IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received December 25, 2020, accepted January 7, 2021, date of publication January 12, 2021, date of current version January 21, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3051170

Spectral Efficiency Improvement and Power Control Optimization of Massive MIMO Networks

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This work was supported in part by the National Natural Science Foundation of China under Project 61701345, Project 61771342, Project 61901301, and Project 61971310; in part by the Natural Science Foundation of Tianjin under Project 18JCZDJC31900; and in part by the Tianjin Higher Education Creative Team Funds Program.

ABSTRACT Higher requirements must be put forward about wireless signal transmission in harsh environments. Energy loss mitigation, channel estimation, noise interference reduction demands high quality of service in wireless communication. In the fifth generation wireless communication, massive multiple-input multiple-output (MIMO) networks have been used and play a significant role to fulfill the requirements. Cell-Free massive MIMO networks are recognized as possible solution in the future wireless communication. Spectral efficiency (SE) is a very important index in assessing massive MIMO networks. This article tries to optimize both SE and power control of cell-free massive MIMO networks. Both uplink and downlink transmission are included in the study. The optimization model contains both SE and power control of massive MIMO networks. To tackle the model, a novel ensemble method is developed inspired by ensemble learning. The ensemble method is built up on the neighborhood field optimization method. The goodness of the developed ensemble method is verified by comparing with genetic algorithm, gradient descent method and Newton method. Extensive simulations are performed to study the optimization of SE and power control. Different wireless sensors are taken into consideration to simulate different requirements of massive MIMO networks. The results demonstrate the effectiveness of the proposed method for applying in massive MIMO networks.

INDEX TERMS Massive multiple-input multiple-output, neighborhood field optimization, optimization, power control, spectral efficiency.

I. INTRODUCTION

Wireless signal is a kind of electromagnetic wave, which is transmitted in a straight line in space. The signal strength will be wakened when it meets obstacles. Especially, hills, trees and metal objects have more obvious influence on shielding and blocking wireless signal. In addition, the wireless signal is subject to other energy loss and various noise interferences. Therefore, under such bad communication environments, how to ensure real-time and accurate data communication has become a research hotspot [1]. Deployment of communication systems in harsh environments, such as high-speed trains, subways, aircraft, deserts, underground mining, etc., must be specially constructed to withstand extreme conditions, such as very high or low temperatures, corrosive humidity, or extreme weather. In general, communications in harsh environments usually consumes more power and energy. Bandwidth limitation in harsh environments requires higher SE [2]. Special wireless communication systems must be designed to adapt to harsh communication conditions and meet the quality of service (QoS), security, and reliability requirements in extreme environments. Massive MIMO systems, which use multiple antennas, play important roles in improving the quantity of wireless communication systems [3]–[5].

Massive MIMO, as one of the key technologies of the fifth generation (5G) wireless communication, has been widely concerned and researched because it can significantly improve transmission rate and SE. SE of massive MIMO system has been a focus in academic areas.

The associate editor coordinating the review of this manuscript and approving it for publication was Qilian Liang.

In [4], the authors focused on exploring the spectrum resource and maximizing the utilization of its bands. They studied recent spectrum sharing (SS) technologies towards 5G development. Moreover, a detailed survey on cognitive radio technology in SS related to 5G was performed. In [5], the authors proposed a novel analytical framework for the performance analysis of green cell-free massive MIMO networks. Numerical results show that the use of designed analytical framework in cell-free massive MIMO networks clearly improve the energy efficiency (EE) and SE. In [2], the authors considered a hybrid beamforming massive MIMO system operating in time-division duplex mode. In [6], the authors evaluated the performance of time-division duplex-based massive MIMO deployment scenario in one of the commercial sites in Turkey. Compared to Frequency-division duplex-based MIMO deployment, time-division duplex-based massive MIMO system has higher throughput and SE. In [7], the authors proposed a dictionary-constrained low-complexity algorithm for hybrid precoding and combining design towards to millimeter-wave massive MIMO systems. The proposed method considers a decoupled optimization scheme between the RF and baseband domains for the SE maximization problem. In [8], the authors developed a novel transmission scheme by superposing the training symbols for active device detection and channel estimation on the data symbols in the uplink transmission to mitigate the cross interference among the superposed signals and improve the efficiency. In [9], the authors showed that cognitive spectrum sensing and power harvesting can be accomplished simultaneously. They focused on cyclostationary spectrum sensing.

Wireless communication speed is slow and often breaks down in some harsh and complex environments. How to guarantee the reliability of wireless communication quality in special environment has become current research hotspot in academic circle. In [10], the authors proposed an enhanced real-time array calibration (ERAC) technique. Accurate positioning was achieved for fast-moving vehicles. In the context of multipath interference, the performance of the tested receiver with ERAC method is superior to that of the traditional receiver with standard single-point positioning. In [11], a novel channel model was proposed, which included important factors that influenced the quality of the visible-light communication link in underground mines. Harsh environments and conditions such as a random positioning and orientation of the transmitter and receiver, tunnels with irregular walls, shadowing by large machinery, and scattering by dust clouds are considered. In [12], to against the active pilot spoofing attack, the authors proposed a new effective solution called the spatial spectrum method which could effectively detect and locate the eavesdropper in MIMO communication systems to ensure the secret and secure transmission of information. Pilot contamination (PC) is a bottleneck for the throughput of multi-cell massive MIMO systems. In [13], the authors proposed a joint pilot allocation and pilot sequences optimization scheme to mitigate the effects of PC in massive MIMO system and maximize the system spectral efficiency. In [14], the performance optimization of multi-user millimeter-wave massive MIMO system was investigated. The authors presented a new pilot mapping to reduce the inter-user interference effect and to achieve more accurate channel estimation. In [15], the authors considered device-to-device (D2D) communication in long-distance and harsh environments. A two-way amplify-and-forward relay was used to assist the underlay D2D communications. The power control problem was also studied in [15]. In [16], the authors studied the mode selection problem for full-duplex-enabled two-way D2D communications to improve SE. In [17], the authors studied both pilot and power allocation for massive MIMO networks. In [18] and [19], the authors had discussed both SE and EE for uplink and downlink transmission massive MIMO networks.

