Artificial Intelligence based Position Detection for Hydraulic Cylinders using Scattering Parameters

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Abstract

Position detection of hydraulic cylinder pistons is crucial for numerous industrial automation applications. A typical traditional method is to excite electromagnetic waves in the cylinder structure and analytically solve the piston position based on the scattering parameters measured by a sensor. The core of this approach is a physical model that mathematically describes the relationship between the measured scattering parameters and the targeted piston position. However, this physical model has shortcomings in accuracy and adaptability, especially in extreme conditions. To overcome this problem, we propose Artificial Intelligence (AI)-based methods to learn the relationship directly data-driven. As a result, all Artificial Neural Network (ANN) models in this paper consistently outperform the physical one by a large margin. Given the success of AI-based models for our task, we further deliberate the choice of models based on domain knowledge and provide in-depth analyses combining model performance with the physical characteristics. Specifically, we use Convolutional Neural Network (CNN)\textsuperscript{s} to discover local interactions of input among adjacent frequencies, apply Complex-Valued Neural Network (CVNN)\textsuperscript{s} to exploit the complex-valued nature of electromagnetic scattering parameters, and introduce a novel technique named \textit{Frequency Encoding} to add weighted frequency information to the model input. By combining these three techniques, our best performing model, a complex-valued CNN with Frequency Encoding, manages to significantly reduce the test error to hardly 1/12 of the one given by the traditional physical model.

Keywords: Artificial intelligence, convolutional neural network, complex-valued neural network, frequency encoding, position detection, scattering parameter

1. Introduction

The ubiquitous aim for automation in industrial processes demands accurate control of their components. One of the most widely used components in industrial automation applications is the hydraulic cylinder. To better control the actual working behavior of a hydraulic cylinder, we need to know the precise position of its piston. Given the characteristics of the interior of hydraulic cylinders, electromagnetic wave is a good medium for detecting the piston position.

LiView (Figure 1) is a sensor that can emit electromagnetic waves and receive their reflections inside a hydraulic cylinder. The LiView system is based on microwave signals with frequencies from 300 MHz to 1.5 GHz that are fed in the cylinder. The signals reflected by the cylinder structure provide signatures that allow a determination of the piston position after the read-out of them.

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In this context, machine learning methods are presumably the most common application of AI which uses a large set of data to tune the parameters of an adaptive model (Bishop & Nasrabadi, 2006). Classical machine learning algorithms, such as Support Vector Machine (SVM), K-Nearest-Neighbor (k-NN), Decision Tree (DT), have been widely adopted in industrial applications (Bertolini et al., 2021; Kang et al., 2020; Narciso & Martins, 2020). They are also popular in machine learning models using scattering related parameters as the input to predict any desired output according to their specific application (Roshani et al., 2021; Akhavanhejazi et al., 2011; Barbosa et al., 2019; Rana et al.; Bader et al., 2021; Hejazi et al., 2011). A typical workflow is to hand design good features from measured scattering parameters with the help of domain knowledge, then pair the generated features with the corresponding target to form the training set, on which the machine learning models are finally trained in a supervised way. The problem of machine learning methods lies directly in step one, the feature extraction process, which requires in-depth domain expertise, and the quality of the features directly affects the final result. We confirm this through experiments, where we apply classical machine learning models directly to the raw data and can only achieve unsatisfactory results for our piston position detection task. Due to the complexity of the environment inside the cylinder, we do not force meticulous engineering on handcrafted features but pin our hopes on deep learning instead.

Deep learning, or Artificial Neural Network (ANN), as an important branch of machine learning, provides a way to avoid the necessity for handcrafted features by learning informative representations automatically with the help of a general-purpose learning procedure. Specifically, deep learning allows computational models composed of multiple processing layers to learn data representations with multiple levels of abstraction. Two quintessential examples of ANNs are Multilayer Perceptron (MLP) and Convolutional Neural Network (CNN), which are multilayer stacks of fully connected and convolutional layers, respectively. They can discover intricate patterns in large data sets by exploiting the backpropagation algorithm (Rumelhart et al., 1986) to indicate how to change its internal parameters are used to compute the representation in each layer from the representation in the previous layer (LeCun et al., 2015). Because of their accuracy and robustness, Artificial Neural Network (ANN) based techniques have also caught the attention of researchers in scattering parameter related projects (Hien & Hong, 2021; Frazier et al., 2022; Husby et al.; Gupta; Travassos et al., 2020; Rana et al.). In this paper, we explore in detail the feasibility of MLP and CNN for piston position detection based on scattering parameters. In all our experiments, deep learning based models consistently outperform both the traditional physical model and classical machine learning models by a large margin. We also investigate the particular impact of general architectures and components of MLP and CNN for this specific task. We find that different activation functions and the application of convolution have significant effects on the model performance for our specific task. We offer explanations in the context of the
AI characteristics of the models and the physical nature of hydraulic cylinders.

The aforementioned machine learning and deep learning models mainly focus on real-valued data. However, complex numbers are often used in many real-world practical applications, such as in telecommunications, robotics, bioinformatics, image processing, sonar, radar, and speech recognition (Bassey et al., 2021). Applications based on electromagnetic scattering parameters are also in the complex domain. One way to cope with complex numbers is to break a complex-valued vector into its real and imaginary parts to form a real-valued vector of two times the length of the original complex-valued vector. This simple approach effortlessly translates the problem from the complex domain to the real domain. Still, it completely loses essential statistical information, such as the correlation between the real and imaginary parts of the numbers. On the other hand, Complex-Valued Neural Network (CVNN) with complex-valued weights, such as complex-valued MLP (Hirose, 2012; Sarroff) and complex-valued CNN (Trabelsi et al., 2018; Zhang et al., 2017), solve the problem directly in the complex domain. They are designed to have more constraints to force the model to mimic calculations in the complex domain. This way, more information about the specific application is introduced to the model, which could improve the model performance.

In addition to internalizing the information that the model should operate in the complex domain by CVNN, other information related to the input can also be introduced into the model by simply adding the information to the input itself. For example, in the original transformer model (Vaswani et al., 2017), the position information of the input words is encoded and added directly to the word embedding. Inspired by this idea, we also applied a model-agnostic technique named Frequency Encoding to add frequency information to our model input after weighting by learnable parameters. To our best knowledge, this is the first work to use frequency information of electromagnetic waves by adding a learned weighted encoding of it directly to the model input. This simple trick significantly improves the model performance by about 36% for both MLP and CNN framework.

