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DATA SCIENCE STUDY PROGRAMME

Master's thesis

Training Data Selection Strategies for Multi-Speaker Text-to-Speech Synthesis in Lithuanian

Mokymo duomenų parinkimo strategijos šnekos sintezės modelio apmokymui lietuvių kalba, naudojant kelių kalbėtojų balsus

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Summary

Developing high-quality Text-to-Speech (TTS) systems for low-resource languages is often hindered by a lack of large, single-speaker datasets. This thesis investigates training data composition strategies for Lithuanian multi-speaker TTS models, specifically testing the hypothesis that data depth is critical for synthesis quality. Using the Liepa-2 corpus, three datasets were constructed with a constant total duration of 22.5 hours, varying the trade-off between breadth (30 to 180 speakers) and depth (45 to 7.5 minutes per speaker). Tacotron 2 and Glow-TTS architectures were trained and evaluated via objective metrics (MCD, F0 RMSE) and subjective listening tests (MOS). Results demonstrate that Tacotron 2 consistently outperforms Glow-TTS in naturalness. Contrary to the hypothesis, statistical analysis reveals no significant difference in synthesis quality across the varying data strategies. This suggests that modern multi-speaker models are insensitive to the breadth-depth trade-off within this range, achieving convergence with as little as 7.5 minutes of data per speaker.

Keywords: text-to-speech, multi-speaker voice synthesis, low-resource language, Tacotron 2, Glow-TTS

Santrauka

Aukštos kokybės šnekos sintezės (TTS) sistemų kūrimą mažai išteklių turinčioms kalboms dažnai sunkina didelių vieno kalbėtojo duomenų rinkinių trūkumas. Šiame darbe tiriamos mokymo duomenų parinkimo strategijos šnekos sintezės modelio apmokymui lietuvių kalba, naudojant kelių kalbėtojų balsus. Tikrinama iškelta hipotezė, kad duomenų gylis yra kritiškai svarbus sintezės kokybei. Naudojant Liepa-2 garsyną, buvo sudaryti trys duomenų rinkiniai, kurių bendra trukmė yra pastovi (22,5 val.), tačiau kinta santykis tarp pločio (nuo 30 iki 180 kalbėtojų) ir gylio (nuo 45 iki 7,5 min. vienam kalbėtojui). Buvo apmokytos Tacotron 2 ir Glow-TTS architektūros bei atliktas jų vertinimas, panaudojant objektyvius rodiklius (MCD, F0 RMSE) ir subjektyvius klausymo testus (MOS). Rezultatai rodo, kad Tacotron 2 pagal natūralumą nuosekliai lenkia Glow-TTS. Statistinė analizė paneigė iškeltą hipotezę ir neatskleidė reikšmingo sintezės kokybės skirtumo taikant skirtingas duomenų strategijas. Tai leidžia teigti, kad šiuolaikiniai kelių kalbėtojų modeliai šiame intervale nėra jautrūs pločio ir gylio santykiui ir geba konverguoti turint vos 7,5 minutės duomenų vienam kalbėtojui.

Raktiniai žodžiai: šnekos sintezė, kelių kalbėtojų balsų sintezė, mažai išteklių turinti kalba, Tacotron 2, Glow-TTS

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Introduction

The goal of creating machines that can speak like humans has captivated researchers for centuries. One of the earliest known attempts dates back to the 18th century, with Wolfgang von Kempelen's mechanical "speaking machine" [1] that utilized a bellows-driven lung and physical models of the tongue and lips to produce rudimentary speech sounds.

Over the centuries, our understanding of human speech and advancements in technology have driven significant progress in this field. Today's state-of-the-art Text-to-Speech (TTS) systems, dominated by end-to-end (E2E) neural models such as Tacotron 2 [2] and Glow-TTS [3], have achieved highly natural speech with unprecedented acoustic quality. Notably, these E2E systems have unified the entire synthesis process into one or two neural networks, learning to map text inputs (graphemes or phonemes) directly to audio outputs, eliminating the need for complex, brittle multi-stage pipelines.

These advancements have transformed TTS from a niche area of academic curiosity into essential tools for daily life. High-quality speech synthesis now powers popular virtual assistants [4] and navigation systems, serving as a primary interface for human-computer interaction. More importantly, it plays a critical role in accessibility, enabling screen readers for the visually impaired [5, 6], providing a voice for the non-verbal, and facilitating access to information [6].

However, the transition to deep learning techniques has introduced a new dependency: data. While modern neural TTS models are capable of producing remarkably natural speech, they lack explicit linguistic prior knowledge, making them heavily reliant on large amounts of high-quality training data to learn implicit mappings from text to speech. The common recommendation is to use at least 10 to 20 hours of high-quality recorded speech from a single speaker to achieve good synthesis quality. The majority of existing research and commercial TTS systems focus on high-resource languages like English, where professionally recorded single-speaker datasets (e.g., LJSpeech [7] with 24 hours of speech) are readily available.

However, low-resource languages, such as Lithuanian, often lack such extensive datasets, and available corpora tend to be crowd-sourced with multiple speakers contributing small amounts of data each. In contrast, multi-speaker TTS models can achieve convergence and reasonable intelligibility with significantly less data per speaker — as little as 15 to 30 minutes — provided the total pooled dataset is sufficiently large to learn the language's phonetics and prosody.

Liepa-2 [8] is a Lithuanian speech corpus, released in 2020, that contains 1000 hours of annotated speech; this data is distributed across 2621 speakers, with most speakers contributing under 30 minutes each. The top speaker has under 2.5 hours of recorded speech, well below the standard recommendation for training a high-fidelity single-speaker TTS model.

Having such a fragmented dataset, or crowd-sourced data, presents an engineering challenge. Using a single speaker's data from such a corpus yields insufficient data for high-quality synthesis. On the other hand, training on the entire 1000-hour corpus is a computationally prohibitive process for the scope of this work. Therefore, a multi-speaker TTS architecture is the necessary solution. It

allows for the aggregation of data from a selected subset of speakers, provided the model can learn to disentangle speaker identity from shared linguistic features.

This necessitates a choice between two competing strategies under a fixed computational budget: prioritizing **breadth** (many speakers with little data each) or **depth** (fewer speakers with more data each). Consequently, the question that arises is: *what is the optimal strategy for sampling multi-speaker data to maximize synthesis quality?*

Current literature generally advocates for transfer learning from large pre-trained models to improve low-resource TTS performance. However, there is a lack of research specifically addressing the internal composition of the training set for morphologically complex languages like Lithuanian. To address this gap and isolate the effects of data distribution without the bias of pre-training, this thesis investigates the optimal data selection strategy for training Lithuanian multi-speaker TTS models from scratch.

The primary **research aim** of this thesis is to: measure how varying the balance between training dataset *breadth* (number of speakers) and *depth* (duration per speaker) affects the synthesis quality of multi-speaker TTS models. The **hypothesis** is that depth is a more critical factor — more specifically, that synthesis quality will degrade as the number of speakers increases, given a constant total training duration.

To achieve this aim, the following **research objectives** are defined:

- Process the Liepa-2 dataset to prepare three TTS training datasets that maintain a constant total duration but vary in speaker distribution.
- Configure and train two distinct acoustic model architectures (one autoregressive, one non-autoregressive) on each of the created datasets.
- Evaluate the synthesis quality of the trained models using objective metrics.
- Develop a subjective evaluation application and conduct a Mean Opinion Score listening test with native Lithuanian speakers to assess naturalness.

The remainder of this thesis is organized as follows: The **Literature Review** presents an overview of relevant concepts in digital signal processing, neural TTS architectures, and the specific challenges of Lithuanian TTS. **Methodology** describes the data selection, model configurations, and experimental design. **Results** presents the findings of the objective and subjective synthesis quality evaluations, analyzing the failure modes of the models. Finally, the **Conclusion** summarizes the key findings and offers potential recommendations for future research in low-resource TTS synthesis.

1 Literature Review

This section reviews the key concepts related to text-to-speech synthesis and traces the evolution from traditional methods to modern neural architectures. The topics are presented in a bottom-up manner, building up from fundamental signal processing concepts to high-level TTS architectures.

1.1 Digital Representation of Audio

At its core, the objective of a TTS system is to generate an audio signal — a continuous pressure wave — that the human ear perceives as speech. The key properties of sound waves include frequency (pitch), amplitude (loudness), and phase. However, digital audio processing, as used in TTS systems, requires converting sound waves into a discrete digital format. This conversion involves two main steps: sampling and quantization.

Sampling is the process of measuring the amplitude of the sound wave at regular time intervals. The rate at which these samples are taken is called the sampling rate. Increasing the sampling rate allows for capturing higher frequency components of the audio signal; however, it also increases the amount of data that needs to be processed and stored. Thus, there is a trade-off between audio quality and data efficiency. According to the Nyquist-Shannon [9] sampling theorem, accurate reconstruction of a continuous signal requires a sampling rate that is strictly greater than twice the highest frequency present in the signal. While frequencies in the range of 300 Hz to 3400 Hz contribute most to human speech intelligibility and recognition [10], high-fidelity synthesis typically uses sampling rates of 22.05 kHz and 24 kHz, which can capture frequencies up to approximately 11 kHz and 12 kHz, respectively.

Quantization (or bit depth) is the mapping of continuous amplitude values to discrete levels for digital representation, which determines the precision of the representation. Similar to sampling rate, there is a trade-off between audio quality and data size. Common bit depths for audio are 16-bit and 24-bit formats. A visual representation of both sampling and quantization is provided in Figure 1.

In neural TTS systems, which typically operate on frequency-domain representations like Mel-spectrograms (discussed below), **Pre-Emphasis** is a common audio pre-processing step applied to the raw waveform. Natural speech signals tend to have more energy in the lower frequencies, with a gradual drop-off towards higher frequencies (approximately -6 dB per octave). This spectral tilt can lead to models focusing disproportionately on low-frequency components, potentially neglecting important high-frequency details. Pre-emphasis compensates for this spectral tilt by boosting high frequencies using a first-order high-pass filter, which is defined as:

$$y[n] = x[n] - \alpha x[n-1] \tag{1}$$

where $y[n]$ is the pre-emphasized signal, $x[n]$ is the original signal, α is the pre-emphasis coefficient (typically between 0.9 and 1.0, and often set to 0.97), and n is the sample index.

This improves the signal-to-noise ratio for high frequencies and prevents the model from neglecting higher-frequency components.

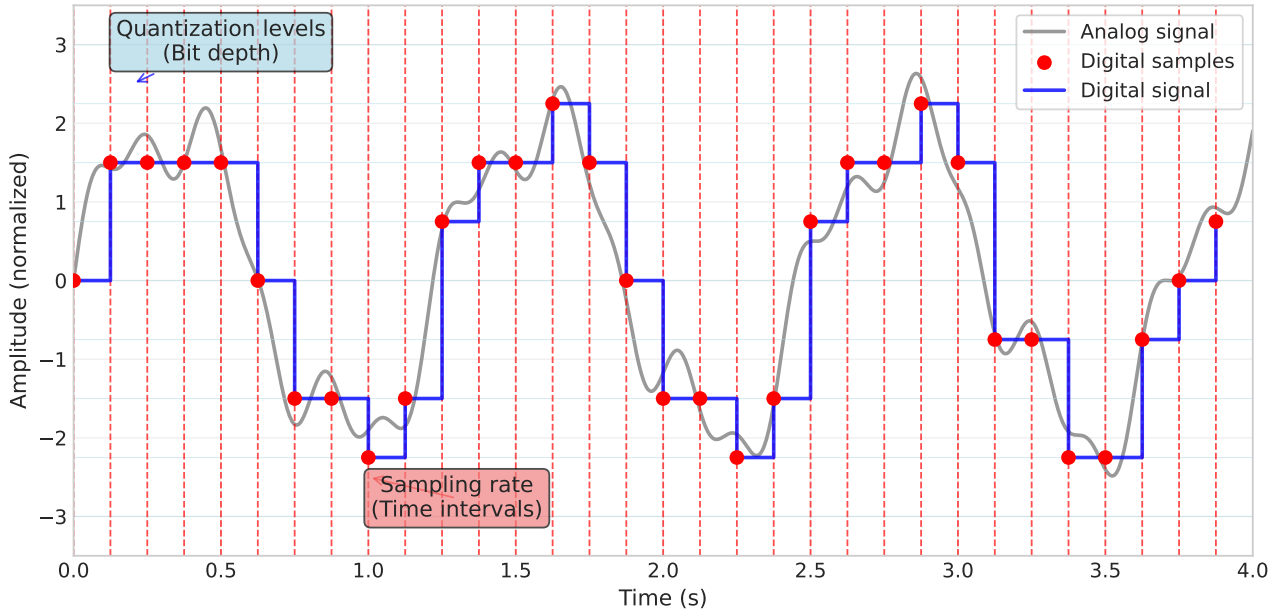


Figure 1 *Visual representation of Analog-to-Digital conversion. The continuous grey line represents the analog signal. The vertical lines represent the* ***sampling rate*** *(time intervals), and the horizontal grid lines represent* ***quantization levels*** *(bit depth).*

1.2 Time-Frequency Analysis

Fourier Transform

TTS systems typically do not operate directly on the raw waveform. Instead, they rely on time-frequency representations that capture the spectral content of the signal over time.

The **Fourier Transform** (FT) is a mathematical technique that transforms a time-domain signal (such as an audio waveform) into its frequency-domain representation. The signal is decomposed into a sum of sine and cosine waves at various frequencies, each with a specific amplitude and phase. This allows us to analyze the frequency content of the signal.

The **Short-Time Fourier Transform** (STFT) [11] extends the FT by applying it to short, overlapping segments (frames) of the signal. This transformation provides a time-frequency representation, showing how the frequency content of the signal changes over time — precisely the features needed for modeling speech.

In TTS applications, the STFT is computed by dividing the audio signal into short frames (usually 20–50 ms) with a certain overlap (usually 50–75%) between frames, windowed by a Hamming or Hann function to reduce spectral leakage.

Spectrogram and Mel-Spectrogram

The **spectrogram** is a visual representation of the STFT, displaying frequency on the vertical axis, time on the horizontal axis, with amplitude represented by color intensity. In TTS systems, spectrogram values are the typical intermediate representation between an acoustic model and a vocoder (discussed later) — the spectrogram being the target output of the acoustic model.

The regular spectrogram uses a linear frequency scale. While it allows a detailed frequency analysis, this has limitations when modeling human speech. The human ear does not perceive frequencies linearly — it is more sensitive to pitch differences at lower frequencies than higher ones. To mimic this perceptual characteristic, the Mel scale [12] maps linear frequency f (in Hz) to a perceptual scale m (in Mels) using the following formula:

$$m = 2595 \cdot \log_{10}\left(1 + \frac{f}{700}\right) \tag{2}$$

Mel-spectrograms are computed by applying a Mel filterbank of overlapping triangular filters (spaced uniformly on the Mel scale) to the magnitude spectrogram obtained from the STFT. Finally, the dynamic range of the amplitudes is compressed by taking the logarithm (usually resulting in decibels), as human loudness perception is logarithmic. This results in a compressed representation of the audio signal that aligns more closely with human auditory perception. Such Mel-spectrograms are commonly used as input features for modern TTS systems. The differences between the raw waveform, the standard spectrogram, and the Mel-spectrogram are illustrated in Figure 2. Note how the Mel-spectrogram has a higher resolution in the lower frequencies, where the majority of speech energy is concentrated.

It is important to note that converting a waveform to a Mel-spectrogram is lossy: phase information is discarded during the magnitude operation, and frequency resolution is reduced by the Mel filterbank. As a result, reconstructing a high-fidelity audio waveform from a generated Mel-spectrogram requires a specialized model component, typically referred to as a vocoder (discussed in Section 1.8).

1.3 Linguistic Representation

In TTS systems, the input text must be pre-processed and converted into a suitable linguistic representation that the synthesis model can use. Although theoretically an end-to-end TTS model could learn to map raw text directly to audio, in practice, pre-processing the text facilitates model convergence and improves the quality of the synthesized speech.

The main goal of this stage is to map the raw sentences into a sequence of symbols that can be more closely mapped to the acoustic features of speech. This process typically involves several steps, such as text normalization, grapheme-to-phoneme conversion, and possibly prosody prediction.

1.3.1 Text Normalization

Text normalization [13] is the process of converting raw written text with non-standard words into a more standardized “spoken” form. Typical steps include expanding abbreviations (e.g., expanding “Dr.” to “Doctor”), punctuation standardization, number normalization (e.g., converting “123” to “one hundred twenty-three”), and lowercasing. While some non-standard punctuation is removed, structural punctuation (commas, periods) is often retained or mapped to special pause tokens to guide prosody. As an example, the input text “Dr. Smith has 2 cats.” could be normalized to “doctor smith has two cats”, which bears closer resemblance to the spoken form.

