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RESEARCH ARTICLE

STRUCTURAL STOCHASTIC ECONOMIC TIME SERIES MODEL OF MAHATMA GANDHI NATIONAL RURAL EMPLOYMENT GUARANTEE ACT (MGNREGA) PROGRAMME IN KARNATAKA STATE

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Abstract

This paper has demonstrated economic time series structural stochastic model from using real data sets of Mahatma Gandhi National Rural Employment Guarantee act Programme (MGNREGA). Socioeconomic status structured questionnaires (Kuppuswamy adopted scale 2020) were administered to 285 beneficiaries in selected districts of Karnataka State and also Secondary data was collected from the Government authority. The Structural Stochastic Economic Time Series Model **(**SSETSM) was build from the real empirical data sets of MGNREGA by varied iteration techniques (Thompson iteration method). The formulated model estimated unobserved components of various economic indicators and it would be plausible to generate accurate forecasting figures , newer model techniques where one also has the choice of using a pooling of contemporaneous predictors on each target series. Model results logically derive its own strength in forecasting from the real fact of national policy intervention ,incepted at rural areas for economically strengthening the unemployed youths , below poverty line and economically weaker section population. Derived model incorporates necessary information's about other associated variables ,rather than merely historical absolute values on its own paradigm.

Introduction:-

Structural time series models are a family of probabilistic models for time series that provide and generalize many unfold standard time series modelling ideas thought of econometrics .Important structural time series widely used in economics for extrapolation of predicting values of unknown values form known variables (Ansley et al. 1986; Apel et al. 1999; Basistha et al. 2007).In econometrics structural time series model is benefitted for smoothening and diagnostic test of predicted and unobserved values , usually we commonly used structural model for autoregressive processes, moving average, local linear trends and regression and variable selection on external co vatriates .Since, structural Stochastic Economic Time Series Model would express an unobserved economic time series as the sum of simpler components (Bazter et al. 1999; Beveridge et al. 2002). The individual components are each time series and are governed by a particular structural assumptions .For example, one component might encode a seasonal effect eg days of weeks effects another local trend and another a linear dependence on some set of covariate of time series (Brewer et al. 1979; Bouman et al. 2007)).Structural time series model can often produce reasonable forecasts from relatively little data, model assumptions are interpretable and we can estimate the prediction by visualizing the decompositions of

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previous data and future forecasts into real forms (structural components) .However , structural forecast model is used as a probabilistic formulation technique , that can naturally handle missing data or observations and also provide a fundamental principle quantification of uncertainties. Further, on the implementation of economic policy system we need to focus on continuous forecasting of stationary series in the vague of development of implemented programme (to achieved short and long term goals). The forecasting of economic feasibility is an important tool to fall on the evaluation of economic status of policy or programme beneficiaries over a period of time on various net work approaches (Camba et al. 2003; Canova et al. 1998; Cappe et al. 2005; Carter et al. 1994; Corinna et al. 1995) .This type of advanced forecasting techniques or tools expressed in time horizon at time ‘t’ (‘t’ can takes the values t=1,2...nth years) . The unique short term forecasting algorithms can be broadly classified as Univariate and multivariate approaches (Bharadwaj,2001) .The Univariate approach is based on modelling of economic conditions with associated variables (such as economic level , QOL status and other related attributes) utilizing observations from single sites , where as developing single model. In addition to evaluate at several sites for prediction of input and output components by multivariate structural model approach (Blei et al. 2017) .Unlike, the Univariate structural model is capable of capturing the temporal as well as the spatial evolution of economic conditions over a period of time by considering various attributes (demographic , health and life style of the beneficiaries). In this present research paper , multivariate structural time series models are applied to know the economic feasibility of MGNREGA programme and assess the livelihood status of economically weaker section population. The driven model is fitted based on the qualitative and quantitative data sets , which is collected from the selected districts of Karnataka state. In a structural multivariate time series model , the evolution of different unobserved components on time series economic data such as trend , seasonal , cyclical and calendar variations with adjusted time to evaluate the beneficiaries economic level or index from driven data sets , it was modelled separately with a mix match techniques of selected variables (stationary stochastic process and no stationary data points). Hence, the model allows us in the decomposition of stationary and non stationary data points .The optimization techniques (Thomson iteration method) were employed for model fitting and diagnostic techniques.

Methodology:-

The primary and secondary data sets were collected from selected districts of Karnataka State , each districts functionally operating MGNREGA programme in accordance with Government of India regularity guidelines. Kuppuswamy revised socioeconomic status (2020) scale was admisntered for beneficiaries to obtain primary data, the scale having numerous economic attributes in relation to quality of life, social and economic well being. A survey was conducted at selected sites for gathering various attributes (direct, indirect and focus group interview).The primary data like allocation of budget with different time period to the concerned districts was collected systematically from the line departments and official websites of concerned authorities. Initially, primary and secondary data was categorized and matched with individual respondents , simultaneously nominal scale of data sets were converted into transformed scale by using suitable statistical methods or tools. Collected data was smoothened and applied Structural Stochastic Economic Time Series Model with time varying state variables ($t_0, t_1, t_2 \ldots t_k$). Missing observations and inclusion of exogenous variables like miscalculation , unspent amount and dishonesty of officers for allocation of fund and other upstream junction can be incorporated at an early stage (before model build) .

