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Research on Automatic Planning Method of TTE Network Communication Link

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Abstract: - Aiming at network transmission efficiency of time-triggered Ethernet (TTE) , especially the message scheduling and link planning in the network also depend on the traditional manual configuration, this paper presents a method of TTE network communication link planning based on brainstorming optimization algorithm.By defining the constraints in the automatic planning of TTE network communication link, a planning model including load balancing and shortest path constraints is established, and a scheme of TTE network communication link planning based on brainstorming optimization algorithm is designed.Finally, the effectiveness and stability of the method are verified by simulation experiments, and the effective automatic planning of the TTE network communication link is carried out to improve the network transmission efficiency.
Keywords: - Time triggered Ethernet,Brainstorming algorithm,load balancing,heuristic algorithm,shortest path

I. INTRODUCTION

Time-triggered Ethernet[1] is an innovative technology improved by Ethernet, which not only retains the flexibility, dynamics and "best-effort" characteristics of traditional Ethernet, but also guarantees the certainty, reliability and security of real-time transmission service.Therefore, the TTE network can not only transmit Time-Triggered (TT) but also support Rate-Constrained (RC) and Best-Effort (BE) services. Thus can satisfy the requirements of aviation spaceflight and weapon equipment.However, the scheduling schedule relied on for sending and receiving data messages for TTE network real-time deterministic services still requires manual configuration, and the scheduling and link planning of the real-time messages are inefficient, which affects the network transmission efficiency.In recent years, scholars at home and abroad have made active research on TTE network and message scheduling and achieved some results. Tamas-selicean D proposed a communication message scheduling algorithm based on Tabu search[3] for time-triggered Ethernet hybrid critical systems.A distributed task load balancing distribution method based on time-triggered Ethernet was proposed by Yu Tang [4] of Beihang University.Tan Shenglan studied the application of simulated annealing genetic algorithm in network load balancing, using simulated annealing algorithm to find the optimal solution of network load balancing by conducting further local optimization search near the global optimal region[5].

Based on an analysis of a large number of related literature, this paper further investigates automated planning methods of TTE network communication links by combining group intelligence with an intelligent heuristic algorithm - the Brainstorming Optimization Algorithm.

II. AUTOMATIC PLANNING MODEL OF TTE NETWORK LINKS

For TTE networks, link planning is actually the planning of the paths for all communication tasks when the tasks are determined. In this paper, constraint planning is mainly focuses on the shortest path and load balancing, so that the entire network communication flow is in a relatively balanced state, avoiding network congestion and improving transmission efficiency.

2.1 Load Balancing

Load balancing is mainly to allocate resources reasonably, so that the whole system can keep good performance. In TTE network, we should reduce the communication load of single equipment as far as possible, make the load balance on nodes and links, reduce the unevenness between nodes, avoid network congestion, and reduce the difficulty of TT service layout, at the same time, it can ensure that each part of the whole network can have enough time free slices left, in order to ensure the normal transmission of RC and BE tasks. Therefore, given the network topology and communication tasks, in order to measure the load of the whole network and avoid network congestion, it is necessary to measure the load of the whole network by defining the following indicators:

$$U(j) = \sum_{i=1}^{N} \frac{L_i^j}{G_i^j} \tag{1}$$

$$U = \sum_{j=1}^{N} \sum_{i=1}^{M} \frac{L_i^j}{G_i^j} \tag{2}$$

$$\mu = \frac{U}{M}, \quad D(j) = (\sum_{i=1}^{N} \frac{L_i^j}{G_i^j} - \mu)^2 \tag{3}$$

$$D = \sum_{j=1}^{M} (\sum_{i=1}^{N} \frac{L_i^j}{G_i^j} - \mu)^2 \tag{4}$$

Where$U(j)$ represents the load of all messages transmitted on the Jth link, N is the number of messages on a link, L_i^j represents the frame length of message I on the Jth Link, and G_i^j is the period of message I on the Jth path; U represents the load sum of all links on the network, and M is the number of links in the network topology; The parameter μ is defined as the load average flowing through all links, $D(j)$ is the variance of the load on the Jth link, and D is the variance of the sum of all links on the network. In the selection of the objective function, the load variance on each node in the TTE network will be used as a measure of load balancing, and the smaller this value is, the better the load balancing is.