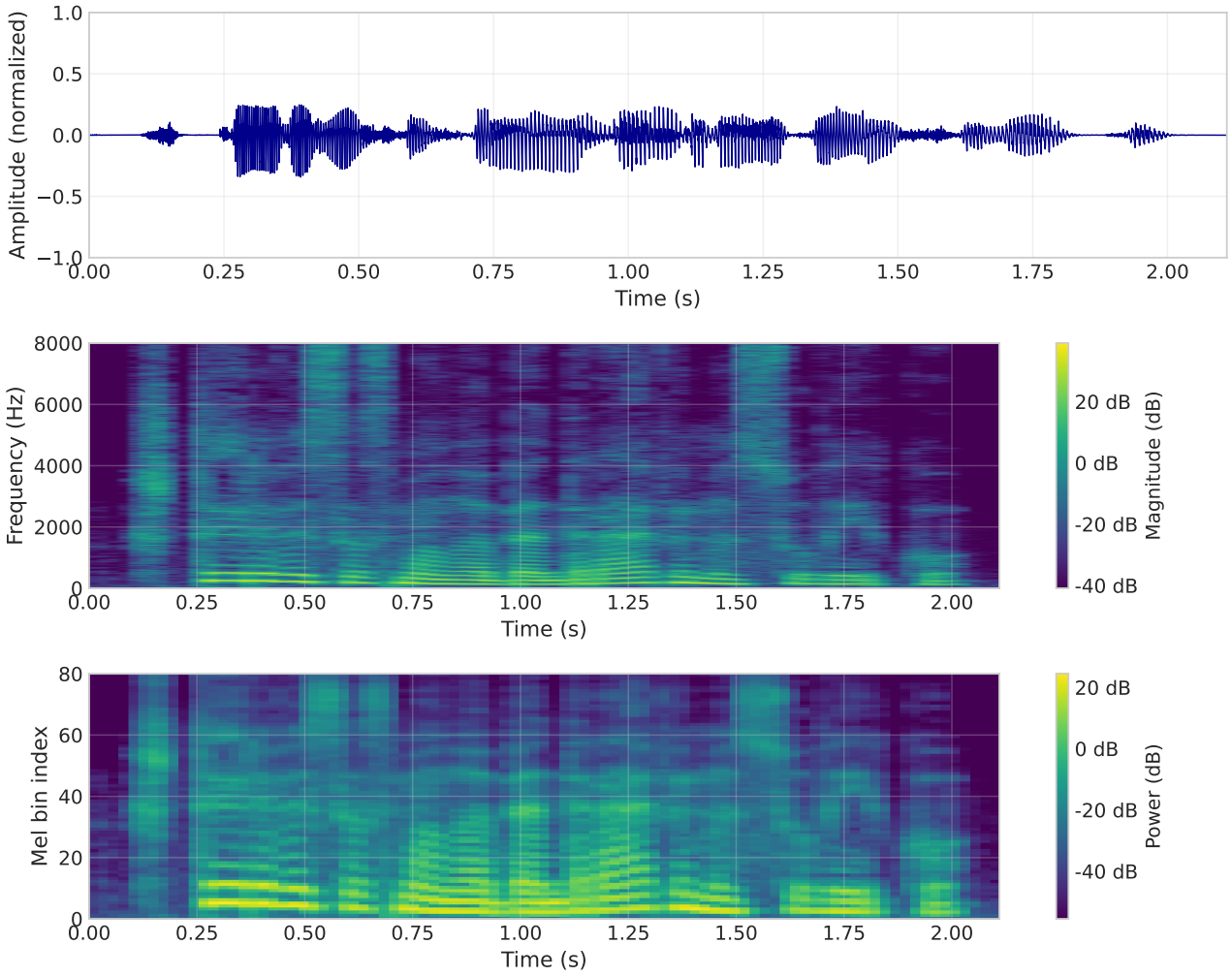


Figure 2 *Raw audio waveform (top), its linear frequency spectrogram (middle), and Mel-spectrogram (bottom) representations for the utterance "Štai ir visas mano bendravimas su vaiku".*

Text normalization helps reduce the variability and complexity in the input text, decreases the number of unique symbols, and removes the ambiguities that could confuse the TTS model. The resulting normalized text is not only easier for the model to process, but can also be further converted into phonemes, which provide an even closer representation of spoken language.

1.3.2 Graphemes versus Phonemes

Text-to-speech systems use a discrete input representation derived from text, generally divided into grapheme-based or phoneme-based sequences.

Grapheme-based models ingest raw character sequences (orthography). This approach simplifies the inference pipeline by eliminating the dependency on external grapheme-to-phoneme (G2P) converters. However, it forces the model to implicitly learn pronunciation rules from data, which can be a significant challenge for languages with complex orthographies or heteronyms (e.g., English "read" /riːd/ and "read" /rɛd/, depending on the tense).

In contrast, the phoneme-based approach uses a phonetic transcription of the text, typically in the International Phonetic Alphabet or ARPABET form. By resolving pronunciation ambiguities prior

to training, phonemes provide a more direct mapping to acoustic features, simplifying the model's task of learning alignment. The downside is that this approach requires an external G2P conversion step [14]. Additionally, errors in the G2P conversion can propagate to the TTS model, affecting the quality of the synthesized speech.

For languages with highly regular orthographies (e.g., Spanish, Lithuanian), there is another approach that augments the grapheme-based representation with explicit lexical stress markers (e.g., tilde, acute, grave accents). This intermediate method helps the model disambiguate pronunciation of homographs and learn prosodic patterns more easily without requiring a full phonetic transcription, particularly in languages where stress placement alters meaning.

1.3.3 Challenges in Lithuanian TTS

Lithuanian is a Baltic language with rich inflectional morphology and a complex prosodic structure. It is a pitch-accent language with free stress, meaning the stress can fall on any syllable in a word, and can change position depending on the grammatical form.

In the context of TTS synthesis, Lithuanian presents several challenges. First, the extensive inflection leads to a high number of unique word forms, which is significantly higher than in English. This results in data sparsity issues, where many valid word forms may not appear in the training set (i.e., a high out-of-vocabulary word rate). Second, the free stress system complicates pronunciation modeling. Typically, stress marks are omitted in written Lithuanian. However, stress position and tone (acute, circumflex, or short) determine the meaning of homographs. Examples are shown in Table 1. A grapheme-based model with accentuation marks has been shown to improve synthesis quality in Lithuanian [15].

Table 1 *Examples of Lithuanian homographs where accentuation determines meaning. A grapheme-only model cannot distinguish these without context or explicit stress marks.*

Word	Accentuation	Meaning
Antis	*ántis* (Acute) *añtis* (Circumflex)	A duck (noun) Bosom/Chest (noun)
Kasa	*kãsa* (Circumflex) *kasà* (Short)	He/she digs (verb) Braid/Pancreas (noun)

From a neural modeling perspective, the highly inflectional nature of Lithuanian increases the effective sequence length of the input. Autoregressive TTS models with location-sensitive attention, such as Tacotron 2, are known to degrade in performance as input sequences grow longer [16]. The complex G2P mapping inherent in the Lithuanian free stress system further complicates the learning objective. The model must reserve capacity to memorize stress patterns for specific inflections rather than just generalizing on acoustic features. This suggests that for Lithuanian, the stability of the alignment mechanism is not only dependent on the amount of available data, but is also affected by the linguistic complexity of the input.

To overcome these challenges, tools like **Kirčiuoklis** [17] (Vytautas Magnus University) are often employed in the text normalization pipeline. Kirčiuoklis automatically assigns stress marks to

each word in the input text. One weakness of Kirčiuoklis is that it relies on a simple word-dictionary lookup, which does not take into account the context of the word. Thus, it suggests multiple possible accentuation variants for homographs, leaving it up to the user to select the correct one.

1.4 Text-to-Speech Synthesis

Text-to-Speech (TTS) synthesis, also known as speech synthesis, is the process of converting written text into human-like spoken words. Nowadays, TTS is a key technology in numerous applications, including virtual assistants, accessibility tools, and language learning platforms.

The *one-to-many* nature of the mapping from text to speech presents a significant challenge, where a single text input can map to multiple speech outputs with a variety of speaking styles, emotions, and prosodic variations [18]. Thus, TTS is inherently a *large-scale inverse problem* [19] — reconstructing the original waveform from incomplete data (text) requires inferring missing information.

1.4.1 Traditional TTS Approaches

Early attempts at artificial speech synthesis evolved from the first mechanical devices in the 18th century to electronic systems. Wolfgang von Kempelen's mechanical speaking machine [1] demonstrated the production of basic phonemes, and later short phrases, using a physical model of the vocal tract. In 1939, Homer Dudley's invention of the Voder [20] became the first electronic speech synthesizer that could produce intelligible speech through operator-controlled acoustic parameters, establishing the foundation for modern electronic synthesis methods.

In the decades that followed, two main approaches for speech synthesis emerged: concatenative synthesis and parametric synthesis.

1.4.2 Concatenative Synthesis

The concatenative synthesis approach [21] generates speech by piecing together pre-recorded segments of human speech. This method involves several steps. First, it requires pre-recording a large database of speech segments spoken by a human voice actor in pristine, highly controlled studio conditions to ensure consistent audio quality and minimize background noise. Each segment is labeled and indexed based on its phonetic and prosodic properties.

During synthesis, the system breaks down the input text into short linguistic units (such as phonemes or syllables) using a text analysis module. Then, it queries the speech database to find the best-matching segments for each unit using selection cost functions [22]. The retrieved segments are blended and concatenated to form a continuous speech waveform. Finally, the system uses signal processing techniques to smooth the transitions between segments and adjust pitch and duration to match the desired output characteristics.

Although concatenative synthesis is a fast method capable of producing high-quality speech, its performance is heavily dependent on the size and quality of the underlying speech corpus [23]. A significant limitation is that the system fails to maintain naturalness when the required speech segments are not present in the database. However, even the largest corpora cannot cover all variants

of contextual speech segments. When the system has to synthesize out-of-database segments, the final audio suffers from audible continuity distortions at the concatenation points [22]. The segments may not blend smoothly due to differences in pitch, duration, and timbre — as a result, stringing disjointed segments together does not capture the natural rhythm and intonation patterns of connected speech.

The creation of a comprehensive corpus for such a purpose is costly and time-consuming. Improving a concatenative system requires language-specific expertise to design and update the corpus with good-quality, well-pronounced word units [23]. These rigid requirements are especially challenging for languages with rich morphology, and especially for low-resource languages like Lithuanian.

1.4.3 Parametric Synthesis

In contrast, statistical parametric speech synthesis [24] (SPSS) uses statistical models, typically Hidden Markov Models (HMMs) [25], to generate the parameters that control a speech waveform.

The workflow has two distinct stages: training and synthesis [24]. In the training stage, the model analyzes a large corpus of recorded speech to learn the relationship between linguistic features (e.g., phonemes, prosody) and the statistical distributions of acoustic features (e.g., spectral envelope, fundamental frequency). In the synthesis stage, the system converts input text into a sequence of linguistic features, the trained model predicts the corresponding acoustic parameters, and finally, a parametric vocoder reconstructs the speech waveform based on these predictions.

Compared to concatenative synthesis, the statistical approach allows for more flexibility and control over the speech synthesis process, enabling the generation of a variety of voices, speaking styles, and emotions.

However, HMM-based synthesis [25] had a persistent problem: the statistical averaging built into the models tended to over-smooth the acoustic features, creating the characteristic “buzzy” or “muffled” sound that lacked the sharpness and detail of natural human speech. In general, well-tuned concatenative synthesis produced higher-quality speech than the best parametric methods. However, the flexibility of the parametric approach laid the groundwork for modern Deep Learning methods, which eventually solved the over-smoothing problem and surpassed concatenative systems in naturalness.

1.5 Deep Learning for End-to-End TTS

The limitations of complex, multi-stage pipelines motivated the creation of E2E models. E2E systems learn the entire speech synthesis process — from input text directly to acoustic output — using a single neural network. This approach promised to eliminate the need for hand-crafted pipelines that were difficult to design, required extensive expertise, and suffered from errors that accumulated across multiple components. By learning directly from text-audio pairs, E2E models showed they could produce speech with higher naturalness and expressiveness than previous methods, representing a significant leap in TTS technology.

Although deep learning TTS models are more robust to variations in data quality compared to concatenative approaches, they are essentially "data-hungry" systems that require large amounts of training data to achieve optimal performance. Extrapolating from results in language modeling, it is observed that model performance follows general scaling laws [26], improving as the amount of training data increases.

1.6 Foundational Neural Network Components

In order to understand modern TTS systems, it is necessary to review the underlying neural network components that form the building blocks of these architectures.

Embeddings and Representation Learning

In machine learning, embeddings are dense vector representations that map discrete entities (such as words, characters, or speaker IDs) to a continuous vector space. Unlike one-hot encodings, which are sparse and highly dimensional, embeddings provide a dense, lower-dimensional representation that captures semantic relationships. For instance, in word embeddings, semantically similar words (e.g., 'king' and 'queen') tend to map to nearby points in the vector space [27]. Capturing such relationships enables models to generalize better — for example, understanding that the letters 'b' and 'p' are phonetically similar can help in learning pronunciation patterns.

Technically, an embedding layer acts as a **lookup table** of parameters that can be either fixed (computed by an external model) or learnable during training. When the network processes an input entity ID, it retrieves the corresponding vector from this table. In trainable embedding layers, the vectors are updated via backpropagation along with the rest of the model parameters, allowing the model to optimize the embeddings in order to minimize the total loss.

In TTS encoders, which are explained in more detail in the following sections, **character embeddings** are responsible for converting a sequence of input symbols (characters or phonemes) into continuous, differentiable feature vectors that can be processed by downstream neural network layers and trained jointly with the rest of the model.

Feedforward Neural Networks

Feedforward Neural Networks (FNNs) are the simplest type of artificial neural networks, consisting of layers of interconnected nodes (neurons) where information flows in one direction — from the input, through hidden layers, to the output. While FNNs can be useful for basic regression or classification tasks, they lack the memory and context-awareness needed for processing sequential data like text and speech. Therefore, FNNs are generally not suitable for sequence modeling in TTS tasks on their own, though they remain building blocks within larger architectures (e.g., projection layers or post-processing nets).

Recurrent Neural Networks

Recurrent Neural Networks (RNNs) [28] are a class of neural networks designed specifically for processing sequential data. Unlike Feedforward networks, RNNs possess an internal state (memory) that allows information to persist across time steps. For every element in the input sequence, the network performs the same task, with the output depending on both the current input and the previous computations. This makes them naturally suited for speech synthesis, where the current acoustic frame is highly dependent on the preceding ones.

However, standard RNNs suffer from the "vanishing gradient" problem, making it difficult to learn dependencies over long sequences [29]. To address this, variants such as Long Short-Term Memory (LSTM) [30] and Gated Recurrent Units (GRU) [31] were introduced. These architectures utilize gating mechanisms to control the flow of information, allowing the network to retain or forget information over longer intervals. In the context of TTS, Bi-directional RNNs [32] are often used in the encoder to capture linguistic context from both past and future text inputs simultaneously.

Attention Mechanism

One of the key challenges in sequence-to-sequence TTS is the misalignment between input and output sequences — the length of the input text (characters) does not match the length of the output audio (frames). The Attention mechanism [33] solves this by allowing the decoder to focus on different parts of the input sequence at every step of generation.

In this framework, the decoder's current hidden state functions as a **query** (Q) that seeks relevant information. The encoded input text is projected into sets of **keys** (K) and **values** (V). At each decoding step, the model compares the current query against all keys to calculate attention weights, which represent the relevance of each input token. These weights are then used to aggregate (weighted sum) the corresponding values into a context vector.

In mathematical terms, this operation can be expressed as:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{3}$$

where d_k is the dimensionality of the keys. The dot product QK^T computes the similarity between the decoder's state (query) and the encoder's representations (keys), determining how much focus to place on each respective value [34].

In TTS, the alignment must be monotonic (reading text from left to right) and continuous. Standard content-based attention (relying solely on the similarity between query and key vectors) can fail in this regard, leading to issues like skipping words or repeating phrases. To solve this, TTS systems typically use Location-Sensitive Attention [35]. This variant extends the standard attention mechanism by allowing the query to access the previous alignment history. By incorporating the model's past "location" into the scoring of keys, it encourages the attention mechanism to move forward sequentially, ensuring a stable and monotonic progression through the sentence.

Encoder-Decoder Framework

The Encoder-Decoder architecture is a neural network design consisting of two components: an encoder and a decoder. The encoder processes the input data and compresses it into a high-dimensional latent representation. This vector captures the meaningful features of the input. The decoder uses this latent representation as context to generate the final output. This architecture is commonly used in sequence-to-sequence (seq2seq) tasks [36], such as machine translation (text-to-text) and text-to-speech synthesis (mapping text to audio frames).

Autoregressive and Non-autoregressive Models

Within the sequence-to-sequence framework, TTS models can be generally categorized into autoregressive and non-autoregressive (parallel) models based on how they generate the output sequence.

Autoregressive models generate each output time-step (sample or frame) sequentially, conditioning the generation on previously generated time-steps. This approach allows the model to capture temporal dependencies effectively, producing high-quality speech. While earlier recurrent neural network-based systems utilized this approach, it was revolutionized by WaveNet [37] for raw waveform generation, and later by Tacotron [19] for spectrogram generation. Autoregressive models were the dominant architecture in neural TTS for several years. However, their sequential nature leads to slow inference times, as each frame must be generated one after another.

Non-autoregressive (parallel) models were developed to address the slow inference speed and stability issues of autoregressive systems. These models generate all output frames simultaneously, allowing for much faster synthesis. Examples include FastSpeech [38] and Glow-TTS [3]. Non-autoregressive models often rely on duration prediction modules to determine how long each input token should be stretched in the output sequence. While these models achieve significant speed-ups during inference, they may struggle to capture fine temporal dependencies, potentially leading to lower naturalness compared to autoregressive models.

1.7 TTS Pipeline and Acoustic Models

As shown in Figure 3, modern neural TTS systems generally follow a two-stage pipeline. An **Acoustic model** first generates intermediate acoustic features (typically Mel-spectrograms) from the input text. Then, a **Vocoder** converts these features into the raw audio waveform.

The following sections detail the specific acoustic models used in this work.

1.7.1 Tacotron 2

Tacotron [19] and Tacotron 2 [2] are notable TTS models based on the autoregressive sequence-to-sequence architecture. The variant that this thesis primarily focuses on is Tacotron 2 with Dynamic Convolution Attention (DCA) [16]. The complete architecture of Tacotron 2 is depicted in Figure 4. The architecture has three main components: an encoder, an attention mechanism, and a decoder.

