Personality-Aware VNF Deployment for Profit Maximization

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***Abstract*—Virtual Network Function (VNF) providers aim to maximize their profits while satisfying diverse users' requirements. However, existing research does not take user personality into account when optimizing the profit of VNF providers, where user personality has a great influence on the VNF providers' profit. In this paper, we investigate personality-aware VNF deployment to maximize the VNF provider's profit. First, we model personalized service chain requests to capture the different requirements of users with different personalities for service requests. We further propose a user satisfaction prediction model according to questionnaires to obtain the attribute values of the above personalized service chain request. Subsequently, we propose a genetic algorithm based personality-aware VNF deployment scheme to maximize the VNF provider's profit while considering diverse personalities of individual users. Simulation results show that our proposed approach can increase the profit of the VNF provider by 9.19% and the request acceptance rate by 20.70%, respectively.**

***Keywords*-Network Function Virtualization, profit, personality, deployment, genetic algorithm**

I. Introduction

Traditional network providers usually require a large number of dedicated hardware devices to implement a wide variety of network functions. This type of network function deployment not only occupies physical space, but also increases capital, operations, and energy costs. In the past few years, Network Function Virtualization (NFV) technique [1] has attained much attention. NFV decouples network functions from dedicated hardware and implements various network functions in software on a general purpose server. Due to the advantages of NFV technology in terms of flexibility, scalability, and cost, many network providers use this technology to provide network services. In particular, the network providers that use NFV technique are called VNF providers [2]. As a business model, the VNF providers are particularly interested in how to maximize their profits while meeting diverse users' requirements.

Considerable research efforts have been devoted to maximizing the profit of VNF providers. Mijumbi et al. [3] study online VNF mapping problem, and propose tabu search-based greedy algorithms to obtain an optimal VNF mapping for optimizing the revenue of VNF providers. However, the link delay and the costs of VNF providers are not considered in their work. Ma et al. [4] take link delay into account and dynamically accept latency-aware requests in the software defined network (SDN) to maximize the revenue of the VNF provider, whereas the cost of the VNF provider is ignored. Sun et al. [5] consider the VNF provider's cost and address the problem of optimizing service function chain deployment by utilizing the technique of cross entropy with restricted Boltzmann machine to provide users with high quality and cost-efficient network services. Racheg et al. [6] consider the cost of the VNF provider when maximizing the profit of the VNF provider by enumerating all possible resource allocation solutions. Nevertheless, their presented enumeration-based method is not suitable for large-scale problems. Ma et al. [7] focus on the offline and online NFV-enabled requests for optimizing the profit of the VNF provider. They propose an efficient algorithm to solve large-scale problems by migrating and releasing VNF instances in the system. The above works optimize the profit of VNF providers from multiple perspectives. However, they fail to take user personality into consideration, thus may miss the opportunities for further profit improvement.

In real-world situations, user personality has a great influence on the profit of VNF providers. For example, some users with high conscientiousness characteristic may care more on service quality (e.g., delay time), while other users with high agreeableness characteristic may endure a lower service quality at lower prices. In this way, VNF providers could increase profits by providing more resources to users who desire high service quality and allocating less resources to users who hope low price. In this paper, we investigate the issue of VNF deployment to maximize the VNF provider's profit considering user personality. The major contributions of this paper are summarized as follows.

- We model personalized service chain requests to capture the differences of service requests, and establish a questionnaire-based user satisfaction prediction model.
- We propose a VNF deployment scheme based on genetic algorithm to maximize the VNF provider's profit while considering diverse personalities of individual users.
- Extensive simulations results show that our personality-aware VNF deployment scheme increases the profit of

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the VNF provider by 9.19% and the request acceptance rate by 20.70%, respectively.

The remaining sections of this paper are organized as follows. Section II introduces the system architecture and models. In Section III, we formulate the VNF provider's profit maximization problem and provide the overview of the proposed approach. The questionnaires based user satisfaction prediction algorithm is introduced in Section IV and our proposed personality-aware VNF deployment scheme to maximize the VNF provider's profit is described in Section V. Section VI verifies the high effectiveness of our proposed approach, and the conclusion is given in Section VII.

II. System Architecture and Models

In this paper, we explore the VNF deployment to maximize the VNF provider's profit considering user personality. The system architecture is shown in Fig. 1. Users first submit service chain requests to the VNF provider. Then, the VNF provider deploys VNFs of the service chain request to physical infrastructure and users pay for the service according to service quality. Specifically, in the service chain request, the traffic is sent from the source to the destination. Service chain requests consist of ordered VNFs, such as intrusion detection systems (IDS), firewalls, and load balancers [8]. The physical infrastructure of the VNF provider consists of multiple point of presents (POPs) distributed across geographical locations. Each POP consists of servers and routers that connect adjacent POPs. When the VNF provider deploy VNFs to POPs, the requirements of resource (i.e., CPU, memory and storage) of the VNFs and the bandwidth of the virtual links need to be met [9]. In the next sections, we introduce the user model and the VNF provider model, respectively.

