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RESIDUAL CONTROL CHART MONITORING FOR AUTOCORRELATED EPIDEMIOLOGICAL DATA: AN APPLICATION TO MONTHLY DENGUE CASES

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Abstract: Dengue fever remains a major public health threat in tropical and subtropical regions, particularly in densely populated urban areas. An effective surveillance system is essential to detect early surges in case numbers and prevent widespread outbreaks. However, conventional Statistical Process Control (SPC) techniques typically assume that observations are independent and identically distributed, an assumption often violated in epidemiological time series data due to temporal autocorrelation. This study proposes a hybrid monitoring framework that integrates time series modelling with SPC to address the autocorrelation structure in monthly dengue case data. First, an autoregressive integrated moving average (ARIMA) model is employed to capture the temporal dependencies in the data. The residuals from the ARIMA model—assumed to be approximately independent—are then analysed using an Individual Moving Range (IMR) control chart. The proposed approach is applied to monthly dengue case data from Makassar, Indonesia, covering January 2013 to December 2024. The results demonstrate that residual-based control charts are more effective in identifying out-of-control signals that align with recorded dengue outbreaks, compared to traditional SPC methods applied directly to raw data. This method provides a statistically robust and practical tool for enhancing early warning systems in dengue surveillance.

Keywords: dengue fever; statistical process control; autocorrelation; ARIMA; IMR control chart.
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1. INTRODUCTION

Dengue fever remains a serious public health concern in tropical and subtropical regions,

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particularly in densely populated urban areas such as those in Indonesia. Transmitted by the Aedes aegypti mosquito, this disease can trigger outbreaks that significantly impact public health systems and the economy. Therefore, regular monitoring of dengue case numbers is critical for timely prevention and control efforts. Early detection of rising case numbers enables health authorities to implement preventive measures in a timely manner to minimize the risk of epidemics [1].

One widely used statistical approach for continuous process monitoring is Statistical Process Control (SPC), which includes control charts such as Shewhart, Exponentially Weighted Moving Average (EWMA), and Cumulative Sum (CUSUM). The Shewhart chart is effective in detecting large shifts in a process; however, it is relatively insensitive to small changes. To address this limitation, the concept of CUSUM was introduced, which accumulates deviations from the target mean to enhance sensitivity to small shifts [2]. CUSUM calculates the cumulative sum of the differences between observations and a target value, making it more responsive to gradual changes compared to Shewhart charts [3]. Subsequently, the EWMA control chart was developed, assigning exponentially decreasing weights to past observations, which allows for early detection of trends or small process shifts [4]. Studies have shown that both EWMA and CUSUM outperform Shewhart charts in detecting small shifts, with CUSUM generally being faster when parameters are correctly tuned, although it is more complex [5].

However, conventional control charts typically assume that data are independently and identically distributed (i.i.d), an assumption that is often violated in epidemiological time series data such as dengue cases, which exhibit autocorrelation due to temporal dependencies. Ignoring autocorrelation may result in an inflated false alarm rate or the failure to detect meaningful changes. Several studies have addressed this issue. It has been emphasized that neglecting autocorrelation can lead to a higher false alarm rate in control chart applications [6]. Additionally, ignoring autocorrelation has been shown to distort in-control variance estimates and control limits, thereby increasing the likelihood of false alarms [7]. Estimation errors can further exacerbate false alarms, particularly when autocorrelation is not properly accounted for [8]. The detrimental effect of autocorrelation on false alarm rates has also been demonstrated, along with the proposal of time series modeling as a strategy to mitigate this issue [4].

To address this issue, several researchers have proposed integrating time series modeling with Statistical Process Control (SPC) [9]. One approach involves using Autoregressive Integrated Moving Average (ARIMA) models to remove autocorrelation before applying control charts [5].

Building on this, residual-based control charts were developed using the residuals from ARIMA models as inputs for EWMA or CUSUM charts, thereby increasing sensitivity to small shifts [10][11]. Further contributions include a review of SPC methods for autocorrelated data [12] and the introduction of the Generalized Likelihood Ratio Test (GLRT) for autocorrelated processes [13]. Earlier research also evaluated the impact of autocorrelation on control chart performance [14], and broader issues in SPC such as challenges in handling autocorrelated data have been discussed in the literature [15]. While these integrated approaches have proven effective in industrial applications, their use in public health surveillance remains relatively limited.

SPC in epidemiology has emerged as a valuable tool for real-time or periodic monitoring of infectious disease trends such as dengue, COVID-19, and influenza. First, it enables early outbreak detection, allowing public health officials to respond proactively before an epidemic develops [16]. Second, SPC facilitates real-time monitoring of disease trends [9]. Third, it enhances data accuracy by identifying variations in data collection and reporting processes [17]. Lastly, adapting SPC methods from manufacturing to healthcare settings has contributed to improvements in the quality and efficiency of epidemiological surveillance systems [18].Therefore, SPC provides a systematic approach for early warning, trend detection, and data quality improvement in public health.Given this context, the present study aims to develop a dengue surveillance framework that integrates SPC with time series modeling to address autocorrelation in epidemiological data. Specifically, the approach employs ARIMA models to capture temporal dependencies in monthly dengue case data, followed by the application of EWMA or Individual Moving Range (IMR) control charts to the resulting residuals. The main contribution of this research is to provide a statistically robust and adaptive monitoring method that supports early warning systems for detecting dengue outbreaks, with a focus on endemic regions such as Makassar, Indonesia.

