Multiobjective Optimization for Green Network Routing in Game Theoretical Perspective

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***Abstract*—In this paper, we study the multiobjective optimization problem for green network routing. Although traditional commonly used multiobjective optimization methods can yield a Pareto efficient solution, they need to construct an aggregate objective function (AOF) or model one objective as a constraint in the optimization problem formulation. As a result, it is difficult to achieve a fair tradeoff among all objectives. Accordingly, we induce a Nash bargaining framework, which treats the two objectives as two virtual players in a game theoretic model, who negotiate how traffic should be routed to optimize both objectives. During the negotiation, each of them announces its performance threat value to reduce its cost, so the model is regarded as a threat value game. Our analysis shows that no agreement can be achieved if each player sets its threat value selfishly. To avoid such a negotiation break-down, we modify the threat value game to have a repeated process and design a mechanism to not only guarantee an agreement, but also generate a fair solution. Finally, to evaluate the efficiency of our proposed framework, we implement it into two multiobjective optimization cases for network green routing. The first case is load balancing and energy efficiency optimization for intradomain routing, and the second one is the energy efficiency optimization of two domains for interdomain routing.**

***Index Terms*—Multiobjective optimization, Green network, routing, Nash bargaining.**

I. Introduction

THE STEADILY rising energy consumption and the need to reduce the global greenhouse gas emission to protect our environment have turned energy efficiency into one of the primary technological challenges in decades [1]. In particular, ICT (Information and Communication Technology) is one of the most promising areas for pursuing energy conservation. ICT is widely used in most aspects of our society and has traditionally had an environment-friendly image. From the data of 2009, ICT consumes about 8% of the total electricity all over the world [2]. Telecom networks, which represent a significant part of the ICT, are penetrating further into our daily lives. The traffic volume of telecom networks is increasing rapidly and so is its energy consumption. Considering both the growing energy price and the increasing concern on the Green House effect which is being translated in government policies, the energy consumption of ICT is already raising questions, and it is imperative to develop energy-efficient telecom solutions. We need to design new networking paradigms so that ICT will maintain the same level of functionality while consuming a lower amount of energy in future.

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There are emerging studies on green network routing for telecom networks [3]–[8]. In general, these studies commonly aggregate traffic onto some networks devices (such as line cards or routers) and turn the low loaded network devices into sleep mode. In [3], the authors first create a generic model for router power consumption and formulate a mixed integer linear programming problem to determine network configurations and routing for energy saving. Due to its NP-hard property, the optimization model presented in [3] is solvable only for small networks. For large ISP (Internet Service Provider) network, the authors of [4] develop efficient two heuristic approaches, named Least Flow and Random. To reduce the computational complexity, Least Flow sorts overall links in increasing order according to its carried flow, while Random treats all links in random order. Both approaches shuts down the sorted links one by one according to the order until the network connective constraint is violated or one of active links becomes overflow. The authors of [5] propose an intra-domain traffic engineering mechanism, GreenTE, which maximizes the number of links that can be put into sleep under given performance constraints such as maximum link utilization (MLU). The authors of [6] focus on minimizing the energy consumption of the network through a management strategy that selectively switches off network devices proportional to the traffic load. Different from the works of [3]–[5], the approach of [6] can be implemented into on-line energy optimization of networks.

The works in [7], [8] study green IP networks with rate adaptive elements. The power consumption of an active network element is a function of the traffic volume. A network element consumes zero power as it is turned off. The authors of [7] propose the min-power iterative greedy method to decide the routing path based on the least marginal cost. The authors of [8] formulate IP network green routing problem considering OSPF link metric optimization. The Lagrangian relaxation technique is used in [8] to transform the problem into its dual problem and propose three heuristic algorithms to resolve it.

The studies of literatures [3]–[8] are all focused into minimizing network energy consumption in telecom networks and considered as the single-objective optimization. However, telecom carriers/operators are not only interested in energy efficiency, some traditional objectives (such as: load balancing, end-to-end delay, hop count, etc.) also need to be carefully take into consideration. It is noteworthy that these traditional objectives are always conflicting with energy efficiency, in that improving one objective hurts the other. For example, green network routing should use as a few links (i.e., line cards in switch or router) to route traffic as possible, so that the idle network devices can be turn to sleep mode for saving energy. Obviously, this objective contradicts to that of load balancing which is to distribute traffic to as many links as possible. Therefore how to achieve a tradeoff between such conflicting objectives is an interesting problem for green network routing.

There are two commonly used traditional methods to solve the optimization problem with multiple objectives [9]. One is to treat all objectives except the most favorite one as constraints, and then optimize the favorite one [10]–[12]. Such a method might work when there were specific performance goals considered desirable for all the other objectives, in the form of the threshold values used to set the corresponding constraints in the optimization problem formulation. However, this is often not the case as there is usually no hard limit on the performance of these objectives. For example, a carrier does not know (nor wants to set) the desired specific performance of load balancing (or energy efficiency). As a result, most likely some *ad hoc* performance thresholds will be specified in the corresponding constraints, and accordingly, only the favorite objective will achieve the best performance at the expense of all the other objectives. If all the objectives need to be pursued without restricting any to its *ad hoc* performance threshold, such a method is not suitable.

The other traditional method is to construct an AOF (Aggregate Objective Function), such as the well-known weighted linear sum of the objectives [13], [14]. It will yield a Pareto optimal solution in theory, but it is difficult to determine the appropriate weight for each objective. This is because these objective values have not only different performance metrics representing different dimensions of interest (e.g., load balancing and energy efficiency), but also have different scales or orders of magnitude. Note that Langarian relaxation has similar limitations in that it may be difficult to determine the appropriate *ad hoc* performance thresholds for different objectives.

