# Deep Neural Network based Minimum Length Scheduling in Wireless Powered Communication Networks

Nasir Khan, *Member, IEEE* and Sinem Coleri, *Senior Member, IEEE*

***Abstract*—Minimization of schedule length is key in ensuring the delay performance of wireless powered communication networks (WPCNs) demanding strict timing and reliability guarantees. Previous solution methodologies proposed for these wireless networks suffer from high run-time complexity, making it very difficult to solve the problem in real time. This paper considers a run-time efficient deep learning based approach for solving minimum length scheduling problem in a full-duplex WPCN. Leveraging upon the universal approximation capability of neural networks, a multi-output feed forward deep neural network based framework is proposed where inputs are the channel coefficients and outputs are the optimal power, transmission length and schedule of users. Simulation results indicate that the proposed deep learning based approach can very well approximate the true outputs with a percentage error below 1% for different network configurations while maintaining a very low run-time complexity.**

***Index Terms*—RF energy harvesting, wireless powered communication network, deep neural network, scheduling.**

## I. Introduction

Energy harvesting and optimal resource management schemes are vital for enhancing the lifetime and efficiency of wireless sensor networks (WSN). Energy harvesting based wireless communication networks have recently gained significant popularity since they eliminate the need for manually replacing batteries and therefore, can reduce the operational cost. Compared to conventional energy harvesting sources (e.g. solar, wind), which depend on environmental conditions and suffer from unpredictability in power supply, radio frequency (RF) based energy harvesting networks can provide ubiquitously, stable and controllable power supply to the low-powered wireless devices [1]. A mandatory requirement for the usage of RF energy harvesting based WPCNs in time-critical applications is to ensure that user demands are met in real time especially in a time-varying environment. This requirement puts a tight constraint on the transmission length of users as well as the time required for computing the optimal resources.

In RF energy harvesting WPCN system, an access point broadcasts RF energy to the users in the downlink and the user nodes harvest this energy to transmit data back to the access point in the uplink. In the context of wireless communication, such networks usually have the objective of throughput maximization by the allocation of optimal resources [3]. However, the throughput maximization generates an unequal distribution of achievable rates among various users such that the users in the vicinity of an access point with good channel conditions are more favored. Recently, some other objective functions have also been considered such as maximizing achievable energy efficiency (EE) [4], maximizing the WPCN sum-rate [5]. Minimum length scheduling has been considered as the objective function in [6], [7]. In [6], the minimum length scheduling problem is addressed for a multi-antenna based half-duplex WPCN system. In [7], a multiple-source-multiple-relay based wireless network is considered for minimizing the total schedule length in a half-duplex setting. These studies do not consider the scheduling of transmissions in the problem formulation as the order of transmission does not matter in half-duplex systems, therefore, no scheduling is considered while formulating the optimization problem.

Full-duplex control in WPCNs has gained much attention recently as it enables concurrent transmission of wireless energy and data reception capability. In a full-duplex RF energy harvesting WPCN, users can harvest energy while other users are broadcasting their information, therefore, scheduling of individual users should also be taken into consideration. Full-duplex WPCNs system has been previously studied mostly with the objective of sum-throughput maximization by considering full-duplex operation either at the access point [8], [9] or at both the access point and the user nodes [10]. Sum-throughput maximization along with the schedule time minimization problem is addressed in [9]. However, these aforementioned studies assume that the energy demand for uplink data transmission is to be satisfied completely by the wireless energy transfer from the access point and do not incorporate the initial user battery level in the problem formulation. Only, [11] addresses the schedule length minimization problem while taking into consideration the transmission order of users. In this work, reduced complexity polynomial-time algorithms are proposed to solve the minimum length scheduling problem. However, simulation results indicate that the run-time complexity of these algorithms increases linearly with the network size, making these algorithms impractical for time-critical applications.