Model formulation:-

Univariate and multivariate structural time series stochastic decomposition models were formulated based on the unobserved components which have a direct interpretation in terms of the temporal variability of the series of economic data with respect to MGNREGA developmental programme. Consequently the evaluation of the components such as trend or seasonality over time and their contribution to the final prediction can be observed clearly. A stochastic STM for varying time series can be described by the following eqn

$$\mathrm{Y(t)} = \mathrm{Y_1(t)} + \mathrm{Y_2(t)} + \mathrm{Y_3(t)} \ldots \mathrm{Y_n(t)} + \epsilon_{ij}$$

$$\mathrm{f(t)} = \mathrm{f_1(t)} + \mathrm{f_2(t)} + \mathrm{f_3(t)} \ldots \mathrm{f_n(t)} + \epsilon_{ij}$$

$$\mathrm{Y_t} = \mu_t + \gamma_t + \Psi_t + \mathrm{V_t} + \varepsilon_t \quad \varepsilon_t \sim \mathrm{NID}\,(0, \sigma_\varepsilon{}^2) \qquad (1.1)$$

Where $t = 1, 2 \ldots T$

Stochastic distribution of the eqn (1.1) is

$$\mathrm{Y_t} \sim \mathrm{f}\,(\theta_k, \mathrm{T_{ik}}, \varepsilon_{tik}) => NID\,(0, \sigma_\varepsilon{}^2) \qquad (1.2)$$

μ_t = trend ; γ_t is the seasonal ; Ψ_t cyclic trend; V_t is the first order AR component and ε_t irregular or the random error associated with various economic attributes. For the purpose of short term impact of policy , the Univariate and multivariate STM are considered to be comprised of three components ; stochastic trend , seasonality and irregular .Hence , the eqn (1.1) reduces to the following mathematical form.

$Y_t = \mu_t + \gamma_t + \varepsilon_t$; $\varepsilon_t \sim NID\ (0, \sigma_\varepsilon{}^2)$ (1.3)

The stochastic trend components μ_t refers to the long term movement in a varied time series at time 't' which can be extrapolated into the future .In case of MGNERGA snap shot economic flow over a month with respect to beneficiaries it has marginally affected overall well being of the community .This long term trend shows significant gradient in the income and sustainability of the individual beneficiaries , in this intervention we modelled the above eqn (1.3) in the form of

$Y_{t-1} = \mu_{t-n+1} + \gamma_{t-1} + \varepsilon_{tn}$; $\varepsilon_t \sim NID\ (0, \sigma_{\varepsilon n}{}^2)$ (1.4)

where $t-n+1$ is the lag period at n[th] year and γ_{t-1} periodic variation of income level of beneficiaries observed over a period of time 't' (t=1,2,3..n)

$\sigma_{\varepsilon n}{}^2$ is mutually correlated with income and socio economic status

In some cases , we wish to know any significant changes with respect to economic indicators (Kuppuswamy scale of measurement 2020) demographic and livelihood of beneficiaries , the above eqn is modelled in the form of the following mathematical derivation

$Y_t = \mu_t + \gamma_t + \Psi_t + V_t + \sum_{i=1}^{j} X_i\ w_j + \varepsilon_t$; $\varepsilon_t \sim NID\ (0, \sigma_\varepsilon{}^2)$

$Y_t = \mu_t + \gamma_t + \Psi_t + V_t + \sum_{i=1}^{j} X_{i-1}\ w_{j-1} + \varepsilon_{t-n+1}$; $\varepsilon_t \sim NID\ (0, \sigma_\varepsilon{}^2)$

$Y_t = \mu_t + \gamma_t + \Psi_t + V_t + \theta_{ijk} \sum_{i=1}^{j} b\ X_{i-1}\ w_{j-1} + \varepsilon_{t-n+1}$ (1.5)

Where θ_{ij} likelihood function of i [th] beneficiary j[th] region k[th] time period

b X_{i-1} is the regression co efficient or slope of the incremental variables movement (either forward and backward direction) associated with independent variables or economic attributes and w_{j-1} weighted income appended with j[th] beneficiaries (categorised based on Kuppuswamy scale 2020).If the datasets lead to massive and obtained from various districts based on stratified sampling or clustered sampling method .The collected data can be modelled by a multivariate structural time series simulation (SMST) method where new tools or techniques were demonstrated with various attributes at singleton compilation , the newer method will allow us to test the hypothesis and predict the future data without any critics , contemporoeusly correlated the dependent and independent variables at greatest accuracy and reproducibility .The eqn (1.5) becomes Y_t is NXN depended variable or observations which depends on unobserved trend components μ_t ; γ_t is seasonal components and irregular components; θ_{ijk} likelihood function associated with independent or exogenous variables and ε_t is the error components and b is the regression co efficient which is extracted from the original time series data sets.

$$\begin{bmatrix} Y_1 \\ Y_2 \\ \cdot \\ \cdot \\ Y_t \end{bmatrix}_{nx1} = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \cdot \\ \cdot \\ \mu_t \end{bmatrix} + \begin{bmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} \\ \gamma_{21} & \gamma_{22} & \gamma_{23} \\ \gamma_{32} & \gamma_{32} & \gamma_{33} \end{bmatrix} + \begin{bmatrix} \Psi_1 \\ \Psi_2 \\ \cdot \\ \cdot \\ \Psi_t \end{bmatrix} + V_t \ x\ \theta_{ijk} \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \\ \cdot \\ \cdot \\ w_t \end{bmatrix} x \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \cdot \\ \cdot \\ \varepsilon_t \end{bmatrix} \quad (1.6)$$

