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Multi-Strategy Particle Swarm Optimization based MOEA/D for VNF-SC Deployment

Xuelin Zhao
Department of Computer Science and Information Technology
Xinyang Normal University
237 Nanhu Road, Henan Xinyang, 464000, China
xlz_cit@xynu.edu.cn

Yansong Zhao
Department of Foreign Languages
Xinyang Normal University
237 Nanhu Road, Henan Xinyang, 464000, China
yansongxn@163.com

Lei You*
Department of Computer Science and Information Technology
Xinyang Normal University
237 Nanhu Road, Henan Xinyang, 464000, China
Corresponding Author: lei_perfect_xynu@126.com

Zhenghui Liu
Department of Computer Science and Information Technology
Xinyang Normal University
237 Nanhu Road, Henan Xinyang, 464000, China
zhenghui.liu@163.com

Hejun Xuan
Department of Computer Science and Information Technology
Xinyang Normal University
237 Nanhu Road, Henan Xinyang, 464000, China
xuanhejun0896@xynu.edu.cn

Yanling Li
Department of Computer Science and Information Technology
Xinyang Normal University
237 Nanhu Road, Henan Xinyang, 464000, China
lyl75@163.com

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Abstract. *Network Function Virtualization (NFV) technology can realize on-demand distribution of network resources and improve network flexibility. It has become one of the key technologies for next-generation communications. Virtual Network Function Service Chain (VNF-SC) deployment is an important problem faced by network function virtualization technology. In this paper, the problem VNFs deployment for VNF-SC in inter-data center elastic optical networks (inter-DC EONs) is investigated. First, a multi-objective mathematical model, which minimizes total time delay and energy consumption, is establish. In this model, VNF-SCs are divide into two classes, i.e., part of required VNFs in each VNF-SC is dependent, others are independent. Second, Multi-Strategy Particle Swarm Optimization based MOEA/D (MSPSO-MOEA/D) is proposed to solve the model effectively. In MSPSO-MOEA/D, Chebyshev decomposition mechanism is used to transform multi-objective optimization problem into a series of single objective optimization subproblems. A new optimal mutation strategy is deeply studied in order to propose a new Particle Swarm Optimization (MSPSO) algorithm with multi-strategy. Finally, to show high performance of the proposed algorithm, large number of experiments are conducted. Experimental results indicate that the proposed algorithm has more advantages than compared algorithms.*
Keywords: Network Function Virtualization, multi-objective, MOEA/D, VNF-SC

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1. **Introduction.** With the emergence of new network technologies such as cloud computing, software-defined network and network function virtualization, the future network operation and maintenance is moving towards the direction of virtualization and intelligence [1, 2]. Network function virtualization provides a method of service node virtualization, which uses the general server to replace the special middleware in the traditional network, which can greatly reduce the construction and operation costs of network operators, and improve the flexibility and expansibility of network management [3-5]. Since network end-to-end services usually require different service functions, it has become an important research topic to construct network service function chain by using virtualization technology, and make reasonable allocation and scheduling of resources, which has attracted extensive attention from academia and industry [6].

In general, traffic needs to be processed by network functions in a specified order to enhance application security and performance. Ordered network functions can be called Service Function Chain (SFC) [7]. In NFV network, SFC is composed of a set of ordered VNFs [8]. Given a series of communication service requests containing SFC requests, the corresponding VNF and its communication path need to be deployed to complete these services. Due to the VNF software nature, its deployment location can be more flexible. Different deployment locations produce different energy and resource consumption [9, 10]. Therefore, for the communication service request containing SFC request, NFV network needs an effective method to determine the VNF deployment location and communication path to reduce energy consumption and resource consumption [11]. This kind of problem is called the VNF initial deployment optimization problem.

In recent years, the existing research usually sets an optimization goal of service function chain mapping according to different service requirements and network scenarios, and designs heuristic algorithm to solve it. Considering the problem of dynamic network function deployment and routing optimization, jointly optimized the acceptable maximum flowrate and energy consumption, established a mixed integer linear programming model, and designed an approximate allocation algorithm based on flow compensation to solve the problem [12]. Literature [13] considered the deployment of SFC in the context of content distribution network, and minimized the deployment cost on the premise of ensuring the delay requirements. The optimization problem was transformed into an integer linear programming problem, and a proactive VNF chain deployment algorithm was proposed to solve the problem. Literature [14] proposed an algorithm of outsourcing service function chain to cloud (MOSC), which transformed the deployment locations of different VNFs on an SFC into hidden states in the implicit Markov model, and solved the model with Viterbi algorithm. Literature [15] takes the workload and basic resource consumption (BRC) into consideration, and establishes a planning model with the goal of minimizing the number of active servers, and then designs a heuristic T-SAT algorithm to solve it. A joint construction and mapping method of service function chain based on backtracking method is proposed [16]. This method starts from the current deployment node and adopts greedy strategy to deploy the next service function. In the deployment process, the state of the whole underlying network is not considered and it is easy to fall into local optimum. Literature [17] proposed link load balancing based on ant colony optimization algorithm, which added link load, delay and packet loss to ant algorithm to identify the shortest routing path and reduce the minimum delay between nodes. Literature [18] proposed a load balancing method based on the response time of the server, in which the controller was used to obtain the response, and the server selected the minimum time or the most stable response time of the server.

