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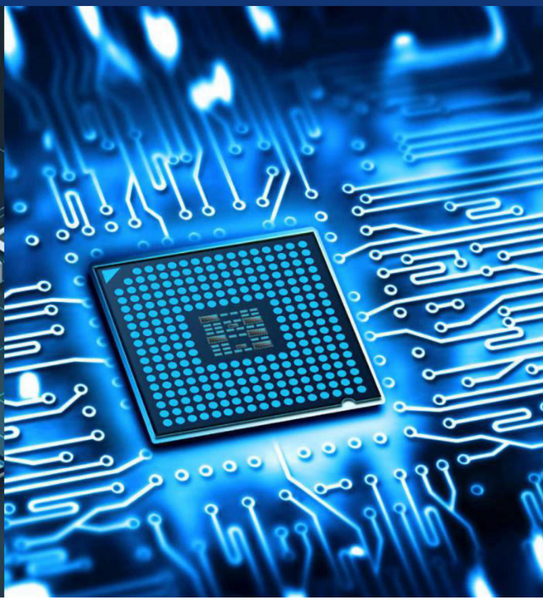


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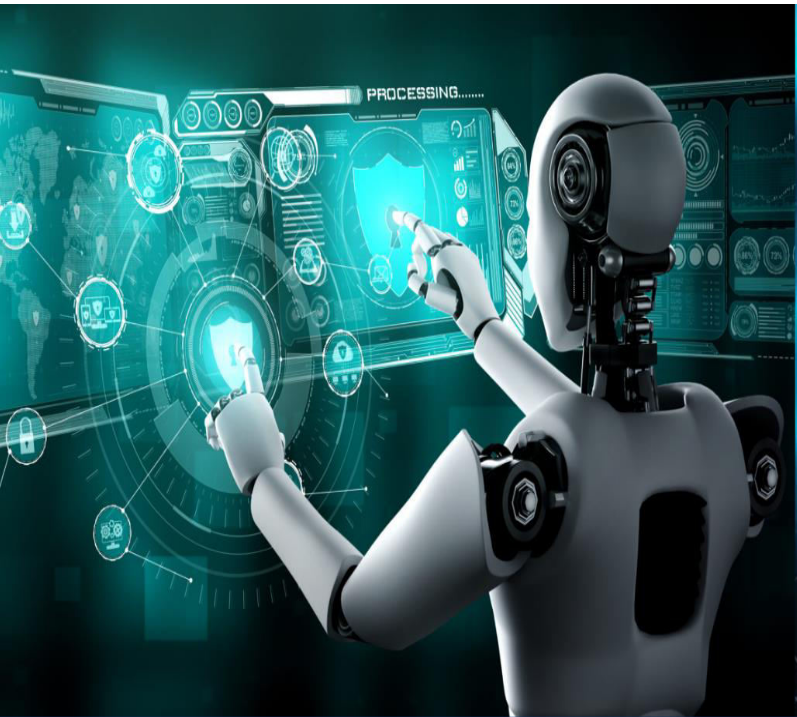

