Time Series forecast of Sea Surface Temperature for Hokkaido fishery ports along coastal line of Japan Sea

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Abstract

Many analysis, correlation and forecast related to sea surface temperature (SST) or air temperature have been surveyed by researchers in the past. Temperature can affect many aspects in our daily life. In Hokkaido, where fishing industry is the largest among Japan's fishing industry, SST can affect quantity and different types of species of fishes. Therefore, accurately knowing and anticipating the temperature can help fishermen to strategize their fishing plans better.

In this paper, a forecast of monthly average sea surface temperature using seasonal ARIMA (Autoregressive Integration Moving Average) models in time series is performed. Many ARIMA models are derived and compared before arriving at a final appropriate and adequate model. After thorough analysis (i.e. identification, evaluation and validation) of various models, an appropriate and the best seasonal ARIMA model, which is ARIMA(2,0,1)(1,1,2)[12], is selected and recommended. Subsequently, the chosen seasonal ARIMA model is used to implement the forecast and the result of the forecast shows that the prediction is very accurate and the seasonal ARIMA(2,0,1)(1,1,2)[12] model is a very good model.

Keywords

Forecast, time series, ARIMA, seasonal ARIMA, sea surface temperature (SST)

1. Introduction

Many research papers related to SST or air temperature have been published. Moreover, many statistical tools and techniques are used to perform those analysis, correlation, prediction or forecast. Among those statistics tools and techniques, time series seems to be the most commonly used. The authors in [1] use time series to analyze the relationship between the temporal and spatial variabilities of SST in Japan Sea to atmosphere forcing. To investigate the source of rapid temperature increased in the air of Antarctic Peninsula, the authors use multiple regression and time series models [2]. The author in [3] uses a time series forecast method called SARIMA to forecast the monthly average air temperature in the Ashanti Region of Ghana. Also, time series is used in [4] to predict trend and seasonality of SST in southwest coast of Portugal as well as to observe cross-correlationship between upwelling indices and SST. Regression and time series analysis is used in [5] to examine the correlation between SST and wind speed in Greenland Sea, and to study how the SST and wind speed relate to NAO (North Atlantic Oscillation) variability.

In this paper, a time series forecast model called seasonal ARIMA model is used to forecast the monthly average SST of Hokkaido fishery ports along the coastal line of Japan Sea. The SST are collected by Japan Meteorological Agency which is the provider of the national weather service in Japan. Section II covers the general theories of the related topics and methods used in the forecast in this paper. It then follows by detail analysis of deriving an appropriate forecast model in section III. After that, forecast and results are shown in section IV. Lastly, in section V, summary of findings and conclusion will be discussed.

2. General mechanisms and approaches

2.1 Stationarity - Augmented Dicker and Fuller Test

A stationary time series is a time series whose joint probability doesn't change over time; that is, the mean and variance of the series remain constant over time. There are many test methods available for testing stationarity in a time series because many mathematics and statistics procedures (include time series analysis) require that a time series to be stationary. Augmented Dicker-Fuller test is one of the popularly tests used by researchers to check stationarity. The underlying test in augmented Dickey-Fuller test (ADF) is a type of statistical test called a unit root test. The **unit root test** is commonly used to test for stationarity of a time series. The intuition behind a unit root test is that it determines how strongly a time series is defined by a trend. Having a unit root in a time series means the time series has some type of regular patterns that is difficult to performance prediction or forecast. Therefore, it is important to know the status of stationarity in a time series. ADF uses the following test hypothesis:

H_0: Series has unit root (series is not stationary)
H_1: Series has no unit root (series is stationary)

If the test statistics is less than the critical value (or p-value < 0.05), we reject the null hypothesis Ho and can conclude that the time series is stationary; otherwise the time series is not stationary.

2.2 ARIMA(p,d,q) Models

ARIMA is an acronym stands Autoregressive Integration Moving Average. It consists of AR models, the integration part I, and MA models. Combining AR and MA models is generally referred to as ARMA models.