In this paper, the problem VNFs deployment for VNF-SC in inter-data center elastic optical networks (inter-DC EONs) is investigated. A multi-objective mathematical model, which minimizes total time delay and energy consumption, is establish. In this model, VNF-SCs are divide into two classes, i.e., part of required VNFs in each VNF-SC is dependent, others are independent. In addition, Multi-Strategy Particle Swarm Optimization based MOEA/D (MSPSO-MOEA/D) is proposed to solve the model effectively.

2. **Problem Formation.**

2.1. **Network and VNF-SC Description.**

Directed graph $G(V, E)$ denotes an inter-data center elastic optical networks (inter-EONs). $V = \{v_1, v_2, \ldots, v_{N_V}\}$ denotes the nodes set, and N_V represents the number of nodes. For $v_i (i = 1, 2, \ldots, N_V)$, it can be described as $v_i = \{C_i, S_i\}$, where C_i and T_i is the CPU and storage resource on v_i. Similar to the previous work, we also assume that only some specific virtual network functions (VNFs) can be applied by a node. For $v_i (i = 1, 2, \ldots, N_V)$, the set of VNFs can be denoted as $VNF_i^V = \left\{VNF_{i_1}, VNF_{i_2}, \ldots, VNF_{i_d}, \ldots, VNF_{i_{N_{vnf}^i}}\right\}$, where N_{vnf}^i is the number of VNFs, and $VNF_{i_d} \in VNF$, where VNF is the set of all the VNFs and can be denoted by $VNF = \{VNF_1, VNF_2, \ldots, VNF_{N_{vnf}}\}$. N_{vnf} is the number of VNFs. The set of optical links represented by $E = \{l_{ij} | v_i, v_j \in V\}$, and the link between node v_i and node v_j denoted by l_{ij}. N_E is the number of links. In each link, there are N_F available frequency slots, and denoted as $F = \{f_1, f_2, \ldots, f_{N_F}\}$.

$R = \{r_1, r_2, \ldots, r_k, \ldots, r_{N_R}\}$ represents a set of VNF-SCs, where N_R is the number of VNF-SC. $r_k (k = 1, 2, \ldots, N_R)$ is denoted as $r_k = (s_k, d_k, b_k, VNF_k^R, SeqVNF_k^R)$. The source node, destination node and initially required frequency slots are denoted as s_k, d_k and b_k, respectively. $VNF_k^R = \{VNF_{k_1}, \ldots, VNF_{k_a}, \ldots, VNF_{k_{N_k^R}}\}$ and $SeqVNF_k^R = \{seqVNF_{k_1}, \ldots, seqVNF_{k_b}, \ldots, seqVNF_{k_{sN_k^R}}\}$ are two classes of VNFs that r_k required, and N_k^R and sN_k^R represents the number of VNFs in VNF_k^R and $SeqVNF_k^R$, respectively. In VNF_k^R, all the required VNFs are independent, that is to say, the order of these VNFs is flexible. In $SeqVNF_k^R$, all the VNFs are dependent, i.e., they must be arranged in a special order.

2.2. **Mathematical Modeling.**

2.2.1. *Objective function.* There are two objectives, it is to minimize the total time delay and energy consumption to serve all the VNF-SCs. The one objective is minimize total time delay to serve all the VNF-SC. The total time delay can be expressed as

$$t_{total} = t_{proc} + t_{trans} + t_{prop} + t_{quene} \tag{1}$$

where t_{proc}, t_{trans}, t_{prop} and t_{quene} represent processing delay, transmission delay, propagation delay and queuing delay. Processing delay is the time it takes to process the VNF-SC on the node. This article adopts the definition of the processing delay model based on the common processor sharing algorithm, namely

