Spatial interpolation method comparison for physico-chemical parameters of river water in Klang River using MATLAB

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Article Info

ABSTRACT

Water quality is one of the most highly debated issues worldwide at the moment. Inadequate water supplies affect human health, hinder food production, and degrade the environment. Using contemporary technology to analyze pollution statistics can help solve pollution issues. One option is to take advantage of advancements in intelligent data processing to conduct hydrological parameter analysis. To perform conclusive water quality studies, a lot of data is necessary. Unfilled data (information gaps) in the long-term hydrological data set may be due to equipment faults, collection schedule delays, or the data collection officer's absence. The lack of hydrological data skews its interpretation. Therefore, interpolation is used to recreate and fill missing hydrological data. From 2012 to 2017, the Klang River's biochemical oxygen demand (BOD) in Selangor, Malaysia, was sampled. This study examined three methods of interpolation for their effectiveness using the MATLAB software: piecewise cubic hermite interpolating polynomial (PCHIP), cubic Spline data interpolation (Spline), and modified Akima partitioned cubic hermite interpolation (Makima). The accuracy is assessed using root mean square error (RMSE). All interpolation algorithms offer excellent results with low RMSE. However, PCHIP delivers the best match between interpolated and original data.

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1. INTRODUCTION

Over the years, numerous international gatherings have focused exclusively on water quality. It has become an endless topic of discussion throughout the world, as degraded water quality has a detrimental effect on social and economic development. Malaysia, too, is not immune to this problem of water pollution. Utilizing the Klang River as an example, it flows for approximately 120 kilometers through the state of Selangor and crosses directly through the heart of Malaysia's capital city, Kuala Lumpur [1]. The Selangor-based Klang River received tributaries from 11 significant rivers to compound matters. The physico-chemical parameters contributing to water pollution are the starting point for calculating the water quality index [2], [3]. Biochemical oxygen demand (BOD), chemical oxygen demand (COD), dissolved oxygen (DO), total suspended solid (TSS), and turbidity are just a few examples of these parameters [4]. In Malaysia, the department of environment (DOE), the country's environment ministry, provides water quality metrics. To analyze the BOD pattern, the

hydrological data were received from DOE for the Klang River from 2012 to 2017. Unfortunately, DOE did not distribute this data consistently. Several were considerably lacking due to various causes, including sensor problems, disruptions in the data collection schedule, and the officers' unavailability at the time. There were only 164 data readings for each type of water parameter during this period, including BOD.

In contrast, based on the number of days in six years, there should have been more than 1000 data collected from the Klang River during this period. For additional technical applications, such as forecasting and prediction procedures based on machine learning techniques like artificial neural networks (ANN), the data should be arranged in an equivalent order on a daily, monthly, or annual basis to enable the study of pollutant data features. The data must be validated and undergo corrective action and improvement before being used in more complex systems. There are two approaches to resolving this issue: manual drawing skills or computational mathematical algorithms [5]. Typically, a mathematical technique called 'interpolation' is advised [6]. The 'extrapolation' method is commonly used when predicting extension data outside the known data range [7]. Spatial interpolation is a frequently used technique to estimate values at unknown data points in a continuous domain area using available data [8], [9]. Spatial interpolation often employs a range of different methodologies and solutions, depending on the available information [10]. A recent study shows about 38 different spatial interpolation algorithms are usually used [11]. This study applied the interpolation technique to real-world data problems using the piecewise cubic hermite interpolating polynomial (PCHIP) [12]. The results were compared to those obtained using cubic Splines piecewise linear functions. The comparison determines the best interpolation model for approximating generic small-arms projectile aerodynamics. The test also demonstrates the performance and variants of polynomial functions in terms of interval and coefficients.