2. MATERIAL AND METHODS

2.1. ARIMA Model (Box–Jenkins)

ARIMA models are used to model time series data that may have trends or autocorrelation. The approach follows three steps: model identification, estimation, and validation.

ARIMA formula (p,d,q):

$$Y_t = c + \sum_{i=1}^{p} \emptyset_i Y_{t-i} + \in_t + \sum_{j=1}^{q} \theta_j \in_{t-j}$$

Y_t : number of DHF cases in month t

p : order of autoregressive component (AR)

d : number of differencing for stationarity

q : order of moving average (MA) component

$\emptyset_i,\ \theta_j$: AR and MA coefficients

$\in_t$: random error at t

c : constant/mean constant

Differentencing (d) is used to make data stationary.

2.2. Model SARIMA untuk Data Musiman

Due to the seasonal pattern in DHF data (increasing cases every rainy season), the model was expanded to SARIMA (p,d,q) (P,D,Q)s:

$$\phi_P(B^s)\emptyset_p(1 - B)^d(1 - B^s)^D Y_t = \Theta_Q(B^s)\theta_q(B) \in_t$$

$s = 12$: yearly cycle

$\phi_P(B^s) = 1 - \phi_1 B^s - \ldots - \phi_P B^{Ps}$ (AR seasonal)

$\Theta_Q(B^s)$: MA seasonal

D : seasonal differencing

B : operator lag

2.3. Individual Moving Range (IMR) Control Chart

Used to monitor the stability of monthly data (one observation per period).

2.3.1. Individual (I) Chart

Displays the mean and control limits:

$$\bar{X} = \frac{1}{n}\sum_{i=1}^{n} X_i$$

$$UCL_X = \bar{X} + 2.66 \cdot \overline{MR}, \quad LCL_X = \bar{X} - 2.66 \cdot MR$$

2.3.2. Moving Range (MR) Chart

Measures variation between observations:

$$MR_i = |X_i - X_{i-1}|, \overline{MR} = \frac{1}{n - 1}\sum_{i=2}^{n} MR_i$$

MR control limits:

$$UCL_{MR} = D_4\overline{MR}, \quad LCL_{MR} = D_3\overline{MR}$$

2.4. Residual IMR Control Chart

Once the SARIMA model is created, the residuals are used to monitor whether the process is stable without seasonal patterns/trends.

1. Calculate residual:

$$e_t = Y_t - \hat{Y}_t$$

2. Compute residual statistics:

$$\bar{e} = \frac{1}{n}\sum_{t-1}^{n} e_t, \quad \overline{MRe} = \frac{1}{n-1}\sum t = 2^n|e_t - e_{t-1}|$$

3. Define residual control limits:

$$UCL_E = \bar{e} + 2.66\overline{MR}_e, \quad LCL_e = \bar{e} - 2.66\overline{MR}_e$$

3. MAIN RESULTS

This study examines the monthly dengue cases in Makassar City, with data from 2013 to 2020 serving as baseline data, and data from 2021 to 2024 used as monitoring data. The data are presented in Table 1.

Table 1. Number of Dengue Fever Sufferers in Makassar City in 2013 – 2024

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2013	8	18	29	38	30	41	62	18	9	3	4	5
2014	11	13	14	19	29	12	11	8	8	5	5	4
2015	10	22	25	17	16	16	11	7	7	5	3	3
2016	16	53	48	36	34	24	15	6	3	5	6	4
2017	11	25	22	12	23	6	9	9	6	4	3	5
2018	10	21	36	33	44	17	29	27	15	7	8	9
2019	21	51	27	31	46	26	21	12	9	7	9	8
2020	23	42	42	16	27	10	6	2	3	1	2	1
2021	4	28	57	87	901	53	35	41	26	18	41	55
2022	108	63	63	45	49	43	45	45	18	25	34	40
2023	48	61	85	66	44	49	39	44	37	30	11	16
2024	47	74	118	110	146	100	68	62	21	17	15	21

Table 1 shows a significant increase seen from 2021 onwards, especially in 2021 and 2024, which shows a spike in the number of cases compared to previous years. In 2021 there was a spike in the number of dengue fever sufferers in May (901 cases) and high numbers in the surrounding months. Meanwhile, in 2024 the number of cases was very high from March (118 cases) to June (100 cases). In Table 1 there is a seasonal pattern, where several years show an increase in cases in the early to mid-year (especially March to July). This is consistent with the trend of dengue fever in tropical areas, where the rainy season (usually early in the year) increases the population of dengue-causing mosquitoes. Based on 2013–2020: The number of cases was relatively low and stable, while in 2021 onwards: There was extreme variation with a very high peak in cases.

