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An Effective Implementation Through Machine Learning And AI- Data Fusion Techniques For Wind Farm Power Forecasting Using Multi Sources

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Abstract:
As wind power rises, it poses hazards and difficulties to power system stability due to its volatility, randomness, and intermittency. In energy storage technologies, the presence of numerous devices will expand, grid operating costs. To avoid major expense increases, wind power prediction accuracy reduces new grid energy generation risk. Proper power forecasting helps renewable energy and avoid power grid losses. The system also offers data for power market transactions and everyday operations and maintenance. Accurate power forecasting will enable stable wind turbine development, demand for wind power forecasting is rapidly increasing to enhance power grid dispatch, electricity market dealings, and everyday operation and maintenance requirements. Forecasting methods fall into three main categories: physical forecasting, statistical forecasting and combination forecasting. AI-ML models use vast amounts of data from sensors, satellites, historical records, and meteorological stations to identify patterns and trends in wind. AI-ML-based wind energy forecasting represents a critical advancement in renewable energy technology. By providing more accurate, efficient, and scalable solutions, these technologies support the global transition to sustainable energy systems and help address the growing demand for clean energy. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) models are highly effective in processing sequential wind data and identifying temporal dependencies. Combining predictions from multiple models enhances accuracy and reliability. Techniques like random forests and ensemble neural networks are widely used. These methods optimize wind farm operations by learning from interaction with the environment, enabling better control of turbine settings.
Key Word: *Intrathecal; Bupivacaine; Buprenorphine; Nalbuphine; Postoperative analgesia*.

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I. Introduction

Wind power forecasting introduced recurrent neural network (RNN) models to replace time series methods. RNN and its upgraded LSTM or GRU models effectively address the aforementioned issues. LSTM The network and GRU increase wind power prediction accuracy. Recently, forecasting methods using the architecture of encoding- decoding have enhanced the precision of multi-layer LSTM methods. Three typical models are Seq2Seq+attention, Auto encoder, and Evolution. Model. However, widespread attention mechanism use has successfully enhanced prediction accuracy. Researchers have observed the efficiency of deep learning models as data increases. Encoding-decoding architecture incorporates recursive models like the LSTM model, which limits model training as data dimension and dataset increase. Thus, the TCN, and Transformer models and their better models have been used.A widespread combination model combining signal decomposition and deep learning is used to improve power forecast accuracy due to the non-stationary nature of wind speed. A comparison of predictions is shown in figure1.

