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A Novel Adaptive Resource Allocation Framework for Sounding Networks

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Abstract. For a long time, the detection of meteorological data is very important for weather prediction. However, in the process of data detection, manual input is often tedious and data duplication is easy to be lost, which is not conducive to the acquisition of meteorological data. To solve this problem, this paper presents a novel framework for the adaptive allocation of sounding network resources and uses a genetic algorithm and simulated annealing algorithm method to optimize the processing of meteorological data. Experimental results based on real data sets show that the method proposed in this paper improves the efficiency of data processing, simplifies the manual operation, and improves the accuracy of data, which provides a new idea for the processing of meteorological data.

Keywords: genetic algorithm, simulated annealing algorithm, meteorological data.

1. Introduction

For a long time, people have been constantly exploring the changing rules of the atmosphere, and balloon-sounding observation has become an important part of comprehensive meteorological observation [1]. Balloon radiosonde observation is to use balloons to lift the radiosonde, to achieve the purpose of high altitude meteorological detection. After release, the balloon radiosonde detects the atmospheric data in real-time and sends the data signal to the signal receiving station. To make the radiosonde send the signal to the signal receiving station, not only the frequency point of the radiosonde signal should be set, but also the signal range of the receiving station should be set. In this process, if there are two radiosonde signal frequency point conflicts, it is likely to cause data error. If the radiosonde is beyond the scope of the station can receive the signal, is likely to lead to the loss of data, at the same time due to external factors, the radiosonde data signal may be affected, especially in bad weather, such as thunder, rain, fog, etc. This will cause the data to be biased and the results to be wrong [2]. Therefore, it is very necessary to study how to set the frequency point of each radiosonde to avoid the signal conflict between two radiosondes, and how to choose the receiving station for the radiosonde to receive the data sent by the radiosonde as accurately as possible.

In this paper, an adaptive resource allocation framework based on a genetic algorithm and simulated annealing algorithm is proposed. This framework automatically allocates frequency points for the sounding instrument and selects the optimal receiving station. The research content of this paper mainly includes the following lists.

- When the radiosonde is released, the sending station needs to assign frequency points to it and set the acceptable frequency band of the receiving station channel, so that the function of communication between the radiosonde and the receiving station can be completed. The framework can solve the problem of frequency band planning of radiosonde, assigning frequency points for each released radiosonde, so that there is no conflict between two radiosondes.
- After the radiosonde is released, the appropriate receiving station should be selected to interact with. To make the signal stronger, we need to make the sum of the distance between the sonde and the

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corresponding receiving station smaller. In addition, in order to avoid loss of signal, the sonde needs to interact with several receiving stations.

2. Related Work

Genetic Algorithm is a heuristic optimization Algorithm proposed by J.Holland in 1975. Because the genetic algorithm starts from multiple initial points and looks for the optimal solution in the global scope, it solves the problem of the local optimal solution to a certain extent and can converge to the globally optimal or satisfactory solution with a large probability in the discontinuous, multi-peak and noisy environment [3]. The purpose of frequency band planning is to assign the optimal frequency point for each radiosonde, so using a genetic algorithm can solve this problem better. In the GSM (Global System of Mobile Communication) network, Xu uses a genetic algorithm to optimize frequency allocation in view of the communication interference problem [4]. In order to improve the spectrum utilization rate of cellular satellite mobile communication, Zhang reasonably planned the carrier frequencies of each beam and proposed a spectrum dynamic planning algorithm based on genetic algorithm and heuristic search to maximize the utility of satellite spectrum resources [5]. In the aspect of military electromagnetic spectrum management, Chen proposed a frequency allocation algorithm based on a genetic algorithm to enable frequency stations to reasonably allocate frequencies so that they do not produce interference between each other or minimize interference [6]. In this paper, genetic algorithm is used to solve the problem of frequency conflict in the communication between radiosonde and receiving station.

