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Massive-MIMO 5G Channel Estimation Using Deep Learning Techniques

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ABSTRACT: In this paper, we propose a deep learning (DL) based channel estimation scheme for the massive multiple-input multiple-output (MIMO) system. Unlike existing studies, we develop the channel estimation scheme for the case that the pilot length is smaller than the number of transmit antennas. The proposed scheme takes a two-stage estimation process: a DL-based pilot-aided channel estimation and a DL-based data-aided channel estimation. In the first stage, the pilot itself and the channel estimator are jointly designed by using both a three-layer neural network (TNN) and a deep neural network (DNN). In the second stage, the accuracy of channel estimation is further enhanced by using another DNN in an iterative manner. The simulation results demonstrate that the proposed channel estimation scheme has much better performance than the conventional channel estimation scheme. We also derive anuseful insight into the optimal pilot length given the number of transmit antennas.

KEYWORDS:- massive MIMO, OFDM, 5G-New Radio, Channel estimation, Deep learning.

I. INTRODUCTION

Multiple-input multiple-output (MIMO) with large-scale antenna arrays, so-called the massive MIMO, is one of the most promising techniques to increase the data rate and to maintain the high communication reliability for future wireless systems [1], [2]. In the massive MIMO system, a large scale antenna array is deployed typically at the base station (BS) to provide a considerable antenna gain, and this antenna gain highly depends on the channel estimation accuracy. Thus, obtaining accurate channel estimation is very important to ensure such benefits of the massive MIMO technique.

In the literature, the issue of channel estimation has been studied for the massive MIMO systems, typically based on the linear minimum mean square error (LMMSE) method, e.g., [3]–[5]. However, the common assumption in all the literature including [3]–[5] is that the pilot length Ls is equal to or larger than the number of transmit antennas Nt , which is (very) large in the downlink of massive MIMO. Without this assumption of Ls ≥Nt , the channel estimation performance is substantially degraded, as demonstrated in [6] for the LMMSE channel estimator. In the massive MIMO system, however, it is hard to justify the assumption of Ls ≤Nt for three main reasons. First, to ensure Ls ≥Nt , substantial amount of time resource should be used for pilot transmission, which results in much reduced resource for data transmission, leading to (very) low spectral efficiency. Second, the computational complexity required for channel estimation also grows as Ls increases. Last, but not least, ensuring Ls ≤Nt might be evenimpossible at all, because Ls cannot be larger than the channel coherence interval, which is usually uncontrollable. Therefore, in the massive MIMO system, developing a channel estimation scheme for Ls <Nt is one of the most important, yet very challenging, issues.

Convolutional Neural Network (CNN) is a deep learning technique which was proposed for channel estimation, combined with Long-Short Term Memory (LSTM) network using time varying method [7]. In [8] the authors proposed the CNN architecture invoking an (LSTM) module which admitted the neural network NN to benefit from exploiting temporal and frequency correlations of wireless channels. The

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concept of channel mapping in space and frequency, was adopted in [9] where the channels at one set of antennas and one frequency band are mapped to the channels at another set of antennas and frequency band using convolutional neural network CNN. Deep CNN was employed in [8] to perform wideband channel estimation for Millimeter Wave (mmWave) massive MIMO systems based on spatial correlation. The results showed that the performance of proposed technique was close to those of the ideal minimum mean-squared error (MMSE) estimator. In [7], the authors introduced an architecture of deep recurrent neural network (RNN) that was used for channel state information (CSI) by making use of compression and decompression capabilities. The architecture was based on splitting feature extraction into spatial and temporal domains, an approach which resulted in an improvement in channel state information (CSI) prediction.