In this article, performance improvement of massive MIMO networks is formulated to a minimization model. Both uplink and downlink data transmission are discussed, which is more realistic than considering uplink or downlink alone. As the number of wireless sensors could be of large scale in massive MIMO networks, the problem model is essentially a large-scale optimization problem. To optimize the model, a novel method is developed inspired by the ensemble learning of artificial intelligence (AI) [20]. Nowadays, AI methods have already been applied to deal with optimization problems in massive MIMO or wireless sensor networks [21], [22]. In this article, the ensemble method is realized based on neighborhood field optimization (NFO) method, which belongs to evolutionary computing approaches [23]. The goodness of our ensemble method is verified compared with original NFO method. Extensive simulations are performed to study the optimization of SE and power control. Different wireless sensors are taken into consideration to simulate the requirements of different massive MIMO networks.

In the following, Section II introduces massive MIMO networks and problem formulation of the networks. Section III reports the optimization method including NFO and the ensemble method. Section IV reports the simulations studying the optimization of SE and power control. The paper is concluded in Section V.

II. MASSIVE MIMO NETWORKS AND PROBLEM FORMULATION

This section briefly introduces cell-free massive MIMO networks. Then, SE and power control of the networks are formulated to optimization problems.

A. MASSIVE MIMO NETWORKS

Massive MIMO refers to the scenario that a base station (BS) is equipped with a number of antennas or antenna arrays, which could provide QoS for a number of users. It is a promising 5G wireless access technology [24]. Massive MIMO systems can serve users with high reliability and system throughput. In general, massive MIMO systems divide covering area to cells to cooperatively serve users. This may not be enough for the next generation wireless communication. As in wireless sensor networks where sensors could work in the form of relay to assist data transmission, it is beneficial to exploit the usage of distributed massive MIMO systems. In distributed systems, service antennas or antenna arrays spread out in a larger area than ordinary massive MIMO systems where antennas or antenna arrays are located in BS. Cell-Free massive MIMO is created based on the above idea in that it aims to remove the limitations of cells or cell boundaries [24]. Moreover, access points (APs), which have a number of antennas or antenna arrays, are distributed over a large area as shown in Fig. 1.

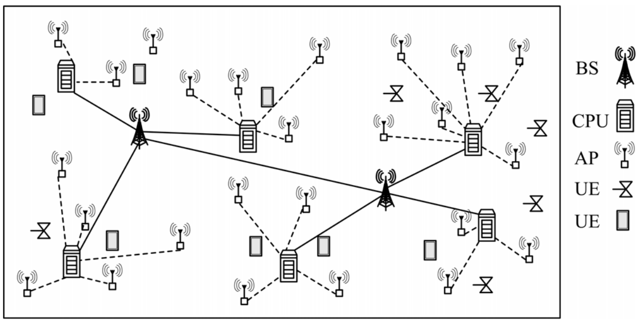

FIGURE 1. Data transmission of cell-free massive MIMO networks.

APs cooperate together to provide QoS without creating cells in cell-free massive MIMO systems. Therefore, cell-free massive MIMO systems can avoid many interference issues that exist in ordinary massive MIMO systems [25]. Although cell-free massive MIMO has solid theory and prospection, it may not be feasible to be used in real massive MIMO networks. This is because its computational complexity and fronthaul requirements are not scalable to the number of users in system [25]. Thus, scalable cell-free massive MIMO systems are proposed to resolve the scalability issue.

Based on the way of data transmission, cell-free massive MIMO networks are divided to two types. One is centralized data transmission, and the other is distributed data transmission. For centralized data transmission network, a number of APs serving the same user sends data to a central processing unit as shown in Fig. 1. There are a number of central processing units (CPUs) in network. CPUs are responsible for channel estimation and data detection of all APs. For distributed data transmission network, an access point (AP) has certain data processing function. AP is responsible for local channel estimation. Then, APs send their collected information to CPUs. The difference between centralized and distributed data transmission network is if AP has local signal estimation capability. Unless otherwise specified, the paper studies centralized data transmission in scalable cell-free massive MIMO network.

In centralized data transmission network, combing vector of partial minimum mean squared error combining (P-MMSE) combining scheme is computed by [25]:

$$v_i = p_i \left(\sum_{k \in \mathrm{M}} p_k D_i h_k h_k^H D_i + Z_k \right)^{-1} D_i h_i \tag{1}$$

where M is the set of APs that serves user i. In case matrix inverse is hard to compute or matrix is nearly singular, pseudo-inverse should be used in the computation.

B. PROBLEM FORMULATION

Without loss of generality, suppose there are K users in the network. A user is denoted as i or k. The transmission power of user i is p_i. Users can be mobile phones, wireless sensors or other wireless devices. Suppose an AP is denoted as l, and the number of APs in the network is L. Users are assumed to have only one antenna, and APs are assumed to have N antennas. Noise is assumed to be complex Gaussian distribution or multi-variate complex Gaussian distribution for multiple variables.

