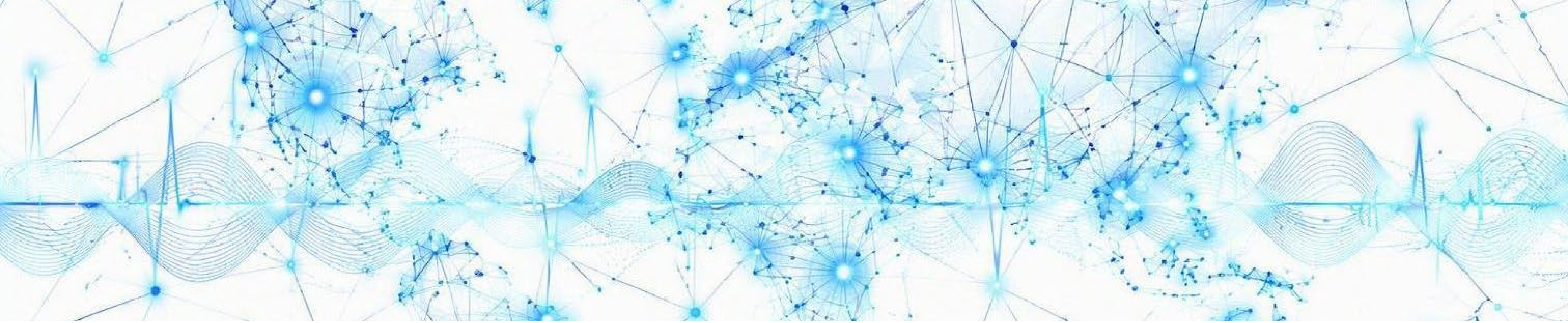

Q13/15, AI/ML in Timing and Sync Networks

AI based Precision Timing, Resilience, and Network Synchronization

Tenth Joint IEEE 802 and ITU-T Study Group 15 Workshop (Montreal, 11th July, 2026)
Ramana Reddy, Sr Director, Timing Platforms, Rakuten

Agenda

Introduction
AI/ML for Clock Selection
Predictive PTP Offset Computation
Real-Time Holdover Forecasting
AI-Powered Sync Anomaly Detection
Clustering for Sync Traffic Steering
Conclusions

Introduction

Why traditional synchronization is reaching its limits—and how AI/ML delivers precision, resilience, and efficiency.

The Dawn of Intelligent Sync Networks

Traditional synchronization is reaching its limits in complexity and scale. AI/ML represents a paradigm shift—moving from static, reactive rule-sets to autonomous, predictive network orchestration.

Key pillars of paradigm shift

- From Static to Adaptive
- From Reactive to Predictive
- From Manual to Autonomous
- Holistic Intelligence

Applications of AI/ML

Clock selection, PTP offset prediction, holdover management, anomaly detection, and traffic steering.

Clock Selection using ML Recommendation Systems

- ML-Powered Decision Making using Content-Based Similarity(recommendation systems).
- Quantify similarity by comparing and calculating distance.
- Calculate and Rank Master from Reference Master Proximity.
- Dynamic Master Selection with least distance.

