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Parameter Estimation on Simultaneous Linear Functional Relationship of Melaka Wind Data with Error Terms

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ABSTRACT

This study extends the parameter estimation from a bivariate linear functional relationship (LFRM) to a simultaneous LFRM designed for multiple linear variables, employing the maximum likelihood estimation (MLE) method. A simulation study was conducted to examine the bias in parameter estimation. The significance of the simultaneous LFRM lies in its ability to explore relationships among multiple linear variables, with particular emphasis on considering error terms for all variables. The study reveals that the estimated parameters exhibit minimal bias. The applicability of this proposed simultaneous model is illustrated using environmental data such as wind speed, temperature, and humidity from Malacca throughout the southwest monsoon for 128 days in 2020.

1. Introduction

A type of error-in-variable model (EIVM) is linear functional relationship model (LFRM) where it is assumed that the underlying variables remain constant. A functional relationship model for the explanatory variable, X and response variable, Y is when X is a mathematical variable [1]. This relationship arises from data or observations that have been obtained or measured from continuous linear variables subject to some sort of errors like observational or individual error variability. The exploration of the linear functional relationship model (LFRM) dates back to the latter part of the 18th century when Adcock delved into the challenge of fitting a linear relationship in situations where both the explanatory and response variables were prone to errors, paving the way for the development of LFRM [2]. Since that time, numerous authors have dedicated their efforts to addressing the challenge of estimating parameters, particularly in the context of the unreplicated linear functional relationship model [1-4].

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This paper extends the bivariate LFRM introduced by Ghapor *et al.,* [1] to a simultaneous LFRM. This enhancement is made to enable the statistical examination of relationships among multiple linear variables. Suppose the variable Y_{ji}, where j ranges from 1 to q, and i ranges from 1 to n while X_i, where i ranges from 1 to n fits the simultaneous LFRM of $Y_j = \alpha_j + \beta_j X$. Let the observation be x_i and y_{ji}, corresponds to the measurement of the true values of X_i and Y_{ji}, made with some random error, δ_i and ε_j . The random error δ_i and ε_j are assumed to be normally distributed with $\delta_i \sim N(0, \sigma_i^2)$ and $\varepsilon_j \sim N\left(0, \tau_j^2\right)$, respectively. The simultaneous LFRM can be written as follows:

$$Y_j = \alpha_j + \beta_j X \tag{1}$$

where $x_i = X_i + \delta_i$ and $y_{ji} = Y_j + \varepsilon_j$ for $j = 1, \ldots, q; i = 1, \ldots, n$.

2. Parameter Estimation Using the Maximum Likelihood Method

In this study, we focus on situations when the ratio of error variances is already known, $\tau_j^2 = \lambda \sigma_i^2$ for all observations on both variables. Thus, there are $(n + q + 1)$ parameters to be estimated, which are α_j, β_j, σ_i^2 and X_i. The equation of the log-likelihood function of the simultaneous LFRM

$$log\, L = -n\, log(\,2\pi) - \tfrac{n}{2} log\, \lambda - n\, log\, \sigma_i^2 \tag{2}$$

$$- \tfrac{1}{2\sigma_i^2}\left\{\textstyle\sum_{i=1}^{n}(x_i - X_i)^2 + \tfrac{1}{\lambda}\sum_{j=1}^{q}\sum_{i=1}^{n}(y_{ji} - \alpha_j - \beta_j X_i)^2\right\}$$

2.1 Maximum Likelihood Estimation of α_j

By differentiating Eq. (2) with respect to α_j we get

$$\frac{\delta}{\delta\alpha_j}(log\quad L) = \frac{1}{\lambda\sigma_i^2}\sum_{i=1}^{n}(y_{ji} - \alpha_j - \beta_j X_i)$$

and by setting $\frac{\delta}{\delta\alpha_j}(log\quad L) = 0$, we obtain

$$\hat{\alpha}_j = \bar{y} - \hat{B}_j \bar{x} \tag{3}$$

where $\bar{y}_j = \frac{1}{n}\sum_{i=1}^{n} y_{ji}$ and $\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$

