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Forecasting Wave-like Patterns of COVID-19 Daily Infected Cases in Iran

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ABSTRACT

The COVID -19 means Corona (CO), Virus (VI), Disease (D), and year 2019 (19), which is COVID-19. The pandemic first appeared in 2019, grabbed more than 177,885,850 infected cases and 3,850,529 death total reported up to date. Iran had been the second Middle East country severely hit by the COVID-19. At present daily infected cases shows a declining trend in Iran. It is a good sign and motivation to combat COVID -19. Hence, the study has designed to forecast the daily infected cases of COVID -19 in Iran. The daily infected cases of Iran for the period of 22nd January 2020 to 17th June 2021 were obtained from the World Health Organization (WHO) database. The pattern recognition of the daily cases examined by time series plots and Auto Correlation Function (ACF). The Sama Circular Model (SCM) and the Seasonal Auto-Regressive Integrated Moving Average (SARIMA) were tested to forecast the daily infected cases. The models were validated by using the Anderson Darling test, ACF, and Ljung-Box Q (LBQ)-test. Mean Absolute Percentage Error (MAPE), Mean Square Error (MSE), and Mean Absolute Deviation (MAD) are the measurements of errors used in both model fitting and verification processes to assess the forecasting ability of the models. The results of the study revealed that both SCM and SARIMA were satisfied all validation criterion, but the performance of SCM was extremely higher than SARIMA. It had been concluded that the SCM is the most suitable model to forecast daily infected cases in Iran. It is strongly recommended to test whether the wave like patterns exist in infected cases of the other countries as well.

Keywords: COVID -19, Seasonal behavior, Daily Infected Cases, SCM

1. INTRODUCTION

1.1 Background of the Study

The Wuhan is the capital of Hubei Province in China where the COVID -19 was the origin. The COVID -19 is the worst pandemic after the Swine Flu (2009-2010). As a result more than 177,885,850 infected cases and 3,850,529 death total reported up to date. The term COVID means Corona (CO), Virus (VI), Disease (D), and year 2019 (19), which is COVID-19 first appeared in 2019 (Sugiyanto & Muchammad, 2020). Novel coronavirus can cause pneumonia (Pan et al, 2020). Pneumonia is an inflammatory lung disease that is characterized by coughing, chest pain, fever, and difficulty breathing (Pan et al., 2020). Iran had been the second Middle East country severely hit by the COVID-19. According to World Health Organization (WHO) statistics, the first infected case reported from Iran on 19th February 2020. The total infected cases in Iran exceeded 3,070,426 and more than 2,708,743 of them recovered. The total number of death reported is more than 82,619. At present daily infected cases shows a declining trend in Iran. It is a good sign and motivation to combat COVID -19.

1.2 Research Problem

The declining trend of the daily infected cases is clearly visible, but there may be hidden behaviors as well. The studies conducted by Konarasinghe, K.M.U.B (2021-a): (2021-b) have reported that there were many seasonal behaviors in daily infected cases in other countires.Identifying such patterns of the outbreak of the pandemic will be a guide to control the situation in a favorable manner. The literature review of the present study also suggested seasonal behavior of the outbreak. But the attention on capturing such behaviors were very limited. Hence, forecasting the patterns of the outbreak of the pandemic in Iran will be another way to fill the knowledge gap.

1.3 Objective of the Study

The objective of the study is to forecast the patterns of daily infected cases of COVID -19 in Iran.

1.4 Significance of the Study

The results of this study could be a lighthouse to develop various health and medical care strategies to combat the pandemic in Iran. Predicted values of the daily cases will be a road map to work out the logistic requirements and produce with minimum waste (Konarasinghe, K.M.U.B., 2020-a). The results can be used to examine the patterns and the speed of the outbreak. This will be a guide for lockdown schedules, implement delivery systems, online activities, control movements of the general public, etc. The result of the study is a useful guide for business developments; e-commerce, and other virtual business activities to satisfy the requirements of the stakeholders'.

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2. LITERATURE REVIEW

The review of the study was focused on forecasting outbreak of the pandemic in Iran. Mathematical, Statistical and Soft computing techniques were applied to predict the outbreak.

