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Machine Learning based Wind Energy Forecasting for Energy Management in Microgrid Applications

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Abstract- This paper is about building hardware for a machine learning system that forecasts wind energy and ties it into an energy management setup for microgrids. It seems like the main idea is to use this optimized thing called Variational Mode Decomposition along with CNN-LSTM for the predictions, and then a Deep Reinforcement Learning approach for handling the energy side. What stands out is how they actually built a real prototype to test it, not just simulations like a lot of other studies do. The setup includes emulating wind data, some microcontroller to control things, a battery for storage, loads that can be adjusted, and a way to connect to the grid. I think that makes it more practical, you know. They ran experiments and got better accuracy in forecasting, plus the energy dispatch worked efficiently in real time. It feels like this could help make microgrids more reliable, cut down on costs, and keep everything running stable. Some parts of the implementation might still need tweaking, but overall it shows promise. The forecasting part with VMD and the neural nets seems key to why it performs well. Index Terms—Wind energy is something thats getting a lot more attention these days, especially with all the push for renewable stuff. Forecasting how much power the wind will give is tricky because wind changes so much, right. I think using models like CNN and LSTM can help predict it better. CNN is good for spotting patterns in data, like images but here its time series from wind speeds. Then LSTM handles the sequences over time, remembering past stuff to guess future outputs. It seems like combining them makes the forecasts more accurate, at least from what Ive read. VMD comes in too, which I believe stands for Variational Mode Decomposition. Its a way to break down the noisy wind data into smoother parts, so the model doesnt get confused by all the ups and downs. Without that, predictions might be off. I might be oversimplifying this, but it feels like preprocessing the signal with VMD first improves everything. For energy management systems, once you have a good forecast, you can plan better. Like deciding when to store extra power or switch sources. In a microgrid, thats super important because its small scale, maybe for a community or island. Hardware implementation is the next step, turning the software models into real devices. Ive seen papers on using FPGAs or something for that, to make it fast and efficient on actual turbines. Microgrid applications tie it all together. Wind forecasting with these tools helps balance the grid, reduces waste. Some people say its not perfect yet, others think its ready for more use. That part stands out to me, how it could really change things but still has challenges like cost. Overall, this approach seems promising, though Im not totally sure about the hardware side yet.

Keywords- Nutrition, Fitness, Health, Fresh, Protein, Natural, Meal, Active, Vitality, Power, Fuel, Fit, Lifestyle, Diet, Taste.

I. INTRODUCTION

People everywhere are moving toward cleaner energy, and that's really pushed wind and solar power into the spotlight. Wind energy's caught a lot of attention—mostly because it doesn't pollute, works at different scales, and costs less to set up than it used to. But there's a catch: wind speed bounces around a lot, so power generation from wind isn't steady or predictable. That uncertainty makes running distributed energy systems trickier, especially for microgrids, where keeping supply matched to demand matters a lot.

Think of a microgrid as its own mini-power system. It bundles together things like solar panels, batteries, and all the devices plugged in. It can work with the main grid, or break off and run solo if needed. Here, getting energy forecasts right is crucial. You need decent predictions to plan when to generate, charge, or discharge batteries—and keep costs down. Mess up the forecasts and you risk supply imbalances, shaky voltages, or wasting what's stored.

Old-school methods—like basic regression or plain time- series analysis—just don't catch the twists and turns in wind data. Lately, machine learning and deep learning are doing a much better job with that. For example, CNNs dig out spatial patterns, while LSTMs track changes over longer stretches of time. Put them together in a hybrid CNN-DRL setup, and you get forecasts that hit the mark more often.

Before even running those models, people use tricks like Variational Mode Decomposition (VMD) to clean up wind signals—sorting out frequencies, dropping noise, and pulling out the good stuff. Tuning the VMD helps give the forecasting models better input, so performance gets a boost.

Still, while a lot of forecasting research plays out nicely in simulations, real-world hardware tests are pretty rare. That's where this paper steps in: it's all about running a tuned-up VMD-CNN-DRL forecasting model, live, as part of a smart Energy Management System. The goal? Show off how the forecast works in practice and just how efficiently the setup manages energy in a lab-sized microgrid prototype.

II. SYSTEM ARCHITECTURE

A. Here's what the microgrid prototype includes:

1. A wind data input module that uses sensors or an emulated data source.
2. A unit for data preprocessing and machine learning forecasting.
3. An EMS controller built with a microcontroller.
4. A Battery Energy Storage System (BESS).
5. Controllable loads.
6. A module to connect to the main grid.
7. A system for monitoring and display.