Ideally, when we pursue multiple objectives for green network routing in telecom networks, we do not want to discriminate against any objective by improving the performance of some objectives more significantly than that of the others due to *ad hoc* constraints or weights assigned for various objectives. In other words, we aim to achieve a fair tradeoff among the objectives we are pursuing under a rational guideline. For instance, from the viewpoint of achieving fairness between multiple objectives, the ones with a relatively larger optimization space should obtain more performance improvement than the ones with a relatively smaller optimization space.

Unfortunately, the traditional multi-objective optimization methods cannot guarantee the fair tradeoffs among different objectives. In the first method mentioned above, all the objectives treated as constraints in the optimization problem are in a weaker position while the one treated as the optimization objective is in a stronger position, resulting in unfair tradeoffs. In the second method mentioned above, the objectives whose values have higher orders of magnitude are likely to be in a stronger position than the objectives that are of lower order of magnitude.

To overcome the difficulty in achieving a fair tradeoff among two objectives for green network routing, in this paper we propose a framework based on Nash bargaining [15] to jointly optimize both objectives and guarantee the fairness between them. We treat both objectives as two virtual game players who are negotiating the solution of routing. In this framework, we assume that each player changes its threat value (performance threshold) to improve its performance. Accordingly, the interaction of each player can be modeled as a threat value game. Our analysis shows that 1) there are an infinite number of Pareto efficient Nash equilibriums in this threat value game, and 2) a player can improve its performance by unilaterally reducing its threat value. This means that if we were to model this problem as a static game, both players would announce the threat value as low as possible to improve its performance, which would prevent an agreement. To ensure an agreement, we modify the threat value game to be a repeated procedure where each player changes its threat value stepwise. Based on this repeated procedure model, we design a framework which can not only guarantee an agreement, but also achieve a fair tradeoff.

The main contributions of our work can be summarized as follows:

1) We analyze the problem of achieving a fair tradeoff between multiple conflicting objectives for green network routing and provide useful insights into the general multi-objective optimization problems.
2) We propose a framework based on Nash bargaining to achieve a fair tradeoff between multiple conflicting objectives in energy-efficient telecom networks. The framework treats the two objectives as two virtual players in a so-called value game, who negotiate with each other in order to achieve an agreement. Our proposed framework overcomes the difficulties of traditional methods in assigning appropriate performance thresholds to the objectives or determining appropriate weights in the AOF.
3) We implement the proposed framework into two multi-objective optimization cases for network green routing. The first case is load balancing and energy efficiency optimization for intra-domain routing, and the second one is the energy efficiency optimization of two domains for inter-domain routing. Computer simulation results approve the efficiency of the framework.

The rest of the paper is organized as follows. Section II present the common mathematic model of two objectives. In Section III, we introduce the Nash bargaining theory which forms the foundation of our model. After that, we analyze the fair tradeoff problem in detail and describe the motivation for using Nash bargaining to solve the problem in Section IV. In

Section V, we propose a framework to achieve a fair tradeoff between two objectives, and determine the initial (and subsequent) threat points which can induce a fair solution. We also present two case studies of our framework and simulation results in Section VI and conclude our paper in Section VII.

II. The Common Mathematic Model of Two Objectives

In this section, we describe the two optimization problems for green network routing using the common mathematic model.

Without loss of generality, we give two objectives for green network routing: *Obj*.1 and *Obj*.2, respectively. The optimization problem of *Obj*.1 can be formulated as follows:

Minimize Obj.1:

$$\sum_{l} f(x_l) \tag{1}$$

Subject to: x_l is determined by the routing solution r

In problem of Eq. (1), x_l represents the rate of flow on link l and $f(.)$ represents the link cost in the network. The "cost" can represent any important performance in telecom networks (such as: energy consumption, traffic congestion, time delay, hop count, etc). In this paper, we assume that $f(.)$ is a convex, continuous and non-decreasing function of x_l. Using such a cost function in the optimization objective will penalize high link cost in the networks.

Similarly, the optimization problem of *Obj*.2 can be formulated as follows:

Minimize Obj.2:

$$\sum_{l} g(x_l) \tag{2}$$

Subject to: x_l is determined by the routing solution r

In problem of Eq. (2), x_l represents the rate of flow on link l and $g(.)$ also represents the link cost in the network. The "cost" can represent any important performance in telecom networks (such as: energy consumption, traffic congestion, time delay, hop count, etc). In this paper, we assume that $g(.)$ is a convex, continuous and non-decreasing function of x_l. Using such a cost function in the optimization objective will penalize high link cost in the networks. Finally, we note that $f(.)$ and $g(.)$ have similar characteristics.

III. Nash Bargaining

Since our framework is based on the Nash bargaining solution [16] to derive a tradeoff between two objectives, we briefly introduce the Nash bargaining solution and analyze its properties in this section.

Consider two players, labeled i=1, 2, that are trying to achieve an agreement over a strategy space X. And the utility function u_i of each player i is defined over the space $X \bigcup T$, where T is the strategy of the two players that leads to a failed agreement. Define the space S to be the set of all possible utilities that the two players can achieve, i.e.,

$$S = \{(u_1(x), u_2(x))|x = (x_1, x_2) \in X\} \tag{3}$$

Let $d = (u_1(t_1, t_2), u_2(t_1, t_2)) = (d_1, d_2)$ be the pair of utility expected to be obtained by the two players when they fail to achieve an agreement, i.e. the disagreement point or threat point. We also say d_1 and d_2 are the threat values of play 1 and player 2, respectively. The threat value can also be comprehended as the minimal utility a player expected to obtain in the agreement.

