WaveGen: Truly End-to-End Waveform Generation via Internal Spectral Trajectory Learning

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Abstract

This work proposes WaveGen, a fully end-to-end diffusion-based text-to-waveform framework based on Spectral Forcing, which jointly learns an internal spectral trajectory and the target waveform trajectory within a single model, enabling direct end-to-end text-to-waveform generation. Unlike recent TTS pipelines, WaveGen does not rely on separately trained or externally decoded intermediate representations, such as neural audio codecs, Mel-spectrogram vocoders, or VAE-based latent models. In addition, WaveGen performs internal text-speech alignment within a single model, eliminating the need for external alignment modules such as duration predictors. To preserve a truly end-to-end formulation, our framework further avoids dependence on self-supervised representations, such as BERT-based text embeddings and Wav2Vec 2.0-based semantic representations, as well as semantic distillation methods for training optimization. To achieve this, we carefully design Spectral Forcing, a model architecture with disentangled diffusion heads, and a training objective based on a multi-scale spectral v-loss. We further validate the scalability of end-to-end TTS models by scaling the model size from 0.1B to 0.6B parameters. Using a single architecture, open-source data, and one-stage training, without external modules such as duration predictor or REPA, WaveGen demonstrates fully end-to-end waveform generation achieving state-of-the-art performance on the Emilia training dataset. In particular, WaveGen achieves a WER of 1.47 and a SIM of 0.75 on the Seed-en benchmark. Source code and checkpoints are available at https://github.com/sh-lee-prml/WaveGen.

1 Introduction

Recent progress in language models and generative models has substantially advanced text-to-speech (TTS) synthesis. Large language model (LLM)-based TTS systems [58, 22] have replaced conventional acoustic representations with neural audio codecs, enabling speech generation through discrete token modeling and in-context voice prompting. In parallel, diffusion and conditional flow matching (CFM)-based TTS models [33, 5] have improved the quality and flexibility of Mel-spectrogram generation through masked infilling and zero-shot voice conditioning. More recently, latent diffusion approaches [75, 47] further improve the efficiency of generative modeling by operating in compressed representation spaces rather than directly modeling high-dimensional audio signals.

Despite these advances, most recent TTS systems still rely on intermediate representations and external waveform decoders. Codec-based models [7, 6, 57] depend on the capacity and quality of neural audio codecs [72, 8, 32, 23, 70, 10, 63, 11]; Mel-spectrogram-based models require separately

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trained neural vocoders; and latent diffusion models require an additional pre-trained latent. These intermediate modules have been highly effective in practice, but they also introduce additional training stages, architectural dependencies, and upper-bound constraints on the final quality. In particular, high-fidelity waveform generation often requires GAN training, carefully designed architectures, or representation-specific optimization, making the overall pipeline increasingly complex.

Meanwhile, although end-to-end (E2E) TTS models [53, 26, 12] were explored in earlier studies, their limited scalability, training instability, and inferior zero-shot quality led the field to converge toward multi-stage pipelines. These limitations stem from the high temporal resolution of raw waveforms, which makes text-speech alignment difficult and often requires complex adversarial training for perceptually realistic waveform generation. Only E3-TTS [17] demonstrated the potential of waveform-level diffusion for TTS. However, it still relies on BERT-based text representations to facilitate text-waveform alignment, and directly applying diffusion modeling to waveform signals imposes a substantial computational burden due to the high temporal resolution of audio.

In this work, we propose **WaveGen**, a fully E2E diffusion-based text-to-waveform framework built upon **Spectral Forcing**. WaveGen directly generates high-resolution waveform from text within a single architecture. The key idea is to revisit the prediction and loss spaces of CFM for raw waveform generation. We found x-prediction with v-loss is essential for E2E waveform generation. Instead of forcing the model to learn waveform dynamics alone, Spectral Forcing jointly guides the model to learn an internal spectral trajectory while optimizing the target waveform trajectory. This design provides a structured inductive bias for high-resolution audio generation while preserving a truly E2E text-to-waveform formulation.

To this end, we carefully design WaveGen architecture with disentangled diffusion heads and introduce a multi-scale spectral loss for stable waveform-level flow matching. We further investigate the scalability of E2E TTS by increasing the model size from 0.1B to 0.6B parameters, showing that direct text-to-waveform generation can benefit from model scaling when the training objective and architecture are properly designed.
Our main contributions are summarized as follows:

- We propose **WaveGen**, a fully E2E text-to-waveform framework that directly generates raw waveform from text without separately trained intermediate representations.
- We introduce **Spectral Forcing**, which jointly learns an internal spectral trajectory and the target waveform trajectory, enabling stable CFM-based optimization in the high-resolution waveform domain.
- We investigate prediction and loss spaces for waveform generation and design a scalable waveform-level diffusion architecture with disentangled diffusion heads.
- We demonstrate that WaveGen achieves state-of-the-art zero-shot TTS performance using a single architecture, open-source data, and one-stage training, providing evidence that fully E2E text-to-waveform generation can be a viable alternative to increasingly complex multi-stage TTS pipelines.

2 Related Work

2.1 Conventional TTS

Traditional TTS systems consist of an acoustic model and a neural vocoder. Acoustic models generate acoustic features such as Mel-spectrogram, and neural vocoders convert acoustic features into raw waveform signals. Tacotron [64] paved the way of deep-learning based TTS system by introducing attention-based encoder-decoder structure to align text with speech, and Tacotron 2 [55] utilized WaveNet [44] to generate waveform from synthetic Mel-spectrogram. Transformer TTS [40] verified the effectiveness of encoder-decoder Transformer. However, these models suffer from unstable attention alignment and slow inference speed due to their autoregressive (AR) nature. To address these issues, FastSpeech [52] introduced parallel synthesis using a duration which is extracted from teacher AR models. Also, GAN-based neural vocoders accelerated TTS research in terms of both quality and inference speed. Specifically, PWG [67] and MelGAN [31] introduced GAN-based vocoder, and HiFi-GAN [29] introduced multi-period discriminator (MPD) which significantly enhances perceptual quality of synthetic speech. BigVGAN [35] scaled up the neural vocoder via snake periodic activation and an anti-aliasing low-pass filter. iSTFTNet [24] and Vocos [56] enhance the sampling efficiency by modeling features in a low-resolution space with iSTFT.

Table 1: Comparison of WaveGen with recent TTS systems. WaveGen uniquely achieves a fully E2E single-stage zero-shot TTS without relying on intermediate representations or auxiliary modules. T, C, W, M, L, and B denote text, codec, waveform, Mel, latent, and BERT, respectively.

Model	Qwen3-TTS	VoiceBox	E2/F5-TTS	CosyVoice3	VoxCPM	VITS	E3-TTS	**WaveGen**
End-to-End (T→W)	✗	✗	✗	✗	✗	✓	✗	✓
Single-stage	✗	✗	✗	✗	✗	✓	✗	✓
Zero-shot	✓	✓	✓	✓	✓	✗	✓	✓
Dependency on Intermediate Representations (Explicit Waveform Decoder)								
Codec	✓	✗	✗	✓	✗	✗	✗	✗
Vocoder	✗	✓	✓	✓	✗	✗	✗	✗
VAE / Latent Model	✗	✗	✗	✗	✓	✗	✗	✗
GAN-based Training	✓	✓	✓	✓	✓	✓	✗	✗
Dependency on External Alignment Modules								
Pre-trained LLM	✓	✗	✗	✓	✓	✗	✓	✗
Duration Predictor	✗	✓	✗	✗	✗	✓	✗	✗
Pipeline Complexity	T→C→W	T→M→W	T→M→W	T→C→M→W	T→L→W	T→W	T→B→W	**T→W**

Neural Codec Language Models With the emergence of large language models, AudioGen [30] introduces language model-based audio generative models based on text prompt and utilize RVQ-based neural audio codec as a discrete audio representation. Then, VALL-E [58] demonstrated neural codec language models can be a strong zero-shot TTS system with large-scale training and speech-level prompting. UniAudio [68] and Moshi [9] proposed efficient RVQ decoding method using multi-scale Transformer. Recently, most models utilize a pre-trained LLM for TTS backbone, and finetuned them to decode semantic token [13, 14] or RVQ tokens [27, 22, 18] which are extracted from large-scale high-quality audio codec via multi-token prediction (MTP) AR Transformer. Metis [62] and OmniVoice [78] employ a discrete diffusion language model using bidirectional Transformer.

