Highlights on a Multiobjective Routing Method for Multiservice MPLS Networks with Traffic Splitting

Rita Girão-Silva, José Craveirinha
DEEC-FCTUC, INESC-Coimbra
Pólo II, Coimbra, Portugal
Email: {rita,jcrav}@deec.uc.pt

João Clímaco
INESC-Coimbra
Coimbra, Portugal
Email: jclimaco@inescc.pt

M. Eugénia Captivo
FCUL, CIO-UL
Lisboa, Portugal
Email: mecaptivo@fc.ul.pt

***Abstract*—A multiobjective routing model for Multiprotocol Label Switching networks with multiple service classes and considering traffic splitting is presented. The routing problem is formulated as a multiobjective mixed-integer program, and an exact resolution method based on the classical constraint method is outlined. Some experimental results on network performance measures, resulting from the application of the routing method in a reference test network, are presented. These results confirm the potential advantages of using a multiobjective optimization model in this routing problem, as we get a compromise solution that tries to balance the two considered objectives.**

Keywords—Routing models; Multiobjective optimization; Telecommunication networks; Network flow approach; Traffic splitting.

I. INTRODUCTION

The routing calculation and optimization problems in modern multiservice networks are quite challenging, as the performance and cost metrics in these networks are multidimensional and often conflicting. There are potential advantages in formulating routing problems in these types of networks as multiple objective optimization problems, because the trade-offs among distinct performance metrics and other network cost function(s) (potentially conflicting) can be analyzed in a consistent manner. In multiobjective optimization problems, see e.g. [1], one seeks to find non-dominated solutions (or Pareto solutions), i.e., feasible solutions such that it is not possible to improve the value of an objective function without worsening the value of at least one of the other objective functions.

In a Multiprotocol Label Switching (MPLS) network, packets are forwarded through Label Switched Paths (LSP). An important problem in traffic engineering is to distribute the traffic trunks, i.e., the aggregation of traffic flows of the same Forwarding Equivalence Class (FEC) on the network by the possible LSPs. This procedure is known as traffic splitting [2], as the traffic trunks are split and mapped onto different paths in the network, satisfying the constraints of the bandwidth required by the traffic trunk of a given service class. This procedure is useful to obtain a balanced distribution of the load in the network and/or a reduction in the routing costs, but it entails the establishment of more LSPs and an increase in the complexity of the network management.

We can mention other works concerned with load balancing. A multiobjective problem formulated in the context of off-line routing in telecommunication networks is presented in [3]. In [4], it is shown that when multimedia traffic flows characterized as batch Markovian arrival processes, are split, the network performance (measured in terms of end-to-end delay, delay variance and cell loss probability) tends to improve. A survey on several multipath routing techniques in the Internet is presented in [5]. According to A. Dixit et al. [6], a fine grained traffic splitting technique used in data center networks leads to a better load-balanced network, when compared to techniques using equal-cost multipath routing.

In our work, a global routing problem i.e. involving the simultaneous calculation of the LSPs for all node-to-node traffic flows is considered. In this type of network-wide optimization approach, the objective functions of the route optimization model depend explicitly on all traffic flows in the network, see [7], [8]. Earlier works focused on routing optimization with traffic splitting are [7], [9]. A bi-objective lexicographic routing problem is formulated in [7]. The objectives are the maximization of the Quality of Service (QoS) traffic revenue and of the Best Effort (BE) traffic revenue. The resolution method is a lexicographic optimization method. At first, only the QoS traffic is considered; afterwards, the BE flows are taken into account, considering only the remaining available bandwidth. A model with three objectives (including the minimization of traffic splitting) is proposed in [9]. The bi-objective routing problem includes a constraint on the total number of paths used in the network. The resolution method is based on a lexicographic weighted Chebyshev metric method. A review on multiobjective routing models can be seen in [10].