In a brief summary, we apply AI based models and techniques on cylinder piston detection using scattering parameters measured by the LiView system. We elaborate on the motivations for the chosen models, compare the performance of different AI based models with the physical one, acquire task-specific findings and prove our assumptions by in-depth analyses based on the model characteristics and physical nature of the task. Our major findings and contributions are as follows:

1. Deep learning based models significantly and consistently outperform both the traditional physical model and classical machine learning models. The relative error of our best performing model, a complex-valued CNN with Frequency Encoding (FE), is less than 1/12 of the traditional physical model.
2. Frequency Encoding dramatically improves the generalization performance of all ANN based models at a negligible cost of extra trainable parameters and without the need to change the backbone structure of the model.
3. Complex-Valued Neural Networks outperform their real-valued counterparts by a large margin, which is strong evidence that more emphasis should be placed on the complex nature of the specific task.
4. CNNs consistently beat MLPs on performance, indicating the local interactions between frequencies play an important role.
5. The performance of models with the same architecture but different activation functions varies greatly, implying that a function choice that more closely matches the physical characteristics of the task is preferred, especially when computational resources limit the total number of parameters of the model.

The rest of the paper is organized as follows. In section 2, we summarize the achievements and our inspirations from them. Then in section 3, we describe the LiView system and the data measurement process, as well as the essential role of scattering parameters in this paper. All the machine learning (Random Forest (RF) and Gradient Boosted Decision Tree (GBDT) in section 4.1), and deep learning models (MLP and CNN in section 4.2) including CVNN (section 4.3) are presented in section 4 together with the novel technique Frequency Encoding (section 4.4). In section 5, we first elaborate the dataset (section 5.1), then give model implementation and training details (section 5.2), and lastly analyze and assess the trained models. Finally, section 6 provides our conclusions.

2. Related Work

Physical Model Based Approaches: There is some variety in the attempts to measure the piston position of a hydraulic cylinder with electromagnetic signals. The difference lies in whether coupling the signal into the cylinder on the side of the piston where the rod is present (Morgan, 1994-06-28; Braun et al., 2014-01-17; 2017-04-05) or on the other side without the rod (Fend et al., 2011-06-30; Büchler et al., 2011-06-30). In the first situation, the cylinder tube and piston rod form a coaxial cavity, while the latter leads to a signal propagating in a hollow waveguide of variable length. Both variants can be modeled so that the position of the cylinder can be extracted, for example, from the analysis of resonant frequencies. But both variants pose difficulties when the piston is near the bottom of the cylinder tube or the piston rod bearing. Then, the model assumptions of a waveguide or a coaxial cavity do not hold anymore and workarounds such as a switch to other models or look-up tables have to be implemented, which demand in-depth expert knowledge and impede a robust implementation that can easily be generalized to...
mechanically differing cylinder types. Machine learning overcomes this restriction and allows for a generic modeling process for various cylinder types.

**Machine Learning Based Approaches:** Machine learning has been widely adopted in industrial applications, using scattering parameters as the input to predict the desired target. For instance, a k-NN based method for monitoring the transformer winding by detecting the winding axial displacement based on the magnitude and phase of the measured scattering parameters is presented in Hejazi et al. (2011). Researchers in the same group followed a similar experiment and implemented a complex-valued MLP and CNN with reasonable adaptions (section 4.2 and 5.2) to fit our task. Note that all previously mentioned models in this section are real-valued models but also applied more promising deep learning models.

Despite the promising results, the applications mentioned above are rooted in relatively simple systems (specifically two-port networks simulated in the lab). In this paper, we used two more sophisticated machine learning models, RF and GBDT, to handle more complicated and noisy real-world experiments. In the meantime, we also applied more promising deep learning models.

**Deep Learning Based Approaches:** Deep Learning has attracted the attention of researchers working with scattering parameters due to the strong potential it shows in both theory and in practice. Hien & Hong (2021) proposed a material thickness classification with the help of a 6-hidden-layer MLP using hand-picked features derived from scattering parameters. They binned the ground truth into eight thickness classes and recorded impeccable average estimation accuracy. Similarly, Husby et al. adopted a 3-hidden-layer MLP to detect the thickness of duplex coatings used for corrosion protection of carbon steel substrates. They were able to reduce the relative standard deviation to 2.5%. In addition to MLP, CNN can also be of help. Gupta described a CNN based hand movement classification from measured scattering parameters and achieved an accuracy of 98%.

Given the above successful demonstrations, we also evaluated MLP and CNN with reasonable adaptions (section 4.2 and 5.2) to fit our task. Note that all previously mentioned models in this section are real-valued models but with complex-valued input. A common way to solve this contradiction is to concatenate a complex-valued vector’s real and imaginary parts to form a double-sized real-valued vector. We adopted this way to construct our real-valued models as well, but also implemented CVNN to handle complex-valued input directly.

**Complex-Valued Neural Network (CVNN)** has also been used for applications related to scattering parameters. Yang & Bose (2005) applied CVNN for landmine detection. They trained CVNN with a single hidden layer on a highly unbalanced small dataset. This can only result in a good average true positive rate after strict outlier removal and data balancing. In a recent study, Frazier et al. (2022) investigated CVNN more thoroughly in their application for the estimation of complex reverberant wave fields using complex-valued scattering parameter as input. They tested a CVNN with complex-valued weights and a hybrid ANN which processes real and imaginary parts of the input independently and only combines these two parts at the very end of the model to generate the output. They compared these two versions of CVNN with their real-valued counterpart and found out that the CVNN with complex-valued weights achieved the best performance and outperformed the real-valued model based only on the magnitude of the scattering parameters by a large margin. Besides complex-valued MLP in the above-mentioned two projects, complex-valued CNN also achieved promising results in other areas, such as image recognition in (Trabelsi et al. 2018). Encouraged by these results, we also implemented both complex-valued MLP and complex-valued CNN for our project.

**Frequency Encoding:** In the aforementioned work, it’s common to use not only scattering parameters but also other extra useful features either deriving from scattering parameters or related to the experimental setup, such as voltage standing wave ratio in Gupta or permittivity in Hien & Hong (2021). However, these extra features, although directly related to the original input, are usually concatenated to the original input, which increases the input dimension and therefore the model size significantly. Another way to introduce additional information to the model is to add extra information to the original input. A typical example is the positional encoding for the Transformer (Vaswani et al. 2017), where sinusoidal functions encode the position of each word (of the input sentence), and the code is directly added to the input embedding. Inspired by the idea of positional encoding, we applied a technique called Frequency Encoding. The difference between positional encoding and our Frequency Encoding is that we do not encode the frequency in a predefined way but with learnable parameters and only add the learned code to the corresponding input.

