage differences.

2.1.5 Hybrid approach

The proposed approach considered time series (yt) as a function of linear and non-linear components. Hence yt= f (Lt, Nt) where yt is a time series data; Lt and Nt represents the linear and nonlinear component respectively. This approach follows the Zhang’s (2003) hybrid approach, accordingly the relationship between linear and nonlinear components can be written as following

Yt= Lt + Nt

The main strategy of this approach is to model the linear and nonlinear components separately by different model. The methodology consists of three steps. Firstly, ARIMA model is applied to the data series to fit the linear part. Let the prediction series provided by ARIMA model denoted as $\widehat{L_t}$. In the second step, instead of predicting the linear component, the residuals denoted as et which are nonlinear in nature are predicted. The residuals can be obtained by subtracting the predicted value $\widehat{L_t}$ from actual value of the considered time series yt.

et= yt- $\widehat{L_t}$

Now the residuals are predicted employing an ANN and SVM model. Let the prediction series provided by ANN/SVM model denoted as$\widehat{N_t}$. Finally, the predicted linear and nonlinear components are combined to generate aggregate prediction.

$\widehat{y_t}= \widehat{L_t} + \widehat{N_t}$

Ljung-Box test is used to test for non-linearity in this study.

The graphical representation of proposed approach is expressed in the figure 2.2 & 2.3

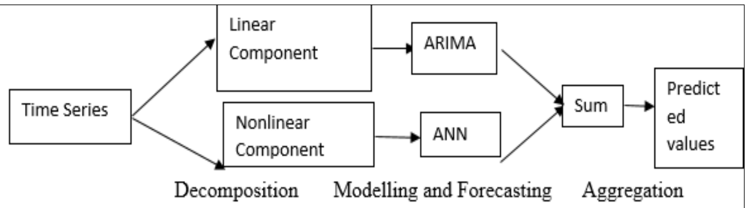


Figure 2.2: Schematic representation of ARIMA-ANN hybrid methodology

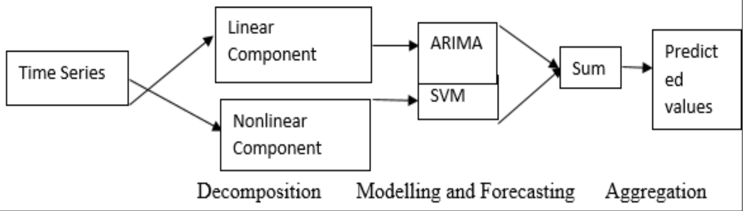


Fig 3: Schematic representation of ARIMA-SVM hybrid methodology

Forecasting Performance

Forecasting Performance of the model has been adjusted by computing mean absolute error (MAE). The model with minimum values of MAE for training and testing data set is preferred for forecasting purpose. The MAE is computed as

$$MAE=\frac{1}{n}\sum_{t=1}^{n}|y_t-\hat{y}_t|$$

Where n is the total number of forecast values. Yt is the actual value at period t and $\hat{y}_t$ is the corresponding forecast value.

3. Results and Discussion

3.3.1 Autumn rice

Table 1: Summary Statistics of time series for Production of Autumn rice

Statistic	Autumn rice Production	Statistic	Autumn rice Production
Observation	68	Maximum	619126.00
Mean	384104.60	Standard deviation	105258.67
Median	374058.50	Skewness	0.332
Range	412776.00	Kurtosis	-0.562
Minimum	206350.00	Coefficient of variation (%)	364.91

Here we have applied hybrid ARIMA approaches using ANN and SVM on production of selected crops from the year 1951 to 2018 whereas from 1951 to 1998 as a training set and 1999 to 2018 as a testing set. Sequence charts for production of Autumn rice is shown in Figure 3.1