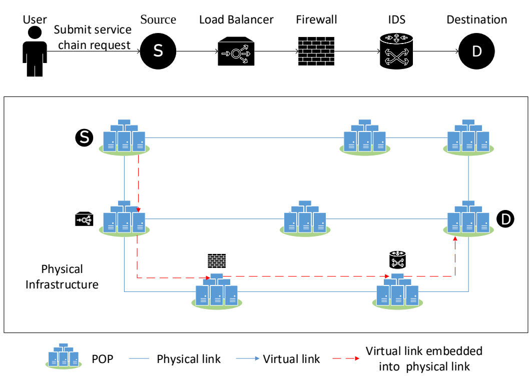


Figure 1. System Architecture.

A. User Model

User request model and user satisfaction model are described in the following subsections.

1) User Request Model: The personalized service chain request is modeled by a tuple $\tau_i = \{\mathbf{N^i}, \mathbf{L^i}, \pi^i_{desired}, \pi^i_{deadline}, \beta^i\}$. $\mathbf{N^i}$ represents the set of all VNFs in service chain request $i \in \mathbf{I}$ where $\mathbf{I}$ is the set of service chain request. Similarly, $\mathbf{L^i}$ denotes the set of all virtual links between the VNFs in service chain request i. Each VNF $n \in \mathbf{N^i}$ has a resource requirement c_n^{ir} where $r \in \mathbf{R}$ is the resource type. $\mathbf{R} = \{1, 2, 3\}$ denotes the set of resource types which are CPU, memory and storage. Each virtual link $l \in \mathbf{L^i}$ has a bandwidth requirement b_l^i. The service chain request i has a desired delay $\pi^i_{desired}$. Furthermore, the service chain request i has a delay deadline $\pi^i_{deadline}$. β^i is the fee decay rate, indicating that when the delay exceeds a certain threshold, the price will decrease as the delay decreases. ε_r and ε_b refer to the price for resource r and the bandwidth price, respectively. The actual delay of request i is expressed as π^i. The price of service chain request i is given by

$$\phi_i = \begin{cases} (\sum\limits_{n\in N^i}\sum\limits_{r\in R} c_n^{ir}\varepsilon_r) + \sum\limits_{l\in L} b_l^i\varepsilon_b, \pi^i \le \pi^i_{desired} \\ (\sum\limits_{n\in N^i}\sum\limits_{r\in R} c_n^{ir}\varepsilon_r) + \sum\limits_{l\in L} b_l^i\varepsilon_b - \left(\pi^i - \pi^i_{desired}\right)\beta^i, \\ \qquad \pi^i_{desired} \le \pi^i \le \pi^i_{deadline} \\ \qquad 0, \pi^i > \pi^i_{deadline}. \end{cases} \tag{1}$$

The detailed description of the price ϕ_i is given as follows. If the actual delay π^i of request i is earlier than desired delay $\pi^i_{desired}$, the VNF provider satisfies the user's requirement and the user will pay the full payment. If the actual delay π^i is later than desired delay $\pi^i_{desired}$ but earlier than delay deadline $\pi^i_{deadline}$, the VNF provider does not satisfy the user's requirement enough, but user can tolerate it. The VNF provider will give some monetary penalty to the user for exceeding the desired delay. The monetary penalty is based on fee decay rate β^i. The user will only pay part of the payment. However, if the actual delay π^i is later than delay deadline $\pi^i_{deadline}$, the VNF provider does not satisfy user's requirement. The user will not pay the payment.

2) User Satisfaction Model: Enhancing user satisfaction can increase the competitiveness of the VNF provider in the competitive market. User satisfaction is affected by service quality and service price. Users can get high satisfaction when service quality is high and service price is low. But for the VNF provider, it is difficult to meet low price and high quality at the same time. The service price will increase as the service quality increases, and decrease as the service quality decreases. There are many studies [10] to improve user satisfaction by balancing service price and service quality. However, they do not consider user personality, which is related to satisfaction. For example, some users hope higher service quality without paying attention to service price, while some users desire cheaper price and do not care about service quality.

We use the latent variable Δ to describe user interest. The variable Δ can be expressed as

$$\Delta = \alpha * o + (1 - \alpha) * p, \tag{2}$$

where p expresses the service price and o denotes the service quality. The weight $\alpha\,(0 \leq \alpha \leq 1)$ measures the user preference between service price and service quality, which is calculated in Section IV. High weight means that user prefers high quality, while low weight means user likes low price. User satisfaction is linearly represented by latent variables Δ, then it is expressed by linear model as follows

$$s = \theta_1 + \theta_2 * \Delta, \tag{3}$$

where s refers to user satisfaction, θ_1 and θ_2 are parameters calculated in Section IV. The user satisfaction can be expressed as

$$s = \theta_1 + \theta_2 * (\alpha * o + (1-\alpha) * p)\,. \tag{4}$$

We use the user satisfaction to obtain fee decay rate, desired delay and the delay deadline in the corresponding service chain request. The fee decay rate β^i in request i is set to $\theta_2 * \alpha$. The desired service quality $\pi^i_{desired}$ is calculated when user satisfaction is maximum according to Eq. (4). $\pi^i_{desired}$ can be calculated from o by solving the expression

$$\max_{o} \left\{\theta_1 + \theta_2 * (\alpha * o + (1-\alpha) * p)\right\}.$$

Meanwhile, the delay deadline $\pi^i_{deadline}$ can be acquired when user satisfaction is minimum according to Eq. (4). $\pi^i_{deadline}$ can be obtained from o by solving the expression

$$\min_{o} \left\{\theta_1 + \theta_2 * (\alpha * o + (1-\alpha) * p)\right\}.$$

B. VNF Provider Model

In this section, we construct the revenue model, the cost model, and the profit model of the VNF provider, respectively.