For uplink (UL) data transmission, an AP l receives signal in terms of a vector:

$$\mathbf{y}_l = \sum_{i=1}^{K} \mathbf{h}_{il} s_i + \mathbf{n}_l \tag{2}$$

where s_i stands for the transmission of signal from AP i, $\mathbf{h}_{il}$ stands for the channel between i and l, and $\mathbf{n}_l$ is thermal noise or Johnson noise. Note that s_i is affected by transmission power p_i of AP i.

For downlink (DL) data transmission, a user k receives signal in terms of a vector:

$$y_k = \sum_{l=1}^{L} \mathbf{h}_{kl}^H \sum_{i=1}^{K} \mathbf{w}_{il} \xi_i + n_k \tag{3}$$

where $\mathbf{w}_{il}$ stands for the precoder of user i allocated by l, and ξ_i is the data signal of user i with unit-power.

The estimation of s_i requires combining method such as maximum-ratio (MR) combining method or minimum mean squared error combining (MMSE) method. Note that MR method is also known as conjugate beamforming [24] or matched filtering [26]. MMSE combining performs better than MR combining in case fading is considered in signal transmission [27], [28]. Thus, MMSE combining is used in the paper.

For a user i, its transmission power p_i and spectral efficiency SE_i can be computed. p_i is allocated by AP. SE_i can be computed based on signal-to-interference-and-noise ratio (SINR), where SINR can be computed by transmission power and channel estimation. In massive MIMO networks, power control is to control the total energy consumed by all users, which is required to be minimized; on the other hand, SE is the total spectral efficiency of the network, which is required to be maximized. In general, a tradeoff of EE and SE is enough for real world applications. To optimize both SE and power control, an optimization objective is built:

$$f=\sum_{i=1}^{K}p_i\Big/\sum_{i=1}^{K}SE_i \tag{4}$$

where $\sum_{i=1}^{K}p_i$ is the total energy of the network, and $\sum_{i=1}^{K}SE_i$ is the total spectral efficiency of the network.

For UL data transmission of data transmission network, the mathematical model is:

$$\begin{aligned}
&\min f\left(p_1,p_2,\cdots,p_K\right)=\sum_{i=1}^{K}p_i\Big/\sum_{i=1}^{K}SE_i\\
&s.t.\ \ SE_i=\frac{\tau_u}{\tau_c}\mathrm{E}\left\{\log_2\left(1+SINR_i\right)\right\}\\
&\quad SINR_i=\frac{p_i\left|v_i^H D_i h_i\right|^2}{\sum_{k\neq i}p_k\left|v_k^H D_k h_k\right|^2+v_k^H Z_k v_k}\\
&\quad p_i^{LB}\leq p_i\leq p_i^{UB}
\end{aligned} \tag{5}$$

where τ_u and τ_c are channels allocated following standard massive MIMO time-division duplex protocol, τ_u is the length of coherence block for uplink data transmission, and τ_c is the total length of coherence block. p_i^{LB} and p_i^{UB} are lower and upper bound of the power of user i.

For DL data transmission of data transmission network, the mathematical model is:

$$\begin{aligned}
&\min f\left(p_1,p_2,\cdots,p_K\right)=\sum_{i=1}^{K}p_i\Big/\sum_{i=1}^{K}SE_i\\
&s.t.\ \ SE_i=\frac{\tau_d}{\tau_c}\mathrm{E}\left\{\log_2\left(1+SINR_i\right)\right\}\\
&\quad SINR_i=\frac{p_i\left|\mathrm{E}\left\{h_i^H D_i w_i\right\}\right|^2}{\sum_{k\neq i}p_k\left|\mathrm{E}\left\{h_i^H D_i w_k\right\}\right|^2+\sigma^2}\\
&\quad p_i^{LB}\leq p_i\leq p_i^{UB}
\end{aligned} \tag{6}$$

where τ_d is the length of coherence block for DL data transmission, σ is standard deviation of noise when user receives signals from APs.

Both models are minimization optimization problems. Clearly, when the number of users K increases, the models are large scale problems, which are difficult to solve. The optimization method will be presented in the next section.

III. SE AND POWER CONTROL OPTIMIZATION METHOD

This section first introduces the NFO method. Then, an ensemble method is proposed based on ensemble learning of AI. Third, the goodness of ensemble NFO method is verified through simulation.

A. NEIGHBORHOOD FIELD OPTIMIZATION METHOD

Traditional mathematical programming approaches have been studied for decades to solve global optimization problems such as gradient descent method, Newton method, etc. Newton method and Quasi-Newton method have fast convergence rate, and may not have global convergence [29]. Global convergence refers to a method is able to reach global optimum of a problem. In general, many traditional mathematical programming approaches have local convergence. That is they are able to reach local optimum. These methods have been widely used in real world applications. This reflects a fact that local optimum could satisfy the requirements of many real world applications. The NFO method is inspired by local cooperation behaviors of species. Under certain assumptions, the NFO method performs similar to gradient descent method. On the other hand, the NFO method is an evolutionary computing (EC) approach, which utilizes randomness and generation during creating new solutions. Thus, the NFO method has both local convergence and global convergence features [23].

