IJAREEIE

e-ISSN: 2278-8875
p-ISSN: 2320-3765

International Journal of Advanced Research

in Electrical, Electronics and Instrumentation Engineering

Volume 11, Issue 7, July 2022

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 8.18

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering (IJAREEIE)

| e-ISSN: 2278 – 8875, p-ISSN: 2320 – 3765| www.ijareeie.com | Impact Factor: 8.18|

||Volume 11, Issue 7, July 2022||

|DOI:10.15662/IJAREEIE.2022.1107029 |

Deep Learning-Based OFDM MIMO 5G Channel Estimation

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ABSTRACT: In a wireless communication system, the quality of the CE has a huge impact on communication performance; whether communication systems can reach channel ability is heavily reliant on the gathering of exact channel state information (CSI). In reality, it might be challenging to estimate CSI accurately. Two typical channel estimators are least squares and minimum mean square error. The unique DLbasedmethodology, which used a deep neural network (DNN) to perform CE, has lately been explored in addition to the conventional model-based CE method that was frequently used. In this article, we propose to use deep learning via a multi-layer perceptron architecture that exceeds the performance of traditional CSI processing methods like least square (LS) and linear minimum mean square error (LMMSE) estimation, thus leading to a beyond fifth generation (B5G) networking paradigm wherein machine learning fully drives networking optimization. By computing the CSI of all pairwise channels simultaneously via our deep learning approach, our method scales with large antenna arrays as opposed to traditional estimation methods. We validate our approach by simulating a 32-element array base station and a user equipment with a 4-element array operating on millimeter-wave frequency band. Results reveal an improvement up to five and two orders of magnitude in BER with respect to fastest LS estimation and optimal LMMSE, respectively, substantially improving the end-to-end system performance and providing higher spatial diversity for lower SNR regions, achieving up to 4 dB gain in received power signal compared to performance obtained through LMMSE estimation.

KEYWORDS:MIMO, Deep Learning, OFDM, B5G, Wireless Communication

I.INTRODUCTION

Large antenna arrays are revolutionizing wireless communications and sensing, with manifestations in programmable surfaces, gesture monitoring, and high rate data delivery through incorporation in the form of massive multiple-input multiple-output (mMIMO) systems. Already envisaged as a key component of 5G, mMIMO utilizes a number of antennas that can be one to two orders of magnitude higher than the classical MIMO WiFi access points and LTE base stations (BSs) available today. However, despite the significant advances in edge computing capabilities, there are practical challenges in processing needs associated with such large antenna arrays. This article is motivated by our desire to decouple the scale of deployment with the limits of classical processing, especially as it pertains to the task of understanding the channel between a given antenna-receiver antenna-element pair for millimeter-wave (mmWave) communication. We accomplish this via training a deep learning (DL) architecture that offers the ability to produce a robust and high fidelity channel matrix between the mobile user and the mMIMO BS in a single forward pass. Since the overhead of the DL-based channel estimation becomes irrespective of the size of the antenna array, we believe this approach will enable a fundamental leap toward beyond 5G (B5G) standards where thousands of coordinated antennas will become the new norm. Emerging B5G networks are envisioned to support edge computing, which will enable rapid optimization and reconfiguration of the network architecture. This is a critical first step toward supporting requirements of emerging high-bandwidth and low-latency applications. Machine learning (ML) and artificial intelligence (AI) algorithms running at the edge computing servers help to (i) scale the optimization problem without proportional increase in complexity and (ii) enable fast response close to the BS, thus meeting strict demands of a time-varying wireless channel. We believe our use case of DL-enabled

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mmWavemMIMO demonstrates the need for tightly integrating AI into emerging wireless standards, which remains a gap even in the ongoing 5G rollout today.

II.BACKGROUND WORKS

Channel estimation is the first step in the larger processing chain associated with decoding the data packet. Its objective is to identify the complex signal transformation imposed on the emitted wireless signal by the channel, and this is inferred via special information bits embedded in the packet preamble. For a spatially multiplexed system, this complex transformation is captured via the so-called channel state information (CSI). Knowing the CSI allows the transmitter to perform additional precoding functions that maximize the signal energy in the direction of interest. Thus, delayed computation of CSI, or worse, an incorrect computation can quickly degrade the performance in systems like mMIMO, where the CSI computation needs to be repeated several dozen times. In the context of the B5G use case we explore in this article, we consider time-division duplexing (TDD) for mMIMO and assume that the channel varies slowly (coherence time of 10–100 ms [1]).