$$t_{proc} = \sum_{k=1}^{N_R} t^i_{proc} = \sum_{k=1}^{N_R} (l^i_p roc/l^i_{flow}) \times f^i_{proc} \tag{2}$$

where l_{proc} denotes the current VNF-SC on the node, l_{flow} is an approximate fraction of the VNF-SC that the VNF-SC will contribute to the node, and f_{proc} is the VNF-SC processing time. Transmission delay of VNF-SC, propagation delay and queueing delay is defined in [19]. We can normalize the objective as

$$f_1 = \frac{t_{proc} + t_{trans} + t_{prop} + t_{quene}}{N_R \times (\max\{t^i_{proc}\} + \max\{t^i_{trans}\} + \max\{t^i_{prop}\} + \max\{t^i_{quene}\})} \tag{3}$$

Since $t^i_{proc} \le \max\{t^i_{proc}\}$, $t^i_{trans} \le \max\{t^i_{trans}\}$, $t^i_{prop} \le \max\{t^i_{prop}\}$ and $t^i_{quene} \le \max\{t^i_{quene}\}$, we have $0 \le f_1 \le 1$.

Another objective is to minimize energy consumption to serve all the VNF-SCs. Let N^i_f denote the number of VNFs on node v_i, the total energy consumption of the node v_i can be calculated by

$$E_i = E^i_s + \sum_{k=1}^{N^i_f} E^k_{f,i} \tag{4}$$

where E^i_s and $E^k_{f,i}$ denote the overhead of the start energy consumption, energy consumption of k-th VNF on v_i, respectively. Thus, the total energy consumption is

$$E_{total} = \sum_{i=1}^{N_V} E_i + \sum_{i=1}^{N_E} \sum_{j=1}^{N_E} \sum_{k=1}^{N^{ij}_f} E^k_{ij} \tag{5}$$

where E^k_{ij} represents the energy consumption of k-th VNF on link l_{ij}. Similar to the first objective, this objective can be normalized as

$$f_2 = \frac{\sum\limits_{i=1}^{N_V} E_i + \sum\limits_{i=1}^{N_E} \sum\limits_{j=1}^{N_E} \sum\limits_{k=1}^{N^{ij}_f} E^k_{ij}}{\sum\limits_{i=1}^{N_V} (E^i_s + \sum\limits_{k=1}^{N_F} E^k_{f,i}) + \sum\limits_{i=1}^{N_E} \sum\limits_{j=1}^{N_E} \sum\limits_{k=1}^{N_F} E^k_{ij}} \tag{6}$$

Similarly, we have $0 \le f_2 \le 1$. Some constraints should be satisfied for the proposed model, all the constraints can be found in our previous work [20].

3. Multi-objective Evolutionary MSPSO-MOEA/D Algorithm.

3.1. **Particle Swarm Optimization.** Particle Swarm Optimization (PSO) is a kind of random searching algorithm based on swarm cooperation designed by simulating the foraging behaviour of birds. The evolutionary process is as follows:
(1) Initialization: Let N_S denote the population size, the position and velocity of the i-th individual can be expressed as $x_i = (x_{i1}, x_{i2}, \ldots, x_{id})$ and $v_i = (v_{i1}, v_{i2}, \ldots, v_{id})$, respectively.
(2) Update: position and velocity of i-th individual can be updated by

$$v_i^{t+1} = wv_i^t + c_1 r_1 (p_i^t - x_i^t) + c_2 r_2 (p_g^t - x_i^t)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1}$$

where x_i^t and v_i^t are current position and velocity of i-th individual on t generation, respectively. p_i^t and p_g^t are the best position of the i-th individual and all the individuals in the population until now. w is inertia weight. $c_i (i = 1, 2)$ are two learning factors. In general $c_1 = c_2 = 2$. r_1 and r_2 are generated randomly in $[0, 1]$.
(3)Selection: Selecting the appropriate individual according to the fitness value of the individual.

3.2. **MOEA/D Algorithm based on Chebyshev Decomposition.** The decomposition-based multi-objective evolutionary algorithm has great advantages in maintaining the distribution of solutions. The distribution of solutions can be optimized by analyzing the information of neighboring problems. The commonly used decomposition methods in MOEA/D include weighted sum method, Chebyshev method and penalty-based boundary intersection method, etc. [21, 22]. Generally speaking, the Chebyshev method is the most widely used method. Using Chebyshev method to decompose a multi-objective optimization problem into a set of optimization sub-problems, mathematically described as follows

$$\begin{cases} \min g^{tch}(x|\lambda^i, z^*) = \max\limits_{1 \le i \le m} \{\lambda^i |f_i(x) - z_i^*|\} \\ s.t.\ x \in \Omega, \end{cases} \tag{7}$$

where $z^* = (z_1^*, z_2^*, \ldots, z_m^*)^T$ is a reference point. $\lambda = (\lambda_1^*, \lambda_2^*, \ldots, \lambda_N)$ represents a set of uniformly distributed weight vectors. For $z_i^* (i = 1, 2, \ldots, m)$, it has $z_i^* < \min\{f_i(x)|x \in \Omega\}$.