2.2 Shortest Path

Due to the arbitrariness of the TTE network topology, there are still several solutions for the transmission path within the same network topology. Shortest path algorithms such as Dijkstra algorithm[6], Bellman-Ford algorithm[7] and Floyd algorithm[8] are generally used in application scenarios where only the shortest path is considered.The TTE network transmission needs to consider not only the shortest path but also load balancing, so the path algorithm used in this paper is to multiply each planned link by the total number of hops of messages in the current topology after each algorithm execution to measure the shortest path constraint of the current planning result.The shortest path constraint function is expressed as follows:

$$R(X) = \sum_{j=1}^{M} \sum_{i=1}^{N} \tag{5}$$

In the formula, M represents the number of all links and N represents the number of messages on the Jth link. The solution set $X = (x_1, x_2, \cdots, x_M)$, $x_k \le N, x_k \in N$, respectively, represents each of the planned links.

2.3 Fitness function

In practical problems, the strength of the network topology needs to be evaluated by the fitness value. Individuals with high fitness will be iterated according to the characteristics of the algorithm, while those with low fitness may be eliminated. The description of fitness function needs to consider many factors. Combining the load balancing $D(X)$ and shortest path $R(X)$ of the TTE network link automatic planning model, a preliminary expression for the constraint function is established as follows:

$$F(X) = D(X) * R(X) \tag{6}$$

However, since the bandwidth of each link in the network topology must meet the corresponding constraints, the link scheduling should take into account the constraints of the links, thus the penalty function is used to transform the constrained optimization problem into an unconstrained optimization problem with a penalty function to be solved, and the non-feasible solutions are processed accordingly to obtain the final constraint function expression:

$$G(X) = F(X) + P \mid \sum_{k=1}^{M} \max(0, b_k - b_{\max_k}) \tag{7}$$

In the formula, b_k is the bandwidth needed to transmit the communication stream, $b_{\max_k}$ is the maximum bandwidth of the communication link in the topology, and the parameter P is a positive integer which is much larger than the value of the objective function. When the constraints of the links in the topology are satisfied, then $b_k - b_{\max_k} \le 0$ is always established, and the objective function at this time is $G(X) = F(X) + P \times 0$, which is the objective function value of the feasible solution.

From equation (7), when the value of G(X) is larger, it means that the more unbalanced the load is, the more unbalanced the path is, the more hops the link goes through, while for the fitness function, when the value of the fitness function is larger, the probability of the individual staying is greater, so the inverse of the objective function can be given as a fitness function. So,the fitness function can be defined as:

$$adapt\ (X) = \frac{1}{G(X)} \tag{8}$$

In the formula, X represents the current individual. At this point, the higher the fitness value, the better the idea, and more likely to be passed on to the next generation.

III. BRAINSTORMING ALGORITHM FOR TTE NETWORK LINKS

3.1 Brain Storm Optimization

Brain Storm Optimization (BSO) [9] was presented at the Second Conference on Group Intelligence in 2011. it is a group intelligence algorithm which simulates the process of human brainstorming and creatively solves problems in complex fields .The BOS algorithm first classifies the solution space through a clustering operation, after which the population is updated through various operations within and between classes. The algorithm flow is as follows:

Step 1:Random initialization of N individuals.

Step 2:Using k-means to cluster N individuals, and calculate the fitness value of N individuals, select the best fitness value of each individual as the cluster center

Step 3:According to the probability, choose whether to randomly generate an individual instead of a randomly selected cluster center.

Step 4:Individuals are updated in four ways, and when an individual is generated, the individual that is well adapted compared to the current individual is used as the new individual for the next iteration.

1) Randomly select the cluster center of a class and add random values to generate new individuals.

2) Randomly select an ordinary individual of a class and add random values to generate a new individual.

3) Randomly select the cluster centers of two classes, merge them and add random values to generate new individuals.

