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GCMD: Genetic Correlation Multi-Domain Virtual Network Embedding Algorithm

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ABSTRACT With the increase of network scale and the complexity of network structure, the problems of traditional Internet have emerged. At the same time, the appearance of network function virtualization (NFV) and network virtualization technologies has largely solved this problem, they can effectively split the network according to the application requirements, and flexibly provide network functions when needed. During the development of virtual network, how to improve network performance, including reducing the cost of embedding process and shortening the embedding time, has been widely concerned by the academia. Combining genetic algorithm with virtual network embedding problem, this paper proposes a genetic correlation multi-domain virtual network embedding algorithm (GCMD-VNE). The algorithm improves the natural selection stage and crossover stage of genetic algorithm, adds more accurate selection formula and crossover conditions, and improves the performance of the algorithm. Simulation results show that, compared with the existing algorithms, the algorithm has better performance in terms of embedding cost and embedding time.

INDEX TERMS Network virtualization, network function virtualization, virtual network embedding, future internet, cross-domain mapping algorithm, genetic algorithm.

I. INTRODUCTION

In recent years, the Internet plays a more and more important role in people's lives and creates great value for the development of society. At present, a variety of innovative business and applications have high demands for the quality of network services, the traditional "best-effort" Internet architectures are difficult to meet those demands. The emergence of network function virtualization (NFV) and virtualization technology provides a new way to solve the traditional Internet problems. NFV uses network virtualization technology to divide the function of network hierarchy into several software function blocks. Network virtualization technologies aim to abstract the various business requirements of users into an isolated virtual network, and multiple virtual networks share the hardware resources of the substrate network [1]. NFV and virtualization technologies allow efficient partitioning of networks based on application requirements, thereby providing applications with high bandwidth traffic and low latency. How to efficiently map the virtual networks to the substrate networks that satisfying the constraints is the research topic of this paper [2].

In the future network architecture, the role of traditional network service providers will be divided into two parts: the service providers (SP) and infrastructure providers (InP). SP can create and manage virtual networks for end users, InP can deploy and unify the available resources of the substrate network flexibly according to different business needs of

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users. So far, the single domain embedding problem of virtual networks has been effectively solved. Many literatures have proposed many methods to solve the single domain embedding problem of virtual networks [3]–[5]. However, for future network models, single domain embedding can not solve practical problems and meet the needs of users, so deploying virtual networks between multiple domains becomes the key to the problem [6].

In the cross-domain embedding process of virtual networks, many users constantly request the substrate networks to use its underlying resources. How to improve the efficiency of the substrate network and deploy the virtual network nodes and links reasonably is the most important issue at present. In literature [7], the authors prove that the partitioning process of virtual network requests in cross-domain virtual network mapping is NP problem, that is, it is impossible to find the optimal solution under limited time cost and resource cost. However, in recent years, many scholars have studied this issue [8], hoping to find a better solution for cross-domain embedding.

The goal of VNE problem is to find a better embedding scheme under resource constraints, which maps as many virtual request networks as possible to the substrate networks and occupies as few substrate resources as possible. For this reason, this paper proposed a Genetic Correlation Multi-Domain Virtual Network Embedding Algorithm: GCMD. The improved genetic algorithm is used to improve the efficiency of VNE in this method. The experimental results show that the proposed GCMD-VNE has better performance compared with other algorithms, the main reason is that compared with the traditional embedding algorithm, the genetic algorithm can carry on the variation, so it is not easy to fall into the local optimal, thus can find the optimal scheme in a larger solution plane, and keep the reasonable part of these schemes for iterative optimization. In terms of average embedding cost and execution time, the PSO-VNE proposed in literature [9] and HTF-VNE, HCDCF-VNE proposed in literature [10] are selected to compare. The proposed GCMD-VNE not only guarantees the minimum embedding cost, but also optimizes the execution time of the algorithm, which greatly improves the efficiency of the VNE process.

The main contributions and the main ideas of this paper are summarized as follows.

(1) In this paper, a genetic correlation multi-domain VNE algorithm is designed. The algorithm encodes the partition and embedding scheme of virtual networks in the form of matrix, and searches iteratively from multiple initial solutions to get the best embedding scheme.