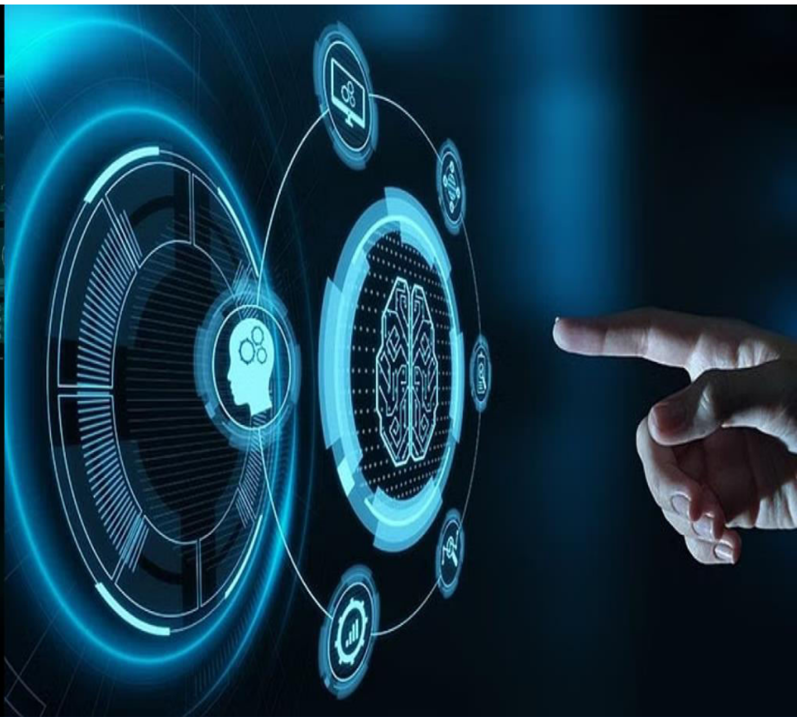

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Optimizing Short-Term Wind Power Forecasting with Corr-ARIMA-LSTM

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ABSTRACT: The global demand for clean energy has intensified the need for efficient utilization of renewable resources, particularly wind energy. However, there are a lot of difficulties because wind power generation is unpredictable. An adaptive Cor-ARIMA-LSTM model with post-processing is proposed. Forecasting is completed through ARIMA with linear dependency, then ARIMA produces residuals, and LSTM uses the residual data to learn the nonlinear patterns. A post-processing module is used to eliminate forecast error with a MLP error correction and seasonality injection. The challenges faced were modeling linear-nonlinear dynamics and reducing errors. The results demonstrate that our method outperformed other models.

KEYWORDS: Wind Power Forecasting; Cor-ARIMA-LSTM; VMD; Time Series Prediction

I. INTRODUCTION

As an ever-increasing rate of wind power generation continues to become integrated into modern energy grids, Short-term power forecasting is turning into a crucial instrument for enhancing grid stability and guaranteeing that the requisite energy is produced when needed. Increases in global warming and its consequent environmental challenges have called for efforts in adopting renewable sources of energy to combat climate change. The unpredictability of demand creates operational inefficiencies and increases cost, making robust forecasting models a key area of research [1].

Understanding the time period (also defined as a horizon) in which we are predicting is essential for tackling Wind Power Forecasting (WPF). WPF can be classified into these time horizons; very short-term, short-term, medium-term, and long-term horizons [2]. Very short-term forecasts are usually between minutes to an hour, short-term forecasts will be between an hour and a few days, medium-term forecasts will cover a few days up to a week, and last but not least long-term forecasts will of course be over a week. Therefore, short-term WPF is the objective of this research, as accurate WPF in the short term are important for managing the grid properly to balance supply with demand, and maximizing the penetration of wind energy into the power grid.

For a long time, traditional statistical models e.g. ARIMA (AutoRegressive Integrated Moving Average) were employed for time-series WPF [3]. But these models often do not work on very nonlinear and stochastic (that is the nature of wind) data. On the other side of the spectrum, we have deep learning approaches like Long Short-Term Memory (LSTM) networks which do exceptionally well in recognizing and capturing complex temporal dependencies, but this usually comes with a drawback as they lack the ability to model linear trends effectively [4]. By decomposing Wind Power Data (WPD) into its linear and nonlinear components, we aim to enhance WPF accuracy using the hybrid model.

II. RELATED WORK

The forecasting technologies for use in wind power have developed enormously in last decades because of the continuously growing integration of wind energy into modern power systems. Time-series forecasting has been mainly used through highly normal statistical methods like ARIMA and its seasonal generalisation SARIMA (Seasonal ARIMA). These are well aware of linear time-series patterns hence can be used for a WPF task. These models are being widely used in many areas like in economic forecasts, meteorology, and most among them WPF [5]. While ARIMA and its seasonal counterpart SARIMA model are based purely on historical data, they do not handle external features, such as weather conditions, well, which may greatly influence the wind power generation [6].

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Deep Learning methods such as LSTMa and Multilayer Perceptrons (MLP) are widely used for WPF because of their capability to learn complex temporal dependencies and non-linear correlations in time-series information[7]. LSTM networks consist of special units that retain information over long time spans, causing them to be better at modeling long term dependencies [8]. This has been especially beneficial in the area of WPF, where historical wind speed and power output data tend to have very complicated temporal correlations.