Despite the notable achievements of the papers regarding AI using scattering parameters, there are still some regretful missing parts. Firstly, the computational resource doesn’t seem to be a concern for most of the work. Considering that we will deploy our model in a microcontroller in the future, the tradeoff between model performance and model size also plays a critical role in this paper. In addition, the authors of the vast majority of the papers in this area focus more on how to directly solve the problem by a chosen AI based approach and usually neglect to provide the motivation for the choice of their specific models or
provide comparisons between different models. We were often unable to find a detailed analysis of the test results, not to mention linking the model performance to practice by explaining why the model works in view of both the properties of the chosen models and the physical characteristics of the task. In our opinion, the motivation and analyses serve as significant guidance for similar projects in the future. Therefore, we provide motivation (section 4), comparison, evaluation and analysis (section 5) of our models in detail. But before all that, we will start our journey by introducing our measurement device: LiView.

3. LiView System

LiView is a sensor that measures the current position of the piston in a hydraulic cylinder via the analysis of electrical fields that are excited within the cylinder (Braun et al., 2017-04-05). Since the measurement depends solely on the cylinder’s interior, the LiView sensor is less exposed to external perturbations than alternative sensors like optical systems or cable potentiometers. As shown in Figure 1a, the LiView system consists of an electronic unit positioned outside the cylinder and two probes connecting the cylinder’s interior with the electronic unit via two coaxial wires. These wires conduct a microwave signal (illustrated as arrows in Figure 1b) that is generated in the electronic unit and capacitively fed into the cylinder (Leutenegger et al., 2017-12-15). The electrical fields that propagate through the cylinder have frequencies in a range from 300 MHz to 1.5 GHz with their phases and amplitudes depending on the piston position.

In the present frequency regime, it is common to employ a formalism based on wave quantities which describe scattering on the linear electrical network that represents the investigated system (White, 2004). (Ludwig & Bretchko, 2000). Given the incident and reflected voltage wave, $E^{inc}$ and $E^{ref}$, of a port $i$, we define two waves $a_i$ and $b_i$ as:

$$a_i = \frac{E^{inc}}{\sqrt{Z_0}},$$

$$b_i = \frac{E^{ref}}{\sqrt{Z_0}},$$

where $Z_0$ is the transmission line’s characteristic impedance, which connects the $i$th port. With the help of $a$ and $b$ waves, a linear electrical network can be characterized by a set of coupled algebraic equations describing the reflected waves from each port in terms of the incident waves at all the ports (White, 2004). The coefficients of the network are called the scattering parameters $S$. For a three-port electrical system as the LiView system, the network can be described in the matrix format as:

$$
\begin{pmatrix}
  b_1 \\
  b_2 \\
  b_3
\end{pmatrix} = 
\begin{bmatrix}
  S_{11} & S_{12} & S_{13} \\
  S_{21} & S_{22} & S_{23} \\
  S_{31} & S_{32} & S_{33}
\end{bmatrix}
\begin{pmatrix}
  a_1 \\
  a_2 \\
  a_3
\end{pmatrix}.
\tag{3}
$$

Figure 2 provides an abstract illustration of the three-port network which models the LiView system. It is a linear electrical network that interacts with three ports. Port 1 and 2 correspond to probe 1 and 2 in Figure 1 respectively. They are connected with the LiView electronic unit via coaxial wires. When measuring, a stimulus is injected at Port 1, and its reflection is finally received by Port 2. Port 3 represents the cylinder tube with the piston moving inside, whose signal can’t be measured by any probe. The cylinder structure among three ports can be considered as the virtual transmission lines. In one measuring cycle, The LiView electronic unit first generates a signal at a predefined frequency and injects it into the cylinder structure through port 1. The injected signal passes from the cylinder bearing to the piston rod which is represented by port 3. It then propagates as electromagnetic waves through the oil inside the cylinder tube until it reaches the piston. The piston then reflects the signal, and the probe at port 2 can then detect this reflected signal.

The quantities that are measured by the electronic unit are the transmission $t$ (at one specific frequency) between the exciting port 1 and receiving port 2 given by

$$t = \frac{b_2}{a_1}.
\tag{4}$$

The piston position $L$, which is defined as the distance between the piston rod bearing and the piston, determines the scattering parameters of the 3rd port:

$$a_3 = T(L) b_3,$n\tag{5}$$

with $T(L)$ modeling the cylinder as a transmission line. Under the assumption of reciprocity $S_{ij} = S_{ji}$, one can extract the relevant transmissions and reflections at ports 1 and 2 by combining Equations 3 and 5. Exemplary, the transmission $t$ for a certain frequency as in Equation 4 for low frequency TEM-modes then reads (Braun et al., 2017-04-05):

$$t = S_{21} - \frac{S_{23} S_{13}}{S_{33} - \frac{1}{T(L)}},$$

$$\tag{6}$$
Note that all wave-related variables \((E, a, b, S, t)\) in previous equations are complex numbers. With Euler’s formula, it follows that any complex number \(z\), with \(r = |z|\) as its amplitude and \(\theta = \arg(z)\) as its phase, can be written as

\[
    z = re^{i\theta} = r\cos \theta + j \, r\sin \theta = Re(z) + j \, Im(z)
\]

where \(j = \sqrt{-1}\) so that the real and imaginary part of \(z, Re(z)\) and \(Im(z)\), are both real numbers. Therefore, the data finally gathered by the LiView system are entries of complex-valued vector \(t\) which has 121 elements corresponding to transmissions at the 121 frequencies, equally distributed in a range from 300 MHz to 1.5 GHz.

Looking at Equation 6, it’s apparent that the transmission \(t\) is nothing but a mathematical expression of scattering parameters and piston position \(L\). The existence of the relation \(t = f(L)\) (abstracted from Equation 6) paves the way towards a position detection method by solving the inverse \(L = f^{-1}(t)\) in the complex domain. It also motivates us to look for inspiration from previous projects regarding scattering parameters, as we have done in section 2.