Interpolation has also been used in signal processing [13]. It is used to distinguish between background noise and non-stationary signals. Barker and McDougall [14] successfully tested two interpolation methods using hydrographic data. Typically, oceanic hydrographic data include the temperature and salinity of the ocean water. The measurements are done at varied pressure rates. Interpolation is critical in this case, as researchers usually adjust the interval to normal pressure. Apart from it is use in the field of hydrography, the interpolation technique is also very useful for determining projectile aerodynamics. This has been proven by Rabbath and Corriveau [12] in determining ballistic projectile aerodynamics based on a discrete set of mach numbers. At the end of their study, they found that the interpolation technique gave significant results against the prediction of the original ballistic projectile. Interpolation techniques have also been shown to be often used in real-world data problems where Abdulrahman *et al.* [15] has made an assessment of surface area with height using global navigation satellite systems (GNSS) and geographical information systems (GIS) techniques. To test the best technique to be used, the researcher has tested the data obtained using different interpolation techniques namely inverse distance weighting (IDW), ordinary kriging, and local polynomial interpolation (LPI). The results found that overall, the use of the interpolation technique gives a small root mean square (RMS) error rate and produces a value close to the actual value. In addition, there are many other examples of the use of interpolation techniques in real data problems as done by Wu *et al.* [16] in his study to see the relationship between weather patterns and climatological dynamics in the field of meteorology. The interpolation technique is used to overcome the problem of uneven sampling points other than the random distribution that is commonly done in practical applications. They found that the use of interpolation technique successfully provided the best fitting between the reading value and the expected value obtained. Another example of the successful use of this interpolation technique is through another author named Wu *et al.* [17] whose study involved previous bathymetry hydrographic data compared with expected interpolation data in the Mississippi river. They found that with more data sample points, then the expected results of bathymetry data would be better [9], [18].

In this work, the comparison of spatial interpolation methods to assess the water quality based on the BOD as one of the physico-chemical parameters for the Klang River is examined. MATLAB software was utilized to carry out the interpolation operation. MATLAB software includes three interpolation algorithms that can be employed, notably PCHIP, cubic spline interpolation (Spline), and modified Akima piecewise cubic hermite interpolation (Makima). Klang River's missing hydrological data gap is recreated and filled based on the software's capabilities employed with the appropriateness technique. The three interpolation techniques were used for comparative analysis to determine which method is the most accurate in filling the gaps in the Klang River data received from the DOE. The interpolation techniques' finding is based on the hydrological data obtained from 2012 to 2017.

2. RESEARCH METHOD

The discussion in this section will be focused on the data that was utilized as samples, as well as the testing procedures that were used. The mathematical equations that were employed in this investigation are also presented.

2.1. Data acquisition

Klang River is situated in the state of Selangor in Malaysia, and it is the fourth largest river basin in the state with an area of around 1,290 square km [19]. Approximately 40 km long from this river flows in the federal region of Kuala Lumpur, Malaysia's capital [20]. Figure 1(a) displays the map of the Klang River that flows together with the two states in Malaysia, which are Selangor and Kuala Lumpur, respectively.

On the other hand, Figure 1(b) depicts the locations of the DOE Malaysia-controlled water sampling stations along the Klang River. The sampling station chosen for this work is 1K06 (in Petaling Bahagia, Kuala Lumpur), situated between this river's upstream and downstream reaches, as illustrated in the latter figure. The BOD, COD, DO, ammoniacal nitrogen, suspended solids, dissolved solids, temperature, pH, and turbidity have all been sampled from this station. Only BOD will be tested in this study using the interpolation method. It was chosen because BOD can determine the level of pollution caused by organic matter in river water [21]. MATLAB 2020 is used to perform the interpolation techniques for all tests.
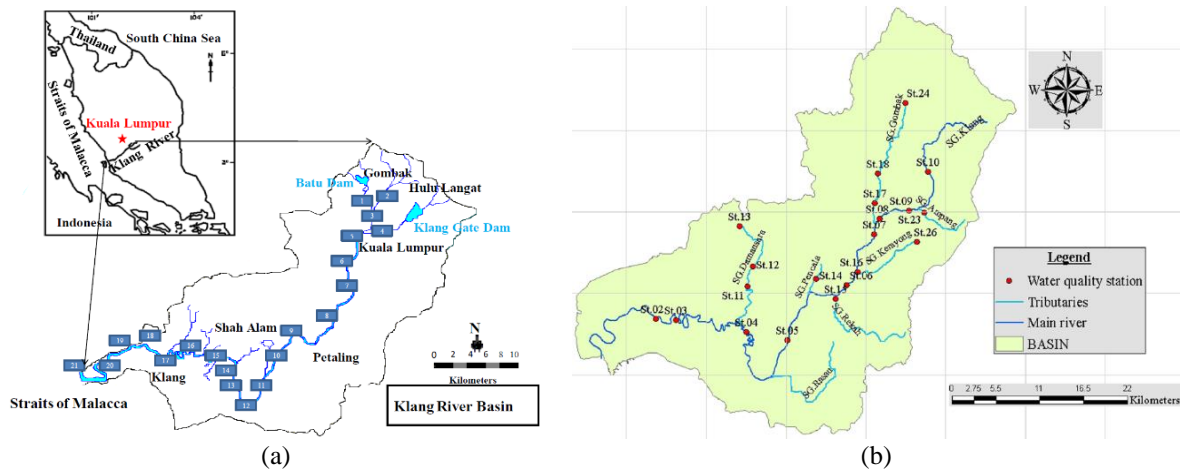

