
QUANTIFYING ROBUSTNESS: A BENCHMARKING FRAMEWORK FOR DEEP LEARNING FORECASTING IN CYBER-PHYSICAL SYSTEMS *

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ABSTRACT

Cyber-Physical Systems (CPS) in domains such as manufacturing and energy distribution generate complex time series data crucial for Prognostics and Health Management (PHM). While Deep Learning (DL) methods have demonstrated strong forecasting capabilities, their adoption in industrial CPS remains limited due to insufficient robustness. Existing robustness evaluations primarily focus on formal verification or adversarial perturbations, inadequately representing the complexities encountered in real-world CPS scenarios. To address this, we introduce a practical robustness definition grounded in distributional robustness, explicitly tailored to industrial CPS, and propose a systematic framework for robustness evaluation. Our framework simulates realistic disturbances, such as sensor drift, noise and irregular sampling, enabling thorough robustness analyses of forecasting models on real-world CPS datasets. The robustness definition provides a standardized score to quantify and compare model performance across diverse datasets, assisting in informed model selection and architecture design. Through extensive empirical studies evaluating prominent DL architectures (including recurrent, convolutional, attention-based, modular, and structured state-space models) we demonstrate the applicability and effectiveness of our approach. We publicly release our robustness benchmark to encourage further research and reproducibility.

Keywords cyber-physical system, deep learning, robustness testing, time series forecasting

1 Introduction

Cyber-Physical Systems (CPS) continuously generate large-scale and complex time series data across industrial domains such as manufacturing, process engineering, and energy distribution, which enable vital tasks including Prognostics and Health Management (PHM) [1]. Deep Learning (DL) has proven effective in modeling complex data, yet despite its predictive capabilities the adoption of DL in industrial CPS remains limited due to concerns over robustness [2]. Robustness, in this context, refers to the model's ability to maintain reliable performance when encountering erroneous or unforeseen inputs [3]. Regulatory developments, such as the European Union's AI Act, have further highlighted the importance of robust DL systems, urging systematic methodologies for robustness assessment [4]. However, consensus

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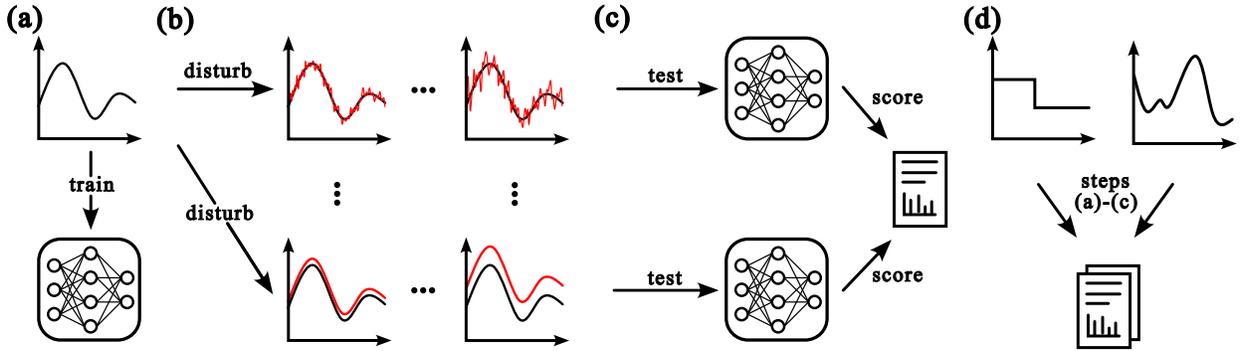


Figure 1: Overview of the proposed robustness evaluation framework. (a) Standardized time series data is partitioned into training, validation, and test subsets, and models are trained accordingly. (b) Realistic disturbances, such as sensor drift, noise, and irregular sampling, are systematically applied to the standardized test subset at varying severity levels. (c) Model predictions are assessed on disturbed test subsets with different severities, and results are used to calculate a robustness score. (d) To ensure comprehensive evaluation, the entire process (a-c) is repeated across multiple datasets for various DL architectures.

on practical robustness testing methodologies remains elusive [5]. While formal verification methods and adversarial robustness studies have been prominent in the literature, their practical relevance to industrial scenarios is limited due to unrealistic assumptions [6]. Recent research emphasizes evaluating model robustness against realistic data quality issues and distributional shifts commonly encountered in real-world settings [7, 8, 9, 10]. However, most research on robustness for CPS either defines robustness theoretically but lacks an extensive evaluation on real CPS data or relies on evaluations on synthetic datasets while missing a comprehensive definition of robustness.

