Bi-Objective Optimization of Information Rate and Harvested Power in RIS-Aided SWIPT Systems

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Abstract—The problem of simultaneously optimizing the information rate and the harvested power in a reconfigurable intelligent surface (RIS)-aided multiple-input single-output downlink multiuser wireless network with simultaneous wireless information and power transfer (SWIPT) is addressed. The beamforming vectors, RIS reflection coefficients, and power split ratios are jointly optimized subject to maximum power constraints, minimum harvested power constraints, and realistic constraints on the RIS reflection coefficients. A practical algorithm is developed through an interplay of alternating optimization, sequential optimization, and penalty-based methods. Numerical results show that the deployment of RISs jointly improves the information rate and the amount of harvested power.

Index Terms—RIS, SWIPT, multi-objective optimization.

I. INTRODUCTION

RECONFIGURABLE intelligent surfaces (RISs) have emerged as a promising technology for sustainable sixth-generation (6G) networks [1], [2]. Thanks to their ability of reflecting and refracting electromagnetic signals in a reconfigurable fashion and with limited energy requirements, RISs can drastically reduce the energy consumption in wireless networks [3]. In this context, RISs have also been studied in conjunction with simultaneous wireless information and power transfer (SWIPT), which is another key technology to improve the energy sustainability of future wireless networks.

Several studies show that the deployment of RISs can improve both the information and power transfer. In [4], the problem of transmit power minimization subject to quality of service (QoS) constraints and minimum energy harvesting requirements is addressed. The optimization problem is tackled by means of a penalty-based algorithm coupled with the alternating optimization technique. In [5], the problem of transmit power minimization for an RIS-assisted SWIPT non-orthogonal multiple-access (NOMA) network is investigated. A two-stage optimization algorithm is proposed to jointly optimize the transmit beamforming vector, the power-split ratio, and the RIS phase shifts under QoS constraints. Semidefinite relaxation coupled with alternating and sequential optimization methods are employed. In [6], the problem of maximizing the weighted sum-rate is investigated in a SWIPT-based multi-user multiple-input multiple-output (MIMO) downlink system, subject to minimum harvested energy constraints. Alternating optimization is used in conjunction with sequential optimization and pricing methods.

In [7], the authors study the problem of resource allocation in RIS-aided SWIPT-based systems, in which a large RIS is split into several tiles that are designed for reducing the computational complexity. A globally optimal algorithm and a practical approach are developed by means of branch-and-bound and sequential methods. In [8], the trade-off between the sum-rate maximization and total harvested power is investigated. The \( \epsilon \)-method coupled with alternating optimization is used to tackle the resulting multi-objective problem. In [9], the data rate maximization problem in an RIS-aided system in which multiple receivers perform information decoding and wireless power reception is analyzed. The problem is tackled by alternating optimization, sequential optimization, and sub-gradient methods.

This letter considers a network in which a multiple-antenna access point (AP) serves single-antenna users with the aid of an RIS. Each receiver jointly performs information decoding and wireless power harvesting by means of power splitting. Unlike previous works, the following contributions are made.

1) We consider the novel bi-objective simultaneous maximization of the information rate and harvested power, subject to minimum downlink rate, minimum harvested power, and maximum transmit power constraints. The resulting non-convex problem is tackled by an interplay of alternating maximization, sequential optimization, and penalty-based methods. Since the receivers perform both information decoding and wireless power harvesting, the optimization of the power split ratio is needed, which is a novel feature compared to most related works on RIS-aided and SWIPT-based systems.

2) We consider the realistic case in which the phases and moduli of the RIS reflection coefficients are not independent of one another, but are coupled by a deterministic function. This further complicates the scenario, making it challenging to find performing resource allocations at an affordable complexity.

3) Numerical results confirm the effectiveness of the proposed algorithm compared to traditional approaches. It is found, in particular, that increasing the number of RIS elements allows harvesting enough power, while at the same time supporting satisfactory sum-rate levels.

Among previous works, [8] and [9] are the most closely related to our work. However, [8] investigates the rate and
harvested energy trade-off for separated information and power receivers, i.e., each receiver performs either information decoding or wireless power harvesting. Also, independent phases and moduli are assumed for the RIS reflection coefficients. In addition, [9] considers integrated information harvesting and independent power receivers, i.e., each receiver performs either information or wireless power harvesting. Also, independent phase settings for each individual receiver are assumed.