A bargaining problem is defined as the pair (S, d) where $S \subset R^2$ and $d \in S$ such that:

1) S is a convex and compact set.
2) There is some $s \in S$ such that $s > d$, by which we mean $s_i \geq d_i$ for $i = 1, 2$ and $s_i > d_i$ for $i = 1$ or 2.

The Nash bargaining solution we are interested in is a mapping f: $(S, d) \rightarrow S$ for every bargaining problem (S, d) (note that $f_i(S, d)$ is used to represent the utility value of player i) which satisfies the following four properties:

1) Pareto efficiency: A bargaining solution $f(S, d)$ is Pareto-efficient means that there is no point $(s_1, s_2) \subseteq S$ such that $s_i \geq f_i(S, d)$ for all i and $s_i > f_i(S, d)$ for some i.
2) Symmetry: If (S, d) is symmetric around $s_1 = s_2$, i.e. $(s_1, s_2) \in S$ iff $(s_1, s_2) \in S$ and $d_1 = d_2$, then $f_1(S, d)$= $f_2(S, d)$.
3) Invariance to equivalent utility representation: Assume the solution of Nash bargaining (S, d) is (s_1, s_2), if it is transformed to (S', d') by taking s_i'=$\alpha_i s_i + \beta_i$ and d_i'=$\alpha_i d_i + \beta_i$, where $\alpha_i > 0$, the solution of (S', d') is $(\alpha_1 s_1 + \beta_1, \alpha_2 s_2 + \beta_2)$.
4) Independence of irrelevant alternatives: Given two bargaining problem (S, d) and (S', d), where $S' \subset S$, if $f(S, d) \in S'$, there must be $f(S, d)$= $f(S', d)$.

Nash's result shows that there is a unique bargaining solution that satisfies the four properties, which is the solution of the following optimization problem:

Maximize:

$$(s_1 - d_1)(s_2 - d_2) \tag{4}$$

Subject to:

$$(s_1, s_2) \in S \tag{5}$$

$$(s_1, s_2) \geq (d_1, d_2) \tag{6}$$

If the utility function of each player is defined to be the opposite number of its cost function, the tradeoff problem defined in Sec. III can be modeled as the following Nash bargaining form:

Maximize:

$$\left(d_{obj_1} - \sum_{l \in E} f(x_l)\right)\left(d_{obj_2} - \sum_{l \in E} g(x_l)\right) \tag{7}$$

Subject to:

x_l is determined by the routing solution r

$$\sum_{l \in E} f(x_l) \leq d_{obj_1} \tag{8}$$

$$\sum_{l \in E} g(x_l) \leq d_{obj_2} \tag{9}$$

where d_{obj_1} and d_{obj_2} are the performance thresholds (maximal cost tolerated by each player) set by Obj.1 and Obj.2, respectively. It should be noted that these performance thresholds correspond to the worst-case performance which can be easily determined. However, they cannot be used by the conventional multi-optimization approach whereby different performance thresholds corresponding to desirable performance are needed for the constraints, not the worst-case possible performance, which is too loose as a performance bound.

IV. Problem Analysis

In this section, we will analyze the desirable properties of the solution obtained by our framework and explain why the Nash bargaining framework is suitable to our problem. For the optimization problems defined in Eq. (1) and Eq. (2), x_l in the objective function can be substituted by the routing solution r, so $f(.)$ and $g(.)$ can be treated as a function of r. From now on, we use $f(r)$ and $g(r)$ to denote the cost function of *Obj*.1 and *Obj*.2 for link cost.

A. Desirable Properties

1) Pareto efficiency: In our problem, the two objectives (i.e., *Obj*.1 and *Obj*.2) are pursued by one operator, so that the solution r^* should not be worse than any solution r for both objectives, i.e. there exists no feasible solution r such that $\sum_{l\in E} f(r) < \sum_{l\in E} f(r*)$ and $\sum_{l\in E} g(r) < \sum_{l\in E} g(r*)$. It also means that the solution of our framework should lie on the Pareto frontier (See Definition 6) and hence no other solution can improve at least one player's performance without hurting the performance of the other one.
2) Fairness: *Obj*.1 and *Obj*.2 are both pursued and any one of them are not preferred more than the other one, so that we should treat them equitably. The fairness is defined as follows:

Definition 1: Let r_{obj_1} and r_{obj_2} be the routing solution to *Obj*.1 and *Obj*.2, respectively, and we define the best case and worst case cost of *Obj*.1 as $O1_{best}$ and $O1_{worst}$, then:

$$O1_{best} = \sum_{l\in E} f(r_{obj_1}) \tag{10}$$

$$O1_{worst} = \sum_{l\in E} f(r_{obj_2}) \tag{11}$$

Similarly, we define the best case and worst case costs of *Obj*.2 as $O2_{best}$ and $O2_{worst}$, then:

$$O2_{best} = \sum_{l\in E} g(r_{obj_2}) \tag{12}$$

$$O2_{worst} = \sum_{l\in E} g(r_{obj_1}) \tag{13}$$

Definition 2 (Proportional Fairness): Assume that s_{obj_1} and s_{obj_2} are the objective values of *Obj*.1 and *Obj*.2 corresponding to a routing solution that achieves some tradeoffs between the two objectives, then the routing solution is proportionally fair if and only if it satisfies the following equation:

$$\frac{O1_{worst} - s_{obj_1}}{O1_{worst} - O1_{best}} = \frac{O2_{worst} - s_{obj_2}}{O2_{worst} - O2_{best}} \tag{14}$$

Definition 2 means that in the solution with a fair tradeoff, both *Obj*.1 and *Obj*.2 obtain the same percentage (or relative) improvement. It is worth noting that although the values of the two utility functions may have significantly different orders of magnitude, and/or their optimization spaces have different sizes, the above definition of a fair tradeoff uses a relative term and as a result, each objective function will result in a proportional improvement over its worst case performance.