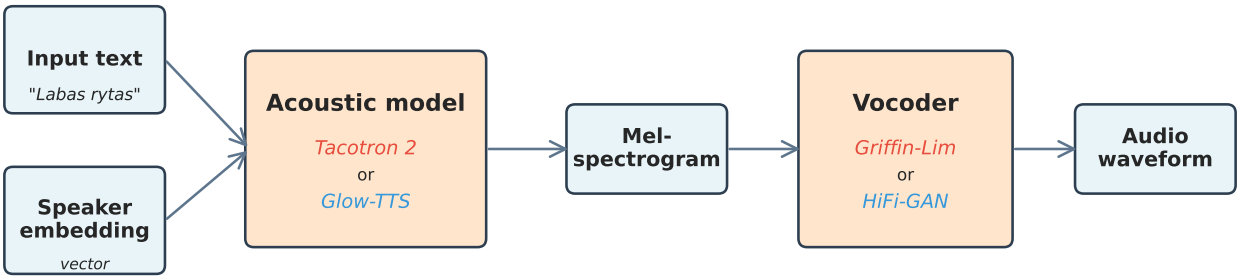


Figure 3 *Text-to-Speech synthesis pipeline. The TTS model generates Mel-spectrograms from input text, which are then converted to raw audio waveforms by a vocoder.*

The **Encoder**'s input is a character or phoneme sequence. A stack of convolutional layers followed by a bidirectional LSTM converts the character sequence into a high-level hidden feature representation.

The **Attention mechanism** bridges the encoder and decoder — it determines which parts of the input text should be attended to when generating each of the output audio frames. While the original Tacotron 2 used Location-Sensitive Attention [35], a more modern variant employs DCA [16], which offers robust alignment for long inputs and prevents the model from repeating or skipping words.

The autoregressive LSTM **Decoder** generates a coarse Mel-spectrogram frame. This output is then passed through a convolutional **Post-net** which predicts a residual to refine the spectral details and improve reconstruction quality.

Additionally, the model includes a **Stopnet** component. This linear layer projects the LSTM decoder's output to a scalar, predicting the probability that the current frame is the "stop token", which halts the synthesis process. This allows the model to dynamically determine the output duration. In some implementations, the Stopnet is separated from the decoder's gradient flow to prevent the stop-token loss from destabilizing the attention alignment.

The model is optimized by minimizing a combination of losses: the mean squared error (MSE) between the predicted and ground truth Mel-spectrograms (both the Decoder and Post-net outputs) and the binary cross-entropy loss for the stop token prediction. Modern implementations of Tacotron 2 include additional loss terms, such as the spectral similarity index (SSIM) loss, and the "guided attention" loss to encourage diagonal alignments.

While Tacotron 2 can generate high-quality speech, being an autoregressive model, it suffers from slow inference times. Additionally, the attention mechanism can suffer from stability issues, such as attention failures that result in skipped or repeated words in the synthesized speech.

1.7.2 Glow-TTS

Glow-TTS [3] is a non-autoregressive TTS model that applies flow-based generative models (normalizing flows [39]), which allow for complex distributions to be modeled by transforming a sim-

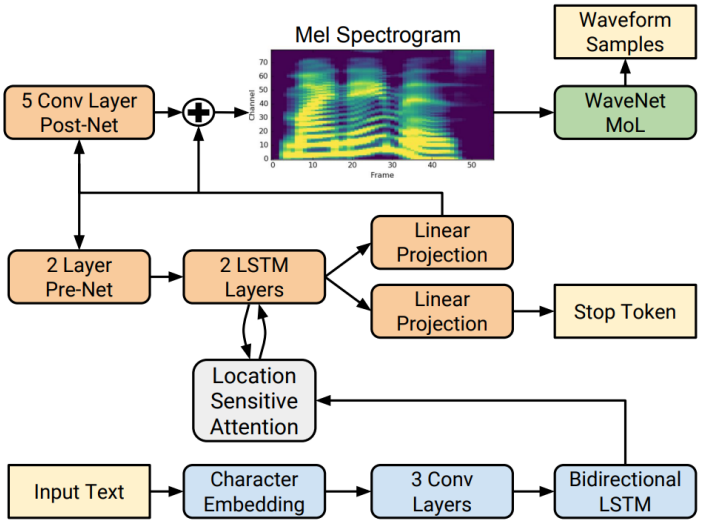


Figure 4 *Tacotron 2 architecture, diagram taken from the original paper [2]. The Attention module connects the Encoder (upstream blocks) with the Decoder (downstream blocks). WaveNet is not part of the acoustic model and is not used in this work.*

ple distribution through a series of invertible mappings. Unlike Tacotron 2, Glow-TTS generates the entire Mel-spectrogram in parallel, significantly speeding up inference.

Compared with earlier parallel models like FastSpeech [38] or FastPitch [40], a distinguishing feature of Glow-TTS is its ability to learn alignment internally, eliminating the dependency on external aligners. To achieve this, Glow-TTS employs Monotonic Alignment Search (MAS) to find the most probable monotonic path between the input text and the target Mel-spectrogram, maximizing the log-likelihood of the data. Architecturally, the decoder uses a stack of normalizing flows — specifically, invertible 1×1 convolutions and affine coupling layers — to transform a simple prior distribution (conditioned on the text encoder outputs) into the complex distribution of Mel-spectrograms.

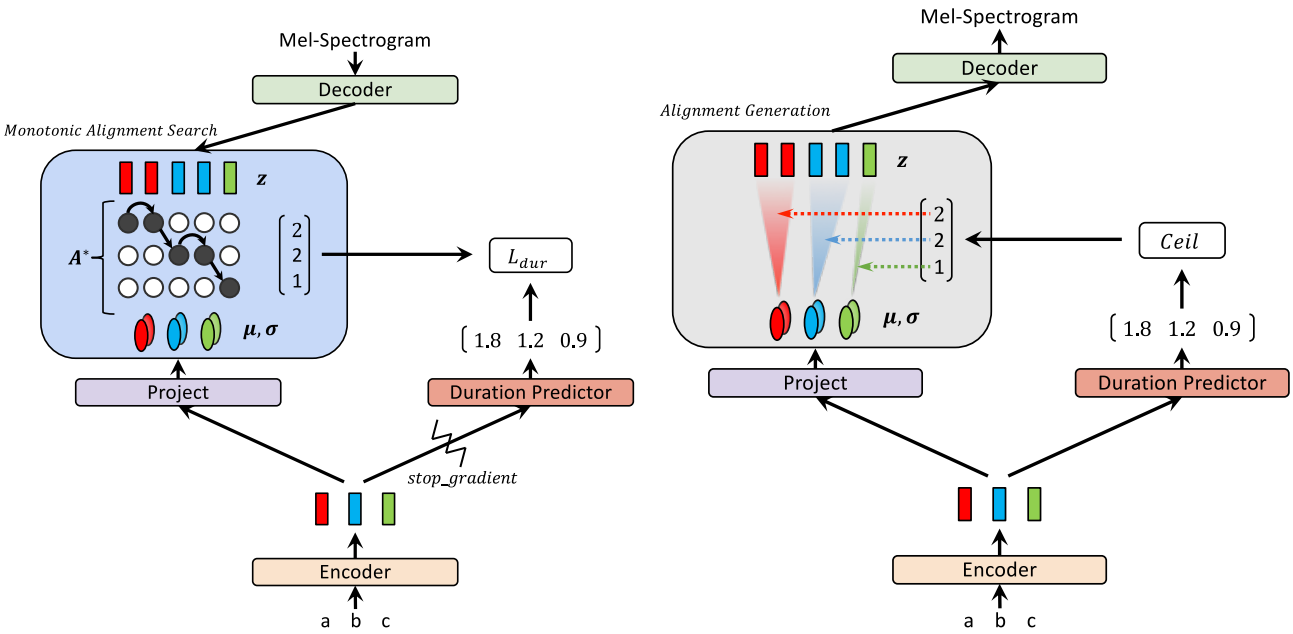
By utilizing the properties of flows, Glow-TTS allows for varied speech synthesis by sampling from the latent space and manipulating the noise temperature.

The high-level architecture of Glow-TTS is illustrated in Figure 5, showing both the training and inference procedures.

The primary advantages of Glow-TTS over Tacotron 2 are inference speed and robustness (the MAS alignment prevents skipping or repeating words).

1.7.3 Other Notable TTS Models

Besides Tacotron 2 and Glow-TTS, other notable TTS architectures include **FastPitch** [40], which uses a feed-forward Transformer architecture with explicit pitch and duration predictors, and **VITS** (Conditional Variational Autoencoder with Adversarial Learning) [41], which combines the acoustic TTS model (Glow-TTS) with a neural vocoder (HiFi-GAN [42]) into a single end-to-end architecture.



(a) *An abstract diagram of the training procedure.* ***(b)*** *An abstract diagram of the inference procedure.*

Figure 5 *Glow-TTS training and inference procedures. During training (a), the model learns to map text to Mel-spectrograms by maximizing the likelihood of the data using Monotonic Alignment Search (MAS). During inference (b), the model generates Mel-spectrograms in parallel by sampling from a prior distribution conditioned on the text encoder outputs [3].*

1.8 Vocoders

As previously illustrated in the pipeline overview Figure 3, acoustic models like Tacotron 2 and Glow-TTS generate Mel-spectrograms rather than raw audio waveforms. Mel-spectrograms are lossy representations that capture the magnitude of the sound frequency bands, but discard phase information. Converting a lossy spectrogram into audio is a non-trivial task, requiring a component called a vocoder to estimate the missing phase and reconstruct the waveform.

Traditionally, the Griffin-Lim algorithm [43] was used to iteratively estimate and reconstruct the phase information from the magnitude spectrogram. However, this method often produces audio with noticeable artifacts and lower quality compared to natural speech. Modern TTS systems use neural vocoders — deep generative models trained to map acoustic features to raw waveforms.

Evolution of Neural Vocoders

WaveNet [37] was one of the first autoregressive models to produce high-fidelity audio, but its sequential generation process made it prohibitively slow for real-time applications. To address these speed limitations, Generative Adversarial Network (GAN) based vocoders were introduced.

HiFi-GAN [42] is currently one of the state-of-the-art neural vocoders. It consists of a Generator that upsamples the Mel-spectrograms using transposed convolutions and a set of Discriminators (multi-scale and multi-period discriminators) that have the role of distinguishing between real and synthesized audio. The adversarial training between the Generator and Discriminators trains the

Generator to produce high-quality waveforms that closely resemble natural speech. HiFi-GANs are highly efficient and capable of a Real-Time Factor significantly less than 1.0 on consumer hardware while maintaining high perceptual quality. HiFi-GAN is also part of the state-of-the-art end-to-end TTS model VITS [41].

Cross-Lingual Vocoding

The framework used in this thesis, Coqui TTS [44], provides a pre-trained HiFi-GAN vocoder trained on the VCTK dataset [45], a large multi-speaker dataset with 110 English speakers.

The use of a vocoder trained on English data for Lithuanian synthesis is justified by the language-agnostic nature of the phase reconstruction task. Neural vocoders' primary function is to model the physics of human speech production rather than linguistic features. While language-dependent phonetic nuances exist, studies have shown that vocoders trained on large, diverse datasets can effectively generalize to unseen speakers and languages [46]. Therefore, this thesis utilizes the pre-trained HiFi-GAN model for waveform generation, ensuring that the acoustic parameters (sampling rate, FFT size, Mel-filterbank limits, etc.) of the input Mel-spectrograms are configured to match those used during the vocoder's training.

1.9 Multi-Speaker TTS

Multi-speaker TTS models are designed to synthesize speech in the voices of multiple speakers within a single model. While the obvious utility of such systems is to provide voice options for virtual assistants or content creation, another motivation for their development is data efficiency.

The standard recommendation for high-quality *single-speaker* TTS is 10 to 20 hours of clean, studio-recorded speech from a professional voice actor. The majority of existing research focuses on high-resource languages like English, where such datasets (e.g., LJSpeech [7] with 24 hours of speech) are readily available. However, for low-resource languages such as Lithuanian, acquiring such extensive single-speaker datasets is often not feasible. Available resources tend to be crowd-sourced, with multiple speakers contributing small amounts of data to a fragmented corpus.

Multi-speaker TTS addresses this by decoupling the learning of linguistic features from speaker identity. By pooling data from multiple speakers, the model learns shared linguistic features — such as phoneme duration and stress patterns — from the global dataset. At the same time, it learns to model individual speaker characteristics through speaker-specific embeddings. This allows the model to synthesize high-quality speech for individuals who contribute only a fraction of the data normally required for single-speaker training, effectively enabling the system to learn "how to speak" from the group and "how to sound" from the individual.

1.9.1 Speaker Embeddings

To enable multi-speaker synthesis, TTS models require a representation of speaker identity to condition the generation process. In these architectures, the network is conditioned on a speaker embedding vector. The model learns a shared representation of phonetics (how text maps to sound

generally) while using this additional input — the speaker embedding — to adjust the timbre and prosodic characteristics specific to a target voice.

Early successful implementations of this approach include Deep Voice 2 [47], which demonstrated effective multi-speaker synthesis by learning speaker-specific embeddings jointly with the generative model. Contemporary approaches generally fall into two categories: external pre-computed embeddings (such as d-vectors and x-vectors) and internal learnable embeddings.

Transfer learning approaches [48] have demonstrated adapting speaker verification models for multi-speaker TTS. A speaker encoder model, pre-trained on massive, noisy datasets (e.g., VoxCeleb [49]) learns the general speaker space. During TTS training, this pre-trained model is applied to reference audio samples to compute fixed speaker embeddings that represent the identity of each speaker. Common variants of external embeddings include **d-vectors** and **x-vectors**.

d-vectors were introduced by Variani et al. [50] — these are derived from a reference encoder (typically LSTM-based) that compresses audio into a vector summarizing timbral characteristics. **x-vectors** are an evolution of d-vectors [51] using Time Delay Neural Networks (TDNN) to capture temporal context more effectively.

While these methods allow for zero-shot adaptation to unseen speakers, they introduce a dependency on the quality of the reference audio. Noisy reference audio can produce embeddings that fail to capture the speaker's true identity, degrading synthesis quality. Additionally, these embeddings are optimized for speaker verification (telling speakers apart), which may not align perfectly with the objective of high-quality speech synthesis.

In the **learnable speaker embeddings** approach, a **learnable** embedding layer (lookup table) is initialized within the TTS model. Each speaker ID in the training set is mapped to a unique, dense vector. These vectors are initialized randomly and updated via backpropagation during TTS model training. This method cannot generalize to new, unseen speakers at inference time, but it is simple and effective when the number of speakers is fixed and known in advance.

1.9.2 Challenges

Compared to single-speaker models, multi-speaker models can achieve convergence and reasonable intelligibility with significantly less data per speaker — as little as 15 to 30 minutes — provided the total pooled dataset is sufficiently large to learn the shared linguistic features. However, one critical question in this domain is data composition: determining the optimal structure of the training dataset to maximize synthesis quality.

In the context of multi-speaker synthesis, there is a trade-off between the **breadth** of the data (number of distinct speakers) and the **depth** of the data (duration of audio per speaker). In theory, training on a dataset with a massive number of speakers, even with limited data per speaker, may allow the model to learn a more generalized latent space of voice characteristics. This high variance in the training data could act as a form of regularization, preventing overfitting to noise and idiosyncrasies of individual speakers, and leading to a more robust internal representation. However, in low depth scenarios, the model may struggle to converge on stable speaker identities, resulting in an 'average' voice that lacks distinctiveness and naturalness. In contrast, datasets with fewer speakers but

high duration per speaker allow the model to capture fine-grained prosodic details specific to those voices, potentially achieving lower generalization, but higher fidelity for the speakers present in the training set. It remains an open question whether the regularization benefit of speaker diversity outweighs the noise introduced by insufficient speaker profiling.

1.10 Evaluation Metrics for TTS

Evaluating Text-to-Speech systems is notoriously difficult because "quality" and "naturalness" are subjective metrics defined by human perception.

Objective Metrics

Several objective metrics have been proposed to quantify the quality of synthesized speech. While there is no single mathematical function that perfectly aligns with human judgement of naturalness and intelligibility, these metrics are easy to compute and can provide useful insights during model development. Common objective metrics are summarized in Table 2. Each metric captures a different aspect of speech quality, including spectral similarity (MCD), pitch accuracy (F_0 RMSE), and perceived audio quality (PESQ).

Table 2 *Common objective metrics for TTS evaluation. These metrics provide quantitative measures of spectral similarity, pitch accuracy, and perceived audio quality.*

Acronym	Full name	Description
MCD [52]	Mel-Cepstral Distortion	Measures spectral distortion between synthesized and reference audio. Lower values indicate better quality.
F_0 RMSE	Fundamental Frequency Root Mean Square Error	Quantifies pitch accuracy by computing the root mean square error of fundamental frequency (pitch). Lower is better.
PESQ [53]	Perceptual Evaluation of Speech Quality	Predicts perceived audio quality on a scale from -0.5 to 4.5. Requires aligned reference audio for comparison. Higher is better.

Subjective Metrics

The gold standard for evaluating speech synthesis quality remains the Mean Opinion Score (MOS), originally derived from telecommunications quality standards (ITU-T P.800) [54].

In a MOS test, human listeners (raters) are presented with a set of synthesized speech audio samples and asked to rate them on a 5-point Likert scale. The standard scale for "naturalness" is presented in Table 3.

The final score is the arithmetic mean of all ratings collected for a specific TTS system. Although MOS is subjective, with a sufficient number of raters (typically, at least 15–20), the scores tend to converge and provide a reliable ranking between different models.

Table 3 *Mean Opinion Score (MOS) scale for TTS evaluation. Raters assign scores based on the perceived naturalness of synthesized speech samples.*

Score	Description
5	Excellent (Imperceptible difference from real speech)
4	Good (Perceptible but not annoying)
3	Fair (Slightly annoying)
2	Poor (Annoying)
1	Bad (Very annoying / Unintelligible)

Latin Square Design

A major challenge in subjective listening tests is controlling for biases. If a rater hears the same sentence produced by different TTS systems in a row, their ratings may be influenced by the repetition (repetition effect) or by the relative order of presentation (order effect). For instance, a "Slightly annoying" sample may be rated more harshly if it follows an "Excellent" sample (contrast effect).