2.2 Maximum Likelihood Estimation of X_i

By differentiating Eq. (2) with respect to X_i we get

$$\frac{\delta}{\delta X_i}(log \quad L) = -\frac{1}{2\sigma_i^2}\frac{\delta}{\delta X_i}\left[\begin{array}{l}\sum_{i=1}^{n}(x_i - X_i)^2 + \\ \frac{1}{\lambda}\sum_{j=1}^{q}\sum_{i=1}^{n}(y_{ji} - \alpha_j - \beta_j X_i)^2\end{array}\right]$$

and by setting $\frac{\delta}{\delta X_i}(log \quad L) = 0$

$$X_i = \frac{\lambda\sum_{i=1}^{n} x_i + \sum_{j=1}^{q}\beta_j\sum_{i=1}^{n}(y_{ji} - \alpha_j)}{\lambda + \sum_{j=1}^{q}\beta_j^2} \tag{4}$$

2.3 Maximum Likelihood Estimation of β_j

By differentiating Eq. (2) with respect to β_j we get

$$\frac{\delta}{\delta \beta_j}(log \quad L) = -\frac{1}{2\sigma_i^2}\frac{\delta}{\delta \beta_j}\left[\begin{array}{l}\sum_{i=1}^{n}(x_i - X_i)^2 + \\ \frac{1}{\lambda}\sum_{j=1}^{q}\sum_{i=1}^{n}(y_{ji} - \alpha_j - \beta_j X_i)^2\end{array}\right]$$

and by setting $\frac{\delta}{\delta \beta_j}(log \quad L) = 0$

$$\hat{\beta}_j = \frac{(S_{yy} - \lambda S_{xx}) + \sqrt{(\lambda S_{xx} - S_{yy})^2 + 4\lambda S_{xy}^2}}{2S_{xy}} \tag{5}$$

where $S_{xx} = \sum_{i=1}^{n}(x_i - \bar{x})^2$, $S_{yy} = \sum_{i=1}^{n}(y_{ji} - \bar{y}_j)^2$, and $S_{xy} = \sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})$.

2.4 Maximum Likelihood Estimation of σ_i^2

By differentiating Eq. (2) with respect to σ_i^2 we get

$$\frac{\delta}{\delta \sigma_i^2}(log \quad L) = -\frac{n}{\sigma_i^2} + \frac{1}{2(\sigma_i^2)^2}\left\{\begin{array}{l}\sum_{i=1}^{n}(x_i - X_i)^2 + \\ \frac{1}{\lambda}\sum_{j=1}^{q}\sum_{i=1}^{n}(y_i - \alpha - \beta X_i)^2\end{array}\right\}$$

To estimate $\hat{\sigma}_i^2$, let $\frac{\delta}{\delta \sigma_i^2}(log\, L) = 0$

$$\hat{\sigma}_i^2 = \frac{1}{2n}\left\{\sum_{i=1}^{n}(x_i - X_i)^2 + \frac{1}{\lambda}\sum_{j=1}^{q}\sum_{i=1}^{n}(y_{ji} - \alpha_j - \beta_j X_i)^2\right\}$$

Since $\hat{\sigma}_i^2$ is an inconsistent estimator of σ_i^2 [7], we multiply by $\frac{2n}{n-2}$ yields the consistent estimator

$$\hat{\sigma}_i^2 = \frac{1}{n-2}\left\{\begin{matrix}\sum_{i=1}^{n}(x_i - X_i)^2 + \\ \frac{1}{\lambda}\sum_{j=1}^{q}\sum_{i=1}^{n}(y_{ji} - \alpha_j - \beta_j X_i)^2\end{matrix}\right\} \quad (6)$$

