

LETTER

Energy Efficiency Optimization for MISO-NOMA SWIPT System with Heterogeneous QoS Requirements

Feng LIU[†], Xianlong CHENG[†], Conggai LI^{†a)}, *Nonmembers*, and Yanli XU[†], *Member*

SUMMARY This letter solves the energy efficiency optimization problem for the simultaneous wireless information and power transfer (SWIPT) systems with non-orthogonal multiple access (NOMA), multiple input single output (MISO) and power-splitting structures, where each user may have different individual quality of service (QoS) requirements about information and energy. Nonlinear energy harvesting model is used. Alternate optimization approach is adopted to find the solution, which shows a fast convergence behavior. Simulation results show the proposed scheme has higher energy efficiency than existing dual-layer iteration and throughput maximization methods.

key words: SWIPT, NOMA, MISO, heterogeneous QoS, energy efficiency

1. Introduction

Simultaneous wireless information and power transfer (SWIPT) is considered as an effective technology to satisfy the terminal's energy requirement [1]. Pursuing high energy efficiency (EE) is a trend for the future green wireless communications.

Multiple antenna technology has been considered to improve the transmission efficiency of the SWIPT system [2]. On the other hand, non-orthogonal multiple access (NOMA) can improve the EE performance [3]. The combination of SWIPT and NOMA has aroused great interest, which can significantly increase wireless power transmission without affecting information decoding [4].

The SWIPT receiver can work in two structures, namely power splitting (PS) and time switching (TS), to decode the information and harvest energy. The TS receiver often causes high complexity due to global search [5]. In contrast, the PS receiver is easier than the TS structure. However, the EE performance of existing approaches such as the dual-layer iteration algorithm [5] are still not satisfactory enough.

This letter studies the EE optimization of the SWIPT system combining multiple input single output (MISO), NOMA, and PS structures with heterogeneous quality of service (QoS) requirements about information and energy for each user. Nonlinear energy harvesting (EH) model is used, while linear model is also applicable. The original problem is non-convex and intractable. To find a solution, transformations are made step by step with the Dinkelbach and semi-definite relaxation (SDR) methods. Then alternate op-

timization with two convex subproblems is obtained, which can be efficiently solved. The proposed scheme has low complexity, fast convergence, and better EE performance. Simulation results are provided to verify its efficiency.

2. System Model and Problem Formulation

2.1 System Model

The system consists of a base station (BS) and K PS-based users, equipped with N_t and single antenna respectively. Let R_{\min}^k and E_{\min}^k denote the heterogeneous QoS requirements about information and energy for the k th user, respectively. The QoS requirements are often different among users and should be satisfied for all users simultaneously.

With NOMA, successive interference cancellation (SIC) is used to cancel multi-user interference at receivers. The transmitted signal at BS is

$$\mathbf{x} = \sum_{k=1}^K \mathbf{w}_k s_k \quad (1)$$

where $\mathbf{w}_k \in \mathbb{C}^{N_t \times 1}$ denotes the transmit beamforming vector, and s_k is the transmitted symbol with $\mathbb{E}[s_k s_k^*] = 1$.

Denote the channel gain from the BS to the k th user as \mathbf{h}_k , where $\mathbf{h}_k \in \mathbb{C}^{1 \times N_t}$. The received signal at receiver k is

$$y_k = \mathbf{h}_k \sum_{j=1}^K \mathbf{w}_j s_j + n_k \quad (2)$$

where $n_k \sim \mathcal{CN}(0, \sigma_k^2)$ is the additive white Gaussian noise.

According to PS with power splitting factor ρ , the received signal for ID is

$$y_k^I = \sqrt{\rho} y_k + z_k \quad (3)$$

where $z_k \sim \mathcal{CN}(0, \delta_k^2)$ denotes additional white Gaussian noise introduced during ID at user k . Similarly, the corresponding received signal available for EH at user k is

$$y_k^E = \sqrt{1 - \rho} y_k \quad (4)$$

SIC is used at receivers to perform multi-user detection (MUD) [6]. Without loss of generality, we assume that the channel gains are sorted such that $|\mathbf{h}_1| \leq |\mathbf{h}_2| \leq \dots \leq |\mathbf{h}_K|$. The sum rate can be written as

Manuscript received March 13, 2022.