Definition 3 (Max-Min Fairness): Assume that s_{obj_1} and s_{obj_2} are the objective values of *Obj*.1 and *Obj*.2 corresponding to a routing solution that achieves some tradeoffs between the two objectives, then, the routing solution is Max-Min fair iff:

$$(s_{obj_1}, s_{obj_2}) = arg\,max_{(s_1,s_2)\in S}\, min \left\{ \frac{O1_{worst} - s_1}{O1_{worst} - O1_{best}}, \frac{O2_{worst} - s_2}{O2_{worst} - O2_{best}} \right\} \tag{15}$$

In other words, a Max-Min fair routing solution maximizes the relative performance improvement of the objective who gets less relative performance improvement, and accordingly tries to minimize the performance gap between the two objective functions (in terms of their relative performance improvement).

Theorem 1: For a Pareto efficient routing solution (s_{obj_1}, s_{obj_2}), if this solution is proportional fair, it must also be max-min fair.

Proof: We prove it by contradiction by assuming that a Pareto efficient routing solution (s_{obj_1}, s_{obj_2}) is proportional fair but not max-min fair.

Let another Pareto solution (s'_{obj_1}, s'_{obj_2})$\neq$(s_{obj_1}, s_{obj_2}) be max-min fair solution such that:

$$\begin{aligned} &min \left\{ \frac{O1_{worst} - s'_{obj_1}}{O1_{worst} - O1_{best}}, \frac{O2_{worst} - s'_{obj_2}}{O2_{worst} - O2_{best}} \right\} > \\ &min \left\{ \frac{O1_{worst} - s_{obj_1}}{O1_{worst} - O1_{best}}, \frac{O2_{worst} - s_{obj_2}}{O2_{worst} - O2_{best}} \right\} = \\ &\frac{O1_{worst} - s_{obj_1}}{O1_{worst} - O1_{best}} = \frac{O2_{worst} - s_{obj_2}}{O2_{worst} - O2_{best}} \end{aligned} \tag{16}$$

the following inequations must be satisfied:

$$\frac{O1_{worst} - s'_{obj_1}}{O1_{worst} - O1_{best}} > \frac{O1_{worst} - s_{obj_1}}{O1_{worst} - O1_{best}} \tag{17}$$

$$\frac{O2_{worst} - s'_{obj_2}}{O2_{worst} - O2_{best}} > \frac{O2_{worst} - s_{obj_2}}{O2_{worst} - O2_{best}} \tag{18}$$

The above two inqualities imply that (s_{obj_1}, s_{obj_2}) is not a Pareto efficiency solution, which is a contradiction. ■

Theorem 1 means that we can focus on finding a tradeoff routing solution which is Pareto efficient and satisfies the proportional fairness property hereafter.

B. Why Nash Bargaining

The key idea of our work is to find a utility allocation method such that the fairness between multiple objectives can be guaranteed. We adopt the Nash bargaining framework because it not only is a classical cooperative game framework which pursues the fairness between the players in the game, but also will obtain a Pareto efficient solution. Since a solution using Nash bargaining is determined by the threat points which can be treated as the performance thresholds of each player, a key issue is to determine the threat point of a Nash bargaining problem such that the fairness between different objectives can be guaranteed.

V. Trading Off Between Two Objectives Using Nash Bargaining

In this section, we realize the tradeoff between two objectives based on Nash bargaining framework. In such a framework, each player announces its threat value to improve its own performance, so that we call it threat value game. In Subsection VI.A, we introduce this game and analyze it in depth. Our analysis shows that such game has an infinite number of Nash equilibriums and when each player selfishly determines threat value, it will prevent the agreement. To achieve the agreement, we modify the threat value game to be a repeated process and design a mechanism to guarantee the agreement in Subsection VI.B. Through this mechanism we can easily determine the initial threat point (and all subsequent threat points) which can result in fair solution. Since the optimization problem Eq. (19) is not in a convex form, we will show how to translate it into a convex form which can be solved more efficiently in Subsection VI.C.

A. Nash Bargaining Model and Threat Value Game

Let a_{obj_1} and a_{obj_2} be some chosen threat values of *Obj*.1 and *Obj*.2, respectively. The Nash bargaining solution can be derived by the following optimization problem:

Maximize:

$$(a_{obj_1} - \sum_{l \in E} f(x_l)(a_{obj_2} - \sum_{l \in E} g(x_l) \tag{19}$$

Subject to:

x_l is determined by the routing solution r

$$\sum_{l \in E} f(x_l) \leq a_{obj_1} \tag{20}$$

$$\sum_{l \in E} g(x_l) \leq a_{obj_2} \tag{21}$$

Obviously, both players can change its threat value to improve its own performance. But neither of them should be allowed to change the threat value arbitrarily, otherwise it may prevent the agreement (leading to no feasible solution to Eq. (19). To analyze such a game in more depth, we first have the following definition.