AR models are models in which the value of the time series $\{y_t\}$ in one period is related to the value in the previous periods called lags. In general, AR(p) is an autoregressive model with p lags and is represented in the following equation:

$$y_t = c + \sum_{i=1}^{p} \gamma_i y_{t-i} + \epsilon_t \tag{1}$$

where c is a constant, γ_i is the coefficient for the lagged variable in time t-i, and ϵ_t is the error term in time t.

Instead of using the past values of the variable as in AR models, MA models comprise of the possibility of a relationship between a time series and the residuals (errors) from the previous periods. So, MA(q) is a moving average model with q lags and is represented in the following equation:

$$y_t = c + \epsilon_t + \sum_{i=1}^{q} \theta_i \epsilon_{t-i} \tag{2}$$

where c is a constant, θ_i is the coefficient for the lagged variable in time t-i, and ϵ_t is the error term in time t.

If a time series is not stationary, a common approach is to apply differencing to the time series, that is

$$\Delta y_t = y_t - y_{t-1}$$

The process of differencing can be done many time until the time series reaches stationarity. So I(d) implies that the time series has been differenced d times.

Putting AR(p) model, MA(q) model and I(d) together, the ARIMA model is normally denoted as ARIMA(p,d,q) and it is used for a non-seasonal time series. By combining equations (1) and (2), the ARIMA(p,d,q) model with d differences can be represented by the following equation:

$$y_t^d = c + \sum_{i=1}^{p} \gamma_i y_{t-i}^d + \sum_{i=1}^{q} \theta_i \epsilon_{t-i} + \epsilon_t \tag{3}$$

where y_t^d is the time series being differenced d times. Applying the backshift notions $By_t = y_{t-1}$ and $B^d y_t = y_{t-d}$ to equation (3) and perform some mathematical manipulation, equation (3) can be rearranged becomes

$$\left[1 - \sum_{i=1}^{p} \gamma_i B^i\right][1 - B]^d y_t = c + [1 + \sum_{i=1}^{q} \theta_i B^i] \epsilon_{t-i} \tag{4}$$

The first term in the square bracket on the left side of the equation is AR(p), the second term $(1-B)^d$ is the d differences, and the term in square bracket on the right side of the equation represents MA(q).

2.3 Seasonal ARIMA(p,d,q)(P,D,Q) Models

For a seasonal time series, the seasonality must be included into the non-seasonal ARIMA mode1 as part of the model. The non-seasonal and seasonal factors are combined to form a multiplicative model and it is normally written as ***ARIMA(p,d,q)×(P,D,Q)$_n$*** where (p, d, q) is the non-seasonal factor, (P, D, Q) is the seasonal factor, p, d, q have been explained above, P is seasonal AR order, Q is seasonal MA order, D is seasonal differencing and n is the number of periods per season.

2.4 ACF and PACF

ACF and PACF stand for autocorrelation function and partial autocorrelation function respectively. In general, they are just measures of correlation between two variables. ACF measures the dependency between current series values and the lags (i.e. its previous values) of itself; whereas PACF is more of a conditional correlation where it measures the correlation of the current series values with its own lagged values by controlling for the values of the time series at all shorter lags. More specifically,

- ACF is a measure of the correlation between series values that are p intervals apart at lag p.
- PACF is a measure of the correlation between series values that are q intervals apart at lag q, taking into account for the values of the intervals between.

Patterns of ACF and PACF plots are very useful tools to help to determine the order of processes in an ARIMA model. ACF is used to determine the numbers of MA terms whereas PACF is used to find the orders in an AR terms. More specifically, the relationship between ARIMA models and the patterns of ACF and PACF plots are described and summarized [7] as follow:

1. If ACF trails off after a lag and has a hard cut-off in the PACF after a lag, then this lag is p and the model is an AR model denoted as AR(p).
2. If the PACF trails off after a lag and has a hard cut-off in the ACF after the lag, then this lag is q and the model is a MA model denoted as MA(q)
3. If both ACF and PACF trail off, then the model is mix of AR and MA model.

