

A DIGITAL TWIN MODEL FOR POINT-INTERVAL-PROBABILITY PREDICTION OF RESERVOIR LANDSLIDE DISPLACEMENTS

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Accurately predicting reservoir landslide displacements remains a significant challenge due to raw data noise, model overfitting, and high uncertainty. This study introduces a “digital twin model” for point-interval-probability prediction of reservoir landslide displacements, addressing these limitations through a hybrid framework. The model employs complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) to decompose displacement sequences into periodic and trend components, effectively reducing noise. For point prediction, a bidirectional gated recurrent unit (BiGRU) is used, with hyperparameters optimized by the triangular topology aggregation optimizer (TTAO) to mitigate overfitting. Adaptive bandwidth kernel density estimation (ABKDE) then provides interval and probability predictions, improving uncertainty quantification. The model's performance was validated on the Jiuxianping landslide dataset. In point prediction, it achieved a coefficient of determination (R^2) of 0.992, a mean absolute error (MAE) of 3.617 mm, a root mean square error (RMSE) of 4.418 mm, and a mean absolute percentage error (MAPE) of 0.005. The model delivered optimal coverage metrics for 95%, 80%, and 70% confidence intervals for interval prediction. In probabilistic prediction, it attained a continuous ranked probability score (CRPS) of 0.135 at the 95% confidence level. The proposed “CEEMDAN-TTAO-BiGRU model” surpasses existing methods in accuracy and robustness, providing valuable insights for early warning and disaster mitigation in reservoir landslide management.

Keywords: Empirical Mode Decomposition, BiGRU, Meta-heuristic algorithm, ABKDE

1. Introduction

Reservoir operations frequently trigger or reactivate landslides, posing serious risks to nearby communities and infrastructure. For example, the Three Gorges Project caused significant landslides like Huangdupo, necessitating the relocation of millions (Yin et al., 2016), while Italy's Vajont Dam disaster led to catastrophic loss of life (Paronuzzi et al., 2013). The increasing frequency of such events highlights the need for accurate landslide displacement prediction to mitigate risks.

Landslide prediction remains challenging due to the influence of reservoir water levels, rainfall, and historical displacements, which lead to complex deformation patterns. Physical models simulate geological processes but require extensive data, limiting practicality (Pecoraro et al., 2018). Data-driven models, particularly those using machine learning, offer faster, cost-effective predictions but often struggle with non-stationary and noisy data (Meng et al., 2024a; Meng et al., 2024b).

Time-series models using techniques like Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) address these issues by separating displacement data into trend and periodic components, reducing noise and improving prediction accuracy (Wang et al., 2022). Neural networks such as BiGRU effectively model nonlinear relationships in landslide displacement but are prone to overfitting and fail to adequately address prediction uncertainty and interpretability.

This study introduces a hybrid digital twin model integrating CEEMDAN for data decomposition, BiGRU for point prediction, the Triangular Topology Aggregation Optimizer (TTAO) for hyperparameter tuning, and Adaptive Bandwidth Kernel Density Estimation (ABKDE) for interval and probability prediction. The proposed

framework enhances accuracy, robustness, and interpretability, providing a practical tool for landslide disaster prevention and management.

2. Methodology

Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) enhances traditional EMD by introducing adaptive Gaussian noise to address mode mixing and residual noise issues. This method effectively extracts meaningful features from noisy displacement data, providing a robust foundation for subsequent analysis. The Bi-directional Gated Recurrent Unit (BiGRU) extends GRU by processing sequential data in both forward and backward directions, capturing temporal dependencies more comprehensively. This dual propagation enables the model to leverage past and future information for improved prediction accuracy.

The Triangular Topology Aggregation Optimizer (TTAO) optimizes BiGRU hyperparameters by balancing global exploration and local refinement. Its adaptive search strategy ensures efficient convergence, reducing risks of local optima and enhancing model performance. Adaptive Bandwidth Kernel Density Estimation (ABKDE) dynamically adjusts kernel bandwidths based on data variability, improving the accuracy of probability density estimation. This approach effectively captures internal uncertainties and external variabilities, enhancing the reliability of interval and probability predictions.

2.5. Model evaluation

To quantitatively assess the performance of point prediction, several evaluation metrics were used: root mean square error (RMSE), mean absolute percentage error (MAPE), mean absolute error (MAE), and correlation coefficient (R^2). To assess the accuracy of interval predictions, various metrics such as Prediction Interval Coverage Probability (*PICP*), Prediction Interval Normalized Average Width (*PINAW*), and Coverage Width Criterion (*CWC*) are utilized. Since *PICP* and *PINAW* are contrasting metrics, the ultimate goal is to achieve accurate predictions within narrower intervals. Therefore, this study uses the *CWC*, which integrates *PICP* and *PINAW*, to assess the overall capability of interval predictions.

3. Case study

The Jiuxianping landslide, situated in Yunyang County, Chongqing, near the Yangtze River, exemplifies a large, deep-seated, bedding rock landslide. The region features a low mountain and gully terrain, with elevations ranging from 85.42 m to 569.52 m. The landslide is characterized by a weak interlayer that drives downslope deformation, with loose upper accumulations and interbedded sandstone and mudstone below.