Furthermore, preliminary data which is the number of monthly DHF sufferers in Makassar City in 2013 - 2020 can be described as follows:

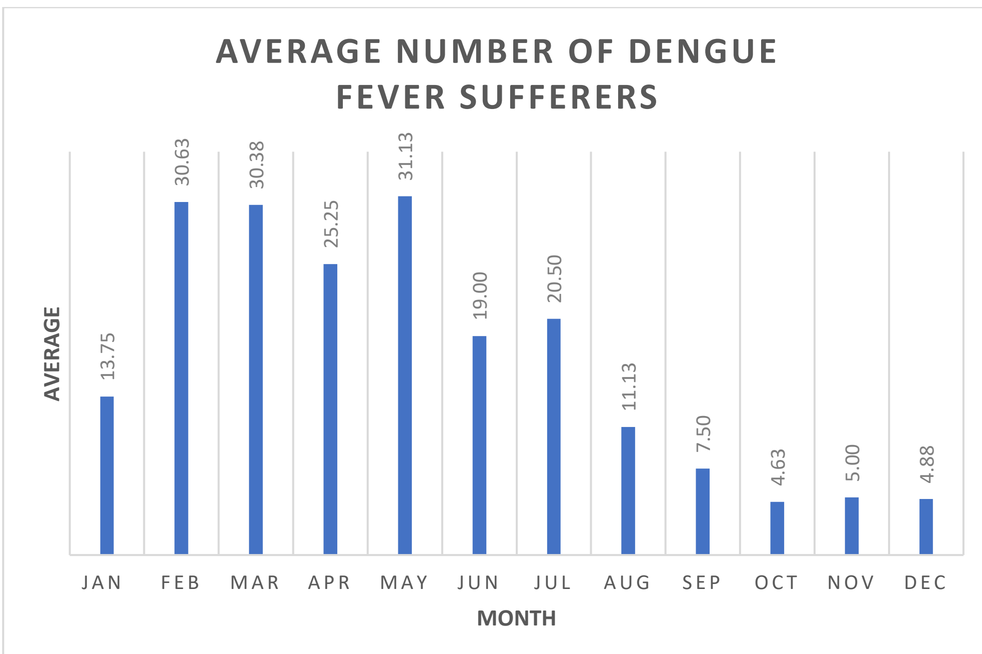

Figure 1. Average Number of Dengue Fever Sufferers per Month 2013-2020 in Makassar City

Figure 1 provides information that the peak of DHF cases occurred in May (31.13), with an increase starting to be seen from January and reaching its highest point in February-May. After May, the number of cases dropped drastically until reaching its lowest point in October (4.63). This is related to the rainy season, in many tropical areas such as Indonesia, the rainy season usually occurs between December and March/April, which creates an ideal environment for the Aedes aegypti mosquito to breed. This graph is consistent with this phenomenon, namely that cases start to increase after the rainy season, reach a peak, then decrease as the dry season enters.

After the peak in May, a gradual decrease was seen in June (19.00), July (20.50), until it dropped to single digits in August-December. This indicates that after intervention or changes in season, transmission began to decrease significantly. Thus, Early Intervention is needed such as fogging, public education, and eradication of mosquito nests which should be started in December or January, before the trend increases sharply. Thus, it can be concluded that the high alert period is February–May, the initial monitoring and preventive intervention period is December–January and the evaluation and maintenance period is June–September. Therefore, in this paper, a time series analysis or control chart (SPC) will be added to monitor whether the increase is within reasonable limits or indicates a potential outbreak. Furthermore, the data per year will be reviewed, the results of which can be seen in Figure 2.