2.1 Studies Based on Modeling Outbreak in Iran

Zareie et al (2020), Sahafizadeh & Sartoli (2020), Zahiri et al (2020), and Deldar et al (2020) have applied SIR (Susceptible-Infectious-Removed) model to predict the infected, death, recovered cases of the pandemic in Iran. Sahafizadeh & Khajeian (2021), Einian & Tabarraei (2020), Azizi & Seifi (2020), Ghaffarzadegan & Rahmandad (2020), Blandenier et al (2020) have applied Susceptible (S), Exposed (E), Infected (I), Removed (R1) (SEIR) model for the purpose. Sedaghat et al (2020) have applied Richards, Gompertz, Logistic, Ratkowsky, and SIRD models, predict the pandemic in Iran. Kafieh et al (2020) have applied machine learning models multilayer perceptron, random forest, long short-term memory to forecast the outbreak in nine countries (Iran, Germany, Italy, Japan, Korea, Switzerland, Spain, China, and the USA). Talkhi et al (2021) have applied the Neural Network Auto Regression Model (NNETAR), Auto-Regressive Integrated Moving Average (ARIMA), ARIMA and NNETAR(Hybrid), Holt-Winter, Bayesian Structural Time-Series (BSTS) BSTS, The phrase Box-Cox transform, ARMA errors, Trend, and Seasonal components (TBATS), automatic forecasting procedure (Prophet), Multilayer perceptron (MLP), Extreme learning machines (ELM), and network models to forecasting the number of confirmed and death cases in Iran. Abdollahi et al (2021) have estimated new cases, the number of deaths, and the number of recovered patients by using Prophet, Long Short-Term Memory (LSTM), Auto-Regressive (AUTO REG), ARIMA Models and Artificial Neural Networks (ANNs) techniques. Ahmadi et al (2020) have applied Gompertz, von Bertalanffy, and least squared error (LSE) to predict the number of patients in Iran. Moghadami et al (2020) have applied an exponential smoothing model to predict the daily cases in Iran. Zhao et al (2021) have applied new generalized-Weibull and new -flexible extended-Weibull (NFE-Weibull) models to predict daily cases and daily death in Iran and China. Ramırez-Aldana et al (2020) have applied Spatial multivariate linear models to predict the number of cases in Iran.

The SEIR and SIR were the most common mathematical models applied to predict the outbreak in Iran. Besides, Richards, Gompertz, Logistic, Ratkowsky, SIRD models, ARIMA, Holt-Winter, BSTS, Gompertz, von Bertalanffy, Exponential smoothing model, NG-Weibull and NFE-Weibull, Spatial multivariate linear models, and LSE are the mathematical and statistical models applied for the purpose. Machine learning models multilayer perceptron, random forest, LSTM, MLP, ELM, MLP, and network models, NNETAR and NNETAR (Hybrid) with ARIMA, the phrase Box-Cox transform, ARMA errors, Trend, and Seasonal components, TBATS, automatic forecasting procedure (Prophet), Prophet, LSTM, and ANN techniques are the soft computing approaches applied to predict the pandemic in Iran. Attention on model verification was less and the forecasting ability was doubtful in few models. Some researchers' concern on seasonal

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behavior but not attempted to model them, may be due to the length of the data series was not sufficient for the purpose.

3. METHODOLOGY

The daily infected cases of COVID-19 in Iran for the period of 22nd January 2020 to 17th June 2021 were obtained from the World Health Organization (WHO) database. The behavior of the series paves the path for the model selection to forecast daily infected cases (Konarasinghe, K.M.U.B. 2016-a; 2016-b) and (Konarasinghe, W.G.S., & Abeynayake, 2014). It gives an insight into the various patterns of trends, seasonal, cyclical variations, heavy and minor volatility within the precise period of the data set (Konarasinghe, W.G.S. & Abeynayake, 2014). Hence, time series plot and Auto Correlation Function (ACF), were used to recognize the pattern, as done by Konarasinghe, W.G.S., & Abeynayake (2014). As per the pattern of the data series, Seasonal Auto-Regressive Integrated Moving Average (SARIMA) and Sama Circular Model (SCM) were selected to test on forecasting the daily infected cases in Iran. The Anderson Darling test, ACF, and Ljung-Box Q (LBQ)-test applied to test the model assumptions (Konarasinghe, W.G.S., et al, 2015). Mean Absolute Percentage Error (MAPE), Mean Square Error (MSE), and Mean Absolute Deviation (MAD) are three measurements of errors used to assess the forecasting ability of the model as per Konarasinghe, K.M.UB. (2015-a; 2015-b). Log transformed data were used for the analysis.