Addressing these limitations, we propose a novel, practical robustness definition tailored specifically to industrial CPS time series forecasting. This definition integrates the principles of distributional robustness by explicitly quantifying model performance degradation under realistic disturbances such as sensor drift, measurement noise, and irregular sampling, which are frequently encountered in real operational environments. Accompanying this definition, we introduce a comprehensive, systematic robustness testing framework designed for assessing and benchmarking diverse DL architectures, including recurrent networks (LSTM, GRU), attention-based models (Transformers, Informers), convolutional models (TCN), modular architectures (RIMs) and structured state-space models (Mamba), on multiple real-world CPS datasets.

Our key contributions are:

- We provide a clear, practical definition of robustness of DL models specifically suitable for industrial CPS.
- We develop a systematic robustness testing framework that quantifies the robustness, bridging theoretical robustness evaluation and real-world applicability.
- We provide empirical robustness evaluations of DL forecasting models across multiple real-world CPS datasets.

Figure 1 illustrates the workflow of our proposed robustness testing methodology. The proposed framework is publicly available at: <https://github.com/awindmann/cps-robustness-benchmark>

2 Related Work

Robustness in DL: Robustness of a DL model is generally described as the ability "to maintain its level of performance under any circumstances" [3], or its capability "to cope with erroneous, noisy, unknown, and adversarial input data" [11]. It is closely related to other concepts such as reliability [12], resilience [13], safety [6] and stability [14]. DL models are known to be highly sensitive to small input perturbations, as first demonstrated by Szegedy et al. [15]. Consequently, much research has focused on adversarial robustness, evaluating model resilience to these small, intentionally crafted perturbations [16, 17], leading to formal guarantees and metrics to measure this type of robustness [18, 19]. However, adversarial perturbations rarely occur naturally, thus recent research emphasizes measuring robustness to broader, more realistic distributional shifts [20, 21]. Traditional adversarial robustness metrics often fail to sufficiently capture these distributional shifts [22, 23]. To address this limitation, recent studies propose evaluating robustness either by assessing performance across multiple distinct environments [24, 25], by applying broad yet realistic natural distribution shifts (e.g., image blur or style changes) [26], or by specifically investigating the impact of data-quality issues [27, 28].

Robustness for Time Series and CPS: Robustness in time series forecasting is generally assessed by evaluating how model performance deteriorates in response to anomalies, commonly measured by increased forecasting errors [29], or by measuring the effect on the output distribution, e.g. by measuring the Wasserstein distance [30]. In CPS, research of robustness has traditionally focused on formal verification [31] or stability in control engineering [14]. Recent studies have specifically investigated the effects of data quality issues such as sensor drift, outliers and missing values on CPS data [8, 9]. Other CPS-focused robustness research has explored adversarial attacks [7], false-positive predictions under varying grades of handicap [32], and model robustness to added random noise [10]. However, most research on robustness for CPS either defines robustness theoretically but lacks an extensive evaluation on real CPS data or relies on evaluations on synthetic datasets while missing a comprehensive definition of robustness.

Prognostics in CPS: In CPS contexts, PHM assesses system health and predicts future system behavior [1, 33]. Many PHM applications rely heavily on DL forecasting models [34, 35]. Commonly used architectures include recurrent neural networks (e.g., LSTM [36], GRU [37]), modular approaches like Recurrent Independent Mechanisms (RIMs) [38], Temporal Convolutional Networks (TCN) [39], attention-based models such as Transformers [40] and Informers [41], and structured state-space models like Mamba [42, 43]. Recent findings indicate that even simple feed-forward neural networks can be competitive [44]. These models represent diverse architectural approaches commonly adopted in CPS forecasting tasks. Despite their widespread application, the robustness of these architectures has primarily been evaluated using synthetic or idealized datasets, potentially masking their real-world vulnerabilities.

In summary, while extensive research has explored general and adversarial robustness in DL, and recent work has begun addressing CPS-specific robustness issues, there remains a notable gap: robustness in CPS has not been explicitly defined or comprehensively evaluated using real-world CPS datasets, which present inherent complexities. This paper addresses this gap by explicitly defining robustness tailored for CPS scenarios and evaluating it thoroughly on real-life CPS datasets, thus providing more realistic and applicable robustness insights.

