Research of Frequency Allocation Based on Improved Genetic Algorithm

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Abstract. With the development of science and technology, more and more attention has been paid to wireless spectrum allocation technology. In this paper, we propose a improved genetic algorithm which is suitable for spectrum allocation on open space platforms. It uses the method of sequential allocation and solves the problem of channel multiplexing by a new designed interference model under the situation of tight spectrum resources. The simulation results show that the improved genetic algorithm can effectively reduce the total interference of signal and improve the convergence speed of realloction after the number of devices has changed.

Keywords: Spectrum Allocation; Genetic Algorithm; Sequential Allocation; Interference Model; Convergence Speed

1 Introduction

Wireless spectrum, the foundation of network speed and quality, is an important but nonrenewable resource. Different signals working on the same frequency may produce mass mutual interference. In addition, the signal working frequency is concentrated, and the spectrum utilization is low [1].. With the further development of technology, more wireless devices will be put into use. It will certainly cause congestion of spectrum resources and inefficient use of frequencies. Thus, more and more attention has been paid to spectrum allocation techniques that can effectively reduce interference between devices and improve spectrum utilization.

Spectrum allocation technology is a soft strategy. It is the process to assign operation frequency for radio equipment, which is the ultimate manifestation of frequency management, in order to make sure that the radio equipments operate normally without any mutual interference [2]..

Traditional distribution methods inlude exhaustive search algorithm and order distribution method. However, in recent years, researchers have proposed many intelligent algorithms that simulate natural ecosystem mechanisms which is suitable for spectrum allocation problems. These methods can effectively increase the speed of algorithm. There are Simulate Anneal (SA) [3]., Ant Colony Optimization (ACO) [4]., Genetic Algorithm (GA) [5]. and etc. So far, several techniques have proposed some spectrum allocation schemes based on genetic algorithms:

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A GA-Based effectivet model for channel allocation is proposed by Yasmina El Morabit et al [6].. In [6], they have proposed GA in cognitive radio network to obtain the optimum radio configurations. They focus on spectrum allocation with the quality of service requirements is specified in the inputs. The objectives are combined to one multi–objective fitness function using weighted sum approach so that each objective can be represented by a rank which represents the importance of each objective.

A radio frequency allocation method based on improved GA is proposed by Changsheng Yin et al [7].. In this paper, they design an improved GA to enhance efficiency and real-time of frequency assignment. They combine GA with greedy algorithm when generating the initial population. Meanwhile, a hybridization method was introduced to improve the roulette selection efficiency. These improve the convergence speed of the algorithm.

However, the existing improved GA algorithm does not take into account the problem of channel channel multiplexing when spectrum resources are limit. To solve this problem, we provide a practical new solution to the frequency allocation problem by improving genetic algorithms. In this algorithms, we considered the power path loss of the signal and the interference tolerance of the devices when designing the fitness function. It can reduce the total interference to the devices in the final allocation result. In addition, the existing improved GA algorithm does not take into account the problem of spectrum reallocation in the actual open space spectrum allocation scenario. In this paper, devices are assigned in groups and we used the sequential allocation method. It can greatly reduce the convergence speed of reallocation.

The rest of this paper is organized as follows. Section 2 outlines the system model of spectrum allocation on open space platforms. Section 3 describes the specific method and principle of the allocation algorithm. Section 4 illustrates the simulation cases and result. Finally, Section 5 concludes the paper.

2 System Model

Fig. 1 illustrates the system model of spectrum allocation on open space platforms. There are multiple platforms in an open space and each platform has multiple devices. All of which are zoned on a same frequency band. If devices on the same platform occuoy the same channel, it will cause a lot of mutual interference. To avoid this situation, we directly prohibit devices from same platform occupying the same channel. In addition, comparing with the distance between platforms, the size of platform can be ignored. Thus we assume that each platform is a single point and all the divices are located at the point in the modeling process. Mutual interference of devices on different platforms is the main factor and spectrum allocation is based on minimum total interference of platform. In order to simulate the frequency characteristics of different devices, each device has a different operating frequency band range.

The following parameters are set in this paper. The available frequency band is (f_L, f_H), f_L as the starting frequency point, f_H as the ending frequency point. Every Δf is set to a channel and there is M free channels. A total of Π platforms are distributed randomly on the circular area with a radius of R, with N devices on each platform.