Forecasting wind power (WPF) employs hybrid WPF models that combine machine learning techniques with traditional statistical approaches in order to improve the accuracy and reliability of forecasts. Traditional time-series forecasting techniques (i.e., ARIMA) are adept at identifying linear trends and patterns within a time-series; whereas, machine learning time-series forecasting models (i.e., LSTM) are adept at identifying nonlinear relationships and patterns over time. Because the combined use of ARIMA and LSTM time-series forecasting techniques has the potential to yield forecasting results that incorporate the strengths of each, hybrid WPF models may provide more accurate and dependable forecasts than either technique would yield on its own. [9].

To address the natural variability and uncertainty of wind power generation, One effective strategy is signal decomposition, which uses methods like Variational Mode Decomposition (VMD) to break complex wind power time series into simpler components. This allows models to independently capture different frequency characteristics, thereby improving forecasting accuracy during highly fluctuating conditions [10]. Furthermore, feature engineering techniques, including adding temporal features (e.g., daily and seasonal patterns) and external meteorological factors, improve the model’s ability to represent underlying physical and environmental influences [11].

III. PROPOSED METHOD

The proposed method consists of the following key components. ARIMA-based linear modeling module, which captures the linear trends and generates initial predictions along with residual output streams. LSTM-based residual learning module, which models nonlinear dependencies present in the residual errors. Adaptive gating mechanism, which dynamically determines the contribution of linear and nonlinear components based on data characteristics. Hybrid prediction module, which combines ARIMA outputs with LSTM-based residual corrections. Post-processing error refinement module, which further improves prediction accuracy through MLP-based error learning and temporal feature-based seasonality injection.

The model achieves a progressive improvement in prediction results through this multi-stage approach. where linear patterns are first extracted, nonlinear components are subsequently modeled, and remaining errors are finally corrected. This hierarchical processing strategy enables more comprehensive handling of complex WPD characteristics. The overall structure of the proposed model is illustrated in Figure 1-1, which presents the complete data flow from input preprocessing to final forecast output.

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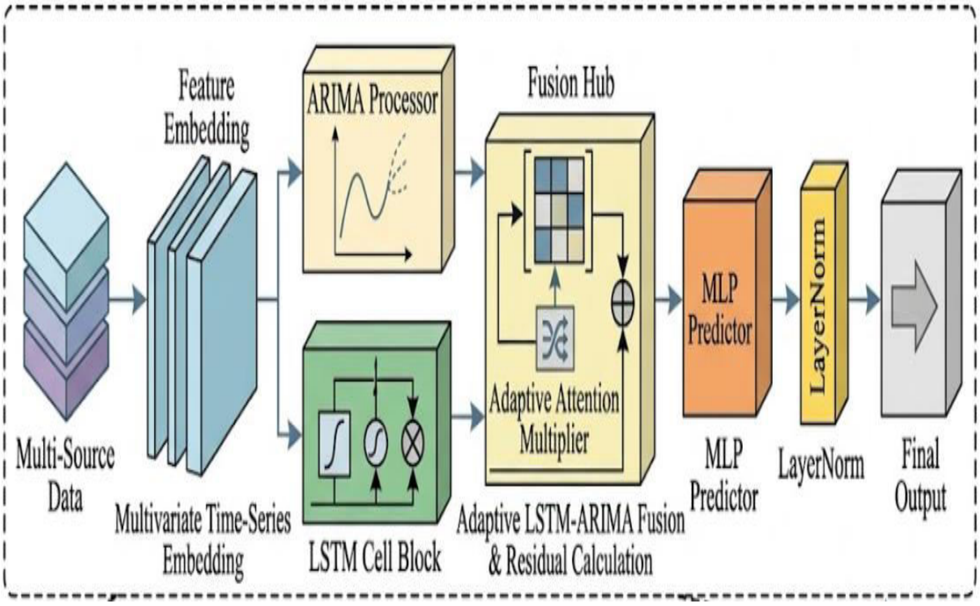

Figure 1-1: Overall Cor-ARIMA-LSTM Model Architecture

Compared with conventional single-model approaches, the proposed framework offers the following advantages. Decoupled modeling of linear and nonlinear components, improving interpretability and prediction performance. Adaptive fusion mechanism, allowing dynamic adjustment between statistical and deep learning predictions. Error refinement strategy, which enhances prediction accuracy by explicitly modeling residual errors. Improved robustness, particularly under highly fluctuating and noisy wind power conditions.