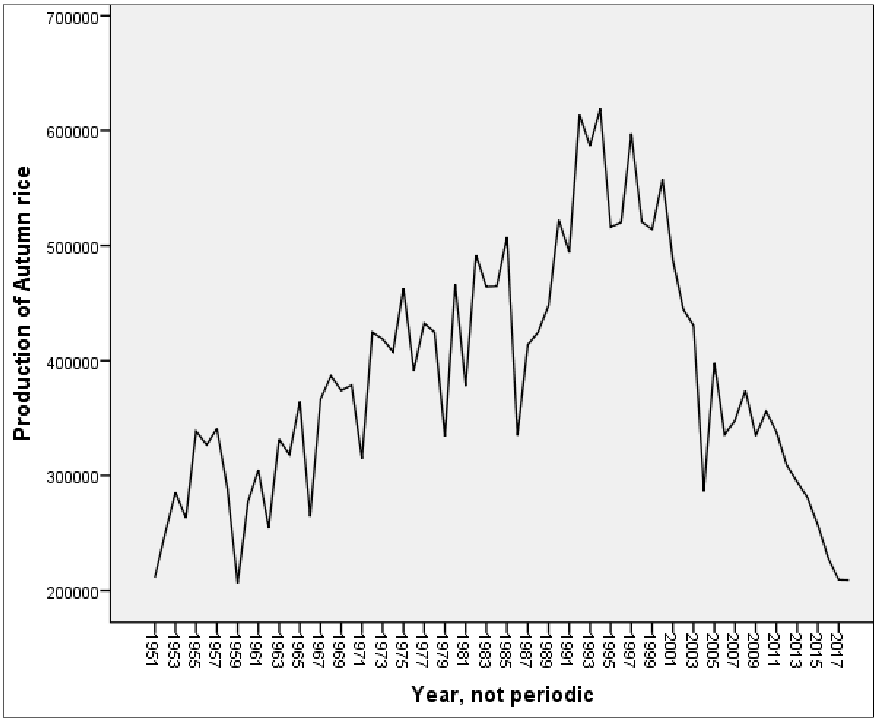


Fig 4: Sequence charts for production of autumn rice

3.2 Forecasting through hybrid univariate linear time series approach

For linear time series models, Auto Regressive Integrated Moving Average (ARIMA) method was applied on the production of Autumn rice from the period 1951-52 to 2018-19 for forecasting over Assam. Based on the minimum values of measures of goodness of fit, like Root Mean Square Error (RMSE), Mean absolute Percentage Error (MAPE), Mean Absolute Error (MAE) given in Table 3.1 (BIC= 22.039), white noise test using Ljung- Box Q test for residuals reported in Table 3.2 (p value= 0.308) and significance of the parameter estimates given in Table 3.3, we selected the model ARIMA (2,1,2) as a best fitted for the production of autumn rice and the same model was found by auto.arima option from R software. By using the linear model ARIMA (2,1,2), we forecasted production value by 2025 which are given in Table 3.5 and graphically presented in the following figure 3.2.

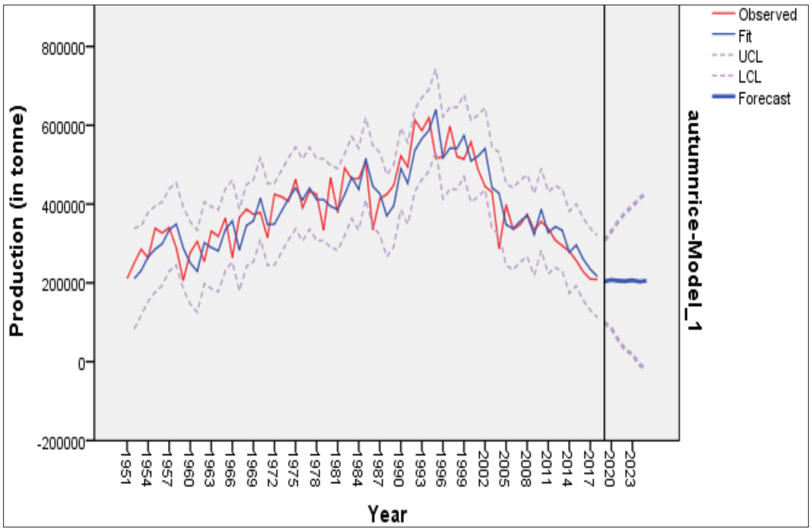


Fig 5: Forecast of production of autumn rice by 2025 using ARIMA (2, 1, 2)

Ljung-Box test was applied to checked the residuals obtained through ARIMA (2,1,2) supports that the residuals are nonlinear because p>0.308, hence we can apply artificial neural network (ANN) approach for modelling and forecasting of residuals. ANN and SVM approaches were applied on the residuals obtained through the selected model ARIMA (2,1,2). For better performance of forecasting of production of autumn rice, we applied hybrid ARIMA approach using ANN and SVM. We have tried different neural networks with different time delays with different hidden nodes on residuals and the results are presented in Table 3.5.

