# ИНФОРМАТИКА

UDC 519.217
MSC 90C40

## Deep neural network based resource allocation in D2D wireless networks*

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**For citation:** Sun Q., Zhang Y., Wu H., Petrosian O. L. Deep neural network based resource allocation in D2D wireless networks. *Vestnik of Saint Petersburg University. Applied Mathematics. Computer Science. Control Processes*, 2023, vol. 19, iss. 4, pp. 529–539.
https://doi.org/10.21638/11701/spbu10.2023.409

The increased complexity of future 5G wireless communication networks presents a fundamental issue for optimal resource allocation. This continuous, constrained optimal control problem must be solved in real-time since the power allocation should be consistent with the instantly evolving channel state. This paper emphasizes the application of deep learning to develop solutions for radio resource allocation problems in multiple-input multiple-output systems. We introduce a supervised deep neural network model combined with particle swarm optimization to address the issue using heuristic-generated data. We train the model and evaluate its ability to anticipate resource allocation solutions accurately. The simulation result indicates that the trained DNN-based model can deliver the near-optimal solution.

*Keywords*: multiple-input multiple-output systems, deep neural networks, heuristics, particle swarm optimization.

**1. Introduction.** With the rise of the Internet of Things and the exponential growth of mobile devices, the next-generation wireless network faces the formidable challenge of keeping up with the growing number of wireless applications. Power and beamforming are essential components of communication systems, playing a crucial role in determining the effective capacity of a wireless channel [1].

Scaling wireless systems requires the appropriate distribution of this resource under time-varying channel characteristics and user demands [2]. Different utility functions, such as the weighted sum rate (WSR), have been created to measure the performance of networked systems in numerous settings. The mutual interference among links and the high coupling of optimization variables make it difficult to optimize utility functions under prac-

* This work was supported by the St. Petersburg State University (ID project: 94062114).

tical restrictions, and solving these issues has shown to be convex and non-deterministic polynomial-time hardness (NP-hard). However, multiple antenna technology plays a key role in communication systems, and solving beamforming and power control problems is critical to achieving optimal performance in large-scale device-to-device (D2D) networks [3].

In the research that has been done so far, many good ideas have been put forward for how to solve problems with interference management [4] and optimal power control. The most well-known is the weighted minimal mean square error (WMMSE), which uses local channel information and converges to a stationary point in the problem of weighted sum-rate maximization [5]. By recasting the initial non-convex issue as a succession of convex problems, fractional programming (FP) can considerably ease the optimization of ratios [6]. Although the approaches above can boost the potential throughputs of systems, in each iteration of these iterative methods, complex calculations like matrix inversion must be performed before convergence. Due to the high computing complexity of the system, it is not viable to implement it in real-time applications [7].

Heuristic algorithms are the most commonly utilized solution for intractable issues in wireless network [8]. Heuristic algorithms can be employed to obtain an approximation of the ideal global solution without the need for a perfect mathematical model. Adaptive particle swarm optimization (PSO) covers the resource allocation problem in wireless sensor networks [9]. A single-layer modified artificial bee colony (ABC) is offered to address the resource allocation problem in the underlying D2D communication network [10]. So far, the heuristic's high time complexity renders it inappropriate for instantaneous optimal management of time-varying systems [11].

Motivated by recent advances, researchers have sought to adapt DL to address NP-hard optimization issues in wireless networks. In supervised settings, deep neural network (DNN) are applied to approximate the input-output mapping of the classic WMMSE algorithm [12, 13]. In unsupervised approaches, some works implement neural networks to parameterize the power allocation function and directly employ the optimization objective as a loss function, obviating the need for solved problem instances [14]. Even though such processes are easy to compute, it does not use prior knowledge to determine the algorithm's architecture or hyper-parameters. Even though this method is easy to compute, no prior knowledge is used to choose the algorithm's architecture or hyperparameters.