3 Defining Robustness for CPS

This definition will form the foundation for the testing framework introduced in Section 4.

A CPS monitors several sensors over time, producing multivariate time series data. We denote this time series as $\mathcal{T} = (\mathbf{x}_i)_{i \in \mathbb{N}}$, where each $\mathbf{x}_i \in \mathbb{R}^n$ represents the sensor readings at time step i . Let $\mathbf{X} \subset \mathbb{R}^{(t+t') \times n}$ be a dataset of samples extracted from \mathcal{T} . Each sample is a time window containing $t + t'$ consecutive sensor readings, with $t, t' \in \mathbb{N}$ and starting from a randomly chosen time step i , and is defined as:

$$(X, Y) = ((\mathbf{x}_i, \dots, \mathbf{x}_{i+t-1}), (\mathbf{x}_{i+t}, \dots, \mathbf{x}_{i+t'-1})) \in \mathbf{X}. \quad (1)$$

In forecasting, the goal is to use the first t sensor readings X to predict the subsequent t' readings Y .

We train a model $f \in F$ from the set of prognostic models

$$F = \{f : \mathbb{R}^{t \times n} \rightarrow \mathbb{R}^{t' \times n}\} \quad (2)$$

on the dataset \mathbf{X} to approximate the target Y based on the input X . The model’s prediction $f(X) = \hat{Y}$ is compared to the actual target Y using a performance measure or loss function

$$\mu : \mathbb{R}^{t' \times n} \times \mathbb{R}^{t' \times n} \rightarrow \mathbb{R}_{\geq 0}. \quad (3)$$

For example, a common choice for μ is the Mean Squared Error (MSE), defined by $\text{MSE}(\hat{Y}, Y) = \|\hat{Y} - Y\|_2^2$. We assume that the performance measure is non-negative, with a value of 0 indicating optimal performance. Since the models are evaluated on a finite dataset, the loss μ is finite and thus integrable. If a performance measure does not naturally meet these criteria, it can be transformed via monotonic transformations.

To better model the forecasting setup, we treat each sample (X, Y) (see Eq. (1)) as a realization of a random variable $(\mathcal{X}, \mathcal{Y})$, where $\mathcal{X} : \Omega \rightarrow \mathbb{R}^{t \times n}$ and $\mathcal{Y} : \Omega \rightarrow \mathbb{R}^{t' \times n}$ for a probability space (Ω, \mathcal{A}, P) . Using this notation, the goal of forecasting is defined as minimizing the expected loss

$$\min_{f \in F} \mathbb{E} [\mu(f(\mathcal{X}), \mathcal{Y})].$$

In other words, we are looking for the prognostic model $f \in F$ that can best predict the values of Y based on the preceding time steps X .

However, this formulation assumes stationarity in the underlying data distribution, which typically does not hold in real-world applications due to changing operational conditions, system wear, or unforeseen disturbances. Consequently,

models often experience performance degradation after deployment. To assess and improve model robustness realistically, we propose applying disturbances that simulate diverse operating conditions encountered in practice. Specifically, we define a disturbance function $d \in \mathcal{D}$ as

$$d : [0, 1] \times \mathbb{R}^{t \times n} \times \mathbb{R}^{t' \times n} \rightarrow \mathbb{R}^{t \times n} \times \mathbb{R}^{t' \times n}, \quad (4)$$

which transforms a input-output sample (X, Y) into a disturbed version of itself. We denote the disturbed sample by

$$\left(X_d^{(s)}, Y_d^{(s)} \right) := d(s, X, Y),$$

where the parameter $s \in [0, 1]$ controls the severity of the disturbance. When $s = 0$, no disturbance is applied; when $s = 1$, the disturbance reaches its maximum realistic intensity. In general, as s increases, we expect the disturbed sample to become less similar to the original. For example, in the case of the Noise disturbance, we add Gaussian noise scaled by s to each affected sensor in X , making the sample progressively less like the original. This results in the disturbance function

$$d_{\text{noise}} : (s, X, Y) \mapsto (X + sZ, Y),$$

where $Z \sim \mathcal{N}(0, \mathbb{I})$ represents Gaussian noise. Figure 2 shows an overview of the disturbances used in this study.

