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A Genetic Algorithm for Solving the First Price Sealed Bid Auction in Communication Networks

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Abstract: - This paper shows the first result obtained in the application of economic mechanisms for the efficient assignment of resources in communication networks. The final objective is to determine which Service Provider will carry their traffic over the network of a Network Provider, which will be the most profitable route and which price the ISPs will pay for it to the Network provider. As the price is a key driver a good approach to select the ISP may be an auction mechanism. The implementation of these kind of auction mechanisms becomes a NP complete problem which is solved in this paper using novel metaheuristics, specifically a genetic algorithm.

Key-Words: - Communication networks, resource assignment, auctions mechanisms, BGP protocol, QoS provision.

1 Introduction

Saying that Internet traffic is growing at a very high rate is not a novelty. Neither that one of the most important challenge for the new services which generate that traffic is the Quality of Service (QoS). The QoS features of the transmission over IP will allow the deployment of high speed real time data services as the well known Voice over IP VoIP [1] or the Video on Demand. QoS depends on several factors but we have to remark mainly three, bandwidth, delay and jitter [2]. These factors are deeply related and can be jointly seen as the problem of traffic congestion.

Pricing has appeared as a very suitable way to avoid congestion through the control of the user demand. The basis of this method consists of the assignment of the network resources to the users that values them most, that is, to the users that are willing to pay more for them, see [3].

Auctions are a very common way to implement pricing and economic policies. An auction rule is characterized by an allocation rule, which defines how the resources are shared between the winner users, and a pricing scheme, which defines the associated imposed costs.

Auctioning can be applied to networking problems in two different levels:

End User Level: In this environment the user competes by the access to a specific network resource related with the QoS, in most cases in the access link of the network, see [4]. Another scenario in the end user level is when instead of competing for the access, the user competes by a complete network route through several links. In this last case the selection auction mechanism becomes more critical because it has direct influence in the final route of the traffic and also in the whole QoS. This kind of issues can be considered as Intradomain problems because we are studying the network of a single administrative entity (only a network operator).

Internet Service Provider Level: Telecommunication network market has been involved in a liberalization process during last decade. Therefore several Service and Network providers have entered the market. From the routing point of view the whole Internet can be considered as a set of independent connected domains, named Autonomous Systems (AS), each one under the different administrations and with different routing policies, see Figure 1. The routing information about possible paths between AS is propagated by the Border Gatewaty Protocol (BGP). The problem on this level consists if the way to select the path from the origin AS to the destiny, satisfying some QoS. Note that each AS can assure the QoS in his own network and in their neighbors (by direct agreement) but it has no control with the second level neighbors. In this line, pricing mechanisms may provide feasible solutions, see [5]. The previous description is named as Interdomain routing problem because it involves several AS.

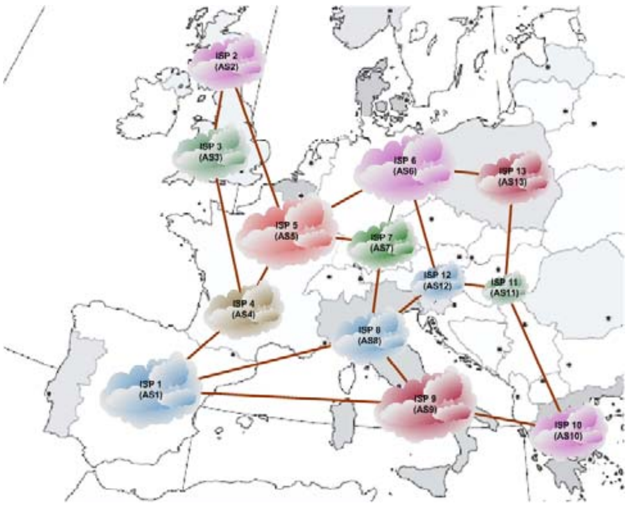

Figure 1: Interdomain Routing Level between Autonomous System (AS)

Two different types of solutions have been proposed for the QoS routing based on economic mechanisms, centralized and distributed approaches. The centralized view considers a single entity which performs a global decision about which demands will be served and which route they will go through. This means that the auction mechanism is executed once for the whole network. Obviously it is used in Intradomain routing problems, because it is non sense to apply it when multiple administrative entities plays the game. Distributed view considers that in each link, i.e. in each interface between two different network nodes or AS, an auction have to be performed in order to select the most suitable path.

We focus on the Intradomain routing under a centralized point of view. In this paper we show the firs result of applying modern heuristic, specifically genetic algorithms, to route problem solving using auction mechanism.

