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Predicting Solar Radiation Using Temporal Convolutional Networks and Long Short-Term Memory: A Comparative Study Based on Automatic Weather Station Data

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ABSTRACT

Solar radiation is a key meteorological parameter for climatology, hydrology, agriculture, renewable energy, and environmental analysis. Direct measurement remains limited because it requires specialised instruments, regular calibration, and high maintenance costs. This study compared Temporal Convolutional Network (TCN) and Long Short-Term Memory (LSTM) models for predicting solar radiation using Automatic Weather Station data from the Aceh Climatological Station. The dataset comprised 4,152 observations from January to December 2023, with rainfall, air temperature, relative humidity, air pressure, wind speed, wind direction, and time features as predictors, while solar radiation served as the target variable. The research process included data quality control, interpolation of invalid values, Min-Max Scaling, time feature engineering, sliding-window sequence generation with 24 time steps, and time-based data splitting using 70:15:15, 80:10:10, and 70:10:20 scenarios. Model performance was evaluated using MAE, RMSE, MAPE, and R^2. The 80:10:10 split produced the best results for both models. The LSTM model achieved slightly better overall performance than TCN based on RMSE and R^2, although both models captured the temporal pattern of solar radiation. The study provides an AWS-based temporal deep learning framework for radiation prediction in tropical regions of Indonesia.

Keywords: solar radiation, LSTM, TCN, deep learning, AWS

1. INTRODUCTION

Solar radiation is a meteorological factor that plays a crucial role in governing various physical processes in the atmosphere and on the Earth's surface. The radiant energy received by the Earth's surface is the primary source regulating atmospheric energy balance, cloud formation, the hydrological cycle, weather dynamics, vegetation growth, and agricultural productivity. Furthermore, solar radiation data is utilised in various fields, such as climate modelling, hydrology, renewable energy, the planning of solar power generation systems, evapotranspiration calculations, and climate change analysis. In tropical regions such as Indonesia, the characteristics of solar radiation tend to be more dynamic as they are influenced by high variability in cloud cover, rainfall, air humidity, temperature, aerosol content, and atmospheric circulation, which change rapidly throughout the day (Hissou et al., 2023; Huang et al., 2021; Wald, n.d.) . Consequently, accurate solar radiation data is a vital component in supporting decision-making across various sectors related to weather and climate conditions.

Despite its vital role, the availability of solar radiation data from direct measurements remains relatively limited. Solar radiation observations generally require specialised instruments, such as pyranometers and pyrheliometers, which entail significant investment in equipment, regular calibration, and complex maintenance. Not all meteorological observation stations are equipped with such instruments, meaning that the continuity and spatial coverage of solar radiation data remain a challenge in many regions. In contrast, meteorological data recorded by AWS, such as air temperature, relative humidity, air pressure, rainfall, wind speed and wind direction, are available more comprehensively, continuously and easily. These parameters are closely related to atmospheric conditions that influence the intensity of solar radiation at the Earth's surface and can therefore be utilised as predictor variables in developing models for estimating or predicting solar radiation (Chen et al., 2019; Hissou et al., 2023; Huang et al., 2021) .

Advances in Artificial Intelligence (AI) and Deep Learning technologies have opened up new opportunities for modelling complex and non-linear meteorological data. Unlike conventional statistical approaches, which generally assume linear relationships between variables, deep learning methods are capable of learning more complex patterns, including temporal relationships in time series data. This capability has led to the increasing application of deep learning in various research projects predicting weather elements, such as rainfall, air temperature, wind speed, evapotranspiration and solar radiation. Neural network-based modelling enables the learning process to be carried out automatically on historical patterns, thereby generating predictions with a higher level of accuracy for data characterised by high fluctuations (Bai et al., 2018; Ehteram et al., 2024; Wang et al., 2023) .

Among the various deep learning architectures, TCN and LSTM are two widely used methods for time series modelling. LSTM is an extension of the Recurrent Neural Network (RNN), designed to address the vanishing gradient problem through memory cells and gates, thereby enabling it to retain historical information over the long term. In contrast, TCN utilises causal convolution and dilated convolution to capture temporal relationships efficiently without relying on recursive processes. This architecture enables parallel computation with a broader scope of historical information, thereby potentially improving training efficiency. Both methods possess distinct characteristics, making them of interest for comparison in the context of solar radiation prediction, which exhibits complex temporal patterns.

A number of previous studies have demonstrated that both Machine Learning and Deep Learning methods are capable of delivering good results in solar radiation modelling. Huang et al. (2021) showed that the use of meteorological variables can improve the accuracy of solar radiation estimates compared to empirical approaches. Hissou et al. (2023) reported that Deep Learning models are better able to capture non-linear relationships between atmospheric parameters than conventional statistical models. Wang et al. (2023) demonstrated that sequence-based neural networks deliver high performance in short-term solar radiation forecasting, while Ehteram et al. (2024) showed that deep learning-based models can improve forecast accuracy for meteorological data characterised by high dynamics. However, the majority of these studies were conducted in subtropical or mid-latitude regions, utilised different data characteristics and diverse model configurations, or evaluated only a single deep learning architecture. Consequently, the results cannot yet be generalised to tropical conditions such as those in Indonesia.

