Resource Allocation of Simultaneous Wireless Information and Power Transmission of Multi-Beam Solar Power Satellites in Space-Terrestrial Integrated Networks for 6G Wireless Systems

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Abstract. The technique of simultaneous wireless information and power transmission (SWIPT) has been applied to wireless sensor networks, which employ static or mobile base stations (BSs) such as drones and ships to charge passively powered devices. SWIPT can be strongly expanded by solar power satellites (SPSs), which collect solar energy and transmit it to the earth through microwaves to alleviate the power shortage problem. Furthermore, multi-beam SPSs can serve a broader range than terrestrial BSs for information transmission. In 6G networks, satellites are core devices in space-terrestrial integrated networks (STINs) supporting super Internet-of-Things (IoT). However, when discussing 6G wireless systems, previous works did not consider SWIPT applied in STINs through multi-beam SPSs. Therefore, this work proposes a novel resource allocation problem for SWIPT performed by multi-beam SPSs in the STIN while optimizing the following two objectives: minimizing deficit or excess of information transmission

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rate and maximizing power transmission based on two receiving architectures of terrestrial devices for information decoding and energy harvesting. Different from previous works, this problem considers not only assigning power to one of multiple satellite beams but also further allocating power in each beam into two parts for information and power transmission. This problem is NP-hard as it includes an NP-hard problem. Artificial intelligence (AI) algorithms can be used to optimize the network resource management. Hence, this problem with continuous decision variables is further solved by a classical and two recent AI algorithms specially designed for continuous variables, i.e., particle swarm optimization, improved harmony search algorithm, and monkey algorithm. Through simulation, the most appropriate AI algorithms to the concerned problem are analyzed, and the results show that for the two special designed receiving architectures of the terrestrial devices, the power splitting (PS) architecture generally outperforms the time switching (TS) architecture.

Keywords: Multi-beam satellite, solar power satellite, simultaneous wireless information and power transmission, space-terrestrial integrated network, 6G, AI algorithm.

1 Introduction

The 5G wireless system has provided significantly increased capacity, massive device connections, and relevant applications since 2019. However, devices, infrastructures, and connections in 5G are still ground based with transmission distance limits. Therefore, space networks which provide seamless communication coverage through satellites and aerial or marine vehicles can be a complement to terrestrial networks. This space-terrestrial integrated network (STIN) which can support massive global internet services with high capacity anytime and anywhere is one of the targets in 6G wireless system [1].

The 6G networks are envisioned to include three major aspects: super Internet-of-Things (IoT), artificial intelligence (AI), and ultra-broadband supported by teraherz (THz) communications. The STIN can be used to achieve super IoT. A typical STIN includes three layers as follows. The spaceborne network layer consists of geostationary Earth orbit (GEO), medium Earth orbit (MEO), and low Earth orbit (LEO) in different altitudes. The airborne network layer includes some aerial devices used as aerial platforms, such as stratospheric balloons, airships, aircrafts, and unmanned aerial vehicles (UAVs). The ground-based network layer includes the ground infrastructure for satellite networks, cellular networks, and wireless local area networks (WLANs). One major node in the STIN for super IoT of 6G wireless systems is the satellite stations [1, 2].

Network planning and optimization are also a crucial issue in wireless systems. However, the current network configurations or optimization is achieved in a manual manner which is no longer suitable for 6G with more user demand, heavier traffic load, and more complicated network topology and radio resource. Hence, AI can optimize the future 6G networks in an intelligent manner. One essential element that needs to be optimized through AI is network resource management [2]. From the literature, there have been numerous AI algorithms that solves network resource management problems, including metaheuristic algorithms and machine learning techniques.

The power resource management of wireless devices has always been a challenging issue in the telecommunication field. Therefore, far-field wireless power transfer (WPT) has drawn increasing attention in communications on account of tremendous energy consumption from rising numbers of wireless communication devices, which are typically powered by batteries and therefore suffer from limited lifetime. The well-known forms of electromagnetic radiation used for far-field WPT are microwaves and lasers. One of the major concerns about the far-field WPT is the power transfer distance, which has been addressed recently by the technology of far-field microwave power transmission (MPT). The MPT is more efficient and less vulnerable to atmospheric attenuation than the WPT through lasers both at the transmitter and receiver [3].

Another major concern on the far-field WPT is the energy resource. Solar energy is one of the best energy resources because of its sustainability and cleanness. The solar power satellite (SPS) that applies the far-field WPT technique and is placed in the GEO (invented by Peter Glaser in 1968 and followed by NASA in 1970) can solve the power shortage problem. Collecting solar energy in outer space has higher efficiency than directly harvesting it through solar panels on earth, because the latter way is apt to be impacted by weather impairments and sunlight intensity. The time-averaged solar power per unit area collected in outer space is 5-10 times larger than that harvested on earth. An SPS system consisting of SPSs and ground segments. In the SPS system, the SPS with the far-field MPT technique enables to collect sunlight through solar panels, convert it into microwave, and propagate it to the earth through spacetenna. The rectenna (rectifying antenna) on earth receives microwave, and converts it into direct current (DC) electricity for supply of power utilities [2], [3].