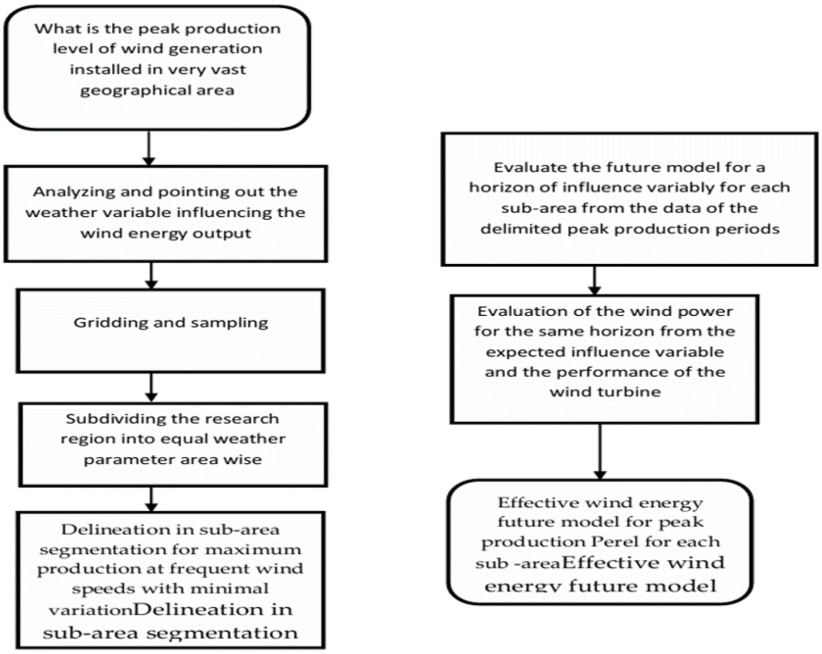


Figure1: A Flow Sketch Of Predictions

Power Forecasting Data Source: This study examines methods and processes to enhance wind power forecasting precision using models based on information and deep learning algorithms for time series problems. Machine learning involves many variables that exist in modelling. The state divides its data into dynamic and static variables. Based on the type of data it is divided into numerical and symbolic variables. Time-based variables are split into historical and future categories. Proper usage of the aforementioned variable types requires different data types. Enhancing model correctness is crucial. The demonstration is shown in Table 1.

Table 1 Variable Power Forecasting

Variable Types		Description	Case
Static	Numeric and Symbol	Historical wind turbine statistics, longitude and latitude. Turbine ID	For instance, everyday electricity generation. Example: 1, 2,
Dynamic	TimeVarying and Invariant	The data includes turbine operation and meteorological NWP data.	Consider factors like wind speed, power, and temperature. Day, hour, month, etc.
Time state	Historical and Future	Data on turbine operation, meteorological information, and reanalysis. - Weather prediction, date, and projected time step.	Examples include wind speed, power, and temperature. Example: 1, 2, 3.

Analysis of Power Forecasting Issues: Intra Attention: Intra-attention is a technique used to represent features by computing the inner product of matrices, revealing a time-dependent correlation. The attention matrix is obtained by combining the value and similarity matrix. The generic attention mechanism structure involves abstracting the input variable, Source, into Key-Value pairs, and calculating the correlation between the target variable and the key matrix, determining the corresponding value and weight coefficient as shown in Figure 2.

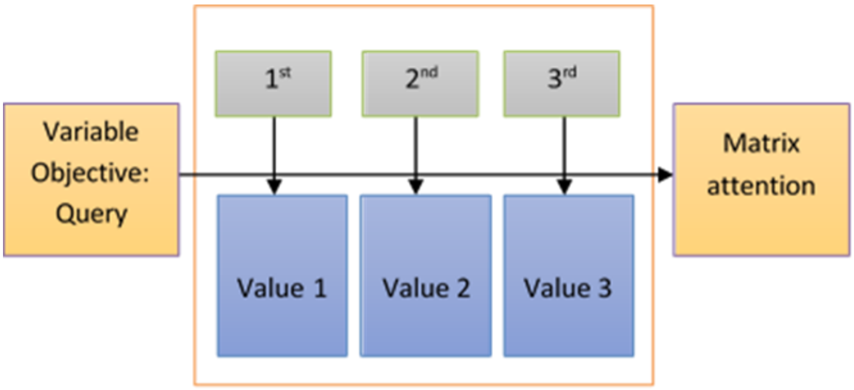
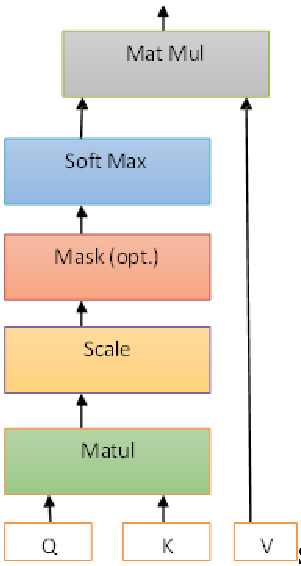


Figure 2 Architecture for Attention Common

The Intra-attention technique calculates similarity utilizing the content of the matrices. Figure 4.2 depicts the computation. Linearly transforming the input variables yields the matrices Q, K, and V. Calculate and scale the inner product of matrices Q and K, then normalize weights by rows. The interior product with matrix V yields the final attention matrix. Formula (1) denotes the computation. The Intra attention method is utilized to attain the mul-head-attention matrix, thereby enhancing self-attention diversity.

$$Ateention(Q, K, V) = Softmax\left(\frac{QK^t}{\sqrt{d_k}}\right) V \qquad (1)$$



Scale

Figure 3 Method of Computation

Fusion of Features: As power forecasting uses multiple data sources, such as wind turbine operation, meteorological masts, and forecast data, effective feature fusion will improve prediction performance. Multi-source data is utilized as a channel for CNN feature fusion to create various feature maps. Residual connections also diminish gradient disappearance, improving feature representation following data fusion. Figure 4.3 depicts the CNN-based feature fusion.

