Optimizing Resource Allocation to Support QoS Requirements in Next Generation Network based on ACO Algorithm

Dac-Nhuong Le
Faculty of Information Technology, Haiphong University, Haiphong, Vietnam
Nhuongld@hus.edu.vn

***Abstract*—Next Generation Network (NGN) is the backbone of the overall network architecture based on IP network, supporting different access network technologies. This integrated wireless system will have to handle diverse types of traffics, such as data, voice, and multimedia, etc. NGN will provide advanced services, such as Quality of Service (QoS) guarantees, to users and their applications. In this paper, I have studied a pricing scheme for next generation multiservice networks and formulated the optimal resource allocation in a network/service node, given the QoS requirements of each service class that the network element serves. The non-linear pricing model responds well to changes of the characteristics in the input traffic, pricing parameters and QoS requirements. Further, I propose a new Ant Colony Optimization algorithm to solving it. Numerical results show that my proposed algorithm is easily and efficiently to any number of service classes.**

Keywords- Resource Allocation; Quality of Service (QoS); Next Generation Network (NGN); Ant Colony Optimization (ACO).

I. INTRODUCTION

In Next Generation Network (NGN), the backbone of the overall network architecture will be IP network, supporting different access network technologies such as wireless Local Area Network (WLAN), UMTS Terrestrial Radio Access Network (UTRAN), and WiMax. Moreover, this integrated wireless system, will have to handle diverse types of traffics: data traffics (e.g. web browsing, e-mail, ftp), voice traffic (e.g. voIP), and multimedia traffics (e.g. video conferencing, online TV, online games), etc... NGN will provide advanced services, such as Quality of Service (QoS) guarantees, to users and their applications. As a result of, these enhancements, it is expected that service providers will face an increasing number of users as well as a wide variety of applications. Under these demanding conditions, network service providers must carefully provision and allocate network resources (e.g. bandwidth, buffer size, CPU capacity) for their customers. Provisioning is the acquisition of large end-to-end network services (connections) over a long time scale. In contrast, allocation is the distribution of these provisioned services (via pricing) to individual users over a smaller time scale [1].

Determining the optimal amounts to provision and allocate remains a difficult problem under realistic conditions. Service providers must balance user needs in the short-term while provisioning connections for the long-term. Furthermore, this must be done in a scalable fashion to meet the growing demand for network services, while also being adaptable to future network technologies. In this paper, I use a Fractional Brownian Motion traffic model, because of its ability to adequately capture characteristics of real network traces, such as self-similarity and the presence of heavy tailed marginal distributions [2].

In [3], Xu Peng et al proposed a measurement-based resource allocation scheme based on a linear pricing model and average queue delay guarantees. This scheme has the disadvantage of not being scalable to large number of service classes. Moreover, average queue delay is not always an appropriate QoS constraint. The authors in [4] perform maximization over a utility function provided from the network users and resources are shared based on the solution of that optimization problem. In [5], the authors study the problem of resource allocation with dynamic pricing in which the network administrator controls the price of the resources that users demand based on the demand the prices are dynamically changed over different time periods so as to maximize the revenue of the administrator. Measurement-based resource allocation has also been studied in different contexts in [6-7]. Finally, Hassan Yeganeh et al presented a novel Particle Swarm Optimization (PSO) algorithm for optimal resource allocation [8].

In this paper, I propose a new algorithm based on Ant Colony Optimization (ACO) to optimizing resource allocation to support QoS requirements in NGN. My objective functions are determined by the provider's profit based on pheromone matrix of ants satisfies capacity constraints to find good approximate solutions. Numerical results show that my proposed algorithm is easily and efficiently to any number of service classes.

The rest of this paper is organized as follows. Section II presents the problem formulation. Section III present my new algorithm for resource allocation to support QoS requirements in NGN based on Ant Colony Optimization algorithm. Section IV presents our simulation and analysis results, and finally, section V concludes the paper.

II. PROBLEM FORMUALTION

The employed modeling framework was introduced in [3].

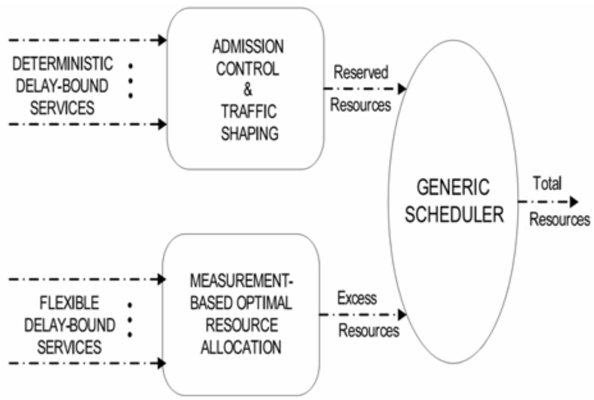

Figure 1. Network Modeling Framework

Figure 1 presents a single network element, which may correspond to either a traditional network component, such as a switch, or a router, or a modern network "service center", like IBM's data power service oriented network appliances [9] or Cisco's application-oriented network message routing systems [10]. It is assumed that the network element serves two categories of traffic classes; deterministic delay-bound classes and flexible delay-bound ones.

