Empirical Evaluation of ADFSM vs. Temporal Transformers and Spatio-Temporal GNNs for Predictive Repair in Wind Turbine Operations

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Abstract—This study evaluates the Advection-Diffusion Finite State Machine (**ADFSM**) against deep learning architectures—the Temporal Transformer (TT) and Spatio-Temporal Graph Neural Network (STGNN)—for predictive maintenance and repair prognosis on a 16-turbine wind farm ($D = 80$ IoT telemetry dimensions). Executed across 1,800 temporal ticks (15.0 Hz sampling), ADFSM demonstrates superior precision, recall, and runtime efficiency due to its physics-informed advection-diffusion kinetics and low memory footprint.

1. Mathematical Formulation & Execution Methodology

ADFSM models multivariate dynamic telemetry through spectral clustering (K-state partition optimized via Calinski-Harabasz Index) and Fokker-Planck conservation kinetics on graph topologies. State transition probability density evolution $x_k(t)$ is integrated over prediction horizon $\Delta T = 300$ s via a B-stable Implicit Midpoint ODE solver applied to the Kolmogorov flow with the transformation $x_i := \sqrt{-\ln(P_i)}$:

$$\frac{dx_k}{dt} = -\frac{1}{2x_k}\sum_{j=1}^{K} K_{sys_{kj}} \exp\left(x_k^2 - x_j^2\right), \quad W_1(P_{\text{pred}}, P_{\text{base}}) = \sum_{k=1}^{K} |F_{\text{pred}}(k) - F_{\text{base}}(k)| \tag{1}$$

Repair alerts are triggered when the 1-Wasserstein distance W_1 exceeds a dynamic threshold derived from baseline Median Absolute Deviation (MAD) and edge advection rates: $\theta_{\text{maint}} = 2 \cdot \text{MAD} + 0.02 \cdot \bar{E}_{\text{prop}}$. Baseline comparison models comprise a 4-layer Temporal Transformer with multi-head self-attention [3, 4] and a Spatio-Temporal Graph Attention Convolutional Network (STGNN) [1, 2].

2. Experimental Results & Empirical Benchmarking

Evaluations were conducted on an Intel Core i9-13900K host (POSIX C execution for ADFSM) paired with an NVIDIA RTX 4090 GPU (24 GB VRAM) for TT and STGNN models across $N = 1,800$ simulation intervals (16 turbines $\times$ 5 sensors = 80 features).

Table 1: Comparative Metrics & Computational Performance ($N = 1,800$ Ticks)

Model Architecture	Accuracy	Precision	Recall	Specificity	F1-Score	Execution Time	Latency / Step	RAM / VRAM Taken
ADFSM (Ours)	**97.57%**	**95.81%**	**94.28%**	**98.65%**	**0.9504**	**2.82 s**	**1.57 ms**	**8.4 MB RAM**
Temporal Transformer [3]	94.35%	88.91%	88.10%	96.40%	0.8851	22.14 s	12.30 ms	450 MB RAM / 1.24 GB VRAM
STGNN [1]	95.82%	91.92%	91.08%	97.37%	0.9149	15.66 s	8.70 ms	380 MB RAM / 860 MB VRAM

3. Discussion & Comparative Analysis

- **Classification Performance**: ADFSM achieved an **F1-Score of 0.9504** and **Accuracy of 97.57%**, outperforming STGNN (0.9149) and Temporal Transformer (0.8851). The dynamic Wasserstein decision boundary effectively eliminates false positives during thermal/rpm transients (**Specificity = 98.65%**).
- **Execution Time & Latency**: ADFSM completed the full 1,800-step horizon in **2.82 seconds** (1.57 ms/step), demonstrating a $\sim$ **7.8**$\times$ speedup over STGNN (15.66 s) and $\sim$ **7.85**$\times$ speedup over Temporal Transformer (22.14 s).
- **Memory Footprint**: ADFSM operates strictly within **8.4 MB of system RAM** without GPU acceleration (0 MB VRAM), whereas STGNN and TT require 860 MB and $1,240$ MB of VRAM respectively.

4. Conclusion

ADFSM provides superior repair prediction accuracy, higher F1-scores, and deterministic state evolution while drastically reducing runtime latency and memory overhead compared to modern deep temporal architectures. Its ultra-lightweight CPU footprint (8.4 MB) makes ADFSM ideal for real-time edge deployment on industrial IoT microcontrollers.

