Forecasting model of small scale industrial sector of West Bengal

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Economic forecasting has long engaged the attention of academicians, 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

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

\[
\Phi_p(B) W_t = C + \theta_q(B) e_t
\]  \text{ ... (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).

\[
\begin{align*}
    r_k(e) &= \frac{\sum_{t=1}^{n-k} e_t e_{t+k}}{\sum_{t=1}^{n} e_t^2} \quad ; \quad k = 1, 2, \ldots, \ell \\
    \quad & \quad \text{...(2)}
\end{align*}
\]

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

\[
Q = n (n+2) \sum_{k=1}^{\ell} r_k(e)^2 (n-k)^{-1} \quad \text{...(3)}
\]

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:

\[
AIC = n \log (SSE) + 2k
\]

... (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:

\[
SBC = n \log (SSE) + k \log (n)
\]

... (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 $Y_t$ 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 $Y_t(\ell)$] made a time $t$ was taken as conditional expectation of $Y_{t+\ell}$, where $t$, is the forecast origin and $\ell$ 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 $\ell$ period ahead forecast was made as under:

$$
\hat{Y}_{t+\ell} = C + \Phi_1 Y_{t+\ell-1} + \ldots + \Phi_p Y_{t+\ell-p} 
$$

...(7)

Table 1: Initial estimate of the Parameters

<table>
<thead>
<tr>
<th>Variable</th>
<th>ARIMA (1,d,0)</th>
<th>ARIMA (0,d,1)</th>
<th>ARIMA (1,d,1)</th>
<th>ARIMA (2,d,2)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>C</td>
<td>AR1</td>
<td>C</td>
<td>MA1</td>
</tr>
<tr>
<td>No. of units</td>
<td>25.3</td>
<td>0.06</td>
<td>25.4</td>
<td>0.05</td>
</tr>
<tr>
<td></td>
<td>9</td>
<td>4</td>
<td>4</td>
<td>749</td>
</tr>
<tr>
<td>Direct employment</td>
<td>114</td>
<td>0.22</td>
<td>124</td>
<td>0.22</td>
</tr>
<tr>
<td></td>
<td>502</td>
<td>072</td>
<td>478</td>
<td>027</td>
</tr>
<tr>
<td>Fixed Investmen</td>
<td>8.52</td>
<td>0.17</td>
<td>0.33</td>
<td>0.33</td>
</tr>
<tr>
<td>t</td>
<td>264</td>
<td>886</td>
<td>2</td>
<td>8</td>
</tr>
<tr>
<td>No. of units</td>
<td>25.3</td>
<td>0.06</td>
<td>25.4</td>
<td>0.05</td>
</tr>
<tr>
<td></td>
<td>9</td>
<td>4</td>
<td>4</td>
<td>749</td>
</tr>
<tr>
<td>Direct employment</td>
<td>114</td>
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<td>0.22</td>
</tr>
<tr>
<td></td>
<td>502</td>
<td>072</td>
<td>478</td>
<td>027</td>
</tr>
<tr>
<td>Fixed Investmen</td>
<td>8.52</td>
<td>0.17</td>
<td>0.33</td>
<td>0.33</td>
</tr>
<tr>
<td>t</td>
<td>264</td>
<td>886</td>
<td>2</td>
<td>8</td>
</tr>
<tr>
<td>Production</td>
<td>58.1</td>
<td>-</td>
<td>61.0</td>
<td>0.51</td>
</tr>
<tr>
<td>Variable</td>
<td>ARIMA (0,d,2)</td>
<td>ARIMA (1,d,2)</td>
<td>ARIMA (2,d,0)</td>
<td>ARIMA (2,d,1)</td>
</tr>
<tr>
<td>-------------</td>
<td>---------------</td>
<td>---------------</td>
<td>---------------</td>
<td>---------------</td>
</tr>
<tr>
<td></td>
<td>C  MA1 M A2  C  MA1 M A2  C  AR 1 AR 2  C  AR 1  AR 2  M A1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No. of units</td>
<td>-  0.05 -  -  24  0.25  0.19  -  24.6  0.0  0.03  -  24.  0.24  0.1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>24.  0.25  0.19  0.0  6  59  487  24.  0.24  0.88  246  9</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Direct empl</td>
<td>-  0.24  -  14  0.63  -  2309.9  -  58  19  -0.2  11.  0.61  0.0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ment</td>
<td>5.5  0.38  0.0  0.3  10  72  1.12  0.1  629  0.3  0.1  11.  0.61  0.0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fixed invest</td>
<td>10.  0.38  0.3  0.3  10  72  1.12  0.1  629  0.3  0.1  11.  0.61  0.0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Product</td>
<td>0.06  0.0  0.0  0.0  0.39  0.5  0.5  0.4  0.32  -  60.  0.2  0.2  71  7</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>62.  0.39  0.5  0.5  0.39  0.5  0.5  0.4  0.32  -  60.  0.2  0.2  71  7</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: In all Cases d=2