The idea of a simulated annealing algorithm was first proposed by Metropolis in 1953. In 1983, Kirkpatrik introduced the idea of annealing into a combinatorial optimization neighborhood. A simulated annealing algorithm is an algorithm based on probability change. According to the principle of solid change annealing, the object will start from the initial high temperature, gradually reduce the temperature according to the temperature parameters, and finally make the object reach a stable state. A simulated annealing algorithm provides a method to find the best solution, but its running efficiency is difficult to control, which has a great obstacle to its application in practical use. To solve this problem, Ingber proposes the Very Fast Simulated Annealing algorithm [7]. Aiming at the problems that genetic algorithm is easy to fall into local optimal, and the convergence speed of simulated annealing algorithm is slow, the TSP optimization algorithm based on improved genetic simulated annealing algorithm is proposed so that the algorithm can avoid falling into local optimal more effectively, and the chromosome jump change has self-adaptability, which is conducive to the algorithm optimization [8]. Li used dynamical system theory to analyze the operation principle and convergence of the simulated annealing algorithm. Li compared the process of searching the optimal solution of the algorithm to the elastic motion of a particle. The change of the function value during the operation of the algorithm is the simple harmonic vibration or damped vibration of the particle. The dynamical system model of the ordinary differential equation is established, which effectively improves the efficiency of the algorithm [9]. Vincent developed simulated annealing with restart strategy, using Boltzmann function and Cauchy function respectively to determine the acceptance probability of poor solution [10]. In this paper, simulated annealing algorithm is used to solve the problem of radiosonde selecting the optimal path of receiving station.

3. Adaptive Resource Allocation Framework for Sounding Networks

The resource adaptive allocation framework of the sounding network proposed in this paper is shown in Figure 1. The framework is mainly divided into two modules: frequency band planning module and intelligent routing module. The frequency band planning module mainly realizes two functions: frequency point allocation of radiosonde and frequency band setting of receiving station. The function of the intelligent routing module is to select the optimal receiving station for the sounding instrument. Specifically, this paper proposes a sounding network resource allocation method based on a genetic algorithm and simulated annealing algorithm, which realizes the function of automatically assigning frequency points for the sounding instrument and selecting the optimal receiving station, so as to realize the stable transmission of meteorological data.

3.1. Frequency Allocation

The purpose of radiosonde frequency point allocation is to avoid signal conflict among all radiosondes. Its essence is an optimization problem with constraint conditions. The simplest way to deal with this kind of problem is to use the exhaustive method, but with the increase of the solving space, the amount of calculation will increase exponentially, resulting in a long allocation time. As an intelligent optimization algorithm, genetic algorithm has been widely used in combinatorial optimization, machine learning, signal processing, adaptive control, and artificial life. Therefore, the genetic algorithm can be used to find the optimal frequency point allocation scheme through continuous iteration. The main process of the genetic algorithm is shown in Figure 2.