3. Simulation Studies and Model Evaluation for Simultaneous LFRM

An evaluation of parameter estimation performance for simultaneous LFRM is carried out through a Monte Carlo simulation study using MATLAB software. The mean, estimated bias, and mean absolute percentage error (MAPE) are evaluated to assess the parameter estimates of $\hat{\alpha}_j$, $\hat{\beta}_j$ and $\hat{\sigma}_i^2$. Without loss of generality, the number of simulations is fixed at $s = 10000$, the response variables, $j = 1, \ldots, q$, is set to be $q = 2$, which is two response variables, y_1 and y_2. The values of α_1 and α_2= 5 while β_1 and β_2= 1 and also σ_1^2 and σ_2^2 = 1. The sample size is set to be, *n* = 30, 50,100, and 150. In the simulation, the value of λ considered is 1 [6-7]. For simplicity, θ_r represent the parameter of α_j, β_j and σ_i^2, and $\hat{\theta}_r$ be the estimated value of $\hat{\alpha}_j$, $\hat{\beta}_j$ and $\hat{\sigma}_i^2$, respectively. $\bar{\hat{\theta}}$ represent the mean value of the estimated value. The following are the measures used to assess the estimation accuracy of $\hat{\alpha}_j$, $\hat{\beta}_j$ and $\hat{\sigma}_i^2$.

a) Mean of $\hat{\theta}$, $\bar{\hat{\theta}} = \frac{1}{s}\sum_{r=1}^{s}\hat{\theta}_r$
b) Estimated bias of $\hat{\theta}$, $EB\left(\bar{\hat{\theta}}\right) = \bar{\hat{\theta}} - \hat{\theta}$
c) Mean absolute percentage error of $\hat{\theta}$, $MAPE(\hat{\theta}) = \frac{1}{s}\sum_{r=1}^{s}\left|\frac{\theta - \hat{\theta}_r}{\theta}\right|$

The specifics of the experimental framework starting with step 1 involves generating a random value for X_i of size n, where i ranges from 1 to n. For simplicity, the slopes, β_j and y -intercept of the parameter, α_j of simultaneous LFRM, for y_1 and y_2 are set at $\beta_1 = 1$, $\beta_2 = 1$, $\alpha_1 = 5$, $\alpha_2 = 5$, $\sigma_1^2 = 1$, $\sigma_2^2 = 1$, and$\lambda = 1$, respectively. Moving on to step 2, we proceed to generate three random error terms, δ_1 from the normal distribution, $N(0, \sigma_i^2)$ while ε_1 and ε_2 from the normal distribution, $N(0, \tau_j^2)$, respectively. In step 3, the observed value of x, y_1 and y_2 are calculated. Subsequently, in step 4, the mean of x, y_1 and y_2 are computed. Moving to step 5, the parameter estimates for $\hat{\alpha}_1$, $\hat{\alpha}_2$, $\hat{\beta}_1$, $\hat{\beta}_2$, $\hat{\sigma}_1^2$, and $\hat{\sigma}_2^2$ are calculated. Finally, in step 6, the mean, estimated bias (EB), and mean absolute percentage error (MAPE) of $\hat{\alpha}_1$, $\hat{\alpha}_2$, $\hat{\beta}_1$, $\hat{\beta}_2$, $\hat{\sigma}_1^2$, and $\hat{\sigma}_2^2$ are computed.

4. Simulation Result and Discussion for Simultaneous LFRM

The outcomes of the simulation, aimed at assessing the accuracy of parameter estimation for the simultaneous linear functional relationship model (LFRM), are outlined in Tables 1 to 6.

Table 1
Simulation result of $\hat{\alpha}_1$, when $\alpha_1 = 5$, $\beta_1 = 1$ and $\sigma_1^2 = 1$

n	Mean	EB	MAPE
30	4.8951	-0.1049	0.0210
50	4.9204	-0.0796	0.0159
100	4.9723	-0.0277	0.0055
150	5.0008	0.0008	0.0002

Table 2
Simulation result of $\hat{\alpha}_2$, when $\alpha_2 = 5$, $\beta_2 = 1$ and $\sigma_2^2 = 1$

n	Mean	EB	MAPE
30	4.6715	-0.3285	0.0657
50	4.6977	-0.3023	0.0605
100	4.9639	-0.0361	0.0072
150	5.0044	0.0044	0.0009

Table 3
Simulation result of $\hat{\beta}_1$, when $\alpha_1 = 5$, $\beta_1 = 1$ and $\sigma_1^2 = 1$

n	Mean	EB	MAPE
30	0.9464	-0.0536	0.0536
50	0.9842	-0.0158	0.0158
100	0.9963	-0.0037	0.0037
150	1.0038	0.0038	0.0038

