Paper

Fair and efficient network dimensioning with the reference point methodology

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Abstract— The dimensioning of telecommunication networks that carry elastic traffic requires the fulfillment of two conflicting goals: maximizing the total network throughput and providing fairness to all flows. Fairness in telecommunication network design is usually provided using the so-called max-min fairness (MMF) approach. However, this approach maximizes the performance of the worst (most expensive) flows which may cause a large worsening of the overall throughput of the network. In this paper we show how the concepts of multiple criteria equitable optimization can be effectively used to generate various fair and efficient allocation schemes. We introduce a multiple criteria model equivalent to equitable optimization and we develop a corresponding reference point procedure for fair and efficient network dimensioning for elastic flows. The procedure is tested on a sample network dimensioning problem for elastic traffic and its abilities to model various preferences are demonstrated.

Keywords— multiple criteria optimization, efficiency, fairness, equity, reference point method, telecommunications, network design, elastic traffic.

1. Introduction

The problem of fairness in the allocation of resources occurs in many contexts, from economics and law to engineering. In all cases, a scarce or constrained resource must be divided among many users in a way that respects fairness and does not ignore efficiency [9, 13]. In the area of telecommunication and computer networks, fair resource allocation usually concerns the allocation of bandwidth to users, services or flows. This problem may be dynamic and solved by adaptive protocols like transmission control protocol (TCP) [3], or it may concern the design or configuration of the network [16, 20]. This paper deals with the problem of fair and efficient network dimensioning.

Telecommunication network design is usually based on a set of estimated traffic demands. The task is then to design the cheapest networks that can satisfy the demands. The estimation of traffic demands is usually possible in networks that are mainly used to communicate voice (like the public switched telephone network – PSTN), since voice communication uses a fixed amount of bandwidth. In data networks, traffic is much more variable and hard to predict; also, data communications does not have quality of service (QoS) requirements that need a fixed bandwidth share. Data traffic is usually carried by the TCP protocol that adapts its throughput to the amount of available bandwidth. Such traffic, called *elastic traffic*, is capable to use the entire available bandwidth, but it will also be able to reduce its throughput in the presence of contending traffic. Nowadays, the network management often faces the problem of designing networks that carry elastic traffic. These network design problems are, essentially, network dimensioning problems as they can be reduced to a decision about link capacities. Flow sizes are outcomes of the design problem, since the flows adapt to given network resources on a chosen path.

Network management must stay within a budget constraint on link bandwidth to expand network capacities. They want to achieve a high throughput of the IP network, to increase the multiplexing gains (due to the use of packet switching by the Internet Protocol – IP). This traffic is offered only a best-effort service, and therefore network management is not concerned with offering guaranteed levels of bandwidth to the traffic. A straightforward network dimensioning with elastic traffic could be thought of as a search for such network flows that will maximize the aggregate network throughput while staying within a budget constraint for the costs of link bandwidth. However, maximizing aggregate throughput can result in extremely unfair solutions allowing even for starvation of flows for certain services. On the other extreme, while looking at the problem from the perspective of a network user, the network flows between different nodes should be treated as fairly as possible [2]. The so-called max-min fairness (MMF) [1, 4] is widely considered as such ideal fairness criteria. Indeed, the lexicographic max-min optimization used in the MMF approach generalizes equal sharing at a single link bandwidth to any network while maintaining the Pareto optimality. Certainly, allocating the bandwidth to optimize the worst performances may cause a large worsening of the overall throughput of the network. Therefore, network management must consider two goals: increasing throughput and providing fairness. These two goals are clearly conflicting, if the budget constraint has to be satisfied.

The purpose of this work is to show that it is possible to balance the two conflicting goals of increasing the total network throughput and providing fairness to all flows. The tradeoff between these two goals can be controlled using a multiple criteria model that allows to represent the overall efficiency and fairness goals. The network manager can choose among many compromise solutions by specifying his preferences using the so-called quasi-satisficing approach to multiple criteria decision problems [22]. The best formalization of the quasi-satisficing approach to multiple criteria optimization was proposed and developed mainly by Wierzbicki [21] as the reference point method. The reference point method (RPM) is an interactive technique where the decision maker (DM) specifies preferences in terms of aspiration levels (reference point), i.e., by introducing desired (acceptable) levels for several criteria. This allows the DM to simultaneously learn about the problem during the process of expressing his (possibly evolving) preferences. Our methods also enable the DM to choose solutions obtained by methods developed in previous work, that depend on maximization of the sum of the flows evaluated with some (concave) utility function. In particular, the so-called *proportional fairness* (PF) approach [5] maximizes the sum of logarithms of the flows. This approach has been further extended to a parametric class of concave utility functions [11]. However, the methods developed in this paper are more general and allow the DM to choose among many solutions, including solutions that would be obtained by other methods.

The paper is organized as follows. In the next section we formalize the network dimensioning problem, we consider. In Section 3, basic fair solution concepts for resource allocation are related to the multiple criteria equitable optimization theory. In Section 4, the reference point methodology is applied to the multiple criteria allowing us to model various fair and efficient allocation schemes with simple control parameters. Finally, in Section 5, we present some results of our initial computational experience with this new approach.

2. The network dimensioning problem

The problem of network dimensioning with elastic traffic can be formulated basically as a linear programming (LP) based resource allocation model as follows [16]. Given a network topology $G =< V,E >$, consider a set of pairs of nodes as the set $I = \{1,2,\dots,m\}$ of services representing the elastic flow from source v_i^s to destination v_i^d. For each service, we have given the set P_i of possible routing paths in the network from the source to the destination. We describe them with binary coefficients $\delta_{eip} = 1$ if link e belongs to the routing path $p \in P_i$ (connecting v_i^s with v_i^d) and $\delta_{eip} = 0$ otherwise.