To assess model robustness, we compare performance on disturbed samples with performance on the original samples. Since the ideal performance measure may vary across applications, we adopt the general performance measure μ as defined in Eq. (3). For a model f (see Eq. 2) and a disturbance function d (see Eq. 4), we define the relative performance as

$$\mu_{\text{rel}}(f, d, s, X, Y) = \frac{\mu(f(X), Y) + \varepsilon}{\mu\left(f\left(X_d^{(s)}\right), Y_d^{(s)}\right) + \varepsilon}, \quad (5)$$

where $0 < \varepsilon \ll 1$ is a small constant added for numerical stability. The relative performance μ_{rel} measures the effect of a disturbance by comparing the performance on the disturbed sample against the original performance. Note that μ_{rel} makes no statement about the inherent performance of the model, it only measures the effect of the disturbances.

We then define the disturbance robustness score for a model f (see Eq. (2)) and a disturbance function d (see Eq. (4)) using the relative performance μ_{rel} (see Eq. (5)) as

$$R_d(f, \mu) = \mathbb{E} \left[\int_0^1 \mu_{\text{rel}}(f, d, s, \mathcal{X}, \mathcal{Y}) ds \right]. \quad (6)$$

In other words, for a given disturbance d , we gradually increase its severity s from 0 to 1 and integrate the relative performance over this range. This score R_d reflects how much the disturbance affects the model’s performance. Values of R_d at or around 1 indicate that the disturbance has little to no negative impact, while values close to 0 suggest that the model’s performance deteriorates sharply. Note that while in theory the data could be sampled from the underlying distribution P , in practice we chose to sample from the test partition of the dataset.

Finally, to evaluate the overall robustness of a model f (see Eq. (2)) using a performance measure μ (see Eq. (3)), we multiply the disturbance robustness scores R_d (see Eq. (6)) across the disturbance functions d (see Eq. (4)):

$$R(f, \mu) = \prod_{d \in \mathcal{D}} R_d(f, \mu). \quad (7)$$

The multiplication ensures that a complete failure in any one disturbance scenario (where R_d is near 0) significantly lowers the overall robustness score, while poor performance across multiple disturbances compounds the effect, providing a nuanced picture of the model’s overall robustness. Alternatively, one could average the scores R_d over all $d \in \mathcal{D}$, but this approach might dilute the impact of a complete failure in one scenario. Another approach would be to pick the minimum disturbance robustness score, which would highlight the worst-case performance but could ignore more gradual degradations in other scenarios.

4 Proposed Framework

To evaluate the proposed definition of robustness, we implemented a framework that simulates disturbances in CPS datasets to quantify the robustness of popular DL model architectures. We focus on a forecasting task as a representative objective, since it requires a deep understanding of the underlying system and is closely related to common industrial applications such as PHM. The framework is openly accessible, supports custom time series data in CSV or Parquet

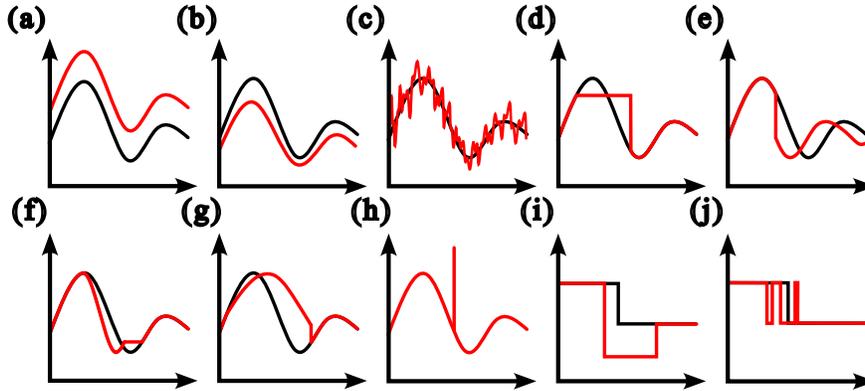


Figure 2: Overview of the disturbance scenarios applied to a subset of sensors of the standardized time series data. The black line indicates the original time series, the red line signifies the time series after the disturbance has been applied. (a) **Drift**: A constant offset is added to the signal. (b) **DyingSignal**: The amplitude diminishes by multiplying the values by a factor smaller than 1. (c) **Noise**: Gaussian noise is added to the signal. (d) **FlatSensor**: The sensor remains constant for a designated time interval. (e) **MissingData**: An entire segment of the time series is removed to simulate missing values. (f) **FasterSampling**: The sampling rate is temporarily increased, followed by a flat sensor period until the time steps realign. (g) **SlowerSampling**: The sampling rate is temporarily decreased until the time steps realign. (h) **Outlier**: The signal exhibits an unusually high spike value at a specific time step. (i) **WrongDiscreteValue**: A discrete sensor is set to an invalid state for a certain period. (j) **OscillatingSensor**: A discrete sensor oscillates between two valid states for a certain duration.

