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Machine Learning-Driven Framework for Atmospheric Stability Prediction Using Off-Site Meteorological Data †

Ben Sonpon [1], Shoaib Usman [2,*], Joseph Smith [1] and Huseyin Sahiner [3]

[1] Nuclear Engineering and Radiation Science Department, Missouri University of Science and Technology, Rolla, MO 65409, USA; bsg4n@mst.edu (B.S.); smithjose@mst.edu (J.S.)
[2] Department of Mechanical and Nuclear Engineering, Tennessee Tech University, Cookeville, TN 38505, USA
[3] Nuclear Engineering Department, Sinop University, Sinop 57000, Türkiye; hsahiner@sinop.edu.tr
* Correspondence: susman@tntech.edu
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Abstract

A machine learning-driven framework is developed to predict on-site atmospheric stability at a nuclear power plant using meteorological data from surrounding weather stations. Callaway nuclear power plant serves as the test case, with Columbia Regional Airport (CRA), Jefferson City Memorial Airport (JMA), and St. Louis Lambert International Airport (STL) as off-site data sources. Using ordinary least squares (OLS) linear regression trained on January 2020 data, the model predicted Callaway's atmospheric stability for January 2021 with an exact match rate of approximately 52% and a within-one-class agreement rate exceeding 95%. The RMSE was 0.68 stability classes and the model's accuracy was confirmed to be significantly better than random classification via binomial testing ($p < 0.05$ on 71% of test days). A supplementary April analysis yielded a Pearson correlation of 0.68, supporting seasonal generalizability. These results establish a foundation for predicting on-site atmospheric stability from readily available off-site data to support regulatory compliance.

Keywords: atmospheric stability; machine learning; nuclear power plant; linear regression; meteorological data; regulatory compliance

1. Introduction

Atmospheric stability is a critical parameter governing pollutant dispersion from nuclear power plants. In the United States, the Nuclear Regulatory Commission (NRC) mandates that all nuclear facilities collect and report meteorological data including wind direction, wind speed, and stability class [1–3]. The Gaussian plume model, widely used for dose assessment, depends heavily on atmospheric stability through its dispersion coefficients [4,5]. Understanding and accurately predicting stability is therefore essential for environmental protection and regulatory compliance.

Atmospheric stability refers to the atmosphere's tendency to resist vertical motion [6]. Stability is typically classified into categories A through G, though the underlying parameters (wind velocity, temperature gradient, Richardson number) are continuous variables. This motivates the treatment of stability as a continuous variable amenable to regression-based methods.

Previous work [7] established an automated protocol for meteorological data import, organization, and station selection. The present study advances that foundation by de-

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veloping a machine learning framework that predicts Callaway nuclear power plant's atmospheric stability using off-site airport data—simulating scenarios where on-site measurements are unavailable while regulatory reporting obligations persist.

2. Methods

2.1. Study Sites and Data Sources

Meteorological data were obtained from three airports near Callaway nuclear power plant: Columbia Regional Airport (CRA, ~23 miles west-northwest), Jefferson City Memorial Airport (JMA, ~20 miles west), and St. Louis Lambert International Airport (STL, ~87 miles east). Hourly observations of wind speed, wind direction, and atmospheric stability class were compiled from station records. Callaway's own data from Met Tower Alpha (10 m height) served as the reference variable, sourced from its 2020 annual report to the NRC [8].

2.2. Data Preprocessing and Feature Selection

Stability classes were encoded numerically (A = 1 through G = 7). Raw data underwent quality control including removal of missing values and timestamp alignment. Six predictor features were selected: stability class and wind direction from each airport (CRA, JMA, STL). The target variable was Callaway's stability at Met Tower Alpha. No feature scaling was applied, as OLS linear regression is invariant to scaling in terms of predictive output.

2.3. Model Formulation and Training

Linear regression was adopted as a reasonable baseline, consistent with Gauss–Markov assumptions standard in atmospheric data synthesis [9–11]. The model takes the form:

$$\textit{Callaway Stability} = \beta^0 + \beta^1 \times (\textit{CRA Stab.}) + \beta^2 \times (\textit{JMA Stab.}) + \beta^3 \times (\textit{STL Stab.}) + \beta^4 \times (\textit{CRA WD}) + \beta^5 \times (\textit{JMA WD}) + \beta^6 \times (\textit{STL WD})$$

Parameter estimation was performed via OLS, minimizing the sum of squared residuals using the normal equations. The model was implemented using Python's scikit-learn library (Version 1.5.2). A same-month cross-year split was adopted: January 2020 for training and January 2021 for testing, controlling seasonal confounding while isolating interannual variability.