3.1 Seasonal Auto Regressive Integrated Moving Average (SARIMA)

ARIMA modeling can be used to model many different time series, with or without trend or seasonal components, and to provide forecasts. The model as follows;
An ARIMA model is given by:

$$\phi(B)(1-B)^d y_t = \theta(B)\varepsilon_t$$

Where; $\phi(B) = 1-\phi_1 B-\phi_2 B^2 ....\phi_p B^p$

$\theta(B)-1-\theta_1 B-\theta_2 B^2 ......\theta_P B^q$ (1)

$\varepsilon_t =$ Error term

D = Differencing term

B = Backshift operator ($B^a Y_t = Y_{t-a}$)

Analogous to the simple SARIMA parameters, these are:
Seasonal autoregressive - (Ps)
Seasonal differencing - (Ds)
Seasonal moving average parameters - (Qs)

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Seasonal models are summarized as ARIMA (p, d, q) (P, D, Q)$_s$
Number of periods per season - S

$$(1-\phi_1 B)(1-\varphi_1 B^s)(1-B)(1-B^s)Y_t = (1-\theta_1 B)(1-\theta_1 B^s)\varepsilon_t \qquad (2)$$

3.2 Circular Model (CM) and Sama Circular Model (SCM)

The development of the CM was based on; Fourier Transformation, the theory of Uniform Circular motion and Multiple Regression Analysis (Konarasinghe, W.G.S., 2016). The SCM is the improved version of the CM (Konarasinghe, W.G.S., 2018-b).

3.2.1 Circular Model (CM)

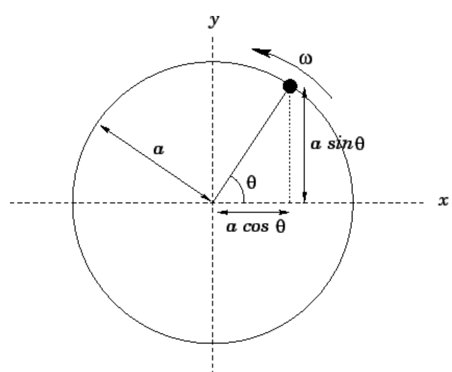
As explained in Konarasinghe (2016), a discrete version of the Fourier transformation for a function *f(x)* is written as:

$$f_x = \sum_{k=1}^{n} a_k \cos k\theta + b_k \sin k\theta \qquad (3)$$

Where a_k and b_k are amplitudes, k is the harmonic of oscillation.

The Fourier transformation is incorporated into a uniform circular motion of a particle in a horizontal circle and basic trigonometric ratios (Konarasinghe, W.G.S., 2016). A particle *P*, which is moving in a horizontal circle of center O and radius *a is* given in Figure 1. The ω is the angular speed of the particle;

Figure 1: Motion of a particle in a horizontal circle



Angular speed is defined as the rate of change of the angle with respect to time. Then;

$$\omega = \frac{d\theta}{dt}$$

$$\int_0^{\theta} d\theta = \int_0^{t} \omega \, dt$$

Hence, $\theta = \omega t$ (4)

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Substitute (4) in (3); $f_x = \sum_{k=1}^{n} a_k \cos k\omega t + b_k \sin k\omega t$ (5)

At one complete circle θ=2π radians. Therefore, the time taken for one complete circle (T) is given by: $T = 2\pi / \omega$

Figure 2 and Figure 3 clearly show how to incorporate a particle in a horizontal circular motion to trigonometric functions;

Figure 2: sine function and reference circle

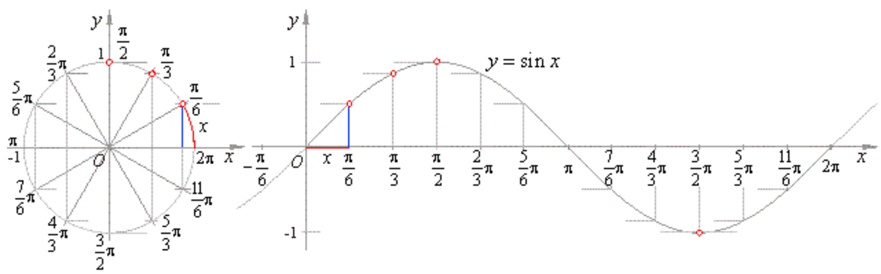
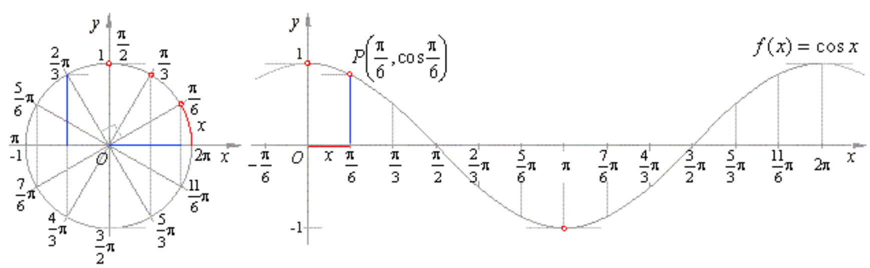


Figure 3: cosine function and reference circle



Reference to Figure (1) ; $\overrightarrow{op} = a(\cos\theta\,\mathbf{i} + \sin\theta\,\mathbf{j})$, where, a is the amplitude or wave height. A wave with constant amplitude is defined as a regular wave and a wave with variable amplitude is known as an irregular wave. In a circular motion, the time taken for one complete circle is known as the period of oscillation.

