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FORECASTING OF AIR TEMPERATURE OF WESTERN PART OF MAHARASHTRA, INDIA

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Abstract: The Seasonal ARIMA time series model is fitted to the monthly average maximum and minimum temperature data sets collected at Desh part region of Maharashtra, India for the years 1969-2018. From the time series analysis, observed that patterns of both the series are quite different (*i.e.* maximum and minimum temperature) and therefore both the series are modeled separately by using Box and Jenkins Method. The daily values of temperatures were collected from ADR, NRCP, Solapur and IMD, Pune for 50 years. These daily values converted in weekly temperature values were used to fit the ARIMA models and SARIMA models of 1st order were selected based on autocorrelation function (ACF) and partial autocorrelation function (PACF). The parameters of the selected models were obtained with the help of maximum-likelihood method. The diagnostic checking of the selected models was then performed with the help of three tests to know the adequacy of the selected models. The **SARIMA** models that passed the adequacy test were selected for forecasting. One year a head forecast (*i.e.* for 2018) of temperature values were obtained with the help of these selected models and compared with the values of temperature obtained from the weather data of 2017 by root mean square error (RMSE).

The results from an analysis shows that, the 1st order model fitted is **SARIMA (0,0,1) $(1,1,0)_{52}$ and SARIMA (0,0,1) $(0,1,1)_{52}$** for maximum and minimum temperature hence, is the best model for forecasting of weekly temperature values. These values would be useful for the appropriate temperature for this forecasting study is towards extreme weather prediction and extreme value analysis would be an approach to predict such external events in western part of Maharashtra regions, India.

Keywords: Maximum and Minimum temperature**,** Time series, Generation, Forecasting and SARIMA Model.

INTRODUCTION

The application of statistical techniques is crucial in understanding phenomena and greatly influences decision making. The air temperature is one of the most important meteorological parameters for climate impact studies, environmental, hydrological, ecological and agricultural/horticultural point of view. Modeling the variability of surface air temperature and producing reliable forecasts underlie the foundation of sound agricultural policies, particularly important for the western part of India because the income of major portion of the local people is low and completely depends on agricultural/horticulture. Moreover,

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temperature is critical input parameter in many eco-environmental models in the fields of crop growth simulation (Verdoodt et al., 2004; Bechini et al., 2006); agro-ecological zoning (Caldiz et al., 2001; Ye et al., 2008) and food security assessment (Ye and Van Ranst, 2009; Ye et al., 2012). Policy analysis using these eco-system models is only possible with an accurate prediction of future temperatures. Several efforts have been made in statistical time series modeling of temperature variations using weekly, monthly average records (Hansen et al., 2006; Rahmstorf et al., 2007). Among them, the univariate time series models gave relative popularity in recent years, partly due to the complexity of mainstream climate models, which are strongly constrained by the current knowledge of the physical climate system (IPCC, 2003). One subcategory univariate models, namely the structural time series models (Lee and Sohn, 2007), has become quite popular due to its trend detecting capability.

Several time series models have been developed in past for modeling of hydrological data *i.e.* runoff, humidity, river flow, evaporation, temperature etc. These include autoregressive (AR) models of different orders (Davis and Rapport, 1974; Salas *et al.* 1980; Kamte and Dahile, 1984; Gorantiwar *et al.* 1995; Narulkar, 1995; Samani *et al.* 1995; Singh, 1998; Reddy and Kumar, 1999; Susbhuaiah and Sahu, 2002 and Patil, 2003), moving average (MA) models for different orders (Gupta and Kumar, 1994 and Verma, 2004), autoregressive moving average (ARMA) models of different orders (Katz and Skaggs, 1981; Srinivasan, 1995; Sharma and Kumar, 1998; Chhajed, 2004 and Katimon and Demon, 2004) for annual stream flow. For monthly or intra-seasonal flows, seasonal or periodic autoregressive integrated moving average (ARIMA) model (Bender and Simonovle, 1994; and Montanari *et al.,* 2000; Trawinski and Mackay, 2008; Khajavi *et al*., 2012; Meshram *et al*., 2012) and fractionally difference ARIMA models (Montanari *et al.*1997) were used.

The models used for generation and forecasting of the annual runoff and evaporation series were AR, MA and ARMA models of different orders. The models SARIMA, PARMA and FARIMA were used for seasonal and periodic runoff and evaporation series. The above stated studies indicated that the time series models were successfully used for the generation of the synthetic sequence of runoff, temperature and evaporation. The SARIMA models showed the ability to forecast other hydrological events such as runoff, evaporation and temperature and finally the appropriate SARIMA model was found for the forecast of weekly maximum and minimum temperature values

In the present study, an attempt has been made to forecast maximum and minimum temperature using weather data (169-2017) for Desh part of Solapur regions, Maharashtra, India. The study describes the stages involved in fitting SARIMA 1^{st} class of models to surface temperature results of application of SARIMA models to surface temperature and an identified appropriate SARIMA model in 1^{st} order. The output of this study will be useful for planning the water resources and the supplemental or life saving irrigations for horticulture and other crops.