Deep neural networks (DNN) have recently been proposed to reduce the run-time complexity of optimization algorithms in WPCNs. Once trained well, neural networks can generate

Nasir Khan and Sinem Coleri are with the department of Electrical and Electronics Engineering, Koc University, Istanbul, Turkey, email: {nkhan20, scoleri}@ku.edu.tr. This work is supported by Scientific and Technological Research Council of Turkey Grant #119C058 and Ford Otosan.

optimal solutions well within the coherence time as they perform simple mathematical operations to generate outputs [12]. A deep reinforcement learning based framework is proposed for throughput maximization problem in WPCN [13]. DNN based approach for minimizing transmit power in a WPCN is proposed in [14]. However, none of these studies consider the schedule length minimization problem in WPCNs. Moreover, these studies consider power and time allocation as decision variables without taking the scheduling of users into account.

In this paper, we propose a deep learning based approach to achieve a low-complexity implementation of the minimum length scheduling problem in a WPCN. The decision variables include transmission time, transmission power and the corresponding schedule of users, whereas the constraints correspond to the maximum transmit power and data rate requirements. The original optimization problem is formulated as a mixed integer nonlinear programming (MINLP) problem, which is non-convex, therefore hard to solve through iterative computation algorithms. This challenge is overcome by proposing a multi-output feed forward neural deep network, which once trained well can easily solve the scheduling problem in sub-millisecond run-time.

The main contributions of this paper are as follows:

- We propose a deep learning based optimization framework for solving the minimum length scheduling problem in a full-duplex WPCN, which we call DEEP-NET. Inputs of this neural network are the channel coefficients, whereas the outputs are the transmit power, time allocation and transmission order of users for minimum schedule length. Our DNN learns the non-linear relationship between these input and output parameters and provides a fairly accurate estimate of the optimal values.
- We show that our proposed deep neural network based approach performs very close to the optimal solution in predicting the schedule length in sub-millisecond run-time, significantly outperforming previously proposed polynomial time algorithms for different network sizes.

The rest of the paper is organized as follows. Section II describes the WPCN system model and assumptions. Section III presents the objective function, constraints and the formulation of the scheduling length minimization problem along with the conventional solution methodologies for solving the problem. Section IV describes DNN based approach for solving the optimization problem. Finally, Section V concludes the paper.

## II. System Model and Assumptions

The full-duplex WPCN system includes a hybrid access point (HAP) and a set of $N$ wireless users. HAP provides an uninterrupted, stable power $P_A$ and is equipped with a single antenna operating in full-duplex manner for simultaneously transferring power and receiving information in the downlink and uplink, respectively. The maximum allowed transmission power for each user is $P_{max}$. The network adopts the harvest-use-store (HUS) protocol, where the harvested energy is used for information transmission first, and any excess energy if available is stored in a battery [15].

A Time Division Multiple Access (TDMA) based protocol is employed for uplink information transmission from the users to the HAP. We assume that the users have fixed initial battery levels $B_i$, at the start of the scheduling frame. Moreover, each user is allowed to harvest energy during its own allocated time slot and the time slots designated for the earlier scheduled users. Furthermore, each user is capable of harvesting energy in the complete scheduling frame duration. If the amount of energy harvested exceeds the amount required for data transmission, user $i$ transmits data in its dedicated time slot and the excess energy is stored in a rechargeable battery. However, if the energy harvested by the user is not sufficient for data transmission then the battery energy is utilized along with the harvested energy.

We consider a block fading channel where channel coefficients remain fixed during the scheduling frame. The channel gains in the uplink and downlink are given by $g_i$ and $h_i$, respectively. We consider the availability of perfect channel state information (CSI) at the HAP, which is a common assumption in many studies [16]. The channel information can be obtained at the start of each block. However, generally in low mobility wireless networks such as wireless sensor networks, the channel is either static or varies at a very slow rate, therefore, the CSI acquisition duration is very short compared to the complete transmission block and is neglected in our work [17]. We utilize a practical non-linear energy harvesting model based on the sigmoidal function [18]. The energy harvesting rate for user $i$ is denoted by $H_i$. Considering the Shannon channel capacity formula for AWGN channel, the transmission rate of user $i$ is given by

$$R_i = W log_2(1 + \Omega_i P_i) \tag{1}$$

where $W$ is the channel bandwidth, $P_i$ is the transmission power of user $i$ and $\Omega_i$ is defined as $g_i/(N_0 W + \mu P_A)$, $\mu P_A$ is the self interference power at the hybrid access point, $\mu$ is the coefficient for self interference and $N_0$ is the associated noise power density.

