Joint Antenna Selection and Power Allocation Method Based on Quantum Energy Valley Optimization Algorithm for Massive MIMO IoT Systems

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Abstract

Massive multiple-input multiple-output (MIMO) has emerged as a pivotal technology to address the escalating communication demands of Internet of Things (IoT). To meet the data transmission needs in IoT systems, we propose an antenna selection method of massive MIMO systems and joint power allocation strategy considering IoT user devices grounded in quantum energy valley optimization (QEVO) in this paper. The derivation of a maximum energy efficiency equation has been established to optimize system resources and provide high quality of service meeting the IoT user devices requirements. To tackle the nonlinear, multi-constrained hybrid optimization challenge proposed for massive MIMO resource allocation in IoT systems, we introduce a quantum energy valley optimization algorithm. This algorithm harnesses the strengths of quantum computation and energy valley optimization (EVO) mechanisms. Simulations indicate that our proposed method can efficiently meet real-time user transmission requirements while markedly enhancing system energy efficiency. When compared with existing power allocation strategies and optimization algorithms applied in massive MIMO communication systems, our approach demonstrates superior performance. The proposed method demonstrates the highest performance across various simulation scenarios when applied to both allocation strategies and system energy efficiency. Our proposed method with highest performance can be properly used on massive IoT devices.

Keywords: Internet of Things, massive MIMO, antenna selection, power allocation, energy efficiency, QEVO

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1. Introduction

The swift progression of information technology has propelled social changes through mobile communication in unprecedented ways [1]. In order to address the growing demand, advancements in Internet of Things (IoT) technology are currently underway [2]. As an important innovation of 5G and 6G, massive multiple-input multiple-output (MIMO) employs numerous antennas at the base station (BS) [3-5]. The main idea behind massive MIMO is to use multiple antennas at each user terminal to simultaneously transmit and receive signals, which can significantly reduce the interference between different cells [6]. Massive MIMO technology can significantly improve the spectral efficiency and data rate of wireless communication system deployment of large-scale antennas to satisfy the demands for energy efficiency and real-time performance in IoT applications [7]. Moreover, massive MIMO can support vehicle-to-everything (V2X) communication, help unmanned aerial vehicle (UAV) communication, and achieve more efficient and secure transmission with intelligent reflecting surface (IRS) [8].

Due to the complex nature of wireless environments, the structure and optimization design of massive MIMO networks in IoT remain a compound challenge [9, 10]. Recently, to enhance system performance, multiple factors have been considered in massive MIMO IoT networks [11-15]. In [11], it introduced a cell-free massive MIMO IoT network model and led to the identification of a maximization problem concerning total spectral efficiency for joint control pilot and data power. In [12], researchers proposed a power allocation strategy based on the water-filling effect to restructure distributed IoT devices in massive MIMO systems. In [13], researchers leveraged the capabilities of massive MIMO technology to enhance the accuracy of channel estimation in near-field IoT environments. Authors proposed a co-temporal co-frequency full-duplex massive MIMO system to address the high spectral efficiency demands within 6G mobile communication networks in [14]. Research on next-generation wireless systems and IoT networks said cost-effective technologies are essential for massive MIMO [15].

While mobile communication offers significant convenience in production and daily life, it also escalates operating costs and carbon emissions [16]. Large scale antenna deployment at the BS inevitably increases system power consumption [17]. Consequently, research into energy efficiency (EE) issues in massive MIMO systems is particularly important [18, 19]. Implement of antenna selection can cut the complexity down of RF links in massive MIMO systems by selecting specific antennas to participate in information transmission [20]. This effectively reduces communication costs and system power consumption. The exhaustive method can achieve maximum system capacity by traversing all antenna subsets. It becomes impractical for massive MIMO systems due to the substantial computational volume of the exhaustive method, and makes it impossible to obtain an optimal antenna selection scheme in real time. In [21], an adaptive antenna design utilizing genetic algorithms (GA) was investigated for massive MIMO systems. While the method exhibited optimal energy efficiency at low signal-to-noise ratio (SNR), it fell at high SNR. A methodology was proposed in [22], involving the selective use of signal-to-interference-noise ratio (SINR) values, utilizing both antenna index and angle of departure as feedback signals. The complexity and computation of the algorithm escalates due to the multitude of factors involved in antenna selection. Despite considering the wireless channel state information (CSI), accurately obtaining and utilizing CSI continues to be a significant challenge. Therefore, determining a reasonable antenna selection scheme that enhances system energy efficiency while maintaining system capacity and reliability remains a challenge for massive MIMO systems [23].

On the other hand, power allocation can effectively mitigate inter-user interference caused by the near-far effect due to differences in transmission channels between users, thereby improving system capacity and reducing energy consumption. In [24], a power allocation method based on fractional programming was proposed, integrating fractional programming theory with continuous convex optimization problems, utilizing the Dinkelbach algorithm to obtain the optimal power allocation scheme. However, this approximate method is susceptible to local optimum. The resource optimization problem in wireless networks is typically articulated as a mixed-integer nonlinear programming problem, which presents significant challenges and often classified as NP-hard. Metaheuristic algorithm exhibits enhanced efficacy in addressing this problem. In [25], a joint channel assignment and power control strategy was proposed utilizing particle swarm optimization (PSO). In [26], to address resource allocation challenges within wireless networks, whale optimization algorithm (WOA) was employed. In recent years, energy valley optimization (EVO) has emerged as a potent method for continuous optimization, garnering widely attention [27]. Notably, conventional algorithms encounter difficulties in addressing high-dimensional problems within the realm of massive MIMO. There exists a notable absence of specialized algorithms for these issues.