The traditional position detection method used before the project in this paper is based on the derivation of \(T(L)\) from Maxwell’s Equations (with more details given in [Braun et al., 2017-04-05]) and the physical model of electrodynamics in the cylinder tube. However, the scattering parameters \(S_{21}, S_{31}\) as well as the product of \(S_{23}\) and \(S_{13}\) in Equation 6 still depend on the specific cylinder structure. They can only be acquired by calibration via measurements or simulations of the respective cylinder. In addition, besides the piston position \(L\), the function \(T\) also depends on the oil permittivity, \(\epsilon_r\), which quantifies the storage and dissipation of energy. \(\epsilon_r\) is sensitive to environmental factors such as temperature, impurities in the oil, etc. Accordingly, the consistency of \(T(L)\) under various environmental effects is challenging to be guaranteed, especially for a high accuracy measurement by approaches based on the physical model. Next, we will show how we overcame the subtleties by switching to ANN-based methods.

4. Methods

Our goal is to learn the mapping relationship \(L = f^{-1}(t)\) between the transmission \(t\) measured by the LiView system and the desired piston position \(L\) by machine learning and deep learning methods. Specifically, an original input of our models is a 1D complex-valued vector with 121 elements corresponding to the 121 equally distributed frequencies in a range from 300 MHz to 1.5 GHz. Depending on the model architecture and the technology applied, we change the actual inputs to the model accordingly (sections 4.2.4.3 and 4.4). The output is simply a scalar referring to the piston position recorded simultaneously when the input is measured.

This section introduces the general architectures of the models and specific methods we use to achieve our goal, as well as the motivations to use them. We apply both the classical machine learning (section 4.1) and deep learning-based models (section 4.2 and 4.3), together with a novel technique named Frequency Encoding (4.4). The implementation details are given in section 5.2 and the model performance is analyzed in section 5.3.

4.1. Machine Learning Models

Random Forest (RF): Random Forest is a combination of tree predictors such that each tree depends on the values of a random vector sampled independently and with the same distribution for all trees in the forest (Breiman 2001). To construct a RF, we first generate \(m\) new training sets from the original training set of size \(N\) and feature dimension \(d\) (with \(d = 242 = 121 \times 2\) since we use real-valued model until section 4.3) by uniformly sampling with replacement. This technique is also known as bootstrapping. For each sampled new training set, we randomly sample \(d’ = \lfloor \sqrt{d} \rfloor\) features and then train a CART (Breiman et al. 1984) on the sampled feature subspace. Finally, all the trained CARTs are aggregated to form the RF and the average prediction result of the trees is the final output. The process of bootstrapping and then aggregating is often abbreviated as bagging.

Gradient Boosted Decision Tree (GBDT): Another classical machine learning method based on the aggregation of decision trees is GBDT. The main difference between GBDT and RF is that the former uses boosting instead of bagging as in the latter. Boosting is a powerful technique for combining multiple ‘base’ classifiers to produce a form of a committee whose performance can be significantly better than any of the base classifiers (Bishop & Nasrabadi 2006). In our case, we use DTs as base regressors and build an ensemble of them in a forward stagewise manner. At each iteration of the forward stagewise procedure, we train a DT to represent the negative gradient of the residual error from the previous iteration and aggregate to the ensemble by steepest descent.

RF and GBDT are both ensemble learner based on DTs. They utilize bagging and boosting respectively to overcome the tendency of overfitting and high variance in a single DT for better generalization performance. Given the excellent performance of both GBDT (Chen & Guestrin 2016a; Dorogush et al. 2018; Ke et al. 2017) and RF (Breiman 2001; Schonlau & Zou 2020) on general regression problems, we adopted these two models for our task. However, these two models do not perform very well on our problem (section 5.3), especially compared to the deep learning-based models presented in the next section.

4.2. Deep Learning Models

Deep learning, or ANN, allows computational models composed of multiple processing layers to learn data representations with multiple levels of abstraction. LeCun et al.
The motivation for the choice of deep learning is to use this mechanism to achieve better generalization performance since traditional machine learning methods are insufficient to learn complicated functions in high-dimensional spaces such as our case (with evidence given in section 5.3). The architecture of a deep learning model is a multilayer stack of simple modules (Figures 3, 4, and 5). In this section, we discuss the structure of our MLP, CNN, and CVNN models.

**Multilayer Perceptron (MLP):** MLP (Werbos & John 1974; Rumelhart et al. 1986) is a feedforward ANN where every single neuron in adjacent layers is connected to each other. Because of the fully connected characteristic, MLP is also named as Fully Connected Neural Network (FCNN). The quintessential advantage of MLPs is that they are universal approximates provided sufficiently many hidden units (Hornik et al. 1989), i.e. they are able to represent a wide variety of functions requiring no special assumptions about the input. For the real-valued MLP (a), we first concatenate the real and imaginary parts of a measured complex-valued transmission $t$ to form a real-valued vector as the new input, and train real-valued MLP to approximate the inverse function $L = f^{-1}(t)$ for prediction of the targeted piston position $L$. We evaluate MLP with different numbers of hidden layers, each consisting of 32 neurons except the last one, which has 16 neurons. We also analyze the effect of four different activation functions, sigmoid, ReLU (Nair & Hinton), Leaky ReLU (Maas et al.), and SELU (Klambauer et al. 2017), on MLPs.

**Convolutional Neural Network (CNN):** CNN (LeCun et al. 1989) are a specialized kind of neural network for processing data that has a known, grid-like topology (Goodfellow et al. 2016). Units in a convolutional layer are organized in feature maps, within which each unit is connected to local patches in the feature maps of the previous layer through a set of weights (LeCun et al. 2015). The result of this locally weighted sum is then passed through the activation function like in MLP, to form the output feature map.

The motivation for CNN is its property that a convolutional layer should learn functions that represent local interactions in input. In our case, the local interactions are among neighboring frequencies. Based on the properties of electromagnetic waves, it is reasonable to assume that transmission $t$ of adjacent frequencies are highly correlated, exhibiting local statistics which are easily detected. In section 5.3, we prove our hypothesis with training results and give a plausible physical reason behind it.

As in real-valued MLP we concatenated the real-valued real and imaginary parts of all 121 complex numbers to form the 1D grid with 242 elements as the input for our real-valued CNNs. Once we converted the complex-valued input to vectors with the shape of 1 × 242, 1D local convolutional filters only to the frequency dimension (instead of the temporal dimension). A 1D CNN can then be constructed using these convolutional layers and trained to predict the targeted piston position. As depicted in Figure 4a, the first convolutional layer has a large kernel size (1 × 22) and stride (11). It’s a common way to reduce dimensionality in frequency-based signal processing, e.g. in Supriya (2020). The first convolutional layer is followed by three convolutional layers with small kernels (1 × 3) and strides to extract informative features. Finally, a fully connected layer exploits those extracted features to make the prediction.