Developed from far-field WPT technologies, the technique of simultaneous wireless information and power transmission (SWIPT) is able to exploit the same electromagnetic wave-field to simultaneously transport information and energy to end terminals, which are capable of decoding information and harvesting energy by their receivers [6]. The multi-beam satellite (Fig. 1a) equipped with a phased array antenna and solid-state power amplifiers (SSPA) can serve a number of beams within the coverage area. The phased array antenna can increase the radiation to a certain direction, and adjust the size and shape of a beam by feeding array elements from SSPA. The terrestrial devices located in the satellite beam area can decode information and harvest energy with their receivers simultaneously under special designed receiving architectures: the time switching (TS) architecture (Fig. 1b) and the power splitting (PS) architecture (Fig. 1c).

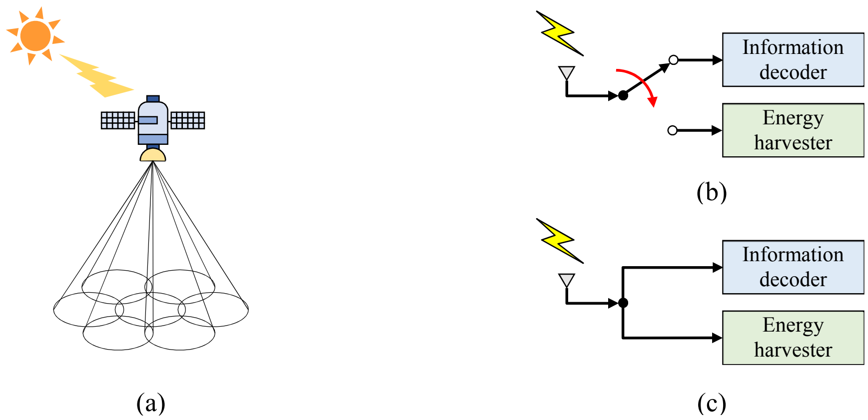

Fig. 1. Illustration of the SWIPT scheme in the STIN using (a) a multi-beam SPS; (b) the time switching (TS) architecture; and (c) the power splitting (PS) architecture.

The SWIPT performed by multi-beam SPSs in the STIN can provide an unlimited power resource transferred from sunlight in outer space and a broader information transmission service range compared with base stations (BSs) and relay stations (RSs) on the earth, and hence this technique is extremely beneficial to communication industry. One application of SWIPT applied in STIN through multi-beam SPSs is emergency communications. Numbers of antennas as substitutes for gateways of RSs and energy harvesting rectennas for power supplying can be placed between the SPS and end user terminals when the terrestrial infrastructures are heavily damaged from disasters [7].

The core of SWIPT systems in the STIN is the multi-beam SPS. Resource allocation (RA) of the multi-beam SPS to optimize utilization or efficiency of the SWIPT processes under the network or system constraints (such as energy, bandwidth, time, and space [8]) becomes an important evaluation factor of STIN on account of limited battery cells capacity of the multi-beam SPS, quality of service (QoS) of the space-terrestrial communication networks, and the huge capital expenditure and operation expenses of satellites. The previous works on RA of multi-beam satellites (e.g., [9]) only focused on investigating the assignment of power for information transmission, but did not consider SWIPT and SPSs in the STIN. Therefore, this work proposes a novel RA problem for SWIPT of multi-beam SPSs in the STIN, which determines not only the assignment of power and bandwidth for information transmission among satellite beams but also the distribution ratios of the power consumed for information and power transmission respectively in each satellite beam to maximize the amount of harvested power of terrestrial devices while satisfying the information rate demand on earth. Since this problem includes an NP-hard problem, it is also NP-hard. Therefore, this work further solves this problem using multiple AI algorithms, including a classical AI algorithm (i.e., particle swarm optimization) and two recent AI algorithms (i.e., improved harmony search algorithm and monkey algorithm). The simulation results show that the PS architecture generally performs well than the TS architecture.

2 Preliminaries

2.1 System framework and problem description

This work considers an STIN consisting of a broadband multi-beam SPS placed in GEO and passively powered communication devices located in the fixed coverage area of satellite beams on earth. In the STIN, the downlink channel is modeled as an additive white Gaussian noise (AWGN) channel [3] and the broadband multi-beam satellite operating in the Ka-band and equipped with solar array panels, phased array antennas, and gallium nitride (GaN) made SSPA, which is capable of collecting sunlight in outer space and converting it into microwave beams to process power transmission to the earth as SPS (Fig. 1a) [4], [10].

After the microwave signals transmitted from the multi-beam SPS to the terrestrial end terminals, the devices are able to split and process the received signals by the information receiver and energy receiver for information decoding and energy harvesting under two receiving architectures: the TS architecture and PS architecture. Based on [3], the receiver in the TS architecture uses the same antenna and changes between the information decoder and the energy harvester circuit periodically (Fig. 1b). In the PS architecture, the receiver separates the received signal into two different power level streams with a certain ratio, and then the two power streams are sent to the information decoder and the energy harvester circuit (Fig. 1c). The receiver design of the terrestrial device is simpler for adopting the TS architecture than the PS architecture in SWIPT; however, this compromises the efficiencies of information and power transmission [6].