(2) In the natural selection stage, the best half of the parents are directly selected into the offspring in the traditional genetic algorithm. In the GCMD-VNE proposed in this paper, the natural selection for parents to enter the next generation is based on specific probability formulas. In the crossover stage, the detection of candidate parents and the restriction of crossover conditions are added. Because crossover is the exchange of alleles between parents, if the parents are identical, crossover will produce the same offspring as the parents. Therefore, the algorithm proposed in this paper increases the detection of crossover parental. If the two parents are completely same, no cross operation will be carried out and the opportunity will be given to other parental combinations.

(3) This paper designs and implements the simulation experiment of VNE algorithm, verifies the advantages of the algorithm from the aspects of cost and time, and summarizes the principle of setting parameters in the algorithm.

The remainder of this paper is organized as follows. Section 2 reviews the existing methods for VN. Section 3 introduces the network model and problem statement. Section 4 describes our proposed algorithm GCMD-VNE in detail. The performance of our method and other methods is evaluated in Section 5. Section 6 concludes this paper.

II. RELATED WORKS

This part mainly reviews some existing literature on virtual network mapping. The virtual network mapping algorithms can be divided into centralized multi-domain algorithms and distributed multi-domain algorithms according to whether the infrastructure provider is needed as a middleman [11]–[13]. In the existing work, there are not only traditional solutions, such as various heuristic algorithms [14], [15], but also the latest methods combined with artificial intelligence [14], [16], [17].

A. THE DISTRIBUTED VNE ALGORITHMS

The authors of [18] proposed a strategy called PloyViNE, which is proposed to map the adjacent substrate network domains of virtual network parts that could not be mapped by a single domain in the process of VNE. It introduces a distributed protocol that coordinates the VN embedding process, ensures competitive pricing for service providers (SPs), and proposes a location-aware VN request forwarding mechanism for faster embedding. For the bidding problem of the substrate network, the authors of [19] proposed a v-mart bidding model. For InPs, it provides a level playing field for them to compete on VN resources, for SPs, it provides a customer-driven virtual resources partition and contract engine. Meanwhile, it adopts the two-stage Vickrey auction model, which is highly flexible to different InPs pricing models and can play a unique role in the heterogeneous multi-commodity market with VNE characteristics. In order to optimize the network resources, maximize the throughput and reduce the network delay, the authors of literature [20] applied the genetic algorithm to the cloud environment, which makes the cloud environment more optimized and has less cost. The authors of [7] divided virtual network embedding technology into two parts: virtual network segmentation process and virtual network embedding process. In this paper, the time delay and cost of splitting VN requests between subdomains are evaluated and compared. In the topology-based abstraction mapping method, the authors of [21] proposed a mechanism to abstract the substrate network providers into nodes. In this mechanism, multiple cloud provider sites are connected through a multi-domain network that supports virtual network technologies. When a user submits a request for a virtual topology, the system will plan a low-cost embedding and orchestrate the request to multiple cloud providers and network transport providers to instantiate the virtual topology according to the plan. Fair allocation of resources in the network is very complex [22], and how to solve this problem is also facing challenges. The authors of literature [23] proposed a resource allocation scheme based on blockchain, which can manage users' resources in a secure environment and make the network environment highly reliable. The authors of [24] carried out priority analysis of node embedding with the improved markov random walk model, and used ILP model to optimize the embedding process. The authors of [25] proposed a method to measure the proximity centrality in the priority analysis of node embedding in the virtual network embedding process. The authors of [26] proposed to sort the priority of node embedding by using the degree value and aggregation coefficient of nodes, but did not consider the relationship between node topologies and resource attributes. Aiming at reducing network power consumption and transmission delay, the authors of [27] proposed a cross-domain network virtualization scheme based on LTE.

