Hybrid Deep Learning and Quantum Network for Typhoon Forecasting in a Wind Power Farm

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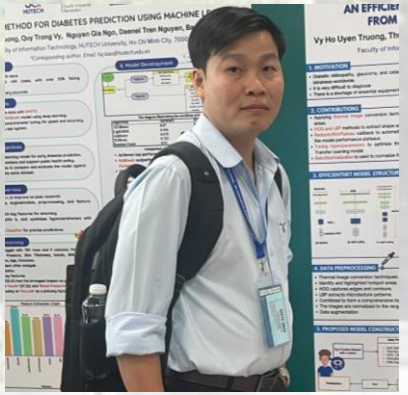

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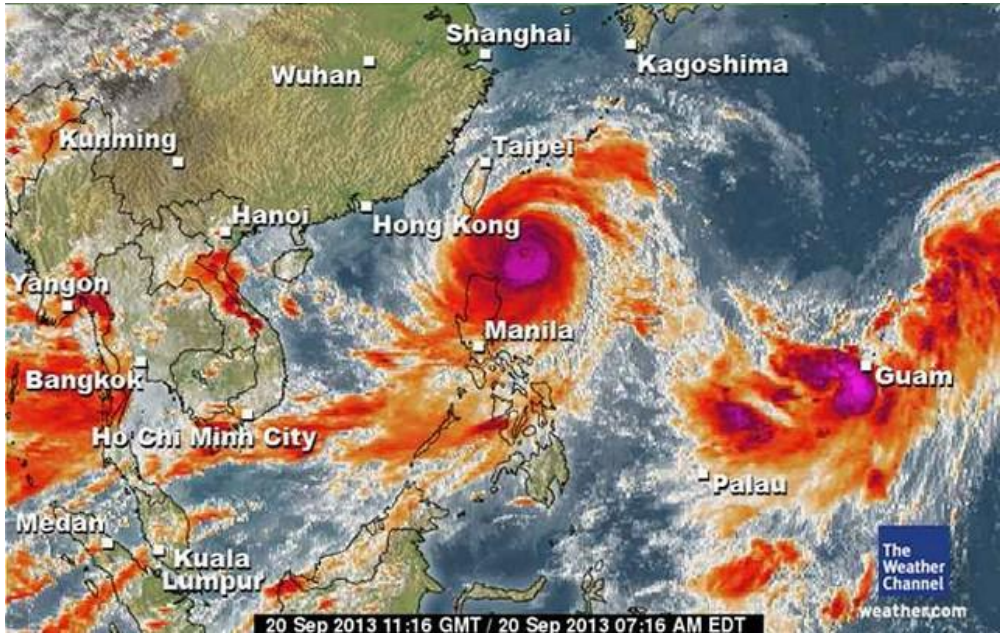
Hybrid Deep Learning and Quantum Network for Typhoon Forecasting in a Wind Power Farm

- Our application is a hybrid quantum-classical deep learning system for comprehensive typhoon forecasting and wind farm risk assessment. The system combines **classical deep learning** for multi-horizon attention-based temporal modeling with **quantum neural networks** for quantum-enhanced sequential pattern recognition. We simultaneously forecast typhoon path, radius, intensity, wind speed, and the operational status of wind farm turbines during extreme weather events.



