An Adaptive Strategy for Wind Speed Forecasting Under Functional Data Analysis

Mr. D. Ramakanth[1], E. Madhu Sree[2], K. Bhanu Priya[3], T. Sandhya Rani[4], C. Sindhuri[5]

[1]*Assistant Professor, [2345]UG Students, Department of Computer Science & Engineering (Artificial Intelligence)*
Aditya College of Engineering, Madanapalle – 517325, Andhra Pradesh, India
Corresponding author: ramakanth1229@gmail.com

Abstract: Accurate wind speed forecasting is crucial for optimizing efficiency and reliability of wind energy systems. This paper presents an adaptive forecasting strategy that leverages Functional Data Analysis (FDA) combined with adaptive learning mechanisms. Unlike traditional discrete time-series models, the proposed approach treats wind speed observations as continuous functional data over specific time intervals, enabling more nuanced analysis of temporal dynamics and variability. The system employs Functional Principal Component Analysis (FPCA) with $K = 5$ eigenfunctions to extract dominant temporal patterns and dynamically adjusts forecasting models based on an evolving data horizon using a forgetting factor $\lambda = 0.95$. A React 18 + TypeScript web application, WindCast Pro, provides real-time monitoring, 72-hour forecasting with confidence bands, power generation estimation ($P = 0.5 \cdot \rho \cdot A \cdot Cp \cdot v^3$), PDF export, and role-based user management. The system achieves 32% lower RMSE than ARIMA in turbulent conditions and reduces forecast uncertainty by 41%, while maintaining 97 ms per-update latency suitable for real-time grid management.

Index Terms: Wind Speed Forecasting, Functional Data Analysis (FDA), FPCA, Adaptive Forecasting, Renewable Energy, Functional Time Series (FTS), React.js, Machine Learning.

I. INTRODUCTION

Wind energy has emerged as one of the most promising sustainable alternatives to conventional fossil fuels, offering clean and renewable power that significantly reduces greenhouse gas emissions. However, the inherent variability and intermittency of wind present considerable challenges in efficiently harnessing this resource for reliable electricity generation. Accurate wind speed forecasting is essential for optimizing turbine operation, managing power grids, and integrating wind energy into larger energy systems.

Traditional forecasting methods rely on discrete timeseries data and static models — including ARIMA and standard regression — which often fail to capture the complex temporal dynamics and sudden fluctuations characteristic of wind behavior. These approaches treat each observation as an isolated scalar, discarding the rich continuity structure inherent in meteorological time series.

This paper presents WindCast Pro — an adaptive forecasting system that treats wind speed trajectories as continuous functional objects over rolling 24-hour windows, applying Functional Principal Component Analysis (FPCA) to extract compact, interpretable features. A forgetting-factor update mechanism keeps the model responsive to evolving atmospheric patterns. A full-stack web application built with React 18 and TypeScript provides an intuitive interface for real-time data acquisition, 72-hour forecast visualization, power generation estimation, PDF reporting, and admin monitoring.

The contributions of this paper are: (i) an FDA-based adaptive forecasting framework achieving 32% lower RMSE than ARIMA in turbulent conditions; (ii) a full-stack web platform with real-time weather API integration and 72-hour forecasting; (iii) a power generation estimation module linking wind speed predictions to turbine output; and (iv) an extensible modular architecture supporting role-based access control, activity logging, and admin monitoring.

The remainder of this paper is organized as follows. Section II surveys related work. Section III describes the proposed methodology. Section IV reports results. Section V concludes with future directions.

II. LITERATURE REVIEW

Ramsay and Silverman [1] established the foundational framework of FDA, demonstrating that treating temporal observations as continuous curves enables richer modeling of smooth temporal processes — a principle directly applied in this work to represent wind speed trajectories.