In other words, the period of oscillation is equal to the time between two peaks or troughs of sine or cosine function. If a time series follows a wave with f peaks in N observations, its period of oscillation can be given as;

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$$T = \frac{\textit{total}\ \text{number of periods}}{\text{total number of peaks}} = \frac{N}{f} \quad (6)$$

Hence, $\omega = 2\pi \frac{f}{N}$ (7)

Therefore, a variable Y_t, with an irregular wave pattern was modeled as;

$$Y_t = \sum_{k=1}^{n} (a_k \sin k\omega t + b_k \cos k\omega t) + \varepsilon_t \quad (8)$$

The model (8) was named as "Circular Model".

Model assumptions of the CM are; the series Y_t is trend-free, k is a positive real number, $\sin k\omega t$ and $\cos k\omega t$ are independent; residuals are Normally distributed and independent.

3.2.2 Sama Circular Model (SCM)

A limitation of the CM is that it is not applicable for a series with a trend. Konarasinghe, W.G.S. (2018-a; 2018-b) suggests the method of differencing to mitigate the limitation of the CM. In usual notation, differencing series of Y_t are as follows;

First differenced series: $Y_t^{'} = Y_t - Y_{t-1} = (1-B)Y_t$ (9)

Second differenced series:

$$Y_t^{''} = Y_t^{'} - Y_{t-1}^{'} = (Y_t - Y_{t-1}) - (Y_{t-1} - Y_{t-2}) = Y_t - 2Y_{t-1} + Y_{t-2} = (1-B)^2 Y_t \quad (10)$$

Similarly, d th order difference is, $Y_t^d = (1-B)^d Y_t$ (11)

Where, B is the Back Shift operator; $BY_t = Y_{t-1}$.

Assume Y_t^d is trend-free. Let, $Y_t^d = X_t$ then X_t could be modeled as;

$$X_t = \sum_{k=1}^{n} (a_k \sin k\omega t + b_k \cos k\omega t) + \varepsilon_t \quad (12)$$

Hence; $(1-B)^d Y_t = \sum_{k=1}^{n} (a_k \sin k\omega t + b_k \cos k\omega t) + \varepsilon_t$ (13)

the model (13); improved Circular Model, is named as "Sama Circular Model (SCM)".

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4. RESULTS

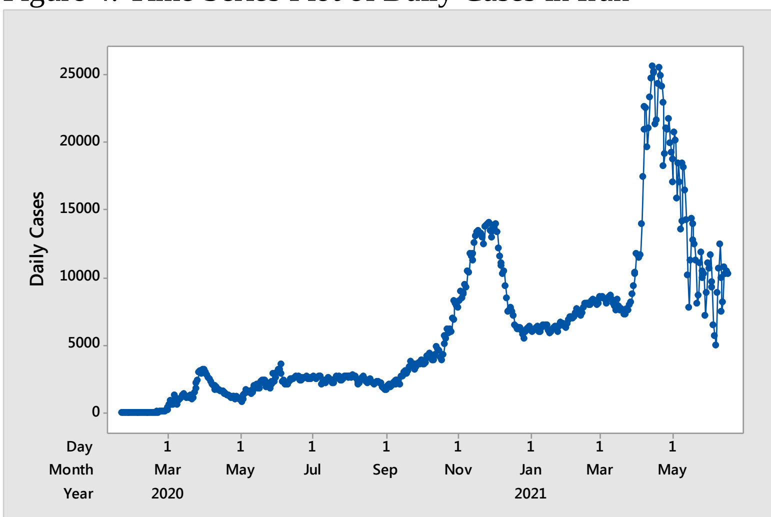
The analysis contains two main parts:

4.1 Pattern recognition of daily infected cases in Iran.
4.2 Forecasting daily infected cases in Iran.

4.1 Pattern Recognition of Daily Infected Cases in Iran

Figure 4 is the time series plot of daily infected cases of Iran for the period of 22nd January 2020 to 17th June 2021. The first confirmed case reported from Iran on 19th February 2020. There were two exponential growths of daily infected cases for the periods of 19th October to 27th November 2020 and 26th March to 20th April 2021. Besides, two declining trends of daily infected cases were observed for the periods from 27th November to 25th December 2020 and 20th April 2021 to 17th June 2021.

Figure 4: Time Series Plot of Daily Cases in Iran



Hence, the data set for the period of 20th April 2021 to 17th June 2021 was used to forecast daily infected cases in Iran and the behavior of the period was examined furthermore. Figure 5 is the time series plot of daily cases for the period of 20th April 2021 to 17th June 2021. According to Figure 5, there is a declining trend of daily infected cases with fluctuations.