The proposed system is responsible for optimally allocating the excess resources to the remaining flexible delay bound classes. These classes enter the Measurement Based Optimal Resource Allocation (MBORA) system proposed in [11] and shown in Figure 2.

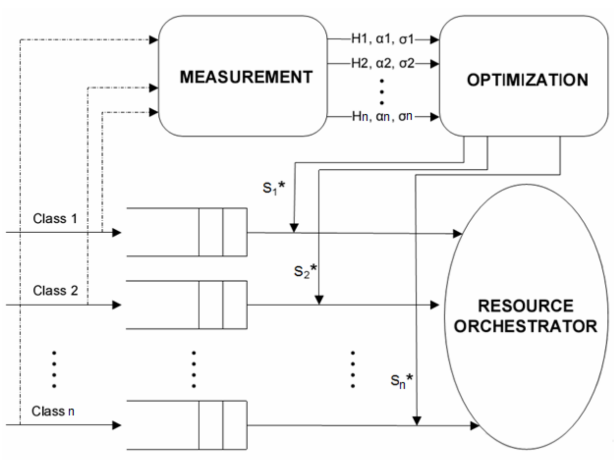

Figure 2. The Measurement Based Optimal Resource Allocation System

The MBORA system consists of a measurement module, an optimization module and a resource orchestrator module. The statistics of the arrival traffic are measured by the measurement module. It is assumed that the traffic can be accurately approximated by a Fractional Brownian motion model, which can account for the burst ness and long-range dependence observed in real traffic traces. Such a model can be fully described by the following parameters: the *Hurst* parameter H, the *mean* arrival rate $\bar{\alpha}$ and the *variance* σ of the marginal distribution.

An algorithm for on-line measurement of these parameters is discussed in [12]. The optimization module receives the traffic characteristics of each class and calculates the optimal allocation of resources by solving the optimization problem use ACO algorithm discussed in Section III. It should be noted that the optimization problem is solved only when there is a significant change in traffic characteristics. The optimal solution is fed to the resource orchestrator which dynamically updates the allocation of resources for each traffic class and forwards the packets (or, more generally, the messages, for example XML) toward their destination.

I start by introducing the pricing model, whose solution yields the optimal allocation of resources to the network service node. Suppose that the node can provide N different types of services. The proportions of these services to be allocated are denoted by $s = (s_1, s_2, ..., s_N)$.

According to [13], the profit of a provider is the difference between the revenue *r(s)* that is obtained for providing these services and the cost *c(s)* that incurs from producing them. The aim of this provider is to maximize the profit function subject to the feasibility constraints is defined by:

$$f(s) = \max\{r(s) - c(s)\} = \max \sum_{i=1}^{N} \left(r_i(s_i) - c_i(s_i)\right) \quad (1)$$

Subject to the feasibility constraints:

$$\begin{cases} s_i \geq 0, \ \forall i = 1..N \\ \sum_{i=1}^{N} s_i \leq 1 \end{cases} \quad (2)$$

The revenue is given by a linear function, while the cost by a nonlinear one. Specifically,

$$r_i(s_i) = p_i \times s_i, \ \forall i = 1..N \quad (3)$$

And the cost function is given by:

$$c_i(s_i) = b_i D_i(s_i) e^{\beta_i(D_i(s_i) - d_i)}, \ \forall i = 1..N \quad (4)$$

Where:

- The coefficient p_i corresponds to the price that the provider charges for the i^{th} service.
- b_i is the amount the provider has to reimburse the users whenever the service level agreement (SLA) [14-17] are not satisfied. A higher priority class u requires better service than a lower one v and thus it is charged accordingly (i.e., $p_u > p_v$ and $b_u > b_v$).

- β_i is the parameter controls the steepness of the cost function.
- $D_i\left(s_i\right)$ denotes the value of the performance metric experienced by users of service *i*.
- d_i is the target level under the SLA.

I adopted a linear from the revenue function so as to represent the *bandwidth profit* (i.e., product of price times bandwidth allocated) that provider would receive. In addition, linearity offers concavity and simplicity which are required characteristic for my optimization problem formulation. On the other hand, my cost function has a nonlinear form show in Figure 3.