2.2 Mathematical Model

In the STIN, the power provided to each beam to transmit information from the multi-beam SPS to terrestrial devices must satisfy the traffic demand in order to meet the requirement of network QoS, and meanwhile, the amount of power must not be oversupplied so as to prevent from decreasing energy efficiency. Under ensuring the information transmission rate, this work aims to maximize transmission of the energy harvested from the multi-beam SPS to terrestrial devices. Therefore, the power allocation problem of SWIPT for the multi-beam SPS is considered from two aspects in this work. First, the total available power which the SPS currently has is allocated to each beam with a different level. Second, the power provided to each beam is further allocated to information decoding and energy harvesting, respectively, in the terrestrial network.

The bi-objective optimization problem concerned in this work is formulated as follows:

$$\begin{cases} \text{Min } \sum_{b=1}^{N} \left| R_{b,demand} - R_b \right| \\ \text{Max } \sum_{b=1}^{N} Q_b \end{cases} \tag{1}$$

where $R_{b,\text{demand}}$ represents the requested traffic demand in the b-th beam of the N-beam SPS and R_b is corresponding information transmission rate; and Q_b denotes the power harvested from the SPS within beam b. The first objective function which aims at meeting the requirement of traffic demand proposes the differential system capacity (DSC) as a figure of merit for optimizing the system network capacity. The work in [11] indicated that the power provided for information transmission in each beam exceeding the traffic demand impacts on the DSC but does not impact on the unmet system capacity (USC) [9]. Hence, minimizing of DSC drives the optimization of power allocation for network QoS and energy efficiency as well. The second objective function aims at maximizing the total power transmission from outer space to terrestrial devices through the SPS.

Although SPSs can harvest the solar power in outer space without any limit theoretically as long as they are not during the eclipse period, the battery cells of SPSs have their respective maximum capacity for storing energy. Hence, Constraint (2) is formulated that the sum of the power P_b allocated to each beam b cannot exceed the total available power P_{total} offered by the SPS. Based on [9], Constraint (3) is reduced from $\sum_{c=1}^{M} P_{b,c} \le P_b^{\max}$ by $P_{b,c} = P_b / M$, where $P_{b,c}$ is the power allocated to the c-th carrier of M carriers in beam b under the practical assumption of equal-powered carriers sharing the total beam power; and $P_b^{\max}$ is the maximum power supplied in beam b.

$$\text{s.t.} \quad \sum_{b=1}^{N} P_b \le P_{total} \tag{2}$$

$$0 \le P_b \le P_b^{\max}, \; b = 1,...,N \tag{3}$$

The receiver of terrestrial devices in TS architecture separates the information receiving and power harvesting process by time division (Fig. 1b). The receiver of terrestrial devices in time switching architecture separates the information receiving and power harvesting process by time division. The information rate R_b of the AWGN channel [12] and harvested energy Q_b [13] integrated with [3] can be written as follow:

$$R_b = (1-\tau_b) W \log_2\left(1+\frac{\alpha_b^2 P_b}{\sigma_{\mathrm{A}}^2+\sigma_{\mathrm{cov}}^2}\right) \tag{4}$$

$$Q_b = (\tau_b)\eta\alpha_b^2 P_b \tag{5}$$

$$0 \le \tau_b \le 1 \tag{6}$$

where W is the transmission bandwidth; α_b^2 represents signal attenuation across each beam b; σ_{A}^2 and σ_{cov}^2 are antenna noise power and signal processing noise respectively; η is efficiency factor of energy harvesting process; τ_b and $(1 - \tau_b)$ ranged from 0 to 1 denote the ratios of expected time interval of processing power transmission and information transmission, respectively, in beam b.

In the PS architecture, the integrated information and energy receiver can separate the received signal into two streams for information decoding and power harvesting process from the SPS (Fig. 1c). The information rate R_b and harvested energy Q_b under the PS architecture can be formulated as follow [3], [13]:

$$R_b = W \log_2\left(1+\frac{(1-\rho_b)\alpha_b^2 P_b}{\sigma_{\mathrm{A}}^2+\sigma_{\mathrm{cov}}^2}\right) \tag{7}$$

$$Q_b = (\rho_b)\eta\alpha_b^2 P_b \tag{8}$$

$$0 \le \rho_b \le 1 \tag{9}$$

where ρ_b and $(1 - \rho_b)$ ranged from 0 to 1 donate the PS coefficient of processing power transmission and information transmission, respectively, in beam b.

