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Hybrid Sequential Denoising Strategy to Improve the Performance and Accuracy of TB Incidence Forecasting

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***Abstract*—*Rapid transmission and low public awareness of tuberculosis (TB) make the TB incidence rate in Indonesia rank second in the world. The incidence of TB with randomly fluctuating dynamics (patterns that change over time) is a challenge for the government to ensure TB transmission control and prevention programs. Several smoothing and denoising methods with various prediction techniques and complex time series data analysis have been exploited by many researchers. Unfortunately, this prediction model does not take into account all non-linear and non-stationary dynamics or heteroscedasticity properly, resulting in biased and inconsistent predictions. Therefore, this study proposes a Hybrid Sequential Denoising Strategy to Improve the Performance and Accuracy of TB Incidence Forecasting. The prediction strategy uses the adaptive moment estimation (ADAM) optimization method, discrete wavelet transform (DWT), Bayesian Optimization (BO) and recurrent neural network (RNN) models. The first stage is preprocessing with a combination of DWT and Bayesian Optimization (BO) on each folds of Timeseries Cross Validation (TSCV), used to prepare data before further analysis such as for denoising and handling heteroscedasticity. By optimizing the combination of optimizations, it will be possible to calculate fluctuations in data variability over time more accurately. The second stage, the results of the combination of DWT and BO are used to optimize the training process using the ADAM optimization algorithm. With this optimization, the learning rate can be adjusted based on the first and second gradient moments, which allows it to adapt to the local conditions of the optimized objective function. The third stage is integrated with RNN to build an optimal prediction model. The proposed technique is evaluated using TB incidence data in Semarang City from 2018–2023. The proposed approach has better performance in improving Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), Signal-to-Noise Ratio (SNR), and Energy.*

***Keywords*— *Bayesian Optimization, Wavelet Transform, RNN, TSCV.*

I. INTRODUCTION

Tuberculosis (TB) remains a significant global health problem. In 2021, there were an estimated 10.6 million cases of TB worldwide, an increase of about 600,000 cases compared to the 10 million cases reported in 2020. Of these, about 4.27 million cases (39.7%) were undetected and unreported, while 6.4 million cases (60.3%) were recorded and undergoing treatment. According to the WHO report in 2023, around 30,000 people are infected with TB every day, and around 4,400 people die from the disease [1].

In 2021, Indonesia was ranked third as the country with the highest number of tuberculosis (TB) cases in the world. However, in 2022, the ranking rose to second place, behind China and surpassing India. In 2022, there were an estimated 969,000 TB cases in Indonesia, or equivalent to one new case every 33 seconds, which represents a 17% increase compared to the 824,000 cases reported in 2021. The prevalence of TB in Indonesia reached 354 cases per 100,000 population. This condition is a serious challenge in efforts to achieve the target of eliminating TB by 2030. To support the achievement of this goal, information technology will be utilized in the provision of comprehensive TB prevention and control services, including risk factor analysis and the development of TB incidence prediction models [2].

A reliable prediction model for TB incidence treatment needs to be developed considering the significant variation in the number of TB treatment cases [3]. Various hybrid approaches have been applied to predict the fluctuating patterns in time series data (noise) to produce more accurate estimates. One of the effective denoising techniques in prediction systems with non-stationary data is signal decomposition. The use of signal decomposition allows the separation of non-stationary components in the time series signal, thereby improving the performance of the prediction model [4].

The application of wavelets in forecasting time series data, especially fluctuating data, continues to grow rapidly. This is due to the ability of Discrete Wavelet Transformation (DWT) which is considered very suitable for time series data because it produces wavelet coefficients and scales that match the length of the data at each level of decomposition. This feature helps overcome the limitations of DWT filtering, which can be applied to various sample sizes. In the context of optimization algorithms, this study proposes a combination of numerical parameters and categorical or structural parameters, such as method selection. This approach includes adaptive wavelet thresholding optimization at each level of decomposition by exploring all possible combinations of numerical parameter values and thresholding methods available in the parameter space.