Similar to most EC approaches, the NFO method starts with a population, which contains a set of solutions randomly created in search space. The main procedures of NFO are localization, mutation operation and crossover operation. Localization refers to locate the neighbors of a solution such that it can learn some information about the direction of optimal solution. In general, a superior neighbor and an inferior neighbor are located with respect to a solution. Denote $\mathbf{x}$ as a solution. Denote $\mathbf{xc}$ and $\mathbf{xw}$ as superior neighbor and inferior neighbor of $\mathbf{x}$. Mutation operation is to perturb a solution:

$$\mathbf{xv}=\mathbf{x}+\alpha\mathbf{r}_1\left(\mathbf{xc}-\mathbf{x}\right)+\alpha\mathbf{r}_2\left(\mathbf{xc}-\mathbf{xw}\right) \tag{7}$$

where α is learning rate, $\mathbf{r}_1$ and $\mathbf{r}_2$ are vectors with random values. Learning rate α is like step size. $\mathbf{r}_1$ and $\mathbf{r}_2$ introduce randomness to the NFO method. Crossover operation is to recombine a solution $\mathbf{x}$ with $\mathbf{xv}$. Before doing crossover operation, a variable is chosen randomly, denoted as i_1:

$$x_i=\begin{cases}xv_i, & i=i_1\ or\ r_3\leq Cr\\ x_i, & otherwise\end{cases} \tag{8}$$

where Cr is crossover rate between 0 and 1, r_3 is a random number. The usage of i_1 is to assure more than one variables being modified after mutation and crossover operations.

B. THE PROPOSED ENSEMBLE METHOD

In the NFO method, mutation operation (7) is designed under local cooperative behavior. Moreover, random factors are also included in (7). Crossover operation (8) is similar to binomial crossover, which has been extensively used in differential evolution [30]. Learning rate α and crossover rate Cr can affect the performance of the NFO method. The authors have tested the sensitivity of α and Cr on extensive benchmark functions. It is found that the range of α should be [0.7, 1.7], and the range of Cr should be [0.1, 0.7]. By default, α and Cr should be 1.5 and 0.2.

Parameter control can improve the performance of EC approaches [31]. To effectively solve the large scale model (5) and (6), we will employ ensemble learning to control parameter α and Cr of the NFO method. Ensemble learning is a meta-method that combines several artificial intelligence approaches together to reduce variance, bias and improve prediction accuracy. Note that ensemble learning is able to combine a set of weak approaches to produce a strong method. Methods created by ensemble learning have shown very good performance in many artificial intelligence benchmark dataset. Ensemble learning methods are generally classified to two types. One is serial combining of several approaches, and the other is parallel combining of several approaches. This article considers serial combining of several parameter values.

Based on previous study, three parameter combinations of α and Cr are chosen as shown in Table 1. The three parameter combinations are abbreviated as Par1, Par2 and Par3.

TABLE 1. Combinations of learning rate and crossover rate.

Combination	Learning rate	Crossover rate
Par1	0.7	0.1
Par2	1.5	0.2
Par3	1.7	0.7

Serial combining of three combinations of Table 1 is not to use them in sequence of the NFO method. Such mechanical usage would be harmful to evolutionary characteristic of NFO. The idea to ensemble three parameter combinations is keep using a combination unless it fails to do a good search towards optimal solution. It is unable to locate optimal solution for an unknown problem. Hence, a solution with better function value is taken as a good search towards optimal solution. Given a solution $\mathbf{x}^t$ at time t, suppose a new solution $\mathbf{x}^{t+1}$ is obtained by using combination Par$i$, $i = \{1,2,3\}$. Then, Par$i$ would be used in the next iteration if $\mathbf{x}^{t+1}$ has better function value than $\mathbf{x}^t$. Mathematically:

$$Par_i = \begin{cases} Par_i, & f\left(\mathbf{x}^{t+1}\right) \le f\left(\mathbf{x}^t\right) \\ Par_j, j \neq i & otherwise \end{cases} \tag{9}$$

Initially, the ensemble method starts with a randomly chosen Par$i$. During the evolutionary process, each parameter combination is possible to be chosen. This is a serial using of different combinations. The resulting method is abbreviated as NFOEnsemble, showing the NFO method with ensemble learning.

C. EFFECTIVENESS OF THE ENSEMBLE METHOD

The effectiveness of the NFOEnsemble method is studied on two test functions: Sphere function and Griewank's function. The formulas of the two functions are:

$$f^{sph}(\mathbf{x}) = \sum_{i=1}^{K} x_i^2 \tag{10}$$

$$f^{gri}(\mathbf{x}) = 1 + \sum_{i=1}^{K} \frac{x_i^2}{4000} + \prod_{i=1}^{K} \cos\left(\frac{x_i}{\sqrt{i}}\right) \tag{11}$$

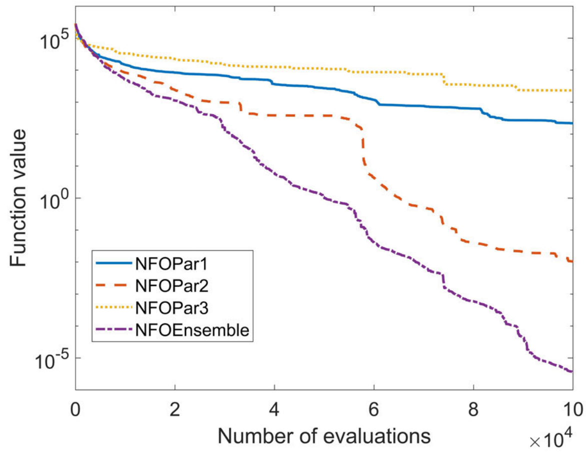

FIGURE 2. Sphere function; comparison of the NFOEnsemble method against the NFO method with three parameter combinations.

