Machine Learning in IIoT Communication

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***Abstract*—The Industrial Internet of Things (IIoT) is essential for improving productivity and security in industrial settings. This study employs two strategies—holistic and step-by-step—to improve IIoT systems from a communication standpoint. The goal of this study is to enhance IIoT performance and support its successful adoption in industrial settings. The holistic approach addresses the overall system architecture and communication protocols, while the step-by-step method concentrates on component-wise improvements.**

***Index Terms*—IIoT, digital communication, machine learning**

I. Introduction

A network of connected equipment, systems, and devices across an industry makes up the Industrial Internet of Things (IIoT). Its goal is to make it easier for these organizations to communicate and share information, thereby increasing decision-making, production, and efficiency processes. Digital communication technologies, at the core of the IIoT, enable seamless data transfer among a variety of devices, sensors, and systems in industrial environments. These systems are essential for integrating the IIoT ecosystem, as they provide ongoing communication, data sharing, and control in industrial settings. The foundation for the full fulfillment of IIoT's promise is provided by the digital communication system by enabling real-time data-driven operations.

This communication system has performance requirements such as reliability, low latency, scalability, and security, etc. to be used in IIoT. Addressing these performance requirements can be done through system design and optimization.

The goal of this paper is to propose improvements to these performance requirements using machine learning techniques.

II. A basic communication system

A fundamental digital communication system is made up of several important parts, as shown in the Fig. 1. The source is the place where the digital data to be transferred first appeared, such as a computer or sensor. The digital data that needs to be communicated is produced by the source. The encoder takes the digital data and transforms it into a transmission-ready format. When digital data is encoded, it is altered using methods like modulation so that it may be transferred over a channel more effectively.

The digital data is prepared for transmission across the channel, which might be a wired or wireless media, once it has been encoded. The modulator takes the encoded signal and transforms it into a format appropriate for channel broadcast. The modulated signal travels through the channel carrying the digital data that has been encoded. The demodulator at the receiver end removes the modulated signal from the channel and reformats it into the original form. Demodulation is the opposite of modulation; it extracts the digital data that has been encoded from the signal that has been received. The decoder receives the signal after it has been demodulated.

To recap, the components of the digital communication system are as follows: a source that produces the digital data, an encoder that formats it appropriately, a modulator that prepares it for transmission, a channel that carries it, a demodulator that extracts the signal from the channel, a decoder that converts the signal back to digital data, and a sink that receives and uses the communicated information. Together, these elements allow a communication system to reliably transmit and receive digital data.

Source message is given by

$$s \in M = \{1, 2, ..., M\}$$

and estimated message is given by

$$\hat{s}$$

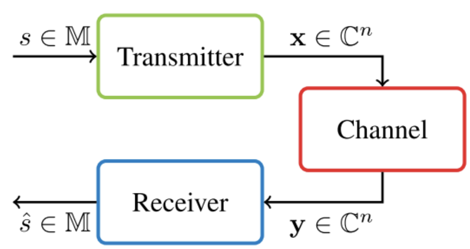

Fig. 1. A basic communication system. [1]

III. performance improvements

We can either consider the digital communication system as a whole system or break it into its individual components. This gives rise to two approaches to improve the digital communication system

A. Holistic approach

Considering the digital communication system as a one block design, an end-to-end communications system can be designed using a machine learning algorithm called autoencoder (shown in Fig. 2). It is an unsupervised Machine learning algorithm based on deep neural networks. It is basically trained on labelled data to recreate the input information at the output.

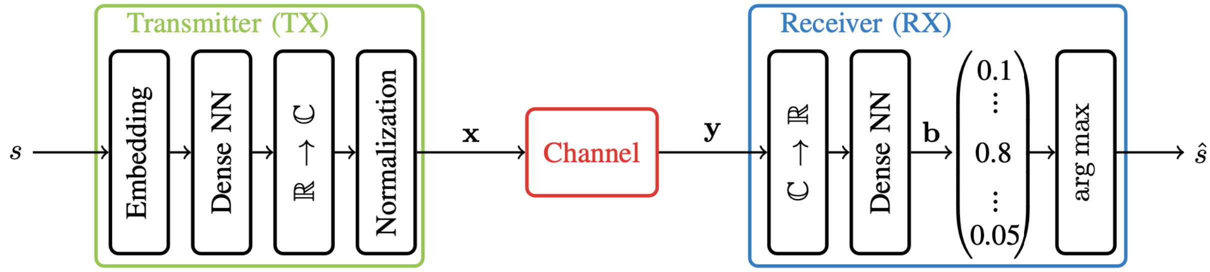

Fig. 2. Communication system using encoder implementation [1]

In our case, the deep neural network (NN) is representative of transmitter and receiver modules [2], which in turn is representative of the encoder, modulator, demodulator and decoder [3]. Such a model is optimised for block error rate (BLER) given by the equation 1 [1]. Optimum block error rate (BLER) results in improvement in the accurate transmission of information.

$$P_e = \frac{1}{M} \sum_s \Pr(\hat{s} = s|s). \tag{1}$$

In addition and deep learning based channel module is used to emulate channel behaviour. However there are challenges in hardware implementation of this model.

B. Step by step approach

Traditional communication systems may perform better with a holistic approach, however using machine learning applications for modulation classification, channel estimation, and channel equalization is another option is to enhance the various communication system subprocesses.

1) deep learning to estimate channels: Channel estimation is the process of correctly estimating the channel state so that the transmitted signal can be efficiently decoded without loss of information. The channel frequency response is modeled as an image. Convolutional neural networks are applied to this image to reconstruct the image and thus estimate the channel characteristics. In this case loss function is Mean squared error is the loss function that our algorithm tries to minimize [4]. The input variable and output variable is given by

$$x \in R^d \text{and } h \in R^d$$

respectively. The channel estimator [5] is given by

$$\|\mathbf{f}(\mathbf{x})\|_2 = \left[\sum_{i=1}^{d} \mathbf{E}\left\{f_i(\mathbf{x})^2\right\}\right]^{1/2} < +\infty \tag{2}$$

2) convolutional neural network (NN) based modulation classification: Modulation classification is a process of identifying which modulation technique is used for transmitting a message. Assuming carrier timing and waveform recovery are already done baseband sequence is given by

$$y(n) = Ae^{j(2\pi f_o nT + \theta_n)} \sum_{l=-\infty}^{\infty} x(l)h(nT - lT + \epsilon_T T) + g(n) \tag{3}$$

where

$$x(l) \text{is symbol sequence, } A \text{ is amplitude factor}$$

We are using support vector machine (SVM) based classification to decide which modulation [6] scheme is in use. Performance improvements comparison of both approaches is provided in Table I.

TABLE I
PERFORMANCE IMPROVEMENTS BETWEEN HOLISTIC AND STEP-BY-STEP APPROACHES

Performance Improvement	**Holistic**	**Step-by-Step**
Overall System Architecture	✓	✗
Communication Protocols	✓	✓
Reliability	✓	✓
Low Latency	✓	✓
Scalability	✓	✓
Security	✓	✓
Modulation Classification	✗	✓
Channel Estimation	✗	✓
Channel Equalization	✗	✓

IV. CONCLUSION

This paper's main goal was to discuss the communication component of the IIoT and provide two methods for enhancing its efficiency. Unlike the step-by-step method, which only takes into account certain system components, the holistic approach also takes into account the whole communication system. By utilizing these tactics, IIoT systems can perform at their peak levels, making it easier for businesses to successfully install them. To advance in the field of IIoT communications more research and efforts are needed as these machine learning-based improvements are in the initial stages of development.

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