

The Impact of Social Distance on Utility Based Resource Allocation in Next Generation Networks

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Abstract—Social networks have been rapidly grown over the last years. The socio-technical information that they include may provide critical information which can be exploited to improve the performance of the network. This is of utmost importance especially in Next Generation Networks (NGNs), which provide multiple services with increased bandwidth requirements. In this paper, the problem of resource allocation in a bottleneck link of an NGN is examined. To this end, a utility based technique is proposed which integrates the information of an overlaid social network expressed by the social distance parameter. In this case, the utility function employed is reformed, so as to incorporate this parameter, which is determined by the users average popularity. Network users are classified into friendship classes according to social distance parameter. Then, the users resource allocation objective is formulated as optimization problem with inequality constraints. Due to the increased problems complexity, a numerical method is employed to estimate the optimal resource allocation is given. Numerical results are presented, which indicate the impact of the social distance parameter on networks resource allocation.

Keywords—social networks; resource allocation; Quality of Service; utility function; next generation networks

I. INTRODUCTION

Next Generation Networks (NGNs) have been rapidly evolved during the recent decade integrating multiple broadband, QoS-enabled wireless access technologies under a unified frame [1]. They enable unfettered access for users to networks and to competing services independently of the underlying transport related technologies supporting at the same time users mobility. The NGNs support various services, such as voice, data, World Wide Web browsing, email and multimedia. Since these services have different Quality of Service (QoS) requirements it is important to design efficient resource allocation schemes among competing set of users in resource constrained networks [2]. Resource allocation schemes aim at maximizing users utility and/or network profit, while satisfying the particular QoS requirements of the SCs supported, such as bandwidth, packet delay, jitter and priority [1, 3].

The problem of network resource allocation has extensively studied in literature and various schemes have been proposed

following different approaches [4]. There are some schemes that focus on Service Class (SC) priority by allocating the resources proportionally to the users priority level or by reserving bandwidth for high priority SC users [5, 6]. Moreover, other schemes employ pricing criteria or utility function to maximize network revenue or overall network utility, respectively [7]. Other schemes are based on game theoretic algorithms where resource allocation decision is obtained through multiple negotiation rounds among the competing users [1]. The main common characteristic of all these approaches is that their based on network characteristics and QoS requirement ignoring the physical and social relationship among communicating users.

One of the latest trends in computer and personal networking is the development of social networks, which consist of users profile, their social links and a set of additional services [8]. These networks facilitate a form of computer mediated social interaction via the development of appropriate software platforms. The corresponding social networking services are web-based and they have been integrated into mobile computing devices. The widespread proliferation of social networks along with the critical information regarding users relationship that they contain may be exploited so as to achieve improved network resource allocation and users utility maximization.

Generally, the communication among network users is not determined randomly but it is driven by their relationships with other users. The information related to users relationships can be obtained from social networks and can be expressed through the social distance parameter. To the author knowledge, little attention has been paid on the integration of social distance into resource allocation networks. A recent work that considers social distance has been introduced in [9], where the authors deal with resource allocation problem in terms of delay and packet loss in a wireless LAN. Our motivation is to address the problem of resource allocation taking into account users social distance and bandwidth requirements instead of delay and packet loss.

In this paper, a new resource allocation scheme is proposed for bandwidth-constrained bottleneck links of an NGN employing social aware users utility function [10, 11]. Unlike other relative studies where user utility functions are based on

QoS requirements and bandwidth allocation, we propose a reformed utility function integrating the social distance parameter [5, 7, 9]. Users bandwidth allocation shares is the outcome of the overall users utility maximization problem under certain conditions, such as link capacity, service bandwidth requirements, etc. To this end, users are classified into groups based on their social distance expressed as the users average level of popularity. Numerical results are provided demonstrating the impact of the social distance parameter on the network resource allocation.

The rest of the paper is organized as below. In Sec. II social networking is described and different approaches to determine social distance parameter are presented. The users utility function along with the reformed utility function, which incorporates the social distance parameter, is given in Sec. III. The network model employed and the social distance aware resource allocation problem are studied in Sec. IV. The numerical results are presented and discussed in Sec. V and conclusions are drawn in Sec. VI.

