Future Prospects of Small Scale Industrial Sector Of Punjab: An Empirical Assessment

DR. SANJEEV GUPTA
Faculty in Management
Department of Humanities & Management
Dr. B R Ambedkar National Institute of Technology
Amritsar Bye Pass, Jalandhar
Punjab, INDIA
E mail: sanjeevguptaeco@gmail.com
M: +919814923812

Abstract

Present study seeks the generation of forecasts of number of units, employment, capital formation and production of small scale industrial sector of Punjab for ensuing decade till 2019-20.Forecasts have been generated for the lead time of thirteen years by using Auto Regressive Integrated Moving Average (ARIMA) model, based on identifying the pattern followed by past values of a each variable and then extrapolating the pattern in the past for short period. The analysis of forecasted figures has revealed that the fixed capital investment and production would experience significant growth during the lead time of thirteen years from 2007-08 to 2019-20. Number of units and employment are expected to observe meager growth during this period indicating low possibility of absorption of labour force in this sector. In the light of the forecasts for low employment, it is imperative that the state government to take concerted economic policy initiatives to strengthen the industrial base in Punjab. In this regard catastrophic changes are required so far as industrial policy of Punjab is concerned.

Key Words: Forecasts, ARIMA, Akaike information criterion, Scheward Bayesian criterion, correlogram.

FUTURE PROSPECTS OF SMALL SCALE INDUSTRIAL SECTOR OF PUNJAB: AN EMPIRICAL ASSESEMENT

Economic forecasting has long engaged the attention of academicians, professionals, planners and policy makers. In the face of uncertainties economic parameters, almost every economic decision depends upon forecasts. If the forecasts suggest a gloomy picture ahead, then economic policy makers may do their best to change the scenario so that gloomy forecasts may not prevail. Forecasting involves predicting future values of economic variables with as little error as possible (Gupta, 2003). For this purpose, forecasters have employed various time series techniques in short run economic forecasting. Among the various methods of forecasting, the Auto-Regressive Integrated Moving Average (ARIMA) model is a powerful method to generate accurate forecasts in the short-run without involving economic theory (Makridakis, 1998).

There are quite a few and noteworthy empirical attempts made by researchers to generate economic forecasts. Notable amongst them are: Sabia (1977) , Bawa (1980) Nachane (1981) , Bowersox (1981), Bowersox (1981), Ibrahim and Otsuki (1982), Armstrong (1983), Mentzer (1984), Fildes (1984), Sarkar (1989), Poonam and Gupta (1990), Diebold and Rudebusch (1991), Fildes (1992), Gupta (1993), Fildes (1995), Mentzer (1995), Fildes (1998Sethi (1999) Razzaque and Ruhul Amin (2000), Naresh (2003), Gupta (2002), Afzal (2002), Gupta (2003), Taylor (2003), Gupta (2004), Armstrong (2005), Armstrong (2006), Taylor (2006) and Gupta (2006) have generated the forecasts of economic variables in India as well as abroad. Forecasting at macro and micro level is quite popular in the west but its application to Indian economic data, especially in industrial sector is rare and there is almost not any comprehensive study dealing with generation forecasts of small scale industrial sector at aggregate and disaggregate level. Keeping this fact into consideration, present study is an endeavor in this direction.

Punjab occupies a place of pride in the industrial map of India which is attributable to its small-scale industrial sector (Lal, 1966). The state inherited a very weak industrial base when partitioned in 1947 and suffered further erosion when it was reorganized in 1966(Singh 1995). More recently it has been through a period of terrorism and social unrest, which not only affected the industrial growth adversely but tended to cause some out migration of industry. With the restoration of peace, the state government tried to activate the process of industrial development with the hope to enter into a new era of progress (Bhatia, 1999).

Objectives of the study

Present study has been conducted keeping in mind the following objectives:

1. To generate forecasts of number of units, direct employment, fixed capital and production of small scale industrial sector of Punjab.
2. To recommend appropriate forecasting model to prepare forecasts of small scale industrial sector of Punjab.