This short paper presents an overview on current work on a multiobjective routing model for MPLS with traffic splitting. We consider a mixed-integer programming (MIP) formulation of the routing optimization model considering two objective functions (global routing cost and load cost) and a constraint on the maximal number of LSPs per flow, as suggested in [9]. The major contribution of the research work concerns: the extension of the aforementioned model to a multiservice case; the development of an exact resolution method for the calculation of non-dominated solutions, with special features related to the nature of the model; an experimental study for evaluation of the results of the method in terms of network performance measures, using a reference test network.

In this paper we describe the addressed model and its MIP formulation in Section II, and outline an exact resolution method (MCC) based on the classical constraint method [11] in Section III. In Section IV, some results with a reference test network are analyzed. Finally, some conclusions are drawn.

II. Model Description

A network $(\mathcal{N}, \mathcal{A})$ with unidirectional arcs (or links) is considered, where $\mathcal{N}$ is the set of nodes in the network and $\mathcal{A}$ is the set of links in the network. The capacity of each network link k is given by u_k [Mbit/s], $k \in \mathcal{A}$.

Let $\mathcal{S}$ be the set of services of the network. Considering that the point-to-point offered bandwidth matrix T_{ij} [Mbit/s], $i, j \in \mathcal{N}$, and the percentage of bandwidth associated with each service ($q_s, s \in \mathcal{S}$, with $\sum_{s\in\mathcal{S}} q_s = 1.0$) are given, the value of the bandwidth offered by each flow $t \equiv (i, j, s)$ (corresponding to the traffic from service $s \in \mathcal{S}$ originating in node i and destined to node j) is $d_t = q_s T_{ij}$. The set of all network flows is $\mathcal{T}$. Let $\mathcal{P}_t = \{p_t^0, p_t^1, \cdots, p_t^{L_t-1}\}$ be the set of L_t feasible paths for flow t.

For each link $k \in \mathcal{A}$, an additive cost per unit of bandwidth, c_k, is considered; C_t^l is the cost of using path p_t^l, the l-th feasible path for flow t; the decision variable x_t^l is the part of the bandwidth offered by flow t which will be carried in the l-th path, hence specifying the traffic splitting solution.

The first objective function is the minimization of the total cost of carrying the bandwidth of all the flows offered to all the feasible paths:

$$\min F_1 = \sum_{t\in\mathcal{T}} \sum_{l=0}^{L_t-1} C_t^l x_t^l \quad (1)$$

with

$$C_t^l = \sum_{k\in p_t^l} c_k, \quad \forall l = 0, \cdots, L_t - 1, t \in \mathcal{T} \quad (2)$$

$$\sum_{l=0}^{L_t-1} x_t^l = d_t, \quad \forall t \in \mathcal{T} \quad (3)$$

$$x_t^l \geq 0, \quad \forall l = 0, \cdots, L_t - 1, t \in \mathcal{T} \quad (4)$$

where the constraint (3) guarantees that the total bandwidth required by flow t is carried by the assigned LSPs.

The second objective function is the minimization of the load cost in all the network links. In this way, a more balanced distribution of load in the network may be accomplished, so as to maximize the possibility of the network accepting more traffic requests in the future [12]. A piece-wise linear cost function ϕ_k is defined for each link $k \in \mathcal{A}$ (see (6)-(11)) as in [13], based on its utilization rate $\frac{f_k}{u_k}$, where f_k is the total load carried in the link. Hence, the second objective function is:

$$\min F_2 = \sum_{k\in\mathcal{A}} \phi_k \quad (5)$$

with

$$\phi_k \geq f_k, \quad \forall k \in \mathcal{A} \quad (6)$$

$$\phi_k \geq 2f_k - 0.5u_k, \quad \forall k \in \mathcal{A} \quad (7)$$

$$\phi_k \geq 5f_k - 2.3u_k, \quad \forall k \in \mathcal{A} \quad (8)$$

$$\phi_k \geq 15f_k - 9.3u_k, \quad \forall k \in \mathcal{A} \quad (9)$$

$$\phi_k \geq 60f_k - 45.3u_k, \quad \forall k \in \mathcal{A} \quad (10)$$

$$\phi_k \geq 300f_k - 261.3u_k, \quad \forall k \in \mathcal{A} \quad (11)$$

$$f_k \leq u_k, \quad \forall k \in \mathcal{A} \quad (12)$$

$$f_k = \sum_{t\in\mathcal{T}} \sum_{l=0}^{L_t-1} a_{t,l}^k x_t^l, \quad \forall k \in \mathcal{A} \quad (13)$$

