Enhanced SA-based Charging Algorithm for WRSN

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***Abstract*—The wireless rechargeable sensor network is a technology to solve lifetime problem for wireless sensor network. Most researches discussed about the outdoor scenario but there are few studies focused on the indoor scenario. Actually, wireless sensor network is very important for the indoor scenario. The reason is that sensors help factory control production for better quality as well as both of disaster relief and prevention are also need to deploy sensors in the indoor scenario. These instances have the concept of sustainable development because sensors cannot be suddenly interrupted so that the expected benefits cannot be realized. As in the example just mentioned, quality of production is no longer to be guaranteed and disaster will not be prevented. That is why the wireless rechargeable sensor network becomes more popular. There are many low cost charger deployment algorithms have been proposed. However, these works almost have opportunity to fall into local optimum. This paper will present a layoff algorithm to combine simulated annealing-based algorithm to achieve optimization for wireless rechargeable sensor network. The simulation results show that the proposed method can reduce the number of chargers efficiently but just need same time with simulated annealing-based algorithm.**

***Index Terms*—Wireless rechargeable sensor network, network planning, and metaheuristic algorithm.**

I. Introduction

In case of people want to take care of their elderly family perfectly as well as increasing their quality of life[1]. They used various sensors to collect heartbeat, blood pressure and sleep quality from their family's body so that people are able to handle any emergencies instantly. Another example, a wrong order may cause soldiers be sacrificed in the war innocently, so army needs to use WSN to get more useful information, so that the order correctness can be guaranteed. Furthermore, people want to investigate some dangerous environments such as volcano[2] and underwater environment[3], but these environments are diffcult to be reached[4][5]. In these scenarios, sensor is a competent technology to sense anything in variety of harsh environments. Obviously, the importance of the WSN is very large.

However, WSN is not perfect. It still has some intrinsic issues. WSN is composed of wireless sensors and relay nodes. Each sensor node will sense various kinds of information then transfer them to relay nodes that all of actions will consume energy, but energy of sensors is limited by battery capacity. It means that their energy will be exhausted someday. As we just mentioned, sensors may be placed in the dangerous places hence we cannot replace the battery immediately for them so that WSN will be paralysed if there was a relay node died. In view of that, researchers proposed some methods to solve network lifetime problem. Some scholars think that all of the sensors should not have to work at the same time because this will cause energy be wasted unnecessarily[6]. So scheduling the working time of sensors can make them use energy efficiently. However, network lifetime of WSN still depends on the battery's capacity that it is a fact which can not be changed[7].

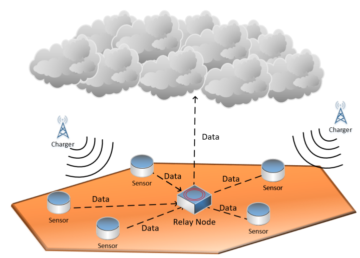

Fig. 1. Wireless Rechargeable Sensor Network

In order to solve this problem, wireless rechargeable sensor network(WRSN)[8] had been proposed due to development of the wireless charging technology[9]. WRSN is composed of charger, sensor and relay node that charger is a main power source to supply energy for other components. Fig. 1 shows that WRSN technology has own suitable environment so that user can choose a different charging equipment according to requirement of them. Of course different charging equipments have different wireless charging ways. For example, wireless charging technology of mobile phone always use the electromagnetic induction.

WRSN can be roughly divided into two types: indoor environment and outdoor environment. The deployment strategy of chargers needs to consider various impacts from the different environments which them belong. In our study, we focus on the indoor environment deployment. This is a complex problem because charger deployment strategy will be impacted by sensor position, RF interference and charger efficiency and those metrics have the very frequent trade-off relationship. Therefore, we have to balance each factor and make sure the

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solution which will not fall into local optimum. In previous work[10], we used simulated anneal(SA) algorithm to solve it. Although its results have been better than the greedy-based methods, it still has a lot of drawbacks need to be improved.