format and can easily integrate models implemented in Python. An overview of the proposed framework is shown in Figure 1.

First, we preprocess a given multivariate time-series dataset by removing missing values and splitting the data into training, validation, and test sets along three disjunct continuous time segments. To mitigate information leakage, we purge a small fraction of the data near the boundaries between these segments, ensuring that the model does not see validation or test data during training. We then standardize all datasets based on the statistics of the training split, which helps during training and ensures that the disturbances are applied consistently. The final training, validation, and test sets are created by randomly sampling time frames from their respective segments, after which the model is trained on the resulting training data.

The disturbances (see Eq. (4)) simulate behavior commonly encountered in real-world CPS environments, like sensor drift, noise and irregular sampling, in gradually increasing severity. Thus, the robustness score (see Eq. (7)) can effectively measure the effect of such critical scenarios, providing a relevant quantification of model robustness. Figure 2 provides an overview of these test scenarios. For each dataset, we affect a subset of 10% of the sensors. Since the dataset is standardized, the effect of each disturbance is comparable across different datasets. Some disturbances apply solely to continuous signals (e.g., Noise), while others are specific to discrete signals or actuators (WrongDiscreteValue, OscillatingSensor). Most disturbances are not applied to the portion of the time series to be forecasted, as it would be infeasible or undesirable to predict faulty sensor values. However, MissingData requires the model to ignore the missing values and forecast using the most recent available time steps, so the section of the time series to predict changes.

The final robustness score based on these disturbances is calculated as explained in Section 3.

5 Experimental Setup

To yield a comprehensive analysis of the robustness score and the aforementioned testing framework, we included a wide range of CPS datasets as well as many commonly used forecasting models. The datasets used in this study include:

- **Electricity**[45]: This dataset provides hourly electricity consumption records for 321 customers over the period from 2012 to 2014.
- **ETT**[41]: The ETT dataset captures measurements from electronic transformers, including load and oil temperature, over a two-year period. It is offered at two temporal resolutions: Hourly aggregated data with 17,420 observations across 7 features (ETT_h1) and data recorded at 15-minute intervals, comprising 69,680 observations across 7 features (ETT_m1).

- **SKAB**[46]: The SKAB dataset contains sensor readings from a water circulation system testbed. Data were collected at a one-second sampling rate over a three-hour period, resulting in 9,405 observations of 8 sensor variables.
- **SWaT**[47]: The Secure Water Treatment (SWaT) dataset by iTrust, Centre for Research in Cyber Security, Singapore University of Technology and Design consists of sensor and actuator measurements obtained from a scaled-down version of an industrial water treatment plant. Data were recorded at one-second intervals continuously over seven days, yielding 449,919 observations with 52 features.
- **Water Quality**[48]: This dataset monitors water quality in the water supply system serving a state in Germany, with 9 sensor readings taken at one-minute intervals from August to November 2016.

In this work, we investigate a diverse set of forecasting models spanning several architectural families, including relatively simple fully connected neural networks, recurrent neural networks (RNN), convolutional neural networks (CNN), state-space models (SSM) and Transformers. In particular, our study considers the following models:

- **DLinear**[44]: A linear forecasting model that integrates a time series decomposition strategy to separately model trend and seasonal components.
- **MLP**[49]: A Multi-Layer Perceptron that employs a series of linear transformations interleaved with ReLU activation functions [50] and batch normalization [51] to enhance convergence and generalization.
- **TCN**[39]: A Temporal Convolutional Network that leverages causal convolutions and dilated convolutions to capture long-range dependencies of temporal data.
- **LSTM**[36]: A Long Short-Term Memory network that incorporates gating mechanisms to mitigate the vanishing gradient problem.
- **GRU**[37]: A Gated Recurrent Unit network that simplifies the LSTM architecture by combining the forget and input gates into a single update gate.
- **RIMs**[38]: A Recurrent Independent Mechanisms model that decomposes the hidden state into multiple independent modules. Each module selectively processes different aspects of the input, thereby enhancing robustness.
- **Transformer**[40]: A self-attention based architecture that abandons recurrence in favor of parallelized computations.
- **Informer**[41]: An efficient variant of the Transformer specifically designed for long sequence forecasting.
- **Mamba**[43]: A SSM that exploits linear time-invariant dynamics to efficiently model sequential data.