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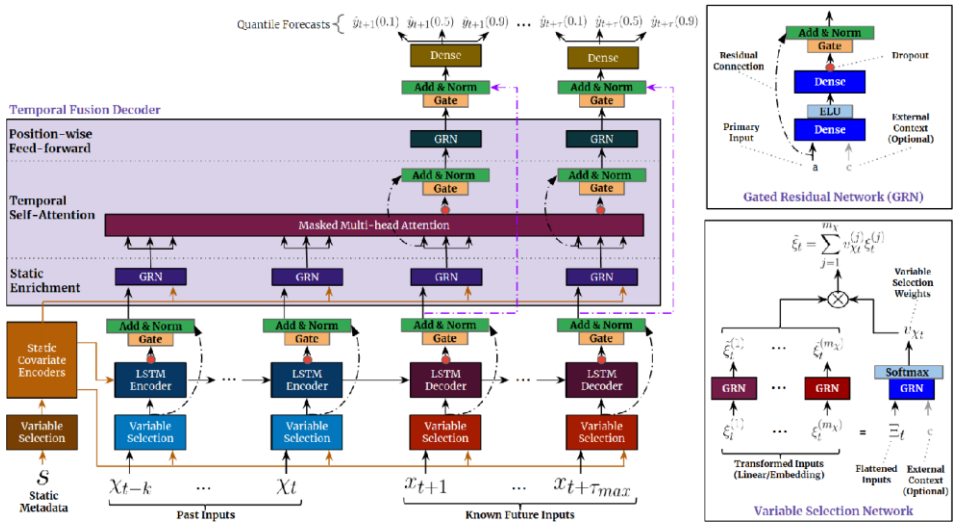
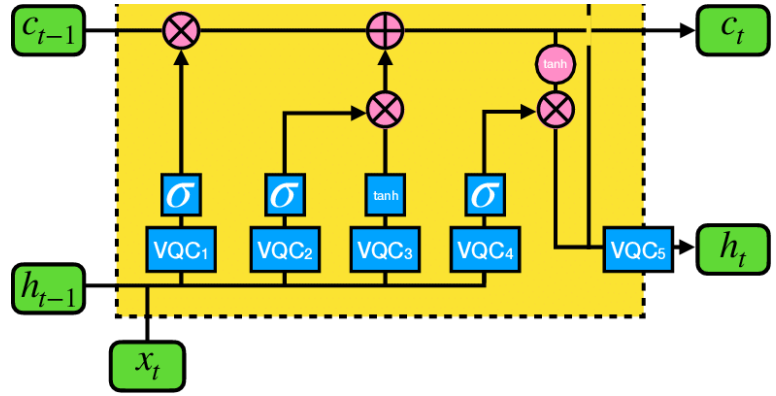
Problem

- Farm-level wind risk from typhoon signals. Inputs: typhoon path (lat/lon), typhoon wind speed, radius (7dir, 10dir); Target: typhoon forecast and wind speed at the wind farm.
- Hackathon goal: maximize training/inference throughput and reduce end-to-end latency across RTX 3080 → A100 → H100, without degrading accuracy.

Scientific Driver

- Temporal Fusion Transformers (TFT) handles multi-horizon temporal dependencies and exogenous selection (great for NWP post-processing).
- Quantum Long Short Term Memory (QLSTM) provides a compact, highly nonlinear temporal inductive bias that can boost tail prediction and calibration, kept fp32 for numeric stability.