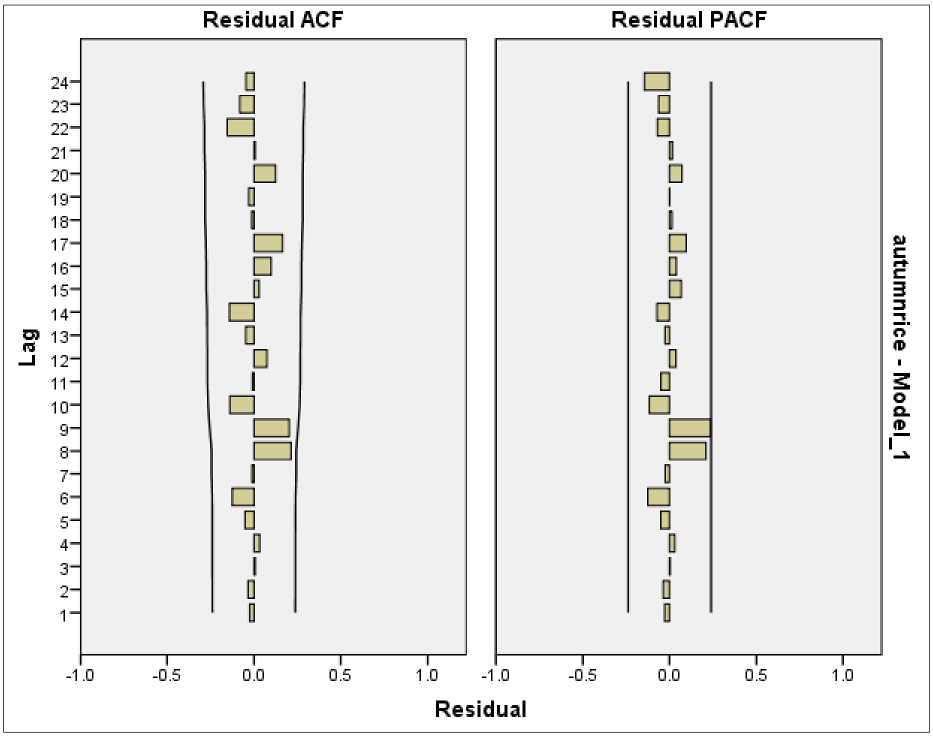
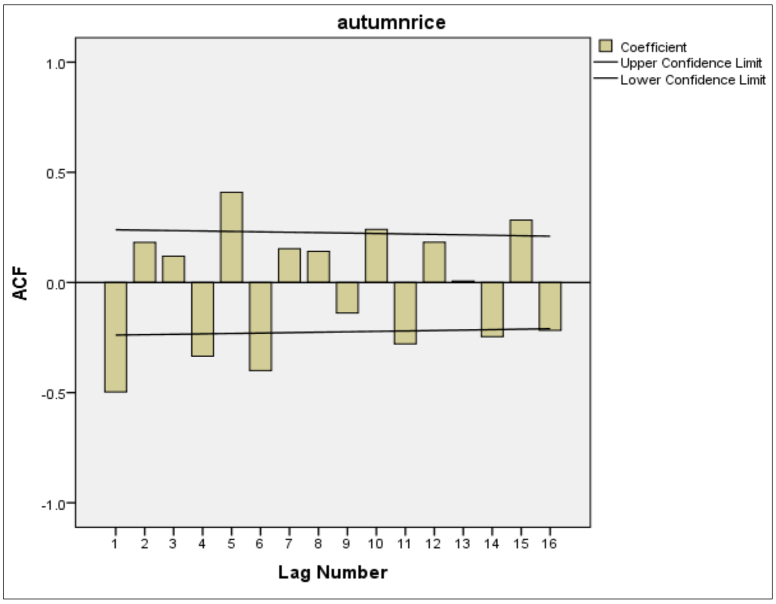