For each service $i \in I$, the elastic flow from source v_i^s to destination v_i^d is a variable representing the model outcome and it will be denoted by x_i. This flow may be realized along various paths $p \in P_i$. The flow may be either split among several paths or a single path must be finally selected to serve the entire flow. Actually, the latter case of nonbifurcated flows is more commonly required. Both bifurcated or nonbifurcated flows may be modeled as $x_i = \sum_{p \in P_i} x_{ip}$ where x_{ip} (for $p \in P_i$) are nonnegative variables representing the elastic flow from source v_i^s to destination v_i^d along the routing p. Although, the single-path model requires additional multiple choice constraints to enforce nonbifurcated flows. This can be implemented with additional binary (flow assignment) variables u_{ip} equal 1 if path $p \in P_i$ is assigned to serve flow x_i and 0 otherwise. Assuming existence of some constant M upper bounding the largest possible total flows x_i, the assignment variables u_{ip} can easily be used to limit the number of positive flows x_{ip} with the following constraints:

$$0 \le x_{ip} \le M u_{ip},\ u_{ip} \in \{0,1\} \qquad \forall\ i \in I;\ p \in P_i\,, \quad (1)$$

$$\sum_{p \in P_i} u_{ip} = 1 \qquad \forall\ i \in I\,. \quad (2)$$

The network dimensioning problem depends on allocating the bandwidth to several links in order to maximize flows of all the services (demands). Typically, the network is already operated and some bandwidth is already allocated (installed) and decisions are rather related to the network expansion. Therefore, we assume that each link $e \in E$ has already capacity a_e while decision variables ξ_e represent the bandwidth newly allocated to link $e \in E$ thus expanding the link capacity to $a_e + \xi_e$. Certainly, all the decision variables must be nonnegative: $\xi_e \ge 0$ for all $e \in E$ and there are usually some bounds (upper limits) on possible expansion of the links capacities: $\xi_e \le \bar{a}_e$ for all $e \in E$. Finally, the following constraints must be fulfilled:

$$\sum_{i \in I} \sum_{p \in P_i} \delta_{eip} x_{ip} \le a_e + \xi_e \qquad \forall e \in E\,, \quad (3)$$

$$0 \le \xi_e \le \bar{a}_e \qquad \forall e \in E\,, \quad (4)$$

$$\sum_{p \in P_i} x_{ip} = x_i \qquad \forall i \in I\,, \quad (5)$$

where Eq. (5) define the total service flows, while Eq. (3) establish the relation between service flows and links bandwidth. The quantity $y_e = \sum_{i \in I} \sum_{p \in P_i} \delta_{eip} x_{ip}$ is the load of link e and it cannot exceed the available link capacity.

Further, for each link $e \in E$, the cost of allocated bandwidth is defined. In the basic model of network dimensioning it is assumed that any real amount of bandwidth may be installed and marginal costs c_e of link bandwidth is given. Hence, the corresponding link dimensioning function expressing amount of capacity (bandwidth) necessary to meet a required link load [16] is then a linear function. While allocating the bandwidth to several links in the network dimensioning process the decisions must keep the cost within available budget B for all link bandwidths. Hence the following constraint must be satisfied:

$$\sum_{e \in E} c_e \xi_e \le B. \quad (6)$$

The model constraints (3)–(6) together with respective nonnegativity requirements define a linear programming feasible set. They turn into mixed integer LP (MILP), however, if nonbifurcated flows are enforced with discrete constraints (1) and (2).

In the simplified problem with linear link dimensioning function and dimensioning of a completely new network

($a_e = 0$ for all links), the cost of the entire path p for service i can be directly expressed by the formula:

$$\kappa_{ip} = \sum_{e\in E} c_e \delta_{eip} \quad \text{for } i = 1,\ldots,m,\ p \in P_i\,. \qquad (7)$$

The cheapest path for each service can then easily be identified and preselected. Having preselected routing path for each demand ($|P_i| = 1$) one may consider variable x_i directly as flow along the corresponding path ($x_i = x_{i1}$). Constraints (6) and (3) may be then treated as equations and together with formula (7) they allow one to eliminate variables ξ_e, thus formulating the problem as a simplified resource allocation model with only one constraint:

$$\sum_{i=1}^{m} \kappa_i x_i = B\,, \qquad \text{where } \kappa_i = \kappa_{i1} \quad \forall\ i \in I \qquad (8)$$

and variables x_i representing directly the decisions. Note that one cannot define directly any cost κ_{ip} of the path $p \in P_i$ (similar to formula (7)) when some capacity is already available ($a_e > 0$ for some $e \in E$). In other words in the problem, we consider, the cost of available link capacity is actually nonlinear (piecewise linear) and this results in the lack of direct formula for the path cost since it depends on possible sharing with other paths of the preinstalled bandwidth (free capacity a_e).

The network dimensioning model can be considered with various objective functions, depending on the chosen goal. One may consider two extreme approaches. The first extreme is the maximization of the total throughput (the sum of flows) $\sum_{i\in I} x_i$. On the other extreme, the network flows between different nodes should be treated as fairly as possible which leads to the maximization of the smallest flow or rather to the lexicographically expanded max-min optimization (the so-called max-min ordering) allowing also to maximize the second smallest flows provided that the smallest remain optimal, the third smallest, etc. This approach is widely recognized in networking as the so-called max-min fairness [1, 4] and it is consistent with the Rawlsian theory of justice [17].

Note that in the simplified dimensioning model (with preselected paths and continuous bandwidth), due to possible alternative formulation Eq. (8), the throughput maximization approach apparently would choose one variable x_{i^o} which has the smallest marginal cost $\kappa_{i^o} = \min_{i\in I} \kappa_i$ and make that flow maximal within the budget limit ($x_{i^o} = B/\kappa_{i^o}$), while eliminating all other flows (lowering them to zero). On the other hand, the MMF concept applied to the simplified dimensioning model (resulting in Eq. (8)) would lead us to a solution with equal values for all the flows: $x_i = B/\sum_{i\in I} \kappa_i$ for $i \in I$. Such allocating the resources to optimize the worst performances may cause a large worsening of the overall (mean) performances as the MMF throughput ($mB/\sum_{i\in I} \kappa_i$) might be considerably smaller than the maximal throughput ($B/\min_{i\in I} \kappa_i$). In more realistic dimensioning models assuming nonlinearities in link dimensioning function (like the existence of a free capacity a_e of preinstalled bandwidth) and nonbifurcation requirements a direct formula for a path cost is not available and the corresponding solutions are not so clear. Nevertheless, the main weaknesses of the above solutions remain valid. The throughput maximization can always result in extremely unfair solutions allowing even for starvation of certain flows while the MMF solution may cause a large worsening of the throughput of the network. In an example built on the backbone network of a Polish Internet service provider (ISP), it turned out that the throughput in a perfectly fair solution could be less than 50% of the maximal throughput [14].