Lab Results

Source	P1	clock class	Accuracy	Variance	P2	Weighted Euclidean	Weighted Cosine	Weighted Jaccard	BMCA
a0:00:00:00:00:01	128	6	21	19250	128	a0:00:00:00:00:01	a0:00:00:00:00:01	a0:00:00:00:00:01	a0:00:00:00:00:01
b0:00:00:00:00:04	128	7	22	19250	128	a0:00:00:00:00:01	b0:00:00:00:00:04	a0:00:00:00:00:01	a0:00:00:00:00:01
a0:00:00:00:00:01	128	6	21	19250	128	a0:00:00:00:00:01	b0:00:00:00:00:04	a0:00:00:00:00:01	a0:00:00:00:00:01
b0:00:00:00:00:04	128	7	22	19250	128	a0:00:00:00:00:01	b0:00:00:00:00:04	a0:00:00:00:00:01	a0:00:00:00:00:01
a0:00:00:00:00:01	128	6	21	19250	128	a0:00:00:00:00:01	b0:00:00:00:00:04	a0:00:00:00:00:01	a0:00:00:00:00:01
b0:00:00:00:00:04	128	7	22	19250	128	a0:00:00:00:00:01	b0:00:00:00:00:04	a0:00:00:00:00:01	a0:00:00:00:00:01
a0:00:00:00:00:01	128	6	21	19250	128	a0:00:00:00:00:01	b0:00:00:00:00:04	a0:00:00:00:00:01	a0:00:00:00:00:01
b0:00:00:00:00:04	128	7	22	19250	128	a0:00:00:00:00:01	b0:00:00:00:00:04	a0:00:00:00:00:01	a0:00:00:00:00:01
a0:00:00:00:00:01	128	6	21	19250	128	a0:00:00:00:00:01	b0:00:00:00:00:04	a0:00:00:00:00:01	a0:00:00:00:00:01
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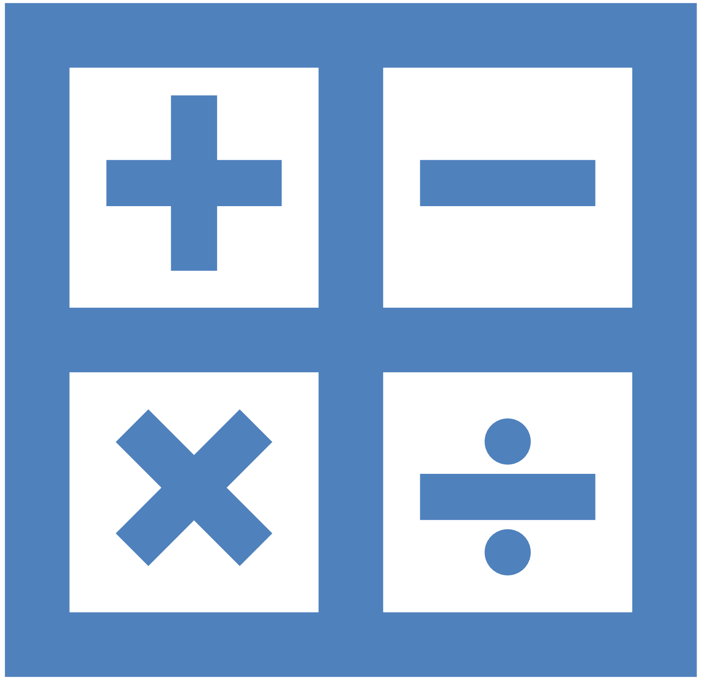
a0:00:00:00:00:01	128	6	21	19250	128	a0:00:00:00:00:01	b0:00:00:00:00:04	a0:00:00:00:00:01	a0:00:00:00:00:01
b0:00:00:00:00:04	128	7	22	19250	128	a0:00:00:00:00:01	b0:00:00:00:00:04	a0:00:00:00:00:01	a0:00:00:00:00:01
a0:00:00:00:00:01	128	6	21	19250	128	a0:00:00:00:00:01	b0:00:00:00:00:04	a0:00:00:00:00:01	a0:00:00:00:00:01
b0:00:00:00:00:04	128	7	22	19250	128	a0:00:00:00:00:01	b0:00:00:00:00:04	a0:00:00:00:00:01	a0:00:00:00:00:01
a0:00:00:00:00:01	128	6	21	19250	128	a0:00:00:00:00:01	b0:00:00:00:00:04	a0:00:00:00:00:01	a0:00:00:00:00:01

Experimental Setup:

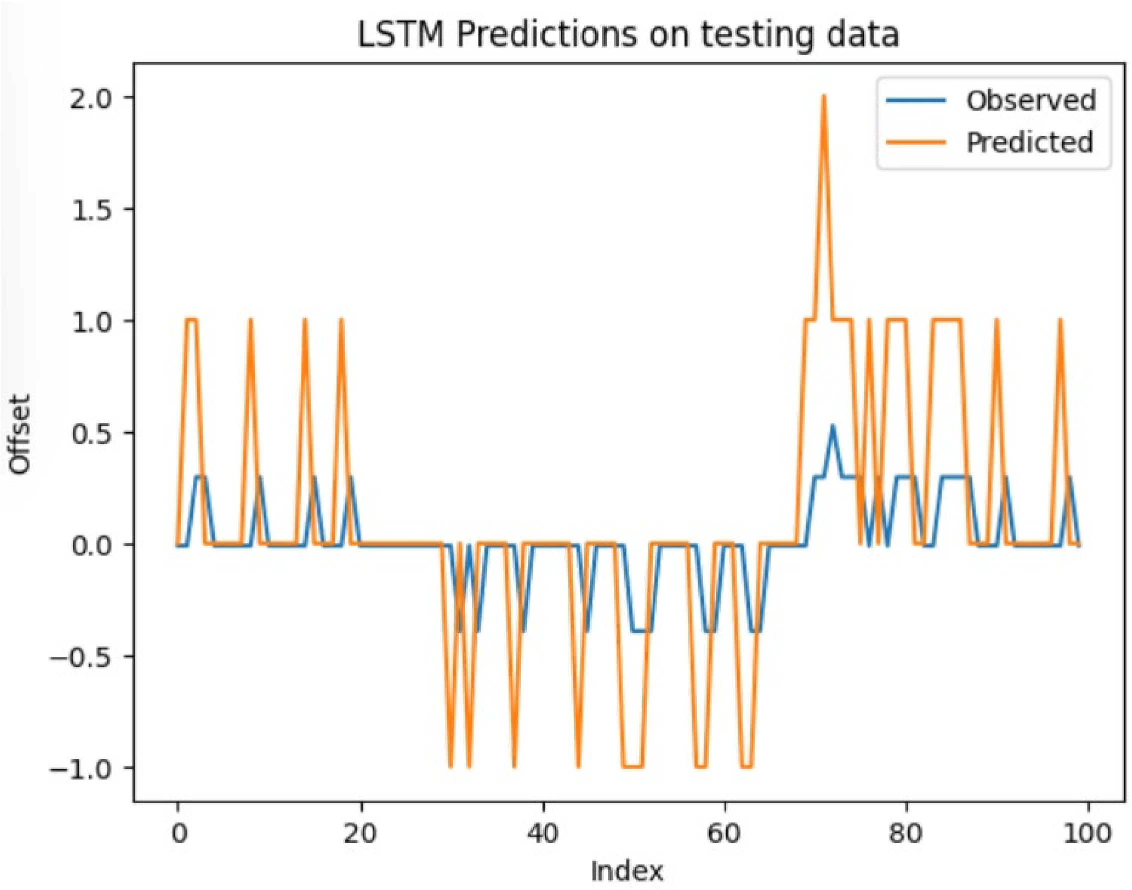
- **Testbed:**
  - Two simulated Grandmasters (M1, M2) via precision timing measurement equipment.
  - Real-time GM parameter manipulation to evaluate model responsiveness.
- **Methodology:**
  - Evaluated predictive performance using three distance metrics: **Euclidean**, **Weighted Cosine**, and **Weighted Jaccard**.
- **Metric:**
  - Lower distance score indicates higher similarity/reliability against the optimal reference.
- **Key Findings:**
  - **Euclidean Distance** outperformed all models, demonstrating the highest accuracy in predicting the optimal Master compared to the traditional BMCA.
  - AI-based selection successfully identified reference stability trends where standard BMCA attributes remained static.