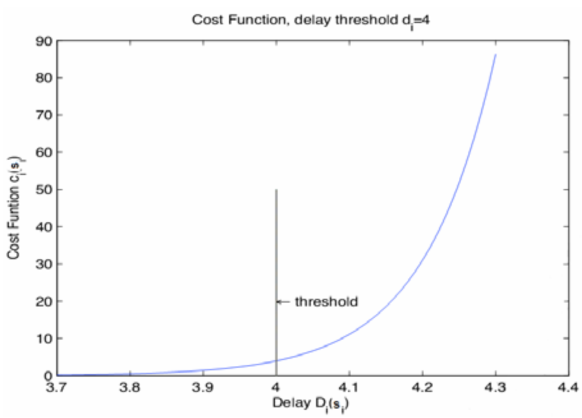

Figure 3. Cost function. Notice that even a small increase of 2.5% above the delay threshold yields an increase above 100% in the cost function. In this case, $\beta_i = 10$

The exponential shape allows a more severe penalization of the provider (i.e., cost penalty), when services experience larger queue delays than those agreed under SLA. Hence, if $D_i\left(s_i\right) > d_i$ the users are not receiving adequate resources from the provider, which would incur a cost, until the situation is rectified. Figure 3 show the steep increase in the cost observed beyond the desired by the users SLA value of threshold d_i would force the provider to adjust the allocation of resources, if possible, in order to satisfy the QoS requirements and maximize profit. If the system is already highly utilized and the re-allocation of resources cannot alleviate the incurred cost, the provider should consider acquiring more resources. It should be noted that prices cannot by a specific QoS performance.

Prices are used as a priority parameter for each service *i* and the intuition is that service that pays more will get more bandwidth. Allocation also depends on the QoS ε_i and the delay threshold d_i. In other words, my utility function represents the level of user satisfaction at the allocated rate and according to the desired QoS.

Probabilistic Delay Constraints: I employ stochastic delay bounds as the metric for QoS considerations. Specifically, I adopt the approach used in [18-19], where traffic is treated as Long Range Dependent (LRD) and is characterized by the *Hurst* parameter *H*, the mean $\bar{\alpha}$ and the variance σ. It is shown that the queue length $Q_i\left(t;s_i\right)$ at any given time t is bounded by a value $q_{i,\max}$ with probability $\varepsilon_i > 0$ related to the desired QoS. In particular, for specific class *i* the following by:

$$\Pr\left\{Q_i\left(t,s_i\right) > q_{i,\max}\left(s_i\right)\right\} \approx \varepsilon_i \quad (5)$$

and

$$q_{i,\max}\left(s_i\right) = \left(s_i C - \bar{\alpha}\right)^{\frac{H_i}{H_i - 1}} \times \left(k_i \sigma_i\right)^{\frac{1}{1-H_i}} \times H_i^{\frac{H_i}{1-H_i}}\left(1 - H_i\right) \quad (6)$$

where

- $s_i C$ is the resources (e.g., bandwidth, CPU, etc.) dedicated to this particular class.
- ε_i is the required QoS
- $k_i = \sqrt{-2\ln\varepsilon_i}$

Thus, since the queue length and expected delay are related using generalize Little's law, we have the following probabilistic delay bound for a first in first out queue by:

$$\Pr\left\{D_i\left(t;s_i\right) > D_{i,\max}\left(s_i\right)\right\} \approx \varepsilon_i \quad (7)$$

where

$$D_{i,\max}\left(s_i\right) = \frac{q_{i,\max}\left(s_i\right)}{s_i C} \quad (8)$$

For simplicity, in my cost function I refer to $D_{i,\max}\left(s_i\right)$ as $D_i\left(s_i\right)$. I have a SLA violation if at given traffic conditions $\bar{\alpha}$, σ_i and H_i, the stochastic delay bound, $D_i\left(s_i\right)$, for the agreed QoS, ε_i is greater than the desired delay bound d_i. A stricter QoS implies a small value of ε_i that generates a larger $D_i\left(s_i\right)$.

Hence, the SLA is more likely to be violated for a given delay threshold d_i and, therefore, the provider is motivated to allocate more resources to that service class.