## III. Problem Formulation

In this section, we introduce the minimum length scheduling problem for a full-duplex WPCN. We first present the formulation of joint optimization problem for schedule length minimization. Then, we present the optimal solution methodology for solving the problem.

### A. Mathematical Formulation

The objective of jointly optimizing the transmit power, time allocation and transmission schedule of users for minimizing the total schedule length is formulated as follows:

$$\min \quad \sum_{i=1}^{N} \tau_i \tag{2a}$$

$$\text{s.t.} \quad W log_2(1+\Omega_i P_i)\tau_i \geq D_i, \quad i \in \{1,\ldots,N\} \tag{2b}$$

$$B_i + \tau_i\left(H_i - P_i\right) + H_i \sum_{j=0}^{N} \lambda_{ji}\tau_j \geq 0 \tag{2c}$$

$$\lambda_{ij} + \lambda_{ji} = 1, i < j, \quad i,j \in \{1,\ldots,N\} \tag{2d}$$

$$P_i \leq P_{\max}, \quad i \in \{1,\ldots,N\} \tag{2e}$$

$$\text{where } \tau_i \geq 0,\ P_i \geq 0,\ \lambda_{ij} \in \{0,1\},\ i,j \in \{1,...,N\} \tag{2f}$$

Variables of the optimization problem are $\tau_i$, the transmission time of user $i$; $P_i$, transmit power of user $i$; $\lambda_{ij}$, variable that is assigned a value of 1 if the $i^{th}$ user is allocated before $j^{th}$ user in the schedule frame, otherwise the variable is assigned a 0 value.

The goal of the optimization problem is to reduce the schedule length while satisfying the constraints of the optimization problem. Traffic demand constraint in Eq. (2b) represents the transmission of at least $D_i$ amount of data to the HAP by each user. Energy causality constraint in Eq. (2c) requires that the energy demand for information transmission should not exceed the total amount of available energy. Eq. (2d) represents the constraint on the transmission order of users, indicating that if user $i$ transmits before user $j$, then user $j$ is not allowed to transmit before user $i$. Lastly, Eq. (2e) represents the upper bound on maximum transmit power.

The optimization problem under consideration is a non-convex mixed integer nonlinear programming (MINLP) problem, therefore achieving the global optimum directly is extremely difficult [19].

### *B. Solution Strategy*

For the solution of the aforementioned optimization problem, we consider the optimal algorithm proposed in [11]. First, for a predetermined schedule, the minimum length scheduling problem is reduced to a convex optimization problem and solved for the optimal power and time allocation. The transmission order of the users is then determined by incorporating an efficient pruning mechanism. Users are first assigned to different levels within the branches in a tree model, where each branch of the tree model corresponds to one of the valid schedule of users. The basic notion of the pruning mechanism is then to remove the nodes from the tree model which cannot lead to a minimum length schedule, based on the penalty value of the individual nodes.

For a predetermined transmission order of the users, the optimal solution for transmit power $P_i$ of user $i$ is given by:

$$P_i = \min\left\{\left(\frac{-1}{\Omega_i} - \frac{W\eta_i}{D_i \ln 2}\boldsymbol{\mathcal{L}}\left(\frac{-D_i \ln 2}{W\Omega_i\eta_i}e^{\beta_i}\right)\right), P_{\max}\right\} \tag{3}$$

for $i \in \{1,\ldots,N\}$; where $\boldsymbol{\mathcal{L}}(\cdot)$ is the Lambert W-function, $\beta_i$ and $\eta_i$ are given by:

$$\beta_i = \left(\frac{-H_i D_i \ln 2}{W\eta_i} - \frac{D_i \ln 2}{W\Omega_i\eta_i}\right) \tag{4}$$

$$\eta_i = \left(B_i + H_i \sum_{j=1}^{i-1} \tau_j\right) \tag{5}$$

Given the optimal power of the user, the optimal transmission time $\tau_i$ of user $i$ can be calculated by:

$$\tau_i = D_i / \left(W \log_2\left(1+\Omega_i P_i\right)\right). \tag{6}$$

The scheduling algorithm utilizes an efficient pruning algorithm (EPA) to determine the optimal transmission order of users without generating all possible schedules. The pruning method is based on the user penalty function value, which is defined as the absolute difference between the real time for transmission and minimum transmission time possible. The EPA allows for the consideration of minimization of the sum of user penalties as an alternative goal to scheduling length minimization problem.