One of the important elements in the signal denoising process is wavelet threshold optimization. Various methods have been developed to improve its performance. The

Artificial Fish Swarm Algorithm (AFSA) algorithm has been applied in wavelet threshold optimization, where conventional methods show less than optimal results [5]. In threshold selection, recent studies have shown that optimization algorithms such as Aquila Optimizer (AO), Gradient-Based Optimizer (GBO), and Modified Gray Wolf Optimizer (GNHGWO) have good potential in benchmark signal denoising [6]. According to Zhu et al. [7], the edge detection-based optimization approach is able to retain edge information while eliminating noise, which results in a better signal-to-noise ratio. In addition, entropy-based optimization has been used to determine the wavelet coefficient threshold in grayscale images contaminated by additive white Gaussian noise, which shows superior performance compared to the universal soft method [8].

The selection of threshold parameters in wavelet thresholding, which is an important approach in nonparametric regression estimation, has a significant impact on the smoothness of the estimated function [9]. To obtain an optimal function estimate, it is necessary to identify the ideal threshold value, which can be done through various methods. Some commonly used approaches include multiple hypothesis testing and the False Discovery Rate (FDR) process, where the threshold value and the smoothness of the resulting function are influenced by the level of significance [10]. In the field of image processing, an efficient multilevel thresholding method has been developed by Figueroa et al. [9]. This algorithm analyzes the image histogram to minimize or maximize the objective function. In addition, research on block-based thresholding estimators in wavelet regression has also been conducted, considering the effect of block size on global estimation.

II. Literature Review

A. Wavelet Analysis.

Wavelet analysis is a mathematical technique that is frequently used in image and signal analysis. The popularity of wavelet transform in recent years is due to its ability to represent non-stationary phenomena with high accuracy. Unlike the Fourier transform, wavelet is more frequently used and is increasingly receiving widespread attention. This is mainly due to its superior ability to estimate smooth functions and analyze various types of data, both stationary and non-stationary [9]. On the other hand, the Fourier transform has several limitations as an analysis tool, especially in handling non-stationary data. Some of these limitations include the inability to localize in the time domain and the higher computational complexity in decomposition techniques.

Signal estimation has relied heavily on noise reduction studies across fields for many years. Recent studies have shown that the presence of noise can hamper the effectiveness of various methods, including identification, parameter estimation, and prediction accuracy [11]. Therefore, data manipulation from an early stage is highly recommended to reduce noise interference without eliminating the intrinsic dynamics of the underlying signal [12].

B. Discrete Wavelet Decomposition (DWD)

A pre-processing technique known as Discrete Wavelet Decomposition (DWD) facilitates the mapping of time series data into a set of orthonormal basis functions. The goal of this transformation is to get more information from the original time domain data. Once DWD is applied, signal analysis can be performed by decoding the data at various frequencies. Low-frequency components generally show identifiable patterns from the original data, thus aiding in the estimation process, while high-frequency components potentially add noise. In this study, the weekly Henry Hub spot price is decomposed into four separate subseries using DWD [13]

C. Wavelet Transformation in Time Series

Wavelet transform is increasingly popular in time series forecasting due to its ability to handle non-stationary data. One of the techniques widely used in time series analysis is the Discrete Wavelet Transformation (DWT). The advantage of DWT lies in its ability to be applied to various sample sizes, because its decomposition technique produces wavelet coefficients and scales at each level that correspond to the length of the data [14]. This flexibility is very important in analyzing TB incidence, which often shows non-stationary characteristics with significant fluctuations.

D. Signal Decomposition and Denoising

Optimization of forecasting methods for non-stationary data relies heavily on the efficiency of signal decomposition. By applying denoising techniques, prediction models can isolate non-stationary components, thereby significantly improving accuracy. According to Elshekhidris, Mohamedamien, and Ahmed [9], Discrete Wavelet Transform (DWT) has been shown to be effective in signal decomposition, providing a stable framework for the denoising process on time series data.