Network management may be interested in seeking a compromise between the two extreme approaches discussed above. One of possible solutions depends on maximization of the sum of the flows evaluated with some (concave) utility function $\sum_{i\in I} U_i(x_i)$. In particular, for $U_i(x_i) = \log(x_i)$ one gets the proportional fairness approach [5]. However, every such approach requires to build (or to guess) a utility function prior to the analysis and later it gives only one possible compromise solution. It is very difficult to identify and formalize the preferences at the beginning of the decision process. Moreover, apart from the trivial case of throughput maximization all the utility functions that really take into account any fairness preferences are nonlinear. Nonlinear objective functions applied to the MILP models we consider results in computationally hard optimization problems. In the following, we shall describe an approach that allows to search for such compromise solutions with multiple linear criteria rather than the use nonlinear objective functions.

3. Fairness and equitable efficiency

The network dimensioning problem, we consider, may be viewed as a special case of general resource allocation problem where a set I of m services is considered and for each service $i \in I$, its measure of realization x_i is a function $x_i = f_i(\xi)$ of the allocation pattern $\xi \in A$. This function, representing the outcome (effect) of the allocation pattern for service i we call the individual objective function. In the network dimensioning problem the measure expresses the service flow and a larger value of the outcome means a better effect. This leads us to a vector maximization problem:

$$\max\ \{(x_1, x_2, \ldots, x_m)\ :\quad \mathbf{x} \in Q\}\,, \qquad (9)$$

where $Q = \{(x_1,\ldots,x_m) : x_i = f_i(\xi) \text{ for } i \in I,\ \xi \in A\}$ denotes the attainable set for outcome vectors $\mathbf{x}$. For the network dimensioning problems, we consider, the set Q is an MILP feasible set defined by basic constraints (1)–(6).

Multiple criteria model (9) only states that for any outcome x_i ($i \in I$) larger value is preferred. In order to make it operational, one needs to assume some solution concept specifying what it means to maximize multiple outcomes. The commonly used concept of the Pareto-optimal solutions, as feasible solutions for which one cannot improve any outcome without worsening another, depends on the rational dominance $\succeq_r$ which may be expressed in terms of the vector inequality: $\mathbf{x}' \succeq_r \mathbf{x}''$ iff $x'_i \geq x''_i$ for all $i \in I$.

The concept of fairness has been studied in various areas beginning from political economics problems of fair allocation of consumption bundles to abstract mathematical formulation [18]. In order to ensure fairness in a system, all system entities have to be equally well provided with the system's services. This leads to concepts of fairness expressed by the equitable rational preferences [6, 12]. The fairness requires impartiality of evaluation, thus focusing on the distribution of outcome values while ignoring their ordering, i.e., in the multiple criteria problem (9) one is interested in a set of outcome values without taking into account which outcome is taking a specific value. Hence, we assume that the preference model is impartial (anonymous, symmetric) thus the preference relation must fulfill the following axiom

$$(x_{\tau(1)}, x_{\tau(2)}, \ldots, x_{\tau(m)}) \cong (x_1, x_2, \ldots, x_m) \qquad (10)$$

for any permutation τ of I. Fairness requires also equitability of outcomes which is formalized in the requirement that the preference model must satisfy the (Pigou–Dalton) principle of transfers, i.e., a transfer of any small amount from an outcome to any other relatively worse–off outcome results in a more preferred outcome vector. As a property of the preference relation, the principle of transfers takes the form of the following axiom: for any $x_{i'} > x_{i''}$

$$\mathbf{x} - \varepsilon \mathbf{e}_{i'} + \varepsilon \mathbf{e}_{i''} \succ \mathbf{x} \quad \text{for } 0 < \varepsilon < x_{i'} - x_{i''}, \qquad (11)$$

where $\mathbf{e}_i$ denotes the ith unit vector. The rational preference relations satisfying additionally axioms (10) and (11) are called hereafter *fair (equitable) rational preference relations*. We say that outcome vector $\mathbf{x}'$ *fairly dominates* $\mathbf{x}''$ ($\mathbf{x}' \succ_e \mathbf{x}''$), iff $\mathbf{x}' \succ \mathbf{x}''$ for all fair rational preference relations $\succeq$. An allocation pattern $\xi \in A$ is called *fairly (equitably) efficient* if $\mathbf{x} = \mathbf{f}(\xi)$ is fairly nondominated. Note that each fairly efficient solution is also Pareto-efficient, but not vice verse.

The relation of fair (equitable) dominance can be expressed in terms of a vector inequality on the cumulative ordered outcomes [6]. This can be formalized as follows. First, introduce the ordering map $\Theta : R^m \to R^m$ such that $\Theta(\mathbf{x}) = (\theta_1(\mathbf{x}), \theta_2(\mathbf{x}), \ldots, \theta_m(\mathbf{x}))$, where $\theta_1(\mathbf{x}) \le \theta_2(\mathbf{x}) \le \cdots \le \theta_m(\mathbf{x})$ and there exists a permutation τ of set I such that $\theta_i(\mathbf{x}) = x_{\tau(i)}$ for $i = 1, \ldots, m$. Next, apply to ordered outcomes $\Theta(\mathbf{x})$, a linear cumulative map thus resulting in the *cumulative ordering map* $\bar{\Theta}(\mathbf{x}) = (\bar{\theta}_1(\mathbf{x}), \bar{\theta}_2(\mathbf{x}), \ldots, \bar{\theta}_m(\mathbf{x}))$ defined as

$$\bar{\theta}_i(\mathbf{x}) = \sum_{j=1}^{i} \theta_j(\mathbf{x}) \quad \text{for } i = 1, \ldots, m. \qquad (12)$$

Quantities $\bar{\theta}_i(\mathbf{x})$ ($i = 1, \ldots, m$) express, respectively: the smallest outcome, the total of the two smallest outcomes, the total of the three smallest outcomes, etc. The theory of majorization [10] includes the results which allow us to derive the following theorem [6].

Theorem 1: Outcome vector $\mathbf{x}'$ fairly dominates $\mathbf{x}''$, if and only if $\bar{\theta}_i(\mathbf{x}') \ge \bar{\theta}_i(\mathbf{x}'')$ for all $i \in I$ where at least one strict inequality holds.

