INTELLIGENT LOW-LEVEL WIND SHEAR ALERT PREDICTION SYSTEM BASED ON ANEMOMETER SENSOR NETWORK AND TEMPORAL CONVOLUTIONAL NETWORK (TCN)

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ABSTRACT:
Wind shear is one of the dangerous meteorological phenomena for aviation. This phenomenon is significant, especially at the lower level. The duration of wind shear events varies greatly, ranging from short to long. The best way to avoid accidents caused by wind shear is by predicting the event and the duration. Recent studies use Machine Learning (ML) as a nonlinear geostatistical method to predict wind shear utilizing wind observing instruments data. The data is conditioned into temporal data which is fed to the ML model. However, the ML model used is not a temporal ML model for time-series data but a generic model for a common type of data. Many studies claimed temporal models are better than generic ones to tackle temporal data. In this study, we propose Temporal Convolutional Network (TCN) to predict incoming wind shear duration and occurrence using an anemometer sensor network i.e., Low-level Wind Shear Alert System (LLWAS). The wind shear occurrence is derived from wind shear duration prediction. The proposed model is compared with other temporal models, i.e., Long-Short Term Memory (LSTM) and Gated Recurrent Unit (GRU). Different schemes of total predictor were tested to find the best predictor scheme for wind shear prediction. To measure the performance of all models in all schemes, accuracy, False Alarm Ratio (FAR), Probability of Detection (POD), and Root Mean Squared Error (RMSE) metrics are used. The result is TCN dominating almost in all metrics used i.e., Accuracy, FAR, and RMSE for all schemes against LSTM and GRU. Scheme with 4 predictors proved to bring the best performance of all models for wind shear duration prediction. The result proves TCN is the best temporal model for wind shear forecasting using LLWAS. For better wind shear duration prediction, the best scheme choice is the 4-predictor scheme.

Key-words: *Wind shear, Aviation, Machine learning, Geostatistical, Temporal Convolutional Network.*

1. INTRODUCTION

Among the cause of aircraft accidents by meteorological phenomena, wind shear is the dominant factor (Huang, 2020). Its unpredictable nature makes an aircraft deviate from its track. By the direction, wind shear is distinguishable into 2 types, i.e., horizontal, and vertical wind shear. Harmful wind disturbances such as downbursts and microbursts are the kind of horizontal wind shear-type when they hit the ground (International Civil Aviation Organization, 2005).

Some instruments have already been developed to detect such phenomena as wind shear, especially horizontal wind shear i.e., Low-level Wind Shear Alert System (LLWAS) (International Civil Aviation Organization, 2005). The LLWAS consists of a network of anemometers distributed around the runway. Using the network any wind divergence that occurs in the runway area captured by LLWAS is an indicator of wind shear occurrence.

Other instruments i.e., Lidar Doppler and Terminal Doppler Weather Radar (TDWR) developed to detect wind shear is remote sensing-based tool (Chen et al., 2017; Chun et al., 2017; International

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Civil Aviation Organization, 2005; Nechaj et al., 2019; Shun and Chan, 2008; Thobois et al., 2019). Those Remote sensing instruments can detect wind shear at any height unlike LLWAS, but they are susceptible to the weather condition. Lidar Doppler is good in fine weather but bad at rainy weather in contrast with TDWR. On the other hand, LLWAS can work well in any weather condition (International Civil Aviation Organization, 2005). Furthermore, LLWAS can detect wind shear faster because have a faster measurement cycle.

For the pilot to better avoid the wind shear area, information on the potential wind shear area must be obtained by the pilot before the wind shear occurs. Therefore, wind shear prediction is a must. Recent research regarding wind shear prediction is dominated by numerical and Geostatistical methods. Geostatistical method used for wind shear prediction dominated by Machine Learning (ML) (Bolgiani et al., 2020; Chan and Hon, 2016; Hou and Wang, 2019; Kwong et al., 2012; Lee et al., 2020; Liu et al., 2012; Wong et al., 2008; Yan et al., 2020). Previous studies suggest numerical methods tend to have longer lead time but need massive computation power and the ML method doesn't need extensive computing resources and produces faster prediction but a shorter lead time. Possessing a shorter lead time is not a problem if the system can produce a swift forecast nevertheless but not everyone has a sizeable computation power.

