Research article

Forecasting Influenza Incidence in Public Health Region 8 Udonthani, Thailand by SARIMA model

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Abstract

Keywords

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Influenza can be easily spread among humans by coughs or sneezes. It is one of the major public health problems caused by viruses. An influenza epidemic occurs in Thailand every year and produces social burdens. Public health forecasts show societal information in advance and can point to the future magnitude of various public health issues. Therefore, this study was to perform the model in order to explain and predict influenza incidence using a seasonal autoregressive moving average model with Box-Jenkins (SARIMA). The monthly influenza virus infection cases in Public Health Region 8, Udonthani, Thailand from January 2016 to December 2018 were used to develop the model. The best fit model was determined by Akaike's Information Criteria (AIC), Bayesian Information Criteria (BIC) and Root Mean Square Error (RMSE). The results showed that SARIMA $(1,0,1)(1,0,0)_{12}$ was the best model for forecasting influenza incidence. This model had the lowest AIC (59.24), BIC (67.16) and RMSE (0.4574). Based on the comparison of actual and forecast values, the mean absolute percentage error (MAPE) was 24.15%. It shows that the model could be used to predict and demonstrate the influenza incidence.

1. Introduction

Influenza is a respiratory disease caused by an influenza virus, and it is a serious health problem all around the world [1-3]. There are 4 types: types A, B, C and D [4] which can infect humans and other animals. Most influenza viruses that infect humans can spread easily and rapidly in crowded areas, and influenza epidemics occur every year in a seasonal fashion. The spread of influenza from person to person occurs via droplets expelled from an infected person [4-6]. People who have influenza infections often have some or all of the following symptoms: fever, or feverish feeling,

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cough, sore throat, runny or stuffy nose, headache, muscle ache, fatigue, and vomiting. Some people who have mild symptoms can recover in a few days, but others with severe symptoms may develop complications such as pneumonia. Moreover, influenza can cause death in people in high risk groups such as the elderly and children [4]. An influenza epidemic can emerge and spread worldwide each year. An endemic outbreak usually occurs every 1-3 years, and pandemic outbreaks occur every 10-40 years [2].

Influenza epidemics occur following seasonal patterns and display rapid transmission [4, 6]. The incidence of influenza generally increases in winter and decreases in summer [7]. However, influenza outbreaks may occur irregularly in tropical regions [4]. Influenza epidemics occur annually and affect the world's population [8]. For worldwide record, there was about 1 billion people infected by influenza, and 3-5 million of them were severe cases and 290,000-650,000 of them were deaths [1-3]. The highest mortality rate from influenza was found in Sub-Saharan Africa (2.8-16.5 per 100,000 individuals) and Southeast Asia (3.5-9.2 per 100,000 individuals) [9]. In Thailand, the incidence of influenza showed an increasing trend in every region over the period 2014 to 2017. The incidences of influenza were 114.13 per 100,000 population in 2014, 119.66 per 100,000 population in 2015, 258.86 per 100,000 population in 2016, and 304.09 per 100,000 population in 2017 [10-13]. However, the influenza incidence decreased to 277.42 per 100,000 population in 2018. The highest incidence was found in the central part of Thailand, followed by the North, North-East, and South. However, the highest mortality rate was found in North-East [14] Public Health Regions 8. The Ministry of Public Health takes responsibility for people's health in 8 provinces in the North-East of Thailand: Loei, Nongkhai, Nongbualamphu, Udonthani, Bueng Kan, Nakhonphanom, Mukdahan, and Sakon Nakhon. The incidence of influenza in this region also fluctuated during 2016 to 2018. The incidence rate was 72.04 per 100,000 population in 2016 and increased to 166.03 per 100,000 population in 2017. The incidence rate decreased to 90.22 per 100,000 population in 2018 [15]. According to influenza situation in Public Health Region 8, forecasting may be necessary and useful for managing and controlling influenza in this area.