MATERIAL AND METHODS

This study was concerned with the forecasting of surface temperature by using SARIMA class 1^{st} order models. The temperature data was used from historical weather data (1969-2018). This section describes the temperature, SARIMA model and stages involved in development of SARIMA model.

Data used: **T**he daily data in respect of maximum ($T_{max,}$ ^{0}C) and minimum ($T_{min,}$ ^{0}C), temperature were collected for 50 years from Agricultural Dry Land Research Center and ICAR-NRC on Pomegranate, Solapur and Indian Meteorological Department, Pune. The maximum and minimum temperature ranged from 24.04 to 43.81^{0}C and 09.30 to 29.6^{0}C and it's mentioned in **Fig.1.**

SARIMA Model

Seasonal autoregressive integrated moving average (SARIMA) are useful for modeling seasonal time series in which the mean and other statistics for a given season are not stationary across the year. The basic ARIMA model in its seasonal form is described as (Hipel *et al.* 1977, Box and Jenkins, 1976 and 1994) a straightforward extension of the non-seasonal ARMA and ARIMA models. A time series involving seasonal data will have relations at a specific lag s which depends on the nature of the data, e.g. for monthly data s = 12 and weekly s = 52. Such series can be successfully modeled only if the model includes the connections with the seasonal lag as well. Such models are known as multiplicative or seasonal ARIMA (SARIMA) models. The general multiplicative seasonal ARIMA (p, d, q) $(P,D,Q)_s$ model has the following form.

Let $Z_{1,}$ Z_2 --------Z_n be a discrete time series measure at approximately equal time intervals. An ARIMA model is given as

$$\boldsymbol{\varphi(B)\Theta(B)^s w_t} \\ \boldsymbol{= \theta(B^S)e} \qquad (\mathbf{1})$$

Where, w_t is a stationary series obtained by differencing the original series, Z_t

Equation 1 can also be written as

$$\varphi(B)\Theta(B)^s\nabla^d\nabla_S{}^D z_t = \theta(B^S)e_t \quad (2)$$

Where, e_t is normal independently distributed white noise residual series with mean zero and variance σ^2, B is the backward shift operator, Φ *and* Θ described an ARIMA structures between seasonal observations, ϕ *and* θ describe a within period ARIMA structure which accounts for week to week dynamics. $\phi(B)$ is the non seasonal autoregressive operator or polynomial of order p and is represented by

$$\varphi(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \ldots\ldots\ldots\ldots\ldots\ldots - \varphi_P B^P \quad (3)$$

Similarly,

$$\Phi(B^s) = 1 - \Phi_1 B^S - \varphi_2 B^{2S} - \cdots\ldots\ldots\ldots\ldots\Phi_P B^{ps} \quad (4)$$

$\theta(B)$ is the non seasonal moving average (MA) operator or polynomial of order q;

$\Theta(B^s)$ is the seasonal MA operator of order Q. $\theta(B) and \Theta(B^s)$ are expressed as:

$$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \ldots\ldots\ldots. -\theta_q B^q \quad (5)$$

$$\Phi(B^s) = 1 - \theta_1 B^s - \theta_2 B^{2s} - \ldots\ldots\ldots. -\theta_Q B^{QS} \quad (6)$$

∇^d *and* $\nabla^D{}_s$ are the non seasonal and seasonal differencing operators of order d and D, respectively, and are represented by

$$\nabla^d = (1 - B)^d \quad (7)$$

$$\nabla^D{}_S = (1 - B^S)^D \quad (8)$$

"S" indicates the length of seasonality and is equal to 52 for weekly ET_r series.

Development of SARIMA Model: The different styles involved in fitting of SARIMA models to historical hydrological series as suggested by Hipel *et al.,*1977 and Box and Jenkins, 1994 are (i) Standardization and normalization of time series variables; (ii) Identification of the models; (iii) Determination of the parameters of selected models; (iv) Diagnostic checking and (v) Selection of the model.

