**Title:** Quantifying the Impact of Meteorological Forecast Uncertainty on Wind Power Prediction Using an Error Propagation Framework

**Abstract:**  
This study presents a novel framework for analyzing how uncertainties in meteorological forecast variables—specifically wind speed, wind direction, temperature, and air density—propagate through a wind power prediction model. Using a function P=f(U,θ,T,ρ) trained on observational data, we assess the effect of substituting forecast variables and evaluate their individual contributions to output uncertainty via a formal error propagation analysis. The findings provide actionable insights into which input variables are most critical for improving power prediction accuracy.

**1. Introduction**

* Motivation: Accurate wind power forecasting is crucial for renewable energy integration.
* Gap: While meteorological inputs are known to affect forecasts, few studies quantify *how* their errors propagate through power models.
* Contribution: Propose a clear error propagation framework based on a trained function using observational data.

**2. Data and Experimental Setup**

* Description of site(s), meteorological observation data, and power output records
* Forecast datasets used for wind speed, direction, temperature, and air density
* Preprocessing: time alignment, quality control, and variable standardization

**3. Model Construction and Function Learning**

* Define the power function f as a multivariate regression (e.g., linear model, MLP)
* Justify model choice: interpretability vs accuracy
* Training strategy using observed inputs and outputs
* Evaluation metrics: RMSE, MAE, R2

**4. Error Propagation Framework**

* Mathematical formulation: Taylor expansion-based propagation  
  Var(P)≈∑i(∂f∂xi)2Var(xi)
* Sensitivity computation: gradient estimation from trained model
* Input error estimation: RMSE of each variable from forecast vs observation
* Standardization to remove scale/units influence

**5. Results and Analysis**

* Sensitivity ranking of meteorological variables
* Contribution of each variable to total power uncertainty
* Case studies: specific weather conditions (e.g., high wind shear, low density)
* Visualization: bar plots, heatmaps of spatial/temporal sensitivities

**6. Discussion**

* Interpretation of dominant error sources
* Implications for NWP improvement and forecast data prioritization
* Limitations: model assumptions, data availability
* Future work: expanding to multiple sites, ensemble forecasts, uncertainty-aware ML models

**7. Conclusion**

* Summary of findings
* Main takeaway: structured understanding of input uncertainty helps optimize forecasting pipeline

**Acknowledgements**  
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**References**  
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