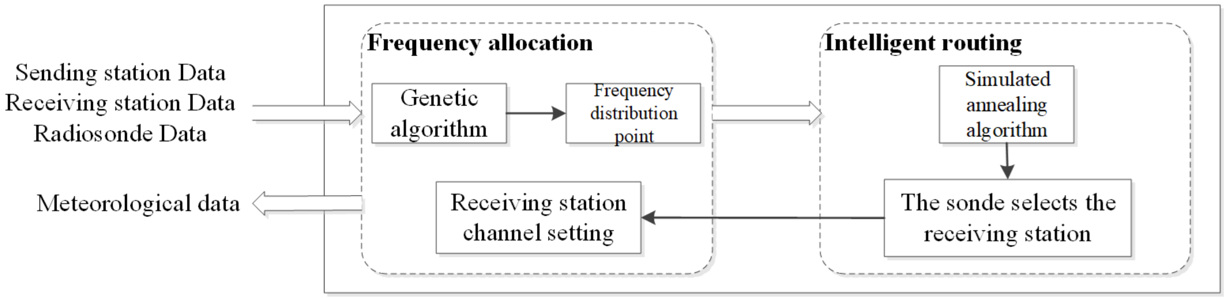

Fig. 1: Adaptive resource allocation framework for sounding networks

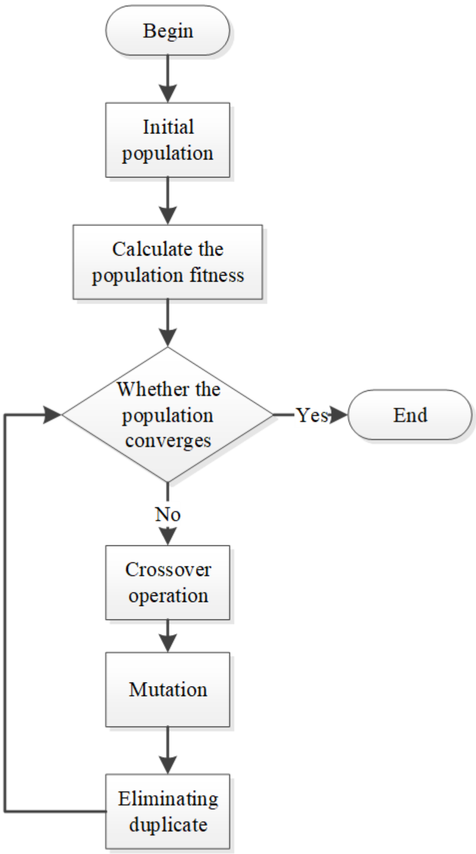

Fig. 2: The main steps of genetic algorithm

According to the main steps of the genetic algorithm, the basic process of realizing the frequency point distribution function of the sounding is as follows:

- Coding: Coding is to transform the feasible solution of the problem into the search space of the genetic algorithm. The feasible solution to the problem is the frequency point such as 401.001. Binary code is often used in genetic algorithm coding. Through the analysis, this paper uses the 13-bit binary code. This paper uses {C0,C1, C2,…,C12} for the 13-bit binary encoding.

- Population initialization: The population size is the number of individuals in the population. The larger the population size, the more likely it is to find the global solution, but it will also reduce the efficiency of the algorithm. Generally, the population size is related to the coding length L, and the population size used in this paper is 20. This paper uses {p1,p2,…,p20} for population.
- Calculation of population fitness: The calculation of population fitness is the core of the genetic algorithm. The constraint condition should be considered in the calculation of fitness. Within the safe distance d_s, the frequency points of any two radiosondes cannot conflict and the bandwidth protection of 1KB is required. The difference between the frequency points assigned to the closer radiosonde should not exceed 0.1. When the distance d<= d_s, the greater the frequency point difference between the two radiosondes, the higher the fitness. For a radiosonde with a long distance, the frequency points allocated between them are not required. The smaller the frequency difference between the two, the more radiosondes can be released in the sky. Calculating fitness in this way allows more radiosondes to be sent over a limited range. If the frequency point difference between the two radiosondes which are close to each other is less than 0.1, the frequency point may have signal conflict, so its fitness is negative and should be eliminated.
- Population renewal iteration: The updating iteration of the population requires the operation of mutation, crossover, elimination, and replication of some individuals in the population. Variation refers to a change in { C0,C1, C2,…,C12} of the individual P in the population. Crossover refers to the exchange of any code value between any two individuals Elimination and replication refers to the calculation of individual fitness according to the method in Step 3. Elimination of individuals with low fitness and replication of individuals with high fitness value.
- Obtain the optimal population: The fitness value of the population converges until it reaches the maximum number of iterations by constantly updating the population.

In this paper, the formula for calculating the fitness of each individual in the population is as follows:

$$f(x,i)=\begin{cases} \Delta x * d_i, & \Delta x>0 \\ \frac{1}{\Delta x} * d_i, & \Delta x<0, d>600 \\ 1000 * \Delta x * d_i \ , & \Delta x \le 0, d \le 600 \end{cases} \tag{1}$$

In the formula (1), $\Delta x=|xi-x|-0.1$. x is the radiosonde frequency point that needs to be allocated by the current radiosonde. xi is the radiosonde frequency point of the allocated frequency point. d_i is the distance between two radiosondes.