In order to mitigate these biases, a Latin square design [55] is often employed for MOS tests. In this experimental design:

1. A set of test sentences (utterances) is selected.
2. Multiple TTS systems (models) generate audio for each test sentence.
3. The listeners are divided into groups.
4. The presentation is balanced such that each listener hears every test sentence exactly once, and every TTS system (model) exactly once per block of trials, but never the same sentence-system combination twice.

For a multi-speaker TTS evaluation (as is the case in this thesis), the Latin square design ensures that the ratings reflect the quality of the model rather than the linguistic content of the sentence or listener fatigue. By rotating the systems and sentences across listener groups, the influence of specific difficult sentences is averaged out across all models. An example Latin square design for 4 TTS systems and 4 test sentences is illustrated in Figure 6.

1.11 Research Gap

While the literature demonstrates the capabilities of modern deep learning TTS architectures like Tacotron 2 and Glow-TTS to produce highly natural-sounding speech, several questions remain unanswered regarding their application to low-resource, morphologically complex languages like Lithuanian.

Firstly, although neural TTS models may follow general neural model scaling laws [26], implying that performance improves with more data, there is limited understanding of the optimal composition of training data under a fixed budget. In low-resource settings, scaling up the dataset size is not always feasible, and this may be further constrained by the computational resources required for

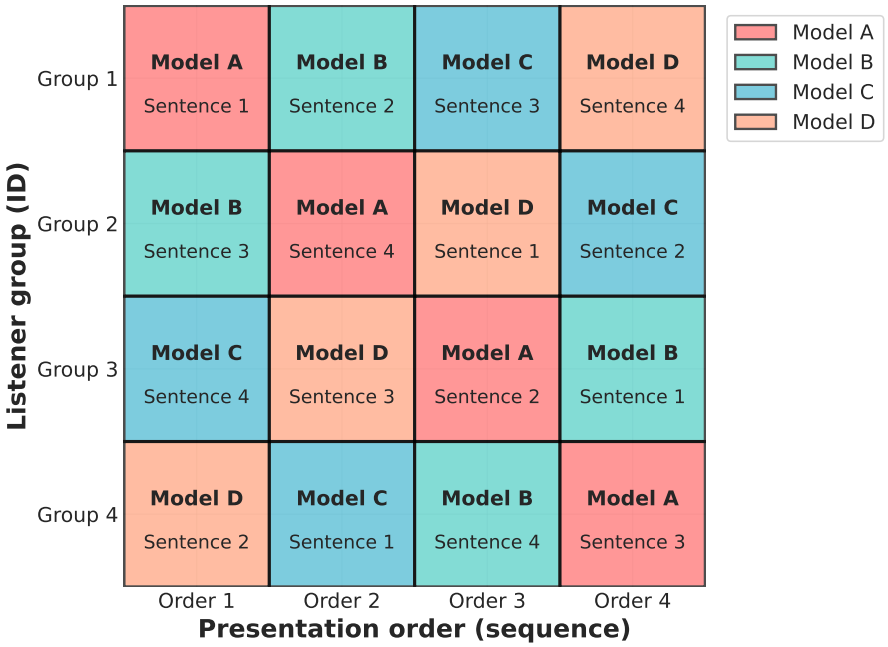


Figure 6 *Latin square design for TTS evaluation. Each listener group hears each sentence exactly once, and each TTS system exactly once per block, ensuring balanced exposure and mitigating order/repetition biases.*

training large models. A critical question is whether it is more beneficial to train on a smaller number of speakers with more data per speaker (high depth) or a larger number of speakers with less data per speaker (high breadth).

Current research primarily focuses on high-resource languages like English, where the availability of large, balanced multi-speaker datasets masks the nuances of this trade-off. For a pitch-accent language like Lithuanian, the requirements may be different. It is hypothesized that high-diversity datasets may help the model learn a richer representation of prosodic patterns, while high-depth datasets may improve the model's naturalness for the target speakers.

Secondly, most multi-speaker TTS research assumes access to large-scale datasets with thousands of utterances per speaker. There have been few studies investigating severe low-depth scenarios — a recent study examined fine-tuning Tacotron, however, it relied on a pre-trained model and did not explore training from scratch [56]. There is a lack of research exploring how different TTS architectures perform when the data per speaker is scarce (e.g., under 10 minutes).

This thesis aims to fill the research gap by systematically evaluating the efficiency of Tacotron 2 and Glow-TTS models trained on Lithuanian speech data. By controlling the total dataset size and varying the distribution of speakers and data per speaker, this study will provide insights into the optimal data composition for training multi-speaker TTS models in low-resource settings.

To summarize, the key research questions this thesis seeks to answer are:

- How does the trade-off between data breadth (number of speakers) and data depth (minutes per speaker) affect the performance of multi-speaker TTS models for Lithuanian?
- How do different TTS architectures (Tacotron 2 and Glow-TTS) perform under varying data selection strategies in low-resource settings?

The experiments will involve training models on three distinct data selection strategies, each with a fixed total training budget of 22.5 hours:

- Low breadth (30 speakers), high depth (45 min each).
- Moderate breadth (60 speakers), moderate depth (22.5 min each).
- High breadth (180 speakers), low depth (7.5 min each).

The extreme low-depth condition (7.5 minutes per speaker) might pose convergence challenges for the models, especially for Tacotron 2, which relies on learning robust attention alignment. Thus, alignment convergence and training stability will be monitored to assess how data composition affects model robustness.

1.12 Summary

This literature review has provided an overview of the theoretical foundations required for modern Text-to-Speech synthesis. The evolution of TTS systems from mechanical apparatuses, through concatenative and statistical methods, to end-to-end deep learning architectures capable of generating natural-sounding speech has been discussed.

We have reviewed the entire TTS pipeline — from signal processing (sampling, quantization, Fourier transforms, and Mel-spectrogram extraction), through text normalization and representation (graphemes versus phonemes), to deep learning architectures for acoustic modeling and vocoding. The literature highlights two architectures for acoustic modeling: the autoregressive Tacotron 2, known for high-quality spectral output but slow inference and stability issues, and the non-autoregressive Glow-TTS, which offers parallel generation and improved robustness.

We have examined the challenges specific to Lithuanian TTS synthesis. Unlike English, the Lithuanian language's high inflectional morphology leads to a large number of unique word forms, and its prosodic system requires handling of free stress and pitch accents, necessitating the use of tools like Kirčiuoklis for accentuation marking.

Finally, we have reviewed the role of speaker embeddings in enabling multi-speaker synthesis and the use of neural vocoders, specifically HiFi-GAN, to reconstruct high-fidelity waveforms from Mel-spectrograms. Despite these advancements, a gap remains in understanding how data diversity and quantity affect model performance for complex, low-resource languages — a challenge this thesis addresses through the experiments detailed in the following chapters.

2 Methodology

This chapter details the experimental setup, data processing pipeline, training configurations, and evaluation protocol used to determine the optimal composition of multi-speaker training data for Lithuanian TTS. The study employed a factorial design to compare the performance of two distinct architectures — Tacotron 2 (autoregressive) and Glow-TTS (non-autoregressive) — under varying degrees of data breadth and depth, while controlling for the total training budget.

The high-level experimental workflow is illustrated in Figure 7.

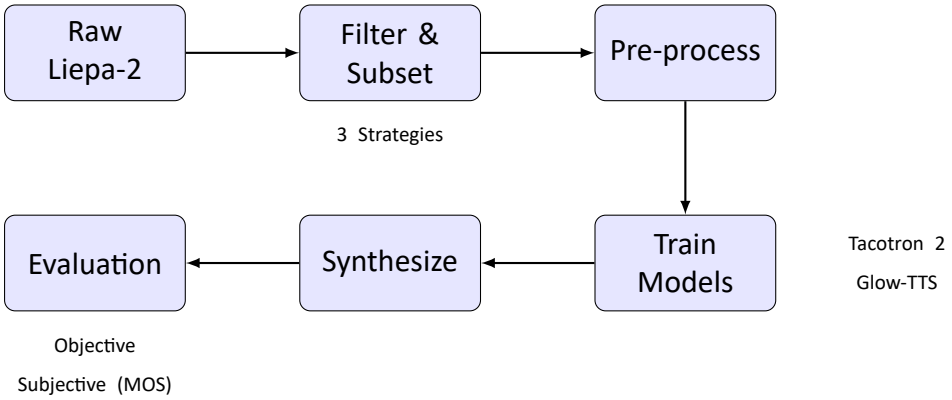


Figure 7 *Experimental pipeline overview. The process flows from raw corpus selection to comparative evaluation.*

2.1 Research Design

To investigate the impact of data distribution on synthesis quality, the experiments varied the balance between the number of speakers (N) and the amount of data per speaker.

Independent Variables:

- **Data selection strategy:** Three subsets varying in speaker count and duration per speaker (breadth versus depth).
- **Model architecture:** Tacotron 2 (autoregressive) and Glow-TTS (non-autoregressive).

Dependent Variables:

- **Objective metrics:** MCD, F_0 RMSE, and attention alignment convergence.
- **Subjective metrics:** Naturalness ratings via MOS.

Controlled Variables:

- **Training budget:** Fixed at 22.5 hours of audio data per model.
- **Training duration:** 90k steps for Tacotron 2 and 180k steps for Glow-TTS, adjusted for convergence characteristics.
- **Vocoder:** Pre-trained HiFi-GAN (frozen).
- **Domain:** Read speech (adults only).

2.2 The Liepa-2 Dataset

The primary dataset of this study is the **Liepa-2** Lithuanian speech corpus [8]. The dataset was obtained from the authors upon request for research purposes. To the best of the author's knowledge, this is currently the largest freely available annotated multi-speaker Lithuanian speech dataset. The full corpus contains 1,000 hours of annotated audio from 2,621 unique speakers. Of this, 939 hours are transcribed speech, while the remaining 61 hours consist of non-speech noise segments. The recordings span diverse speech styles and contexts, including read speech (audiobooks, studio recordings, dictaphone) and spontaneous speech (phone, radio, TV), sampled at 16 kHz in 16-bit PCM WAV format.

According to the documentation, the dataset filenames encode metadata about each recording. These filenames were used to retrieve the following information about each audio file: lossiness (lossy or raw), speech type (read or spontaneous), recording type (audiobook, dictaphone, phone, radio, studio, TV), gender (male or female), age group (0–12, 13–17, 18–25, 26–60, 60+), speaker ID, recording sequence number, and utterance number.

The documentation notes that speaker IDs are unique only within the context of an annotator, but not globally across the entire corpus. However, the documentation claims that duplicate speakers are rare, though not specifically marked in the dataset. Thus, speaker IDs were treated as globally unique for the purposes of this study.

2.2.1 Corpus Analysis and Filtering

The dataset was analyzed to determine the distribution of audio duration, sentence length, and speaker distributions across different speech types and recording conditions.

Analysis revealed that of the 939 hours of transcribed speech, read speech constitutes the majority (855 hours), while spontaneous speech accounts for under 9% (84 hours). Synthesizing spontaneous speech is more challenging due to disfluencies, high variability, and syntactic conventions different from those of written language [57]. Read speech, on the other hand, is generally more suitable for TTS training due to its consistent pronunciation and prosody.

Of the read speech, studio recordings account for the largest portion (577 hours, 67%), followed by dictaphone (220 hours, 25%) and audiobooks (25 hours, 3%). The remaining 33 hours (4%) are from TV, phone, and radio recordings. The latter three categories of read speech recordings were excluded due to the potentially less controlled recording conditions, or distinct acoustic characteristics that could introduce unwanted variability into the training data. Thus, the focus was placed on the more abundant studio, dictaphone, and audiobook sources, all of which were deemed more likely to be recorded in controlled environments favourable for TTS training.

Additionally, it was decided to exclude speakers under 18 years of age to maintain compatibility with the pre-trained HiFi-GAN vocoder. Speakers in the 0–17 age group constitute a small fraction (76 hours, 8%) of the total corpus duration, so their exclusion was not expected to significantly impact the available training data.

Finally, samples shorter than 1 second or longer than 15 seconds were filtered out. Samples

under 1 second are very short utterances that provide limited linguistic context. These short samples comprise 32 hours (4%) of the read speech data. On the other hand, samples longer than 15 seconds have been found to cause GPU memory overflows during Tacotron 2 training due to the increased sequence lengths. Longer samples account for 34 minutes (0.07%) of the read speech data.

To summarize, the filtering criteria applied to the Liepa-2 dataset were as follows:

- Speech type: Read speech only
- Recording type: Audiobook, Dictaphone, Studio
- Age group: Adults only (18–25, 26–60, 60+ age groups)
- Duration: Between 1 and 15 seconds

After applying these filters, the resulting dataset contained 723 hours of read speech from 1,794 unique adult speakers. Table 4 summarizes the statistics of the filtered Liepa-2 dataset. A number of speakers have multiple recording types (e.g., both studio and dictaphone), so the total unique speaker count is less than the sum across categories.

Table 4 *Statistics of the filtered Liepa-2 dataset.*

Source	Sum Duration (h)	Mean Sent. Len. (char.)	Speakers	Files
Audiobook	24.32	39.45	50	33,826
Dictaphone	188.26	37.12	453	256,386
Studio	510.77	42.81	1,303	649,651
Total	**723.35**	**—**	**1,794**	**939,863**

2.3 Experimental Training Data Subsets

The Liepa-2 corpus presents a challenge as most speakers contribute under 30 minutes of audio, while the speaker with the most data has only 2.5 hours of annotated speech. In order to isolate the impact of data breadth and depth, it was decided to create controlled training subsets from the filtered Liepa-2 data that vary in the number of speakers and the amount of data per speaker. However, the duration per speaker within each subset had to be uniform to prevent speaker imbalance from confounding the results.

The filtered Liepa-2 dataset was analyzed to determine feasible data configurations. For each gender (male and female), the speakers were sorted by total available duration. Figure 8 shows the rank against cumulative duration to visualize the depth versus breadth trade-off. It was determined that the *15-th* most data-rich male and female speakers had approximately 47 and 48 minutes of audio, respectively, while the *180-th* most data-rich speakers had 30 (male) and 34 (female) minutes. Data depth was clearly the limiting factor, as very few speakers had more than 1 hour of audio.

Thus, three training datasets were generated from the filtered Liepa-2 data. All strategies maintained a fixed total training budget of 22.5 hours. Based on the speaker duration analysis (Figure 8), it

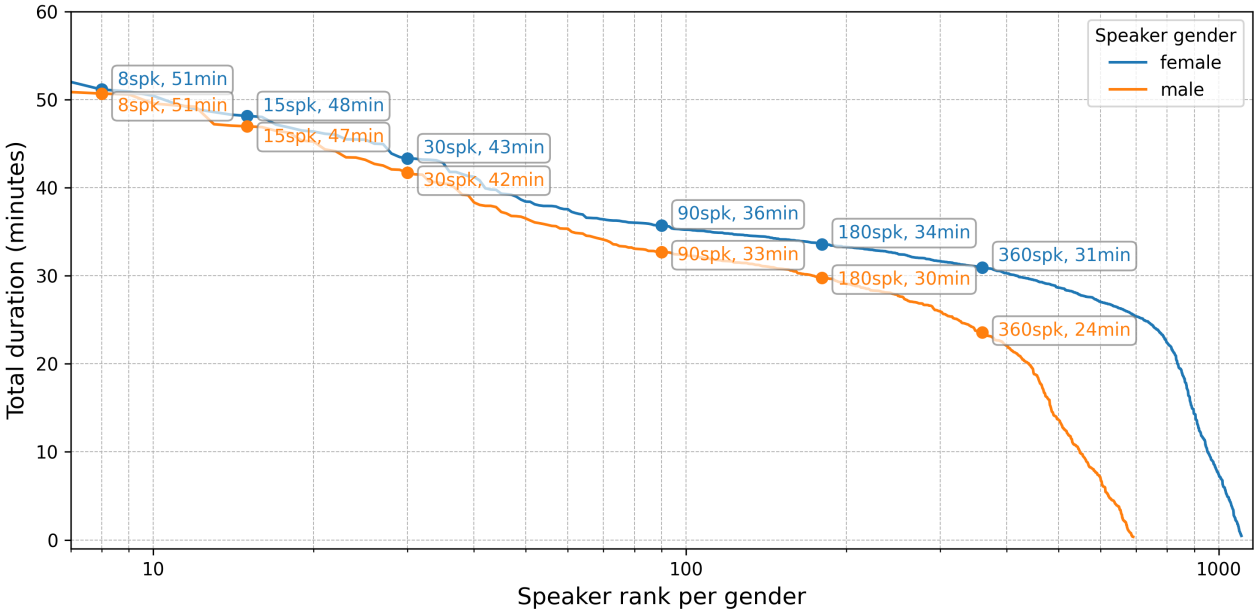


Figure 8 *Speaker duration distribution in the filtered Liepa-2 dataset. The plot illustrates the trade-off between the number of speakers (X axis) and available data per speaker (Y axis).*

was decided that the dataset with the highest depth would have 45 minutes per speaker, allowing for 30 speakers (15 male, 15 female), and two additional datasets would contain 60 and 180 speakers, respectively. The configurations are defined in Table 5 and visually represented in Figure 9.

The validation set was not predefined — a random 1% subset of each training dataset was selected for validation. In order to ensure that different training jobs on the same dataset used the same validation set, a fixed random seed was used when sampling the validation data.