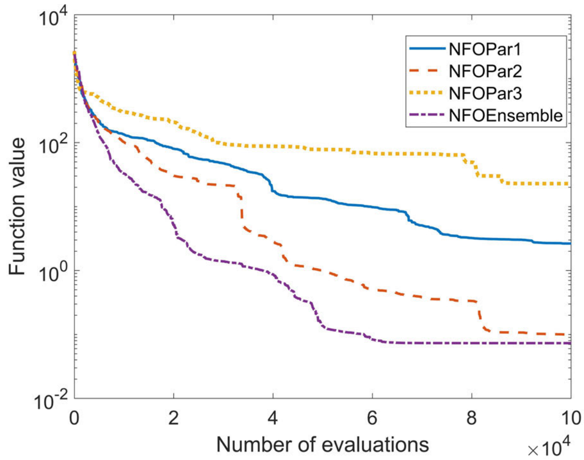

FIGURE 3. Griewank's function; comparison of the NFOEnsemble method against the NFO method with three parameter combinations.

where (10) shows Sphere function and (11) shows Griewank's function. The two functions have extensively been used in studying EC approaches [23], [32], [33]. The NFO method is also tested on the two functions. NFO with each combination is abbreviated as NFOPar1, NFOPar2 and NFOPar3.

The comparison on Sphere function of the NFOEnsemble method against the NFO method with three parameter combinations is shown in Fig. 2. Note that the target is to find global minimum, hence the lower the curve in Fig. 2, the better the method is. It can be seen from the figure that NFOPar3 is the worst, following are NFOPar1 and NFOPar2. The NFOEnsemble method is the best on Sphere function. A large gap is observed between NFOPar1, NFOPar2 and NFOPar3. Also the gap between NFOPar3 and NFOEnsemble is also large.

The comparison on Griewank's function of the NFOEnsemble method against the NFO method with three parameter combinations is shown in Fig. 3. It can be seen from the figure that NFOPar3 is the worst, following are NFOPar1 and NFOPar2. The NFOEnsemble method is the

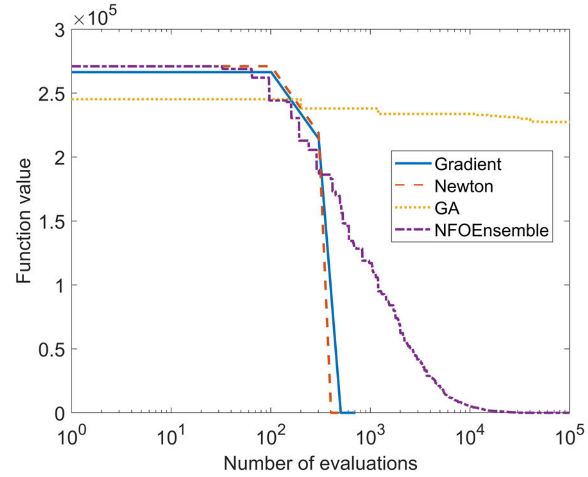

FIGURE 4. Sphere function; comparison of the NFOEnsemble method against GA, Gradient and Newton methods.

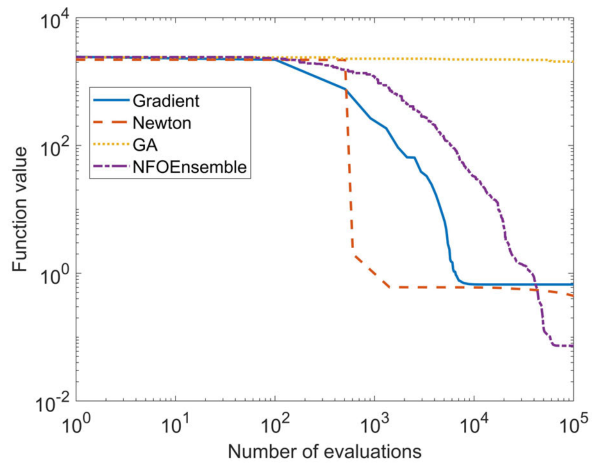

FIGURE 5. Griewank's function; comparison of the NFOEnsemble method against GA, Gradient and Newton methods.

best on Sphere function. A large gap can be observed between the NFO method with three combinations, while the gap between NFOPar2 and NFOEnsemble becomes small at the last stage.

The comparison on Sphere function of the NFOEnsemble method against genetic algorithm (GA), gradient descent method (Gradient) and Newton method (Newton) is shown in Fig. 4. The comparison on Griewank's function of these methods is shown in Fig. 5.

It can be seen from Fig. 4 and Fig. 5 that the convergence curve of GA is above the curves of the other methods after about 200 function evaluations. This shows that GA performs worse than the Gradient, Newton and NFOEnsemble methods. On Sphere function, the NFOEnsemble method performs better than the Gradient and Newton methods before 300 evaluations; then the Gradient and Newton methods converges much faster than the NFOEnsemble method; finally the three methods reach a similar function value. On Griewank's function, the Gradient method performs better than the Newton and NFOEnsemble methods before 600 evaluations; then the Newton method converges much faster than the Gradient and NFOEnsemble methods before 40,000 evaluations; finally, the NFOEnsemble method reaches a smaller function value than the Gradient and Newton methods.

The study on two functions demonstrates that a positive ensemble effect is observed in the NFOEnsemble method. The NFOEnsemble method overall converges better than the GA method. On Sphere function, the Gradient and Newton method converge better than the NFOEnsemble method. On Griewank's function, the NFOEnsemble method is outperformed by the Gradient and Newton methods in the former stage; while the NFOEnsemble method converges better than the Gradient and Newton methods in the later stage. This shows the effectiveness of the proposed NFOEnsemble method.

IV. SIMULATION RESULT

This section describes the simulation settings of massive MIMO networks and the ensemble method. Simulations are performed by considering different kinds of wireless sensors. The results are reported and discussed.

A. SIMULATION SETTINGS

Suppose considering a massive MIMO network locating at a square area. Simulation setting of the network is shown in Table 2.

TABLE 2. Simulation setting of the massive MIMO network.

