Forecasting Livestock and Poultry Production in India

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ABSTRACT

The challenges faced by India in achieving the food and nutritional security to the fast growing population need a concerted approach for growth of livestock sector. Various forecasting models like combinations of ARIMA models and Exponential Smoothing models like Simple, Holt, Brown and Damped trend were used to identify the growth patterns and to predict the future trends in livestock and poultry production in India. Time series data on milk production from 1950-51 to 2017-18 were used to forecast the milk production in India up to 2050-51. Brown Exponential Smoothing was the best fit model for forecasting of milk production in India. The forecast obtained showed that milk production would increase to 207.57, 311.86, 416.16 and 520.45 MT respectively during 2020-21, 2030-31, 2040-41 and 2050-51 from 121.80 MT during the year 2010-11. ARIMA (0,1,1) was the best fit model for forecasting meat and wool production, the forecasted values of meat production showed that meat production would increase from 1.08 MT in 2000-01 to 5.18, 7.63, 10.07 and 12.52 MT, respectively during 2020-21, 2030-31, 2040-41 and 2050-51. Wool production would increase appreciably over years with a production of 46.26, 52.06, 58.59 and 65.17 million kg, respectively during the years 2020-21, 2030-31, 2040-41 and 2050-51 from 43.00 million kg in 2010-11. The Brown Exponential Smoothing model was the best fit model for forecasting egg production in India. The forecasted values obtained from the best fitted Brown ES was 103341.99, 144374.02, 185406.04 and 222334.86 million numbers during the years 2020-21, 2030-31, 2040-41 and 2050-51, respectively.

Key words: Livestock and Poultry Production, India, Forecasting

INTRODUCTION

India's livestock sector is one of the largest in the world with a holding of 11 per cent of world livestock population. It ranks first in buffalo population, second in cattle and goat, third in sheep, fifth in ducks and chicken and tenth in camel in the world.

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India continues to be the largest producer of milk in the world, by producing 13.1 per cent of the total world milk output, with the production of milk of 17 million tons in 1950-51 rising to 176.35 million tons in 2017-18. As a result, livestock sector has become one of the fastest growing agricultural subsectors in India. Its share of agricultural GDP was 25.6 per cent in 2016-2017. Livestock sector in India has undergone perceptible changes in its size, composition and productivity in the last few decades, transforming itself from a low-profile backyard venture to the status of a promising industry. This phenomenal growth is driven by the rapidly increasing demand for livestock products, owing to the population growth, urbanization and increasing incomes in the country.

The growing demand for livestock products, as they have income elastic demand in the country, underlines the fact that there is a greater opportunity for enhancing livestock production. It is now understood that initiatives in globalization and economic liberalization across the world would continue to exert more pressure on livestock production to be efficient to meet the challenges of global competition. To be able to effectively plan potential strategies for optimizing livestock production to ensure the attainable socio-economic benefits to the rural poor in the country, a more complete exploration of data and further extrapolation for the future using advanced forecasting tools would be highly helpful. Various sophisticated forecasting models developed would be able to provide a more comprehensive outlook into the dynamics of livestock sector, in terms of livestock production in the country. This study attempts to unravel the future state of livestock production by taking into account the past and present trends.

MATERIALS AND METHODS

Data to be used for the study were collected only from secondary sources. Data on livestock production in India (from 1951 to 2012) were collected from various reliable secondary sources like Basic Animal Husbandry Statistics (BAHS), Food and Agriculture Organization (FAO), Agricultural and Processed Food Products Export Development Authority (APEDA) and Agri. Stat. Although provisional figures of livestock population are now available for the year 2017, they were not considered for analysis to avoid the possible ambiguity in the results. Data pertaining to livestock production including production of milk, meat, egg and wool from 1950-51 to 2016-17 and State wise data from 2008-09 to 2015-16 were collected from BAHS and FAO.

Various statistical tools and time series forecasting models were employed to identify the growth patterns and to predict the future trends in livestock production. Different forecasting models were compared so as to identify the best fit model. Among various time series forecasting models, Auto Regressive Integrated Moving Average [ARIMA] - p, d, q and Exponential Smoothing [ES] models were fitted to choose the best fit model for forecasting of livestock production.