1) Revenue Model: The total revenue of the VNF provider can be expressed as

$$\mathrm{Rev}enue = \sum_{i \in I} \phi_i z_i, \tag{5}$$

where $z_i \in \{0,1\}$ represents whether the request i is accepted or not. The request is accepted when the VNF provider can satisfy the resource requirements of the VNF and the bandwidth of the virtual link.

2) Cost Model: POPs of multiple different areas construct the physical infrastructure of the VNF provider [6]. It is modeled by an undirected graph $\widetilde{\mathbf{G}} = (\widetilde{\mathbf{N}}, \widetilde{\mathbf{L}})$, where $\widetilde{\mathbf{N}}$ represents the set of POPs and $\widetilde{\mathbf{L}}$ represents the set of physical links between the POPs. The energy consumption of POP $\widetilde{n}$ is represented by $E_{\widetilde{n}}$, and the POP $\widetilde{n}$ consists of a set of servers $\widetilde{\mathbf{M}}_{\widetilde{\mathbf{n}}}$. As in [11], the energy consumption of a server is computed by a linear model. To simplify, we consider all servers $\widetilde{m} \in \widetilde{\mathbf{M}}_{\widetilde{\mathbf{n}}}$ within the same POP $\widetilde{n}$ have same CPU capacity and consumption model [12]. Hence, each server $\widetilde{m}$ energy consumption is the same when idle (represented by $E^{idle}_{\widetilde{n}}$) and its energy consumption growth slope is $\psi_{\widetilde{n}}$ [13]. That is, the energy consumption of server $\widetilde{m}$ is given by

$$E_{\widetilde{m}} = E^{idle}_{\widetilde{n}} + \psi_{\widetilde{n}} U_{\widetilde{m}}, \tag{6}$$

where $U_{\widetilde{m}}$ is the utilization of the server $\widetilde{m}$. The total energy consumption of POP is the sum of its servers energy consumption. It can be expressed as

$$E_{\widetilde{n}} = \sum\nolimits_{\widetilde{m}=1}^{\left|\widetilde{\mathbf{M}}_{\widetilde{\mathbf{n}}}\right|} \left(E^{idle}_{\widetilde{n}} + \psi_{\widetilde{n}} U_{\widetilde{m}}\right). \tag{7}$$

Since energy consumption of servers is the same in the same POP, the total energy consumption of POPs $\widetilde{n}$ can be expressed as

$$E_{\widetilde{n}} = \left|\widetilde{\mathbf{M}}_{\widetilde{\mathbf{n}}}\right| E^{idle}_{\widetilde{n}} + \psi_{\widetilde{n}} \sum\nolimits_{\widetilde{m}=1}^{\left|\widetilde{\mathbf{M}}_{\widetilde{\mathbf{n}}}\right|} U_{\widetilde{m}}. \tag{8}$$

The sum of the CPU utilization of all servers in POP $\widetilde{n}$ (i.e., $\sum_{\widetilde{m}=1}^{\left|\widetilde{\mathbf{M}}_{\widetilde{\mathbf{n}}}\right|} U_{\widetilde{m}}$) can be expressed as the sum of all CPU resources consumed by the VNFs deployed into POP $\widetilde{n}$ (i.e., $\sum_{i\in\mathbf{I}}\sum_{n\in\mathbf{N^i}} x^i_{n\widetilde{n}} c^{i1}_n$) divided by the total available CPU resource in the POP $\widetilde{n}$ (i.e., $c^1_{\widetilde{n}}$). $x^i_{n\widetilde{n}} \in \{0,1\}$ represents if the VNF n in service chain request i is deployed into the POP $\widetilde{n}$. $c^r_{\widetilde{n}}$ represents the resource r capacity of POP $\widetilde{n}$. The total energy consumption in one POP can be expressed as

$$E_{\widetilde{n}} = \left|\widetilde{\mathbf{M}}_{\widetilde{\mathbf{n}}}\right| E^{idle}_{\widetilde{n}} + \frac{\psi_{\widetilde{n}}}{c^1_{\widetilde{n}}} \sum\nolimits_{i\in\mathbf{i}} \sum\nolimits_{n\in\mathbf{N^i}} x^i_{n\widetilde{n}} c^{i1}_n. \tag{9}$$

In summary, the total cost of the VNF provider is calculated as

$$Cost = \sum\nolimits_{\widetilde{n}\in\widetilde{\mathbf{N}}} \lambda_{\widetilde{n}} E_{\widetilde{n}}, \tag{10}$$

where $\lambda_{\widetilde{n}}$ is the energy price at POP $\widetilde{n}$.

3) Profit Model: The profit of the VNF provider is given by

$$Profit = Revenue - Cost, \tag{11}$$

where the components of Eq. (11) are given in Eq. (5) and Eq. (10), respectively.

III. Problem Definition and Overview of the Proposed Approach

In this section, we define the VNF provider's profit maximization problem considering the user personality. Subsequently, we briefly describe the proposed approach.