Prior research about wind shear prediction using ML, the source data used is from wind shear's instrument detection system. Mostly use Lidar Doppler as a data source for the ML model (Kwong et al., 2008; Liu et al., 2012; Wong et al., 2008). Other studies used an anemometer and LLWAS (Liu et al., 2012; Ryan et al., 2021). Lidar Doppler as a data source of the ML model will have the same cons which can't predict wind shear in rainy conditions (Gultepe et al., 2019). An anemometer can only forecast in a narrow area. On the other hand, LLWAS can do a forecast in any weather condition and cover the entire runway area (Ryan et al., 2021).

Wind shear occurs with varying duration. Wind shear happens in a matter of seconds, minutes, or hours (International Civil Aviation Organization, 2005). Prior studies using ML to predict wind shear only have a limited time frame prediction so it can't handle all possible wind shear.

This paper proposes a new approach to predict wind shear using a Temporal Convolutional Network (TCN) as an ML model and LLWAS in Soekarno-Hatta airport as the data source. TCN is used to forecast the duration of incoming wind shear. Ryan et al (2021) suggest TCN exceeds the generic ML model for wind shear prediction i.e. Multi-layer Perceptron (MLP). Nevertheless, the model has not been compared against another time-series model. This paper will compare TCN against Long-short Term Memory (LSTM) and Gated Recurrent Unit (GRU). Another difference is the model will do a regression task to predict the duration of incoming wind shear instead of a classification task. When the duration's prediction is below the threshold, it's treated as "no wind shear" conversely "wind shear occurrence". Using this approach, the model can predict multiple tasks without using multiple models which is an efficient approach compared with previous studies.

2. STUDY AREA

Soekarno-Hatta airport is in Tangerang, Indonesia at 6^o 7' 32.0016" latitude South and 106^o 39' 20.9880" longitude East. The airport has 2 runway zones and 12 LLWAS anemometers are surrounding them as shown in **Fig. 1.** The blue star icon in **Fig. 1** is an anemometer and 2 red lines are runway zones. A runway zone is an area that aircraft will approach or use for landing and takeoff necessities. Thus, runway zone not only includes the runway itself but along its way needed for landing and takeoff. LLWAS Wind shear warning data is derived from wind speed and direction data through a divergence analysis algorithm (Wilson, 1991). The analysis of the divergence area is conducted by involving a combination of 3 sensors from 12 existing sensors and comparing their wind measurement. Those 3 sensors represent the zone surrounded by them.

When a particular area has a divergence value that surpasses the threshold, LLWAS will treat the area as a wind shear zone. Since there are 2 runways in Soekarno-Hatta airport, LLWAS divides the runway area into 4 parts for each end of the existing runway.