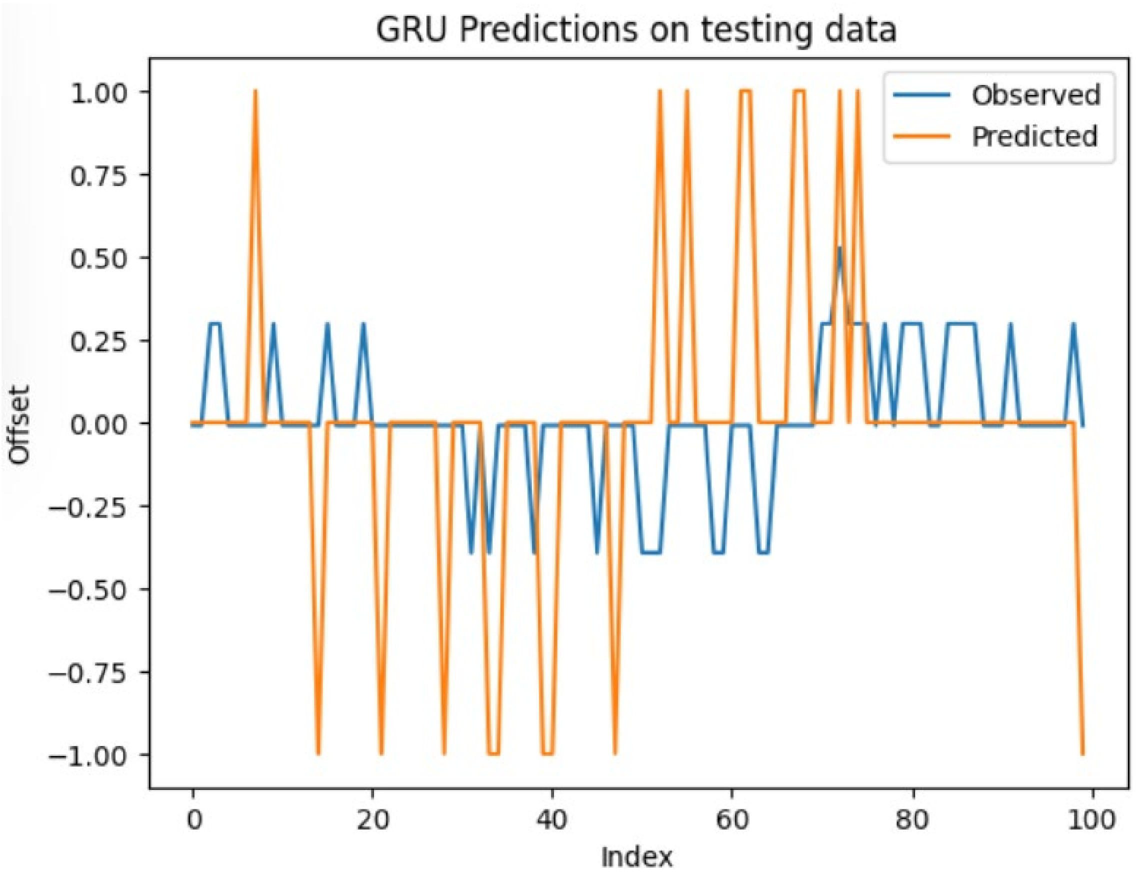
PTP Offset Computes using DL

- Due to Dynamic nature of OFM, influenced by network latency, jitter, and clock drift, traditional methods struggle with its non-linear and time-dependent nature.
- Use Deep Learning for PTP Offset computes.
- Predicts future PTP offset, allowing for feed-forward compensation and pre-emptive clock adjustments.



Results : LSTM vs GRU





AI-Powered Real-Time Holdover Management

Predictive Holdover Intelligence

- **Dynamic Duration Estimation:** Continuously forecasts local oscillator drift to calculate precise, element-specific holdover limits.

Proactive Service Continuity

- **Automated Failover:** Triggers pre-emptive switches to redundant timing sources before performance degrades below compliance masks.
- **Adaptive Mitigation:** Recommends service-level adjustments (e.g., coverage/bandwidth throttling) in extreme scenarios to maintain minimal synchronization integrity.

Intelligent Operations

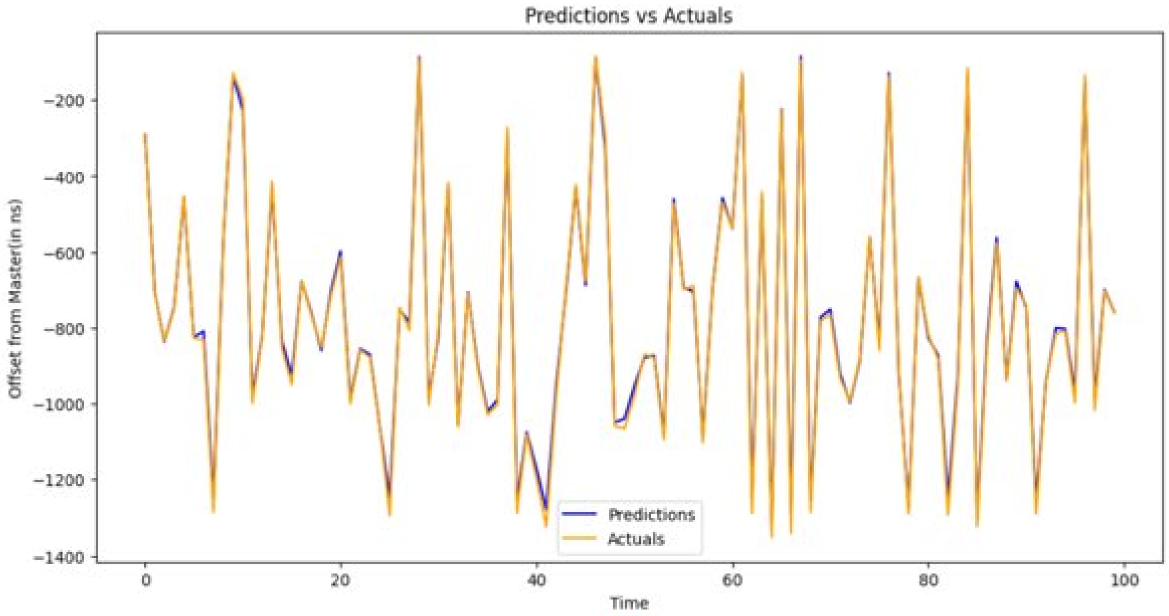
- **Severity-Based Escalation:** Generates context-aware alerts based on predicted degradation, enabling prioritized, data-driven incident response.