For each pareto solution, there is always a weight vector to make the solution of Eq. (8) the optimal solution, which corresponds to the Pareto optimal solution of the multi-objective optimization problem.Chebyshev polymerization method is added in the method of chebyshev ρ parameters, is a weighted sum polymerization method and chebyshev method. By adjusting the ratio of the two methods, it combines the fast convergence of the weighted summation polymerization method and the good distribution of Chebyshev method. The mathematical description of Chebyshev polymerization is as follows:

$$\min g^{AT}(x|\lambda, z^*) = \max_{1 \le i \le m} \{\lambda^i |f_i(x) - z_i^*|\} + \rho \sum_{i=1}^{m} \lambda^i f_i(x) \tag{8}$$

3.3. **MSPSO-MOEA/D Algorithm.** This algorithm decomposes a multi-objective optimization problem into a series of single-objective optimization sub-problems, and optimizes these sub-problems at the same time. Then the MSPSO algorithm is used to replace the genetic algorithm in MOEA/D, which realizes the effective solution of the problem. The pseudo code of MSPSO-MOEA/D is as follows:

Algorithm 1: Pseudocode of MSPSO-MOEA/D

1 Initialize the population N, set the weight vectors of evenly distributed as $\lambda = (\lambda_1^*, \lambda_2^*, \ldots, \lambda_N)$, and the number of weight vectors in each neighborhood is T.
2 Set EP as the empty set.
3 Calculate the Euclidean distance of any two weight vectors and find the nearest T weight vectors of each weight vector. For each $i = 1, 2, \ldots, N$, let $B(i) = i_1, i_2, \ldots, i_T$. For each $j \in B(i)$, λ^j is T neighborhood vector of λ_i.
4 The initial population $x^1, x^2, \ldots, x^N$ is generated uniformly and randomly in the feasible space.
5 For each $i = 1, 2, \ldots, N$, calculating $FV^i = F(x^i)$.
6 Initialization the reference point $z^* = (z_1, z_2 \ldots, z_m)^T$.
7 Genetic recombination: an individual y is randomly selected from $B(i)$ and a new solution is generated using MSPSO.
8 Improvement: by using heuristic method to improve y for special problems, the solution y' is generated.
9 Function evaluation: evaluation function $F(y')$.
10 Update z: for each $j = 1, 2, \ldots, m$, if $z_j > f_j(y')$, let $z_j = f_j(y')$.
11 Update the neighborhood solution: for each $j \in B(i)$, if $g^{tch}(y'|\lambda, z) \leq g^{tch}(x^j|\lambda, z)$, let $x^j = y', FV^j = F(y')$.
12 Update EP: Remove all vectors dominated by $F(y')$ from EP.
13 If none of the vectors in EP dominated by $F(y')$, add $F(y')$ to EP.
14 Terminal condition: if the ending condition is met, the algorithm stops and outputs EP. Otherwise go to Step 3.

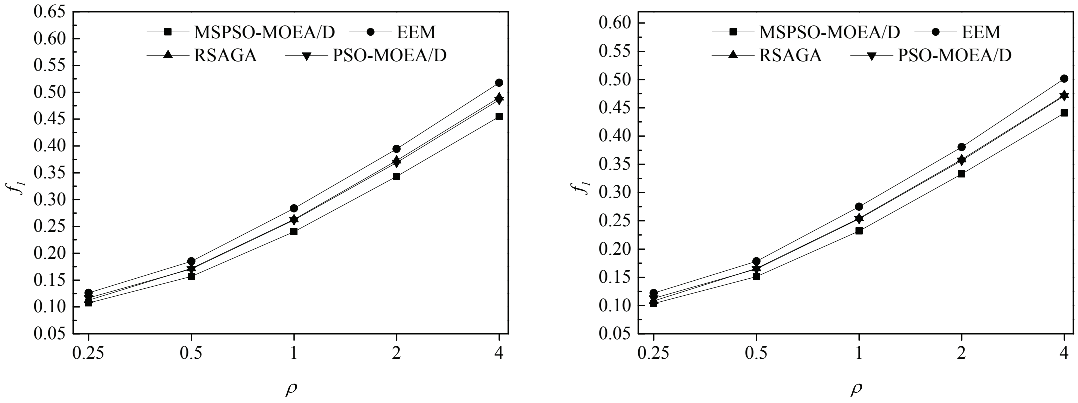
4. **Experiments and Analysis.** In order to verify the effectiveness and efficiency of the algorithm, experiments were carried out on two widely used networks. In the section 4.1, the parameters used in the algorithm will be given. The experimental results are obtained in section 4.2. Then, the experimental results are analyzed in section 4.3.