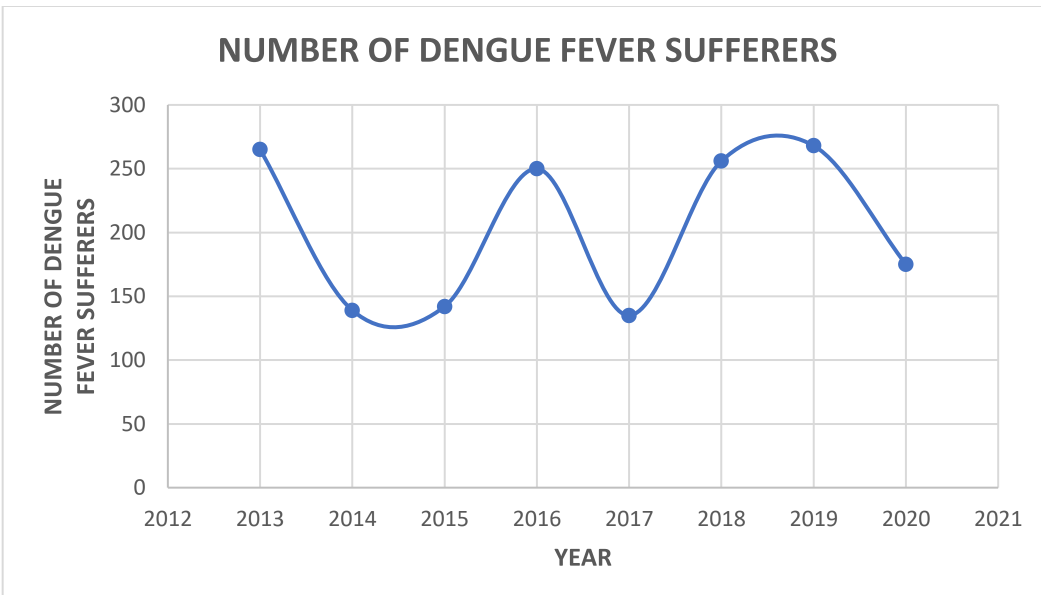

Figure 2. Number of Dengue Fever Sufferers per Year in Makassar City 2013-2020.

Figure 2 shows that the number of dengue fever sufferers in Makassar City in 2013–2020 has a Periodic Fluctuating Pattern (2-year cycle), this can be seen from the up-and-down pattern that repeats every two years. The peak cases occurred in: 2013, 2016, 2018, 2019 and a significant decline was seen in: 2014, 2017, 2020. This indicates the existence of an endemic cycle of dengue fever in Makassar that repeats periodically, possibly related to annual climate change (rainy season), mosquito population changes or decreasing population immunity after two years.

Highest Peak Around 2019 (almost 275 cases), lowest Around 2014 and 2017 (around 130–140 cases). This indicates the existence of years with major outbreaks. Indications of Potential Outbreaks are seen because of the sharp increase from 2017 to 2018 and continuing into 2019 indicating a surge that should be watched out for. The year 2020 appears to have decreased. However, this decrease could also be influenced by the COVID-19 pandemic, which may have an impact on the reporting system or community behavior. In this paper, Time Series Modeling and Control Charts (SPC) will be used to detect years outside normal control or Intervention Planning so that the Health Office can estimate high-risk years and increase prevention campaigns before a spike occurs.

Data on the number of dengue fever sufferers in Makassar City per month from 2013 - 2020 can be displayed in the following graph:

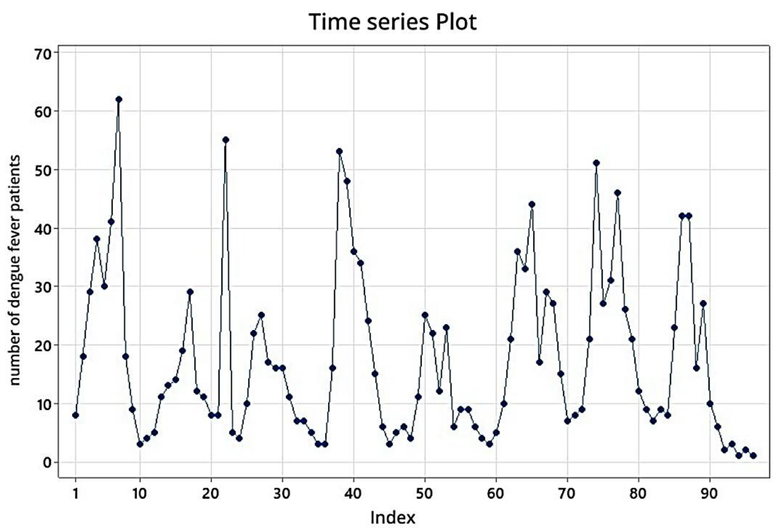

Figure 3. Time Series Plot of Dengue Fever Sufferer Data in Makassar City 2013-2020

Figure 3 shows the presence of data peaks that appear periodically at almost fixed intervals. This indicates the presence of a seasonal component in this data. Each cycle shows a pattern: the value rises sharply to a peak, then decreases gradually before increasing again. This reflects a monthly periodic cycle.

The data movement is very volatile with significant differences between the minimum and maximum points. The peak value can reach around 60–65, while the lowest value is close to 0. This indicates high variability, which is important to note in forecasting or control.

Some peaks (for example at index 5, 20, 40, 70) appear much higher than other points, possibly indicating extreme events or outliers that can be caused by extraordinary factors. The conclusion of this analysis will be further studied using the Sarima seasonal time series model. This graph is data on the number of dengue fever sufferers in the city of Makassar 2013-2020. This pattern suggests the need for periodic vigilance because events tend to recur in certain periods.