B. THE CENTRALIZED VNE ALGORITHMS

Since the introduction of network virtualization technologies [28], there have been many studies on virtual network single domain mapping [29], but later people found that single domain mapping can hardly meet the users' needs, because users want to enjoy cross-domain embedding service. For the problem of multi-domain embedding, the authors of [30] proposed an estimation scheme to deal with the unknown intra-domain topologies and generated an augmented network graph to coordinate node embedding and link mapping, so as to solve the virtual network request in polynomial time. The authors of [31] used traffic matrix to describe the virtual network, which relaxed the integer limit in the virtual network request decomposition, thus reducing the time complexity and running time. The authors of reference [32] used the blockchain technology to improve the data distribution problem in the network, which is to realize the load balance of the network, and reduce the resource management cost and transmission delay. The authors of document [33] used the virtual network technology in the IoT, which transforms the resource allocation in the IoT into the virtual network embedding problem, and reasonably solves the resource allocation. The authors of [34] inherited the idea of [31], and adopted a heuristic virtual network request decomposition method based on particle swarm optimization algorithm. The authors of [35] proposed the cross-domain embedding algorithm of virtual network based on genetic algorithm which is a meta-heuristic algorithm. The purpose of the algorithm is to make a reasonable plan for the substrate resources of the substrate network and to embed more virtual networks

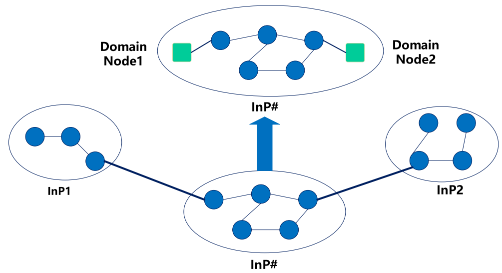

FIGURE 1. The model of domain view transformation.

on the substrate network. Compared with single-domain embedding, cross-domain virtual network embedding can provide better substrate resource allocation for users' business. However, cross-domain virtual network embedding needs to optimize the additional costs brought by cross-domain embedding. In addition, how to meet the greed and selfishness of the basic setup service providers should also be considered. In order to solve this problem, a virtual network cross-domain embedding strategy is proposed. The transformation model for the domain view is shown in FIGURE.1.

III. NETWORK MODEL AND PROBLEM STATEMENT

The intra-domain VNE problem is well-defined in literature [36]. In this section, we formally defined the inter-domain virtual network embedding problem. First, we will describe the substrate network model, and then, we will introduce the virtual network request model, third, we will state the multi-domain VNE problem.

A. SUBSTRATE NETWORK MODEL

The entire substrate network can be modeled as an undirected graph $G_s = (N_s, L_s)$, where N_s and L_s represent the set of substrate nodes and substrate links respectively. G_s is composed of N domains managed by N InPs, which are interconnected by multiple inter-domain links. We assume that the infrastructure providers are composed of N domains managed by different InPs. The k-th substrate domain can be defined as $G_{s,k} = (N_{s,k}, L_{s,k})$, where $N_{s,k}$ and $L_{s,k}$ represent the set of substrate nodes and substrate links which are managed by k-th InP. In addition, we define the set of inter-domain substrate links as $E_{s,I}$. Thus, G_s can be formulated as:

$$G_s = G_{s,1} \cup G_{s,2} \cup \ldots \cup G_{s,N} \cup E_{s,I}, \tag{1}$$

$$V_s = V_{s,1} \cup V_{s,2} \cup V_{s,3} \ldots \cup V_{s,N}, \tag{2}$$

$$L_s = L_{s,1} \cup L_{s,2} \cup \ldots \cup L_{s,N} \cup E_{s,I}. \tag{3}$$

In FIGURE.2, the entire substrate network is comprised of three domains and three inter-domain substrate links. As shown in FIGURE.2, ellipses represent different domains, circles represent substrate nodes, and lines represent substrate links. The substrate network (a) is divided into three domains containing 13 substrate nodes, each of which has a corresponding CPU capacity (the number in the circle), and con-

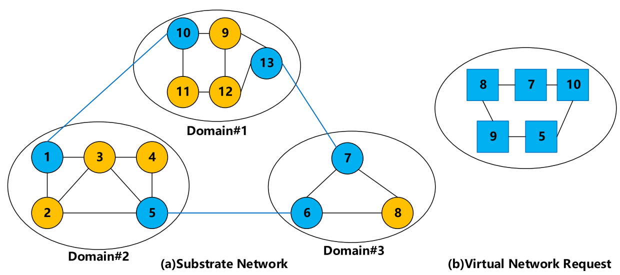

FIGURE 2. The multi-domain substrate infrastructure.

tains 19 links, including inter-domain links and intra-domain links, black links represent intra-domain links and blue links represent inter-domain links.