In this paper, we focus on the resource allocation problem of facilitating adaptation to time-varying conditions [15]. To handle this issue, we present a novel deep learning-based approach for computationally intensive and time-sensitive power allocation problems, with a particular emphasis on its theoretical and practical efficiency for wireless multi-antenna multi-user interference management challenges. We want to develop a supervised machine learning algorithm (PSO-NN) to learn the mapping of PSO to achieve the performance of PSO as much as possible. The key concept is to perform feature engineering to filter the effective features, then treat the given heuristic algorithm as a black-box and try to learn its input-output mapping relationships by using deep neural networks.

According to the summary and analysis of the results of the comparative experimental demonstrations in the literature, our proposed algorithm has significant performance advantages for DL algorithms based on or modified from WMMSE. In [16], the Bayesian Predictive Networks (BPNet) is trained offline using a two-step training strategy based on a heuristic solution structure of an optimal MMSE. It shows 10 % more performance enhancement than WMMSE. In [17], unfolding WMMSE maps a fixed number of iterations of the WMMSE algorithm into trainable neural network layers. The performance is improved about 11 %. In [18], learning aided gradient descent (LAGD) algorithm optimizes sending precoders by iterations based on implicit gradient descent and increase the performance by 4 %. In our reaserach, PSO-NN shows 15 % performance enhancement than WMMSE in large scale network, and can achieve 92 % the overall performance of the PSO.

This paper's primary contributions are as follows:

• we generate the dataset using a near-global optimal heuristic algorithm PSO. Compared to other heuristic algorithms, this algorithm excels in the general scenario of wireless communication networks [19];

• the experimental results show that the performance of our proposed model is significantly improved in terms of sum rate compared to WMMSE based methods.

The rest of this paper is organized as follows. After the introduction, Section 2 discusses the system model, the formulation of the power allocation and beamforming issues, and the representation for capturing the interference connections between various links. Section 3 offers the methodology of our DNN-based approach. Section 4 presents the numerical result to verify the framework's performance. Finally, Section 5 concludes the paper.

**2. System model and problem formulation.** In this study, we investigated a single-cell D2D network like Figure 1 in which several transceiver pairs compete for a fixed amount of bandwidth $B$. We assume that a single data stream may be sent and

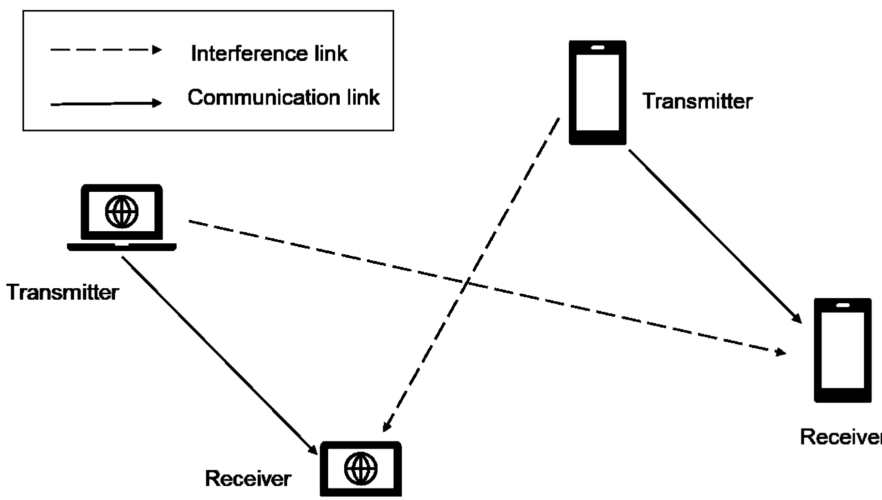


*Figure 1.* Example of D2D network with 2 transceiver pairs

received simultaneously across each connection. This throughput optimization problem aims to design a beamformer transmitter for each data stream on each live connection [20]. Consider there are $K = \{1, ..., k\}$ communication links; in other words, $k$ transmit antennas serve $k$ single-antenna user equipments (UEs). The channel response from the link transmitter $j$ to the receiver $i$ are $h_{ij}$. here $i$ and $j$ are indexs of receiver and transmitter. Let $x_i$ be the beamforming vector for the $i$ connection. Accordingly, the signal received at receiver $i$ is the superposition of signals from numerous transmitters, as described by