Data base and Analytical Framework

Present study is based on secondary data for the periods of 1970-71 to 2006-07. The aggregate data relating to the variables are: number of units, direct employment, fixed capital and production of small-scale manufacturing industry groups of Punjab were culled from Directorate of Industries, Punjab. The forecasts of the above mentioned variables for a lead time of thirteen years were generated applying of Box-Jenkins' ARIMA method.

The present paper is an endeavor to generate forecasts by applying univariate Box-Jenkins ARIMA modeling. Univariate Box-Jenkins (UBJ) approach is based on identifying the pattern followed by past values of a single variable and then extrapolating the pattern in the past for near future as well (Pankratz, 1983; Makridakis 1987).One of the advantages of Box-Jenkins over other forecasting models is that this modeling approach is not based on economic theory and is capable of capturing slightest variation in the data (Makridakis, 1978). Box-Jenkins methodology rests on the simplifying assumption that the process which has generated a single time series, is the stationary process but unfortunately most time series encountered are rarely stationary, still it is possible to transform them to stationary by the appropriate level of differencing (maximum up to second level) (Box &Jenkins, 1968; SPSS, 1999). The degree of differencing transforms a non-stationary series into a stationary one. If non-stationary is added to a mixed ARIMA model, then the general ARIMA (p, d, q) is obtained, it has the form as under:

$$\Phi_P(B)\ (1\text{-}B)^d\ Y_t = C + \theta_q\ (B)\ e_t \quad \ldots (1)$$

or

$$\Phi_P(B)\ W_t = C + \theta_q\ (B)\ e_t$$

which will be non-stationary unless d=0.

The model is said to be of the order (p, d, q), where p, d and q are usually 0, 1 or 2 (Makridakis, 1998; Hanke, 2001). Having tentatively identified one or more models that seem likely to provide parsimonious and statistically adequate representation of available data, the next step is to estimate the values of the parameters. Sum of squares of the residuals (error component or unaccounted variance) were computed by using maximum likelihood estimation (MLE) method given the respective initial estimates of the parameters, optimum values of the parameters were searched by improving the initial estimates iteratively by supplementing them with the information contained in the time series. For a given model involving "k" number of parameters, the iterative procedure continued till the difference between successive values of sum of squared residual became so small that could be ignored for practical considerations (Box, Jenkins and Reinsell, 1994, p.225). This approach minimizes the error component and maximizes the dependability of the expected outcome, thus yielding a reliable forecast.

In order to make an assessment of the statistically valid forecasts based on the estimated ARIMA models for the given time series, following diagnostic measures were worked out:

(a) Autocorrelations of residuals: The autocorrelation coefficient was worked out by applying the formula given in the following equation (2).

$$r_k\ (e) = \frac{\sum_{t=1}^{n-k} e_t \cdot e_{t+k}}{\sum_{t=1}^{n} e_t^{\,2}}; \quad k = 1,2,\ldots \ell \qquad \ldots (2)$$

The major concern of ACF of residuals was that whether the residuals were systematically distributed across the series or they contain some serial dependency (Box & Pierce, 1970). Acceptance of the hypotheses of serial dependency concludes that the estimated ARIMA model is inadequate.

(b) Portmanteau Test: Ljung-Box Q statistics was computed from the model's residuals for each variable to test the hypothesis of randomness as a measure to confirm the appropriateness of ARIMA model to make forecasts. Ljung-Box Q statistics was computed from the model's residuals by using the following equation

$$Q = n\ (n+2) \sum^{\ell} r_k\ (e)^2\ (n\text{-}k)^{-1} \quad \cdots (3)$$

Non-significance of portmanteau test was taken to imply the generated residuals could be considered a white noise, thereby indicating the adequacy of estimated model (DeLurgio. 1998).

(c) Sum of Squares of Error (SSE): In the present analysis we have also computed Sum of squares of the errors of fitted models and we selected that model adequate in case of which SSE was minimum.