B. VIRTUAL NETWORK REQUEST MODEL

Similar to the substrate network, we define virtual network requests (VNR) as a weighted undirected graph represented by $G_v = (N_v, L_v)$. Each virtual node in a VNR has a CPU capacity requirement, and each virtual link from a VNR has a bandwidth resource requirement. As shown in FIGURE.2, squares represent virtual nodes, and lines represent virtual links. The virtual network request (b) contains 5 virtual nodes, each of which has a corresponding CPU capacity (the number in the square), and contains 5 virtual links.

C. MULTI-DOMAIN VIRTUAL NETWORK EMBEDDING PROBLEM

The embedding process of single domain virtual network means that virtual nodes and links are embedded into the corresponding substrate network meanwhile satisfying the constraints of CPU capacity on nodes and bandwidth resource on links. Different from the single domain VNE process, the multi-domain VNE problem is associated with more than one substrate networks, and thereby causing the decomposition and composition of virtual network requests. A multi-domain VNE instance is shown in FIGURE.3.

As shown in the figure, InP publishes the virtual resource types and corresponding resource information that can be provided by the autonomous domain to the system, and then it is used to support the embedding algorithm and partition algorithm. In addition, the process can also obtain the topology information and connection cost information between boundary nodes from Internet exchange points. In the resource matching algorithm, the matching of virtual nodes is to find the type of virtual nodes that meet the mapping constraints, the matching of virtual links is to find a substrate path, so that each substrate link on the path can meet the mapping constraints of the virtual link. The whole substrate network consists of three autonomous domains and their interconnections. The squares in each domain represent the bottom substrate nodes, the hexagons represent the edge substrate nodes, and the lines between the regular pentagons represent the connection relationship between the boundary nodes.

IV. GENETIC CORRELATION MULTI-DOMAIN VIRTUAL NETWORK EMBEDDING ALGORITHM

This section mainly describes the algorithms in detail. In the first part, we introduce the genetic algorithm. In the second part, based on the existing genetic algorithm and the cross-domain embedding algorithm, we propose a genetic correlation multi-domain virtual network embedding algorithm (GCMD-VNE), the main steps of our algorithm are as follows.

A. GENETIC ALGORITHM

Genetic algorithm originates from the theory of heredity put forward by Darwin. It is a computer simulation study on the biological evolution process of natural selection and genetic evolution. Genetic algorithm is an efficient global search method based on natural evolution, which simulates biological gene transfer process. Genetic algorithm can directly optimize structural objects without the constraint of derivative and continuity of functions. The implicit parallelism and excellent global optimization performance are welcomed by algorithm workers. The genetic evolution algorithm starts from the solving set of problems to be solved, which is composed of a certain number of individuals who complete the genetic coding. The genes of each individual are the entity with its unique characteristics. The randomization technique is used to explore each individual efficiently.

B. GENETIC CORRELATION MULTI-DOMAIN VIRTUAL NETWORK EMBEDDING ALGORITHM

In literature [37], a virtual network model based on genetic algorithm is proposed, which applies the genetic algorithm to the problem of virtual network embedding and maps the virtual network requests to the infrastructure providers managing the substrate network. The GCMD-VNE algorithm proposed in this paper has many improvements compared with the original algorithm.

First of all, in the natural selection stage, in the original algorithm, the best performing half of the parents are directly selected into the offspring. In the algorithm proposed in this paper, natural selection of parents into the next generation is carried out according to the probability formula(4).

$$P(X_i) = \begin{cases} 1, & i = 0 \\ 1 - (\mathrm{i} - 1)/(\mathrm{N} - 2), & 1 \le i < N, \end{cases} \tag{4}$$

where N is the total number of individuals in each generation, $i \in \{0, 1, \ldots, N-1\}$ is the descending order of fitness function of parental individual X_i, in this paper, it is the ascending order of mapping cost, $i = 0$ is the best individual, $i = N - 1$ is the worst individual. The calculation of probability formula is mainly based on the following two considerations.