Diffusion/CFM Grad-TTS [49] demonstrated the effectiveness of diffusion models for TTS. VoiceBox [33] and P-Flow [28] propose CFM-based TTS models via a masked-infilling training strategy, which significantly improve zero-shot speech synthesis through speech prompting. E2-TTS [15] introduces novel text-speech alignment learning with filler tokens. F5-TTS [5] and ZipVoice [77] introduce efficient CFM-based TTS models without any external duration predictor. Also, hybrid models such as CosyVoice [13, 14] utilized CFM-based Mel-spectrogram decoder conditioned on semantic tokens. Meanwhile, latent diffusion models (LDM) [34] have been investigated for efficient TTS modeling. Furthermore, continuous language models such as VoxCPM [75] and VibeVoice [47] show their effectiveness of AR diffusion via highly-compressed latent representation.

2.2 End-to-End TTS

E2E TTS has long been investigated as a way to simplify conventional cascaded speech synthesis pipelines. Early neural TTS systems such as Tacotron [64] established a unified sequence-to-sequence framework for text-to-acoustic modeling, but still required a Griffin-Lim algorithm [19]. ClariNet [48] explored parallel waveform generation through knowledge distillation from autoregressive WaveNet models. FastSpeech 2s [53] extended non-autoregressive TTS toward direct waveform generation. EATS [12] jointly optimized learnable duration modeling and waveform generation with adversarial training. VITS [26] introduced a strong text-to-waveform framework by combining variational inference, normalizing flows [25], and adversarial waveform training [29].

Despite these advances, prior E2E TTS systems still have important limitations: many rely on adversarial training to obtain perceptually realistic waveforms, which require carefully designed multiple discriminators, auxiliary losses, and significantly long training. More importantly, most of these models were not primarily designed for zero-shot speech synthesis, where the model must generate high-quality speech for unseen speakers from text and speech prompts. As a result, recent zero-shot TTS research has largely shifted toward codec-based language models, Mel-spectrogram diffusion models, or LDM rather than direct waveform-level generation.

Recently, E3-TTS [17] revisited diffusion-based text-to-waveform generation, demonstrating the potential of waveform-level generative modeling for TTS; however, it still relies on pretrained BERT-based text representations to facilitate text-waveform alignment, and directly applying diffusion modeling to high-resolution waveform signals introduces substantial computational cost. In contrast, this paper revisits fully E2E TTS under a stricter formulation: a single model directly generates waveform from text without neural audio codecs, Mel-spectrogram decoders, VAE, neural vocoders, duration predictors, self-supervised representations, or adversarial training as indicated in Table 1.

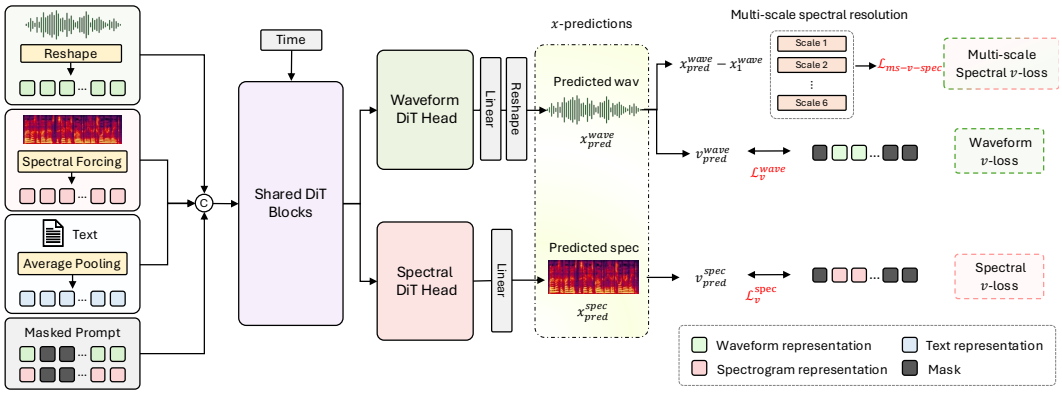


Figure 1: E2E text-to-waveform diffusion training details. We reshape high-resolution waveform signals (24,000 Hz) into a low-resolution space (100 Hz) for efficient E2E waveform diffusion. Then, we introduce Spectral Forcing for internal spectral guidance and simply concatenate average-upsampled text embeddings. We use shared DiT blocks for text-speech alignment and disentangled DiT heads for representation refinement. We adopt x-prediction as the prediction space, and v-loss as the target loss space, and introduce a new multi-scale v-space spectral loss

3 WaveGen

In this paper, we propose a fully E2E single-stage diffusion-based text-to-waveform generative model as illustrated in Figure 1. We analyze raw waveform as generative targets (Section 3.1), introduce a novel framework (Section 3.2), and efficient architecture (Section 3.3). Also, we revisit the prediction space and loss space for raw waveform (Section 3.4) and introduce the improved loss (Section 3.5).

3.1 CFM-based Waveform Generation

Recently, diffusion and CFM-based waveform generation models [54, 65, 38, 36] have emerged as a promising alternative to GAN-based models, offering a new direction for high-fidelity speech synthesis. PeriodWave [39] introduced a CFM-based periodic-aware generator for waveform generation. RFWave [42] presented efficient CFM-based models with STFT/iSTFT. Flow2GAN [69] improved CFM objective of waveform in spectral space. StreamFlow [6] proposed streaming flow matching for streaming waveform generation and efficient waveform diffusion Transformers using linear-reshape transformation. However, these works only employ waveform-level diffusion with strongly aligned acoustic conditions such as Mel-spectrogram or pre-trained neural audio codec. In our study, basic CFMs fail to align text-speech in high-resolution waveform space without any external modules.

3.2 Spectral Forcing

Due to the difficulty of waveform-level generation, previous works utilize intermediate representations such as Mel-spectrogram. To bridge the gap between text and waveform, we introduce Spectral Forcing, a method to jointly learn an internal spectral trajectory and the target waveform trajectory, enabling stable CFM-based optimization in the high-resolution waveform space. Specifically, we introduce a low-resolution spectral trajectory as an auxiliary generation target, which provides a structured inductive bias for text-speech alignment. Unlike cascaded approaches, the spectral trajectory is jointly generated within the same model and is used only as internal frequency-rich guidance, rather than as an external intermediate representation.

We adopt a simple DiT [45]-only architecture with AdaLN-SOLA [20]. The model takes as input the concatenation of the reshaped noisy waveform x_t^{wave} and its noisy spectral representation x_t^{spec} which is a lower-resolution Mel-spectrogram with 64 bins. For text conditioning, we adopt average pooling of ZipVoice [77, 76] that expands the average-pooled text embeddings along the temporal dimension to match the speech length without any external encoder. Following [33, 5], we utilize masked-infilling training for prompted generation by concatenating masked representations together.

3.3 Disentangled DiT Heads

We found that concatenating input representations is necessary for better text-speech alignment, but disentangling DiT heads for each representation is required for robust estimation. We use shared DiT blocks as an alignment backbone, and simply add shallow disentangled DiT heads as representation-specific generation. Baseline model uses 14 shared DiT blocks and two disentangled heads. We only compute the loss on the masked regions of the target representation.

3.4 Decoupled Prediction and Loss Spaces for Raw Waveform Generation

Recent flow matching-based waveform reconstruction models, such as PeriodWave [39] and RFWave [42], have demonstrated the potential of flow-based models for raw waveform reconstruction by improving periodic modeling and sampling efficiency. Despite these advances, we observe that conventional velocity-based objectives can be insufficient for preserving fine-grained waveform energy, often leading to degraded perceptual quality in generated audio.