II. SOCIAL NETWORKING FRAMEWORK

Undoubtedly, the convenience of Internet access combined with the increasing speed of communications facilities resulted in the emergence of a new scope on Internet services, known as Web 2.0 [12]. New services and applications are emerging to exploit new technologies and the notion of cooperation which characterises the Web 2.0.

One of the most widespread services of Web 2.0 is social networking. The main characteristics of social networks are a) they are web-based services, b) the individuals are allowed to create a profile within a bounded system, c) users are allowed to form connections with other users and develop network communities based on their social relations, d) users can view other user profiles and traverse their connections, e) participate in groups based on their preferences and f) share multimedia content, such as photographs and videos, and use shared services, namely VoIP and IPTV [8].

Social networks can be represented by graph. The nodes denote the users of the social network, i.e. people or organizations. The edges correspond to the co-dependence between nodes, for example relations of friendship, trades, common interests, use of shared services.

Popularity or centrality in graph theory and in social network analysis quantifies the relative reputation, namely the importance of a peak within one graph or respectively how popular is a person in a social network. Evidently, a node with high popularity has an increased possibility of linking with other nodes within the network and is characterised by an increased data generation and transfer rate. On the other hand, a node with low popularity has limited connections with other nodes and is regarded as a community member with reduced communication load.

There are various ways by which the popularity can be measured. The three most widespread are the degree centrality, closeness and betweenness [13, 14].

Degree centrality is defined by the degree of a node. Let $C_{D,n}$ denote the degree of n node, i.e. the number of other nodes ($n \neq j$) which are directly linked to n node [15]. Evidently, high values of degree centrality correspond to an increased number of links among n node and the rest network nodes. Degree centrality for a given node n is given by

$$C_{D,n} = \frac{1}{N-1} \sum_{\substack{k=1 \\ n \neq k}}^N a(n,k) \quad (1)$$

where N is the number of graph nodes, $n, k \in S$, $S = \{1, \dots, N\}$, $a(n,k)$ is 1 or 0 if and only if n and k , ($n \neq k$), are connected by an edge or not, respectively.

Betweenness is a centrality measure based on the frequency that a node falls on the shortest or geodesic paths that connect pairs of other nodes [13, 15]. A node which is involved in communication paths among other nodes could potentially control their contact. This potential control of communication can be a potential popularity metric.

High betweenness correspond to an increased involvement of the node under consideration to the communication paths of other pairs of nodes. Thus, nodes with high betweenness can control many interactions of the nodes which link. Besides, nodes with low betweenness have limited involvement in the communication between other nodes. In terms of a social network, a user with low betweenness has a limited social environment. Betweenness of a given n node is given by

$$C_{B,n} = \sum_{\substack{j,k \in S \\ j < k}} \frac{g_{jk}(n)}{g_{jk}} \quad (2)$$

where g_{jk} is the total number of geodesic paths linking j and k nodes, $j, k \neq n$, and $g_{jk}(n)$ is the number of those geodesic paths that include n node.

Closeness centrality is determined by the mean geodesic distance $d(n,k)$, $n \neq k$, which is the shortest path between the n and k nodes. The closeness of a node provides a metric that indicates the independence of node communication from other nodes [15]. Thus, if a node has a central position in the graph, then it has a low dependence by the rest nodes to relay its messages. Hence, higher closeness values for a node correspond to less control in its communication by other nodes, since it has direct link in the network. Closeness for a given n node is given by

$$C_c(n) = \frac{N-1}{\sum_{k=1}^N d(p_i, p_k)} \quad (3)$$

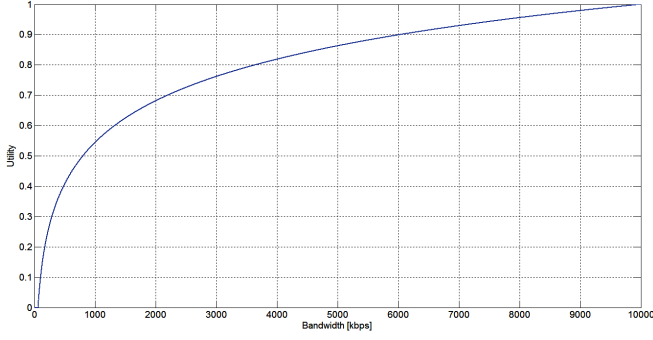


Figure 1. Users utility function for variable bandwidth allocation.

where $i \neq k$.