(1) $P(X_0) = P(X_1) = 1$, that is, the optimal two individuals in the parental generation will definitely enter the offspring generation. Since the crossover must be carried out between the two parents, this can ensure that the crossover operation can be carried out.

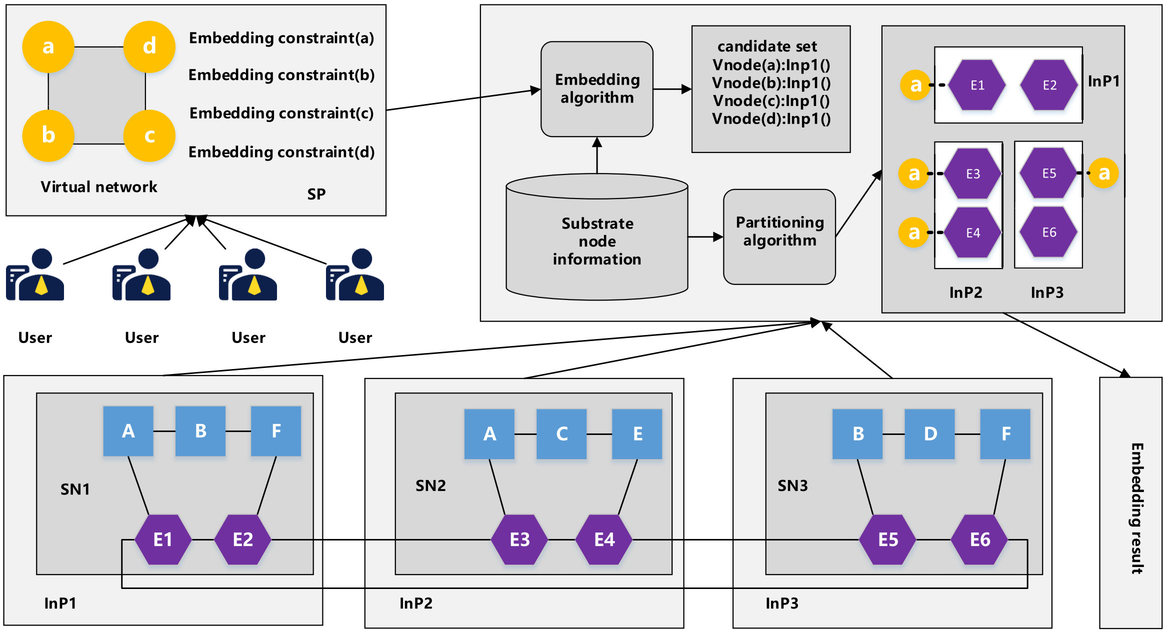

FIGURE 3. The virtual network cross-domain mapping instance.

(2) $\sum_{i=0}^{N-1} P(X_i) = (N+1)/2$, the mathematical expectation for the number of individuals entering the next generation is $(N+1)/2$, about half the number of parents.

Secondly, in the crossover stage, the detection of crossover parents and the restriction of crossover conditions are added. Since the crossover operation is the exchange of alleles between two parents, if two parents are identical, the crossover operation will definitely yield the same offsprings as the parents, which is of no significance to the optimization of solutions. In the small network embedding process, the probability of this situation is high. Therefore, the algorithm proposed in this paper increases the detection of cross parental. If the two parents are completely the same, no cross operation will be carried out and the opportunity will be given to other parental combinations.

However, in the simulation experiments, the execution efficiency of the algorithm with detection is low. After analyzing, it is found that most individuals will find the optimal solution after several iterations when the solution plane is small, which results in that most parents are the same and the optimal. Because the crossover algorithm starts from the optimal parental combination, it often falls into a long cycle in the crossover section, and even cannot converge. Therefore, in addition to parental detection, this algorithm also adds a restriction on crossover conditions. If a specified number of cross-operations have been performed (including those abandoned because the parents are the same), subsequent cross-operations will no longer be limited by parental differences, preventing the algorithm from falling into an endless loop.