3.2. Intelligent Routing

The goal of intelligent routing is to select a suitable receiving station for radiosonde and ensure the stable reception of signals. This problem is selective. The methods to solve this kind of problem include the enumeration method, mountain climbing algorithm, and simulated annealing algorithm. The mountain-climbing algorithm will select a solution from the current solution space as the optimal solution each time until a local optimal solution is reached. However, the mountain climbing algorithm cannot get the global optimal solution, and the simulated annealing algorithm will not stop running after getting the local optimal solution. The simulated annealing algorithm will select the two sides of the local optimal solution with a certain probability to carry out the swing search, so that there is a certain probability to search for other local optimal solutions, and then compare to get the global optimal solution. For y=f(x), the problem is to find its maximum value. Find the starting point, increment the domain x, compare the values of f(x+1) and f(x), if f(x+1) >f (x), then update Max = f(x+1), otherwise, if f(x+1) < f(x), the simulated annealing algorithm will not simply give up the value, but with a certain probability to determine whether to accept the value. The selection of probability is determined according to the Metropolis criterion, which is proposed by combining the variation law of particles in mechanics with combinatorial optimization problems [11]. In the annealing process, when the temperature is T, the cooling probability of the particle with an energy difference of dE is P(dE), which can be expressed as:

$$P(dE)=\exp\left(\frac{dE}{kT}\right), \tag{2}$$

In formula (2), where k is Boltzmann constant and $dE<0$. So the higher the temperature T, the greater the probability of a cooling. The simulated annealing algorithm starts from the initial value, enters the cycle, constantly calculates the new solution in the current situation, compares it with the old value, and determines whether to accept or discard it according to the Metropolis criterion. The current solution at the termination of the algorithm is the approximate optimal solution. This is a heuristic random search process based on Monte Carlo iterative solution method. The flow chart of the simulated annealing algorithm is shown in Figure 3.

The algorithm steps are as follows:

- Count the number of radiosondes in the sky. If the number is less, skip to step 2, otherwise skip to step 3.
- The distance between the radiosonde and each receiving station is calculated respectively, and several receiving stations with the closest sum of distance are selected for interaction and the interaction situation is saved in the interaction matrix.
- After entering the cooling cycle, the interaction matrix is updated with a certain probability in each cycle. After getting the new interaction matrix, the sum of the distance between the radiosonde and the receiving station interacting with it is calculated.
- The sum of the new distances obtained in the third step is compared with the current nearest distance. If the sum of the new distances is smaller, it is assigned to the current nearest distance.
- If the sum of the current closest distances is smaller, then the Metropolis criterion is used to update the sum of the current closest distances with a certain probability.
- Iterate according to the set number of iterations and output the interaction matrix.

3.3. Set Receiving Station Frequency Range

After setting frequency points for the radiosonde and selecting the optimal receiving station, it is also necessary to set the receiving frequency band of the receiving station so that the receiving station can receive data signals of specific frequency points sent by the radiosonde. This function is realized by the frequency allocation module. The intelligent routing module selects one or more receiving stations for the radiosonde and returns the number of receiving stations to the frequency band planning module, which will automatically set the receiving frequency band of idle or useless channels of these receiving stations, and finally realize the function of receiving stations to receive data signals sent by the radiosonde stably.

4. Experiments

To verify the superiority of the resource allocation model of the sounding network, the sequential search algorithm is used in this paper for comparison. The exhaustion method is used in frequency band planning and the enumeration method is used in intelligent routing. These two algorithms are used to form a sequential search for frequency band allocation and intelligent routing. The sequential search method is faster and can ensure that the assigned frequency points and receiving stations meet the requirements of the system. This paper considers the validity of the experimental results from the following aspects.

In frequency allocation, the radiosonde signals may interfere with each other. The system should ensure that there will be no mutual interference between the radiosondes in a certain area or minimize the possibility of conflict between all the radiosondes signals in the system. Therefore, when considering the superiority of the model, the factors to be considered include the frequency points distributed by the radiosondes and the distance between the radiosondes. At the same time, when the system scale expands, releasing more radiosondes in a limited range is also a consideration, which involves the utilization rate of the frequency band. The higher the utilization rate, the better the model. Therefore, Formula (3) and Formula (4) are used in this paper to calculate the score of radiosonde frequency point planning.