Fig 6: Residual ACF and Residual PACF for production of Autumn rice



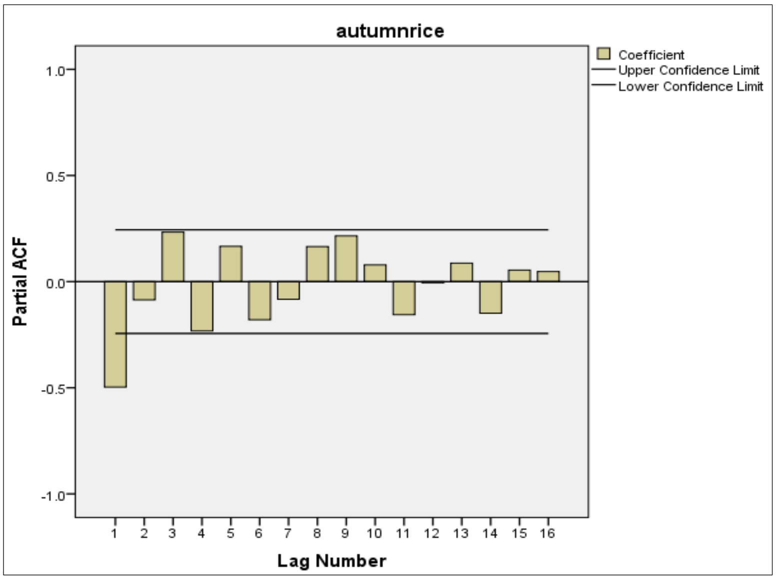


Fig 7: ACF and PACF for production of Autumn rice

Table 2: Goodness of fit Statistics

Fit Statistic	ARIMA (0, 1, 1)	ARIMA (1, 1, 0)	ARIMA (1, 1, 1)	ARIMA (2, 1, 2)
Stationary R-squared	0.211	0.247	0.250	0.365
R-squared	0.705	0.719	0.720	0.763
RMSE	56802.731	55516.814	55822.411	52193.929
MAPE	12.433	12.188	12.160	11.093
MAE	44829.698	43991.414	43853.843	39637.856
MaxAPE	56.715	52.705	53.77	49.223
MaxAE	162391.898	151164.585	153958.739	140939.816
Normalized BIC	22.020	21.974	22.048	22.039

Table 3: Test for white noise

Model	Ljung-Box Q		
	Statistics	DF	Sig.
ARIMA (0,1,1)	42.336	17	0.001
ARIMA (1,1,0)	35.11	17	0.006
ARIMA (1,1,1)	33.37	16	0.007
ARIMA (2,1,2)	16.083	14	0.308

Table 4: Parameter Estimates

Models	Parameter Estimate	SE	t	Sig.
ARIMA (0,1,1)	0.432	0.113	3.819	0.000
ARIMA (1,1,0)	-0.492	0.107	-4.580	0.000
ARIMA (1,1,1)				
AR Lag1	-0.416	0.228	-1.825	0.073
MA Lag1	0.105	0.250	0.419	0.677
ARIMA (2,1,2)				
AR Lag1	-1.512	0.102	-14.824	0.000
AR Lag2	-0.855	0.097	-8.811	0.000
MA Lag1	-1.152	0.174	-6.637	0.000
MA Lag2	-0.507	0.172	-2.950	0.004

Table 5: Forecast of production of Autumn rice

Year	Forecast	LCL	UCL
2019	203619	99695	307542
2020	207599	84244	330954
2021	205378	54487	356270
2022	204427	29740	379114
2023	206858	19094	394622
2024	203088	-8198	414374
2025	205804	-17053	428661

For Neural Network, we have used different combinations of models with different time delays and hidden nodes on the residuals and the results are displayed in Table 3.5.

Table 6: MAE for Neural Network models for production of Autumn rice

Model parameters	MAE for Training	MAE for Testing
1:2s:1l	43629.893	18580.947
1:4s:1l	43642.795	18320.961
1:6s:1l	43647.906	18250.484
1:8s:1l	43683.425	18326.779
1:10s:1l	43686.446	18237.912
2:2s:1l	43542.275	17520.877
2:4s:1l	43610.568	17303.224
2:6s:1l	43602.981	17245.121
2:8s:1l	43607.486	17109.543
2:10s:1l	43656.433	17245.666
3:2s:1l	44308.342	10843.859
3:4s:1l	44314.650	9752.612
3:6s:1l	44400.694	9645.414
3:8s:1l	44331.938	10339.909
3:10s:1l	44437.409	10496.772
4:2s:1l	44187.676	12127.238
4:4s:1l	44058.561	11330.821
4:6s:1l	44184.256	10903.354
4:8s:1l	44135.111	10559.592
4:10s:1l	44196.801	10823.428
5:2s:1l	44195.893	10237.859
5:4s:1l	44271.599	9486.224
5:6s:1l	44328.632	9349.118
5:8s:1l	44091.904	9276.554
5:10s:1l	44234.232	9143.112
6:2s:1l	43466.079	8947.597
6:4s:1l	43131.595	8758.463
6:6s:1l	42372.488	8385.163
6:8s:1l	41553.955	8116.532
6:10s:1l	36031.685	19707.669