In this paper, two different scenarios are designed, that is sufficient spectrum scenarios and insufficient spectrum scenarios, by changing the above parameters.

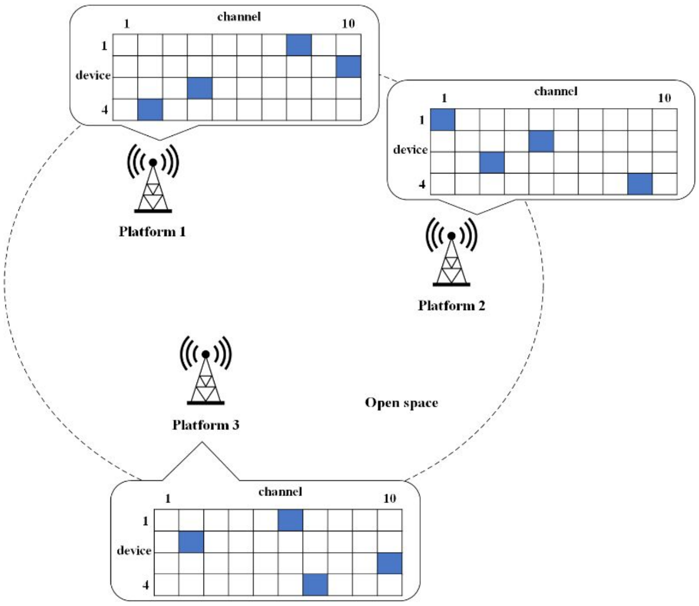

Fig. 1. System model

2.1 Scenario 1: Sufficient spectrum resources

In this scenario, we simulate a situation with sufficient channels. The number of channels required by the devices are less than the number of free channels, so that different devices are able to occupy different channels. In theory, we can find an allocation scheme without mutual interference between devices. We get the final allocation scheme through the algorithm and calculate the interference and convergence speed.

After the initial allocation, keep the position of platforms and the number free channels unchanged. Add a new platform with a random position and the past allocation scheme no longer meet new requirement. The spectrum needs to be reallocated and then calculate the interference and convergence speed.

2.2 Scenario 2: Insufficient spectrum resources

In this scenario, we simulate a situation with insufficient channels. The number of channels required by the devices are more than the number of free channels, so that different devices are not able to occupy different channels. In theory, some channels will be occupied by multiple devices simultaneously. Thus, an allocation scheme that allows efficient channel multiplexing is vital. We get the final allocation scheme through the algorithm and calculate the interference and convergence speed.

After the initial allocation, keep the position of platforms and the number free channels unchanged. Add a new platform with a random position and the past allocation scheme no longer meet new requirement. The spectrum needs to be reallocated and then calculate the interference and convergence speed.

3 Improved Genetic Algorithm

3.1 Genetic Algorithm

The genetic algorithm(GA), a search algorithm based on the mechanics of natural selection and genetics, combines a strategy of "survival of the fittest" with a random exchange of information, but structured[6]..

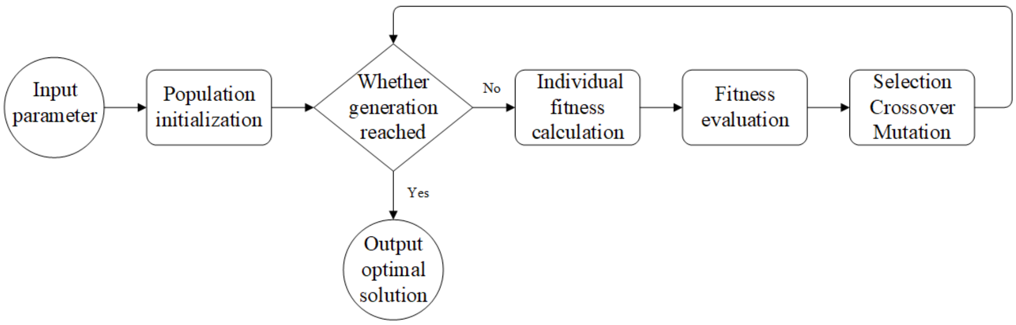

Fig. 2. GA flow chart.