A. Problem definition

The VNF provider's profit maximization problem is described as follows

$$\text{maximize:} Profit, \tag{12}$$

$$\text{subject to:} \sum_{i\in\mathbf{I}} \sum_{n\in\mathbf{N^i}} x^i_{n\widetilde{n}} c^{ir}_n \leq c^r_{\widetilde{n}} \;\; \forall \widetilde{n} \in \widetilde{\mathbf{N}}, r \in \mathbf{R}, \tag{13}$$

$$\sum_{\widetilde{n}\in\widetilde{\mathbf{N}}} x^i_{n\widetilde{n}} \leq 1 \;\; \forall i \forall n, \tag{14}$$

$$\sum_{i\in\mathbf{I}} \sum_{l\in\mathbf{L^i}} b^i_{l\widetilde{l}} \leq b_{\widetilde{l}} \;\; \forall \widetilde{l} \in \widetilde{\mathbf{L}}, \tag{15}$$

$$s \geq s_{th}. \tag{16}$$

Eq. (12) is the object function given by Eq. (11). Eq. (13) indicates that the total resource consumption of one POP $\widetilde{n}$ is not beyond its resource capacity $c^{ir}_{\widetilde{n}}$ (i.e., CPU, memory and storage). Eq. (14) guarantees that each VNF can only be mapped in one POP. $b^{i}_{l\widetilde{l}}$ represents the bandwidth of the virtual link l mapping on the physical link $\widetilde{l}$ in request i. $b_{\widetilde{l}}$ denotes the bandwidth capacity of the physical link $\widetilde{l}$. Eq. (15) ensure that total bandwidth consumption of physical link $\widetilde{l}$ is not beyond its resource capacity $b_{\widetilde{l}}$. s_{th} represents the user satisfaction threshold. Eq. (16) represents that user satisfaction is be guaranteed.

B. *Overview of the proposed approach*

In the above sections, for users, we first model the personalized service chain request to capture the service quality requirements (e.g., desired delay and delay deadline) of users with different personalities. To obtain the attribute values of the personalized service chain request, we further establish a questionnaire based user satisfaction prediction model. For the VNF provider, we model its revenue, cost, and profit models, respectively. Subsequently, based on the above models, we formalize the profit maximization problem, which is given in Eqs. (12)-(16), for the VNF provider. To this end, we proposed a genetic algorithm based personality-aware VNF deployment scheme combined with the user satisfaction prediction algorithm to maximize the VNF provider's profit considering diverse personalities of individual users.

IV. Questionnaire Based User Satisfaction Prediction Algorithm

Personality refers to the difference between individual behavioral, feeling and thinking patterns [14]. People with different personalities will have different attitudes and make different choices when they encounter the same situation. Personality is usually characterized by the Big-Five traits (i.e., Openness to Experience (O), Neuroticism (N), Conscientiousness (C), Agreeableness (A), and Extroversion (E)) to describe the personality of a person. Each trait corresponds to a characteristic of the person [15]. To assess the person personality, the Ten Personality Questionnaire (TIPI) is often used in existing literature, which contains a questionnaire for 10 questions [16]. Through the TIPI questionnaire, we use a vector of five scores (each score ranges from 1 to 7) to describe a user personality, and the vector is named as the personality score. User satisfaction is influenced by user personality in research [17]. We obtain user satisfaction scores by asking users to rate the different service price-quality levels. The service quality is affected by delay time. The baseline service quality level is the highest service quality (100%), and the other 5 levels of service quality are 90%, 80%, 70%, 60% and 50% of the baseline, respectively. Similarly, for service price level, the baseline is the most expensive price (100%), and the other 5 levels of service price are 95%, 90%, 85%, 80% and 75% of the baseline, respectively. 6 service price levels and 6 service quality levels constitute 36 price-quality levels. User rates the 36 price-quality levels and the score ranges from 1 to 10.

Sixty participants fill out our questionnaire and we use two representative participants to illustrate the relationship between personality and satisfaction. As shown in Table I and Table II, different personality users have different satisfaction scores in the same price-quality level. The user A has agreeableness characteristic, while user B has conscientiousness characteristic. For example, in the third column of Table I with the service quality of 90%, user satisfaction varies little with service quality. However, in the fourth row where the service price is 90%, user satisfaction varies greatly with the service price. Therefore, user A is more concerned with the service price than with the service quality. For user B, service quality has a great impact on satisfaction, while service price has little effect on satisfaction. For example, in the fourth column of Table II with the service quality of 80%, user satisfaction varies greatly with service price. However, in the sixth row where the service price is 80%, user satisfaction varies little with the price of the service. Obviously, the user personality has a strong influence on user satisfaction score.