The RA problem of multi-beam satellites in this work is different from previous works by augmenting the traditional RA problem with the concept of two receiving architectures of terrestrial devices with SWIPT technologies into STIN by SPS which can easily and efficiently collect solar energy in outer space. The objective function of RA problem in [14] only aimed at minimizing the deficit or excess between the required and the information rate supply. Besides the traffic demand satisfied objective function from previous works, this work considers maximization of power transmission from the multi-beam SPS as the second objective function without impacting too much of required traffic demand. Most of the previous works on information and power transmission [13], [15] discussed the rate-energy tradeoff of TS and PS schemes of terminal devices. Differently, this work considers an integrated network from the origin (multi-beam SPS in outer space) to the end terminals (the communication devices on the earth) with SWIPT technology. Finally, this work proposes an optimization RA problem model in which the available power is not only allocated among satellite beams (which is mainly studied in [9], [14]) but also further allocated to two parts for information and power transmission in each beam.

The optimization RA problem in this work aims at minimizing the difference between traffic demand and information rate in each satellite beam and maximizing the total power transmission. The simplified version of this problem, which is maximizing the total data transmission in each satellite beam, has been shown to be the NP-hard sum rate maximization problem [9]. Since the special case of the general RA problem is NP-hard, the problem in this work is NP-hard as well.

2.3 Related Works

This subsection reviews the related works on RA problems and their problem solving methodologies, SWIPT technology, and different receiving architectures of terrestrial devices.

RA in multi-beam satellite communication systems includes power allocation and bandwidth allocation. The work in [9] had shown the general RA to be a NP-hard problem and studied the power allocation of the multi-beam satellite based on the traffic requirements of each beam by USC for optimizing the capacity as the first objective and minimizing the DC power consumption of the satellite as the second objective. The work in [14] allocated different number of beams and beam power based on traffic demand and channel conditions with power and delay constraints for maximizing the spectral efficiency. The work in [16] proposed a novel joint power and bandwidth allocation algorithm and took the inter-beam interference, channel conditions, delay factor, capacity, and bandwidth utilization variance into consideration for optimizing the capacity according to specific traffic requirements and channel conditions. A power and bandwidth allocation problem is studied in work [17] as well. Different from [16], the bandwidth of each beam can be traded with adjacent beam. A multi-objective optimization problem of uplink and downlink satisfaction and spectrum efficiency with cache constraints was investigated in work [18]. The work in [19] further considered the terrestrial cellular network with BSs into the satellite network and integrated the terrestrial-satellite network with cloud for the purpose of maximizing terrestrial system capacity while limiting the interference to the satellite.

There were various methodologies to solve RA problems for particular objectives under different system or network constraints. The multi-objective optimization problem in [9] was solved by metaheuristic algorithms in two stages: the GA-SA at the first stage and non-dominated sorting genetic algorithm II (NSGA-II) at the second stage. [12], 12], and [20] introduced a non-negative Lagrange multiplier into the problem model. The work in [14] differentiated the Lagrange function to applied Karush-Kuhn-Tucker condition. The works in [12] and [20] adopted sub-gradient algorithm to update the Lagrange multiplier to optimize the problem. The work in [19] solved the optimization problem by the dual decomposition method.

The work in [5] surveyed advances and challenges of SWIPT technologies. Microwave power beam is less vulnerable to atmospheric attenuation caused by water vapor or dust and more efficient than laser beams for far-field WPT. Hence, the idea of multi-beam satellite performing WPT to the ground devices via microwave beams has been proposed. Multi-beam SPS with SWIPT technology can alleviate the power shortage problem of communication devices, especially under harsh environments [7]. The work in [6] proposed a framework for realizing SWIPT in a broadband wireless system and power control algorithms for different network configurations. The work in [21] maximized the sum rate of the STIN under the constraint of per-antenna transmit power and QoS requirements of both satellite and cellular users and further transformed the non-convex problem into an equivalent convex one with iterative penalty function-based beamforming (BF) scheme based on the user clustering.

SWIPT technology is able to simultaneously transfer information and power from origins (i.e., SPS or BS). However, the fundamental design of end terminal devices requires changes for capability and efficiency of wirelessly harvesting power and decoding information concurrently. The work in [13] proposed a general receiver operation, dynamic PS, which separates the received signal with different ratios for the information decoding and the energy harvesting of end terminal devices, and investigated the special case of dynamic PS – TS architecture, static PS, and on-off PS. In order to approach a real SWIPT scheme, [15] considered the practical scenario of nonlinear energy harvesting and proposed the generalized on-off PS scheme. The work in [22] considered a practical scenario of nonlinear energy harvesting. To address the critical nonlinearity issue due to the saturation, multiple energy harvesting circuits in parallel was proposed to maximize the achievable rate by jointly optimizing Tx power allocation and Rx power splitting.

3 The Proposed Algorithm

3.1 Solution encoding

Let N denote the number of multi-beam SPS beams. The RA problem in this work includes two continuous decision variables: P_b is the amount of power provided from the SPS allocated to the satellite beam b and under the TS architecture of terrestrial devices receiver, τ_b is the expected time interval of the satellite processing power transmission to the terrestrial device in corresponding beam. Therefore, the candidate solution is encoded as (χ_1, χ_2, …, χ_{2N}) = (P_1, P_2, …, P_N | τ_1, τ_2, …, τ_N). Besides the TS architecture, this work further considers the PS architecture. Hence, the candidate solution is encoded as (χ_1, χ_2, …, χ_{2N}) = (P_1, P_2, …, P_N | ρ_1, ρ_2, …, ρ_N), where ρ_b denotes the PS coefficient of power provided from the satellite allocated for power transfer to the terrestrial device in beam b. The range of P_b lies between 0 and $P_b^{\max}$. The range of τ_b and ρ_b lies between 0 and 1.