Fig. 2 illustrates basic flows of the GA. Brief explanations of each step involved of the GA is as follow [8]..

Population initialization: Randomly generate a chromosome of length i based on the available matrix defined by the input parameters. An initial population includes j chromosomes.

Fitness: It represents the evaluation of fitness of each chromosomes.

Selection: Selecting the superior chromosome from the population and eliminating the inferior chromosome is called selection.

Crossover: Crossover refers to the operation of replacing and reorganizing part of the structure of two parent chromosomes to generate new chromosomes.

Mutation: Mutation is a random change in some genes on the chromosomes.

3.2 Interference Model

Co-channel interference is the most basic form of interference. It refers to the wanted signal and other unwanted interference occupying same channel. This interference signal may originate from devices of other platform or intentionally applied interference signals.

The past allocation method only distinguished whether interference exist when analyzing co-channel interference. It makes the allocation scheme suitable for scenarios with sufficient spectrum resources to avoid co-channel interference. However, this kind of method does not take into account the problem of channel multiplexing in spectrum tight scenarios. In the process of spectrum allocation with channel multiplexing, it is necessary to keep the total system interference to a minimum. Thus, more complex evaluation criteria for interference values are demanded.

In this paper, we use the total power of the interference signal of each channel as the criterion for evaluating the interference. Assume that there is a device A on a platform and device B on another platform, and they occupy the same channel. Device A may interferes with B. The signal power of A is P_A dBm. During signal transmission, the power of the signal will be attenuated. When the signal reaches another platform, the signal power decays to P_A'. We regard P_A' as the interference of device A to B. The formula for path loss is:

$$L = 32.44 + 20 * \lg(D) + 20 * \lg(M) \tag{1}$$

Where in (1) , L represents the signal path loss, and its unit is dB. D represents the distance of signal traveling in space, which can be simplified to the distance between two platforms in our scenarios, and its unit is km. M represents the aignal operating frequency, and its unit is MHz.

According to the system model setting above, there is seventy devices on seven platforms and a divice may occupy plural channels. Therefore, a channel may be occupied by more than two devices. The interference experienced by one device is the superposition of the power of other devices. The formula for power superposition is:

$$I = 10 * \lg\left[\sum_{k=1}^{n} 10^{\left(\frac{I_K}{10}\right)}\right]$$

(2)

Where in (2), n represents the number of interfering divices. I represents the total interference, and its unit is dBm. I_K represents interference from each device, and its unit is dBm.

We use interference matrix to represents the interference of each device on a platform. The form of the matrix is shown in (3).

$$\begin{pmatrix} I_{11} & \cdots & I_{1M} \\ \vdots & \ddots & \vdots \\ I_{N1} & \cdots & I_{NM} \end{pmatrix}$$

(3)

Where in (3), M represents the number of channels. N represents the number of devices. I_{MN} represents total interference of a device in one channel.

In addition, the actual communication devices has a certain anti-interference ability. Small amplitude interference will not affect the transmission of wanted signals. We set the interference threshold in order to simulate the anti-interference ability of devices. When the total interference power is less than I_0, we can account that the interference will not affect the operation of devices. This kind of interference will not affect channel multiplexing. Thus, it can be removed from the interference matrix when calculating reward.

3.3 Sequential Spectrum Allocation

Scenarios for spectrum allocation on open space platforms are more complicated than the ordinary allocation. All devices is naturally classified by each platform. Differences between platforms are issues that need to be analyzed. Besides, each platform is not connected to the network at the same time, but in a certain order. Therefore, we carried out sequential spectrum allocation in order to reflect the differences of each platform.

The ordinary GA is limited by population and length of chromosome. It has a problem with early convergence, especially in complex scenarios. In these scenarios, the ordinary GA often fails to get the global optimal solution. Sequential spectrum allocation can solve this kind of problem. It split a long chromosome into segments to reduce the length, improving gene richness and ability to find needed genes. Therefore, sequential spectrum allocation can effectively improve the ability to find global optimal solutions in complex scenarios and reduce the amount of calculations per generation.

However, sequential spectrum allocation brings a new proplem with the increasing number of generations. We set a new parameter T_m to reduce generations. In one GA process, if fitness value has not changed for T_m generations, this GA process ends and the next GA process starts. Besides, if the fitness value meet the upper limit $Maximum\ fitness$, this GA process ends too. The methods can greatly reduce the number of useless generations, especially in the first few GA processes.