The main steps of the proposed algorithm are as follows.

- Chromosome Construction

The total number of mid-locus genes in a chromosome is equal to the number of substrate networks that can be used to service multiple virtual network requests. The size of each allele in the chromosome remains the same as the largest of all substrate networks serving VN requests, the one with the largest number of nodes. The values in each allele are again filled in a random manner, and VN requests the VN vertex to fill the random position of the allele, representing the particular substrate network.

- Cross Operation

After the random initial population is generated, the parental chromosomes are crossed.

- Feasibility Checking

The solutions of operations are rarely invalid. Therefore, feasibility tests are needed for future generations.

- Mutation Operation

After crossover, mutation is carried out to make the genetic algorithm overcome local optimization and introduce new genes into the population. During the mutation phase, individual elements of each suballele are disrupted, and mutation probabilities are further discussed in the performance evaluation section.

- Selection Operation

Selection is the selection of parental chromosomes for the reproduction of offspring. Selected chromosomes are allocated to reproductive opportunities. There are several types of parental selection methods, such as roulette, random selection, rank selection, elitist selection, tournament selection, etc. In this work, selection is done by sequencing, in which the best half chromosome associated with fitness score is selected as the parent chromosome.

Because the virtual network node and link embedding to each substrate node and link requires a certain cost, and in general, the cost of inter domain link is higher than that of intra domain link, so the main consideration in the embedding is the embedding cost. The objective of the proposed scheme is to minimize the cost of multi domain VNE, and the objective function can be expressed by the following formula.

$$\min Cost = \sum_{num(N_v)} C(N_v)C(N_s) + \sum_{num(L_v)} Bw(L_v)Bw(L_s). \tag{5}$$

wherein, $num(N_v)$ represents the number of virtual nodes in the VNR, $num(L_v)$ represents the number of virtual links in the VNR, the first summation on the right represents the product of the CPU demand of each virtual network node and the CPU unit price of its corresponding substrate node, that is, the node mapping cost of the mapping scheme. The second summation term is the product of the bandwidth requirement of each virtual link and the total bandwidth of the corresponding substrate link. Therefore, minimizing the embedding cost is to minimize the sum of node embedding cost and link embedding cost.

The Algorithm 1 describes the detailed steps of GCMD-VNE.

Algorithm 1 Genetic Correlation Multi-Domain Virtual Network Embedding Algorithm

1: Get substrate network and VN requests;
2: Initialize the parents and children;
3: Calculate the adaptive value of individual;
4: Select the parents to next generation;
5: Cross the parents according to crossover probability;
6: Mutate children based on the mutation probability;
7: Find the optimal solution;
8: Calculate substrate resources and embedding cost;
9: Return embedding result.

V. SIMULATION EXPERIMENTS AND ANALYSIS

In this section, we describe the setup of the simulation environment in detail in the first part, and give the simulation results in the second part. In the following experiments, we compared the GCMD-VNE proposed in this paper with the existing methods including PSO-VNE, HTF-VNE and HCDCF-VNE, respectively showing the average embedding cost and average embedding time of the four algorithms with different node numbers in normal and abnormal network environments.

A. EXPERIMENTAL ENVIRONMENT SETTINGS

The simulation process of cross-domain virtual network mapping was completed on a computer with 8GB memory and 64-bit win10 operating system. The network topology used in the simulation experiment was generated randomly by code in Visual Studio 2012. The code was written by C++ programming language and compiled by Visual Studio 2012. The analysis of experimental results and the drawing of line chart were completed by OriginLab OriginPro 8.5. The parameters of the simulation experiment are set as follows.

TABLE 1. The settings of parameters.