Motivated by JiT [41], which highlights the effectiveness of clean-data prediction for high-dimensional raw signals, and Latent Forcing [2] and ReGen [37], which leverage latent-assisted generation trajectories to better structure raw-space generation, we revisit the design of prediction and loss spaces in raw waveform CFM. Specifically, our model predicts clean waveform and spectral targets through Waveform DiT and Spectral DiT, while computing the training objective in the velocity space. This decoupled x-prediction and v-loss strategy enables effective waveform energy modeling without introducing the severe audible artifacts observed with direct x-loss optimization. Following the standard flow interpolation, we construct the intermediate sample in each domain $d \in \{\text{wave}, \text{spec}\}$ as $x_t^d = (1-t)x_0^d + tx_1^d$, where x_0^d is Gaussian noise and x_1^d is the clean target. Instead of directly predicting the velocity field, the model predicts the clean target x_{pred}^d. We then convert this prediction into the velocity space as:

$$v_{pred}^d = \frac{x_{pred}^d - x_t^d}{1-t}, \qquad v_t^d = \frac{x_1^d - x_t^d}{1-t}. \tag{1}$$

The loss is computed only on the masked generation region:

$$\mathcal{L}_v^d = \frac{\left\| \mathcal{M}^d \odot \left(v_{pred}^d - v_t^d \right) \right\|_2^2}{\|\mathcal{M}^d\|_1}, \qquad d \in \{\text{wave}, \text{spec}\}, \tag{2}$$

where $\mathcal{M}^d$ denotes the domain-specific training mask and $\odot$ is element-wise multiplication. This yields the waveform velocity loss $\mathcal{L}_v^{wave}$ and the spectral velocity loss $\mathcal{L}_v^{spec}$.

3.5 Multi-Scale Energy-Normalized Spectral v-Loss

Flow2GAN [69] introduces spectral energy-adaptive loss scaling to alleviate the loss-perception mismatch in flow matching. Following this insight, we adopt energy-normalized spectral supervision for the CFM velocity objective and extend it to multiple spectral resolutions, enabling the model to capture time-frequency structures at different resolutions. As described in Section 3.4, our model adopts x-prediction while computing the objective in the velocity space. We define the waveform-domain velocity difference as:

$$\Delta_v^{wave} = x_{pred}^{wave} - x_1^{wave} = (1-t)\left(v_{pred}^{wave} - v_t^{wave} \right). \tag{3}$$

We use Δ_v^{wave} for spectral supervision. For each scale $k \in \mathcal{K}$, we first compute a power spectrogram and apply a linear filterbank projection:

$$\Phi_k(x) = \left| \text{STFT}_k(x) \right|^2 \mathbf{F}_k, \tag{4}$$

where $\mathbf{F}_k$ denotes the linear filterbank matrix at the k-th spectral resolution. The proposed multi-scale spectral v-loss is then defined as:

$$\mathcal{L}_{ms\text{-}v\text{-}spec} = \sum_{k \in \mathcal{K}} \frac{\left\| \mathcal{M}_k^{wave} \odot \Phi_k(\Delta_v^{wave}) \odot \left(\Phi_k(x_1^{wave}) + \epsilon \right)^{-\frac{1}{2}} \right\|_1}{\|\mathcal{M}_k^{wave}\|_1}, \tag{5}$$

where $\mathcal{M}_k^{wave}$ is the mask for the k-th spectral resolution. Here, $\mathcal{K}$ is a set of spectral configurations with $n_{\text{bin}} = [512, 256, 128, 64, 32, 16]$, $n_{\text{fft}} = w = [1920, 960, 480, 240, 120, 60]$, and $h = [480, 240, 120, 60, 30, 15]$, where w and h denote the window size and hop size, respectively. The linear filter projection decomposes wave-domain velocity difference across frequency bands, and the ground-truth energy normalization prevents high-energy regions from dominating the loss. We follow Flow2GAN [69] for the scaling hyperparameters, using $\epsilon = 10^{-7}$ and clamping the scale to $[0.01, 100]$. The final objective is denoted as:

$$\mathcal{L}_{total} = \mathcal{L}_v^{wave} + \lambda_{spec}\mathcal{L}_v^{spec} + \lambda_{ms}\mathcal{L}_{ms\text{-}v\text{-}spec}, \tag{6}$$

where $\lambda_{spec} = 0.1$ and $\lambda_{ms} = 0.1$.

Table 2: Zero-shot TTS results on Seed-en Benchmark. Note that parameter size (Params) of baseline models only indicates their TTS module, but they require additional modules for waveform decoding.

Model	E2E	Params	Data	Vocoder	Codec	VAE	SPK Enc.	LLM	GAN	Diffusion	**WER** ↓	**SIM** ↑
GT	-	-	-	-	-	-	-	-	-	-	2.14	0.73
SparkTTS [59]	✗	0.5B	100k	✗	✓	✗	✓	✓	✓	✗	1.98	0.58
TadiCodec-AR [60]	✗	4B	100k	✓	✓	✗	✗	✓	✓	✓	2.28	0.65
F5-TTS [5]	✗	0.3B	100k	✓	✗	✗	✗	✗	✓	✓	2.00	0.67
ZipVoice [77]	✗	0.1B	100k	✓	✗	✗	✗	✗	✓	✓	1.70	0.69
CosyVoice2 [13]	✗	0.5B	166k	✓	✓	✗	✓	✓	✓	✓	3.09	0.65
CosyVoice3-RL [14]	✗	0.5B	-	✓	✓	✗	✓	✓	✓	✓	1.68	0.69
Qwen3-TTS [22]	✗	0.6B	-	✓	✓	✗	✓	✓	✓	✗	1.68	0.70
Qwen3-TTS [22]	✗	1.7B	-	✓	✓	✗	✓	✓	✓	✗	1.50	0.71
MOSS-TTS [18]	✗	1.7B	-	✓	✓	✗	✓	✓	✓	✗	1.93	0.73
VibeVoice [46]	✗	1.5B	-	✗	✗	✓	✗	✓	✓	✓	3.04	0.68
VibeVoice-RT [46]	✗	0.5B	-	✗	✗	✓	✗	✓	✓	✓	2.05	0.63
VoxCPM-Emilia [75]	✗	0.5B	100k	✗	✗	✓	✗	✓	✓	✓	2.34	0.68
VoxCPM [75]	✗	0.5B	-	✗	✗	✓	✗	✓	✓	✓	1.85	0.72
WaveGen-S	✓	0.1B	120k	✗	✗	✗	✗	✗	✗	✓	4.42	0.53
WaveGen-B	✓	0.4B	120k	✗	✗	✗	✗	✗	✗	✓	1.77	0.63
WaveGen	✓	0.6B	100k	✗	✗	✗	✗	✗	✗	✓	1.47	0.75

Table 3: Subjective evaluation results on Seed-en benchmark

Model	GT	F5-TTS	CosyVoice3	Qwen3-TTS-0.6B	Qwen3-TTS-1.7B	WaveGen-S	WaveGen-B
nMOS	4.117±0.112	3.938±0.119	3.917±0.128	3.883±0.123	3.954±0.117	3.958±0.129	4.000±0.126
sMOS	3.932±0.038	3.989±0.037	3.972±0.038	3.968±0.037	4.008±0.037	3.952±0.037	3.988±0.037

4 Experiment and Result

4.1 Experimental Setup

Dataset For small-scale TTS and ablation studies, we utilized LibriTTS (CC-BY-4.0) [73]. LibriTTS is a high-quality speech dataset with a sampling rate of 24,000 Hz in WAV format. We filtered LibriTTS to include only utterances with durations of up to 12s for efficient training (319,627 samples). For large-scale training, WaveGen-S/B (v0.1) use the English subsets of Emilia (CC-BY-NC-4.0) and Emilia-YODAS (CC-BY-4.0) [21] provided as MP3-compressed audio with a sampling rate of 24,000 Hz. Following [5], we filter out several speakers and use utterances with durations of up to 30s. We also released WaveGen (0.6B) trained with multilingual Emilia datasets.

Training We train LibriTTS models with a learning rate of 1×10^{-4} using the AdamW optimizer [43], a fixed batch size of 128 for 1.1M steps. We train Emilia models with a learning rate of 1×10^{-4} using AdamW optimizer [43], a dynamic batch size with total 480s frame of waveform for 1.1M steps. All models except for the 0.6B models are trained on four GPUs using mixed precision. Due to limited computational resources, we train the models only for four epochs. We train WaveGen (0.6B) on eight GPUs for 11 epochs. During training, we use a masked-infilling strategy by dropping the speech prompt and text condition (0.3 and 0.2, respectively).