The input of EPA is the number of users $\mathcal{U}$ and outputs are the schedule length $\mathcal{T}^*$ and corresponding transmission sequence of users $\mathcal{S}^*$. The algorithm starts by storing the set of users in an array $\mathcal{D}$ and initializing the schedule length to infinity. Consider a tree model with $\mathcal{U}$ levels where $\mathcal{U}$ denotes the number of users to be scheduled. Each level of the tree indicates the user assigned in the $k$-th time slot. A branch of the tree corresponds to one feasible schedule of $\mathcal{U}$. Moreover, a node of the tree at the $k$-th level indicates the set of users allocated in the first $k$ slots. Then, at each iteration the largest node size $z_{max}$ and the corresponding set of nodes with this size $\mathcal{D}_{z_{max}}$ are determined where the size of the node $d$ is defined as the number of scheduled users; i.e., a node at the $k$-th level of the tree has size $k$. Unless the array $\mathcal{D}$ contains the branch node $\mathcal{U}$, the algorithm selects the node with minimum penalty. If the penalty value for the node is zero, then the corresponding nodes with the same size $z_{max}$ and the same ascendant nodes with $d_{min}$ are pruned out. Further, node $d_{min}$ is pruned out if the current schedule length is less than the schedule length for node $d_{min}$. Otherwise, node $d_{min}$ is split into its children nodes $\mathcal{K}_{d_{min}}$ and added to the user set $\mathcal{D}$. The efficient pruning based mechanism is summarized in Algorithm 1.

The pruning algorithm performs iterative computation to keep track of the users that are not evaluated so far and to assess whether it outperforms the current best possible user schedule. The algorithm terminates once all the user nodes have been evaluated and therefore, generates the optimal schedule length and corresponding transmission order of users. Although the pruning based algorithm provides an exact optimal solution to the scheduling length minimization problem, it incurs an exponential complexity, therefore, cannot be implemented in real-time for large size networks.

## IV. A Low-Complexity Implementation Using a Multi-Output Deep Neural Network

In this section, we first describe our deep neural network architecture to be used as a low time-complexity alternative for solving the minimum length scheduling problem. Then,

**Algorithm 1** Efficient Pruning Algorithm (EPA)

**Input:** Set of users $\mathcal{U}$
**Output:** schedule length $\mathcal{T}^*$, transmission sequence $\mathcal{S}^*$
**Initialization:**
$\mathcal{D} \leftarrow \{\{1\},\{2\},...,\{\mathcal{U}\}\}$,$\mathcal{T}^* \leftarrow \infty$
**while** $\mathcal{D} \neq \emptyset$ **do**
  determine maximum sized node $z_{max}$ of $\mathcal{D}$,
  $\mathcal{D}_{z_{max}} \leftarrow$ the set of nodes $\in \mathcal{D}$ having size $z_{max}$,
  **if** $z_{max} = |\mathcal{U}|$ **then**
    $d_{max} \leftarrow z_{max}$
    **if** $\mathcal{T}_{d_{max}} < \mathcal{T}^*$ **then**
      $\mathcal{S}^* \leftarrow d_{max}$, $\mathcal{T}^* \leftarrow \mathcal{T}_{d_{max}}$
    **end if**
    remove node $d_{max}$ from $\mathcal{D}$,
  **end if**
  $(d_{min}) \leftarrow$ the node with the minimum penalty $\rho_{min}(d)$,
  **if** $\rho_{min}(d) = 0$ **then**
    remove all nodes $\in \mathcal{D}$ with size $z_{max}$ and having common ascendant node with $d_{min}$,
  **end if**
  **if** $\mathcal{T}_{d_{min}} \geq \mathcal{T}^*$ **then**
    remove node $d_{min}$ from the branch,
  **else**
    branch $d_{min}$ into set of children nodes $\mathcal{K}_{d_{min}}$,
    $\mathcal{D} \leftarrow \mathcal{D}$ + $\mathcal{K}_{d_{min}}$,
  **end if**
  remove node $d_{min}$ from $\mathcal{D}$,
**end while**

we describe the data generation process for the training and testing set.