Note that we perform downsampling directly by convolutional layers, instead of max pooling layers, with a stride of more than one. The two ways result in a similar model structure considering the dimension of the feature maps of each layer and are experimentally proved in section 5.3 to have similar effects on generalization performance for our project. We prefer the latter from the perspective of intuitive comparisons between real-valued and complex-valued CNN described in the next section.

### 4.3 Complex-Valued Neural Network (CVNN)

CVNNs are ANNs that operate in complex space with complex-valued input and weights. The main reason for their advocacy lies in the difference between the representation of the arithmetic of complex numbers, especially the multiplication operation (Bassey et al. 2021). Figure 5 illustrates our implementation of the complex-valued operation inside a layer of a CVNN. In the illustration, $Re(X)$ and $Im(X)$ refer to the real and imaginary parts of a complex-valued input, while $Re(W)$ and $Im(W)$ refer to the real and imaginary parts of the layer weight. To imitate the multiplication of complex numbers, we first split the real and imaginary parts of the complex-valued input and weight as stated, then calculate the components $Re(X) \ast Re(W)$, $Re(X) \ast Im(W)$,
Figure 4: CNN architecture. The backbone of the real-valued (a) and complex-valued (b) CNN is 1D convolutional (Conv) and 1D complex-valued convolutional (ComplexConv) layers, respectively. For each layer in the illustration, the kernel size is presented as the first term of the description text and the number of output channels is given in parentheses. Different strides are used for downsampling.

At the end of all CNNs, there is always a Fully Connected (FC) layer. The symbol $*$ in the figure represents multiplication for ComplexFC layer and convolution for ComplexConv layer.

Figure 5: An illustration of one layer in a CVNN. Both the input and the output are complex numbers. Layers in CVNN mimic calculations in complex domain. The symbol $*$ in the figure represents multiplication for ComplexFC layer and convolution for ComplexConv layer.

layer is implemented by two FC(16) layers representing $Re(W)$ and $Im(W)$, respectively.

The choice of CVNN is motivated by the fact that the input are complex numbers, where the real and imaginary parts, or more specifically their amplitude and phase, are statistically correlated. Although we may represent a complex number as an ordered pair of two real numbers, as in the previous sections, CVNNs have dynamics different from that of real-valued neural networks. In short, in CVNNs, we can reduce the ineffective degree of freedom in learning or self-organization to achieve better generalization characteristics (Hirose 2012).

The mechanism of CVNN can also be seen as enforcing a strong prior to the original MLP and CNN forcing them to operate in the complex domain. This could be (and is proved in section 5.3 to be) useful since we’re giving the models more information about the real-world application. Guided by this idea, we further introduce another technique named Frequency Encoding.

4.4. Frequency Encoding (FE)

FE encodes the (normalized) frequencies $f$ for each channel of the complex-valued input, and then the code $c$ is added element-wise to the input after weighting by a learnable parameter $w$. Formally, the FE pipeline in this paper can be expressed as:

$$c = w \ast f,$$

$$Re(x') = Re(x) + c,$$

$$Im(x') = Im(x) + c,$$  \hspace{2cm} (8)

where $x'$ and $x$ are the encoded and original 1D input vector, respectively. Both consist of 121 elements corresponding to the 121 frequencies. As illustrated in Figure 6, the 121 frequencies from 300 MHz to 1.5 GHz are uniformly scaled to $[0,1]$ at first. The normalized frequency vector is denoted as $f$. Then the uniformly encoded frequencies $f$
Learnable weights $w$

Data from sensor $\mathbf{x}$

Input for models $\mathbf{x'}$

Learned frequency encoding $c$

Uniform frequency encoding $f$

Figure 6: Sketch of the Frequency Encoding (FE) procedure. The normalized frequencies $f$ are multiplied with the learnable weights $w$ which leads to the code $c$. This $c$ then serves as an additive bias for the original model input $\mathbf{x}$. Therefore, the frequency information is encoded and injected to the final input for models $\mathbf{x'}$.

are multiplied by corresponding learnable weights to generate the code $c$. Note that the weights $w$ for frequency encoding are learned by backpropagation during training, just like any other learnable parameters in the model. After that, the code for each frequency is then added equally to both the real and imaginary parts of the original input $\mathbf{x}$, or more specifically, the measured transmission $t$, at the corresponding frequency, forming the new input under FE $\mathbf{x'}$ for our models.

FE allows us to add the information about the frequency values and inject it into the model. We believe that injecting frequency information should be helpful because the precise value of the frequency will significantly impact the transmission $t$ at that frequency and, therefore, the piston position prediction. Since we cannot precisely confirm a priori the impact of each frequency value, the learnable weights are introduced to correct the initial uniform encoding. We prefer FE over intuitive concatenation, mainly for the following reasons. Firstly, it uses the summation of corresponding elements to avoid the explosion of the input dimension and further the model parameters. Secondly, the frequency information is accurately introduced into the correct corresponding input element instead of letting the model find the correspondence between the two by training itself. Another advantage of FE is that it’s also a model-agnostic technique, i.e., we can easily apply it to any learning-based models benefiting from backpropagation without any particular change of the model structure. It turns out that FE significantly affects model performance. More details about the evaluation results can be found in section 5.3.

5. Experiments

5.1. Dataset

Experimental Configuration: Our experiments for the measurement of the transmission $t$ and the recording of the piston position $L$ are carried out at a wide variety of temperatures in the range from 25°C to 95°C. In all experiments, a LiView device is mounted on the same hydraulic cylinder with a stroke of 1815 mm and keeps measuring transmissions at 121 frequencies uniformly distributed in a range from 300 MHz to 1.5 GHz as described in section 3.

A hydraulic power unit drives the cylinder, and a magnetostrictive position measuring system measures the piston position. Other than the input and output for the models, metadata such as operating frequency, cylinder temperature, and timestamps are also recorded. Three typical experiment recordings are shown in Figure 7. As we can see from the three graphs on the left side of Figure 7, typical piston movements are uniform linear motions shown as straight lines in the figures. To test the performance under different working conditions, we also adopt varying speed profiles by mixing end-to-end and jittering movements at different speeds during different experiments, shown respectively in different slopes of lines in the upper left and the zigzag patterns in the middle. The amplitudes of the corresponding measured input are drawn on the right side of Figure 7. It’s evident that the transmission $t$ changes with the piston position $L$, which verifies our assertion of the existence of $t = f(L)$.