4.1. **Parameters Setting.** Two widely used networks (NSFNET and US backbone) were used in the experiments. FSs is 12.5 GHz, and the transmission distances of BPSK, QPSK, 8QAM, and 16QAM are selected as 9600, 4800, 2400, and 1200 km, respectively. In two topologies, all VNF-SCs in each group satisfy an uniform distribution. In order to make the algorithm converge to the optimal solution, $t_{max} = 2000$ is used. Generally speaking, when the population is large, longer calculation time is required. In addition, when the population size is small, it will lead to poor population diversity. Therefore, the population size selected in the experiment is $N_P = 100$. Each VNF-SC that the frequency slots meet the uniform distribution in [1, 10], and each link has 2000 frequency slots, that is, $N_F = 2000$.

4.2. **Experimental Results.** In order to verify the performance of the proposed algorithm, we compared the proposed algorithm MSPSO-MOEA/D with the other three algorithms. The first algorithm is EEM, which is cited in the literature [23]. Another method proposed in the literature quotes [24], denoted as RSAGA. In order to improve the network performance index, RSAGA studied the VNF-SC deployment problem combining modulation level allocation and spectrum allocation. In addition, we also compared MSPSO-MOEA/D and PSO-MOEA/D.

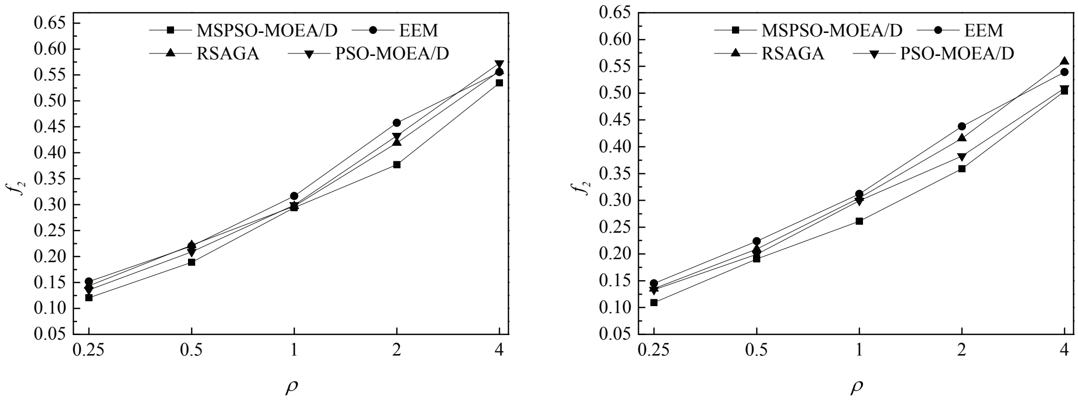
The number of data center nodes are fixed as $N_D = N_V/4$, $N_D = N_V/2$ and $N_D = 3N_V/3$. In each experiment, number of VNF-SCs are set as $N_R = \rho N_V(N_V - 1)$, and

$\rho = 0.25$, 0.5, 1, 2 and 4, respectively. Figure 1 and Figure 2 show the total time delay and energy consumption obtained in NSFNST and US Backbone when $N_D = N_V/4$. The total time delay and energy consumption obtained in NSFNST and US Backbone when $N_D = N_V/2$ are shown in Figure 3 and Figure 4, respectively. Figure 5 and Figure 6 show the total time delay and energy consumption obtained in NSFNST and US Backbone when $N_D = 3N_V/4$.



(a) Time delay in NSFNET (b) Time delay in US Backbone

FIGURE 1. Total time delay obtained when $N_D = N_V/4$.