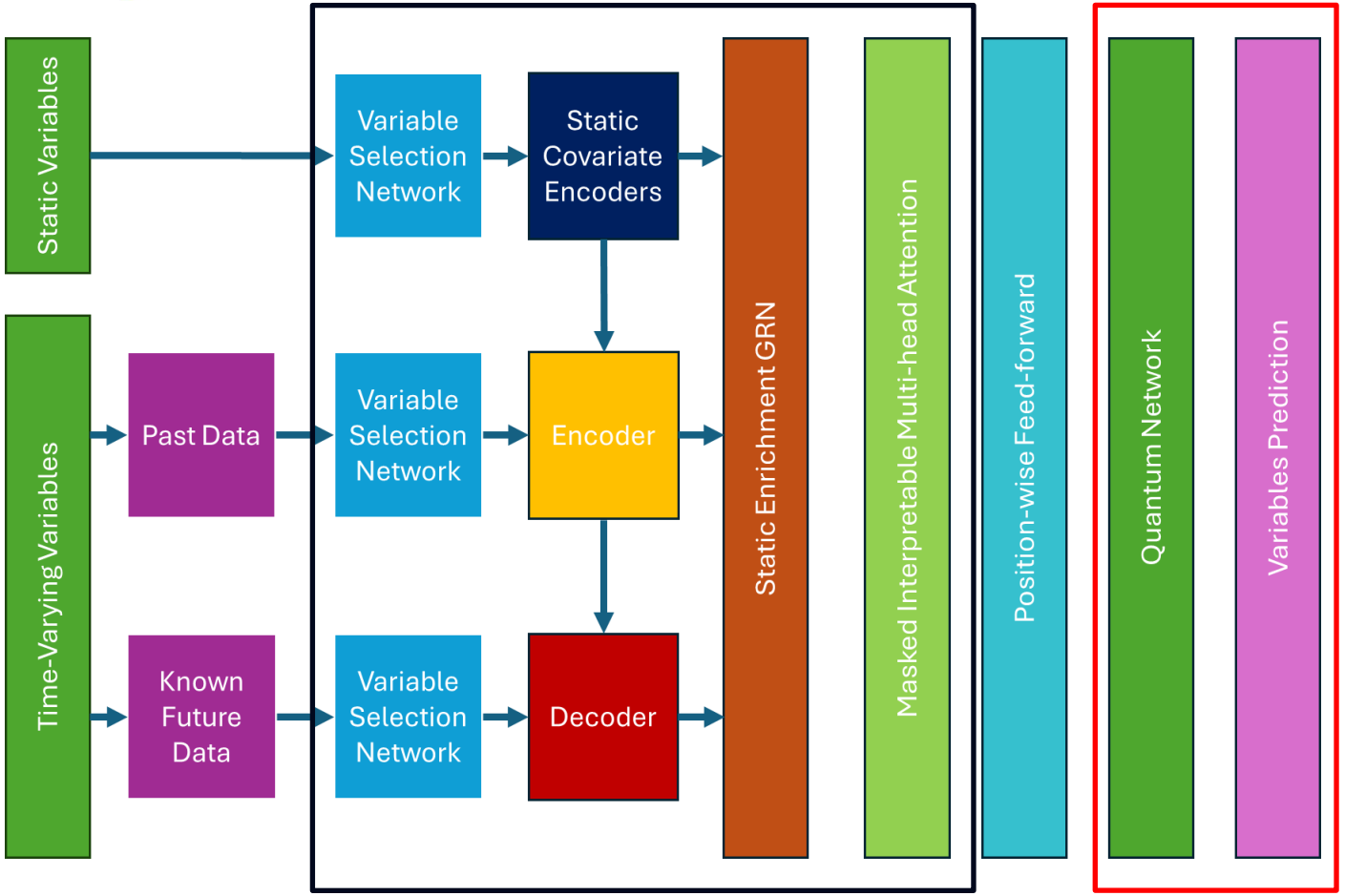




Accelerated by

cuDNN PyTorch

Basic Architecture



- Algorithm Motif: Hybrid Quantum-Classical Multi-Task Architecture:
- Classical TFT Component
- Quantum LSTM

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Evolution and Strategy

Goal

- **Turn CWB NWP into farm-scale decisions.** Predict typhoon track (lat/lon), intensity, 7/10-dir radii, and farm wind & gust (multi-horizon).
- **Win on speed**. Demonstrate big end-to-end acceleration across RTX 3080 → A100 → H100 while keeping accuracy within tight guardrails.
- **Make it deployable.** Low-latency inference suitable for operations (curtailment, yaw/park, crew windows).

Evolution and Strategy

Initial strategy

- **Model:** Hybrid **TFT + QLSTM**, plan to sweep **qubits 4–64** and **layers 1–5**, multi-task quantile losses.
- **Scale: DDP on A100/H100**, classical path **bf16-mixed**, quantum path **fp32**; large global batch via grad accumulation.
- **Kernels:** torch.compile (max-autotune), Flash/SDPA attention, fused optimizers.
- **Ablations:** Compare quantum placement (pre/post-attention), encodings, and compute-matched classical baselines.

Evolution and Strategy

How the strategy changed

- **Stability over ambition.** DDP + bf16 in quantum blocks and container issues caused friction (NCCL timeouts, dtype fallbacks), so we locked to single-GPU runs for final scoring.
- **Lean quantum.** Fixed QLSTM to 4 qubits, 1 layer (fp32) for reliability and simpler profiling.
- **Throughput first.** Focused on precision policy per GPU (3080 fp16+TF32; A100/H100 bf16-mixed), Flash-SDPA, torch.compile, and dataloader tuning (pin/persistent/prefetch).
- **Tight targets.** Kept full target set (lat, lon, typhoon wind, 7dir, 10dir, farm wind/gust) but simplified heads/loss masking for missing radii.
- **Metric framing.** Reported epoch-averaged throughput/latency (training-only) as the scoreboard, with inference estimates for bs=1/128.

MAE measures average absolute error, RMSE is like MAE but penalizes large errors more, and R^2 shows variance explained—so smaller MAE/RMSE (closer to 0) and R^2 nearer to 1 mean better performance.

