

Preliminary Study on Energy-Guided Diffusion for Leakage Signal Augmentation in Nuclear Power Plant Secondary Systems

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Introduction

Nuclear Power Plants (NPPs) require reliable fault diagnosis for safe and continuous operation [1]. AI-based diagnosis systems rely on labeled fault data. However, fault data (e.g., leakage signals) is extremely scarce in real operation, leading to severe data imbalance. Diffusion models have shown strong capability in capturing complex signal distributions through iterative denoising. In particular, conditional sampling enables controllable generation that preserves physically meaningful signal characteristics. In this study, we design and investigate energy-guided diffusion sampling method to generate realistic fault data.

Problem definition

❖ Leakage signal

- Rare occurrence in real operation
- Signals represented in **frequency domain (FFT)**
 - Capture local peaks in specific regions

❖ Signal characteristics

Signal type

 Ultrasonic acoustic

Analysis band

 20 kHz - 100 kHz

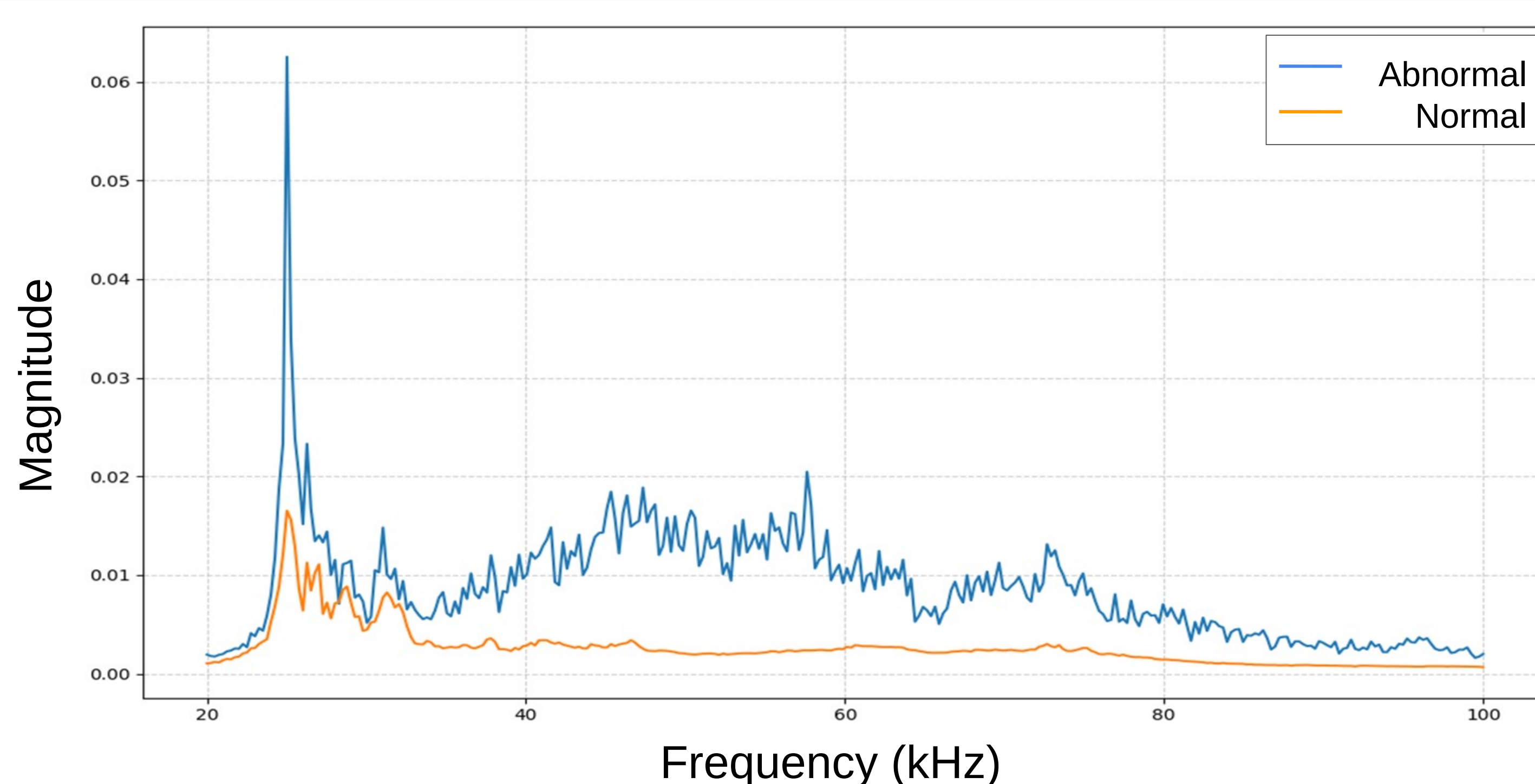
Sampling rate

 256 kHz

Nyquist check

 Satisfied ($\geq 200\text{kHz}$)