In addition, sequential spectrum allocation can greatly reduce the convergence speed of reallocation. Assume that the first allocation has ended and there is a paltform that changes its position. Traditional GA requires a new spectrum allocation for all platforms. However, new allocation scheme in this paper has completely different reallocation methods. Due to the independence of the device allocation process on each platform, it allows use to directly read the previous allocation results and reallocate spectrum for the new platform based on the past results.

The basic steps of the sequential spectrum allocation are:

Algorithm 1 Sequential Spectrum Allocation;

Input: Π, $Maximum\ fitness$, T_m

Output: Allocation scheme matrix Λ and

fitness of the best gene of each generation $Max-Reward$

```
T = 150;
randomly initialize chromesomes;
for i = 1 : Π do
    T_π = 0; t = 0; i = i + 1;
    while (t < T) do
```

Calculate $\textit{Max-Reward}$ (i) ← best fitness of chromesomes;
Calculate Λ (i) ← $\textit{Max-Reward}$ corresponding allocation scheme;
Selection; Crossover; Mutation; t = t + 1;
if $\textit{Max-Reward}$ unchanged then T_s = T_s + 1;
else T_s = 0;
endif
if($\textit{Max-Reward}$ == $\textit{Maximum fitness}$) then t = 150;
if(T_s == T_m) then t = 150;
endif
end while
end for

3.4 Algorithm Convergence Criterion

Improved Genetic Algorithm is a kind of optimization problem. The allocation scheme is to find the optimal solution under the current conditions. We use the sum of the interference from each channel as the fitness function in the genetic algorithm and define a standard named $Max-Reward$ to evaluate it.

$$\begin{aligned} &\textit{Max-Reward} = \max\left\{ \textit{Maximum fitness} - \sum_{i=1}^{TT}\sum_{m=1}^{M}\sum_{n=1}^{N}\left(I_{mn}(i) * a_{mn}(i) \right) \right\} \\ &s.t. I_{mn}(i) \in I, a_{mn}(i) = 0 \text{ or } 1, \textit{Maximum fitness} = const, \\ &\quad \forall i \in (1,2,\cdots,TT), \forall m \in (1,2,\cdots,M), \forall n \in (1,2,\cdots,N), \end{aligned}$$

(4)

Where in (4), matrix a is the allocation schemes under the constraints of TT, M, N and other parameters. The product of I and a represents total interference to the devices. During the improved Genetic Algorithm, our purpose of the algorithm is to find an allocation scheme that maximizes $Max-Reward$.

Since the first generation $t = 1$, we define one selection, crossover, and mutation as one generation . The algorithm converges when all platforms are allocated and $Max-Reward$ has not changed multiple generations in a row. Convergence speed is the number of generations required. We think that the less generations the algorithm needs, the faster the convergence speed.

4 Simulation

4.1 Scenario 1: Sufficient spectrum resources

In this scenario, we set a simulation where the spectrum resources are sufficient. This scenario is described above.

The unchanged parameters are shown in **Table 1.**

First, we make an initial allocation with four platforms that need no more than forty channels. The comparison result is shown in the **Fig. 3.**

Table 1. Parameters of GA and improved GA in Scenario 1.

Parameters	GA	improved GA
1 Scenario Parameters		
Area radius/R(km)	50	50
Spectrum range(MHz)	850-1000	850-1000
Channel bandwidth/ Δf (MHz)	3	3
Number of free channels/M	50	50
Number of platforms/TT	4/5	4/5
Number of devices per platform	10	10
2 Algorithm Parameters		
Population	300	300
Generation/t	150	150
T_m		20
Maximum fitness	2000	2000
Crossover rate	0.8	0.8
Mutation rate	0.01	0.01
Interference threshold(dBm)		-60