Table I
Satisfaction score of user A.

service quality / service price	100%	90%	80%	70%	60%	50%
100%	8	7	5	4	2	1
95%	8	7	6	4	2	1
90%	9	8	6	5	3	1
85%	9	8	7	5	3	2
80%	10	9	7	5	3	2
75%	10	9	7	5	3	2

Table II
Satisfaction score of user B.

service quality / service price	100%	90%	80%	70%	60%	50%
100%	2	2	2	1	1	1
95%	4	3	3	3	2	2
90%	6	6	5	5	4	4
85%	7	7	7	6	6	5
80%	8	8	7	7	6	6
75%	10	10	9	9	8	8

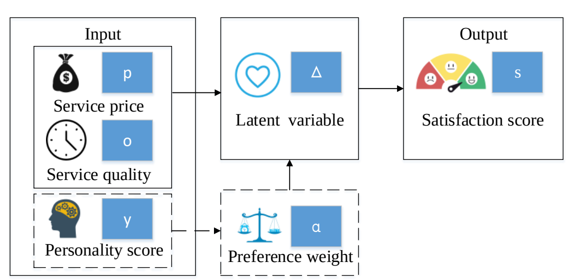


Figure 2. The user satisfaction prediction model

The user satisfaction prediction model is shown in Fig. 2. The input of user satisfaction model is service quality, service price and personality score. The output is satisfaction score. The satisfaction score is given in Eq. (3). The set of participants in the questionnaire is expressed as **T**, and the set of price-quality levels is expressed as **D**. The preference weight of participant $t \in \mathbf{T}$ is denoted as α_t. For each service price-quality level $d \in \mathbf{D}$ of the participant t, the latent variable, satisfaction score, service price and service quality are denoted by $\Delta_{t,d}$, $s_{t,d}$, $p_{t,d}$ and $o_{t,d}$, respectively. Then the parameters θ_1 and θ_2 can be calculated by the mean square error equation

$$\min_{\theta_1,\theta_2,\alpha_1,\cdots,\alpha_{|\mathbf{T}|}} \sum\nolimits_{t=1}^{|\mathbf{T}|} \sum\nolimits_{d=1}^{|\mathbf{D}|} \left(s_{t,d} - \theta_1 - \theta_2 * \Delta_{t,d}\right)^2, \quad (17)$$

where

$$\Delta_{t,d} = \alpha_t o_{t,d} + (1-\alpha_t)\, p_{t,d}.$$

Eq. (17) is hard to solve directly. Hence, an iterative algorithm is used to solve it. First, preference weight α_t is initialized for each participant. Then we calculate latent variable $\Delta_{t,d}$ for each participant using Eq. (2). Therefore, parameters θ_1 and θ_2 can be acquired by solving the standard linear regression

$$\min\nolimits_{\theta_1,\theta_2} \sum\nolimits_{t=1}^{|\mathbf{T}|} \sum\nolimits_{d=1}^{|\mathbf{D}|} \left(s_{t,d} - \theta_1 - \theta_2 * \Delta_{t,d}\right)^2.$$

As θ_1 and θ_2 is calculated, for each participant t, Eq. (17) can be converted to

$$\min\nolimits_{\alpha'_t} \sum\nolimits_{d=1}^{|\mathbf{D}|} \left(\frac{s_{t,d}-\theta_1}{\theta_2} - (1-\alpha'_t)\, p_{t,d} - \alpha_t o_{t,d}\right)^2. \quad (18)$$

We can solve Eq. (18) by linear regression solver, and the updated preference weight α'_t can be obtained. If α_t and α'_t for each participant t are close enough, the iteration stops. The preference weight α_t for each participant t, the parameters θ_1 and θ_2 are obtained.

Afterwards, the relationship between the personality score and the preference weight is explored. The personality score of participant t is denoted as $y_t = [y_{t,O}, y_{t,ES}, y_{t,C}, y_{t,A}, y_{t,E}]$, which represents the score of the five traits O, ES, C, A and E, respectively. For all participants, we use matrix Y of $|\mathbf{T}| * 5$ to express their personality scores, and vector W of $|\mathbf{T}| * 1$ to express their preference weights. A linear regression model is established to estimate the relationship between personality score and preference weight. The parameter η (a $5 * 1$ vector) can be obtained by calculating

$$\min_{\eta} \|\mathrm{W} - \mathrm{Y} * \eta\|^2.$$

In this way, given the personality score y_t of participant t, we can calculate his/her preference weight α_t by multiplying η. Finally, we get the value of the parameters θ_1, θ_2 and η. Therefore, we can predict user satisfaction s from user personality score y, service price p and service quality o, as shown in Fig. 2.

V. Personality-Aware VNF Deployment Scheme for Profit Maximization

Genetic algorithm is first proposed by Goldberg as a stochastic heuristic search algorithm to simulate biological evolution [18]. We utilize genetic algorithm as our optimization method to obtain VNF deployment to maximize the VNF provider's profit for the following reasons. Firstly, genetic algorithm directly carries out various genetic operations on structural objects, and it does not require continuous derivable search space. In this paper, the VNF deployment has discrete attributes in the search space. Secondly, genetic algorithm search process has the characteristics of parallelism, so it can be efficient to solve the optimization problem. Finally, the crossover and mutation operations in genetic algorithm are random, so local best solutions can be avoided.