E. Wavelet Thresholding

Wavelet thresholding is an important technique in the process of denoising time series data, where a threshold value is chosen to filter out noise while retaining relevant signal components. Various thresholding methods, such as hard and soft thresholding, have been studied, with each offering its own advantages based on the characteristics of the data used [15]. The success of removing noise is highly dependent on the thresholding method applied and the selection of the optimal threshold value.

F. Hyperparameter Optimization

Optimizing hyperparameters is an important step in improving the performance of wavelet thresholding. The success of the denoising process is highly dependent on hyperparameters such as threshold value and decomposition level. An exhaustive search approach has been shown to be effective in determining the best configuration for complex datasets, by evaluating every possible combination of hyperparameter values [16]. This detailed process ensures the selection of optimal settings, thereby improving forecasting accuracy and denoising effectiveness.

G. Combining Numerical and Categorical Parameters

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The integration of numerical and categorical parameters in wavelet thresholding optimization has been the focus of recent developments. This holistic approach combines method selection with numerical parameter tuning, allowing for a more comprehensive exploration of the parameter space. This combination improves the overall model performance by supporting adaptive wavelet thresholding optimization tailored at each decomposition level [16],[17].

III. Research and Methode

In this study, an analysis was conducted to determine the effectiveness of wavelet-based threshold optimization with a folds segmentation approach on each folds of the time series cross validation (TSCV). To achieve the best possible denoising, the research process includes several steps: preprocessing, segmentation, threshold optimization, and signal reconstruction. At the threshold optimization stage, this process is applied to each segment formed using the k-means method to group data based on similar patterns or characteristics. This approach aims to allow more precise treatment of each segment. Evaluation of the decomposition function is carried out by applying a different wavelet basis to each segment than to each folds of the time series cross validation (TSCV).

Threshold optimization includes two main aspects, namely estimator optimization and hyperparameter combination optimization. In estimator optimization, a combination of ridge regression and lasso regression algorithms is used with complexity control through regularization. Meanwhile, at the hyperparameter optimization stage, the Bayesian optimization algorithm is applied to control the complexity of cross validation in time series cross-validation. To determine the optimal threshold value for each segment, a composite evaluation is performed using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Signal-to-Noise Ratio (SNR), and energy. After the optimal threshold is obtained for each segment at each cD level, the approximate wavelet coefficients and wavelet coefficients at each cD level are reconstructed using the inverse Stationary Wavelet Transform (ISWT). Thus, the signal can be restored to its original form cleanly and free from noise interference.

The smoothness of the curve in the Function Approach using the wavelet thresholding method is influenced by various parameters. These parameters include the type of wavelet function selected, the resolution level, the type of thresholding function, and the thresholding value used. To obtain optimal results, an optimization process is carried out on each parameter. This optimization process consists of two stages. The first stage focuses on optimizing the wavelet basis and the resolution level used in the wavelet transform process, as well as selecting the threshold function applied in the thresholding process [18], [17]. Furthermore, the second stage aims to optimize the specific threshold value that acts as a limit in the thresholding process. This optimization is carried out by utilizing the Bayesian Optimization method.