(d) Akaike Information Criteria (AIC): AIC was computed to determine both how well the estimated model fits the observed series, and the number of parameter used in the fit. We compared the value AIC with other fitted model to the same data set and we selected that fitted model adequate in case of which AIC was minimum. The AIC is computed as under:

$$\mathbf{AIC = n \log (SSE) + 2k} \quad \ldots (4)$$

where

k = Number of parameters that are fitted in the model

log = Natural logarithm

n = number of observations in the series

SSE = Sum of Squared Errors

While selecting adequate model a difference in AIC value of 2 or less was not regarded as substantial and we selected the simple model with lesser parameters.

(e)Schwarz Bayesian Information Criteria (SBC): SBC is a modification to AIC; it is based on Bayesian consideration. Like AIC it was computed to determine how well the model fits amongst the competing models, and we selected that model adequate in case of SBC was minimum. The SBC is as under:

$$\mathbf{SBC = n \log (SSE) + k \log (n)} \quad \ldots (5)$$

On the basis of above mentioned yardstick, finally selected model for each variable was used for forecasting as discussed as follows.

Forecasting

For making forecasts equation (2) was unscrambled to express Yt and e_t by using the relation $W_t = (1-B)^d Y_t$. Given the data up to time t the optimal forecasts of $Y_{t+\ell}$ [designated by $\hat{Y}_t(\ell)$] made a time t was taken as conditional expectation of $Y_{t+\ell}$, where t, is the forecast origin and ℓ is the forecast lead-time. Error term e_t completely disappeared once we made forecasts more than q period ahead. Thus for ℓ > q, then ℓ period ahead forecast was made as under:

$$\hat{\mathbf{Y}}_{t+\ell} = \hat{\mathbf{C}} + \hat{\mathbf{\Phi}}_1 \hat{\mathbf{Y}}_{t+\ell-1} + \ldots + \hat{\mathbf{\Phi}}_p \hat{\mathbf{Y}}_{t+\ell-p} \quad \ldots(6)$$

Results and Discussion

The results have been discussed in brief under the following sub-heads:

Stationary Time-Series

In order to confirm the mean stationary and to calculate appropriate level of differencing, correlogram and Ljung Box Q-statistics were computed for original and after differencing of data up to second level (figures and results for the original series are not shown here for the cause of simplicity and briefness). All the empirical results confirmed that after the second differencing all the four variables achieved stationary (details are not discussed here).

Model Identification

In this step after comparing Sample Autocorrelation Functions and Partial Autocorrelation functions with their theoretical counterparts, it was found that the value of AR and MA process did not exceeded the order 2. In order to overcome the subjectivity in selection of the appropriate order of ARIMA model in the present study we have considered al the possible eight combinations of ARIMA models depending on the values of p, d, q as p and q can take any value out of 0,1,2. The possible combinations are: {(1,d,0); (2.d,0); (0,d,1); (1,d,1); (2,d,2); (0,d,2); (1,d,2) & (2,d,1.)}. Here, for all the eight models the value of'd' as already identified 1s 2.

Estimation of different Ordered ARIMA models

As discussed earlier, in order to make choice for suitable forecasting models, ARIMA process of the order (1,2,0), (2.2,0) ,(0,2,1) ,(1,2,1), (2,2,2), (0,2,2), (1,2,2), (2,2,1) were estimated on all the data of four variables. For estimating parameters of selected models, we have started with some initial values of C_i Φ_1, Φ_2, θ_1 θ_2 for different ordered models as exhibited in Table 1.

Table 1: Initial Estimate of the Parameters.