Dataset Split: The main idea of our dataset split is that we selected two test sets deliberately in two different ways to test which one reflects the true generalization ability of our models. We generated 534K data pairs ($t, L$) among 73 experiments in total, where $t$ is a 1D vector with 121 complex-valued elements corresponding to transmissions at 121 frequencies and $L$ stands for the targeted piston position. We randomly split the data from 68 datasets at a ratio of 80 to 20 for the training and the first test set.
There is also a second test set composed of the remaining five datasets. To distinguish the two test sets, we named them "test set from random split" and "test set from new datasets" (since the latter one is "new" to the training set) in Figure 8 respectively. The final ratio of the data volume in three datasets is 10/2/1 (training/test1/test2).

We split the data this way to show that only the second test set, "test set from new datasets", is the only suitable set to test generalization. As can be seen from Figure 8 the performance of all ML models on the first test set, "test set from random split", is almost identical to the performance on the corresponding training sets. We argue that, although both test sets are kept from the training process, the test set from the random split shares too many influential factors with the training set since they are from the same experiments, which makes the data in the two not quite the same but very close. These influential factors could be explicit ones such as speed profile and temperature, or implicit ones like chamber pressure, oil quality, parts aging effect, etc. The second test set, consisting of complementary datasets, doesn’t suffer from the issue and therefore is the only suitable test set that reflects the actual generalization performance. That said, the test set from the random split is not entirely useless. It is still an indicator to show what will happen if there are only slight changes, which was helpful in the model selection phase and could help if we could cover a broader range of working conditions of the cylinder. But in the following sections, unless otherwise specified, we refer to "the test set" as the one from the new datasets.

5.2. Implementation and Training Details

Since the input for our models are 1D vectors with 121 complex-valued elements, we treat them for both classical machine learning models and real-valued ANNs as real-valued input with 242 features each by concatenating their real and imaginary parts. On the other hand, CVNNs can use the measured data off-the-shelf with 121 complex-valued features. We also tried to represent complex numbers using magnitude and phase, but the final results of the two ways to handle complex numbers were almost indistinguishable. Frequency Encoding was also applied to the models as stated in section 4.2 by choice.

To preserve the possibility of running the model on a microcontroller or integrating it into the current LiView electronic unit in the future, we limited the total parameters for each model to just under 10K.

We leveraged the scikit-learn implementation of random forest regressor. For GBDT we used LightGBM (Ke et al. 2017), which can in theory significantly outperform XGBoost (Chen & Guestrin 2016b), another popular implementation of GBDT in terms of computational speed and memory consumption according to Ke et al. (2017). For both RF and GBDT we fine-tuned the hyperparameters in 500 trials sampled by TPE (Tree-structured Parzen Estimator) algorithm in a large hyperparameter space which covered both shallow and deep models with the help of the hyperparameter optimization framework Optuna (Akiba et al. 2019). The test performance of both models with the best hyperparameter set is given in Table 1.

We also trained all ANNs using the hyperparameters acquired by fine-tuning in 500 trials with the help of Optuna. It turned out that the best hyperparameter sets for MLP, CNN and CVNN were very similar. Accordingly, we chose the final hyperparameters as the following. At the beginning of the training process, we always initialized the biases to zeros and the weights using Xavier uniform random initialization procedure (Glorot & Bengio 2010). Instead of random initialization procedure (Glorot & Bengio, 2010). For training, we used the AdamW optimizer (Loshchilov & Hutter, 2017a), which is the combination of the classical Adam (Kingma & Ba, 2017), with $\beta_1 = 0.9$ and $\beta_2 = 0.999$, and the decoupled weight decay regularization of which we set the coefficient to $10^{-4}$. We chose the learning rate of $10^{-3}$ and a learning rate scheduler that linearly decreased the learning rate starting at half of the fixed total epochs from $10^{-3}$ to 0. This simple learning rate was proved to achieve better generalization compared to no scheduler or delicate ones such as cosine annealed warm restart scheduler (Loshchilov & Hutter, 2017b) for all models. The batch size was set to 128 for MLP and 64 for CNN. We also applied Batch Normalization (BN) (Ioffe & Szegedy, 2015) to some models (Tables 2 and 3) and early stopping mechanism to all models. Another regularization we tested was Dropout (Srivastava et al. 2014), but it did not help the generalization in all our trials. We also compared four activation functions (sigmoid, ReLU, Leaky ReLU, and SELU) under the same model structure and went along only with the best-performing one, sigmoid, after the comparison (section 5.3).
assessment of the model performance by other standards in industry, we also provide test Mean Error (ME) and Mean Absolute Error (MAE) for some models. RMSE, ME, and MAE are all given in millimeter. Accordingly, we calculate the Relative Error (RE) as the ratio between RMSE and the stroke of the cylinder 1815 mm. Since the ME of our models are all close to 0, the more commonly used error expression in industry, which is ME±standard deviation, can be approximated as ME±RMSE in our case.

**Baseline Model:** We started our analysis by setting up the baseline model. In consideration of the pervasiveness and flexibility of MLP, we trained MLP with different numbers of hidden layers with sigmoid activation function but without applying Batch Normalization and Frequency Encoding at first. The evaluation results based on RMSE are given in Figure 8. Note that only the RMSE on test set from new datasets is the proper indicator of the generalization performance (as described in section 5.1). Looking at the test set performance shown in the orange curve in Figure 8, it is apparent that increasing the depth of the model further after two hidden layers surprisingly brings down the model performance. Similar observations were also reported in [He & Sun, 2014] [Zeller et al., 2013] [Simonyan & Zisserman, 2015], where aggressively increasing the depth leads to saturated or degraded accuracy. Since two-hidden-layer MLP already provided the best generalization performance, we chose the two-hidden-layer MLP as the baseline.