Further information about the experimental setup include:

Objective and Hyperparameter Tuning: Our training objective is to forecast the next 30 time steps given the previous 90 time steps, with all models optimized to minimize the MSE using backpropagation. Extensive hyperparameter tuning is performed via grid search on each dataset separately. In total, over 10,000 models across 9 model architectures and 6 datasets have been trained. The specific hyperparameter and their respective ranges are available in our online repository.

Data Splitting and Preprocessing: Each dataset is partitioned into fixed time splits, allocating 70% for training, 15% for validation, and 15% for testing. To mitigate potential data leakage, we insert a purging gap equivalent to 1% of the data between each split. The training data is standardized using its own statistical properties, and the same transformation is applied to the validation and test sets.

Optimization and Batching: All models are trained using a batch size of 64. The fixed learning rate is chosen as part of the hyperparameter tuning. The optimization is carried out using the Adam optimizer [52].

Early Stopping and Model Checkpointing: Early stopping is employed with a patience of 5 epochs based on the validation loss. The checkpoint corresponding to the lowest MSE on the validation set is retained as the final model for each architecture and dataset.

Computational Resources: All training is executed on a Kubernetes cluster comprising three nodes, each equipped with 128 CPU cores and 500GB of memory, alongside a total of 4 NVIDIA A30 GPUs. Similar to the approach presented in [53], we orchestrated the execution of the experiments using Kubeflow pipelines.

Table 1: Forecasting performance by model architecture. Values are the mean \pm standard deviation across six datasets; lower values indicate better performance. Best performance values are shown in bold and second-best values are underlined.

Architecture	Model	Validation MSE	Test MSE
Fully Connected	DLinear [44]	0.2174 \pm 0.1393	0.2587 \pm 0.1809
Fully Connected	MLP [49]	0.2284 \pm 0.1523	0.3916 \pm 0.2460
Convolution	TCN [39]	0.2470 \pm 0.1550	0.4362 \pm 0.2834
Recurrent	LSTM [36]	0.2575 \pm 0.1758	0.5016 \pm 0.3676
Recurrent	GRU [37]	0.2393 \pm 0.1679	0.4620 \pm 0.3209
Modular	RIMs [38]	0.2383 \pm 0.1655	0.3868 \pm 0.2250
Attention	Transf. [40]	<u>0.2200</u> \pm 0.1575	0.3576 \pm 0.2123
Attention	Informer [41]	0.2203 \pm 0.1550	<u>0.3552</u> \pm 0.2006
SSM	Mamba [43]	0.3047 \pm 0.1945	0.7177 \pm 0.7299

Reproducibility: A fixed random seed is set across all individual model trainings to ensure reproducibility. Furthermore, the entire framework and experiment configuration is documented and publicly available in our online repository.

6 Results

In this section, we present the forecasting performance of the evaluated models across multiple real-world CPS datasets, quantify their robustness using the robustness score (Eq. (7)), and further analyze the specific disturbance scenarios.

6.1 Baseline Forecasting Performance

Table 1 summarizes the forecasting performance, reporting mean and standard deviation of the MSE for validation and test sets across six standardized datasets. DLinear achieves the best overall forecasting performance, closely followed by Transformer-based models. Notably, a simple MLP outperforms dedicated time-series models such as TCN, LSTM, GRU and Mamba, indicating the efficacy of simpler architectures. The Mamba model performs poorly and exhibits considerable variability across test datasets, highlighting its sensitivity to dataset-specific features.

Additionally, we observe the generalization capabilities of the models, reflected by their performance consistency between validation and test datasets. DLinear exhibits minimal variation between validation and test performance, indicating good generalization. Transformer variants, MLP, and RIMs display moderate generalization capabilities with slightly larger performance drops. In contrast, models such as TCN and LSTM experience more significant reductions, suggesting weaker generalization.