The general form of the ARIMA model is denoted as ARIMA(p, d, q), where p, d, and $q$represent the autoregressive order, differencing order, and moving average order. the optimal values of p, d, and $q$are determined through a combination of statistical analysis and model selection criteria. The residual output stream plays a critical role in the hybrid framework, as it serves as the input to the nonlinear modeling stage. Once the ARIMA model is trained on the preprocessed WPD, it produces a one-step-ahead prediction representing the linear component of the time series. Let y_t^{ARIMA}denote the predicted value at time step t. The residual series r_t, which captures the unexplained nonlinear component, is then computed as:

$$r_t = y_t - y_t^{ARIMA} \tag{3-1}$$

The core objective of the LSTM module is to learn the nonlinear patterns embedded in the residual output stream obtained from the ARIMA model. Since the residual series r_t represents the portion of the signal that cannot be explained by linear modeling, it inherently contains higher-order temporal dependencies and nonlinear structures. By explicitly modeling this component, the overall forecasting accuracy can be significantly improved. To effectively integrate the outputs of the linear and nonlinear models, an adaptive gating mechanism is introduced. Instead of directly summing the ARIMA and LSTM outputs, a dynamic weight $a_t \in [0,1]$ is learned to control the contribution of the nonlinear component at each time step. This allows the model to adaptively adjust its reliance on linear or nonlinear predictions depending on the data characteristics. The final hybrid prediction $\hat{y}_t$is computed as:

$$\hat{y}_t = y_t^{ARIMA} + a_t \cdot y_t^{LSTM} \tag{3-2}$$

Where a_t can be determined based on statistical properties of the residuals or learned through a lightweight neural network. The adaptive fusion strategy enhances the flexibility of the model by enabling dynamic adjustment between

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linear and nonlinear components. In periods where the time series exhibits strong linear trends, the model relies more heavily on ARIMA, whereas in highly volatile or nonlinear regimes, greater emphasis is placed on the LSTM output. Although the adaptive ARIMA–LSTM hybrid framework effectively captures both linear and nonlinear components of the wind power time series, residual errors may still persist due to unmodeled dynamics, noise, and complex temporal dependencies. To further enhance prediction accuracy, a post-processing and error refinement module is introduced. It consists of two main components: an MLP-based error learning mechanism and a seasonality injection strategy based on temporal feature encoding. Following the hybrid prediction stage, the residual error between the predicted and actual values is defined as:

$$e_t = y_t - \hat{y}_t^{(hybrid)} \tag{3-3}$$

where y_t denotes the actual wind power output and $\hat{y}_t^{(hybrid)}$ represents the prediction obtained from the adaptive ARIMA–LSTM model. The MLP is designed to learn a nonlinear mapping between relevant input features and the residual error. The input feature vector typically includes: Hybrid prediction values, Historical residual output streams, Auxiliary temporal features. The MLP function can be expressed as:

$$\hat{e}_t = f_{MLP}(X_t) \tag{3-4}$$

where X_t denotes the input feature vector at time step t, and $\hat{e}_t$ is the predicted error. Once the error estimate is obtained, the corrected prediction is computed as:

$$\hat{y}_t^{(refined)} = \hat{y}_t^{(hybrid)} + \hat{e}_t \tag{3-5}$$

This process enables the model to compensate for systematic biases and capture residual nonlinearities that are not fully learned during the primary modeling stages.

Explicitly encoding temporal information can further enhance the model's predictive capability. To achieve this, temporal features are constructed and incorporated into the post-processing stage. These features provide explicit representations of periodic behavior and help the model generalize across different time intervals. Commonly used temporal features include: Hour-of-day indicators, Day-of-week indicators, Cyclical encodings using trigonometric functions. The cyclical encoding of time can be represented as:

$$Time_{sin} = sin\left(\frac{2\pi t}{T}\right), Time_{cos} = cos\left(\frac{2\pi t}{T}\right) \tag{3-6}$$

Where T denotes the period of the cycle (e.g., $T = 24$ for daily periodicity). These encoded features are concatenated with the input vector X_t of the MLP, incorporating both residual dynamics and periodic structures simultaneously.