where (12) guarantees that the link capacity is not exceeded. The parameter $a_{t,l}^k$ is binary and specifies whether a link k belongs to path p_t^l, i.e., $a_{t,l}^k = 1$ iff $k \in p_t^l, k \in \mathcal{A}, l = 0, \cdots, L_t - 1, t \in \mathcal{T}$ and $a_{t,l}^k = 0$ otherwise.

A third objective function minimizing the number of used paths for each flow can also be considered. If the number of used paths per flow increases, then the network routing control and management may become increasingly costly and complex because the signaling and processing tasks increase. Let y_t^l be the binary variable representing whether the path p_t^l is used, i.e., $y_t^l = 1$ iff the l-th path $p_t^l, l = 0, \cdots, L_t - 1$ is used by flow $t \in \mathcal{T}$ and $y_t^l = 0$ otherwise. Therefore, the third objective function is

$$\min F_3 = \max_{t\in\mathcal{T}} \left\{ \sum_{l=0}^{L_t-1} y_t^l \right\} \quad (14)$$

with

$$x_t^l \leq d_t y_t^l, \quad \forall l = 0, \cdots, L_t - 1, t \in \mathcal{T} \quad (15)$$

$$y_t^l \in \{0; 1\}, \quad \forall l = 0, \cdots, L_t - 1, t \in \mathcal{T} \quad (16)$$

A constraint on the maximal number of links D_s for the paths associated with a service $s \in \mathcal{S}$ is also considered: for flows with QoS requirements in real-time, e.g., voice and video services, D_s is the network diameter (maximal number of links of the shortest paths for all the network pairs of nodes); for flows of QoS services without real-time requirements, e.g., *Premium* data services, D_s is the network diameter + 1; for BE service flows, e.g., plain data services, no technical limits on the maximal number of links are imposed, so $D_s = |\mathcal{N}| - 1$.

The multiobjective routing problem may be formulated as

$$\min\{F_1, F_2, F_3\} \quad (17)$$

subject to: (3)-(4), (6)-(13), (15)-(16) (18)

constraint on $D_s, \forall s \in \mathcal{S}$ (19)

An important change to this main problem is that the third objective function F_3 will no longer be an objective and will rather be included in the constraints. The number of used paths per flow should be limited in practice for technical reasons to prevent excessive overheads related to control and signaling costs. Let $N_L \in \mathbb{N}$ be the maximal value allowed for the total number of paths used by any traffic flow. The new problem P_0 to be addressed will be

$$\min\{F_1, F_2\} \tag{20}$$

$$\text{subject to:} \quad \sum_{l=0}^{L_t-1} y_t^l \leq N_L, \forall t \in \mathcal{T} \tag{21}$$

$$\text{(18)-(19)} \tag{22}$$

The total number L_t of feasible paths for each flow t can now be written as $L_t = \min\{N_L, N_t\}$. The maximal number of paths in the network for flow t, N_t, satisfies a constraint on the maximal number of links $D_s, s \in \mathcal{S}$. This constraint is usually defined for technical reasons, associated with transmission or traffic engineering and signaling requirements related to service type. For the generation of the set $\mathcal{P}_t$ for each flow t, the K-shortest path MPS algorithm [14] was used.