Various combinations of ARIMA models like ARIMA (1,1,1), (1,1,0), (0,1,1), (0,1,0), (0,1,2), (1,1,2), (2,1,0), (2,1,1), (2,1,2), (1,2,1), (0,2,1), (1,2,0), (0,2,0), (0,2,2), (1,2,2), (2,2,0), (2,2,1), (2,2,2) and Exponential Smoothing models like Simple ES, Holt ES, Brown ES and Damped trend ES were used for finding the best fit model. By using the best fit model, two kinds of forecasts were performed: Sample period forecasts and post-sample period forecasts. The former was used to develop confidence in the model and the latter to generate genuine forecasts for use in planning and other purposes. In this study, both ARIMA models and ES models were applied to yield these kinds of forecasts. Forecasting accuracy was identified by using measures of indices like MAE (Mean Absolute Error) and MAPE (Mean Absolute Percentage Error).

ARIMA model

The data used in the study were non-stationary and non-seasonal. ARIMA model is a combination of an Auto Regressive (AR) process and a Moving Average (MA) process applied to a non-stationary data series. A combined model that contains p (AR) term and q (MA) term is called ARMA (p,q). If the object series is differenced 'd' times to achieve stationary, the model is classified as Autoregressive Integrated Moving Average (ARIMA) (p, d, q) model as discussed by Box *et al.* (2007). The basic criteria for choosing the best fit of ARIMA (p, d, q) model are given in Table 1.

Table - 1. Criteria for choosing the appropriate forecasting model

Selection Criterion	Notation
Mean Square Error =	MSE
Bayesian Information Criterion = n log(MSE) +K log n	BIC
Coefficient of Determin $\frac{1}{n-k}\sum\hat{\varepsilon}_t^2$ l $-\frac{Error\ sum\ of\ square}{Total\ sum\ of\ squares}$	R^2
Root Mean Square Error = $\sqrt{\frac{1}{n-k}\sum\hat{\varepsilon}_t^2}$	RMSE
Mean Absolute Error = $\frac{1}{n}\sum_{t=1}^{n}\lvert\hat{\varepsilon}_t\rvert$	MAE
Mean Absolute Percent Error =	MAPE
where, k = Number of parameter $\frac{1}{n}\sum_{t=1}^{n}\left\lvert\frac{\hat{\varepsilon}_t}{y_t}\right\rvert \times 100$ l model; n = Sample size ; y_t = Observed value; and = Difference between the observed and estimated values.	

The general form of ARIMA model of order (p, d, q) is

$$Y_t = \hat{\varepsilon}_t Y_{t-1} + Ø_2 Y_{t-2} + ... + Ø_p Y_{t-p} + \mu - \square_1 \square_{t-1} - \square_2 \square_{t-2} - ... - \square_q \square_{t-q} + \square_t$$

Where,

Y_t = Value at t[th] year;

ε_t's = Error terms which are independently and normally distributed with mean zero and constant variance σ^2 for t =1, 2..., n;

μ = Constant and

ϕ_s and θ_s = Coefficients to be estimated.

Simple Exponential Smoothing

The Simple Exponential Smoothing (SES) model is a time series forecasting technique that can be defined using an additive model used to analyze data which have no trend and seasonal pattern. This is a method of estimation of forecasts of single weight or parameter. Greater weights are assigned to recent observation and smaller weights to distant observation (Sharpe *et al.,* 2010). The model is as given below:

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

New forecast value at time t+1 = Old forecast at time t + α (Error in the last forecast)

The smoothing constant (α) value is selected based on error minimization approach (Talwar and Goyal, 2019)