The foundation of any predictive modeling effort lies in the quality and structure of the dataset. This study utilizes a publicly available WPDset released during the KDD Cup 2022 competition by [12]. The dataset is sourced from operational wind turbines across multiple locations in China, offering rich temporal and spatial information recorded at 10-minute intervals. To evaluate the relationships between input variables and the target variable (active power output, Patv), both Pearson and Spearman correlation coefficients were computed. The results indicate that wind speed (Wspd) exhibits a strong positive correlation with power output, with a Pearson coefficient of 0.754 and a Spearman coefficient of 0.798. This confirms that wind speed is the dominant factor influencing turbine power generation. In time series analysis, ensuring that the data is stationary is a crucial step before applying models like ARIMA. To check for stationarity, the Augmented Dickey-Fuller (ADF) test is was used.

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IV. RESULTS

Several model variants are constructed for comparison: ARIMA, LSTM, ARIMA–LSTM (No Gating), ARIMA–LSTM (No Post-Processing) and our proposed model Cor-ARIMA-LSTM. Across all model variants, the ARIMA-only baseline records the weakest performance, with an MAE of 3.524 and RMSE of 8.168 — the highest error figures in the comparison. Its R^2 of 0.919, while not negligible, sits below all other configurations, reflecting the well-documented limitations of linear autoregressive modelling when applied to the nonlinear and irregularly fluctuating nature of wind.

The LSTM-only variant improves upon ARIMA across every metric, reducing MAE by 0.426 and RMSE by 2.026, with R^2 rising to 0.921. This confirms that the temporal feature extraction capability of LSTM provides a meaningful advantage over purely statistical approaches, though the margin of improvement remains modest when the model operates without the complementary residual correction provided by the ARIMA component.

The two intermediate ablation variants, ARIMA–LSTM without gating and ARIMA–LSTM without post-processing demonstrate the incremental contribution of each architectural element. Removing the gating mechanism produces only marginal gains over LSTM alone, with MAE declining by 0.107 and MAPE by a negligible 0.014 percentage points, suggesting that the post-processing stage is the more impactful of the two components. Reintroducing post-processing while omitting gating yields a more substantial improvement, bringing MAE down to 2.085 and R^2 up to 0.932, highlighting that residual correction plays a central role in closing the gap between initial forecast and true output.

The full Cor-ARIMA-LSTM model surpasses all variants across every reported metric. It achieves an MAE of 1.894, RMSE of 3.331, MAPE of 6.721%, and R^2 of 0.934 — the strongest values in the comparison. The MAE advantage over the ARIMA-only baseline amounts to 1.630, while the margin over LSTM-only reaches 1.204, underscoring the complementary relationship between the two constituent modelling strategies. The gap relative to the best-performing ablation variant narrows to 0.191 in MAE and 0.124 percentage points in MAPE, indicating that both the gating mechanism and the post-processing stage contribute independently to the final performance, and that their combined effect is greater than either in isolation. All this is shown in table 1. This consistent superiority across all configurations reflects the ability of Cor-ARIMA-LSTM to leverage the linear trend-capturing strengths of ARIMA alongside the nonlinear representational capacity of LSTM, producing a more comprehensive and stable forecasting framework than either component achieves independently. Fig 1.2 and Fig 1.3 show the prediction of each model over a period of 1 day.