(i) Standardization and normalization of time series variables**:** The first step in time series modeling is too standardized and transforms the time series. In general the standardization is performed by normalizing the series as follows.

$$y_{i,j} = \frac{x_{i,j} - x_i}{\sigma_i} \quad (9)$$

Where,

$y_{i,j}$ – Stationary stochastic component in the mean and variables for week I or the year j; $x_{i,j}$ – Weekly reference crop evapotranspiration in the week I of the year j; x_i – Weekly mean and σi – Weekly standard deviation

(ii) Identification of the model: The first and foremost important step in the modeling is the identification of the tentative model type to be fitted to the data set. In the proposed study the procedure stated by Hipel *et al.* (1994) were adopted for identifying the possible ARIMA models. A time series with the seasonal variation may be considered stationary if the theoretical autocorrelation function (ρ_k) and theoretical partial autocorrelation function (ρ_{kk}) are zero after a lag k = 2s + 2 (Where‘s’ is the seasonal period; in this study, s=52). The requirement of identification procedure is as: *i.e.* Plot of the original series, Plot of the standardized series, Autocorrelation function (ACF) analysis and Partial autocorrelation function (PACF) analysis. The estimates of theoretical autocorrelation function (e_m) i.e. r_m is given by equation (10). The autocorrelation function will vary between -1 and +1, with values near ± 1 indicating stronger correlation.

$$r_m = \frac{\sum_{i=1}^{n-m}(x_i - \bar{x})(x_{i+m} - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \quad (10)$$

Where,

n – The number of observations; $\bar{x}$ - The average of the observations and r_m - Autocorrelation function at lag m

The estimate of theoretical partial autocorrelation function (e_{kk}) i.e. Φ_{mm} is given by the equation (11). The partial autocorrelation function will vary between – 1 and +1, with values near ± 1indicating stronger correlation. The partial autocorrelation function removes the effect of shorter lag autocorrelation from the correlation estimates at longer lags.

$$\Phi_{mm} = \frac{r_{m-\sum_{j-1}^{m-1}\Phi_{m-1,j}r_{m-1}}}{1-\sum_{j-1}^{m-1}\Phi_{m-1,j}r_j} \quad (11)$$

Where,

Φ_{mm} −Partial autocorrelation function at lag k

It is considered that ρ_k and ρ_{kk} equal to zero if (Maier and Dandy, 1995)

$$\rho_k = 0 \text{ i.e. } |r_k| \leq \frac{2}{T^{0.5}} \quad (12)$$

$$\rho_{kk} = 0 \text{ i.e. } |r_{kk}| \leq \frac{2}{T^{0.5}} \quad (13)$$

Where,

r_k - Sample autocorrelation at lag k; r_{kk} - sample autocorrelation at lag k; and T – Number of observation

If the sample autocorrelation function (ACF) of analyzed series does not meet the above condition, the time series needs to the transformed into a stationary one using different differencing schemes. For example, for (d = 0, D = 1, s = 52) according to the expression given by equation (13)

$$y_t = (1 - B)^d\ (1 - B^x)^D\ x_t = (1 - B^{12})$$

$$ET_{0,t} \quad (14)$$

The time series y_t is stationary, if the ACF and PACF cut off at lags less than k = (2s + 2) seasonal periods. Thus, it is necessary to test the stationary of the transformed time series obtained by differencing the original times series according to different orders of differencing (non seasonal and seasonal). The differenced series that pass the stationary criteria needs to be considered for further analysis. Thus on the basis of information obtained from the ACF and PACF, several forms of the SARIMA model need to the identified tentatively.

(iii)Estimation of parameters of the model: After the identification of model, the parameters of the selected models were estimated. The parameters of the identified models are estimated by the statistical analysis of the data series. The most popular of the approaches of the parameters estimation is the method of maximum likelihood.

(iv)Diagnostic checking of the model: Once a model has been selected and parameters calculated, the adequacy of the model has to be checked. This process is called diagnostic checking. There are number of diagnostic checking methods to test the suitability of the estimated model. These include Box-Pierce method; Portmanteau lack–of–fit test and t-statistics, standard error of the models parameters, observing ACF and PACF of the residuals, Akaike Information Criteria (AIC) and Bayes Information Criteria (BIC). Nevertheless, in this study following three tests were used.

(1) ***Examination of standard error:*** A high standard error in comparison with the parameter values points out a higher uncertainty in parameter estimation which questions the stability of the model. The model is adequate, if it meets the following condition.

$$\mathbf{t} = \frac{cv}{se} > 2 \qquad (15)$$

Where,

cv – parameter value and se – standard error

(2) ***ACF and PACF of residuals:*** If the model is adequate at describing behavior of ET_r time series, the residuals of the model should not be correlated i.e. all ACF and PACF should lie within the limits calculated by equations (12) and (13) after lag k = 2s + 2, where s = number of periods.