The rest of the paper is structured as follows: in the second section we describe the general Intradomain routing problem related with the auction theory. Next, we introduce the general genetic algorithm and the concrete formulation of the problem. Section 4 shows the result obtained in several scenarios and finally section 6, explains the conclusions and future worklines.

2 Auctions Applied to Intradomain Routing.

We tackle the following problem for Intradomain routing. Consider an established network topology. Consider also that there are several user-customer demands which have to be routed from a determined origin point of the network No_i to an end point Nd_i requiring some capacity q_i. The problem appears when the capacity of the links is not enough to carry all the demands. Each user-customer, is willing to pay a maximum price per capacity unit p_i. Figure 2 shows an scheme of the described situation

The network Provider will tender the capacities of his network links to the user-customer using some auction procedures in order to obtain the maximum revenue. Note further that the origin and destiny nodes may be not directly connected, so it is possible that a specific demand has to travel through several network links. Therefore the same demand has to win several auctions in order to reach its destiny. To get the problem harder, there is not a single demand path from an origin to a destiny because the network topology may be more or less meshed

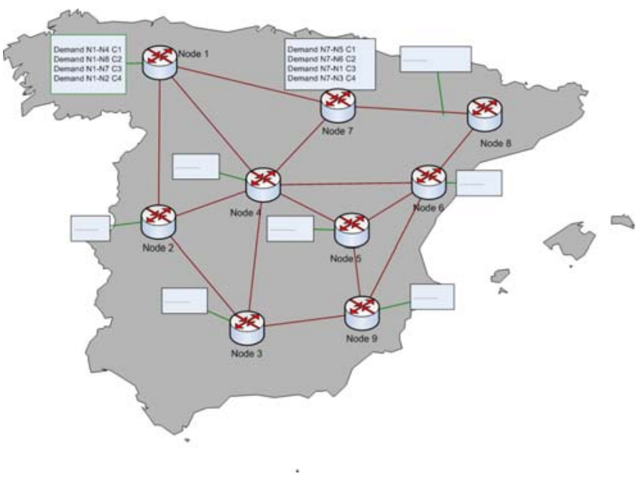

Figure 2: General scheme of the Intradomain routing problem.

Therefore we have to tackle three complexity increasing problems.

1. Solve the capacity assignment for a single link,
2. For each demand in the network define a single origin-destiny route and find the whole configuration, that is, which demand are carried (and which not) and the revenue of the service provider.

3. Define multiple paths for the demands and find the optimum configuration.

In this paper we will focus on the first problem. Network resources, composed of many links with different bandwidths can be considered as multiple items (links) with multiple units (bandwidth units). A simultaneous ascending auction is known to be an effective approach. However its main disadvantage is that it can give raise to *a free rider problem* among the customers. To avoid this, it is better to apply simultaneous one-round auctions, which technical name is "*sealed bid auction"s*. Next we state the mathematical formulation of the problem.

Consider ***i=1…M*** user-customers competing for the bandwidth of a link with capacity $\boldsymbol{Q}$. The social welfare is given by $\sum_i \theta_i$, where θi is the valuation function of the user also named willingness to pay function.

Therefore we have to design a mechanism to compute a feasible solution $\boldsymbol{a(\theta)}$ for the assignment of capacity $\boldsymbol{q_i}$ to the user $\boldsymbol{i}$ which fulfils $\sum_i q_i \leq Q$,and maximizes the social welfare.

Obviously the users have to pay some reward to the network provider, that is, to the owner of the link. The definition of the price is a very complicated problem. A current trend is based on using some economic mechanism like the auction, specifically generalized Vickrey auctions [6]. Under a Vickrey auction, the price paid for each user $\boldsymbol{c_i}$, is the loss of declared welfare he imposes to the others users due to his presence in the auction and is defined by the following equation.

$$c_i = Max \sum_{\substack{j=1 \\ j \neq i}}^{M} \theta_j\left(x_j\right) - \sum_{\substack{j=1 \\ j \neq i}}^{M} \theta_j\left(a(\theta)\right)$$

This expression requires further explanation: To calculate the price $\boldsymbol{c_i}$ for the user $\boldsymbol{i}$ we remove him from the list of bidders. Then we calculate a new optimal assignment of capacity ($\boldsymbol{x_j}$) to the rest of bidders, and therefore we compute the price they bid using their valuation function θ_i (note that this procedure requires solving a NP-hard problem similar to the original one, but removing one variable). The result of this calculation is the first term of the equation. The second term is calculated using the initial solution $\boldsymbol{a(\theta)}$ and computing the total amount of bids, excluding the one which corresponds to the user $\boldsymbol{i}$.