Sampling We adopt the Euler method as the ODE solver. For CFG scheduling, we build upon the strategy used in ZipVoice, where the text condition is dropped only at early time steps, and all ablation studies are conducted using this. However, when using a threshold of $t < 0.5$, we found that this substantially degrades speaker similarity in our model. Therefore, we restrict text-condition dropout to $t < 0.02$. We fix NFE to 32 and CFG to 2 in our experiments.

4.2 Zero-shot TTS results

We evaluate zero-shot TTS performance on the Seed-en benchmark dataset [1]. We compute WER and SIM to assess speech intelligibility and speaker similarity using Whisper and WavLM-Large, respectively. Table 2 demonstrates the effectiveness of E2E TTS training without relying on external modules, and shows the scalability of the proposed models by achieving promising performance compared to large-scale TTS systems that require multi-stage training.

We also conduct a subjective evaluation using Amazon Mechanical Turk (MTurk) with details provided in Appendix D. We compare WaveGen with publicly available strong baselines, including F5-TTS [5], CosyVoice3 [14], and Qwen3-TTS [22]. Notably, our model achieves comparable mean opinion scores (MOS) for both naturalness (nMOS) and similarity (sMOS) as reported in Table 3. We encourage readers to listen to the audio samples on our demo page. Additionally, we provide extensive ablation studies in the following subsections.

4.3 Spectral Forcing

We found that learning the waveform trajectory alone does not guarantee text-speech alignment. To bridge the gap between text and speech, we introduce Spectral Forcing, which jointly learns an internal spectral trajectory within a single model. We first use a linear spectrogram as the target spectral representation, but it leads to unstable training. We therefore adopt the Mel-spectrogram as a target representation and analyze the effect of the number of Mel bins in Table 4. Larger Mel bins make the model focus more on waveform reconstruction rather than text-speech alignment. In contrast, smaller Mel bins provide a stronger information bottleneck, encouraging earlier alignment and faster convergence. We adopt 64 Mel bins, which offers a favorable trade-off between alignment, convergence, and high-frequency detail generation.

Table 4: Comparison of Spectral Forcing

Type	Bin	WER	SIM	DNSMOS	Analysis
No SF	-	123.67	0.19	3.20	Fails to align
Mel	256	126.50	0.35	3.17	Denoising
Mel	128	18.67	0.52	3.55	Reconstruction
Mel	80	6.80	0.50	3.62	Mel Bins ↓↑
Mel	64	4.96	0.47	3.72	Faster
Mel	32	4.26	0.48	3.64	Convergence
Linear	481		NaN		
Linear	128		NaN		Unstable
Linear	64		NaN		

4.4 End-to-End Waveform Generation

To evaluate the effectiveness of E2E training, we train a two-stage TTS system consisting of a text-to-Mel model and a vocoder. For both stages, we use the same DiT architecture with masked-infilling training. Table 5 shows that the vocoder can be successfully trained even without GAN-based training. However, the two-stage pipeline still suffers from the inherent limitations of cascaded generation, where the intermediate Mel representation constrains the waveform generation process and errors from the acoustic model can propagate to the vocoder. In contrast, E2E models directly optimize text-to-waveform generation within a single model, achieving better WER, SIM, and DNSMOS under the same NFEs (total NFE of 32). These results demonstrate the advantage of E2E over cascaded TTS systems. We also report the real-time factor (RTF) on NVIDIA A100 without inference optimization.

Table 5: Comparison of E2E and cascaded models

Method	Params.	NFE	RTF	WER	SIM	DNSMOS
End-to-End	407M	32	0.24	2.91	0.53	3.67
End-to-End	210M	32	0.12	4.68	0.50	3.71
End-to-End	113M	32	0.08	4.96	0.47	3.72
Vocoding (GT Mel)	113M	32	0.08	1.47	0.70	3.32
Vocoding (GT Mel)	113M	16	0.04	1.57	0.70	3.33
Two-Stage	226M	32 + 32	0.16	4.39	0.46	3.53
Two-Stage	226M	16 + 16	0.09	5.17	0.47	3.59

4.5 Architecture Design

We compare the effectiveness of disentangled DiT heads for multi-representation generation. Using only shared DiT blocks shows poor performance, suggesting that a fully shared architecture is insufficient for generating multiple representations. We therefore add shallow disentangled DiT heads on top of shared DiT blocks, enabling the model to maintain a shared alignment backbone while learning representation-specific refinement. Table 6 shows that this design substantially improves WER, SIM, and DNSMOS. However, using too many disentangled blocks degrades performance due to degraded alignment. We therefore adopt 14 shared DiT blocks with 2 disentangled DiT blocks.

Table 6: Disentangled DiT Heads

#Shared DiT	# Disentangled DiT	WER	SIM	DNSMOS
18	0	7.83	0.44	3.60
14	2 (4)	4.96	0.47	3.72
10	4 (8)	7.64	0.46	3.65

4.6 Decoupled Prediction and Loss Spaces

We investigate the prediction and loss spaces for E2E TTS. Unlike previous CFM-based waveform generation models, which generate waveforms conditioned on Mel-spectrograms, E2E TTS must directly learn the energy distribution of target waveforms without relying on ground-truth acoustic conditioning during generation. Although v-prediction yields slightly better text-speech alignment and speaker similarity where v-prediction focuses low-frequency information due to noisy target velocity, we observe that it lacks the ability to accurately estimate waveform energy, resulting in significant degradation in perceptual quality. In contrast, Table 7 shows that x-prediction generates waveforms with more accurate energy distribution and significantly improves the perceptual quality of speech. This observation is particularly important because it suggests that high-quality waveform generation can be achieved without adversarial training. Note that the x-loss space introduces significant metallic noise and should therefore be avoided in current systems.

Table 7: Comparison of prediction space

Pred	Loss	SF	WER	SIM	DNSMOS
x-pred	v-loss	✗	123.67	0.19	3.20
v-pred	v-loss	✗	119.52	0.16	2.65
x-pred	v-loss	✓	5.57	0.46	3.45
v-pred	v-loss	✓	3.93	0.48	2.94

4.7 Multi-scale Spectral v-loss

To further improve high-frequency detail reconstruction in CFM-based waveform generation, we investigate an enhanced CFM objective in the spectral domain. Flow2GAN [69] introduced a novel spectral loss that minimizes waveform errors with spectral energy scaling, enabling balanced frequency-wise optimization. This differs from conventional spectrogram losses, which directly minimize the discrepancy between predicted and target spectrograms. However, we found that such a loss tends to overemphasize high-frequency details at the expense of low-frequency structure, which can make text-speech alignment more difficult in E2E TTS. Unlike neural vocoders, E2E TTS models cannot rely on ground-truth spectral inputs during generation. To address this issue, we propose a multi-scale spectral v-loss that balances time-frequency optimization across multiple resolutions. The proposed loss improves overall frequency details and leads to better speaker similarity and perceptual quality as reported in Table 8. The final training objective combines the original CFM losses for wave and spec domains with our proposed multi-scale spectral v-loss.

Table 8: Loss Comparison

Method	Loss	WER	SIM	DNSMOS
Orig. CFM [39]	$\mathcal{L}_v$	5.57	0.46	3.45
Modified CFM [69]	$\mathcal{L}_{v\text{-}spec}$	68.82	0.46	3.49
Ours (Ablation)	$\mathcal{L}_{ms\text{-}v\text{-}spec}$	16.98	0.51	3.57
Ours (Final)	$\mathcal{L}_v + \lambda_{ms}\mathcal{L}_{ms\text{-}v\text{-}spec}$	4.96	0.47	3.72

4.8 Preliminary Study on REPA

The results reported for our main WaveGen models do not use representation alignment (REPA) [71] or any external modules. However, recent studies on REPA suggest that external representation guidance can improve diffusion training. We conduct a small-scale preliminary experiment (WaveGen-S, LibriTTS) to examine whether REPA can further improve E2E waveform generation. We apply REPA to the middle layer (10th layer) using semantic representations extracted from the encoder output of Whisper-small, and adopt a cosine similarity-based alignment loss weighted by $\lambda_{repa} = 0.1$. As shown in Table 9, REPA improves WER and SIM while maintaining comparable DNSMOS, suggesting faster convergence and improved training stability. We leave further improvements with REPA for future work.

