# Demo Abstract: Using Neural Networks as Modulators for IoT Gateways


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## ABSTRACT

A digital modulator plays a crucial role in converting symbols into signals in an IoT gateway. However, the ever-increasing modulation schemes pose practical challenges, such as flexibility for different schemes and portability with different hardware platforms. To address these challenges, we propose a new approach that employs a neural network as an abstraction layer for physical layer modulators, called the NN-defined modulator. We will demonstrate that the NN-defined modulator functions like traditional modulators and offers high portability and efficiency with example communication to ZigBee and WiFi.



## KEYWORDS

IoT communication, neural networks, digital modulation

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## 1 INTRODUCTION

The Internet of Things (IoT) has rapidly developed, and different wireless technologies [1, 3, 4] are designed for IoT connections. IoT gateways play a vital role in setting up wireless communication links for IoT devices. However, existing gateway designs have limited extensibility due to hardware-based solutions with fixed functionalities and platforms. Software-defined radio (SDR) offers a highly extensible alternative for IoT gateway [5], but lacks portability, requiring specific signal processing toolkits or libraries for particular host platforms connected with SDR hardware. Thus, there is a need to create a highly extensible and portable IoT gateway.

Our study presents a novel approach for developing IoT gateway functionalities, especially physical layer modulation schemes, utilizing neural network (NN) models. Our work is based on two key observations: the wide availability of NN modules on different hardware platforms and the possibility of implementing signal processing operations in modulators through neural network operations. Therefore, we propose an NN-defined modulator for IoT gateways, offering an extensible and portable design as depicted in Figure 1. Compared to existing SDR-based modulators that require

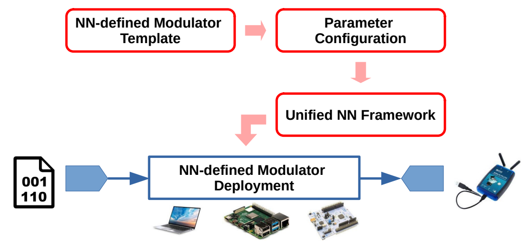



**Figure 1: Design and deployment of NN-defined modulator**

platform-specific DSP tools or libraries, our modulators use a unified NN framework, enabling easy deployment on various platforms. In summary, our study proposes an NN-defined modulator for IoT gateway design, utilizing a model-driven approach based on a solid mathematical foundation. We implement and port the modulator to various platforms, with results showing improved portability and faster performance than conventional SDR modulators under specific settings.

## 2 SYSTEM DESIGN

Figure 1 illustrates the design of the proposed Neural-Network-Defined (NN-Defined) modulator. This involves establishing the mathematical foundation of digital modulation, developing the modulator structure (*template*), setting parameters for specific schemes, and converting it into a unified NN framework for various platforms.

### 2.1 Model-Driven NN Template for Modulators

We use a model-driven approach to design a template for various modulation schemes by modeling linear modulation schemes such as PAM, PSK, QAM, and multicarrier modulation schemes like OFDM [2].

Based on this method, a discrete-time signal $S_i[n]$ modulated from a symbol $s_i$ is considered a linear combination of the set of basis functions. The synthesis process is given as

$$S_i[n] = \sum_{j=1}^{N} s_{ij}\phi_j[n] \tag{1}$$

where $\phi_j[n] \in \{\phi[n]\}^N$ is the $j$-th function in the set of $N$ basis functions and $s_{ij}$ is the $j$-th elements of the $N$-dimensional vector representation of the input symbol $s_i$.

Considering the complex-valued representation of baseband signals, we decompose them into In-phase and Quadrature signals. We

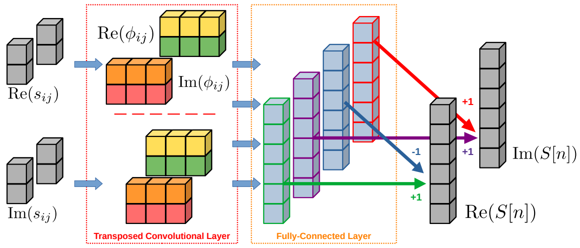
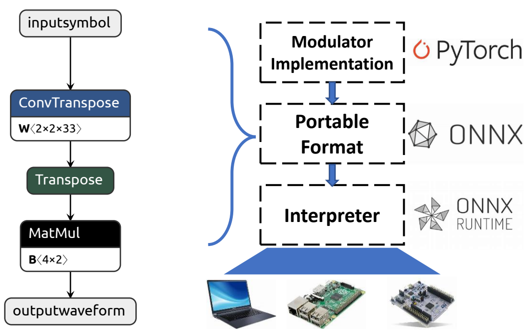



