WIND POWER FORECASTING USING TRANSFER LEARNING

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Introduction

Wind power forecasting is crucial for integrating renewable energy into power grids, but **cross-regional variability** poses significant challenges. Traditional forecasting models, trained on data from specific locations, often struggle to generalize to regions with different climatic conditions. Issues like data resolution discrepancies, varying meteorological conditions, and the availability of key features hinder accurate forecasting across diverse geographical areas.

To overcome these challenges, **transfer learning** has emerged as a promising solution. This technique leverages knowledge gained from data-rich regions (e.g., China) and applies it to regions with limited data (e.g., the U.S.), enhancing the model's ability to generalize. Transfer learning can significantly improve forecasting accuracy, even in areas with scarce data.

Key concepts in this research include:

•**Transfer Learning**: A method where models trained on one dataset are adapted to another related dataset, improving forecasting accuracy in data-scarce regions.

•**Climatic Variability**: Natural fluctuations in weather patterns that impact wind power generation and forecasting accuracy.

•**LSTM Networks**: A type of recurrent neural network well-suited for time-series forecasting, making it ideal for modeling wind power data.

This study explores how transfer learning can address regional challenges in wind power forecasting, ultimately improving **grid stability** and supporting **decarbonization** efforts. By enhancing the generalizability of forecasting models, we aim to facilitate the broader adoption of wind energy and contribute to a sustainable, low-carbon future.

Methodology

Data Preprocessing

To prepare the datasets for wind power forecasting, the following preprocessing steps were applied:

•**Normalization**: Meteorological features (e.g., wind speed, temperature) were scaled using the **MinMaxScaler** to ensure uniformity and prevent any feature from dominating the model.

•**Missing Data Handling**: **Zero-padding** was used for regions with sparse data to preserve sequence integrity, while **interpolation** filled significant gaps in data.

•**Feature Alignment**: The **Chinese dataset**, with a rich feature set, was aligned with the **U.S. dataset** by filling missing features using **interpolation**.

•**Input Sequences**: Data was structured into time-series sequences using a **sliding window** technique, enabling the model to capture temporal dependencies in wind power generation.

Models and Algorithms

•**LSTM Networks**: Used for capturing long-term dependencies in wind power data due to their ability to model sequential data effectively.

•**Transfer Learning**: The model was pretrained on the **Chinese dataset** and fine-tuned on the **U.S. dataset** to improve performance on data-scarce regions.

•**Attention Mechanism**: Enhances the model's focus on key features and time steps during training, improving prediction accuracy.

Evaluation Metrics

The model performance was evaluated using:

•**RMSE (Root Mean Squared Error)**

•**MAE (Mean Absolute Error)**

•**R^2 (Coefficient of Determination)**

The model showed significant improvement in prediction accuracy after transfer learning, especially for the **U.S. dataset**.