Theorem 1 permits one to express fair solutions of problem (9) as Pareto-efficient solutions to the multiple criteria problem with cumulated ordered objectives

$$\max \{(\eta_1, \ldots, \eta_m) : \quad \eta_k = \bar{\theta}_k(\mathbf{x}) \ \forall \ k \in I, \ \mathbf{x} \in Q\}. \qquad (13)$$

Alternatively one may consider problem (13) with normalized objective functions $\mu_k(\mathbf{x}) = \bar{\theta}_k(\mathbf{x})/k$ thus representing for each k the mean of the k smallest outcomes, called the worst conditional mean [13]. Note that the last (mth) objective in (13) represents the sum of outcomes thus corresponding to throughput maximization. Standard maximin optimization corresponds to maximization of the first objective in (13). The complete MMF solution concept represents the lexicographic approach to multiple criteria in (13):

$$\operatorname{lexmax} \{(\eta_1, \ldots, \eta_m) : \quad \eta_k = \bar{\theta}_k(\mathbf{x}) \ \forall \ k \in I, \ \mathbf{x} \in Q\}.$$

Hence, the MMF is only a specific (extreme) solution concept while the entire multiple criteria problem (13) may serve as a source of various fairly efficient allocation schemes. Although the definitions of quantities $\bar{\theta}_k(\mathbf{x})$ are very complicated, they can be modeled with simple auxiliary constraints. Note that for any given vector $\mathbf{x}$, the quantity $\bar{\theta}_k(\mathbf{x})$ is defined by the following LP problem:

$$\begin{array}{rcl} \bar{\theta}_k(\mathbf{x}) & = & \min \sum_{i \in I} x_i u_{ki} \\ & & \text{s.t.} \ \sum_{i \in I} u_{ki} = k, \ 0 \le u_{ki} \le 1 \ \forall \ i \in I. \end{array} \qquad (14)$$

Exactly, the above problem is an LP for a given outcome vector $\mathbf{x}$ while it begins nonlinear for a variable $\mathbf{x}$. This difficulty can be overcome by taking advantages of the LP dual to Eq. (14):

$$\begin{array}{rcl} \bar{\theta}_k(\mathbf{x}) & = & \max \ kt - \sum_{i \in I} d_i \\ & & \text{s.t.} \ t - x_i \le d_i, \ d_i \ge 0 \ \forall \ i \in I, \end{array} \qquad (15)$$

where t is an unrestricted variable while nonnegative variables d_i represent, for several outcome values x_i, their downside deviations from the value of t [15].

Formula (15) allows us to formulate the multiple criteria problem (13) as follows:

$$\begin{array}{lll} \max & (\eta_1, \ldots, \eta_m) \ \text{s.t.} \ \mathbf{x} \in Q & \\ & \eta_k = k t_k - \sum_{i \in I} d_{ik} & \forall \ k \in I \\ & t_k - d_{ik} \le x_i, \quad d_{ik} \ge 0 & \forall \ i, k \in I. \end{array} \qquad (16)$$

The problem (16) adds only linear constraints to the original attainable set Q. Hence, for the basic network dimensioning problems with the set Q defined by constraints (1)–(6), the resulting formulation (16) remains in the class of (multiple criteria) MILP. For the simplified LP model (3)–(6) with flows bifurcation allowed and continuous bandwidth the multiple criteria formulation (16) remains in the class of (multiple criteria) LP.

The expanded model (16) introduces m^2 additional variables and constraints. Although the constraints are simple linear inequalities they may cause a serious computational burden for real-life network dimensioning problems. Note that the number of services (traffic demands) corresponds to the number of ordered pairs of network nodes which is already square of the number of nodes $|V|$. Thus, finally the expanded multiple criteria model introduces $|V|^4$ variables and constraints which means polynomial but fast growth and can be not acceptable for larger networks. For instance, rather small backbone network of Polish ISP [14], we analyze in Section 5, consists of 12 nodes which leads to 132 elastic flows ($m = 132$) resulting in 17 424 constraints and the same number of deviational variables d_{ik}. In order to reduce the problem size we will restrict the number of criteria in the problem (13).

Consider a sequence of indices $K = \{k_1, k_2, \ldots, k_q\}$, where $1 = k_1 < k_2 < \ldots < k_{q-1} < k_q = m$, and the corresponding restricted form of the multiple criteria model (13):

$$\max\ \{(\eta_{k_1}, \ldots, \eta_{k_q}) : \quad \eta_k = \bar{\theta}_k(\mathbf{x})\ \forall\ k \in K, \quad \mathbf{x} \in Q\} \quad (17)$$

with only $q < m$ criteria. According to Theorem 1, the full multiple criteria model (13) allows us to generate any fairly efficient solution of problem (9). When limiting the number of criteria we restrict these capabilities but still one may generate reasonable compromise solutions as stated in the following theorem.

Theorem 2: If $\mathbf{x}^o$ is an efficient solution of the restricted problem (17), then it is an efficient (Pareto-optimal) solution of the multiple criteria problem (9) and it can be fairly dominated only by another efficient solution $\mathbf{x}'$ of (17) with exactly the same values of criteria: $\bar{\theta}_k(\mathbf{x}') = \bar{\theta}_k(\mathbf{x}^o)$ for all $k \in K$.

Proof: Suppose, there exists $\mathbf{x}' \in Q$ which dominates $\mathbf{x}^o$, i.e., $x'_i \geq x^o_i$ for all $i \in I$ with at least one inequality strict. Hence, $\bar{\theta}_k(\mathbf{x}') \geq \bar{\theta}_k(\mathbf{x}^o)$ for all $k \in K$ and $\bar{\theta}_{k_q}(\mathbf{x}') > \bar{\theta}_{k_q}(\mathbf{x}^o)$ which contradicts efficiency of $\mathbf{x}^o$ in the restricted problem (17).

