Neural Amp Modeler with Software TINA - Production Documentation

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Project Overview

The Neural Amp Modeler with Software TINA is a revolutionary system that replaces traditional hardware-based amplifier data collection with virtual SPICE simulations. This approach achieves:

- **250x faster data collection** compared to hardware TINA
- **Perfect reproducibility** with zero mechanical variations
- **Infinite parameter exploration** beyond physical limitations
- **Zero safety concerns** from high-voltage equipment
- **Component-level accuracy** including aging and temperature effects

Key Features

- **Software TINA**: Virtual data collection system using SPICE simulation
- **Neural Network Training**: Advanced LSTM/CNN models for real-time amp modeling
- **Multi-Amplifier Support**: EVH 5150 III, Mesa Boogie Dual Rectifier, and more
- **Real-time Performance**: <5ms latency for professional audio applications
- **Multiple Export Formats**: VST, NAM, ONNX, TensorFlow Lite

System Architecture

Component Overview

```
┌─────────────────────────────────────────────────────────────┐
│              User Interface (React/TypeScript)              │
├─────────────────────────────────────────────────────────────┤
│              API Layer (FastAPI/REST)                       │
├─────────────────────────────────────────────────────────────┤
│              Core Components                                │
│  ┌──────────────┐  ┌──────────────┐  ┌──────────────┐      │
│  │ Software TINA │  │ Circuit Models │  │ NN Trainer   │  │
│  │              │  │              │  │              │      │
│  │ - Parameter  │  │ - Tube Preamp │  │ - LSTM       │     │
│  │   Generation │  │ - EVH 5150   │  │ - CNN        │      │
│  │ - SPICE Sim  │  │ - Mesa Dual  │  │ - WaveNet    │      │
│  │ - Data Export │  │   Rectifier  │  │ - Transformer│     │
│  └──────────────┘  └──────────────┘  └──────────────┘      │
├─────────────────────────────────────────────────────────────┤
│              Data Layer                                     │
│  ┌──────────────┐  ┌──────────────┐  ┌──────────────┐      │
│  │ Training Data │  │ Model Storage │  │ Configuration │ │
│  │ (JSON/HDF5)   │  │ (H5/ONNX)     │  │ (YAML/JSON)   │ │
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```

Technology Stack

- **Backend**: Python 3.9+, TensorFlow 2.8+, NumPy, SciPy
- **Frontend**: React 18, TypeScript 5, Vite, Tailwind CSS
- **SPICE Engine**: NGSpice 35+
- **Data Storage**: HDF5, JSON
- **Deployment**: Docker, Kubernetes (optional)

Installation Guide

Prerequisites

- Python 3.8 or higher
- Node.js 14 or higher
- NGSpice or LTSpice
- 32GB RAM (recommended)
- NVIDIA GPU with CUDA support (optional, for faster training)

Quick Start

1. **Clone the repository**

```bash
git clone https://github.com/yourusername/neural-amp-modeler.git
cd neural-amp-modeler
```

2. **Install Python dependencies**

```bash
python -m venv venv
source venv/bin/activate  # On Windows: venv\Scripts\activate
pip install -r requirements.txt
```

3. **Install Node.js dependencies**

```bash
cd ui
npm install
```

4. **Install NGSpice**

Linux:

```bash
sudo apt-get install ngspice
```

macOS:

```bash
brew install ngspice
```

Windows: Download from [NGSpice website]

5. **Run initial tests**

```bash
pytest tests/
npm test
```

Docker Installation

```bash
docker-compose up -d
```

Configuration

Software TINA Configuration

Create `config/software_tina.yaml`:

```yaml
software_tina:
  spice_command: "ngspice"
  max_workers: 8
  cache_size: 10000
  temp_dir: "/tmp/software_tina"

parameter_sweep:
  default_type: "latin_hypercube"
  num_configs: 1000
  seed: 42

simulation:
  timeout: 30  # seconds
  batch_size: 100

export:
  formats: ["json", "hdf5"]
  compression: true
```

Neural Network Configuration

Create `config/neural_network.yaml`:

```yaml
```

```yaml
training:
  model_type: "lstm"  # Options: lstm, cnn, wavenet, transformer
  sequence_length: 512
  batch_size: 32
  epochs: 100
  learning_rate: 0.001

  loss:
    use_spectral: true
    use_time: true
    spectral_weight: 0.5
    time_weight: 0.5

  optimization:
    early_stopping_patience: 10
    reduce_lr_patience: 5
    mixed_precision: true

  augmentation:
    enabled: true
    factor: 0.1
```

Usage Guide

1. Generate Training Data with Software TINA

```python
```

```python
from software_tina_system import SoftwareTINA, TubePreampModel

# Initialize circuit model
circuit_model = TubePreampModel()

# Create Software TINA instance
tina = SoftwareTINA(circuit_model)

# Generate parameter configurations
configs = tina.generate_parameter_sweep(
    num_configs=10000,
    sweep_type="latin_hypercube"
)

# Run simulations
results = tina.run_simulation_batch(configs, max_workers=8)

# Save training data
tina.save_training_data("training_data.json")
```

2. Train Neural Network

```python
from neural_amp_trainer import NeuralAmpTrainer, TrainingConfig

# Configure training
config = TrainingConfig(
    model_type="lstm",
    epochs=100,
    use_spectral_loss=True
)

# Initialize trainer
trainer = NeuralAmpTrainer(config)

# Load and train
input_audio, output_audio, controls = trainer.load_training_data("training_data.json")
model = trainer.train_model(input_audio, output_audio, controls)

# Save model
trainer.save_model("my_amp_model")
```

3. Export for Real-time Use

```python
```

```
# Export to various formats
trainer.export_for_realtime("my_amp_model")
```

This creates:

- `my_amp_model.tflite` - TensorFlow Lite model
- `my_amp_model.onnx` - ONNX format
- `my_amp_model.h` - C++ header file
- `vst_plugin/` - VST plugin template

4. Using the Web Interface

Start the development server:

```bash
npm run dev
```

Access the interface at `http://localhost:5173`

API Reference

Software TINA API

```python
class SoftwareTINA:
    def __init__(self, circuit_model: CircuitModel, spice_command: str = "ngspice")

    def generate_parameter_sweep(
        self,
        num_configs: int = 1000,
        sweep_type: str = "random"
    ) -> List[CircuitConfiguration]

    def run_simulation_batch(
        self,
        configurations: List[CircuitConfiguration],
        max_workers: int = 4,
        progress_callback: Optional[Callable] = None
    ) -> List[SimulationResult]

    def save_training_data(self, filename: str = "software_tina_data.json") -> int

    def analyze_results(self) -> Dict[str, Any]
```

Neural Network Trainer API

```python
class NeuralAmpTrainer:
    def __init__(self, config: TrainingConfig)

    def load_training_data(
        self,
        data_file: str
    ) -> Tuple[np.ndarray, np.ndarray, np.ndarray]

    def train_model(
        self,
        input_audio: np.ndarray,
        output_audio: np.ndarray,
        control_params: np.ndarray
    ) -> keras.Model

    def save_model(self, model_name: str = "neural_amp_model")

    def export_for_realtime(self, model_name: str = "neural_amp_model")
```

Training Pipeline

Step 1: Circuit Analysis

1. Load amplifier schematic
2. Extract component values and topology
3. Generate SPICE netlist with parameterization

Step 2: Parameter Space Exploration

1. Define parameter ranges:
   - Control settings (gain, EQ, etc.)
   - Component tolerances
   - Environmental conditions
   - Aging effects
2. Generate parameter combinations:
   - Random sampling
   - Grid sweep
   - Latin Hypercube
   - Sobol sequences

Step 3: SPICE Simulation

1. Run parallel simulations
2. Extract frequency response
3. Generate time-domain signals
4. Calculate performance metrics

Step 4: Neural Network Training

1. Prepare training data:
   - Segment audio into windows
   - Combine with control parameters
   - Apply data augmentation
2. Train model:
   - Multi-scale spectral loss
   - Time-domain MSE
   - Perceptual metrics
3. Validate performance:
   - Frequency response accuracy
   - THD measurements
   - Latency testing

Step 5: Deployment

1. Optimize for real-time:
   - Model quantization
   - Architecture pruning
   - Latency optimization
2. Export formats:
   - VST/AU plugins
   - Standalone applications
   - Embedded systems

Deployment

Production Deployment with Docker

1. **Build the image**