Landslide activity is influenced by seasonal rainfall and reservoir water fluctuations. The area receives 1145.1 mm of annual rainfall, mostly between May and October. Reservoir levels fluctuate between 145 - 175 m, causing immersion, erosion, and delayed deformation during water level drawdowns. From 2005 to 2020, eight monitoring points recorded step-like displacement patterns, with peaks during flood seasons when rainfall and reservoir drawdowns overlap. Central monitoring point YY0209 was selected to develop the predictive model, with seasonal rainfall and reservoir regulation identified as key influencing factors for AI-based predictions.

4. Results

4.1. Model performance

The proposed digital twin model's performance was assessed through point, interval, and probability predictions. Figs. 2 and 3 show that the CEEMDAN-TTAO-BiGRU model aligns closely with observed displacement data, outperforming BiGRU and TTAO-BiGRU models, which show significant deviations. CEEMDAN's data decomposition simplifies prediction by isolating trend and periodic components, while TTAO enhances accuracy during sudden displacement shifts.

Fig. 4 illustrates narrower and more consistent confidence intervals for the CEEMDAN-TTAO-BiGRU model compared to other configurations. CEEMDAN reduces noise, while TTAO stabilizes predictions by optimizing hyperparameters. This combination ensures reliable interval coverage and reduced variability.

The CEEMDAN-TTAO-BiGRU model accurately captures displacement probability distributions, with predictions clustering around high-probability regions and reduced variance. This validates its effectiveness in probabilistic forecasting and adaptability to dynamic displacement patterns.

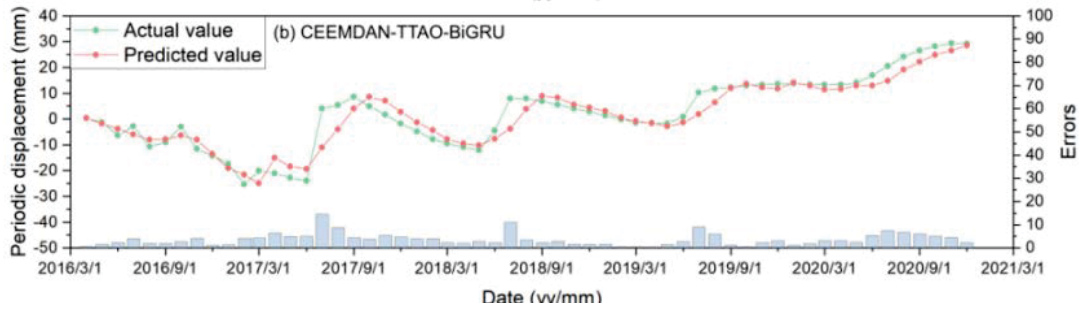


Fig. 2. Point prediction curves of periodic displacement.

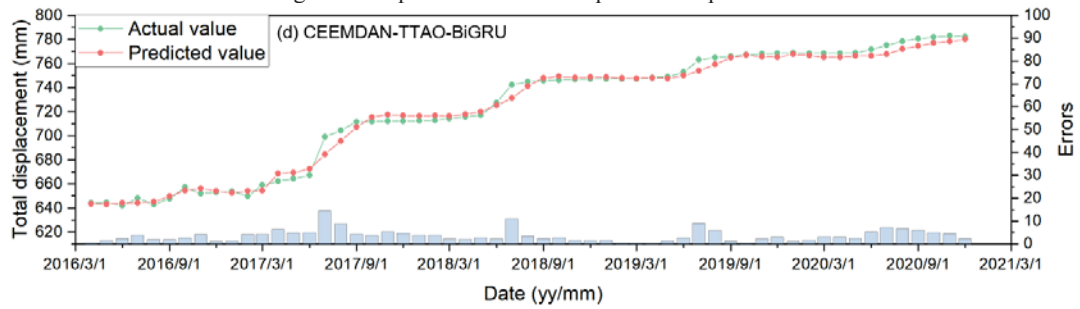
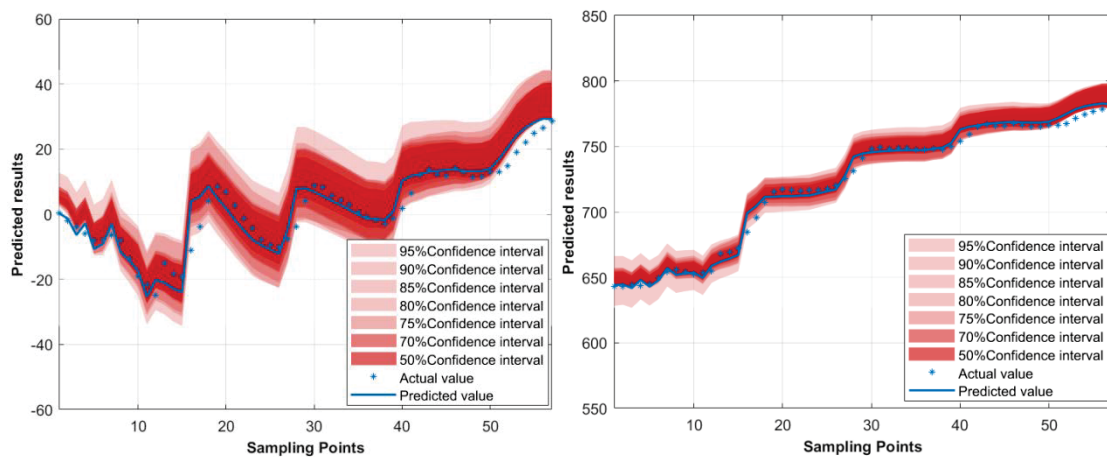


Fig. 3. Point prediction curves of total displacement.