Suppose now that $\mathbf{x}' \in Q$ fairly dominates $\mathbf{x}^o$. Due to Theorem 1, this means that $\bar{\theta}_i(\mathbf{x}') \geq \bar{\theta}_i(\mathbf{x}^o)$ for all $i \in I$ with at least one inequality strict. Hence, $\bar{\theta}_k(\mathbf{x}') \geq \bar{\theta}_k(\mathbf{x}^o)$ for all $k \in K$ and any strict inequality would contradict efficiency of $\mathbf{x}^o$ within the restricted problem (17). Thus, $\bar{\theta}_k(\mathbf{x}') = \bar{\theta}_k(\mathbf{x}^o)$ for all $k \in K$ which completes the proof. □

According to Theorem 2 while solving the restricted multiple criteria model (17) we can essentially still expect reasonably fair efficient solution and only *unfairness* may be related to the distribution of flows within classes of skipped criteria. In other words, we have guaranteed some rough fairness while it can be possibly improved by redistribution of flows within the intervals $(\theta_{k_j}(\mathbf{x}), \theta_{k_{j+1}}(\mathbf{x})]$ for $j = 1, 2, \ldots, q-1$. Since the fairness preferences are usually very sensitive for the smallest flows, one may introduce a grid of criteria $1 = k_1 < k_2 < \ldots < k_{q-1} < k_q = m$ which is dense for smaller indices while sparser for lager indices and expect solution offering some reasonable compromise between fairness and throughput maximization. In our computational analysis on the network with 132 elastic flows (Section 5) we have preselected 24 criteria including 12 the smallest flows. Note that any restricted model (17) contains criteria $\bar{\theta}_1(\mathbf{x}) = \min_{i \in I} x_i$ and $\bar{\theta}_m(\mathbf{x}) = \sum_{i \in I} x_i$ among others. Hence, it provides more detailed fairness modeling than any bicriteria combination of max-min and throughput maximization.

4. Reference point approach

Taking adavantages of model (17) and Theorem 2 we may generate various fairly efficient network dimensioning patterns as efficient solutions of the multiple criteria problem:

$$\begin{aligned} \max \quad & (\eta_k)_{k \in K} \quad \text{s.t.} \quad \mathbf{x} \in Q \\ & \eta_k = kt_k - \sum_{i \in I} d_{ik} \qquad \forall\ k \in K \\ & t_k - d_{ik} \leq x_i, \quad d_{ik} \geq 0 \quad \forall\ i \in I,\ k \in K, \end{aligned} \quad (18)$$

where $K \subseteq I$ and the attainable set Q is defined by constraints (1)–(6). Actually, in the case of the complete multiple criteria model ($K = I$), according to Theorem 1, all fairly efficient allocations can be found as efficient solutions to (18) while in the case of restricted set of criteria $K \subset I$ some minor unfairness related to the distribution of flows within classes of skipped criteria may occur (Theorem 2). The simplest way to generate various fairly efficient dimensioning patterns may depend on the use some combinations of criteria $(\eta_k)_{k \in K}$. In particular, for the weighted sum with weights $w_k > 0$

$$\sum_{k \in K} w_k \eta_k = \sum_{k \in K} w_k \bar{\theta}_k(\mathbf{x}) = \sum_{i \in I} (\sum_{k \in K : k \geq i} w_k) \theta_i(\mathbf{x})$$

one apparently gets the so-called ordered weighted averaging (OWA) [23] with weights $v_i = \sum_{k \in K : k \geq i} w_k\ (i \in I)$. If the weights v_i are strictly decreasing, i.e., in the case of full model ($K = I$), each optimal solution corresponding to the OWA maximization is a fair (fairly efficient) solution of (9) while the fairness among flows within classes of equal weights v_i (of skipped criteria) may be sometimes improved. Moreover, in the case of LP models, as the simplified network dimensioning (3)–(6), every fairly efficient allocation scheme can be identified as an OWA optimal solution with appropriate strictly monotonic weights [6]. Several decreasing sequences of weights provide us with various aggregations. Indeed, our earlier experience with application of the OWA criterion to the simplified problem of network dimensioning with elastic traffic [14] showed that we were able to generate easily allocations representing the classical fairness models. On the other hand, in order to find a larger variety of new compromise solutions we needed to incorporate some scaling techniques originating from the reference point methodology. Better controllability and the complete parameterization of nondominated solutions even for non-convex, discrete problems can be achieved with the direct use of the reference point methodology.

The reference point method was introduced by Wierzbicki [21] and later extended leading to efficient implementations of the so-called aspiration/reservation based decision support (ARBDS) approach with many successful applications [8, 22]. The approach is an interactive technique allowing the DM to specify the requirements in terms of aspiration and reservation levels, i.e., by introducing acceptable and required values for several criteria. Depending on the specified aspiration and reservation levels, a special scalarizing achievement function is built which generates an efficient solution to the multiple criteria problem when maximized. The generated solution is accepted by the DM or some modifications of the aspiration and reservation levels are introduced to continue the search for a better solution. The ARBDS approach provides a complete parameterization of the efficient set to multi-criteria optimization. Hence, when applying the ARBDS methodology to the ordered cumulated criteria in (13), one may generate any (fairly) equitably efficient solution to the original problem (9).

In order to guarantee that for any individual outcome η_k more is preferred to less (maximization), the scalarizing achievement function must be strictly increasing with respect to each outcome. A solution with all individual outcomes η_k satisfying the corresponding reservation levels is preferred to any solution with at least one individual outcome worse (smaller) than its reservation level. Next, provided that all the reservation levels are satisfied, a solution with all individual outcomes η_k equal to the corresponding aspiration levels is preferred to any solution with at least one individual outcome worse (smaller) than its aspiration level. That means, the scalarizing achievement function maximization must enforce reaching the reservation levels prior to further improving of criteria. In other words, the reservation levels represent some soft lower bounds on the maximized criteria. When all these lower bounds are satisfied, then the optimization process attempts to reach the aspiration levels.

The basic scalarizing achievement function takes the following form [21]:

$$\sigma(\eta) = \min_{k\in K}\{\sigma_k(\eta_k)\} + \varepsilon \sum_{k\in K} \sigma_k(\eta_k), \qquad (19)$$

where ε is an arbitrary small positive number and σ_k, for $k \in K$, are the partial achievement functions measuring actual achievement of the individual outcome η_k with respect to the corresponding aspiration and reservation levels (η_k^a and η_k^r, respectively). Thus the scalarizing achievement function is, essentially, defined by the worst partial (individual) achievement but additionally regularized with the sum of all partial achievements. The regularization term is introduced only to guarantee the solution efficiency in the case when the maximization of the main term (the worst partial achievement) results in a non-unique optimal solution.