Manuscript revised June 20, 2022.

Manuscript publicized August 18, 2022.

[†]The authors are with the College of Information Engineering, Shanghai Maritime University, Shanghai, China.

a) E-mail: cgli@shmtu.edu.cn

DOI: 10.1587/transfun.2022EAL2025

$$R_{\text{sum}} = \sum_{k=1}^K \log_2 \left(1 + \frac{\rho_k |\mathbf{h}_k \mathbf{w}_k|^2}{\delta_k^2 + \rho_k \sigma_k^2 + \rho_k \sum_{i=k+1}^K |\mathbf{h}_k \mathbf{w}_i|^2} \right) \quad (5)$$

According to [7], we consider a nonlinear EH model. The total harvested power is expressed as

$$\begin{aligned} E_{\text{total}} &= \sum_{k=1}^K E_k = \sum_{k=1}^K \frac{A_k - a_3 \cdot B}{1 - B} \\ A_k &= \frac{a_3}{1 + \exp(-a_1 \cdot (P_k^{\text{in}} - a_2))} \\ B &= \frac{1}{1 + \exp(a_1 \cdot a_2)} \end{aligned} \quad (6)$$

where E_k is the harvested power for user k , a_1 and a_2 are the constants determined by its detailed circuits, a_3 denotes the maximum harvested power in the saturated region, and P_k^{in} is input power of energy harvester for user k :

$$P_k^{\text{in}} = (1 - \rho_k) \left(\sum_{j=1}^K |\mathbf{h}_k \mathbf{w}_j|^2 + \sigma_k^2 \right) \quad (7)$$

2.2 Problem Formulation

The EE measurement is defined as the ratio between the sum rate R_{sum} and the total power consumption P_{total} .

The energy consumption can be expressed as

$$P_{\text{total}} = \zeta \sum_{k=1}^K \|\mathbf{w}_k\|^2 + P_c - E_{\text{total}} \quad (8)$$

where ζ is the power inefficiency of amplifier, P_c stands for the constant power consumption of the transceivers.

According to (8), the EE expression is given by

$$\lambda_{\text{EE}}(\mathbf{w}_k, \rho_k) = \frac{\sum_{k=1}^K \log_2 \left(1 + \frac{\rho_k |\mathbf{h}_k \mathbf{w}_k|^2}{\delta_k^2 + \rho_k \sigma_k^2 + \rho_k \sum_{i=k+1}^K |\mathbf{h}_k \mathbf{w}_i|^2} \right)}{\zeta \sum_{k=1}^K \|\mathbf{w}_k\|^2 + P_c - E_{\text{total}}} \quad (9)$$

The EE optimization problem can be formulated as

$$\mathbf{P1} : \max_{\mathbf{w}_k, \rho_k} \lambda_{\text{EE}}(\mathbf{w}_k, \rho_k) \quad (10a)$$

$$\text{s.t. } R_k \geq R_{\text{min}}^k \quad (10b)$$

$$\sum_{k=1}^K \frac{A_k - a_3 \cdot B}{1 - B} \geq E_{\text{min}}^k \quad (10c)$$

$$\sum_{k=1}^K \|\mathbf{w}_k\|^2 \leq P_{\text{max}} \quad (10d)$$

$$0 \leq \rho_k \leq 1 \quad (10e)$$

3. Proposed Algorithm

3.1 Non-Linear Problem Transformation

According to the Dinkelbach method [8], with a given parameter λ , the original problem P1 can be recast as

$$\begin{aligned} \mathbf{P2} : \max_{\mathbf{w}_k, \rho_k} & R_{\text{sum}} - \lambda P_{\text{total}} \\ \text{s.t. } & (10b) - (10e) \end{aligned} \quad (11)$$

3.2 Solution to Problem P2

Based on Dinkelbach method, we propose an iterative algorithm for solving problem P2 as Algorithm 1.