Figure 1. Klang River flow network (a) through the state of Selangor and Kuala Lumpur, Malaysia [22] and (b) the water sampling station along the river basin [2]

2.2. Interpolation technique comparison

Spatial interpolation is frequently used in time series analysis when observation data lack complete information or gaps between them or continuous data measurements unavailable at a specific time, date, or location [23]. Interpolation is frequently used to convert numeric data to a constant function. Precautions should be taken when calculating existing data and data to be determined, as this can result in significant errors [6]. A theoretical review is required to determine the most appropriate technique, either interpolation or extrapolation. Numerous scientific studies have used interpolation to solve spatial and temporal problems, but few in water quality [23].

The Spline method is a frequently used method for interpolation. The Spline is a piecewise polynomial function. Each data set subjected to interpolation must keep the monotone nature of the original data set [24]. This is done to retain the original signal's concave and convexity. Each signal function is often constrained by a $ti < t(i+1)$ data point knot, requiring specific procedures to be satisfied before proceeding to the following step. Simultaneously, for each Spline with a derivative angle 'a', a degree angle of '$a-1$' is required to estimate the slope of each link. This derivative function is necessary along with the data point knot connection on cubic Splines using a grade 3 polynomial Spline.

2.2.1. Cubic spline interpolation

Cubic Spline Interpolation is a fundamental polynomial cubic Spline of grade 3. Each Spline has its weighted attachment to the data connection point [25]. This is referred to as Spline derivatives [26]. The weights or coefficients of the cubic polynomial are used to interpolate the data. Bending the data coefficients ensures that the graph line can pass through each data point without exhibiting any unpredictable behaviour [27]. The cubic Spline interpolation mathematical expression is as shown in:

$$f_i(x) = B_3(x - x_i)^3 + B_2(x - x_i)^2 + B_1(x - x_i) + B_0 \tag{1}$$

where the cubic Spline has the function of $f(x_i) = Y_i$. The function interpolating the partition of $x_0 < x_1 < ... < x_{n-1}$. The polynomial function consists of n-1 cubic polynomial f_i defined in $[x_i, x_{i-1}]$. The function of f_i is join at $(i = 1, ..., n-2)$.

2.2.2. Piecewise cubic hermite interpolating polynomial

The PCHIP frequently interpolates tightly around the data points. It usually does not overshoot unrealistically [28]. It always bordered around the data points. The cubic polynomial of PCHIP is determined using the data points knots values and the value of the derivative being set at the data points knots. The piecewise cubic hermite interpolation has proven to be more durable, accurate, and adaptable [29]. The mathematical expression of the cubic hermite interpolation is given as in (2).

$$P(x) = h_1 + (x - x_i)h_2 + (x - x_i)^2 h_3 + (x - x_i)^3 h_4, \tag{2}$$

where $x_i \leq x \leq x_{i+1}$,

$$h_1 = f_i, \; h_2 \dot{f}_i, \; h_3 = \frac{3C_{i+\frac{1}{2}} - \dot{f}_{i+1} - 2\dot{f}_i}{\Delta x_{i+\frac{1}{2}}}, \; h_4 = \frac{2C_{i+\frac{1}{2}} - \dot{f}_{i+1} - \dot{f}_i}{\Delta x^2_{i+\frac{1}{2}}} \tag{3}$$

The data point is given by f_i, $\dot{f}_i$ is the slope at the value of x_i for $1 <= I <= n$.