Generally, metaheuristic algorithms have larger opportunity to find out the better solution, however the process of metaheuristic algorithm must to make iteration continuously, it will spend more computation time for convergence. Another problem is that quality of solution will be worse, which means that there were some sensors not be covered by coverage of chargers. This situation explained that solution may have fell into local optimum. In order to ensure all sensors can be charged, the number of chargers must to be increased so that deployment cost and power consumption are also increased. Therefore, we think we have to exclude the unessential solution so that the computation time can be decreased as well as ensuring the remained solution which is able to let all sensors can be covered. In detail, we must ensure that all sensors can be covered by at least a charger in each iteration. In the above process, some used-less candidate chargers will be remove out of solution space so that we are able to find out a better solution within an acceptable computation time.

The simulation results show that the proposed method can help metaheuristic-based algorithms to avoid to fall into local optimum as well as it can provide WRSN a more stable working environment.

The rest of the paper is organized as follows. Section II introduces background about WRSN and related works which includes previously proposed SA-based charging algorithm(SABC). Section III depicts the problem definition. Section IV discuss that our proposed method how to improve metaheuristic algorithm. The simulation results are show in section V. Finally, we will summarize the contributions and discussing the future works in last section.

II. Related Works

As previously said, our goal is to enhance metaheuristic-based algorithm. In order to clearly present our study, we will introduce backgrounds of WRSN which include an introduction of our previously proposed metaheuristic-based algorithm.

A. *Wireless Rechargeable Sensor Network*

Wireless charging technologies can be divided into four types. The first type is magnetic resonance which uses coil to creat a magnetic field. In general case, coil is able to produce shock as long as there is the same frequency nearby this coil, and then current can be generated. An common application is like mobile phone charging. The second type is magnetic induction. Difference with magnetic resonance is that electric current will be generated when magnetic field is changed. This method is also commonly used to mobile phone charging . The third type is laser light sensing. Concept of this type is like conversion of solar energy. Charging distance of laser light sensing is longest than the others. But it has too high energy that it may harm the human, so this technology has not been common used for daily life. The final type is mico-wave conversion. Fundamentally, radio frequency(RF) has energy itself, hence we are able to collect energy as long as converting energy of RF to become normal current. This type of wireless charging technology has two ways for RF transmission. First way is directional transmission, another one is omni-directional transmission. Energy transmission of directional type is centralized , and omni-directional transmission is contrary. Generally, omni-directional transmission suits to outdoor or high mobility environment, because it can provide robust coverage. The directional transmission is commonly used to static environment, because the targets cannot move so that charger is able to support power with more concentrated.

B. *Movable-Charger-Based Algorithm*

In previous work [11], the proposed method presented a Movable-Charger-Based Algorithm(MCBA) for charger deployment problem. The charging way used the directional transmission. In order to expand the charging area, we set the motor on each charger so that charging angle becomes movable. Chargers are placed on the ceiling then they are able to emit RF down to cover the sensor nodes. In this way, we not only reduce many cabling costs but also adding the more flexibility.

MCBA has two steps to find out the solution. The first step is to find candidate chargers. We can get position of each sensor by aGPS and then we map transmission range of sensor nodes to the ceiling so that we can see there are many circles which may have some overlapping area with their neighbors. So called candidate charger is represented by the point which is in the overlapping area. It means that sensor can be covered as long as there is a charger be set in here. Second step is to find a best from a set of found candidate chargers. Best solution means that there are more sensors can be covered in overlapping area. According to such criteria, we can find a better way to deploy all of chargers.

C. *SA-Based Charging Algorithm(SABC)*

Although MCBA is a good method for deployment of chargers, it is a kind of greedy algorithm. Typically, greedy method is difficult to find better solution because it is easier to fall into local optimum. In order to achieve lower cost, we have to find better position to deploy chargers as well as the found solution must to be avoided to fall into local optimum. Depending on these conditions, metaheuristic algorithm is a good choice. In previous work, we used simulated annealing(SA) as a basic method to design a novel algorithm for charger deployment in WRSN that is called SA-based charging algorithm(SABC)[12]. Most of metaheuristic algorithms need more computing time, but WRSN environment may be frequently changed. We chose SA that is because convergence rate of SA is quicker than most of metaheuristic algorithms. The main idea of SABC is that it can accept lower quality solution which may cover lower sensors or it has less overlapping area. In this way, this algorithm has more direction for searching so that the optimal solution has higher opportunity to be found.