In order to solve the non-convex problem of the quadratic terms of \mathbf{w}_k and ρ_k in P2, we introduce the SDR method. The optimization problem P2 can be transformed into P3 as

$$\mathbf{P3} : \max_{\mathbf{W}_k, \rho_k} \sum_{k=1}^K \log_2(1 + \text{SINR}_k) - \lambda P_{\text{total}} \quad (12a)$$

$$\text{s.t. } \log_2(1 + \text{SINR}_k) \geq R_{\text{min}}^k \quad (12b)$$

$$\sum_{k=1}^K \frac{A_k - a_3 \cdot B}{1 - B} \geq E_{\text{min}}^k \quad (12c)$$

$$\sum_{k=1}^K \text{Tr}(\mathbf{W}_k) \leq P_{\text{max}} \quad (12d)$$

$$0 \leq \rho_k \leq 1 \quad (12e)$$

$$\text{Tr}(\mathbf{W}_k) \geq 0 \quad (12f)$$

$$\mathbf{W}_k \geq \mathbf{0} \quad (12g)$$

$$R(\mathbf{W}_k) = 1 \quad (12h)$$

where we define

$$\text{SINR}_k \triangleq \frac{\rho_k \text{Tr}(\mathbf{H}_k \mathbf{W}_k)}{\sigma_{id_k}^2 + \rho_k \sigma_k^2 + \rho_k \sum_{i=k+1}^K \text{Tr}(\mathbf{H}_k \mathbf{W}_i)} \quad (13)$$

Algorithm 1 Proposed iterative algorithm based on the Dinkelbach method for solving P2

-
- 1: Initialize: $\lambda^{(0)} = 0$, $n = 0$, and set $\epsilon \geq 0$ as the maximum tolerance;
 - 2: **repeat**
 - 3: Obtain the solution $\mathbf{w}_k^{(n)}$ and $\rho_k^{(n)}$ by solving P2 with fixed $\lambda^{(n)}$;
 - 4: **if** $R_{\text{sum}}(\mathbf{w}_k^{(n)}, \rho_k^{(n)}) - \lambda^{(n)} P_{\text{total}}(\mathbf{w}_k^{(n)}, \rho_k^{(n)}) \leq \epsilon$ **then**
 - 5: Convergence = True;
 - 5: Return $\mathbf{w}_k^* = \mathbf{w}_k^{(n)}$ and $\rho_k^* = \rho_k^{(n)}$;
 - 6: **else**
 - 7: Convergence = False, and $n = n + 1$;
 - 7: $\lambda^{(n)} = \frac{R_{\text{sum}}(\mathbf{w}_k^{(n)}, \rho_k^{(n)})}{P_{\text{total}}(\mathbf{w}_k^{(n)}, \rho_k^{(n)})}$;
 - 8: **end if**
 - 9: **until** Convergence=True.
-

$$P_{\text{total}} \triangleq \zeta \sum_{k=1}^K \text{Tr}(\mathbf{W}_k) + P_c - E_{\text{total}} \quad (14)$$

and $\text{Tr}(\cdot)$ denotes the trace operation of a matrix.

By adopting the SDR method with dropping the rank-one constrains [9], P3 can be relaxed as

$$\begin{aligned} \mathbf{P3}' : \max_{\mathbf{W}_k, \rho_k} & \sum_{k=1}^K \log_2(1 + \text{SINR}_k) \\ & - \lambda(\zeta \sum_{k=1}^K \text{Tr}(\mathbf{W}_k) + P_c - E_{\text{total}}) \\ \text{s.t.} & (12b) - (12g) \end{aligned} \quad (15)$$

Problem P3' is still non-convex because of the coupling variables \mathbf{W}_k and ρ_k . We turn to the alternate optimization approach to find an approximate solution.

3.3 Alternate Optimization Solution to Problem P3'

Since the two variables \mathbf{W}_k and ρ_k are involved, we need to optimize one by fixing the other. Firstly, we calculate the optimal \mathbf{W}_k according to a fixed ρ_k . Then, we calculate optimal ρ_k with the obtained \mathbf{W}_k in the first step. In such an alternate way, the solution can be iteratively converged.