Nowadays, mathematical model approaches are being applied to study and explain disease epidemic. They can be used as tools to provide early warning of health problems. Many types of models have been used to explain disease situations and predict future situations. For example, the SIR model was established to explain the dynamics of influenza by considering the numbers of susceptible individuals, infected individuals and recovered individuals [16, 17]. The regression model has been used to describe the incidence of influenza and examine the association between dependent variables and independent variables [18-21]. Time series analysis is a statistical technique for a series of data points indexed in a time period, with the data related to trend, seasonality, and cycle. Other methods that have been used for time series prediction are the ARIMA, SARIMA and Neural Networks models, and these have also been applied in the area of influenza forecasting [22-25]. However, time series analysis was notably used and applied to sequences of data indexed in time order. Many time series models in time series analysis were used to explain the phenomena of influenza, and examples include the autoregressive moving average model (ARIMA), the Holt-Winters Exponential Smoothing model (HWES), and the Seasonal Autoregressive Moving Average (SARIMA) [22, 23, 26-29]. However, the SARIMA model was the most famous one used to predict seasonal data [24, 26, 29, 30]. Since the model depends on the characteristics of a historical series of data, the SARIMA model can be formed in different patterns for the different places. He *et al*. [24] reported that the SARIMA $(1,0,0)(0,1,1)_{12}$ and the SARIMA $(0,0,1)(1,0,1)_{12}$ models were effective in forecasting the positive rates of influenza virus B (Yamagata) and A (H3N2) among children in Wuhan, respectively. Zhang *et al*. [26] also showed that SARIMA with Google Trend and temperature data could be used to predict the performance of influenza outbreak. The study in China by Song *et al*. [29] presented SARIMA models for forecasting influenza incidence in 7 provinces. $\mathrm{SARIMA}(0,1,1)(0,1,1)_{12}$ was the model of best fit for influenza incidence in Hebei Province, Guizhou Province, Henan Province, and Shandong Province while SARIMA

$(1,0,0)(0,1,1)_{12}$, SARIMA $(3,1,1)(0,1,1)_{12}$ and SARIMA $(0,1,1)(0,0,1)_{12}$ were models to predict influenza incidence in Gansu Province, Tianjin City, and Hunan Province, respectively. According to previous studies conducted in Thailand, SARIMA models were used to predict influenza cases. For instance, SARIMA $(0,1,0)(1,1,1)_{12}$ was the best model for forecasting influenza cases in Bangkok [30]. SARIMA $(1,0,1)(0,1,1)_{12}$ was the suitable model for predicting influenza cases in people aged under 25 years in Phitsanulok [31].

Therefore, the aim of this study was to perform the model for forecasting the incidence of influenza in Public Health Regions 8, Ministry of Public Health, Thailand. SARIMA model with monthly period of time was used in this study to forecast the incidence of influenza in 2019-2020. The best fit model was selected on the basis of the lowest Akaike's Information Criteria (AIC), Bayesian Information Criteria (BIC) and Root Mean Square Error (RMSE). The strength of evidence in favor of one model over other models was assessed by Akaike weights (w_i). A comparison of the predicted incidence and the real incidence in 2019-2020 was presented, and the prediction accuracy of forecasting was determined by the mean absolute percentage error (MAPE).

2. Materials and Methods

This study was conducted after receiving the ethics approval from the Ethics Review Committee of Human Research (Protocol No.14/2563). The monthly influenza incidence from January 2016 to December 2018 of Public Health Region 8 were used in the analysis, and used to generate the SARIMA model. They were collected from the National Disease Surveillance (Report 506), Bureau of Epidemiology, Department of Disease Control, Ministry of Public Health, Thailand. The augmented Dickey-Fuller test was used to test whether the time series was stationary. The Unit Root test by the Augmented Dickey-Fuller test, took the form:

$$\Delta Y_t = \alpha_1 + \beta t + \delta Y_{t-1} + \sum_{i=1}^{p} \emptyset_i \Delta Y_{t-i} + e_t \qquad (1)$$

The seasonal trend decomposition was also plotted to identify trend cycles and seasonal patterns.

The SARIMA$(p,d,q)(P,D,Q)_s$ model equation is given below:

$$y_t = \frac{\varphi_Q(L^s)\theta_q(L)\varepsilon_t}{\beta_P(L^s)\emptyset_p(L)(1-L)^d(1-L^s)^D} \qquad (2)$$

Where y_t is evidence monthly influenza incidence, $\varphi_Q(L^s)$ is coefficient of seasonal moving average (SMA) at Q order and S seasonal period, $\theta_q(L)$ is coefficient of moving average (MA) at q order, $\beta_P(L^s)$ is coefficient of seasonal autoregressive (SAR) at P order and S seasonal period, $\emptyset_p(L)$ is coefficient of autoregressive (AR) at p order, d is order of different monthly period, D is order of seasonal different monthly period, ε_t is white noise or error term of model, and t is monthly period time.