Definition 4: A threat value game is a tuple $G = (N, (A_i)_{i \in \{Obj.1, Obj.2\}}, (c_i)_{i \in \{Obj.1, Obj.2\}})$, where

1) A_i is the set of available strategies for player $i \in \{Obj.1, Obj.2\}$. In our model, $A_{Obj.1} = [O1_{best}, O1_{worst}]$ and $A_{Obj.2} = [O2_{best}, O2_{worst}]$. We use a_i to denote a special strategy for player i.
2) c_i is the cost for player $i \in \{Obj.1, Obj.2\}$. The value of c_i depends on the solution of optimization problem Eq. (19).

The threat value can also be treated as the performance threshold of each player to sign the agreement. If there exists no feasible solution to Eq. (19) (which means no agreement can be achieved), $c_i = \infty$ for each player. Otherwise,

$$c^*_{obj_1} = \sum_{l \in E} f(r^*) \tag{22}$$

$$c^*_{obj_2} = \sum_{l \in E} g(r^*) \tag{23}$$

where r^* is the routing solution of Eq. (19).

Lemma 1: For each player in the threat value game, reducing its threat value unilaterally will improve its performance or prevent the agreement.

Proof: Without loss of generality, we assume that player *Obj*.2 reduces its threat value unilaterally, and as a result, the threat point is moved from (a_{obj_1}, a_{obj_2}) to (a_{obj_1}, a'_{obj_2}), where $a_{obj_2} > a'_{obj_2}$.

If there exists no feasible solution for the threat point (a_{obj_1}, a'_{obj_2}), the agreement will be broken, and the cost for both players is ∞. Otherwise, we denote the optimal solution before and after player *Obj*.2 reduces its threat value by r and r' respectively, then we know:

$$\begin{aligned}&\left(a_{obj_1} - \sum_{l \in E} f(r)\right)\left(a_{obj_2} - \sum_{l \in E} g(r)\right)\\ &\quad > \left(a_{obj_1} - \sum_{l \in E} f(r')\right)\left(a_{obj_2} - \sum_{l \in E} g(r')\right)\end{aligned} \tag{24}$$

$$\begin{aligned}&\left(a_{obj_1} - \sum_{l \in E} f(r)\right)\left(a'_{obj_2} - \sum_{l \in E} g(r)\right)\\ &\quad > \left(a_{obj_1} - \sum_{l \in E} f(r')\right)\left(a'_{obj_2} - \sum_{l \in E} g(r')\right)\end{aligned} \tag{25}$$

From the Eq. (24) and Eq. (25), we can see:

$$\frac{a_{obj_2} - \sum_{l \in E} g(r)}{a'_{obj_2} - \sum_{l \in E} g(r)} > \frac{a_{obj_2} - \sum_{l \in E} g(r')}{a'_{obj_2} - \sum_{l \in E} g(r')} \tag{26}$$

Eq. (26) can be converted to be:

$$(a'_{obj_2} - a_{obj_2})\left(\sum_{l \in E} g(r') - \sum_{l \in E} g(r)\right) > 0 \tag{27}$$

Since $a_{obj_2} > a'_{obj_2}$, we obtain:

$$\sum_{l \in E} g(r) > \sum_{l \in E} g(r') \tag{28}$$

■

Definition 5: Let S be the set of all the possible cost pairs for two players. We say that the cost pair $(a_{obj_1}, a_{obj_2}) \in S$ is dominated by $(a'_{obj_1}, a'_{obj_2}) \in S$ iff:

1) $a_{obj_1} \geq a'_{obj_1}$ and $a_{obj_2} \geq a'_{obj_2}$.
2) $a_{obj_1} > a'_{obj_1}$ or $a_{obj_2} > a'_{obj_2}$.

Definition 6: A Pareto frontier is a subset of S, such that all the points in the Pareto frontier are not dominated by any points in S.

Theorem 2: Every point (a_{obj_1}, a_{obj_2}) in Pareto frontier is a Nash equilibrium point in the threat value game.

Proof: From Lemma 1, we know that if a player increases its threat value unilaterally, it will increase its cost, so that it is cost inefficient for any player to increase its threat value unilaterally. On the other hand, if a player reduces its threat value, there will be no feasible solution, which can be proven by contradiction as follows:

Without loss of generality, we assume that player $Obj.2$ reduces its threat value to $a'_{obj_2} < a_{obj_2}$ and there exists a feasible solution x' to Eq. (19). From Lemma 1, we know that:

$$\sum_{l \in E} g(r') < \sum_{l \in E} g(r) \tag{29}$$

Combining with Eq. (24), we have:

$$\sum_{l \in E} f(r') > \sum_{l \in E} f(r) \tag{30}$$

where r is the optimal routing solution to Eq. (19) before the player $Obj.2$ reduces its threat value. Since (a_{obj_1}, a_{obj_2}) is not dominated by any point in S,

$$a_{obj_1} = \sum_{l \in E} f(r) \tag{31}$$

$$a_{obj_2} = \sum_{l \in E} g(r) \tag{32}$$

must be satisfied. Otherwise (a_{obj_1}, a_{obj_2}) will be dominated by the cost pair associated with the solution of Eq. (19). ■

B. How to Derive a Fair Solution

From Lemma 1, when each player pursues its performance selfishly, each of them wants to set its threat value to be the minimal value in its own strategy space. Unfortunately, the threat value combined with the best performance of each player will make the optimization problem of Eq. (19) infeasible and prevent the agreement achievement. In order to avoid such an undesirable situation, we modify the model formulated in the previous subsection to be a repeated Nash bargaining problem as shown in Fig. 1.