In [9], $c_k = 1, \forall k \in \mathcal{A}$. We have chosen to consider $c_k = \frac{\alpha}{u_k} + \beta l_k$ with $\alpha, \beta > 0$ and l_k [km] representing the length of the link. The first term reflects the economy of scale and the decrease in transmission times associated with increased capacity. The second term is related to propagation delays, which increase with the physical length of the link.

III. Resolution Method

For solving P_0 we developed an algorithm based on the constraint method [11], where a feature for the exploration of a specific part of the Pareto front was added, allowing for the choice of an adequate non-dominated solution to the problem.

With the classical constraint method [11], only one objective is optimized, while all the other objectives are constrained to some value. The obtained single objective problem can be solved by conventional methods. The optimal solution to this problem is a non-dominated solution to the original multi-objective problem (see [11]). The bounds that are imposed on the constrained objectives have to be carefully chosen, so that a single optimal solution to the obtained single objective problem exists and so as to guarantee that different non-dominated solutions may be obtained.

In Fig. 1, an example of the application of the MCC method is presented. We consider a single objective problem of minimization of the objective function F_2, whereas a constraint is formulated for the other objective function, i.e., $F_1 \leq F_{1\text{lim}}$. This constraint establishes a new feasible region where we seek to optimize F_2. In this figure the extreme solutions of the Pareto front are shown, where $X \equiv (F_1^{\min}, F_2^{\max})$ and $Y \equiv (F_1^{\max}, F_2^{\min})$.

In the resolution method proposed here, problem P_0 is initially solved by the classical constraint method, where we consider a total of Δ different constraints. The Δ solutions obtained when solving this problem are non-dominated and constitute an approximation to the Pareto front. In Fig. 2 an example of the result after the initial resolution of the routing problem is presented. Note that the proposed algorithm enables that unsupported non-dominated solutions, i.e., non-dominated

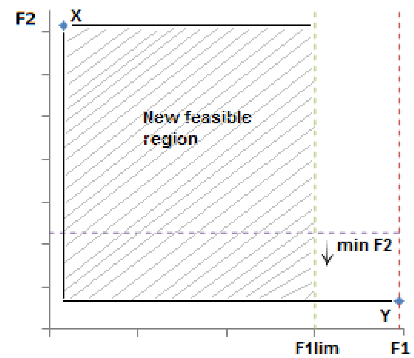

Figure 1. Example of the application of the classical constraint method

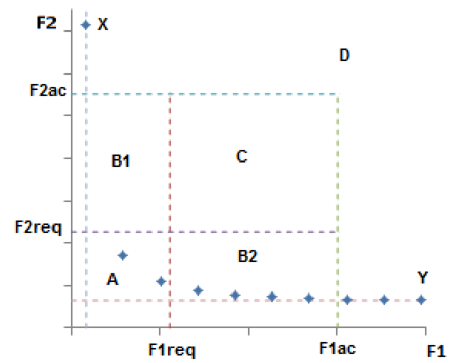

Figure 2. Example of the definition of priority regions in the bidimensional objective function space

solutions located in the interior of the convex hull of the feasible solution set, may be found.

Afterwards, an area of the Pareto front that deserves to be more thoroughly analyzed is chosen, by considering preference regions in the bidimensional objective function space obtained from aspiration and reservation levels (preference thresholds) defined for the two objective functions (see Fig. 2): $F_\varrho^{\text{req}} = \frac{F_\varrho^{\min} + F_\varrho^{\text{av}}}{2}$ and $F_\varrho^{\text{ac}} = \frac{F_\varrho^{\max} + F_\varrho^{\text{av}}}{2}$, with $F_\varrho^{\text{av}} = \frac{F_\varrho^{\min} + F_\varrho^{\max}}{2}$, $\varrho = 1, 2$.

The ideal optimum is obtained when both objective functions are optimized separately. In the 1st priority region A, the requested (req) levels are satisfied for both objective functions; in the 2nd priority regions B_1 and B_2, only one of the requested values is satisfied and an acceptable (ac) value is guaranteed for the other objective function; in the 3rd priority region C, only acceptable values are guaranteed for both objective functions. The least priority region is D. Considering these priority regions, an area of the Pareto front that will be looked into with more detail can be chosen. Firstly, region A will be considered; if there is no possible solution in region A, then region B_1 will be considered; and so on, exploring in succession, regions B_2 and C, if necessary.