In summary, existing power allocation schemes for massive MIMO systems in IoT seldom consider transmission rate and power consumption on system energy efficiency comprehensively. In this paper, a joint intelligent antenna selection and power allocation method based on quantum energy valley optimization in view of the system EE of massive MIMO systems has been proposed. Simulation experiments show that the energy efficiency of the method offers a wider application potential compared to the Dinkelbach algorithm, metaheuristic algorithms, and other strategies. The main contributions of this paper are delineated as follows:

- Considering the varying transmission demands from users across different time slots in practical communication systems, we establish a comprehensive model for intelligent antenna selection for massive MIMO uplink systems. Furthermore, we derive an equation which determine its maximum energy efficiency to achieve power allocation efficiently.
- To enhance efficiency in problem-solving, we are inspired from the advantage of quantum theory [28] and energy valley optimization (EVO) mechanism designed quantum energy valley optimization algorithm (QEVO), involving the adaptive adjustment of the selection of antenna number utilized while the transmission power of user data at the BS.
- Simulation results show that QEVO we proposed performs better compared with other metaheuristic algorithms. Besides, QEVO can not only be used in massive MIMO system, it's a general algorithm which can also address other complicated problem in wireless communication systems.

The remainder of our work is structured as follows: Section 2 shows the system model and provides an analysis of energy efficiency. A joint intelligent antenna selection and power allocation approach grounded in QEVO is introduced in Section 3. Analysis of energy efficiency derived from simulation results under various conditions is presented in Section 4, while the subsequent section, Section 5 concludes our discussion.

Notation: In this paper, we indicate the following notation: Matrix and vector by boldface upper and lowercase letters respectively; $\mathbb{E}[\cdot]$ represents the statistical average; superscripts $(\cdot)^{\mathrm{T}}$ and $(\cdot)^{\mathrm{H}}$ denote transpose and conjugate transpose, respectively; $\|\cdot\|$ and $|\cdot|$ denote the Euclidean norm, respectively; $\boldsymbol{I}_N$ denotes identity matrix.

2. System Model and Analysis

Fig. 1 illustrates a single-cell massive MIMO system in IoT, comprising one base station equipped with K antennas and E single-antenna IoT devices. Assume that the location of user is randomly distributed within the base station coverage area. To facilitate energy conservation, we have chosen a subset of antennas for participation in the communication process, taking the specific requirements of the practical system into consideration. It is assumed that power allocation is not necessary for antenna systems that are not required during data transmission. The antenna selection strategy is elaborated in the subsequent section. Suppose K_s antennas are chosen at the base station, $K_s \le K$.

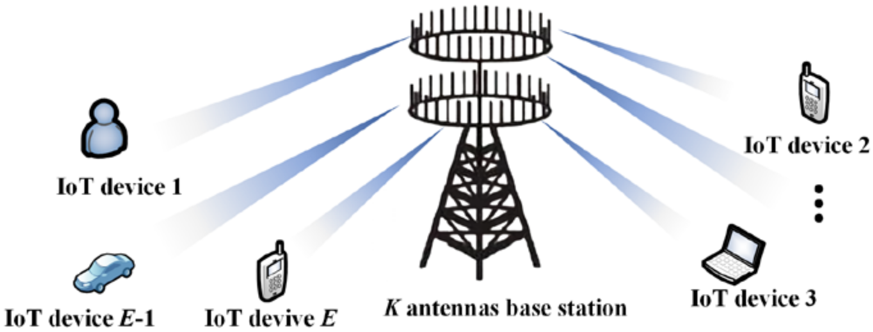

Fig. 1. The massive MIMO IoT communication systems

In massive MIMO uplink system, the CSI [11, 12, 18, 19] between the e th IoT device and the base station can be expressed by

$$\boldsymbol{g_e} = \sqrt{\beta_e}\boldsymbol{h_e} \tag{1}$$

where $\boldsymbol{g_e} \in \mathbb{C}^{1\times K_s}$, $\boldsymbol{h_e} \in \mathbb{C}^{1\times K_s}$, $e = 1, 2, ..., E$, $\boldsymbol{h_e}$ is the small-scale fading vector from device e to the BS, $\boldsymbol{h_e} \sim \mathcal{CN}(0, \boldsymbol{I}_{K_s})$. $\sqrt{\beta_e}$ represents the large-scale fading factor from IoT device e to the BS. β_e can be obtained by

$$\beta_e = \left(\frac{r_e}{r_0}\right)^{-v_0} \tag{2}$$

where r_e represents the distance between device e and the BS, r_0 is the reference distance which is equivalent to the radius of the BS, whereas v_0 denotes the path loss exponent [19].