3.2 Fitness evaluation

With regard to the bi-objective function, the performance of the candidate solution is evaluated as the cost function:

$$\omega \cdot \sum_{b=1}^{N} \frac{\left|R_{b,demand} - R_b\right|}{R_{b,demand}} + (1-\omega) \cdot \sum_{b=1}^{N} \frac{1}{1+Q_b} + \kappa \cdot \max\left[0, \sum_{b=1}^{N} P_b - P_{total}\right] \tag{10}$$

where κ is the penalty cost which occurs when the total power supplied is over the total available power of SPS. The first item aims at satisfying the first objective function of minimizing the gap between the terrestrial traffic demand and the information rate transmitted from the satellite. The second item aims at satisfying the second objective function of maximizing the total power harvested from the satellite. The weights between first and second objective function are denoted by ω and (1 – ω), respectively. The maximizing objective function makes the harvested power Q_b in cost function in the denominator, which causes the second item to be scaled between 0 and 1. Therefore, in order to fairly evaluate the contribution to information transmission and power transmission from the allocated power P_b, $\left|R_{b,\text{demand}} - R_b\right|$ in the first item is normalized by dividing by traffic demand $R_{b,\text{demand}}$. As the result, each value in the first and second item of cost function relative to both objective function is in the same scale between 0 and 1.

The bi-objective optimization RA problem in this work has been shown to be NP-hard [9], and the decision variables $\{P_b\}$, $\{\tau_b\}$, and $\{\rho_b\}$ are continuous variables. Hence, this work adopts continuous-population-based metaheuristic algorithms, which are suitable for extensively searching the candidate solution space. Particle Swarm Optimization (PSO) is a typical population-based search technique which improves solutions based on historic best solutions. In order to avoid possible concern about solution falling in local optima, the improved harmony search (IHS) algorithm is adopted in this work as well. Besides improving solutions from existing solutions, IHS has chance to improve each value in solutions randomly from the search space, which increases the exploration of solutions. However, IHS has less exploitation for not refining the exist solutions. Therefore, this work also adopts monkey algorithm (MA). Its climb process helps refine the solutions; watch-jump process and somersaults process allow MA to search for a new domain base.

3.3 PSO

PSO proposed by Kennedy and Eberhart [23] simulates the bird flocking adjusting their physical movement to seek for food based on swarm intelligence. The solutions, which are called "particles", have their own fitness values and speed to decide the moving direction. Each particle improves its fitness value by referring to other particles and itself, and then moves iteratively to the optimal solution. PSO is a derivative-free technique which makes it easy to be applied to various problems and requires a few of parameters, including inertia weight factor w affecting previous velocity on new one, two learning rates φ_1 and φ_2 randomly drawn between 0 and 1, and two coefficients c_1 and c_2 governing the cognition and social components [24].

In this work, PSO starts with randomly generating d initial particle vectors within feasible space. In each particle solution, the values of $\{P_b\}$ are generated between 0 and $P_b^{\max}$, and values of $\{\tau_b\}$ or $\{\rho_b\}$ are generated between 0 and 1. And, the initial velocity vectors of each particle are generated between the maximum and minimum velocity values. The best position found so far by particle i is saved as p_i, and the best position among all the particles is saved as p_g. At each iteration t, the velocity vectors and particle positions are updated by $v_i(t+1) = wv_i(t) + c_1\varphi_1(p_i - x_i(t)) + c_2\varphi_2(p_g - x_i(t))$ and $x_i(t+1) = x_i(t) + v_i(t+1)$, respectively. The inertia weight factor w will linearly decrease from w_{UB} to w_{LB}. When the particle moving process is repeated until the position values of all particles converge, the termination criterion is meet. The PSO algorithm is given in Algorithm 1.

Algorithm 1 PSO

```
Initialize a population of particles
Initialize position x_i of each particle i randomly within its search space
Initialize velocities v_i of particles i randomly within the velocity range
repeat
    for each particle i do
        Calculate the fitness value f(x_i) of particle i
        if f(x_i) is better than f(p_i) do
            Update p_i as x_i and f(p_i) as f(x_i)
        end if
    end for
    Update p_g as the best position found so far among all particles
    for each particle i do
        Update velocity v_i of particle i
        Update position x_i of particle i
    end for
until the termination criterion is meet
return the best particle
```

3.4 IHS algorithm

Harmony search (HS) algorithm proposed by Geem [25] imitates musicians improvise different pitches to obtain the best harmony. Different from traditional optimization algorithms, HS has fewer mathematical requirement to implement and generates new solution with stochastic random search technique. Hence, the derivative regarding the objective function is not required for solution improvement. Also, HS requires less adjustable parameters and has quick convergence. HS has good exploration for searching other promising solutions in solution space while has poor exploitation ability for refining the solutions. Therefore, this work adopts an IHS algorithm [26] to solve the concerned problem.