After exploring the chosen area of the Pareto front in more detail (again using the constraint method), a few more non-dominated solutions will have been obtained. Finally, the algorithm will proceed to the choice of the most satisfactory

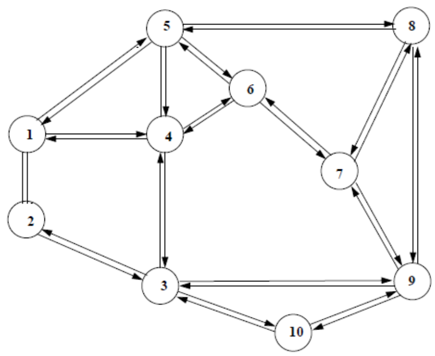

Figure 3. Network in [9, Fig.2]

non-dominated solution in the Pareto front. For this purpose, a Chebyshev weighted metric will be used in the context of priority regions: the approach chosen to select the "best" solution in the Pareto front relies on the minimization of a weighted Chebyshev distance to a reference point, following a method as in [15]. Therefore, this approach will allow us to choose the non-dominated solution whose maximum weighted distance to the reference point is minimum. Notice that the Chebyshev weighted metric will only be applied to the non-dominated solutions found in the best possible priority region. With this approach, we are considering that in the best possible priority region both objective functions F_1 and F_2 have equal importance.

IV. Experimental Results

Experimental results for the network in Fig. 3 (given in [9, Fig.2]), with 10 nodes and 32 unidirectional links, are presented. The capacities of the links and the offered traffic between the different nodes are in [9]. We have superimposed the network on a rectangular grid with 400*240 points where the mesh space unit corresponds to 10 km, as in [15]. Therefore, the maximal horizontal distance in the grid is $l_{\max} = 4000$ km. With this value as reference, we have obtained values for $l_k, k \in \mathcal{A}$.

In [9], the link capacity is the same for all the links, so we have decided not to include it in the link cost c_k, as it affects all the links in the same way. We assumed that $c'_k = \alpha + \beta l'_k$, with a normalized value of l_k: $l'_k = \dfrac{l_k - \min_{\kappa\in\mathcal{A}} l_\kappa}{\max_{\kappa\in\mathcal{A}} l_\kappa - \min_{\kappa\in\mathcal{A}} l_\kappa}$.

The values of network performance measures, relevant from a teletraffic engineering point of view, for the routing solutions obtained with the algorithms were calculated. Some of these performance parameters are 'standard' measures of network performance often used in the evaluation of routing models, such as the one in [16]: total fraction of used capacity, $FUC = \frac{\sum_{k\in\mathcal{A}} f_k}{\sum_{k\in\mathcal{A}} u_k}$; sum of the link utilizations, $SLU = \sum_{k\in\mathcal{A}} \frac{f_k}{u_k}$; maximal link utilization, $MLU = \max_{k\in\mathcal{A}} \left\{\frac{f_k}{u_k}\right\}$. Other performance measures allow for a comparison of the final solutions with the ideal solutions that would be obtained if a single objective problem was considered: relative variation,

TABLE I. NETWORK PERFORMANCE MEASURE VALUES, FOR THE NETWORK IN [9]

Method	F_1	F_2	RV_1	RV_2	FUC	SLU	MLU
S_1	368.73	5913.53		446.54%	0.5928	18.9710	0.9960
S_2	415.51	1082.00	12.69%		0.5391	17.2500	0.7000
S_{MCC}	378.08	2017.48	2.54%	86.46%	0.5752	18.4073	0.8000

$RV_\varrho = \left|\frac{F_\varrho^{\text{sol}} - F_\varrho^{\text{opt}}}{F_\varrho^{\text{opt}}}\right|$ (with $\varrho = 1, 2$) and where F_ϱ^{sol} is the value of F_ϱ calculated for a specific multiobjective solution and F_ϱ^{opt} is the optimal value of F_ϱ for the same problem. Different solutions are obtained: S_1, the solution obtained when only F_1 is minimized; S_2, the solution obtained when only F_2 is minimized; S_{MCC}, the solution obtained when the algorithm based on the constraint method is used to solve the multiobjective problem.