Model	Parameters	No. of Units	Direct Employment	Fixed Investment	Production
ARIMA (1,d,0)	**C**	-25.39	-114.502	8.52264	58.1952
	AR1	0.061244	-0.22072	-0.17886	-0.33037
ARIMA (0,d,1)	**C**	-25.44	-124.478	8.88019	61.0669
	MA1	-0.0574	0.22027	0.33259	0.51621
ARIMA (1,d,1)	**C**	-24.964	-120.728	11.21315	68.0826
	AR1	0.355006	-0.07906	0.596046	0.63614
	MA1	0.290875	0.15054	0.993615	0.9927
ARIMA (2,d,2)	**C**	-22.6176	-54.1442	11.2804	61.70584
	AR1	-0.4174	0.8672	-0.4304	-0.8845
	AR2	0.361625	-0.69468	0.569131	-0.65238
	MA1	-0.56961	1.132019	-0.00247	-0.44587
	MA2	0.4008	-0.99517	0.99208	0.49198
ARIMA (0,d,2)	**C**	-24.62	-115.5	10.867	61.66
	MA1	-0.055	0.242	0.3887	0.0645
	MA2	-0.042	-0.045	0.337	0.065
ARIMA (1,d,2)	**C**	-24.44	-140.2	10.87	62.02
	AR1	0.256	-0.82	0.721	-0.81
	MA1	0.1989	-0.637	1.1209	-0.396
	MA2	-0.0316	0.2352	-0.121	0.5269
ARIMA (2,d,0)	**C**	-24.66	-129.1	9.0158	59.313
	AR1	0.059	-0.234	-0.219	-0.446
	AR2	0.03487	-0.0744	-0.2	-0.3287
ARIMA (2,d,1)	**C**	-24.59	-132.2	11.312	60.425
	AR1	0.2478	-1.074	0.6133	-0.21
	AR2	0.02463	-0.2724	-0.0405	-0.2522
	MA1	0.1888	-0.865	0.9972	0.2719

Note: In all Cases d=2

We further modified initial values by small steps, while observing sum of squared residual. We have selected those values of parameters as the final estimates in case of which sum of squared residuals were least. The estimates of parameters here used in the last stage to calculate new values (forecasts) of the series. In the present exercise estimation was performed on transformed (differenced) data and before generating forecasts we have integrated (inverse of differencing) the series to make forecasts compatible with the input data. Estimation of the Models' parameters was carried out through maximum likelihood method (Box, Jenkins and Reinsell, 1994, p. 225).

Diagnostic testing of different ARIMA models

At this stage, selection of best fitted models and its adequacy was checked on the basis of various criteria as mentioned earlier in equations 2 to 5. As per the above mentioned measures, a model is considered best for next stage i.e. forecasting if it possesses minimum sum of squares of residuals, minimum value of standard error, minimum AIC value, minimum value of SBC, and minimum value of non-significant Box-Ljung Q statistics. Alternative models for each variable were examined comparing the values of these parameters. Only that model in case of each variable has been selected which satisfied maximum number of above mentioned criterion. Values of the above mentioned criterion (except correlogram of residuals) computed from the different ordered ARIMA models for each variable have been presented in Table 2. Almost in all the cases for different order ARIMA models, correlogram of residuals showed no serial dependency (Correlogram for residuals are not shown here as the number of figures were large).

Table 2: Comparative Results from Various Models.