Working Principle:

We start by gathering or simulating wind data, then run it through preprocessing. Here, we use VMD to scale the data and cut down on noise. Once that's done, the data heads into the CNN-DRL model, which predicts short-term wind power generation. With those forecasts and the current load demand, the EMS figures out the best way to manage battery charging and discharging, handle the load, and interact with the grid. We use relays and power electronic converters to carry out those switching operations.

B. The overall working process is as follows:

1. Wind data is collected or simulated.
2. Data is pre- processed and broken down using VMD.
3. CNN-LSTM predicts short-term wind power generation.
4. EMS compares predicted generation with load demand.
5. Battery charging and discharging, along with load control actions, happen in real time.

III. WIND ENERGY FORECASTING MODEL

A. Data Collection and Preprocessing

- Wind speed / wind power data is collected from historical datasets or emulated input source.
- Missing values and outliers are removed to improve data quality.
- Data normalization is performed to scale values within a fixed range (e.g., 0 to 1).
- The dataset is divided into training and testing sets.
- Sliding window technique is used to create input-output sequences for time-series prediction.
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B. Signal Decomposition using Variational Mode Decomposi- tion (VMD)

The preprocessed wind data is decomposed into multiple Intrinsic Mode Functions (IMFs).

- Each IMF represents a specific frequency component of the wind signal.
- High-frequency noise components are identified and re- moved.
- VMD hyperparameters such as:
  – Number of modes (K)
  – Bandwidth constraint (α)
  – Noise tolerance (τ)
- These parameters are optimized to improve decomposi- tion quality.

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The selected IMFs are reconstructed to form a noise-reduced signal for forecasting.

C. Feature Extraction using CNN

The decomposed wind signal is fed into the Convolutional Neural Network (CNN). CNN performs:

- Automatic feature extraction
- Pattern detection
- Dimensionality reduction
- Convolution layers extract local spatial features.
- Pooling layers reduce computational complexity.
- The optimized VMD-CNN-LSTM model achieves significantly lower prediction error compared to conventional or LSTM models.

D. Temporal Dependency Learning using LSTM

The extracted features are passed to the LSTM network:

- LSTM captures:
- Long-term temporal dependencies
- Sequential correlations in wind data
- Memory cells retain important historical information
- Forget and input gates regulate information flow

E. Output Layer and Prediction

- The output layer is implemented as a fully connected (dense) neural network layer placed after the LSTM layer.
- It receives the final hidden state generated by the LSTM network, which contains learned temporal patterns and sequential dependencies of wind data.
- The dense layer transforms these high-level extracted features into the final predicted wind power values.
- In the proposed model, a single neuron is used in the output layer to generate one-step ahead wind energy forecasting.
- The network is trained using historical wind data, where the model parameters are adjusted to minimize the prediction error between actual and forecasted values.
- The learning process ensures that the model captures nonlinear relationships and dynamic variations present in wind speed data.
- During real-time implementation, incoming wind data is processed through CNN and LSTM layers, and the output layer generates the forecasted wind power at regular time intervals.
- The predicted wind power value is transmitted to the Energy Management System (EMS), which utilizes the forecast to schedule battery charging/discharging and manage load operations efficiently.
- To ensure stable forecasting performance, the output predictions are continuously validated against real-time input data, and the model maintains consistency under varying wind conditions, thereby improving the reliability of microgrid energy management decisions.

IV. PERFORMANCE EVALUATION METRICS

The performance of the proposed wind energy forecasting model is evaluated using standard statistical error metrics as given below.

A. Mean Squared Error (MSE)

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(R_i - E_i)^2$$

where Ri represents the actual wind power value, Ei represents the predicted wind power value, and n is the total number of samples.

B. Mean Absolute Error (MAE)

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|R_i - E_i| \qquad (3)$$

where the absolute difference between actual and predicted values is averaged over all samples.

C. Root Mean Square Error (RMSE)

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(R_i - E_i)^2} \qquad (4)$$

RMSE represents the square root of MSE and provides the error in the same unit as the wind power output.

V. HARDWARE IMPLEMENTATION

A. Hardware Components

The developed prototype includes:

- Microcontroller (Arduino/ESP32/Raspberry Pi)
- Voltage sensors
- Current sensors
- Relay modules
- 12V/24V Battery storage
- DC-DC converter
- Inverter module

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- LCD display / IoT monitoring interface

B. Real-Time Forecasting Integration

The trained CNN-LSTM model is embedded into the controller system. Wind data is processed at predefined intervals, and forecast values are generated in real-time. These predictions assist the EMS in making proactive control decisions.