AI/ML Regression Models and Their Results

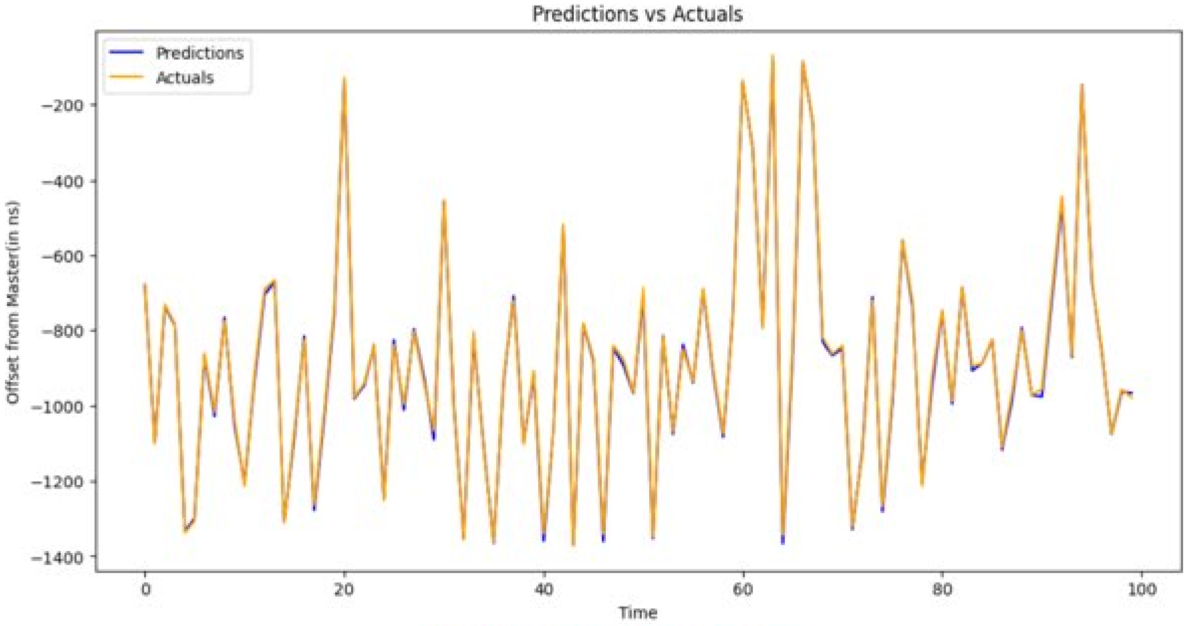
	Model	R-squared (Train)	MSE (Train)	RMSE (Train)	R-squared (Test)	MSE (Test)	RMSE (Test)
0	GradientBoostingRegressor	0.998128482	169.934879517	13.035907315	0.998124181	170.189446433	13.045667727
1	LinearRegression	0.566163390	39392.606232972	198.475706909	0.566429937	39336.975862640	198.335513367
2	DecisionTreeRegressor	0.998721518	116.086843992	10.774360491	0.998717216	116.384528323	10.788166124
3	XGBRegressor	0.997618388	216.251699834	14.705498966	0.997607720	217.046973423	14.732514158
4	Sequential_Conv1D_RELU	0.998531206	133.374628606	11.548793383	0.998533514	133.014129875	11.533175186
5	Sequential_Conv1D_SELU	0.998089812	173.455640709	13.170255909	0.998087373	173.480356833	13.171194207
6	LSTM	0.996858942	285.225375334	16.888616738	0.996856470	285.126473146	16.885688412
7	GRU	0.980488032	1771.794331511	42.092687388	0.980484163	1770.138043080	42.073008486