In this work, IHS algorithm starts with generating the harmony memory size (HMS) amount of initial solutions within possible value bound (PVB) and storing them to the harmony memory (HM) matrix. When executing the improvisation process to generate a new solution, each value in the new solution processes memory consideration, i.e., choosing one corresponding value randomly from solutions stored in the HM matrix under the probability of harmony memory considering rate (HMCR), or randomly choosing within the range PVB under the probability (1 – HMCR). Every value x_i chosen from the HM matrix has a chance to adjust its pitch by $x_i = x_i \pm \mathrm{rand}() \cdot bw$ (in which bw is ranged from different bounds for $\{P_b\}$ and $\{\tau_b\}/\{\rho_b\}$) under the probability of pitch adjusting rate (PAR), or to remain unchanged under the probability (1 – PAR). IHS linearly increases PAR by $\mathrm{PAR}_{\mathrm{LB}} + \left(\mathrm{PAR}_{\mathrm{UB}} - \mathrm{PAR}_{\mathrm{LB}}\right) \cdot i / \mathrm{NI}$ and exponentially decreases bw by $\mathrm{BW}_{\mathrm{UB}} \cdot \exp(\ln(\mathrm{BW}_{\mathrm{LB}} / \mathrm{BW}_{\mathrm{UB}}) \cdot i / \mathrm{NI})$ with iteration i, for faster convergence and finer solution. The new solution with a better fitness value than any solution in the HM matrix replaces the worst one. The termination criterion is achieved when the improvisation process is repeated until the total number of iterations reaches the maximal number of improvisations (NI). The IHS algorithm is given in Algorithm 2.

Algorithm 2 IHS algorithm

```
Initialize all parameters
Initialize the HM matrix with size HMS
while the termination criterion is not achieved do
    Update PAR and bw based on iteration number i
    for each note in the new harmony do
        if rand() ≤ HMCR do
            Choose a note value from the HM matrix
            if rand() ≤ PAR do
                Adjust the note value with bandwidth bw
            end if
        else
            Choose a note value randomly within range PVB
        end if
    end for
```

if the new harmony is better than any harmony in HM
    Replace the worst harmony in HM by the new harmony
end if
end while
return the best harmony solution in HM

3.5 MA

MA [27] simulates monkeys living in the mountains aims at reaching the highest mountaintop by executing three processes: the climb process, the watch-jump process, and the somersault process. MA is able to solve complex optimization problems featuring high dimensionality with a faster convergence rate and requires a few parameters, which give less manual operating on the parameter tuning, making it easily to implement.

In this work, MA starts with randomly generating the positions of monkeys within the feasible space respecting the problem model. Next, each monkey conducts the climb process for N_c iterations with the step lengths a_1 and a_2 with different scales for $\{P_b\}$ and $\{\tau_b\}/\{\rho_b\}$. Different from the original MA that accepts any new feasible solution, this work only updates the solution that has a better fitness value after climb process; otherwise, the solution remains unchanged. Next, monkeys conduct watch-jump process for N_w iterations to accelerate the search process by looking around within the range of the eyesight b_1 and b_2 with different scales for $\{P_b\}$ and $\{\tau_b\}/\{\rho_b\}$, respectively, for higher positions to jump to. Finally, monkeys conduct somersault process for N_s iterations to further explore new search domain by somersaulting along the direction from their current positions to the pivot, the barycenter of all the monkeys' current positions, with the distance of a value randomly generated within the somersault interval [*c*, *d*]. Different from the original MA that accepts any different feasible solution, this work only accepts the new solution with a better fitness value. When the climb process, watch-jump process, and somersault process are executed iteratively until the cyclic number N_M is reached, the termination criterion of MA algorithm is achieved. The MA is given Algorithm 3.

Algorithm 3 MA

Initialize a population of monkeys
while the termination criterion is not achieved **do**
    Conduct a *climb process* on each monkey
    Conduct a *watch-jump process* on each monkey
    if any monkey jumps to a better positon **do**
        Conduct a *climb process* on the monkey
    end if
    Conduct a *somersault process* on each monkey
end while
return the best solution of population

4 Implementation and Experimental Results

This work simulated the multi-beam SPS allocating its total available power among 37 beams to the terrestrial devices under two receiving architectures: the PS architecture and TS architecture, respectively. The total available power of multi-beam SPS is 2350 W and the power allocated to each beam cannot exceed 100 W [9]. The antenna noise power and signal processing noise is set as 1, and the efficiency factor of energy harvesting process is assumed to be 60% [13]. This work equally evaluated the information and power transmission from the multi-beam SPS to terrestrial devices, and hence the weights of first and second items in the cost function is set to be 0.5. The traffic demand from the earth is set at a normal distribution with mean of 1Gbps and standard deviation of 0.2Gbps. The experimental parameters of multi-beam SPS and algorithms are shown in Table 1.