3.3.1 Optimize \mathbf{W}_k with Fixed ρ_k

The power splitting factor ρ_k should be properly initialized. Meanwhile, the SINR expression has a complex fractional form. Here we introduce an auxiliary variable γ to replace the SINR. Then, we can reformulate P3' as

$$\mathbf{P4} : \max_{\mathbf{W}_k, \gamma_k} \sum_{k=1}^K \log_2(1 + \gamma_k) - \lambda P_{\text{total}} \quad (16a)$$

$$\text{s.t.} \frac{\rho_k \text{Tr}(\mathbf{H}_k \mathbf{W}_k)}{\sigma_{id_k}^2 + \rho_k \sigma_k^2 + \rho_k \sum_{i=k+1}^K \text{Tr}(\mathbf{H}_k \mathbf{W}_i)} \geq \gamma_k \quad (16b)$$

$$\gamma_k \geq 2^{R_{\min}^k} - 1 \quad (16c)$$

$$\sum_{k=1}^K \frac{A_k - a_3 \cdot B}{1 - B} \geq E_{\min}^k \quad (16d)$$

$$\sum_{k=1}^K \text{Tr}(\mathbf{W}_k) \leq P_{\max} \quad (16e)$$

$$\text{Tr}(\mathbf{W}_k) \geq 0 \quad (16f)$$

$$\mathbf{W}_k \geq \mathbf{0} \quad (16g)$$

However, due to the fractional variable coupling in the constraint (16b), the optimization problem is still non-convex. Constrains (16b) can be transformed to

$$\left(\sigma_{id_k}^2 / \rho_k + \sigma_k^2 + \sum_{i=k+1}^K \text{Tr}(\mathbf{H}_k \mathbf{W}_i) \right) \gamma_k \leq \text{Tr}(\mathbf{H}_k \mathbf{W}_k) \quad (17)$$

As shown in formula (17), we can see that it conforms to the basic form of the algorithm-geometric mean (AGM) inequality. For any non-negative optimization variables x , y , z , the inequality $xy \leq z$ can be relaxed as

$$xy \leq (ax)^2 + (y/a)^2 \leq 2z \quad (18)$$

where the equality holds true if and only if $a = \sqrt{y/x}$. Consequently, an approximation of (17) is given by

$$\begin{aligned} & \left(a^{(n)} \gamma_k \right)^2 + \left(\frac{\sigma_{id_k}^2}{a^{(n)} \rho_k} + \frac{\sigma_k^2 + \sum_{i=k+1}^K \text{Tr}(\mathbf{H}_k \mathbf{W}_i)}{a^{(n)}} \right)^2 \\ & \leq 2 \text{Tr}(\mathbf{H}_k \mathbf{W}_k) \end{aligned} \quad (19)$$

where $a^{(n)}$ represents the updated value of a after n iterations. Therefore, problem P4 can be reformulated as P4':

$$\mathbf{P4}' : \max_{\mathbf{W}_k, \gamma_k} \sum_{k=1}^K \log_2(1 + \gamma_k) - \lambda P_{\text{total}} \quad (20a)$$

$$\text{s.t.} (19) \quad (20b)$$

$$(16c) - (16g) \quad (20c)$$

When the value of $a^{(n)}$ is given, problem P4' is convex, which can be efficiently solved by tools such as CVX.

3.3.2 Optimize ρ_k with Fixed \mathbf{W}_k

Now, the optimal \mathbf{W}_k has been obtained, based on which we can find the corresponding optimal ρ_k . In a similar way, we can reformulate P3' as

$$\mathbf{P5} : \max_{\rho_k, \gamma_k} \sum_{k=1}^K \log_2(1 + \gamma_k) - \lambda P_{\text{total}} \quad (21a)$$

$$\text{s.t.} \frac{\rho_k \text{Tr}(\mathbf{H}_k \mathbf{W}_k)}{\sigma_{id_k}^2 + \rho_k \sigma_k^2 + \rho_k \sum_{i=k+1}^K \text{Tr}(\mathbf{H}_k \mathbf{W}_i)} \geq \gamma_k \quad (21b)$$

$$\gamma_k \geq 2^{R_{\min}^k} - 1 \quad (21c)$$

$$\sum_{k=1}^K \frac{A_k - a_3 \cdot B}{1 - B} \geq E_{\min}^k \quad (21d)$$

$$0 \leq \rho_k \leq 1 \quad (21e)$$

Similarly, there is coupling of ρ_k and γ_k in the constraint (21b). Again by the above AGM inequality, an approximation of (21b) is

$$\begin{aligned} & \left(b^{(n)} \gamma_k \right)^2 + \left(\frac{\sigma_{id_k}^2}{b^{(n)} \rho_k} + \frac{\sigma_k^2 + \sum_{i=k+1}^K \text{Tr}(\mathbf{H}_k \mathbf{W}_i)}{b^{(n)}} \right)^2 \\ & < 2 \text{Tr}(\mathbf{H}_k \mathbf{W}_k) \end{aligned} \quad (22)$$

Therefore, problem P5 can be reformulated as P5'

Table 1 Algorithm complexity analysis.