Table 1. Relation of ACF and PACF with ARIMA model

Model	**ACF**	**PACF**
AR(p)	Trails off	Cuts off after p lag
MA(q)	Cuts off after q lag	Trails off
ARMA(p,q)	Trails off	Trails off

2.5 BIC (Bayesian Information Criteria)

BIC stands for Bayesian information criterion is a method for model selection among a finite set of models based on some information criteria. The computation of BIC is based on the empirical log-likelihood and does not require the specification of priors. The BIC is an asymptotic result derived under the assumptions that the data distribution is in the exponential family. The formula for the BIC is

$$-2\ln p(x|k) \;=>\; BIC = -2\ln L + k\ln(n) \tag{5}$$

where

- x = the observed data;
- n = the number of data points in x, the number of observations, or equivalently, the sample size;
- k = the number of free parameters to be estimated. If the estimated model is a linear regression, k is the number of regressors, including the intercept;
- $p(x|\, k)$ = the probability of the observed data given the number of parameters; or the likelihood of the parameters given the dataset;
- L = the maximized value of the likelihood function for the estimated model.

Under the assumption that the model errors or disturbances are independent and identically distributed according to a normal distribution and that the boundary condition that the derivative of the log likelihood in respect to the true variance is zero, the BIC equation (5) above becomes:

$$BIC = n\ln\left(\frac{RSS}{n}\right) + k\ln(n) \tag{6}$$

where RSS is the residual sum of squares which is defined as

$$RSS = \frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2 \tag{7}$$

From (6), the BIC is an increasing function of RSS and an increasing function of k. That is, unexplained variation in the dependent variable and the number of explanatory variables increases the value of BIC. Hence, lower BIC absolute value implies either fewer explanatory variables, better fit, or both. So, given any two estimated models, the model with the lower absolute value of BIC is the one to be preferred.

2.6 AIC (Akaike Information Criteria)

An AIC stand for Akaike Information Criterion and it is a criterion for measuring the relative goodness of fit of a statistical model. The AIC formula is given as

$$AIC = 2k + n\log\left(\frac{RSS}{n}\right) \tag{9}$$

where k is the number of parameters in the statistical model, n is the sample size and RSS is the residual sum of squares of the dataset. The first term on the right-hand side of (9) is a measure of the lack-of-fit of the chosen model, while the second term measures the increased unreliability of the chosen model due to the increased number of model parameters. So, the best approximating model using AIC is the one with the minimum AIC in the class of the competing models. In other words, given a set of candidate models for the data, the preferred model is the one with the minimum AIC value. In other words, the lowest values of either AIC or BIC is commonly used as a criterion to select good ARIMA model.

3. Analysis

3.1 Data Preparation

The sea surface temperature (SST) used in this paper is provided by Japan Meteorological Agency. The SST data used are the temperature collected from 18 fishery ports in Hokkaido along the coastal line of Japan Sea. For each fishery port, the SST data consists of daily temperature dated from January 1982 to July 2016 which contributed to 12631 days of temperature data per port. Like many other data collected, there are missing temperatures in each fishery port's data. The percentage of missing daily temperature range from 0.11%-20.3% and less than 5 fishery ports have missing temperature more than 15%. Due to the fact that the percentage of missing temperature is small and the monthly average temperature is used in this paper to do forecast, the final decision made to handle those missing temperature is to just ignore them. The SST data from the 18 fishery ports are then combined and converted to monthly average data. Therefore, there are all together 415 monthly average SST from January 1982 to July 2016.

3.2 Box-Jenkins Method

Box-Jenkins method, a widely used and popular method for analysis and model selection, is used to develop the seasonal ARIMA models in this paper. As the method name suggested, this method is proposed by George Box and Gwelym Jenkins in 1970 [6]. There are basically three main steps involves in this method, namely model identification, model estimation and model diagnostics test or validation.