### A. Deep Neural Network Architecture

We propose a deep learning based optimization framework for the aforementioned minimum length scheduling problem. The optimization problem described in Section III can be expressed as a non-linear mapping function from the channel coefficients to the optimal power, time allocation and the corresponding schedule of users as follows:

$$\mathcal{F} : \mathbf{h} \in \mathbb{R}^{N\times 1} \rightarrow \{\mathbf{p}, \boldsymbol{\tau}, \mathbf{S}\} \in \mathbb{R}^{3(N\times 1)}$$

where $\mathbf{h}$ is the input vector with the $i^{th}$ entry containing the channel coefficient $h_i$, $\mathbf{p}$ is the output power vector with the $i^{th}$ entry corresponding to the transmit power $p_i$ of user $i$, $\boldsymbol{\tau}$ is the output time allocation vector with the $i^{th}$ entry corresponding to the allocation time $\tau_i$ of user $i$, $\mathbf{S}$ is the output sequence vector with the $i^{th}$ entry corresponding to the scheduling slot $s_i$ of user $i$, $\mathcal{F}(\cdot)$ is the continuous function approximation for obtaining transmit power, time allocation and schedule of users given the input channel coefficients. Based on this formulation, we consider a multi-output deep neural network which we call (DEEP-NET) to approximate the transmit power, transmission time and transmission order of users.

Our proposed deep neural network architecture is implemented through a fully connected feed forward structure, employing three output branches with $L_1$, $L_2$ and $L_3$ hidden layers, respectively. We consider $L_1 = 5$ with $256, 128, 64, 32, 16$ neurons, $L_2 = 5$ with $256, 128, 32, 32, 16$ neurons, and $L_3 = 5$ with $256, 128, 32, 32, 16$ neurons, respectively as shown in Fig. 1. Furthermore, we utilize ReLU and eLU activation functions alternatively for the hidden layers as this scheme performs better in approximating the true optimal values. For the output layers, we use linear activation function for the optimal power and time allocation, whereas we use a customized activation function: $\min(\max(x, 0), N)$ in the output layer for predicting the transmission sequence of users.

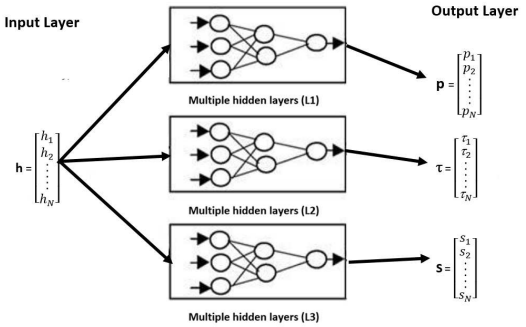



Figure 1: The DNN structure used in this work.

### B. Data Generation and Training

For training the neural network, data is generated in the following manner: Channel coefficients are generated by randomly distributing the nodes within a circle through uniform distribution and then utilizing Rayleigh distribution with the scale parameter set to average power level calculated using the path loss model: $PL(d) = PL(d_0) + \log_{10}(\frac{d}{d_0})^{(\gamma 10)} + Z$, where $PL(d_0)$ is the free space path loss at reference distance $d_0$ in dB, $d$ is the distance between the receiver and the transmitter, $\gamma$ is the path loss exponent, and $Z$ is a Gaussian random variable with zero-mean and a standard deviation of $\sigma$. The optimal power, optimal time allocation, and user schedule are determined using the optimal exponential-time algorithm [11] presented in Section III. For each network size $i \in \{1, \ldots, N\}$; we run the simulation $N_T$ times, where $N_T$ is the number of training samples, to generate the entire training data set. We then train our deep neural network with this training data to optimize the weights of the neural network. For optimal power and time allocation approximation, we use the mean squared error (MSE), defined as the average squared difference between the estimated values and the actual values, as the cost function. On the other hand, for user schedule evaluation we utilize the mean absolute error (MAE), defined as the mean value of the absolute error between the true values and the predictions.