Algorithm	COMPLEXITY ANALYSIS
Proposed algorithm	$O\left(K^{2.376} \frac{1}{\epsilon^2} \log(K) \left(\log\left(\frac{1}{\epsilon}\right)\right)^2\right)$
Dual research	$O\left(K^{3.376} \frac{1}{\epsilon^4} \log(K)^2 \left(\log\left(\frac{1}{\epsilon}\right)\right)\right)$

$$\mathbf{P5}' : \max_{\rho_k, \gamma_k} \sum_{k=1}^K \log_2(1 + \gamma_k) - \lambda P_{\text{total}} \quad (23a)$$

$$s.t. \quad (22) \quad (23b)$$

$$(21c) - (21e) \quad (23c)$$

When $b^{(n)}$ is given, $\mathbf{P5}'$ is a convex optimization problem, which can be efficiently solved.

3.4 Complexity Analysis

The computational complexity of the SIC operation is approximately of order $O(K^{2.376})$ [10]. The complexity of the Dinkelbach method is $O(\frac{1}{\epsilon^2} \log(K))$ [8]. The complexity of the alternative optimization procedure is $O(\log(\frac{1}{\epsilon}))$. The total complexity can be approximately expressed as $O(K^{2.376} \frac{1}{\epsilon^2} \log(K) (\log(\frac{1}{\epsilon}))^2)$. For comparison, we present the algorithm complexity of our proposed algorithm and the dual-layer approximation algorithm [5] in Table 1. When the number of users is at a large scale, the complexity of our proposed algorithm will be much lower than that in [5].

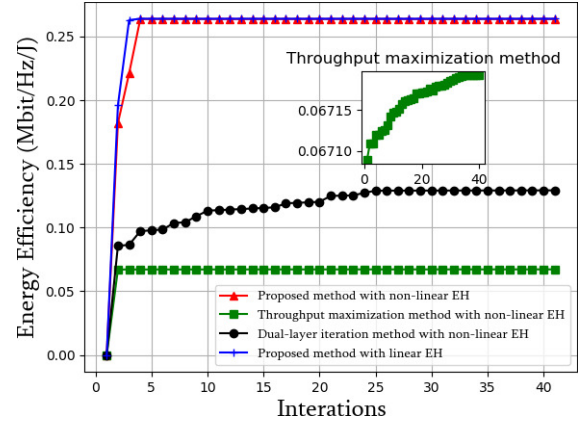
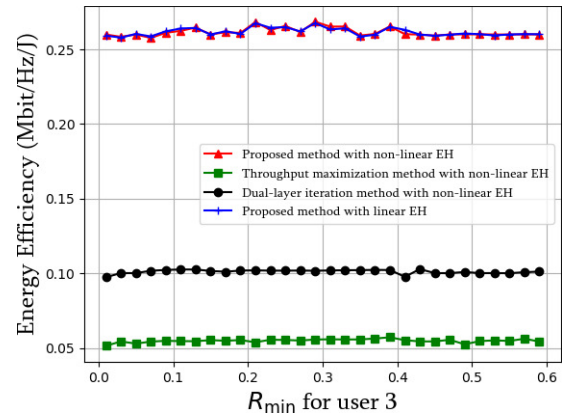
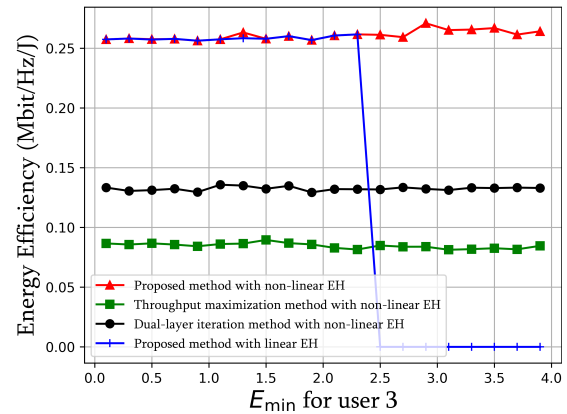
4. Simulation Results