4)Randomly select a common individual from two classes, merge them and add random values to create a new individual

Step 5:Repeat 4) until N individuals have been updated, at which point N new individuals are generated, completing an algorithm iteration.

Step 6:Go back to operation 2) and proceed to the next iteration. The algorithm stops until the maximum number of iterations is reached.

3.2 BOS algorithm in TTE networks

3.2.1 Population initialization

Table 3-1 coding examples

Communication flow	Start node	Termination node	Feasible path	number	weight	encode
Message1	0	5	0-3-6-5(4)	1	5	例：121...
			0-3-8-10-7-6-5(7)	2	0	
			...	...		
Message1	1	4	1-3-6-7-8-4(6)	1	3	
			1-3-7-8-4(5)	2	8	
			...	...		
Message1	2	9	2-6-3-7-8-9	1	6	
			2-6-7-10-8-9	2	4	
			...	...		

The first step of the brainstorming algorithm is to randomly generate N ideas as the initial population. In TTE network link planning, an idea represents a path, so the population initialization requires the generation of N paths. In this paper, the natural number is used to encode so that each encoding length is determined, which is equal to the number of communication flows and independent of the total number of feasible routes. Each communication flow has a different set of feasible paths containing multiple paths to choose from, and an initial set of populations can be generated as input to the brainstorming algorithm by substituting the weight factor of each path for an iterative operation. TTE network coding examples are shown in Table 3-1.

3.2.2 Classifying clusters

The populations were clustered by calculating the Euclidean distance between each individual and the others. Assume that the population is $X = \{x_1, x_2, \cdots, x_i, \cdots x_n\}$,where x_i is d-dimensional data, and the population is divided into K classes, that is class $C = \{c_1, c_2, \cdots, c_i, \cdots c_k\}$, the cluster centre of each class is

c_j. The distance between an individual x_i in a population X and the cluster centre c_j is denoted by $dist\ (x_i, c_j)$, and the standard function for cluster center measurement is expressed as follows:

$$E = \sum_{i=1}^{k} \sum_{x_i \in c_j} dist\ (x_i, c_j) \tag{9}$$

$$dist\ (x_i, c_j) = \sqrt{(D_j - D_i)^2 + (R_j - R_i)^2} \tag{10}$$

In the formula, E is the sum of all intra-class distances and $dist\ (x_i, c_j)$ denotes the Euclidean distance between the object and the clustering centre. The smaller E is, the more compact the cluster result is. After the clustering operation is completed, the individuals within the class are ranked according to the fitness value, and the individual with the largest fitness value is taken as the cluster centre. The calculation of the fitness value can be completed by formula (8).

3.2.3 Replacement of clustering centers

The Brainstorming Optimization algorithm has three ways to achieve cluster centre replacement: random thinking, independent thinking and fusion thinking, and this paper takes random thinking as an example to replace cluster. A random number $r_1 \in (0,1)$ is generated and compared with a predetermined probability value P_r, if $r_1 < P_r$, a cluster centre P_c is randomly selected from a different class and a random individual is used to replace this selected cluster centre.

$$P_c = X_{\min} + r_1 (X_{\max} - X_{\min}) \tag{11}$$

IV. SIMULATION AND ANALYSIS

The brainstorming algorithm is used to simulate the automatic planning of TTE network communication links, and is compared with a traditional swarm intelligence algorithm, the genetic algorithm, to verify the correctness and superiority of the results of the brainstorming optimization algorithm.

4.1 Experimental environment

The experimental environment mainly consists of the network topology environment and the communication information environment, and the coding simulation is implemented on QT after construction. The topology environment is shown in Fig. 4-1, which contains 13 nodes and link numbers. Each link is a two-way communication. In this experiment, each message frame length is set to a different value and the period is T = 4ms, without considering network congestion and its resulting delay.

In this paper, the number of communication flows is set to 500 and the number of routecounts per flow is a variable value, with each flow having a different number of feasible routes. Also, in the configuration of the algorithm environment, the population size popsize is set to 50 and the number of clusters k is 5.