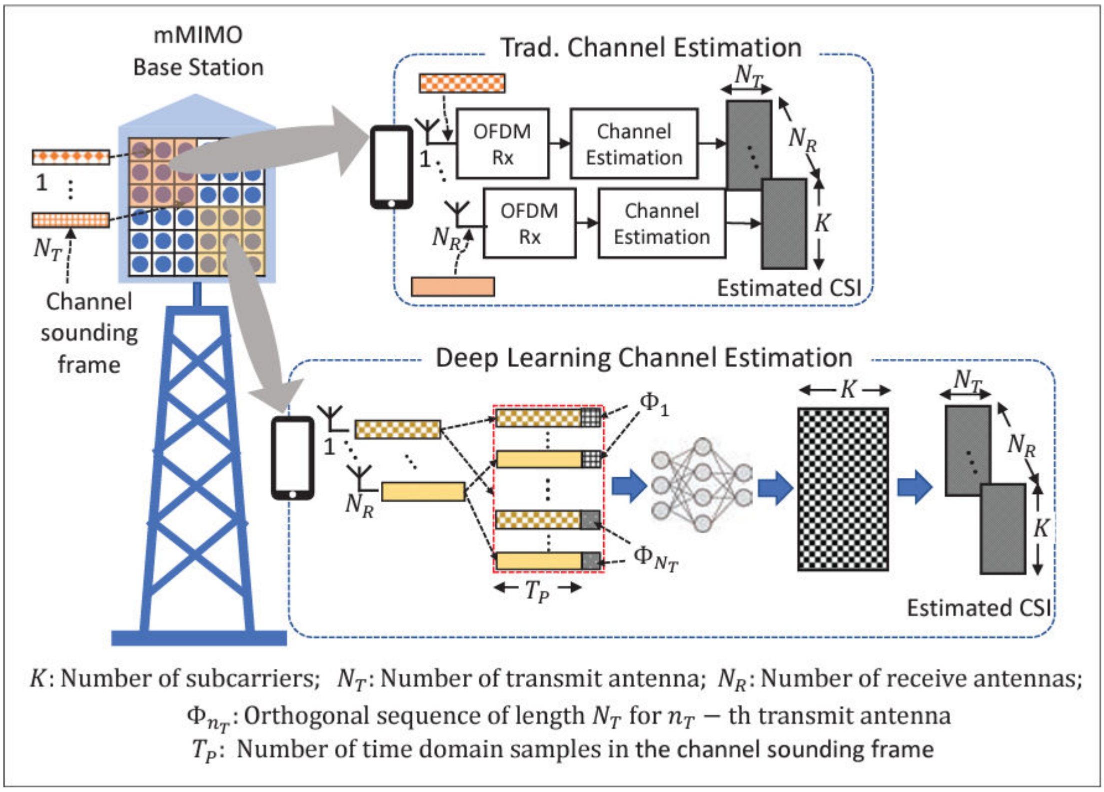

Fig. 1: Tradition and neural network based channel estimation

II. SYSTEM MODEL

Consider uplink of a Multi User MIMO system where NT single transmit antenna users used to transmit data to a base station (BS) having NR receive antennas. The propagation path between each receive-transmit antenna pair is assumed to be Frequency flat fading and remain constant for one transmitted packet. The standard MIMO channel model for this scenario is given below:

$$\mathbf{y} = \mathbf{Hx} + \mathbf{n} \quad (1)$$

Where is received message vector, is unknown transmitted message vector of equiprobable and independent symbols, is MIMO channel matrix and is independent identically distributed Gaussian noise of zero mean and variance . In this paper we have assumed that channel matrix H has random coefficients with known distribution and is perfectly known to the receiver.Consider a MIMO-OFDM system where the transmitter has N antennas, the receiver has M antennas, and all the transmitted symbols share K subcarriers. The frequency do- main transmitted sequence from the n-th (n = 1, · · · , N)transmit antenna is represented

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by Xn,k, where k = 1, · · · , Krepresents the k-th OFDM subcarrier. The sequence receivedby the m-th (m = 1, · · · , M) receive antenna is expressed where Hm,n,k is the frequency response of the channel between the n-th transmit antenna and the m-th receive antenna for the k-th subcarrier, ζm,k is the frequency response of zero- mean additive white Gaussian noise (AWGN) with a one-sided power spectral density of N0. Let us define the signaltransmitted on the k-th subcarrier from all the N transmit antennas as Xk = [X1,k, X2,k, · · · , XN,k]T , where (·)T denotes transpose. The received signal as a function of the respective CSI matrix Hk can be expressed as

$$\begin{aligned} \boldsymbol{Y}_k &= [Y_{1,k},\ Y_{2,k},\ \cdots,\ Y_{M,k}]^T \\ &= \begin{bmatrix} H_{1,1,k} & H_{1,2,k} & \cdots & H_{1,N,k} \\ & & \vdots & \\ H_{M,1,k} & H_{M,2,k} & \cdots & H_{M,N,k} \end{bmatrix} \boldsymbol{X}_k + \begin{bmatrix} \zeta_{1,k} \\ \zeta_{2,k} \\ \vdots \\ \zeta_{M,k} \end{bmatrix} \\ &= \boldsymbol{H}_k \boldsymbol{X}_k + \boldsymbol{\zeta}_k. \qquad (2) \end{aligned}$$