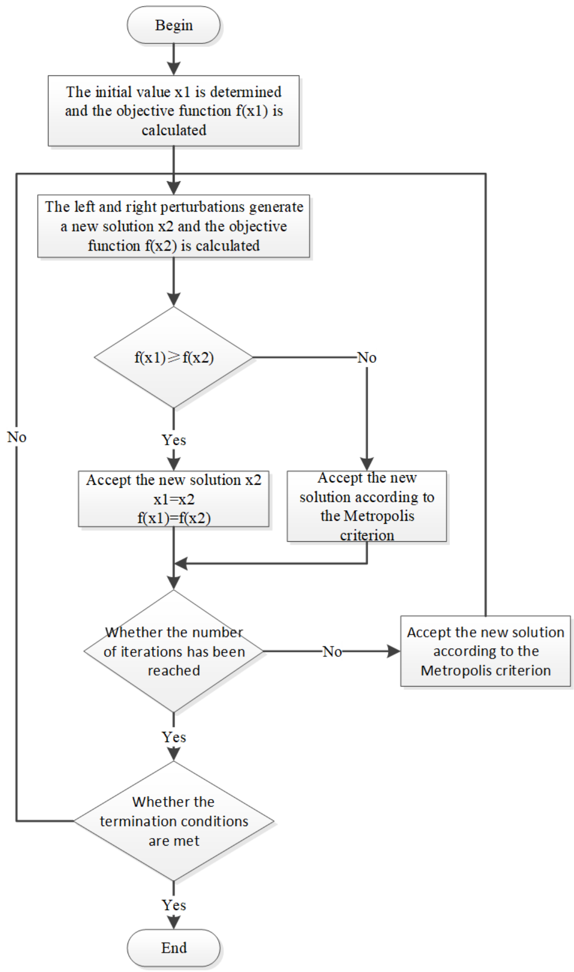

Fig. 3: Flow chart of simulated annealing algorithm

$$f(x, x_i) = \begin{cases} d \times |x - x_i|, & d < d_s \\ \frac{d}{|x - x_i|}, & d \geq d_s \end{cases} \tag{3}$$

$$F(\mathrm{x}) = \sum_{i=1}^{n} f(x, x_i) \tag{4}$$

In formula (3) and (4), x is the frequency point of the current radiosonde, x_i is the frequency point of the existing radiosonde in the sky, d is the distance between two radiosondes.

The distance between receiving station and radiosonde is an important factor for intelligent routing. Intelligent routing is mainly to ensure that the data signal sent by the radiosonde can be received stably by the receiving station. The receiving station closer to the radiosonde should be selected. At the same time, in order to avoid the failure of the receiving station and the loss of data, the system needs to select more effective receiving stations for the radiosonde to receive data. Therefore, when evaluating the superiority of the model, formula (5) is used to calculate the score of receiving station selection.

$$h(x) = \frac{\sum_{i=1}^{n} d_i}{n} \tag{5}$$

In formula (5), d_i is the distance between the radiosonde and the receiving station, n is the number of receiving stations assigned to the sonde.

After obtaining the score F(x) of frequency point planning of the radiosonde and the score h(x) of intelligent path selection, formula (6) is used to calculate the final score of information transmission between the radiosonde and the receiving station.

$$H(x) = \frac{F(x)}{h(x)} \tag{6}$$

The comparison results are shown in Figure 4. In Figure 4, the vertical axis represents the number of times that the final score obtained by the resource allocation framework of sounding network and the sequential search algorithm is better than that of the other party, and the horizontal axis represents the number of existing radiosondes.