The partial achievement function σ_k can be understood as a measure of the DM's satisfaction with the current value (outcome) of the kth criterion. It is a strictly increasing function of outcome η_k with value $\sigma_k = 1$ if $\eta_k = \eta_k^a$, and $\sigma_k = 0$ for $\eta_k = \eta_k^r$. Thus the partial achievement functions map the outcomes values onto a normalized scale of the DM's satisfaction. Various functions can be built meeting those requirements [22]. We use the piecewise linear partial achievement function introduced in [12] as

$$\sigma_k(\eta_k) = \begin{cases} \gamma\lambda_k(\eta_k - \eta_k^r) & \text{for } \eta_k \le \eta_k^r, \\ \lambda_k(\eta_k - \eta_k^r) & \text{for } \eta_k^r < \eta_k < \eta_k^a, \\ \beta\lambda_k(\eta_k - \eta_k^a) + 1 & \text{for } \eta_k \ge \eta_k^a, \end{cases}$$

where $\lambda_k = 1/(\eta_k^a - \eta_k^r)$ while β and γ are arbitrarily defined parameters satisfying $0 < \beta < 1 < \gamma$. This partial achievement function is strictly increasing and concave which guarantees its LP computability with respect to outcomes η_k.

In our network dimensioning model (18) outcomes η_k represent cumulative ordered flows x_i, i.e., $\eta_k = \sum_{i=1}^k \theta_i(\mathbf{x})$. Therefore, the reference vectors (aspiration and reservation) represent, in fact, some reference distributions of outcomes (flows). Moreover, due to the cumulation of outcomes, while considering equal flows ϕ as the reference (aspiration or reservation) distribution, one needs to set the corresponding levels as $\eta_k = k\phi$. Certainly, one may specify any desired reference distribution in terms of the ordered values of the flows (quantiles in the probability language) $\phi_1 \le \phi_2 \le \ldots \le \phi_m$ and cumulating them automatically get the reference values for the outcomes η_k representing the cumulated ordered flows. However, such rich modeling technique may be too complicated to control effectively the search for a compromise solution. Therefore, we rather consider to begin the search with a simplified approaches based on the reference flow distribution given as a linear sequence $\phi_k = \phi_1(1 + (k-1)r)$ with the (relative) slope coefficient r thus leading to the cumulated reference levels increasing quadratically $\bar{\theta}_k(\phi) = \phi_1 k(2 + (k-1)r)/2$. Although, special meaning of the last (throughput) criterion should be rather operated independently from the others. Such an approach to control the search for a compromise fair and efficient network dimensioning has been confirmed by the computational experiments.

5. Computational analysis

The reference distribution approach has been tested on a sample network dimensioning problem with elastic traffic. The outcome of the network dimensioning procedure (using elastic traffic) are the capacities of links in a given network, because the flows will adapt to the bandwidth available on the links in the designed network. The data to a network dimensioning problem with elastic traffic consists of a network topology, of pairs of nodes that specify sources and destinations of flows, of sets of network paths that could be used for each flow, and of optional constraints on the capacities of links or on flow sizes. Moreover, there are also given pricesof a unit of link capacity (possibly different for each link, c_e in (6)), and the budget amount for purchasing link capacity (B in (6)). The given network topology may contain information about preinstalled link capacities (a_e in (3)): the budget is then spent on additional link capacities that extend the present capacity of a link.

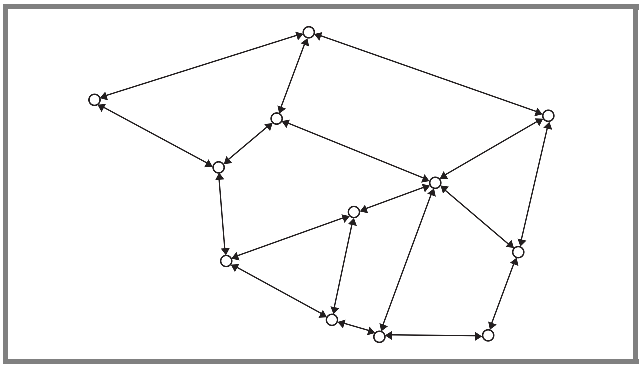

Fig. 1. Sample network topology patterned after the backbone network of Polish ISP.

For our computational analysis we have used the network (Fig. 1) patterned after the network topology of the backbone network of Polish ISP [14]. The network consists of 12 nodes and 18 links. Flows between any pair of different nodes have been considered (i.e., $144-12=132$ flows). In real networks flows are usually realized on small number of paths. Therefore, we have used lists with only 2 alternative paths for one flow. We have used a single-path formulation (nonbifurcation formulation (1) and (2)), meaning that the entire flow had to be switched to the alternative path. Flows could not be split, which is consistent with several traffic engineering technologies used today.

We set all unit costs $c_e = 1$, and the total budget amount $B = 1000$. For certain links, free link capacity was set to values from 5 to 20, and the upper limit on the capacity of certain links was set to 20. Due to the presence of free link capacity and upper limits on link capacity, the MILP solver found solutions where certain flows had to use alternative paths rather than shortest paths. These flows were more expensive than other flows that were allowed to use their shortest paths.

A simplified LP model for network dimensioning problem without additional constraints on link capacity, with a limitation that flows could only use the shortest path has been studied in [14]. For such a problem it is simple to calculate the solution obtained by the MMF and PF methods. Indeed, in [14] we have calculated these solutions and have shown the appropriate OWA aggregations allows us to obtain similar results. Additionally, using the OWA criterion, it was possible to obtain alternative solutions. Here, we focus on extensions of the problem studied in [14] that make the studied models more practical and realistic. Our extension allowed flows to choose one of two paths for transport (1) and (2), added constraints that limited the capacity of certain links from above and added free link capacity for certain links (3). The intention behind the modification has been to model a situation when the network operator wishes to extend the capacity of an existing network. In this network, certain links cannot be upgraded beyond a certain values to the use of legacy technologies, due to prohibitive costs or administrative reasons (for instance, it may be cheap to use already installed fiber that has not been in use before, but it may be prohibitively expensive to install additional fiber). The existence of free link capacity and of link capacity constraints may be the reason for choosing alternative paths for certain flows. The extended model we consider is too complex for a simple application of MMF and PF methods. To apply either of these methods to the discussed problem extensions, it would be necessary to solve a nonlinear optimization problem or a sequence of MILP problems with changing constraints.