III. METHODOLOGY

For a spatially multiplexed system, availability of channel information at the transmitter allows for precoding to be applied to maximize the signal energy in the direction and channel of interest. Under the assumption of a slowly varying channel, this is facilitated by sounding the channel first. The BS sounds the channel by using a reference transmission that the MS receiver uses to estimate the channel. The MS transmits the channel estimate information back to the BS for calculation of the precoding needed for the subsequent data transmission. The following schematic shows the processing for the channel sounding modeled.

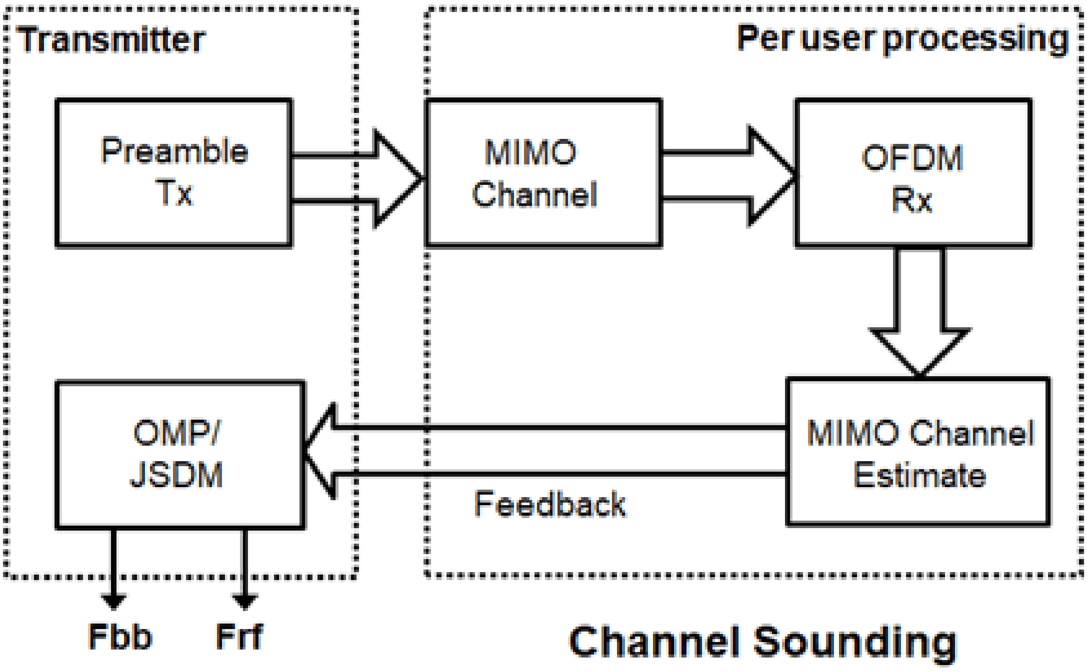

Fig. 2: MIMO-OFDM Channel estimation method block diagram

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For the chosen MIMO system, a preamble signal is sent over all transmitting antenna elements, and processed at the receiver accounting for the channel. The receiver antenna elements perform pre-amplification, OFDM demodulation, and frequency domain channel estimation for all links. For a multi-user system, the channel estimate is fed back from each MS, and used by the BS to determine the precoding weights. The example assumes perfect feedback with no quantization or implementation delays.

IV. RESULT AND DISCUSSION

The COST 2100 model [3] is used to simulate MIMO channels and generate training samples. We set the MIMO-OFDM system to work on a 20 MHz bandwidth using Uniform Linear Array (ULA). The parameters utilized in both indoor and outdoor channel scenarios are given in table 1. Data sets are generated by randomly setting different start places with for indoor and outdoor scenarios. We perform the simulations at CR values with the first channel $\boldsymbol{H1}$" compressed under 1/4. The Training, validation, and testing sets given in table 1. Some parameters are preloaded from the CsiNet for initialization (Epochs from 500 to 1000, Learning rate is 0.001 and batch size is 200) as in illustrated in table 1.