Furthermore, previous studies generally utilised different datasets, data splitting scenarios, sliding window lengths, forecast horizons, and training parameters, making comparisons between architectures less objective. These configuration differences make it difficult to determine whether a model's performance improvement truly stems from its architectural characteristics or is influenced by differences in experimental design. On the other hand, research on the utilisation of AWS data as a basis for developing solar radiation prediction models within the operational environment of the Indonesian Agency for Meteorology, Climatology and Geophysics (BMKG) remains relatively limited. Yet, AWS data is routinely available at most observation stations and has the potential to be utilised as an alternative information source in locations that do not yet have solar radiation sensors.

Given these circumstances, there remains a research gap that needs to be addressed. Firstly, there has been little research directly comparing the performance of TCN and LSTM using the same dataset, input variables, sliding window length, data splitting scenarios, forecast horizon, and evaluation metrics, so that the comparison results truly reflect the differences in the capabilities of the two architectures. Secondly, research on solar radiation prediction based on AWS data in tropical regions of Indonesia remains limited, particularly studies employing a temporal deep learning approach. Thirdly, there is currently no standardised framework available that can serve as a reference for developing a support system for estimating solar radiation based on routine meteorological data within the BMKG environment.

Based on these research gaps, this study offers several novelties. Firstly, the study conducts a comparative evaluation between the TCN and LSTM models using the same dataset, identical input variables, a sliding window length of 24 time steps, a one-step-ahead prediction horizon, and three time-based data partitioning scenarios, thereby yielding a more objective comparison. Secondly, the study utilises AWS data from the Aceh Climatological Station as a representation of the atmospheric characteristics of Indonesia's tropical region, thereby making the research findings more relevant to national operational conditions. Thirdly, the study produces a framework for solar radiation forecasting based on AWS data that can be utilised to support the reconstruction of missing radiation data, quality control of observational data, agroclimatic services, evapotranspiration calculations, and the development of artificial intelligence-based climatological information systems.

Based on the above, this study aims to compare the performance of the TCN and LSTM models in predicting solar radiation using AWS data from the Aceh Climatological Station. The comparison was carried out across three time-based data splitting scenarios, utilising the MAE, RMSE, MAPE and R^2 metrics. The research results are expected to provide empirical evidence regarding the most suitable deep learning model for solar radiation prediction in the tropical regions of Indonesia, whilst also serving as a reference for the development of artificial intelligence-based meteorological prediction systems within the BMKG's operational environment, as well as for further research in the fields of climatology and computer science.

2. RESEARCH METHOD

This research was carried out through several main stages, namely the collection and description of the dataset, data pre-processing to improve data quality, the creation of relevant features, the transformation of time-series data using a sliding window approach, the development of TCN- and LSTM-based prediction models, and the evaluation of model performance using various evaluation metrics to measure the models' accuracy and generalisation ability.

2.1. DATASET

The research data utilised observations from the Aceh Climatological Station's AWS, obtained from the BMKG AWS Centre. The data comprised secondary data covering the period January-December 2023, with observations taken at 10-minute intervals. Following data quality control and data cleaning, a total of 4,152 observations were obtained for use in the modelling process. The research variables consist of one target variable and six meteorological predictor variables. In addition, two time features (hour_sin and hour_cos) were included to represent diurnal cycle patterns.

Table 1. The performance of speed

No	Variable	Unit	Description
1	Solar Radiation (Rs)	W/m²	Target
2	Rainfall (RR)	mm	Predictor
3	Air Temperature (T)	°C	Predictor
4	Relative Humidity (RH)	%	Predictor
5	Air Pressure (P)	hPa	Predictor
6	Wind Speed (WS)	m/s	Predictor
7	Wind Direction (WD)	°	Predictor
8	Hour_sin	-	Time feature
9	Hour_cos	-	Time features

Solar radiation is used as the target variable, whilst all meteorological parameters are used as predictor variables as they are related to the intensity of solar radiation received by the Earth's surface.

2.2. FLOWCHART

The research was conducted in several stages, namely AWS data acquisition, data quality checks, interpolation of invalid data, data normalisation, creation of time features, generation of time series data using a sliding window, dataset splitting, development of TCN and LSTM models, model training, evaluation using MAE, RMSE, MAPE and R², followed by a comparative analysis of the performance of the two models. The complete research workflow is shown in Figure 1.