From eqn (1.6) we smoothened the observations and predicted the future values

$Y_t = \mu_t + \gamma_t + \Psi_t + V_t + \theta_{ijk} \sum_{i=1}^{j} b\ X_{i-1}\ w_{j-1} + \varepsilon_{t-n+1}$ (1.7)

$\widehat{Y_t} = \widehat{\mu_t} + \widehat{\gamma_t} + \widehat{\Psi_t} + \widehat{V_t} + \widehat{\theta_{ijk}} \sum_{i=1}^{j} b\ X_{i-1}\ w_{j-1} + \hat{\varepsilon}_{t-n+1}$ (1.8)

We applied Durbin Watson Diagnostic test for testing the seasonal and cyclic trend of unobserved data from various error components

$D = \frac{\sum_{i=0}^{n}(\varepsilon_i - \hat{\varepsilon}_i)^2}{e_i}$ The possible $0 < D < 4$

If 'D' closed to 2 or less , then hypothetical findings and predictions is really true and reject the null hypothesis

If 'D' value > 2, then hypothetical findings and predictions is really not true and accept the null hypothesis

Results:-

Table 1:- Income level of MGNREG beneficiaries in Karnataka state –decompose with age, livelihood, CPI and other associated state variable (Structural time series stochastic model - Lag period 3 months).

Parameter	Estimated Value	SD

rate	0.00064	0.00011

Structural Time Series Model -- Interpolation					
t	Observed Value (Lakhs in Rupees)	Level (Rupees)	Slope (Rupees)	Seasonal (Rupees)	Stand. Residuals
BLR (Ur)	732	732	0	0	0
BLR (R)	786	756.30	2.456	2.45	0.061
Chitradurga	1420	1041.6	22.68	22.68	0.836
Kolar	1204	1113.14	25.33	25.33	0.15
Shivamoga	1962	1465.75	39.63	39.63	1.04
Tumkur	2472	1881.36	53.63	53.63	1.21
Mysore	1894	1896.87	52.37	52.37	-0.124
Chikkamagaluru	1704	1829.8	48.737	48.73	-0.39
DK	1585	1741.63	44.82	44.82	-0.453
Hassan	1962	1838.66	46.24	46.24	0.173
Kodagu	750	1413.72	33.93	33.93	-1.56
Mandya	1798	1573.77	37.11	37.11	0.420
Belagaum	3886	2278.46	-36.231	398.54	3.11
Bijapur	1642	1985.44	-46.53	-46.53	-0.70
Dharwad	987	1772.49	-41.71	-41.71	-1.67
Uttarkannada	1587	1690.0	-42.40	-42.40	-0.135
Gulberga	1792	1721.90	-41.26	-41.260	0.24
Bellary	1543	1642.39	-41.81	-41.81	-0.12
Bidar	1389	1533.29	-42.73	-42.73	-0.22
Raichur	1391	1468.05	-43.03	-43.03	-0.075
Yadgiri	957	1256.78	-45.22	-45.22	-0.56
Davanagere	1567	1370.11	-43.20	-43.20	0.535
Ramaganaram	1000	1078.03	-30.63	336.93	-0.99
CB Pura	1115	1089.72	-29.53	-29.53	0.12
Chamarajanagar	940	1022.92	-30.25	-30.25	-0.119
Udupi	1143	1065.38	-29.15	-29.15	0.239
BagalKote	1309	1156.66	-27.63	-27.63	0.402
Gadag	829	1020.88	-28.83	-28.83	-0.36
Haveri	1596	1242.64	-26.30	-26.30	0.84
Koppal	1111	1185.08	-26.59	-26.59	-0.105
Total	44053	42864.82			

Table 2:- Expected income for MGNREG beneficiaries (12 months period March 2020 to April 2021) lag 3 months.

Structural Time Series Model -- Extrapolation			
t	Observed (Rupees /per respondent)	Level Rupees per respondent)	Seasonal Differences (Rupees)
Jan	1099.08	1401.32	-302.23
Feb	1254.21	1490.74	-236.53
Mar	814.07	1580.17	-766.09
April	1825.38	1669.60	155.78
May	2077.39	1759.02	318.37
Jun	2083.37	1848.45	234.92
Jul	2377.60	1937.880	439.72
Aug	2168.94	2027.306	141.64
Sep	2207.49	2116.73	90.761
Oct	1983.18	2206.15	-222.97

Nov	2639.53	2295.58	343.951
Dec	2187.70	2385.01	-197.30
Total	22717.94	22717.96	0.022

The table (1&2) depicts several data points predicted by STM model and is worth noting. The two intervention seasonal , cyclic trend was found to be statistically insignificant with 5% level of significance and the cycle loop will explain most of the model variations , which is implied by the slope and seasonal variation (table 1.1) accord with the standard residual , the results clearly observed that, the residual data points being expressed as negative data points with greatest epoch for predicting the cyclical trend and seasonal differences. Extrapolation of the predicted values is very easy from the formulated model and also error components are ignorable (Durbin Watson statistics D=2) .All predicted data points were not being expressed as irregular components (zero) , which can explain that all variations in the income level of MGNREGA periodic variation was generated with absence of cyclic intervention ($p<0.05$).The prediction of data points were succeeded be Durbin Watson test and found to be significant which coincides with actual data sets for the post period , the null hypothesis was rejected, i.e after induction of policy, all respondents were benefited and their livelihood status has been improved over a period of time. The Fig (1.1 & 1.2) of each components inculcate more intuitive information about the time varying structural time series model