The signal received at the base station is articulated as

$$\boldsymbol{y} = \sum_{e=1}^{E} \sqrt{p_e} g_e s_e + \tilde{\boldsymbol{n}} \tag{3}$$

where p_e denotes the transmission power of device e , $\boldsymbol{s_e}$ represents the signal transmitted by user device e , which satisfy $\mathbb{E}\{\| \boldsymbol{s_e} \|^2\} = 1$. System noise is additive Gaussian white noise (AGWN), the noise vector denoted as $\tilde{\boldsymbol{n}}$.

Assuming the availability of complete CSI is available [14], the BS receives signals by maximum ratio combining (MRC) [19]. And the received matrix can be denoted by $\boldsymbol{W} = [\boldsymbol{w_1}, \boldsymbol{w_2}, ..., \boldsymbol{w_e}]$, in which $\boldsymbol{w_e} = \boldsymbol{h_e} / \| \boldsymbol{h_e} \|$. The SINR at the base station side experienced by IoT device e is shown as

$$\gamma_e = \frac{p_e \left| \boldsymbol{w}_{\boldsymbol{e}}^{\mathrm{H}} \boldsymbol{g}_{\boldsymbol{e}} \right|}{\sigma_e^2 + \sum_{j=1, j \neq e}^{E} p_j \left| \boldsymbol{w}_{\boldsymbol{e}}^{\mathrm{H}} \boldsymbol{g}_{\boldsymbol{j}} \right|^2} \tag{4}$$

where σ_e^2 denotes the noise power at IoT device e, $\sum_{j=1, j \neq e}^{E} p_j \left| \boldsymbol{w}_{\boldsymbol{e}}^{\mathrm{H}} \boldsymbol{g}_{\boldsymbol{j}} \right|^2$ represents the interference power of other IoT devices. The data transmission rate of e th device is given by

$$r_e = B \log_2 \left(1 + \gamma_e\right) \tag{5}$$

where B is the bandwidth of the system.

The achievable rate of the massive MIMO uplink system can be obtained by

$$R = \sum_{e=1}^{E} B \log_2 \left(1 + \gamma_e\right) \tag{6}$$

2.1 Antenna Selection

In actual communication systems, there is a significant surge in user numbers in IoT system during peak periods, and a subsequent decrease during low-peak periods. This fluctuation in user counting is primarily due to the varying demands for data transmission at different period. To optimize system resources and provide meeting the user data transmission requirements, we select $K_s (K_s \leq K)$ antennas from the BS to participate in communication.

K_s can be calculated by

$$K_s = \lceil \varepsilon K \rceil \tag{7}$$

where $\lceil \cdot \rceil$ denotes the ceiling function, ε represents the coefficient in antenna selection processing.

While an exhaustive method can yield the optimal antenna selection scheme, it is not feasible in massive MIMO networks equipped large volume of antennas. To conserve computing resources, this paper introduces a low complexity antenna selection strategy. Assume that the antennas at the BS operate independently from each other, and all IoT devices possess identical transmission power.

The method is formulated as follows. First, the antenna selection coefficient ε is determined. Subsequently, we compute the cumulative user data transmission rates received by each antenna through Eq. (6). Then rank the results calculated by Eq. (6) in descending order. Based on the antenna selection coefficient, we select the top K_s antennas with the highest reception rate and K_s is obtained by Eq. (7). Notably, the antenna selection coefficient ε can be dynamically adjusted, which is in response to the change of user data transmission demands.

2.2 Energy Efficiency

The power consumption in massive MIMO networks primarily encompasses both circuit power consumption and transmission power when applied in practical scenarios. Given that the energy in wireless communication cannot be entirely received for the perspective of users, it is inevitable that the transmission efficiency will not achieve a 100% rate. Thus, the total consumed power P_Σ is given as

$$P_\Sigma = K_s p_k + \sum_{e=1}^{E} p_{c,e} + \frac{1}{\eta} \sum_{e=1}^{E} p_e \tag{8}$$

where p_k denotes the power consumed by each antenna, $p_{c,e}$ represents the circuit power consumption generated between IoT device e and the BS, η denotes transmission efficiency, p_e denotes transmission power when comes to IoT device e.

The network energy efficiency (EE) can be quantified by calculating the ratio of the sum of the transmission rates to the total power consumption, which is shown by

$$\varphi = \frac{R}{P_\Sigma} = \frac{\sum_{e=1}^{E} B\log_2(1+\hat{\gamma}_e)}{K_s p_k + \sum_{e=1}^{E} p_{c,e} + \frac{1}{\eta}\sum_{e=1}^{E} p_e} \tag{9}$$

where $\hat{\gamma}_e$ represents the SINR of IoT device e after antenna selection received at the BS.

Considering the quality of service (QoS) for the massive MIMO system, the transmission power of IoT user device e cannot exceed the maximum transmission power limit, which is shown by

$$0 < p_e \le p_{\max} \tag{10}$$

$$\frac{1}{E}\sum_{e=1}^{E} B\log_2\left(1+\hat{\gamma}_e\right) \ge r_{\min} \tag{11}$$

where $p_{\max}$ represents the maximum transmission power, $r_{\min}$ denotes the average minimum achievable rate. According to Eq. (10) and (11), we define $\boldsymbol{p} = [p_1, p_2, ..., p_E]$ as the set of satisfying power allocation results.