From the above table, the model 6:10s:1l was found to be the best one on the basis of minimum values of MAE for training=36031.685 and testing= 19707.669. From this selected model we have got the estimated values of residuals and fitted values of production of autumn rice obtained by ARIMA (2,1,2) then forecast value of production was obtained through hybrid approach i.e., ARIMA (2,1,2)-ANN. The goodness of fit measure MAE for hybrid ARIMA-ANN was found to be 34615.361 as compare to 39637.856 ARIMA (2,1,2). Residuals obtained by using ARIMA (2,1,2) were applied on the non-linear approach support vector machine using radial basis function as kernel. Forecast values of production obtain through ARIMA (2,1,2) were corrected by using the residuals through SVM and estimated the value MAE for hybrid ARIMA-SVM. MAE for hybrid ARIMA-SVM was found to be 29464.313 as compare to 39637.856 of ARIMA (2,1,2) and 34615.361 of hybrid ARIMA-ANN. Hence the performance of hybrid model found to be better than ARIMA (2,1,2) alone.

For the purpose of forecast value of production through hybrid approach, we have got forecast of residuals through the best neural model (06:10s:1l) till 2025. Based on the forecasted value of residuals we found the forecast value of production through hybrid approaches and presented in Table 3.6 along with forecast values by ARIMA (2,1,2).

Table 7: Experimental Results of forecast of Production of Autumn rice

Year	Actual values of Production	Forecast Yield by ARIMA (2, 1, 2)	Forecast Yield by Hybrid Approach using ANN
1951	211134		
1952	249611	210865	
1953	285522	231104	
1954	263186	266022	
1955	338552	285776	
1956	326720	299227	
1957	340832	334583	
1958	289590	349257	329340.8176
1959	206350	288725	279376.007
1960	277201	250461	248998.8477
1961	304958	229531	222580.365
1962	254277	301830	284201.6907
1963	331538	289675	292655.3855

1964	318251	281258	289635.9993
1965	364395	335182	335462.6454
1966	264466	357446	333586.5288
1967	366293	282933	276934.8415
1968	386815	345752	339956.6762
1969	374107	357327	337695.2466
1970	378683	414998	392049.1486
1971	314372	348397	349993.3148
1972	424749	349227	352887.6175
1973	418736	381658	364963.3485
1974	407513	413506	392247.5206
1975	462770	440598	433869.5288
1976	391142	410396	410814.7916
1977	432519	440365	433165.3775
1978	424728	411493	394144.3297
1979	333822	411494	400259.2784
1980	466423	394297	392989.9472
1981	377857	386442	376705.0959
1982	491723	424155	421316.4698
1983	464149	467818	452063.4200
1984	464585	437582	437355.0821
1985	507490	515837	511007.5994
1986	334881	445391	430514.1456
1987	413865	426814	424745.5351
1988	424719	370207	364975.7666
1989	447598	396089	387535.7563
1990	522189	489748	469719.0300
1991	494223	452372	457358.0349
1992	613696	536464	548038.5617
1993	586620	566175	548859.5072
1994	619126	587175	563216.8478
1995	516032	639368	618969.2824
1996	520191	517371	512245.3925
1997	597478	541917	535319.5257
1998	520605	541556	527496.2023
1999	514156	573881	557141.6866
2000	557764	509330	516420.3408
2001	487719	521956	530518.7550
2002	444884	540555	529946.1189
2003	430474	441115	435869.2287
2004	286328	427268	431638.0429
2005	398077	348014	360757.6804
2006	335708	337694	332364.9565
2007	347992	356643	365763.4917
2008	374010	370866	383328.8082
2009	334655	322493	332016.9339
2010	355825	386617	398153.0709
2011	338015	327248	315240.0518
2012	308745	342744	336863.6888
2013	294440	333626	330975.6788
2014	280693	277839	273504.8056
2015	256729	296244	292069.7783
2016	228146	259750	260494.0810
2017	209349	234539	232708.2498
2018	209122	216287	221725.0736
2019		203619	204014.740
2020		207599	204044.9789
2021		205378	208686.3637
2022		204427	204914.9598
2023		206858	204553.8971
2024		203088	197319.5446
2025		205804	199750.2013