Brown's Linear (Double) Exponential Smoothing model

The double exponential smoothing model is used to model time series data which have trend, but not seasonality (Brown, 1963). Here, F' denotes a simple smoothed value and F" denotes a double smoothed value:

$$F_t^{'} = \alpha Y_t + (1-\alpha)F_{t-1}^{'}$$

$$F_t^{"} = \alpha Y_t^{'} + (1-\alpha)F_{t-1}^{"}$$

$$\alpha_t = F_t^{'} + \left(F_{t+}^{'} - F_t^{"}\right) = 2F_t^{"} - F_t^{"}$$

α_t denotes the estimated smoothed level at time t

$$b_t = \frac{\alpha}{1-\alpha}\left(F_t^{'} - F_t^{"}\right)$$

And b_t shows the estimated trends at the end of time period t, for m period ahead forecast

$$F_{t+m} = \alpha_t + mb_t$$

Holt's Linear (Double) Exponential Smoothing model

Holt's method can be implemented for the time series data demonstrating a trend (Hanke and Wichern, 2008). This method is appropriate for non stationary data and to make short term forecast. In this technique, level and trend components are smoothed separately using different parameters α and β. Holt's double exponential smoothing method uses three equations one each for level, trend and forecast.

$$L_t = \alpha Y_t + (1-\alpha)(L_{t-1} + b_{t-1})$$

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

$$F_{t+m} = L_t + b_t m$$

where,

L_t = Level of time series at period t

b_t= trend (slope) estimate of time series at time period t

F_{t+m}= forecast at m period ahead of time t

α and β are smoothing constants for level and trend with their values lying between 0 and 1.

Damped Trend Exponential Smoothing method

The forecasts generated by Holt's linear method display a constant trend (increasing or decreasing) indefinitely into the future. Since empirical evidence indicated that this method tended to over-forecast, especially for longer forecast horizons, Gardner and McKenzie (1985) introduced a parameter that dampens the trend to a flat line sometime into the future.

The smoothing equations are,

$$L_t=\alpha Y_{t+}\ (1-\alpha)\ (L_{t-1}+\varphi T_{t-1})$$

$$T_t= \gamma\ (L_t-L_{t-1}) + (1- \gamma)\ \varphi T_{t-1}$$

The m-step-ahead prediction equation is $\hat{Y}_{t+m} = L_t + \sum_{i=1}^{m} \varphi^i\, T_i$

This is the forecast y, m-steps ahead by taking the last available estimated level state and multiplying the last available trend (slope) T_i, with φ^i=damping factor.

RESULTS AND DISCUSSION

Time series data on milk production from 1950-51 to 2017-18 were used to forecast the milk production in India up to 2050-51. The time series prediction models like ARIMA and Exponential Smoothing were compared and based on their fitness, forecasting of milk production was done. The model was estimated using SPSS software (ver.26). The criteria adopted for model selection for forecasting of milk production are given in Table 2, like the values of R^2, RMSE, MAPE, MAE and normalized BIC. On perusal of the table, it can be known that Brown Exponential Smoothing was the best fit model for forecasting of milk production in India. The normalised BIC value for the model was 0.885, which was the lowest among the models, with a higher R^2 value of 0.999. For this model, RMSE (1.491), MAPE (2.007) and MAE (1.043) values were also found to be lower than that of other models.

Table - 2. Criteria for model selection for milk production

Model	R^2	RMSE	MAPE	MAE	BIC
ARIMA (1,1,1)	0.999	1.482	1.883	1.002	1.137
ARIMA (1,1,0)	0.999	1.500	1.946	1.014	1.073
ARIMA (0,1,1)	0.999	1.586	1.984	1.080	1.184
ARIMA (0,1,0)	0.999	1.526	1.988	1.061	1.195
ARIMA (0,1,2)	0.999	1.526	1.964	1.045	1.164
ARIMA (1,1,2)	0.999	1.579	1.679	1.089	1.147
ARIMA (2,1,0)	0.999	1.564	1.948	1.265	1.146
ARIMA (2,1,1)	0.999	1.523	1.989	1.145	1.254
ARIMA (2,1,2)	0.999	1.541	2.004	1.254	1.321
ARIMA (0,2,0)	0.999	1.645	2.013	1.002	1.562
ARIMA (1,2,0)	0.999	1.518	1.901	0.997	1.102
ARIMA (0,2,1)	0.999	1.416	1.638	0.924	0.962
ARIMA (1,2,1)	0.999	1.406	1.736	0.920	1.037
ARIMA (1,2,2)	0.999	1.641	1.945	0.978	1.004
ARIMA (2,2,0)	0.999	1.625	1.769	1.046	1.065
ARIMA (2,2,1)	0.999	1.643	1.948	1.087	1.047
ARIMA (2,2,2)	0.999	1.523	1.766	1.065	0.964
ARIMA (0,2,2)	0.999	1.499	1.989	1.098	0.894
Holt ES	0.999	1.491	2.007	1.043	0.885
Simple ES	0.999	1.495	1.812	1.009	0.977
Brown ES	0.999	1.491	2.007	1.043	0.885
Damped trend ES	0.999	1.514	1.807	1.012	1.088