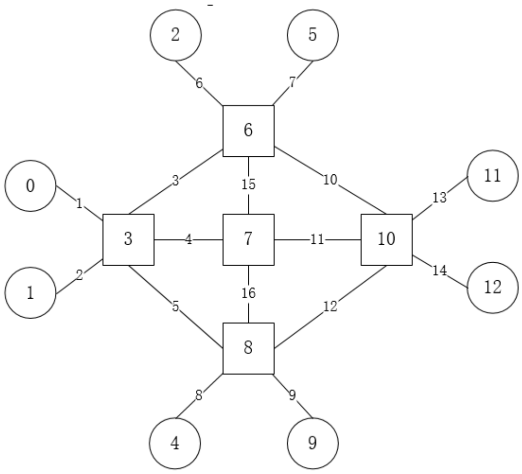

Fig. 4-1 Abstract network topology

4.2 Comparative experiment and result analysis

Firstly, in order to verify the difference between the results of the brainstorming algorithm and the genetic algorithm before and after iteration, the changes of the best individual fitness, the mean squared deviation and the number of link hops elapsed in the initial and final populations of the two algorithms are given respectively, and a longitudinal comparison within the algorithms is carried out to verify whether the two algorithms have an optimization effect; Then, the distribution of messages in the core region of the topology after planning of the two algorithms is given, which indicates the distribution of the optimal solution in the topology. Finally, the convergence trend of the two algorithms is analyzed longitudinally according to the change curve of the fitness in the iteration of the algorithms, and the two algorithms are compared and analyzed.

Tables 4-2 and 4-3 list the experimental parameters of genetic algorithm and brainstorming algorithm.

Table 4-2 Experimental parameters of genetic algorithm

Population size (popsize)	Crossover rate P_c	Mutation rate P_m	Iterations
50	0.6	0.04	200

Table 4-3-1 Experimental parameters of brainstorming algorithm 1

Population size(popsize)	clustering number k	Random thinking probability P_c
50	5	0.2

Table 4-3-2 Experimental parameters of brainstorming algorithm 2

Independent/Fusion thinking probability P_{ot}	Independent thinking probability P_{oc}	Fusion thinking probability P_{tc}
0.8	0.5	0.5

The planning results of two algorithms were obtained under these sets of experimental parameters. Tables 4-4 and 4-5 show the fitness, mean variance and number of links for the optimal individuals before and after iterations of the brainstorming and genetic algorithms.

Table 4-4 Optimal individual information before and after iterations of the brainstorming algorithm

Initial population			Final population		
fitness	Mean variance	Number of links passed	fitness	Mean variance	Number of links passed
14.75	121856	2350	88.65	28416	2025

Table 4-5 Optimal individual information before and after iterations of the genetic algorithm

Initial population			Final population		
fitness	Mean variance	Number of links passed	fitness	Mean variance	Number of links passed
17.64	105476	2290	82.23	26347	2056

From tables 4-4 and 4-5, we can see the changes of each metric, including fitness, mean variance and the number of links passed, before and after iterations of the two algorithms. The specific data are analysed as follows:

Table 4-6 Individual index change table before and after algorithm iteration

brainstorming algorithm			genetic algorithm		
fitness	Mean variance	Number of links passed	fitness	Mean variance	Number of links passed
↑501%	↓76.68%	↓325	↑336%	↓75.02%	↓234

From Tables 4-6, the percentage change in the best individual fitness, mean variance and number of links in the population before and after iteration of the brainstorming and genetic algorithms respectively can be obtained. The fitness represents the strength of the individual population, the mean variance measures the current individual topological load balance, and the number of links passed represents the number of hops travelled. The table shows that the brainstorming algorithm improved the fitness of the best individuals in the population by 501%, reduced the mean variance by 76.68% and reduced the number of links passed by 325 hops before and after the iteration. In contrast, the genetic algorithm improved the fitness by only 366%, reduced the mean variance by 75.02% and reduced the number of links passed by 234 hops. This shows that the brainstorming algorithm gives better planning results than the genetic algorithm.