The selection of an appropriate measure for the popularity depends on the implementation framework. In case where we are interested in expressing the popularity of a social network user in terms of its communication activity, then the degree centrality is employed. Otherwise, if we are interested to determine the popularity by the involvement of a user into the communication paths of other users, the betweenness is the most suitable metric. Alternatively, closeness is employed when the analysis is focused on the independence of nodes communication [16].

In social networks, the concept of social distance parameter, is employed to express the distance between communicating entities or groups of entities. Thus, given a graph where the nodes and edges correspond to users and interactions among users, respectively, the social distance can be determined by a centrality metric. In what follows, the social distance parameter is defined by the degree centrality, $C_{D,n} \in [0,1]$, in order to express the average popularity of a social network user, since we are interested in direct communication activity of a node in relation to the others.

Let χ_n denote the social distance parameter of n user. High users average popularity values express high users interaction with other users within the social network and correspond to low social distance values. Therefore, $\chi_n = 1 - C_{D,n}$. Evidently, users characterized by low social distance values have increased requirements in terms of network resources, due to their increased communication needs.

III. INTERGRATION OF SOCIAL DISTANCE IN UTILITY FUNCTIONS

The notion of users utility is employed to quantify users relative satisfaction to the QoS level offered by the network. The term of users utility has been introduced in economic studies to measure customers benefit and then applied to communications networking. The integration of behavioral characteristics according to users preferences and relationships into the utility function can led to an improved description of user satisfaction. This is achieved by taking into account the social distance parameter which leads to improved network performance according to users service.

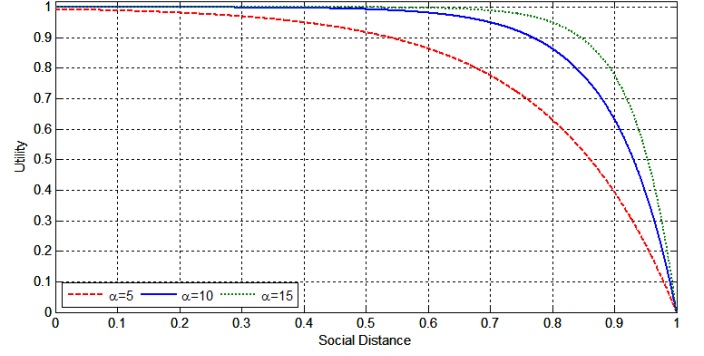


Figure 2. Social distance impact on users utility for various α parameter values.

Generally, users utility depends on several network parameters, e.g. delay, jitter, packet loss rate, but is usually determined by its allocated bandwidth, b , which ranges from the minimum, $B_{\min}$, to the maximum, $B_{\max}$, bandwidth requirement according to service specification. Bandwidth less than $B_{\min}$ cannot satisfy users demands; thus, users utility in this case should be equal to zero. User utility is an increasing function of b and reaches its maximum value when b equals $B_{\max}$. A utility function with such characteristics is the following

$$U(b) = \frac{\ln(b/B_{\min})}{\ln(B_{\max}/B_{\min})} \frac{\text{sgn}(b - B_{\min}) + 1}{2} \quad (4)$$

where $0 \leq b \leq B_{\max}$ and $\text{sgn}(x)$ is the well-known signum function. The utility function $U(b)$ is depicted in Fig. 1, where $B_{\min} = 64\text{kbps}$ and $B_{\max} = 10\text{Mbps}$. Evidently, $U(b) = 0$ when $b < B_{\min}$ and $U(B_{\max}) = 1$.

To incorporate the socio-technical information into the utility function, $U(b)$ should be reformed so as to include the social distance parameter. Thus, the new utility function, $U(b, \chi_n)$, is given by

$$U(b, \chi_n) = U(b) \cdot S(\chi_n) \quad (5)$$

where $S(\chi_n)$ is a function which quantifies the social distance impact on n users utility.