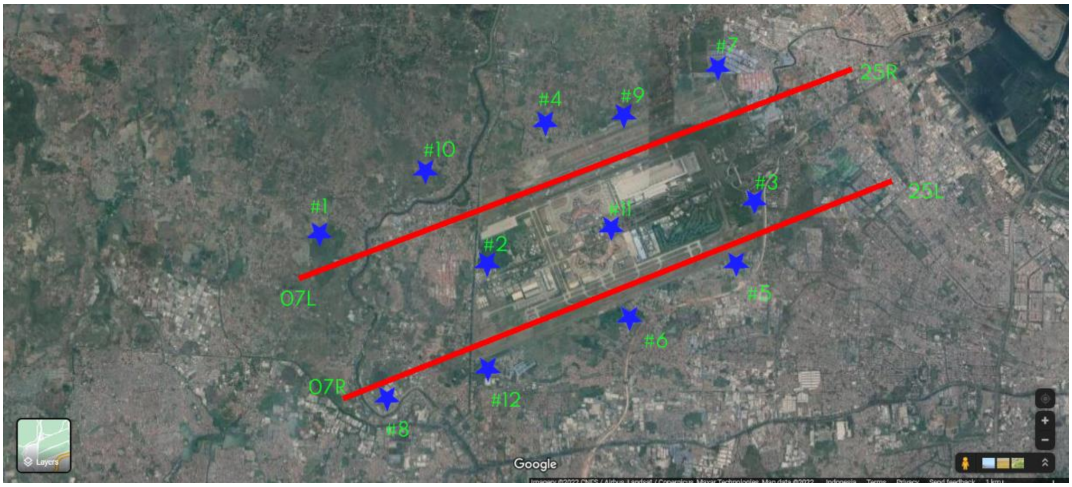

Fig. 1. LLWAS anemometer placement at Soekarno-Hatta airport.

The name of the runway area is presented in **Table 1**. Wind shear events detected by LLWAS can be in 1 area or more overlap with the other 3 areas. The Detection cycle of LLWAS is done every 10 seconds.

Table 1.

All runway zone name in Soekarno-Hatta airport.

Runway zone name	Tip Coordinate	
	Latitude	Longitude
07L	6° 8' 2.3" S	106 ° 36' 10.1" E
25R	6 ° 5' 45.6" S	106 ° 42' 2.6" E
07R	6 ° 9' 19.3" S	106 ° 36' 37.4" E
25L	6 ° 6' 59.3" S	106 ° 42' 30.8" E

3. DATA AND METHODS

3.1. Low-level Wind Shear Alert System (LLWAS) data

LLWAS data consist of wind speed and direction data and wind shear warning data. Wind speed and direction data become predictors meanwhile wind shear data is the predictand. The data period used for the experiment is from February 1 to April 18, 2020. The total dataset from the period is 2661128. Wind shear warning labeled data content made up only 0.042% and the rest is no wind shear warning data. Under-sampling was applied to manage this unbalance dataset. All "wind shear warning" labeled data is included in the dataset and "no wind shear warning" labeled data is chosen randomly from the whole dataset as much as wind shear warning data total. Data quality is also checked, any datum with typing error or empty discarded. After quality control and under-sampling, the total dataset used for each scheme is listed in **Table 2**.

Table 2.

Total each label in the dataset for every experiment scheme.

Scheme	Wind Shear Occurrence	No Wind Shear
4 Predictors	915	955
6 Predictors	675	715
12 Predictors	352	392

3.2. Temporal Convolutional Network (TCN)

TCN is a one-dimensional Convolutional-based neural network model for temporal data (Lea et al., 2016). Besides the dimension, TCN has an additional property called dilation (d) which depend on dilation rate (r) as in (1). The dilation value will expand the more the TCN layer (l) increase.

$$d = r^l \tag{1}$$

How dilation affects processing data in TCN is shown in **Fig. 2**. In most cases, dilation is set to 2 (Hewage et al., 2020; Yan et al., 2020). Dilation is a gap among data treated by a TCN filter in a layer.