While ML- and DL-based architectures have been traditionally deployed in the image, video, speech, natural language processing, and healthcare [5] domains, there have also been efforts in solving challenging tasks in the RF domain, such as modulation recognition, radio identification [6], and network resource allocation. In the area of channel estimation, [7] presents an end-to-end OFDM symbol decoding method using MLP by treating a single-input single-output (SISO) channel model as a black box. In the context of mMIMO, [8] proposes a compressive method for generating CSI feedback based on encoder-decoder DL architecture.

Applying DL-based approaches for CSI estimation in mMIMO is still at a nascent stage. Due to the high dimensionality in mMIMO, especially when involving OFDM techniques, the majority of existing solutions use complex and deep architectures to estimate large channel matrices. These solutions treat the multi-dimensional input signal as a single entityand often require additional prior or post-estimation steps.the large CNNs in both [9, 10] have limitations in real-time implementations. In the context of single-carrier systems, [11] devises an uplink (UL) transmission for single-antenna users and multiple-antenna BSs using a six-layer MLP to first estimate direction of arrival (DoA) and then determine the channel for each user, by expressing the channel estimate as a function of DoA and solving an additional linear system of equations. Recently, [12] described an online training method based on the Deep Image Prior scheme, using a 6-layer architecture based on 1 □ 1 convolutions and upsampling, which performs denoising of the received signal before a traditional LS estimation.

The general approach to channel estimation is to insert known reference pilot symbols into the transmission and then interpolate the rest of the channel response by using these pilot symbols. The main contributions of this work are listed below:

We propose a deep-learning-based CSI estimation method for MIMO OFDM that incurs a fixed computational cost, irrespective of the number of antenna elements, by exploiting the inherently parallel nature of DNNs.

We discuss the limitations of traditional estimation techniques and compare the inference time complexity of the state of the art in DL-based channel estimation with the proposed approach, demonstrating its suitability for edge applications.

We validate the performance of CSI estimation by simulating downlink transmissions between a BS and a single UE.

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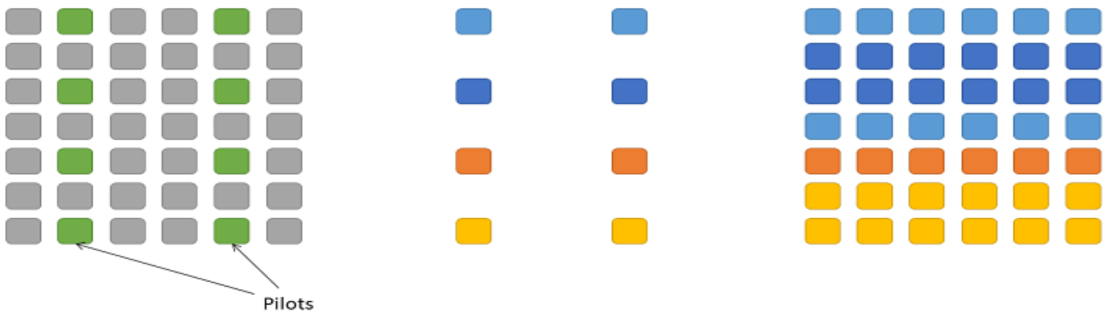

(a) (b) (c)

Fig. 1(a): Resource grid with pilots (b): Extracted pilot symbols that were affected by the channel
(c): Channel estimation based on the extracted pilots

III.RESEARCH METHODOLOGY

This section deals with the methodology used by us to do the channel estimation. Here, we use deep learning techniques to perform channel estimation. For example, by viewing the resource grid as a 2-D image, we can turn the problem of channel estimation into an image processing problem, similar to denoising or super-resolution, where CNNs are effective.

Using Matlab's 5G Toolbox, we can customize and generate standard-compliant waveforms and channel models to use as training data. UsingMatlab's Deep Learning Toolbox, we use this training data to train a channel estimation CNN. This paper shows how to generate such training data and how to train a channel estimation CNN. The work also shows how to use the channel estimation CNN to process images that contain linearly interpolated received pilot symbols. The work concludes by visualizing the results of the neural network channel estimator in comparison to practical and perfect estimators.

Figure 2 represents the methodology that are being used to simulate the work described in this paper.