III. Problem Definition

Chargers deployment issues can be simply divided into indoor environment and outdoor environment. Different environments will affect the problem definition and the coding way of sub-solutions. This study focus on the deployment problem in indoor scenario. In order to suit for indoor stacked machine, we deploy chargers on the ceiling so that these obstacles can be avoided. Each charger will emit a radio wave down to cover the sensors which had been placed on the machine. Any chargers have the effective charging distance. When it is closer to the charger, the charging efficiency is better and vice versa. In order to ensure each sensor can be charged effectively, we assume that the height of indoor scenario must less then the such effective charging distance.

The reason is that deployment problem will be limited by deploying order. It means that a change of candidate charger position will cause several candidate charger position are also changed, hence the optimization of this problem is very difficult to be found within an acceptable time, not to mention SA is almost one of the fastest metaheuristic-based algorithms. Therefore, this study focus on how to enhance SA for charger deployment problem. In order to ensure its accuracy and fairness, all experiment scenario and coding way are follow SABC. And sensors are also randomly deploy in a three-dimensional space as well as each charger also combine motor to extend the charging area. The temperature adjust it according to SA rule.

According to the mentioned expected goals, we define a linear programming model for this problem:

$$\begin{aligned} &Minimize \sum_{i=1}^{n} F_i \\ &s.t. \\ &\qquad \sum_{j=1}^{m} P_{i,j}^{S}(d) \geq W_i^{S} \\ &\qquad P_{i,j}^{C} \geq P_{i,j}^{S} \\ &\qquad d_{i,j} \leq E \\ &\qquad 0^\circ \leq \theta_i \leq 180^\circ \\ &\qquad S_j \geq 1 \end{aligned} \tag{1}$$

F_i represents the status of i^{th} candidate charger. Because F_i is a boolean value, hence minimization of $\sum_{i=1}^{n} F_i$ is our major goal that means that we are able to use minimal number of chargers to guarantee all sensors can work continuously. Notice that too many chargers need to spend more deployment cost, and too less chargers will lead to sensor dead soon. So balancing these two metrics is an important point. We try to define several restrictions to illustrate this problem scenario. The first restriction shows that collected total power of sensor must be larger than the consumed power. It ensures the sensor will not run out of energy. Transfer power from the charger to the sensor must be larger than received power of sensor because transmission of radio frequency will be attenuated that is described in the second restriction. The third restriction is that distance between sensor and charger must be less than the effective charging distance E. E is an adjustable parameter in the different environment. The forth restriction limits the movable angle of motor which only works on a plane, so this value is limited between 0° to 180°. S_j means that number of chargers which covered i^{th} sensor. The value of S_j must greater than or equal to 1 because we need to make sure all of sensors will be covered by at least one charger.

TABLE I
Important Symbol List

Values	Definition
$P_{i,j}^{S}$	Received power from the j^{th} charger to i^{th} sensor
G_c	Value of antenna gains of chargers
G_s	Value of antenna gains of sensor nodes
η	Value of rectifier efficiency
L_p	Polarization loss
λ	Wavelength of RF
$d_{i,j}$	Distance from i^{th}sensor to j^{th} charger
β	An adjustable parameter in indoor environment
$P_{i,j}^{c}$	Generated power from j^{th} charger to the i^{th} sensor
W_i	Power consumption of i^{th} sensor
R	Effectual charging distance
V_c	Set of candidate chargers
V_s	Set of sensor nodes which are covered by C_i
V_e	Set of finalized position of deployed chargers

IV. Proposed Mechanism

A. Wireless Charging Model

The received power of any sensors are different because each sensor has different power of conversion rate and different distance from a charger. Therefore, we must to calculate the received power of each sensor via [11] :

$$P_{i,j}^{S}(d) = \frac{G_c G_s \eta}{L_p} \left(\frac{\lambda}{4\pi(d_{i,j}+\beta)}\right)^2 P_{i,j}^{C}, \tag{2}$$

$P_{i,j}^{S}(d)$ represents received power from the j^{th} charger to i^{th} sensor. $P_{i,j}^{C}$ is power which transfer from j^{th} charger to i^{th} sensor. G_c is a value of antenna gains of chargers, and G_s is a value of antenna gains of sensor nodes. η is a value of rectifier efficiency. L_p represents polarization loss. λ is wavelength of RF. β is an unique adjustable parameter in the indoor environment. Effectual charging distance(ECD) is an important factor in our study. ECD means that a range which lets charger has acceptable charging efficiency within there. To make sure each sensor can be charged, we further define the ECD that is shown in Eq. (3).