Table 1. Multi-Beam Solar Power Satellite and Algorithms Parameters

Parameter	Definition	Value
N	Number of satellite beams	37
P_{total}	Total available power (W)	2350
$P_b^{\max}$	Maximum power of each beam b (W)	100
W	Bandwidth (MHz)	187.5
α_b^2	Signal power attenuation	0.9
σ_A^2	Antenna noise power	1
σ_{cov}^2	Signal processing noise	1
η	Efficiency factor of energy harvesting process	0.6
ω	Weight of Information transmission	0.5
$1\text{-}\omega$	Weight of power transmission	0.5
κ	Penalty cost	10
Decision variable	Definition	Value
P_b	Power allocated to the beam b	[0, 100]
τ_b	Expected time interval for power transmission	[0, 1]
ρ_b	Power splitting coefficient for power transmission	[0, 1]
PSO parameter	Definition	Value
d	The number of particles	20
w_{UB}, w_{LB}	Upper and lower bound of inertia weight factor	0.9, 0.4
c_1, c_2	learning rates governing the cognition and social components	2.0, 2.0
$V_{\max}$, $V_{\min}$	Extreme value of velocity	10, -10
IHS parameter	Definition	Value
HMS	Harmony memory size	20
HMCR	Harmony memory considering rate	0.9
PAR_{UB}, PAR_{LB}	Upper and lower bound of pitch adjusting rate	0.9, 0.2
BW_{1_UB}, BW_{1_LB}	Upper and lower bound of bandwidth for first part decision variables	5.0, 0.01
BW_{2_UB}, BW_{2_LB}	Upper and lower bound of bandwidth for second part decision variables	0.1, 0.002
MA parameter	Definition	Value
m	The number of monkeys	20
N_c	The number of climb process iterations	20

N_w	The number of watch-jump process iterations	20
N_s	The number of somersault process iterations	20
a_1, a_2	Climbing step length for first and second part decision variables	0.1, 0.001
b_1, b_2	Eyesight range for first and second part decision variables	0.5, 0.005
[c, d]	Somersault distance interval	[-1, 1]

The information rates offered by multi-beam SPS among 37 satellite beams under PS and TS architectures, denoted by "R_b in PS" and "R_b in TS", respectively, compared by the traffic demand from terrestrial devices, denoted by $R_{b,\text{demand}}$, are in Fig. 2. From Fig. 2, the offered information rate matches most of the traffic demands from each satellite beam by solving the concerned RA problem. Also, the information offered under PS architecture is slightly more than that under TS architecture in most of satellite beams, because the receiver design of terminal devices for TS architecture cannot perform decoding information and harvesting energy concurrently, leading to less efficiency than receiver design for PS architecture.

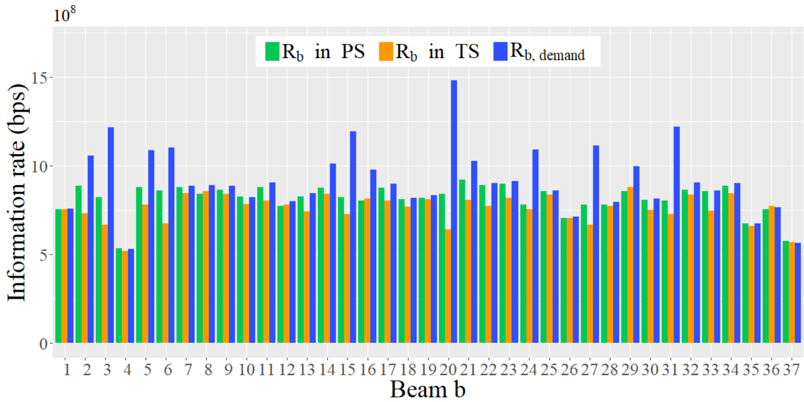

Fig. 2. Information rate offered under PS and TS architecture, and the traffic demand from terrestrial devices.

Fig. 3 shows the result of the bi-objective function of each satellite beam. The power allocation for power transmission Q_b in PS architecture clearly surpasses power transmission Q_b in TS architecture in majority of satellite beams. Also, the information offered gaps in PS architecture are lower than most of gaps in TS architecture. Fig. 3 gives the conclusion that the receiver design for PS architecture surpasses that for TS architecture of terrestrial devices. From Fig. 2 and Fig. 3, the higher information gaps of beams 2, 3, 5, 6, 15, 20, 24, 27, and 31 are corresponded to the beams with higher traffic demand. Hence, the higher information gaps are caused by extremely higher traffic demands rather than the power allocated for power transmission, ensuring that the information transmission is not impacted by power transmission in the SWIPT.