Figure 1. Research Flowchart

2.3. DATA QUALITY AND INTERPOLATION

A quality control stage was carried out to ensure the quality of the data obtained from the Automatic Weather Station (AWS) before it was used in modelling. The checks included the identification of missing values, invalid data, and outliers based on the physical limits of each meteorological variable. Values that did not meet these limits were converted to NaN, then corrected using linear interpolation to maintain the continuity of the time series. Linear interpolation is performed using the following equation.

$$x_t = x_1 + \frac{t - t_1}{t_2 - t_1}(x_2 - x_1) \qquad (1)$$

Explanation:
x_t= interpolated value at time t
x_1= observed value prior to the missing data
x_2= observed value after the missing data
t_1= time before the missing data

t_2= time after data loss
t= interpolated time

This method was chosen because it preserves the continuity of the time series data without altering the main patterns of the data, meaning the resulting dataset is better suited for use in training TCN and LSTM models.

2.4. DATA NORMALIZATION

All variables w ere normalised using the Min-Max Scaling method to ensure a uniform range of values, thereby accelerating the convergence process of the *Deep Learning* model. Normalisation was carried out using the following equation.

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (2)$$

Explanation
x_{norm}= normalised value
x= original value
x_{min}= minimum value of the variable
x_{max}= maximum value of the variable

The normalisation parameters are calculated using training data, and are then applied to the validation and test data to avoid *data leakage*.

2.5. TIME FEATURE ENGINEERING

To represent daily cycle patterns, the observation times are transformed into a periodic form using sine and cosine functions.
The transformation is carried out using the following equations.

$$Hour_{sin} = \sin\left(2\pi \frac{t}{24}\right) \quad (3)$$

$$Hour_{cos} = \cos\left(2\pi \frac{t}{24}\right) \quad (4)$$

Explanation
t= observation time
24 = the number of hours in a day

This transformation enables the model to recognise relationships between times that are periodically close together, for example 23:00 and 00:00.

2.6. FORMATION OF TIME SERIES DATA (SLIDING WINDOW)

Multivariate data is converted into a sequence using the Sliding Window method over 24 time steps. Each input consists of the previous 24 observations, whilst the target is the solar radiation value at the next time step (*t + 1*). Thus, the model is able to learn the temporal relationships between observations before generating a prediction.

2.7. MODEL ARCHITECTURE

2.7.1. Temporal Convolutional Network (TCN)

The TCN model consists of several Residual Temporal Blocks, each comprising a Conv1D layer, ReLU, Dropout, Layer Normalisation, and a Residual Connection. *Causal* convolution and *dilated convolution* are used to enable the model to learn long-term temporal relationships without utilising information from the future. The model configuration uses 64 filters, a kernel size of 3, dilation rates of 1, 2, 4 and 8, *the* Adam *optimiser* with *a learning rate* of 0.001, *a batch size* of 32, and a maximum of 100 *epochs*.

2.7.2. Long Short Term Memory(LSTM)

The LSTM model utilises a single LSTM layer comprising 64 units, followed by a Dense layer with a ReLU activation function. The training process employs *the* Adam *optimiser*, *a learning rate* of 0.001, *a batch size* of 32, a maximum of 100 *epochs* ( ), a *dropout* rate of 0.2, and an Early Stopping mechanism to prevent *overfitting*. All configurations were set identically to those of the TCN model to ensure an objective comparison.

2.8. MODEL EVALUATION

Model performance was evaluated using four metrics: MAE, RMSE, MAPE and R^2 .

Mean Absolute Error (MAE)

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i | \qquad (5)$$

Root Mean Squared Error (RMSE)

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \qquad (6)$$

Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{100}{n}\sum_{i=1}^{n} | \frac{y_i - \hat{y}_i}{y_i} | \qquad (7)$$

Coefficient of Determination (R^2)

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \qquad (8)$$

Explanation
y_i= actual value
$\hat{y}_i$= predicted value
$\bar{y}$= mean of actual values
n= number of test data points

The best model is determined based on the smallest MAE, RMSE and MAPE values, as well as the R^2 value closest to one.

3. RESULT AND ANALYSIS

An evaluation of the TCN and LSTM models was carried out to assess the ability of both architectures to represent the temporal relationship between meteorological parameters and solar radiation. The analysis was not only based on measures of prediction accuracy, but also took into account the models' ability to capture the temporal patterns of the data, the stability of the training process, and the consistency of performance across various data splitting scenarios. The experimental results were then interpreted based on evaluation metrics and visual analysis, and compared with the findings of previous studies to gain a more comprehensive understanding of the characteristics of each model.

3.1. RESEARCH DATA CHARACTERISTICS

Before the model training process was carried out, the research data characteristics were analysed using descriptive statistics to provide an overview of the distribution and variation of each variable used in the modelling. This analysis is important for identifying the range of values, the central tendency of the data, and the level of dispersion of each meteorological and solar radiation variable. This information forms the basis for understanding the characteristics of the dataset whilst also supporting the pre-processing stage before the data is used as input for the TCN and LSTM models. A summary of the descriptive statistics for all research variables is presented in Table 2.