Putting the revenue and cost components together, the provider's profit problem becomes:

$$f = \max_S\left\{\sum_{i=1}^{N} p_i \times s_i \times C - \sum_{i=1}^{N} d_i \times D_i \times \left(s_i\right) \times e^{\beta_i\left(D_i\left(s_i\right) - d_i\right)}\right\} \quad (9)$$

The cost function to the feasibility constraints previous described, plus the constraints:

$$s_i > \bar{\alpha}_i, \ \forall i = 1..N \tag{10}$$

It should always stand true due to the fact that whenever $s_i \le \bar{\alpha}_i$, we have

$$\Pr\{Q(t) > q_{\max}\} = 1 \tag{11}$$

this implies that we are in an unstable case and the queue would never be able to accommodate the incoming traffic.

III. Ant Colony Optimization for the optimal allocation of resources

A. Ant Colony Optimization

The ACO algorithm is originated from ant behavior in the food searching. When an ant travels through paths, from nest food location, it drops pheromone. According to the pheromone concentration the other ants choose appropriate path. The paths with the greatest pheromone concentration are the shortest ways to the food. The optimization algorithm can be developed from such ant behavior.

The first ACO algorithm was the Ant System [20], and after then, other implementations of the algorithm have been developed [21-22].

B. Solving the optimal allocation of resources based on ACO

In this section, we present application of ACO technique for the optimal allocation of resources problem. My new algorithm is described as follows. I consider that configurations in the evolution algorithm are sets of *N* different types of services. The encoding of the ant *k* configuration is by means of real array of length *N*, say ant $k = \{s_1, s_2, ..., s_N\}$ where s_i is the proportions of these services to be allocated and s_i is generated as uniformly distributed random number within the interval [0, 1].

I use fully random initialization in order to initialize the ant population. In my case the pheromone matrix is generated with matrix elements that represent a location for ant movement, and in the same time it is possible receiver location. We use real encoding to express an element of matrix A_{N*N} (where *N* is the number of services). a_{ij} is the profit distance of two providers given by:

$$a_{ij} = [r_i(s_i) - c_i(s_i)] - [r_j(s_j) - c_j(s_j)] \tag{12}$$

Each ant can move to any location according to the transition probability defined by:

$$p_{ij}^k = \frac{[\tau_{ij}]^{c_1}[\eta_{ij}]^{c_2}}{\sum_{l \in N_i^k}[\tau_{ij}]^{c_1}[\eta_{ij}]^{c_2}} \tag{13}$$

where,

- τ_{ij} is the pheromone content of the path from service s_i to service s_j
- N_i^k is the neighborhood includes only locations that have not been visited by ant *k* when it is at service s_i.
- η_{ij} is the desirability of service s_j, and it depends of optimization goal so it can be my cost function.
- The influence of the pheromone concentration to the probability value is presented by the constant c_1, while constant c_2 do the same for the desirability. These constants are determined empirically and our values are $c_1=1$, $c_2=10$.

The ants deposit pheromone on the locations they visited according to the relation.

$$\tau_j^{new} = \tau_j^{current} + \Delta\tau_j^k \tag{14}$$

where, $\Delta\tau_j^k$ is the amount of pheromone that ant *k* exudes to the service s_j when it is going from service s_i to service s_j.

This additional amount of pheromone is defined by:

$$\Delta\tau_j^k = \frac{1}{f(s)} \tag{15}$$

In which, *f(s)* is maximize the profit function given by

$$f(s) = \max \sum_{i=1}^{N} \left(r_i(s_i) - c_i(s_i) \right) \tag{16}$$

The cost function for the ant *k* is the provider's profit given by:

$$f_k = \max_S \left\{ \sum_{i=1}^{N} p_i s_i C - \sum_{i=1}^{N} d_i D_i(s_i) e^{\beta_i (D_i(s_i) - d_i)} \right\} \tag{17}$$

The stop condition I used in this paper is defined as the maximum number of interaction N_{max} (N_{max} is also a designed parameter).

The Figure 4 presents process of our algorithm to solving the optimal allocation of resources based on ACO.