Table 9: REPA result

Method	Loss	WER	SIM	DNSMOS
Ours (Final)	$\mathcal{L}_v + \lambda_{ms}\mathcal{L}_{ms\text{-}v\text{-}spec}$	4.96	0.47	3.72
+REPA (Optional)	$+\lambda_{repa}\mathcal{L}_{repa}$ (Whisper)	3.54	0.54	3.70

4.9 Scalability

Table 10: Model comparison with respect to model size and dataset scale

Model	Params.	Data (hours)	Training Steps	Basic CFG (2.0) WER ↓	Basic CFG (2.0) SIM ↑	Basic CFG (2.0) DNSMOS ↑	Modified CFG (2.0) WER ↓	Modified CFG (2.0) SIM ↑	Modified CFG (2.0) DNSMOS ↑
WaveGen-S	113M	0.5k	1.1M	4.96	0.47	3.72	4.64	0.49	3.57
WaveGen-B	407M	0.5k	1.1M	2.91	0.53	3.67	2.93	0.55	3.59
WaveGen-S	113M	120k	1.1M	4.27	0.49	3.60	4.42	0.53	3.56
WaveGen-B	407M	120k	1.1M	2.37	0.59	3.60	1.77	0.63	3.60

We investigate the scalability of E2E TTS models with respect to both model size and dataset scale. Specifically, we train two model variants, S and B, with 0.1B and 0.4B parameters, respectively. Each model is trained on both LibriTTS (0.5k hours) and Emilia (120k hours). As shown in Table 10, the proposed models show consistent improvement in intelligibility and similarity as both model size and dataset scale increase. Furthermore, we find that the modified CFG strategy improves speaker similarity, suggesting that the initial sampling steps play an important role in adapting speaker characteristics. We provide additional results with different training steps in Table 14. Based on the trends observed from extended training and the REPA results in Table 9, we believe that further training can improve the overall quality of our models. However, due to limited computational resources, we train the models for only four epochs in this study.

We further investigate the effect of NFE on E2E TTS. Table 11 presents the results of WaveGen-B with different NFE settings. We find that speaking style is adapted in the early sampling stages, and high-quality waveform generation requires at least eight steps. Increasing the number of sampling steps generally improves similarity and perceptual quality. These results suggest that early sampling steps play a crucial role in establishing text-speech alignment and adapting speaking style, whereas additional steps mainly refine waveform.

Table 11: Analysis of NFE (Seed-en)

Model	NFE	WER	SIM	DNSMOS
WaveGen-B	4	52.0	0.39	3.06
	8	4.85	0.61	3.48
	16	2.16	0.63	3.56
	32	1.77	0.63	3.60
	50	1.87	0.64	3.61
	100	1.84	0.64	3.63

Table 12: Multilingual TTS results using F5-TTS architecture and large-scale training configuration. For a fair comparison, all models are trained with the open-source Emilia dataset about 100k hours (English and Chinese). With end-to-end waveform generation, our models achieve the state-of-the-art performance on Seed-TTS-Eval benchmarks using public-available datasets.

Model	E2E	SF (Drop)	Anchoring	Hz	Hop (Frame)	Params	Data	seed-en			seed-zh		
								WER ↓	SIM↑	UTMOS ↑	CER ↓	SIM↑	UTMOS ↑
GT	-	-	-	24k	-	-	-	2.06	0.73	3.53	1.26	0.76	2.78
Seed-TTS [1]	✗	✗	-	24k	-	-	-	2.25	0.76	-	1.12	0.79	-
VoxCPM-Emilia [74]	✗	✗	-	16k	-	0.5B	100K	2.34	0.68	-	1.11	0.74	-
MaskGCT [61]	✗	✗	-	24k	-	2.2B	100K	2.88	0.71	3.55	2.40	0.77	2.63
OmniVoice-Emilia [78]	✗	✗	-	24k	-	0.8B	100K	1.72	0.71	3.88	0.89	0.76	3.05
ZipVoice [77]	✗	✗	-	24k	256 (93.75)	123M	100K	1.70	0.69	3.82	1.40	0.75	3.15
E2-TTS [15]	✗	✗	-	24k	256 (93.75)	333M	100K	2.19	0.71	3.20	1.97	0.73	2.27
F5-TTS [5]	✗	✗	-	24k	256 (93.75)	336M	100K	1.83	0.67	3.76	1.56	0.76	2.95
BareWave [16]	✓	✗	-	24k	768 (31.25)	983M	19.4K	1.75	0.60	3.72	-	-	-
WavTTS [4]	✓	✗	-	16k	160 (100)	673M	100K	1.50	0.65	3.92	1.59	0.73	3.08
WaveGen-16k	✓	✓(0.5)	✗	16k	160 (100)	676M	100K	1.51	0.71	3.90	1.65	0.77	3.09
WaveGen-16k	✓	✓(0.5)	✓	16k	160 (100)	676M	100K	1.69	0.75	3.79	1.92	0.80	3.01
WaveGen	✓	✓(0.2)	✗	24k	480 (50)	680M	100K	1.55	0.72	3.68	1.66	0.78	2.84
WaveGen	✓	✓(0.2)	✓	24k	480 (50)	680M	100K	1.47	0.75	3.68	1.75	0.80	2.87
WaveGen (Ablation)	✓	✓(0)	✗	24k	480 (50)	680M	100K	2.07	0.73	3.60	2.33	0.79	2.76
WaveGen (Ablation)	✓	✓(0)	✓	24k	480 (50)	680M	100K	1.97	0.75	3.70	2.11	0.80	2.85
WaveGen (Ablation)	✓	✓(0.5)	✗	24k	480 (50)	680M	100K	1.39	0.70	3.81	1.58	0.76	2.97
WaveGen (Ablation)	✓	✓(0.5)	✓	24k	480 (50)	680M	100K	1.56	0.74	3.70	1.74	0.79	2.87

4.10 Multilingual TTS results

We conduct large-scale multilingual TTS experiments on the English (En) and Chinese (Zh) subsets of the Emilia dataset, and adopt F5-TTS-based architectures including ConvNeXt-based text encoder and filler token-based conditioning and hyperparameters of WavTTS including waveform scaling and time scheduling for fair comparison.[2] Table 12 shows that WaveGen achieves strong performance across all evaluation metrics, demonstrating the effectiveness of direct waveform modeling and spectral forcing. Specifically, WaveGen achieves speaker similarities of 0.75 and 0.80 on the seed-en and seed-zh benchmark using only the publicly available Emilia dataset. Notably, we do not employ REPA when training WaveGen, suggesting further room for improvement through additional representation alignment techniques. In the following subsections and Appendix F, we further provide detailed analyses of the waveform diffusion optimization techniques used in WaveGen.

4.11 Information bottleneck pre-net for multi-representation generation

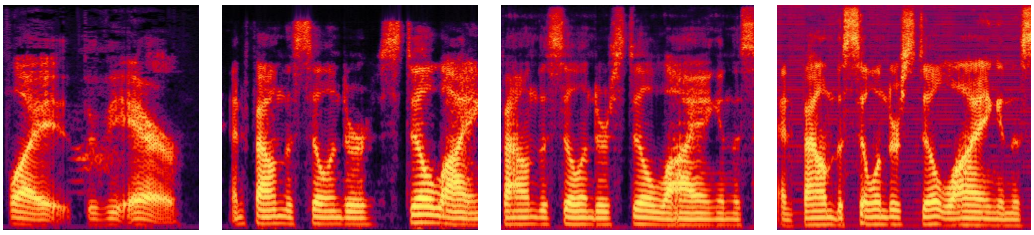
We further investigate the effect of Spectral Forcing during large-scale training. When using a large-scale dataset, the dependency of Spectral Forcing increases because the model has difficulty aligning text with speech at the initial stage. While Spectral Forcing is weak guidance, the model is prone to learn to reconstruct waveforms from Spectral Forcing, resulting in delayed emergence of text-speech alignment. To reduce this limitation, we revisit the simple techniques, pre-net used in Tacotron [64] by adding information bottleneck layers with two MLP layers and dropout to reduce dependency on teacher forcing for AR training. Specifically, we utilize 8n Mel bins and smaller bottleneck dimension of 32 similar to [3]. We apply this bottleneck layer with dropout of 0.2 during training and inference. It improves the robustness of multi-representation generation by learning to generate waveform from multiple conditions. We investigated the effect of dropout ratio on Spectral Forcing in Appendix F.2.