Parameter Items	The Range
Substrate Network	
The number of substrate domains	4
The number of nodes in substrate network domains	30
The substrate node initial CPU resources	U[100,300]
The CPU unit price for substrate nodes	U[1,10]
The substrate network domain connection rate	0.5
The intra-domain link initial bandwidth resources	U[1000,3000]
The bandwidth unit of each intra-domain link	U[1,10]
The substrate domain boundary nodes	2
The bandwidth unit of each inter-domain link	U[5,15]
Virtual Network	
The virtual network request nodes	U[4,14]
The CPU requirements of each virtual node	U[1,10]
The virtual node candidate embedding domains	2
The connection rate of each virtual network link	0.5
The virtual link bandwidth requirements	U[1,10]
Genetic Algorithm	
The number of individuals of each generation	50
the number of genetic iterations	100
The probability of crossover between individuals	0.7
Gene mutation probability	0.2
Node mutation probability	0.2
The limit threshold for crossover operations	100

B. EXPERIMENTAL RESULTS AND ANALYSIS

In this part, there are altogether four experiments, which are divided into two parts. The first part includes two experiments, respectively comparing the average embedding cost of four algorithms in normal network environment and abnormal network environment. The second part consists of two experiments, respectively comparing the average embedding time of four algorithms in normal network environment and one field network environment.

Experiment 1: Comparison of average embedding costs under normal network.

In order to compare the average embedding costs of the three algorithms under normal network environment when the number of virtual nodes is different, simulation experiments are carried out on the simulation platform, and the experimental results are shown in FIGURE. 4. As can be seen from the FIGURE. 4, with the increase of the number of virtual network nodes, the average embedding cost showed a steady upward trend. The average embedding cost of GCMD-VNE algorithm proposed in this paper is much lower than PSO-VNE algorithm and slightly lower than the original HTF-VNE and HCDCF-VNE algorithm. Therefore, the GCMD-VNE algorithm proposed in this paper has certain advantages.

Experiment 2: Comparison of average embedding costs under poor network.

Because some links are easily affected by some uncertain factors, the cost is too high. Therefore, we designed the comparative experiments of four algorithms in the abnormal network environment, compared the average mapping cost when the number of virtual nodes is different, and carried out the simulation experiments on the simulation platform. The experimental results are shown in FIGURE. 5. As can be seen from the FIGURE. 5, with the increase of

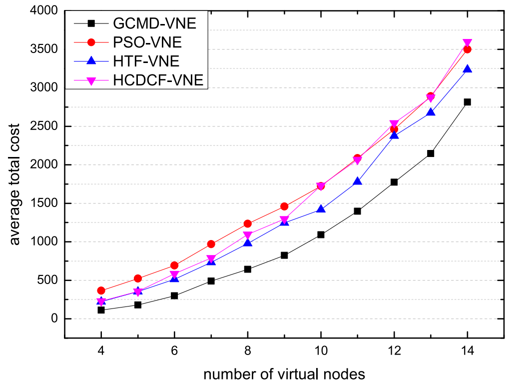

FIGURE 4. Comparison of average embedding costs under normal network.

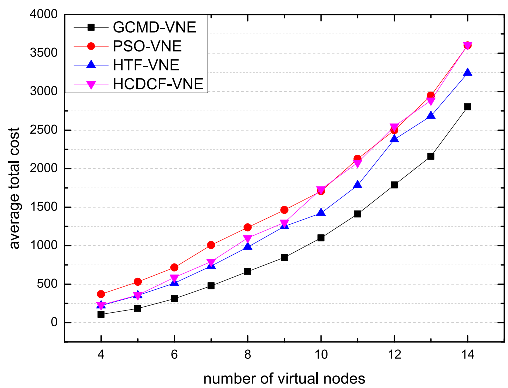

FIGURE 5. Comparison of average embedding costs under poor network.

the number of virtual network nodes, the average embedding cost shows an increasing trend. The average embedding cost of GCMD-VNE algorithm proposed in this paper is much lower than PSO-VNE algorithm and slightly lower than the HTF-VNE and HCDCF-VNE algorithm. Therefore, the GCMD-VNE algorithm proposed in this paper has lower cost and better performance in abnormal network environment.

From the average embedding cost diagram, it can be seen that the GCMD-VNE algorithm proposed in this paper is more optimized than the particle PSO-VNE in terms of embedding cost. The main reason is that compared with the traditional embedding algorithm, genetic algorithm can simultaneously compare a large number of embedding schemes and retain the reasonable parts of these schemes for iterative optimization. Compared with PSO-VNE, genetic algorithm is not easy to fall into local optimal due to mutation and can search for optimal solution in a larger solution plane.