Table 1. COST 2100 Model Data – Sets and System, Parameters

MIMO OFDM	20 MHz bandwidth	
$\boldsymbol{H}$	32×32	
$\boldsymbol{N_t}$	32 Antennas	
$\boldsymbol{N_C}$	1024 Subcarriers	
Training Samples	100,000	
Validation Samples	30,000	
Testing Samples	20,000	
Epochs	500 - 1000	
Learning Rate	0.001	
Batch size	200	
$\boldsymbol{\partial t}$	0.04 s	
$\boldsymbol{T}$	10 s	
$\boldsymbol{CR}$	4, 16, 32, 64	
Channel Model	**Indoor Scenario**	**Outdoor Scenario**
Speed	Pico, 5.3 GHz,	Rural, 300 MHz
$\boldsymbol{v}$	0.0036 km/h	4.24 km/h
$\boldsymbol{\Delta t}$	30 s	0.56 s

Simulation is carried out through m-files implemented on a Python 3.7 platform. We compare the performance of the proposed architecture with the pervious similar modeling approaches of CSI.

Figs. 3 shows the upper bound of the throughput curves of MIMO-OFDM schemes versus SNR. It is observed that for a throughput of 80Mbps, the 2×3 system attains an approximate 4.2dB gain over the 2×2 system, and the 3×4 has a gain of 3.6dB over the 3×3 system. These results match well with the results obtained by using Eq. (19): 4.2257dB gain for 2×3 over 2×2, and 3.5950dB gain for 3×4 over 3×3. Theimprovement provided by an extra receive antenna is attributedto having fewer ill-conditioned channels.

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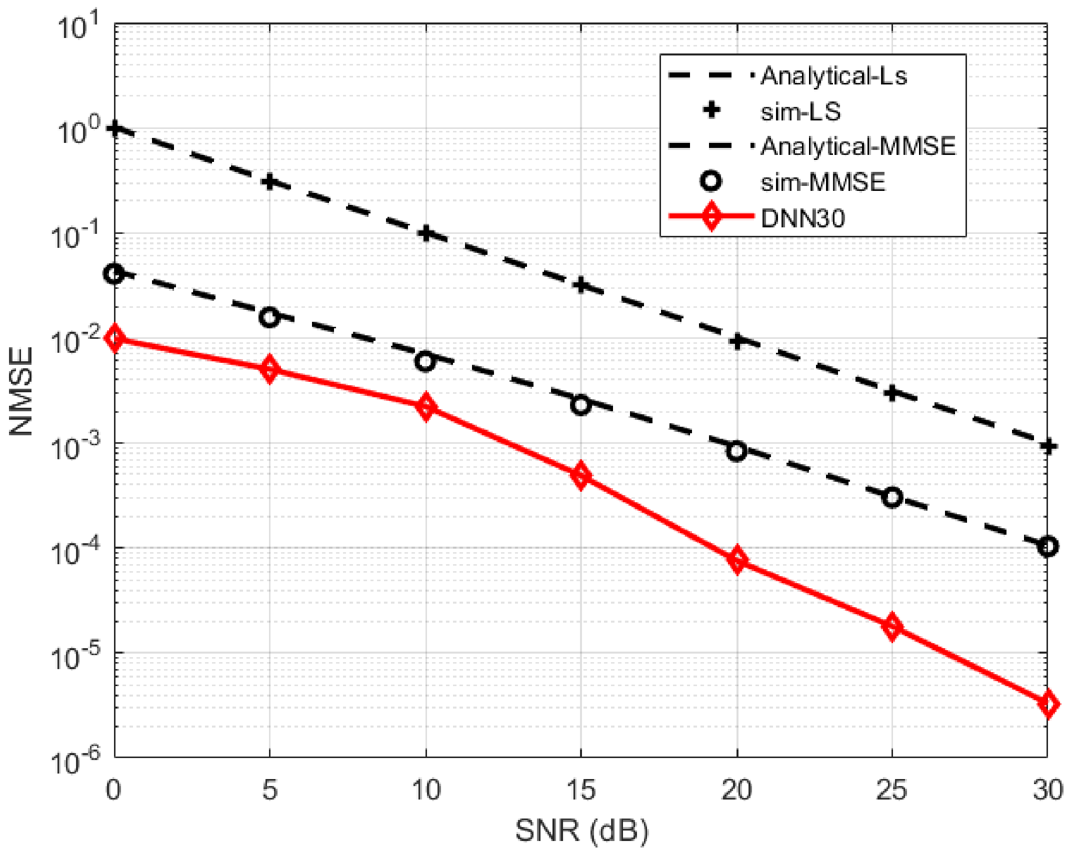