Table 2. Descriptive statistics of the research data

Variable	Number of points	Mean	Median	Mode	Standard Deviation	Variance	Max	Min
Rainfall (mm)	4152	0.518	0	0	5.383	28.979	0	177.6
Wind Speed (m/s)	4152	2.15	1.886	0	1.071	1.147	0	6.23
Wind Direction (°)	4152	175.861	154.59	0	61.315	3759.558	0	323.85
Air Temperature (°C)	4152	28.567	28.874	30.283	3.383	11.447	13,398	36,292
Relative Humidity (%)	4152	74.744	75.627	91.083	14.903	222.108	16.22	99.9
Air Pressure (hPa)	4152	1005.134	1005.186	1003.389	2.256	5.091	958,331	1,012,015
Solar radiation (W/m²)	4152	384.81	345.187	0	285.67	81607.13	0	1,063

Based on Table 1, all variables have the same number of observations, namely 4,152 data points, indicating that the dataset has a complete and consistent structure for the modelling process. The solar radiation variable, as the target of the prediction, has a mean of 384.810 W/m² with a standard deviation of 285.670 W/m², indicating a fairly high variation in radiation intensity during the observation period. Meanwhile, the meteorological variables exhibit varying distribution characteristics, such as rainfall dominated by zero values, relatively stable air temperature, and relative humidity with considerable variation. The differences in the range of values between variables indicate data-scale heterogeneity, making normalisation a necessary step to produce a more balanced dataset before using it to train the TCN and LSTM models.

In addition to descriptive statistics, the characteristics of the dataset were also analysed through the visualisation of each variable's distribution using box plots. This visualisation aims to provide an overview of the data distribution, the median, the interquartile *range*, and the presence of outliers in each meteorological and solar radiation variable. Analysis of data distribution is necessary to evaluate the quality of the dataset following *quality control* and to ensure that the data used meets the required characteristics prior to the TCN and LSTM model training process.

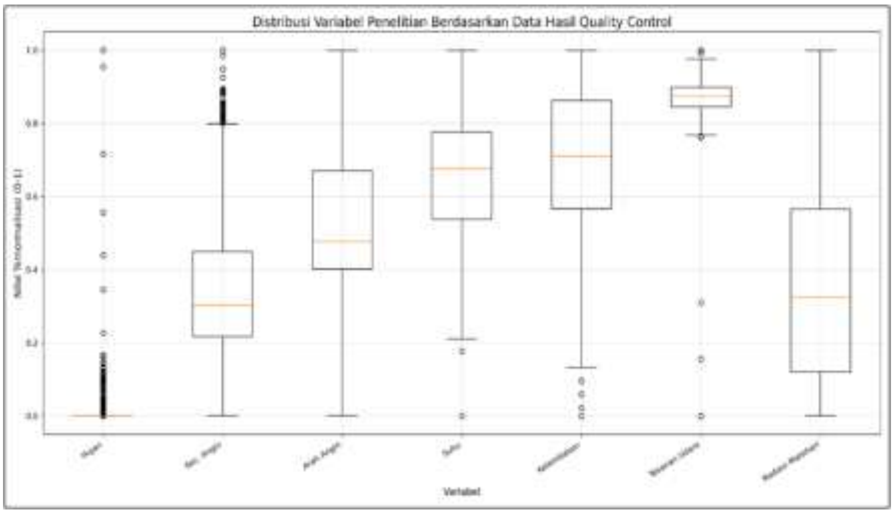

Figure 2. Distribution of meteorological and solar radiation variables

Based on Figure 2, all variables exhibit distinct distribution characteristics in line with their physical properties. The rainfall variable has a very low median with a number of high-value outliers, reflecting the predominance of dry conditions occasionally interspersed with episodes of heavy rainfall. The wind speed, wind direction, air temperature, relative humidity and air pressure variables show relatively stable distributions, with data points falling within a reasonable range of observations, although some outliers were still identified. Meanwhile, solar radiation has a fairly wide range of values, indicating high variability in radiation intensity during the observation period due to the influence of daily cycles and atmospheric dynamics. Overall, the visualisation results indicate that the quality control process has produced a consistent dataset suitable for use as input in the Deep Learning modelling process, without compromising the natural characteristics of the meteorological data required for model training.

3.2. MODEL EVALUATION

To evaluate the influence of the training data proportion on model performance, this study applied three data split scenarios: 70:15:15, 80:10:10, and 70:10:20. The TCN and LSTM models were evaluated using four metrics: MAE, RMSE, MAPE and R^2. The evaluation results for all scenarios are presented in Table 3.