In order to maximum the EE for massive MIMO system, it is imperative to dynamically adjust antenna selection and power allocation strategies in response to real-time IoT user device data transmission demands. The maximum EE problem is as follow

$$\begin{aligned} \max\ \ \varphi = {} & \frac{\sum_{e=1}^{E} B\log_2(1+\hat{\gamma}_e)}{K_s p_k + \sum_{e=1}^{E} p_{c,e} + \frac{1}{\eta}\sum_{e=1}^{E} p_e} \\ & \text{s. t.} \quad 0 < \varepsilon \le 1 \\ & 0 < p_e \le p_{\max},\ \forall e \\ & \frac{1}{E}\sum_{e=1}^{E} B\log_2(1+\hat{\gamma}_e) \ge r_{\min} \end{aligned} \tag{12}$$

3. Joint Antenna Selection and Power Allocation Method Based on Quantum Energy Valley Optimization Algorithm

Intelligent optimization algorithms, characterized by their simplistic modeling, broad applicability, and robust optimization capabilities, have gained significant traction in wireless communication over recent years. However, the substantial gap between the definition domain intervals of problem variables which need to be addressed by the EE as equation (12) in massive MIMO systems, presents a challenge for many existing intelligent optimization algorithms. Consequently, this paper proposes a quantum energy valley optimization algorithm (QEVO) aimed to address issues within antenna selection and power allocation inherent in massive MIMO IoT networks. In this section, the principle of QEVO is given, followed by the discussion on its application in the schemes we proposed.

3.1 Quantum Energy Valley Optimization Algorithm (QEVO)

In QEVO, denote the population of quantum particles by D, and the dimension of each quantum particle is M (M is the dimension of considered optimization problem). The t th iteration in the i th quantum particle is defined by

$$\boldsymbol{x}_{\boldsymbol{i}}^{\boldsymbol{t}} = [x_{i,1}^t, x_{i,2}^t, ..., x_{i,m}^t, ..., x_{i,M}^t] \tag{13}$$

where $0 \le x_{i,m}^t \le 1$, $i = 1,2,...,D$, $m = 1,2,...,M$. Then $\overline{\boldsymbol{x}}_{\boldsymbol{i}}^{\boldsymbol{t}} = [\overline{x}_{i,1}^t, \overline{x}_{i,2}^t, ..., \overline{x}_{i,m}^t, ..., \overline{x}_{i,M}^t]$ represents the position of the i th quantum particle in t th iteration. Then through the mapping rule, $\overline{\boldsymbol{x}}_{\boldsymbol{i}}^{\boldsymbol{t}}$ can be obtained by

$$\overline{x}_{i,m}^t = \left(\overline{x}_m^{\max} - \overline{x}_m^{\min}\right) x_{i,m}^t + \overline{x}_m^{\min} \tag{14}$$

where $\overline{x}_m^{\max}$ represents the upper and $\overline{x}_m^{\min}$ denotes the lower bounds of the m th variable.

The fitness function is utilized to calculate the neutron enrichment level (NEL) of quantum particles. Then, ζ_i^t represents the solution value of the i th quantum particle in t th iteration. For a maximization optimization problem, the global optimal quantum particle with the highest NEL is denoted as $\boldsymbol{b}^{\boldsymbol{t}} = [b_1^t, b_2^t, ..., b_M^t]$ among the t th iteration. τ^t means the enrichment bound for quantum particles and the mathematical presentation is shown as

$$\tau^t = \sum_{i=1}^{D} \zeta_i^t \Big/ D \tag{15}$$

The stability level of the i th quantum particle in t th iteration can be calculated as

$$\vartheta_i^t = \begin{cases} (\zeta_i^t - \zeta_{\max}) / (\zeta_{\min} - \zeta_{\max}), & \zeta_{\max} \ne \zeta_{\min} \\ rand, & \zeta_{\max} = \zeta_{\min} \end{cases} \tag{16}$$

where $\zeta_{\max}$ and $\zeta_{\min}$ represent the best and worst values up to the t th iteration found of NEL, respectively.

In the main search loop of QEVO, calculate the Euclidean distance between $\boldsymbol{x}_{\boldsymbol{i}}^{\boldsymbol{t}}$ and other quantum particles, which is shown as

$$\kappa_{i,j}^t = \sum_{m=1}^{M} \sqrt{\left(x_{i,m}^t - x_{j,m}^t\right)^2} \tag{17}$$

where $\kappa_{i,j}^t$ is the distance between the i th and j th quantum particle. Then, sort the quantum particles based on ascending distance, and $\overline{\kappa}$ denotes an integer in the range of $[2, D]$, the neighboring quantum particle $\tilde{\boldsymbol{x}}^{\boldsymbol{t}} = [\tilde{x}_1^t, \tilde{x}_2^t, ..., \tilde{x}_M^t]$ in t th iteration can be determined by the average of the first $\overline{\kappa}$ nearest quantum particles. The center quantum particle in t th iteration is been calculated by

$$\hat{x}_m^t = \frac{1}{D} \sum_{i=1}^{D} x_{i,m}^t \tag{18}$$

where $\hat{x}_m^t$ denotes the m th center quantum particle variable.

There are three types within the decay process depend on different stability level of quantum particle. In the t th iteration, compare the NEL of $\boldsymbol{x}_{\boldsymbol{i}}^{\boldsymbol{t}}$ with the enrichment bound.