### Table 2: Comparative Results from Various Models

<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimate</th>
<th>ARIMA (1,d,0)</th>
<th>ARIMA (0,d,1)</th>
<th>ARIMA (1,d,1)</th>
<th>ARIMA (2,d,2)</th>
<th>ARIMA (0,d,2)</th>
<th>ARIMA (1,d,2)</th>
<th>ARIMA (2,d,0)</th>
<th>ARIMA (2,d,1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of units</td>
<td>Sum of Squares</td>
<td>1.66E+ 08</td>
<td>1.66E+ 08</td>
<td>1.65E+ 08</td>
<td>159315</td>
<td>396</td>
<td>165401</td>
<td>646</td>
<td>165401</td>
</tr>
<tr>
<td></td>
<td>Standard error</td>
<td>2274.7 63</td>
<td>310.05 7</td>
<td>2309.9 49</td>
<td>2317.4 78</td>
<td>2309.6 644</td>
<td>2347.2 68</td>
<td>2309.5 86</td>
<td>2347.5 677</td>
</tr>
<tr>
<td></td>
<td>AIC</td>
<td>624.10 63</td>
<td>624.11 6</td>
<td>626.15 12</td>
<td>629.03 157</td>
<td>626.14 387</td>
<td>628.24 3</td>
<td>626.14 15</td>
<td>628.25 078</td>
</tr>
<tr>
<td></td>
<td>SBC</td>
<td>627.15 9</td>
<td>627.16 7</td>
<td>630.73 3</td>
<td>636.66 337</td>
<td>630.72 293</td>
<td>634.34 85</td>
<td>630.72 05</td>
<td>634.35 622</td>
</tr>
<tr>
<td>Direct empl</td>
<td>Sum of Squares</td>
<td>1.57E+ 09</td>
<td>1.57E+ 09</td>
<td>1.57E+ 09</td>
<td>148726</td>
<td>0178</td>
<td>1.569E +09</td>
<td>09</td>
<td>1.55E+ 09</td>
</tr>
<tr>
<td>ment</td>
<td>Standard error</td>
<td>7009.6 98</td>
<td>7003.9 58</td>
<td>7112.9 73</td>
<td>6874.5 335</td>
<td>7108.4 871</td>
<td>7175.3 3</td>
<td>7102.0 94</td>
<td>7134.2 047</td>
</tr>
</tbody>
</table>
Table 3: Optimum Model for Forecasting

<table>
<thead>
<tr>
<th>Variable</th>
<th>Optimum Model</th>
<th>C</th>
<th>AR1</th>
<th>AR2</th>
<th>MA1</th>
<th>MA2</th>
<th>AIC</th>
<th>SBC</th>
<th>Q</th>
<th>Iterations</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of units</td>
<td>ARIMA(1, d,0)</td>
<td>-</td>
<td>0.061</td>
<td>244</td>
<td></td>
<td></td>
<td>624.1</td>
<td>627.1</td>
<td>9.3</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>25.39</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>063</td>
<td>59</td>
<td>98</td>
<td></td>
</tr>
<tr>
<td>Direct employment</td>
<td>ARIMA(2, d,2)</td>
<td>-</td>
<td>0.867</td>
<td>29</td>
<td>0.694</td>
<td>68</td>
<td>1.132</td>
<td>019</td>
<td>704.7</td>
<td>5.8</td>
</tr>
<tr>
<td></td>
<td></td>
<td>54.14</td>
<td>42</td>
<td>0.993</td>
<td>515</td>
<td></td>
<td>063</td>
<td>161</td>
<td>26</td>
<td>12</td>
</tr>
<tr>
<td>Fixed Investment</td>
<td>ARIMA(1, d,1)</td>
<td>-</td>
<td>0.596</td>
<td>046</td>
<td>0.993</td>
<td>615</td>
<td>381.0</td>
<td>161</td>
<td>5.5</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td></td>
<td>11.21</td>
<td>315</td>
<td></td>
<td></td>
<td></td>
<td>019</td>
<td>161</td>
<td>14</td>
<td></td>
</tr>
<tr>
<td>Production</td>
<td>ARIMA(0, d,1)</td>
<td>-</td>
<td>0.516</td>
<td>212</td>
<td>482.3</td>
<td>277</td>
<td>485.3</td>
<td>804</td>
<td>5.5</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>61.06</td>
<td>698</td>
<td></td>
<td></td>
<td></td>
<td>277</td>
<td>804</td>
<td>83</td>
<td></td>
</tr>
</tbody>
</table>
Note: In all Cases d=2

Table 4: Forecasts on the basis of Optimum Model

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

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 all 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 is 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 $C_1, \Phi_1, \Phi_2, \theta_1 \theta_2$ 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 4.532 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.
**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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