Experiment 3: Comparison of average embedding time under normal network.

Experiment 3 is the comparison of average embedding time of the four algorithms for the same group of virtual network requests under normal network conditions. As can be seen from FIGURE. 6, the average embedding time of the four algorithms increases steadily with the increase of VN scale.

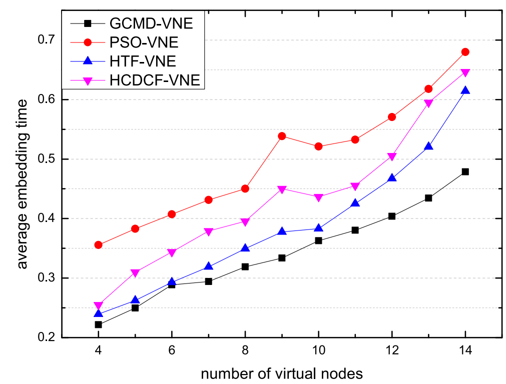

FIGURE 6. Comparison of average embedding time under normal network.

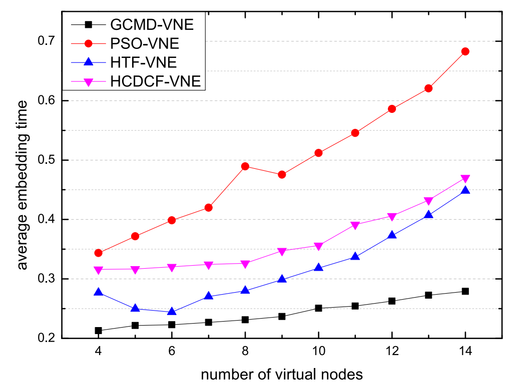

FIGURE 7. Comparison of average embedding time under poor network.

Among them, the GCMD-VNE proposed in this paper has the shortest embedding time, and PSO-VNE has the longest. It can be seen that the modified algorithm in this paper has a great improvement in embedding time compared with the previous genetic algorithm, and the effect is significant.

Experiment 4: Comparison of average embedding time under poor network.

Similar to Experiment 3, Experiment 4 compares the average embedding time of the four algorithms for the same group of virtual network requests in the case of abnormal network. As shown in FIGURE. 7, four algorithms of the average run time along with the growth of the virtual network scale is more stable, among them, the embedding time of GCMD-VNE significantly shorter than the other three algorithms, thus, under the condition of the network extension, in this paper, the improved algorithm has a great improvement on embedding time compared with the previous genetic algorithm.

This is because genetic algorithm and particle swarm optimization can share information between chromosomes, which can make the whole population move to the optimal region more evenly, so it has faster convergence time. At the same time, genetic algorithm has a mature convergence analysis method in the aspect of convergence, while PSO and traditional methods are relatively weak in this aspect, so the speed of genetic algorithm is faster.

VI. CONCLUSION

Aiming at the problem of cross-domain VNE, this paper further studies the application of genetic algorithm in VNE, and proposes a genetic correlation multi-domain virtual network embedding algorithm (GCMD-VNE). Firstly, this paper briefly introduces the research status of virtual network cross-domain embedding and its significance to future network theory. Then the key steps in solving the cross-domain embedding problem are introduced emphatically. In order to better prove the performance of the algorithm, the GCMD-VNE algorithm proposed in this paper is compared with the existing PSO-VNE, HTF-VNE and HCDCF-VNE algorithms through simulation experiments, and the simulation results are analyzed. Simulation results show that GCMD-VNE algorithm proposed in this paper has better performance than other two algorithms in average mapping cost, no matter in normal or abnormal network environment. And in terms of average mapping time, it has a more prominent performance and significant advantages. In the future work, we will consider more network embedding indicators, such as network security, fluency and so on. This will be the direction of our future efforts.

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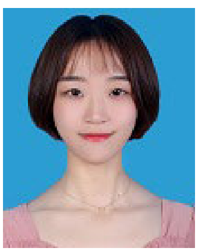

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