(a) Energy consumption in NSFNET (b) Energy consumption in US Backbone

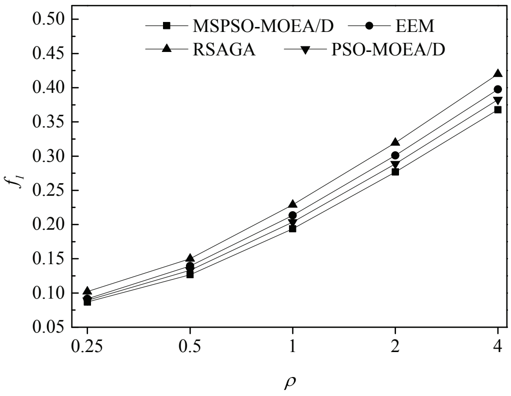
FIGURE 2. Energy consumption obtained when $N_D = N_V/4$.

To demonstrate the uniformity, convergence, diversity of the proposed algorithm [25, 26], the following two metrics are used to evaluate the pareto solutions:

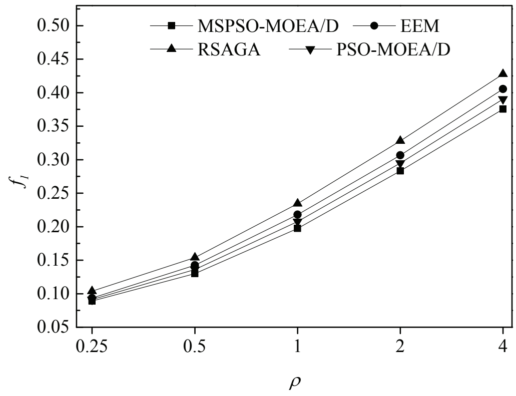
- *Spacing Index*(SI): defined by Eq.(9) below.

$$\begin{cases} SI(A) = \sqrt{\frac{1}{|PF^*|-1} \sum\limits_{z \in PF^*} \left(\bar{d} - d(z)\right)^2} \\ d(z) = \min\left\{\|z - z'\| | z \neq z', z' \in PF^*\right\} \\ \bar{d} = \frac{1}{|PF^*|} \sum\limits_{z \in PF^*} d(z) \end{cases} \tag{9}$$

Spacing Index is used to metric the uniformity of the pareto solution. The smaller of SI, the better of the solutions.

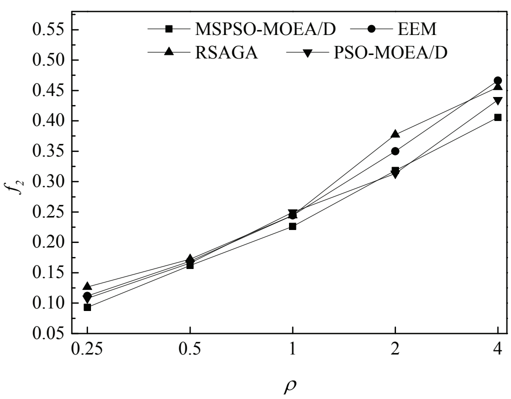


(a) Time delay in NSFNET

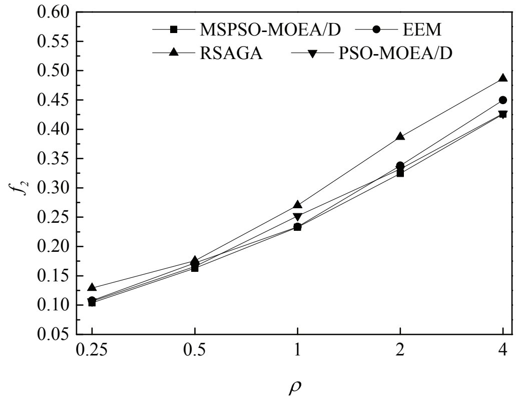


(b) Time delay in US Backbone

FIGURE 3. Total time delay obtained when $N_D = N_V/2$.

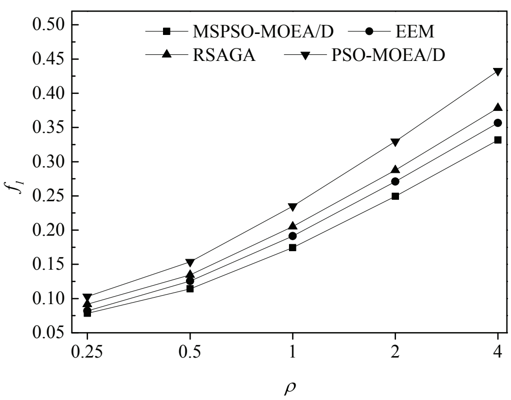


(a) Energy consumption in NSFNET

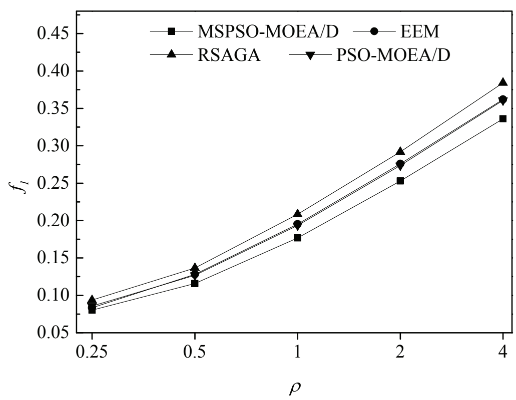


(b) Energy consumption in US Backbone

FIGURE 4. Energy consumption obtained when $N_D = N_V/2$.