To identify the possible SARIMA$(p,d,q)(P,D,Q)_s$, Autocorrelation Functions (ACF) and Partial Autocorrelation Functions (PACF) were used to identify the possible p, d, q , P, D, Q. The model with the lowest Akaike Information Criterion (AIC), the lowest Bayesian Information Criteria (BIC) and the lowest Root Mean Square Error (RMSE) was considered as the best forecasting model. Moreover, the Akaike weights (w_i) were used to assess the strength of evidence in favor of one model over other models [32]. The model accuracy was determined by comparison of real data and prediction during January 2019 to December 2020. The mean absolute percentage error (MAPE) was also calculated by:

$$\text{MAPE} = \left(\frac{1}{n}\sum\frac{|\text{Actual}-\text{Forecast}|}{|\text{Actual}|}\right)\times 100 \tag{3}$$

The models were estimated and identified using R software [33].

3. Results and Discussion

The monthly influenza data from January 2016 to December 2018 was plotted in Figure 1. It shows that there were four outbreaks at the beginning of 2016, and at the end of years 2016, 2017 and 2018. The augmented Dickey-Fuller test shows that the incidence of influenza was stationary data (p-value = 0.034). Moreover, the seasonal trend decomposition in Figure 2 shows that the incidence of influenza followed seasonal and trend patterns. Therefore, it is possible to use the SARIMA model to estimate the incidence of influenza in 2019-2020 [29, 31, 34-36].

According to the Autocorrelation Functions (ACF) and Partial Autocorrelation Functions (PACF) in Figure 3, the p order was random from 0 to 2. The q order was random from 0 to 1. The d order was 0. The P order was random from 0 to 2. The Q order was 0 and the D order was 0. The possible of SARIMA$(p,d,q)(P,D,Q)_{12}$ models were generated and a list of potential models for forecasting influenza incidence was given in Table 1. Parameters of the potential models and the Ljung-Box statistic were presented in Table 2 and Table 3, respectively. The Ljung-Box test showed that the models did not exhibit lack of fit.

The best model was SARIMA $(1,0,1)(1,0,0)_{12}$ which had the lowest AIC (59.24), BIC (67.16), and RMSE (0.4574). The parameters of this model were significant (p-value $<$ 0.05) and were 1^{st} AR (0.4225, S.E. = 0.1724, p-value = 0.01423), 1^{st} MA (0.7188, S.E.= 0.1263, p-value < 0.0001) and 1^{st} seasonal AR (0.3875, S.E.= 0.1809, p-value = 0.03218). Moreover, the Akaike weight also showed that SARIMA $(1,0,1)(1,0,0)_{12}$ was the best model of the potential models.

The forecasting influenza incidence in 2019-2020 and their 95%CI were presented in Table 4. The actual influenza incidence data in 2016-2018 and forecasting data from the SARIMA $(1,0,1)(1,0,0)_{12}$ were visualized in Figure 4. The Mean Absolute Percentage Error (MAPE) was 24.15%. Therefore, SARIMA $(1,0,1)(1,0,0)_{12}$ proved to be a reasonable forecasting model. Consequently, this model was suitable and beneficial for providing early warning information to plan for prevention and control of influenza. According to the forecasting results, the influenza incidence cases were seasonal. The influenza seasons ranged from February-April and August-October. It was also observed that there were two waves of influenza circulation. This was the same as influenza circulation in 2010, with the first wave lasting for a few months at the beginning of 2010 and the second occurring from August to September [37]. The same pattern of the epidemic was found in 2016-2018.

However, this study was a basic model based on historical data. It did not include other factors affecting the incidence of influenza such as socio-demographic ones, climate, and vaccination, and other variables in the surveillance system. Therefore, further study of those variables in order to get more accuracy in forecasting is needed.