Fig. 1. Illustration of the MISO RIS-assisted SWIPT system model.

II. SYSTEM MODEL AND PROBLEM FORMULATION

We consider an RIS-based multi-user multiple-input single-output (MISO) downlink indoor scenario in which an access point (AP) equipped with \( M \) antennas serves \( K \) single-antenna user equipment (UEs) employing SWIPT. The \( k \)-th UE employs a fraction \( \rho_k \) of the received power for information decoding (ID), while the rest is used for power harvesting (PH). The channels from the AP to the RIS, from the AP to the \( k \)-th user, and from the RIS to the \( k \)-th user are denoted by \( \mathbf{G} \in \mathbb{C}^{N \times M} \), \( \mathbf{h}_{d,k} \in \mathbb{C}^{1 \times M} \), \( \mathbf{h}_{r,k} \in \mathbb{C}^{1 \times N} \), respectively, and are assumed to follow the Rician fading model.

The reflection coefficient vector of the RIS is denoted by \( \mathbf{v} = [v_1, \ldots, v_N] \in \mathbb{C}^{N \times 1} \), where \( v_n = f_n(\theta_n) e^{j\phi_n} \) is the reflection coefficient of the \( n \)-th reflecting element of the RIS, with \(-\pi \leq \theta_n \leq \pi \) and, e.g., \( f_n(\theta_n) = f_{\min} + (1 - f_{\min})(\sin(\theta_n - \phi) + 1)\alpha \) is a function that relates the phase of the reflection coefficient to its modulus, where \( f_{\min} \geq 0 \), \( \alpha \geq 0 \), and \( \phi \geq 0 \) are circuit implementation constants \([10]\). The proposed approach can be applied to any continuous and differentiable function \( f_n(\theta_n) \). Given this notation and defining \( \mathbf{H}_{r,k} = \text{diag}(\mathbf{h}_{r,k}) \mathbf{G} \), the sum-rate is:

\[
R_{\text{ID}} = \sum_{k=1}^{K} \log \left( 1 + \frac{\eta_k (1 - \rho_k)}{\sigma_t^2 + \sigma_n^2} \sum_{i=1, i \neq k}^{K} |(\mathbf{h}_{d,k} + v_i H_{r,k}) \mathbf{w}_i|^2 \right)
\]  

(1)

where \( \mathbf{w}_k \in \mathbb{C}^{M \times 1} \) is the transmit beamforming vector, and \( \sigma_t^2 \) and \( \sigma_n^2 \) model the power of the thermal noise and of the noise due to the conversion of the RF signal to the baseband. Furthermore, considering a linear harvesting model, the power harvested by the \( k \)-th UE is \( P_{H,k} = \eta_k (1 - \rho_k) \sum_{i=1}^{K} |(\mathbf{h}_{d,k} + v_i H_{r,k}) \mathbf{w}_i|^2 \), where \( \eta_k \in [0, 1] \) is the efficiency of the power harvesting circuit. Similar to [11], we consider the associated rate function:

\[
R_{\text{PH}} = \sum_{k=1}^{K} \log \left( 1 + \frac{\xi_k (1 - \rho_k)}{\sigma_t^2 + \sigma_n^2} |(\mathbf{h}_{d,k} + v_i H_{r,k}) \mathbf{w}_i|^2 \right)
\]  

(2)

where \( \xi_k \in [0, 1] \) is the efficiency of the conversion from baseband power to RF power.

The goal of this letter is to maximize a weighted sum of \( R_{\text{ID}} \) and \( R_{\text{PH}} \), namely:

\[
R_{\text{sum}}^E (\rho, \mathbf{w}, \mathbf{v}, \{\theta_n\}) = R_{\text{ID}} + \lambda R_{\text{PH}}
\]  

(3)

where \( \lambda \) is a parameter to be tuned by the network operator according to the priorities granted to ID and PH \([11]\).