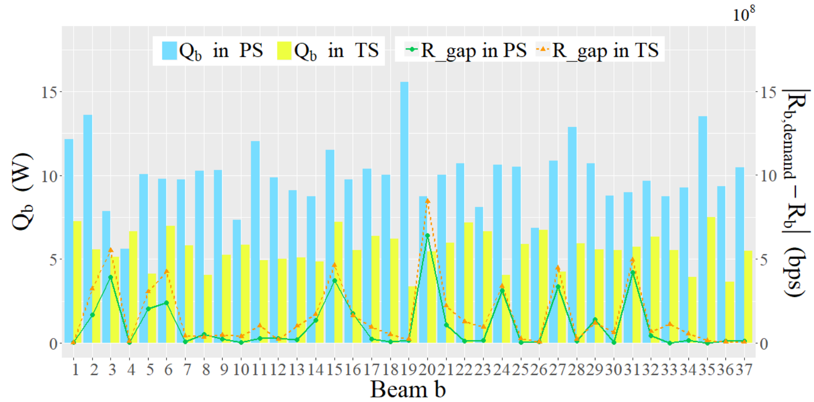

Fig. 3. Power harvested and information offered gaps under PS and TS architecture.

This work solves the problem by three metaheuristic algorithms, PSO, MA, and IHS, in 100,000 iterations 20 run times. In Fig. 4, the experimental results show that the IHS can achieve the lowest cost value of 3.751683 than the other two algorithms. The reason why the IHS performs better than MA can be surmised that the improvisation process of IHS can achieve better exploration than watch-jump process and somersault process of MA at the end of iterations.

Fig. 5 shows the power allocated to each satellite beam as the solution of the concerned bi-objective RA problem, which came out from the IHS algorithm, for power and information transmission under different power splitting coefficients of the PS architecture and expected time intervals of the TS architecture. It can be observed that the power allocated for power transmission in every beam of the PS architecture is higher than that of the TS architecture. It implies that when running the TS architecture experiment, the algorithm tends to sacrifice power transmission for information transmission with respect to the cost function.

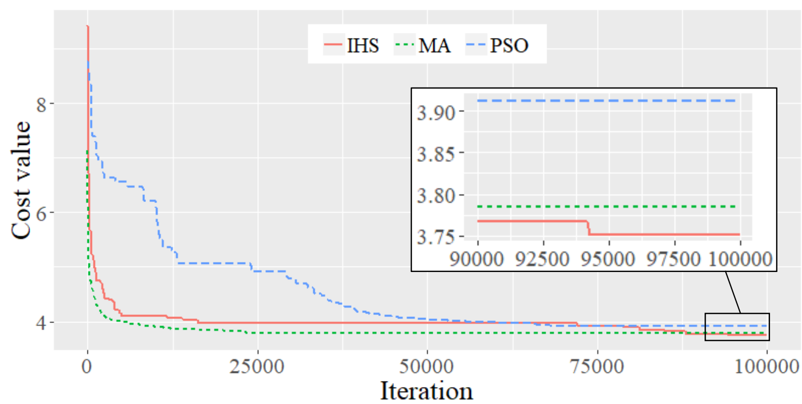

Fig. 4. Convergence analysis of the PSO, MA, and IHS algorithms.

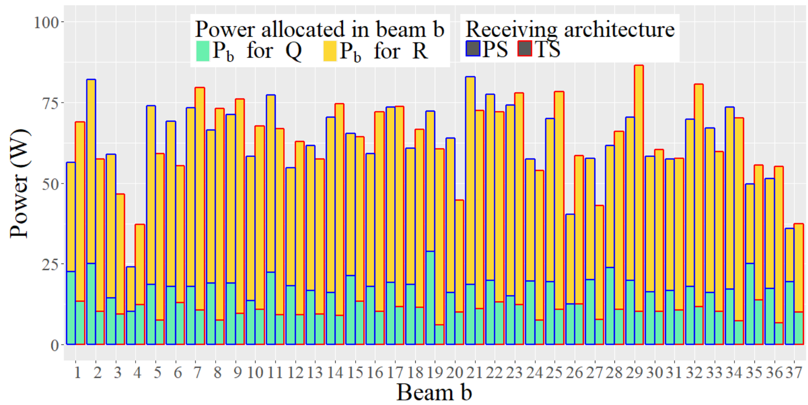

Fig. 5. Satellite power allocated for information (R) and power transmission (Q) under the PS and TS architectures.

5 Conclusion

This work has proposed a novel RA problem of multi-beam SPS performing SWIPT in the STIN. The bi-objective function of minimizing the difference between information transmission and traffic demand and maximizing power transmission is optimized by distributing different levels of power among satellite beams and allocating power in each beam into two parts for information and power transmission. The TS and PS architectures of terrestrial devices are also considered in the system framework. From experimental results, the IHS algorithm can maximize the power transmission without impacting on information transmission, which can be used for emergency communication. In addition, the PS architecture performs better than TS architecture in both information and power transmission.

However, the advantages of TS architecture, like easy implementation, are not considered in the problem model. Hence, it would be of future interest to cover more characteristics of two receiving architectures in this model. Also, the RA problem can be expended to the dynamic problem by considering different traffic demands and channel conditions under time series since the multi-beam SPS is able to process cross time-zone demand. In addition, the satellite studied in this work is a single LEO satellite serving all the terminal communication devices on Earth. The hybrid STIN containing GEO, MEO, LEO satellites or mobile BS can be discussed in the future work for network flexibility applied to software-defined network (SDN) and diverse application such as IoT and edge computing.

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