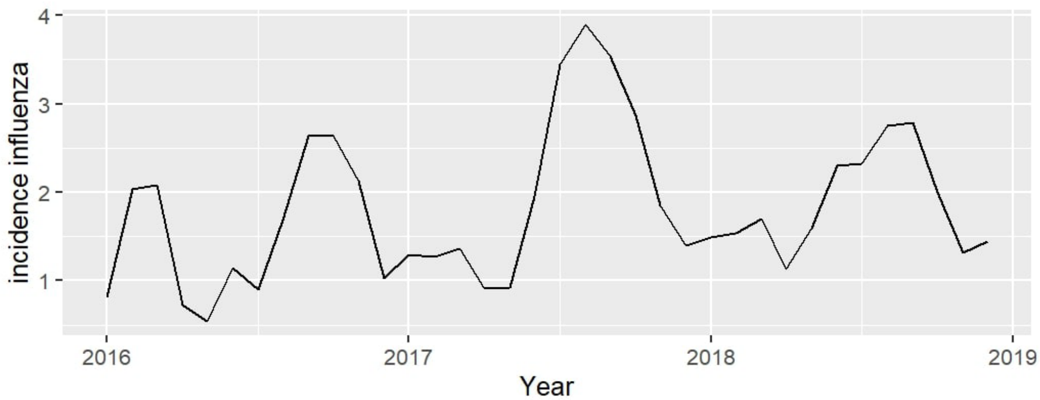

Figure 1. Monthly influenza incidence (per 100,000 population) in Public Health Region 8 Udonthani, Thailand from January 2016 to December 2018

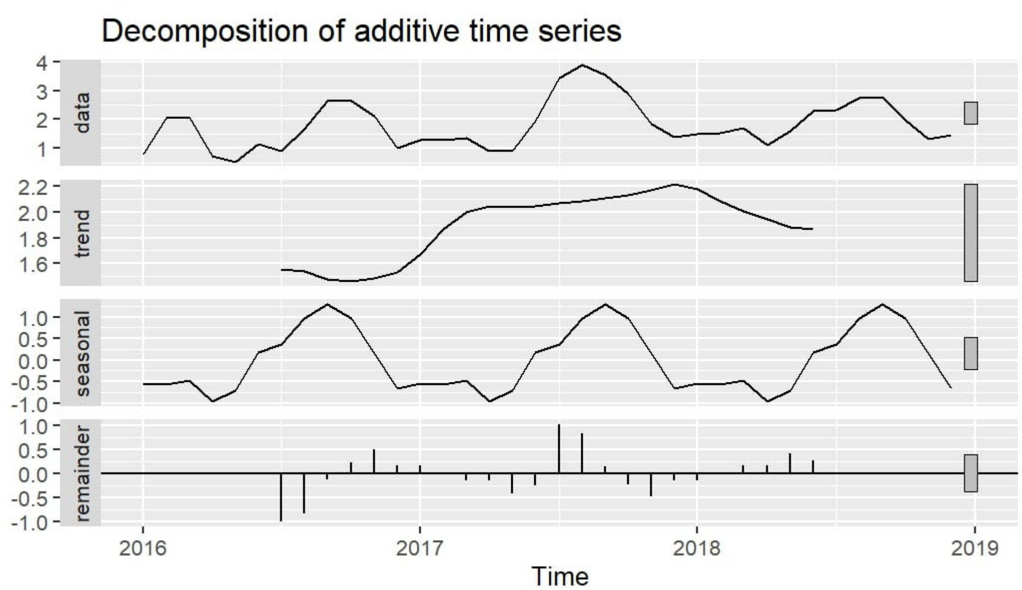

Figure 2. Decomposition of influenza incidence (per 100,000 population) in Public Health Region 8 Udonthani, Thailand from January 2016 to December 2018