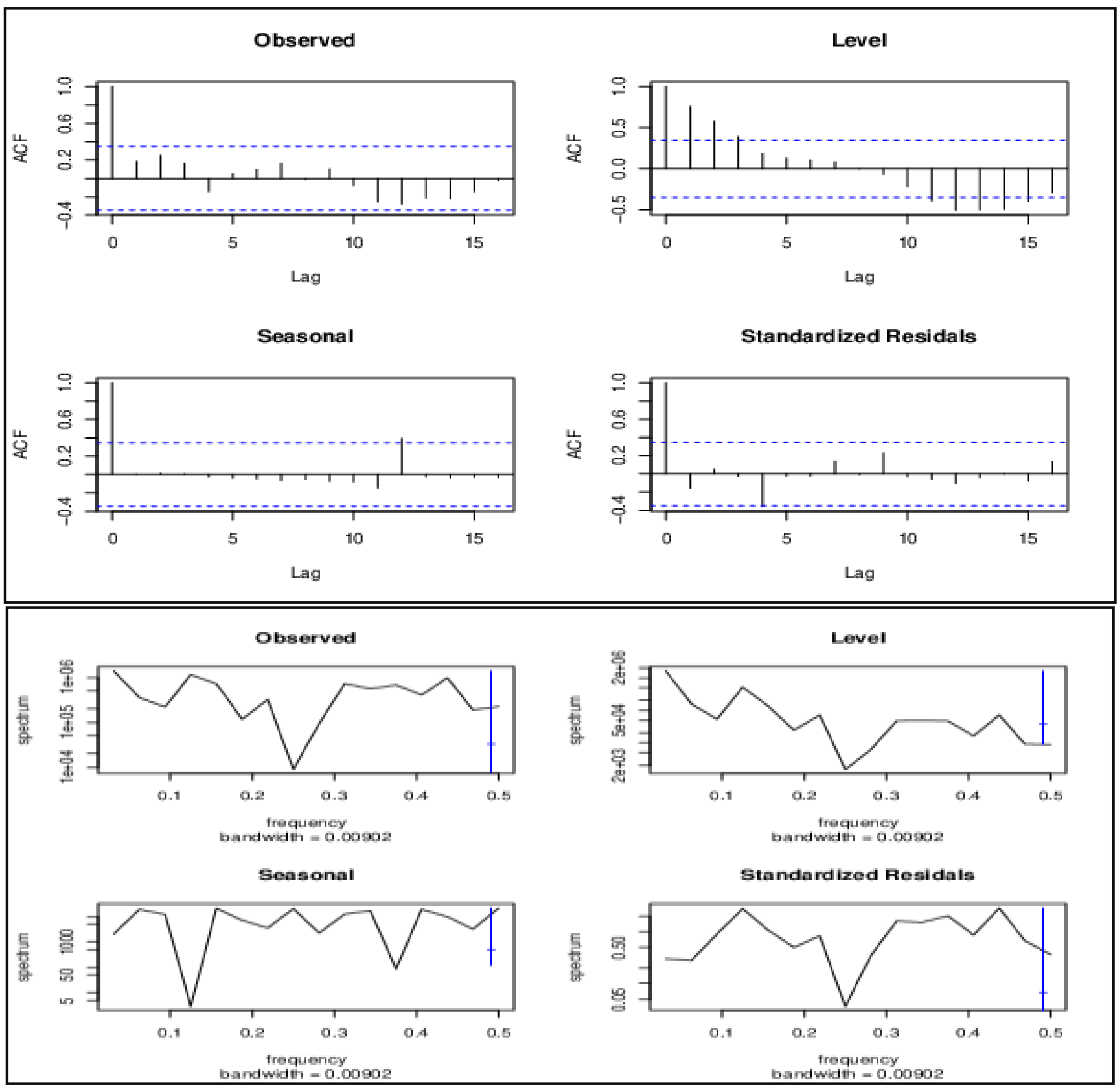

Fig.1.1:- Various income trends of MGNREG beneficiaries.

Fig 1.1 shows graphs for each components of trend , the slope of the curve varies a fewer ,which makes the trend become more stochastic. From the above cited graphs of the observed and seasonal trend components with respect age, socioeconomic standards were found to be significantly correlated , all respondents livelihood status was improved marginally with an average ACF (0.20) that means (20%) of livelihood status has been toll . During the study period and from inherent data sets we noticed that MGREGA beneficiary forwarded upstream development for providing education to the children, purchasing of needy commodities and procurement of agricultural implementation from the earned income MGNREG wage employment programme. It is interesting to compare the results with the report of National Bureau of Economics Research , which represents the clear and real data at population level.