Table 1 Component specific Quantitative Results

Model Variant	MAE	RMSE	MAPE (%)	R^2
ARIMA Only	3.524	8.168	7.351%	0.919
LSTM Only	3.098	6.142	6.938%	0.921
ARIMA–LSTM (No Gating)	2.991	4.435	6.924%	0.929
ARIMA–LSTM (No Post-Processing)	2.085	4.128	6.845%	0.932
Proposed Model Cor-ARIMA-LSTM	**1.894**	**3.331**	**6.721%**	**0.934**

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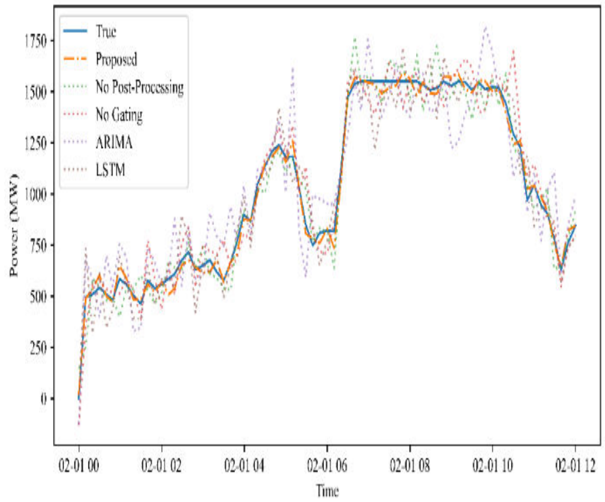

Fig 2 Evaluation comparison of ablation

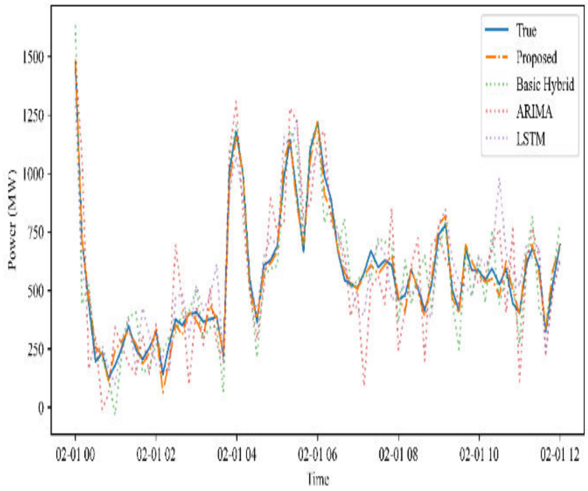

Fig 3 Comparative evaluation of different models

The results demonstrate that each component contributes positively to the overall performance, as verified through ablation studies. Comparative experiments further confirm that Cor-ARIMA-LSTM is a good approach to dealing with WPF. In addition, stability analysis shows that the model maintains consistent performance across multiple runs and varying data conditions. Overall, the proposed adaptive Cor-ARIMA–LSTM model with post-processing refinement achieves high forecasting accuracy, robustness, and stability, making it a reliable approach for short-term wind power prediction tasks.

V. CONCLUSION AND FUTURE WORK

This thesis investigated the problem of short-term WPF under conditions of high variability, nonlinearity, and data disturbance. To address these challenges, two advanced hybrid forecasting frameworks were proposed, each designed to improve prediction accuracy, robustness, and stability through structured modeling strategies.

The first contribution is an adaptive ARIMA–LSTM hybrid model with post-processing error refinement. This model separates linear and nonlinear components of WPD, enabling ARIMA to model stable linear trends while LSTM captures complex nonlinear residual patterns. An adaptive gating mechanism dynamically balances these components, improving flexibility across varying data conditions. Additionally, a post-processing module incorporating MLP-based error correction and temporal feature-based seasonality injection further refines predictions. Experimental results, including ablation and comparative studies, confirmed that each module contributes positively to performance, with the full model achieving better accuracy compared to baseline methods.

While the proposed models show strong performance, several areas remain for further improvement and exploration. First, future work can focus on enhancing computational efficiency. Both hybrid and decomposition-based models introduce additional complexity, which may limit real-time deployment in large-scale systems. Model optimization, lightweight architectures, or pruning techniques could be explored to reduce computational cost without sacrificing accuracy. Second, the integration of more diverse and high-resolution data sources offers potential for improvement. Incorporating additional meteorological variables, spatial correlations across multiple wind farms, or real-time sensor data may further enhance predictive performance, particularly in multi-site forecasting scenarios. Finally, real-world deployment and adaptability remain important directions. Future research could explore online learning, model updating mechanisms, and robustness under extreme weather conditions to ensure sustained.

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