1. Model Identification
   The identification step can normally be categorized into two processes. The first process is to determine the stationarity and seasonality status of a time series. If a time series is not stationary, then some techniques have to applied to make it stationary. Similarly, if a time series consists of seasonality, it has to be de-seasonalized by taking seasonal differencing. Normally the unit root tests are used to detect stationarity in a time series. After that, the second process can be carried out to identify the appropriate orders of AR and MA models by employing the ACF and PACF plots mentioned in section II(D) above.
2. Model Estimation (and selection)
   This step involves estimation of the parameters (i.e. p, d, q, P, D, Q) of the different ARIMA models obtained in the identification step above and proceeds to select the first ARIMA models using information criteria. An information criterion is normally used to measure the goodness of fit of the model. Besides the two information criteria (BIC and AIC) described in section II above, there are other information criteria such as AICc (corrected version of AIC), HQIC (Hannan-Quinn Information Criteria) and SBIC (Schwarz BIC) which are used as criteria to choose a model.
3. Model Diagnostics

This step is to test and determine whether the model(s) specified and estimated in the previous step is adequate. If the estimated model is inadequate, repeat from identification step onwards to obtain a better model. In this diagnostic checking, the residuals (i.e. error terms) of the ARIMA model is used for the diagnostic. The residuals should satisfy the normality assumption and the weak white noise assumption. Weak white noise means the residuals is small and no systematic or predictable patterns should be left in the residuals. Normality can easily be observed by using the Q-Q (Quartile-Quartile) plot or the histogram plot of the residuals. Q-Q plot is a graphical method to compare two probability distributions by plotting their quartiles against each other. One common used of the Q-Q plot is to compare the distribution of a sample (i.e. residuals of the model in this paper) to a theoretical standard normal distribution [8]. If the quartiles coincide in a straight line, this will imply normality in the sample (i.e. residuals). Whereas the weak white noise can be detected by using Box-Pierce test, Ljung-Box test or/and the ACF plot of the residuals. The Box-Pierce test and the Ljung-Box test have the following similar hypotheses:

H_0: The residuals are independent

H_1: The residuals are not independent

If the p-value is less than α=0.05, the null hypothesis Ho is rejected and implies that the residuals are not independent.

3.3 Model Identification

There are varieties of patterns in a time series. Before going into more detail identification, it is always important to understand the underlying patterns of the time series so to improve the forecast. An additive model is used here to decompose the monthly average SST time series into four different components (i.e. original time series, trend, seasonal and random components) which exhibit different patterns in the time series. A decomposition plot is then produced as shown in Figure 1 to get some preliminary understandings of the time series. From the plot, it can be clearly observed that the time series has seasonality and the seasonal variation is constant over time and repeats from year to year. However, the trend of the series is not really obvious, but it seems that the series has a very slight upward momentum. It also appears that the series is stationary with constant mean and variance over time.