Table 4
Simulation result of $\hat{\beta}_2$, when $\alpha_2 = 5$, $\beta_2 = 1$ and $\sigma_2^2 = 1$

n	Mean	EB	MAPE
30	0.9478	-0.0522	0.0067
50	0.9701	-0.0299	0.0299
100	0.9935	-0.0065	0.0065
150	0.9936	-0.0064	0.0064

Table 5
Simulation result of $\hat{\sigma}_1^2$, when $\alpha_1 = 5$, $\beta_1 = 1$ and $\sigma_1^2 = 1$

n	Mean	EB	MAPE
30	0.9141	-0.0859	0.0859
50	0.9161	-0.0839	0.0839
100	0.9978	-0.0022	0.0022
150	1.0013	0.0013	0.0013

Table 6
Simulation result of $\hat{\sigma}_2^2$, when $\alpha_2 = 5$, $\beta_2 = 1$ and $\sigma_2^2 = 1$

n	Mean	EB	MAPE
30	0.9390	-0.0610	0.0610
50	0.9510	-0.0490	0.0490
100	0.9748	-0.0252	0.0252
150	0.9943	-0.0057	0.0057

From Tables 1 to 6, the mean of $\hat{\alpha}_1$, $\hat{\alpha}_2$, $\hat{\beta}_1$, $\hat{\beta}_2$, $\hat{\sigma}_1^2$, and $\hat{\sigma}_2^2$ decreases when the sample size increases. There is a positive indication of the accuracy and reliability of the estimation process. This is often a result of improvements in the quality of the data used for estimation. Next, when the sample size increases, the estimate tends to approach the true value, indicating consistency because the estimate bias (EB) approaches zero. Additionally, the mean absolute percentage error (MAPE) demonstrates a slight decrease with an increase in sample size. Hence, the estimation appears to be satisfactory for the majority of sample sizes.

5. Application to Real Data

In this study, our objective is to investigate the relationship among wind speed, temperature, and humidity data in Malacca state, Malaysia, throughout the southwest monsoon in 2020. We intend to represent this relationship using a simultaneous linear functional relationship model (LFRM). Malacca, situated in the southwestern part of peninsular Malaysia (2.16 °N, 102° 15'E), experiences consistently high temperatures and humidity with little variation throughout the year [8]. The data are from the southwest monsoon from 18th May 2020 until 22nd September 2020 [9]. The data were obtained from the Malaysian Meteorological Department (2022). With a sample size, n of 128, for $i = 1, 2, 3, \dots, n$ the variable x represents the daily maximum wind speed data of Malacca (ms^{-1}); the variable y_1 represents the 24-hour mean relative humidity of Malacca, %, and the variable y_2 represents the 24-hour mean temperature of Malacca, $°C$. Figure 1 illustrates the geographical location of Malacca in Malaysia.

Fig. 1. Location of Malacca in Malaysia

The Weibull distribution is a commonly employed statistical distribution for modelling wind speeds [4]. The shape parameter of the Weibull distribution can be fitted using a normal distribution [10,11]. For example, Dookie *et al*., [12] identified that normal distribution is suitable for evaluating wind speed in Trinidad and Tobago compared to distributions such as Weibull, Birbaum-Saunders, Exponential, Gamma, Nakagami, and Rayleigh distributions [12]. Graphical comparisons were employed to assess the distributions, while the parameters were estimated using maximum likelihood estimation. It has been observed that the expected power predicted difference from the actual values in Trinidad and Tobago, when modelled by the normal distribution, is lower than when modelled by the Weibull distribution. In a study by Jamaliyatul *et al*., [4] the normal distribution was employed to model the relationship between wind speed data in Pulau Langkawi throughout the southwest monsoon seasons in 2019 and 2020 [4]. As a result, the normal distribution will be utilized in this study to model the relationship within the wind speed data in Malacca throughout the southwest monsoon in 2020.

Next, the distribution of humidity and temperature data depends on various factors, including geographic location, time of day, and weather conditions. In many cases, humidity and temperature data may approximate a normal distribution, especially if the sample size is large enough and the data are collected under diverse conditions. Nevertheless, it is crucial to acknowledge that humidity data typically range between 0% and 100%, and normal distributions are theoretically unbounded. Additionally, temperature data may display some skewness or be constrained by its upper and lower limits. Hence, it is crucial to evaluate the distribution of humidity and temperature data through graphical methods and statistical tests. The normality of the wind speed, temperature, and humidity data is examined using the Kolmogorov-Smirnov test, a well-established and commonly used method for assessing whether data follows a normal distribution [13]. The null hypotheses, denoted as H_0 and the alternative hypotheses, denoted as H_A, used in a Kolmogorov-Smirnov test as follows:

H_0: The distribution of the data is normal.
H_A: The distribution of the data is not normal.