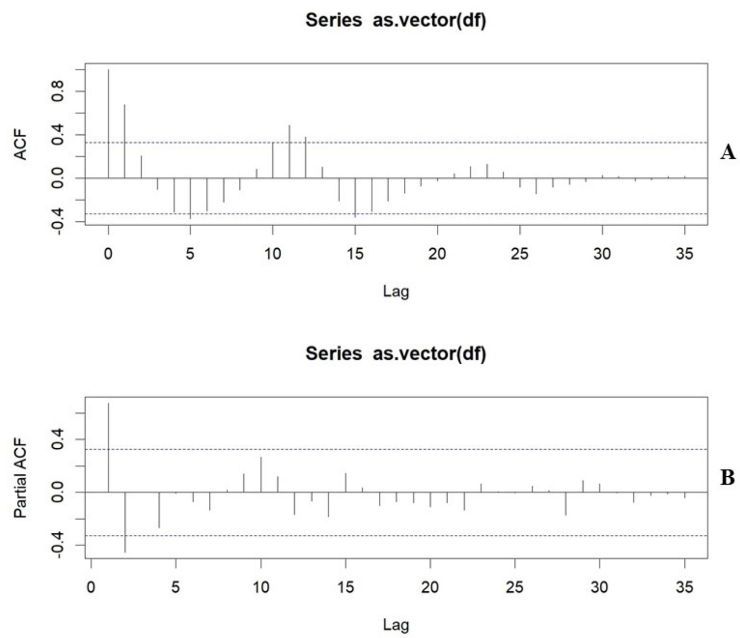

Figure 3. ACF (A) and PACF (B) of influenza incidence (per 100,000 populations) in Public Health Region 8 Udonthani, Thailand from January 2016 to December 2018

Table 1. Log-Likelihood, Akaike's Information Criterion (AIC), Bayesian Information Criterion (BIC), Akaike weights (w_i), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE) of SARIMA model

Model	Log-likelihood	AIC	BIC	w_i	RMSE	MAPE
SARIMA $(0,0,1)(0,0,0)_{12}$	-29.96	65.92	70.67	0.0168	0.5470	30.79
SARIMA $(1,0,0)(0,0,0)_{12}$	-32.66	71.33	76.08	0.0011	0.5942	32.28
SARIMA $(1,0,1)(0,0,0)_{12}$	-26.49	60.98	67.31	0.1990	0.4946	27.63
SARIMA $(2,0,0)(0,0,0)_{12}$	-26.50	61.00	67.33	0.1970	0.4953	29.05
SARIMA $(0,0,0)(1,0,0)_{12}$	-40.75	87.49	92.24	<0.001	0.7248	35.47
SARIMA $(0,0,1)(1,0,0)_{12}$	-27.13	62.26	68.59	0.1049	0.4889	24.88
SARIMA $(1,0,0)(1,0,0)_{12}$	-29.98	67.95	74.29	0.0061	0.5336	26.65
SARIMA $(1,0,1)(1,0,0)_{12}$	-24.62	59.24	67.16	0.4750	0.4574	24.15

Table 2. Parameters of potential SARIMA models

Model	Parameters	Estimate	SE	t	p-value
SARIMA $(0,0,1)(0,0,0)_{12}$	MA(1)	0.8349	0.0748	11.164	<0.001
SARIMA $(1,0,0)(0,0,0)_{12}$	AR(1)	0.6895	0.1185	5.819	<0.001
SARIMA $(1,0,1)(0,0,0)_{12}$	AR(1)	0.4830	0.1626	2.970	0.003
	MA(1)	0.6947	0.1219	5.698	<0.001
SARIMA $(2,0,0)(0,0,0)_{12}$	AR(1)	1.0924	0.1427	7.657	<0.001
	AR(2)	-0.5531	0.1401	-3.949	< 0.001
SARIMA $(0,0,0)(1,0,0)_{12}$	AR(1), seasonal	0.4337	0.1485	2.921	0.003
SARIMA $(0,0,1)(1,0,0)_{12}$	AR(1), seasonal	0.4338	0.1620	2.678	<0.001
	MA(1)	0.8416	0.0735	11.444	<0.001
SARIMA $(1,0,0)(1,0,0)_{12}$	AR(1)	0.6695	0.1194	5.609	<0.001
	AR(1), seasonal	0.4265	0.1630	2.617	0.009
SARIMA $(1,0,1)(1,0,0)_{12}$	AR(1)	0.4225	0.1724	2.451	0.014
	AR(1), seasonal	0.3875	0.3049	2.142	0.032
	MA(1)	0.7188	0.1263	5.691	<0.001

Table 3. The Ljung-Box statistics of potential SARIMA models

Model	Ljung-Box Q	df	p-value
SARIMA $(0,0,1)(0,0,0)_{12}$	14.219	12	0.287
SARIMA $(1,0,0)(0,0,0)_{12}$	8.089	12	0.778
SARIMA $(1,0,1)(0,0,0)_{12}$	6.791	12	0.871
SARIMA $(2,0,0)(0,0,0)_{12}$	10.583	12	0.565
SARIMA $(0,0,0)(1,0,0)_{12}$	12.852	12	0.380
SARIMA $(0,0,1)(1,0,0)_{12}$	8.604	12	0.736
SARIMA $(1,0,0)(1,0,0)_{12}$	17.416	12	0.135
SARIMA $(1,0,1)(1,0,0)_{12}$	11.700	12	0.47

