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Multivariate Imputation Chained Equation on Solar Radiation in Automatic Weather Station

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Abstract: Solar radiation is one of the crucial weather observation variables Its variable has a role in renewable energy solutions, agriculture, meteorology, and hydrology. AWS is one of instrument that use to observing weather especially solar radiation. AWS has a pyranometer sensor used to measure solar radiation. Unfortunately, the instrument has problem like the igh cost of supplying, installing, maintaining, and calibrating the equipment. Due to this, there is a lot of empty data, and the actual data cannot be properly measured. Imputation of solar radiation data using MICE algorithm can be solution. This study using BLR, NRR and RFR estimator to estimating solar radiation data. AWS Staklim Banten as target and other AWS as input. The period from January 1, 2018 - February 12, 2024. The performance evaluation of the solar radiation imputation estimator is still according to WMO operational requirements for solar radiation measurements, which can be seen from the resulting MAPE value < 8%.

Keywords: AWS; Imputation; MICE; Missing data; Solar radiation

Introduction

Solar radiation is one of the crucial weather observation variables, the form of energy or radiation emitted by the Sun (Haque et al., 2022; Krishnan et al., 2023). Its variable has a role in renewable energy solutions, agriculture, meteorology, and hydrology (Al-Quraan et al., 2023; Engeland et al., 2017; Kisi et al., 2020). Automatic Weather Station (AWS) is one of instrument that use for observing weather especially solar radiation. AWS has a pyranometer sensor that is used to measure solar radiation (Geuder et al., 2015). The density of observation instrument is critical to improve the accuracy of meteorological information (Joe et al., 2022; Nsabagwa et al., 2019). Unfortunately, solar radiation observation instruments have obstacles such as the high supply cost, installation and maintenance, and equipment calibration (Ağbulut et al., 2021; Betancur et al., 2023; Narvaez et al., 2021). Therefore, there is a lot of empty data, and actual data cannot be measured properly.

Imputation is a solution to estimate missing data, Imputation of solar radiation intensity data has been done by Concepción Crespo Turrado et al. The study used pyranometer sensors located at eight meteorological observation stations. The methods used are Inverse Distance Weighting (IDW), Multiple Linear Regression Models (MLR Models), and Multiple Imputation by Chained Equation (MICE) algorithms. The results showed that the RMSE value of the RMSE algorithm was 13.37%, MLR was 28.19%, and IDW was 31.68% (Turrado et al., 2014). The Multivariate Imputation by Chained Equations (MICE) method to find imputation of Hepatocellular Carcinoma (HCC) data. The results showed that the number of imputations $m = 3$ and iterations of 20 times showed good imputation results and converged for each variable that experienced missing data.

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Based on this, this study will conduct temporal and spatial Imputation by involving several instrument AWS in several locations and using estimator Bayesian Linear Regression (BLR), Nystroem Ridge Regression (NRR), and Random Forest Regressor (RFR). Imputation using AWS Staklim Banten as target and AWS PIK, AWS BSD Serpong and AWS Golf Modern as input. The correlation of spatial and temporal with estimator based iterative imputation can improve the accuracy of solar radiation dataset imputation.

Method

MICE algorithm developed by van Buuren and Groothuis-Oudshoorn aims to generate imputation values for a point through an iteration process (Buuren et al., 2011; Costantini et al., 2023). This algorithm combines joint modeling (JM) and wholly conditional specification (FCS) methods in imputing multivariable data. JM analyzes the distribution of multivariable data. Then, FCS determines the variable-by-variable imputation model based on the Markov Chain Monte Carlo technique (Elasra, 2022; Wicaksana et al., 2023). MICE estimators can take the form of regression methods. These regression methods include Bayesian Linear Regression (BLR), Nystroem Ridge Regression (NRR) and Random Forest Regressor (RFR). BLR uses a linear regression approach based on the probability distribution of the data. NRR uses regression based on the Nystroem approximation. This approximation simplifies the kernel polynomial to estimate the regression results. RFR developed a *decision tree-based* regression. This regression analogizes the estimation results to a population of trees in a forest.

Imputation data starts with outlier detection, then normalization data, missing data scenario, imputation estimator, and evaluation. Figure 1 describes the research flow chart.