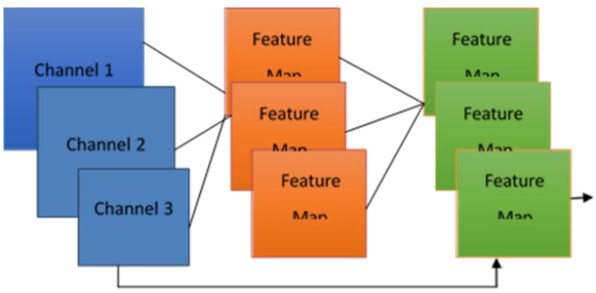


Figure 4 CNN-Based Feature Fusion

Feature selection: This paper presents a feature selection framework for data mining or machine learning, focusing on a non-linear gated residual network (GRN) and the add-attention technique. The GRN receives the D-Dimensional vector of every step time, calculates variable weights, normalizes them using SoftMax, and achieves the final feature selection results by performing the Hadamard elemental operation between the feature and weights selecting outcomes of every step. This is seen in Figure 4 In feature selection, the GRN is crucial. This formula calculates it.

$$GRN_w(a,c) = layernorm\left(a + GLU_w(\eta_1)\right) \quad (2)$$

$$\eta_1 = W_{1,w}\eta_2 + b_{1,w} \quad (3)$$

$$\eta_2 = ELU(W_{2,w}a + W_{3,w}c + b_{2,w}) \quad (4)$$

Residual connectivity and layer normalization. Static context information (c), gate linear unit (GLU), exponential linear unit (ELU), and weight information (w) comprise input characteristics. GLU determines

$$GLU_w(\Upsilon) = \sigma\left(W_{4,w}\Upsilon + b_{4,w}\right)e\left(W_{5,w}\Upsilon + b_{5,w}\right) \quad (5)$$

An elemental Hadamard product operation after a non-linear transformation and linear input change causes feature forgetting.

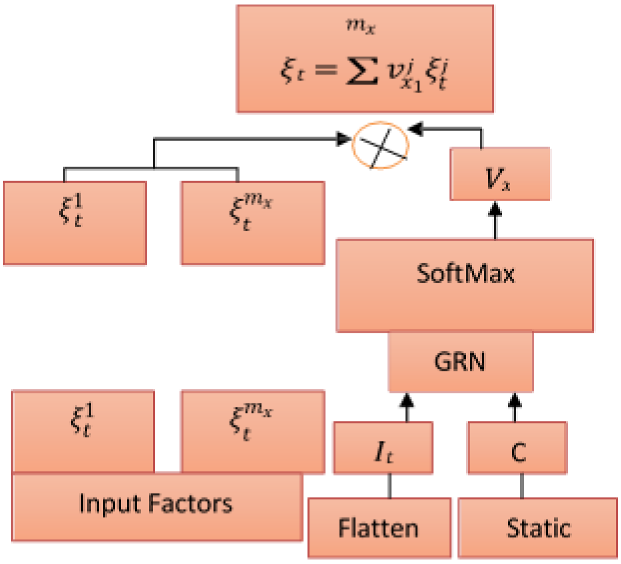


Figure 5: Selection of Feature Architecture

Power Forecasting Figure 6 displays a wind farm short-term power prediction model, incorporating static, historical, future, encoder-decoder architecture, and attention modules, after researching related issues.

Procedure1: Utilizing variable coding for future selection is the static variable method, encompassing longitude latitude, turbine ID, and monthly and day-to-day electric amounts.

Procedure 2: The archival dynamic variable utilizes multiple-source information and fusion for wind turbine operation and meteorological mast data, including, wind speed, power,the direction of the wind, pitch angle, rotation speed and temperature ambient.

Procedure 3: Forecast weather data, day month and hour information, and forecast data provide input data to the future dynamic variable

Procedure 4: The process, GLU, and residual connection components comprise the encoder-decoder architecture.