**Figure 2: Diagram of the template of NN-defined modulator. 0-weight connections are omitted in Linear Layer.**




(a) (b)

**Figure 3: (a) Example converted ONNX format of a QAM NN-defined modulator, (b) Diagram of converting NN-defined modulator and usage.**

convert this pattern to a neural network as the NN-defined modulator template as in Figure 2. The template consists of two parts, the transposed convolutional layer followed by a fully-connected (FC) layer. The transposed convolutional layer serves as the function to generate multiplication results and the fully-connected layer combines the results to form the final I/Q signal samples.

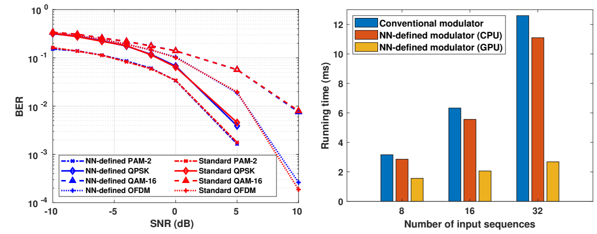
## 2.2 Specific NN-defined Modulators

**Single Carrier Amplitude/Phase Modulation:** For amplitude/phase modulation on the single carrier, without loss of generality, we consider the most general case, quadrature amplitude modulation (QAM). The QAM symbols are complex scalars and are passed through the pulse-shaping filter to generate signals. Using the NN-defined modulator template, we can configure the parameters of the transposed convolutional layer to the corresponding values of the shaping filter $p[n]$.

**Multicarrier Modulation:** We also extend our design to encompass multicarrier modulation schemes, particularly the widely-used OFDM scheme. The modulation process for OFDM involves mapping the complex symbol vector $\mathbf{s} = [s_0, s_1, \cdots, s_{N-1}]$ of $N$ dimensions to a signal $S[0], \cdots, S[N-1]$ using a set of basis functions, $\phi_i[n] = e^{j(2\pi ni/N)}, i = 0, 1, \cdots, N-1$. So, the parameters are configured based on $e^{j2\pi ni/N}$. Subsequently, the output from the transposed convolutional layer is supplied to the fully-connected layer to generate the I/Q signals.

## 2.3 Conversion to Unified NN Framework

To effectively deploy NN-defined modulators, they must be converted into a widely adopted framework. The Open Neural Network




(a) (b)

**Figure 4: (a) BER performance of NN-defined modulators and conventional modulators in AWGN channel, (b) Running time of NN-defined QAM-4 modulator and conventional modulator on Nvidia Jetson Nano.**

Exchange (ONNX) [6] is the target framework, which allows storing and importing neural network models onto new platforms. Our modulators are exported using ONNX's common set of operators, and an example graph representation of a QAM modulator is shown in Figure 3a as for validation.

The NN-defined modulator, once converted to ONNX, can run on devices with the ONNX interpreter, as illustrated in Figure 3b. The interpreter is optimized for model execution and can utilize accelerators with ease. Unlike SDKs provided by hardware vendors that require significant effort to master, the ONNX framework has integrated acceleration tools, making it simpler to take advantage of accelerators.

## 2.4 Preliminary Results and Demonstration

For preliminary evaluation, we apply NN-defined modulators for typical IoT modulation schemes and compare the Bit Error Rates (BER) performance in AWGN channel with conventional DSP-library-based modulators. Figure 4a shows that our signals achieve near-similar error performance to the conventional design. In addition, Figure 4b shows that our modulator runs much faster, utilizing the GPU acceleration on the target platform, indicating its potential to port to different platforms efficiently.

At the demo booth, we will show that the NN-defined modulators are able to be integrated into the current SDR pipeline for IoT communication. The NN-defined modulators will modulate the ZigBee and WiFi symbols, and the generated signals are sent over the air using an SDR front-end to commercial receivers.


# ACKNOWLEDGMENTS

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