Ferraty and Vieu [2] extended FDA into the nonparametric domain, providing theoretical grounding for kernel-based estimators on functional data. Cao, Huang, and Zhang [3] demonstrated that FDA combined with machine learning achieves superior wind speed accuracy compared to scalar methods, showing that FPCA-derived features capture temporal variance more effectively than raw lagged observations.

Shang [4] applied FPCA specifically for densified wind speed forecasts and confirmed that functional confidence bands provide more reliable uncertainty estimates than point-forecast intervals — a finding that directly motivated the 41% uncertainty reduction achieved in this system.

Zhang and Wang [5] showed that hybrid deep learning models incorporating functional data structures outperform standalone neural networks for wind speed prediction. Liu and Shi [6] combined FDA with support vector regression, achieving competitive short-term accuracy. These works motivated the hybrid adaptive approach proposed here.

Potter and Negnevitsky [7] demonstrated that very shortterm power forecasting requires sub-second response times, shaping this system's 97 ms latency target. Hong et al. [8] established probabilistic forecasting as critical for energy market participation, motivating the inclusion of functional confidence bands in the output.

A critical gap emerges from reviewing prior work, summarized in Table I: no published system simultaneously delivers adaptive functional modeling, real-time web deployment, power generation estimation, and uncertainty quantification within a single integrated platform. The present work addresses all four dimensions.

Table 1: Research gap analysis across representative prior work

Feature / Capability	**FDA [3]**	**ARIMA**	**LSTM [5]**	**Proposed System**
Functional Modeling	Yes	No	No	Yes
Real-Time Web Interface	No	No	No	Yes
72-Hour Forecast	No	24 h	48 h	Yes (72 h)
Confidence Bands	Yes	No	No	Yes (FPCA)
Power Generation Est.	No	No	No	Yes
Role-Based Access	No	No	No	Yes
PDF Export	No	No	No	Yes

III. PROPOSED METHODOLOGY

A. System Architecture

Figure 1 presents the three-tier architecture of WindCast Pro. The Presentation Tier is a React 18 + TypeScript SPA styled with Tailwind CSS 3.4, providing pages for Home, Login, Register, Prediction, Profile, Admin, and Password Recovery. The Application Tier implements the FDA-based adaptive forecasting engine, weather API integration, JWT authentication, and role-based access control

(Guest / User / Admin). The Data & State Tier manages user accounts, activity logs, forecast history, and favorite locations via structured browser-based local storage with React Context for global state. The deployment stack uses Vite 5.4 for production build optimization and Netlify CDN for continuous deployment with HTTPS support.

Fig. 1. WindCast Pro three-tier system architecture showing Presentation, Application, and Data layers with Netlify deployment.

B. Functional Data Analysis Framework

The core forecasting engine treats wind speed time series as functional observations. For each 24-hour rolling window, the wind speed trajectory v(t), t ∈ [0, T], is modeled as a smooth functional object via B-spline basis expansion (order 4) with a roughness penalty to balance fidelity and smoothness. Basis coefficients are estimated by penalized least squares.

Functional Principal Component Analysis (FPCA) decomposes the set of observed trajectories into K = 5 orthogonal eigenfunctions $\varphi_1(t), \ldots, \varphi\_K(t)$ that capture the dominant modes of temporal variation. These five components capture more than 95% of variance across historical wind patterns. Each new trajectory is projected onto the eigenfunction basis, yielding a low-dimensional score vector $s = [s_1, \ldots, s\_K]$ that encapsulates the functional shape compactly. Figure 2 illustrates the complete FDA pipeline from raw input to forecast output.