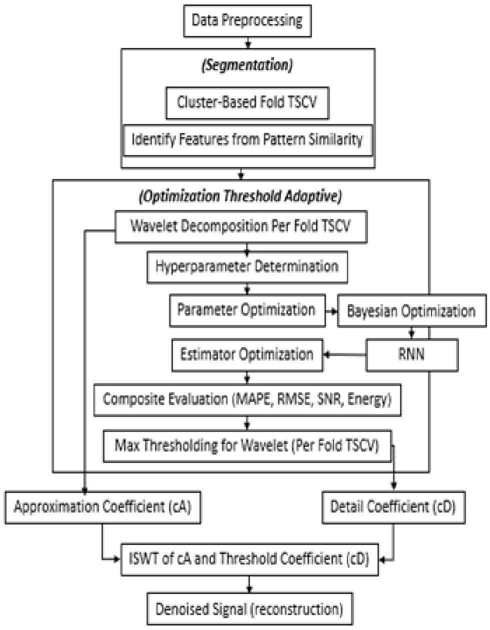

Fig. 1. Proposed overall system model of the present study

IV. Result and Discussion

A. *Optimization with Hybrid Bayesian Optimization and RNN.*

This function is designed to find the optimal threshold efficiently by setting various adaptive thresholding parameters, such as wavelet type, decomposition level, and thresholding method identified in the hyperparameter space. Bayesian optimization algorithm and RNN are used to determine the best parameters for the estimator based on the predetermined objective function, namely minimizing the Mean Absolute Precentage Error (MAPE) and Root Mean Squared Error (RMSE), and maximizing the Signal-to-Noise Ratio (SNR) and Energy Preservation (seeing the signal energy after the denoising process). This process includes various strategies to explore the parameter space and refine the parameters to achieve optimal results. This algorithm will evaluate different parameter combinations by training the estimator and measuring its performance based on predetermined evaluation metrics. Bayesian optimization iteratively tries various parameter combinations and updates the search strategy based on previous results. In this study, the Bayesian Optimization method is used to optimize the regression model. The results of the hybrid optimization will be compared with the results of the Multiresolution Analysis (MRA) and wavelet-based optimization approaches.

B. *Wavelet Decomposition Result*

Figure 2 shows the components resulting from the discrete wavelet decomposition process at level 1 to level 5. The approximation and detail components are divided up to the third level, from bottom to top. These components are presented in three orders. The discrete wavelet decomposition process can be done using various methods, such as

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Daubechies, Coiflets, Symlets, or Discrete Meyer. Among these methods, Daubechies and Symlets allow perfect reconstruction with the largest number of lost moments. Symlets have perfect symmetry, while Daubechies does not. The Daubechies wavelet is selected for this study because symmetry can restrict the freedom with which data may be represented. Three optimal values from each folds at each level (MAPE, RMSE, SNR and Energy) are used to measure the optimization based on the optimal parameter combination.

