A Appendix

A.1 LTC-NN model recovery robustness results

Table S1 5 shows the performance of LTC-NN architecture described in Figure 4 of the main paper on model recovery for different benchmark examples available in Kaiser et al. (2018).

For each evaluation experiment, we use two metrics:

Root mean square error in model coefficients (**$RMSE_\Theta$**) and **Root mean square error in signal** (**$RMSE_Y$**). Given the estimated model coefficients Θ_{est} and measured variables Y_{est} for any technique we computed them as:

$$RMSE_\Theta = \sqrt{\frac{1}{p}\sum_{j=1\dots p}(\Theta^j_{est} - \Theta^j)^2}, \tag{4}$$

$$RMSE_Y = \frac{1}{n}\sum_{l=1\dots n}\sqrt{\frac{1}{k}\times\sum_{j=1\dots k}(Y^l_{est}(j) - Y^l(j))^2}. \tag{5}$$

Table 5: S1: Comparison of LTC-NN architecture with baseline SINDY-MPC only and other RNN architectures on standard benchmarks. LTC-NN-MR represents model recovery with LTC-NN architecture shown in Figure 4. The LTC-NN can be replaced by CT-RNN or NODE. Value in () is standard deviation

Example	RMSE	SINDY-MPC	LTC-NN-MR	CT-RNN-MR	NODE-MR
Lotka	$RMSE_\Theta$	0.059 (0.02)	0.048 (0.015)	0.054 (0.03)	0.064 (0.02)
Volterra	$RMSE_Y$	0.03 (0.02)	0.03 (0.018)	0.05 (0.02)	0.088 (0.03)
Chaotic	$RMSE_\Theta$	0.014 (0.008)	0.015 (0.006)	0.022 (0.009)	0.044 (0.012)
Lorenz	$RMSE_Y$	1.7 (0.6)	1.68 (0.4)	3.66 (1.1)	8.1 (3.6)
F8	$RMSE_\Theta$	7.9 (3.2)	6.8 (2.9)	10.5 (4.8)	19.9 (7.4)
Crusader	$RMSE_Y$	3.2 (2.1)	1.57 (1.4)	3.46 (2.6)	7.22 (5.7)
Pathogenics	$RMSE_\Theta$	0.5 (0.2)	0.39 (0.23)	0.43 (0.3)	0.42 (0.3)
attack	$RMSE_Y$	27.8 (9.1)	28.3 (6.2)	28.8 (7.7)	29.5 (9.6)

A.2 Description of real world datasets

We used three real datasets:

Server Machine Database: The Server Machine Dataset (SMD) is a newly curated dataset that spans a period of five weeks, collected from a major Internet company known for its extensive server infrastructure Su et al. (2019). This dataset, which includes detailed logs and metrics related to server machine performance, has been made publicly available on GitHub to support research in anomaly detection and related fields.

The SMD dataset comprises a wide range of features, including CPU utilization, memory usage, disk I/O, and network traffic, collected at regular intervals. For practical analysis, we have divided the dataset into two equal-sized subsets: the first subset, which covers the initial period of the data collection, is used as the training set. The second subset, covering the remaining period, is designated as the testing set.

In the testing subset, domain experts have meticulously identified and labeled anomalies, along with their specific dimensions, based on a thorough examination of incident reports and historical data. These labels provide valuable insights for evaluating anomaly detection algorithms and enhancing their accuracy.

Soil Moisture Active Passive Satellite: The Soil Moisture Active Passive (SMAP) satellite Liu et al. (2024) is a NASA mission designed to measure and monitor soil moisture levels across the globe. SMAP employs a combination of active radar and passive radiometer technologies to provide high-resolution measurements of soil moisture, which are crucial for understanding water cycles, weather patterns, and climate change. The satellite records key performance indicators (KPIs) related to its operational status and performance metrics, including data on the satellite's health, instrument functionality, and environmental conditions. These KPIs are essential for ensuring the proper functioning of the spacecraft and for diagnosing and addressing any issues that may arise during its mission.

Mars Science Laboratory Rover (MSL): The Mars Science Laboratory (MSL) rover Liu et al. (2024), commonly known as Curiosity, is a NASA rover mission designed to explore the surface of Mars. Equipped with a suite of scientific instruments, the MSL rover conducts a variety of experiments to study Mars' geology, climate, and potential for past habitability. The rover records KPIs

Table 6: S2: Comparison of SPIE-AD with latest baseline techniques on real world datasets and ablation studies. The datasets all satisfy A3.

Method	SMD								
	A2			¬ A2			¬ A1		
	Pr	Re	F1	Pr	Re	F1	Pr	Re	F1
AT	83	100	90.7	29	58.6	38.8	0	0	0
GANF	39.5	93	78.6	28	78	41.2	30.6	1.8	3.4
USAD	28	94	43.1	12.2	80	21.2	12.2	80	21.2
AnomalySimpleton	98.2	94.4	96.2	35.1	1.0	2.0	0	0	0
SPIE-ADS	64	87.7	74	63	86.7	73	63	86.7	73
SPIE-ADL	84	88	86	83	89	86	83	89	86
Method	SMAP								
	A2			¬ A2			¬ A1		
AT	83.8	100	91.2	12.7	90	22.3	0	0	0
GANF	57.5	96	71.9	19.9	93	32.8	0.6	7	1.1
USAD	45	100	62	15.1	94	26	15.1	94	26
AnomalySimpleton	86.4	95.1	90.5	13.6	2.4	4	0	0	0
SPIE-ADS	55	89	68	52	87	65	52	87	65
SPIE-ADL	69.8	91	79	65.7	82.1	73	65.7	82.1	73
Method	MSL								
	A2			¬ A2			¬ A1		
AT	79.5	100	88.6	8.7	27	13.1	0	0	0
GANF	64	85	73	16	48	24	0	0	0
USAD	44.5	38	41	14.5	23.8	18	14.5	23.8	18
AnomalySimpleton	89.6	89.4	89.5	20.9	2.7	4.8	0	0	0
SPIE-ADS	80.2	86	83	80.2	86	83	80.2	86	83
SPIE-ADL	80.3	85.8	83	80.3	85.8	83	80.3	85.8	83

related to its operational performance, such as power consumption, temperature readings, and communication status. These performance metrics are critical for monitoring the health and functionality of the rover, managing its systems, and troubleshooting any technical challenges that arise during its exploration of the Martian surface. The data collected helps scientists and engineers ensure the rover's effective operation and mission success.

A.3 Extended table for real world dataset

Table S2 6 shows the extended results for Table 4 in the main paper with precision and recall values.

A.4 SPIE-AD hyper-parameter optimization

Given a threshold of $r\%$, the hyper parameters of the SPIE-AD method extracts the hyper-paramters of the SPIE-AD method so that atleast $r\%$ data from the training set falls within the robustness interval $[\rho_1, \rho_2]$, while minimizing $(\rho_2 - \rho_1)$. The algorithm currently is a brute force search through all possible hyper-parameter combination to find the best hyper-paramters that matched the above-mentioned conditions.

A.5 Data and Code Availability

The data and code for model recovery using SINDY-MPC are available in `https://anonymous.4open.science/r/U2Recognition-5502/`

To use LTC-NN a manual transfer of model coefficient is required and the pipeline is not entirely automated. Hence, the models available in `https://anonymous.4open.science/r/LTC-NN-MR-4420/` has to be run first and the saved model coefficients needs to be transferred to the U2Recognition github and then run the files described in the U2Recognition github.

The AnomalySimpleton also known as SMDTrash is available in `https://anonymous.4open.science/r/AnomalyAbsurd-5CED/`