Table 8: MAE of different models for production of Autumn rice

Data	ARIMA	ANN	SVM	ARIMA-ANN	ARIMA-SVM
Training	38736.970	36031.6851	34675.234	33316.415	30673.163
Testing	26144.451	19707.6694	17141.346	16761.394	15351.431

From the above table, the value of MAE under training set for different models ARIMA (2,1,2), ANN (06:10s:1l), SVM, ARIMA-ANN and ARIMA-SVM are found to be 38736.970, 36031.6851, 34675.234, 33316.415 & 30673.163 respectively, whereas the value of MAE under testing set are found to be 26144.451, 19707.6694, 17141.346, 16761.394 & 15351.431 respectively. Based on these results, the model ARIMA-SVM can be recommended for forecasting of production of crop because of the minimum value of MAE both under training and testing set.

4. Conclusion

In order to enhance the performance of the ARIMA model for forecasting of Autumn rice production. For this purpose, we have used time series data of Assam from 1951-2018. ARIMA (2,1,2) model was selected as suitable model for Autumn rice and MAE for hybrid ARIMA (2,1,2)-ANN was found to be 34615.361 as compare to 39637.856 of ARIMA (2,1,2), MAE for hybrid ARIMA (2,1,2)-SVM was found to be 29464.313 as compare to 39637.856 of ARIMA (2,1,2) and 34615.361 of hybrid ARIMA-ANN. Hence, the performances of hybrid ARIMA-ANN and ARIMA-SVM were found to be better than that of ARIMA for both under training as well as testing data sets. And from the results, we found hybrid approach gives better results for forecasting of crop production.

5. References

1. Alexandridis AK, Zapranis AD. Wavelet neural networks: A practical guide. Neural Networks. 2013;42:1-27.
2. Alam MW, Sinha K, Ranjan RK, Ray M, Rathod S, Singh KN. Development of Hybrid time series models using Machine learning techniques for forecasting crop yield with covariates. Indian Agricultural Statistics Research Institute, New Delhi; c2018.
3. Banakar A, Azeem MF. Artificial wavelet network and its application to neuro-fuzzy models. Appl. Soft. Computing. 2008;8:1463-1485.
4. Box GEP, Pierce DA. Distribution of Residual Autocorrelations in Autoregressive-Integrated Moving Average Time Series Models. Journal of the American Statistical Association. 1970;65(332):1509-1526. doi:10.1080/01621459.1970.10481180. JSTOR 2284333.
5. Box GEP, Jenkins GM, Reinsel GC. Time Series Analysis: Forecasting and Control (3rd ed.). Holden-Day, San Francisco; c1994.
6. Broock W, Scheinkman JA, Dechert WD, LeBaron B. A test for independence based on the correlation dimension. Econ. Rev. 1996;15:197-235.
7. Cao LJ, EH Tay. Support vector with adaptive parameters in financial time series forecasting. IEEE Trans. Neural Network. 2001;14:1506-1518
8. Flake GW, Lawrence S. Efficient SVM regression training with SMO. Machine learning. 2002;46:271-290
9. Ljung GM, Box GEP. On a Measure of a Lack of Fit in Time Series Models. Biometrika. 1978;65(2):297-303. doi:10.1093/biomet/65.2.297
10. Jha GK, Sinha K. Time-delay neural networks for time series prediction: an application to the monthly wholesale price of oilseeds in India. Neural Comput. Appl. 2014, 24(3).
11. Makridakis S, Wheelwright SC, Hyndman RJ. Forecasting: Methods and Applications (3rd ed.). Wiley, Chichester; c1998.
12. Vapnik VN. The nature of Statistical learning Theory. 1st edn., Springer-Verlog, New York; c1995. ISBN: 0-387-94559-8
13. Zhang G. Time series forecasting using a hybrid ARIMA and neural network model. Neurocomputing. 2003;50:159-175.
14. Zhao CY, Zhang HX, Liu MC, Hu ZD, Fan BT. Application of support vector machine (SVM) for prediction toxic activity of different data sets. Toxicology. 2006;217:105-119.