Chromosome definition: The proposed chromosome structure is encoded by binary encoding. In this way, the individuals of population consist of a binary matrix, as shown below.

$$A_k^h = \begin{bmatrix} a_{11}^h & a_{12}^h & \cdots & a_{1v}^h \\ a_{21}^h & a_{22}^h & \cdots & a_{2v}^h \\ \vdots & \vdots & \ddots & \vdots \\ a_{u1}^h & a_{u2}^h & \cdots & a_{uv}^h \end{bmatrix}$$

If there are u VNFs (the sum of VNFs in all service chain requests) and v POPs (the sum of all POPs in physical infrastructure), the individual of population is a $u \times v$ matrix. $Q_k = \{A_k^1, A_k^2, ..., A_k^H\}$ represents the population where $A_k^h = (a_{e,f}^h)_{u\times v}$ denotes the individual where $h \in \{1, 2, \cdots, H\}$ is h-th individual of population, H is the individual number of population and k is the k-th generation population. The element $a_{e,f}^h$ needs to satisfy the constraints

$$\sum_{f=1}^{v} a_{e,f}^h = 1, \forall e \in \{1, 2, \cdots, u\}, \quad (19)$$

$$a_{e,f}^h \in \{0, 1\}, \forall e \in \{1, 2, \cdots, u\}, \forall f \in \{1, 2, \cdots, v\}. \quad (20)$$

Eq. (19) represents each VNF can only be mapped in one POP. Eq. (20) indicates whether the VNF e is mapped to the POP f.

Chromosome evaluation: The fitness function measures the degree of individual adapting to the environment. If the value of the fitness function of the chromosome is large, it means that the chromosome is closer to the optimal solution. The chromosome represents deployment solution, and the goal of the genetic algorithm based method is to obtain the chromosome that maximizes the VNF provider's profit. Therefore, the fitness function is represented by the objective function Eq. (11).

Chromosome selection: In this paper, we use the Elitist Selection Strategy (ESS) based on the traditional roulette selection method. ESS ensures that the optimization problem converges to the global optimal solution.

Chromosome crossover: The crossover operation of genetic algorithm refers to the exchange of genetic information of two parents in a certain way to generate two new offspring chromosomes. We apply multi-row matrix crossover which exchanges the genetic information with the probability $P_c\,(0 \leq P_c \leq 1)$ and the exchange position is random. The rows below the exchange position are swapped between the two parent chromosomes. For example, parent $A_k^{h_1}$ and parent $A_k^{h_2}$ are described as follows.

$$A_k^{h_1} = \begin{bmatrix} a_{11}^{h_1} & a_{12}^{h_1} & \cdots & a_{1v}^{h_1} \\ a_{21}^{h_1} & a_{22}^{h_1} & \cdots & a_{2v}^{h_1} \\ \vdots & \vdots & \ddots & \vdots \\ a_{u1}^{h_1} & a_{u2}^{h_1} & \cdots & a_{uv}^{h_1} \end{bmatrix} A_k^{h_2} = \begin{bmatrix} a_{11}^{h_2} & a_{12}^{h_2} & \cdots & a_{1v}^{h_2} \\ a_{21}^{h_2} & a_{22}^{h_2} & \cdots & a_{2v}^{h_2} \\ \vdots & \vdots & \ddots & \vdots \\ a_{u1}^{h_2} & a_{u2}^{h_2} & \cdots & a_{uv}^{h_2} \end{bmatrix}$$

Parent $A_k^{h_1}$ and parent $A_k^{h_2}$ swap the rows below row 2 and generate offspring $A_k^{\overline{h_1}}$ and offspring $A_k^{\overline{h_2}}$ as follows.

$$A_k^{\overline{h_1}} = \begin{bmatrix} a_{11}^{h_1} & a_{12}^{h_1} & \cdots & a_{1v}^{h_1} \\ a_{21}^{h_2} & a_{22}^{h_2} & \cdots & a_{2v}^{h_2} \\ \vdots & \vdots & \ddots & \vdots \\ a_{u1}^{h_2} & a_{u2}^{h_2} & \cdots & a_{uv}^{h_2} \end{bmatrix} A_k^{\overline{h_2}} = \begin{bmatrix} a_{11}^{h_2} & a_{12}^{h_2} & \cdots & a_{1v}^{h_2} \\ a_{21}^{h_1} & a_{22}^{h_1} & \cdots & a_{2v}^{h_1} \\ \vdots & \vdots & \ddots & \vdots \\ a_{u1}^{h_1} & a_{u2}^{h_1} & \cdots & a_{uv}^{h_1} \end{bmatrix}$$

Chromosome mutation: In addition to crossover, mutation generates new chromosome by changing gene values in the chromosome with a random mutation rate $P_k^h\left(0 \leq P_k^h \leq 0.1\right)$. The mutation rate P_k^h can change automatically with changes in fitness as follows [19]

$$P_k^h = \begin{cases} \frac{fit_{max} - fit\left(A_k^h\right)}{fit_{max} - fit_{avg}}, & fit\left(A_k^h\right) < fit_{avg} \\ k_1, & fit\left(A_k^h\right) \geq fit_{avg}, \end{cases} \tag{21}$$

where fit_{max} is the biggest fitness value of the current population. fit_{avg} is the average fitness value of the current population. Each individual A_k^h has the fitness value $fit\left(A_k^h\right)$, and $k_1\ (0 \leq k_1 \leq 1)$ is coefficient. The adaptive mutation rate makes individuals with lower fitness have greater probability of mutating, thereby increasing the probability of individuals transforming into optimal individuals. In the mutation operation, the genes of a certain row or rows of a matrix chromosome A_k^h are changed according to the probability P_k^h with satisfying the constraints of the problem.

We obtain the most profitable VNF deployment solution for the VNF provider by using genetic algorithm. The chromosome is the VNF deployment solution. Each physical link is selected using the criteria of the lowest delay path. For the physical infrastructure of the VNF provider, the physical link delay between any POP is known and the lowest delay path can be obtained in advance, thus simplifying the solution of the problem.