2.2.3. Makima interpolation

Makima is a technique that evolved from Akima [30]. Originally, Akima was based on a cubic polynomial. Makima interpolation employs the same method as Akima but has additional elements to ensure that the slope end area has a value close to zero [27]. This eliminates overshoot and undershoot issues and strengthens signal prediction. The modified Akima piecewise cubic hermite interpolation is expressed mathematically (4).

$$d_i = \frac{s_1}{s_1 + s_2} \delta_{i-1} + \frac{s_2}{s_1 + s_2} \delta_i, \tag{4}$$

where,

$$s_1 = |\delta_{i+1} - \delta_i| + \frac{|\delta_{i+1} + \delta_i|}{2}, \; s_2 = |\delta_{i-1} - \delta_{i-2}| + \frac{|\delta_{i-1} + \delta_{i-2}|}{2} \tag{5}$$

In (4) and (5), d_i is the derivative value, δ_i, δ_{i-1}, δ_{i-2}, δ_{i+1}, δ_{i+2} is the slope value and s_1 is the slope edge. When δ_i and $\delta_{i-1} = 0$, will force s_1 into 0. This prevents overshoot when the data node line contains unchanged data compared to the original Akima equation.

The most critical feature following the interpolation process is ensuring that the shape of the new data does not significantly alter compared to the original data. Correlation tests cannot be done on newly created data between two existing points since they require the inclusion of new data. Correlation tests should compare the original and interpolated data sets based on the same total amount of data. Regrettably, this work's overall actual data is smaller than the total number of interpolated data. As a result, the correlation test is ruled out to compare accuracy. Each curve and line that supports the original data curve will have its values following the interpolation procedure. The peak curve and valley of the graph are noticed and compared to the positions of the initial values. This is accomplished by performing the root mean square error (RMSE) test on the peak curve and also on the valleys of the graph. The peaks of the original graph represented the original BOD data point, while the valleys of the original chart represented the original BOD data point.

3. RESULTS AND DISCUSSION

Interpolation techniques compensate for the missing data, resulting in daily data for each day over six years. Figure 2 depicts the graph's original shape before the interpolation process. The initial data from DOE Malaysia contained only 164 BOD parameter points and was not collected daily. These data will produce data acquisition time intervals relatively far apart for six years.

The graph's position is adjusted to correspond to the original day's when the data was retrieved to obtain accurate interpolation data. Figure 3 depicts the BOD data in its original location from the 222nd day in 2012 to the 1902nd day in 2017. As illustrated in Figure 3, the graph retains its original shape. Still, the actual data points have been relocated to the correct day point over the six years. Additionally, notice how the number of days in the interpolated data increased from 164 in Figure 2 to 1902 in Figure 3.
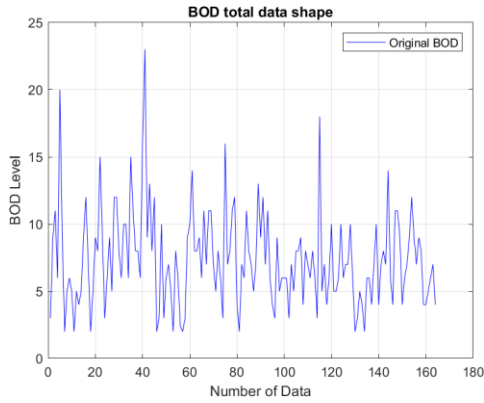
Figure 2. Original shape of BOD data from Klang River with only 164 data points in six consecutive years
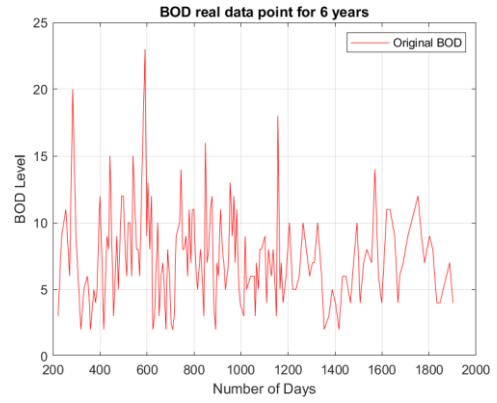
Figure 3. The original position of BOD data in 1902 days