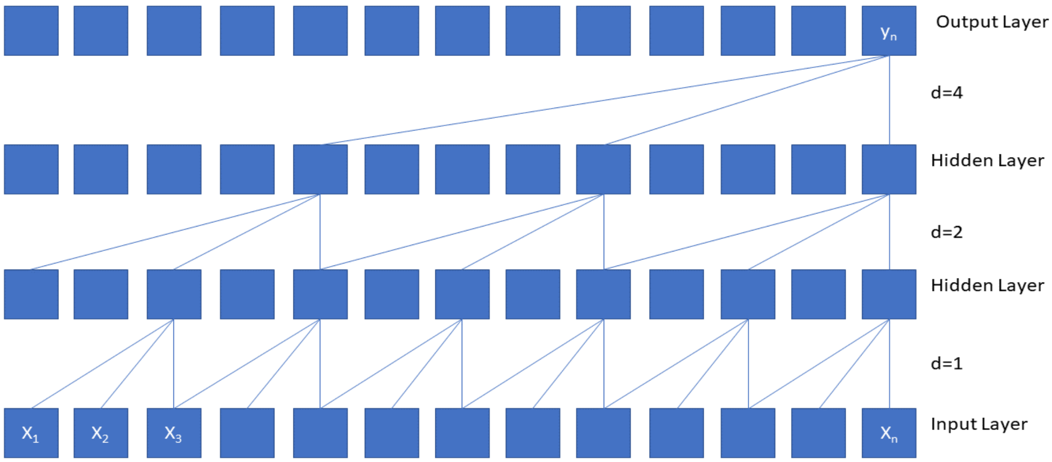

Fig. 2. TCN with dilation rate set as 2.

Another difference between TCN and ordinary Convolutional Neural Network (CNN) is the layer-to-layer processing data as shown in **Fig. 3**. There is no Max/Average Pooling after the activation function (Hewage et al., 2020; Yan et al., 2020). To avoid vanishing or exploding gradients due to deep layers, layer to layer processing data in TCN employ Residual Network (ResNet) (Tai et al., 2017). That is one extra process after filtering and activation function. Normally, TCN using Rectifier Linear Unit (ReLU) as an activation function (Abueidda et al., 2021; Hewage et al., 2020; Ryan et al., 2021).

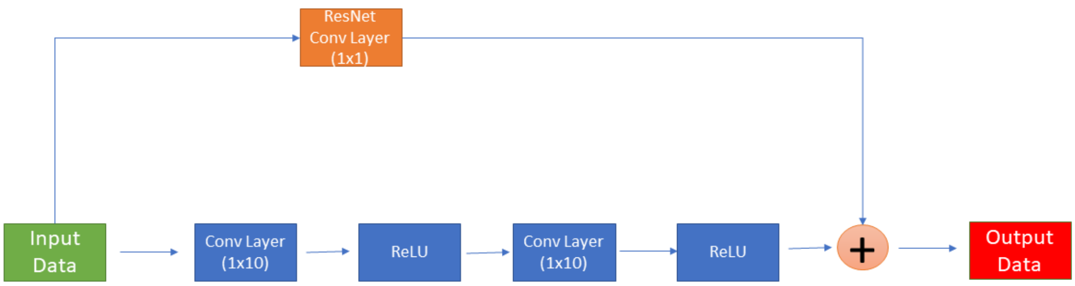

Fig. 3. Data processing block in TCN using ResNet for this study.

3.3. Long-Short Term Memory (LSTM)

LSTM is a popular Recurrent Neural Network (RNN) variant model that specializes in the time series model. An RNN has a loopback block computation that uses input data and output from the previous loop of the block. A vanilla RNN can't handle too long time series data because it can trigger a vanishing gradient (Fei and Tan, 2018). To patch this problem, a new variant of RNN with additional operation from base RNN was invented i.e., LSTM (Zhao et al., 2018). The extra operation in LSTM is represented in forget gate (f),input gate (i),memory gate (g) and output gate (o) as shown in **Fig. 4**.

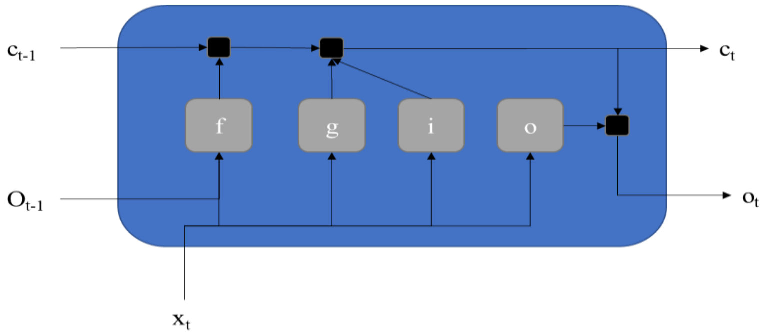

Fig. 4. LSTM architecture.