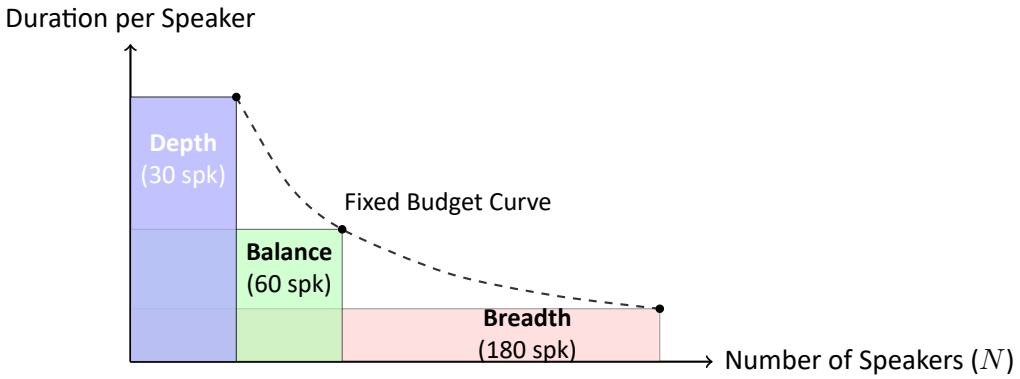


Figure 9 *Visual representation of the data strategies. The area of each rectangle (Total Audio) remains constant (≈ 22.5 hours), illustrating the trade-off between speaker diversity (Breadth) and data density (Depth).*

Only speakers with at least the required minimum duration for the specific subset were eligible for selection (e.g., at least 45 minutes for the 30-speaker set). For each selected speaker, a fixed set of utterances (10 per speaker) was held out for testing. The durations listed in Table 5 represent idealized targets, with actual durations varying slightly due to the discrete nature of utterance selection.

Table 5 *Experimental training data subsets. Total duration is constant, while speaker count (N) and duration per speaker vary inversely.*

Number of Speakers (N)	Time/Speaker	Total Time
30	45.0 min	22.5 hours
60	22.5 min	22.5 hours
180	7.5 min	22.5 hours

To ensure fair evaluation, speaker sets were nested: the 30 speakers in the 30-speaker set were included in the 60-speaker set, which were in turn included in the 180-speaker set. An exact 50/50 male-female split was maintained in all datasets to avoid gender bias.

This nesting strategy ensured that the 'core' 30 speakers were present in every model. This enabled a direct, side-by-side comparison of synthesis quality for the exact same target voices, effectively isolating the impact of the trainset composition without confounding factors from speaker identity.

The datasets were generated using a custom Python script. In order to ensure that each speaker would have at least the required minimum duration, speakers were first filtered based on their total available audio. From each eligible speaker, a random subset of utterances was selected until the cumulative duration met or exceeded the target.

The statistics of the actual training datasets are summarized in Table 6. The slight variations in total utterance count and total word count could be attributed to speakers having varying speaking rates and utterance lengths — these differences are minimal and not expected to significantly impact the results. The minimum and maximum durations within each dataset are very similar, confirming that there is no significant speaker-level imbalance.

Table 6 *Final statistics of the experimental training datasets.*

Speakers	Utterances	Total Words	Unique Words	Duration per Speaker (s), Min / Max
30	29,091	164,347	46,138	2700.2 / 2705.3
60	30,372	163,883	46,746	1350.1 / 1356.5
180	30,493	168,738	49,581	450.0 / 458.0

2.4 Data Preparation

2.4.1 Text Normalization and Accentuation

In the absence of a high-quality, context-aware G2P converter for Lithuanian, this study focused on grapheme-based TTS synthesis. The raw transcripts from the Liepa-2 dataset were pre-processed to standardize the text. A prior study [15] has shown that text normalization has a significant impact on grapheme-based TTS quality for Lithuanian.

Raw Liepa-2 transcripts are largely normalized — numbers, dates, abbreviations, and acronyms are expanded. An analysis of the raw text revealed that some annotators did not use any punctuation

(e.g., commas, periods), while others used punctuation consistently. Otherwise, the transcripts were of high quality. Due to the high volume of training samples, no manual correction of transcripts was performed. Some examples of raw transcripts are presented below:

> *"Berželio Sodų šeštoji septyniolika"* (ordinal and number written out)
> *"Anoniminis darbdavys pasiūlė šimtas penkiasdešim tūkstančių eurų už tai"* (number 150,000 written out)
> *"ir kabindavo makaronus apie vė dė vė didybę ir galingumą"* (acronym VDV written as it was pronounced)
> *"nenumanau šypsodamasis atsakė jis bet spėju kad netrukus sužinosime"* (punctuation omitted)

However, additional normalization was required to standardize the text for grapheme-based TTS training. The following normalization steps were applied:

1. **Cleaning:** Rare and non-standard punctuation was mapped to a standard set (.,-?!) and remaining extraneous characters were removed.
2. **Whitespace:** Consecutive whitespace characters were collapsed, and leading/trailing whitespace was trimmed.
3. **Accentuation:** Raw text was processed using **Kirčiuoklis** [17] for automatic stress assignment. The stress marks were decomposed into separate characters (‘’ for acute, “’ for grave, ‘ ’ for circumflex) and inserted immediately after the accented grapheme.
4. **Lowercasing:** All text was converted to lowercase to reduce the vocabulary size.
5. **Letter substitution:** Non-Lithuanian letters were replaced with equivalents (‘q’ $\rightarrow$ ‘k’, ‘w’ $\rightarrow$ ‘v’, ‘x’ $\rightarrow$ ‘ks’).

The accentuation step required dealing with ambiguity. As discussed in the literature review, the Lithuanian language has many homographs that can have different stress patterns, depending on the word's meaning and context. Kirčiuoklis, being a word dictionary-based tool, does not take into account the context of the word, and returns all possible accentuation options for homographs. Of 406 thousand unique words in the entire filtered Liepa-2 corpus, 72% (293 thousand) had a single accentuation option, 18% (75 thousand) had none (e.g., proper nouns (‘Trento’), foreign words (‘siut’), typos and neologisms (‘babkių’)), and 9% (38 thousand) had multiple accentuation options (e.g., ‘namo’, ‘pažintų’). In order to avoid introducing incorrect accents into the training data, only unambiguous words were accented — the rest of the words were left unaccentuated, instead relying on the models to infer prosody from context. Listening tests revealed that implementing Kirčiuoklis-based accentuation moderately improved the prosody of synthesized speech, especially for certain complex words. Overall, 82% of words in the training datasets were accentuated.

A few examples of raw and normalized text pairs are presented in Table 7.

Table 7 *Examples of text normalization and accentuation.*

Raw Text	Normalized Text
Antrasis vyras – gerokai jaunesnis	antra`sis vy´ras – gero´kai jaune`snis
(...) pusšimtį kilogramų Extasy	(...) pu`sšimtį kilogra~mų ekstasy
Visa tai atskleidžiama „Karaliaus Lyro" pradžioje,	visa tai atskleidžiama karaliaus lyro pradžioje`,

As a result of these normalization steps, the character vocabulary size was reduced from 140 characters to 41 characters. The final alphabet used for training contains only lowercase Lithuanian letters, stress marks, space, and basic punctuation:

a ą b c č d e ę ė f g h i į y j k l m n o p r s š t u ų ū v z ž ´ ` ~ (space) . , - ? !

2.4.2 Audio Preprocessing

Audio recordings were resampled from their original **16,000 Hz** to **22,050 Hz**. While resampling to a higher frequency does not add new information, the resampling was performed to match the pre-trained HiFi-GAN vocoder described in the **Vocoder** section below. Leading and trailing silence was trimmed. Acoustic features were extracted using the parameters in Table 8.

Table 8 *Mel-spectrogram extraction parameters.*

Parameter	Value
Sampling rate	22,050 Hz
FFT size	1024 samples (46 ms)
Hop length	256 samples (11.6 ms)
Window length	1024
Mel-spectrogram channels	80
Frequency range	0–8000 Hz
Pre-emphasis	0.98

A complete list of audio parameters is presented in the Appendix 5.

2.5 Model Architectures

For each data selection strategy, two acoustic models were trained: an autoregressive Tacotron 2 and a non-autoregressive Glow-TTS. These architectures were chosen due to their popularity and to represent two modern TTS paradigms, namely seq2seq attention-based generation and flow-based parallel generation. VITS, despite its state-of-the-art quality, was not included due to substantially higher computational requirements required for training, and VITS being a combination of Glow-TTS acoustic model and HiFi-GAN vocoder, which is already covered in this study. It was

decided to isolate the acoustic model performance, before considering end-to-end models like VITS in future work. All models were implemented using the **Coqui TTS** [44] framework.

2.5.1 Vocoder

HiFi-GAN [42] was chosen as the vocoder for this study due to its widespread adoption and ability to generate high-fidelity audio with significantly lower computational latency compared to autoregressive vocoders (e.g., WaveNet [37], WaveGlow).

More specifically, a HiFi-GAN model pre-trained on the multi-speaker VCTK corpus [45] was used. The vocoder's weights were frozen to isolate the performance differences to the acoustic models only. As described in the **Audio Preprocessing** section, the acoustic parameters of both Tacotron 2 and Glow-TTS were matched to those of the pre-trained HiFi-GAN to ensure compatibility.

2.5.2 Tacotron 2

The autoregressive model used was **Tacotron 2**, modified with DCA to improve alignment stability for long-form utterances, on which the standard location-sensitive attention was observed to struggle.

The architecture details are displayed in Table 9.

Table 9 *Tacotron 2 with DCA architecture details.*

Component	Configuration
Text Encoder	3-layer convolution + Bi-LSTM (512 units)
Attention Mechanism	Dynamic Convolution Attention (DCA)
Separate Stopnet	True
Decoder	2-layer LSTM (1024 units)
Speaker Embedding	512 dimensions

The training objective $\mathcal{L}_{T2}$ is a weighted sum of auxiliary losses:

$$\mathcal{L}_{T2} = \mathcal{L}_{L1} + \mathcal{L}_{Post} + \lambda_{SSIM}(\mathcal{L}_{SSIM}) + \lambda_{attn}(\mathcal{L}_{Guided}) + \lambda_{stop}(\mathcal{L}_{Stop}) \tag{4}$$

Where $\mathcal{L}_{Guided}$ enforces diagonal attention alignment, critical for preventing repeating or skipping words in long-form synthesis.

2.5.3 Glow-TTS

The non-autoregressive model used was **Glow-TTS**, a flow-based architecture. The main architectural hyperparameters used in this study are detailed in Table 10.

The objective function maximizes the log-likelihood of the data:

$$\log P_X(x|c) = \sum_{j=1}^{T_{mel}} \log \left| \det \frac{\partial z_j}{\partial x_j} \right| + \sum_{j=1}^{T_{mel}} \log \mathcal{N}(z_j; \mu, \sigma) \tag{5}$$

Table 10 *Glow-TTS architecture details.*

Component	Configuration
Encoder Type	Rel. Pos. Transformer
Encoder Layers	6
Encoder Heads	2
Encoder Hidden Dimensions	192
Decoder Hidden Dimensions	192
Decoder Flow Blocks	12
Decoder Block Layers	4
Decoder Kernel Size	5
Duration Predictor	256 hidden channels
Speaker Embedding	512 dimensions

Additionally, a duration predictor is trained via MSE loss $\mathcal{L}_{Dur}$ to predict phoneme durations.

2.5.4 Speaker Conditioning

In this work, learnable speaker embeddings (Look-Up Tables) are used for both Tacotron 2 and Glow-TTS models. The primary reason is that this study focuses on synthesis for a known set of speakers, where learnable embeddings can outperform pre-computed vectors [47]. They allow each model to learn a latent representation for each voice that reflects the features most relevant for each model architecture, rather than features used specifically to distinguish between speakers in a classification task. This eliminates the information bottleneck or noise introduced by an external verification model.

In Tacotron 2, the speaker embedding is broadcast-concatenated with the output of the text encoder. This conditions the decoder at every time step, allowing the autoregressive mechanism to factor in speaker identity when generating each Mel-spectrogram frame.

In Glow-TTS, the embedding conditions the flow-based decoder. Specifically, it is applied as global conditioning within the affine coupling layers of the flow steps [3]. This allows the model to learn a multi-speaker distribution by adapting the flow transformation function to map the speaker-agnostic latent representation to the target speaker's Mel-spectrogram.

2.6 Model Training Configurations

Environment and Framework

Experiments were conducted on a personal workstation equipped with an AMD Epyc 7642 CPU, 256 GB RAM, and NVIDIA GeForce RTX 3090 (24 GB) GPU. The software environment included Ubuntu 25.04, Python 3.13.3, Coqui TTS v0.27.2, and CUDA 13.0 for GPU acceleration. The pipeline was automated via Make, with separate steps for data preprocessing, model training, inference, and synthesized sample deployment to an evaluation web app.

The exact Python environment configuration is provided in the accompanying GitHub repository, file `pyproject.toml`.

In the TTS training stage, the validation loss was evaluated every epoch ($\approx$ 450 steps) using a held-out (randomly selected) 1% validation split. The best model checkpoint was selected based on the lowest validation loss.

Tacotron 2 Configuration

The model optimization utilized a composite loss function consisting of Decoder L1 loss ($\alpha = 0.25$), Post-net L1 loss ($\alpha = 0.25$), Decoder and Post-net SSIM losses ($\alpha = 0.25$ each), Guided Attention loss ($\alpha = 5.0$), and a weighted Stop token loss (weight $= 15.0$).

The default learning rate scheduler in Coqui TTS, NoamLR, was experimentally found to cause high gradient values, instability, and slow convergence for Tacotron 2. The original Tacotron 2 implementation [2] used an exponential decay schedule with a starting learning rate of 0.001, which at 50,000 steps began exponentially decaying to 10^{-5}. Coqui TTS configurations do not support starting gradual exponential decay at a specific step. Additionally, the original Tacotron 2 learning rate of 0.001 was found to cause numerical instability and exploding gradients in preliminary experiments, hence the lower starting learning rate of 0.0005 was chosen. To approximate a decay profile similar to the original Tacotron 2 paper, a MultiStepLR scheduler with stepwise decay of 0.5 every 10,000 steps (20k, 30k, …, 70k) was used instead, starting from an initial learning rate of 0.0005, and reaching $\approx 7.81 \times 10^{-8}$ at 70,000 steps. Unlike the original Tacotron 2 paper, no warmup period was used, as it was found to be unnecessary for training from scratch.

This schedule yielded more stable training and faster convergence, as observed in TensorBoard plots. Additionally, the RAdam optimizer [58] was used instead of the default Adam, as it provided more stable convergence in preliminary experiments. The total training duration was set to 200 epochs ($\approx$ 90,000 steps), which took approximately 22 hours per model to train. The main training hyperparameters are shown in Table 11.

Table 11 *Tacotron 2 with DCA training configuration.*

Parameter	**Value**
Validation split	1%
Batch size	64
Initial Learning Rate	0.0005
Optimizer	RAdam
LR schedule	MultiStepLR (Decay 0.5 at steps 20k, 30k, …, 70k)
Max epochs	200 ($\approx$ 90,000 steps)
Reduction factor	2
Number of speakers	30 / 60 / 180

Glow-TTS Configuration

The Glow-TTS model was trained using Negative Log-Likelihood (NLL) for the flow decoder and a monotonic alignment search. Glow-TTS converged stably with the NoamLR scheduler used in the original implementation, but required a higher number of epochs (400 epochs, or $\approx$ 180,000 steps)

for convergence. The loss function was a combination of NLL loss for the flow-based decoder, and MSE for the duration predictor.

Based on preliminary experiments, the models were trained for 300 epochs ($\approx$ 135,000 steps) with the NoamLR scheduler, followed by an additional 100 epochs ($\approx$ 45,000 steps) with an exponentially decaying learning rate (ExponentialLR scheduler), with a starting LR of 0.001, decay rate 0.95 every epoch, final LR $\approx$ 0.00008. This two-stage schedule yielded small but consistent improvements in all tracked loss metrics on the training and validation sets, as observed in TensorBoard plots. The total training time per model was approximately 25 hours. The configuration is shown in Table 12.

Table 12 *Glow-TTS training configuration.*

Parameter	**Value**
Validation split	1%
Batch size	64
Maximum Learning Rate	0.001
Optimizer	RAdam
LR scheduler	NoamLR (300 epochs), ExponentialLR (100 epochs)
Warmup steps (NoamLR)	4000
Decay rate (ExponentialLR)	0.95 per epoch
Max epochs	300 + 100 ($\approx$ 180,000 steps)
Number of speakers	30 / 60 / 180

2.7 Evaluation Protocol

The synthesized speech from the trained models was evaluated using a combination of objective and subjective metrics.

2.7.1 Model Convergence

Alignment stability during training was monitored via attention alignment plots, provided by the TensorBoard [59] integration in Coqui TTS.

The **attention alignment plots** were generated during every epoch, and inspected regularly. A failure to converge to a diagonal alignment would indicate that the model has failed to learn the text-to-audio mapping. This was especially relevant for the 180-speaker scenario to detect convergence failures caused by data sparsity.

2.7.2 Objective Evaluation

A held-out test set of 60 standardized sentences (using 6 seen speakers) was used to calculate objective metrics. The metrics selected for evaluation were MCD and F_0 RMSE, as they capture different aspects of synthesis quality: spectral fidelity and intonation accuracy, respectively. PESQ [53] was considered for inclusion, but ultimately not used due to its sensitivity to slight temporal misalignments between synthesized and reference audio — a known limitation when evaluating generative TTS models that produce valid but non-aligned prosody.

Mel-Cepstral Distortion (MCD): MCD [52] evaluates the timbre and spectral envelope of synthesized speech. It measures the difference between the Mel-frequency cepstral coefficients of the synthesized and reference speech. A lower MCD value indicates closer spectral similarity, i.e., better timbre reconstruction. The MCD is defined as:

$$\text{MCD} = \frac{10}{\ln 10}\sqrt{2\sum_{n=1}^{K}(c_n^{\text{synth}} - c_n^{\text{ref}})^2} \tag{6}$$

where c_n^{synth} and c_n^{ref} are the n-th coefficients of the synthesized and reference frames, respectively, and K is the number of coefficients (here: 24).

Fundamental Frequency Root Mean Square Error (F_0 RMSE): F_0 RMSE measures the Root Mean Square Error between the fundamental frequency (F_0) contours of the synthesized and reference speech. Lower F_0 RMSE values indicate better pitch accuracy, i.e., closer intonation reproduction. F_0 RMSE is defined as:

$$\text{RMSE}_{F_0} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(F_0^{\text{synth}}(t) - F_0^{\text{ref}}(t))^2} \tag{7}$$

$F_0^{\text{synth}}(t)$ and $F_0^{\text{ref}}(t)$ are the fundamental frequency values at time t for synthesized and ground truth speech, respectively, and T is the total number of frames where both signals are voiced. Lower values indicate more accurate intonation.