In this repeated Nash bargaining model, each player changes its threat value stepwise to optimize it performance. Let $(a^{(k)}_{obj_1}, a^{(k)}_{obj_2})$ denote the threat point during the k^{th}-iteration, and $r^{(k)}$ be the optimal solution to Eq. (19) corresponding to threat point $(a^{(k)}_{obj_1}, a^{(k)}_{obj_2})$. We assume that each player updates its threat value during the k^{th}-iteration as a function of its current threat value ($a^{(k)}_{obj_1}$ for player $Obj.1$ and $a^{(k)}_{obj_2}$ for player $Obj.2$) and the optimal solution to Eq. (19) ($x^(k)$). Therefore, we have:

$$a^{k+1}_{obj_1} = h_{obj_1}(a^k_{obj_1}, r^{(k)}) \tag{33}$$

$$a^{k+1}_{obj_2} = h_{obj_2}(a^k_{obj_2}, r^{(k)}) \tag{34}$$

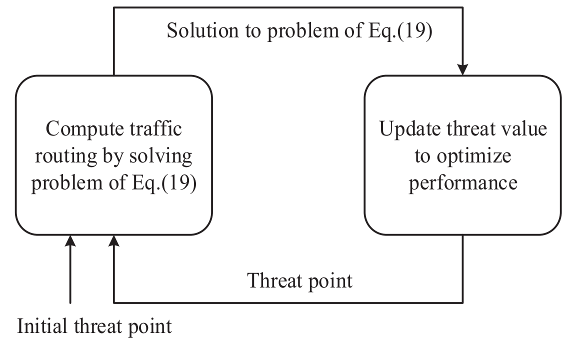


Fig. 1. Procedure of repeated threat value game.

To guarantee the fairness of the solution, we first find a threat point to induce a fair solution as follows.

Theorem 3: If the cost function of both $Obj.1$ and $Obj.2$, i.e. $f(.)$ and $g(.)$ for all $l \in E$, are continuous, then the threat point of problem Eq. (19) $(O1_{worst}, O2_{worst})$ will yield a fair solution.

Proof: Let r^* be the solution to Eq. (19) with $(a^{(k)}_{obj_1}, a^{(k)}_{obj_2})= (O1_{worst}, O2_{worst})$ and we denote the cost of $Obj.1$ and $Obj.2$ associating with the solution to problem Eq. (19) by s_{obj_1} and s_{obj_2}, respectively.

Construct a new bargaining problem (S', d'), by setting $s'_{obj_2} = \alpha s_{obj_2} + \beta$ and $d'_{obj_2} = \alpha d_{obj_2} + \beta$, where

$$\alpha = \frac{O1_{worst} - O1_{best}}{O2_{worst} - O2_{best}} \tag{35}$$

$$\beta = \frac{O1_{best} O2_{worst} - O1_{worst} O2_{best}}{O2_{worst} - O2_{best}} \tag{36}$$

The cost of $Obj.1$ and $Obj.2$ in (S', d') are denoted by s'_{obj_1} and s'_{obj_2}, respectively. In such a bargaining problem, we have:

$$O2'_{worst} = O1'_{worst} \tag{37}$$

$$O2'_{best} = O1'_{best} \tag{38}$$

where $O1'_{best}$ and $O1'_{worst}$ (or $O2'_{best}$ and $O2'_{worst}$) are in the best and worst case of $Obj.1$ (or $Obj.2$) cost problem, respectively. Due to the fact that $f(.)$ and $g(.)$ are continuous and non-decreasing for all $l \in E$, the cost function of $Obj.1$ and $Obj.2$ have the same range in (S', d').

If (y_{obj_1}, y_{obj_2}) is a feasible solution of (S', d'), then we consider the following equation group:

$$\begin{cases} \sum_{l \in E} [\alpha f(x_l) + \beta] = y_{obj_2} \\ \sum_{l \in E} [\alpha g(x_l) + \beta] = y_{obj_1} \\ flow\ conservation\ equations \end{cases} \tag{39}$$

As $f(x)$ and $g(x)$ are continuous function, and the left hand side of the first two equation has the converse trend according to the change of $\{x_l\}$, a solution must exist. It means that (y_{obj_1}, y_{obj_2}) is also a feasible outcome of (S', d'). Hence, $s'_{obj_1} = s'_{obj_2}$ must be satisfied in (S', d'). Based on the Nash bargaining's property of invariance to equivalent utility representation, we obtain:

$$O1_{best} = \alpha O2_{best} + \beta \tag{40}$$

$$s_{obj_1} = \alpha s_{obj_2} + \beta \tag{41}$$
$$O1_{worst} = \alpha O2_{worst} + \beta \tag{42}$$

We subtract Eq. (41) from Eq. (42):

$$O1_{worst} - s_{obj_1} = \alpha(O2_{worst} - s_{obj_1}) \tag{43}$$

Similarly, we subtract Eq. (40) from Eq. (42):

$$O1_{worst} - O1_{best} = \alpha(O2_{worst} - O2_{best}) \tag{44}$$

We divide Eq. (43) by Eq. (44):

$$\frac{O1_{worst} - s_{obj_1}}{O1_{worst} - O1_{best}} = \frac{O2_{worst} - s_{obj_2}}{O2_{worst} - O2_{best}} \tag{45}$$

■

Theorem 3 gives an initial threat point which can yield a fair tradeoff between *Obj*.1 and *Obj*.2. Such a threat point is easy to determine as it correspond to the worst case performance of *Obj*.1 and *Obj*.2, respectively, independent of the other objective. The following mechanism is designed to prevent players from deviating from such a fair solution when they are optimizing its performance selfishly by changing its threat value.