Procedure5: To increase prediction accuracy, the attention model employs the multi head-attention layer to describe time steps and determine their link to global time.

Procedure 6: The fully connected layer predicts each time step using Time Distributed, resulting in a multi-step power

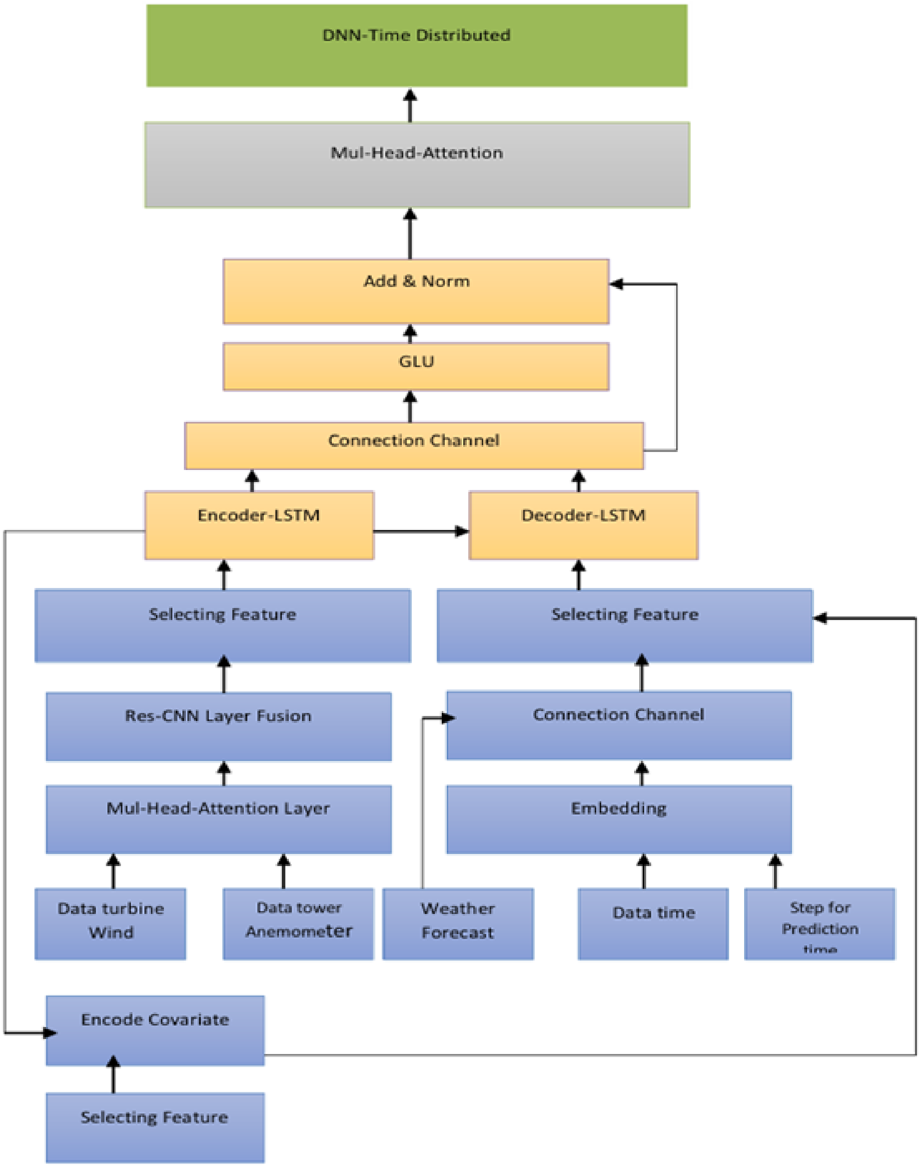


Figure 6. Wind Farm Short-Term Power Prediction Model

II. Case Studies:

Overview of Dataset: The study used wind power generation data from the Central Electricity Authority and information about weather from various weather stations in the Kutch region of Gujarat for trend analysis. The data included date/time, wind speed, climatic conditions, wind direction, density of the air, humidity, and energy production data. The correlation between features is presented in Figure 7, with data from the Kutch region used in the study.