3.1. Result analysis

Following interpolation algorithms (PCHIP, Spline, and Makima), 1681 data points are created throughout the same period. The results of the interpolation of BOD data are depicted in Figures 4(a)-(c). The graphs in Figures 4(a)-(c) depict the data after it has been interpolated using the PCHIP, Spline, and Makima approaches. The resulting graph for the interpolated data is almost identical to the original data graph presented in Figure 3. The graph in Figure 5 depicts the peak and valley locations for the original BOD data. The data will then be marked in order to compare the change in location position between the original BOD data and the BOD data after interpolation.
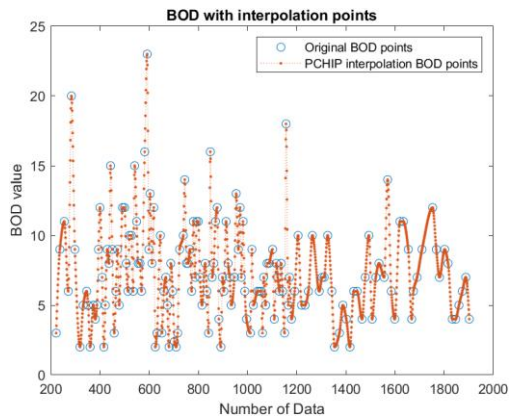
(a)
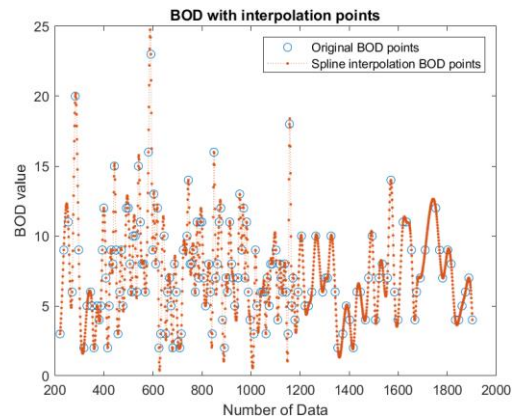
(b)
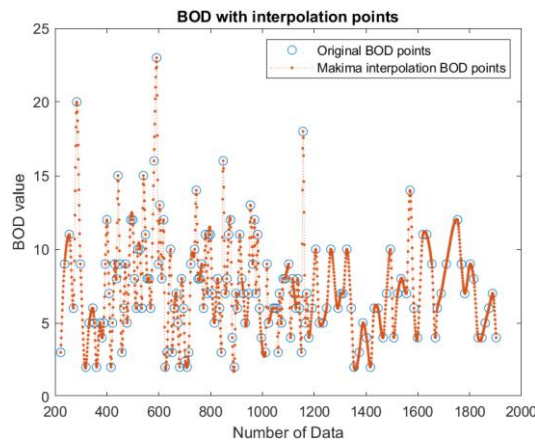
(c)

Figure 4. The graph result of interpolated BOD data using (a) PCHIP, (b) Spline, and (c) Makima

Figure 6 displays the aggregation of graphs between the original BOD data and interpolation data utilizing PCHIP, Spline, and Makima algorithms. By looking at this graph, the differences between the three procedures and also the shape of the original graph can be seen. Basically, the curvature of the original graph is generally still kept, but there is still little difference between the actual pattern and the pattern after the interpolation procedure is carried out. This is owing to the specific traits found in each interpolation technique.
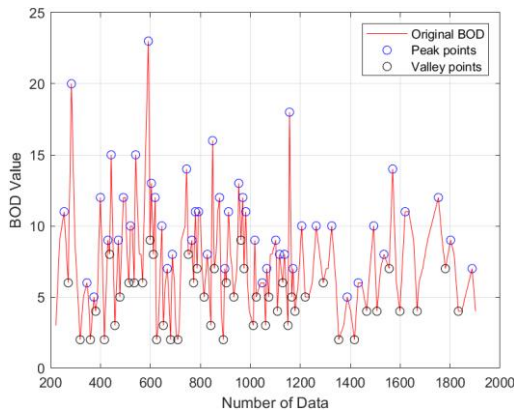
Figure 5. The peak and valleys point from the original data points
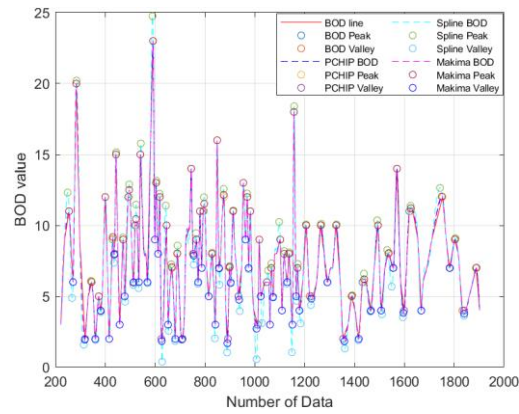
Figure 6. The original data's peaks and valleys were compared to those of the three interpolated data sets