A total of $|\mathcal{S}| = 4$ services were considered: $s = 0$, a QoS video service with $q_0 = 0.1$; $s = 1$, a QoS *Premium* data service with $q_1 = 0.25$; $s = 2$, a QoS voice service with $q_2 = 0.4$; $s = 3$, a BE data service with $q_3 = 0.25$. In the expression for c'_k, we have considered $\alpha = 0.1$ and $\beta = 1 - \alpha = 0.9$. In these experiments, $N_L = 4$ and $\Delta = 10$.

The results for the considered network are in Table I. The execution time of the algorithm was 2.08 s using CPLEX 12.3 in a laptop computer with i7 processor, 2.2 GHz clock and 1 GB of RAM, running on a Linux VM over Windows.

These results confirm that F_1 and F_2 are indeed conflicting, as the minimization of one of them entails an increase in the value of the other objective function. This confirms the potential advantages of using a multiobjective optimization model, rather than a single objective one, in this routing problem as we get a compromise solution that tries to balance the cost of carrying the bandwidth and the global effect of the utilization of the links. When we optimize only F_1 (results identified by S_1) the total cost of carrying the bandwidth of all the flows is indeed lower, but that is accompanied by a noticeable increase in the utilization of the links, as the values of FUC, SLU and MLU tend to be higher than when only F_2 is optimized (results identified by S_2) or when the multiobjective problem is considered (results identified by S_{MCC}). When we optimize only F_2, the utilization of the links is lower, which makes sense as the minimization of the function F_2 tends to minimize the total utilization of the links. The decrease in the utilization of the links can be confirmed not only by the lower value of F_2 but also by the lower values of the performance measures FUC, SLU and MLU. However, the cost of carrying the bandwidth of all the flows greatly increases, as can be seen by analyzing the value of F_1.

When we solve the bi-objective problem, we realize that the obtained solution has compromise values for functions F_1 and F_2 and also for the performance measures, as one would expect. A balance between the two objective functions can be achieved, so as to guarantee that neither the routing cost is too high (which would happen if only F_2 was optimized) nor the load is unbalanced (which would happen if only F_1 was

 ISBN: 978-1-61208-263-9

optimized).

V. Conclusions and Further Work

In this paper, we presented a multiobjective routing model for MPLS networks with different service types. The routing problem is formulated as a multiobjective MIP, where the objectives were the minimization of the bandwidth cost and the minimization of the load cost in the network links. A constraint related to the splitting of traffic trunks was considered. An exact method was developed for solving the formulated problem, the MCC algorithm. Some experiments have allowed us to obtain results on relevant network performance measures.

The obtained results show that F_1 and F_2 are conflicting and confirm the potential advantages of using this multiobjective routing model, rather than solving a single objective formulation. In this way, the trade-offs between F_1 and F_2 can be analyzed and explored.

The proposed routing method can only be applied in a centralized manner. This type of routing method can be implemented at a network management level (for example in a dynamic routing method with a large update routing period), assuming that the information on the available link capacities is provided.

Further work includes the development of an alternative exact method based on the modified constraint method [17] and an extensive experimental study using other reference networks and randomly generated networks.

Acknowledgment

This work was financially supported by programme COMPETE of the EC Community Support Framework III and cosponsored by the EC fund FEDER and national funds (FCT – PTDC/EEA-TEL/101884/2008 and PEst-C/EEI/UI0308/2011).