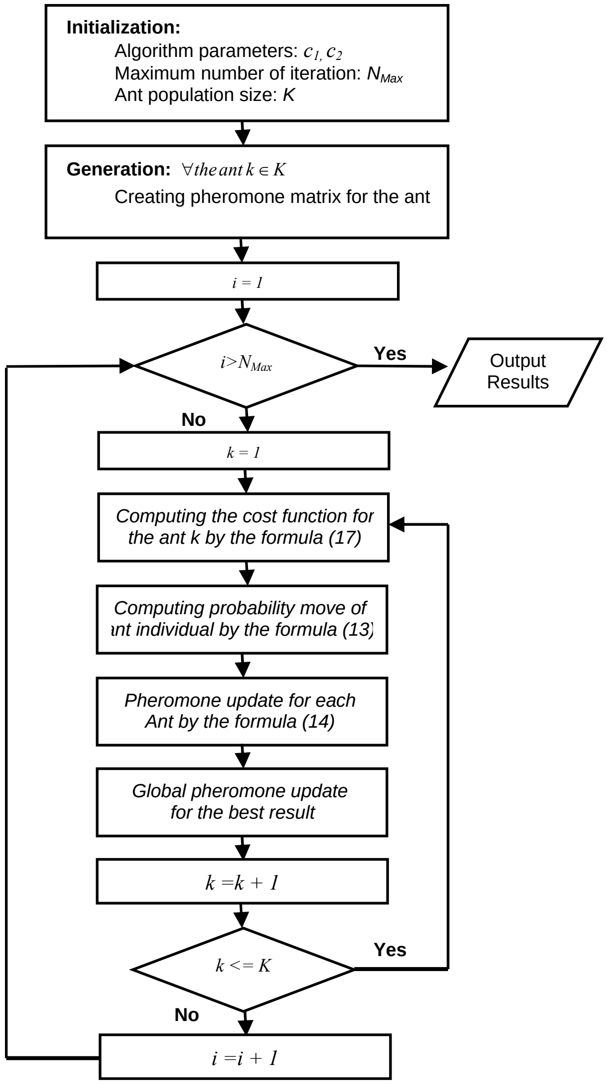

Figure 4. The Ant Colony Optimization algorithm's flow chart

I. Experiments and Results

In this section, my goal is to investigate how the utility function $f(\bar{x})$, and the resource allocation vector $\bar{x}$ respond to changes of various parameters, including the mean arrival rate $\bar{\alpha}_i$, the price p_i, the delay threshold d_i and the Hurst parameter H_i.

I start my analysis with a simple system of two service classes (s_1, s_2). Hence, the corresponding cost function is given by:

$$f(s_1,s_2) = p_1 s_1 C + p_2 s_2 C - b_1 D_1(s_1) e^{10(D_1(s_1)-d_1)} - b_2 D_2(s_2) e^{10(D_2(s_2)-d_2)} \quad (18)$$

where,

$$D_i(s_i) = \frac{(s_i - \bar{\alpha}_i)^{\frac{H_i}{H_i-1}} \times (k\sigma_i)^{\frac{1}{1-H_i}} \times H_i^{\frac{H_i}{1-H_i}} (1-H_i)}{s_i}, i = 1,2 \quad (19)$$

The optimization problem is given by:

$$f = \max_S \{ f(s_1, s_2) \} \quad (20)$$

$$\text{Subject to } \begin{cases} s_1 + s_2 = 1 \\ s_1 > \bar{\alpha}_1 \\ s_2 > \bar{\alpha}_2 \end{cases}$$

The parameters of cost function used in my experience are shown in Table I below:

TABLE I. Parameters of each service class *i (i=1,2)*

Parameters	Classes	
	s_1	s_2
$p_i(price\_unit / Mbps)$	1	1
$b_i(price\_unit / ms)$	0.1	0.1
$d_i(delay\_unit)$	0.01	0.01
QoS ($=\varepsilon$)	10^{-6}	10^{-6}
$\bar{\alpha}_i$	0.2	0.2
σ_i	0.01	0.01
H_i	0.7	0.7

In which, the traffic parameters $\bar{\alpha}_i$ and σ_i are normalized to the capacity C. In my experiment, I analysis fifteen problems with three cases:

- The first case, the arrival rate $(\bar{\alpha}_1, \bar{\alpha}_2)$ varies while all other parameters are held fixed (see in Table I). The optimal allocations (normalized to C) are shown in Table II.

TABLE II. Changing the arrival rates $(\bar{\alpha}_1, \bar{\alpha}_2)$

Problem	Parameters		(s_1^*, s_2^*)	$f(s_1^*, s_2^*)$
	$\bar{\alpha}_1$	$\bar{\alpha}_2$		
#1	0.2	0.2	(0.5, 0.5)	9.9821
#2	0.3	0.2	(0.5446, 0.4554)	9.9363
#3	0.4	0.2	(0.5893, 0.4107)	9.8154
#4	0.4	0.3	(0.5198, 0.4802)	7.8219
#5	0.4	0.5	(0.4503, 0.5497)	6.7246

- The second case, the delay threshold (d_1, d_2) varies while all other parameters are held fixed. The optimal allocations are shown in Table III.