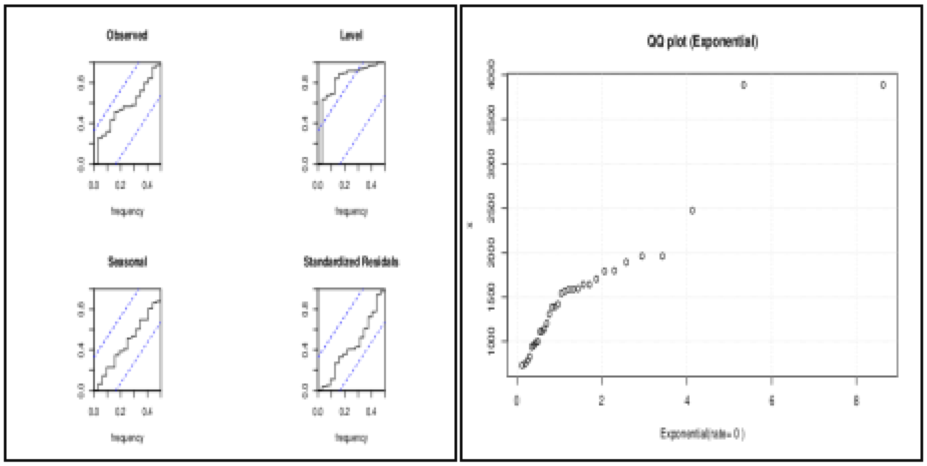

Fig 1.2:- QQ plot exponential trend or distribution of Income.

The automatically selected interventions were decomposed when we include them into model. STMP will be able to detect movement s in the income level of MGNREGA respondents by testing the normality of the residuals of each components or selected variables (Fig 1.4) and also tested exponential distribution of income gain of (Fig 1.2) shows ,the income level was significantly correlated after the participation in the developmental MGNREGA programme. Since, the programme has realized positively that an intervention in a construction of new houses with support of other state programmes .This means that there is an explained movement in the formulated model .The biggest shortcoming of a fitted model is that we filter the income level by frequentisitc approach and reproducibility of generating results takes more time and epoch , because we have substituted the covariance components in the formulated model. The intervention of Bangalore rural , Chitradurga ,Kolar , Shivamoga and Tumkur resulted average income level is more stochastic trend by means of change in slope variance . As we noted that, the model application is somewhat clear for sure ,since we should identify the background problems of beneficiaries to increase the levels as well as outlier expenditure form the MNGREG programme.

Table 3:- Autocorrelation function (ACF) and Partial auto correlation function (PACF) income level of beneficiaries.

Autocorrelation Function				Partial Autocorrelation Function		
Time lag k	ACF(k)	t-Stat	P-value	PACF(k)	t-Stat	P-value
1	0.227701	1.2472	0.110993	0.227701	1.2472	0.110993
2	-0.113775	-0.6232	0.268941	-0.174679	-0.9568	0.173169
3	0.166138	0.91	0.185045	0.257114	1.4083	0.084665
4	0.112173	0.6144	0.271793	-0.030252	-0.1657	0.434753
5	-0.020596	-0.1128	0.455466	0.02609	0.1429	0.443661
6	0.022785	0.1248	0.450757	0.003038	0.0166	0.493417
7	0.22788	1.2481	0.110816	0.225381	1.2345	0.113306
8	-0.039722	-0.2176	0.414621	-0.200112	-1.0961	0.140887
9	-0.050716	-0.2778	0.391542	0.129144	0.7073	0.242404
10	-0.046972	-0.2573	0.399361	-0.258197	-1.4142	0.083799

11	-0.252079	-1.3807	0.088787	-0.152582	-0.8357	0.204958
12	-0.251397	-1.377	0.089357	-0.241847	-1.3246	0.097645
13	-0.073988	-0.4052	0.344085	0.047495	0.2601	0.398266
14	-0.055889	-0.3061	0.380814	-0.175151	-0.9593	0.172528