4.12 Prompt Anchor

Following [66], we observe a train-inference mismatch in iterative generation under masked-infilling training. During training, the prompt region is fixed to the GT speech and is therefore not explicitly optimized for iterative updates. At inference time, however, repeatedly updating x_t in the prompt region can introduce undesirable deviations from the GT prompt trajectory.

To address this issue, we anchor the prompt region to a GT-based intermediate state during iterative sampling. Specifically, at each sampling step, we construct the prompt-region x_t by interpolating between the corresponding x_0 and x_1, rather than using the model-updated values. This simple prompt anchoring strategy substantially improves speaker similarity by reducing the train-inference mismatch introduced by masked-infilling training.

[2]To the best of our knowledge, WaveGen is the first CFM-based end-to-end waveform TTS model to outperform conventional multi-stage TTS systems on the Emilia dataset. WaveGen also achieves the best performance among the evaluated waveform diffusion TTS models, including WavTTS and BareWave, both of which were released after our NeurIPS 2026 submission. Nevertheless, we acknowledge that WavTTS provides valuable analyses of optimization strategies for waveform diffusion, which complement our findings and offer useful insights into improving the training of waveform TTS systems.



(a) Prompt Audio (MP3 Format) (b) Gen. Audio (Trained with Emilia) (c) Gen. Audio (Trained with LibriTTS) (d) Gen. Audio (Trained with v-pred)

Figure 2: Spectral analysis with respect to audio format and prediction space

5 Spectral Analysis of Audio Format and Prediction Space

Impact of Audio Compression Neural vocoders and audio codecs are commonly trained on high-quality waveform datasets, and their training can often be effective even with relatively small datasets. By contrast, modern TTS models require large-scale training datasets to model diverse speaking styles including prosody and timbre in zero-shot scenarios. Although Emilia enables large-scale training, its MP3-compressed audio can limit the amount of recoverable high-frequency detail, which is particularly important for end-to-end waveform generation. As a result, models trained on such data tend to struggle with generating high-frequency components above 8 kHz. In contrast, models trained on LibriTTS preserve and generate richer high-frequency information as illustrated in Figure 2. This observation highlights the importance of carefully curating training data for E2E TTS, where the model must directly learn both linguistic alignment and high-fidelity waveform generation.

Effect of Prediction Space x-prediction plays a crucial role in high-quality waveform generation. As shown in Figure 2, the model trained with v-prediction fails to recover a reliable energy distribution because the target velocity is highly noisy, resulting in substantially degraded waveform quality.

6 Potential Broader Impact

Societal Positive Impact Our work proposes an E2E TTS model that directly generates high-quality waveform from text, thereby simplifying existing complex multi-stage TTS pipelines and enhancing training and inference efficiency. This efficient simplification, which enables speech generation with a single model without relying on external modules, enhances the accessibility of speech technologies and provides a foundation for broader adoption in both academic and industrial settings. Furthermore, in terms of application technology, this method can have a positive impact on diverse fields such as voice interfaces, education, and media content. In particular, the generation of clear and natural speech can improve the user experience and contribute to the advancement of speech language model.

Societal Negative Impact Although the model and method proposed in this work do not directly raise ethical issues, there is a possibility of misuse when combined with voice cloning due to their ability to generate high-quality speech. For example, the model could be used to imitate a specific speaker's voice or generate realistic fake speech to convey misleading information, which may lead to issues such as voice phishing or impersonation. To mitigate these potential risks, it is necessary to pursue complementary research on fake audio detection as well as speech safety, including methods for identification and authenticity verification. As part of future work, we plan to further explore watermarking and authentication techniques to enable tracing the origin of generated audio.

Limitation We introduce an E2E TTS model that does not rely on any external modules, including SSL models. Nevertheless, SSL-based guidance, such as REPA, can be incorporated to accelerate training. Due to limited computational resources, we restrict large-scale training to four epochs. The observed scaling trend suggests that longer training may further improve performance, which we leave for future work. In addition, we plan to extend our model to 48 kHz waveform generation.

7 Conclusion

We proposed WaveGen, a fully E2E diffusion-based text-to-waveform TTS system. Unlike previous TTS systems, WaveGen directly generates raw waveforms from text without separately trained intermediate representations. By introducing Spectral Forcing, disentangled DiT heads, and a multi-scale spectral v-loss, WaveGen enables stable CFM-based optimization in the high-resolution waveform domain. Our results show that direct text-to-waveform generation can achieve promising zero-shot TTS performance and benefit from model and dataset scaling, suggesting a simple and scalable alternative to increasingly complex cascaded TTS pipelines.

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A Implementation Details

Table 13: Hyperparameters of WaveGen

Module	Hyperparameter	WaveGen-S	WaveGen-B	WaveGen
Waveform	Sampling Rate	24000	24000	24000
	Reshape	(100, 240)	(100, 240)	(50,480)
	Diffusion Resolution	100Hz	100Hz	50Hz
Spectral Forcing	Hop	240	240	480
	Window	960	960	1920
	FFT	960	960	1920
	Filter	Mel	Mel	Mel
	Bin	64	64	80
	IB	-	-	32
Text Embedding	Dimension	384	384	512
	ConvNeXt	-	-	4
	Conditioning	Average	Average	Filler Token
DiT	Input Dim.	768	1024	1158
	Hidden Dim.	1536	4096	4632
	Shared Layer	14	24	24
	Disentangled Layer	2	2	2
	Head	12	16	16
	Type	Scale-DiT	Scale-DiT	DiT
	AdaLN	AdaLN-SOLA (rank=32)	AdaLN-SOLA (rank=32)	AdaLN-Zero
Training	Training Step	1.1M	1.1M	1.3M
	Epoch	4	4	11
	GPU	4	4	8
	Learning Rate	1×10^{-4}	1×10^{-4}	7.5×10^{-5}
	Warm-up Scheduling	20,000 steps	20,000 steps	20,000 steps
	Learning Scheduling	Cosine Decay	Cosine Decay	Linear Decay
	λ_{sf}	0.1	0.1	0.1
	$\lambda_{\text{v-stft}}$	0.1	0.1	-
	$\lambda_{\text{x-stft}}$	-	-	0.05
	Audio/Token Drop	0.3/0.2	0.3/0.2	0.1 (Joint)
	Model Size	113M	407M	680M
Dataset	Max Frame	480s	480s	384s
	Length	3-30s	3-30s	3-30s
t scheduling	-	Uniform	Uniform	Logit normal (μ=-0.8, σ=0.8)
Data Scaling	Waveform	Max Normalization + x0.95	Max Normalization + x0.95	x9
Noise Scaling	Waveform Noise	0.25	0.25	1
	Spectral Noise	1	1	1
Sampling	ODE Method	Euler	Euler	Euler
	Steps	32	32	50
	CFG	2	2	3
Objective	Prediction Space	x-pred	x-pred	x-pred
	Loss Space	v-loss	v-loss	v-loss
	x to v conversion	$(x_\theta - x_t)/(1-t)$	$(x_\theta - x_t)/(1-t)$	$(x_\theta - x_t)/(1-t)$
	t_{clip}	0.05	0.05	0.02
Multi-scale Spectral v-loss	Hop	[480, 240, 120, 60, 30, 15]	[480, 240, 120, 60, 30, 15]	-
	Window	[1920, 960, 480, 240, 120, 60]	[1920, 960, 480, 240, 120, 60]	-
	FFT	[1920, 960, 480, 240, 120, 60]	[1920, 960, 480, 240, 120, 60]	-
	Filter	Linear	Linear	-
	Bin	[512,256,128,64,32,16]	[512,256,128,64,32,16]	-
Multi-scale Spectral x-loss	Hop	-	-	[512, 256, 128, 64, 32, 16, 8]
	Window	-	-	[2048, 1024, 512, 256, 128, 64, 32]
	FFT	-	-	[2048, 1024, 512, 256, 128, 64, 32]
	Filter	-	-	Mel
	Bin	-	-	[320,160,80,40,20,10,5]

B Implementation Details for Baselines

Spark-TTS Spark-TTS[3] [59] is an LLM-based zero-shot TTS with BiCodec, a single-stream speech codec that represents speech with semantic tokens for linguistic content and global tokens for speaker attributes.