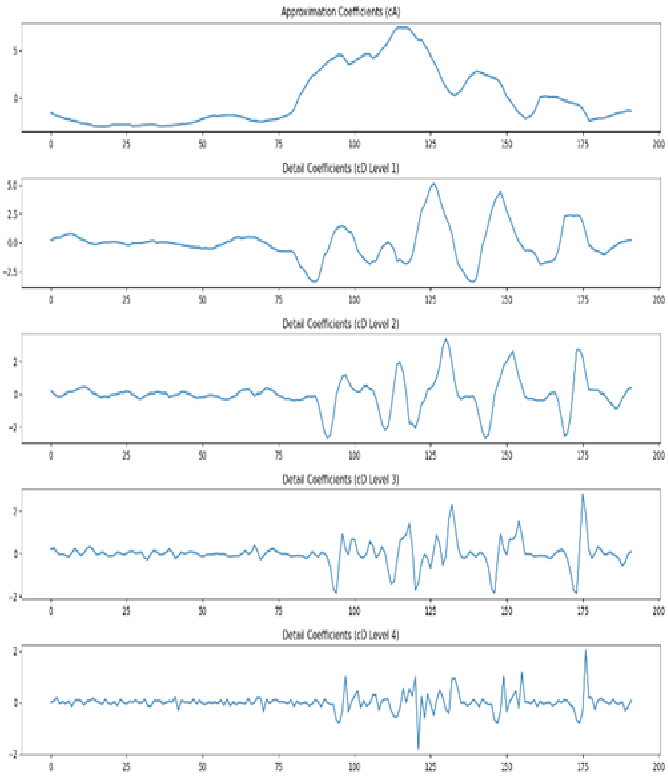

Fig. 2. Level 5 Coefficient Decomposition

C. *Adaptive Threshold Optimization at Each cD Level*

To optimize the threshold specifically, parameter tuning is performed at each level at each TSCV fold on cD (adaptive threshold) in wavelet denoising. A hybrid approach is needed between Bayesian optimization and wavelet-based RNN that is able to find the optimal threshold value independently for each cD level on each TSCV fold. Figure 1 shows the steps of Adaptive Threshold Optimization at each cD level, using wavelet transform to illustrate the signal decomposition process. At the wavelet transform stage, the original signal is decomposed to obtain the approximation coefficient (cA) and detail coefficient (cD) at various levels. One approximation coefficient (cA5) and four detail coefficients (cD1, cD2, cD3, cD4, and cD5) are produced by utilizing wavelet db4 at the ideal level of decomposition. The next stage is adaptive threshold optimization at each fold that has a specific character for optimization so as to obtain a specific threshold value. Then with the Bayesian approach to find the optimal parameters in finding the threshold results on each folds after going through the evaluation of MAPE, RMSE, SNR and Energy. This is a denoising process with the aim of the model recognizing patterns well and finding optimal accuracy and not losing important information.

TABLE I. Initialization Parameters for Optimization.

Hyperparameter Space	Value
Wavelet_methode	'db3', 'db4', 'haar', 'sym4'
Max_level	1, 2, 3, 4, 6
Threshold_cD	'hard', 'soft'
Thresholding_method_cD	'sureshrink', 'statistical'
Sigma_method	'median', 'mean'
Denoising_method	'wavelet', 'kalman', 'lowpass'
Transform_type	'wavedec', 'swt'

At each cD level (e.g. cD1, cD2, cD3, cD4, cD5), threshold optimization must be performed separately. This process involves finding the optimal threshold value for each level that can minimize the error or meet certain evaluation criteria, such as Minimizing Mean Squared Error (MSE), Minimizing Root Mean Squared Error (RMSE), Maximizing Signal-to-Noise Ratio (SNR), and Energy Preservation (looking at the signal energy after the denoising process). The evaluation results produce the optimal threshold value and the best parameters at each cD level, as shown in Table 2.

TABLE II. Best threshold evaluation and parameter optimization results hybrid model optimization vs wavelet threshold with MRA optimization

Fold	**Evaluations Metrics with threshold adaptive optimization (hybrid bayesian and RNN) / Fold TSCV**	**Evaluations Metrics with MRA optimization**
Fold 1	RMSE: 0.7482 SNR: 27.204793 Energy: 0.995693 MAPE: 0.039818	RMSE': 0.34516420694317 SNR': 9.23948492733044 Energy': 0.72435302447508 MAPE': 55.49758961853511
Fold 2	RMSE: 0.9762 SNR: 27.395303 Energy: 1.001345 MAPE: 0.038334	RMSE': 0.10007061067542 SNR': 19.9938689989754 Energy: 0.91783639813059 MAPE': 20.5765735770563
Fold 3	RMSE: 0.69671 SNR: 24.025643 Energy: 0.997767 MAPE: 0.060843	RMSE: 0.06589673335754 SNR': 23.622722275632366 Energy: 0.96249080395291 MAPE': 11.9204822955061
Fold 4	RMSE: 0.21736 SNR: 23.299262 Energy: 0.995695 MAPE: 0.102794	RMSE': 0.21249537307176 SNR: 13.4530104389819 Energy: 0.80606529220261 MAPE: 37.07449927049839
Fold 5	RMSE: 0.32453 SNR: 22.655326 Energy: 0.994977 MAPE: 0.118683	RMSE: 0.02419738389783 SNR: 32.324631705309564 Energy: 0.99833103814587 MAPE: 4.30960225778361

Table 2. shows the combination of various parameters used in thresholding optimization at each level of detail coefficient (cD) in the wavelet denoising process.