In our analysis while using the RPM methodology we do not have used all 132 criteria η_k as in [14]. Instead, we have selected only 24 criteria by choosing the indices $1,2,3,\ldots,10,11,12,18,24,30,36,48,60,72,\ldots,120,132$. As a result, the computation time has dropped from around one hour for each problem to the order of seconds. At the same time, the ability to control the outcomes using the reservation levels has not deteriorated; we were able to obtain similar results with the reduced set of criteria as with the full set. For our approach the final input to the model consisted of the reservation and aspiration levels for the sums of ordered criteria. For simplicity, all aspiration levels were set close to the optimum values of the criteria, and only reservation levels were used to control the outcome flows. One of the most significant parameters was the reservation level for the sum of all criteria (the network throughput). This value denoted by η^r_m was selected (varying) separately from the other reservation levels. All the other reservation levels were formed following the linearly increasing sequence of the ordered values with slope (step) r and where the reservation level for minimal flow was taken $\phi_1 = 1$. Hence, for the final criteria $\eta_k = \bar{\theta}_k(\mathbf{x})$ representing the sums of ordered outcomes in model (16), the sequence of reservation levels increased quadratically (except from the last one). Thus, the three parameters have been used to define the reference distribution but we have managed to identify various fair and efficient allocation patterns by varying only two parameters: the reservation level η^r_m for the total throughput and the slope r for the linearly increasing sequence.

In the experiment, we have searched for various compromise solutions that traded off fairness against efficiency while controlling the process by the throughput reservation level η^r_m and the slope r. The throughput reservation has been varied between 500 and 1100. The linear increase of the other reservation levels was controlled by the slope parameter r. In the experiment this parameter have set to values of: 0.02, 0.03 and 0.04. The results of the experiment are shown in Figs. 2–4 with the corresponding absolute Lorenz curves [7]. The figures present plots of cumulated ordered flows $\bar{\theta}_k(\mathbf{x})$ versus number k (rank of a flow in ordering according to flow throughput) which means that the normalizing factor $1/m = 1/132$ has been ignored (for both the axes). The total network throughput is represented in the figures by the altitude of the right end of the curve ($\bar{\theta}_{132}(\mathbf{x})$). A perfectly equal distributions of flows would be graphically represented by an ascending line of constant slope.

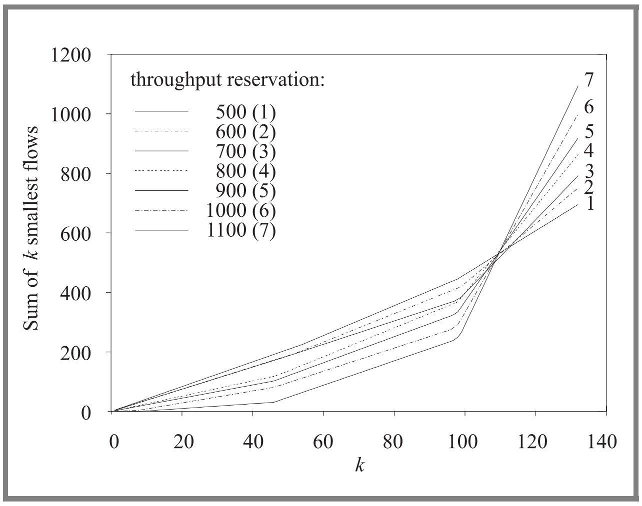

Fig. 2. Flows distributions for varying throughput reservation with $r = 0.02$.

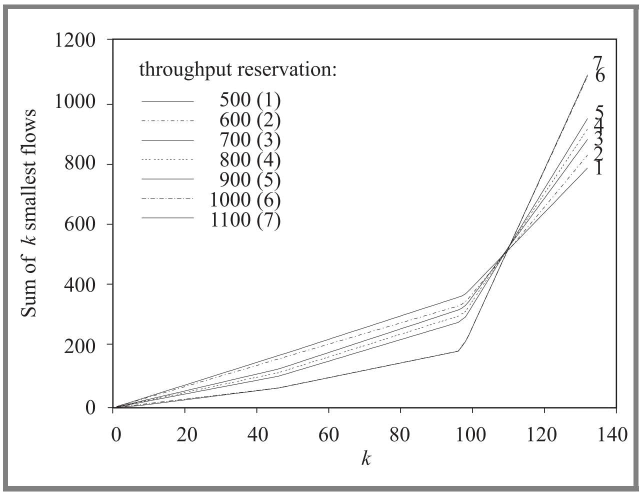

Fig. 3. Flows distributions for varying throughput reservation with $r = 0.03$.

As throughput reservation η^r_m increases, the cheaper flows receive more throughput at the expense of more expensive (longer) flows. For values of η^r_m above 1100, some flows were starved, and therefore these outcomes were not considered further. Under moderate throughput requirements, as r increases, the medium flows gain at the expense of the larger ones thus enforcing more equal distribution of flows (one may observe flattening of the curves). On the other hand, with higher throughput reservations the larger flows are protected by this requirement and increase of r causes that the medium flows gain at the expense of the smallest flows (one may observe convexification of the curves). For values of r higher than 0.04, the increase of the throughput reservation resulted in flow starvation.

Note from Fig. 4 that the boundary between the smallest flows for $\eta^r_m = 500$ and for $\eta^r_m = 1100$ is not in the same position. The reason for this is the upper constraint on link capacities. For $\eta^r_m = 500$, there are 8 flows that ought be in the middle group of flows but they cannot, since flows in the middle group receive so much throughput that the con-

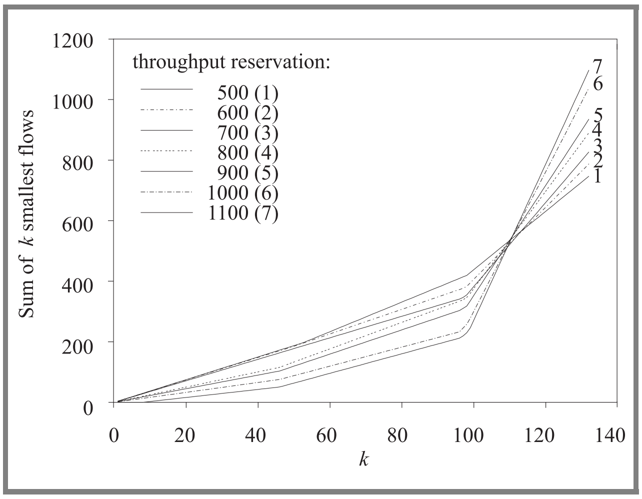

Fig. 4. Flows distributions for varying throughput reservation with $r = 0.04$.

straints on link capacity would be violated. Consequently, these flows are downgraded to the group of smallest flows and they receive the same amount of throughput as the smallest flows, due to the fairness rules.

