BAB 1 INTRODUCTION

Global climate change has become a critical issue world- wide, with consequences felt worldwide. In response, many countries have developed policies related to carbon trading mechanisms designed to regulate the value of carbon emissions in order to reduce greenhouse gas emissions [1], [2]. However, the complexity and volatility of carbon emissions assets pose significant difficulties for policymakers and investors in their decision-making [3].

The volatility of carbon emission prices is influenced by many factors, such as developments in energy markets, policy changes, and supply and demand dynamics [3]. This underlies the urgent need for accurate and reliable carbon price forecast- ing models to support carbon trading activities.

Hybrid methods integrating signal decomposition and ma- chine learning have been investigated to improve the per- formance of carbon price prediction [4]. While time series models such as ARIMA have been applied in this context [5], they often struggle to capture the nonlinear and nonstation- ary characteristics of carbon price data. This shortcoming has motivated the shift to deep learning models, particularly LSTMs, which are far superior in learning long-term temporal dependencies in time series data [6].

The performance of LSTMs themselves can suffer if the input data is contaminated with mixed-frequency noise. Pre- vious studies have attempted to mitigate this by incorporating volatility modeling or entropy-based preprocessing steps be- fore entering the deep learning phase [7], [8]. To improve the quality of decomposition results, the new research adopts the superior Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) method, which is able to show strong ability to learn long-range temporal patterns in complex time series [9].

This paper aims to address the limitations of prior work by proposing a hybrid CEEMDAN-LSTM model specifically for carbon price forecasting. We explore an IMF selection strategy based on signal frequency and informational content and evaluate the model's performance comprehensively using MAE, RMSE, and MAPE metrics. It is anticipated that this framework will yield more precise and robust carbon price predictions, even when faced with the complexities and high variability of carbon emission trading systems.