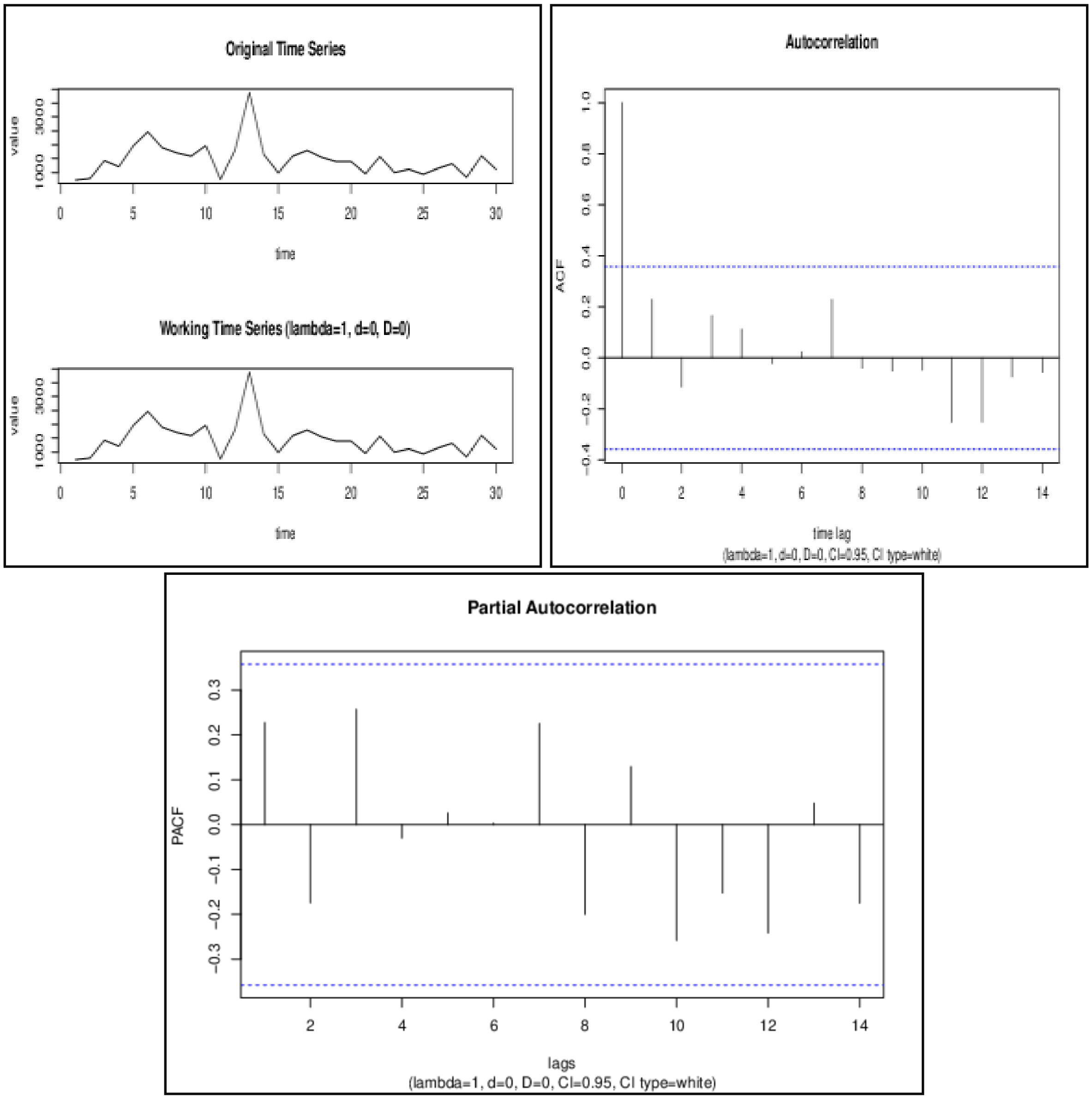

Fig 1.3:- ACF and PCF of income data sets.

Table 3:- Economic status –assessed by Kuppuswamy revised scale -2020.

Total score	SES	Ramanagaram	Tumkur	Hassan	Total
26-29	Upper class	3(1.05%)	1(0.35%)	2(0.70%)	6(2.11%)
16-25	Upper middle	5(1.75%)	2(0.70%)	3(1.05%)	10(3.51%)
11-15	Lower middle	10(3.51%)	8(2.81%)	11(3.86%)	29(10.18%)
5-10	Upper lower	31(10.88%)	35(12.28%)	36(12.63%)	102(35.79%)
<5	Lower	46(16.14%)	49(17.19%)	43(15.09%)	138(48.42%)

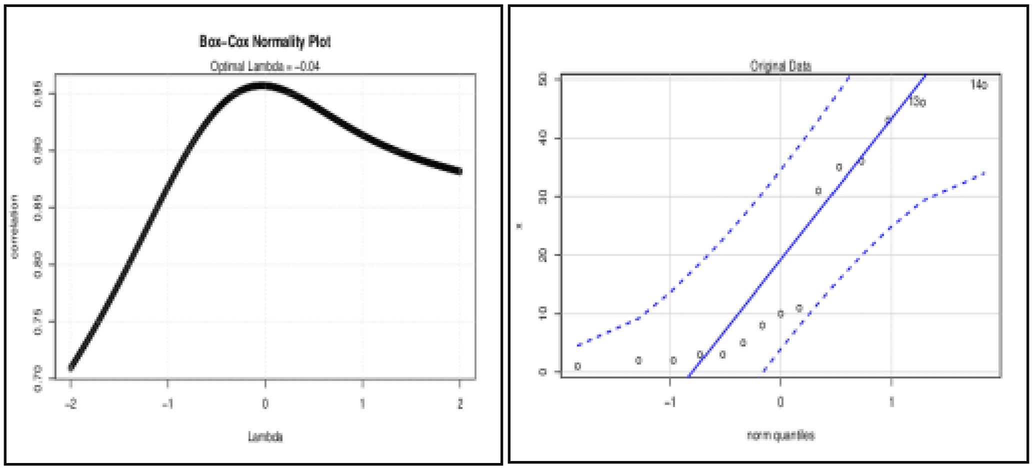

Fig 1.4:- Box –Cox normality curve (Gaussianity).

The STM stochastic model is quite sensitive to the data as we have noticed before , we obtain different models by including an intervention. After examination of real data sets of MGNREGA income and social changes , it is clear that we must take into consideration the key role played by the acyclic components for the prediction or simulation of real values .When we use STM to forecast the cyclic movement of small and massive data to extrapolate the accurate trend in association with demographical parameter and also estimate the likelihood ratio function from the formulated model. We suggest that, using the forecasted growth rate for future prediction in the STM by using massive data which while include information from both trend cycle .

Table 4:- Family Income of the MGNREG participants (Kuppuswamy revised scale 2020).