Table 3. Evaluation results TCN and LSTM model Across Various Data Split Scenarios

Model	Scenario	Data Split	MAE	RMSE	MAPE	R^2
TCN	S1	70:15:15	127.075	161.676	1333.764	0.658
	S2	80:10:10	117.058	157.060	1374.330	0.685
	S3	70:10:20	123.158	162.849	725.845	0.672
LSTM	S1	70:15:15	123.663	157.935	1214.607	0.674
	S2	80:10:10	117.105	152.998	1564.568	0.701
	S3	70:10:20	126.056	161.261	965.735	0.678

Based on Table 3, both models performed best under the 80:10:10 data split scenario, which strikes a balance between the amount of training data and the model's generalisation ability. For the TCN model, this scenario yielded an MAE of 117.058, an RMSE of 157.060, and an R^2 of 0.685, whilst the LSTM model achieved the lowest RMSE of 152.998 and the highest R^2 of 0.701, indicating a better ability to represent variations in solar radiation. Although the MAPE values in some scenarios appear higher than in others, this metric is less representative for solar radiation data as it is influenced by the presence of actual values that are very small or close to zero. Therefore, the evaluation of model performance in this study focuses more on a combination of MAE, RMSE and R^2 values, which shows that the LSTM model performs slightly better overall than the TCN model in predicting solar radiation based on AWS data.

3.3. MODEL CONVERGENCE

In addition to being evaluated using quantitative metrics, the model training process was also analysed via the training loss and validation loss curves under the optimal data split scenario (80:10:10). The analysis of the loss curves aims to evaluate the model's convergence process and the stability of the learning process, as well as to identify the possibility of overfitting or underfitting. A comparison of the loss curves for the TCN and LSTM models is shown in Figure 3.

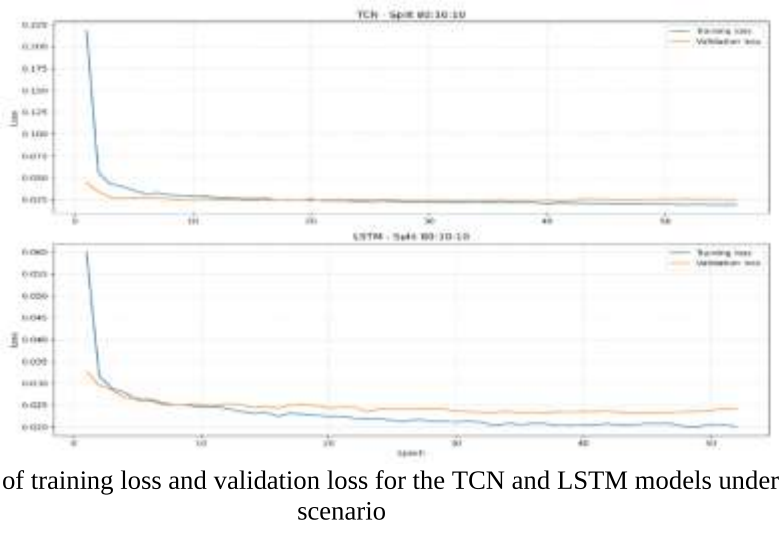

Figure 3. Comparison of training loss and validation loss for the TCN and LSTM models under the 80:10:10 scenario

Based on Figure 3, both models show a significant decrease in training loss and validation loss values during the first few epochs, before reaching a relatively stable state until the end of the training process. The training loss and validation loss curves for both models follow similar patterns without showing any significant divergence, indicating that the training process converged and did not experience significant overfitting. Visually, the TCN model achieved convergence more quickly, with stable loss values after the first few epochs, whilst the LSTM model showed a more gradual reduction in loss but produced a lower final value. These results are consistent with previous quantitative evaluations, which showed that the LSTM model provides slightly better predictive performance than the TCN, although both models exhibit good learning stability.

3.4. MODEL PERFORMANCE COMPARISON

Once the optimal data split scenarios for each model had been identified, a comparative analysis of the performance of TCN and LSTM was carried out using configuration S2 (80:10:10). The comparison focused on the best model from each architecture to evaluate their ability to predict solar radiation more objectively based on the MAE, RMSE, MAPE and R^2 metrics. A summary of the evaluation results for the two best models is presented in Table 4.

Table 4. Evaluation results TCN and LSTM model Across Various Data Split Scenarios

Model	Scenario	Data Split	MAE	RMSE	MAPE	R^2
TCN	S2	80:10:10	117.058	157.060	1333.330	0.685
LSTM	S2	80:10:10	117.105	152.998	1564.568	0.701

Based on Table 4, both models demonstrate relatively comparable predictive performance with a small difference in evaluation values. The TCN model produces a slightly lower MAE value than the LSTM, indicating an almost identical mean absolute error for both models. However, the LSTM model achieved a lower RMSE and a higher R^2, indicating a better ability to reduce large prediction errors and to explain the variation in solar radiation data in the test set. Although the MAPE value for the LSTM was higher than that of the TCN, this metric was not used as a primary indicator as it is sensitive to actual solar radiation values approaching zero. Therefore, based on a combination of the MAE, RMSE and R^2 values, the LSTM model was assessed as delivering slightly better overall performance than the TCN, and was thus selected as the best model for solar radiation prediction in this study.