TABLE III. Optimization results for each cD level each folds TSCV (fold 1, fold 2, fold 3, fold 4, fold 5) based on evaluation metrics

	Hybryd Bayesian and RNN Optimatian Base TSCV.	MRA optimization
MAPE	0.072094	25.862336
RMSE	0.5978052	0.1923659
SNR	24.916065	19.726742
Energy	0.997095	0.8816314

Each element in the list represents the optimized parameter value, with a score obtained based on various evaluation metrics. This score is the result of model evaluation after thresholding with a combination of these parameters. The

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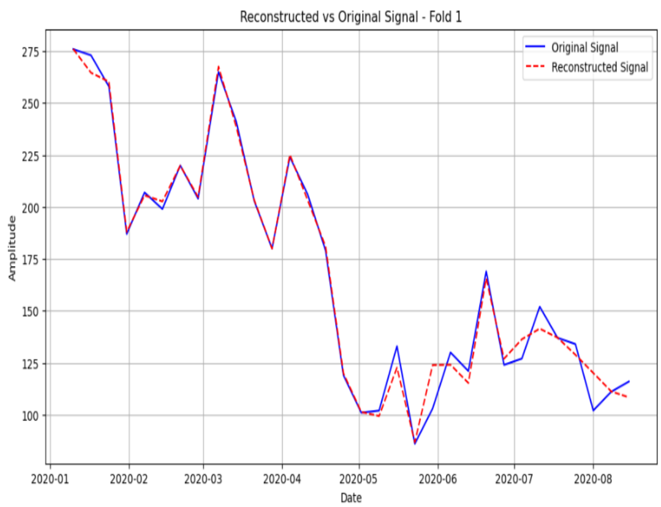
assessment is carried out using metrics such as MSE, RMSE, SNR, MAPE, and Energy. The lower the score, the better the model performance on the test or validation data. The evaluation results show that thresholding optimization provides better performance compared to thresholding using MRA optimization. In addition, the threshold value in thresholding optimization is more specific compared to MRA-based thresholding, which tends to have a uniform value without considering the characteristics of the signal at each cD level.

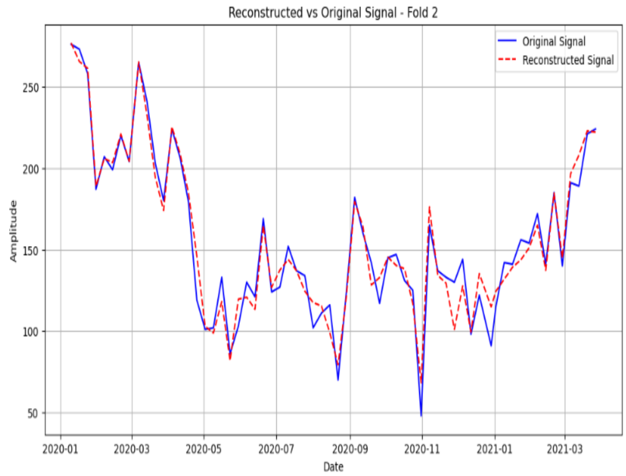
For each cD level and each folds TSCV threshold optimization is carried out independently. This entails determining the best threshold value for each level that either minimizes error or satisfies other established evaluation metrics. Table 3. shows the results Average Metrics across all folds of calculating evaluation metrics at each cD level and folds then used as a reconstruction by combining all cD levels where the results show that threshold optimization with Bayesian optimization is better than without optimization.