Forget gate is used to decide which part of the input to ignored, the input and memory gate determine which part to update, and the output gate computes the output LSTM block (Sadique and Sengupta, 2021). LSTM block will output 2 values i.e., cell state (c) and the real output (o) which will become for the next loop.

3.4. Gated Recurrent Unit (GRU)

GRU is another popular RNN besides LSTM. GRU has the same gate as LSTM except it doesn't have an output gate (Sadique and Sengupta, 2021). Similar to LSTM, GRU is immune to the vanishing gradient. Because of the lack of output gate, GRU has fewer trainable weights and biases. Thus, GRU is slightly more lightweight to run than LSTM.

3.5. Experiment Scheme

In this study, TCN will be used to do a regression task to forecast incoming wind shear duration. Wind speed and direction data from LLWAS transformed to west-east (U) and south-north (V) components. Furthermore, U and V data packed to become time-series data for every anemometer in LLWAS. The length of the time-series data tested in this study is 10 minutes. LLWAS has 10 seconds resolution data consequently time-series data length used is 60.

Wind shear duration (ω_d) data were obtained by using wind shear warning data. The number of consecutive warning times (ω_c) by LLWAS times resolution (2).

$$\omega_d = \omega_c \times 10 \tag{2}$$

The minimum consecutive is 1, so the minimum duration value is 10. This minimum value is set as the TCN threshold to predict the presence or absence of wind shear shortly. The data processing to produce a prediction for wind shear duration and wind shear event is summarised in **Fig. 5**. The model used for the processing is TCN, LSTM, and GRU alternately.

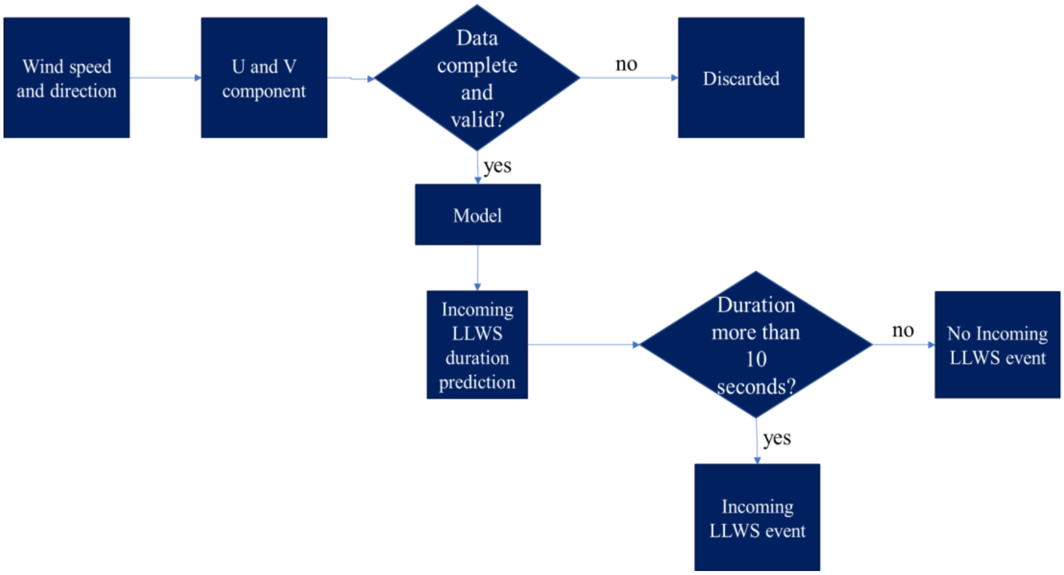

Fig. 5. Flowchart for data processing to produce wind shear prediction.

Four areas monitored by LLWAS also become forecast zone for TCN. In this study, 4, 6, and 12 anemometers were tested as the predictor to do a wind shear forecast for each area. Selected anemometers for every region in every scheme with 4 and 6 predictors are shown in **Table 3**. Twelve anemometers scheme predict every area using all anemometers. The selection is based on the nearest anemometers to the forecast area. The nearest sensor is the best data source to know the condition in a particular region (Gutierrez-Corea et al., 2016).