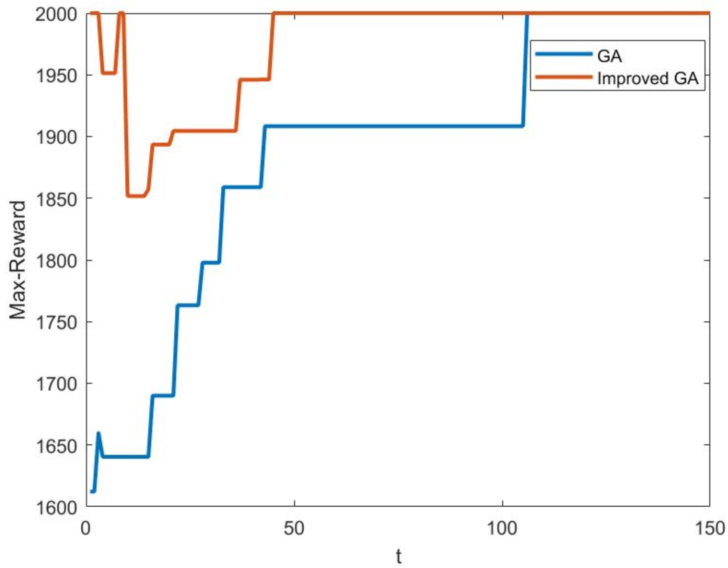

Fig. 3. The max-reward of each generation in the initial allocation.

As the result illustrates, both GA and improved GA reach maximum fitness and figure out the global optimal solution. However, the convergence speed of improved GA is much faster than ordinary GA. Therefore, the improved GA can significantly reduce the number of iterations in the situation where the spectrum resources is sufficient.

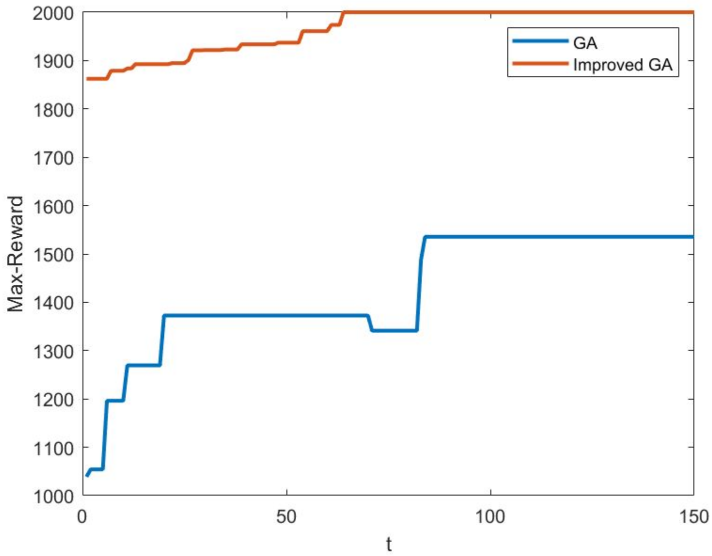

Fig. 4. The max-reward of each generation in the reallocation.

Then, add a new platform and reallocate the sprctrum. There are fifty devices and fifty free channels. The improved GA is able to analysis the past allocation scheme and only allocate new platform based on the past solutions. However, the ordinary GA needs to reallocate all the five paltforms. The comparison result is shown in the **Fig. 4.**

As the result illustrates, the improved GA reaches maximum fitness and figures out the global optimal solution but the ordinary GA fails. Besides, the convergence speed of improved GA is faster than the ordinary GA.

The improved GA sgnificantly reduced length of chromosomes, which gives every excellent gene more chance to inherit. However, ordinary GA, limited by length of chromosomes, has converged before finding the optimal solution. In addition, the improved also sgnificantly reduced number of platforms that need to reallocate, which improved convergence speed.

4.1 Scenario 2: Insufficient spectrum resources

In this scenario, we set a simulation where the spectrum resources are insufficient. This scenario is described above.

The unchanged parameters are shown in **Table 2.**

First, we make an initial allocation with six platforms. In this situation, interference is inevitable. The purpose of the allocation is to reduce interference and multiplex channels. The comparison result is shown in the **Fig. 5.**

Table 2. Parameters of GA and improved GA in Scenario 2.