References

[1] R. E. Steuer, Multiple Criteria Optimization: Theory, Computation and Application, ser. Probability and Mathematical Statistics. John Wiley & Sons, 1986.

[2] F. Le Faucheur and W. Lai, "Requirements for support of differentiated services-aware MPLS traffic engineering," Request for Comments 3564, Network Working Group, Jul. 2003.

[3] J. Knowles, M. Oates, and D. Corne, "Advanced multi-objective evolutionary algorithms applied to two problems in telecommunications," BT Technology Journal, vol. 18, no. 4, Oct. 2000, pp. 51–65.

[4] H.-W. Ferng and C.-C. Peng, "Traffic splitting in a network: Split traffic models and applications," Computer Communications, vol. 27, 2004, pp. 1152–1165.

[5] J. He and J. Rexford, "Towards Internet-wide multipath routing," IEEE Network, vol. 22, no. 2, Mar.-Apr. 2008, pp. 16–21.

[6] A. Dixit, P. Prakash, and R. R. Kompella, "On the efficacy of fine-grained traffic splitting protocols in data center networks," in Proceedings of SIGCOMM11, Toronto (Ontario), Canada, Aug. 15-19 2011, pp. 430–431.

[7] D. Mitra and K. G. Ramakrishnan, "Techniques for traffic engineering of multiservice, multipriority networks," Bell Labs Technical Journal, vol. 6, no. 1, Jan. 2001, pp. 139–151.

[8] J. Craveirinha, R. Girão-Silva, and J. Clímaco, "A meta-model for multiobjective routing in MPLS networks," Central European Journal of Operations Research, vol. 16, no. 1, Mar. 2008, pp. 79–105.

[9] S. C. Erbas and C. Erbas, "A multiobjective off-line routing model for MPLS networks," in Proceedings of the 18th International Teletraffic Congress (ITC-18), Berlin, Germany: Elsevier, Amsterdam, 2003, pp. 471–480.

[10] J. C. N. Clímaco, J. M. F. Craveirinha, and M. M. B. Pascoal, "Multicriteria routing models in telecommunication networks – Overview and a case study," in Advances in Multiple Criteria Decision Making and Human Systems Management: Knowledge and Wisdom, Y. Shi, D. L. Olson, and A. Stam, Eds. IOS Press, 2007, pp. 17–46.

[11] J. L. Cohon, Multiobjective Programming and Planning, ser. Mathematics in Science and Engineering. Academic Press, 1978.

[12] B. Fortz and M. Thorup, "Internet traffic engineering by optimizing OSPF weights," in Proceedings of INFOCOM 2000, vol. 2. Tel Aviv, Israel, Mar. 26-30 2000, pp. 519–528.

[13] J. M. F. Craveirinha, J. C. N. Clímaco, M. M. B. Pascoal and L. M. R. A. Martins, "Trafic splitting in MPLS networks – A hierarchical multicriteria approach". Journal of Telecommunications and Information Technology, no. 4, 2007, pp. 3–10.

[14] T. Gomes, L. Martins, and J. Craveirinha, "An algorithm for calculating k shortest paths with a maximum number of arcs," Investigação Operacional, vol. 21, 2001, pp. 235–244.

[15] J. C. N. Clímaco, J. M. F. Craveirinha, and M. M. B. Pascoal, "An automated reference point-like approach for multicriteria shortest path problems," Journal of Systems Science and Systems Engineering, vol. 15, no. 3, Sep. 2006, pp. 314–329.

[16] S. Srivastava, G. Agrawal, M. Pióro, and D. Medhi, "Determining link weight system under various objectives for OSPF networks using a Lagrangian relaxation-based approach," IEEE Transactions on Network and Service Management, vol. 2, no. 1, 2005, pp. 9–18.

[17] A. Messac, A. Ismail-Yahaya, and C. A. Mattson, "The normalized normal constraint method for generating the Pareto frontier," Structural and Multidisciplinary Optimization, vol. 25, no. 2, 2003, pp. 86–98.