(a) Time delay in NSFNET

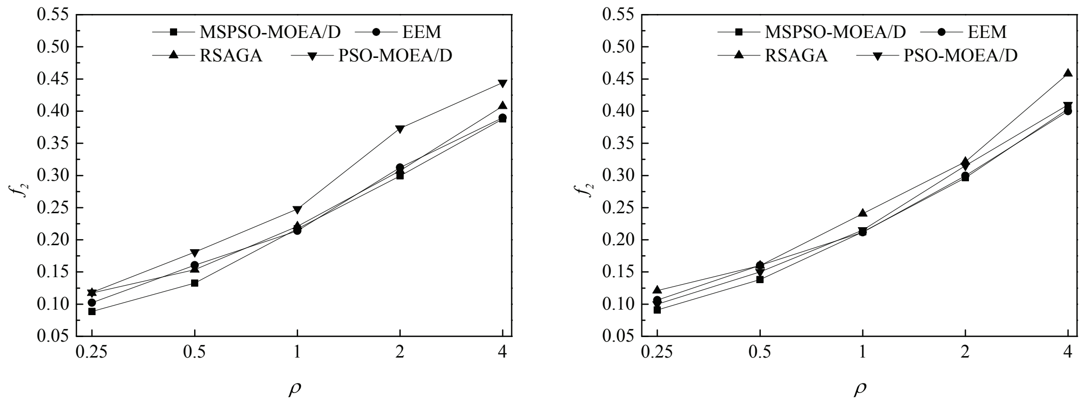


(b) Time delay in US Backbone

FIGURE 5. Total time delay obtained when $N_D = 3N_V/4$.

- *Hypervolume Index*(HI): which is used to test the uniformity, convergence and diversity of the solutions, and defined by the following Eq.(10).

$$HI(PF^*) = \bigcup_{z \in PF^*} vol(z) \tag{10}$$



(a) Energy consumption in NSFNET (b) Energy consumption in US Backbone

FIGURE 6. Energy consumption obtained when $N_D = 3N_V/4$.

TABLE 1. Statistical results (Mean and Standard Deviation) of the SI and HI.

		NSFNET		USBackbone	
		SI	HI	SI	HI
0.25	0.25	2.7804(1.82E-02)	9.9096(3.56E-01)	1.9816(2.13E-02)	10.9964(4.48E-01)
	0.5	3.1554(2.15E-02)	10.1947(4.12E-01)	2.2841(2.36E-02)	11.2921(4.95E-01)
	1	3.7260(3.29E-02)	10.9833(4.89E-01)	2.5355(3.43E-02)	12.1934(5.32E-01)
	2	4.0251(4.29E-02)	11.2486(5.79E-01)	2.7852(4.98E-02)	13.4140(6.28E-01)
	4	4.5996(5.38E-02)	12.5158(6.48E-01)	3.4457(5.73E-02)	14.5094(7.12E-01)
0.5	0.25	3.2356(3.58E-02)	10.1947(4.12E-01)	3.1245(3.43E-02)	11.2839(4.87E-01)
	0.5	4.2568(3.95E-02)	10.8574(4.97E-01)	3.9854(3.89E-02)	12.6741(5.39E-01)
	1	5.9872(4.13E-02)	11.3684(6.12E-01)	5.2812(4.25E-02)	13.5876(6.24E-01)
	2	6.3871(4.74E-02)	12.0258(6.81E-01)	6.1578(5.37E-02)	14.5231(6.97E-01)
	4	7.0217(5.23E-02)	12.9852(7.35E-01)	6.9756(6.04E-02)	15.0124(7.42E-01)
0.75	0.25	3.3482(3.76E-02)	10.8752(4.34E-01)	3.7631(3.87E-02)	11.6732(4.98E-01)
	0.5	4.5632(4.08E-02)	11.2874(5.21E-01)	4.2418(4.05E-02)	12.9742(5.75E-01)
	1	6.1274(4.91E-02)	11.8736(6.54E-01)	5.6397(4.64E-02)	13.6741(6.63E-01)
	2	6.7452(5.18E-02)	12.5416(7.01E-01)	6.7468(5.80E-02)	14.8762(7.21E-01)
	4	7.5687(5.87E-02)	13.2461(7.72E-01)	7.1846(6.29E-02)	15.9715(7.76E-01)

where $vol(z)$ is the hypervolume of area which is surrounded by z and the reference point $r = (r_1, r_2, \ldots, r_m)$. m is the dimensionality of the objective space.