Note that the DNN based algorithm is trained on the data obtained from the optimal algorithm, which essentially involves iteratively solving the scheduling length problem for many network realizations, and hence, requires a significant amount of computation time. However, the data is generated offline. Therefore, a higher complexity can be afforded and the real-time evaluation constraints do not apply in the training data generation phase.

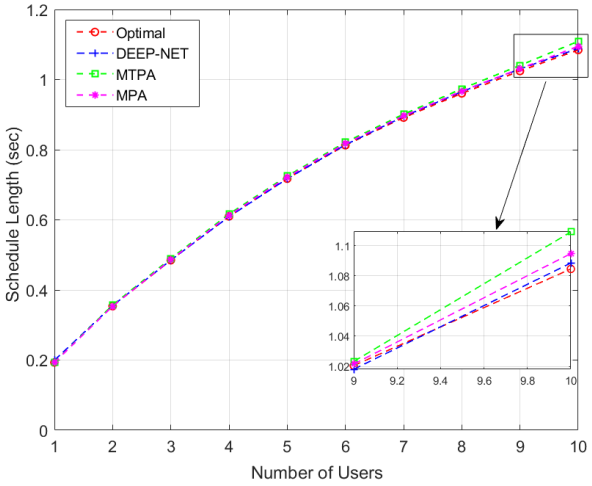



Figure 2: Schedule length of the algorithms for different network sizes.

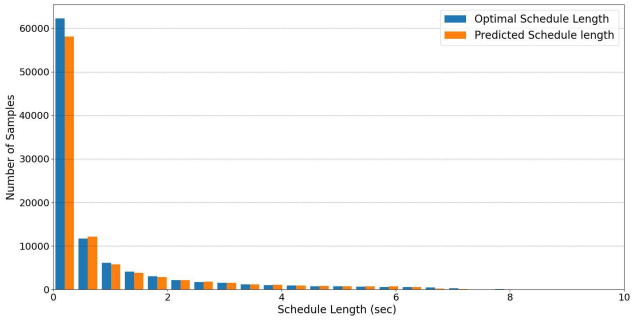



Figure 3: Distribution of minimum schedule length for the DNN based approach and optimal scheduling algorithm in a network of 6 users.

## V. Performance Evaluation

In this section, we demonstrate the performance of our deep neural network based approach DEEP-NET and compare it to the previous exponential-time optimal solution and polynomial-time heuristic solutions given below:

- **MPA:** A polynomial-time heuristic algorithm described in [11] which considers minimizing the sum of user penalties expressed in terms of difference between the real transmission time and the minimum possible transmission time.
- **MTPA:** A polynomial-time heuristic algorithm described in [11] which picks the user able to afford transmission at maximum power among all users.
- **Exact Iterative Optimal Algorithm:** An exact fast enumeration algorithm with exponential-time complexity based on the smart pruning mechanism described in [11], and summarized in Section III.

Simulations are carried out over 1000 independent random network realizations. Users are randomly distributed with uniform distribution within a circle of radius 10 m. Parameters used for the simulations are $D_i = 100$ bits for $i \in \{1, \ldots, N\}; W =$ 1MHz, $\mu = -70$ dBm, $P_A = 1$W, $P_{\max} = 1$mW and the fixed initial battery level is $10^{-9}$ J. The path loss $PL(d_0)$ is 30 dBm, $d_0 = 1$m, $\gamma = 2.76$, and $\sigma = 4$ [11], [21].

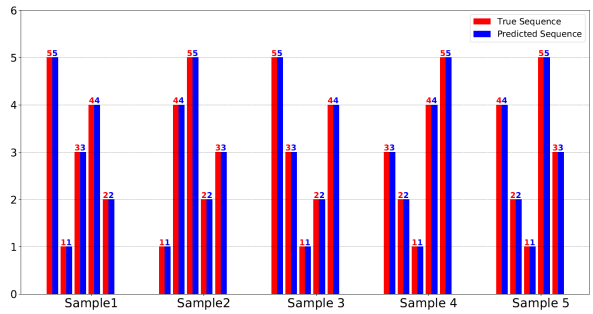



Figure 4: Transmission order of the users in the considered WPCN with 5 users for the DNN-based approach and the optimal scheduling algorithm.