TABLE III. CHANGING THE DELAY THRESOLDS (d_1, d_2)

Problem	Parameters		(s_1^*, s_2^*)	$f(s_1^*, s_2^*)$
	d_1	d_2		
#6	0.01	0.01	(0.5, 0.5)	9.9821
#7	0.01	0.03	(0.5327, 0.4673)	9.9607
#8	0.01	0.06	(0.4813, 0.5187)	9.9645
#9	0.01	0.09	(0.4735, 0.5265)	9.9782
#10	0.01	0.12	(0.4512, 0.5488)	9.9817

- The final case, the coefficient (p_1, p_2) varies while all other parameters are held fixed. The optimal allocations are shown in Table IV.

TABLE IV. CHANGING THE PRICING FACTORS (p_1, p_2)

Problem	Parameters		(s_1^*, s_2^*)	$f(s_1^*, s_2^*)$
	p_1	p_2		
#11	1	1	(0.5, 0.5)	9.9821
#12	2	1	(0.6892, 0.3108)	17.693
#13	3	2	(0.6534, 0.3466)	39.165
#14	4	1	(0.7231, 0.2769)	32.658
#15	4	3	(0.5748, 0.4252)	45.752

Figure 5 show the function's concavity over both arguments of s_1 and s_2.

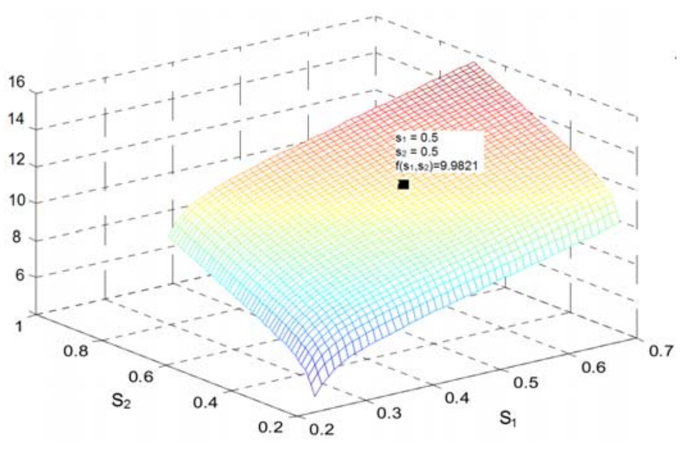

Figure 5. Cost function of s_1 and s_2

Figure 6 show that when the arrival rate varies the optimal solution can be observed. In the equal arrival rates case the resource are equally shared (if a class bring more traffic load, then it is assigned a large portion of resources). Moreover, the system becomes more stressed when the overall profit of the provider decreases substantially.

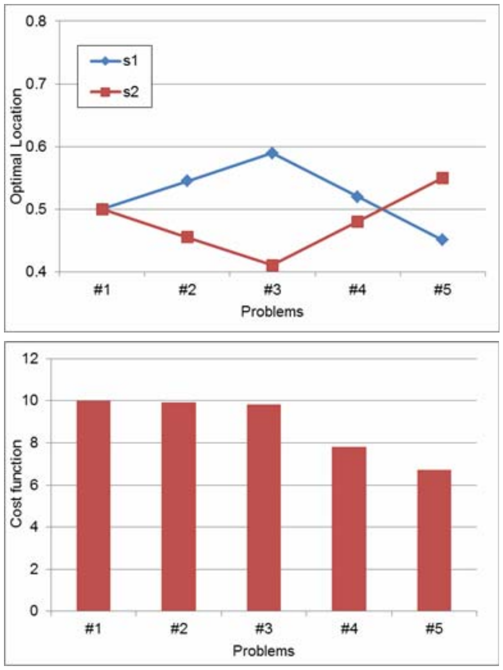

Figure 6. Sensitivity to mean arrival rate

Figure 7 show the sensitivity of my model with respect to the delay threshold d_i. The threshold increases, the profit of the provider also increases which is due to the fact that $\frac{\partial f}{\partial d_i} = b_i \beta_i D_i e^{\beta_i (D_i - d_i)} > 0$. And, it is also worth notice that, the class with stricter QoS requirements is allocated more resources.

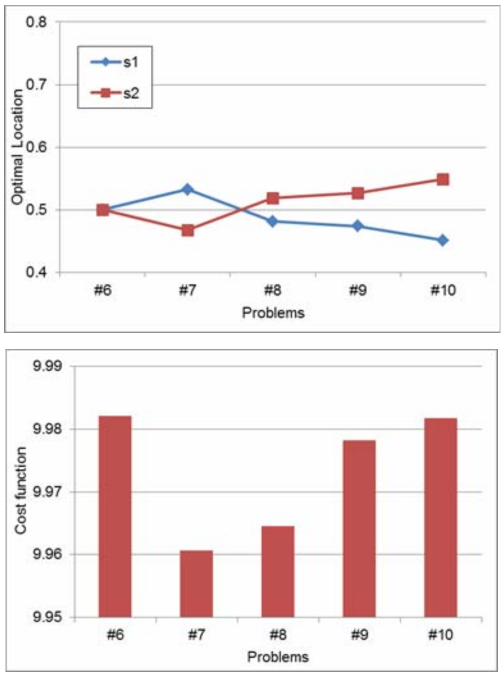

Figure 7. Sensitivity to mean delay thresolds

Figure 8 show the sensitivity of my model with respect to the price coefficient. If equal prices we obtain equal allocation, while the allocation of resources exhibits a strong sensitivity to the price ratio p_1/p_2 .