It’s also worth mentioning that we also kept computational resources in mind when choosing the baseline. Although a high-end GPU (NVIDIA 3090) currently did all the training and analyses, we plan to deploy the model on a microcontroller in the future. In fact, the two-hidden-layer MLP is not necessarily always the best-performing model without computational limitations. One argument is that the shape of the test performance curve in Figure 8 is a good match for the double-descent risk curve in [Belkin et al., 2019], which indicates that introducing more hidden layers could lead to even lower RMSE on the test set. Another clue lies in the training error. Except for the fact that it almost overlapped with the curve of "RMSE on the test set from random split" as explained in section 5.1, the training error slightly rises rather than falls once the model size exceeds three hidden layers. This phenomenon where the training error increases as the model gets bigger is the degradation problem reported in [He et al., 2015] and [Srivastava et al., 2015]. The degradation problem could be solved by techniques such as residual learning reformulation [He et al., 2015]. However, considering the tradeoff between the computational burden and model performance, as well as the fact that even this simple baseline already outperforms the traditional physical model (section 5.3), we still prefer the two-hidden-layer MLP as the baseline. To make the comparisons among models below and the baseline fair, we limited the parameter numbers of all the following models to a roughly equivalent range of about 10K. Based on this guiding principle, we chose the real- and complex-valued CNNs as illustrated in Figure 4 and discussed in section 4.

| Framework | train RMSE | test RMSE | RE (%) |
|-----------|------------|----------|--------|
| MLP (baseline) | 1.99 | 5.56 | 0.31 |
| Physical model | - | 13.61 | 0.75 |
| RF | 0.89 | 44.35 | 2.44 |
| GBDT | 4.77 | 38.56 | 2.12 |

1 We evaluated the traditional physical model only on the test set since it doesn’t need a training process (so its training RMSE is left as blank). The RMSE of 13.61 mm, which corresponds to a RE of 0.75%, is the average performance of the physical model on the test set.

| Table 1: Performance comparison of baseline | Multilayer Perceptron (MLP) (deep learning) | Random Forest (RF) (classical machine learning) |
|------------------------------------------|-------------------------------------------|--------------------------------------------------|
| Physical model | - | 13.61 | 0.75 |
| RF | 0.89 | 44.35 | 2.44 |
| GBDT | 4.77 | 38.56 | 2.12 |

Baseline vs Classical: We first compare the baseline MLP model with the traditional physical model [Braun et al., 2017-04-05] and classical machine learning models described in section 4.1.

The physical model generally performs well in a mild and stable environment. However, its accuracy drops when dealing with our complex working scenarios and a wide range of temperature changes. We tested the performance of the physical model on the test set and calculated an average RMSE of 13.61 mm obtained from measurements ranging from room temperature up to 84°C. For a cylinder stroke of 1815 mm, it corresponds to an RE of 0.75%, which is outperformed by the baseline model with a test RMSE as 5.56 mm.

Both RF and GBDT suffer from poor generalization behavior in our case, which can be inferred from the massive gap between the train and test RMSE, especially for RF. The performance of GBDT is inferior to our baseline MLP or even the traditional physical model. Considering that the models for both frameworks are already the best choice after extensive hyperparameter fine-tuning with 500 trials each, we thus confirm our hypothesis that it’s the lack of well-designed features with domain knowledge that makes it difficult for classical machine learning methods to obtain comparable performance on our piston position task using scattering parameters. We therefore placed our hopes entirely on deep learning from then on and only adapted ANN models to enhance their performance.

**Batch Normalization (BN):** The first technique we applied to the baseline model was BN [Ioffe & Szegedy, 2015]. As can be seen from the first two lines of Table 3, it helps improve the test RMSE by 30% from 5.56 to 3.89 mm. However, this is not the case for CNN or models with Frequency Encoding which hardly benefit from BN in our case.

Another point worth mentioning is that BN does help stabilize the training process for deep MLPs. As can be
seen in Figure 9, the 6-hidden-layer MLP without BN cease to advance for more than 20 epochs by showing a long plateau of training errors likely to be caused by vanishing gradients, especially for deeper models, while BN eliminates this phenomenon, shown as the training process of a shallow model (2-hidden-layer MLP).

Activation Functions: The choice of activation functions in deep networks has a significant effect on the training dynamics and task performance (Ramachandran et al., 2017). Table 2 compares the generalization performance (ME, MAP, RMSE, and RE on the test set) of 2-hidden-layer batch-normalized MLPs with four different activation functions. Previous research such as Glorot et al. (2011) shows that ReLU generally performs better in most deep learning models, especially for image and text data. For our case, it converges faster too, but can not provide promising results in our case. Its variant, Leaky ReLU, exhibits similar behavior. Sigmoid, on the other hand, outperforms other activations. We believe this intriguing result is attributed to the fact that the sigmoid function, \( f(z) = 1/(1 + \exp(-z)) \), is more in line with the physical characteristic of the input transmission \( t \) expressed as Equation 7, since exponential function dominates in it. Components that are better reflections of the real physical world allow models to learn the relationship \( L = f^{-1}(t) \) better, especially for shallow ANN modes like our baseline, where the representation learning ability is restricted by the depth and parameters of the model. This assumption also explains why SELU, a half-linear-half-exponential function, comes in between the more exponential sigmoid and the more linear ReLU. Because of the excellent performance of sigmoid, we adopted it as the activation function for all the following models.

Ablation Study: Evaluation results of MLPs and CNNs are provided in Table 3. The top and bottom parts of the table show models in these two frameworks separately. For models in both frameworks, Batch Normalization (BN), Frequency Encoding (FE), and Complex-Valued Neural Network (CVNN) were applied to them selectively. We kept only the promising models and omitted poorly performing ones. Since BN doesn’t perform well along with the other two techniques in our test, we always applied FE and CVNN without BN. In the following paragraphs, we first focus on the MLP part of the table to discuss the outcome of FE and the impact of CVNN. Finally, we compare MLP and CNN and relate the model performance to the physical characteristic of our data.

Frequency Encoding (FE): This simple technique is able to reduce the test RMSE by more than half from 5.56 to 2.5 mm, as shown by the first and the third row of Table 3. As stated in section 4.4, we apply FE with learnable weights in a multiplicative way and add the weighted codes to the original input. This also means the significant improvement by FE was achieved by just adding 121×2 = 242 parameters to our baseline, which is a model with about 10K parameters in total. In other words, FE boosts the model performance by 55% at the cost of merely 2% of more parameters. This result strongly supports our hypothesis that providing the model with frequency information will significantly improve the model’s performance. It also suggests that we should build Artificial Intelligence (AI) models as physically close to the real-world application as possible. As a side note, we also tested a variant of the standard positional encoding, which encodes the frequency by sinusoidal functions and directly adds to the input without any weighting process. This mode only slightly improves the model performance compared to the baseline. The reason lies in the fact that we are not able to determine in advance the specific effect of frequency on the input. Modeling this impact by a blindly chosen function, which only makes the frequencies unique instead of informative, turns out not to be a good design. Thus, we prefer the implementation with learnable weights.