2.7.3 Subjective Evaluation

Subjective evaluation was conducted via a web-based listening test employing a **Latin square design** to mitigate order and repetition biases. An application was developed specifically for this study, using the **Flask** web framework, **Google Cloud Run** app hosting service, **Google Cloud Storage** for audio file hosting, and **PostgreSQL** for storing ratings. The complete source code is available in the accompanying GitHub repository linked in the Appendix 5, folder `tts_rating_app`.

Naturalness was rated using the standard 5-point MOS scale. The test samples were generated using the 6 experimental models plus a human ground truth baseline. The test samples were 60 sentences from the held-out test set: for 6 randomly selected speakers (3 male, 3 female, from the 30-speaker subset), 10 held-out sentences were selected from the Liepa-2 dataset, resulting in a total of 60 test samples.

The participants were native Lithuanian speakers recruited through university networks and social media platforms. Each rater evaluated a randomized block of sentences, ensuring balanced exposure to all models and sentences.

2.7.4 Rating Procedure

Raters accessed the web application via a public URL[1]. The application required raters to sign in using their Google account (Appendix 5, Figure 12 (a)). This was done to automatically assign a unique internal identifier and prevent duplicate submissions. Upon signing in, raters were presented with a welcome page detailing the study's purpose, data usage, confidentiality assurances, and explaining the rating procedure (Appendix 5, Figure 12 (b)). Only those who provided informed consent could proceed to the evaluation.

Once the evaluation began, raters were presented with audio samples one at a time, along with the corresponding text prompt (Appendix 5, Figure 12 (c)). Raters listened to each sample and rated its naturalness on a scale from 1 (Bad) to 5 (Excellent). Audio samples could be replayed multiple times as needed before submitting each rating. Submitted ratings were immediately stored in a PostgreSQL database, and the next sample was presented. A progress bar indicated the number of samples rated out of the expected total (60 samples per rater). Once a rater completed all assigned samples, they were thanked for their participation and informed that their responses had been recorded (Appendix 5, Figure 12 (d)).

2.7.5 Statistical Analysis

Collected MOS ratings were screened for outliers and inconsistencies. Only raters who completed 100% of their assigned samples were included in the final analysis. The mean MOS ratings and 95% confidence intervals (CI) were computed for each model and data subset.

The 95% confidence intervals were calculated using the Student's t-distribution:

$$CI = \bar{x} \pm t_{0.975,N-1} \cdot \frac{s}{\sqrt{N}} \tag{8}$$

where $\bar{x}$ is the arithmetic mean of the ratings, s is the sample standard deviation, N is the number of ratings, and $t_{0.975,N-1}$ is the critical t-value for a two-tailed 95% confidence level with $N-1$ degrees of freedom.

To determine whether the observed differences in MOS were statistically significant, a one-way Analysis of Variance (ANOVA) was conducted. The F-statistic is calculated as the ratio of between-group variance to within-group variance:

$$F = \frac{MS_{between}}{MS_{within}} \tag{9}$$

Upon finding significant main effects (i.e., $p < 0.05$), Tukey's Honestly Significant Difference (HSD) post-hoc test was applied to identify specific pairwise differences. Two means are considered significantly different if their absolute difference exceeds the HSD critical value:

$$HSD = q_{\alpha,k,\nu}\sqrt{\frac{MS_{within}}{N}} \tag{10}$$

[1] `https://tts-rating-app-6128007182.europe-west1.run.app/`

where q is the critical value from the Studentized range distribution for significance level α, k groups, and ν degrees of freedom, and N is the number of samples per group. All statistical tests were performed at a significance level of $\alpha = 0.05$.

2.8 Qualitative Analysis

A qualitative analysis of these speakers' original recordings, transcripts, and synthesis outputs was conducted by the study author. The primary goal was to identify possible factors related to synthesis quality. This included examining aspects such as audio quality, voice characteristics, and prosody. Particular attention was paid to speakers exhibiting extreme synthesis quality (both high and low) to identify potential contributing factors.

3 Results and Analysis

This chapter presents the quantitative and qualitative findings of the study. The performance of the autoregressive (Tacotron 2) and non-autoregressive (Glow-TTS) models was analyzed across the three data subsets defined in Chapter 3: 30 speakers (45 minutes per speaker), 60 speakers (22.5 minutes per speaker), and 180 speakers (7.5 minutes per speaker).

3.1 Objective Evaluation

Table 13 summarizes the MCD and F_0 RMSE on the held-out test set.

Table 13 *Objective synthesized speech evaluation results. Lower is better. Bold indicates best performance per architecture.*

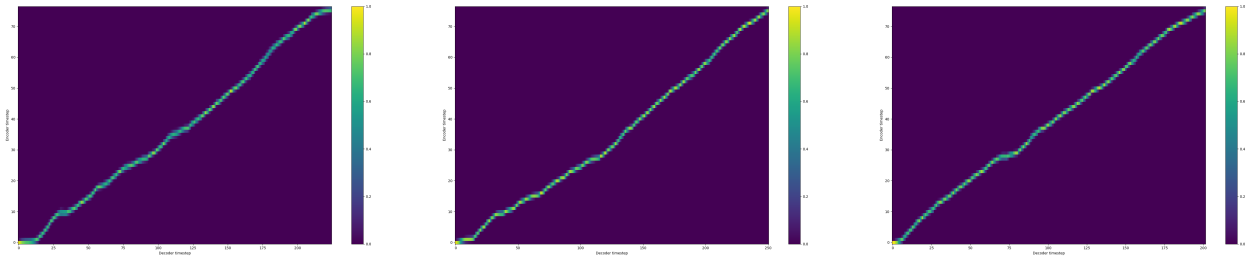
Model	Speaker Count (N)	MCD (dB)	F_0 RMSE (Hz)
Tacotron 2	30	9.58	31.28
	60	**9.55**	**30.49**
	180	9.63	31.06
Glow-TTS	30	**9.90**	37.86
	60	10.00	36.18
	180	9.98	**35.69**

Both model architectures showed significant robustness to the data composition strategy in terms of objective metrics. Minimal intra-model variations were observed for MCD — the highest difference between data subsets was under 0.1 dB, with Tacotron 2 achieving its best MCD on the 60-speaker subset, and Glow-TTS on the 30-speaker subset. Similarly, F_0 RMSE varied only slightly across datasets for both architectures — less than 1.0 Hz difference was observed for Tacotron 2, and under 2.2 Hz for Glow-TTS. The 180-speaker configuration achieved the best F_0 RMSE for Glow-TTS (35.69 Hz), suggesting that increased speaker diversity did not harm pitch modeling, and may have even helped generalization. Across all data subsets, Tacotron 2 moderately but consistently outperformed Glow-TTS in MCD (between 0.32–0.45 dB lower) and F_0 RMSE (between 4.63–6.58 Hz lower).

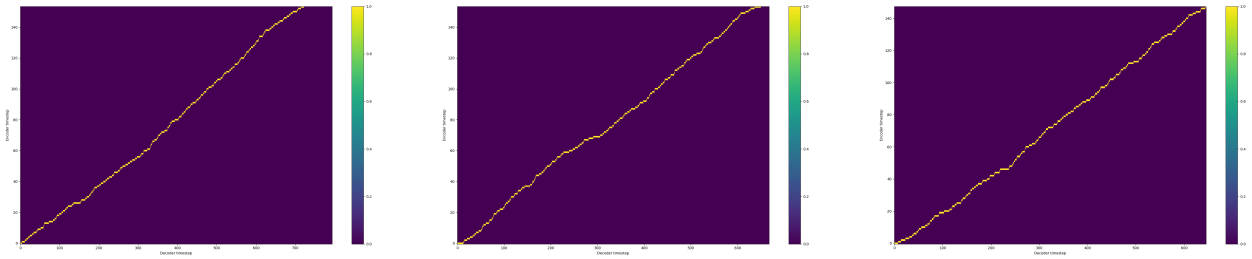
3.1.1 Alignment Convergence

Tacotron 2 demonstrated no visible sensitivity to data sparsity. On all subsets, the attention mechanism converged to a clear diagonal alignment within 10k steps. While there were occasional minor misalignments during training, by the end of training, all models exhibited stable alignments on all test sentences.

As seen in Figure 10, the attention maps for Tacotron 2 remain stable across all data subsets, indicating robust alignment learning even in low-resource conditions. Glow-TTS, utilizing MAS, also converged successfully across all three subsets.



(a) *Tacotron 2, 30 speakers* ***(b)*** *Tacotron 2, 60 speakers* ***(c)*** *Tacotron 2, 180 speakers*



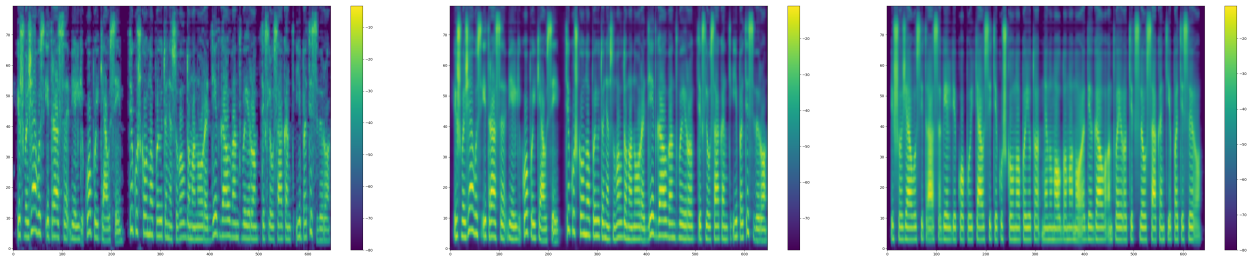
(d) *Glow-TTS, 30 speakers* ***(e)*** *Glow-TTS, 60 speakers* ***(f)*** *Glow-TTS, 180 speakers*

Figure 10 *Attention alignments after training: Tacotron 2 (a–c) and Glow-TTS (d–f) across 30, 60, and 180 speaker configurations. All models exhibit clear monotonic alignments, indicating successful convergence.*

3.1.2 Pitch and Spectral Accuracy

Tacotron 2 consistently outperformed Glow-TTS in pitch accuracy (F_0 RMSE), achieving values around 31 Hz compared to Glow-TTS's 36 Hz. Furthermore, Tacotron 2 achieved slightly lower MCD scores on all subsets, suggesting it captures fine-grained spectral details better than the flow-based decoder. The raters noted that Glow-TTS outputs often sounded monotone, though the predicted pitch contours had sudden jumps and drops in the fundamental frequency, possibly due to Glow-TTS not having an explicit pitch predictor.

Spectral analysis confirms the objective metrics. As illustrated in an example of Mel-spectrogram comparison Figure 11, Tacotron 2 captures visibly more fine-grained spectral details and intonation contours more accurately than Glow-TTS, which tends to produce flatter, less dynamic outputs.



(a) *Ground truth* ***(b)*** *Tacotron 2 output* ***(c)*** *Glow-TTS output*

Figure 11 *Comparison of ground truth Mel-spectrogram (a), Tacotron 2 (b) and Glow-TTS (c) outputs for the same speaker and input text. Note how Glow-TTS produces flatter pitch contours.*

3.2 Subjective Evaluation

Naturalness was evaluated via a Latin square design listening test with 24 native speakers, who rated samples from all six experimental models plus the ground truth on a 5-point MOS scale. 3 raters were excluded for incomplete submissions, resulting in a final count of 21 raters. Each rater evaluated 60 samples, yielding a total of 1,260 ratings (21 raters $\times$ 60 samples). The results are presented in Table 14.

Table 14 *MOS results per model and data subset with 95% confidence intervals. Bold indicates best performance per architecture.*

Model	Speaker count (N)	MOS (95% CI)
Ground Truth	—	$\mathbf{4.84 \pm 0.06}$
Tacotron 2	30	3.11 ± 0.16
	60	$\mathbf{3.12 \pm 0.17}$
	180	3.03 ± 0.18
Glow-TTS	30	2.13 ± 0.12
	60	2.18 ± 0.15
	180	2.03 ± 0.14

Statistical Significance

The one-way ANOVA revealed significant differences among the six experimental models ($F(5, 1074) = 46.8490, p < 0.001$). Tukey's HSD post-hoc analysis identified 9 significant pairwise differences at $\alpha = 0.05$. The full list of tested pairs and their significance is provided in Appendix 5, Table 18. When analyzing the significant differences, all of them were between different model architectures (Tacotron 2 vs. Glow-TTS) rather than data subsets within the same architecture.

Notably, within each architecture, there were no statistically significant differences between the three data composition strategies (30, 60, or 180 speakers). While the 60-speaker configuration achieved marginally higher mean MOS scores for both models (3.12 for Tacotron 2, 2.18 for Glow-TTS), and the 180-speaker setup showed slights decreases (3.03 for Tacotron 2, 2.03 for Glow-TTS), these differences were not statistically significant. ANOVA tests conducted separately for Tacotron 2 ($p = 0.71$) and Glow-TTS ($p = 0.34$) also failed to reject the null hypothesis that speaker count affects MOS, indicating that data composition did not have a measurable impact on naturalness within the tested range.

Architecture Comparison

The MOS results revealed a significant performance gap between the two architectures.

Tacotron 2 achieved a consistently higher synthesis quality in the study, with the 60-speaker configuration scoring 3.12 ± 0.17. Listeners noted that Tacotron 2 produces highly expressive prosody for some of the speakers. Increasing the speaker count to 180 caused a moderate, albeit statistically insignificant, drop in naturalness to 3.03 ± 0.18.

Glow-TTS lagged behind Tacotron 2 in naturalness, with the 60-speaker configuration scoring 2.18 ± 0.15. The listeners reported that Glow-TTS seemed to have strong robotic artifacts, and was at times unintelligible. This was especially pronounced in the 180-speaker condition where the MOS dropped to 2.03 ± 0.14.

Speaker MOS Analysis

An analysis of individual speakers' MOS scores was conducted to identify any patterns related to speaker identity. Table 15 summarizes the average MOS per speaker and model architecture.

Table 15 *MOS results per speaker and model architecture with 95% confidence intervals. Bold indicates highest score per architecture.*

Speaker ID	Tacotron 2 MOS	Glow-TTS MOS
AS009	$\mathbf{4.17 \pm 0.20}$	$\mathbf{2.61 \pm 0.23}$
IS031	3.26 ± 0.20	2.13 ± 0.19
IS038	3.48 ± 0.21	2.51 ± 0.19
MS052	2.26 ± 0.17	1.88 ± 0.16
VP131	2.43 ± 0.19	1.93 ± 0.16
VP427	2.92 ± 0.22	1.60 ± 0.14

Notably, speaker **AS009** consistently received the highest ratings across both models (Tacotron 2 MOS: 4.17, Glow-TTS MOS: 2.61), suggesting that certain speaker or dataset characteristics (e.g., clear articulation, consistent recording quality, or clean transcripts) may facilitate better synthesis quality. On the other hand, speakers like **MS052** and **VP427** scored significantly lower, indicating potential data quality issues or inherent speaker traits (e.g., strong accents, background noise) that challenge the TTS models.

3.3 Qualitative Analysis

Consistent with the MOS findings, the author observed no subjective correlation between synthesis naturalness and the data composition strategy (speaker count). Thus, any observations below apply across all data subsets.

- **AS009 (low male voice):** Source audio is clear, neutral accent; transcripts are unpunctuated.
  Tacotron 2: Highly natural output with accurate prosody. Closely resembled the target speaker.
  Glow-TTS: Suffered from pitch instability, frequently shifting into a falsetto-like register (approximately one octave higher than the target).

- **IS031 (low female voice):** Source audio is clear, neutral accent; transcripts are unpunctuated.
  Tacotron 2: Good prosody, though minor robotic artifacts were audible.
  Glow-TTS: Intelligible but had intonation issues — it was either monotone, or had pitch issues (jumping up by several semitones, or dipping into bass range).

- **IS038 (average male voice):** Source audio is clear, neutral accent; transcripts are unpunctuated.
  Tacotron 2: Prosody was accurate, but minor voice artifacts ('scratchy' quality, higher-frequency noise) were present.
  Glow-TTS: Intelligible, but failed to capture the speaker's timbre. Exhibited pitch issues similar to IS031.

- **MS052 (average female voice):** Source audio sounds muffled, likely due to room acoustics, neutral accent; transcripts are punctuated.
  Tacotron 2: Mostly good prosody and intonation, but a muffled voice quality, more pronounced than in the original audio.
  Glow-TTS: Mostly intelligible, but the voice did not match the original audio. Monotone, often very low-pitched intonation in the male range.

- **VP131 (young, higher female voice):** Source audio has slight reverberation, neutral accent; transcripts are punctuated.
  Tacotron 2: Intelligible, good prosody, but the voice sounded muffled and older than the target speaker.
  Glow-TTS: Mostly intelligible and matched the true voice quite well, but had monotone intonation and 'scratchy' voice quality. Interestingly, no pitch jump artifacts were observed for this speaker.

- **VP427 (young, higher male voice):** Source audio is clear, but slight accent on certain phonemes; transcripts are punctuated.
  Tacotron 2: Good prosody, but had moderate artifacts in the high-frequency range.
  Glow-TTS: Significantly distorted, with a 'scratchy' voice quality, monotone intonation, and artifacts in the high-frequency range.

A recurring issue with Glow-TTS was the generation of unnatural pitch jumps and octave errors. To investigate this, the Glow-TTS outputs were re-synthesized using the Griffin-Lim vocoder instead of HiFi-GAN.

While the Griffin-Lim samples remained monotone, the prevalence of sudden pitch jumps decreased. However, the synthesized voices had strong harmonics, indicating poor spectral quality. This suggests that Glow-TTS may have generated ambiguous fundamental frequency contours with excessive harmonic content. When fed into HiFi-GAN, these ambiguities may have confused the vocoder, causing it to 'flip' between different harmonics, interpreting them as the fundamental frequency.