Defining \( \bar{h}_k = \mathbf{h}_{d,k} + v_i H_{r,k} \), the problem to be tackled in the rest of this letter is formulated as:

\[
P_A : \max_{\rho, \mathbf{w}, \mathbf{v}, \{\theta_n\}} R_{\text{sum}}^E (\rho, \mathbf{w}, \mathbf{v}, \{\theta_n\})
\]  

s.t. \( C_1 : \frac{|\mathbf{h}_i \mathbf{w}_i|^2}{\sum_{i=1}^{K} |\mathbf{h}_i \mathbf{w}_i|^2 + \sigma_t^2 + \sigma_n^2} \geq \gamma_{\text{min}}, \ k = 1, \ldots, K \)  

(4)

\[
C_2 : \eta_k (1 - \rho_k) \sum_{i=1}^{K} |(\mathbf{h}_i \mathbf{w}_i)|^2 \geq \rho_{\text{min}}, \ k = 1, \ldots, K
\]  

(5)

\[
C_3 : \sum_{k=1}^{K} ||\mathbf{w}_k||^2 \leq P_{RF}, \ 0 \leq \rho_k \leq 1
\]  

(6)

\[
C_4 : v_n = f_n(\theta_n) e^{j\phi_n}, \ n = 1, \ldots, N
\]  

(7)

\[
C_5 : -\pi \leq \theta_n \leq \pi, \ n = 1, \ldots, N
\]  

(8)

It can be seen that \( P_A \) is a non-convex problem due to the non-convexity of both the objective function and the constraints \( C_1, C_2, C_3, C_4, C_5 \). Thus, traditional methods do not apply.

III. PROPOSED APPROACH

To tackle \( P_A \), we first reformulate the sum of logarithms into a more tractable form by applying the method from \([12]\) to each sum in the objective function. This yields:

\[
P_{\mathcal{A}} : \max_{\alpha_1, \beta_1, \alpha_E, \beta_E, \rho, \mathbf{w}, \mathbf{v}, \{\theta_n\}} f_{\mathcal{A}} (\alpha_1, \beta_1, \alpha_E, \beta_E, \rho, \mathbf{w}, \mathbf{v}, \{\theta_n\})
\]  

s.t. \( (C_1), (C_2), (C_3), (C_4), (C_5) \)  

(9)

wherein \( f_{\mathcal{A}} \) is shown in \([11]\), shown at the bottom of the next page, with \( \bar{n}_k = \xi_k \eta_k \) and \( \Re \) being the real part operator. In order to tackle \( (10) \), the first step is to embed \( C_4 \) into the objective, resorting to a penalty-based approach, which yields:

\[
P_{\mathcal{B}} : \max_{\alpha_1, \beta_1, \alpha_E, \beta_E, \rho, \mathbf{w}, \mathbf{v}, \{\theta_n\}} f_{\mathcal{A}} (\alpha_1, \beta_1, \alpha_E, \beta_E, \rho, \mathbf{w}, \mathbf{v}, \{\theta_n\}) - \Gamma \sum_{n=1}^{N} |v_n - f_n(\theta_n) e^{j\phi_n}|^2
\]  

s.t. \( (C_1), (C_2), (C_3), (C_5) \)  

(10)

wherein \( \Gamma \) represents the penalty coefficient used for penalizing the violation of the equality constraint \( C_4 \). If \( \Gamma \rightarrow \infty \), the solution of the original problem is obtained. Problem \( (12) \) is tackled by alternating optimization, as explained next.
A. Optimization of $\alpha_{1,k}, \alpha_{E,k}, \beta_{1,k}, \beta_{E,k}, \rho_k$

The optimal $\alpha_{1,k}, \alpha_{E,k}, \beta_{1,k}, \beta_{E,k}$ are found by setting the gradient of the objective to zero, which yields:

\[
\alpha_{1,k} = \frac{r^2 + r \sqrt{r^2 + 4}}{2}, \quad \beta_{1,k} = \frac{\sqrt{\rho_k (1 + \alpha_{1,k})} \eta \nu_k w_k}{\sum_{i=1}^K \rho_k |h_k w_i|^2 + \rho_k \sigma_k^2 + \delta_k^2} \tag{13}
\]

\[
\alpha_{E,k} = \frac{\tilde{r}^2 + \tilde{r} \sqrt{\tilde{r}^2 + 4}}{2}, \quad \beta_{E,k} = \frac{\sqrt{\eta_k (1 - \rho_k)} \sum_{i=1}^K h_k w_i}{\eta_k (1 - \rho_k) \sum_{i=1}^K |h_k w_i|^2 + \sigma_k^2} \tag{14}
\]

with $\tilde{r} = \sqrt{\rho_k R \{h_k w_k\}}$.