	MAE			RMSE			R2		
	RTX3080	**A100**	**H100**	**RTX3080**	**A100**	**H100**	**RTX3080**	**A100**	**H100**
Longitude	**1.9526e-4**	1.9724e-4	1.9922e-4	**3.2416e-4**	3.7164e-4	4.1912e-4	0.9279	0.9836	**0.9986**
Latitude	**2.2198e-4**	2.2749e-4	2.3299e-4	**3.1986e-4**	4.0799e-4	4.9611e-4	0.9304	0.9944	**0.9984**
Wind Speed	2.0685e-3	2.061e-3	**2.0538e-3**	**5.3174e-3**	5.7867e-3	6.2559e-3	0.9097	0.9772	**0.9972**
7Dir	2.4946e-3	2.4289e-3	**2.3627e-3**	**0.01116**	0.01437	0.01757	0.9166	0.9753	**0.9853**
10Dir	**2.2015e-5**	8.1751e-4	1.613e-3	**0.01043**	0.01398	0.01752	0.9332	0.9509	**0.9909**
Gaomei Wind Speed	**8.1471e-3**	8.217e-3	8.2879e-3	**0.01740**	0.01890	0.02041	0.8375	0.9234	**0.9334**
Gaomei Wind Gust	6.731e-3	6.577e-3	**6.4237e-3**	**0.01442**	0.01576	0.01709	0.8824	0.9340	**0.9540**

3.3 days → **5+ hours** → **4 hours**

RTX3080
(FP16 Precision-TF32, Epochs=50)

A100
(BF16-Mixed Precision, Epochs=50)

H100
(BF16-Mixed Precision, Epochs=50)

H100 runs reduced computation time and, across most targets, produced lower MAE/RMSE (loss) and R^2 values closer to 1 than the RTX 3080/A100.

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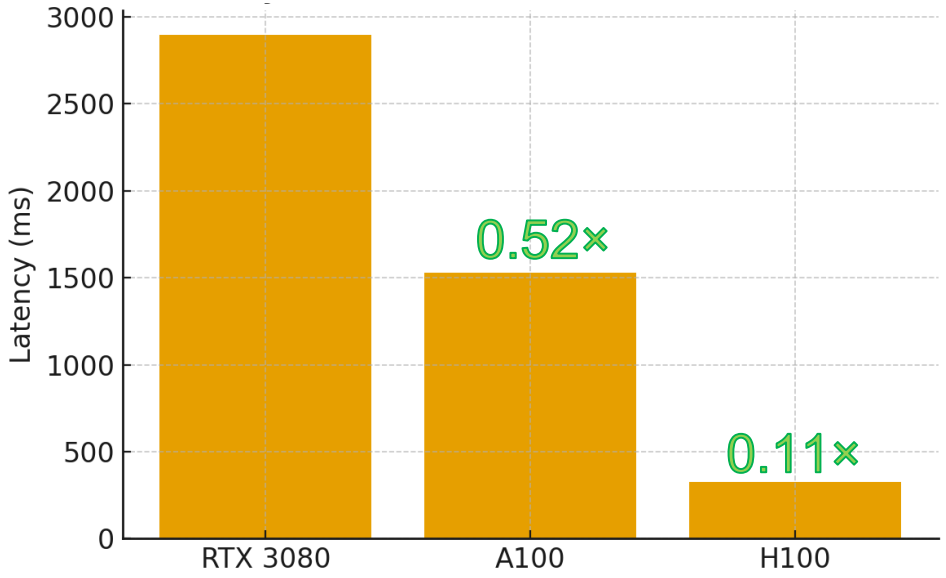
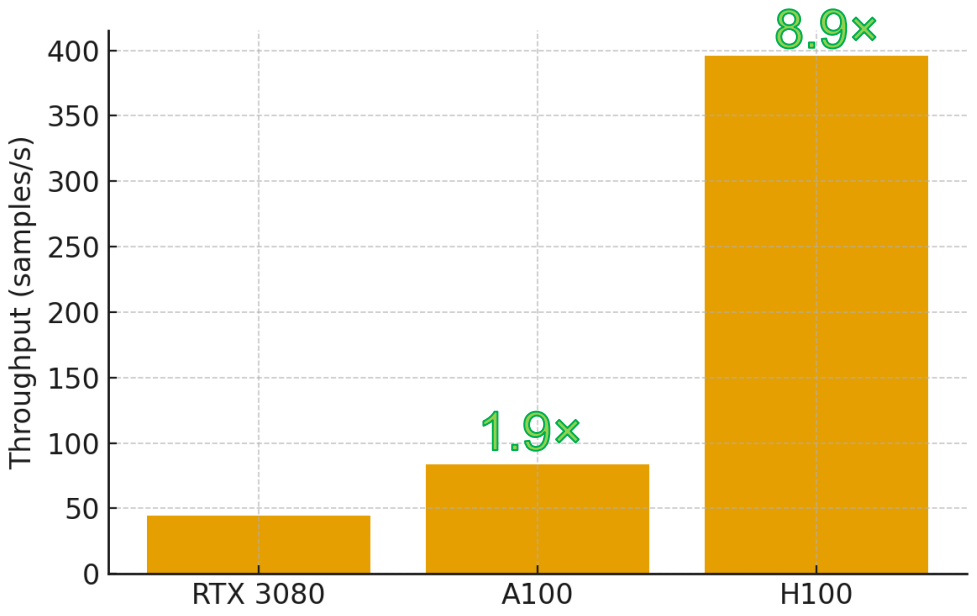
Latency and Throughput