Variable	Estimate	ARIMA (1,d,0)	ARIMA (0,d,1)	ARIMA (1,d,1)	ARIMA (2,d,2)	ARIMA (0,d,2)	ARIMA (1,d,2)	ARIMA (2,d,0)	ARIMA (2,d,1)
No. of units	Sum of Squares	1.66E+08	1.66E+08	1.65E+08	159315396	165401646	1.65E+08	1.65E+08	165364076.8
	Standard error	2274.763	-310.057	2309.949	2317.478	2309.6644	2347.268	2309.586	2347.5677
	AIC	624.1063	624.115	626.1512	629.03157	626.14387	628.243	626.1415	628.25078
	SBC	627.159	627.1677	630.7303	636.66337	630.72293	634.3485	630.7205	634.35622
	Q	9.398	9.465	9.275	8.693	9.196	9.197	9.2	9.234
Direct employment	Sum of Squares	1.57E+09	1.57E+09	1.57E+09	1487260178	1.569E+09	1.55E+09	1.57E+09	1535761371
	Standard error	7009.698	7003.958	7112.973	6874.5335	7108.4871	7175.33	7102.094	7134.2047
	AIC	700.6783	700.6224	702.674	704.77747	702.63687	704.3382	702.5763	704.00241
	SBC	703.731	703.6751	707.2531	712.40927	707.21595	710.4437	707.1553	710.10785
	Q	8.781	8.709	8.745	5.826	8.785	7.646	8.708	7.573
Fixed Investment	Sum of Squares	14326.48	139926	122744.8	122214.5	130387.34	125146.8	138538	122374.63
	Standard error	66.89299	66.01239	61.0522	62.611696	64.224265	62.75614	66.73694	61.780526
	AIC	384.3288	383.5076	381.0161	384.97594	383.14065	383.7338	385.2448	382.95364
	SBC	387.3816	386.5604	385.5952	392.60775	387.71973	389.8393	389.8239	389.05908
	Q	6.828	6.382	3.954	4.083	3.816	4.721	4.636	3.78
Production	Sum of Squares	2820709	2560315	2729291	2448286	2552215.4	2453854	2499160	2475513.7
	Standard error	296.3917	281.574	288.5202	286.96581	285.68924	283.0097	282.4836	285.64443
	AIC	485.6312	482.3277	486.4785	487.05498	484.29146	485.0175	483.573	485.35054
	SBC	488.6839	485.3804	491.0576	494.68678	488.87054	491.123	488.1521	491.45599
	Q	7.458	5.583	7.246	5.069	5.466	5.018	4.532	4.701

Note: In all Cases d=2

Table 2 depicts the values of all the parameters in case of all the four variables. Examination of Table 2 has revealed that in case of number of units, AIC and SBC model fit criteria were minimum i.e. 624.10628 and 627.159 respectively for the model (1, 2, 0) as compared to other competing models. Sum of square of errors was observed lowest for the model (1, 2, 2) to the tune of 165326897.2, while lowest value (8.693) of Q-statistics was found for the model of the order (2, 2, 2).While lowest standard error was observed as 2275.068 in case of the model (0, 2, 1). Further perusal of Table 2 shows that AIC (700.62235) and SBC (703.67507 were least in case of the model (0, 2, 1) while sum of square of errors (1987260177.9), standard error (6874.5335) as well as Q-statistics (5.826) observed minimum for the model (2,2,2). Further glance at Table 2 exhibited that sum of square of errors (122214.50) and Q-statistics (3.870) were minimum for the models (2, 2, 2) and (2, 2, 1) respectively in case of the fixed capital investment. A close examination of Table 2 has revealed that in case of the production, the standard error (281.57397), AIC (482.32769) and SBC (485.38041) were minimum for the model (0,2,1), while in case of Q- statistics minimum value of 4.532 was observed in case of model of the order (2,2,0) as compared to other competing models, whereas least sum of square of errors was detected minimum i.e. 2448286.0 for the model (2,2,2).

The optimum models (based on satisfaction of maximum number of criterion by a particular model) have been expressed in Table 3. Perusal of Table 3 revealed that the models (1,2,0), (2,2,2), (1,2,1), and (0,2,1) were optimum in case of the variables: number of units, direct employment, fixed capital investment and production respectively.

Table 3: Optimum Model for Forecasting.

Variable	**No. of units**	**Direct employment**	**Fixed Investment**	**Production**
Optimum Model	ARIMA(1,d,0)	ARIMA(2,d,2)	ARIMA(1,d,1)	ARIMA(0,d,1)
C	-25.39	-54.1442	11.21315	61.06698
AR1	0.061244	0.86729	0.596046	
AR2		-0.69468		
MA1		1.132019	0.993615	0.516212
MA2		-0.99517		
AIC	624.1063	704.7775	381.0161	482.3277
SBC	627.159	712.4093	385.5952	485.3804
Q	9.398	5.826	3.594	5.583
Iterations	1	12	10	3

Note: In all Cases d=2

Forecasts

After extracting the optimum models for generation of forecasts, the next step is to prepare forecasts of number of units, employment, capital investment and production of small scale industrial sector of Punjab. Table 4 highlights forecasts of number of units, employment, fixed capital, investment and production for lead time of 13 years based on optimal models.