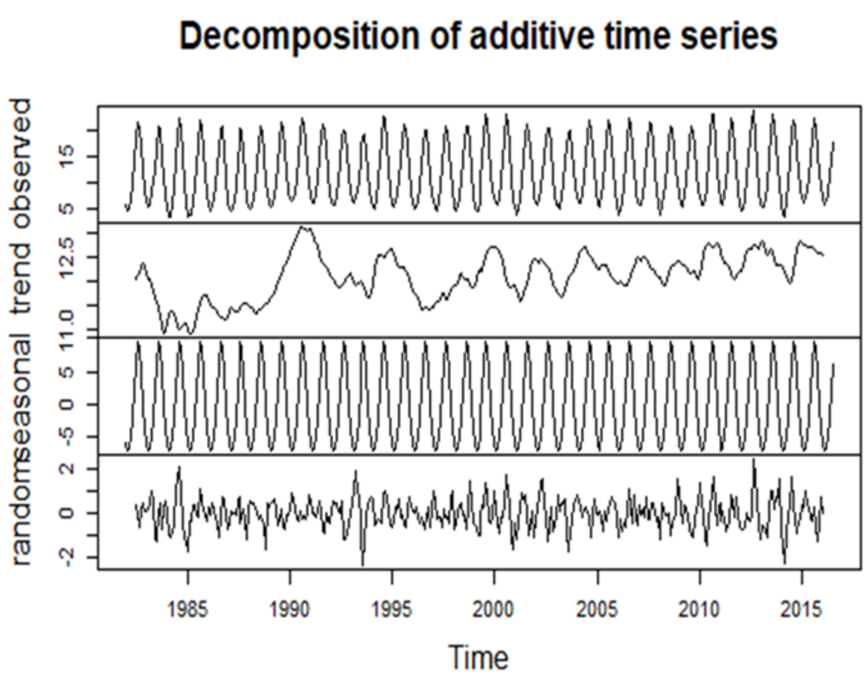

Figure 1. Decomposition plot of time series

To further test the stationarity of the time series, a widely used method called Augmented Dicker-Fuller test (ADF) is used. Table 2 below shows the resulted test statistics and p-value obtained from ADF.

Table 2. ADF results

	Test Statistics	P-value
ADF test	-16.751	0.01

Since the p-value is less than 0.05, the null hypothesis that the time series has unit root is rejected assuming a 5% chance of making a mistake and hence conclude that the monthly average SST time series is stationary.

The pattern showed in ACF plot in Figure 2 below clearly consistent with what has been seen in the decomposition plot in Figure 1 that the SST is a seasonal time series.

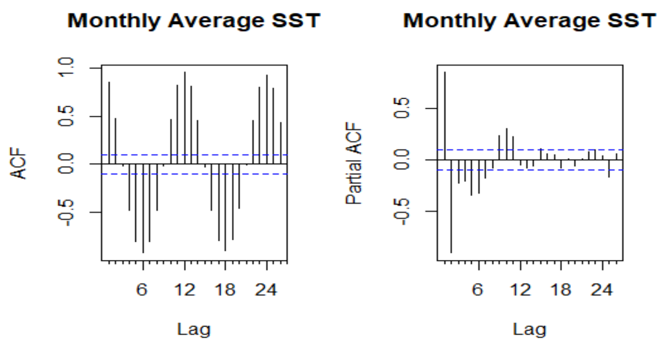

Figure 2. ACF and PACF plots of time series

The trend and the seasonal components in the time series have to be removed before any ARIMA models can be derived. To de-seasonalized, a lag-12 seasonal differencing is applied. After that, the ACF and PACF plots of the de-seasonalized time series are produced as shown in Figure 3. It is noticeable from the figure that the ACF plot suggests a non-seasonal MA(2) component since lags 1 and 2 spike out of the confidence limits and are significantly different from zero. Of the lags that are multiple of 12, ACF plot shows that there is only lag 12 which spikes out and significant from zero. This means that the order of the seasonal MA component is 1. As for non-seasonal AR model, the PACF plot shows that lags 1 and 2 are significantly spike out of the confidence limits and this will give the order of non-seasonal AR term to be 2. Since the seasonal and non-seasonal MA terms have been identified and to start with simple model, therefore, combine all the information obtained above together with the consideration of the seasonal differencing, the seasonal ARIMA model ARIMA(2,0,2)(0,1,1)[12] would be used as a guide for further estimation.

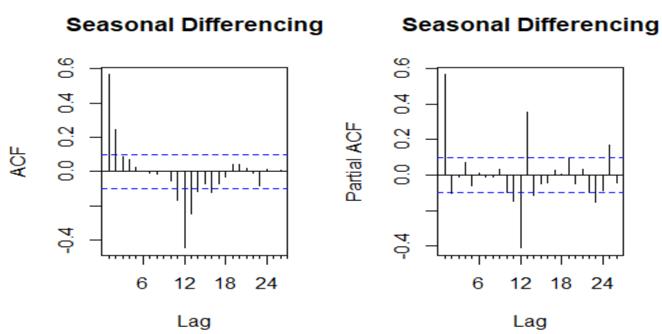

Figure 3. ACF & PACF - 1 Seasonal Difference

3.4 Model Estimation (and selection)

Before the estimation is carried out, the monthly average SST time series is being divided into a training data and test data (i.e. ratio of 90:10). The reasons of splitting the time series are that out of sample forecast can be performed and the accuracy of the forecast can be assessed. More than 50 seasonal ARIMA models with different combination of parameters are being used and fitted to the training data; but only 10 models with better overall information criteria are being considered here. Table 3 shows the 10 models with their associated information criteria AIC, AICc and BIC.