$$y_i = h_{ii}^H x_i + \sum_{j \neq i} h_{ij}^H x_j + n_i,$$

here $n_i \sim \mathcal{N}\left(0, \sigma_i^2\right)$ denotes the additive white Gaussian noise. The achievable sum rate of link $i$ can be expressed as the function

$$R_i\left(X\right) = W \log\left(1 + \frac{\left\| h_{ii}^H x_i \right\|_2^2}{\sum_{j \neq i} \left\| h_{ij}^H x_j \right\|_2^2 + \sigma_i^2}\right),$$

where $X$ is a set of all beamforming vectors, and $X = (x_1, ..., x_k)$. When a single antenna is utilized at transmitters, the beamforming design simplifies to a problem of power distribution.

Typically, the aggregate performance of the communication system is determined by a utility function of the possible connection rates. Weighted sum rate is the utility function used here. Given each transmitter's power restriction, the optimization issue is formulated as

$$\max_X \sum_i w_i R_i\left(X\right) \qquad s.t. \left\| x_i \right\|_2^2 \leqslant P_{\max} \quad \forall i,$$

where $w_i$ denotes the weight of link $i$, and $P_{\max}$ indicate the transmit power constraint of each communication link. When all connection weights are set to 1, the problem can be considered a sum rate maximization problem.

**3. Methodology.** In this section, we build an efficient DNN-based framework for solving resource allocation issues in MIMO networks. In order to achieve a near-global optimal sum rate in real-time, we presented a two-step DNN-based power allocation technique. In the initial phase, we employ a heuristic random search approach to identify the optimal power allocation that optimizes the system sum rate for each static channel state. In the second phase, we predict the allocated powers in real-time online applications using a well-trained DNN model. The following describes the introduction of the PSO algorithm and the design of the DNN framework for optimal beamforming.

***3.1. PSO algorithm.*** PSO is an optimization approach that Kennedy and Eberhart presented in 1995 [15]. This algorithm is inspired by the swarm intelligence, social behavior, and food-seeking strategies of bird flocks and schools of fish. It can be used to solve optimization problems in a variety of wireless communication domains due to its simplicity and low number of required parameters [21]. The swarm of particles begins randomly moving throughout the search space until the optimal solution is identified. Each particle is represented by a solution, and collectively, the solutions constitute a swarm. Based on its prior experience and additional factors, each particle in the swarm generates the most optimal solution.

Algorithm demonstrates a PSO implementation designed to optimize the resource allocation problem. The optimization variable of the communication network optimization problem is denoted by $X = (x_1, ..., x_k)$, which comprises the set of beamforming vectors given to each channel.

In the optimization problem considered in this paper, PSO first generates a group of candidate solutions $\{X_{id}\}$, which move in the search space according to certain rules. A guide to the best-known positions of $\{X_{id}\}$. When improved positions are found, these positions guide the movement of neighboring $\{X_{id}\}$. This process is repeated and will eventually converge to a satisfactory solution.

**Algorithm.** PSO

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**Require:** Generate initial population
**Ensure:** The best vector
  **while** Termination condition not met **do**
    **for** Each particle $X_{id}$ with position $p_i$ **do**
      Compute the achieved sum rate.
      **if** fitness value is greater than the current best value $p_{best}$ **then**
        Set current best value as $p_{best}$
      **end if**
    **end for**
    Select the particle with the overall best fitness value and set it as $g_{best}$
    **for** Each particle **do**
      Calculate particle velocity
      Update position of particle
    **end for**
  **end while**

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We use $l_{id}^t$ and $v_{id}^t$ to represent the position and velocity of each particle $X_{id}$ at iteration $t$. The parameter $d$ is the population size, $i$ is the index of each particle and $t$ is the number of iterations, $c_1$ and $c_2$ are learning factors, $p_i$ represents value explored by $i$th particle, $p_g$ represents value explored by neighbours of the $i$th particle. The updated steps are formulated as follows:

$$v_{id}^{t+1} = v_{id}^t + c_1 \cdot \text{rand}\,(0,1) \cdot \left(p_{id}^t - l_{id}^t\right) + c_2 \cdot \text{rand}\,(0,1) \cdot \left(p_{gd}^t - l_{id}^t\right),$$

$$l_{id}^{t+1} = l_{id}^t + v_{id}^t.$$

The fitness function incorporates a penalty function in order to enforce the optimization problem's constraints. This indicates that the accompanying fitness function deteriorates significantly when a prospective solution breaches a constraint.