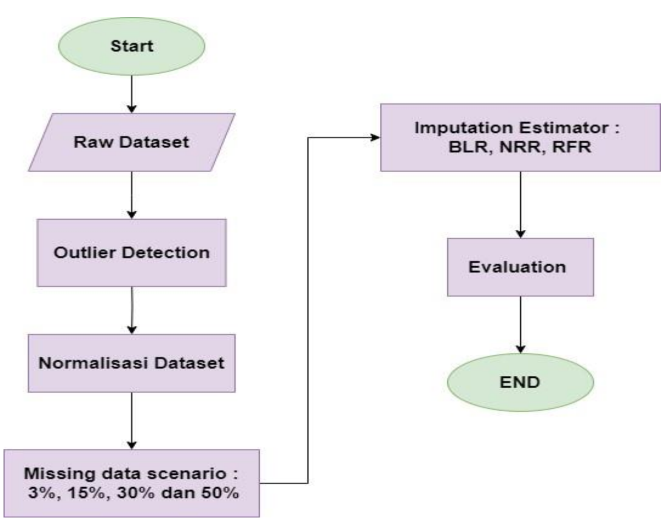

Figure 1. Flowchart of this study

The MICE stages carried out in this study are: Preparing raw data: Performing multiple linear regression analysis on complete initial data; Formation of missing data with four percentages of missing data, namely at a percentage of 3%, 15%, 30% and 50%. Deletion is carried out sequentially with the type of missing data, namely MAR and non-monotonous missing data patterns, namely multivariate patterns; Performing data imputation using three estimators like BLR, RFR and RFR; Evaluate estimator using the coefficient of determination, RMSE and MAPE; Comparing each estimator from the parameter evaluation that has been done.

Based on figure 2, on step outlier detection, we are using range check and step check. Range check is a data check which is based on the historical values ranging of solar radiation intensity range of 0 -1500 W/m^2 (Pahlepi et al., 2023), and step check is a temporal linkage check where there is no more than 800 W/m^2 during 5 minutes. Then, missing rate with a scenario of 3%, 15%, 30% and 50% of the intensity data of solar radiation at the location of AWS Staklim Banten. In this study, we make experiment using multiple of 300 data. If the missing rate is 3%, then the number of missing data is 10 data sequnces. If the missing rate is 15%, then the number of missing data is 50 data sequences. If the missing rate is 30%, then the number of missing data is is 100 data sequences. If the missing rate is 50%, then the number of missing data is 150 data sequences.

This study is using AWS Staklim Banten as target, AWS PIK, AWS Golf Modern and AWS BSD Serpong as input. The sample period of this study in January 1, 2018 - February 12, 2024.

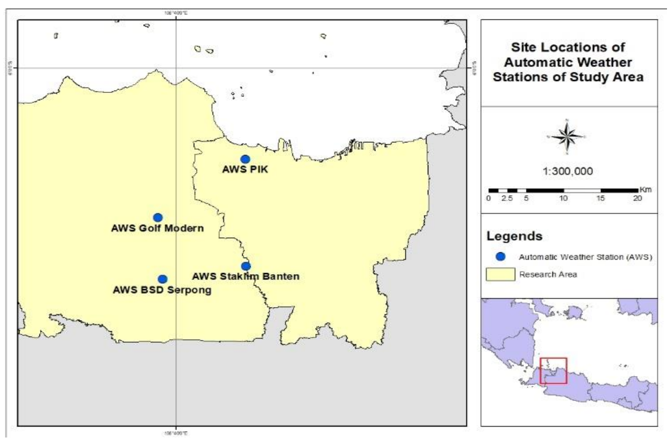

Figure 2. Site location of AWS in this study

Figure 1 shows the map of the research location consisting of AWS Staklim Banten, AWS Golf Modern, AWS BSD Serpong and AWS PIK. Collecting data from AWS via AWS server in BMKG Database Center. Table 1 shows the coordinates of the AWS locations based on figure 2.

Table 1. Coordinates Instrument of this Study

AWS	Coordinate	
	Latitude	Longitude
AWS Golf Modern	-6.19	106.64
AWS BSD Serpong	-6.27	106.65
AWS Staklim Banten	-6.26	106.75
AWS PIK	-6.12	106.75

Evaluation estimator imputation using the coefficient of correlation (R-squared), mean absolute percentage error (MAPE) and root mean squared error (RMSE) (Ananda et al., 2023; Shams et al., 2024; Tkachenko et al., 2020).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y_i})^2}{\sum_{i=1}^{n}(\bar{y} - \hat{y_i})^2} \quad (1)$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y_i})^2} \quad (2)$$

$$\mathrm{MAPE} = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{\hat{y_i} - y_i}{y_i}\right| \quad (3)$$

The coefficient of correlation show relation between the actual solar radiation measurement and the imputed value of estimator on a range of 0 to 1. MAPE describe the error value of the imputation model in percentage form RMSE describe the error value of the imputation model in units of W/m^2.