(3) ***Akaike Information Criteria (AIC):*** For selection of the most appropriate model for forecasting ET_r series, the adequacy of the identified models was tested. The popular decision rules for diagnostic checking are the Akaike Information Criteria (AIC) (Akaike,1974). The AIC are computed as

$$\mathbf{AIC = 2k + \left(\ln\left(\frac{2\,\pi v_r}{T}\right) + 1\right)T} \qquad (16)$$

Where,

AIC – Akaike information criteria; k – Number of model parameters; vr – Residuals variance and T – Total number of observations.

(v) Selection of the most appropriate model: The following criteria are used for selecting the most appropriate model of SARIMA amongst all the models that passed the adequacy test or diagnostic checking. RMSE shows how close the actual values of temerature are with forecasted temperature. Lower the value of RMSE, superior is the model. The actual and forecast values are compared by RMSE. The root mean square error (RMSE) was estimated for each model.

$$\mathbf{RMSE} = \frac{\sqrt{\sum_{i=1}^{n}(\mathbf{T_{act}} - \mathbf{T_{for}})^2}}{\mathbf{n}} \qquad (17)$$

Where,

RMSE–Root mean square error; T_{act}–Actual value of surface temperature (^{0}C); T_{for}–Forecast value of temperature (^{0}C) and N–Total number of observation used for computing RMSE. This model that gives the least values of RMSE was selected as the most appropriate model for forecasting of Temperature.

RESULTS AND DISCUSSION

Temperature: The weekly values for 52 standard weeks from the period 1969 to 2018. The weekly values of the important statistical properties such as number of observations, mean, standard deviation, variance of maximum and minimum temperature time series are shown in **Table 1.**

Fitting of ARIMA Model: The weekly temperature values were used for generating and forecasting, development and validation for the best model. The results obtained from the study have been presented and discussed under the following heads.

Standardization and normalization of time series variables: As stated in the section of methodology, the ARIMA model has the provision to differentiate the time series. Therefore, standardization and normalization was not performed.

Identification of the model: One of the basic conditions for applying ARIMA class of models for particular time series is its stationary. The autocorrelation function (ACF) and partial autocorrelation function (PACF) were examined to known the stationary of time series.

As stated in above section, time series with seasonal variation (in this case weekly) may be considered stationary, if ACF and PACF are zero after lag k =2s+2. ACF and PACF are considered zero if they lie within the range specified by eq. (12) and (13). The ACF and PACF of temperature time series were estimated for different lags. These are shown with upper and lower limits. It is seen from Figs. that ACF lie outside the limit after lag k =2s+2 i.e. 106. Thus, SARIMA model cannot be applied to the original time series of temperature. Therefore, the time series was transformed using following differencing schemes. d= 0; D=0; d= 0; D=1;d= 1;D=0; d=1; D=1

The ACF and PACF along with the upper and lower limits as estimated by eqs. (13) and (14) are shown in Figs. 3 to 6 for above showed differencing schemes. It is observed from the Figure that ACF of d = 0, D = 1 and d = 1, D =1 lie within the limits of range specified by eqs. (12) and (13) after lag 104. However, for d=1, D=0, ACF does not lie within the limits after the lag 104. Therefore, following differencing schemes were used for developing SARIMA model for weekly temperature time series. d=0; D=0; d=1; D=1; d =0; D=1; d=1; D=1

On the basis of information obtained from ACF and PACF and using the guidelines provided in the section of methodology, the orders of autoregressive (AR) and moving average (MA) terms were identified as one. Based on this, several forms of SARIMA models were identified.

Determination of parameters of model: The following parameters of the selected models as discussed in methodology section were calculated by maximum likelihood method

1.$\emptyset_1$ 2. θ_1 3. Φ_1 4. Θ_1 5. c

The values of the parameters for all models (36 Nos.) SARIMA models are presented in Table-1.

Diagnostic checking: Once a model has been selected and parameters calculated, the adequacy of model needs to be checked. This is called diagnostic checking. There are several tests to check the adequacy of the model mentioned in the section of methodology; out of which following three tests were used: Standard error; Autocorrelation function (ACF) and Partial autocorrelation function (PACF) of residual series; Akaike Information Criteria (AIC)

Standard Error: **A** high standard error in comparison with the parameters values points out a higher uncertainty in parameters estimation which questions the stability of the model. The model is adequate if it meets the condition given by eq.(15)

The t values of equation for the models that were identified for these studies are given in Table-2. It is observed from the Table-2, out of thirty six ARIMA models that were identified 6 models each of maximum and minimum in (^{0}C) satisfied test for all the parameters.

ACF and PACF of residual series: If the model is adequate at describing behavior of evapotranspiration time series, the residuals of model should be correlated *i.e.* all ACF and PACF should lie within the limits calculated by equations (12) and (13) after lag k = 2s+2, where s = number of periods. In this case, value of k is 106. It is observed from the ACF and PACF residual series 18 models lie within the limits prescribed by eqs. (12) and (13) after lags.