The $S(\chi_n)$ should be a monotonically increasing function of the users average popularity, since high average popularity levels should correspond to also great impact on utility values. As χ_n ranges from 0 to 1, where 0 and 1 correspond to the highest and the lowest average popularity level, respectively, $S(\chi_n)$ should be a monotonically decreasing function of χ_n . Hence, $S(\chi_n)$ is given by

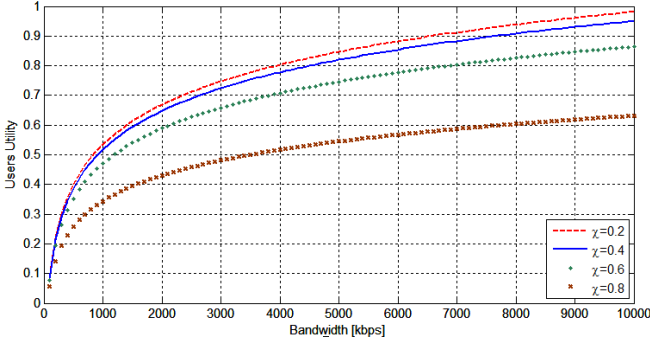


Figure 3. The social aware utility function for various social distance parameter values.

$$S(\chi_n) = 1 - e^{\alpha(\chi_n - 1)} \quad (6)$$

where α is a parameter which determines the steepness of the decent of $S(\chi_n)$ and expresses the impact degree of χ_n on $S(\chi_n)$.

In Fig. 2, the $S(\chi_n)$ function is plotted with respect to χ_n for variable levels of α . The maximum value of $S(\chi_n)$ occurs when the user has the highest average popularity level. As χ_n increases, $S(\chi_n)$ gradually decreases. As depicted in Fig. 2, lower values of α parameter correspond to higher impact of χ_n on $S(\chi_n)$.

In Fig. 3, the reformed utility function is depicted for variable users bandwidth allocation with $\alpha = 5$. As χ_n increases, the reformed users utility decreases for a given users bandwidth allocation. Thus, $U(b, \chi_n)$ can model the effect of the parameters χ_n and b on users utility, as was originally intended.

IV. SOCIAL DISTANCE CONCEPT IN RESOURCE ALLOCATION

In the following, the resource allocation scheme which incorporates the social aware utility function is examined. In the first subsection, the network model under consideration is described, while, in the second one the optimization problem is studied.

A. Network Model

Consider a single link of an NGN network with bandwidth capacity C . Let N denote the number of ongoing users utilizing this link. Users may be classified into different service classes, such as VoIP, FTP, TCP and IPTV, based on their QoS requirements. VoIP users have a relatively low bandwidth requirement, i.e. 64 kbps. Thus, $B_{\min}$ is set equal to 64 kbps, so as $U(b, \chi_n)$ can satisfy even the lowest bandwidth specification of the network users.

Furthermore, users can be classified upon socio-technical criteria into different groups, called Friendship Classes (FCs). In particular, the criterion employed in this study is the social distance χ_n , as determined by the users relationships within a social network. We assume two user FCs, FC_i , $i = \{1, 2\}$, which correspond to different social distance parameter values χ_i . Then, χ_i represents the social distance of all user in FC_i , which is the average of all users social distance in the class. Let N_i denote the number of users belonging to FC_i ; then,

$$N_1 + N_2 = N \text{ and } \chi_i = \frac{1}{N_i} \sum_{n=1}^{N_i} \chi_n.$$

Users belonging to the same FC_i are assumed to be provided with equal utility for the same bandwidth allocation.

B. Resource Allocation Problem

The efficiency of the resource allocation strategy is related with network performance optimization. An improved network performance is obtained through the maximization of the aggregate network utility by all user FCs, $U(\mathbf{b}, \boldsymbol{\chi})$, defined as below

$$U(\mathbf{b}, \boldsymbol{\chi}) = \sum_{i=1}^2 N_i U_i(b_i, \chi_i) \quad (7)$$

where, $U_i(b_i, \chi_i) = U(b_i) \cdot S(\chi_i)$ denotes the users utility of the i th FC. Thus, the resource allocation problem is transformed into a utility maximization problem, defined as below

$$\text{Maximize} \quad U(\mathbf{b}, \boldsymbol{\chi}) = \sum_{i=1}^2 N_i U_i(b_i, \chi_i), \quad (8a)$$

$$\text{Subject to} \quad \sum_{i=1}^2 N_i b_i \leq C, \quad (8b)$$

$$B_{\min} \leq b_i \leq B_{\max}. \quad (8c)$$

However, it is difficult to solve this maximization problem following a method based on the derivatives of the functions employed, such as the Lagrange method, since the users utility function $U_i(b_i, \chi_i)$ embraces the signum function, which its first derivative is the Dirac delta function. Hence, a numerical method is employed to determine the solution of the problem based on the following algorithm.