TadiCodec-AR TaDiCodec[4] [60] is a text-aware diffusion speech tokenizer that compresses speech into a low frame rate discrete representation using a diffusion autoencoder with text-guided decoding.

F5-TTS F5-TTS [5] is a non-autoregressive zero-shot TTS model based on flow matching with a Diffusion Transformer. It removes explicit duration modeling and phoneme-level alignment by padding text tokens to the speech length, and uses ConvNeXt-based text refinement to improve alignment robustness. For evaluation, we utilize the official implementation and released checkpoint.[5]

ZipVoice ZipVoice[6] [77] is a compact zero-shot TTS model based on flow matching. It employs a Zipformer-based text encoder and vector-field estimator, uses average upsampling for initial speech-text alignment, and introduces flow distillation to reduce the number of sampling steps.

CosyVoice2 CosyVoice2[7] [13] is an LLM-based TTS model with a chunk-aware causal flow matching decoder. It improves speech token utilization with FSQ and supports both streaming and non-streaming synthesis within a unified framework.

CosyVoice3 CosyVoice3 [14] extends CosyVoice2 toward in-the-wild multilingual zero-shot TTS through larger-scale pre-training, a supervised multi-task speech tokenizer, and RL post-training. In our comparison, CosyVoice3-RL refers to the reward-optimized with differentiable reward optimization. For evaluation, we utilize the official implementation and released checkpoint.[8]

Qwen3-TTS Qwen3-TTS [22] is an LLM-based TTS system built on the Qwen3 backbone. It employs a 12Hz speech tokenizer with a multi-codebook RVQ consisting of 16 codebooks to represent both semantic and acoustic information. To efficiently model the multi-codebook sequence, it adopts multi-token prediction decoding. For evaluation, we utilize the official implementation and evaluate both the 0.6B and 1.7B checkpoints.[9]

MOSS-TTS MOSS-TTS[10] [18] employs the MOSS-Audio-Tokenizer to convert waveform into a unified sequence of discrete representations capturing both semantic and acoustic information.

VibeVoice VibeVoice [46] is a long-form and multi-speaker TTS model designed to generate expressive conversational speech from text. It employs continuous speech tokenizers operating at low frame rate and uses next-token diffusion to autoregressively generate continuous speech representations. They release their open-source implementation[11] and real-time model[12].

VoxCPM VoxCPM[13] [75] uses hierarchical semantic-acoustic modeling, where semantic-prosodic planning and residual acoustic modeling are coupled with a local diffusion decoder for high-fidelity speech generation.

[3] https://github.com/SparkAudio/Spark-TTS
[4] https://github.com/AmphionTeam/TaDiCodec
[5] https://github.com/SWivid/F5-TTS
[6] https://github.com/k2-fsa/ZipVoice
[7] https://github.com/FunAudioLLM/CosyVoice
[8] https://github.com/FunAudioLLM/CosyVoice
[9] https://github.com/QwenLM/Qwen3-TTS
[10] https://github.com/OpenMOSS/MOSS-TTS
[11] https://github.com/microsoft/VibeVoice
[12] https://huggingface.co/microsoft/VibeVoice-Realtime-0.5B
[13] https://github.com/OpenBMB/VoxCPM

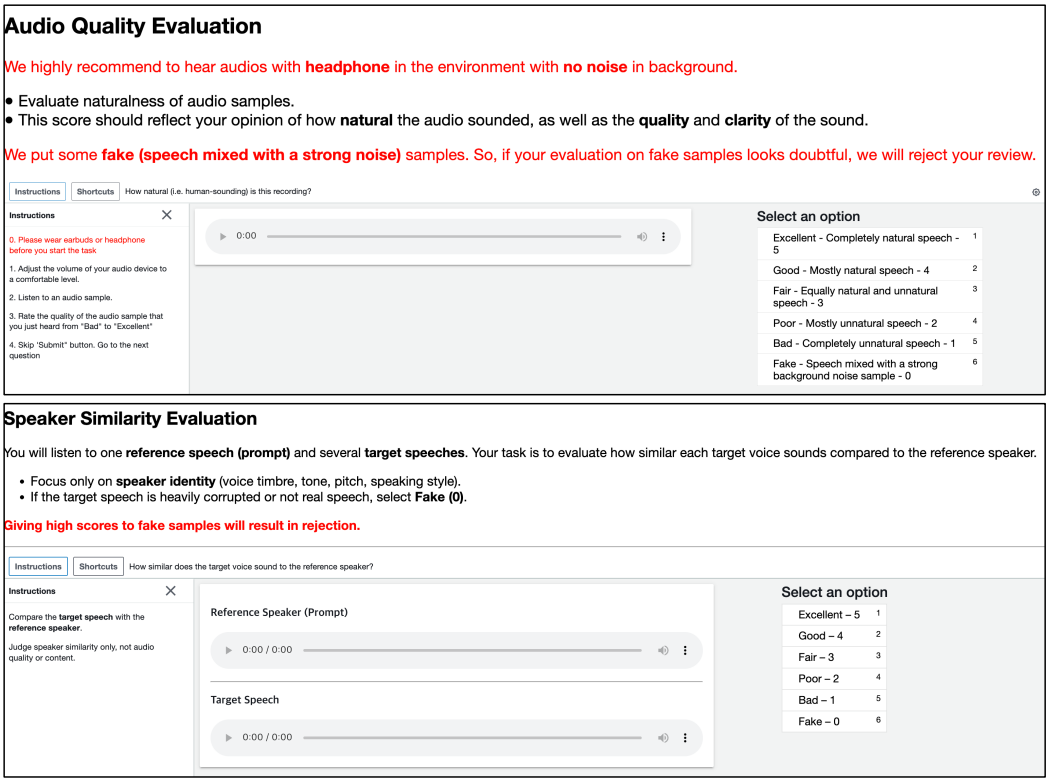

Figure 3: MOS interfaces

C Evaluation Details

WER We calculate word error rate (WER) using open-source automatic speech recognition model, Whisper [50]. We utilize the official implementation of Whisper-large-v3[14] to evaluate speech intelligibility.

SIM For evaluating speaker similarity quality, we utilized WavLM-large which is fine-tuned by speaker verification task[15]. We calculate cosine similarity between prompt and generated samples.

DNSMOS To assess the naturalness of the synthetic samples, we utilized the open-source Mean Opinion Score (MOS) prediction model, DNSMOS[16][51].

D Crowdsourcing Details

We conducted Mean Opinion Score (MOS) evaluations using Amazon Mechanical Turk (MTurk)[17] to qualitatively assess the quality of synthesized speech from the TTS. Specifically, we carried out two types of evaluations: nMOS, which measures the naturalness of the generated speech, and sMOS, which measures the similarity of the generated speaker timbre to that of the prompt speaker. For each evaluation, 20 native speakers of American English participated. Each participant rated 100 samples per model on a 5-point scale ranging from 1 to 5. To reduce unreliable responses, such as participants randomly selecting scores, and to improve the reliability of the MTurk evaluation, we included Gaussian-noise samples as control samples. Responses from participants who failed to identify these samples as fake were excluded from the final analysis. In addition, only MTurk workers with a prior task approval rate of at least 80% and at least 100 approved HITs were allowed to participate in the evaluation.

[14] https://github.com/openai/whisper
[15] https://drive.google.com/file/d/1-aE1NfzpRCLxA4GUxX9ITI3F9LlbtEGP/view.
[16] https://github.com/Lightning-AI/torchmetrics
[17] https://www.mturk.com/

Table 14: Comparison with respect to training steps.