The Kolmogorov-Smirnov statistic, *D* is defined as

$$D = \max_{1 \le i \le n} \left(F(Y_i) - \frac{i-1}{n}, \frac{i}{n} - F(Y_i) \right) \tag{7}$$

where *F* is the theoretical cumulative distribution. The null hypothesis, H_0 is rejected if the Kolmogorov-Smirnov statistic, D exceeds the critical value obtained from the table provided by Massey [14-15]. The critical value is determined by the maximum absolute difference between the cumulative distributions of the sample and the population for a given sample size, n [15]. For a significance level of α = 0.05 and a sample size over 35, the critical value is calculated as $\frac{1.36}{\sqrt{n}}$, according to Massey (1951) [18]. By substituting the sample size, $n = 128$, into the equation for the critical value of $D = \frac{1.36}{\sqrt{128}}$, the critical value is found to be 0.1202. The table below presents the Kolmogorov-Smirnov statistic (D) for wind speed, temperature, and humidity data throughout the Malacca southwest monsoon in 2020.

Table 7
Kolmogorov-Smirnov statistic (D) for Wind Speed, Humidity, and Temperature Throughout the Malacca Southwest Monsoon in 2020

Variable	Kolmogorov-Smirnov statistic (D)
Wind speed	0.1188
Humidity	0.0480
Temperature	0.0713

Based on Table 7, all the D values are below the critical value, indicating that H_0 cannot be rejected. This suggests that the wind speed, temperature, and humidity data in Malacca throughout the southwest monsoon in 2020 can be reasonably assumed to follow a normal distribution. Consequently, the extended model in this study, assuming a normal distribution, is deemed suitable for depicting the relationship among wind speed, temperature, and humidity data in 2020.

To visually assess the goodness-of-fit to the normal distribution, Q-Q plots for wind speed, temperature and humidity data in Malacca throughout the southwest monsoon in 2020 are constructed. Q-Q plots illustrate the distribution of data, with points aligning on a reference line if the data follows a normal distribution. The Q-Q plots for wind speed, temperature, and humidity data in Malacca throughout the southwest monsoon in 2020 are presented in Figure 2, Figure 3, and Figure 4, respectively.

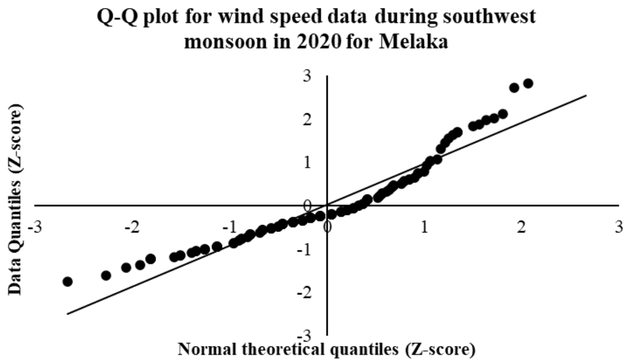

Fig. 2. Q-Q plot for Malacca wind speed data throughout the southwest monsoon in 2020

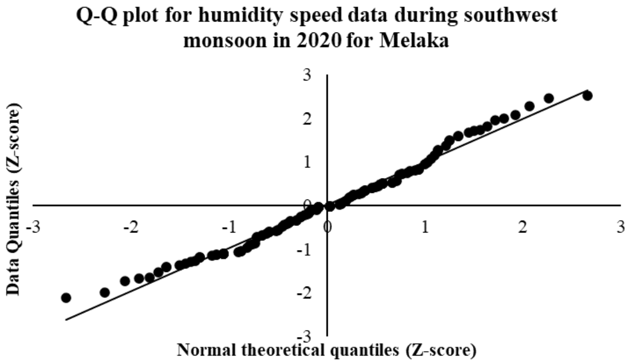

Fig. 3. Q-Q plot for Malacca humidity data throughout the southwest monsoon in 2020