Table 4: Forecasts on the basis of Optimum Model.

Year	**No. of units**	**Direct employment**	**Fixed Investment**	**Production**
2007-08	206499.3423	961401.2809	6387.31395	32816.15406
2008-09	207261.0613	971969.6597	6761.29781	35065.83157
2009-10	207997.3964	982991.4036	7150.873	37376.57606
2010-11	208708.3467	993409.3768	7554.27094	39748.38755
2011-12	209393.9123	1002943.965	7970.43748	42181.26602
2012-13	210054.0931	1012087.03	8398.74427	44675.21148
2013-14	210688.8891	1021459.398	8838.81681	47230.22393
2014-15	211298.3004	1031257.823	9290.43188	49846.30336
2015-16	211882.3268	1041221.673	9753.45642	52523.44979
2016-17	212440.9686	1050988.224	10227.81112	55261.6632
2017-18	212974.2255	1060423.946	10713.44872	58060.9436
2018-19	213482.0977	1069665.002	11210.34103	60921.29098
2019-20	213964.585	1078922.248	11718.47127	63842.70536
CAGRs	0.3	0.96	5.18	5.68

Perusal of Table 4 revealed that in the years of 2007-08, the predicted numbers of units of direct employment are 205712, expected to rise to 207261 in 2009-10 and to 211882 in 2015-16 and finally expected to be 213964 by the year 2019-20. Examination of Table 4 depicts that the forecasts for the direct employment in small scale industrial sector of Punjab are 961401 in 2007-08 and 982991 in 2009-10 and further expected to increase to 1012087 in 2012-13 and would probably grow to 1078922 in 2019-20. Further examination of Table 4 shows that fixed capital investment was expected to be 67387.32 Rs. Crore in the year 2007-08, would probably rise to 7970.43 Rs. Crore in 2011-12 and then to 10713.44 Rs. Crore in 2017-18 and finally expected to expand to 11718.47 Rs. Crore in 2019-20.Table 4 also revealed that production is anticipated to expand from 32816.15 Rs. Crore in 2007-08 to 35065.83 Rs. Crore in 2008-09. It is further anticipated that the production figure would grow to 52523.44 Rs. Crore in 2015-16 and then to 63842.70 Rs. Crore till 2019-20. As far growth of number of units is concerned, they are expected to grow at compound annual rate of 0.30 while employment, investment and production would probably grow at the rate of 0.96, 5.18 and 5.68 percent respectively. This clearly indicates that in the coming days not only productivity of capital but capital intensity will also increase. But the meager rate of growth of employment confirms that in subsequent years due to establishment of new units in other states will lead to almost stagnation in in increase in number of units, therefore less scope for labour absorption in the Small Scale Industrial of Punjab.

Concluding Remarks

Punjab is an agricultural state but it has made honest efforts to provide impetus to the industrial sector especially small scale industrial sector (Gupta, 2006). The Auto Regressive Integrated Moving Average (ARIMA) model through Box-Jenkins approach has been used to generate forecasts regarding variables of small scale industrial sector of Punjab. It is expected that number of units and employment would probably grow at a slower pace as compared to investment and production. The forecasts have depicted a bright picture ahead but with low scope of employment opportunities. These forecasts can provide Government and policy makers a direction to design policies accordingly to pushup growth in this sector.

In the light of the forecasts it is required on the part of the state government to take all sort concerted efforts to strengthen the industrial base in Punjab In this regard catastrophic changes are required so far as industrial policy of Punjab is concerned. Punjab government should announce package of incentives not only for existing industrialists but also for new venturists. Moreover tax benefits, loan on soft-terms and infrastructural facilities should be in the priority list of industrial blueprint of Punjab. Last but not the least woman entrepreneurship should be promoted in the state at par with leading industrial economies of the world, to provide strong footing to small Scale industry of Punjab.

References

[1] Afzal Mohammad (et al.), "Forecasting: A Dilemma of Modules," *Pakistan Economic and Social Review* , **40(1)**, 2002, pp.1-18.