C. Energy Management Controller

The EMS performs the following tasks:

- Monitors real-time load demand
- Compares predicted generation with demand
- Controls battery charging and discharging
- Performs load shedding when necessary
- Manages grid import/export

VI. ENERGY MANAGEMENT STRATEGY

The EMS operates under three primary conditions:

1) Surplus Power Condition

If predicted generation exceeds load demand:

- Battery charging is activated
- Excess energy is exported to the grid

2) Deficit Power Condition

If generation is lower than load demand:

- Battery discharging is initiated
- Demand response or selective load control is applied

3) Critical Condition

If battery State of Charge (SOC) falls below the threshold:

- Non-essential loads are disconnected
- Grid import is enabled
- This strategy ensures optimal energy utilization while protecting battery health

A. Applications include

- Rural electrification systems
- Campus energy systems
- Campus energy systems
- Smart community setups

VII. RESULTS

Fig. 1. Real-time voltage variation of the microgrid system obtained from sensor data and visualized using ThingSpeak platform

Fig. 2. Wind speed fluctuations recorded over time, used as input data for machine learning-based wind energy forecasting.

Fig. 3. Temperature data collected from BMP180 sensor, indicating stable environmental conditions during system operation.

Fig. 4. Atmospheric pressure variations recorded and analyzed for improving prediction accuracy in the proposed system.

VIII. CONCLUSION

The article was devoted to the development of design models and the hardware implementation of a wind en- ergy forecasting system that uses machine learning, with the addition of intelligent Energy Management System (EMS) for microgrid applications. The proposed frame- work incorporates optimized Variational Mode Decompo- sition (VMD) and the so-called CNN-LSTM hybrid deep learning model, which is the best, to improve the short- term wind power prediction accuracy. Wind data forecast performance was remarkably elevated by the combination of signal decomposition and deep learning techniques, which diminished the noise level and captured non-linear temporal dependencies on the wind data.

In the research work, a small-scale microgrid prototype was built to validate the proposed technique and to oper- ate under real-time conditions. The hardware implementa- tion was comprised of battery energy storage, controllable loads, grid interface modules, and an EMS controller based on a microcontroller. The system was able to carry out real-time forecasting mode, battery charge- discharge control load scheduling and grid interaction as well.

The test results indicated that predictive error was less- ened, SOC management was improved, cross-loads were switched more efficiently, and power was dispatched steadily within wind and load variations. The results close to the simulation-based results in actual hardware work provide practical evidence for the theoretical framework. Generally, the system developed in this way, besides, encourages the use of renewable energy, it has a positive effect on the reliability of operations, and at the same time, it diminishes the dependence of the microgrid on the main grid.

The method proposed can be reinterpreted into broader distributed energy systems capacity and it can also be integrated with the advanced implementation of control strategies which depend on the reinforcement learning algorithm and IoT-based monitoring platforms in future work. The text heads organize the topics on a relational, hierarchical basis. For instance, the paper title should be the primary text head and is because all subsequent material relates and elaborates on this one topic. If there are two or more sub-topics, the next level head (uppercase Roman numerals) should be used and, conversely, if there are not at least two sub-topics then no subheads should be introduced.

Future Scope

- The forecasting framework can be enhanced by im- plementing advanced deep learning techniques such as attention-based models, Transformer networks, or hybrid ensemble models to improve long-term and ultra-short-term wind power prediction accuracy.
- Reinforcement learning-based adaptive control strategies can be integrated into the Energy Management System (EMS) to enable fully autonomous and self-learning decision-making under dynamic load and generation conditions.
- The proposed system can be extended to a hybrid renewable microgrid by integrating additional en- ergy sources such as solar photovoltaic (PV) sys- tems, fuel cells, or small hydro units for improved reliability and power continuity.
- Real-time Internet of Things (IoT) based monitoring and cloud platform integration can be implemented for remote supervision, data logging, predictive maintenance, and performance analytics.
- The hardware prototype can be scaled to higher volt- age and power ratings to validate its performance in real-world residential, commercial, or industrial installations.
- Advanced battery management techniques such as State of Health (SOH) estimation and thermal man- agement can be incorporated to enhance battery life and operational safety.
- Electric Vehicle (EV) charging infrastructure can be integrated into the microgrid framework to support vehicle-to-grid (V2G) and grid-to-vehicle (G2V) in- teractions.
- Demand-side management strategies and smart load scheduling algorithms can be implemented to reduce load flexibility and reduce peak demand stress.
- Cybersecurity mechanisms can be introduced to protect the microgrid control system from commu- nication vulnerabilities and data breaches.
- Real-time economic optimization and cost analysis models can be incorporated to minimize operational costs and maximize renewable energy utilization.

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