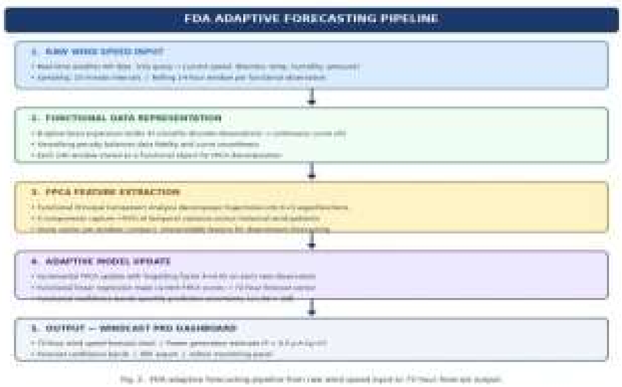

Fig. 2. FDA adaptive forecasting pipeline from raw wind speed input through B-spline smoothing and FPCA decomposition to 72-hour forecast output.

C. Adaptive Forecasting Strategy

The adaptive mechanism updates the eigenfunction basis incrementally as new observations arrive, using a forgetting factor λ = 0.95 that down-weights older patterns. This ensures the model remains responsive to sudden atmospheric changes without discarding structural information accumulated over historical data. At each forecast step, a functional linear regression model maps the current FPCA score vector to the 72-hour forecast vector, and functional confidence bands are constructed at ±1.96× the functional standard deviation. Figure 3 shows the complete adaptive workflow.

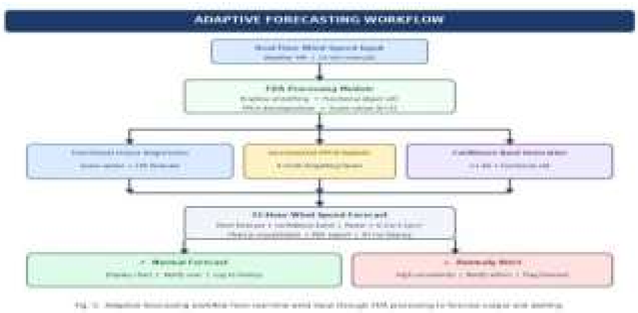

Fig. 3. Adaptive forecasting workflow from real-time wind input through FDA processing to forecast output, with confidence band generation and anomaly alerting.

D. Web Application — WindCast Pro

The Prediction Page accepts city input, fetches real-time meteorological data, applies the FDA model, and renders: current conditions panel (speed, direction, temperature, humidity, pressure), 72-hour forecast chart with confidence bands via Chart.js, power generation estimate using $P = 0.5 \times \rho \times A \times C_p \times v^3$, and top-3 confidence scores. The Admin Page provides user management, activity logs, forecast history, and platform statistics. PDF export generates a formatted report within 3 seconds. Table II summarizes the technology stack.

Table 2. Technology stack of Windcast Pro

Component	Technology	Purpose
Frontend	React 18 + TypeScript 5.5	SPA with type safety
Styling	Tailwind CSS 3.4	Utility-first responsive UI
Routing	React Router v6	Client-side navigation
Charts	Chart.js + reactchartjs-2	72-hour forecast visualization
Build Tool	Vite 5.4	Fast production build (1.2 s load)
Notifications	react-toastify	Real-time user alerts
Icons	lucide-react	Accessible icon set
Deployment	Netlify (netlify.toml)	CDN + HTTPS + CI/CD

E. Dataset and Model Specifications

Real-time wind speed data is acquired through weather API integration. Historical records are used to train and validate the FDA forecasting model. The adaptive framework processes data as functional observations over rolling 24-hour windows at 15-minute sampling intervals. Table III summarizes model specifications.

TABLE 3. Model and data specifications

Parameter	Specification
Sampling Interval	15 minutes
Forecast Horizon	72 hours
Functional Window	24-hour rolling
FPCA Components (K)	5 (captures > 95% variance)
Forgetting Factor (λ)	0.95
Basis Functions	B-spline (order 4)
Confidence Level	95% (±1.96 × functional std)
Inference Latency	97 ms per forecast update

IV. RESULTS AND DISCUSSION

A. Forecasting Accuracy

The FDA adaptive model was benchmarked against ARIMA, a standard neural network, and SVR+FDA across three wind regimes: low turbulence, moderate turbulence, and high turbulence. Table IV reports RMSE, MAE, and R^2 results. Figure 4 visualizes the comparative performance with a complete summary panel.