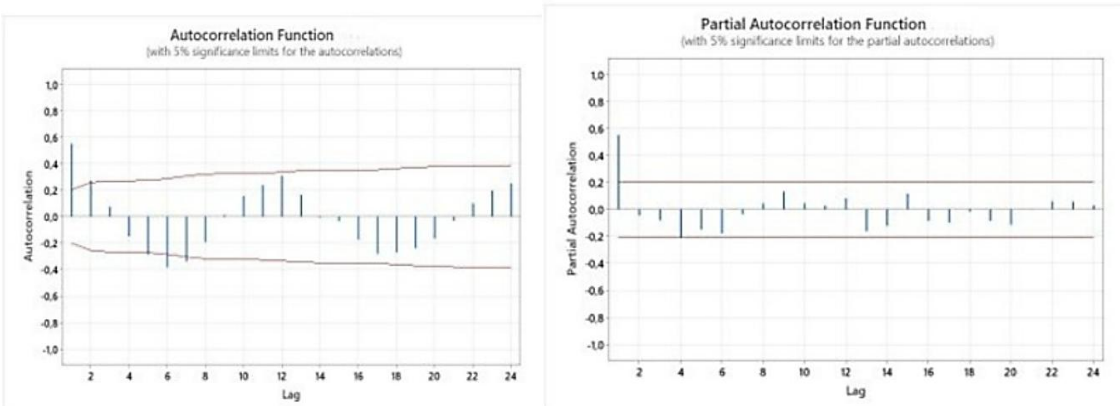

Figure 4. ACF and PACF from Makassar City Dengue Fever Sufferer Data 2013-2020

Figure 4 shows that the ACF decreases slowly (decays exponentially). This is a characteristic of the AR (autoregressive) component. Based on the PACF (Partial Autocorrelation Function) value, only lag 1 is significant, the rest are small and within the confidence limit. So based on the ACF and PACF patterns, the most suitable model is most likely AR (1). Based on the Augmented Dickey-Fuller (ADF) Test, the statistical test results can be obtained as -0.509907 while the critical point for the 5% significance level is -2.8948. Thus, p-value = 0.000 < significance level = 0.05. Therefore, we will reject the null hypothesis, so that the data does not contain a unit root, which means the data is stationary. Next, the ARIMA model will be determined from the Data.

Table 2. Estimation table of ARIMA Data model

Parameter	Coef	SE	T-Value	P-Value
AR(1)	0.516	0.160	3.23	0.002
MA(1)	-0.065	0.185	-0.35	0.727
Constant	8.31	1.30	6.41	0.000

Table 2 provides information that the AR(1) component has a significant effect on the model or shows that there is a data dependency on previous values. The seasonal effect will also be investigated.

Table 3. Estimation table of the SARIMA Data model

Component	**Coefficient**	**SE (Standard Error)**	**T-Value**	**P-Value**
AR(1)	0.5357	0.0888	6.03	0.000
SMA(12)	-0.315	0.102	-3.07	0.003
Constant	7.99	1.52	5.25	0.000
Mean	17.20	3.27	—	—

Table 3 shows that the model can be written as follows:

$$Y_t = 7.99 + 0.53537Y_{t-1} - 0.315 \in_{t-12} + \in_t$$

Dimana:

Y_t : current predicted value

$\in_t$: current error

Y_{t-1} : previous value

$\in_{t-12}$: error 12 periods ago

All parameters are significant because the p value < 0.05. so this model can be said to be good at capturing data patterns and the presence of SMA(12) indicates the possibility of an annual seasonal pattern because the data is monthly.

Table 4. Modified Box-Pierce (Ljung-Box) Chi-Square Statistic

Lag	**12**	**24**	**36**	**48**
Chi-Square	8.52	20.11	37.32	44.31
DF	9	21	33	45
P-Value	0.482	0.515	0.277	0.501

The P-values are all > 0.05. meaning there is no significant evidence of autocorrelation in the residuals at various lags. So the model is good enough because the residuals do not show autocorrelation and the model does not leave any patterns that have not been captured. This confirms that the AR(1) and SMA(12) models chosen are suitable and valid for the data. The residuals from this model are

$$\hat{\in}_t = Y_t - \hat{Y}_t$$

The residual control chart for this model can be written as follows:

$$UCL = \mu_{\hat{\in}} + 3\sigma_{\hat{\in}}$$

$$CL = \mu_{\hat{\in}}$$

$$UCL = \mu_{\hat{\in}} - 3\sigma_{\hat{\in}}$$

Keterangan:

$\hat{\in}_t$: ARIMA residual

$\mu_{\hat{\in}} \approx 0$ if the model is good

$\sigma_{\hat{\in}}$: residual standard deviation

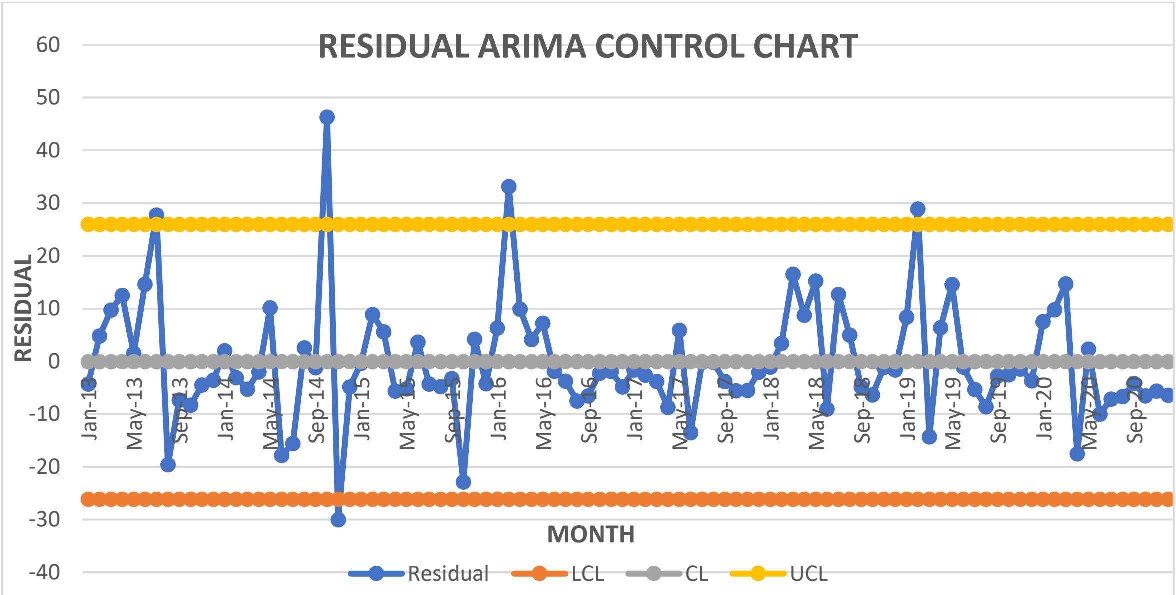

Figure 5. Residual ARIMA Control Chart on Dengue Fever Patients Data in Makassar City 2013-2020

The majority of residuals are within the control limits. indicating that the ARIMA model is good enough to explain data variation. Several residual points outside the control limits indicate outliers or extraordinary events (eg: dengue fever outbreak). Since most points are within the control limits. the process can be considered to be in a statistically stable condition. after the seasonal and trend effects are removed by ARIMA. In the case of dengue fever. points outside the control limits can indicate a spike in extraordinary cases (KLB) and require further epidemiological investigation.

The points that appear outside the control limits (visually) are points above the upper control limit or below the lower control limit. namely there are at least 5 observations that are out of control. namely in July 2013. October 2014. November 2014. February 16 and February 2019. The resulting control limits are the lower control limit is -26 and the upper control limit is 26. If these control limits are used to monitor subsequent data. namely Dengue Fever Patients Data in Makassar City from 2021-2024. the results are as follows:

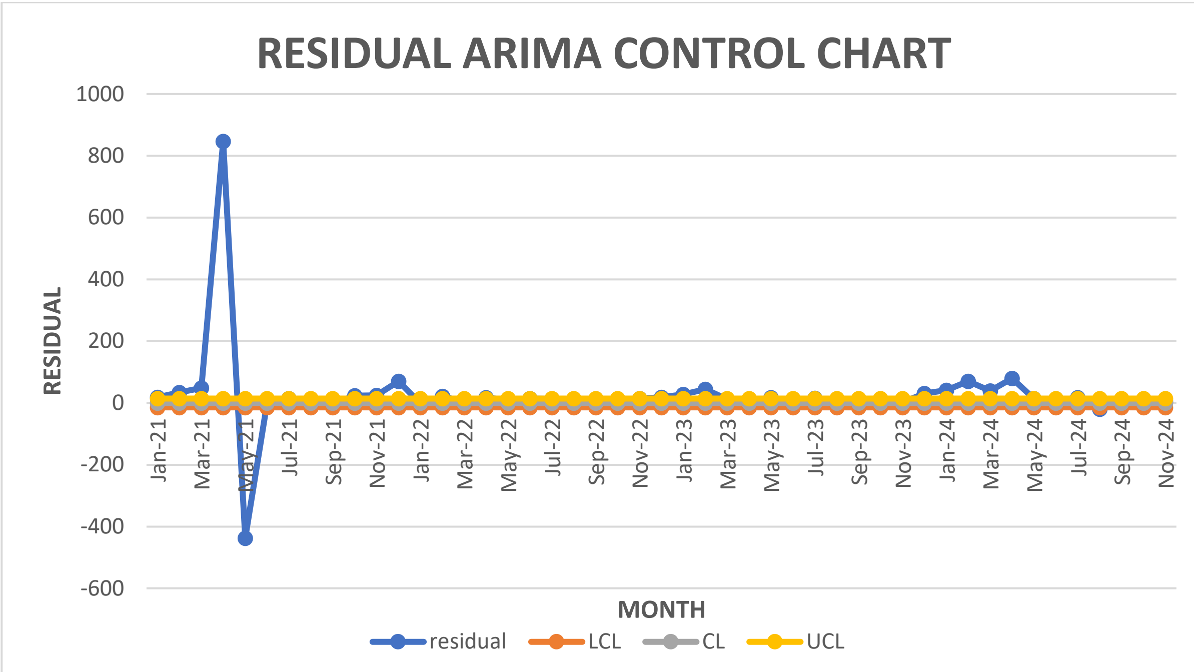

Figure 6. Monitoring with Residual ARIMA Control Chart on Dengue Fever Patients Data in Makassar City from 2021-2024