Complex-Valued Neural Network (CVNN): Besides real-valued MLPs (with architecture illustrated in Figure 3a) and performance given in the first three rows of section 4, Table 3 also displays the test performance of complex-valued MLPs (with structure depicted in Figure 3b) indicated by check marks in the column CVNN. As discussed in section 4.2, one layer of our CVNN model consists of two standard layers to represent the real and imaginary parts of complex-valued weights, respectively. We combine them in a way to mimic the calculation of complex numbers. To make the comparison between complex-valued and real-valued model fair, we carefully adjusted the depth and width for each CVNN so that their total number of parameters were close to their real-valued counterparts. We believe that CVNN could help the model performance due to the complex-valued characteristic of the model input and traditional physical model we would like to approximate. We confirm our hypothesis by comparing the first and fourth row of Table 3. The complex-
Table 2: Performance comparison for models with different activation functions. All models in the table are 2-hidden-layer real-valued MLPs with Batch Normalization (BN). The only difference among them are their activation functions.

| Framework | BN | Activation | ME  | MAE  | RMSE | RE(%) |
|-----------|----|------------|-----|------|------|-------|
| MLP       | ✓  | Sigmoid    | -0.18 | 2.08 | 3.89 | 0.21  |
| MLP       | ✓  | SELU       | -0.08 | 4.3  | 5.88 | 0.32  |
| MLP       | ✓  | ReLU       | -0.06 | 4.00 | 5.96 | 0.33  |
| MLP       | ✓  | LeakyReLU  | 0.00  | 4.79 | 8.3  | 0.46  |

Table 3: Performance comparison for models with different architectures. Both frameworks, MLP (Figure 3) and CNN (Figure 4) are tested with techniques Batch Normalization (BN) and Frequency Encoding (FE). Check marks in the Complex-Valued Neural Network (CVNN) column mean that we adopted complex-valued Multilayer Perceptron (MLP) (Figure 3b) or complex-valued Convolutional Neural Network (CNN) (Figure 4b) for the model in that specific row. The model performance is shown by Mean Error (ME), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Relative Error (RE) based on RMSE.

| Framework | BN | FE | CVNN | ME  | MAE  | RMSE | RE(%) |
|-----------|----|----|------|-----|------|------|-------|
| MLP (Baseline) |    |    |      | -0.1 | 2.04 | 5.56 | 0.31  |
| MLP       | ✓  |    |      | -0.18 | 2.08 | 3.89 | 0.21  |
| MLP       | ✓  | ✓  |      | -0.11 | 1.24 | 2.5  | 0.14  |
| MLP       | ✓  | ✓  |      | -0.07 | 0.95 | 1.53 | 0.08  |
| CNN       |    | ✓  |      | 0.34  | 1.27 | 2.32 | 0.10  |
| CNN       | ✓  |    |      | 0.82  | 1.69 | 2.35 | 0.13  |
| CNN       | ✓  | ✓  |      | 0.11  | 0.8  | 1.47 | 0.08  |
| CNN       | ✓  | ✓  |      | 0.45  | 1.02 | 1.53 | 0.08  |

value 2-hidden-layer MLP significantly cuts down the test RMSE by over 72% to 1.53 mm. This improvement comes only at a price of about 7% of more model parameters.

Incorporating FE into CVNN can further enhance model performance. As a result, the integration of these two components leads to the best performance for models based on the MLP framework. The test RMSE drops by 78% to 1.23 mm while the model is only 9% bigger than the baseline. Compared to the fact that we have known from Figure 8 that stacking layers blindly is, instead of an upgrade, but a downgrade of the model performance, by FE and CVNN is undoubtedly phenomenal.

MLP vs CNN: Finally, we demonstrate the best framework tested in this paper: CNN. First, the enhancement due to Frequency Encoding and CVNN on CNN is in line with the progress they made on MLP. What really stands out about CNN (as listed in the Table 3) is that their overall performance is consistently better than that of MLP in all cases. For example, our best-performing model after all trials is the complex-valued CNN with Frequency Encoding which manages to reduce the test RMSE by 82% compared to the baseline MLP model and makes the Relative Error plummet to hardly 1/12 of the one given by the traditional physical model.

We believe the superiority of CNN has two main reasons. Firstly, it is for the sake of the parameter sharing mechanism of CNN which enables it to contain more layers with the same number of model parameters. Therefore, limiting the number of model parameters results in the fact that CNNs are able to take advantage of the extra depth. A deeper architecture provides an exponentially increased expressive capability and is more likely to learn rich distributed representations of data, which is beneficial to the regression task of the final layer. More importantly, local connections between the frequencies also play an essential role here. For example, the position of the piston will have a local effect on the frequency spectrum of the input transmission \( t \). As shown in Figure 10, the shape and form of the peaks and valleys in the spectrum are different when the corresponding piston position changes. We know from the physical model that the damping of the peak is frequency-dependent, and the location of the peak hinges on the piston position. Those local changes of peak patterns can be easily detected by a CNN since its feature maps for each layer only focus on local patches.

6. Conclusion

In this work, we evaluate AI-based models for the piston position detection task inside a cylinder. It is demonstrated that deep learning models (MLP and CNN) consistently outperform classical machine learning methods (RF and GBDT) and the traditional physical approach. Based on this result, we further apply Frequency Encoding and CVNN to the deep learning models. An ablation study reveals that these two techniques significantly improve the generalization performance by 55% and 72% compared to the baseline at the cost of merely 2% and 7% of more model parameters, respectively. The final best-performing...
model is the integration of the three winning components, or more specifically, a complex-valued CNN with FE, which manages to reduce the error to hardly 1/12 of the one calculated by the traditional physical model.

In addition to the remarkable model performance, this paper also attaches importance to the motivation for choosing different models and analyzing the reasons behind the model’s performance. We also take great care of our data. The input of our models, transmission $t$, is a mathematical expression of scattering parameters of a three-port network and is measured by a device named LiView in experiments mirroring the real-world working conditions. The training and test set are carefully chosen to reflect our models’ generalization performance best.

Considering the possibility of future integration of our model into the LiView electronic unit, we restrict the number of parameters to about 10K for all models.

The potentials of the combination between AI and scattering parameters are far from being limited to the position detection task. We plan to extend the paradigm to predictive maintenance and investigate oil permittivity problems. We are excited about the future of an AI-based LiView.

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