Our proposed VNF deployment scheme is shown in Algorithm 1. The input of the algorithm includes personalized service chain request $\mathbf{\Gamma} = \{\tau_1, \tau_2, \cdots, \tau_{|\mathbf{I}|}\}$ and physical infrastructure $\widetilde{\mathbf{G}}$ in the VNF provider. The output is the profit maximization solution. Line 1 initializes the crossover probability P_c, initial population Q_0, population size H and the maximum iteration K. The iteration variable k is set in line 2. Line 3 represents that the algorithm will loop until the iteration variable k reach the maximum iteration K. Lines 3-19 display the iterative process of the algorithm. Lines 4-6 calculate the fitness of all chromosomes in the population using Eq.(11). The largest fitness $fit_{\max}$ is obtained and the profit maximization solution $A_{\max}$ is recorded in line 7. Line 8 selects the appropriate chromosome according to ESS to generate the group $Q_k^{'}$. Lines 9-12 show the crossover operation and line 13-16 show the mutation operation. Lines 17-18 update population and iterative variable. Line 20 returns the profit maximization solution $A_{\max}$.

Algorithm 1 Personality-aware VNF deployment algorithm

Input: User service chain request $\mathbf{\Gamma}$, physical infrastructure in the VNF provider $\widetilde{\mathbf{G}}$

Output: Profit maximization solution $A_{\max}$

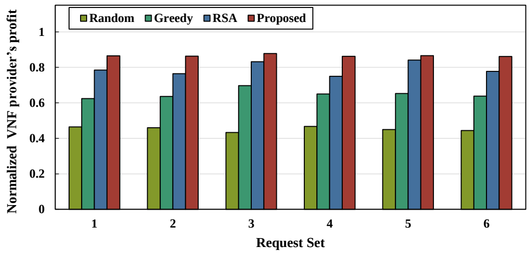
1: Initialize crossover probability P_c, initial population Q_0, population size H and the maximum iteration K;
2: Set iteration variable $k = 0$;
3: **while** $k \leq K$ **do**
4:     **for** $h = 1, h \leq H, h++$ **do**
5:         Calculate and evaluate fitness $fit\left(A_k^h\right)$ of chromosome A_k^h using Eq. (11);
6:     **end for**
7:     Obtain the largest fitness $fit_{\max}$ and record the profit maximization solution $A_{\max}$;
8:     Select the appropriate chromosome according to ESS based on the traditional roulette selection to generate the population Q_k';
9:     **for** $h = 1, h \leq H/2, h++$ **do**
10:         Crossover of A_k^{2h-1} and A_k^{2h} is operated with probability P_c;
11:     **end for**
12:     Update the population Q_k';
13:     **for** $h = 1, h \leq H, h++$ **do**
14:         Mutation is operated with probability P_k^h using Eq. (21);
15:     **end for**
16:     Update the population Q_k';
17:     $Q_{k+1} \leftarrow Q_k'$;
18:     $k = k + 1$;
19: **end while**
20: **return** profit maximization solution $A_{\max}$;

VI. Evaluation

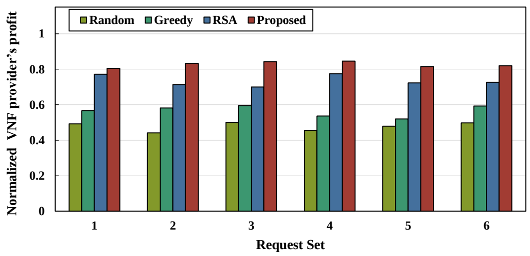
We verify the high efficiency of our proposed approach through a large number of simulations in this section.

A. Simulation Setup

We use Python to simulate the experiment. The physical network topology of the VNF provider is the NSFNET, which consists of 14 POPs connected by 21 physical links. We set the capability of physical links according to the Amazon data center [20]. To simplify, we consider that each POP consists of 2 same servers. The parameters of each POP are shown in Table III. The users' personality scores are obtained from 60 participants. And the 60 participants submit service chain requests to generate 6 request sets.

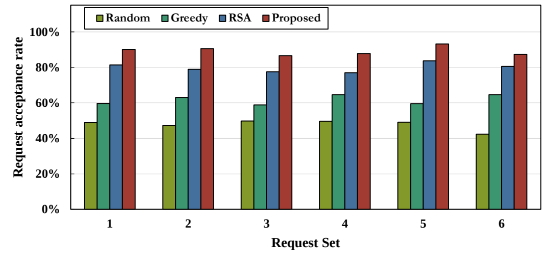


(a) User satisfaction threshold s_{th} = 7

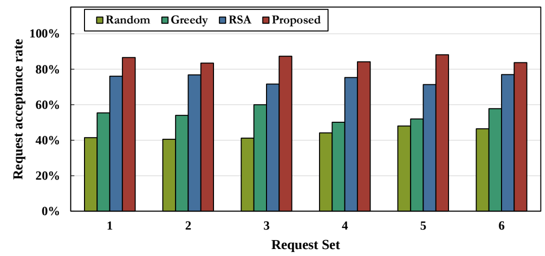


(b) User satisfaction threshold s_{th} = 9

Figure 3. The normalized profit of 6 request sets realized by our proposed approach and three benchmarking algorithms.