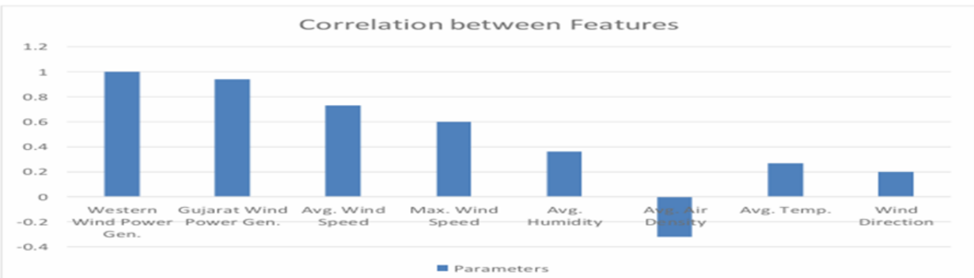


Figure 7. Correlation between Features Chart

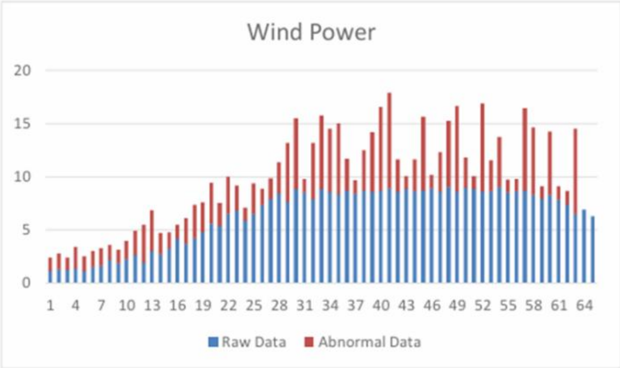


Figure 8. Wind Turbine Chart Figure

Figure 8 shows a wind turbine chart, with a deep learning model predicting future power at a temporal resolution using wind turbine ID, longitude, and latitude to identify short-term power projection results.

Evaluating Benchmark Model: This research compares its model to the TFT and Seq2Seq+attention models. The TFT model uses multi-source data channels for promotion impact, without using Res CNN network feature fusion. The Seq2Seq+attention method uses an additive attention technique to compare recursive and direct prediction. The multi-step prediction and multi-source data fusion techniques differ most across the three models, as depicted in Table .2.

Table 2 Description of Benchmark

Method	**Feature Fusion Yes/No**	**Predicting Multi-step Technique**
Suggested Method	Yes	Predict Directly
TFT	No	Predict Directly
Seq2Seq	Yes	Predict Recursively

Comparison of Training Set Convergence Rates

This part uses one wind turbine for model training for comparison. Three models are examined for convergence speed on a single wind turbine dataset. Figure 10 shows loss function changes during model training.