D. Signal Reconstruction

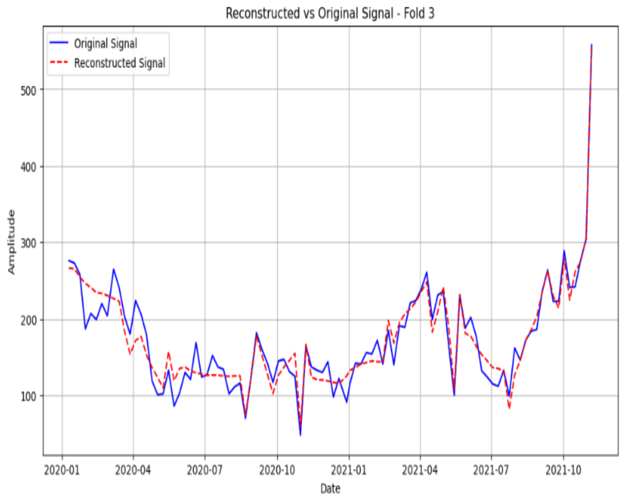
After finding the optimal threshold value for each cD level in each TSCV fold, the denoising process is then applied to the detail coefficients as part of the signal reconstruction. The inverse wavelet transform (ISWT or IDWT) is used to reconstruct the signal from the denoised coefficients during signal reconstruction. This process involves recombining the noise-cleaned approximation coefficients (cA) and detail coefficients (cD) at each level. The findings are evaluated using metrics such as MSE, MAPE, SNR, and Energy to make sure the reconstructed signal is free of interference. Figure 2 shows the results of the wavelet decomposition reconstruction at each fold (the combination of all optimization results from each TSCV fold), while Figure 3 shows the overall reconstruction results with a combination of threshold optimizations applied at each cD level with the wavelet-based MRA optimization approach.



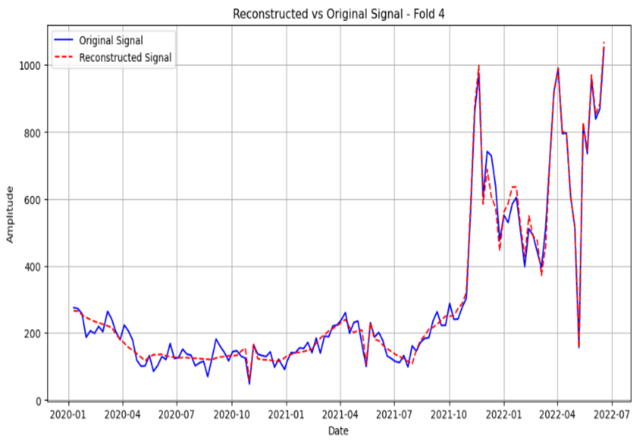
(a). wavelet reconstruction on fold 1



(b). wavelet reconstruction on fold 1 + fold 2



(c). wavelet reconstruction fold 1 + fold 2 + fold 3



(d). wavelet reconstruction on fold 1 + fold 2 + fold 3 + fold 4

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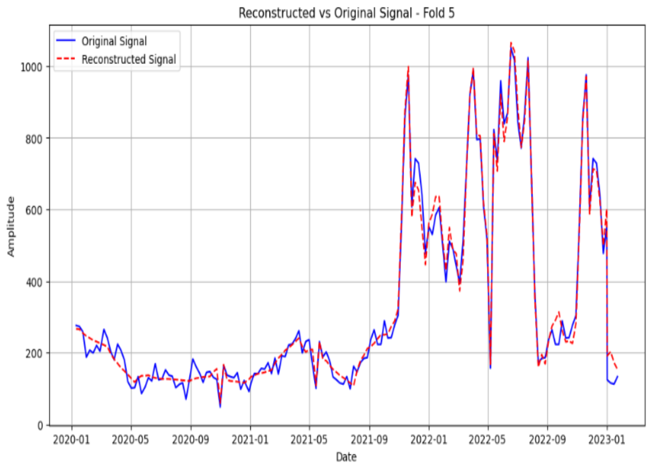

(e). wavelet reconstruction on fold 1 + fold 2 + fold 3 + fold 4 + fold 5
Fig. 3. Reconstruction from each TSCV fold (a) reconstruction fold 1, (b) reconstruction fold 1 + fold 2, (c) reconstruction fold 1 + fold 2 + fold 3, (d) reconstruction fold 1 + fold 2 + fold 3 + fold 4, (e) reconstruction fold 1 + fold 2 + fold 3 + fold 4 + fold 5.