To provide a visual evaluation of the models' ability to predict solar radiation, a comparison was carried out between actual values and predicted values using the best model from each architecture, namely, TCN and LSTM, under an 80:10:10 data split scenario (S2). This visualisation aims to evaluate the ability of both models to capture the temporal patterns of solar radiation and to identify the degree of agreement between the predicted results and the observed data during the testing period. A comparison of the actual values and the predicted results from both models is presented in Figure 4.

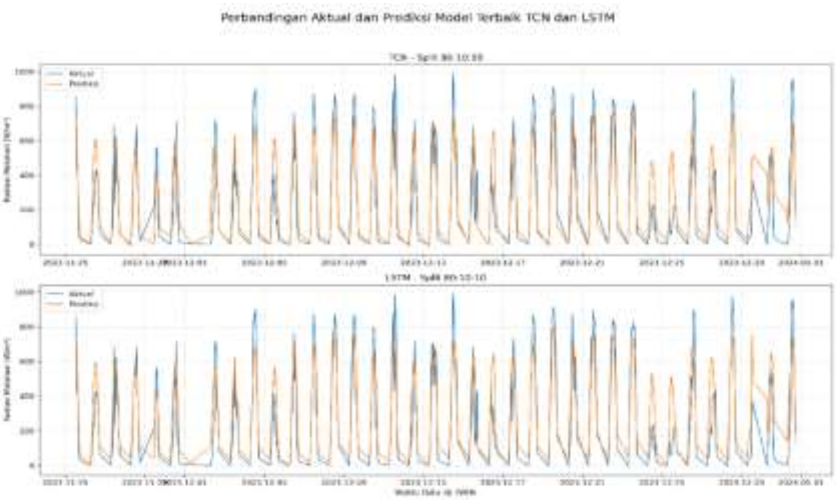

Figure 4. Actual values and predicted results from the best TCN and LSTM models

As shown in Figure 4, both the TCN and LSTM models were able to capture the temporal patterns of solar radiation as indicated by the observational data. Both models successfully represented the daily cycle of solar radiation, characterised by an increase in intensity during the day and a decrease to near zero at night. This indicates that both architectures were able to learn the periodic characteristics of the solar radiation data from the meteorological parameters used as input variables. Nevertheless, some discrepancies remain between the predicted and actual values, particularly during periods of rapid changes in radiation intensity. These deviations indicate that sudden atmospheric changes, such as cloud formation or shifts in weather conditions, still pose a challenge for both models in producing predictions that fully align with actual conditions.

When compared visually, the LSTM model produces a prediction curve that more consistently follows the pattern of the actual data than the TCN model, particularly during periods of high radiation fluctuations. The LSTM prediction curve appears better able to track changes in both the amplitude and timing of radiation peaks, resulting in relatively smaller deviations from the observed data. Conversely, the TCN model tends to produce a smoother curve; consequently, at some radiation peaks, there is still a tendency to underestimate the actual values. These visualisation results are consistent with the quantitative evaluation, which shows that the LSTM model achieves a lower RMSE and a higher R^2 than the TCN model. Thus, the visual analysis in Figure 4 reinforces the results of the quantitative evaluation, indicating that the LSTM model is slightly better at representing the temporal dynamics of solar radiation, although overall both models demonstrate good predictive performance and are capable of capturing the main patterns of solar radiation variation during the testing period.

3.5. ANALYSIS

The research results show that the LSTM model performs better than the TCN model in predicting solar radiation based on AWS data. This superiority is demonstrated by lower MAE and RMSE values, as well as a higher R^2 value compared to the TCN model. These findings indicate that LSTM is better at learning the non-linear relationships and temporal dependencies that are key characteristics of meteorological data. Solar radiation is influenced by dynamic and continuous changes in atmospheric conditions; consequently, historical information plays a crucial role in the forecasting process. The mechanism of the memory cell, combined with the input gate, forget gate and output gate, enables the LSTM to retain relevant information over the long term whilst minimising information loss during the training process. These characteristics make LSTMs more effective at representing temporal patterns than conventional neural network architectures or temporal convolutional models (Hochreiter & Schmidhuber, 1997; Gers et al., 2000; Greff et al., 2017).

The findings of this study are consistent with various previous studies reporting that RNN-based architectures, particularly LSTMs, remain one of the most effective approaches in meteorological time series modelling. (Huang et al., 2021) demonstrate that LSTMs are capable of improving the accuracy of solar radiation forecasts due to their ability to learn long-term temporal relationships between meteorological parameters. Similar results were also reported by (Wang et al., 2023) , which stated that LSTM models are better able to track fluctuations in solar radiation compared to several machine learning-based approaches. Furthermore, (Hissou et al., 2023) , through its literature review, concluded that deep learning methods generally outperform traditional statistical models as they are capable of capturing complex non-linear relationships between atmospheric variables. Thus, the results of this study further strengthen the empirical evidence that the use of LSTM architectures is a suitable alternative for predicting solar radiation in tropical regions characterised by high atmospheric dynamics.