Table 3. Information Criteria of Seasonal ARIMA models

Model	**AIC**	**AICc**	**BIC**
ARIMA(2,1,1)(0,1,1)[12]	741.17	741.34	760.67
ARIMA(2,1,1)(1,1,1)[12]	742.07	742.31	765.47
ARIMA(2,0,2)(1,1,2)12]	740.86	741.26	772.08
ARIMA(2,0,2)(0,1,1)[12]	741.88	742.11	765.29
ARIMA(3,0,2)(0,1,1)[12]	741.01	741.32	768.33
ARIMA(2,1,1)(2,1,3)[12]	741.99	742.50	777.09
ARIMA(2,1,1)(3,1,1)[12]	741.49	741.89	772.69
ARIMA(2,1,1)(1,1,2)[12]	742.25	742.56	769.55
ARIMA(2,1,1)(0,1,2)[12]	742.22	742.46	765.62
ARIMA(2,0,1)(0,1,1)[12]	742.57	742.74	762.09

Notice that the first differencing is incorporated into some of the ARIMA models in Table 3 above. Recall from the decomposition plot in Figure 1 that the trend of the SST time series is not so obvious but it does show a very little upward trend; and this is the main reason why the first differencing is being considered here. There are a few options to select the best ARIMA model from Table 3 depending on which are the information criteria being used. If the value of either AIC or AICc is used, ARIMA(2,0,2)(1,1,2)[12] model would be selected since it has the lowest AIC and AICc values. On the other hand, if BIC value is used, the model ARIMA(2,1,1)(0,1,1)[12] would be the best model since it has the lowest BIC value. However, even though ARIMA(2,0,2)(1,1,2)[12] has the lowest AIC and AICc values, its BIC value is the third highest as shown in Table 3; whereas the AIC and AICc values of ARIMA(2,1,1)(0,1,1)[12] model are very close to that AIC and AICc values of ARIMA(2,0,2)(1,1,2)[12] model. Moreover, by comparing the accuracy of the two models using forecast errors such as Root Mean Square error (RMSE), Mean Absolute Percentage Error (MAPE) and Mean Absolute Scaled Error (MASE) as shown in Table 4 below, the ARIMA(2,1,1)(0,1,1)[12] model seems to have an overall lower error terms than the ARIMA(2,0,2)(1,1,2)[12] model, and hence better accuracy.

Table 4. Comparison of the Forecast Errors

Model	**RMSE**	**MAPE**	**MASE**
ARIMA(2,1,1)(0,1,1)[12]	0.6058	4.8544	0.5405
ARIMA(2,0,2)(1,1,2)[12]	0.6078	4.9031	0.5462

Therefore, by taking into account the overall arguments and considerations mentioned above, the best model to be considered is the seasonal ARIMA(2,1,1)(0,1,1)[12] model and it would be selected and recommended in this paper to perform forecast.

3.5 Model Diagnostics

As mentioned in the Analysis section III above that a good model is a model whose residuals satisfy the white noise and normality assumptions. In this section, those tools and techniques covered in section III will be used to verify the two assumptions. To detect normality in the residuals after fitting the time series into the selected seasonal ARIMA(2,1,1)(0,1,1)[12] model, the histogram and the Q-Q plot of the residuals are obtained and shown in Figure 4 below. It can be easily observed from the histogram that the residuals are from a normal distribution since it has a bell-shape like of distribution. As for Q-Q plot, it can be seen that the quartiles of the residuals coincide with the theoretical normal distribution in a straight line. This implies that the residuals satisfy the normality assumption.