Algorithm to estimate the optimal resource allocation.

- Step A: The algorithm determines b_2 as a function of b_1 from (4c) as $b_2 = (C - N_1 b_1) / N_2$.
- Step B: Then, the aggregated utility function $U(\mathbf{b}, \boldsymbol{\chi})$ given in (4a) becomes a function of b_1 and χ_i , $U^*(b_1, \boldsymbol{\chi})$.

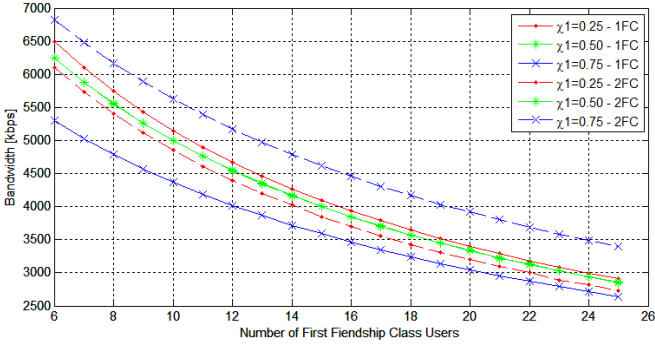


Figure 4. Bandwidth allocation for variable number of FC1 users under different social distance parameter, $N_2 = 10$.

- Step C: For two certain FCs, i.e. for given values of χ_i , $U^*(b_i, \chi)$ can be rewritten as a function of b_1 , $U^*(b_1)$. Then, the maximum value of $U^*(b_1)$, $U_{\max}^*(b_1^*)$, can be determined and the corresponding b_1^* can be estimated. In case where multiple b_1^* exists and $\chi_1 \geq \chi_2$, then the maximum b_1^* value is selected. Otherwise, i.e. $\chi_1 < \chi_2$, the minimum but acceptable b_1^* value is selected.
- Step D: Evidently, $b_2^* = (C - N_1 b_1^*) / N_2$.

The complexity of the problem already studied is limited to one utility function and two FCs in order to focus the analysis on the impact of social distance parameter obtained by the social network on the resource allocation. The problem can be expanded in order to encompass multiple FCs, i.e. users are classified into multiple groups according to χ_i value. Furthermore, different utility functions can be employed to model user satisfaction for each users service class. In this case, the optimal resource allocation can be obtained through an analytical approach, such as the Langrange method, or a numerical approximation.

V. NUMERICAL RESULTS AND DISCUSSION

In this section, the performance of the social aware resource allocation technique is examined. Numerical results are obtained to examine the case of two FCs. Thus, variable values of χ_i parameters are employed. Moreover, the impact of the number of users for both FCs on the resource allocation technique is presented.

The corresponding parameter values employed throughout the performance evaluation are: $C = 100\text{Mbps}$, $\chi_2 = 0.5$, $B_{\min} = 64\text{kbps}$ and $B_{\max} = 10\text{Mbps}$. The α parameter is set equal to 5 in order to achieve an increased impact degree of χ_i on the users utility. Moreover, the number of users belonging to FC1 varies from 6 to 25. In what follows, we investigate the resource allocation results under three scenarios regarding the