Parameter	Value
Area	1000m×1000m
K	[100, 150]
L	400
N	[1, 4]
Bandwidth	20MHz
Path loss exponent	3.76
Noise	7dB

Besides the parameters of Table 2, the lower and upper power bounds of wireless devices are shown in Table 3. Currently, most mobile users are the fourth generation (4G), and many commercial companies are promoting 5G mobile. For wireless sensors, Bluetooth are mature but expensive, while ZigBee are cheap and of low transmission rate. Network throughput of Bluetooth is lower than ZigBee network. This makes ZigBee network suitable choice for the massive MIMO networks with different types of sensors.

Two simulations are performed in this section. One is a massive MIMO network containing 4G and 5G mobiles. The other is a network containing 4G mobile, 5G mobile, and ZigBee devices. The parameter setting of the NFOEnsemble and the NFO method follows the verification in Section III-C. Note that network simulation is a moderate computational time problem. The function evaluations are limited to 1000 for the saving of time.

TABLE 3. Simulation setting of power of wireless devices.

Wireless device	Lower bound	Upper bound
5G mobile	65 mW	400 mW
4G mobile	32 mW	200 mW
ZigBee	1 mW	3 mW
Bluetooth	1 mW	100 mW

B. SIMULATION OF CELLULAR NETWORKS

In this simulation, the number of 4G mobile users is 50, and the number of 5G mobile users is also 50. The power range is shown in Table 3. First, a comparison of convergence process is done as shown in Fig. 6. The results are for solving UL centralized network model (5).

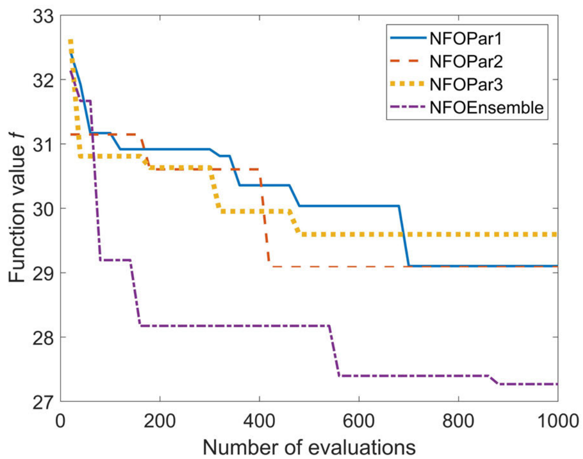

FIGURE 6. Comparison of convergence process of the NFOPar1, NFOPar2, NFOPar3 and NFOEnsemble methods.

It can be seen from Fig. 6 that NFOPar3 is the worst, following are NFOPar1 and NFOPar2. The NFOEnsemble method is the best on model (5). The performance of the four methods is similar to that shown in Fig. 2 and Fig. 3. Moreover, NFOPar1 and NFOPar2 converge to nearly the same solution in the final stage. The NFOEnsemble method finds the best solution amongst the four methods.

The cumulative distribution function (CDF) of SE of the four methods is shown in Fig. 7. It can be seen from the figure that the curve of the NFOEnsemble method is mostly below the curves of the NFOPar1, NFOPar2 and NFOPar3 methods. This means that SE of the NFOEnsemble method is better than the other three methods. The SE curve of the NFOPar3 method is mostly above of the others. This means that the NFOPar3 method reaches the worst SE of the four methods.

The CDF of power control of the four methods is shown in Fig. 8. In this simulation, $K = 100$. The curves of Fig. 8 are plots of energies of 100 mobile users. The curve of the NFOEnsemble method is mostly above of the curves of the NFOPar1, NFOPar2 and NFOPar3 methods. This means that the solution found by the NFOEnsemble method consumes less energies than the other methods. The worst method is

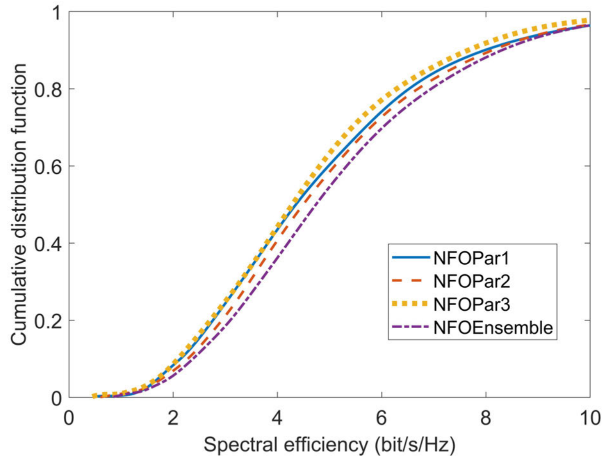

FIGURE 7. Comparison of SE of the NFOPar1, NFOPar2, NFOPar3 and NFOEnsemble methods on UL cellular network.

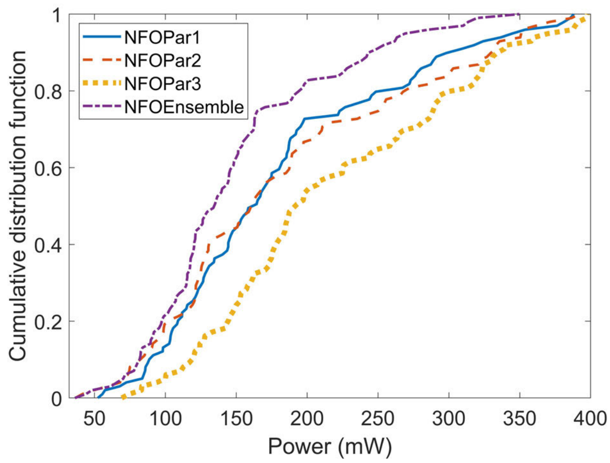

FIGURE 8. Comparison of power control of the NFOPar1, NFOPar2, NFOPar3 and NFOEnsemble methods on UL cellular network.

the NFOPar3 from the curves of Fig. 8. The curves of the NFOPar1 and NFOPar2 methods are alternatively below of each other. This means that the energy consumption of both methods is nearly the same.