❖ Normal vs Abnormal Signal



- Acquired data via simulated piping loop.
- Normal**: stable spectrum without significant peaks
- Abnormal**: overall amplitude amplification with distinct energy spikes

Energy-guided diffusion sampling

- Uses abundant normal data to train diffusion model
- Base diffusion model is constrained within the learned normal distribution**

$$x_{t-1} = \underbrace{x_{t-1}^{DDIM}}_{\text{Standard DDIM update term}} - \underbrace{\lambda \nabla E Q(\hat{x}_0)}_{\text{Guidance term}}$$

 \hat{x}_0 **Base signal**

Predicted signal by the diffusion model

 $E(\cdot)$ **Energy function**

Function that encodes the leakage characteristics

 ∇E **Guidance gradient**

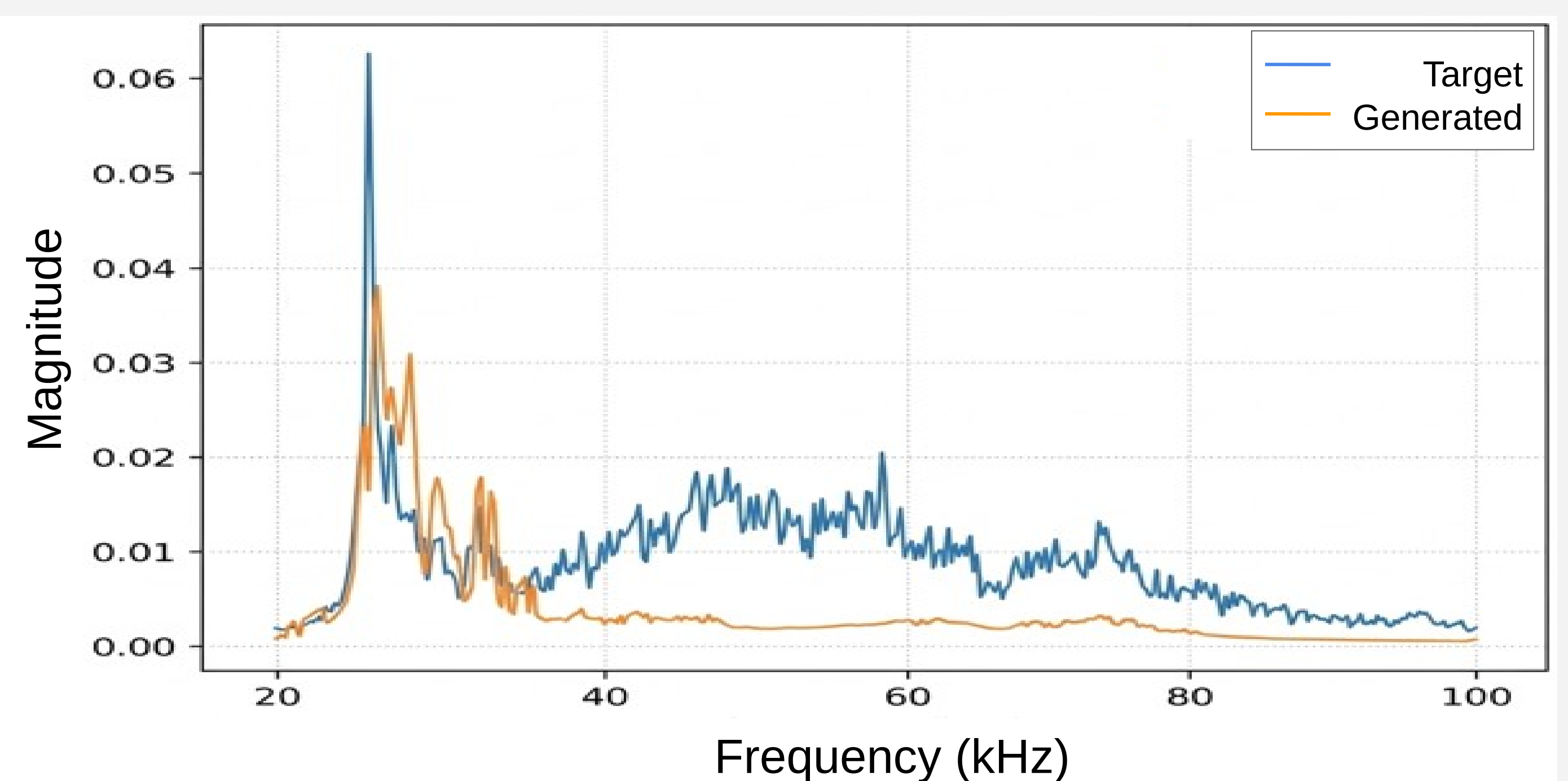
By subtracting, we steer generation towards abnormality