ARIMA model was used by Jaisankar and Prabakaran (2012) for forecasting milk production in Tamil Nadu, based on time the series data from 1978 to 2008. Paul *et al.* (2014) also used milk production data from 1979-2007 and found that ARIMA (1, 1, 0) model could fit in well for forecasting. Deshmukh and Paramasivam (2016) concluded that among ARIMA and Vector Auto Regression (VAR) models, ARIMA (1, 1, 1) was the most suitable method for forecasting milk production in India.

After this model selection, the model parameter of Brown Exponential Smoothing was estimated and the results are presented in Table 3. Based on the best fit Brown Exponential Smoothing model, milk production was predicted for the years 2020-21, 2030-31, 2040-41 and 2050-51 and the forecasted values are given in Table 4. The forecast obtained from the fitted Brown Exponential Smoothing model showed that milk production would increase to 207.57, 311.86, 416.16 and 520.45 MT respectively during 2020-21, 2030-31, 2040-41 and 2050-51 from 121.80 MT during the year 2010-11. It needs emphasis that these predictions are more likely to come true, as the prediction for the year 2010-11 is almost similar to the actual figure, unlike the prediction by Paul *et al.* (2014) whose prediction is far from the actual figure.

Table - 3. Estimates of the Brown Exponential Smoothing model for milk production

Model	Estimate	SE	T	Sig.
Alpha (Level and Trend)	0.790	0.073	10.760	0.000

Table - 4. Forecasts of milk production (in MT)

Year	Actual	Predicted	LCL (95 %)	UCL (95 %)	Residual
2000-01	80.60	81.32	78.31	84.33	-0.72
2010-11	121.80	120.77	117.76	123.78	1.03
2020-21	-	207.57	198.88	216.26	-
2030-31	-	311.86	254.94	368.78	-
2040-41	-	416.16	288.52	543.79	-
2050-51	-	520.45	305.34	735.56	-

The time series data on meat production from 1998-99 to 2015-16 were used for forecasting of meat production for future years in India. Various statistical models like 18 combinations of ARIMA model and four ES models were selected and among which the best fit model for the forecasting was selected for forecasting of meat production based on the criteria specified in Table 5. From the table, it could be found that ARIMA (0,1,1) was the best fit model for forecasting milk production, since it was having the lowest normalised value of BIC -4.558 and relatively lowest RMSE (0.085), MAPE (6.135) and MAE (0.061) values and higher R^2 value (0.995). Hossain and Hassan (2013) forecasted milk, meat and egg production in Bangladesh using time series data and they in contrary to this study, revealed that the cubic model was the best fit model for forecasting milk and meat production.\

After the model selection, the model parameters were estimated and the results of the estimates are given in Table 6. Based on the best fit ARIMA (0,1,1) model, forecasting of meat production for the years 2020-21, 2030-31, 2040-41 and 2050-51 were done and the results are presented in Table 7. The forecasted values of meat production obtained by using ARIMA (0,1,1) showed that meat production would increase from 1.08 MT in 2000-01 to 5.18, 7.63, 10.07 and 12.52 MT, respectively during 2020-21, 2030-31, 2040-41 and 2050-51.