The above analysis shows that the NFOEnsemble method performs better than the NFOPar1, NFOPar2 and NFOPar3 methods. In the next simulation, we concentrate on analyzing spectral efficiency and power control in scalable cell-free massive MIMO networks. Moreover, the NFOEnsemble method is compared with the NFOPar2 method and the method of [9]. As shown in Fig. 9 and Fig. 10, the results are for solving DL data transmission network model (6).

It can be seen from Fig. 9 that the SE curve of NFOEnsemble is below the curves of the P-MMSE and NFOPar2 methods. This means that the NFOEnsemble method attains better SE than the other two methods. The NFOPar2 method also performs better than the P-MMSE method.

It can be seen from Fig. 10 that the power curve of the NFOEnsemble method is mostly above the curve of

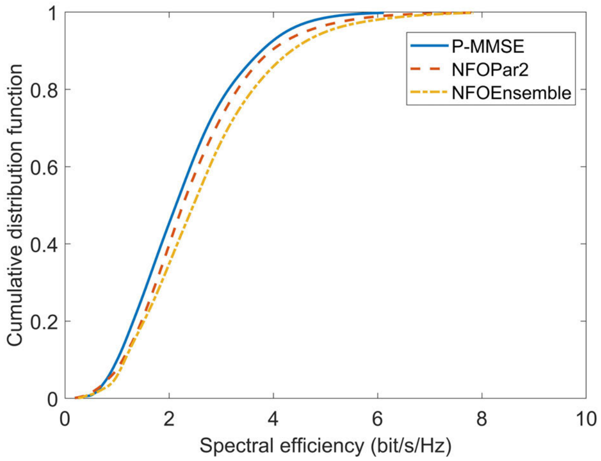

FIGURE 9. Comparison of SE of the P-MMSE, NFOPar2 and NFOEnsemble methods on DL cellular network.

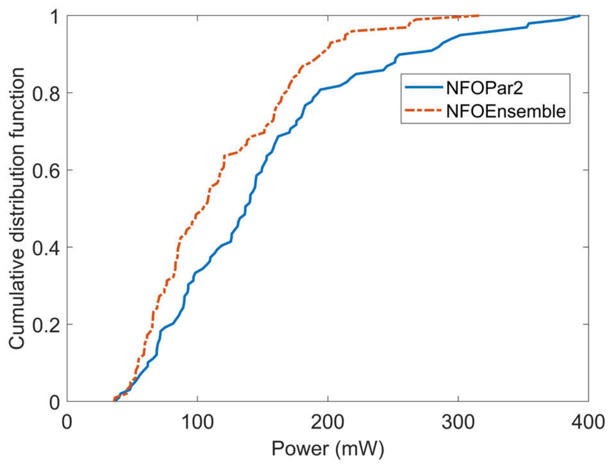

FIGURE 10. Comparison of power control of the NFOPar2 and NFOEnsemble methods on DL cellular network.

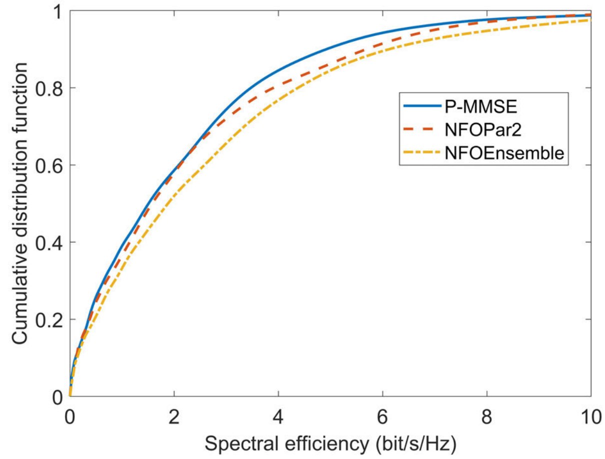

FIGURE 11. Comparison of SE of the P-MMSE, NFOPar2 and NFOEnsemble methods on UL network.

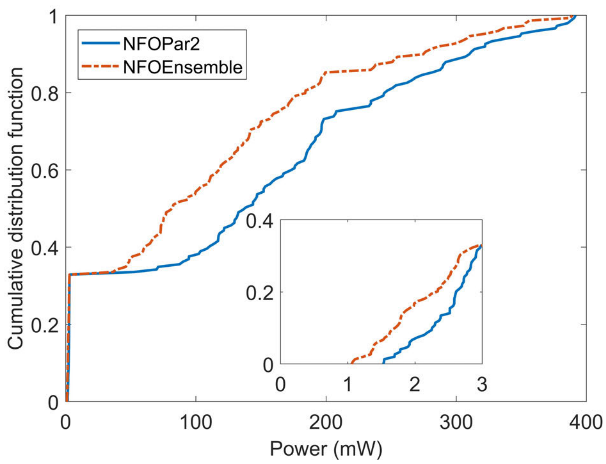

FIGURE 12. Comparison of power control of the NFOPar2 and NFOEnsemble methods on UL network.

the NFOPar2 method. This means that the NFOEnsemble method saves energy in a period of time than the NFOPar2 method. Although for some wireless devices the NFOPar2 method assigns nearly the same power, it assigns larger power values for most wireless devices than the NFOEnsemble method.