It is straight forward to see that the price paid by the user $\boldsymbol{i}$ is always less or equal than the bid they offer for the amount of bandwidth θ_i.

Vickrey Auction is a useful mechanism, because it satisfies the following conditions, [7]:

1. ***Incentive compatibility:*** For each user, bidding truthfully is a dominant strategy. This means that the valuation function they present to the auctioneer is the real function.

2. ***Individual rationality:*** Each truthful player obtains a non-negative utility. The utility of each user is defined by: $U_i\left(a, c_i\right) = \theta_i\left(a\right) - c_i$

   Note that $\boldsymbol{a}$ is the solution found, that is the capacity assigned to each user.

3. ***Efficiency:*** Social welfare is maximized

Of course this mechanism has some clear disadvantages. In [8] it is stated the Vickrey auction mechanism is hard to compute even for simple problems. For a first step we are going to reduce the model considering inelastic demand, which means a valuation function defined by: $\boldsymbol{\theta_i(ai)=\beta_i \cdot \Pi\ a_i<\alpha}$., see Figure 3.

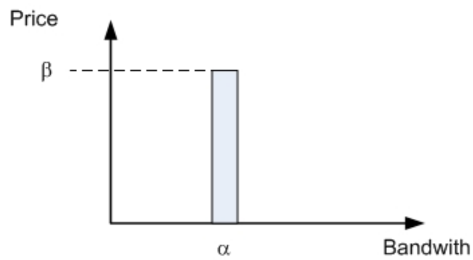

Figure 3: Inelastic Demand Function

In this case even if the price paid by each user $\boldsymbol{c_i}$ is null, the problem of maximizing the social welfare under link capacity constraints, $\boldsymbol{Q}$, is NP-complete, in fact it is the classical "knapsack problem".

Several algorithms have been proposed to solve the knapsack problem, see [8] and [9] as an example. We introduce a genetic algorithm seeking for a more general procedure which will allow us to expand it to consider elastic demand with $\boldsymbol{c_i}$ no null.

3 Genetic Algorithm for the First Price Sealed Bid Auction.

Genetic algorithms are robust problem's solving techniques based on natural evolution processes. They are population-based techniques which codify a set of possible solutions to the problem, and evolve it through the application of the so called genetic operators [10]. The standard genetic operators in a GA are:

Selection: where the individuals of a new population are selected from the old one. In the standard implementation of the Selection operator, each individual has a probability of surviving for the next generation proportional to its associated fitness value (roulette wheel).

Crossover: where new individuals are searched starting from couples of individuals in the population. Once the couples are randomly selected, the individuals have the possibility of swapping parts of themselves with its couple, the probability. Tthis happens is usually called crossover probability, ***Pc***.

Mutation: where new individuals are searched by randomly changing bits of current individuals with a low probability ***Pm*** (probability of mutation).

Genetic algorithm works as follows, see Figure 4:

1. Generate the initial population, usually randomly. Each individual of the population is named ***gene*** and it is a chain of binary values named ***chromosome***. Each gene is a feasible solution of the problem, fair or bad, which has to be evaluated

2. Calculate the fitness function of each gene. The fitness function is the objective value which measures the goodness or badness of each solution-gene of the population.

3. Apply the operators defined above.

4. Evaluate the fitness of the new population generated by the Selection-Crossover-Mutation operators.

5. Repeat the process for all generations specified in the algorithm.

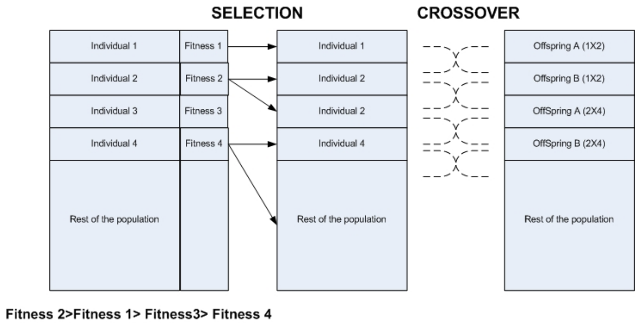

Figure 4: General Scheme of the Operation of a Genetic Algorithm

To apply the genetic algorithm to the knapsack problem we consider the following codification for each individual-gene:

$$gene = \{x_i\}_{i=1}^{N} \Leftrightarrow \begin{cases} x_i = 0 & \textit{Capacity Not Assigned} \\ x_i = 1 & \textit{Capacity Assigned} \end{cases}$$