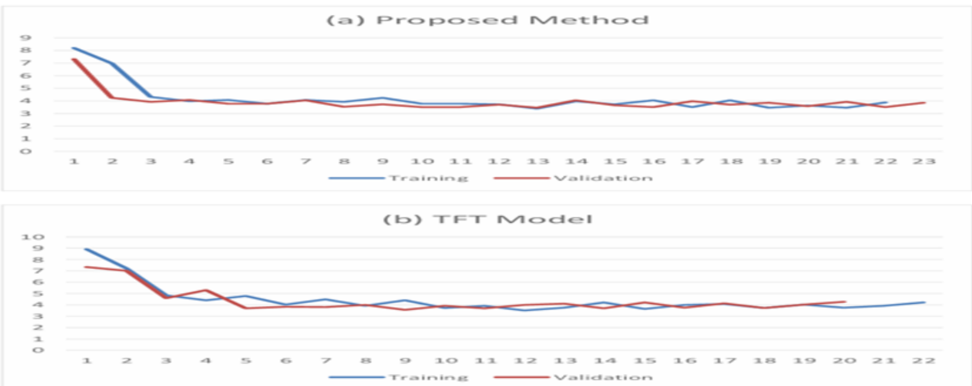


Figure 9 Loss Function Changes during Model Training

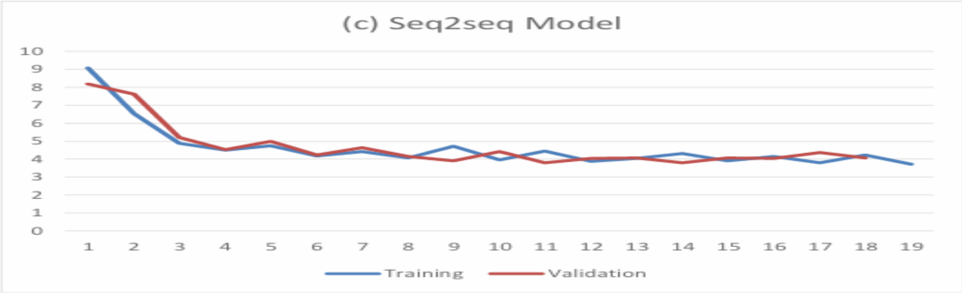


Figure 9 Loss Function Changes during Model Training

III. Conclusion And Future Work

Using Artificial Intelligence (AI) for wind energy forecasting has become a game-changer in the field, improving the accuracy and reliability of predictions. AI models, particularly machine learning (ML) and deep learning (DL), are able to handle complex, non-linear relationships in large datasets, which is essential for wind energy forecasting where factors like wind speed, direction, and environmental conditions interact in intricate ways.

1. Handling Complex Patterns: Traditional methods, like statistical approaches or numerical weather predictions, can struggle to model the intricate and nonlinear dynamics of wind systems. AI can handle large volumes of diverse data and learn from historical patterns to make better predictions.
2. Real-time Adaptability: AI models can be trained to continuously update based on new data, improving accuracy as more information becomes available (e.g., changing weather conditions, updated wind measurements).
3. Large Data Handling: Wind data, weather conditions, and turbine performance data can come from multiple sources (e.g., weather stations, sensors, satellite data, IoT devices). AI can handle these massive datasets and extract meaningful insights.
4. Forecasting Accuracy: o AI can improve the forecasting horizon and accuracy for short-term (hourly to daily) and even medium-term forecasts (several days ahead). This reduces the errors associated with conventional weather models.

Key AI Techniques Used in Wind Energy Forecasting:

1.Supervised Learning (Regression and Classification): • Regression Models: These models predict wind speed or power generation directly based on input features (e.g., historical wind data, weather conditions). Common algorithms include: Linear Regression, Support Vector Machines (SVM), Decision Trees Random Forests , Artificial Neural Networks (ANNs) .

Classification Models: These models categorize the wind energy production into classes (e.g., low, medium, high). For example, a classification model might help decide whether the wind farm will operate at full capacity or if there is a need for backup energy.

2. Deep Learning (DL) Models: • Artificial Neural Networks (ANNs): ANNs are used to model highly non linear relationships between various input features (e.g., wind speed, direction, time of day, temperature, historical production). Deep learning can capture complex, multi-dimensional relationships, and is highly effective for large datasets. • Convolutional Neural Networks (CNNs): While commonly used in image and video processing, CNNs have been applied to geospatial data (like satellite images) to predict wind patterns. • Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM): These models are great for time-series forecasting. They help predict future wind energy output by learning from past sequences of data, such as wind speed fluctuations, and are particularly good at handling the temporal dependencies in wind data.

3. Ensemble Learning: • Boosting and Bagging: Techniques like XGBoost, LightGBM, and AdaBoost combine multiple models to improve prediction accuracy. These ensemble methods can reduce overfitting and improve generalization to unseen data.

4. Reinforcement Learning (RL): • Optimization of Wind Farm Operations: Reinforcement learning can optimize the operation of individual turbines and wind farms. The system learns to adjust turbine settings (e.g., pitch angle) to maximize energy production, minimize wear-and-tear, and optimize maintenance schedules based on real-time feedback from the system.

5. Hybrid AI Models: • Combining different AI techniques, such as NWP models with machine learning, can improve forecasting accuracy. For instance, weather predictions might be used as inputs to an ML model to fine-tune predictions of energy output.

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