Akaike Information Criteria (AIC): AIC values are computed by using procedure explained in methodology for all the thirty six identified ARIMA models and are presented in **Table-2.** The models with less AIC values are considered as the best. First ten models with less AIC that satisfy the standard error and ACF and PACF of residuals criteria as explained in methodology are selected for further validation.

Selection of the best model: Several models qualify based on the diagnostic checking explained in above section. However, for selecting the best models amongst these, the model should forecast evapotranspiration with minimum error. Hence, after passing validation test, ten models were used for generation of weekly temperature values. For this purpose, the evapotranspiration values were forecast for one year with the help of identified SARIMA models. These values were compared with the actual values for one year by calculating the root mean square error (RMSE) between them as explained in section. The RMSE values for all identified values are given in **Table-3.** It is observed from the Fig., that seasonal pattern of temperature series is maintained in generated values by all the ARIMA models.

Based on the values of RMSE, the SARIMA (0,0,1) $(1,1,0)_{52}$ and (0,0,0) $(0,1,1)_{52}$ for maximum and minimum temperature of models are selected for forecasting. The values of the parameters of the ARIMA model which is finalized for forecasting of parameters are: $\emptyset_1$ **= 0.3054,** θ_1 **= 0.9895,** Θ_1 **=0.9336 and C= -0.001**

CONCULSIONS

The maximum and minimum temperature (^{0}C) time series pertaining to Western part of Maharashtra regions has been investigated in this paper. The applicability of seasonal ARIMA model was studied and compared with actual values of maximum and minimum temperature. The SARIMA model is viable tool for forecasting the temperature. The system studies reveals that if sufficient length of data are used in model building, then frequent updating of model may not be necessary. This forecasted temperature can be advantageously used in deriving the optimal irrigation system. The **SARIMA (0,0,1) $(1,1,0)_{52}$ and (0,0,1) $(0,1,1)_{52}$** for maximum and minimum temperature gave the lower values of RMSE and hence is the best Seasonal ARIMA model for generation and forecasting of weekly temperature values. It is concluded that seasonal ARIMA models can successfully used for forecasting of temperature for having inbuilt seasonal pattern. The forecasting performance of the seasonal ARIMA model was found to be satisfactory. The main use of this forecasting study is towards extreme weather prediction and extreme value analysis would be an approach to predict such external events.

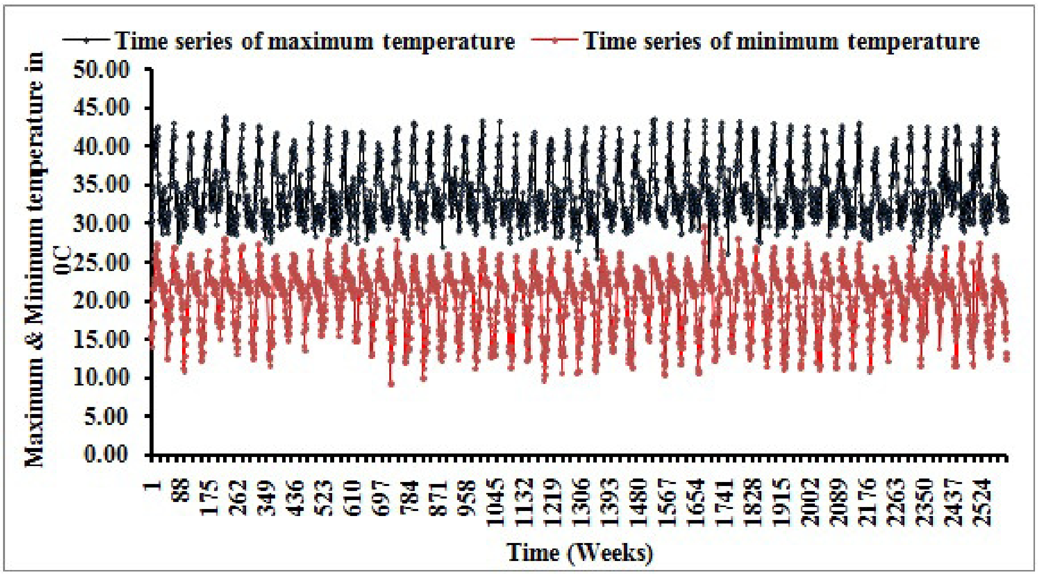

Fig. 1: Weekly maximum and minimum temperature series pertaining to Solapur region from1969 to 2018