To verify that a linear model was appropriate, a Random Forest regression was also evaluated. The linear model yielded $R^2 = 0.34$ and RMSE = 0.68, compared to $R^2 = 0.28$ and RMSE = 0.72 for Random Forest, confirming the sufficiency of the linear formulation.

2.4. Evaluation Metrics

Performance was assessed using R^2, root mean square error (RMSE), mean absolute error (MAE), exact match rate, and within-one-class agreement rate. A binomial test evaluated whether the exact match proportion significantly exceeded the random baseline of 1/7 (≈14.3%), corresponding to uniform assignment among seven stability classes.

3. Results and Discussion

3.1. Overall Model Performance

The model was trained on January 2020 data and evaluated on all 31 days of January 2021. Table 1 summarizes aggregate performance metrics.

The R^2 of 0.34 indicates that approximately one-third of Callaway's hourly stability variance is explained by six off-site features. While moderate, this is reasonable given the inherent difficulty of predicting microclimate conditions from stations 23–87 miles away. The RMSE of 0.68 and MAE of 0.49 confirm sub-class prediction errors. Critically,

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over 95% of predictions fell within ±1 stability class, and approximately 52% were exact matches—approximately 3.6 times the random baseline of 14.3%.

Table 1. Aggregate model performance metrics for January 2021.

Metric	Value
R^2 (Coefficient of Determination)	0.34
RMSE (stability classes)	0.68
MAE (stability classes)	0.49
Exact Match Rate	~52%
Within ±1 Class Agreement	>95%
Mean Daily Std. Dev.	0.44
Mean Daily Uncertainty	0.09

3.2. Daily Prediction Consistency

Table 2 presents the standard deviation, uncertainty, exact matches, and binomial test *p*-values for each day of January 2021. Four days achieved perfect predictions (zero deviation); the maximum standard deviation was 0.82. Of 31 days, 22 (71%) achieved statistically significant accuracy ($p < 0.05$), confirming that the model consistently outperforms random classification.

Table 2. Daily prediction statistics for January 2021 (selected days shown; full data available from authors).

Day	Std. Dev.	Uncert.	Exact Matches	*p*-Value
Jan 1	0.58	0.12	10/23	$6.74 \times 10^{-'}$
Jan 3	0.51	0.11	12/23	2.08×10^{-5}
Jan 5	0.49	0.10	20/23	1.43×10^{-14}
Jan 13	0.29	0.06	21/23	3.38×10^{-16}
Jan 15	0.00	0.00	0/23	1.00
Jan 25	0.00	0.00	23/23	3.65×10^{-20}
Jan 27	0.82	0.17	7/23	3.67×10^{-2}
Jan 30	0.46	0.10	21/23	3.38×10^{-16}

Days with $p = 1.0$ (e.g., Jan 15) had zero exact matches but all predictions were within one stability class.

3.3. Statistical Validation

A binomial test assessed whether the model's exact match rate significantly exceeds random classification. Using January 3 as an example (n = 23, 12 exact matches), the null hypothesis H_0: $p = 1/7$ was tested against H_1: $p > 1/7$. The resulting *p*-value of 0.00002 confirms that the model's accuracy is significantly better than chance. While the ~52% exact match rate may appear modest, it is 3.6 times the random baseline, and the >95% within-one-class agreement demonstrates that errors are small in magnitude—a practically meaningful result for regulatory compliance, where adjacent stability classes produce similar dispersion patterns.

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3.4. Seasonal Generalizability

Additional testing using April data assessed the model's performance under more variable springtime conditions. The model was retrained on April 2020 and evaluated on April 2021. The Pearson correlation between predicted and recorded stability was 0.68, with a standard deviation of 0.69. Of 24 hourly observations on April 1, four predictions deviated by two classes and one by three classes, all during the afternoon boundary layer transition period. The remaining 19 predictions were within one class. These results confirm that the model captures dominant stability patterns across seasons, though accuracy decreases during periods of greater atmospheric variability.

4. Conclusions

This study demonstrates the feasibility of predicting atmospheric stability at Callaway nuclear power plant using off-site airport meteorological data via a machine learning framework. A linear regression model achieved an RMSE of 0.68 stability classes, a within-one-class agreement rate exceeding 95%, and an exact match rate 3.6 times the random baseline. The comparison with Random Forest confirmed that a linear formulation is sufficient for this spatial correlation task. Supplementary April analysis (Pearson r = 0.68) supports seasonal generalizability while revealing a systematic positive bias during afternoon hours linked to differential boundary layer transitions.

Future work should include expanding training data to multiple years, incorporating additional features (solar radiation, cloud cover), exploring nonlinear methods (Gaussian Processes, Neural ODEs, Sparse Polynomial Chaos Expansion), and extending the analysis to other seasons and nuclear facilities.

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