$$R = \frac{\lambda}{4\pi\sqrt{\left(\frac{W_{Max} L_p}{n G_c G_s \eta P_{i,j}^{S}(d)}\right)}} - \beta, \tag{3}$$

where R is ECD, W_{Max} represents the maximum power consumption of all sensors. n is the number of needed chargers for the most power-hungry sensor. We assume $P^S_{i,j}(d) = W_{Max}$. It means a most power-hungry sensor that its remained the power will be run out exactly. According this assumption, R is also equal to $d_{i,j}$. We can deduce Eq. (3) by Eq. (2). For the better fairness, we assume all of chargers have same ability of power supporting. By this assumption, this study can be more close to real scenario, because in real scenario, many sensors may need over one charger for charging. And when distance between sensor and charger is less then R, the charging efficiency is better and vice versa.

In MCBA, it has calculated set of candidate charger $V_c = \{C_1, C_2, ..., C_n\}$, set of be covered sensor nodes $V_s = \{S_1, S_2, ..., S_n\}$, set of finalized position of deployed chargers $V_e = \{E_1, E_2, ..., E_n\}$ and the power consumption of i^{th} sensor with W_i. These targets can help to find the better deployement position from V_c so that number of chargers can be reduced.

B. Layoff Algorithm

In just mentioned, SABC still has very long computation time and it still has opportunity to fall into local optimum. The reason is that SABC will choose charger which has most number of covered sensors. This will have a contradictory phenomenon because chargers deployment is ordered. The early chosen charger has more opportunity to select a better position, but later one is not, so that metaheuristic algorithm will continue to repeatedly match all of the solutions until the best solution be found. In other words, SABC must spend more time for iteration in order to ensure the quality of solution. This means that it still can fall into local optimum if deliberately reducing the number of iterations. In this view point, we hypothesize that the quality and performance will be better as long as let all of sensors are be covered in every iterations. In order to achieve this ideal, we will modify the coding way of solution firstly.

The concept of our proposed method is like layoff in a company. Each employee must be examined his performance or attitude. The difference is that MCBA and SABC will retain all of the original employees, but our proposed method may fire employee if he has been unable to provide performance for company. So we call proposed method as layoff algorithm(LA). The main idea is that each position of candidate charger likes the employee. We do not need useless position of candidate charger so we will move such an useless sub-solution out. However, how to layoff is a most important part in this study. We will well define fitness function like that each company has a sincerely convinced policy for layoff.

The design of fitness function is according to the linear programming model:

$$F(x) = S_{covered}/S_{overlapping}. \tag{4}$$

$S_{covered}$ represents the sensors which are covered by charger. $S_{overlapping}$ represents that an area is composed of two or more circle. In layoff algorithm, we mentioned we must to make sure all of sensors will be covered through each iteration, so we can modify Eq. (4) to Eq. (5).

Algorithm 1 Layoff algorithm (LA)

Input: V_c, V_s
Output: V_e

1: Calculated size of N_c;
2: Calculate original fitness function ;
3: **repeat**
4: Randomly choose a candidate charger from C_i;
5: Fitness Function(N_c,C_i);
6: **If** fitness is not better
7: C_i will be recovered ;
8: **end**
9: **until** the termination criterion does not met

Algorithm 2 Fitness function

Input: N_c, V_i
Output: $f(x)$

C_i will be laid off;
$S_{covered}$ =calculate the number of covered sensors ;
If $S_c = N$
$S_{overlapping}$ = calculate the number of overlapped sensor;
end
$f(x) = 1/S_{overlapping}$;

$$F(x) = 1/S_{overlapping}. \tag{5}$$

In LA, the first step is to calculate size of N_c and $f(x)$. N_c represents total number of candidate charger. Next it will randomly choose a candidate charger C_i and calculate fitness function that is shown in line 4-5 of Algorithm 1. Fitness function $f(x)$ can be calculated by Algorithm 2. Criterion of layoff depends on candidate charger selection and fitness function. For a simple instance, if $f(x)$ is not better than the before, original C_i can be recovered that is shown in line 6-8 of Algorithm 1. It wil stop until the termination is met. LA is just a screening scheme for selection and deletion of candidate charger. It can not work alone but it is able to combine any metaheuristic algorithm. In next part, combination of LA and SA will be introduced .