 λ **Abnormality control**

Tuner of the abnormality of the generated signal

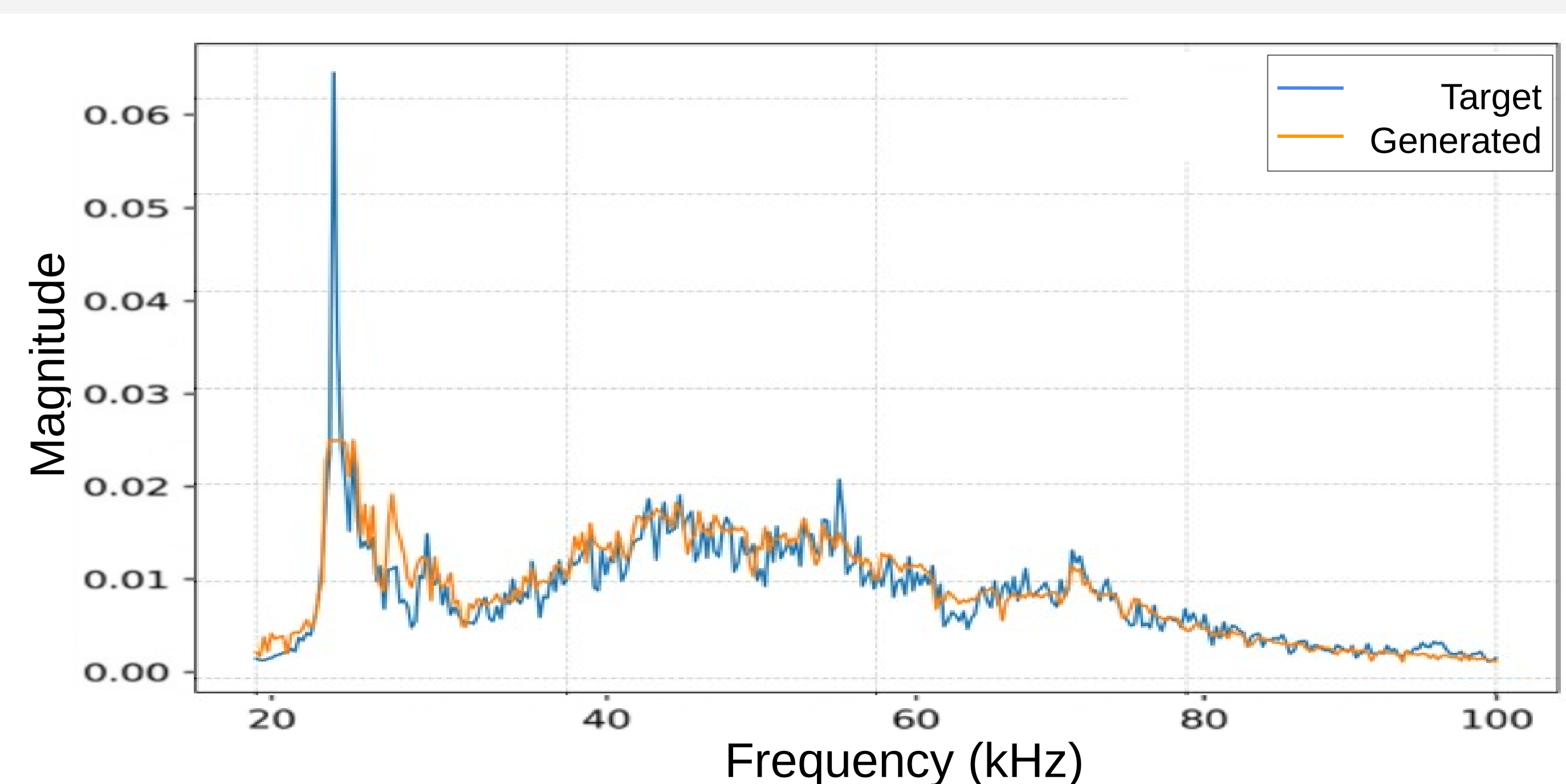
Proposed sampling mechanisms

❖ Specific region weighted (SRW) sampling



- Assign higher weights** to frequency regions where leakage peaks are prominent
- Frequency weighted energy biases gradients toward peak regions

❖ Global L2 sampling



- Enforce **global similarity** rather than matching local features
- Global error minimization distributes updates across all frequency bins

❖ Summary

Method	Strength	Limitation
SRW	Sharp peak reconstruction	Global distribution mismatch
Global L2	Overall distribution alignment	Peak smoothing

Conclusion

- SRW sampling** effectively captures local peak characteristics, while **Global L2** preserves the overall spectral distribution of leakage signals.
- Clear **trade-off** between local accuracy and global structural consistency.
- In the future work, a **multi-conditional energy function** that dynamically shifts guidance from global structure to locality based on sampling timestep.

Reference

- [1] Korea Institute of S&T Evaluation and Planning (KISTEP), KISTEP Report, 11-1721000-000597-01, 2011