To assess the difference between the actual and interpolated graphs, tests on the original graph's peak curves and valleys are performed. This is done to ensure that they all adhere to the initial curvature. Figure 6 illustrates the peaks and valleys of each graph. These indicators make it easy to tell the difference between the actual and interpolated graph curves. To compare these discrepancies, the RMSE method is used on all three interpolation approaches. The data set as a whole is divided into two comparable peaks and valleys. This deliberate data separation identifies any major alterations, which simplifies the examination of these discrepancies. The RMSE is used to compare these two groups, and the findings are summarized in Table 1.

Table 1. Peak and valleys data comparison between the original and interpolated data using RMSE

	Original BOD	
	Peak	Valley
PCHIP	0	0
Spline	0.58	0.75
Makima	0.13	0.094

As seen in Table 1, there is a discrepancy between the actual BOD data and the interpolated BOD data. The results indicate that when the PCHIP technique interpolates the BOD data, the RMSE in the peaks and valleys is zero. Additionally, it is the most precise curve point compared to Spline and Makima. The RMSE value indicates that the Spline interpolation has an error of 0.58 and 0.75 at the graph's peak and valley. Additionally, it can be shown that the Makima interpolation has an inaccuracy in their peak and valley graphs. Makima has a smaller RMSE than Spline interpolation. The Makima interpolation has a peak error of approximately 0.13 and a valley error of roughly 0.094. Between the Spline and Makima interpolations, the Spline interpolation has a minor mistake at the graph's peak. In contrast, the Makima interpolation has a small error in the graph's valleys.

To determine the causes of the error values on the RMSE for Spline and Makima interpolation and graph form using PCHIP, data samples over a shorter period was taken from the overall interpolated data to visualize the graph curve formed using three different types of interpolation. The curves between the original BOD data points and the interpolated data points using PCHIP, Spline, and Makima are shown in Figure 7. This figure depicts the original data's BOD data graph for 475th to 505th data points. This data range is used as a case study to illustrate the difference between the initial BOD data graph and the graph curve after interpolation.
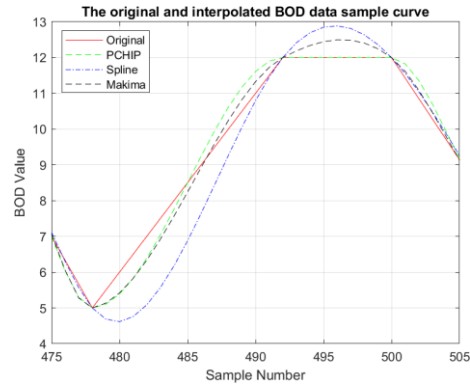
Figure 7. The difference between the original BOD data curve and interpolated data curve

Additionally, it can be seen that each of the three types of interpolation takes a unique way of constructing and facilitating the original data points. This is the primary reason for the technique's disparate RMSE results. Graphs were created for each type of interpolation to help visualize the differences between each form of interpolation and the actual BOD data. The charts in Figures 8(a)-(c) depict the original data and three distinct forms of interpolation graphs. Interpolation is illustrated in Figure 8(a) using PCHIP, in Figure 8(b) using Spline interpolation, and in Figure 8(c) using Makima interpolation.