If $\zeta_i^t > \tau^t$, which means the quantum particle will update based on decay process. A random number $\hat{\vartheta}_i^t$ is generated within $[0,1]$, which emulates the stability bound.

If $\vartheta_i^t > \hat{\vartheta}_i^t$ is met, it is assumed that the decay of alpha and gamma occurs. In this process, generate two random integers as α^t and γ^t in the range of $[1, M]$. Then generates a vector $\hat{\boldsymbol{\alpha}}^t$ with the size of $1 \times \alpha^t$ and each variable is a random integer within $[1, M]$. And vector $\hat{\boldsymbol{\gamma}}^t$ with $1 \times \gamma^t$ and each variable randomly produced within $[1, M]$. The i th quantum particle undergoes two types of decay and two new quantum rotations are produced as follow

$$\theta_{l,m}^{t+1} = \begin{cases} b_m^t, & m = \hat{\alpha}_m^t \\ x_{i,m}^t, & m \neq \hat{\alpha}_m^t \end{cases} \tag{19}$$

$$\theta_{l+1,m}^{t+1} = \begin{cases} \tilde{x}_m^t, & m = \hat{\gamma}_m^t \\ x_{i,m}^t & m \neq \hat{\gamma}_m^t \end{cases} \tag{20}$$

where $\theta_{l,m}^{t+1}$ and $\theta_{l+1,m}^{t+1}$ denote the m th quantum rotation angle of the i th quantum particle produced by alpha and gamma decay, $l = 2i - 1$, $\hat{\alpha}_m^t$ and $\hat{\gamma}_m^t$ represent the m th $\hat{\boldsymbol{\alpha}}^t$ and $\hat{\boldsymbol{\gamma}}^t$ in case that $\hat{\alpha}_m^t$ and $\hat{\gamma}_m^t$ are available.

If $\vartheta_i^t \leq \hat{\vartheta}_i^t$, bate decay is considered to happen. In this aspect, mathematically formulates as

$$\theta_{l,m}^{t+1} = \zeta_i^t x_{i,m}^t + \varpi_1(\beta_1 b_m^t - \beta_2 \hat{x}_m^t) \tag{21}$$

$$\theta_{l+1,m}^{t+1} = \tau^t x_{i,m}^t + \frac{\varpi_2}{\zeta_i^t}\left(\beta_3 b_m^t - \beta_4 \tilde{x}_m^t\right) \tag{22}$$

where ϖ_1 and ϖ_2 are weight values, β_1 and β_3 are the random variable uniformly distributed within $[0,1]$, and similarly, β_2 and β_4 are the random variable uniformly distributed within $[-1,1]$, $\hat{x}_m^t$ denotes the m th center quantum particle variable, and $\tilde{x}_m^t$ is the m th neighboring quantum particle variable.

If $\zeta_i^t \leq \tau^t$, the quantum particle tends to undergo position emission. In this regard, the new quantum rotation is produced as

$$\theta_{l,m}^{t+1} = \varpi_3(x_{i,m}^t - b_m^t) + \zeta_i^t \rho_1(\hat{x}_m^t - \tilde{x}_m^t) \tag{23}$$

where ϖ_3 is weight value, ρ_1 is the random variable uniformly distributed within $[-1,1]$.

After that, new candidate quantum particles obey the following updating process based on quantum rotation as

$$\chi_{l,m}^{t+1} = \left| x_{i,m}^t \cos(\theta_{l,m}^{t+1}) + \sqrt{1-(x_{i,m}^t)^2} \sin(\theta_{l,m}^{t+1}) \right| \tag{24}$$

$$\chi_{l+1,m}^{t+1} = \left| x_{i,m}^t \cos(\theta_{l+1,m}^{t+1}) + \sqrt{1-(x_{i,m}^t)^2} \sin(\theta_{l+1,m}^{t+1}) \right| \tag{25}$$

where $\chi_{l,m}^{t+1}$ and $\chi_{l+1,m}^{t+1}$ represent new candidate quantum particles. For the quantum particle with higher NEL in which $\zeta_i^t > \tau^t$, there are two newly generated candidate quantum particles. For the quantum particle in which $\zeta_i^t \leq \tau^t$, only $\chi_{l,m}^{t+1}$ is generated.

Upon completion of the main loop within QEVO, the newly proposed quantum particles are incorporated into the existing population. The top D prominent particles are selected to form the new population for subsequent search iterations.

3.2 Process of QEVO-based Antenna Selection and Power Allocation

In this subsection, consider the implementation details of joint intelligent antenna selection and power allocation based on QEVO. As we have outlined in Section 2, our objective is to find the optimal antenna selection in BS and user transmit power for massive MIMO within IoT systems, with the ultimate goal of maximizing EE.