Figure 6 shows that there are points that are Out of Control (outside UCL/LCL). namely May 2021 has a residual reaching > 800 (very far above UCL) and July 2021 with residual < -400 (very far below LCL). Both of these points are far outside the control limits. this indicates an anomaly or extraordinary event (KLB) in the DHF patient data at that time. Most of the observation points are within the control limits from around July 2021 to the end of 2024. all residuals are relatively stable and are between LCL and UCL. This indicates that the ARIMA model is quite good at predicting data after the anomalous period in early 2021 and it can be shown that there is data outside the control limits as much as 5.

Next. it will be shown how the control map of the individual number of DHF data in Makassar City 2013 - 2020 without involving residuals from the ARIMA model. The results can be obtained as follows:

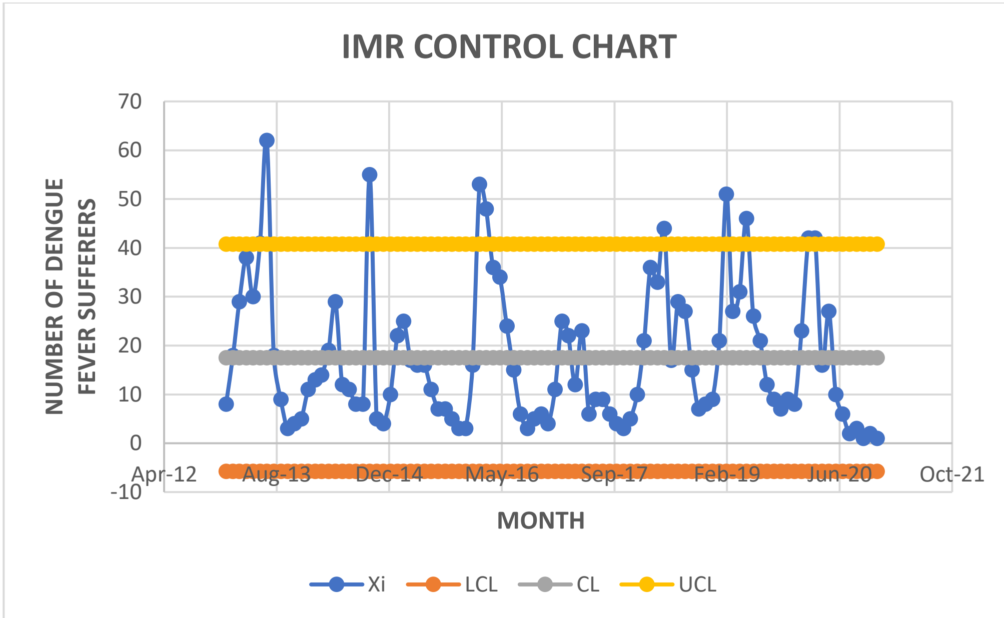

Figure 7. Individual Moving Range (IMR) Control Chart of Dengue Fever Patients Data in Makassar City 2013-2020.

High Fluctuating Data at the Beginning. namely between 2013 and 2016. there were several points that approached or exceeded the UCL (~40–60). This indicates that during that period. the number of cases tended to be unstable and there were indications of an uncontrolled process. the possibility of an extraordinary event (KLB). Meanwhile. around 2017 to 2020. the data was more often between CL and UCL. and there were no more extreme spikes. This shows that the system is more under control. and there is no specific signal from this graph that indicates a major anomaly. From mid-2020 to the end of the graph. the Xi value decreased drastically and even approached zero. This could be due to a decrease in cases due to effective intervention. the impact of the COVID-19 pandemic. namely a decrease in reporting of DHF cases due to the focus on COVID).

Based on the results of the analysis using individual control charts (I-charts). five observation points were found that were outside the upper control limit (UCL). namely in August 2013. July 2014. January 2016. May 2018. and February 2019. These points indicate a significant deviation from the normal pattern of the number of DHF cases in Makassar City. This indicates that during this period. the disease spread process was not under statistical control and had the potential to be an extraordinary event (KLB) or extreme fluctuation that requires further investigation. The existence of points above the UCL is a statistical signal that the DHF control system during this period was not running optimally.