These observations underline the significant role of audio quality and speaker characteristics in determining synthesis quality. Speakers with clean recordings free from reverberation (e.g., AS009, IS031) yielded higher synthesis quality across both architectures. On the other hand, speakers with slightly muffled audio (MS052, VP131) or idiosyncratic vocal features (VP427) resulted in degraded performance. Glow-TTS outputs exhibited pronounced issues with intonation, often pro-

ducing monotone speech, or significant pitch jumps to unnatural ranges, which were not observed in Tacotron 2 outputs.

3.4 Discussion

The results provide several insights into the effects of data composition and model architecture on multi-speaker TTS quality in low-resource settings.

Firstly, objective metrics (F_0 RMSE, MCD) exhibited minor variations across the data strategies, with no clear trend indicating a substantial performance degradation for higher speaker counts. The maximum observed differences within each architecture were under 0.1 dB for MCD and under 2.2 Hz for F_0 RMSE. Glow-TTS achieved its best F_0 RMSE in the 180-speaker configuration, suggesting that increased speaker diversity did not harm pitch modeling, and may have even helped generalization.

Secondly, the autoregressive Tacotron 2 moderately but consistently outperformed the non-autoregressive Glow-TTS in both objective (F_0 RMSE, MCD) and subjective (MOS) metrics, across all dataset configurations. Tacotron 2 achieved a peak MOS score of **3.12** in the 60-speaker setup, while Glow-TTS reached a maximum MOS of **2.18**. The consistent superiority of Tacotron 2 suggests that in low-resource constraints, the stability of its explicit alignment mechanism may outweigh the benefits of Glow-TTS and MAS.

Data composition had no statistically significant effect on synthesis quality within either architecture. One-way ANOVA tests for each model separately failed to detect significant differences between the 30-, 60-, and 180-speaker configurations (Tacotron 2: $p = 0.71$; Glow-TTS: $p = 0.34$). Although small numerical variations existed (60-speaker slightly higher, 180-speaker slightly lower), these were not beyond statistical noise. This null result suggests that within the tested range, the total data volume (22.5 hours) acts as the primary constraint, and that the specific distribution strategy (breadth versus depth) does not meaningfully impact naturalness. Instead, per-speaker data quality appears to be the dominant factor.

Indeed, speaker-specific analysis revealed that certain speakers consistently yielded significantly higher synthesis quality across models and data strategies. Within both architectures, speaker **AS009** consistently received the highest ratings (Tacotron 2 MOS: 4.17, Glow-TTS MOS: 2.61), while speakers like **MS052** and **VP131** scored significantly lower, the highest MOS being only 2.43 for Tacotron 2 and 1.93 for Glow-TTS. Qualitative analysis suggests that speaker characteristics and data quality play a crucial role in TTS performance.

4 Conclusion

This thesis set out to measure the effects of training data composition on the quality of multi-speaker TTS models for the Lithuanian language under a fixed resource budget. All research objectives were achieved. Three training datasets were constructed and pre-processed from the Liepa-2 corpus, each containing a total of 22.5 hours of speech, but varying in the number of speakers and amount of data per speaker: 30 speakers with 45 minutes each, 60 speakers with 22.5 minutes each, and 180 speakers with 7.5 minutes each. An autoregressive (Tacotron 2) and a non-autoregressive (Glow-TTS) architecture was trained on each dataset. The synthesis quality of the trained models was evaluated using objective metrics (F_0 RMSE, MCD) and a subjective MOS listening test using a web-based evaluation application developed for this study.

Summary of Findings

The experimental results do not support the initial hypothesis that data depth is more important than breadth for multi-speaker synthesis quality. Instead, the findings indicate that data composition had **no statistically significant effect** on synthesis quality within either architecture. Statistical analysis confirmed that when the total data volume is held constant at 22.5 hours, the choice between 30, 60, or 180 speakers does not meaningfully affect subjective naturalness. Objective metrics (MCD, F_0 RMSE) similarly showed minimal variation across data subsets for both architectures.

Despite the low data volume per speaker in the 180-speaker subset (7.5 minutes), both architectures successfully converged. This indicates that 7.5 minutes of data per speaker is above the 'critical threshold' required to learn stable alignments and synthesize intelligible speech for Lithuanian, contradicting concerns that low-depth settings would prevent convergence.

Regarding the architecture, Tacotron 2 consistently outperformed Glow-TTS across all data configurations. Subjective feedback indicated that Tacotron 2 produced more natural and expressive speech, while Glow-TTS outputs suffered from robotic intonation and artifacts, described as 'scratchy voice'. It is unclear what specific architectural, language, or dataset features led to this gap, but it could be attributed to Glow-TTS lacking an explicit pitch predictor.

Finally, speaker-specific analysis revealed that certain speakers consistently yielded higher-quality synthesis regardless of the data strategy. Qualitative analysis suggested that these differences may stem from audio quality issues (e.g., muffled recordings, room acoustics) or speaker traits (e.g., accents, vocal characteristics).

Contributions

This work makes several contributions to the field of multi-speaker TTS.

Firstly, it provides an empirical evaluation of the trade-off between speaker breadth and depth for training multi-speaker TTS models for Lithuanian. The primary finding — a null result — reveals that modern architectures are insensitive to data composition within the tested range (30–180 speakers) when total volume is held constant. This negative result is scientifically valuable: it suggests that

practitioners working with low-resource languages should prioritize maximizing total data volume and ensuring high per-speaker quality rather than optimizing the breadth-depth balance.

Additionally, this study establishes benchmark results for Tacotron 2 and Glow-TTS on the Lithuanian Liepa-2 corpus in several multi-speaker settings. It demonstrates that Tacotron 2 can achieve reasonable synthesis quality with as little as 7.5 minutes of data per speaker when using learnable speaker embeddings.

Finally, the development of a web-based MOS evaluation application for Lithuanian TTS provides a reusable tool for future subjective evaluations in this language. The application source code is made publicly available for reuse and adaptation. [2]

Limitations

The first limitation of this work is the language and dataset specificity. The experiments were exclusively focused on the Lithuanian language and read speech from the Liepa-2 speech corpus. Therefore, the findings may not generalize to other languages, datasets, or speech styles.

Secondly, the fixed training budget of 22.5 hours is a practical constraint and may not reflect performance in higher-resource settings (e.g., 100 hours or more).

Finally, as discussed in the qualitative analysis, the training data had variable quality across speakers. The synthesis quality of certain speakers (MS052, VP131, VP427) was consistently rated as poor regardless of data strategy or model architecture.

Future Work

There are several potential directions for future research building on this study. First, replicating the experiments on different languages and datasets would help validate the cross-lingual generalizability of the findings. It would be valuable to test languages with phonetic or prosodic characteristics distinct from Lithuanian (e.g., non-phonemic orthographies like English or highly regular orthographies like Italian) to determine if the observed insensitivity to data composition holds. Additionally, exploring a wider range of data budgets could provide insights into scaling effects; for instance, a 100-hour budget could reveal different or more pronounced trade-offs than the 22.5-hour setting used here.

Furthermore, future work should focus on data quality and selection strategies. If a cleaner multi-speaker dataset for Lithuanian becomes available, replicating the experiments on such a dataset could help isolate the effects of data composition from recording artifacts. This would likely achieve higher synthesis quality overall. In the absence of new data, automated quality assessment could be used to filter out recordings with low signal-to-noise ratios or excessive reverberation. Additionally, given the significant variability in synthesis quality observed between speakers — even among those with subjectively good audio quality — future research could aim to systematically identify and prioritize speakers with favourable characteristics (e.g., vocal clarity, intonation patterns).

[2] See Appendix 5 for the GitHub repository link.

Such targeted selection of high-quality voices may yield greater improvements than simply increasing dataset size or performing manual curation.

Finally, extending the study to include more TTS architectures, such as VITS or FastSpeech 2, would provide a broader understanding of how different model types respond to data composition strategies. This could help identify architectures that possess greater robustness to low-depth data settings compared to the Tacotron 2 and Glow-TTS models evaluated here.

5 References

[1] H. Dudley, T. H. Tarnoczy. “The Speaking Machine of Wolfgang von Kempelen.” In: *The Journal of the Acoustical Society of America* 22.2 (1950), pages 151–166.

[2] J. Shen, R. Pang, R. J. Weiss, M. Schuster, et al. “Natural TTS Synthesis by Conditioning Wavenet on MEL Spectrogram Predictions.” In: *International Conference on Machine Learning* (2018), pages 4779–4788.

[3] J. Kim, S. Kim, J. Kong, S. Yoon. *Glow-TTS: A Generative Flow for Text-to-Speech via Monotonic Alignment Search*. 2020. URL: https://arxiv.org/abs/2005.11129.

[4] M. B. Hoy. “Alexa, Siri, Cortana, and More: An Introduction to Voice Assistants.” In: *Medical Reference Services Quarterly* 37.1 (2018). PMID: 29327988, pages 81–88. https://doi.org/10.1080/02763869.2018.1404391. URL: https://doi.org/10.1080/02763869.2018.1404391.

[5] I. Isewon, J. Oyelade, O. Oladipupo. “Design and implementation of text to speech conversion for visually impaired people.” In: *International Journal of Applied Information Systems* 7.2 (2014), pages 25–30.

[6] P. Taylor. *Text-to-Speech Synthesis*. Cambridge University Press, 2009.

[7] K. Ito, L. Johnson. *The LJ Speech Dataset*. https://keithito.com/LJ-Speech-Dataset/. 2017.

[8] Vilnius University. *Lietuvių šneka valdomų paslaugų plėtra - LIEPA 2 (Development of Services Controlled by Lithuanian Speech - LIEPA 2)*. Project funded by the European Regional Development Fund. Available at https://xn--ratija-ckb.lt/liepa-2/apie-projekta-liepa-2/. 2020.

[9] C. E. Shannon. “Communication in the Presence of Noise.” In: *Proceedings of the IRE* 37.1 (1949), pages 10–21.

[10] S. Jothilakshmi, V. Gudivada. “Chapter 10 - Large Scale Data Enabled Evolution of Spoken Language Research and Applications.” In: *Cognitive Computing: Theory and Applications*. Edited by V. N. Gudivada, V. V. Raghavan, V. Govindaraju, C. Rao. Volume 35. Handbook of Statistics. Elsevier, 2016, pages 301–340. https://doi.org/https://doi.org/10.1016/bs.host.2016.07.005. URL: https://www.sciencedirect.com/science/article/pii/S0169716116300463.

[11] D. Gabor. “Theory of communication. Part 1: The analysis of information.” In: *Journal of the Institution of Electrical Engineers - Part III: Radio and Communication Engineering* 93 (26 1946), pages 429–441. https://doi.org/10.1049/ji-3-2.1946.0074. URL: https://digital-library.theiet.org/doi/abs/10.1049/ji-3-2.1946.0074.

[12] S. S. Stevens, J. Volkmann, E. B. Newman. “A Scale for the Measurement of the Psychological Magnitude Pitch.” In: *The Journal of the Acoustical Society of America* 8.3 (1937), pages 185–190.

[13] R. Sproat, A. Black, S. Chen, S. Kumar, M. Ostendorf, C. Richards. “Normalization of Non-Standard Words.” In: *Computer Speech and Language* 15 (2001), pages 287–333. https://doi.org/10.1006/csla.2001.0169.

[14] M. Bisani, H. Ney. “Joint-sequence models for grapheme-to-phoneme conversion.” In: *Speech Communication* 50.5 (2008), pages 434–451. ISSN: 0167-6393. https://doi.org/https://doi.org/10.1016/j.specom.2008.01.002. URL: https://www.sciencedirect.com/science/article/pii/S0167639308000046.

[15] P. Kasparaitis, D. Antanavičius. “Investigation of Input Alphabets of End-to-End Lithuanian Text-to-Speech Synthesizer.” In: *Baltic Journal of Modern Computing* 11 (2023). https://doi.org/10.22364/bjmc.2023.11.2.05.

[16] E. Battenberg, R. Skerry-Ryan, S. Mariooryad, D. Stanton, D. Kao, M. Shannon, T. Bagby. *Location-Relative Attention Mechanisms For Robust Long-Form Speech Synthesis*. 2020. URL: https://arxiv.org/abs/1910.10288.

[17] V. M. University. *Kirčiuoklis*. URL: https://kalbu.vdu.lt/mokymosi-priemones/kirciuoklis/ (viewed 2025-12-07).

[18] A. Jawaid, S. S. Chandra, J. Lu, B. Sisman. *Style Mixture of Experts for Expressive Text-To-Speech Synthesis*. 2024. URL: https://arxiv.org/abs/2406.03637.

[19] Y. Wang, R. Skerry-Ryan, D. Stanton, Y. Wu, et al. “Tacotron: Towards End-to-End Speech Synthesis.” In: *Interspeech*. 2017, pages 4006–4010.

[20] H. Dudley, R. Riesz, S. Watkins. “A synthetic speaker.” In: *Journal of the Franklin Institute* 227.6 (1939), pages 739–764. ISSN: 0016-0032. https://doi.org/https://doi.org/10.1016/S0016-0032(39)90816-1. URL: https://www.sciencedirect.com/science/article/pii/S0016003239908161.

[21] A. J. Hunt, A. W. Black. “Unit selection in a concatenative speech synthesis system using a large speech database.” In: *1996 IEEE International Conference on Acoustics, Speech, and Signal Processing Conference Proceedings*. Volume 1. IEEE. 1996, pages 373–376.

[22] A. Black, N. Campbell. “Optimising Selection Of Units From Speech Databases For Concatenative Synthesis.” In: 1 (1996).

[23] K. Kuligowska, P. Kisielewicz, A. Włodarz. “Speech synthesis systems: Disadvantages and limitations.” In: *International Journal of Engineering and Technology(UAE)* 7 (2018), pages 234–239. https://doi.org/10.14419/ijet.v7i2.28.12933.

[24] H. Zen, K. Tokuda, A. W. Black. “Statistical parametric speech synthesis.” In: *Speech communication* 51.11 (2009), pages 1039–1064.

[25] K. Tokuda, Y. Nankaku, T. Toda, H. Zen, J. Yamagishi, K. Oura. “Speech Synthesis Based on Hidden Markov Models.” In: *Proceedings of the IEEE* 101.5 (2013), pages 1234–1252. https://doi.org/10.1109/JPROC.2013.2251852.

[26] J. Kaplan, S. McCandlish, T. Henighan, T. B. Brown, et al. *Scaling Laws for Neural Language Models*. 2020. URL: https://arxiv.org/abs/2001.08361.

[27] T. Mikolov, K. Chen, G. Corrado, J. Dean. *Efficient Estimation of Word Representations in Vector Space*. 2013. URL: https://arxiv.org/abs/1301.3781.

[28] D. E. Rumelhart, G. E. Hinton, R. J. Williams. "Learning representations by back-propagating errors." In: *nature* 323.6088 (1986), pages 533–536.

[29] Y. Bengio, P. Simard, P. Frasconi. "Learning long-term dependencies with gradient descent is difficult." In: *IEEE Transactions on Neural Networks* 5.2 (1994), pages 157–166. https://doi.org/10.1109/72.279181.

[30] S. Hochreiter, J. Schmidhuber. "Long Short-Term Memory." In: *Neural Computation* 9.8 (1997), pages 1735–1780. https://doi.org/10.1162/neco.1997.9.8.1735.

[31] K. Cho, B. van Merrienboer, C. Gulcehre, D. Bahdanau, F. Bougares, H. Schwenk, Y. Bengio. *Learning Phrase Representations using RNN Encoder-Decoder for Statistical Machine Translation*. 2014. URL: https://arxiv.org/abs/1406.1078.

[32] M. Schuster, K. Paliwal. "Bidirectional recurrent neural networks." In: *IEEE Transactions on Signal Processing* 45.11 (1997), pages 2673–2681. https://doi.org/10.1109/78.650093.

[33] D. Bahdanau, K. Cho, Y. Bengio. *Neural Machine Translation by Jointly Learning to Align and Translate*. 2016. URL: https://arxiv.org/abs/1409.0473.

[34] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, I. Polosukhin. *Attention Is All You Need*. 2023. URL: https://arxiv.org/abs/1706.03762.

[35] J. Chorowski, D. Bahdanau, D. Serdyuk, K. Cho, Y. Bengio. *Attention-Based Models for Speech Recognition*. 2015. URL: https://arxiv.org/abs/1506.07503.

[36] I. Sutskever, O. Vinyals, Q. V. Le. *Sequence to Sequence Learning with Neural Networks*. 2014. URL: https://arxiv.org/abs/1409.3215.

[37] A. v. d. Oord, S. Dieleman, H. Zen, K. Simonyan, O. Vinyals, A. Graves, N. Kalchbrenner, A. Senior, K. Kavukcuoglu. "Wavenet: A generative model for raw audio." In: *arXiv preprint arXiv:1609.03499* (2016).

[38] Y. Ren, Y. Ruan, X. Tan, T. Qin, S. Zhao, Z. Zhao, T.-Y. Liu. *FastSpeech: Fast, Robust and Controllable Text to Speech*. 2019. URL: https://arxiv.org/abs/1905.09263.

[39] D. J. Rezende, S. Mohamed. *Variational Inference with Normalizing Flows*. 2016. URL: https://arxiv.org/abs/1505.05770.

[40] A. Łańcucki. "FastPitch: Parallel Text-to-speech with Pitch Prediction." In: *ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE. 2021, pages 6588–6592.

[41] J. Kim, J. Kong, J. Son. "Conditional Variational Autoencoder with Adversarial Learning for End-to-End Text-to-Speech." In: *arXiv preprint arXiv:2106.06103* (2021).

[42] J. Kong, J. Kim, J. Bae. "HiFi-GAN: Generative Adversarial Networks for Efficient and High Fidelity Speech Synthesis." In: *NeurIPS*. 2020.