[2] Armstong, J. S., "Relative Accuracy of Judgmental and Extrapolative Methods in Forecasting Annual Earnings," *Journal of Forecasting*, **15(2)**, 1983, pp. 437–447**.**

[3] Armstrong J. S., "The Forecasting Canon: Nine Generalizations to Improve Forecast Accuracy'" *Foresight* **1(1)**, 2005, pp. 49- 65**.**

[4] Armstrong J. S., "Findings from Evidence-Based Forecasting: Methods for Reducing Forecast Error," Forthcoming (after revisions) in the *International Journal of Forecasting.* 2006.

[5] Bartlett, M. S.,"On the Theoretical Specification of Sampling Properties of Autocorrelated Time Series," *Journal of Royal Statistical Society,* **8(27)**, 1946, pp 345-367.

[6] Bawa, R. S. and G. S. Kainth, "A Time Series Analysis of Net National Product of India," *Margin,* 1980.**12(3)**, pp. 51 – 80.

[7] Bhatia G. S., "The Impact of New Economic Policy on Output And Employment in Manufacturing Sector: A Case Study of Punjab" in V. S. Mahajan (ed.), *Economic*

*Reforms and Liberalisation,*1999., New Delhi: Deep & Deep.

[8] Bowersox J. Donald, (et al.).,"Simulated Product Sales Forecasting: A model for Short-Range Forecasting Operational Decision Making.," *Research in Marketing* **4(2)**, 1981, pp.39-68.

[9] Box, G. E. P. and D. A. Pierce, "Distribution of Residual Autocorrelations in ARIMA Time Series Models," Journal *of American Statistical Association*, **65(4),** 1970, pp. 1509 – 1526.

[10] Box, G. E. P., G. M. Jenkins, and G. C. Reinsell. *Time series analysis: Forecasting and control,* 1994, Englewood Cliffs, N. J.: Prentice – Hall.

[11] Box, G. E. P., G. M. Jenkins., "Some Recent Advance in Forecasting and Control," *Applied Statistics,* 1968*,* pp.91 – 109.

[12] DeLurgio, *Forecasting Principles and Application*, 1998, New York: McGraw-Hill International Edition.

Fildes Robert, M. Makridakis (et al.)," Generalising About Univariate Forecasting Methods: Further Empirical Evidence," *International Journal of Forecasting* **14**, 1998, pp. 339–358.

[13] Fildes, R.,"The Evaluation of Extrapolative Forecasting Method," *International Journal of Forecasting* **8(1),** 1992, pp. 81 – 98.

[14] Fildes, R. and E. J. Lusk,"The Choice of a Forecasting Model," *Omega,* **12(5)**, 1984, pp. 427–435.

[15] Fildes, R. and S. Makridakis., "Forecasting and Loss Function," *International Journal of Forecasting* **4(3)**, 1998, pp. 545–550.

[16] Fildes, R. Makridakis, S.,"The Impact of Empirical Accuracy Studies on Time Series Analysis and Forecasting," *International Statistical Review* **63,** 1995, pp. 289–308**.**

[17] Francis X. Diebold and Glenn P. Rudebusch, "Forecasting Output With the Composite Leading Index: A Real Time Analysis.," *Journal of American Statistical Association,* **86(4)**, 1991, pp. 603-610.

[18] Gupta, Sanjeev and R. S. Bawa, "An Analysis of Long -Term Trends and Forecasts of Oilseeds Output in India," *Indian Journal of Quantitative Economics* **17(1-2)**, 2002, pp. 111-131**.**

[19] Gupta, Sanjeev and R. S. Bawa, "Growth Performance and Sales Forecasts of Two-Wheeler Industry in India," Indian *Journal of Applied Economics*, **1(1),** 2004, pp. 158-165.

[20] Gupta, Sanjeev and R. S. Bawa, "Growth Performance and Sales Forecasts of Automobile Industry in India. Forthcoming in the *Indian Journal of Quantitative Economics,* **21(1-2)**, 2006.

[21] Gupta, Sanjeev, *Forecasting of Agricultural Output in India,* 2003, New Delhi: Saloni Publishing House.