Family Income	Score	No	%	P-value
≥2000	12	8	2.81	≥0.05
1000-1999	10	6	2.11	≥0.05
750-999	6	11	3.86	≥0.05
500-749	4	25	8.77	≥0.05
300-499	3	125	43.86	≥0.05
101-299	2	98	34.39	≥0.05
<100	1	12	4.21	≥0.05
	Total	285	100.00	

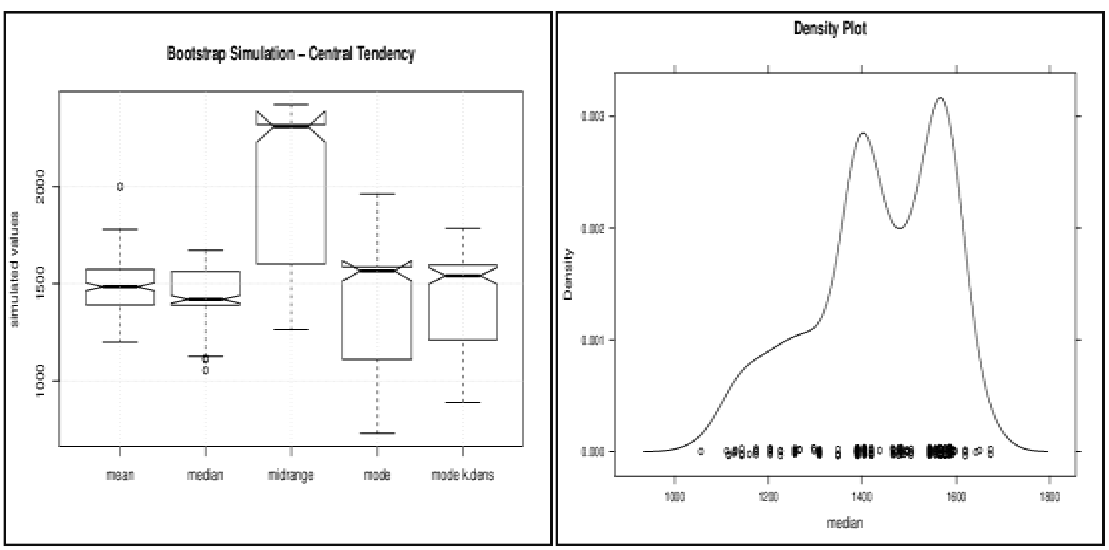

Fig 1.5:- Income level of beneficiaries estimated by Bootstrap techniques with combined variables.

New income value =2.86*(old value x 4.63x4.93); All India average CPI for Industrial workers in 2018-2019

$$\text{Total monthly income} = \frac{\text{Total average monthly Income of family}}{\text{Total average number of members in family}}$$

$$\text{Total monthly income} = \frac{1529}{6}$$

$$\text{Total monthly income} = 254.25$$

Total income annually = 12*254.25 = Rupees 3058

New income value = 2.86*(105 x 4.63 x 4.93)

NIV = Rupees 6854.61 income of the family after participation of MNREGA programme.

Consumer price Index (CPI) = $\frac{\text{Cost of market in a given year}}{\text{Cost of market basket at base year}} x100$

Consumer price Index (CPI) = $\frac{\text{Cost of market in a given year (t)}}{\text{Cost of market basket at base year (t0)}} x100$

Price Index (I) = P_1/P_0 *100

P_0 = Price at base time P_1 : Current price

$PI = \prod_{I=1}^{N} \left(\frac{P_n{}^1}{P_n{}^0}\right)^{1/N}$ Where, $P_n{}^1$ is the price of item n(n=1...N) in period 1

$P_n{}^0$ is the price of item n(n=1...N) in base period

Iy (Relative index) =$\frac{Y_t}{Y_0}$x100

Where Iy =Index number of commodity

Y_t = Value of commodity Y at time 't'

Y_0 = Value of commodity in Y at base

Simple CPI= $\frac{\text{Current year index of all purchased items}}{\text{Number of items purchased by the respondents}}$

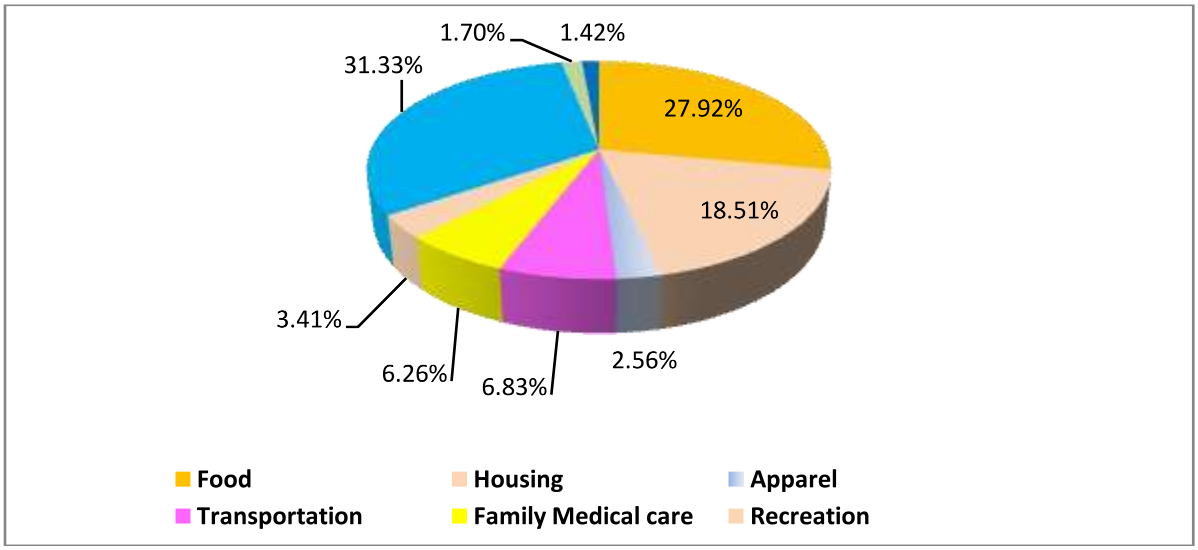

Fig 1.6:- Percentage variation of Income shared different components by the MGNREG beneficiaries.