Visual

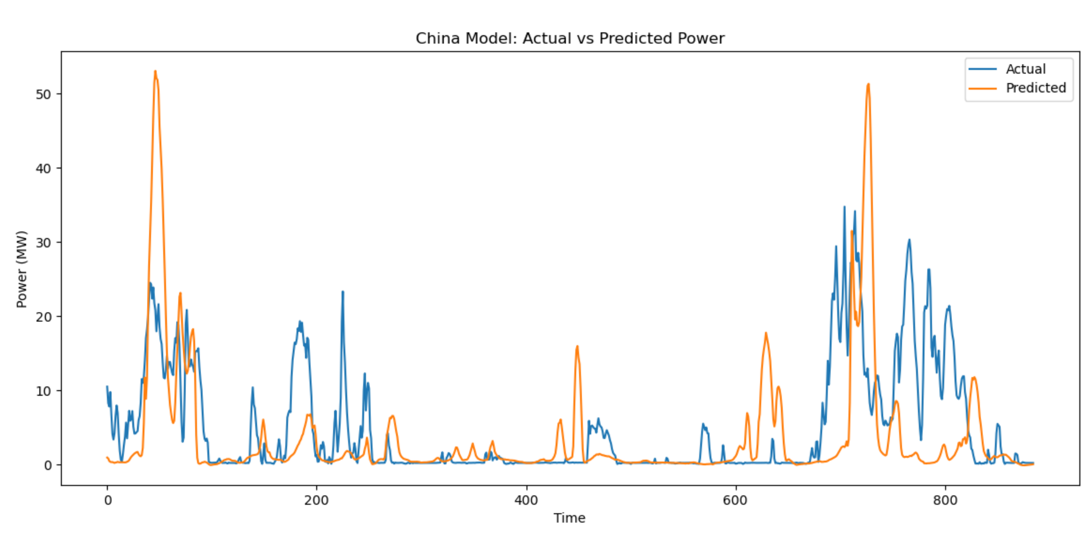

Figure 1: LSTM model performance on the Chinese dataset

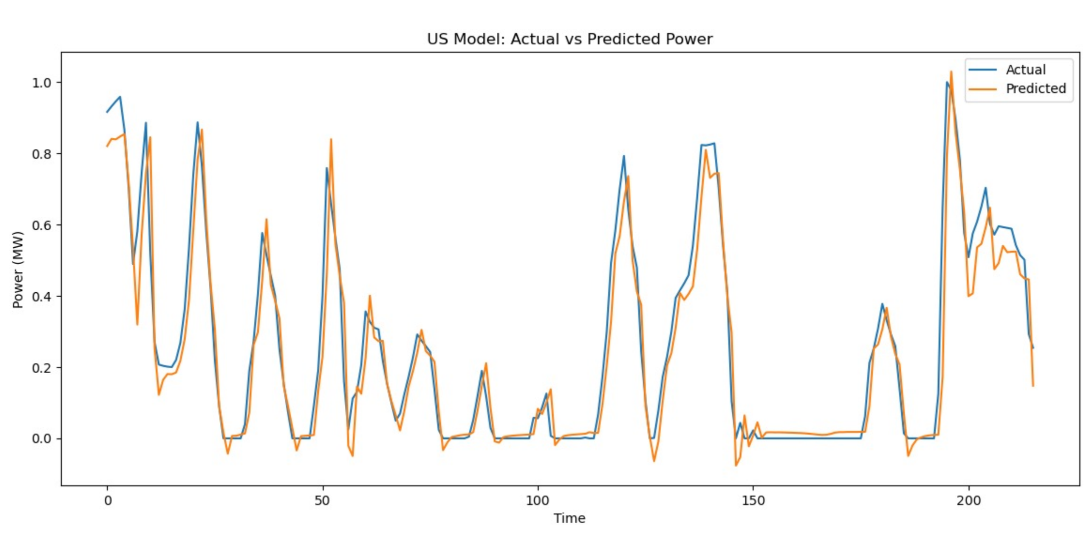

Figure 2: LSTM with transferred weight model performance on the US dataset

	LSTM	LSTM+Transfer
RMSE (Mean ± SD)	8.80 ± 1.89	0.087 ± 0.006
MAE (Mean ± SD)	4.97 ± 0.87	0.063 ± 0.008
R^2 (Mean ± SD)	-0.516 ± 0.730	0.907 ± 0.015

Table 1: Performance Metrics

Results

•**Transfer Learning Improvements**: Transfer learning significantly improved forecasting accuracy. Pretraining the model on the **Chinese dataset** and adapting it to the **U.S. dataset** addressed data scarcity challenges and improved predictions.

•**Pretrained Models vs. Region-Specific Models**: Models pre-trained on the **Chinese dataset** outperformed those trained solely on the **U.S. dataset**, showing the importance of using feature-rich datasets for model generalization across regions.

•**Key Features**: **Wind speed** and **wind direction** were identified as critical features for model accuracy, emphasizing the value of high-quality meteorological data in wind power forecasting.

Evaluation Results:

The following improvements were observed after transfer learning:

•**RMSE**: Reduced from 8.80 (Chinese model) to 0.087 (U.S. model).

•**MAE**: Decreased from 4.97 to 0.063.

•**R^2**: Increased from -0.516 to 0.907.

These results demonstrate the effectiveness of transfer learning for improving forecasting performance across regions with differing data availability.

Feature Importance:

•**Wind speed** and **wind direction** were identified as the most influential features.

•The **attention mechanism** helped the model focus on critical time steps and key features, enhancing prediction accuracy.

Conclusion

This study demonstrates the effectiveness of **transfer learning** in overcoming cross-regional variability challenges in wind power forecasting. Traditional models, limited by local data, struggle to generalize across regions with different climatic conditions and data resolutions. By transferring knowledge from data-rich regions like **China** to data-scarce regions like the **U.S.**, transfer learning significantly enhances model generalization and forecasting accuracy.

Key findings include:

•**Transfer learning** improved forecasting accuracy compared to region-specific models, addressing data scarcity.

•Models pretrained on the **Chinese dataset** outperformed those trained solely on the **U.S. dataset**, showing the value of feature-rich datasets.

•**Wind speed** and **wind direction** were critical for model performance.

These results highlight transfer learning's potential to improve wind power forecasting, enhance **grid stability**, and support **decarbonization**, contributing to a sustainable, low-carbon future.

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