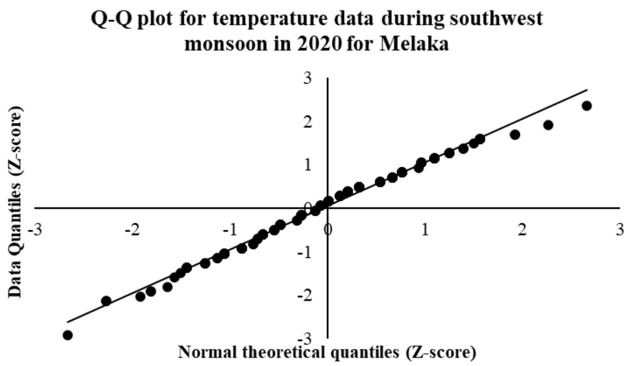

Fig. 4. Q-Q plot for Malacca temperature data throughout the southwest monsoon in 2020

The results from the Kolmogorov-Smirnov test and the Q-Q plots provide approval for treating the wind speed, humidity, and temperature data of Malacca throughout the southwest monsoon season in 2020 with a normal distribution. The procedure for simulating the wind speed (x), humidity (y_1), and temperature data (y_2) of Malacca throughout the southwest monsoon season in 2020 for simultaneous LFRM starting with step 1, insert the data of x, y_1, and y_2. Let $\lambda = 1$. Moving on to step 2, calculate the mean of x, y_1, and y_2. In step 3, apply the simultaneous LFRM from eq. (2) to fit the data. Finally, calculate the parameter estimates of $\hat{\alpha}_1$, $\hat{\alpha}_2$, $\hat{\beta}_1$, $\hat{\beta}_2$, $\hat{\sigma}_1^2$, and $\hat{\sigma}_2^2$.

Table 8
Parameter estimates of Malacca wind speed, humidity, and temperature throughout the southwest monsoon in 2020

Variable	Value
$\hat{\alpha}_1$	60.5530
$\hat{\alpha}_2$	19.7260
$\hat{\beta}_1$	2.0183
$\hat{\beta}_2$	0.8266
$\hat{\sigma}_1^2$	0.0836
$\hat{\sigma}_2^2$	0.2992

From Table 8, it can be observed that the extended model for wind speed, temperature, and humidity data in Malacca throughout the southwest monsoon in 2020 is $Y_1 = 60.5530 + 2.0183X$ and $Y_2 = 19.7260 + 0.8266X$ with a small value of variance, which indicates a good estimation for $\hat{\alpha}_1$, $\hat{\alpha}_2$, $\hat{\beta}_1$, and $\hat{\beta}_2$.

4. Conclusions

This study extends parameter estimation from a bivariate linear functional relationship model (LFRM) to a simultaneous LFRM by using the maximum likelihood estimation (MLE) method to study relationship between multiple linear variables. The application of the simultaneous LFRM is examplified using data from Malacca, specifically focusing on wind speed, humidity, and temperature throughout the southwest monsoon season in 2020. The model considers error terms for the data and MLE is employed to estimate parameters for the wind speed, temperature, and humidity data. The simultaneous LFRM obtained for wind speed, temperature, and humidity data collected from Malacca throughout the southwest monsoon of 2020 are $Y_1 = 60.5530 + 2.0183X$ and $Y_2 = 19.7260 + 0.8266X$. This model proves valuable in managing outdoor activities by providing calculations for wind speed, temperature, and humidity data in Malacca throughout the southwest monsoon in 2020, considering weather conditions and safety. Additionally, this model could establish a basis for future research endeavors aimed at investigating the interplay between wind speed, temperature, and humidity data, portraying it as a simultaneous functional relationship model across diverse locations.