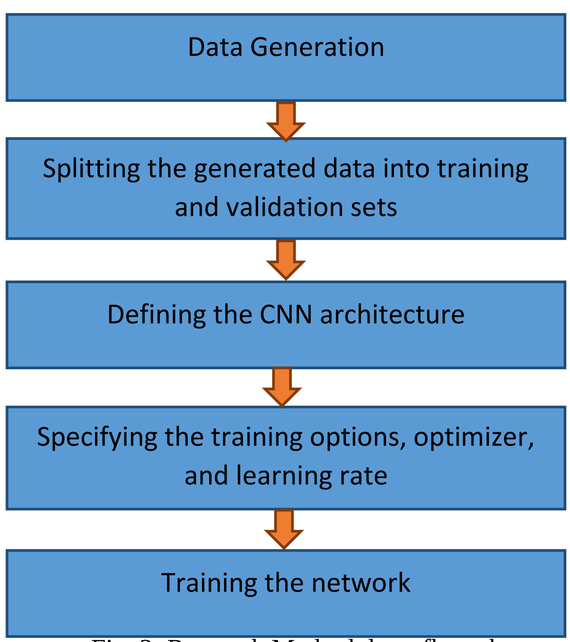

Fig. 2: Research Methodology flow chart

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Data generation is set to produce 256 training examples or training data sets. This amount of data is sufficient to train a functional channel estimation network on a CPU in a reasonable time. For comparison, the pretrained model is based on 16,384 training examples.

Training data of the CNN model has a fixed size dimensionality, the network can only accept 612-by-14-by-1 grids, i.e. 612 subcarriers, 14 OFDM symbols and 1 antenna. Therefore, the model can only operate on a fixed bandwidth allocation, cyclic prefix length, and a single receive antenna.

The CNN treats the resource grids as 2-D images, hence each element of the grid must be a real number. In a channel estimation scenario, the resource grids have complex data. Therefore, the real and imaginary parts of these grids are input separately to the CNN. In this example, the training data is converted from a complex 612-by-14 matrix into a real-valued 612-by-14-by-2 matrix, where the third dimension denotes the real and imaginary components. Because you have to input the real and imaginary grids into the neural network separately when making predictions, the example converts the training data into 4-D arrays of the form 612-by-14-by-1-by-2N, where N is the number of training examples.

To ensure that the CNN does not overfit the training data, the training data is split into validation and training sets. The validation data is used for monitoring the performance of the trained neural network at regular intervals, as defined by valFrequency, approximately 5 per epoch. Stop training when the validation loss stops improving. In this instance, the validation data size is the same as the size of a single mini-batch due to the small size of the data set.

The returned channel estimation CNN is trained on various channel configurations based on different delay spreads, doppler shifts, and SNR ranges between 0 and 10 dB.Inspect the composition and individual layers of the model. The model has 5 convolutional layers. The input layer expects matrices of size 612-by-14, where 612 is the number of subcarriers and 14 is the number of OFDM symbols. Each element is a real number, since the real and imaginary parts of the complex grids are input separately.

IV.SIMULATION RESULTS

After successful implementation, we have tested the proposed method using software simulation. For software simulation, we have used Matlab environment with deep learning and 5G toolboxes. For clarity and to show the effectiveness of the work, we have compared the obtained result with some standard OFDM MI O channel estimation schemes. Here we perform and compare the results of perfect, practical, and neural network estimations of the same channel model. To perform perfect channel estimation, use the nrPerfectChannelEstimateMatlabfunction using the value of the path gains provided by the channel.To perform practical channel estimation, use the nrChannelEstimate function from Matlab 5G toolbox. This function will estimate the channel with taking into account some standard errors and noises during the transmission.

Table 1: Details of the Neural Network model

S. No.	Layer	Layer Name	Layer Details
1.	'imageinput'	Image Input	612x14x1 images
2.	'conv_1'	Convolution	64 9x9x1 convolutions with stride [1 1] and padding [4 4 4 4]
3.	'relu_1'	ReLU	ReLU
4.	'conv_2'	Convolution	64 5x5x64 convolutions with stride [1 1] and padding [2 2 2 2]
5.	'relu_2'	ReLU	ReLU
6.	'conv_3'	Convolution	64 5x5x64 convolutions with stride [1 1] and padding [2 2 2 2]
7.	'relu_3'	ReLU	ReLU
8.	'conv_4'	Convolution	32 5x5x64 convolutions with stride [1 1] and padding [2 2 2 2]
9.	'relu_4'	ReLU	ReLU
10.	'conv_5'	Convolution	1 5x5x64 convolutions with stride [1 1] and padding [2 2 2 2]
11.	'regressionoutput'	Regression Output	mean-squared-error with response 'Response'