D. *Evaluation of Algorithm Effectiveness*

After the optimization algorithm model is formed, the next step is to evaluate the stability of the model in finding a solution based on a combination of parameters obtained during the optimization process using evaluation metrics. The objective function values of evaluation metrics, such as MSE, RMSE, SNR, MAPE, and Energy, are used to measure the performance of the model or solution in achieving the desired goal. Figure 4 shows the results of the stability analysis of the proposed hybrid model in finding a solution even though the number of iterations continues to increase. The graph illustrates the trend of decreasing error or loss over time until it reaches a stable minimum value. Figure 5 shows the results of the stability analysis of the model in finding a solution even though the number of iterations continues to increase from the MRA optimization approach. This indicates that the proposed hybrid adaptive threshold optimization algorithm successfully identifies parameters that have stability and generality, resulting in a more optimal solution.

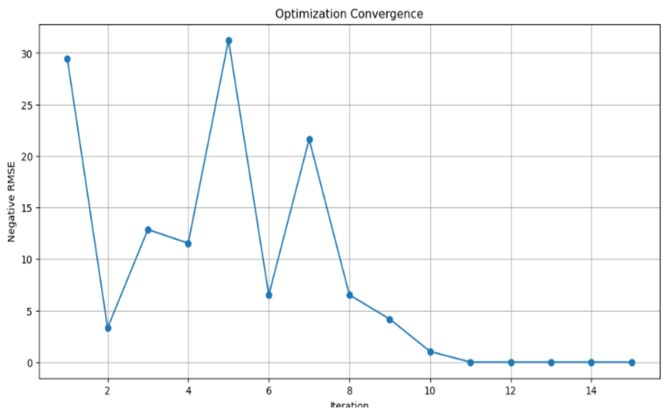

Fig. 4. Stability and generality graph of hybrid optimization model (Bayesian optimization and RNN) based on adaptive wavelet threshold at each fold

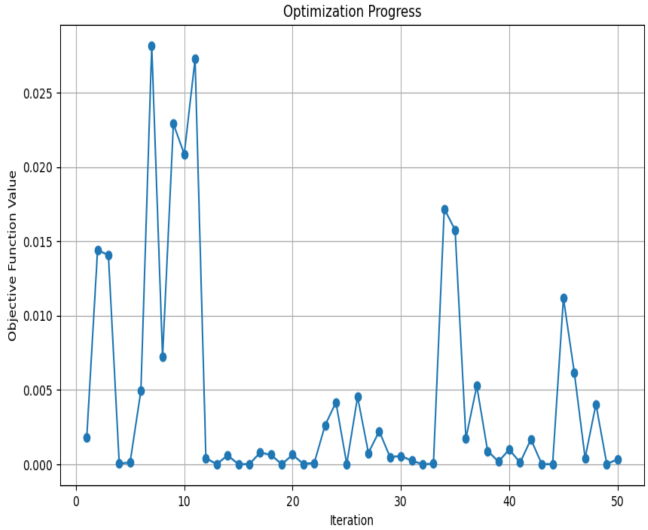

Fig. 5. Stability and generality graph of MRA optimization model based on adaptive threshold wavelet at each cD level

V. CONCLUSION

Based on the identification of the problem, the results of data analysis and discussion in the case study experiments of the two optimization models above, it was concluded that the application of the Adaptive Wavelet Thresholding denoising case study on complex, non-stationary and non-linear TB incidence data, the proposed model (Bayesian optimization and RNN based on adaptive wavelet threshold at each fold) has better accuracy and performance compared to MRA optimization. This can be seen from the comparison of the composite values or scores of various RMSE, MAPE evaluation metrics. In addition to looking at the results of the SNR and Energy evaluations, the proposed hybrid model can recognize complex data patterns better, is more stable and does not lose important information in performing denoising. So it can be concluded in general that for the TB incidence denoising case study which has random fluctuations from 2019-2022, the proposed hybrid denoising method performs better than MRA optimization, but from several evaluation metrics the MSE value in MRA optimization has a better value, this can be a consideration for improving further optimization research.

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