C. Layoff SA-Based Charging Algorithm

Difference between SABC and LSABC is that LSABC will carry out layoff in each iteration. When a charger has been laid off, it cannot be reinstated in the following iteration. Notice that all of candidate chargers will be employed to cover whole field of interest(FoI) in the first round. In contrast, SABC cannot guarantee full coverage in any rounds because deployment of chargers is randomly, so that many sensors may not be covered by chargers. Moreover, some not selected chargers still have a chance to return to the ranks of candidates so that SABC will have some redundancy.

In LSABC, first step must to set an initial temperature according to annealing schedule basic concept of annealing as well as create an initial solution N_c. All of candidate chargers will be employed in the begining. To have more chance to find better solution. We set L control group, L is a value which can be adjusted by user freely that is shown in line 1-3 of Algorithm 1. Next it will select the candidate chargers

Algorithm 3 Layoffs SA-Based Charging Algorithm(LSABC)

Input: V_c, V_s
Output: V_e

1: Set the initial temperature according to the annealing schedule;
2: Create the initial solution N_c
3: Copy L control group ;
4: **repeat**
5: Randomly choose a candidate charger from C_i;
6: Fitness Function(N_c,C_i);
7: **If** fitness is not better and temperature is not adapted
8: Recover C_i;
9: **else**
10: Replaced the experimental group
11: **end**
12: **until** the termination criterion does not met

C_i randomly. When a charger has been selected, it will be laid off then we will recalculate its $f(x)$ that is shown in line 5-6 of algorithm 1. The spirit of SA is that it has the opportunity to accept a not best solution. In this way, solution will not fall into local optimum that is shown in line 7-11 of algorithm 2. The process of LSABC is shown in Fig. 2. The coding of LSABC is that each solution has N_s bit and each bit represents the candidate charger position. The value 1 means that the candidate charger will be deployed and vice versa.

V. Simulation

A. Simulation setting

In this section, the simulation is performed by utilizing MATLAB (Version 7.11, R2010b). The scenario of our study is in a $30 \times 25 \times 3$ indoor environment. The sensor nodes are randomly deployed. The effectual charging distance is $4(m)$. Number of sensor nodes are set as 50 to 400. The details are shown in Table II.

B. Simulation results

Fig. 3 and Fig. 4 show the deployment of SABC and LSABC. We can see that SABC has been able to cover most of sensors. But a sensor is ignored that is shown in upper left corner of Fig. 3. It means that SBAC still cannot completely overcome the local optimum problem. In Fig. 4, LSABC is able to cover all of sensors as well as the density of the overlapping area is less than SABC. It represents that the final solution of LSABC is closer to the optimization than SABC.

The Fig. 5 shows the comparison of number of chargers with LSABC and SABC. X-axis represents number of sensors, and Y-axis represents number of chargers. In order to ensure objectivity, all of algorithms will perform 1,000 rounds. Obviously,

TABLE II
SIMULATION PARAMETERS

Parameters	Values
Size of venue	$30 \times 25 \times 3(m^3)$
Number of sensor nodes	50 400
Effectual charging distance	$4(m)$