V. CONCLUSION

We present a DL-based CSI estimation technique for 5G massive MIMO-OFDM systems, 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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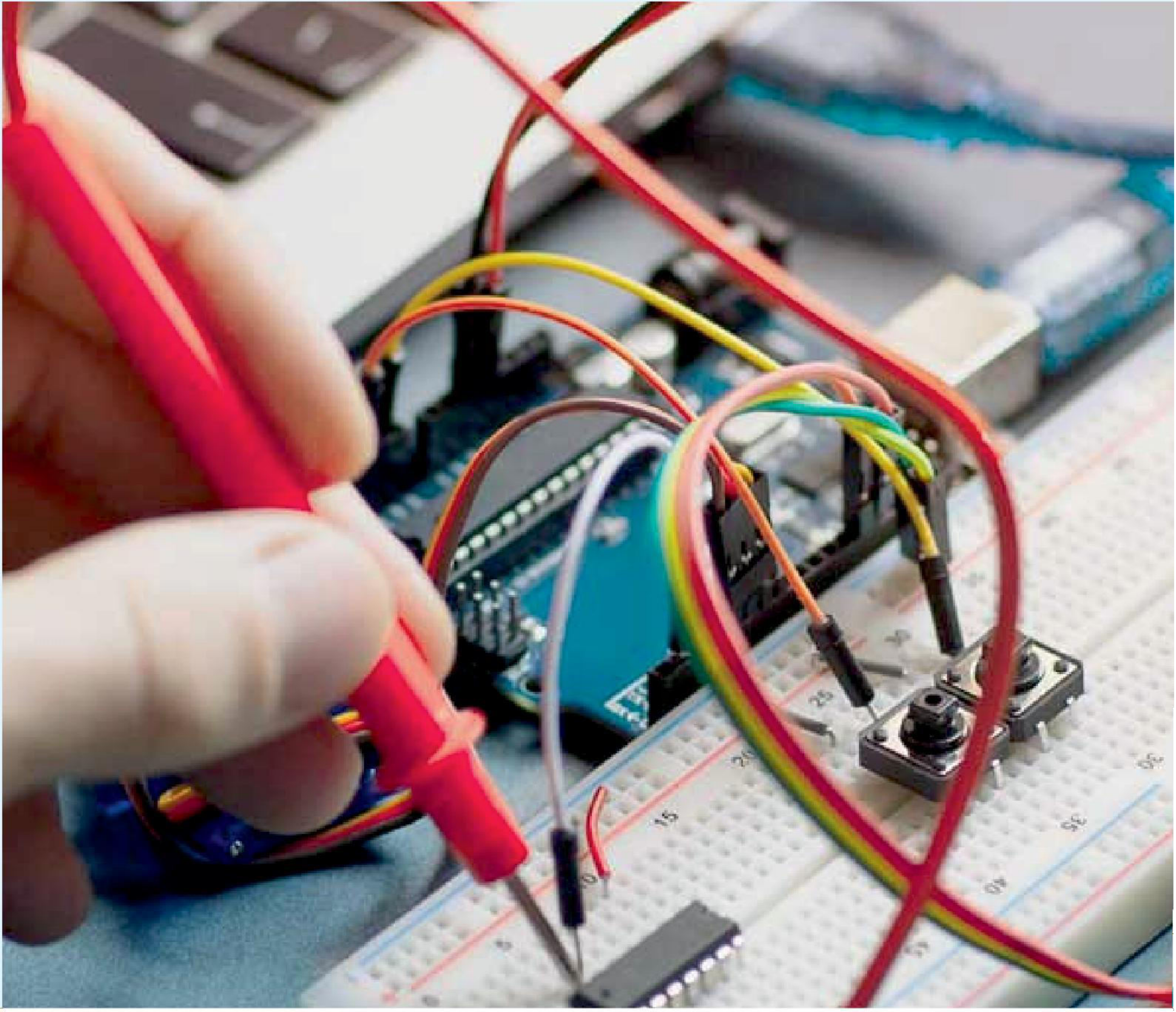

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