Our proposed algorithm is based on a supervised learning approach that requires a large number of labeled samples during training. Therefore, we randomly generate the initial position of the UE in the communication network, and calculate the optimal allocation strategies under different network conditions through PSO, and record the characteristics of the UE at this time, that is, the channel state. As input vectors, we use the channel gain of each user as features, while the output vector $X$ comprises the set of beamforming vectors given to each channel.

***3.2. DNN model.*** We develop a fully-connected DNN architecture that predicts the optimal resource allocation for $K$ downlink UEs [3]. The objective is to discover a policy $P(\cdot)$ that simulates the mapping of PSO which denoted by $F$ to estimate the optimal allocated resource $\hat{P} \triangleq \{\hat{p}_k\}$. We select a DNN parameterization of the policy $P(\cdot)$ with learnable parameters, and beamforming vectors are estimated as $\hat{P} = P_\theta(F)$.

In the first stage of the process, offline supervised learning, the computationally demanding PSO algorithm determines the best-allocated strategy and employs it as the output label. The interference relations characterized as a set of channel coefficients $\{h_{ij}\}$, the communication relation characterized as a set of channel coefficients $\{h_{ii}\}$. Note that $h$ is a complex function consisting of a real part and a complex part. We take these two parts as features and input them into the neural network. Parameter $Z_0$ represent the input layer's feature vector, $R$ is set of real number. The input feature of DNN can be formulaed as

$$Z_0 = \left[h_{ii}^{\text{complex}}, ..., h_{ii}^{\text{real}}, ..., h_{ij}^{\text{complex}}, ..., h_{ij}^{\text{real}}, ...\right],$$

where $L_0 = 2k^2$ is the dimension of input feature. Scaling and vectorization of input features are applied at the inputs of the proposed DNN. We use the largest absolute proportion to the optimal distributed strategy, which is similar to the input features [22]:

$$\bar{x}_k = \frac{x_k^{\text{optimal}}}{\max\left(x_1^{\text{optimal}}, ..., x_k^{\text{optimal}}\right)} \in [0, 1].$$

To handle the non-linear computations, we employ the rectified linear unit (ReLU) as activation function at the hidden layers. There are $L_i$ neurons at the hidden layer $i$, where $i = 1, 2, 3$; $Z_0$ is the input factor, the output of the hidden layer $i$ is determined as $Z_i = f_r\left(w_{i-1}Z_{i-1} + b_{i-1}\right) \in R^{L_i}$, and $f_r(Z) = \max(0, Z)$ is the weight matrix and bias vector, respectively. To match the output layer predictions between 0 and 1 as stated by the output labels, the sigmoid function $f_\sigma(Z) = \frac{1}{1+e^{-Z}}$ is used at the output layer. The dimension of output facter is $k$. Thus, the predicted resource allocation for $K$ downlink UEs using the DNN framework are expressed as follows:

$$[\hat{x}_1, \hat{x}_2, \cdot\cdot\cdot, \hat{x}_k] = f_\sigma\left(W_3 Z_3 + b_3\right),$$

where $W_i$ is the weight matrices and $b_i$ is bias vectors which are adjusted to reduce the loss and more accurately forecast the optimal power allocation values. We evaluate the loss functions based on the predicted and ideal power values: mean square error (MSE). The formula for the MSE loss function is

$$L_{\text{MSE}} = \frac{1}{K}\sum_{k=1}^{K}\left(\bar{x}_k - \hat{x}_k\right)^2.$$

The structure of DNN is show in Figure 2. Back-propagation is a process in which the gradient of the loss function is transmitted from the output layer to the input layer. As a result, the weight matrix $W_i$ and the bias vector $b_i$ are updated in order to decrease the loss, which allows for more effective learning of samples and more accurate prediction of the optimal resource allocation strategy.