The control chart obtained from historical data for 2013-2020. if used to monitor subsequent data.

namely for data for 2021-2024. the results are as follows:

Table 5. Monitoring of Individual Moving Range (IMR) Control Chart for Dengue Fever Data in Makassar City 2021-2024

Months	Number of Dengue Fever Sufferers	LCL	CL	UCL	Description
Jan-21	4	-5.76428	17.5	40.76428	in-control
Feb-21	28	-5.76428	17.5	40.76428	in-control
Mar-21	57	-5.76428	17.5	40.76428	out-control
Apr-21	87	-5.76428	17.5	40.76428	out-control
May-21	901	-5.76428	17.5	40.76428	out-control
Jun-21	53	-5.76428	17.5	40.76428	out-control
Jul-21	35	-5.76428	17.5	40.76428	in-control
Aug-21	41	-5.76428	17.5	40.76428	out-control
Sep-21	26	-5.76428	17.5	40.76428	in-control
Oct-21	18	-5.76428	17.5	40.76428	in-control
Nov-21	41	-5.76428	17.5	40.76428	out-control
Dec-21	55	-5.76428	17.5	40.76428	out-control
Jan-22	108	-5.76428	17.5	40.76428	out-control
Feb-22	63	-5.76428	17.5	40.76428	out-control
Mar-22	63	-5.76428	17.5	40.76428	out-control
Apr-22	45	-5.76428	17.5	40.76428	out-control
May-22	49	-5.76428	17.5	40.76428	out-control
Jun-22	43	-5.76428	17.5	40.76428	out-control
Jul-22	45	-5.76428	17.5	40.76428	out-control
Aug-22	45	-5.76428	17.5	40.76428	out-control
Sep-22	18	-5.76428	17.5	40.76428	in-control
Oct-22	25	-5.76428	17.5	40.76428	in-control
Nov-22	34	-5.76428	17.5	40.76428	in-control
Dec-22	40	-5.76428	17.5	40.76428	in-control
Jan-23	48	-5.76428	17.5	40.76428	out-control
Feb-23	61	-5.76428	17.5	40.76428	out-control
Mar-23	85	-5.76428	17.5	40.76428	out-control
Apr-23	66	-5.76428	17.5	40.76428	out-control
May-23	44	-5.76428	17.5	40.76428	out-control
Jun-23	49	-5.76428	17.5	40.76428	out-control

Jul-23	39	-5.76428	17.5	40.76428	in-control
Aug-23	44	-5.76428	17.5	40.76428	out-control
Sep-23	37	-5.76428	17.5	40.76428	in-control
Oct-23	30	-5.76428	17.5	40.76428	in-control
Nov-23	11	-5.76428	17.5	40.76428	in-control
Dec-23	16	-5.76428	17.5	40.76428	in-control
Jan-24	47	-5.76428	17.5	40.76428	out-control
Feb-24	74	-5.76428	17.5	40.76428	out-control
Mar-24	118	-5.76428	17.5	40.76428	out-control
Apr-24	110	-5.76428	17.5	40.76428	out-control
May-24	146	-5.76428	17.5	40.76428	out-control
Jun-24	100	-5.76428	17.5	40.76428	out-control
Jul-24	68	-5.76428	17.5	40.76428	out-control
Aug-24	62	-5.76428	17.5	40.76428	out-control
Sep-24	21	-5.76428	17.5	40.76428	in-control
Oct-24	17	-5.76428	17.5	40.76428	in-control
Nov-24	15	-5.76428	17.5	40.76428	in-control
Dec-24	21	-5.76428	17.5	40.76428	in-control

Table 5 provides information that the Shewhart control chart for the number of Dengue Hemorrhagic Fever (DHF) sufferers in Makassar City during the period January 2021 to December 2024. found 30 observation points that were above the Upper Control Limit (UCL). These points are spread across various months. such as March-May 2021. January-August 2022. and March-August 2024. which indicate statistically uncontrolled fluctuations in DHF cases.

The existence of these points outside the control limits indicates that the DHF surveillance and control system has experienced significant deviations. which may be caused by seasonal factors. environmental conditions. or failure of the prevention system. Especially in May 2021 (901 cases) and May 2024 (146 cases). the increase in the number of cases was very striking and needs to be followed up with further epidemiological studies and more intensive public health intervention strategies.

4. CONCLUSION

This study concludes that the approach to monitoring the number of Dengue Hemorrhagic Fever (DHF) cases using a combination of the SARIMA time series model and the residual-based

Individual Moving Range (IMR) control chart provides more effective and accurate results compared to the application of conventional control charts directly to raw data. The SARIMA model successfully captures seasonal patterns and trends in monthly DHF data in Makassar City. so that the residuals produced are free from autocorrelation. The application of control charts to these residuals is able to identify points that truly reflect extraordinary events (KLB). without being affected by normal fluctuations due to seasonality. In contrast. control charts applied directly to raw data show many false signals because they do not take into account the autocorrelation structure. Therefore. this hybrid approach is proven to be more reliable as an epidemiological monitoring tool and has the potential to be used as an early warning system in controlling infectious diseases such as DHF in tropical regions.

CONFLICT OF INTERESTS

The authors declare that there is no conflict of interest.

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