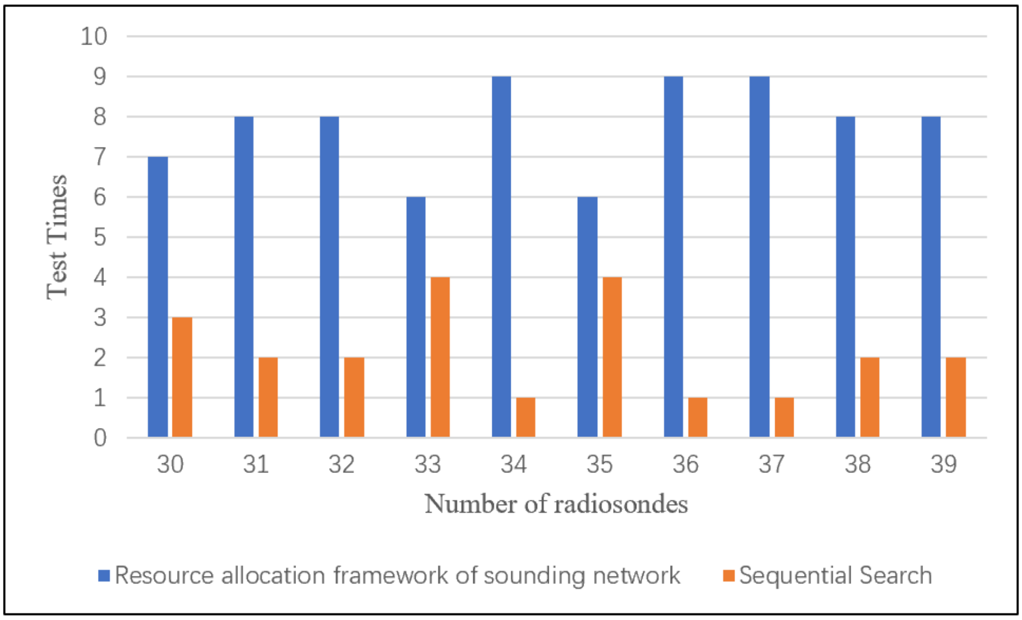

Fig. 4: Compare the results in a bar chart

5. Conclusion

This paper studies the automatic communication between the radiosonde and the receiving station in the meteorological problem and improves the situation that the radiosonde frequency point is set manually in the past. In this paper, genetic algorithm and simulated annealing algorithm are used to propose a sounding resource allocation framework to improve the communication efficiency and accuracy of meteorological sounding and receiving station, which provides an efficient method for the planning of meteorological sounding.

6. Acknowledgements

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7. References

[1] Qiyun Guo, Rongkang Yang, Yuan Qian, Xiaozhong Cao and Yong Lei. A Comparative Analysis of Radiosonde Ascending with Balloon and Descending with Parachute. *Meteorological*. 2018, 44(08):1094-1103.

[2] Lihong Du. The Influence of Inclement Weather on High Altitude Exploration and Coping Techniques.*Agriculture and Technology*. 2019,39(11):150-151.

[3] Yan Li, Hongyu Yuan, Jiaqiao Yu, Gengwei Zhang and Keping Liu. Application of Genetic Algorithm in Optimization Problem. *Shandong Industrial Technology*. 2019(12):242-243.

[4] Bingbo Xu. Simulation and Analysis of Frequency Allocation based on Genetic Algorithm. Xidian University, 2012.

[5] Hong Zhang, Yong Gong, Zhisong Pan and Guyu Hu. Dynamic Programming of Satellite Spectrum Resources based on Genetic Algorithm and Heuristic Search. *Journal of Beijing University of Posts and Telecommunications*. 2017,40(S1):5-9.

[6] Ziwei Chen, Qiang He and Yongcheng Yu. Research on Battlefield Frequency Allocation Based on Genetic

Algorithm. *Computer and Digital Engineering.* 2015,43(07):1221-1225.

[7] Ingber L. Very Fast Simulated Annealing. *Math Conput Modeling.* 1989,12:967-973.

[8] Qing He, Yile Wu and Tongwei Xu. Application of Improved Genetic Simulated Annealing Algorithm in TSP Optimization. *Control and decision making.* 2018,33(2):219-225.

[9] Xiangyuan Li, Zhenglong Xiang and Jiening Xia. Dynamic System Model and Convergence Analysis of Simulated Annealing Algorithm. *Journal of Computer Science.* 2019,42(6):1161-1173.

[10] Vincent F.Yu, A.A.N. Perwira Redi, Yosi Agustina Hidayat and Oktaviyanto Jimat Wibowo. A Simulated Annealing Heuristic for the Hybrid Vehicle Routing Problem. *Applied Soft Computing.* 2017,53:119-132.

[11] Arts E, Korst J. Simulated annealing and Boltzmann Machine. New York:Wiley & Sons, 1989.