Multi-core CPU vs GPU (training, 50 epochs)

Platform	Avg / epoch	50-epoch total	Train it/s (≈)	Speedup vs CPU-16c
CPU (16 cores)	~13.7 h	~28.4 days	~0.008	1.0×
CPU (32 cores)	~9.1 h	~19.0 days	~0.012	1.5×
CPU (64 cores)	~5.5 h	~11.4 days	~0.020	3.4×
RTX 3080	**1h36m**	**3.33 days**	**~0.068**	**11.2×**
A100	**7m**	**5h50m**	**~0.936**	**77.8×**
H100	**5m**	**4h10m**	**~1.31**	**109.2×**

Computation Time Comparison

GPU Model	Configuration	Batch Size	Computation Speed	Status
RTX 3080	4Q / 1L	1024	0.19it/s	✓ Optimal
RTX 3080	Higher configs	—	—	✗ Infeasible
A100	4Q/ 1L	1024	0.20it/s	✓ Baseline
A100	4Q /1L	2048	0.36it/s	✓ Feasible
H100	4Q/ 1L	2048	1.70it/s	✓ Feasible

Energy Efficiency

INPUTS	
# CPU Cores	64
# GPUs (H100)	1
Application Speedup	109.2x
Node Replacement	499.2x

GPU NODE POWER SAVINGS			
	Intel Dual SPR 8480c	**8x H100 80GB SXM4**	**Power Savings**
Compute Power (W)	549,120	9,290	539,830
Networking Power (W)	23,181	186	22,995
Total Power (W)	**572,301**	**9,476**	562,825

Node Power efficiency	**60.4x**

ANNUAL ENERGY SAVINGS PER GPU NODE			
	Intel Dual SPR 8480c	**8x H100 80GB SXM4**	**Power Savings**
Compute Power (kWh/year)	4,810,291	81,380	4,728,911
Networking Power (kWh/year)	203,067	1,627	201,440
Total Power (kWh/year)	**5,013,359**	**83,008**	**4,930,351**

$/kWh	$	0.18
Annual Cost Savings	$	887,463.20
3-year Cost Savings	$	2,662,389.59

Metric Tons of CO_2	3,496
Gasoline Cars Driven for 1 year	754
Seedlings Trees grown for 10 years	57,784

(source: Link)

What problems have you encountered?

- **Legacy app structure**
  - Monolithic script; hard-coded paths/params; .item() in hot path; no feature cache/logging.
  - **Fix:** modularize (data/ model/ train/ utils/), config (Hydra/argparse), remove graph-breaking ops, add cached datasets + unified metrics.
- **Algorithms**
  - QLSTM unstable in bf16; radii (7/10-dir) mask misalign; lat/lon MAE ≠ distance; loss weights drift.
  - **Fix:** keep QLSTM **fp32** (autocast off), strict per-horizon masks, **Haversine** track metric + quantile heads, **uncertainty weighting**, Flash/SDPA + grad-checkpoint.

What problems have you encountered?

- **Tool gaps**
  - CUDA-Q lacks bf16/FP8; no built-in great-circle/fused quantile loss; TFT doesn't expose Flash everywhere.
  - **Fix:** custom Haversine + fused pinball/CRPS, manual SDPA hooks, quantum kept fp32 while classical runs mixed-precision.

- **System setup**
  - Apptainer missing fuse/binds → no GPU; NCCL timeouts; over-threaded dataloaders → OOM/pickle errors.
  - **Fix:** verify nvidia-smi in container, correct --nv --bind --pwd, install fuse; set NCCL_*, gradient_as_bucket_view=True; workers **8–16/GPU**, pin_memory, persistent_workers, sane prefetch_factor.