The optimization with respect to the coefficients $\{\rho_k\}$ is performed as follows. With respect to $\{\rho_k\}$, the objective function is strictly concave and the constraints (C2), (C3) are affine. Moreover, (C1) can be rewritten in a linear form as follows, for any $k = 1, \ldots, K$:

\[
\rho_k |h_k w_i|^2 - \gamma_{\text{min}} \rho_k \sum_{i=1, i \neq k}^K |h_k w_i|^2 + \rho_k \sigma_k^2 + \delta_k^2 \geq 0 \tag{15}
\]

Thus, with respect to $\{\rho_k\}$, the problem is convex and can be solved by standard convex optimization algorithms [13].

B. Optimization of $w_k$

When all the other variables are fixed, the objective function is a concave function in the transmit beamforming vectors $w_k$. However, constraints (C1) and (C2) are still not convex. To deal with them, we use the successive convex approximation (SCA) method [6], [14]. Specifically, the convex term $|h_k w_k|^2$ is upper-bounded by its first-order Taylor expansion as follows:

\[
w_k H_h H h_k w_k \geq 2 R\{w_k^{(t)} H h_k w_k\} - \left(w_k^{(t)} H_H h_k w_k^{(t)}\right) \tag{16}
\]

wherein $w_k^{(t)}$, $\forall k$, is the solution from the previous iteration. Thus, defining $d_k^{(w)} = w_k^{(t)} H H h_k w_k^{(t)}$, exploiting (16) and elaborating, (C1) can be recast as:

\[
\gamma_{\text{min}} \left(\sum_{i \neq k} |h_k w_i|^2 + \sigma_k^2 + \delta_k^2 + d_k^{(w)}\right) - 2 R\{w_k^{(t)} H_H h_k w_k\} \leq 0
\]

Similarly, (C2) can be reformulated as follows:

\[
\eta_k (1 - \rho_k) \sum_{i=1}^K 2 R\{w_i^{(t)} H h_k w_i\} - w_i^{(t)} H H h_k w_i^{(t)} \geq P_{\text{min}}
\]

By replacing (C1) and (C2) with their reformulated versions, we obtain the convex surrogate problem to be solved in each iteration of the SCA method for optimizing $w_k$.

C. Optimization of $v$

The approach is similar to that used for the optimization of $w_k$. In fact, the objective is concave in $v$, while the constraints (C1) and (C2) can be handled by the SCA method. Specifically, (C1) can be replaced by the convex constraint:

\[
\gamma_{\text{min}} \left(\sum_{i \neq k} |(h_{d,k} + v H h_{r,k}) w_i|^2 + \sigma_k^2 + \delta_k^2 \rho_k\right) + 2 R\{(h_{d,k} + v H h_{r,k}) w_i (h_{d,k} + v H H h_{r,k})\} \leq 0 \tag{17}
\]

and (C2) by the convex constraint:

\[
\eta_k (1 - \rho_k) \sum_{i=1}^K 2 R\{(h_{d,k} + v H h_{r,k}) w_i (h_{d,k} + v H H h_{r,k})\} \geq P_{\text{min}} \tag{18}
\]

By replacing the constraints (C1) and (C2) with (17) and (18), we obtain the convex surrogate problem to be solved in each iteration of the SCA method for optimizing $v$.

D. Updating $\theta_n$

The RIS phase shifts are the solutions of the problem:

\[
\max_{\{\theta_n\}} - \sum_{n=1}^N 2 f_n(\theta_n) |v_n - f_n(\theta_n)| e^{i \theta_n} , \text{ s.t. } -\pi \leq \theta_n \leq \pi \tag{19}
\]

It can be seen that the problem is separable over $n$, i.e., each summand can be optimized separately. Thus, defining $\varphi_n = \arg(v_n)$, the optimal $\theta_n$ is the solution of the problem:

\[
\max_{\theta_n \in [-\pi, \pi]} 2 f_n(\theta_n) |v_n\cos(\varphi_n - \theta_n) - f_n^\varphi(\theta_n) \tag{20}
\]

which can be solved by standard numerical methods.