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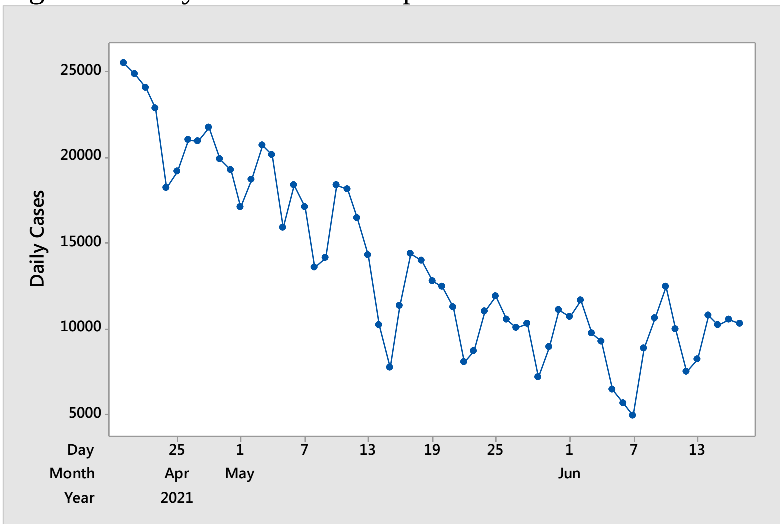
Figure 5: Daily Cases of 20th April to 17th June 2021



The ACF of the daily infected cases is shown in Figure 6. It shows several seasonal behaviors with a declining trend. There were few significant lags. It confirms the weak stationary of the series. Based on the behavior of the ACF, it was assumed that the seasonality is possible with lengths of 6 or 7 days. Hence, SCM and SARIMA techniques were tested to capture the seasonal behavior.

Figure 6: ACF of Daily Cases

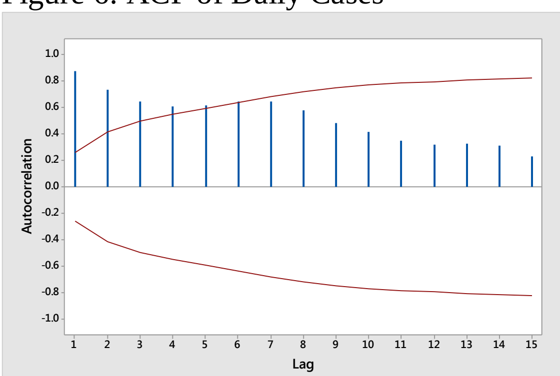


Figure 7: First Difference Series

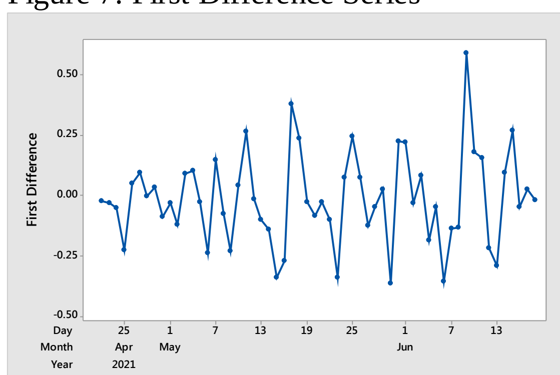


Figure 7 is the plot of the first difference series of the daily infected cases. The first difference series should obtain to examine the wave pattern of the series to apply SCM (Konarasinghe, W.G.S., 2019). The series shows a wave-like pattern with low volatility at the beginning and high at the end. The behavior of the series in Figure 7 is another evidence to select the SCM to forecast daily infected cases in Iran.

4.2 Forecasting Daily Infected Cases in Iran

Initially the SCM was run on 28 trigonometric series. The results of the Table 1 is the model summary of SCM.

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Table 1: Model Summary of SCM

Model	Model Fitting		Model Verification	
$Y_t = Y_{t-1} - 0.0724\sin 3.5\omega t - 0.1271\sin 5.5\omega t - 0.0719\cos 3.5\omega t$	MAPE	1.0063	MAPE	1.9743
	MSE	0.0150	MSE	0.0435
	MAD	0.0953	MAD	0.1786
	Normality	P= 0.586		
	Independence of Residuals	Yes		

The results of the Table 1 revealed that there were 3 significant trigonometric series out of 28. They are; and. $\sin 3.5\omega t, \sin 5.5\omega t,$ and $\cos 3.5\omega t$. The model has confirmed the normality and independence of the residuals. The measurements of errors are very low under the fitting and verifications. Figure 8 is the actual vs. fits of SCM. The patterns of actuals and fits are similar, deviations between them were very less.