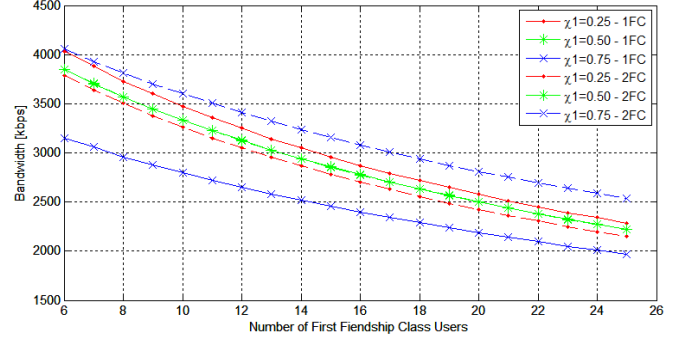


Figure 5. Bandwidth allocation for variable number of FC1 users under different social distance parameter, $N_2 = 20$.

value of χ_1 , while χ_2 is constant. Each scenario represents different relation levels among the social distance of the two FCs. The values of χ_1 and its relation with χ_2 are given in Table I.

TABLE I. SOCIAL DISTANCE SCENARIOS

Case	Value of χ_1	Comments
#1	0.25	$\chi_1 < \chi_2$
#2	0.5	$\chi_1 = \chi_2$
#3	0.75	$\chi_1 > \chi_2$

In Fig. 4 the performance of the social aware resource allocation technique is presented concerning the three cases, where $N_2 = 10$. The bandwidth allocated to each user is plotted with respect to the number of FC1 users for both FCs. In the first case, the bandwidth allocated to the FC1 users is higher compared to the one allocated to the FC2 users. This occurs due to $\chi_1 < \chi_2$, which denotes that FC1 users are assigned higher priority over FC2 users. In the third case the performance of the allocation technique is inversed, since $\chi_1 > \chi_2$. Evidently, in the second case, where $\chi_1 = \chi_2 = 0.5$, the bandwidth allocated to each user is the same for the two FCs.

Note that the difference between the values of the social distance parameters in the case #1 and #2 is the same, i.e. $|\chi_1 - \chi_2| = 0.25$. However, the corresponding difference among the bandwidth allocated to users of the two FCs is dissimilar. This occurs since the $|\chi_1 - \chi_2|$ difference in the first case is obtained for lower values of social distance parameters compared to the third case, where the social distance parameters correspond to higher values. Thus, the users bandwidth demand in the first case, as implied by the social distance parameters value, is higher compared to the corresponding one in the third case.

In Fig. 5 and Fig. 6 the bandwidth allocated to network users is plotted versus variable number of FC1 users, where N_2 is equal to 20 and 30, respectively. The same remarks already

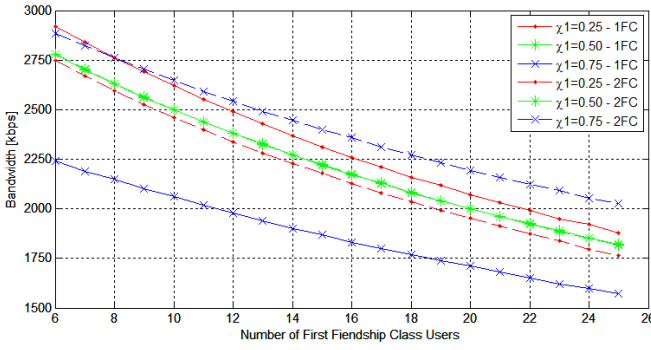


Figure 6. Bandwidth allocation for variable number of FC1 users under different social distance parameter, $N_2 = 30$.

described for Fig. 4 are valid in these figures. Moreover, the curves drawn in Figs. 5 and 6 exhibit the same trend as in Fig. 4. However, as N_2 increases the bandwidth allocated to each user is evidently reduced.

VI. CONCLUSION

Several utility based resource allocation schemes for NGNs have already proposed in literature, which are focused on pure technical methods. In this paper, a social aware resource allocation technique is proposed based on utility functions with explicit dependencies on social networks information. To this end, a reformed utility function is defined based on the social distance parameter. Thus, the information contained in social networks is exploited, so as to achieve efficient resource allocation. The numerical results demonstrate the impact of social distance parameter on networks resource allocation satisfying users QoS requirements. Therefore, users with higher average popularity are assigned with increased bandwidth.

The proposed technique can be further extended to multiple service classes. Thus, apart from the classification of the users into FCs, they can be classified at the same time into service classes according to calls content. We are also working towards the integration of social distance aware resource allocation techniques with call admission control schemes.

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