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References

[1] Ghapor, A. A., Y. Z. Zubairi, A. S. M. A. Mamun, and A. H. M. R. Imon. "On Detecting Outlier in Simple Linear Functional Relationship Model Using Covratio Statistic." *Pak. J. Statist* 30, no. 1 (2014): 129-142

[2] Mohd Arif, Azuraini, Yong Zulina Zubairi, and Abdul Ghapor Hussin. "Parameter estimation in replicated linear functional relationship model in the presence of outliers." *Malaysian Journal of Fundamental and Applied Sciences* 16, no. 2 (2020): 158-160. https://doi.org/10.11113/mjfas.v16n2.1633

[3] Saari, Mohd Faisal, Abdul Ghapor Hussin, Mohd Syazwan Mohamad Anuar, and Yong Zulina Zubairi. "General unreplicated linear functional relationship model for circular With Wind Direction Application." *Zulfaqar Journal of Defence Science, Engineering & Technology* 6, no. 1 (2023).

[4] Jamaliyatul, N. A. A. H., B. Badyalina, N. A. Mokhtar, A. Rambli, Y. Z. Zubairi, and A. Abdul Ghapor. "Modelling Wind Speed Data in Pulau Langkawi With Functional Relationship." *Sains Malaysiana* 52, no. 8 (2023): 2419-2430. https://doi.org/10.17576/jsm-2023-5208-18

[5] Yun, Fah Chang, Rijal O. M., and S. A. R. Abu Bakar. “Multidimensional Unreplicated Linear Functional Relationship Model with Single Slope and Its Coefficient of Determination.” *Wseas Transactions on Mathematics* 9, no. 5 (2010): 295-313.

[6] Mohd Arif, Azuraini, Yong Zulina Zubairi, and Abdul Ghapor Hussin. "Outlier detection in balanced replicated linear functional relationship model." *Sains Malaysiana* 51, no. 2 (2022): 599-607. https://doi.org/10.17576/jsm-2022-5102-23

[7] Mohd Arif, Azuraini, Yong Zulina Zubairi, and Abdul Ghapor Hussin. ‘"Maximum Likelihood Estimation of Replicated Linear Functional Relationship Model." *Applied Mathematics and Computational Intelligence* 10, no. 1 (2021a): 301–308.

[8] Manteghi, Golnoosh, Tasneem Mostofa, and M. P. B. M. Noor. "A Field Investigation on the Impact of the Wider Water Body on-Air, Surface Temperature and Physiological Equivalent Temperature at Malacca Town." *International Journal of Environmental Science and Development* 11, no. 6 (2020). https://doi.org/10.18178/ijesd.2020.11.6.1264

[9] Jabatan Meteorologi Malaysia, ‘Laporan Tahunan 2020 Jabatan Meteorologi Malaysia’, 2020.

[10] Amirinia, Gholamreza, Bahareh Kamranzad, and Somayeh Mafi. "Wind and wave energy potential in southern Caspian Sea using uncertainty analysis." *Energy* 120 (2017): 332-345. https://doi.org/10.1016/j.energy.2016.11.088

[11] Kwon, Soon-Duck. "Uncertainty analysis of wind energy potential assessment." *Applied energy* 87, no. 3 (2010): 856-865. https://doi.org/10.1016/j.apenergy.2009.08.038

[12] Dookie, Isa, Sean Rocke, Arvind Singh, and Craig J. Ramlal. "Evaluating wind speed probability distribution models with a novel goodness of fit metric: a Trinidad and Tobago case study." *International journal of energy and environmental engineering* 9 (2018): 323-339. https://doi.org/10.1007/s40095-018-0271-y

[13] Zakaria, Mohd Normani. "The Limitation of Widely Used Data Normality Tests in Clinical Research." *Auditory and Vestibular Research* 31, no. 1 (2022): 1-3. https://doi.org/10.18502/avr.v31i1.8127

[14] Brano, Valerio Lo, Aldo Orioli, Giuseppina Ciulla, and Simona Culotta. "Quality of wind speed fitting distributions for the urban area of Palermo, Italy." *Renewable Energy* 36, no. 3 (2011): 1026-1039. https://doi.org/10.1016/j.renene.2010.09.009

[15] Massey Jr, Frank J. "The Kolmogorov-Smirnov test for goodness of fit." *Journal of the American statistical Association* 46, no. 253 (1951): 68-78. https://doi.org/10.2307/2280095

[16] Hawkins, Del I., and Gopal K. Kanji. “100 Statistical Tests.” *Journal of Marketing Research* 32, no. 1 (1995): 112. https://doi.org/10.2307/3152117