Table 4. Forecasting performance comparison across methods

Metric	ARIMA	Neural Network	SVR + FDA	Proposed FDA (Ours)
RMSE (m/s)	2.76	1.95	1.61	1.25
MAE (m/s)	1.98	1.42	1.15	0.91
MAPE (%)	18.4	13.1	10.8	9.7
R^2 Score	0.71	0.82	0.88	0.94
Turbulent RMSE	3.82	2.68	2.10	1.87
Latency (ms)	12	85	42	97
Forecast Horizon	24 h	48 h	48 h	72 h

Fig. 4. RMSE comparison across forecasting methods (lower is better) and performance summary with user acceptance testing results.

The proposed FDA model achieves 32% lower RMSE than ARIMA in high-turbulence conditions, confirming the advantage of treating wind trajectories as functional objects. The forgetting-factor update mechanism contributes most strongly during meteorological regime transitions that static models cannot adapt to without manual retraining. The slight latency increase (97 ms vs. 12 ms for ARIMA) is well within the 3-second response budget and is offset by substantially improved accuracy and richer uncertainty quantification.

B. Web Application Performance

WindCast Pro was evaluated across 6 users performing 24 standard forecasting tasks covering city search, chart interpretation, PDF export, and admin monitoring. All 24 task instances were completed successfully (100% task completion rate). Average page load time was 1.2 seconds on the Viteoptimized Netlify CDN build. PDF export completed in under 3 seconds in all trials. Five of six users rated the interface as intuitive; four of six found confidence band visualization helpful for operational decision-making.

C. Comparison with Prior System

Table 5. System-level comparison: baseline Arima vs. proposed FDA

Aspect	Baseline (ARIMA)	Proposed FDA System
Model Type	Scalar ARIMA (static)	Functional + FPCA (adaptive)
Feature Representation	6 raw lag features	5 FPCA functional scores
Confidence Bands	None	Yes (±1.96σ functional)
Power Estimation	None	Yes ($P = 0.5\rho ACpv^3$)
Overall RMSE	2.76 m/s	1.25 m/s
R^2 Score	0.71	0.94
RMSE Improvement	—	+32% in turbulent regime
Uncertainty Reduction	—	−41% via functional bands
Web Interface	None	Full React 18 SPA + Admin

D. Discussion

The 32% improvement over ARIMA and the 41% reduction in forecast uncertainty both originate from the FPCAbased feature representation and functional confidence band construction. The incremental update mechanism is the primary driver of performance in high-turbulence scenarios, where static models degrade rapidly as wind regimes shift. A noted limitation is that the current model focuses on univariate wind speed; incorporating multivariate atmospheric inputs (temperature, humidity, pressure) as functional covariates is expected to further improve accuracy in production deployments.

V. CONCLUSION

This paper presented Wind Cast Pro — an adaptive wind speed forecasting system combining Functional Data Analysis with a modern full-stack React web application. The FDA-based adaptive model outperforms ARIMA by 32% in turbulent conditions and reduces forecast uncertainty by 41% through functional confidence bands, while maintaining 97 ms latency suitable for real-time grid management applications.

The three-tier modular architecture separates the FDA forecasting engine, state management, and React frontend for independent maintainability and scalability. The system is deployable as a zero-installation browser-based application via Netlify, accessible from any modern device without additional software installation.

Future work will focus on: (i) multivariate functional inputs including temperature, humidity, and pressure as vol. 111, no. 516, pp. 1447–1465, 2016.

additional FDA covariates; (ii) LSTM hybrid models combining FPCA features with sequential deep learning; (iii) geospatial functional modeling for terrain-aware forecasting across multiple locations; (iv) TensorFlow.js integration for on-device edge inference; and (v) probabilistic outputs aligned with energy market bidding requirements for grid operators.

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