Figure 8: Actual vs. Fits of SCM

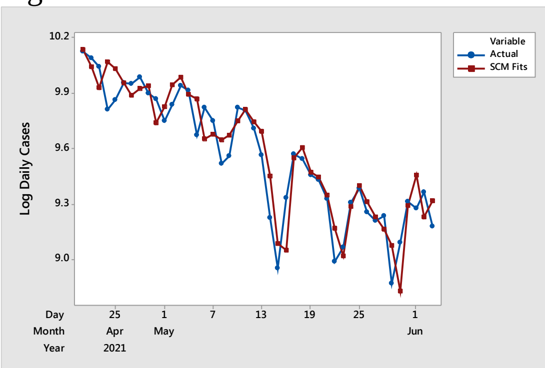

Figure 9: Actual vs. Forecast of SCM

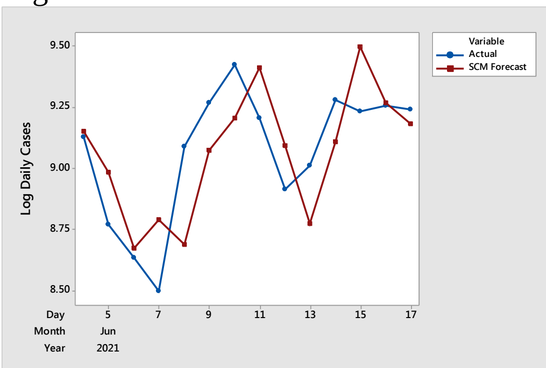

Figure 9 is the actual vs. forecast of SCM. The deviation between actual and forecast was less. The pattern of the SCM forecast follows quite similar to the actual series. Satisfying the model validation criterion, least measurements of errors, and the similar patterns of the actual, fits and forecast confirmed that, the SCM is a suitable model to forecast daily infected cases in Iran. Further, SCM provides more information about the seasonal lengths within the significant trigonometric series.

$$Y_t = Y_{t-1} - 0.0724\sin 3.5\omega t - 0.1271\sin 5.5\omega t - 0.0719\cos 3.5\omega t \quad (14)$$

There were 3 significant trigonometric series in the best fitting SCM (14). They are; $\sin 3.5\omega t, \sin 5.5\omega t,$ and $\cos 3.5\omega t$ shown in Figures 10, 11 and 12. Figure 10 shows that

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there were two wavelengths of 4 and 5 days. That means daily infected cases in Iran rise and fall in 4 and 5 days intervals.

Figure 10: Plot of $\sin 3.5\omega t$

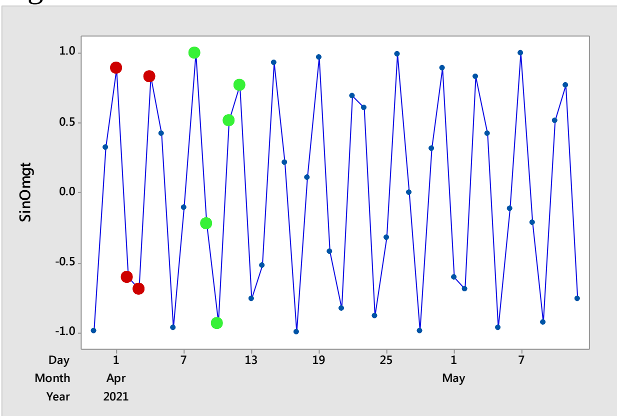

Figure 11 is the significant plot of $\sin 5.5\omega t$. The plot shows that there were two wavelengths of 8 and 9 days. That means daily infected cases in Iran rise and fall in 8 and 9 days intervals.