Based on the simulation results on cellular networks, it can be seen that SE and power control can be resolved for the scalable cell-free massive MIMO networks. The proposed method is able to deal with both UL and DL data transmission. The NFOEnsemble method outperforms the NFOPar1, NFOPar2 and NFOPar3 methods in terms of convergence, spectral efficiency and power control. Moreover, the NFOEnsemble method shows good performance in comparison with the P-MMSE method.

C. SIMULATION OF NETWORKS WITH DIFFERENT SENSORS

In this simulation, the number of 4G and 5G mobile users is 50 and 50, respectively. The number of ZigBee users is also 50. Hence, there are 150 wireless devices in total. The power range is shown in Table 3. The results shown in Fig. 11 and Fig. 12 are for solving UL data transmission network model (5).

It can be seen from Fig. 11 that the SE curve of the NFOEnsemble method is below the curves of the P-MMSE and NFOPar2 methods. This means that the NFOEnsemble method attains better SE than the other two methods. The SE curve of NFOPar2 method sometimes overlaps with that of the P-MMSE method.

It can be seen from Fig. 12 that the power curve of the NFOEnsemble method is mostly above the power curve of the NFOPar2 method. This means that the NFOEnsemble method reaches a better power control than the NFOPar2 method. Although for some wireless devices the NFOPar2 method assigns nearly the same power, it assigns larger power values for most wireless devices than the NFOEnsemble method.

The results shown in Fig. 13 and Fig. 14 are for solving DL data transmission network model (6). It can be seen from Fig. 13 that the SE curve of the NFOEnsem-

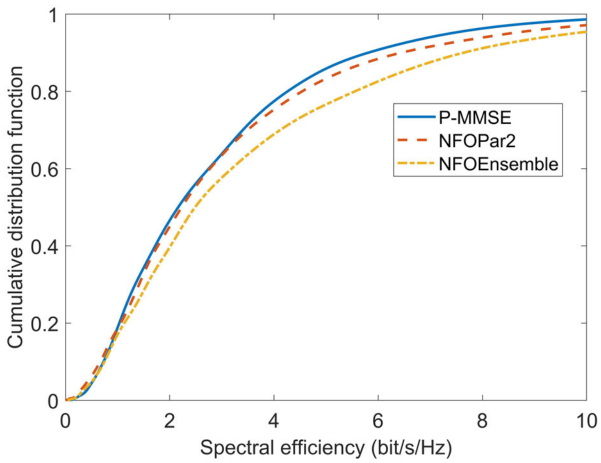

FIGURE 13. Comparison of SE of the P-MMSE, NFOPar2 and NFOEnsemble methods on DL network.

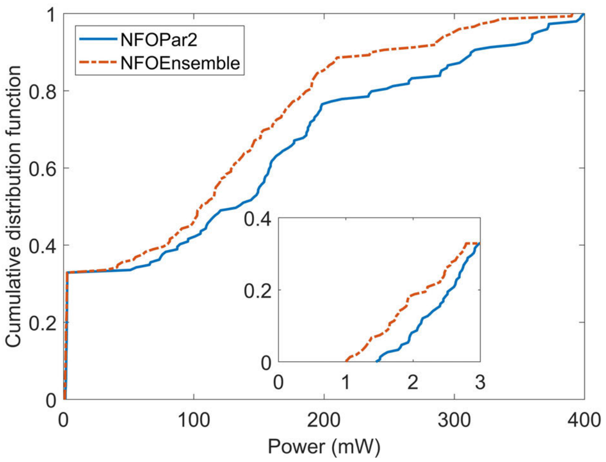

FIGURE 14. Comparison of power control of the NFOPar2 and NFOEnsemble methods on DL network.

ble method is mostly below the curves of the P-MMSE and NFOPar2 methods. This means that the NFOEnsemble method attains better SE than the other two methods. The SE curve of NFOPar2 method sometimes overlaps with that of the P-MMSE method, while a small gap is observed between the two methods.

It can be seen from Fig. 14 that the power curve of the NFOEnsemble method is mostly above the power curve of the NFOPar2 method. This means that the NFOEnsemble method reaches a better power control than the NFOPar2 method. Although for some wireless devices the NFOPar2 method assigns nearly the same power, it assigns larger power values for most wireless devices than the NFOEnsemble method.

Based on the simulation results on massive MIMO networks, it can be seen that SE and power control can be resolved for the scalable cell-free massive MIMO networks. The proposed method is able to deal with both UL and DL data transmission. The NFOEnsemble method shows good performance in comparison with the P-MMSE and the NFOPar2 methods.

V. CONCLUSION

In this article, both SE and EE power control are optimized for cell-free massive MIMO networks. Both uplink and downlink transmission are considered in the study. To optimize the two models, the NFOEnsemble method is developed inspired by ensemble learning. Extensive simulations are performed to study the SE and power control in massive MIMO networks. The results demonstrate the effectiveness of the proposed method for applying in massive MIMO networks with different sensors.

As shown in Fig. 4 and Fig. 5, the NFOEnsemble method is comparable to the Gradient and Newton methods in the former optimization stage. The Gradient and Newton methods converge better in the middle optimization stage. The NFOEnsemble method can attain similar or better solutions than the Gradient and Newton methods in the later optimization stage. Hence, for deploying massive MIMO networks in real-time, the NFOEnsemble method needs to be fine-tuned.

An overhead of the proposed method is that it assigns large power to many wireless devices in the network. Some prior knowledge about communication power could be given to the AI method in initialization. Moreover, as discussed in [19], [34], there is a tradeoff between SE and EE; more advanced strategies have to be developed to optimize both EE and SE indices in massive MIMO networks.

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