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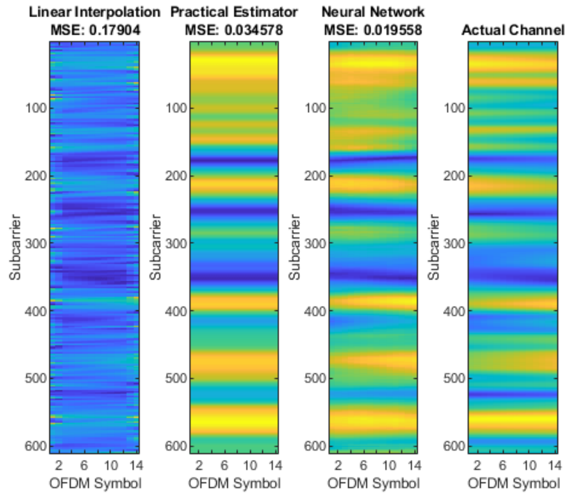

Fig. 3: Channel estimation Output with various models.

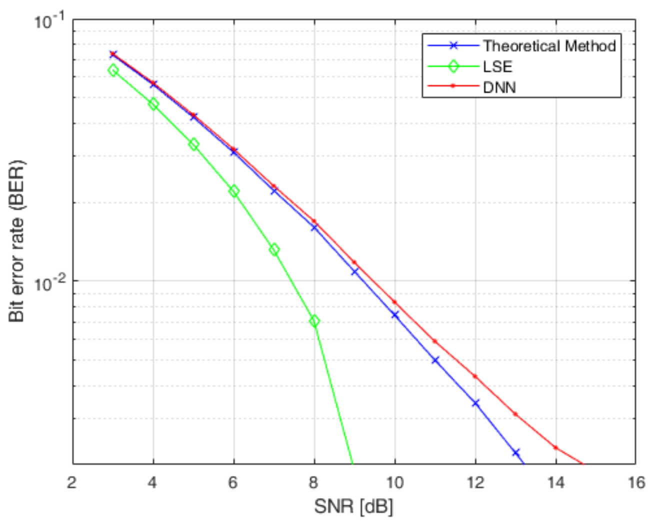

Fig. 4: Bit error rate vs SNR for channel estimation with the proposed method as well as some conventional methods.

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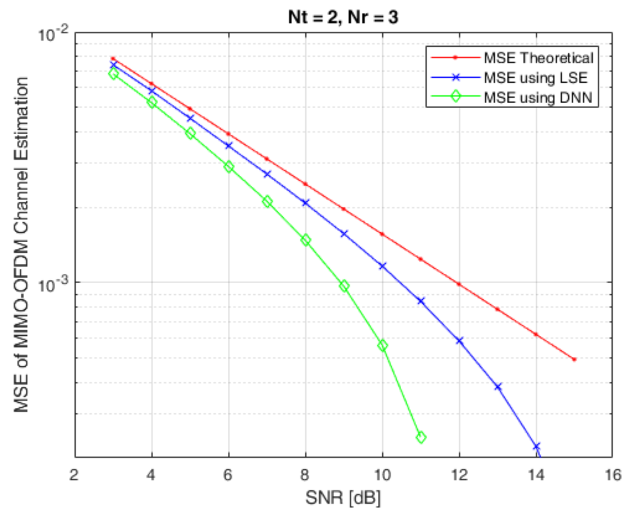

Fig. 5: Mean square error (MSE) while estimating channel vs SNR for proposed method as well as other channel estimation methods.

Fig 3 represents the result of channel estimation with (a) linear interpolation method (b) Practical estimator method, (C) neural network based proposed method and (d) the actual channel. Here from this figure, it is clear that the linear interpolation method shows a MSE of 0.17904, MSE of practical estimator is 0.034578 and the MSE of the proposed neural network based method is 0.019588 which is the lowest among all three. Fig. 4 represents the bit error rate vs SNR for a transmitter-receiver system having the proposed model as a channel estimation method with some other channel estimation methods such as Least Square Estimate (LSE) method and theoretical method. Here the DNN based our approach shows similar BER than the theoretical method. Fig. 5 represents the Mean square error (MSE) while estimating channel vs SNR for proposed method as well as other channel estimation methods. From this figure. It is clear that we are getting the minimum mean square error for the channel estimation using the proposed DNN based channel estimation method.