In our experiments the throughput reservation was effectively used to find outcomes with the desired network throughput. Note that, especially for large throughput reservations, the optimization procedure automatically found outcomes that divided flows into four categories according to their path costs. This demonstrates that our methodology is cost-aware, and that it guarantees fairness to all flows with the same path cost (if link capacity constraints do not interfere). For the lowest throughput reservation of $\eta^r_m = 500$ and $r = 0.04$, the outcome was close to a perfectly fair distribution. Thus methodology described in this paper, can offer the user an opportunity to choose from a large gamut of different outcomes and control the trade-off between fairness and efficiency.

We have also tested an alternative scheme of the preference modeling within our reference point method implementation. Namely, we analyzed the initial scheme (see Section 4) based on the reference flow distribution given as a linear sequence $\phi_k = \phi_1(1+(k-1)r)$ with the (relative) slope coefficient r thus leading to the cumulated reference levels increasing quadratically $\bar{\theta}_k(\phi) = \phi_1 k(2+(k-1)r)/2$ is strictly implemented. The sequence was applied to construct all the reservation levels including η^r_1 for the minimum flow and η^r_m for the network throughput. Although the value of η^r_m, due to the represented throughput criterion, had to be selected (varying) directly. Therefore, all the other reservation levels were formed according to the linearly increasing sequence of the ordered values with slope (step) r where the reservation level for the minimal flow ϕ_1 had allocated a value guaranteeing that $\eta^r_m = \phi_1 m(2+(m-1)r)/2$. Thus, the two parameters have been used to define the reference distribution: the reservation level η^r_m for the total throughput and the slope r for the linearly increasing sequence but (opposite to the scheme from Section 5) ϕ_1 has not been fixed.

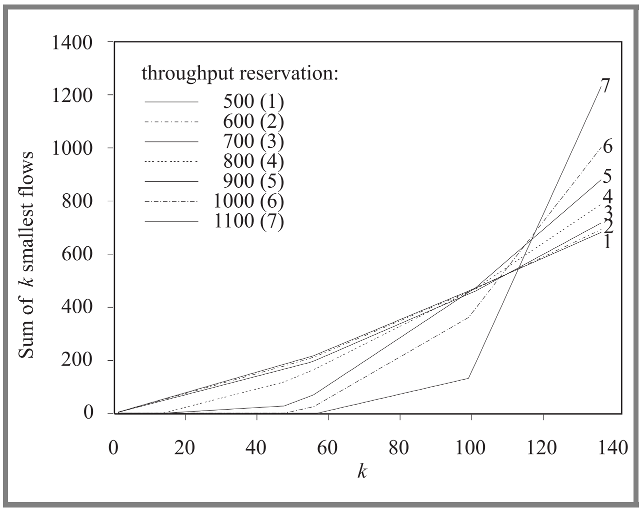

Fig. 5. Results for varying throughput reservation with $r = 0.02$ defining all other reservation levels.

We have applied this preference model to the first network dimensioning problem consisted of the single paths requirements, free link capacity and upper limits on capacity for certain links. The results of the experiment with $r = 0.02$ and varying η_m^r are shown in Fig. 5 with the corresponding absolute Lorenz curves. As η_m^r increases, the cheaper flows receive more throughput at the expense of more expensive (longer) flows. It turned out that except from relatively minor throughput requirements (values 500 to 700), increasing values of η_m^r introduced significant inequity among flows and numerous flows were starved. Similar solutions appeared for various values of r. Therefore, we have abandon such a two parameter control scheme and we have decided that the throughput criterion should be rather operated independently from the others. Such an approach to control the search for a compromise fair and efficient network dimensioning has been confirmed by the computational experiments as described in Section 5.

Overall, the experiments on the sample network topology demonstrated the versatility of the described methodology for equitable optimization. The use of reference levels, actually controlled by a small number of simple parameters, allowed us to search for compromise solutions best fitted to various possible preferences of a network designer. Using appropriate reference point based procedure, one should be able to find a satisfactory fair and efficient network dimensioning pattern in a few interactive steps.

6. Concluding remarks

Network dimensioning problems today must take into account the existence of elastic traffic. The usual approach is to maximize the amount of elastic traffic that uses the best-effort network service, since this increases the multiplexing gain. This approach is equivalent to maximizing network throughput for elastic traffic in a network dimensioning problem. However, this may lead to a starvation and unfair treatment of diverse network flows and, as a consequence, to customer dissatisfaction. While it is true that elastic traffic has no strict QoS requirements, it is also true that the utility of a customer that uses best-effort network services depends on the amount of available throughput.

These considerations lead to the problem of fair and efficient network dimensioning for elastic traffic. In our previous research and in this paper, we have shown that this problem leads to a tradeoff between fairness (where the goal is to decrease differences in throughput for different flows) and efficiency (increasing total network throughput). We have also shown that the problem of fair and efficient network dimensioning is a multiple criteria problem that has many possible solutions (Pareto-optimal solutions that are also optimal for the initial problem without fairness constraints). Previous work on the problem always found a single solution. This did not allow to control the basic tradeoff between fairness and efficiency.

In this paper, we have used the reference point methodology, a standard multiple criteria optimization method that allows for good controllability and the complete parameterization of nondominated solutions. While looking for fairly efficient network dimensioning, the reference point methodology can be applied to the cumulated ordered outcomes. Our initial experiments with such an approach to the problem of network dimensioning with elastic traffic have confirmed the theoretical advantages of the method. We were easily able to generate various (compromise) fair solutions, although the search for fairly efficient compromise solutions was controlled by only two parameters. One of these parameters was a reservation level for the network throughput. The second parameter allowed the network designer to control the difference in throughputs of cheaper and more expensive flows. Still, flows with the same cost were always treated fairly. Moreover, the obtained solutions divided flows into categories determined by flow cost. These characteristics demonstrate that the model is cost-aware and fulfills the axioms of equitable optimization. Also, the achieved total network throughputs in our solutions were higher than the throughput obtained by the max-min fairness method.

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