Parameters	**GA**	**improved GA**
1 Scenario Parameters		
Area radius/R(km)	50	50
Spectrum range(MHz)	850-1000	850-1000
Channel bandwidth/ Δf (MHz)	3	3
Number of free channels	50	50
Number of platforms	6/7	6/7
2 Algorithm Parameters		
Population	500	500
Generation/t	200	200
T_m		20
Maximum fitness	2000	2000
Probability of crossover	0.8	0.8
Probability of mutation	0.01	0.01
Interference threshold(dBm)		-60

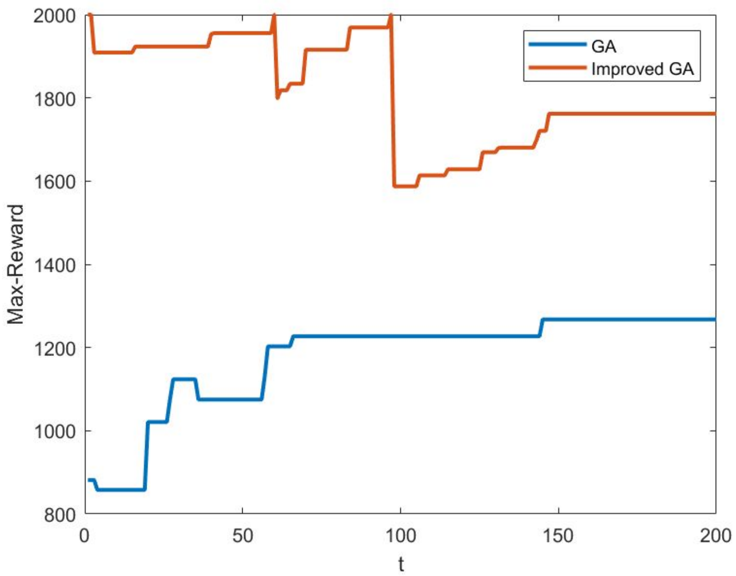

Fig. 5. The max-reward of each generation in the initial allocation.

As the result illustrates, neither ordinary GA nor improved GA reach maximum fitness. This complex scenario increases generations of the improved GA. In return, the improved GA provides an ability on greatly reducing interference when multiplex channels.

Then, add a new platform and reallocate the sprctrum. Spectrum resources become more scarced. The comparison result is shown in the **Fig. 6.**

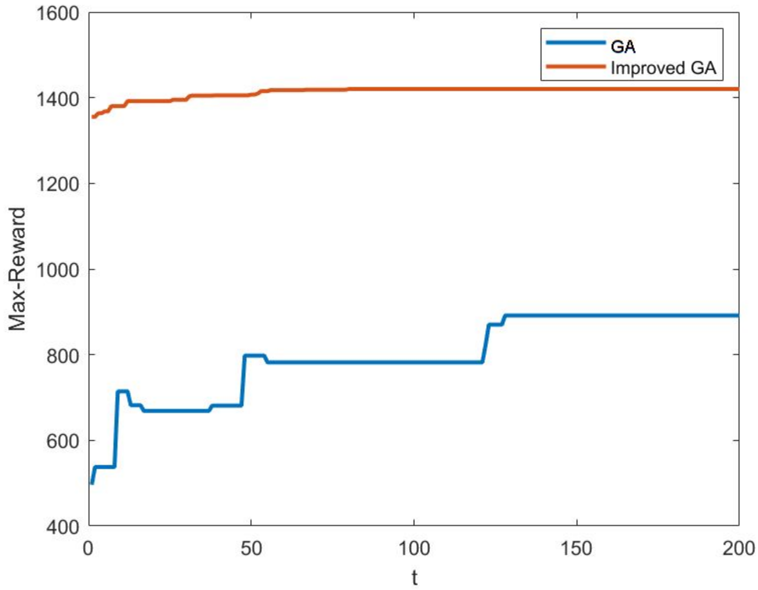

Fig. 6. The max-reward of each generation in the reallocation.

As the result illustrates, both ordinary GA and improved GA scheme are suffer from a huge interference. However, the improved GA has better max-reward and convergence speed.

The ordinary GA does not take space factor into account but the improved GA does. Therefore, especially in the complex scenario where the spectrum resources are insufficient, improved GA can effectively reduce interference between co-channel signals and increase the speed of reallocation.

5 Conclusion

In this paper, a new spectrum allocation on open space platforms based on improved Genetic Algorithm has been proposed. The major differences are sequential spectrum allocation and interference model using in the improved Genetic Algorithm. Finally, the simulation shows that the algorithm is more efficient to reduce co-channel interference and increase convergence speed.

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