(a) User satisfaction threshold s_{th} = 7



(b) User satisfaction threshold s_{th} = 9

Figure 4. Request acceptance rate of 6 request sets realized by our proposed approach and three benchmarking algorithms.

Furthermore, service chain requests follow a Poisson distribution with an average rate of 0.2. The number of VNFs in each request is generated randomly from 1 to 5. Normalized requirements (CPU, memory and storage) in each VNF are randomly generated from 0.01 to 0.05 [6]. The price for resource and the bandwidth price are ranging from 0.006 to 0.105 dollars per hour according the Amazon EC2 [20]. The bandwidths and latency requirements of requests are randomly generated in [0.5, 10] MB and [100, 200] ms, respectively [6]. All simulations are conducted on a machine with Intel Core i5 3 Ghz CPU and 8 GB of RAM.

B. Simulation Results

Three benchmarking algorithms are compared with our proposed approach to verify the efficiency of our proposed approach. The first one is Random algorithm, which deploys VNF randomly while satisfying users' requirements. The second one is Greedy algorithm, which deploys VNF by maximizing profit of the new arrived request. However, it causes request acceptance rate decreasing, and thus the total profit of the VNF provider may not be high. The third one is Restrictive Search Algorithm (RSA), which explores all the solution to find the optimal one that maximizes the profit under path utilization constraint [6].

Comparison of VNF provider's profit: Fig. 3 illustrates the normalized profit achieved by our proposed approach and three benchmarking algorithms under different user satisfaction thresholds. The figure presents that our proposed approach has the highest VNF provider's profit compared to the other three algorithms. For instance, as shown in Fig. 3(a), when user satisfaction threshold s_{th} is set to 7, compared to Random, Greedy and RSA our proposed approach increases VNF provider profit by 92.33%, 26.88% and 11.32%, respectively. As shown in Fig. 3(b), when user satisfaction threshold s_{th} is set to 9, compared to Random, Greedy and RSA our proposed approach increases the VNF provider's profit by 91.65%, 28.37% and 9.19%, respectively.

Table IV
THE NORMALIZED RUNNING TIME OF THREE ALGORITHMS

User satisfaction threshold	Greedy	RSA	Proposed
$s_{th} = 7$	0.81	10.57	1
$s_{th} = 9$	0.77	11.32	1.17

Comparison of request acceptance rate: Fig. 4 shows the request acceptance rate achieved by our proposed approach and three benchmarking algorithms under different user satisfaction thresholds. The figure shows that our proposed approach has the highest request acceptance rate compared to the other three algorithms. As shown in Fig. 4(a), in the case of user satisfaction threshold $s_{th} = 7$, compared to Random, Greedy and RSA our proposed approach increases request acceptance rate by 224.33%, 46.80% and 29.85%, respectively. As shown in Fig. 4(b), in the case of user satisfaction threshold $s_{th} = 9$, compared to Random, Greedy and RSA our proposed approach increases request acceptance rate by 187.18%, 44.44% and 20.70%, respectively.

Comparison of running time: The normalized running time of Greedy, RSA and our proposed approach is shown in Table IV. The running time of Random is less than 1s, and it is faster than our proposed approach. However, our proposed approach increases the VNF provider's profit by 91.65% and request acceptance rate by 187.18%. When user satisfaction threshold s_{th} is 7, our proposed approach is

Table III
POP PARAMETERS (NOTE: CPU CAPACITY, MEMORY CAPACITY, AND STORAGE CAPACITY ARE NORMALIZED)

POP ID	Number of Servers	Server model	CPU Capacity	Memory Capacity	Storage Capacity	Electricity Price
1,5,9	2	Dell Power Edge R210	0.08	0.0625	0.9	2.16×10^{-3}
2,6,10	2	Dell Power Edge R515	0.25	0.5	0.9	2.88×10^{-3}
3,7,11	2	HP DL385 G7	0.5	0.25	1	3.6×10^{-3}
4,8,12,14	2	HP DL585 G7	1	1	1	4.32×10^{-3}

10.57 times faster than RSA. Greedy is 1.21 times faster than our proposed approach, but our proposed approach increases the VNF provider's profit by 26.88% and request acceptance rate by 46.80%. When user satisfaction threshold s_{th} is 9, our proposed approach is 11.32 times faster than RSA. Greedy is 1.51 times faster than our proposed approach, but our proposed approach increases the profit of the VNF provider by 28.37% and request acceptance rate by 44.44%.

The reason why our proposed approach is superior to the other three benchmarking algorithms is that the calculation result of our algorithm is the global optimal solution, not the local optimal solution.

VII. CONCLUSION

In this paper, we study the personality-aware VNF deployment to maximize the profit of the VNF provider. First, we model the personalized service chain request to capture the different service requirements of individual users with different personalities. Afterward, we formalize the VNF provider's profit maximization problem. Subsequently, we proposed a satisfaction prediction model to obtain the attribute values of the above personalized service chain request. Finally, we propose a VNF deployment scheme based on genetic algorithm to maximize the VNF provider's profit, taking into account the different personalities of individual users. The simulation results show that compared with the other three benchmarking algorithms, our solution increases the profit of the VNF provider and request acceptance rate by 9.19% and 20.70%, respectively.

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