On the other hand, the TCN model also demonstrates competitive performance, although it remains slightly below that of the LSTM. The TCN has the advantage of utilising causal convolution and dilated convolution, which enable the model to learn temporal dependencies efficiently without requiring recurrent computational processes. Furthermore, the implementation of residual connections makes the training process more stable and helps mitigate the vanishing gradient problem in deep neural networks (Bai et al., 2018; Lea et al., 2017). However, in this study, the TCN still faced limitations in tracking rapid changes in solar radiation, particularly when changes in cloud cover and atmospheric dynamics caused short-term fluctuations in radiation. These conditions indicate that, although the TCN offers high computational efficiency, the model's ability to retain long-term historical information has not yet fully matched the memory mechanisms possessed by the LSTM. These results suggest that the choice of model architecture must take into account the characteristics of the data being analysed, particularly meteorological data which exhibit seasonal patterns, diurnal cycles, and non-linear relationships between variables (Hissou et al., 2023; Huang et al., 2021) .

In addition to differences in model architecture, predictive performance is also influenced by the quality of the input data and the dataset construction strategy. This study implemented quality control steps, interpolation of invalid data, normalisation using Min-Max Scaling, and the creation of time-based features (hour_sin and hour_cos) to represent daily periodic patterns. These steps produced a more consistent dataset, thereby optimising the model training process. Goodfellow et al. (2016), Chollet (2021), and Géron (2022) state that the success of Deep Learning models is not solely determined by architectural complexity, but is also significantly influenced by data quality and pre-processing. Furthermore, this study demonstrates that the 80:10:10 data split scenario yields the best performance compared to other scenarios. A larger proportion of training data allows the model to acquire more comprehensive historical information, thereby enhancing the model's generalisation ability. These results are consistent with those of Brownlee (2018) and Hyndman and Athanasopoulos (2021), who explain that the use of a time-based split on time-series data is more appropriate than a random data split, as it preserves the temporal order of the data and reduces the risk of data leakage during both the training and testing processes.

Although the MAPE values obtained by both models are relatively high, these results must be interpreted with caution as they are influenced by the presence of very low or near-zero solar radiation values at the beginning and end of the irradiation period. Under such conditions, relatively small absolute errors can result in very large percentage error values, rendering MAPE less representative as the sole evaluation indicator. Therefore, the interpretation of model performance in this study places greater emphasis on a combination of MAE, RMSE and R^2 values, which are considered more robust to the presence of extreme values (Willmott & Matsuura, 2005; Chai & Draxler, 2014). Overall, the results of this study reinforce various previous studies which state that the Deep Learning approach is an effective method for predicting solar radiation based on meteorological data (Ehteram et al., 2024; Hissou et al., 2023; Huang et al., 2021; Wang et al., 2023) . In addition to producing prediction models with a high level of accuracy, this research also contributes a framework for solar radiation prediction based on AWS data with a standardised experimental configuration, thereby enabling a more objective evaluation of the TCN and LSTM models. This framework has the potential to be applied as a basis for the development of solar radiation prediction systems, the reconstruction of missing observational data, quality control of climatological data, and the development of artificial intelligence-based meteorological services within the BMKG, as well as for further research in the field of hydrometeorology.

4. CONCLUTION

This study successfully developed and evaluated an AWS-based solar radiation prediction model using two *deep learning* architectures, namely TCN and LSTM. The results indicate that both models are capable of learning the temporal relationships between meteorological variables and solar radiation, thereby effectively representing patterns of solar radiation variation in the test data. Of the three data split scenarios evaluated, the 80:10:10 scenario yielded the best performance for both models. Based on a combination of evaluation metrics—MAE, RMSE, MAPE and R^2 —the LSTM model demonstrated slightly better overall performance compared to the TCN, particularly in minimising large prediction errors and explaining the variation in solar radiation data. Nevertheless, the quantitative evaluation metrics indicate that the difference in performance between the two models is relatively small, meaning both have equal potential for application in solar radiation modelling based on routine meteorological data. These findings suggest that the use of *deep learning* architectures can serve as an effective alternative to address the limitations of data availability from direct solar radiation measurements, particularly in regions not yet equipped with solar radiation observation instruments.

The main contribution of this research lies in the development of a solar radiation prediction framework that compares two *Deep Learning* architectures using identical experimental configurations, including the dataset, input variables, *sliding window* length, data splitting scenarios, training parameters, and evaluation metrics. This approach enables a more objective evaluation, ensuring that the observed performance differences better reflect the characteristics of each architecture rather than the influence of the experimental configuration. Furthermore, this study demonstrates that meteorological data routinely recorded by AWS hold significant potential for use as an information source in the development of solar radiation prediction models. The results of this study are expected to support the reconstruction of missing radiation data, the improvement of climatological data *quality control* processes, the estimation of solar radiation at stations without radiation sensors, and the development of artificial intelligence-based climatological and agroclimatic services within the BMKG.