- **Tool bugs**
  - "LightningRanger object is not callable"; BF16-unsupported ops in metrics; torch.compile breaks from prints/.item(); Triton first-run hiccups.
  - **Fix:** pin versions, cast metrics to fp32, purge graph-breaking calls, warm-up compile.


Thank you
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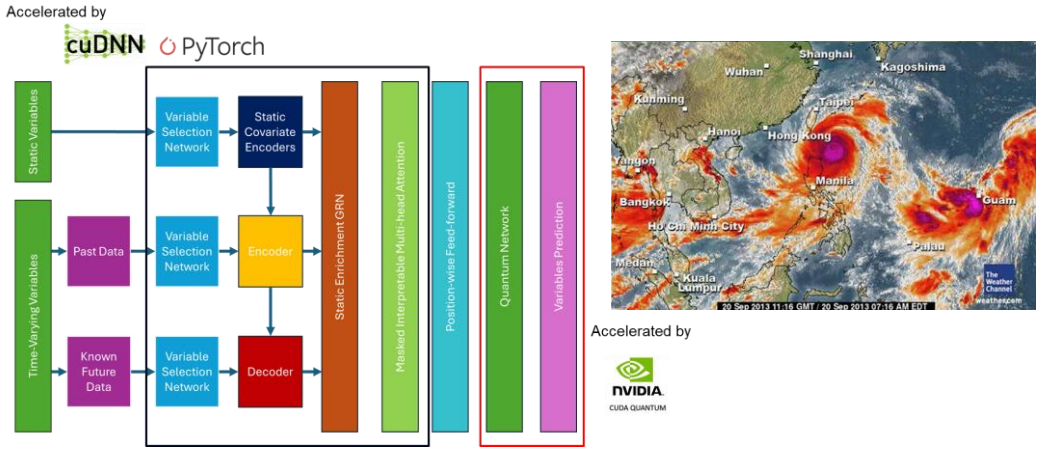
Hybrid Deep Learning and Quantum Network for Typhoon Forecasting in a Wind Power Farm

A production-oriented forecasting pipeline that predicts typhoon track, arrival time, site-level wind speed/gusts, and risk bands for a wind farm. It blends a proven deep-learning forecaster (for long-range temporal patterns) with a small variational quantum sub-network (for richer, non-linear feature mixing and uncertainty cues). The output supports safer turbine operations, curtailment planning, crew scheduling, grid trading, and early-warning dashboards.



Model → Reality: TFT+QLSTM pipeline (left) forecasting the West Pacific typhoon scene (right) from 72 h history to 24 h ahead.

Hackathon Objectives and Approach

- **Objectives**
- **72→24 hourly forecast** (use last 72 h to predict next 24 h).
- **Accuracy**: lower MAE/RMSE, higher R^2; per-step & arrival-time error.
- **Speed**: maximize **single-GPU** throughput/latency; profile 3080/A100/H100
- **Deliverables**: reproducible pipeline, simple REST/CLI.
- **Approach**
- **Data**: Taiwan **CWB** + best-track; hourly interpolation, cleaning, normalization, route clustering.
- **Model**: **TFT backbone + compact QLSTM** mixer (A/B toggle).
- **Training (single-GPU)**: PyTorch Lightning, **bf16**, Flash/SDPA, grad-checkpointing, torch.compile, **batched quantum** eval using CUDA Quantum
- **Eval/Deploy**: MAE/RMSE/R^2 per variable & step, reliability diagrams; containerized API + lightweight dashboard.

Achieved: Production-style **72→24 h** forecasting pipeline (wind, gust, lat/lon) with TensorBoard, per-step metrics, calibrated arrival time; **better loss and higher R^2** than classical TFT.
How: bf16, SDPA/Flash-Attention, torch.compile, grad-checkpointing, larger stable batches, **batched quantum eval**, Parquet + mem-map, pinned/persistent DataLoaders.
Speedup: 0.19→0.36→1.70 it/s (RTX3080 → A100 → H100) = **1.9×**, **8.9×**, **4.7×**; 50-epoch wall-time ≈ **80 h**, **42.2 h**, **8.9 h**.
Why it matters: Enables **hourly refresh forecasts** with higher confidence for curtailment, crew scheduling, and trading—while **cutting compute time/cost and accelerating experimentation**.

Platform	Avg / epoch	50-epoch total	Train it/s (≈)	Speedup vs CPU-16c
CPU (16 cores)	~13.7 h	~28.4 days	~0.008	1.0×
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