4.3. **Experimental Analysis.** Figure 1, Figure 3 and Figure 5 show the total time delay obtained by the algorithm MSPSO-MOEA/D and compared benchmark algorithms (EEM, RSAGA and PSO-MOEA/D) in two networks. In Figure 1, the total time delay is obtained in two network when $N_D = N_V/4$. It can be seen from the experimental results that the total delay obtained by MSPSO-MOEA/D is smaller than the comparison algorithm with the same number of VNF-SCs. Similarly, the total time delay obtained are shown in Figure 3 and Figure 5 when $N_D = N_V/2$ and $N_D = 3N_V/4$, respectively. It can be seen from the experimental results that the total delay obtained by MSPSO-MOEA/D is smaller than the comparison algorithm with the same number of VNF-SCs. In each figure, the total time delay increases as the number of VNF-SCs increases. when $N_D = N_V/4$, the total time delay obtained by the MSPSO-MOEA/D is 3.1% to 4.7% less than that obtained by EEM, RSAGA and PSO-MOEA/D when the number of VNF-SCs is $0.25N_V(N_V - 1)$. When the number of VNF-SCs is $4N_V(N_V - 1)$, the total time delay obtained by MSPSO-MOEA/D is 7.1%-11.2% less than those obtained by EEM, RSAGA and PSO-MOEA/D, respectively.

Figure 2, Figure 4 and Figure 6 show the energy consumption obtained by the algorithm MSPSO-MOEA/D and three benchmark algorithms (EEM, RSAGA and PSO-MOEA/D) in two networks. In Figure 1, the energy consumption is obtained in two network when $N_D = N_V/4$. It can be seen from the experimental results that the total delay obtained by MSPSO-MOEA/D is smaller than the comparison algorithm with the same number of VNF-SCs. Similarly, the energy consumption obtained are shown in Figure 3 and Figure 5 when $N_D = N_V/2$ and $N_D = 3N_V/4$, respectively. It can be seen from the experimental results that the MSPSO-MOEA/D algorithm obtains a smaller energy consumption than the algorithm with the same number of VNF-SCs. In each figure, energy consumption increases as the number of VNF-SCs increases. when $N_D = N_V/4$, the energy consumption obtained by the MSPSO-MOEA/D is 2.8% to 4.1% less than that obtained by EEM, RSAGA and PSO-MOEA/D when the number of VNF-SCs is $0.25N_V(N_V - 1)$. When the number of VNF-SCs is $4N_V(N_V - 1)$, the total time delay obtained by MSPSO-MOEA/D is 7.6%-12.8% less than those obtained by EEM, RSAGA and PSO-MOEA/D, respectively.

Table 1 demonstrates the distance index and overcapacity index (mean and standard deviation) on the two networks. This shows that the MSPSO-MOEA/D algorithm can find various Pareto optimal solutions under the conditions of different numbers of VNF-SCs and data centers. In this way, it is more likely to meet the requirements of decision makers. In addition, it can be seen from Table 1 that SI and HI indexes, as well as MSPSO-MOEA/D, can obtain better PF for our dual-objective optimization model.

5. **Conclusions.** In this paper, the problem VNFs deployment for VNF-SC in inter-data center elastic optical networks (inter-DC EONs) is investigated. A multi-objective mathematical model, which minimizes total time delay and energy consumption, is establish. In this model, VNF-SCs are divide into two classes, i.e., part of required VNFs in each VNF-SC is dependent, others are independent. Second, Multi-Strategy Particle Swarm Optimization based MOEA/D (MSPSO-MOEA/D) is proposed to solve the model effectively. In MSPSO-MOEA/D, Chebyshev decomposition mechanism is used to transform multi-objective optimization problem into a series of single objective optimization subproblems. A new optimal mutation strategy is deeply studied in order to propose a new particle swarm optimization (MSPSO) algorithm with multi-strategy. Finally, to show high performance of the proposed algorithm, large number of experiments are conducted. Experimental results indicate that the proposed algorithm has more advantages than compared algorithm.

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