Model	Params.	Data	Training Steps	Basic CFG (2.0) WER(↓)	Basic CFG (2.0) SIM(↑)	Basic CFG (2.0) DNSMOS(↑)	No CFG WER(↓)	No CFG SIM(↑)	No CFG DNSMOS(↑)
WaveGen-S	113M	0.5k	0.3M	104.23	0.32	3.53	129.85	0.25	3.31
WaveGen-S	113M	0.5k	0.5M	26.33	0.40	3.55	92.88	0.27	3.22
WaveGen-S	113M	0.5k	0.7M	8.75	0.45	3.68	76.66	0.33	3.38
WaveGen-S	113M	0.5k	0.9M	6.02	0.47	3.65	58.53	0.35	3.37
WaveGen-S	113M	0.5k	1.1M	4.96	0.47	3.72	56.58	0.36	3.36
WaveGen-B	407M	0.5k	0.3M	28.19	0.42	3.60	93.01	0.31	3.33
WaveGen-B	407M	0.5k	0.5M	9.19	0.49	3.60	76.53	0.33	3.20
WaveGen-B	407M	0.5k	0.7M	4.32	0.51	3.66	51.43	0.39	3.32
WaveGen-B	407M	0.5k	0.9M	3.69	0.52	3.65	44.82	0.39	3.33
WaveGen-B	407M	0.5k	1.1M	2.91	0.53	3.67	41.56	0.40	3.30
WaveGen-S	113M	120k	0.3M	91.23	0.32	3.27	148.32	0.21	3.02
WaveGen-S	113M	120k	0.5M	23.40	0.43	3.47	108.22	0.29	3.17
WaveGen-S	113M	120k	0.7M	8.50	0.45	3.60	77.88	0.33	3.25
WaveGen-S	113M	120k	0.9M	5.00	0.48	3.59	69.43	0.34	3.25
WaveGen-S	113M	120k	1.1M	4.27	0.49	3.60	69.69	0.35	3.28
WaveGen-B	407M	120k	0.3M	63.51	0.44	3.47	143.51	0.29	3.15
WaveGen-B	407M	120k	0.5M	18.37	0.53	3.48	90.07	0.38	3.23
WaveGen-B	407M	120k	0.7M	4.42	0.56	3.58	58.73	0.40	3.22
WaveGen-B	407M	120k	0.9M	2.91	0.57	3.56	60.91	0.42	3.22
WaveGen-B	407M	120k	1.1M	2.37	0.59	3.60	41.91	0.46	3.29

Table 15: Additional Training Results

Model	Params.	Data	Training Steps	Basic CFG (2.0) WER(↓)	Basic CFG (2.0) SIM(↑)	Basic CFG (2.0) DNSMOS(↑)	No CFG WER(↓)	No CFG SIM(↑)	No CFG DNSMOS(↑)
WaveGen-B	407M	120k	1.1M	2.37	0.59	3.60	41.91	0.46	3.29
WaveGen-B	407M	120k	1.2M	1.98	0.59	3.61	39.67	0.46	3.31
WaveGen-B	407M	120k	1.3M	1.85	0.60	3.60	36.67	0.46	3.30

Table 16: CFG results

Model	Params.	Data	Training Steps	CFG	Modified CFG (2.0) WER(↓)	Modified CFG (2.0) SIM(↑)	Modified CFG (2.0) DNSMOS(↑)
WaveGen-B	407M	120k	1.1M	0.5	4.26	0.605	3.55
WaveGen-B	407M	120k	1.1M	1	2.61	0.625	3.60
WaveGen-B	407M	120k	1.1M	2	1.77	0.635	3.60
WaveGen-B	407M	120k	1.1M	3	1.93	0.637	3.52
WaveGen-B	407M	120k	1.1M	4	1.87	0.633	3.37

E Additional results

Table 14 shows the objective evaluation results of each model with respect to the number of training steps. The results indicate that model performance consistently improves as the number of training steps increases.

Due to limited computational resources, we trained the model only up to 1.1M steps, corresponding to four epochs on the Emilia dataset. Nevertheless, WaveGen-B continued to improve with additional training steps, as shown in Table 15. These results suggest that end-to-end TTS models have strong potential for further improvement with larger-scale training.

Table 16 shows the effect of CFG on the WaveGen-B model. Increasing the CFG scale substantially improves intelligibility, reducing WER from 4.26 to 1.77 when the CFG scale is increased from 0.5 to 2.0. Speaker similarity also improves consistently up to CFG 3.0, indicating that stronger conditioning helps the model better preserve the target speaker characteristics. However, excessively large CFG values slightly degrade perceptual quality, as reflected by the decrease in DNSMOS at CFG 3.0 and 4.0. These results show that CFG provides an effective trade-off between intelligibility, speaker similarity, and audio quality, with CFG 2.0 achieving the best overall balance in our experiments.

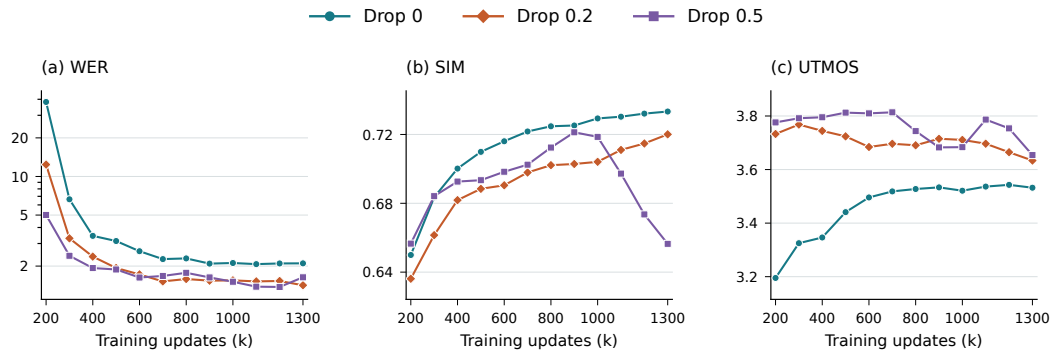

Figure 4: Spectral Dropout

F Multilingual WaveGen

We conducted multilingual text-to-speech comparison using Emilia (EN and ZH) datasets. For a fair comparison, we utilize the same architecture of F5-TTS to demonstrate the effectiveness of waveform-level diffusion training and Spectral Forcing. Then, we adopt the time scheduling methods of WavTTS to compare the effect of Spectral Forcing. For efficient waveform generation, we employ 50Hz resolutions using hop size of 480 for 24 kHz waveform diffusion.

F.1 Spectral Loss

Basically, we introduce multi-scale spectral v-loss for our models. However, we adopt multi-scale Mel-spectrogram x-loss to compare Spectral Forcing based on WavTTS implementation. We observe that multi-scale Mel-spectrogram loss could improve the initial alignment learning and entire objective performances including WER and SIM. However, this loss induces buzzing sound on the generated waveform. To address this perceptual limitation, we released the perceptually-improved models together using multi-scale spectral v-loss which could significantly improve the perceptual quality. While it shows lower performance in objective metrics, we highly recommend adopting our new objectives for perceptual quality. We released the model finetuned with multi-scale spectral v-loss for perceptually improved speech synthesis.

F.2 Spectral Dropout

We further investigated the use of spectral dropout in spectral forcing to improve robustness to noise in multilingual datasets. Figure 4 presents the objective evaluation metrics for different spectral dropout rates. The results suggest that higher dropout rates can improve initial alignment when training on noisy waveforms, but may also cause the spectral path to collapse during training. Without spectral dropout, the model tends to rely on the noisy Mel-spectrogram for waveform reconstruction. We therefore selected a dropout rate of 0.2 to reduce this reliance while maintaining the stability of the spectral path.

F.3 Sampling Steps

With large-scale training, Table 17 shows that the model achieves better performance across all evaluated NFEs than that reported in Table 11. Furthermore, we plan to release an accelerated version of WaveGen that enables efficient speech synthesis in only a few sampling steps.

Table 17: Analysis of NFE (Seed-en, WaveGen)

Model	NFE	WER	SIM	UTMOS
WaveGen	1	93.10	0.19	1.30
	2	23.71	0.42	1.31
	4	2.76	0.64	2.34
	8	1.70	0.75	3.44
	10	1.72	0.75	3.53
	16	1.69	0.76	3.65
	32	1.50	0.75	3.68
	50	1.47	0.75	3.68

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