Table 3.
Predictor for every runway area in scheme 4 and 6 predictors.

Anemometer	**Scheme**							
	4 Predictors				**6 Predictors**			
	07L	**25R**	**07R**	**25L**	**07L**	**25R**	**07R**	**25L**
#1	✓				✓			
#2	✓		✓		✓		✓	
#3				✓		✓		✓
#4	✓	✓			✓	✓		
#5				✓		✓		✓
#6			✓	✓			✓	✓
#7		✓				✓		✓
#8			✓				✓	
#9		✓				✓		✓
#10	✓				✓		✓	
#11		✓		✓	✓	✓	✓	✓
#12			✓		✓		✓	

To benchmark the TCN's performance, LSTM and GRU will be the criterion model. All Hyperparameter configurations for those 3 models used for the experiment are listed in **Table 4**. These configurations were founded after trial and error which means to produce the best performance. LSTM and GRU will also have a similar threshold prediction as TCN and the same predictor set.

Table 4.
Hyperparameter configuration used for experiment.

Hyperparameter	Model		
	TCN	**GRU**	**LSTM**
Layers	12	1 Stack	1 Stack
Filter Size	10	-	-
Neurons	15	15	15
Mini Batch Size	20	20	20
Epoch	100	100	100
Learning algorithm	Adam	Adam	Adam

3.6. Validation metric

Cross-validation 5-fold is used to measure all models' skills regardless of the scheme used. Thus, the dataset is split into 5 groups. Four groups will become the training dataset and the rest is the validation dataset. All groups alternately become validation datasets. Therefore there will be 5 times looping processes from training to validation Models performance is measured using Root Mean Squared Error (RMSE) for wind shear duration and contingency table as shown in **Table 5**. Ground truth is obtained from cross-validation which is predictand of validation data. Furthermore, prediction value is a prediction obtained by using validation predictors data as an input model. Contigency table metric then derived to get accuracy (acc), Probability of Detection (POD) and False Alarm Ratio (FAR) given in (3-5) (Thobois et al., 2019). Since the performance was measured using cross-validation 5-fold, at the end of the experiment there will be 5 RMSE and contingency table derived metric values. The average of all metric values is calculated to summarize them.

Table 5.
Contingency table product.

		Prediction Value	
		Right	**Wrong**
Ground Truth	**Right**	Hit (H)	Miss (M)
	Wrong	False Alarm (FA)	Correct Negative (CN)

$$acc = \frac{H+CN}{H+CN+M+FA} \tag{3}$$

$$POD = \frac{H}{H+M} \tag{4}$$

$$FAR = \frac{FA}{FA+CN} \tag{5}$$

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\bar{d}_r - d_r)^2}{n}} \tag{6}$$

where:

$acc = accuracy$
$POD =$ Probability of Detection
$FAR =$ False Alarm Ratio
$RMSE =$ Root Mean Squared Error

4. RESULTS

The output of this intelligent system is presented in a web display application as shown in **Fig. 6 and 7**. **Fig. 6** is a display condition when the model predicts wind shear duration below 10 seconds for all runways zones. Therefore, the model predicts that is there is no incoming wind shear for all runway zones. **Fig. 7** shows the display when there is wind shear in several runway zones. The display shows the wind shear duration estimation when the model predicts incoming wind shear in that runway zone.

Fig. 6. Display condition when there is no wind shear incoming predicted.