Hence, for the proposed QEVO, to ensure the diversity of quantum particles population, the initial variable for each quantum particle is randomly generated within a quantum interval $[0,1]$. The fitness function of t th iteration in the i th quantum particle is defined as follows

$$f(\bar{\boldsymbol{x}}_i^t)=\begin{cases}\varphi(\bar{\boldsymbol{x}}_i^t), & \text{satisfy the constrains in (12)}\\ 0, & \text{else}\end{cases} \tag{26}$$

where the position of quantum particle $\bar{\boldsymbol{x}}_i^t$ represents a set of parameters to be optimized, $\bar{\boldsymbol{x}}_i^t=[p_{i,1}^t,p_{i,2}^t,\ldots,p_{i,e}^t,\ldots,p_{i,E}^t,\varepsilon_i^t]$, where $\boldsymbol{p}_i^t=[p_{i,1}^t,p_{i,2}^t,\ldots,p_{i,E}^t]$ denotes a power allocation scheme, ε_i^t represents an antenna number choice for massive MIMO systems. The procedural steps involved in implementing the QEVO-based antenna selection and power allocation are succinctly summarized below.

Step 1: Establish the joint intelligent antenna selection and power allocation model discussed in Section 2, derive the energy efficiency equation, and identify variables for optimization.

Step 2: Randomly initialize the quantum particle and establish the parameter settings.

Step 3: Map the quantum particle $\boldsymbol{x}_i^t$ to its positions $\bar{\boldsymbol{x}}_i^t$, calculate the NEL ζ_i^t of each quantum particle based on equation (26), and mark the quantum particle with the best NEL as the global optimal quantum particle $\boldsymbol{b}^t$. Obtain the center quantum particle $\hat{\boldsymbol{x}}^t$ and the neighboring quantum particle $\tilde{\boldsymbol{x}}^t$.

Step 4: According to different decay processes quantum particles depended on stability level, perform the evolution process.

Step 5: Calculate the NEL, refresh the quantum particle population and the global optimal quantum particle.

Step 6: If the current iteration number is less than the maximum iteration count, proceed Step 4; otherwise, terminate whole iteration process, output the global optimal quantum particle. By applying mapping rules, determine the most effective antenna selection and power allocation strategy has been found for massive MIMO in IoT networks.

4. Simulation Results

In this section, considering different communication scenarios in IoT with massive MIMO systems, the simulation results are given to examine the efficacy of QEVO-based antenna selection and power allocation method.

4.1 Performance Comparison of QEVO

Consider a single-cell massive MIMO system comprising E IoT users, with a system bandwidth of B. In the simulation, it is that the BS is situated at $(0,0)$ m, has a coverage radius of 500 m, and the users are randomly distributed within this coverage. The communication network channel transmission model is based on [19]. Assume that all users possess identical maximum transmission power and circuit power consumption. Furthermore, all system noises are Gaussian white noise with power spectral density N_0. The specific parameters of massive MIMO systems are detailed in **Table 1**.

Table 1. Parameter settings for massive MIMO in IoT system.

Symbol	Parameter	Value
K	Antenna number	128
E	Number of IoT user device	5
r_0	Radius of the BS	100 m
v_0	Path loss exponent	3.8
η	Transmission efficiency	50%
p_k	Power consumption at antenna	0
$p_{c,e}$	Circuit power of IoT device e	10 dBm
$p_{\max}$	Maximum transmission power	30 dBm
B	System bandwidth	1 MHz
$r_{\min}$	Minimum achievable rate	1 Mbit / s
N_0	Noise power spectral density	-174 dBm / Hz

This study examines the performance of joint antenna selection and power allocation strategies for EE maximization. The strategies under consideration include QEVO, energy valley optimization (EVO), whale optimization algorithm (WOA), particle swarm optimization (PSO), Dinkelbach algorithm [24], and half-power allocation (HPA) [29] scheme. For the proposed QEVO, we set $\varpi_1 = 0.4$, $\varpi_2 = 0.15$, $\varpi_3 = 0.65$. For comparison purposes, the population size $D = 20$ and the dimension of considered problem M are the same within QEVO, EVO, WOA and PSO. The parameters for EVO, WOA, and PSO can be found in [27], [26], and [25], respectively. All results are the average of 100 simulations.

The energy efficiency of the system plotted against iteration count is depicted in **Fig. 2**. The results indicate that the proposed QEVO outperforms other algorithms such as the EVO, PSO, WOA, and Dinkelbach algorithm. Specifically, WOA and PSO exhibit slow convergence rates, EVO demonstrates rapid convergence but lacks robust optimization capabilities, while the Dinkelbach algorithm tends towards local convergence. This superior performance can be attributed to the QEVO ability to effectively integrate the benefits of both energy valley optimizer and quantum computing. The diverse range of quantum evolution strategies employed by QEVO significantly improves convergence speed. Furthermore, the evolution equation of quantum coding remains insensitive to the changes in each dimensional definition interval. Consequently, the QEVO algorithm overcomes the limitations of traditional intelligent optimization algorithms and the Dinkelbach propensity for local optimum solutions. It successfully identifies an antenna selection and power allocation scheme that maximizes system EE in massive MIMO systems while satisfying transmission requirements of IoT devices.