E. Convergence and Complexity

Finally, the overall algorithm to solve the optimization problem is obtained by iteratively optimizing the different optimization variables. Each iteration monotonically increases the objective value, which guarantees convergence. Moreover, the computational complexity is polynomial in the number of variables, since only the solution of convex problems is required. Thus, the complexity of optimizing $\{\rho_k\}$ is $O(K^{n_\rho})$, while the complexity of optimizing $\{w_k\}$ and $v$ are $O(I_w(MK)^{n_w})$, and $O(I_v N^{n_v})$, respectively, with $I_w$

1We recall that a convex problem can be solved with a complexity $C = O(L^n)$, where $L$ is the number of variables and $1 \leq \eta \leq 4$ [15].
and \(I_o\) being the number of iterations of the SCA methods used to optimize \(w\) and \(v\). On the other hand, the optimal \(\{\alpha_{E_k}, \alpha_{E_k}, \beta_{E_k}, \beta_{E_k}\}\) are available in closed-form in (13), (14) and thus the complexity required for their computation can be neglected. Similarly, the complexity of the problem in (19) can also be neglected, as it is linear in \(N\). In fact, the problem can be decoupled over the \(N\) optimization variables, and, for each \(N\), the optimal \(\theta_n\) is obtain by solving (20). Thus, the overall complexity of the proposed method is given by \(C = I(O(K^M) + O(I_w(MK^N)) + O(I_w(M^N))\), where \(I\) is the number of alternating optimization iterations to be run until convergence. The exponents of the polynomial are not available in closed-form, but it is known that they are upper-bounded by 4 [18]. A typical value is 3.5, which comes up when interior-point methods are used [13].

IV. Numerical Results

We consider an RIS-assisted MISO communication system in a typical indoor scenario, in which \(M = 32\) transmit antennas are arranged in a uniform linear array, and each antenna has 6 dBi gain. Unless stated otherwise, we set \(K = 4\) UEs and \(N = 400\) RIS elements. The UEs are randomly and uniformly distributed within a disk of 2 m radius centered at \((10\,\text{m}, 10\,\text{m})\). An \(N\)-element RIS is located at \((0\,\text{m}, 5\,\text{m})\). All the channels are modeled as \(X = L_{X}\left(\sqrt{\frac{x}{1+r^2}}X^{LOS} + \sqrt{\frac{x}{1+r^2}}X^{NLOS}\right)\), where \(X^{LOS}\) and \(X^{NLOS}\) are the line-of-sight (LOS) and non-LOS (NLOS) components, and \(X\) is either \(G\), \(h_{r,k}\), or \(h_{A,k}\). The NLOS component follows the Rayleigh fading model, while the LOS component is \(X^{LOS} = a_N(\theta^{AoA})\hat{a}_N(\theta^{AoA})\), with:

\[
a_N(\theta^{AoA}) = [1, e^{j \frac{2\pi d}{\lambda} \sin(\theta^{AoA})}, \ldots, e^{j \frac{2\pi d (N-1)}{\lambda} \sin(\theta^{AoA})}]^T
\]

\[
a_M(\theta^{AoD}) = [1, e^{j \frac{2\pi d}{\lambda} \sin(\theta^{AoD})}, \ldots, e^{j \frac{2\pi d (M-1)}{\lambda} \sin(\theta^{AoD})}]^T
\]

where \(d\) and \(\lambda\) are the inter-antenna distance and the wavelength, respectively. We assume \(d/\lambda = 1/2\). The path-loss is \(L = C_0\left(\frac{r}{D_0}\right)^{-x}\), where \(r\) is the link distance and \(D_0 = 1\) is the reference distance at which the reference path-loss \(C_0 = -30\ \text{dB}\) is defined, \(x\) is the path-loss exponent. Other simulation parameters are listed in Table I and are in agreement with [9]. For comparison, we evaluate the performance gain obtained by the proposed algorithm against the “No-RIS” scenario, where no RIS is deployed in the network.