The neural network is trained on data set of $N_T = 1000,000$ training samples generated independently for each network size. We use 90% training data to optimize the weights of the neural network and 10% data for validation. For optimization, we use the Adam training algorithm and for weight initialization, we use glorot_uniform initialization method. For testing the neural network, we generate $100,000$ input samples using the same distribution as used for generating the training data. The neural network is implemented in Keras with TensorFlow as the back-end. The batch size, learning rate, and epochs are adjusted on a trial and error basis to minimize the combined loss function for all three outputs keeping in view that the model does not overfit. Training and testing is performed on a 10-Core Intel(R) Xenon(R) Silver 4114, 2.2GHz system equipped with an Nvidia Quadro P2000 graphics processing unit (GPU).

Fig. 2 depicts the minimum schedule length obtained by algorithms for different number of users. Our DNN based learning approach outperforms both polynomial-time algorithms for all considered network sizes and performs very close to optimal. The percentage error in predicting the minimum schedule length by our DNN is below 1% for all considered network sizes.

Fig. 3 illustrates the distribution of minimum schedule length in a network of 6 users over the entire test data set. Our deep neural network based optimization methodology very well approximates the entire profile generated by the optimal iterative algorithm for minimum schedule length problem.

Fig. 4 shows the uplink transmission sequence of users in a network of 5 users. The proposed deep learning based solution can predict transmission sequence accurately for different number of users within network. Scheduling of users in a full-duplex WPCN is important and our DNN based methodology perfectly mimics the ideal transmission schedule based on minimum length scheduling even as the network size increases.

Fig. 5 illustrates the average run-time of the algorithms

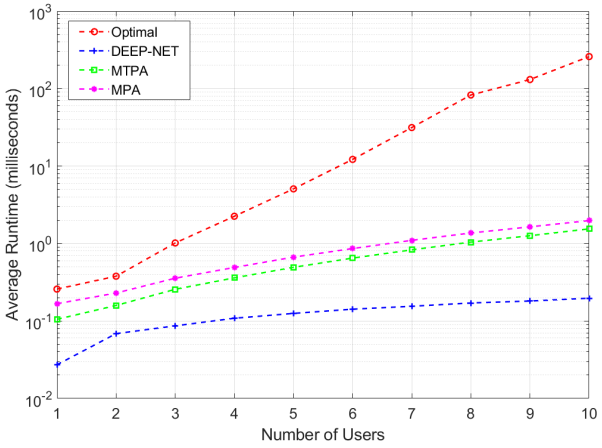



Figure 5: Average run-time of the various algorithms for different number of users.

for different number of users in the wireless network. As the network size increases, the run-time complexity increases almost linearly for MTPA and MPA algorithms. Our proposed DNN based algorithm performs significantly better than the polynomial-time heuristics algorithms MTPA and MPA. For $10$ users, the run-time of DNN based approach is only $11\%$ and $15\%$ of the run-time of MPA and MTPA algorithms, respectively. This means that our deep learning based system has the potential for real-time implementation especially for recent $5G$ and future $6G$ enabled wireless networks with a large number of users within the network.

## VI. CONCLUSION

In this paper, we propose a deep learning based optimization framework for solving the minimum length scheduling problem. The original problem is non-convex, therefore, hard to solve for the global optimum. We consider a feed forward deep neural network which we call DEEP-NET to estimate optimal power, allocation time and the corresponding transmission order of the users as an alternative to the optimal algorithm with exponential run-time complexity. Our proposed deep neural network is demonstrated to perform with fairly high accuracy and much lower run-time complexity compared to the previously proposed polynomial-time heuristic algorithms. The percentage error in estimating the schedule length remains below $1\%$ for different network sizes. In the future, we plan to extend this research with deep reinforcement learning to make it more robust to changes in user channel distribution.

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