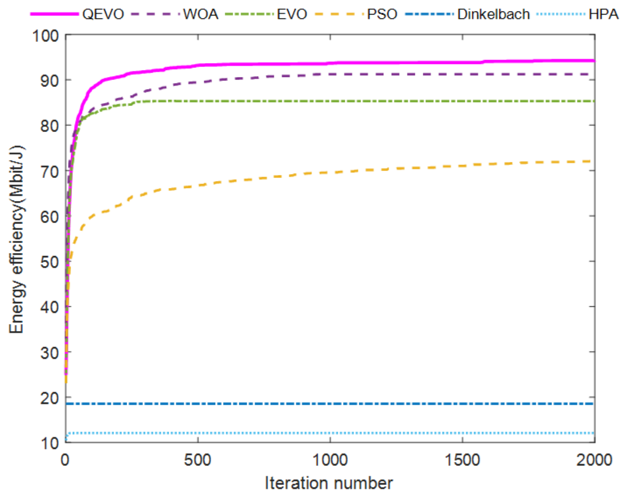

Fig. 2. Convergence curves of 6 algorithms with system EE

Fig. 3 shows the simulation results demonstrated the maximum transmission power of users within 20 to 40 dBm. As the user number increases, the EE of both QEVO and WOA tends towards stability. Notably, QEVO exhibits superior performance when the IoT user transmission power is substantial. The optimization capability of the EVO fluctuates with changes in user transmission power. Furthermore, the system EE of PSO, Dinkelbach, and HPA methods diminishes as the maximum transmission power of users escalates. The simulation results underscore the robust global optimization ability of the QEVO. The iteration number of each algorithm are 500 times, and setup with the same number at the following simulation form **Figs. 4** to **7**.

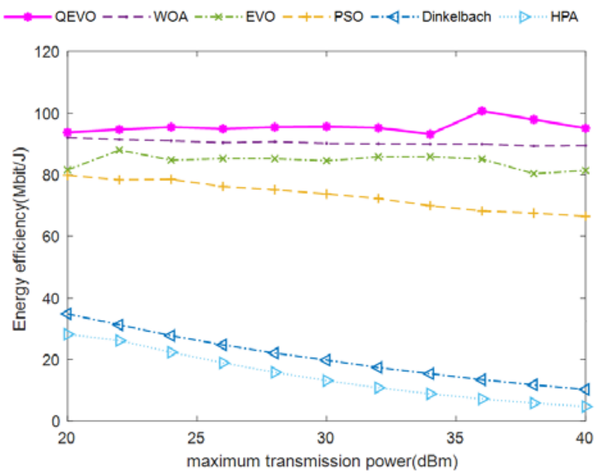

Fig. 3. System EE comparison of 6 algorithms with maximum IoT user transmission power

The curve of system EE comparison of 6 algorithms with IoT device illustrated in **Fig. 4**. Results indicate that as the number of IoT devices increases, systems EE for massive MIMO diminishes. This decline can be attributed to co-channel interference between users, which escalates with an increase in user count. Additionally, the SNR from the BS to users diminishes, leading to a reduction in user transmission rates. Concurrently, system energy consumption rises with increasing numbers. Under identical conditions, QEVO achieves optimal system EE. The number of BS antennas and IoT user devices are assumed to remain constant.

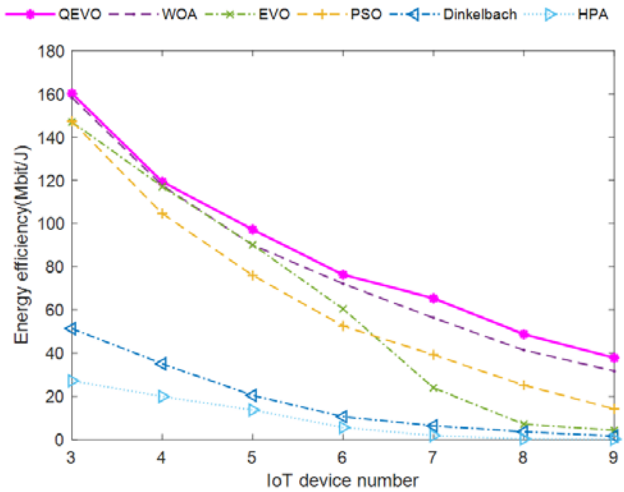

Fig. 4. System EE comparison of 6 algorithms with IoT device number

4.2 Impact of Different Parameters

In the subsequent subsection, we explore the influence of various system parameters on the efficacy of our proposed joint antenna selection and power allocation scheme.

Fig. 5 shows the curve of EE versus different antenna selection coefficient ε and IoT device number E , which considers that increases from 0.1 to 1, while the number of IoT users is set at 3, 5, 7, 9, and 11 respectively. The data suggests that when ε remains constant, there is a direct correlation between EE and the increase in user number. In other words, as user number remains constant, a lower ε corresponds to higher EE. Consequently, for smaller user populations, judiciously reducing antenna number involved in BS communication can significantly decrease system energy consumption and improve EE. However, as the IoT device number escalates, adding more antennas to the communication has minimal impact on EE. As the IoT device number escalates, adding more antennas to the communication has minimal impact on EE.