[43] D. Griffin, J. Lim. “Signal estimation from modified short-time Fourier transform.” In: *IEEE Transactions on Acoustics, Speech, and Signal Processing* 32.2 (1984), pages 236–243. https://doi.org/10.1109/TASSP.1984.1164317.

[44] Coqui. *Coqui TTS*. https://github.com/coqui-ai/TTS. 2021.

[45] J. Yamagishi, C. Veaux, K. MacDonald. *CSTR VCTK Corpus: English Multi-speaker Corpus for CSTR Voice Cloning Toolkit (version 0.92)*. https://datashare.ed.ac.uk/handle/10283/3443. doi:10.7488/ds/2645. 2019.

[46] J. Lorenzo-Trueba, T. Drugman, J. Latorre, T. Merritt, B. Putrycz, R. Barra-Chicote, A. Moinet, V. Aggarwal. *Towards achieving robust universal neural vocoding*. 2019. URL: https://arxiv.org/abs/1811.06292.

[47] S. Arik, G. Diamos, A. Gibiansky, J. Miller, K. Peng, W. Ping, J. Raiman, Y. Zhou. *Deep Voice 2: Multi-Speaker Neural Text-to-Speech*. 2017. URL: https://arxiv.org/abs/1705.08947.

[48] Y. Jia, Y. Zhang, R. J. Weiss, Q. Wang, et al. *Transfer Learning from Speaker Verification to Multispeaker Text-To-Speech Synthesis*. 2019. URL: https://arxiv.org/abs/1806.04558.

[49] A. Nagrani, J. S. Chung, A. Zisserman. “VoxCeleb: A Large-Scale Speaker Identification Dataset.” In: *Interspeech 2017*. ISCA, 2017. https://doi.org/10.21437/interspeech.2017-950. URL: http://dx.doi.org/10.21437/Interspeech.2017-950.

[50] E. Variani, X. Lei, E. McDermott, I. L. Moreno, J. Gonzalez-Dominguez. “Deep neural networks for small footprint text-dependent speaker verification.” In: *2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. 2014, pages 4052–4056. https://doi.org/10.1109/ICASSP.2014.6854363.

[51] D. Snyder, D. Garcia-Romero, G. Sell, D. Povey, S. Khudanpur. “X-Vectors: Robust DNN Embeddings for Speaker Recognition.” In: *2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. 2018, pages 5329–5333. https://doi.org/10.1109/ICASSP.2018.8461375.

[52] R. Kubichek. “Mel-cepstral distance measure for objective speech quality assessment.” In: *Proceedings of IEEE Pacific Rim Conference on Communications Computers and Signal Processing*. Volume 1. IEEE. 1993, pages 125–128.

[53] A. Rix, J. Beerends, M. Hollier, A. Hekstra. “Perceptual evaluation of speech quality (PESQ)-a new method for speech quality assessment of telephone networks and codecs.” In: *2001 IEEE International Conference on Acoustics, Speech, and Signal Processing. Proceedings (Cat. No.01CH37221)*. Volume 2. 2001, 749–752 vol.2. https://doi.org/10.1109/ICASSP.2001.941023.

[54] ITU-T. *P.800 : Methods for subjective determination of transmission quality*. Recommendation P.800. International Telecommunication Union, 1996.

[55] E. J. Williams. “Experimental Designs Balanced for the Estimation of Residual Effects of Treatments.” In: *Australian Journal of Chemistry* 2 (1949), pages 149–168. URL: https://api.semanticscholar.org/CorpusID:96306494.

[56] R. Jain, M. Yiwere, D. Bigioi, P. Corcoran, H. Cucu. *A Text-to-Speech Pipeline, Evaluation Methodology, and Initial Fine-Tuning Results for Child Speech Synthesis*. 2022. URL: https://arxiv.org/abs/2203.11562.

[57] É. Székely, G. E. Henter, J. Beskow, J. Gustafson. "Spontaneous Conversational Speech Synthesis from Found Data." In: *Interspeech*. 2019. URL: https://api.semanticscholar.org/CorpusID:202751929.

[58] L. Liu, H. Jiang, P. He, W. Chen, X. Liu, J. Gao, J. Han. *On the Variance of the Adaptive Learning Rate and Beyond*. 2021. URL: https://arxiv.org/abs/1908.03265.

[59] M. Abadi, A. Agarwal, P. Barham, E. Brevdo, et al. *TensorFlow: Large-Scale Machine Learning on Heterogeneous Distributed Systems*. 2016. URL: https://arxiv.org/abs/1603.04467.

[60] Google. *Gemini*. Large language model. Accessed: 3 January 2026. 2026. URL: https://gemini.google.com/ (viewed 2026-01-03).

[61] GitHub. *Copilot*. AI coding assistant. Accessed: 3 January 2026. 2026. URL: https://github.com/features/copilot (viewed 2026-01-03).

Appendix 1: AI Tool Usage

This appendix documents the use of Generative AI tools in the preparation of this thesis. Table 16 lists the specific versions and access dates of the tools employed.

Table 16 *List of AI tools used*

Tool Name	Models/Versions	Usage Dates
Google Gemini [60]	2.5 Flash, 3.0 Flash	2025-09-02–2026-01-03
GitHub Copilot Code Generation [61]	Claude Haiku 4–4.5 Claude Sonnet 4–4.5	2025-09-02–2026-01-03
GitHub Copilot Code Completion [61]	Plugin versions 1.5.53–1.5.62	2025-09-02–2026-01-03

Text Drafting and Refinement

Tool used: Google Gemini [60] 2.5 Flash, 3.0 Flash
Extent of usage: The tool was used for drafting specific subsections of the literature review and methodology, suggesting citations, refining the author's original text (paraphrasing, grammar correction), and providing critical feedback on logical flow.
Method of usage: Interaction was text-based via the chat interface. An author's prompt would be submitted, and the AI-generated response was reviewed and edited by the author.

- *Drafting literature review, methodology:* Generating the initial outline and draft text for specific subsections of the literature review based on provided key points, unstructured notes, and reference lists.
  Prompt pattern: "Based on my notes below and this list of references, draft a latex outline / literature review subsubsection on [Topic]: — Notes: [Insert Notes] — References: [Insert References]"

- *Citation suggestions:* The author provided a topic or claim, and the AI suggested relevant academic references to support it. All suggested references were manually verified for existence and actual relevance.
  Prompt pattern: "Find academic references for these claims: — [Insert Claims]"

- *Refinement and paraphrasing:* The author pasted original drafts to improve clarity.
  Prompt pattern: "Review the following MSc thesis draft for academic tone, grammar errors, and sentence structure. Paraphrase only where unclear. Do not change the technical meaning unless necessary: [Insert Text]"

- *Critique:* Used to identify gaps in argumentation.
  Prompt pattern: "Act as a thesis reviewer. Read the following thesis subsection, identify notable logical gaps, unclear explanations, missing citations. Provide critique and suggest improvement. — [Insert Text]"

Author contribution: The author conducted the primary literature review, selected all references, and defined the structure of the review. All AI-suggested drafts were fact-checked against original sources. The author accepted or rejected the AI critiques and phrasing or structure. Over 90% of AI suggestions were rejected, with the remaining 10% being used as templates for updates or basis for rephrasing.

Code Completion and Generation

Tool used: GitHub Copilot [61]
Extent of usage: Used for code completion, generating boilerplate code for the MOS rating application, drafting Python code for figure generation, data preprocessing, and dataset generation scripts.
Method of usage: Usage occurred within the Visual Studio Code environment via the GitHub Copilot plugin. The author wrote code comments or partial code snippets, and Copilot Code Completion provided real-time suggestions for completing lines or generating functions. Additionally, the Copilot Code Generation feature was used to generate drafts of larger Python code blocks based on descriptive prompts.

- *Inline code completion:* In the Visual Studio Code editor, GitHub Copilot provided real-time predictive text for line completions based on the active file context (variable names, function definitions). This was used primarily for coding efficiency in Python scripts for data preprocessing, analysis, and MOS rating application development.

- *Generative chat:* The author described functionality to generate/alter specific code blocks for dataset generation and MOS app features.
  Prompt pattern: "Add static consent form that displays study information below, saves user agreement in session storage, and prevents proceeding to /rate if not agreed. Use flask and jinja2 — study information: [Insert Study Info]"

- *Figure drafting:* The author provided data structures and requested plotting code.
  Prompt pattern: "For pd.DataFrame df with columns ['model', 'rating', 'user_email'] plot grouped bar chart using matplotlib, place the legend outside plot area on the upper right"

Author contribution: The author designed the overall model training pipeline, software architecture of the MOS rating app and defined all functional requirements. AI was used strictly as an implementation assistant to speed up generation of boilerplate code and routine functions. The author manually reviewed, tested, and debugged all generated code. The author verified that the generated figures accurately represented the underlying data and manually adjusted visual styles as needed.

Appendix 2: Source Code

All steps outlined in this work were implemented in Python, SQL, or JavaScript using open-source libraries. The complete source code for data preprocessing, model training, inference, and evaluation is available in the author's GitHub repository[3].

The structure of the repository is as follows:

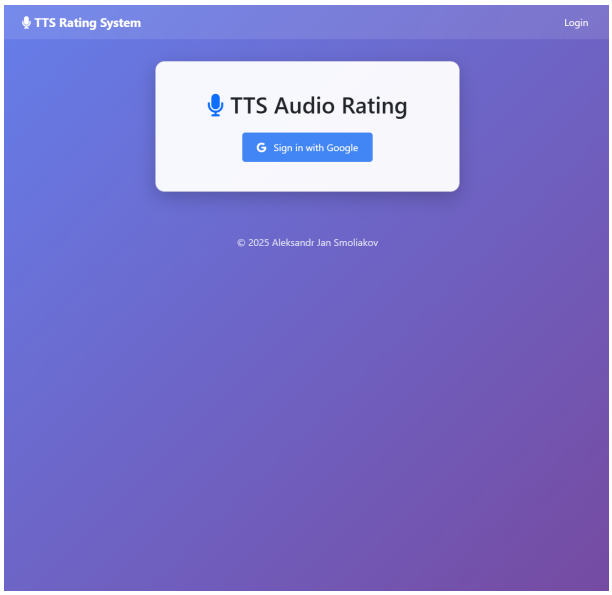
- `configs/`: Configuration files for model hyperparameters and training settings.
- `data/`: Not included due to size constraints; contains raw and preprocessed audio data.
- `latex/`: LaTeX source files for the thesis document.
- `Makefile`: Build instructions for running experiments and generating results.
- `notebooks/`: Jupyter notebooks for exploratory data analysis and visualization.
- `pyproject.toml`: Python project configuration file, specifying package dependencies.
- `python/`: Python scripts for data preprocessing, model training, and evaluation.
- `training_output/`: Training logs, checkpoints (not included due to size constraints), and TensorBoard summaries.
- `tts_rating_app/`: Source code for the web-based MOS rating application.

The repository relies on the raw Liepa-2 corpus [8], which is not included due to size constraints. Liepa-2 is not publicly available due to the sheer size of the dataset ($> 100GB$). It was obtained from the authors upon request for research purposes.

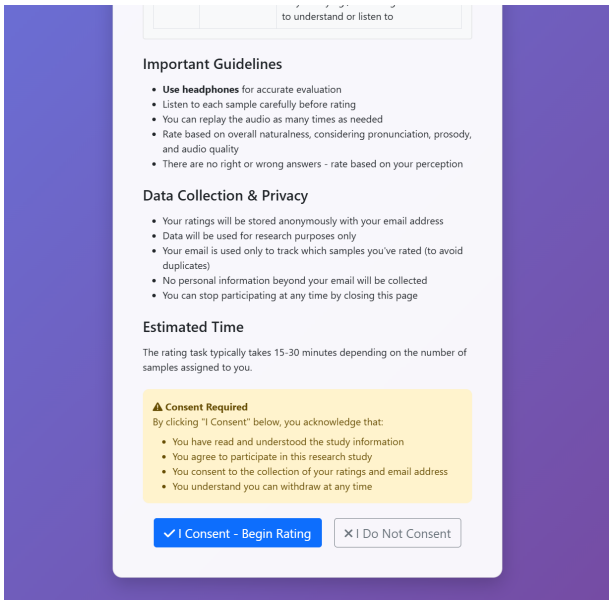
[3] `https://github.com/spacegrapefruit/msc-thesis`

Appendix 3: MOS Rating Application Interface

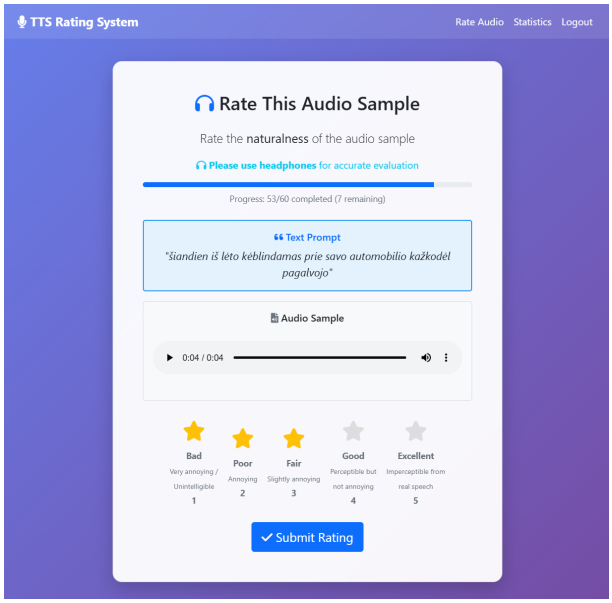
This appendix presents the complete user interface of the web-based MOS evaluation application used for the perceptual study. The application guides raters through four main screens: login, consent, rating, and completion.



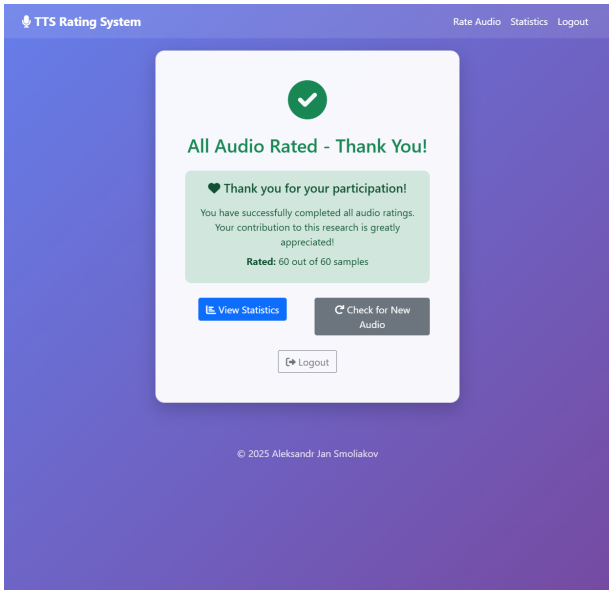
(a) *Login screen*



(b) *Consent screen*



(c) *Rating screen*



(d) *Completion screen*

Figure 12 *Web application interface: (a) login requiring Google authentication, (b) consent screen with study information and MOS instructions, (c) rating screen with text prompt and audio player, (d) completion screen thanking participants.*

Appendix 4: Audio Preprocessing Parameters

The following Mel-spectrogram extraction parameters were used by all models (Tacotron 2, Glow-TTS, and HiFi-GAN vocoder):

Table 17 *Complete Mel-spectrogram extraction parameters.*

Parameter	Value
fft_size	1024
win_length	1024
hop_length	256
frame_length_ms	null
frame_shift_ms	null
stft_pad_mode	“reflect”
sample_rate	22050
resample	false
preemphasis	0.98
ref_level_db	20
do_sound_norm	false
log_func	“np.log10”
do_trim_silence	true
trim_db	60
do_rms_norm	false
db_level	null
power	1.5
griffin_lim_iters	60
num_mels	80
mel_fmin	0.0
mel_fmax	8000.0
spec_gain	20
do_amp_to_db_linear	true
do_amp_to_db_mel	true
pitch_fmax	640.0
pitch_fmin	1.0
signal_norm	true
min_level_db	-100
symmetric_norm	true
max_norm	4.0
clip_norm	true
stats_path	null

Appendix 5: ANOVA Statistical Test Details

This appendix provides the full list of tested model pairs and the significance of their mean MOS differences.

Table 18 *Tukey's HSD post-hoc test results for pairwise comparisons of MOS scores between all model and data composition combinations.*

Model A	Model B	Mean Diff.	p-adj	Lower	Upper	Reject
Glow-030spk	Glow-060spk	0.050000	0.997700	-0.266600	0.366600	False
Glow-030spk	Glow-180spk	-0.100000	0.946100	-0.416600	0.216600	False
Glow-030spk	Tacotron2-030spk	0.977800	0.000000	0.661200	1.294300	True
Glow-030spk	Tacotron2-060spk	0.994400	0.000000	0.677900	1.311000	True
Glow-030spk	Tacotron2-180spk	0.900000	0.000000	0.583400	1.216600	True
Glow-060spk	Glow-180spk	-0.150000	0.755200	-0.466600	0.166600	False
Glow-060spk	Tacotron2-030spk	0.927800	0.000000	0.611200	1.244300	True
Glow-060spk	Tacotron2-060spk	0.944400	0.000000	0.627900	1.261000	True
Glow-060spk	Tacotron2-180spk	0.850000	0.000000	0.533400	1.166600	True
Glow-180spk	Tacotron2-030spk	1.077800	0.000000	0.761200	1.394300	True
Glow-180spk	Tacotron2-060spk	1.094400	0.000000	0.777900	1.411000	True
Glow-180spk	Tacotron2-180spk	1.000000	0.000000	0.683400	1.316600	True
Tacotron2-030spk	Tacotron2-060spk	0.016700	1.000000	-0.299900	0.333200	False
Tacotron2-030spk	Tacotron2-180spk	-0.077800	0.981800	-0.394300	0.238800	False
Tacotron2-060spk	Tacotron2-180spk	-0.094400	0.957500	-0.411000	0.222100	False