Figure 11: Plot of $\sin 5.5\omega t$

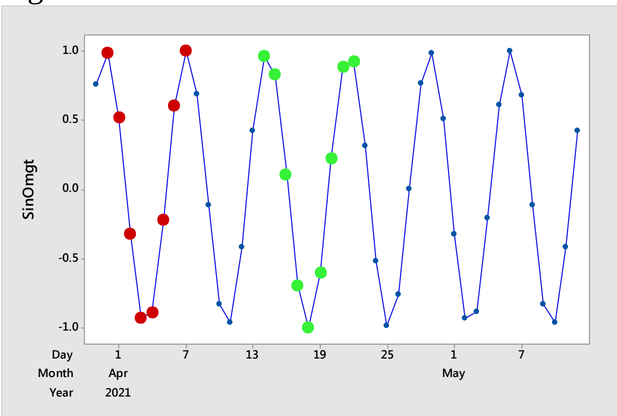

Figure 12: Plot of $\sin 3.5\omega t$

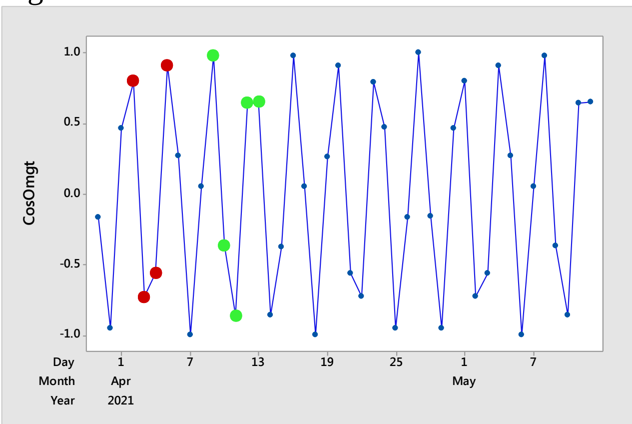

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Figure 12 is the significant plot of $\cos 3.5\omega t$. The plot shows that there were two wavelengths of 4 and 5 days similar to Figure 10. The significant trigonometric series of Figures 10, 11, and 12 show nearly 4 seasonal behaviors with the lengths of 4, 5, 8, and 9 days.

The SARIMA model runs with several seasonal lengths. Some of the seasonal lengths have identified from ACF in Figure 6. The model runs with 6 and 7 seasonal lengths at the beginning. But the seasonal length of 6 is not significant. Hence, the model runs with 5, 7, and 8 seasonal lengths. There were three SARIMA models fitted and the performances show in Table 2.

Table 2: Model Summary of SARIMA

Model	Model Fitting		Model Verification	
ARIMA$(2,0,0)(0,1,2)_5$	MAPE	0.9707	MAPE	3.8709
	MSE	0.0137	MSE	0.1509
	MAD	0.0914	MAD	0.3505
	Normality	P= 0.559		
	Independence of Residuals	Yes		
ARIMA$(0,0,1)(0,1,1)_7$	MAPE	0.7795	MAPE	3.3859
	MSE	0.0089	MSE	0.1319
	MAD	0.0737	MAD	0.3048
	Normality	P= 0.913		
	Independence of Residuals	Yes		
ARIMA$(0,0,1)(0,1,1)_8$	MAPE	1.1443	MAPE	3.0350
	MSE	0.0184	MSE	0.0982
	MAD	0.1072	MAD	0.2742
	Normality	P= 0.667		
	Independence of Residuals	Yes		

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The normality and the independence of the residuals confirmed by the Anderson Darling test, LBQ test, and the ACF. The measurements of errors are low under the fitting and verifications of all fitted SARIMA models. ARIMA $(0,0,1)(0,1,1)_8$ has lowest errors have reported under the model verification.

Figure 13 and 14 are the actual, fits and forecast of ARIMA $(0,0,1)(0,1,1)_8$. Actual and fits in Figure 13 have the least deviation and fits follow similar patterns of the actual. The deviation between actual and forecast in Figure 14 is more and it does not follow the similar pattern of the actual.

Figure 13: Actual vs. Fits

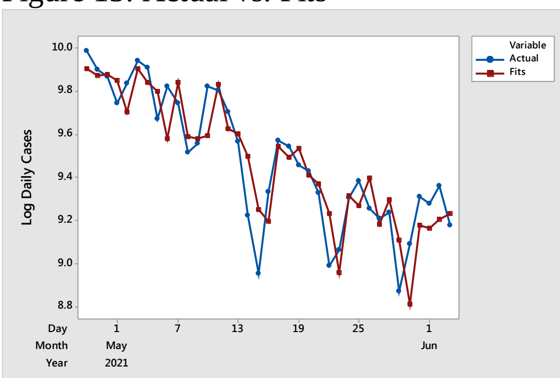
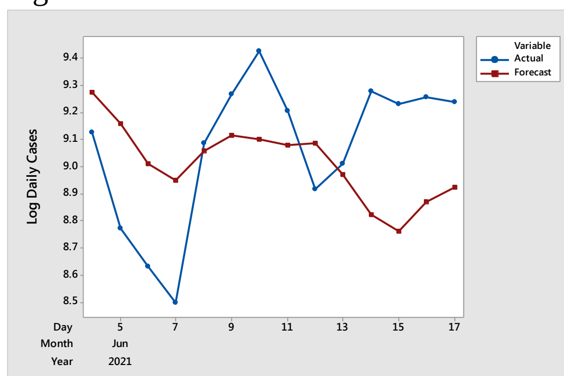
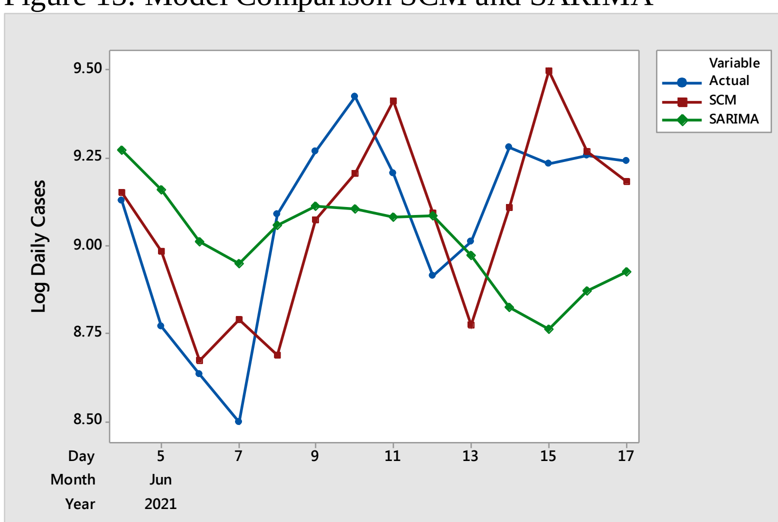