Mechanism 1: Let $(a_{obj_1}^{(k)}, a_{obj_2}^{(k)})$ denote the threat point during the k^{th}-iteration and $x^{(k)}$ be the optimal solution to Eq. (19), we initialize the threat point at $(O1_{worst}, O2_{worst})$ and the threat value updating of each player must satisfy the following two constraints:

$$\begin{aligned} a_{obj_1}^{(k+1)} &\geq a_{obj_1}^{(k)} - \frac{a_{obj_1}^{(k)} - \sum_{l\in E} f(r^{(k)})}{2} \\ &= \frac{1}{2}\left(a_{obj_1}^{(k)} + \sum_{l\in E} f(r^{(k)})\right) \end{aligned} \tag{46}$$

$$\begin{aligned} a_{obj_2}^{(k+1)} &\geq a_{obj_2}^{(k)} - \frac{a_{obj_2}^{(k)} - \sum_{l\in E} g(r^{(k)})}{2} \\ &= \frac{1}{2}\left(a_{obj_2}^{(k)} + \sum_{l\in E} g(r^{(k)})\right) \end{aligned} \tag{47}$$

With the two constraints Eq. (46) and Eq. (47), each player can only claim to occupy half of the performance gap between its threat value and its cost corresponding to the solution of Eq. (19).

Lemma 2: Let r^* be the optimal solution of optimization problem Eq. (19) associated with threat point (a_{obj_1}, a_{obj_2}), then r^* is also the optimal solution of problem Eq. (19) associated with the threat point $(\frac{1}{2}(a_{obj_1} + \sum_{l\in E} f(r^*)), \frac{1}{2}(a_{obj_2} + \sum_{l\in E} g(r^*)))$.

Proof: r^* is a feasible solution for the problem Eq. (19) when the threat point is (a_{obj_1}, a_{obj_2}), so:

$$\sum_{l\in E} f(r^*) \leq a_{obj_1} \tag{48}$$

Then:

$$\sum_{l\in E} f(r^*) = \frac{1}{2}\left(a_{obj_1}^{(k)} + \sum_{l\in E} f(r^{(k)})\right) \tag{49}$$

Similarly,

$$\sum_{l\in E} g(r^*) = \frac{1}{2}\left(a_{obj_2}^{(k)} + \sum_{l\in E} g(r^{(k)})\right) \tag{50}$$

The above means that r^* is also a feasible solution to the optimization problem Eq. (19) associated with the threat point

$$\left(\frac{1}{2}\left(a_{obj_1} + \sum_{l\in E} f(r^*)\right)\right), \left(\frac{1}{2}\left(a_{obj_2} + \sum_{l\in E} g(r^*)\right)\right) \tag{51}$$

On the other hand, the objective of Eq. (19) is equivalent to maximize:

$$log\left(a_{obj_1} - \sum_{l\in E} f(r)\right) + log\left(a_{obj_2} - \sum_{l\in E} g(r)\right) \tag{52}$$

Since r^* is the optimal solution of Eq. (19) associated with the threat point (a_{obj_1}, a_{obj_2}), so we have:

$$\frac{\sum_{l\in E} \nabla f(r^*)}{a_{obj_1} - \sum_{l\in E} \nabla f(r^*)} + \frac{\sum_{l\in E} \nabla g(r^*)}{a_{obj_2} - \sum_{l\in E} \nabla g(r^*)} = 0 \tag{53}$$

When the threat point is:

$$\left(\frac{1}{2}\left(a_{obj_1} + \sum_{l\in E} f(r^*)\right)\right), \left(\frac{1}{2}\left(a_{obj_2} + \sum_{l\in E} g(r^*)\right)\right), \tag{54}$$

we should maximize:

$$\begin{aligned} F(r) = log&\left(\frac{1}{2}\left(a_{obj_1} + \sum_{l\in E} f(r^*)\right) - \sum_{l\in E} f(r)\right) \\ &+ log\left(\frac{1}{2}\left(a_{obj_2} + \sum_{l\in E} g(r^*)\right) - \sum_{l\in E} g(r)\right) \end{aligned} \tag{55}$$

The gradient of $F(r)$ is:

$$\begin{aligned} \nabla F(r) = &\frac{\sum_{l\in E} \nabla f(r)}{\frac{1}{2}\left(a_{obj_1} + \sum_{l\in E} f(r^*)\right) - \sum_{l\in E} f(r)} \\ &+ \frac{\sum_{l\in E} \nabla g(r)}{\frac{1}{2}\left(a_{obj_2} + \sum_{l\in E} g(r^*)\right) - \sum_{l\in E} g(r)} \end{aligned} \tag{56}$$

We should note that $r = r^*$ will yield $\nabla F(r) = 0$. Due to the fact that there is only one optimal solution for each Nash bargaining problem, accordingly, r^* is also the optimal solution of Eq. (19) associated with the threat point

$$\left(\frac{1}{2}\left(a_{obj_1} + \sum_{l\in E} f(r^*)\right)\right), \left(\frac{1}{2}\left(a_{obj_2} + \sum_{l\in E} g(r^*)\right)\right). \tag{57}$$

■

Theorem 4: If each player optimizes its performance selfishly by changing its threat value under Mechanism 1, traffic routing will be constant as if the threat point was never changed.