In this section, we provide simulation to verify our scheme. The CVXPY with MOSEK solver is used in the Python platform. Basic parameter configuration is set as $K = 3$, $P_{\text{max}} = 20\text{W}$. For comparison, we also provide the simulation results of our proposed method with the linear EH model, where the harvested power by user k is expressed as

$$E_k^{\text{linear}} = \eta(1 - \rho_k) \left(\sum_{j=1}^K |h_k w_j|^2 + \sigma_k^2 \right) \quad (24)$$

where η is the power conversion efficiency. In the simulation it is set as 0.1 for all users.

Firstly, the convergence of EE performance with different QoS for each user is compared with that of the dual-layer iteration algorithm in [5] and throughput maximization method referring to [11]. We set R_{\min} as 0.001 Mbit/s, 0.02 Mbit/s, 0.4 Mbit/s and E_{\min} as 0.1 W, 0.2 W, 0.4 W for user 1 to 3, respectively. As shown in Fig. 1, we can see that the proposed algorithm has faster convergence speed than the dual-layer iteration method. Four iterations are good enough for our algorithm. Moreover, the achieved EE performance is about 2- and 4-fold increase of that by methods in [5] and [11], respectively. Although the throughput maximization method also shows a fast convergence, its EE performance is the lowest among these three methods. The proposed method with linear EH model shows a little bit EE improvement than

**Fig. 1** Convergence comparison of the EE performance.**Fig. 2** EE performance versus R_{\min} for user 3.**Fig. 3** EE performance versus E_{\min} for user 3.

the one with nonlinear EH model.

Then we do simulations to show the effect of increasing QoS on the EE performance. Both rate and power aspects are considered, as shown in Fig. 2 and Fig. 3, respectively. For the simulation of Fig. 2, we set the information rate requirements R_{\min} for users 1 and 2 to be 0.001 Mbit/s and 0.02 Mbit/s, and set E_{\min} for users 1/2/3 as 0.01 W, 0.2 W, 0.4 W respectively. The information rate requirement of

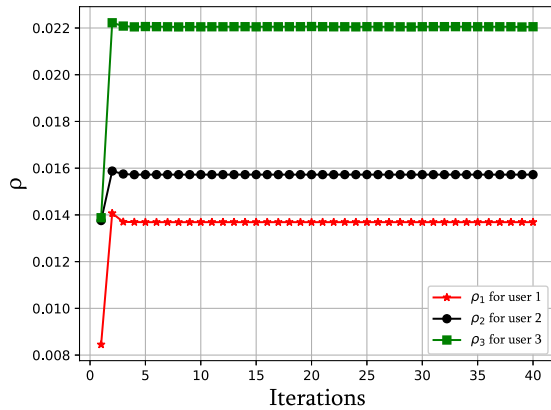


Fig. 4 Convergence behavior of ρ for each user.

user 3 is set from 0.001 Mbit/s to 0.6 Mbit/s. Fig. 2 shows the EE results of the systems versus R_{\min} for user 3. It can be seen that the change of the minimum information rate requirement of user 3 has little effect on the system energy efficiency, which is basically maintained at a horizontal level with some fluctuations. This phenomenon repeats with little difference from Fig. 3, which covers the range of User 3's minimum EH requirements, from 0.01 W to 4 W. In this simulation of Fig. 3, we set the minimum EH requirements for users 1 and 2 to be 0.01 W and 0.2 W, and set R_{\min} for the three users as 0.001 Mbit/s, 0.02 Mbit/s, 0.4 Mbit/s, respectively. From Fig. 3, we can see that as the minimum EH requirement for user 3 continues to increase, the energy efficiency of the proposed method with the linear EH model drops to 0 at $E_{\min} = 2.5$ W. This is due to the failure of the CVXPY solver for the linear EH model. However, the proposed method with nonlinear EH model still works and significantly outperforms the dual-layer iteration and throughput maximization methods. From Fig. 2 and Fig. 3, we can see that the proposed method shows nearly the same EE performance for both cases, while the other two methods show quite different EE levels. This phenomenon may be due to the fact that the scope of our investigation is not large enough. In fact, with the increase of R_{\min} or E_{\min} , each scheme will not support the required QoS from a certain point, resulting in zero EE.