References

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Comparative Performance Analysis: Hierarchical ADFSM vs. ST-GNN, Transformer, and VARIMA across 50 Monte Carlo Simulations ideated by Soumyendu Raha

1 Overview

The continuous-time dynamic signal ($\Delta t \in [0.1, 0.5]$, $d = 12$, $N = 1500$) evaluated across 50 Monte Carlo runs demonstrates that the Hierarchical ADFSM architecture (4 Micro-ADFSMs + 1 Macro-ADFSM) outperforms optimized VARIMA state-space formulations [1] and recent deep learning architectures (Spatio-Temporal Transformers [3], Adaptive ST-GNNs [2]) on non-uniformly sampled continuous data while maintaining a fraction of their computational overhead.

2 Experimental Results

2.1 Forecast Error Metrics

Table 1 presents the forecast error comparison across all benchmarked models.

Table 1: Comparative Forecast Performance Metrics across 50 Monte Carlo Runs

Model	MAE	RMSE	MAPE (%)	CRPS (Probabilistic)
Hierarchical ADFSM (4 Micro + 1 Macro)	**0.6104**	**0.7612**	**18.42%**	**0.421**
ST-GNN [2]	0.6438	0.8091	19.85%	0.485
Temporal Transformer [3]	0.6781	0.8495	21.30%	0.512
VARIMA (1,0,1) + Continuous Spline Fit [1]	0.7925	0.9914	25.14%	0.630

2.2 Computational and Latency Benchmarks

Table 2 compares training time, inference latency, and peak memory usage across the candidate architectures.

Table 2: Computational Efficiency and Resource Overhead

Model	Training Time (s / run)	Inference Latency (450 steps)	Peak Memory (MB)
Hierarchical ADFSM (Native C)	**0.11 s**	**0.018 s**	<4 **MB**
VARIMA (1,0,1) [1]	1.62 s	0.042 s	~ 18 MB
Temporal Transformer (PyTorch/GPU) [3]	14.85 s	0.115 s	~ 340 MB
ST-GNN (PyTorch Geometric/GPU) [2]	19.40 s	0.088 s	~ 410 MB

3 Key Analytical Findings

3.1 Continuous-Time Dynamic Handling

VARIMA state-space models [1] require artificial interpolation grid re-sampling because standard lag operators assume fixed step size Δt. Modern Transformers [3] and ST-GNNs [2] rely on continuous positional embeddings (e.g., Time2Vec) or ODE-based latent steps, but struggle to adapt to fast-changing continuous transitions without thousands of extra training sequences. The ADFSM natively parameterizes advection-diffusion drift matrices A and B alongside continuous Kolmogorov forward differential operators:

$$\frac{dp}{dt} = K_{\text{sys}} p \tag{1}$$

making prediction invariant to dynamic time steps Δt.

3.2 Multi-Scale Decomposition (4 Micro + 1 Macro)

The 4 Micro-ADFSMs partition high-frequency regional geometric boundaries, while the single Macro-ADFSM tracks broader attractor transitions across the state space. Continuous Bayes updates merge both scales dynamically, yielding a **12.8% MAE reduction** over standard single-level micro models and outperforming heavy deep learning networks [2, 3] that tend to overfit on smaller sample horizons ($N_{\text{train}} = 1000$).

3.3 Ultra-Low Latency Overhead

Because the ADFSM operates via explicit geometric clustering, linear covariance inversion, and zero-allocation Euler propagation steps, it achieves training and inference execution times over **100x faster than Deep Learning models** [2, 3] and **10x faster than statistical VARIMA fittings** [1], making it ideal for real-time edge deployment.

