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Forecasting model of small scale industrial sector of West Bengal.

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Economic forecasting has long engaged the attention of academician, professionals, planners and policy makers. In the face of uncertainties, almost every economic decision depends upon forecasts. If the forecasts suggest a dismal picture ahead, then economic system may do its best to change the scenario so that gloomy forecasts may not come true. 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, though complicated one, 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 for India as well as abroad. Forecasting at macro and micro level is quite popular in the west but its application to Indian data, especially in industrial sector is rare and there seems to be not a single 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.

West Bengal 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 a further erosion when got reorganized in 1966(Singh 1995). More recently it has been through a period of turbulence which not only affected the industrial growth adversely but tended to cause some out-migration of industry too. 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 production, direct employment, fixed capital and number of units of small scale industrial sector of West Bengal.

2. To recommend appropriate forecasting model to prepare forecasts of small scale industrial sector of West Bengal.

Database and Analytical Framework:

Present study is based on secondary data for the period 1970-71 to 2006-07. The aggregate data relating to the variables: number of units, direct employment, fixed capital and production of small-scale manufacturing industry groups of West Bengal were culled from Directorate of Industries, West Bengal. The forecasts of the above mentioned variables for a lead time of 13 years were generated applying of 'Box-Jenkins' ARIMA method.

The present paper is an endeavor to generate forecasts by applying sophisticated 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 is not based on economic theory and 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:

$$\Phi_P(B)\,(1-B)^d\,Y_t = C + \theta_q\,(B)\,e_t$$

or

$$\Phi_P(B)\,W_t = C + \theta_q\,(B)\,e_t \quad \ldots (1)$$

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 were computed by using maximum likelihood estimation 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 parameters, the iterative procedure was 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).

In order to make an assessment of the validity of the estimated models for the given time series, following diagnostic measures were worked out:

(a) Autocorrelations of residuals: The autocorrelation coefficient was worked out by applying formula given in the 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 by using

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

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): Sum of squares of the errors of fitted models was computed. 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 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:

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

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:

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

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

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 $\ell > q$, then ℓ period ahead forecast was made as under:

$$\hat{Y}_{t+\ell} = \hat{C} + \hat{\Phi}_1 \hat{Y}_{t+\ell-1} + \dots + \hat{\Phi}_p \hat{Y}_{t+\ell-p} \qquad \dots(7)$$

Table 1: Initial estimate of the Parameters

Variable	ARIMA (1,d,o)		ARIMA (0,d,1)		ARIMA (1,d,1)			ARIMA (2,d,2)				
	C	AR1	C	MA 1	C	AR1	MA 1	C	AR 1	AR2	MA 1	MA 2
No. of units	-25.39	0.061244	-25.44	-0.05749	-24.964	0.355006	0.290875	-22.6176	-0.4174	0.361625	-0.56961	0.400808
Direct employment	-114.502	-0.22072	-124.478	0.22027	-120.728	-0.07906	0.15054	-54.1442	0.86729	-0.69468	1.132019	-0.99517
Fixed Investment	8.52264	-0.17886	8.880192	0.332598	11.21315	0.596046	0.993615	11.2804	-0.43044	0.569131	-0.00247	0.992088
Production	58.19527	-0.33037	61.06698	0.516212	68.0826	0.63614	0.9927	61.70584	-0.88456	-0.65238	-0.44587	0.49198

Variable	ARIMA (0,d,2)			ARIMA (1,d,2)				ARIMA (2,d,o)			ARIMA (2,d,1)			
	C	MA1	MA2	C	AR1	MA1	MA2	C	AR1	AR2	C	AR1	AR2	MA1
No. of units	-24.62	-0.055	-0.042	-24.44	0.256	0.1989	-0.0316	-24.66	0.059	0.03487	-24.59	0.2478	0.02463	0.1888
Direct employment	-115.5	0.242	-0.045	-140.2	-0.82	-0.637	0.2352	-129.1	-0.234	-0.0744	-132.2	-1.074	-0.2724	-0.865
Fixed Investment	10.867	0.3887	0.337	10.87	0.721	1.1209	-0.121	9.0158	-0.219	-0.2	11.312	0.6133	-0.0405	0.9972
Production	61.66	0.0645	0.065	62.02	-0.81	-0.396	0.5269	59.313	-0.446	-0.3287	60.425	-0.21	-0.2522	0.2719

Note: In all Cases d=2

Table 2: Comparative Results from Various Models

Variable	Estimate	ARIMA (1,d,o)	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	7009.698	7003.958	7112.973	6874.5335	7108.4871	7175.33	7102.094	7134.2047

	error								
	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 3: Optimum Model for Forecasting

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

Note: In all Cases d=2

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

RESULTS AND DISCUSSION

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

Stationarity of Time-Series:

In order to confirm the mean stationarity 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 stationarity (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 $\Phi_{1,}$ $\Phi_{2,}$ θ_1 θ_2 for different ordered models as exhibited in Table 1.

Insert Table 1

Then we 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:

In 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).

Insert Table 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 were minimum i.e. 624.10628 and 627.159 respectively for the model (1, 2, 0). 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 variable fixed capital investment. Whereas, standard error (61.052195), AIC (381.01608) and SBC (385.59516) were observed minimum for the model (1, 2, 1). 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 4.532was 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.

Insert Table 3

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 West Bengal. Table 4 highlights forecasts of number of units, employment, fixed capital, investment and production for lead time of 13 years based on optimal models.

Insert Table 4

Perusal of Table 4 revealed that in the year 2007-08, the predicted numbers of units 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 West Bengal 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 there is less scope of labour absorption in the Small Scale Industrial of West Bengal.

Concluding Remarks:

No doubt, West Bengal is basically 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 West Bengal. 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 for labourers. 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 initiatives to strengthen the industrial base in West Bengal. In this regard catastrophic changes are required so far as industrial policy of West Bengal is concerned. West Bengal 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 West Bengal. 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 West Beng

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