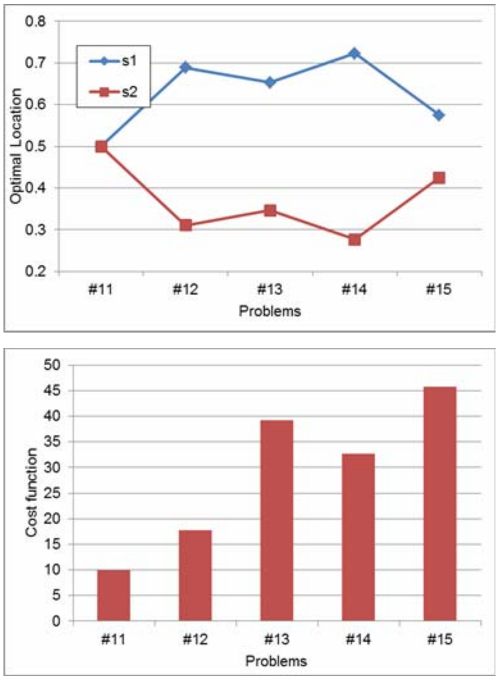

Figure 8. Sensitivity to mean price coefficient

IV. CONCLUSION

In this paper, I have studied a pricing scheme for next generation multiservice networks and formulated the optimal resource allocation in a network/service node, given the QoS requirements of each service class that the network element serves. The non-linear pricing model responds well to changes of the characteristics in the input traffic, pricing parameters and QoS requirements. I propose a new Ant Colony Optimization algorithm to solving it. Numerical results show that my proposed algorithm is easily and efficiently to any number of service classes. Additionally, it is sensitive to traffic changes and responds well to pricing parameters and QoS requirements. Optimal dynamically allocate the available resources in a network of multiple service intermediaries and optimal allocation of multiple types of resources will be my next research goals.

REFERENCES

[1] G. Huston, *ISP Survival Guide: Strategies for Running a Competitive ISP*, John Wiley & Sons, 1999.

[2] Leland W., Taqqu M., Willinger W., Wilson D., *On the Self-Similar Nature of Ethernet Traffic (Extended Version).* IEEE/ACM Trans.Networking, pp.115, Feb, 1994.

[3] Xu P., Devetsikiotis M., Michailidis G., *Profit-oriented Resource Allocation Using Online Scheduling in Flexible Heterogeneous Networks*. Telecommunication Systems, pp.289-303, 2006.

[4] Kalyanasundaram S., Chong E. K., Shroff N. B. *Optimal Resource Allocation in Multiclass Networks with User Specified Utility Functions*. The International Journal of Computer and Telecommunications Networking, pp.613-630, April, 2002.

[5] Savagaonkar U., Chong E. K., Givan R. L., *Online pricing for bandwidth provisioning in multi-class networks*. Comput. Networks, pp.835–853, 2004.

[6] Chandra A., Gong W., Shenoy P. Dynamic Resource Allocation for Shared Data Centers Using Online Measurements. *In Proceedings of ACM/IEEE Intl Workshop on Quality of Service*, pp 381-400, 2003.

[7] Knightly E., Shroff N., *Admission Control for Statistical QoS: Theory and Practice*. IEEE Network 13(2), pp 20-29, 1999.

[8] Hassan Yeganeh, Maryam Shakiba, Mehdi Samie, *Optimal Resource Allocation in Next Generation Network Services using Engineering Optimization with Linear Constraint Particle Swarm*, International Journal of Computer Science and Network Security, VOL.8 No.11, pp.238-334, 2008.

[9] Oltsik J., SOA Appliance Case Studies - Web Services Meet the Network.

[10] Cisco Systems, Cisco AON: A Network Embedded Intelligent Message Routing System, Product Bulletin No. 2886, 2005.

[11] Xu P., *QoS Provisioning and Pricing in Multiservice Networks: Optimal and Adaptive Control over Measurement-based Scheduling*. PhD Dissertation, North Carolina State University, 2005.