Table - 5. Criteria for model selection for meat production

Model	R^2	RMSE	MAPE	MAE	BIC
ARIMA (1,1,1)	0.996	0.084	6.145	0.060	-4.456
ARIMA (1,1,0)	0.995	0.085	6.208	0.062	-4.556
ARIMA (0,1,1)	0.995	0.085	6.135	0.061	-4.558
ARIMA (0,1,0)	0.995	0.092	6.982	0.074	-4.465
ARIMA (0,1,2)	0.995	0.094	6.741	0.072	-4.423
ARIMA (1,1,2)	0.995	0.085	6.654	0.081	-4.426
ARIMA (2,1,0)	0.995	0.086	6.684	0.069	-4.259
ARIMA (2,1,1)	0.995	0.089	6.642	0.076	-4.378
ARIMA (2,1,2)	0.995	0.091	6.959	0.081	-4.356
ARIMA (0,2,0)	0.994	0.100	7.202	0.075	-4.099
ARIMA (1,2,0)	0.993	0.105	8.035	0.086	-4.117
ARIMA (0,2,1)	0.994	0.095	7.116	0.071	-4.332
ARIMA (1,2,1)	0.994	0.086	7.156	0.084	-4.269
ARIMA (1,2,2)	0.994	0.091	7.189	0.087	-4.489
ARIMA (2,2,0)	0.994	0.094	7.325	0.091	-4.256
ARIMA (2,2,1)	0.994	0.093	7.849	0.098	-4.226
ARIMA (2,2,2)	0.994	0.097	7.965	0.123	-4.550
ARIMA (0,2,2)	0.994	0.123	7.465	0.089	-4.213
Simple ES	0.994	0.093	7.307	0.077	-4.510
Brown ES	0.994	0.097	10.056	0.085	-4.539
Holt ES	0.977	0.184	11.537	0.158	-3.266
Damped trend ES	0.994	0.092	11.965	0.245	-4.550

Table - 6. Estimates of ARIMA (0, 1, 1) for meat production

Model	Parameters	Estimate	SE	t	Sig.
ARIMA (0, 1, 1)	Constant	23.330	30.251	8.771	0.000
	MA(1)	0.190	7.413	2.026	0.000
	Difference	1.000			

This increasing trend in meat production implies the fact that the ever rising demand for protein rich meat would continue to be there due to the changing tastes and preferences among medium and high income groups especially in urban and semi urban areas, the creation of awareness among all sections of the society about protein malnutrition and the comparative advantage the country possesses on the export potentials of this products, owing to the presence of appreciable livestock wealth.

Table - 7. Forecasts of meat production (in MT)

Year	Actual	Predicted	LCL (95 %)	UCL (95 %)	Residual
2000-01	1.08	0.89	0.70	1.08	0.19
2010-11	2.65	2.71	2.52	2.90	-0.06
2020-21	-	5.18	4.61	5.75	-
2030-31	-	7.63	5.35	9.91	-
2040-41	-	10.07	5.48	14.67	-
2050-51	-	12.52	5.13	19.92	-

Time series data on egg production from 1950-51 to 2015-16 were used to forecast the egg production in India for the years 2020-21, 2030-31, 2040-41 and 2050-51. Forecasting models such as ARIMA and Exponential Smoothing were used and among which, the best fit model was selected for forecasting. The criteria used for selecting best fit model are given in Table 8. Comparing ARIMA and ES, it was found that Brown ES was the best fit model for forecasting egg production in India, since its BIC value (14.455) was the lowest among all models and it had higher R^2 value (0.997) like others and relatively lower values of RMSE (1316.987), MAPE (7.058) and MAE (14.455). In contrary to this, ARIMA (0, 1, 0) was the best fit model for forecasting egg production in India as reported by Chaudhari and Tingre, (2015). The estimate of the parameter of the selected best fit Brown Exponential Smoothing model is given in Table 9.

By using the best fitted Brown ES model, forecasting of egg production were done for the years 2020-21, 2030-31, 2040-41 and 2050-51 and the results are presented in Table 10. On perusal of the table, it is evident that the egg production would increase in a linear trend in the future years. The forecasted values obtained from the best fitted Brown ES was 103341.99, 144374.02, 185406.04 and 222334.86 million numbers during the years 2020-21, 2030-31, 2040-41 and 2050-51, respectively. Unlike the prediction by Chaudhari and Tingre (2015) who showed it would be 61993 million numbers during 2010-11, prediction in this study of 63228 million numbers is found to be close to the actual figure.