Figure 8(a) illustrates that the PCHIP technique preserves the original data form as best possible. PCHIP interpolation follows the actual data line smoothly due to the system's monotone character. The PCHIP approach minimizes oscillation effects while generating new data points along the original path. There will be no overshoot when the data curves undergo an abrupt change by strictly limiting the oscillation effect. This is necessary for the PCHIP to interpret the data comparable to the original BOD data possible. Figure 8(b) illustrates that the Spline interpolation technique exhibits strikingly different features than the PCHIP techniques. The Spline technique has a predisposition to identify the presence of a relatively strong swing following a curve's direction change. This is common when a curve is fitted using the Spline fitting method [31]. Additionally, it is necessary to observe the incidence of overshoot on the curve side. This is since it produces data points with a high degree of smoothness. This may significantly affect the accuracy of data generated using the Spline interpolation technique [32]. This technique is well suited for interpolating data that demands smoothness on the data curve. Finally, Figure 8(c) illustrates the Makima interpolation method. This technique is quite similar to PCHIP interpolation. While Makima is not as aggressive as PCHIP, it can deal with oscillations in the flat portion of the data. Makima tends to flow precisely through flat regions while simultaneously decreasing the instability caused by a sudden change in angle. Makima makes a concerted effort to avoid peak overshoot and mitigate the danger of it occurring.

(a)   (b)   (c)
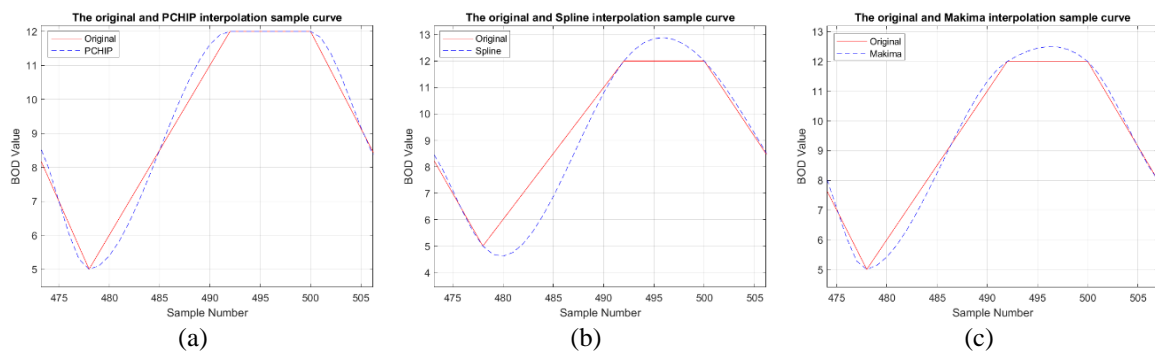
Figure 8. Graph curve from the sample taken from (a) PCHIP interpolation, (b) Spline interpolation, and (c) Makima interpolation

The inconsistency in the time intervals between data collecting along the Klang River impairs the data's validity and can obstruct other processes such as prediction and forecasting. By attempting to employ

the interpolation method, one can improve the overall expectation of the data. While interpolation techniques do widely used, it is necessary to analyze them using several approaches to ascertain their accuracy rates. Comparison only used three strategies using MATLAB-testable programs: PCHIP, Spline, and Makima. According to the research performed, PCHIP interpolation delivers the highest level of accuracy when compared to Spline and Makima interpolation when it comes to reproducing the original form of BOD data. This action is a necessary consequence of PCHIP's aggressive attempt to preserve the actual shape of the original data. Makima is the second choice due to its less aggressive tendency to follow the original form. Still, it provides the best results in producing a curve almost identical to the original graph. It is more appropriate to utilize Spline interpolation when the margin of error from the original graph point is flexible. Spline will attempt to roll the curve when it encounters a rapidly shifting turn. These studies discovered that the differences between these three strategies to be pretty slight. While PCHIP interpolation provides the optimal answer, Makima and Spline interpolation are still viable options for filling in a group of missing data since they have their own identity and characteristics that satisfy the needs of the interpolation process itself. Finally, it is up to the user to determine the most appropriate technique for spatial interpolation based on their specific requirements.

4.   CONCLUSION

Overall, this study has successfully improved the accuracy of the frequently used data for river water characteristics to determine river water quality by completing missing critical data for subsequent data processing. After the comparison between PCHIP, Spline, and Makima interpolation offered by MATLAB has shown different characteristics among them. The results shows that the PCHIP interpolation gives the best level of accuracy in producing a convincing interpolation data compared to the original BOD data. The PCHIP experiments results show very small error gaps between the original and the interpolated data. This is very important especially in keeping long term data as original as possible without losing too much data on the curves.

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