Although the study produced good predictive performance, it still has several limitations that need to be taken into account when interpreting the results. The dataset used is still limited to a single observation location and a one-year observation period; consequently, the model's generalisation ability regarding climatic characteristics and atmospheric conditions in other regions cannot yet be comprehensively evaluated . Furthermore, the predictor variables used are derived from AWS meteorological parameters and therefore do not take into account other factors known to influence solar radiation, such as cloud cover, duration of sunshine, atmospheric aerosols, or satellite-based remote sensing data. This study also focuses on *one-step-ahead forecasting*; consequently, the model's capability to generate multi-horizon forecasts has not yet been explored. Furthermore, the high MAPE value indicates that this metric is less suitable for use as a primary indicator for solar radiation data, where many actual values are close to zero; consequently, an interpretation of the model's performance is more accurately based on a combination of MAE, RMSE and R^2 values.

Based on these findings, it is recommended that future research expand the scope of the dataset to include a longer observation period and several observation stations representing different climatic characteristics, so that the model's generalisation ability can be evaluated more comprehensively. Model development could also be pursued through the inclusion of atmospheric variables, the integration of satellite data, *hyperparameter* optimisation, and the application of more advanced *deep learning* architectures, such as *Transformers, Temporal Fusion Transformers* (TFT), Informers, or hybrid approaches combining convolutional and recurrent models. Furthermore, validating the model in an operational environment using observational data from various BMKG stations is a crucial step in assessing the model's reliability before it is implemented as a support system for observations, solar radiation data reconstruction, or the provision of operational climatological information. With these developments, the resulting prediction models are expected to possess higher levels of accuracy, robustness and adaptability, thereby making a broader contribution to both research and meteorological services in Indonesia.

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REFERENCES

Bai, S., Kolter, J. Z., & Koltun, V. (2018). An empirical evaluation of generic convolutional and recurrent networks for sequence modelling. arXiv. https://arxiv.org/abs/1803.01271

Brownlee, J. (2018). Deep learning for time series forecasting: Predict the future with MLPs, CNNs and LSTMs in Python. Machine Learning Mastery.

Chai, T., & Draxler, R. R. (2014). Root mean square error (RMSE) or mean absolute error (MAE)? Arguments against avoiding RMSE in the literature. Geoscientific Model Development, 7(3), 1247-1250. https://doi.org/10.5194/gmd-7-1247-2014

Chen, J., Liu, H., Wu, W., & Xie, D. (2019). Application of automatic weather station data for meteorological prediction and environmental monitoring. Atmospheric Research, 218, 240-251.

Chollet, F. (2021). Deep learning with Python (2nd ed.). Manning Publications.

Ehteram, M., Kisi, O., Deo, R. C., Mosavi, A., & Bonakdari, H. (2024). Deep learning approaches for solar radiation prediction: A review of recent advances and future perspectives. Renewable and Sustainable Energy Reviews.

Gers, F. A., Schmidhuber, J., & Cummins, F. (2000). Learning to forget: Continual prediction with LSTM. Neural Computation, 12(10), 2451-2471. https://doi.org/10.1162/089976600300015015

Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. MIT Press.

Greff, K., Srivastava, R. K., Koutník, J., Steunebrink, B. R., & Schmidhuber, J. (2017). LSTM: A search space odyssey. IEEE Transactions on Neural Networks and Learning Systems, 28(10), 2222-2232. https://doi.org/10.1109/TNNLS.2016.2582924

Géron, A. (2022). Hands-on machine learning with Scikit-Learn, Keras, and TensorFlow (3rd ed.). O'Reilly Media.

Hissou, Y., El Moukhtari, J., & El Markhi, H. (2023). Deep learning techniques for solar radiation forecasting: A systematic review. Renewable and Sustainable Energy Reviews.

Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. Neural Computation, 9(8), 1735-1780. https://doi.org/10.1162/neco.1997.9.8.1735

Huang, X., Zhang, Y., Li, H., & Wang, J. (2021). Solar radiation prediction using deep learning models based on meteorological variables. Solar Energy, 224, 1020-1032.

Hyndman, R. J., & Athanasopoulos, G. (2021). Forecasting: Principles and practice (3rd ed.). OTexts.

Lea, C., Flynn, M. D., Vidal, R., Reiter, A., & Hager, G. D. (2017). Temporal convolutional networks for action segmentation and detection. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops (pp. 156-162).

Wald, L. (n.d.). Solar radiation. In Encyclopedia of Atmospheric Sciences.

Wang, Y., Liu, X., Zhang, H., & Li, Z. (2023). Short-term solar radiation forecasting using deep learning models based on meteorological observations. Energy Reports, 9, 5621-5635.

Willmott, C. J., & Matsuura, K. (2005). Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance. Climate Research, 30(1), 79-82. https://doi.org/10.3354/cr030079