V.CONCLUSION

We present a DL-based CSI estimation technique for massive MIMO antenna arrays, which will facilitate faster channel sounding for beyond 5G wireless networks. It will also achieve higher throughput for extremely low SNR scenarios, as is generally also applicable for mmWave and THz bands. The proposed DNN uses two hidden MLP layers and a linear output layer to jointly perform the task of OFDM demodulation and CSI matrix generation for mMIMO downlink transmission. We substantially improve the end-to-end system performance, achieving up to 5 and 2 orders of magnitude reduction in BER with respect to practical LS and optimal LMMSE, respectively, and higher spatial diversity for lower SNR regions, achieving up to 4 dB gain in received power signal compared to performance obtained through LMMSE estimation. Finally, we discuss the importance of model compression techniques to be applied on trained models in order to be easily deployed in edge devices, enabling higher data rates for edge computing over B5G mmWave communication.

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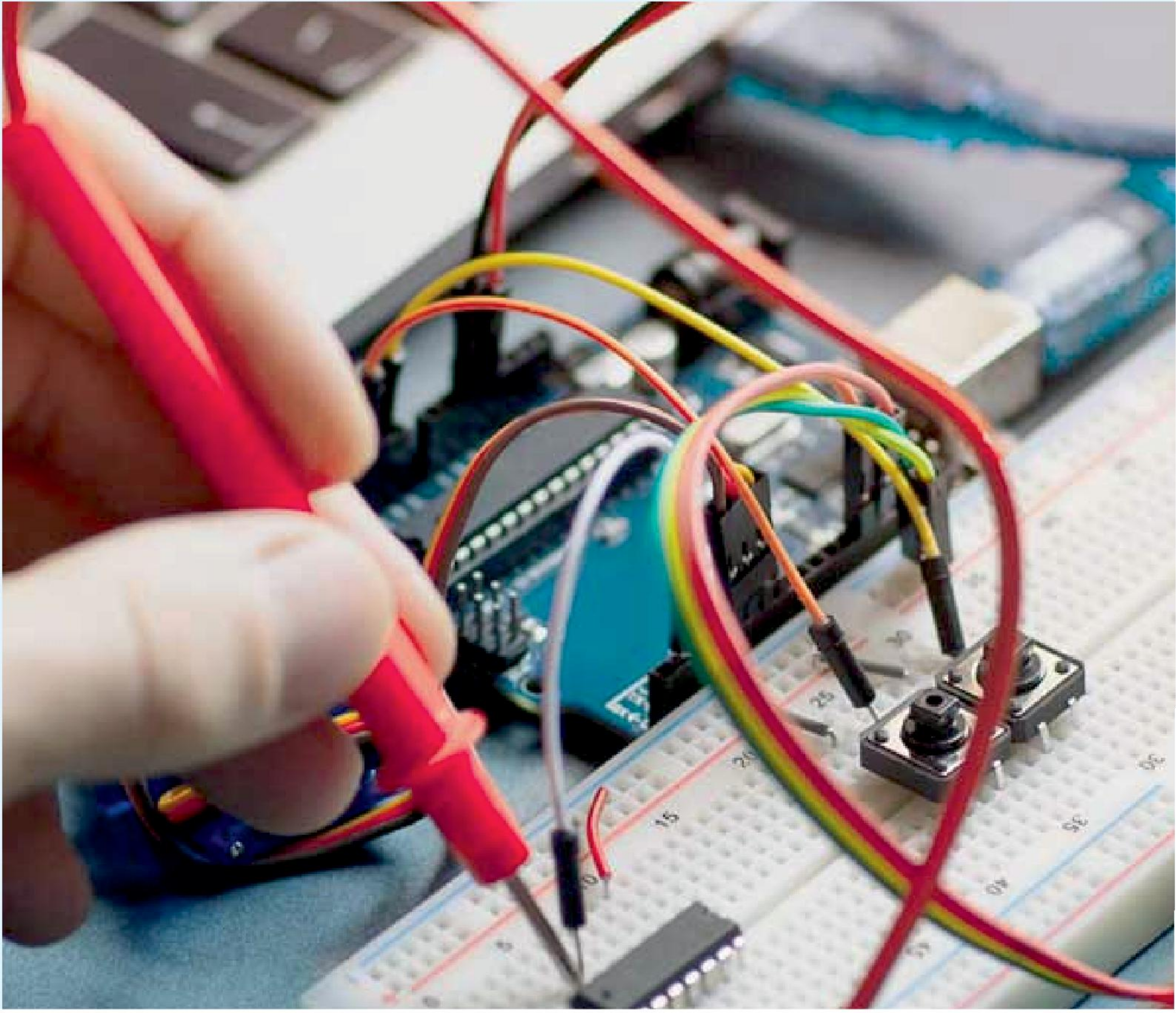

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