***3.3. Dataset generation and model training.*** The simulation parameters of the system is shown in Table. We create a dataset for the offline supervised learning procedure with the number of samples $S = 5 \cdot 10^5$. The channel gains, and UE locations with respect to the BS are randomly distributed in the area to produce the channel vector for each UE. The PSO algorithm is used to determine the associated optimally assigned powers, which are calculated and stored in the dataset [25].

*Table.* **Simulation parameters**

| Parameters | Size |
|---|---|
| Number of antennas | $M = 256$ |
| Cell radius | 200 m |
| BS transmit power | 20 dBm |
| Path loss exponent | $\eta = 3.76$ |
| Noise PSD | $-174$ dBm/Hz |
| Channel bandwidth | 10 kHz |

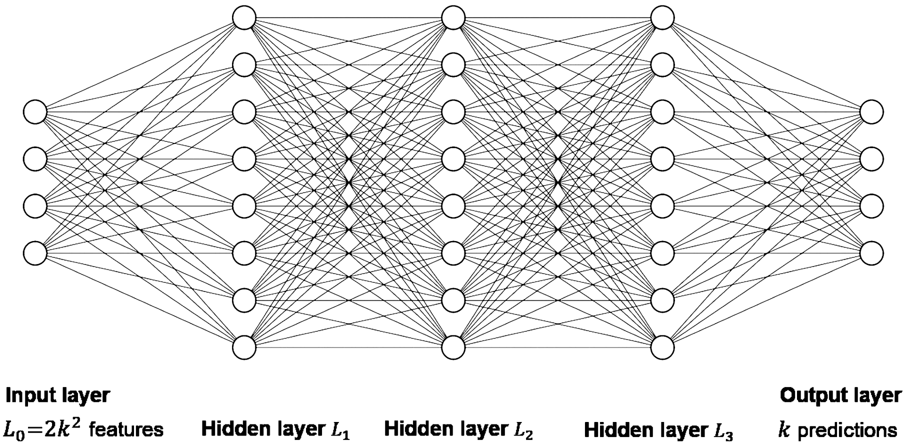


*Figure 2.* Structure of the DNN

The complete available dataset is split into 80 % training and 20 % validation sets during the offline learning process. We consider the hyper-parameters of DNN with 0.001 learning rate, 32 batch size, and ADAM optimizor. After the supervised learning, a brand-new test dataset evaluates the online power allocation in time-varying scenes. The proposed algorithmic technique is implemented using open-source DL framework in PyTorch [26].

**4. Simulation results and analysis.** To evaluate the performance of the DNN based algorithm, we mainly compare it with the WMMSE based approach, which is a widely used benchmark in the literature of sum rate maximization problem. The following benchmarks are considered for comparison. All results on the test performance of WMMSE are the average from 100 independent trials:

• WMMSE [5]: An approach based on optimization that converts the problem of weighted mean square error reduction from the sum rate maximization difficulties in MIMO interfering broadcast channels;

• WMMSE-NN [23]: A 3-layer supervised DNN that learns the mapping of classical WMMSE;

• PSO [24]: An iterative stochastic optimization technique based on swarm intelligence.

Figure 3 demonstrates the comparative performance of DNN with different structures in relation to the size of the training set. Either by adding more convolution layers or by parameterizing with larger MLPs, the performance of DNN could be boosted. To demonstrate the benefits of expanding MLPs, we show the results of DNNs with layer numbers (2 and 3) and the hidden size of MLPs (256 and 512). When $5 \cdot 10^5$ samples are input, the relative performance of a 3-layer DNN with a hidden size of 512 is 91.5 %. Adding extra hidden layers to the DNN does not result in a substantial improvement; rather, it can easily lead to overfitting. In order to balance performance and complexity, we use this DNN structure in the subsequent trials.

Figures 4 and 5 depict the sum-rate and runtime findings in relation to the number of UEs. As seen in Figure 4, the DNN-based approach outperforms its WMMSE counterpart as the number of UEs increases. The relative sum-rate performance of DNN compared to the optimal PSO algorithm is 91.5 %.