6.2 Robustness Evaluation

The robustness scores based on MSE are summarized in Table 2. Despite demonstrating strong forecasting performance, DLinear exhibits the lowest robustness score, indicating high susceptibility to disturbances. Recurrent architectures (LSTM, GRU, and the modular RIMs) achieve the highest robustness scores, with LSTM performing best overall. These findings imply inherent robustness characteristics associated with recurrent-based architectures.

None of the evaluated models attain robustness scores approaching the ideal value of 1 or above, highlighting the challenging nature of the proposed benchmark framework. Furthermore, the substantial variation in robustness scores across datasets emphasizes the necessity of multi-dataset evaluations to reliably quantify and compare model robustness.

6.3 Detailed Scenario Analysis

As described in Section 3, each disturbance was evaluated with increasing severity to assess model susceptibility comprehensively, which is exemplary illustrated for DLinear on SWaT in Figure 3. The results show scenario-specific sensitivities: scenarios such as FasterSampling and SlowerSampling have no negative impacts, whereas OscillatingSensor and Outlier notably degrade performance. Generally, increased severity corresponds to decreased relative performance. However, in the MissingData scenario, removing more time steps occasionally improved performance at certain severity levels, reflecting the periodic characteristics of CPS data.

Table 2: Robustness scores based on MSE by model architecture. Values are the mean \pm standard deviation across six datasets; higher scores indicate greater robustness. Best performance is shown in bold and the second-best value is underlined.

Architecture	Model	Robustness Score
Fully Connected	DLinear [44]	0.2754 \pm 0.2455
Fully Connected	MLP [49]	0.4577 \pm 0.2494
Convolution	TCN [39]	0.4498 \pm 0.2814
Recurrent	LSTM [36]	0.6411 \pm 0.3412
Recurrent	GRU [37]	<u>0.5948</u> \pm 0.3543
Modular	RIMs [38]	<u>0.5886</u> \pm 0.2856
Attention	Transf. [40]	0.4745 \pm 0.2577
Attention	Informer [41]	0.4748 \pm 0.2670
SSM	Mamba [43]	0.5186 \pm 0.3804

Relative Performance Based on MSE Across Severity Levels for DLinear

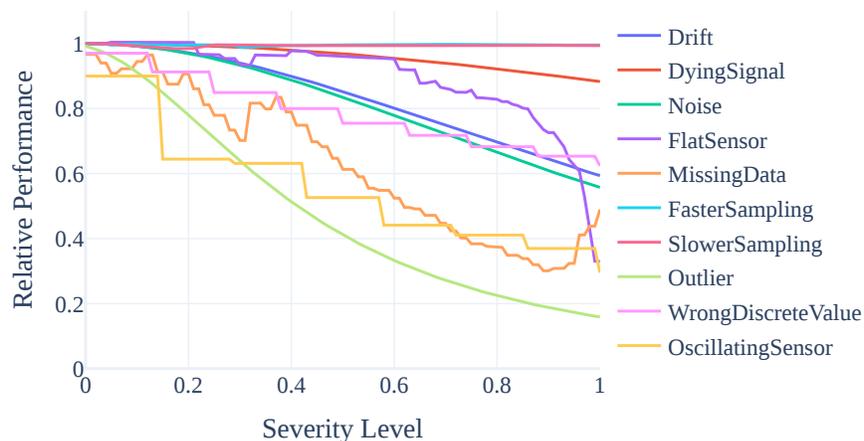


Figure 3: Relative performance of DLinear on the SWaT dataset for multiple test scenarios across severity levels, computed from MSE (Eq. (5)).

Figure 4 provides a comprehensive comparison of the models’ robustness across individual disturbance scenarios, averaged across all severity levels and datasets. Here, the disturbance robustness score (see Eq. (6)) quantifies the models’ robustness to individual scenarios. Most scenarios demonstrate moderate negative impacts with substantial variability across datasets. The MissingData scenario consistently had the greatest adverse effect overall, with notable architectural differences: recurrent models (LSTM, GRU, RIMs) and Mamba exhibited higher robustness compared to other architectures. Nevertheless, inter-architecture differences for each disturbance scenario remain relatively modest when considering the high variability across datasets.