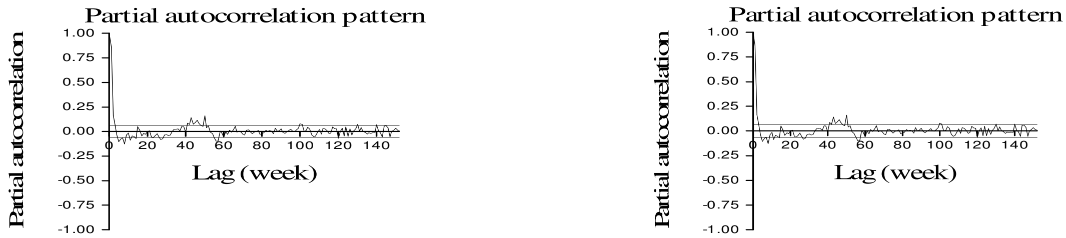

Fig. 2: Partial autocorrelation pattern and autocorrelation pattern of original time series of temperature (d=0, D=0)

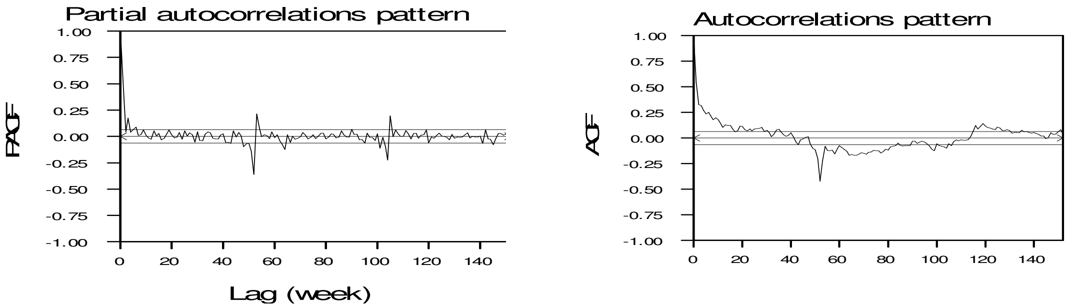

Fig. 3: Partial autocorrelation pattern and autocorrelation pattern of the differenced time series of temperature (d=0, D=1)

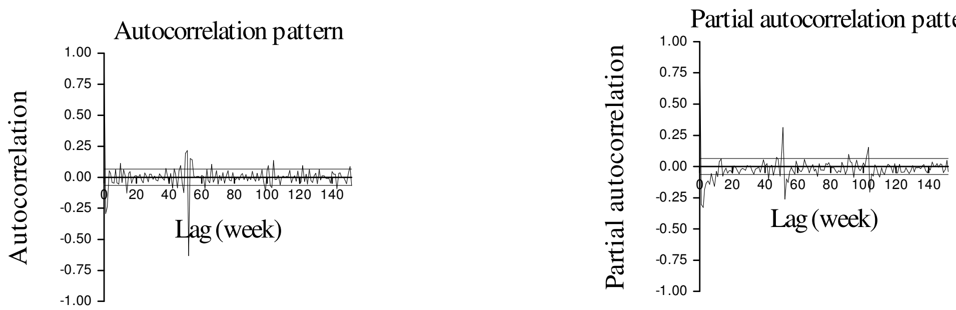

Fig. 4: Partial autocorrelation pattern and autocorrelation pattern of the differenced time series of temperature (d=1, D=0)

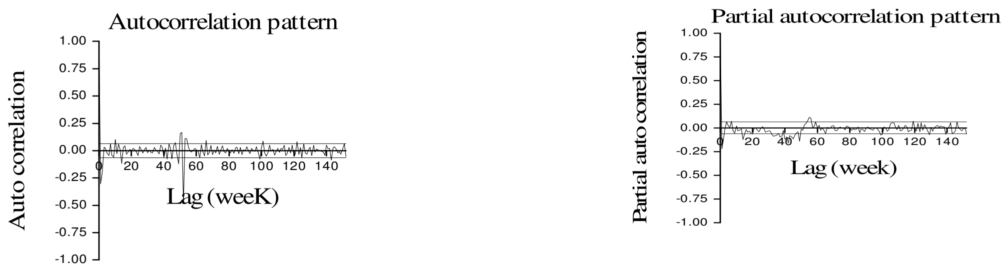

Fig. 5: Partial autocorrelation pattern and autocorrelation pattern of the differenced time series of temperature (d=1, D=1)