Figure 2 depicts the relation between the number of RIS elements versus the sum-rate and the harvested power. We see that employing more RIS elements leads to a monotonic growth of the amount of harvested power and sum-rate. The figure reveals the effectiveness of the proposed algorithm compared to the “No RIS” case (denoted by “\(\text{w/o RIS}\)”). This monotonic gain is due to the appropriate design of the phase shifts of the RIS elements, which results in strong virtual LOS paths between the AP and the UEs. Also, the figure shows two special cases in which we optimize only the achievable rate, i.e., \(\lambda = 0\), and only the harvested power, i.e., \(\lambda \to \infty\). The proposed bi-objective optimization problem allows us to obtain the desired trade-off between sum-rate and harvested power by varying \(\lambda\), and it can be utilized to optimize only the sum-rate or the harvested power as two special cases.

In Fig. 3, we explore the trade-off between the sum-rate and harvested power as a function of the number of RIS elements. The case without RIS is reported for comparison. We observe that employing more RIS elements enhances the sum-rate and harvested power, and the proposed algorithm outperforms the “No RIS” scenario. Moreover, the figure highlights the impact of the parameter \(\lambda\), which is utilized to determine the service priority between optimizing the sum-rate (i.e., small values of \(\lambda\)) or optimizing the harvested power (i.e., large values of \(\lambda\)). When the system prioritizes power harvesting, the proposed algorithm allocates more power to the power harvesting receiver, and thus the sum-rate decreases. Similarly, reducing the value of \(\lambda\) gives higher priority to the information decoding receiver. The figure shows the trade-off between the sum-rate and harvested power for any values of \(\lambda\). The extreme points to the left and to the right of the curves correspond to the single-objective sum-rate maximization and to the single-objective harvested power maximization, respectively.

In Fig. 4, we examine the trade-off between the sum-rate and harvested power with the minimum value of the amplitude of the reflection coefficient \(f_{min}\) of the RIS elements. We see that the sum-rate and harvested power increase with \(f_{min}\), with \(f_{min} = 1\) corresponding to the ideal case for an RIS.

In Fig. 5, finally, we investigate the trade-off between the sum-rate and harvested power as a function of the number of UEs. We see that the Pareto region is characterized by a larger

### Table I

**Simulation Parameters**

| Parameters | Values |
|------------|--------|
| Number of RIS elements / UEs | 400 / K = 4 |
| Maximum transmission power | \(P_T = 40\ \text{dBm}\) |
| Path-loss exponent - RIS-aided channels | \(x_{L} = 2.2\) |
| Path-loss exponent - Direct channel | \(x_S = 3.6\) |
| Rician factor | \(\kappa = 5\ \text{dB}\) |
| Power conversion noise | \(\delta^2 = \sigma^2 = -50\ \text{dBm}\) |
| Thermal noise power | \(\sigma^2 = -40\ \text{dBm}\) |
| Minimum harvested power | \(P_{min} = -20\ \text{dBm}\) |
| Minimum SINR requirement | \(\gamma_{min} = 0\ \text{dB}\) |
| Power conversion efficiency | \(\eta = 0.7\) |
| Combining weight | \(\lambda = [0 : 0.2 : 1]\) |
| Conversion efficiency (uplink) | \(\xi_k = 0.001\) |

**Fig. 2.** Sum-rate and harvested power versus the number of RIS elements for different values of \(\lambda (K = 4)\).
excursion of the harvested power as the priority parameter $\lambda$ varies, while the sum-rate shows a less significant variation. This is due to the stringent requirement that we imposed on the minimum harvested power, which forces the optimization algorithm to allocate more resources for power harvesting, which inevitably leads to a lower sum-rate. Higher values of sum-rate can be obtained by reducing the value of the minimum acceptable harvested power. Nevertheless, satisfactory values of both the sum-rate and harvested power can be obtained by deploying a sufficient number of RIS elements. Compared with the “No RIS” case, we see, e.g., that the harvested power increases from 0.11 mW to 0.19 mW while guaranteeing the same sum-rate of 29 bps/Hz if $K = 4$ and $N = 400$. The sum-rate and the harvested power can be further increased by deploying larger RISs.

V. CONCLUSION

We have investigated the trade-off between the sum-rate and harvested power in a multi-user RIS-aided downlink MISO system with SWIPT. Enforcing QoS constraints and practical phase shift constraints, the beamforming vector, the power splitting ratio, and the RIS reflection coefficients are jointly optimized by a two-layer penalty-based algorithm. Simulation results show that the proposed algorithm significantly outperforms conventional approaches in the absence of RISs.

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