Finally, we also provide the convergence behavior of the power splitting factor for different users, as shown in Fig. 4. We set R_{\min} as 0.001 Mbit/s, 0.02 Mbit/s, 0.4 Mbit/s and E_{\min} as 0.001 W, 0.02 W, 0.4 W for users 1/2/3, respectively. As the iteration progresses, each ρ_k quickly converges as the EE performance in Fig. 1. The difference of the converged values of ρ among the three users might be caused by the NOMA mechanism, which requires different power levels for each user.

5. Conclusion

In this letter, we addressed the EE optimization of the SWIPT system with MISO, NOMA and PS structure. The heterogeneous QoS support can help each user obtain its individual demand for information and energy. By some mathematical transformations, the original problem can be well solved in an alternate way. The proposed method shows a lower complexity and higher EE performance than the others.

Acknowledgments

This research was funded by the Innovation Program of Shanghai Municipal Education Commission of China under Grant 2021-01-07-00-10-E00121 and the Natural Science Foundation of Shanghai under Grant 20ZR1423200.

References

- [1] K. Xu, M. Zhang, J. Liu, N. Sha, and L. Chen, "SWIPT in mMIMO system with non-linear energy-harvesting terminals: Protocol design and performance optimization," *EURASIP J. Wireless Commun. Networking*, vol.2019, no.1, 2019.
- [2] Y. Lu, K. Xiong, P. Fan, Z. Ding, Z. Zhong, and K.B. Letaief, "Secrecy energy efficiency in multi-antenna SWIPT networks with dual-layer PS receivers," *IEEE Trans. Wireless Commun.*, vol.19, no.6, pp.4290–4306, 2020.
- [3] J. Zhou, Y. Sun, Q. Cao, S. Li, H. Xu, and W. Shi, "QoS-based robust power optimization for SWIPT NOMA system with statistical CSI," *IEEE Trans. Green Commun. Netw.*, vol.3, no.3, pp.765–773, 2019.
- [4] P.D. Diamantoulakis, K.N. Pappi, Z. Ding, and G.K. Karagiannidis, "Wireless-powered communications with non-orthogonal multiple access," *IEEE Trans. Wireless Commun.*, vol.15, no.12, pp.8422–8436, 2016.
- [5] J. Tang, J. Luo, M. Liu, D.K.C. So, E. Alsusa, G. Chen, K.K. Wong, and J.A. Chambers, "Energy efficiency optimization for NOMA with SWIPT," *IEEE J. Sel. Topics Signal Process.*, vol.13, no.3, pp.452–466, 2019.
- [6] S.M.R. Islam, N. Avazov, O.A. Dobre, and K.s. Kwak, "Power-domain non-orthogonal multiple access (NOMA) in 5G systems: Potentials and challenges," *IEEE Commun. Surveys Tuts.*, vol.19, no.2, pp.721–742, 2017.
- [7] S. Mao, S. Leng, J. Hu, and K. Yang, "Power minimization resource allocation for underlay MISO-NOMA SWIPT systems," *IEEE Access*, vol.7, pp.17247–17255, 2019.
- [8] W. Dinkelbach, "On nonlinear fractional programming," *Management Science*, vol.13, no.7, pp.492–498, 1967.
- [9] J. Liu, K. Xiong, Y. Lu, P. Fan, Z. Zhong, and K.B. Letaief, "SWIPT-enabled full-duplex NOMA networks with full and partial CSI," *IEEE Trans. Green Commun. Netw.*, vol.4, no.3, pp.804–818, 2020.
- [10] X. Huang and V.Y. Pan, "Fast rectangular matrix multiplication and applications," *J. Complexity*, vol.14, no.2, pp.257–299, 1998.
- [11] J. Tang, Y. Yu, M. Liu, D.K.C. So, X. Zhang, Z. Li, and K.K. Wong, "Joint power allocation and splitting control for SWIPT-enabled NOMA systems," *IEEE Trans. Wireless Commun.*, vol.19, no.1, pp.120–133, 2020.