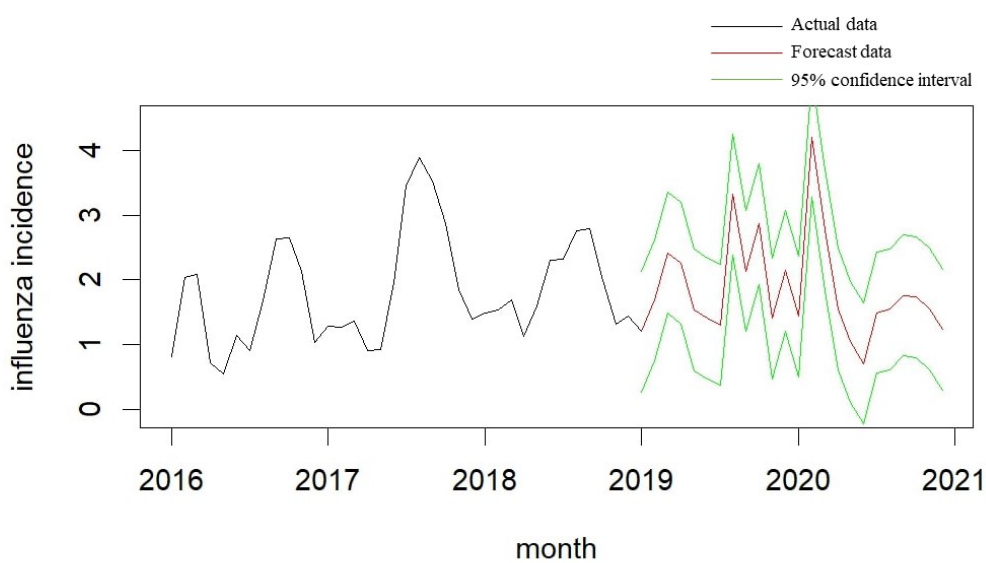

Figure 4. The influenza incidence forecasting and confidence intervals for forcasts during January 2019 to December 2020

Table 4. The influenza incidence forecasting and confidence intervals for forecasts during January 2019 to December 2020

month	$\hat{Y}_t$	LCL	UCL
Jan, 2019	1.20386	0.26969	2.13803
Feb, 2019	1.68587	0.75170	2.62004
Mar, 2019	2.41819	1.48402	3.35236
Apr, 2019	2.25797	1.32380	3.19214
May, 2019	1.53601	0.60184	2.47018
Jun, 2019	1.40739	0.47322	2.34156
Jul, 2019	1.30323	0.36906	2.23740
Aug, 2019	3.31899	2.38482	4.25316
Sep, 2019	2.13731	1.20314	3.07148
Oct, 2019	2.86538	1.93121	3.79955
Nov, 2019	1.40521	0.47104	2.33938
Dec, 2019	2.14343	1.20926	3.07760
Jan, 2020	1.43872	0.50455	2.37289
Feb, 2020	4.20613	3.27196	5.14030
Mar, 2020	2.77100	1.83683	3.70517
Apr, 2020	1.55130	0.61713	2.48547
May, 2020	1.04877	0.11460	1.98294
Jun, 2020	0.71044	-0.22373	1.64461
Jul, 2020	1.49724	0.56307	2.43141
Aug, 2020	1.54769	0.61352	2.48185
Sep, 2020	1.76195	0.82778	2.69612
Oct, 2020	1.73346	0.79929	2.66763
Nov, 2020	1.55228	0.61811	2.48645
Dec, 2020	1.23547	0.30130	2.16964

4. Conclusions

In this study, SARIMA model was used to forecast influenza incidence. Based on the secondary data from 2016-2018, the best fitting model with the actual data was SARIMA $(1,0,1)(1,0,0)_{12}$ which had the lowest AIC (59.24), BIC (67.16) and RMSE (0.4574). This model can be used to predict influenza incidence, and this information can then be used for planning to meet general needs outlined by the prediction, managing Thailand influenza incidence control and prevent, and readying surveillance and rapid response teams (SRRT). However, the study also indicated that a range of factors such as socio-demographic influences, climate, vaccinations, and other variables in the surveillance system were associated with influenza incidence. Thus, further study should include all related factors in the analysis model.

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