Therefore the knapsack problem is defined as finding the optimal assignment ***x*** such that:

$$\sum_{i=1}^{N} x_i q_i \leq Q \,,$$

which maximizes

$$\sum_{i=1}^{N} x_i \, p_i \,.$$

The equation above is the fitness function we are going to use for the genetic algorithm. Note that the genetic operators (Selection-Crossover-Mutation) may produce a number of $\boldsymbol{x_i=1}$ in a gene which does not satisfy the capacity constraint. Hence we need to apply a restriction operator to limit the number of $\boldsymbol{x_i=1}$ in the individual. This is implemented as a randomly remover of user in the system.

4 Experiments and results

We have performed a large number of experiments with the genetic algorithm but for the sake of simplicity we will show a subset of two. The first one is a very simple case which allows us a better understanding of the knapsack problem. This example has been used as a test for our algorithm. The number of users, the capacity requirements and the bids are shown in Table I

User	Capacity	Bid	User	Capacity	Bid
1	1	1	11	1	1
2	1	1	12	1	1
3	1	1	13	1	1
4	1	1	14	1	1
5	1	1	15	1	1
6	1	1	16	1	1
7	1	1	17	1	1
8	1	1	18	1	1
9	1	1	19	1	1
10	1	1	20	20	20

Table I: Input values for experiment 1

The parameters of the genetic algorithm are:

- Population: The number of independent and feasible solutions that the genetic algorithm uses to evolve towards the optimal solution: 101
- Generations: Number of iterations, 100.
- We are going to use the concept named elitism which means that the best individual is granted to be in the next generation

The capacity of the link is set to 20 units. Under the established condition $c_i=0$, the optimal solution is to assign all the capacity to the last user to maximize the social welfare, $\sum_i \theta_i$, that is, the final solution:

$$a(\theta) = \{0\,0\,0\,0\,0\,0\,0\,0\,0\,0\,0\,0\,0\,0\,0\,0\,0\,0\,1\}$$

Second example is a, let say, real situation. In this case we have 17 users with different requirements in term of capacity and bid, as it is shown in Table 2

User	Capacity	Bid	User	Capacity	Bid
1	2	5	11	11	11
2	6	9	12	14	13
3	9	11	13	7	9
4	10	16	14	5	6
5	21	12	15	6	14
6	26	28	16	2	17
7	8	40	17	3	8
8	5	21			
9	14	13			
10	16	9			

Table II: Input values for experiment 2

The genetic algorithm parameters and the link capacity are the same that for experiment 1.The result is the following assigment vector:

$$a(\theta) = \{1\,0\,0\,0\,0\,0\,1\,1\,0\,0\,0\,0\,0\,0\,0\,1\,1\,0\,0\,0\}$$

And the result of the social welfare is **91.** In the Figure 5 you can see the evolution of the social welfare through the generations.

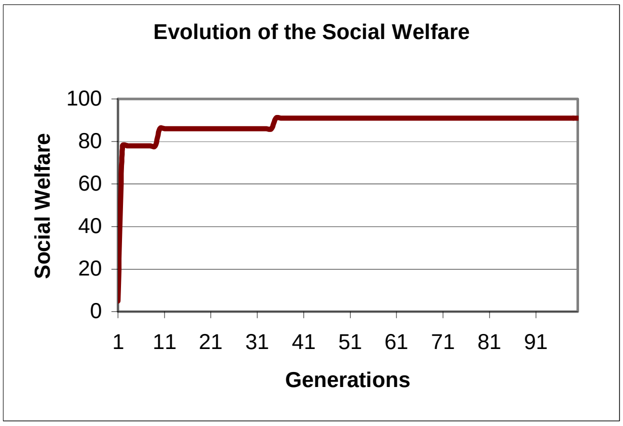

Figure 5: Evolution of the social welfare through the generations

Note that the optimum value is obtained before 50 % of generations have passed

5 Conclusion

We have presented here an algorithm for solving the knapsack problem applied to a Firs Price Sealed Bid Auction in a communication network link. The algorithm is based in modern heuristics, specifically genetic algorithms. The algorithm has demonstrated a very good performance both in the goodness of the solution obtained as well as in computational time. These features make it a very good candidate to try to solve much more complex problems related with Vickrey Auctions with c_i no null.

The future work is related with the establishment of the complete route of a specific service demand in a Intradomain environment. For this purpose the algorithm developed may be a good candidate due to its low computational load.

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