Figure 14: Actual vs. Forecast



In this study, fitted SARIMA models do not follow the wave patterns of actual in forecasting. The deviations of all fitted SARIMA models were high in forecasting. The model comparison between SCM and ARIMA $(0,0,1)(0,1,1)_8$ in Figure 15.

Figure 15: Model Comparison SCM and SARIMA



The wave pattern of ARIMA $(0,0,1)(0,1,1)_8$ in forecasting does not follow the similar pattern of actual daily cases. The SCM shows the least deviation and it follows the similar wave pattern of the actual daily cases in Iran. Figure 15 is another evidence to say

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that the SCM outperformed all fitted SARIMA models in this study. This is another evidence to prove that the SCM is capable to follow a wave – like patterns. Konarasimghe, W.G.S. (2020).

5. CONCLUSION AND RECOMMANDATION

It is concluded that the SCM is the best-suited model in forecasting daily infected cases in Iran due to the least measurement of errors and capturing the wave – pattern of the actual daily cases. There were 3 SARIMA models fitted, but the SCM outperformed all fitted SARIMA models in this study.

This is the second study of applying SCM in COVID -19 data. The performance of the SCM was extremely high. The output of SCM provided valuable information related to the patterns of the changes of daily cases in Iran. The output of SCM in this study have identified 4 seasonal behaviors within the daily infected cases in Iran at a time with minimum effort. The changes of the daily cases would be rise and fall in 4, 5, 8, and 9 days. This behavior would be one of the perfect guidelines to control the outbreak of the pandemic in Iran. It can be used to control the movements of the general public, preparing of an effective lockdown schedule, preparing of transportation schedules for the essential services, etc.

There were few vaccines introduced as prevention from COVID -19. It is a part of medical care. Medical care constitutes only 10% to 20% of health outcomes approximately (AIM, 2019). That is not sufficient to prevent from the pandemic. The remaining 80% to 90% incorporates several social factors including other healthcare practices. Healthy lifestyles, working styles, food habits, and other non-pharmaceutical activities are few factors associate with healthcare practices (AIM, 2019). Non-pharmaceutical interventions are the primary mitigation strategy to control and minimize the outbreak of the COVID-19 pandemic (Kantor & Kantor, 2020). Hand washing, Hand sanitizer, Avoiding handshakes, Tissue/ elbow sneeze, Avoiding face touching, Wearing masks, Wearing eye Protection, Social distancing, Avoiding travel, Required to stay at home/ quarantine are few non-pharmaceutical practices. There should be an effective and efficient logistic requirements to enhance non-pharmaceutical practices. The rise and fall of the daily cases indicated by this study would be a guide to work out logistic requirements. Production capacities of health and medical care products would be decided with the help of the results of this study.

The quarantine procedures should be followed strictly and monitored by the medical and healthcare authorities from time to time. The government should concentrate to produce food and beverages to improve the immunity of the human body and restrict unhealthy food and beverages for the long run and to ensure a healthy society and economy. Improve the self-discipline of the general public is one of the most important traits to control the outbreak. The results of the study would be important to implement proactive measures to avoid the outbreak and combat the pandemic. Konarasinghe (2021-b) has mentioned there could be several seasonal behaviors in other COVID -19 datasets. Further, his study emphasized that capturing the seasonal behavior of other databases

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would be more important. Hence it is strongly recommended to conduct similar studies for countries to capture the seasonal behaviors.

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