At the same time, the fitness trend of the brainstorming algorithm and the genetic algorithm before and after the iteration were taken to find the mean values by multiple values, then the data were fitting analysed in MATLAB, and the changes of fitness trend graphs are shown below:

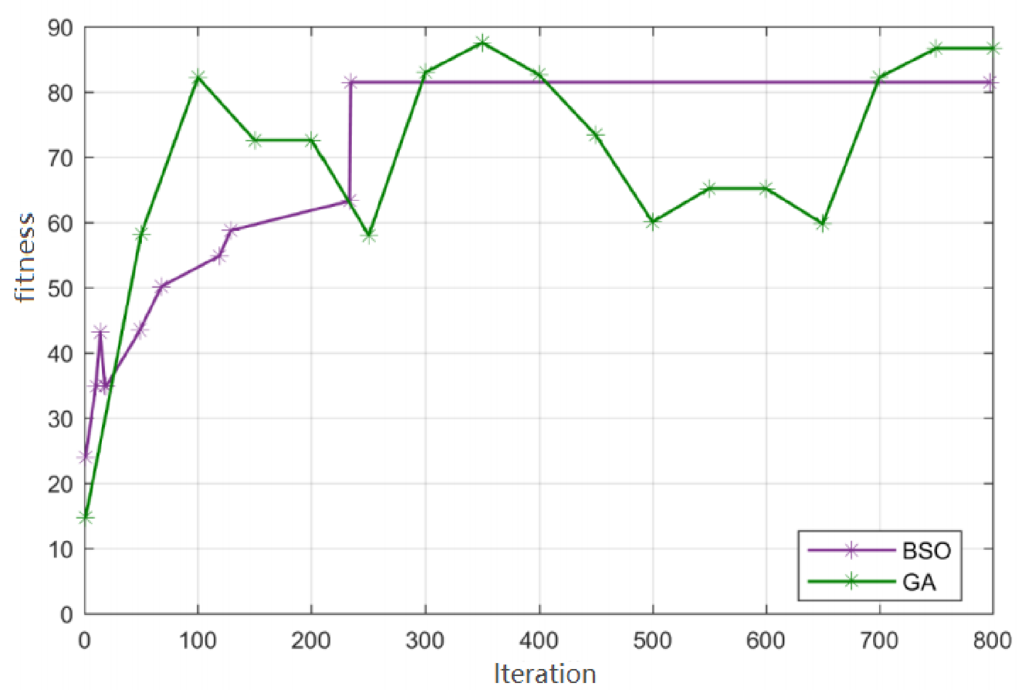

Fig. 4-7 fitness curve for two algorithm

Fig. 4-7 shows a comparison of the fitness curves for the genetic algorithm and brainstorming algorithm simulated on MATLAB, using the parameters in Tables 4-2 and 4-3. We can see from the figure that both the genetic algorithm and the brainstorming algorithm can reach near optimal solutions after iteration, and the difference between the algorithms is not particularly large, proving the effectiveness of the brainstorming algorithm. As can be seen from the figure, the genetic algorithm quickly reaches near-optimal solutions from 50 iterations onwards, but the obvious disadvantage of the genetic algorithm is that although it may have reached near-optimal solutions, the algorithm is less stable as the number of iterations increases, with large ups and downs compared to the brainstorming algorithm. However, the brainstorming algorithm can not reach near-optimal solution quickly, but it has a stable performance in the later stage of the algorithm and does not appear fluctuation. It can be seen that the brainstorming algorithm performs slightly better than the genetic algorithm, it has a good performance and good application in the planning of communication links in TTE networks.

V. CONCLUSION

In order to optimize network transmission efficiency and further enhance the security and reliability of TTE networks, this paper investigates the automatic planning method for communication links in TTE networks based on an analysis of the current status of link planning in existing TTE networks. In this paper, we propose to apply the brainstorming optimization algorithm to link scheduling planning of TTE networks, overcoming the shortcomings of manual configuration and using the adaptive nature of the algorithm itself to automatically perform path planning for TTE messages in topological environments, improving the efficiency of TTE network transmission and enhancing the real-time performance and reliability of TTE networks. The next step will be to further optimize the algorithm, expand the network topology and use a variety of methods to experiment and extend the universality of the experimental results.

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