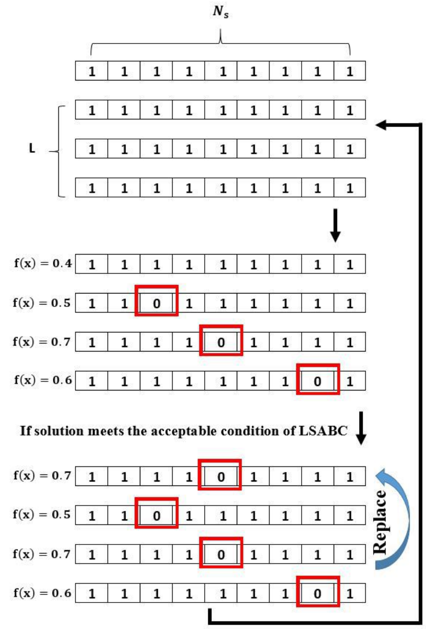

Fig. 2. Process of LSABC

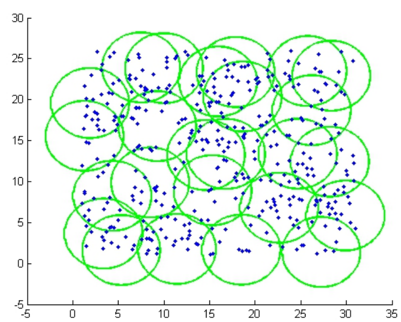

Fig. 3. Deployment diagram of SABC

number of chargers of LSABC is lower than SABC that this phenomenon will become evident increasingly when number of sensor is increased. That is because LSABC always makes sure the full coverage so that LSABC cannot fall into local optimum.

The Fig. 6 shows the comparison of computation time. Times show of iteration is set as 1000 rounds. The simulation results that LSABC spends lower computation time than SABC, because LSABC will move the unnecessary subsolution out so that the space of solution will become smaller progressively. In general, most of computing time of all the SA-based algorithm is used for calculate fitness function for any subsolutions. Therefore, we can see that the gap between these two lines are growing.

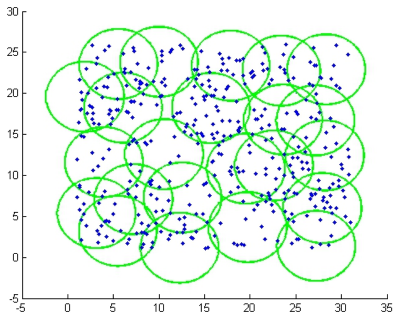

Fig. 4. Deployment diagram of LSABC

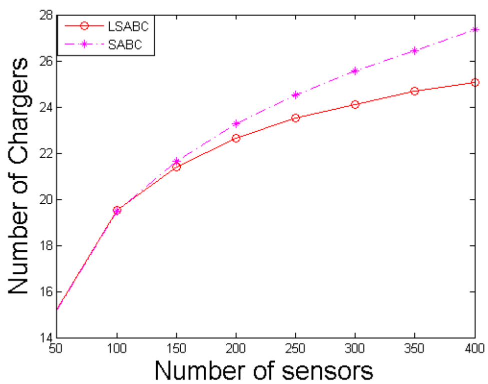

Fig. 5. Comparison of number of chargers

VI. Conclusion

Most of existing researches adopted greedy-based algorithm to deploy chargers in the indoor scenario because it is easier to implement. However, greedy-based algorithm always not find the best deployment strategy. A well-known reason is greedy-based algorithm which has very high opportunity to fall into local optimum so that whole WRSN may be crashed because many sensors cannot be covered by chargers. In order to solve this problem, we had proposed a metaheuristic-based algorithm to try to find the optimization. Although SA is currently one of the fastest metaheuristic algorithm, SA-based method still consumes a huge computing time for calculation of fitness function. Even the results of SBAC is still not perfect that is due to the escaping scheme of local optimum. In this paper, we propose a Laoff algorithm to remove unnecessary solution out from the solution space so that computing time will be reduced significantly. We also redesign a strategy for chargers candidate selection so that full coverage can be guaranteed. The contribution of this paper is that Layoff algorithm is not only to enhance SA-based charger deployment, but also suit for any metaheuristic-based algorithms. In the future work, we will consider a realistic environment, such as the dynamic target or charger. It is a very difficult problem because the interaction between each sensor is higher than the current problem. Additionally, we will apply proposed Layoff algorithm to the other metaheuristic-based algorithms according to various deployment issues.

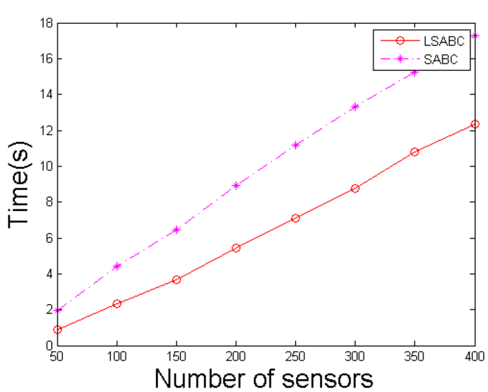

Fig. 6. Comparison of computation time

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