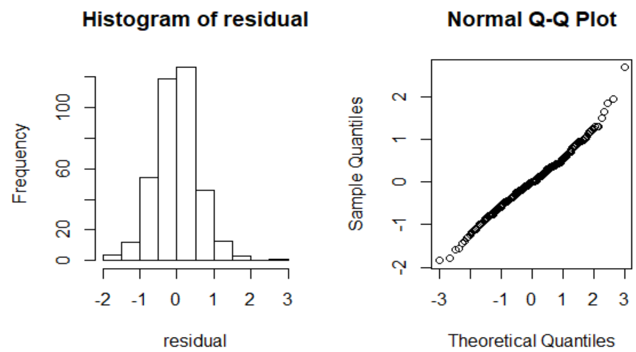

Figure 4. Histogram and QQ Plot of the residuals

To diagnose the white noise assumption, the residuals plot and the ACF plot of the residuals are constructed and are shown the Figure 5 below:

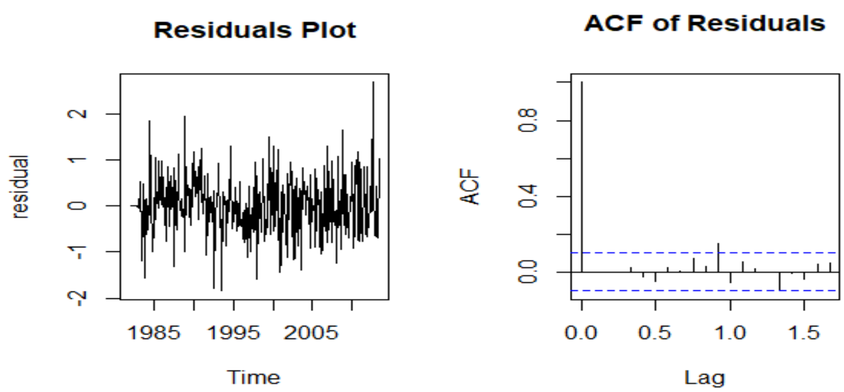

Figure 5. Residuals and ACF Plots of the residuals

It can be observed from the residuals plot that the plot shows the randomness in the residuals; and the residuals are condensed between -2 and 2 indicating it has zero mean and constant variance. These imply that the residuals are not correlated. The ACF plot further enhances the uncorrelated observation since the plot shows the residuals are all zero (i.e. within the confidence limits of -1 to 1). To double confirm the uncorrelation (white noise), Ljung-Box test is carried out. The test shows that the p-value obtained is 0.383 which is greater than α=0.05 (assume 95% confidence interval). So, the null hypothesis (i.e. Residuals are independent) cannot be rejected and hence the residuals are not correlated. This means the residuals satisfy the white noise assumption. Therefore, the selected seasonal ARIMA(2,1,1)(0,1,1)[12] model satisfies the model assumptions. This indicates that the selected model is good to be used for the forecast.

4. Forecast and Results

An out of sample test dataset will be used in the forecast as mentioned in section III(D). To be exact, 38 out of 415 monthly mean SST temperatures are being used as test dataset. However, due to space constraints here, only the last 19 months' results are shown. The actual and forecast values, together with its "Lower 80%" and "Upper 80%" confidence limits, are tabulated as shown in Table 5 below:

Table 5. Actual and Forecast Values

	Actual	**Forecast**	**Lower**	**Upper**
Jan2015	7.22789	6.59777	5.51948	8.24686
Feb2015	6.08534	5.58668	4.50829	7.23593
Mar2015	7.10378	5.88249	4.80401	7.53189

Apr2015	8.25462	7.58609	6.50751	9.23563
May2015	10.89734	10.45673	9.37805	12.10643
Jun2015	14.50143	14.51495	13.43618	16.16479
Jul2015	18.36394	18.53209	17.45242	20.18331
Aug2015	22.33037	21.87014	20.78983	23.52233
Sep2015	20.74511	21.23424	20.15356	22.88700
Oct2015	15.77066	17.03376	15.95281	18.68693
Nov2015	11.94714	12.49809	11.41689	14.15164
Dec2015	9.47275	8.64729	7.56585	10.30122
Jan2016	6.66128	6.62584	5.54419	8.28008
Feb2016	5.85351	5.61475	4.53299	7.26915
Mar2016	6.42046	5.91057	4.82871	7.56513
Apr2016	7.75934	7.61416	6.53220	9.26887
May2016	11.31163	10.48481	9.40274	12.13967
Jun2016	14.15963	14.54303	13.46086	16.19805
Jul2016	17.86530	18.56017	17.47708	20.21661

Figure 6 below shows the forecast plot of the actual data from Jan 2009 to July 2016 and the test data from July 2013 to July 2016. The blue solid line represents the forecast values and the black dotted line is the actual values of the time series. The shaded areas are the lower and the upper forecast confidence limits.