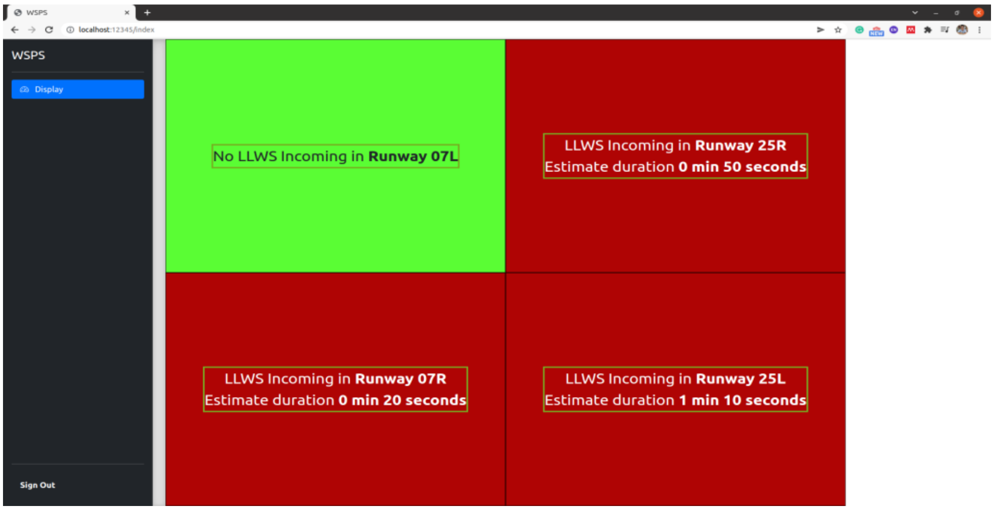

Fig. 7. Display condition when there is a wind shear predicted in several runway zones.

The TCN, LSTM, and GRU mean error convergence can be seen in **Fig. 8**. All models show the error decreased rapidly at the beginning phase of training and converged at some point. All models look converged after epoch 20. GRU looks converged a little late compared with TCN and LSTM. The validation error pattern for all models looks similar to training errors which means the training dataset has an alike pattern with training data. Overall, error in train and test data set for all models are very close which mean they can learn well.

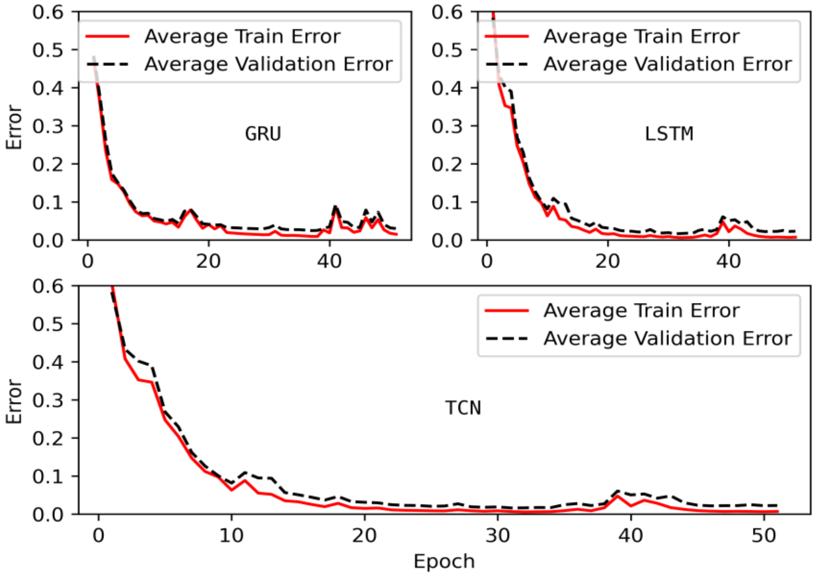

Fig. 8. Error convergence of all models.

All models' performance for all schemes is listed in **Table 6**. In the 4 predictors scheme, TCN has the best score in all metrics. Thus, TCN has the best performance for predicting wind shear duration and occurrence in the 4 predictors scheme. The second-best model is LSTM which all metrics show superiority over GRU.

Table 6.

All models' performance.