[22] Gupta, Sanjeev and R. S. Bawa, "Growth Performance of Small Scale Industry in Punjab: A Comparative Study Of Pre–Liberalization & Liberalization Periods, *Apeejay Journal of Management & Technology*," **1(1)**, 2006, pp. 50-55

[23] Hanke, J. E. (et al.), *Business Forecasting*, 2001, *New* Delhi: Pearson Education.

[24] Ibrahim, I. B, and T, Otsuki, "Forecasting GNP Components Using the Method of Box and Jenkins," *Southern Economic Journal,* 1982, pp. 461 – 470.

[25] Kumar Naresh and Balraj Singh, "Forecasts of Indian Automobile Industry Using Mathematical Models," *Paradigm,* **3(2),** 2003, pp. 105-116.

[26] Ljung G. M. and G. E. P. Box, "On Measurement of Lack of Fit in Time Series Models," *Biometrika*. **65**, 1978, pp. 67–72.

[27] Makridakis, S. (et al.), *The Forecasting Accuracy of Major Time Series Methods,* 1984, Chichester: John Wiley.

[28] Makridakis, S. and S. C. Wheelwright, *The Handbook of Forecasting: A Manager's Guide,* 1987, New York: John Wiley.

[29] Makridakis, S., and S. C. Wheelwright, and R. J. Hyndman, *Forecasting: Methods and Applications,* 1998, New York: John Wiley & Sons.

[30] Makridakis, S., and Wheelwright, S. C., *Interactive Forecasting: Univariate and Multivariate Methods,* 1978, San Francisco CA: Holden-Day.

[31] Mentzer John T. and James E. Cox, "Familiarity, Application, and Performance of Sales Forecasting Techniques," Journal *of Forecasting,* **3(1),** 1984, pp. 276-278.

[32] Mentzer John T. and Keneneth B Kah., "Forecasting in consumer and industrial markets," *Journal of Business Forecasting,* 199, pp. 21-28.

[33] Nachane, D. M. (et al), "Forecasting Freight and Passenger Traffic on Indian Railways: Generalized Adaptive Filtering Approach," *The Indian Economic Journal* **29(2),** 1981, pp. 99-116.

[34] Newbold, P. and C. W. J. Granger, "Experience With Forecasting Principles Abstract of Handbook Article Forecasting Univariate Time Series And The Combination Of Forecast," Journal *of Royal Statistics Society* **137(3)**, 1974, pp. 131–165.

[35] Pankratz, A. *Forecasting with Univariate Box-Jenkins Models: Concepts and Cases,* 1983, .New York.
[36] Ramaswamy, K. V., "Small-Scale Manufacturing Industries-Some Aspects of Size, Growth and Structure," Economic *and Political Weekly,* **29(9)**, 1994, pp. 13 -22.
[37] Sabia, J. L. M.,"Autoregrassive Integrated Moving Average (ARIMA) Model for Birth Forecasting. *Journal of the American Statistical Association* **72(354),** 1977, pp. 264 – 270.
[38] Sethi, A. S., "Forecasting Savings in India in Post - Liberalization Scenario: A Note," *Indian Journal of Quantitative Economics*, **14(2),** 1999, pp. 159 – 166.
[39] Singh Lal, "Geographical Distribution of Industrial Activity in Punjab, *Asian Economic Review,* 1963, pp. 220-235.
[40] Singh P, *Punjab Economy: The Emerging Pattern,* 1995, Enkay Publishers Pvt. Ltd.: New Delhi.
[41] Statistical Package for Social Sciences, *SPSS Trends 10.0*, 1999. SPSS Inc.:Chicago.
[42] Taylor James W., "Exponential Smoothing With a Damped Multiplicative Trend," *International Journal of Forecasting* 19(**2**), 2003, pp. 715-725.
[43] Taylor James W., "A Comparison of Univariate Methods for Forecasting Electricity Demand Up to A Day Ahead," *International Journal of Forecasting,* **22,** 2006, pp. 1-16.