7 Discussion

In this paper, we have introduced a practical definition of robustness tailored specifically to industrial CPS time series and evaluated this definition through a comprehensive forecasting benchmark involving multiple DL architectures. One insight is the strong performance of relatively simple models such as DLinear, confirming earlier findings [44]. However, despite its excellent predictive accuracy on both validation and test datasets, DLinear was highly vulnerable to disturbances, achieving the lowest robustness score among all tested architectures. This shows that standard evaluation methods might not detect overfitting and fail to quantify robustness, which is further affirmed by empirical research in the deployment of machine learning models [54].

Overall, recurrent architectures (LSTM, GRU, and modular RIMs) demonstrated high robustness scores. This could be attributed to their design, which inherently emphasizes recent temporal dependencies, enabling them to better withstand disturbances affecting earlier time steps. In particular, LSTM exhibited the highest robustness score, potentially

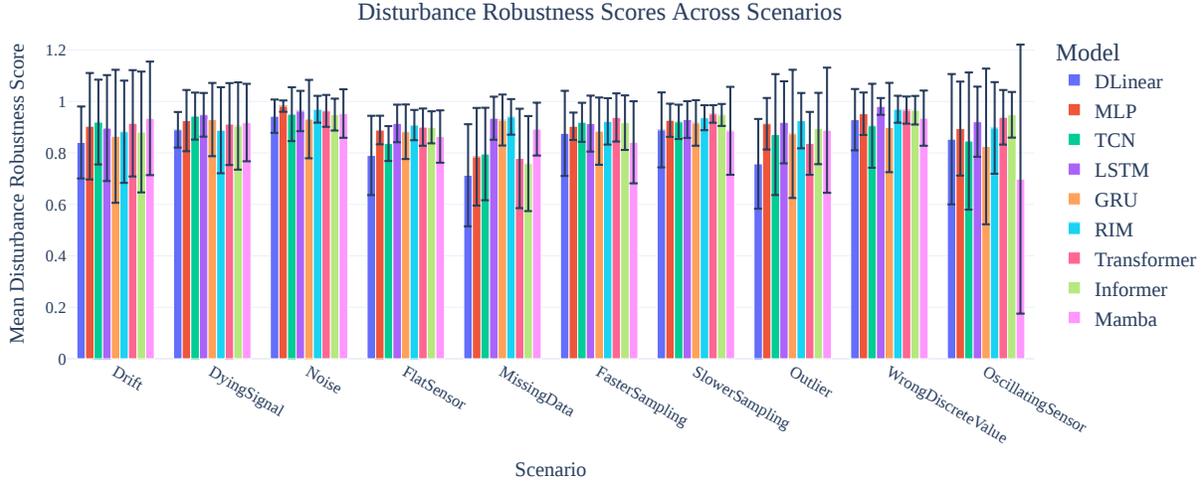


Figure 4: Grouped bar chart of the disturbance robustness scores based on the MSE for various models across testing scenarios. For each model/scenario combination, the disturbance robustness score (defined in Eq. (6)) is computed and then averaged across six datasets. Error bars denote one standard deviation of the dataset-level averages. Details about the testing scenarios are provided in Fig. 2.

explaining its widespread adoption in CPS deployments despite its moderate forecasting performance. The Transformer-based models displayed strong forecasting performance and moderate robustness, suggesting they could be a suitable compromise between robustness and prognostic accuracy. Surprisingly, the recently developed Mamba architecture performed poorly both in forecasting accuracy and robustness.

The disturbance robustness scores displays a large variability across some datasets, which shows the complexity in designing realistic yet challenging disturbance scenarios. This emphasizes the importance of multi-dataset, multi-scenario evaluations to reliably assess and compare model robustness.

Future work should systematically evaluate additional relevant model classes, including interpretable statistical models, hybrid statistical-DL approaches, physics-informed models, graph-based architectures, large-scale pretrained foundation models and other state-of-the-art methods. Furthermore, the disturbances could be used during training to improve model robustness.

8 Conclusion

This paper introduced a definition of robustness for prognostic models in CPS and a benchmarking framework to evaluate their robustness under disturbance scenarios. Our experiments show that while simpler linear models often achieve higher baseline predictive accuracy than complex deep learning models, they are less robust. Recurrent neural networks offer improved robustness with moderate forecasting performance, whereas Transformers provide a balanced compromise between accuracy and robustness. These results underscore the importance of jointly considering robustness and forecasting performance during model selection for CPS applications.

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