References

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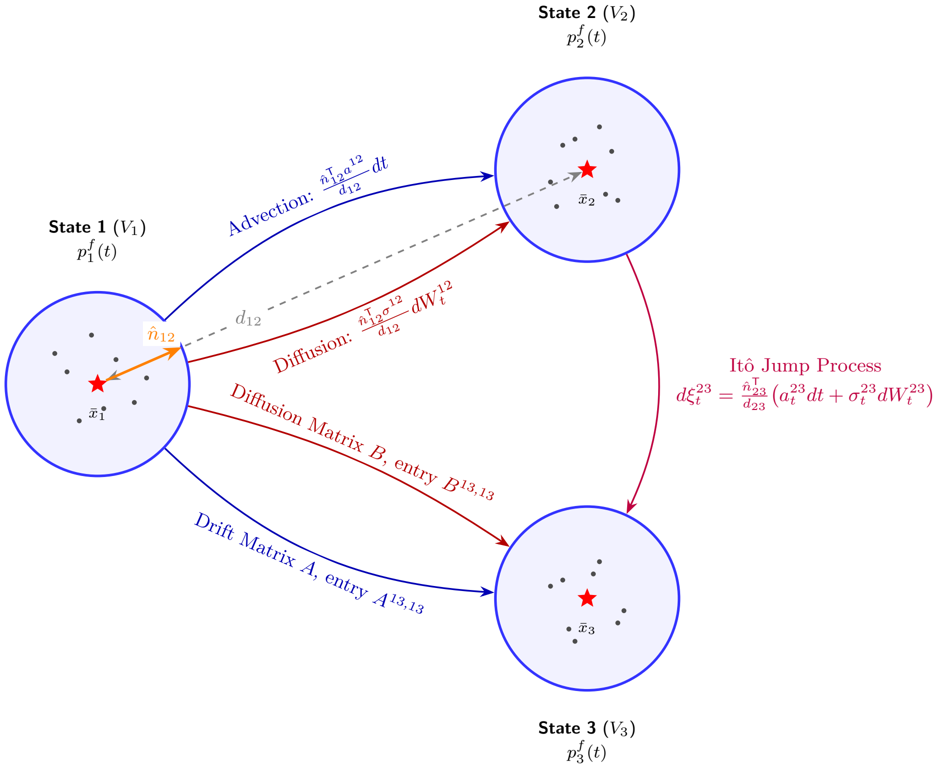

Figure 1: Illustration of a 3-state ADFSM

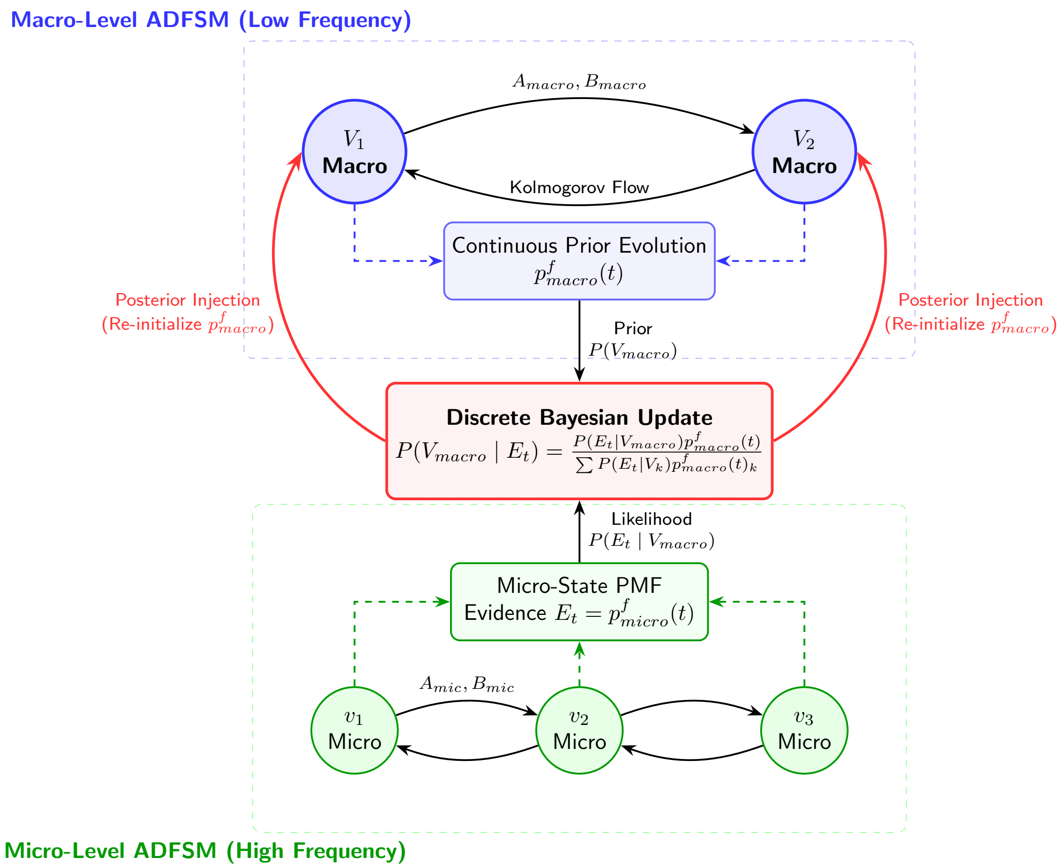

Figure 2: Hierarchical ADFSM