(a) Periodic displacement. (b) Total displacement.
Fig. 4. Interval prediction of periodic and total displacement.

4.2. Comparison of algorithm

To evaluate the proposed digital twin model's performance, we compared it with baseline models across point, interval, and probability prediction tasks. Results highlight the contributions of CEEMDAN for data decomposition and TTAO for optimization. Table 1 shows that the CEEMDAN-BiGRU model outperforms the BiGRU model, with higher R^2 and lower MAE, RMSE, and MAPE values, confirming the benefits of CEEMDAN in reducing noise and improving prediction. When TTAO is added, the CEEMDAN-TTAO-BiGRU model achieves further improvements, significantly reducing errors, and demonstrating CEEMDAN and TTAO's synergistic effects.

Tables 2 and 3 summarize interval prediction performance at different PINC levels. Models with CEEMDAN and TTAO achieve lower CWC values, indicating better reliability. The CEEMDAN-TTAO-BiGRU model consistently outperforms others, demonstrating the combined benefits of decomposition and optimization for interval predictions.

Table 4 highlights CRPS reductions for probabilistic forecasts. The CEEMDAN-TTAO-BiGRU model achieves the lowest CRPS values, outperforming other configurations in total and periodic displacement predictions. This underscores its reliability in capturing uncertainty.

Table 1. The evaluation metrics of point prediction performance of ablation experiments.

Method	Periodic displacement				Total displacement			
	R ²	MAE	RMSE	MAPE	R ²	MAE	RMSE	MAPE
BiGRU	-	-	-	-	0.983	16.54	15.503	0.022
TTAO-BiGRU	-	-	-	-	0.987	11.92	10.843	0.016
CEEMDAN-BiGRU	0.733	6.152	9.101	1.987	0.975	6.487	9.126	0.009
CEEMDAN-TTAO-BiGRU	0.909	3.132	4.314	0.692	0.992	3.617	4.418	0.005

Table 2. Evaluation metrics in three PINCs of periodic displacement.

Model	PINC=95%			PINC=80%			PINC=70%		
	PINAW	PICP	CWC	PINAW	PICP	CWC	PINAW	PICP	CWC
CEEMDAN-BiGRU	0.556	0.807	3.061	0.440	0.719	0.057	0.333	0.614	0.031
CEEMDAN-TTAO-BiGRU	0.421	0.754	1.768	0.266	0.701	0.013	0.201	0.666	0.012

Table 3. Evaluation metrics of interval prediction of total displacement.

Model	PINC=95%			PINC=80%			PINC=70%		
	PINAW	PICP	CWC	PINAW	PICP	CWC	PINAW	PICP	CWC
BiGRU	0.475	0.841	0.221	0.415	0.701	0.057	0.362	0.614	0.031
TTAO-BiGRU	0.262	0.790	1.273	0.240	0.701	0.136	0.225	0.649	0.030
CEEMDAN-BiGRU	0.259	0.789	3.060	0.203	0.666	0.136	0.155	0.614	0.030
CEEMDAN-TTAO-BiGRU	0.160	0.824	0.527	0.109	0.719	0.056	0.083	0.631	0.031

Table 4. CRPS in 95% confidence of periodic and total displacement.

Displacement	Models	CRPS
Periodic displacement	CEEMDAN-BiGRU	0.237
	CEEMDAN-TTAO-BiGRU	0.212
	BiGRU	0.233
Total displacement	TTAO-BiGRU	0.222
	CEEMDAN-BiGRU	0.150
	CEEMDAN-TTAO-BiGRU	0.135

5. Conclusion

This study introduces a digital twin model, the CEEMDAN-TTAO-BiGRU-ABKDE framework, for point, interval, and probability prediction of reservoir landslide displacements. The model effectively addresses the challenges of nonlinearity, instability, and uncertainty in displacement data, offering a robust and interpretable solution for predictive modeling in geotechnical engineering. Key contributions include:

- (1) CEEMDAN for Data Decomposition: CEEMDAN reduces noise and complexity in the displacement sequence, enhancing pattern recognition and prediction accuracy.
- (2) TTAO for Optimization: The TTAO algorithm efficiently tunes BiGRU hyperparameters, improving model performance by reducing risks of overfitting and local optimization.
- (3) ABKDE for Uncertainty Quantification: ABKDE generates reliable probability density functions (PDFs), enabling accurate interval and probabilistic predictions critical for decision-making.

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