Moreover, Figure 5 illustrates the runtime comparison between PSO, WMMSE-NN and WMMSE for 1000 systems states. AI inference is performed on an Nvidia 2070s deve-

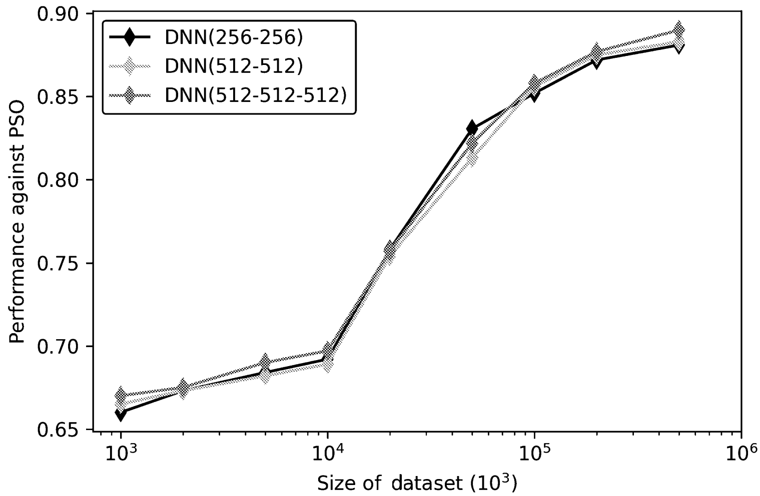


*Figure 3.* Percentage performance of PSO for models with different number of convolutional layers and hidden layer sizes on datasets of different sizes

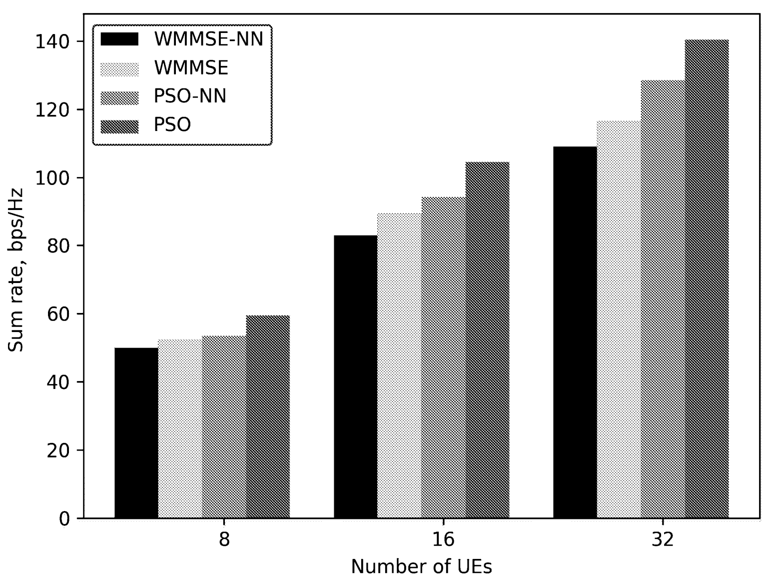


*Figure 4.* General sum rate for DNN with different UEs density

lopment card using offline-trained DNN architecture. We observe that the proposed DNN approach outperforms the computationally intensive WMMSE technique by drastically lowering its execution time. In the case of $K = 12$ UEs, for example, WMMSE requires 1056 sec whereas DNN requires only 0.08 sec. For iterative WMMSE, the running time increases dramatically with the size of the problem dimension. In contrast, DNN-based power allocation requires less processing time and is much less variable. For a trained DNN model, the number of computations is constant. The processing time fluctuation comes from the uncertainty of the computation of different floating point numbers and