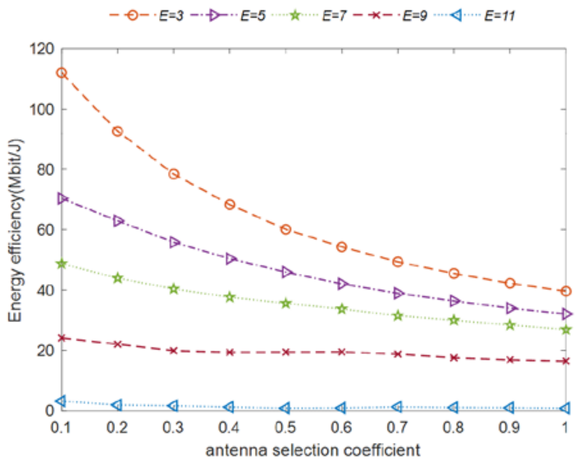

Fig. 5. System EE comparison with different antenna selection coefficient and IoT device number

Fig. 6 shows curves of EE with the variation of different antenna number, where the antenna number K increases from 50 to 500 in the simulation experiment. In **Fig. 6**, antenna selection coefficient ε takes values from 0.1 to 0.9 with an interval of 0.2, respectively. As can be inferred, both antenna selection coefficient and antenna number exert a significant influence on EE. It is mostly attributed to the fact that with a fixed antenna selection coefficient, an extensive increase in antenna number equipped in the base station invariably elevates the system power consumption. Conversely, when antenna number is held constant, selecting fewer antennas can effectively reduce the power consumption among whole communication system. However, within the context of practical communication systems, it is imperative to consider user data transmission demands. Unilaterally reducing the number of antennas utilized in communication to enhance EE is not feasible. To ensure system reliability, the joint antenna selection and power allocation method we proposed can modify the antenna selection coefficient and transmission power of IoT user device in response to changes antenna number.

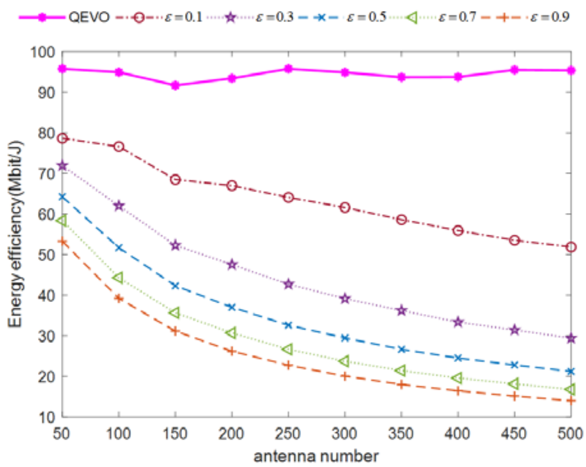

Fig. 6. System EE comparison of two antenna selection methods with different antenna number and antenna selection coefficient

Fig. 7 illustrates the system EE comparison of 6 algorithms with different antenna number. As the simulation results shows in **Fig. 7**, the intelligence algorithms significantly outperform Dinkelbach and HPA in scenarios involving a large number of antennas. Compare to WOA, EVO and PSO, the novel intelligent algorithm QEVO proposed this paper can achieve maximum EE when fixed the antenna selection coefficient $\varepsilon = 0.1$ of the BS.

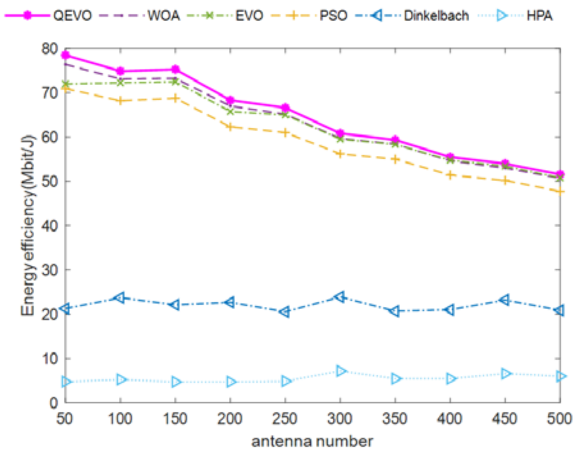

Fig. 7. System EE comparison of 6 algorithms with different antenna number ($\varepsilon = 0.1$)

As illustrated in **Figs. 2** to **7**, it is evident that QEVO consistently outperforms other methods across all tested conditions. Given a fixed maximum user transmission power, due to the superior EE of the QEVO-based joint antenna selection and power allocation method, it requires less transmission time to complete identical data transmission tasks. When compared to other strategies, the method proposed achieves maximum EE and can be applied to practical IoT networks design.

5. Conclusion

This paper introduces an advanced method achieved joint intelligent antenna selection and power allocation for massive MIMO in IoT networks. This approach takes into account the varying transmission demands of users across different time slots in practical communication systems. It derives a maximum EE equation specific to massive MIMO systems and employs a QEVO to address this complex, nonlinear, multi-constraint optimization problem associated with antenna selection and power allocation. The proposed QEVO integrates the benefits of quantum computing with the principles of energy valley optimization. Simulation results demonstrate that method we proposed, grounded on QEVO, is not only capable of meeting the real-time data transmission requirements of users but also significantly enhances EE. In various simulation scenarios, the proposed method outperforms existing algorithms and alternative intelligent algorithms technique. The algorithm introduced in this study can extend to intricate engineering problems. In subsequent research, we aim to incorporate additional performance metrics and practical constraints in intelligent extreme massive MIMO systems. Alternatively, multi-objective optimization algorithms can yield a more balanced outcome particularly within the intricate communication scenarios of a sea-air-ground network.

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