Result and Discussion

The number of raw datasets of AWS Staklim Banten is 321.69. Solar radiation data at AWS BSD Serpong, AWS Golf Modern and AWS PIK as input for the algorithm estimator. Table II describe the evaluation performance estimator of solar radiation imputation.

Table 2. Evaluation Performance Estimators

	Evaluation		
	R^2	RMSE	MAPE (%)
Missing Rate: 3 % (10			
BLR	0.98	166.33	0.05
RFR	0.98	154.19	0.05
NRR	0.98	164.60	0.07
Missing Rate: 15 % (50			
BLR	0.88	167.74	0.13
RFR	0.90	155.48	0.26
NRR	0.88	165.93	0.17
Missing Rate: 30 % 100			
BLR	0.77	166.86	0.17
RFR	0.80	154.90	0.11
NRR	0.77	165.69	0.10
Missing Rate: 50 % 150			
BLR	0.65	166.94	0.14
RFR	0.70	154.75	0.20
NRR	0.66	165.46	0.20

Based on table II describe that estimator MICE can produces accurate imputation values, it can be seen from the coefficient of correlation. If the missing data is more than 15%, there is a decrease in the coefficient of determination. Estimator BLR, RFR and NRR for solar radiation data imputation performance still according World Meteorological Organization (WMO) operations for measurements with MAPE values still below 8%. The performance of the three estimators has no significant difference based on the coefficient of determination and RMSE values. The RFR estimator has the highest coefficient value for each missing data scenario and MAPE value of 0.26 at 15% missing data.

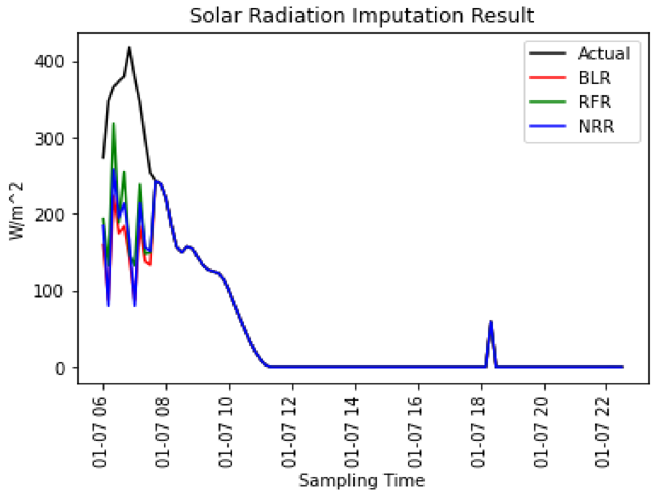

Figure 3. Evaluation estimator on scenario missing rate 3%

Based on figure 3 compares actual data with estimator model using plotting graph on 3% scenario (10 missing data). In this scenario, it shows that the all estimators can follow the pattern of the actual data, this can be seen from the three estimators close to the actual measurement.

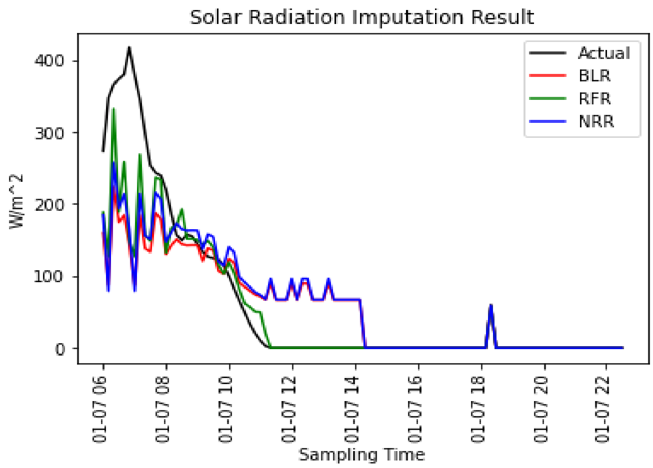

Figure 4. Evaluation estimator on scenario missing rate 15%

Based on figure 4 compares actual data with estimator model using plotting graph on 15% scenario (50 missing data). There is a shift in BLR and NRR, the RFR plot is closer to the other patterns.