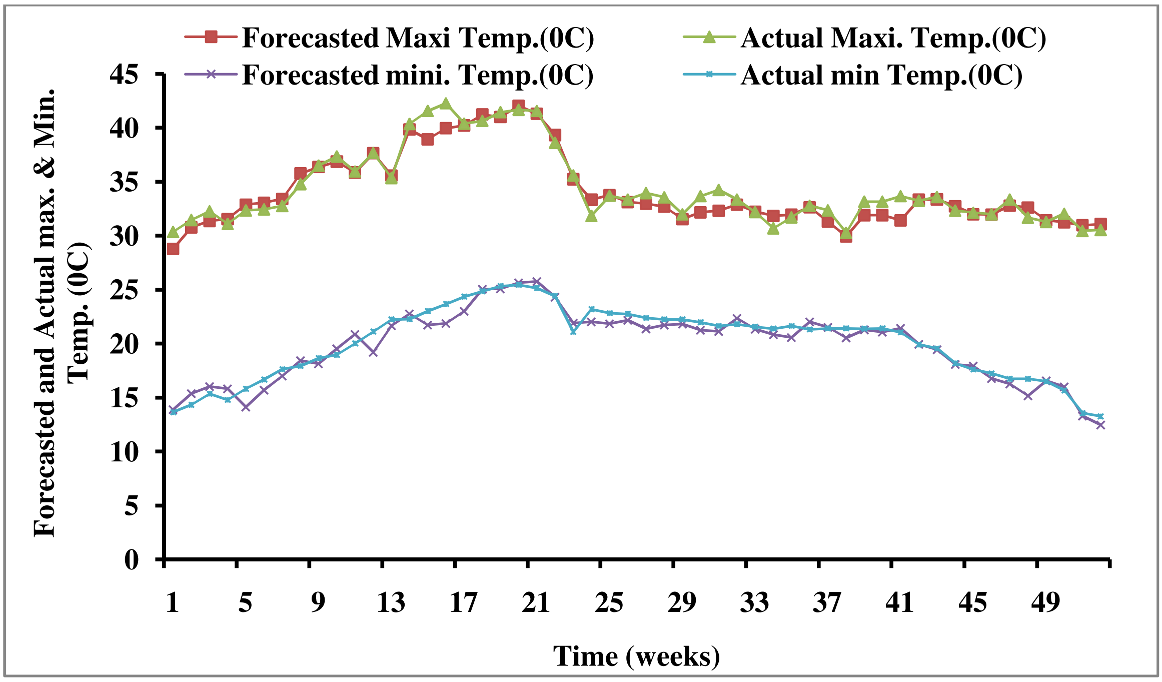

Fig. 6: Comparison of forecasted and actual maximum and minimum temperature in ^{0}C by **ARIMA (0,0 ,1)(1,1,0)$_{52}$** and **ARIMA (0,0 ,1)(0,1,1)$_{52}$** model.

Table 1: Basic statistics of weekly temperature in Solapur station (mm)

No. of observations	Mean	St.Dev.	Variance	Max.	Min.
2600	**34.20**	**3.08**	**5.25**	43.81	9.3

Table 2: Parameter estimates, standard error, corresponding t values and AIC values for different ARIMA models

Maximum Temperature (^{0}C)											
Models	$\emptyset_1$	θ_1	Φ_1	Θ_1	C	Models	$\emptyset_1$	θ_1	Φ_1	Θ_1	C
ARIMA(1,1,1)(0,1,1)$_{52}$						ARIMA(1,0,0)(1,1,1)$_{52}$					
Estimate	0.336	0.9146	0.014	0.9303	0.00212	Estimate	0.3343		0.045	0.9287	0.0001
SE	0.0366	0.0154	0.0378	0.0271	0.00353	SE	0.0307		0.0371	0.026	0.0215
t-value	9.18	59.41	0.38	34.3	0.6	t-value	10.9		1.22	34.74	0.01
AIC	6236.08					AIC	6442.37				
ARIMA(1,1,1)(1,0,1)$_{52}$						ARIMA(1,0,0)(0,0,1)$_{52}$					
Estimate	0.3499	0.9095	0.4837		0.0054	Estimate	0.3095		0.503		0.001
SE	0.0368	0.0157	0.0286		0.0175	SE	0.0311		0.0281		0.104
t-value	9.52	58.06	16.92		0.31	t-value	9.96		17.89		0.01