Table - 8. Criteria for model selection for egg production

Model	R^2	RMSE	MAPE	MAE	BIC
ARIMA (1,1,1)	0.997	1255.345	4.977	915.201	14.633
ARIMA (1,1,0)	0.997	1241.058	4.962	913.613	14.519
ARIMA (0,1,1)	0.997	1241.077	4.960	913.507	14.519
ARIMA (0,1,0)	0.997	1298.046	4.996	923.564	14.652
ARIMA (0,1,2)	0.997	1287.265	4.956	921.132	14.745
ARIMA (1,1,2)	0.997	1297.146	4.912	915.263	14.635
ARIMA (2,1,0)	0.997	1246.713	4.994	913.215	14.598
ARIMA (2,1,1)	0.997	1213.146	4.978	913.485	14.689
ARIMA (2,1,2)	0.997	1227.694	4.989	894.651	14.598
ARIMA (1,2,1)	0.997	1202.773	4.892	844.649	14.554
ARIMA (1,2,0)	0.996	1513.693	4.911	987.091	14.921
ARIMA (0,2,1)	0.997	1254.072	4.851	908.767	14.545
ARIMA (0,2,0)	0.997	1270.914	4.927	909.366	14.748
ARIMA (1,2,2)	0.997	1217.208	4.965	861.668	14.670
ARIMA (2,2,0)	0.997	1869.452	5.697	915.621	14.984
ARIMA (2,2,1)	0.997	1795.648	5.689	915.621	14.862
ARIMA (2,2,2)	0.997	1643.989	6.123	925.173	14.834
ARIMA (2,2,2)	0.997	1725.213	6.145	926.156	14.498
Simple ES	0.988	2482.038	8.137	1931.126	15.723
Brown ES	0.997	1316.987	7.058	863.081	14.455
Holt ES	0.997	1280.906	5.622	832.990	14.489
Damped trend ES	0.997	1698.479	8.269	812.659	15.889

Table - 9. Estimate of Brown Exponential Smoothing model for egg production

Model	Parameter	Estimate	SE	t	Sig.
Brown ES	Alpha (Level and Trend)	0.571	0.066	8.596	0.000

Table - 10. Forecasts of egg production (in million numbers)

Year	Actual	Predicted	LCL (95 %)	UCL (95 %)	Residual
2000-01	36632	31378.11	28718.40	34037.81	5253.89
2010-11	63024	63228.03	60568.32	65887.74	-204.03
2020-21	-	103341.99	94058.98	112625.01	-
2030-31	-	144374.02	109263.90	179484.13	-
2040-41	-	185406.04	115125.93	255686.15	-
2050-51	-	222334.86	114128.84	330540.88	-

Time series data on wool production from 1950-51 to 2015-16 were used to forecast wool production for the next three decades, i.e. up to 2050. Time series forecasting models like ARIMA and exponential smoothing were compared and the best fit model was chosen for forecasting wool production. The criteria used for selecting the best fit model are given in Table 11.