Testing Results

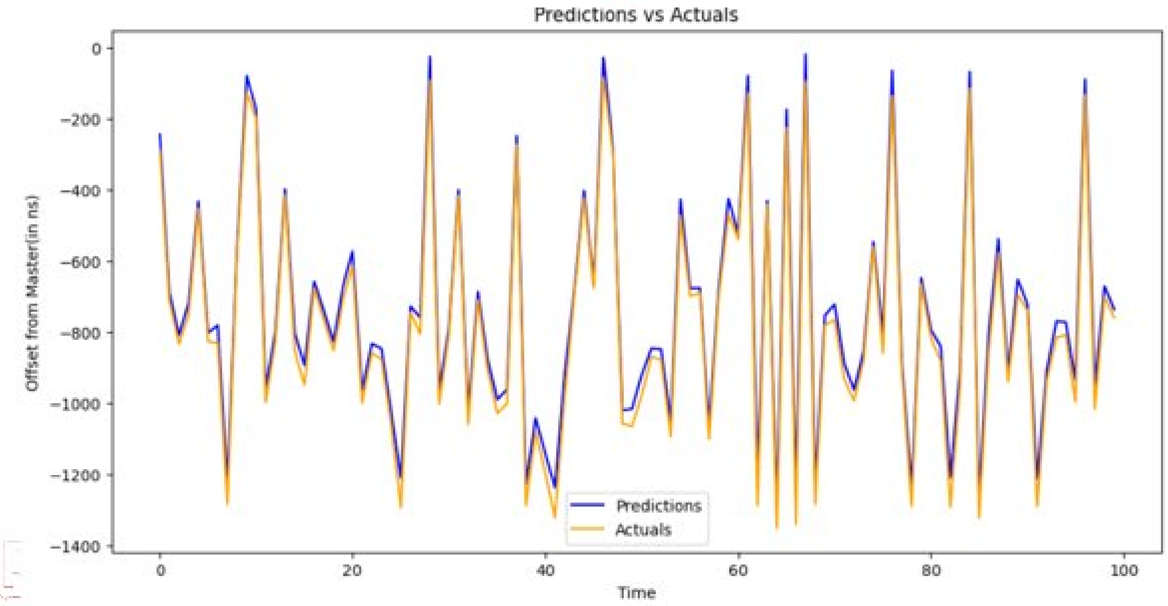
LSTM



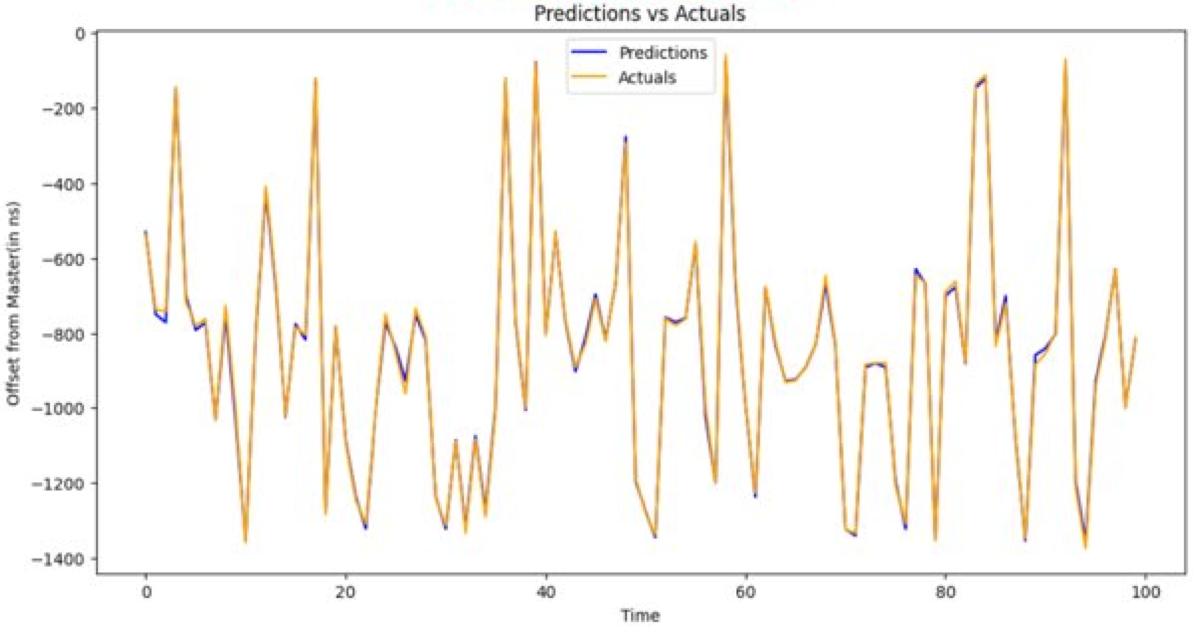
Sequential_Conv1D_RELU



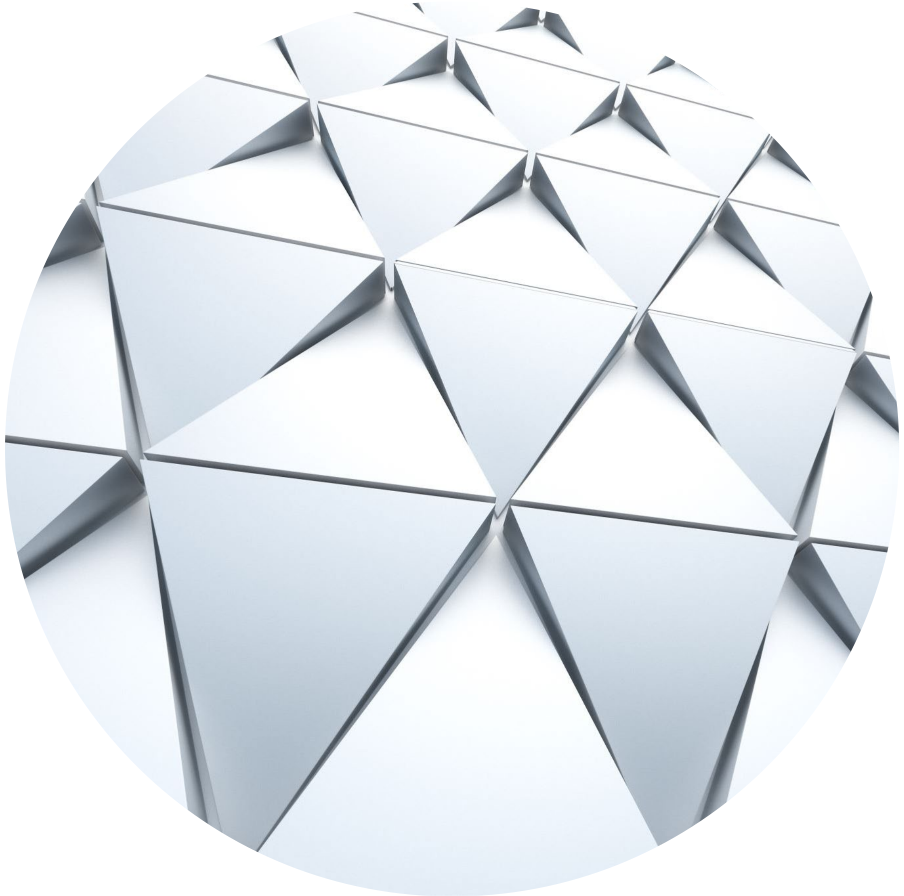
GRU



GradientBoostingRegressor



Sync Anomaly Detection



AI/ML transforms sync monitoring from reactive to predictive, ensuring the unwavering reliability of our critical network timing.

Traditional monitoring struggles to keep pace with network complexity and the subtle, evolving threats to synchronization integrity.

Need Next-Gen Defense Against Sync Disruptions.

Implement AI-driven monitoring for identifying synchronization anomalies, outliers, and network vulnerabilities.

Conclusions
The Path Forward: Standardizing AI/ML in Timing

Urgent Need for Standardization - To fully unlock the potential of these AI/ML applications, we must collectively work towards integrating AI/ML considerations into timing standards.

Call to Action - We strongly urge industry colleagues and companies to actively contribute to ITU-T and IEEE 1588 specifications to define best practices, data models, and interoperability frameworks for AI/ML-driven timing solutions.

Collective Innovation - This collaborative effort is vital to ensure that AI/ML truly revolutionizes sync across the network, fostering innovation, ensuring interoperability, and safeguarding the pulse of our critical infrastructure for years to come.

Thank You

For any questions reach me @ ramana.machireddy@ rakuten.com

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