AIC	6529.43					AIC	6738.53				
ARIMA(0,1,1)(0,1,1)$_{52}$						ARIMA(0,0,1)(1,0,0)$_{52}$					
Estimate	0.3006	0.8251	0.99588	0.9159	0.003	Estimate	0.3054		0.9895	0.9336	0.001
SE	0.0412	0.0244	0.00688	0.0162	0.155	SE	0.03		0.0185	0.0285	0.27
t-value	7.3	33.75	0.0162	56.67	0.02	t-value	10.19		53.53	32.71	0
AIC	6293.04					AIC	6416.19				
ARIMA(0,1,1)(1,1,0)$_{52}$						**ARIMA(0,0,1)(1,1,0)$_{52}$**					
Estimate	0.158	0.4602	0.1841		0.001	**Estimate**	**0.3054**		**0.9895**	**0.9336**	**0.001**
SE	0.078	0.0691	0.0325		0.131	**SE**	**0.03**		**0.0185**	**0.0285**	**0.27**
t-value	2.02	6.66	5.67		0.01	**t-value**	**1.19**		**53.53**	**32.71**	**0**
AIC	6467.47					**AIC**	**6416.19**				
Minimum Temperature (^{0}C)											
ARIMA(0,1,1)(0,1,1)$_{52}$						ARIMA(1,0,0)(0,1,1)$_{52}$					
Estimate	0.3405	0.9181		0.9426	0.00216	Estimate	0.3325		0.945		0.0001
SE	0.0357	0.015		0.0238	0.00335	SE	0.0301		0.0237		0.0217
t-value	9.53	61.32		39.54	0.64	t-value	11.06		39.92		0
AIC	6234.21					AIC	6441.91				
ARIMA(0,1,1)(1,0,1)$_{52}$						ARIMA(1,0,0)(1,1,0)$_{52}$					
Estimate	0.1683	0.4531		0.138	0.001	Estimate	0.2336			0.101	0
SE	0.0997	0.0904		0.0325	0.126	SE	0.0303			0.0319	0.151
t-value	1.69	5.01		4.26	0.01	t-value	7.71			3.19	0
AIC	6479.6					AIC	6423.7				
ARIMA(1,0,1)(1,0,1)$_{52}$						ARIMA(1,0,1)(0,1,1)$_{52}$					
Estimate	0.1783	0.5531		0.138	0.001	Estimate	0.1883	0.4531		0.138	0.001
SE	0.0998	0.0804		0.0325	0.126	SE	0.0947	0.0904		0.0325	0.126
t-value	1.78	3.01		4.26	0.01	t-value	1.79	6.01		5.26	0.03
AIC	6785.6					AIC	6774.6				
ARIMA(1,0,1)(0,1,1)$_{52}$						**ARIMA(0,0,1)(0,1,1)$_{52}$**					
Estimate	0.1783	0.4631		0.138	0.001	**Estimate**	**0.1683**	**0.4531**		**0.138**	**0.001**
SE	0.09977	0.0904		0.0325	0.126	**SE**	**0.0997**	**0.0904**		**0.0425**	**0.146**
t-value	1.679	6.01		4.26	0.01	**t-value**	**1.69**	**7.01**		**4.26**	**0.02**
AIC	6785.6					**AIC**	**6474.6**				

Table 3: **Root mean square error values**

Maximum Temperature (^{0}C)		**Minimum Temperature (^{0}C)**	
Models	**RMSE**	**Models**	**RMSE**
ARIMA(1,1,1)(1,0,1)$_{52}$	0.72	ARIMA(1,1,1)(1,0,1)$_{52}$	0.33
ARIMA(1,1,1)(1,1,1)$_{52}$	0.91	ARIMA(1,1,1)(1,1,1)$_{52}$	0.60
ARIMA(1,0,1)(1,0,1)$_{52}$	0.63	ARIMA(1,0,1)(1,0,1)$_{52}$	0.61
ARIMA(1,0,1)(0,1,1)$_{52}$	0.60	ARIMA(1,0,1)(0,1,1)$_{52}$	0.61
ARIMA(1,1,0)(1,1,1)$_{52}$	0.62	ARIMA(0,1,1)(0,1,1)$_{52}$	0.26
ARIMA(1,1,0)(1,0,1)$_{52}$	0.62	ARIMA(0,1,1)(1,0,1)$_{52}$	0.26
ARIMA(0,1,1)(1,1,0)$_{52}$	0.16	ARIMA(0,1,1)(1,1,1)$_{52}$	0.33
ARIMA(0,1,1)(1,1,1)$_{52}$	0.15	ARIMA(0,0,1)(1,1,1)$_{52}$	0.44
ARIMA(0,0,1)(1,1,0)$_{52}$	**0.13**	**ARIMA(0,0,1)(0,1,1)$_{52}$**	**0.16**
ARIMA(0,0,1)(1,1,1)$_{52}$	0.17	ARIMA(0,0,1)(1,0,0)$_{52}$	0.25
ARIMA(1,0,0)(1,1,1)$_{52}$	0.15	ARIMA(1,0,0)(1,1,1)$_{52}$	0.23
ARIMA(1,0,0)(1,1,0)$_{52}$	0.15	ARIMA(1,0,0)(1,1,0)$_{52}$	0.28

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