Rate of inflation = $\frac{CPI_{x+1} - CPI_x}{CPI_x}$

Where, CPI_x is Consumer Price Index of Initial Year and ; CPI_{x+1} is Consumer Price Index of next year.In certain cases , we need to calculate the rate of average inflation over a number of years .The formula is

$CPI_{x+1} = CPI_x * (1 + r)^n$ Where CPI_x is Consumer Price Index , n is the number of years after initial CPI year; CPI_{x+1} is the consumer price index of n years after the initial CPI year, r is the rate of interest

Cost of each items = Price of each items purchased by beneficiaries * Quantity of goods

Discussion:-

The structural stochastic time series model originally based on the advanced decomposition into various trends of time series data , the formulated model is very easy for the estimation of seasonal and irregular components in correlation with various components (Stephen et al. 2013; Vardharajan et al. 2013). A number of methods were included for the estimation of likelihood estimation by using real time series massive data sets (Harvey et al. 1989; Beveridge et al .1981) . These include direct maximization of various economic attributes which are collected from the survey or micro economic traits. The asymptotic properties of the estimation can be easily reproduced by adding multiple parameters at a time . Prediction of the model is more epoch and comparison between the various methods in terms of computational efficiency and accuracy has been made by considering explanatory variables and algebraically extended to propagate new intervention of micro economic studies at full-blown (Francois et al. 2006; Harvey et al. 1989;2006; Jolta et al. 1970). In recent advances, econometrician have demonstrated traditional STM model for prediction with short term stationary series. Since, the present formulated model faintly describes overall trend components in lucid manner, than we need process to extrapolate the newer figures subsequently without any loss of information. Most of the stationary stochastic process model examines or estimates the breakup points or trends .Instead ,they are highly persistent and integrated in the process that are sometimes called stochastic trend (Kay et al. 2015; Kushreshtha et al. 1972; Kuppuswmay ,1981). The STM estimated likelihood function associated with linearity of Gaussian distribution, deterministic trend was extracted from the driven time series data. Integrated process can be made stationary by taking differences over the observed and theoretical frequencies (Lehel et al. 2002; Prasad et al.1961; Parikh et al. 1964). Although , the simple time variable of survey data sets has been extracted and compiled with satisfactory options for time series data of any frequencies .The driven model is capable of customizing the time state variable with variety of associated economic indicators obtained from various time intervals (monthly, quarterly and yearly basis) it is being the ones commonly used by the economists and policy makers. As per the scientific term structural time series stochastic model "briefly describes various classes of parametric models that are specified directly in terms of unobserved components which capture essential features of the time economic series , the present model greatly estimates the trends of MGNREGA national programme impart to assess the socioeconomic changes and livelihood status of economically weaker section population .The cited literature (Harvey et al.2006) briefly narrates the entire empirical findings and practicability of STM model substituted many economic cofounders to know the relative economic changes and impact of participation level of various policies (MGNREGA) with respect to incremental derivation of state variables and varied stationary points. However, one of the important challenges we have faced by the economists is to break the hypothetical statements for characterizing the dynamic behaviour of micro and macro economic variables , such as output of income , unemployment, inflation and assessment of government policy through survey based mechanisms triggered separate trend cycles, as such decomposition of economic time series has a long tradition , dating back to the century , in this precipitation newer analytical models are very essential for estimation of accurate interventions for testing the null hypothesis. The underlying idea and mechanism of modelling is very easy to estimate the trends and cycles , that can be ascribed to different mechanisms and understanding of their real determinants to help us refine the policy targets and provide formidable measures for implementation of policy .

Conclusion:-

In present study we have proposed a Stochastic random state varied structural time series model for dealing with the estimation of unobservable data points (eg income level , economic feasibility and livelihood status of beneficiaries of MGNREGA in selected sites of Karnataka State) formulated model that helps us to estimate the likelihood and forecasting figures in the presence of related explanatory state variables (SES) . We evaluated the forecast performance of formulated model by using simulated and empirical methods , we found that, the demonstrated model is very robust in nature and support to extrapolate the predicted figures accurately without any bias. This superior performance has been attributed mainly to the following few points. Firstly, the driven model logically derives its own strength in forecasting from the real fact of national policy intervention ,incepted at rural areas , that is incorporate necessary information about other associated variables ,rather than merely historical absolute values of its own paradigm. Secondly , model benefits from taking relationships among multiple unobservable and observable components obtained from the stationary series which helps boost the forecasting figures of both known and unknown parameters. Therefore , this model is obtained as expected and is able to provide more accurate forecasts of both seasonal time series of economic massive data sets. Model is excellent in reproducibility and derives on time performance for economists for assessing the economic level from short and long-term stationeries, the model comes with high computation requirements in any unfold iteration and algebraic equations. In addition to that , newer techniques clearly signifies that one would also not expect this model to show more advanced merits over the other traditional time series model , when multiple unobserved components target the series that are independent of each other. The driven demonstrated new model is very useful for the economists, policy makers to draw and formulate the new policy effectively at national level.

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