[12] Sun Q., Pleich R., Sauerwein R., On-Line Measurement and Analysis of Fractional Brownian Traffic. *Proceedings of the IEEE Conference on High Performance Switching and Routing*, pp 395-400, 2000.

[13] Courcoubetis C., Weber R., *Pricing Communication Networks*. John Wiley & Sons, 2003.

[14] V. Firoiu, J. L. Boudec, D. Towsley, Z. Zhang, *Theories and models for internet quality of service*, 2002 (URL: citeseer.ist.psu.edu/article/ firoiu02theories.html).

[15] S. Wright, *Admission Control in Multi-Service IP Networks: A Tutorial*, Communications Surveys and Tutorials, IEEE 9 (2) (2007) 72–87.

[16] L. Georgiadis, R. Guerin, V. Peris, K. N. Sivarajan, *Efficient network QoS provisioning based on per node traffic shaping*, IEEE/ACM Trans. Netw. 4 (4) (1996) 482–501.

[17] L. Breslau, S. Jamin, S. Shenker, *Comments on the performance of measurement-based admission control algorithms*, in: INFOCOM (3), 2000, pp. 1233–1242.URLciteseer.ist.psu.edu/breslau00comments.html

[18] Fonseca N., Mayor G. S., Neto C. A. V., *On the Equivalent Bandwidth of Self-Similar Sources*. ACM Transactions on Modeling and Computer Simulation, Vol. 10, No. 2, pp 104-124, April, 2000.

[19] Norros I., The Management of Large Flows of Connectionless Traffic on the Basis of Self-similar Modeling. In Proceedings of IEEE International Conference on Communications, pp 451-455.

[20] M. Dorigo, V. Maniezzo, and A. Colorni, *Ant system: Optimization by a colony of cooperating agents*, IEEE Trans. on System, MAN, and Cybernetics-Part B, vol. 26, pp. 29-41, February 1996

[21] E. Rajo-Iglesias, O. Quevedo-Teruel, "Linear Array Synthesis using an Ant Colony Optimization based Algorithm", IEEE Trans. on Antennas and Propagation, 2005.

[22] M. Dorigo, M. Birattari, and T. Stitzle, "*Ant Colony Optimization: Artificial Ants as a Computational Intelligence Technique*", IEEE computational intelligence magazine, November, 2006.

[23] J.-W. Lee, R. R. Mazumdar, N. B. Shroff, *Non-convex optimization and rate control for multi-class services in the Internet*, IEEE/ACM Trans Netw. 13 (4) (2005) ,pp.827–840.

[24] K. Ma, M. Ravi, J. Luo, On the performance of primal/dual schemes for congestion control in networks with dynamic flows, *in: Proceedings of IEEE INFOCOM 2008*.

[25] T. Wolf, Service-centric end-to-end abstractions in next-generation networks, *in: Proceedings of 15th IEEE International Conference on Computer Communications and Networks*, Arlington, VA, 2006, pp.79-86.

[26] Y. Li, M. Chiang, A. R. Calderbank, Congestion control in networks with delay sensitive traffic, *in: Proc. IEEE GLOBECOM, 2007*.

[27] Y. Hung, G. Michailidis, A measurement based dynamic policy for Switched Processing Systems, *IEEE International Conference on Communications, 2007*. ICC '07,pp.301–306.

[28] Vinh Trong Le, Nhu Gia Nguyen, Dinh Huu Nghia, "A Novel PSO-Based Algorithm for Gateway Placement in Wireless Mesh Networks", *in Proc,3rd IEEE International Conference on Communication Software and Networks* (ICCSN), China, 2011, pp. 41-46.

[29] Dac-Nhuong Le, Nhu Gia Nguyen, and Vinh Trong Le, *A Novel PSO-Based Algorithm for the Optimal Location of Controllers in Wireless Networks*, International Journal of Computer Science and Network Security (IJCSNS), Vol.12 No.08, pp.23-27, August 30, 2012, Korea.

[30] Dac-Nhuong Le, *PSO and ACO Algorithms Applied to Optimizing Location of Controllers in Wireless Networks*, International Journal of Computer Science and Telecommunications (IJCST), Vol.3, No.10, pp.1-7, October 2012, England.

AUTHORS PROFILE

Dac-Nhuong Le received the BSc degree in computer science and the MSc degree in information technology from College of Technology, Vietnam National University, Vietnam, in 2005 and 2009, respectively. He is a lecturer at the faculty of information technology in Haiphong University, Vietnam. He is currently a Ph.D student in computer science at Hanoi University of Science, Vietnam National University. His research interests include theory, computer network, wireless network and networks security.