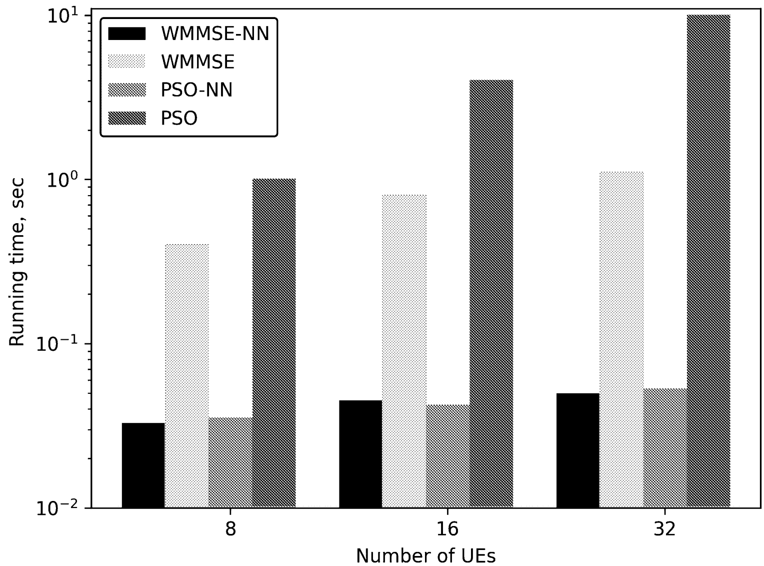


*Figure 5.* Average run time for 100 experiments

the read system time. For the heuristic algorithm, the time fluctuations mainly come from the different initializations, i. e., different search starting points can lead to significant differences in the time required to find the optimal solution.

**5. Conclusion.** We proposed a supervised learning-based framework PSO-NN for solving the sum rate maximization issue in MIMO networks, which can detect interference in complicated real-world wireless communication settings. Using specific network setups and use cases, we illustrate the quality of the PSO-NN solution. In principle, the approximations of the heuristic approach, can be applied to any network and scenario, as it has been demonstrated that DNNs are capable of approximating any function arbitrarily closely with sufficient training [27]. We can conclude that well trained PSO-NN outperforms WMMSE based algorithms in terms of computation time and performance; it is slightly inferior to PSO in terms of performance by 92 %, but can save 99 % of the computation time.

However, there are several difficulties that we have not addressed in this study and for which additional research is required. For the DNN's (predictive) capabilities, it is crucial to identify the optimal DNN structure, which is dependent on the setup of the large-scale MIMO system and the selection of the hyperparameters. In the future, we will investigate the feasibility of building optimum solution structures for more complicated power allocation issues and implementing them into a DNN-based framework to boost learning efficiency even more.

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Received: September 19, 2023.
Accepted: October 12, 2023.

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## Распределение ресурсов на основе глубокой нейронной сети в беспроводных сетях D2D*

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Российская Федерация, 199034, Санкт-Петербург, Университетская наб., 7–9

**Для цитирования:** *Sun Q., Zhang Y., Wu H., Petrosian O. L.* Deep neural network based resource allocation in D2D wireless networks // Вестник Санкт-Петербургского университета. Прикладная математика. Информатика. Процессы управления. 2023. Т. 19. Вып. 4. С. 529–539. https://doi.org/10.21638/11701/spbu10.2023.409

Возросшая сложность будущих сетей беспроводной связи 5G представляет собой фундаментальную проблему для оптимального распределения ресурсов. Эта непрерывная, ограниченная задача оптимального управления должна решаться в режиме реального времени, поскольку распределение мощности должно соответствовать мгновенно меняющемуся состоянию канала. В статье особое внимание уделяется применению глубокого обучения для разработки решений проблем распределения радиоресурсов в системах с несколькими входами и несколькими выходами. Контролируемая модель глубокой нейронной сети представлена в сочетании с оптимизацией роя частиц для решения проблемы с использованием эвристически сгенерированных данных. Мы обучаем модель и оцениваем ее способность точно прогнозировать решения по распределению ресурсов. Результат моделирования показывает, что хорошо обученная предложенная модель может обеспечить почти оптимальное решение.

*Ключевые слова*: системы с несколькими входами и несколькими выходами, глубокие нейронные сети, эвристика, оптимизация роя частиц.

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* Работа выполнена при финансовой поддержке Санкт-Петербургского государственного университета (проект ID: 94062114).