It can be observed from Table 5 above that the actual values and the forecast values are very close to each other. Moreover, Figure 6 also displays that the two lines represent the actual and forecast values are almost coincide together and they are well within the confidence limits (except for the year 2014 where the February and March mean monthly temperatures are very much lower than the rest of other years' February and March temperatures). Therefore, it can be concluded that the forecast is very accurate and reliable. Hence, this implies that the seasonal ARIMA(2,1,1)(0,1,1)[12] is a very good model.

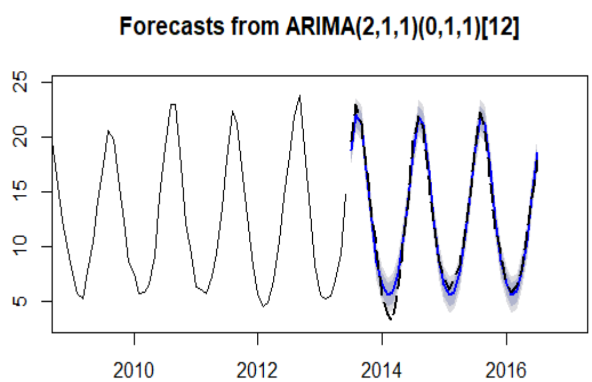

Figure 6. Plot of Actual and Forecast values

5. Summary and Conclusion

In summary, forecast of temperatures are common and have been conducted by many researchers in various disciplines and applications. Different researchers use different forecast models. To use ARIMA model to perform forecast, one must check for stationarity, seasonality and trend of a time series. If it is not stationarity, it has to be made stationary by applying some transformation techniques such as differencing, reciprocals or logs functions. If it is seasonal and has trend (up or down), it must be de-seasonalized using seasonal differencing and de-trend using differencing. In this paper, the ACF plot of the time series and the ADF test are used to check for stationarity and found that the monthly mean SST time series is stationary. From the seasonal component of the time series decomposition plot shows that the series is seasonal and hence it is de-seasonalized using one seasonal differencing. The trend component does not show an obvious upward trend, so it is ignored at first place but then being reconsidered later. To identify the first appropriate ARIMA model, the ACF and PACF plots are used and the resulted in the ARIMA(2,0,2)(0,1,1)[12] model to be used as a guide for further estimation. Under model estimation and selection processes, more than 50 models with different combination of parameters (include some models with single differencing) are being used for comparison and selection. The model ARIMA(2,1,1)(0,1,1)[12] is selected as best overall model based on lowest BIC value and the better forecast accuracy. Then the model diagnostics process on the model selected shows that the model satisfies the white noise and normality assumptions, and hence indicates that the model is a good fit. Lastly, the model is used to forecast and predict the time series The forecast results shown in Table 5 and Figure 6 implies that ARIMA(2,1,1)(0,1,1)[12] is a very good model.

In conclusion, it is not an easy task to derive a good and accurate model for the forecast. One has to have sufficient knowledge in statistics and time series in order to understand many underlying theories, concepts and applications in forecasting. Moreover, as the size of data are getting huge (i.e. Big data) nowadays and many candidate models need to be considered and compared, manually computations and graphing are near to impossible without utilizing software and faster computer. In this paper, R programming language is used in data preparation and model computations. Sometimes, there may be a few suitable models to be used for the forecast, but one has to take into the consideration of overfitting and the amount of computations needed. For example, if the ARIMA(p,d,q)(P,D,Q) model uses large values in p, d, q, P, D, Q, the computations will take longer time. Lastly, the recommended seasonal ARIMA(2,1,1)(0,1,1)[12] model should be a useful model to help fishing industry in Hokkaido to predict the sea surface temperature.

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