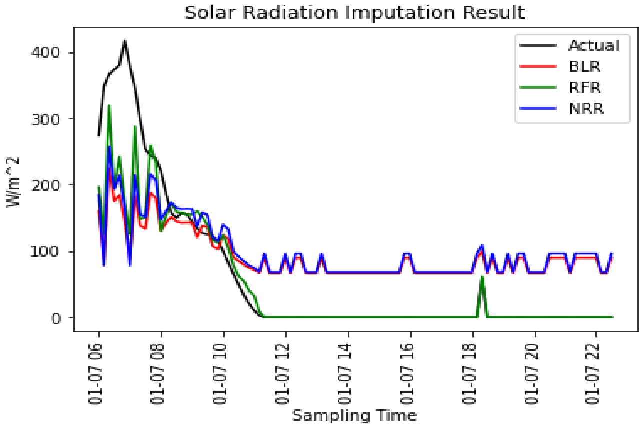

Figure 5. Evaluation estimator on scenario missing rate 50%

Based on figure 5 compares actual data with estimator model using plotting graph on 50% scenario (150 missing data). The BLR and NRR estimator patterns are getting away from the actual data pattern, and the RFR pattern is still close to the actual data. Scenario 30% and 50% missing data patterns have similar patterns. The RFR estimator compared to other estimators has a pattern that is close and tends to follow the actual data. This is in accordance with the results of the highest RFR estimator correlation value in each scenario.

Solar radiation is the energy emitted by the Sun through electromagnetic waves and life on Earth depends on it. In addition to determining atmospheric and climatological dynamics and trends, it makes plant photosynthesis possible, among other processes (Durand et al., 2021; Elbasiouny et al., 2022; Keenan et al., 2023; Ort et al., 2022). If you want to know more, such as what types of radiation there are and what their harmful effects on health are (Abu Bakar et al., 2019), especially on the skin in summer, Without solar radiation, there would be no life on earth; moreover, it currently allows us to produce photovoltaic energy, which is essential in the fight against climate change (Chowdhury et al., 2020; Masson et al., 2014; Victoria et al., 2021). However, it can also be harmful to human health, for example, due to its effects on our skin, and these effects have become more dangerous in recent years due to the greenhouse effect, which also influences the rising temperatures on our planet (Abbass et al., 2022).

Solar radiation is measured on a horizontal surface by means of a radiation sensor or pyranometer, which is placed in a south-facing, shadow-free location (Baltazar et al., 2014; Khalil, 2022; Maleki et al., 2017; Mubarak et al., 2017). Data are collected in units of power, watts per square metre (W/m^2), at all weather stations and tend to be taken at ten-minute or 24-hour intervals to establish averages. In the case where it is desired to convert solar radiation from power units to energy units, the data in W/m2 must be multiplied by the number of seconds comprising ten minutes (600) or 24 hours (86.400) and the result will be provided in joules per square metre (J/m^2).

Radiation that enters the earth's atmosphere undergoes several types of processes – some of the radiation is mixed by particles in the atmosphere, some is absorbed by these particles, some is absorbed by the earth's surface (Liu et al., 2020). The total of shortwave radiation that reaches the earth's surface (horizontal) is usually referred to as global radiation or global horizontal radiation (Korevaar, 2022; Mamassis et al., 2012; Paszkuta et al., 2024). This global radiation consists of two types of components, namely the direct radiation component and the diffuse radiation component (Babikir et al., 2018; Stamatis et al., 2023; Yu et al., 2023).

Conclusion

Implemented Estimator BLR, RFR, and NRR of MICE can cover the imputed missing solar radiation data on the pyranometer sensor. AWS Staklim Banten is using Target, and the input is from AWS BSD Serpong, AWS Golf Modern, and AWS PIK. The MAPE value of each estimator obtained is still below 8%; this shows that this algorithm's imputation performance is still according to WMO operational requirements. In this research, RFR has better evaluation and computation than BLR and NRR; this can be seen from the highest correlation value produced in each scenario. The RFR estimator data pattern tends to follow the actual pattern compared to other estimators. However, this study still uses radiation data at night, whose value is close to 0, so to produce better estimation performance, data should be used in the morning to evening.

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Author Contributions

Field data collection, G.A; Methodology P.P, A; Data Processing N.A; Data Correction P.P; Calculation data N.A; Analysis data N.A, G.A, P.P; Mapping A; Writing original drafting N.A, A., G.A. All, author have read and agree to the published version of manuscript.

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Conflicts of Interest

The authors declare no conflict of interest.

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