Model	**Scheme**	**Average**			
		Accuracy	**FAR**	**POD**	**RMSE**
GRU	4 predictors	0.857	0.202	0.933	22.874
	6 predictors	0.888	0.148	0.933	25.597
	12 predictors	0.860	0.201	0,962	78.718
LSTM	4 predictors	0.903	0.122	0.936	21.912
	6 predictors	0.899	0.139	0.944	36.549
	12 predictors	0.918	0.118	0.971	68.780
TCN	4 predictors	0.925	0.088	0.942	17.534
	6 predictors	0.920	0.104	0.948	20.611
	12 predictors	0.918	0.083	0.919	81.723

TCN still becomes the best model in the 6 predictors scheme. All metrics show TCN excellence over any other models in the scheme. TCN metrics in this scheme are not much different from TCN in the 4 predictors scheme. In this scheme, LSTM becomes the second-best model for predicting wind shear occurrence for having better average accuracy, FAR, and POD. Nevertheless, GRU exceeds LSTM regarding wind shear duration with a big margin in the average RMSE.

For the 12 predictors scheme, LSTM is the best performance model. LSTM and TCN have same average accuracy. LSTM average POD in this case is the biggest in all schemes against any model.

In contrast with other scheme, TCN here has the biggest average RMSE which means the worst for predicting wind shear duration.

The best model in average accuracy and RMSE is TCN in 4 predictors scheme. For FAR metric, the best model with the lowest average FAR is TCN using 12 predictors. That average FAR value is nearly same with TCN in the 4 predictors scheme which is the second-best model in average FAR metric. Their average FAR difference is subtle (only 0.005). In the average POD metric, the best model is LSTM using 12 predictors.

5. DISCUSSION

The metrics value in **Table 6** shows TCN superiority over criterion. From 4 metrics, TCN reign in 3 metrics as the best model. The superiority of TCN over other time-series models match fed with prior studies (Hewage et al., 2020; Yan et al., 2020; Zhu et al., 2020). Different from previous studies, this study proves TCN can outmatch classification tasks derived from regression values. TCN can detect incoming wind shear well in all schemes (POD > 0.9) with minimum false alarm (FAR >= 0.1) against other models.

The TCN performance for predicting incoming wind shear looks not significantly affected by total predictors. This also applies to criterion models. There is no significant difference in the average accuracy, POD, and FAR for the same model with a different scheme. However, in predicting wind shear duration, the different scheme brings significantly different average RMSE value. TCN with 4 and 6 predictors do not have a significantly different average RMSE but have a great difference with 12 predictors. This also applies with GRU, which is the difference average RMSE value between 4 and 6 predictors scheme is 2.723 but against 12 predictors scheme, the difference is 55.784. This is different with LSTM where all schemes have a significant difference in average RMSE (>5). However, the experiment shows the fact that the 12 predictors scheme has the biggest average RMSE for all models.

The increase in the number of predictors must be accompanied by an increase in the dataset. Nonetheless, the scheme with the largest total predictor in this experiment has the lowest total dataset. This causes the model can't learn well the general pattern of the dataset. For a regression model, the effect is an increase in RMSE value. Wind shear duration is a product of the regression model, that why the average RMSE value for 12 predictors is huge compared with another scheme. For wind shear duration prediction, the best scheme is the 4 predictors scheme which is has a biggest total dataset. This finding underlines the importance of the total dataset over the model used for wind shear duration prediction.

Overall, the experiment show TCN outperforms all criterion models slightly for this case. The criterion models have high performance because they are specializing in time series problems. Therefore, the difference in performance between TCN and criterion models is not significant. This finding is similar to (Gopali et al., 2022) and (Sadique and Sengupta, 2021) in a different case. Previous studies already confirm that convolutional network architecture is better than generic recurrent network architecture for sequence modeling across different tasks (Bai et al., 2018). Additional property for a convolutional network in TCN i.e., dilation makes the model can handle a long sequence data to perfect the model for sequence modeling.

6. CONCLUSIONS

This paper introduced a new way to predict wind shear using ML which can predict the wind shear occurrence and duration with just 1 model. The proposed model can reign over criterion models almost in all metrics. The proposed model can predict well if fed with enough training datasets. The proposed model's RMSE increases significantly as the total dataset decrease and the total predictor increase. Nevertheless, the proposed model can achieve high accuracy (>0.9) in any scheme. Furthermore, the proposed model can converge fast enough against criterion models.

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