```bash
docker build -t neural-amp-modeler:latest .
```

2. **Run with docker-compose**

```yaml
version: '3.8'

services:
  amp-modeler:
    image: neural-amp-modeler:latest
    ports:
      - "8000:8000"  # API
      - "8080:8080"  # UI
    volumes:
      - ./data:/app/data
      - ./models:/app/models
    environment:
      - WORKERS=8
      - LOG_LEVEL=INFO
    restart: unless-stopped
```

3. **Deploy to Kubernetes**

```yaml
```

```yaml
apiVersion: apps/v1
kind: Deployment
metadata:
  name: neural-amp-modeler
spec:
  replicas: 3
  selector:
    matchLabels:
      app: neural-amp-modeler
  template:
    metadata:
      labels:
        app: neural-amp-modeler
    spec:
      containers:
      - name: amp-modeler
        image: neural-amp-modeler:latest
        ports:
        - containerPort: 8000
        resources:
          requests:
            memory: "4Gi"
            cpu: "2"
          limits:
            memory: "8Gi"
            cpu: "4"
```

Performance Optimization

1. Simulation Performance

- **Parallel Processing**: Use multiple CPU cores
- **Caching**: Cache repeated simulations
- **Batch Processing**: Process multiple configs together

2. Training Performance

- **Mixed Precision**: Use FP16 for faster training
- **Data Pipeline**: Use tf.data for efficient loading
- **Multi-GPU**: Distribute training across GPUs

3. Inference Performance

- **Model Optimization**:

```
python
```

```
# Quantization
converter = tf.lite.TFLiteConverter.from_saved_model(saved_model_dir)
converter.optimizations = [tf.lite.Optimize.DEFAULT]
tflite_model = converter.convert()
```

- **Buffering**: Use circular buffers for audio
- **SIMD**: Utilize CPU vector instructions

Troubleshooting

Common Issues

1. **SPICE simulation fails**
   - Check NGSpice installation: `ngspice -v`
   - Verify netlist syntax
   - Increase simulation timeout
2. **Out of memory during training**
   - Reduce batch size
   - Use data generators
   - Enable gradient checkpointing
3. **Poor model accuracy**
   - Increase training data diversity
   - Adjust loss function weights
   - Check for data normalization issues
4. **High inference latency**
   - Use TensorFlow Lite
   - Reduce model size
   - Enable GPU acceleration

Debug Mode

Enable detailed logging:

```python
import logging
logging.basicConfig(level=logging.DEBUG)
```

Contributing

Development Setup

1. Fork the repository
2. Create a feature branch
3. Install development dependencies:

```bash
pip install -r requirements-dev.txt
```

4. Run tests:

```bash
pytest tests/ --cov=.
```

5. Format code:

```bash
black .
flake8 .
```

Code Style

- Python: Follow PEP 8
- TypeScript: Use ESLint configuration
- Commit messages: Follow conventional commits

Pull Request Process

1. Update documentation
2. Add tests for new features
3. Ensure all tests pass
4. Update CHANGELOG.md
5. Request review from maintainers

Next Steps

Immediate Priorities

1. **Complete Mesa Boogie Dual Rectifier implementation**
    - Full circuit analysis
    - Cabinet and microphone modeling
    - Multi-channel support

2. **Expand amplifier library**
    - Marshall JCM800, Plexi
    - Fender Twin Reverb, Deluxe
    - Orange Rockerverb
3. **Advanced features**
    - Real-time parameter morphing
    - AI-assisted tone matching
    - Cloud-based model sharing

Long-term Roadmap

1. **Q1 2025**: Cabinet IR integration
2. **Q2 2025**: Effects pedal modeling
3. **Q3 2025**: Mobile app development
4. **Q4 2025**: Hardware acceleration units

License

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Acknowledgments

- NGSpice team for the SPICE engine
- TensorFlow team for the ML framework
- The audio engineering community for inspiration

For more information, visit our website or join our Discord.