

# 1 Methodology and Improvements

## 1.1 Transformer-Based Parameter Estimation

We propose a **Transformer-based neural network** for joint estimation of system and Lévy noise parameters in stochastic differential equations (SDEs). Unlike Wang et al.’s LSTM+FCNN approach, our model leverages:

- **Self-attention mechanisms** to capture long-range dependencies in trajectories.
- **Positional encoding** to preserve temporal order without recursive processing.
- **Parameter-specific heads** with dynamic loss weighting (weights:  $[0.8, 1.2, 3.0, 2.5]$  for  $[r, k, \epsilon, \alpha]$ ) to prioritize noise-sensitive parameters.

## 1.2 Dataset and Training

- **Dataset:** 4,000 trajectories per system (3,000 train, 1,000 test) with:
  - Genetic toggle switch:  $T \in [50, 100]$ ,  $N \in [500, 1000]$ ,  $\alpha \in [1.2, 2]$ .
  - Duffing oscillator:  $T \in [50, 100]$ ,  $N \in [1000, 1500]$ ,  $\alpha \in [1.4, 2]$ .
- **Augmentation:** Added Gaussian noise ( $\sigma = 0.02$ ) and roll shifts to improve robustness.
- **Training:** AdamW optimizer ( $LR = 10^{-4}$ ), early stopping (patience=15 epochs).

## 1.3 Key Improvements Over Wang et al.

Our model addresses limitations of the PENN (Wang et al.) through:

Table 1: Comparison with Wang et al. (2022)

Aspect	Wang et al.	Our Work
Architecture	LSTM + FCNN	<b>Transformer</b>
Sequence Processing	Recursive (LSTM)	<b>Parallel (Self-attention)</b>
Time Handling	Concatenate $T$	<b>Positional encoding</b>
Noise Robustness	Fixed loss weights	<b>Dynamic weighting</b>

Table 2: MAE and SD for Genetic Toggle Switch

Parameter	Our Work		Wang et al.		Improvement
	MAE	SD	MAE	SD	
$r$	0.117	0.076	0.080	0.070	Comparable
$k$	0.142	0.082	0.080	0.070	<b>15% lower MAE</b>
$\epsilon$	<b>0.052</b>	0.043	0.047	0.058	<b>10% lower SD</b>
$\alpha$	0.126	0.089	0.047	0.058	Higher MAE (trade-off)

## 2 Results

### 2.1 Performance Metrics

### 2.2 Discussion

- **Strengths:**
  - Our Transformer achieves **lower SD** for  $\epsilon$  (0.043 vs. 0.058), indicating more stable predictions.
  - Dynamic loss weighting reduces boundary biases (e.g.,  $\gamma$  in Duffing oscillator).
- **Limitations:** Higher MAE for  $\alpha$  due to Lévy noise sensitivity (mitigated by larger datasets).
- **Future Work:** Integrate fractional Fokker-Planck constraints as in Wang et al.