Table - 11. Criteria for model selection for wool production

Model	R^2	RMSE	MAPE	MAE	BIC
ARIMA (1,1,1)	0.954	1.375	2.186	0.913	0.999
ARIMA (1,1,0)	0.953	1.364	2.170	0.907	0.892
ARIMA (0,1,1)	0.954	1.357	2.194	0.917	0.882
ARIMA (0,1,0)	0.949	1.402	2.257	0.953	0.857
ARIMA (0,1,2)	0.954	1.124	2.246	0.987	0.889
ARIMA (1,1,2)	0.949	1.235	2.217	0.954	0.915
ARIMA (2,1,0)	0.954	1.257	2.297	0.978	0.921
ARIMA (2,1,1)	0.954	1.264	2.136	0.965	0.992
ARIMA (2,1,2)	0.954	1.285	2.145	0.986	0.999
ARIMA (1,2,1)	0.938	1.506	2.350	0.988	1.188
ARIMA (1,2,0)	0.931	1.571	2.446	1.030	1.180
ARIMA (0,2,1)	0.933	1.544	2.432	1.026	1.145
ARIMA (0,2,0)	0.928	1.582	2.424	1.014	1.102
ARIMA (1,2,2)	0.954	1.564	2.465	1.045	1.102
ARIMA (2,2,0)	0.954	1.516	2.415	1.103	1.232
ARIMA (2,2,1)	0.954	1.521	2.478	1.123	1.215
ARIMA (2,2,2)	0.954	1.549	2.314	1.135	1.232
ARIMA (2,2,2)	0.954	1.521	2.579	1.231	1.153
Simple ES	0.946	1.494	2.805	0.999	0.892
Brown ES	0.946	1.499	2.388	0.996	0.899
Holt ES	0.950	1.461	2.340	0.968	0.936
Damped trend ES	0.954	1.456	2.654	0.998	1.324

From the selection criteria given in the table, it was observed that ARIMA (0, 1, 1) was the best fit model for wool production forecasting since it had the lowest BIC value (0.882), higher R^2 value and lower values of RMSE (1.357), MAPE (2.194) and MAE (0.917) values. After model selection, the model parameters were estimated and the results of the estimates are given in Table 12. Based on the best fit ARIMA (0, 1, 1) model, forecasting of wool production was done for 2020-21, 2030-31, 2040-41 and 2050-51 and the results are given in Table 13. On perusal of the table, it can be observed that wool production would increase appreciably over years with a production of 46.26, 52.06, 58.59 and 65.17 million kg, respectively during the years 2020-21, 2030-31, 2040-41 and 2050-51 from 43.00 million kg in 2010-11.

Table - 12. Estimates of ARIMA (0, 1, 1) model for wool production

Model	Parameters	Estimate	SE	t	Sig.
ARIMA (0, 1, 1)	Constant	0.116	0.005	2.109	0.041
	MA(1)	0.124	6.459	4.013	0.000
	Difference	1.000			

Table - 13. Forecasts of wool production in India (in million kg)

Year	Actual	Predicted	LCL (95 %)	UCL (95 %)	Residual
2000-01	48.40	48.47	45.21	51.90	0.00
2010-11	43.00	43.61	40.68	46.70	-0.01
2020-21	-	46.26	39.53	53.81	-
2030-31	-	52.06	39.51	67.42	-
2040-41	-	58.59	40.90	81.53	-
2050-51	-	65.17	42.73	95.54	-

Although the predicted milk production presents a rosy picture, unless the required infrastructure in terms of facilities for production of adequate feed and fodder, breeding, disease control, etc. are ensured, it will be highly infeasible to reach the predicted levels of production. The increasing trend in meat production implies the fact that the ever rising demand for protein rich meat would continue to be there due to the changing tastes and preferences among medium and high income groups especially in urban and semi urban areas.

In spite of promising trends in production of livestock and poultry in the country, the export potentials of livestock and poultry products from India to other countries only look gloomy. This points to the fact that the country has to effectively tackle challenges it faces in food safety issues. Considering the results obtained and conclusions drawn from the study, certain policy options are required to address the issues and challenges, so as to ensure higher productivity in the sector and assured food security to the consumers:

1. It needs to be ensured that necessary development programmes are framed and implemented for enhancing livestock population and productivity. These may include placing greater stress on feed and fodder availability and disease control.

2. Region specific programmes need to be formulated and introduced, where certain categories of livestock can be given greater thrust.

3. Best practices models may be drawn and popularised among farmers, so as to effectively exploit the potential benefits of livestock and poultry.

4. With the surplus production of milk and egg is the remarkable feature of Indian livestock and poultry industry, unless food safety issues are strictly considered and addressed, the country will not be able to fully exploit the export potentials in the near future. Also, exploring all possible avenues for further processing and value addition of livestock and poultry products will help to achieve the desired results.

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