Proof: During k^{th}-iteration, each player can at most reduce its threat value to:

$$\left(\frac{1}{2}\left(a_{obj_1}^{(k)} + \sum_{l\in E} f(r^{(k)})\right)\right) and \left(\frac{1}{2}\left(a_{obj_2}^{(k)} + \sum_{l\in E} g(r^{(k)})\right)\right) \tag{58}$$

which are larger than:

$$\sum_{l \in E} f(r^{(k)}) \quad and \quad \sum_{l \in E} g(r^{(k)}) \tag{59}$$

respectively. So the reduction of threat value will not lead to agreement break-down and an infinite cost to the players.

According to Lemma 1, player *Obj*.1 will reduce its threat value to be $(\frac{1}{2}(a_{obj_1}^{(k)} + \sum_{l \in E} f(r^{(k)}))$ and player *Obj*.2 will reduce its threat value to be $(\frac{1}{2}(a_{obj_2}^{(k)} + \sum_{l \in E} g(r^{(k)}))$ during k^{th}-iteration.

From Lemma 2, we know that the optimal solution of Eq. (19) will be the same as if the threat point was never changed. ■

Corollary 1: If we set the initial threat point at any points on the line connecting threat point (a_{obj_1}, a_{obj_2}) and the optimal solution of (19) corresponding to this threat point, we will derive the same solution as if the initial threat point is (a_{obj_1}, a_{obj_2}).

Proof: This corollary can be proven in the same method as Lemma 2. Due to space limitation, we omit the detail of proof here. ■

Corollary 1 tells us that all the points on the line connecting $(O1_{worst}, O2_{worst})$ will lead to a fair solution by setting it as the threat point of Eq. (19).

Corollary 2: If the initial threat point is not set as $(O1_{worst}, O2_{worst})$ or any point along the line connecting $(O1_{worst}, O2_{worst})$ to the optimal solution to Eq. (19), then the solution will not converge to the fair tradeoff.

Intuitively, this is because starting with a different threat point than $(O1_{worst}, O2_{worst})$ hides some of the players optimization space information. Note that although this corollary states that the fair solution cannot be derived from any arbitrary initial threat points, it has no negative implication as one can easily find (and use) the initial threat point $(O1_{worst}, O2_{worst})$.

C. Conversion to Convex Optimization Form

The optimization problem Eq. (19) is not in a convex optimization form. To solve it more efficiently, we should convert it into the form of standard convex optimization form without changing its solution.

Theorem 5: If the optimization problem Eq. (19) is feasible, its solution will be the same with that of problem Eq. (60):

Maximize:

$$log(a_{obj_1} - t_{obj_1}) + log(a_{obj_2} - t_{obj_2}) \tag{60}$$

Subject to:

x_l is determined by the routing solution r

$$t_{obj_1} \geq \sum_{l \in E} f(x_l) \tag{61}$$

$$t_{obj_2} \geq \sum_{l \in E} g(x_l) \tag{62}$$

Proof: To maximize objective of Eq. (60), the variable t_{obj_1} and t_{obj_2} should be as little as possible. Therefore, $t_{obj_1} = \sum_{l \in E} f(x_l)$ and $t_{obj_2} = \sum_{l \in E} g(x_l)$ must be satisfied in the optimal solution. So that problem Eq. (60) is equivalent to maximize:

$$log\left(a_{obj_1} - \sum_{l \in E} f(x_l)\right) + log\left(a_{obj_2} - \sum_{l \in E} g(x_l)\right) \tag{63}$$

When the problem Eq. (19) is feasible, we have:

$$\sum_{l \in E} f(x_l) \leq a_{obj_1} \tag{64}$$

$$\sum_{l \in E} g(x_l) \leq a_{obj_2} \tag{65}$$

In this case, the variable maximizing the objective of Eq. (19) also maximizes Eq. (63), because $log(.)$ is an increasing function of its argument on R^+. ■

Theorem 6: If $f(.)$ and $g(.)$ are both convex functions, problem Eq. (19) is a convex optimization problem.

Proof: Theorem 6 can be verified easily by checking that it does satisfy the definition of convex optimization. ■

Theorem 5 and Theorem 6 guarantee the Nash bargaining solution can be solved efficiently.

VI. Case Studies

In this section, we will present two case studies for our framework. The first one is how to derive a fair tradeoff between load balancing and energy efficiency, which are two common objectives in traffic engineering. The second one is on inter-domain traffic routing with the objective to minimize the energy consumption for each domain. These case studies not only present how our framework works but also verify the correctness of our work. All the computations are carried out on a computer with Duo-Core 2.20 GHz intel CPU using CVX1.22 [17].

A. Load Balancing vs. Energy Efficiency

Load balancing and energy efficiency are two common objectives in traffic engineering. However, the optimal solution for each objective is different from that to the other one. Accordingly, how to find a traffic routing and scheduling scheme that fairly optimizes both objectives is an important issue. This subsection is exactly on how to find such a fair solution with the framework that we propose.

1) Load Balancing Model: Load balancing is a classic objective for traffic engineering in telecom networks [18]. The main goal of load balancing is to enhance the performance of network traffic while utilizing network resource economically. To achieve load balancing, traffic should be distributed among all the links uniformly, so as to reduce the carried traffic on each link. It could improve the performance of network traffic, in terms of reduced queueing delay, and enhanced network scalability. we first describe the network model and formulate the standard load balancing optimization problem.

Consider a network represented by a directed graph G=(V, E), where V denotes the set of nodes and E denotes the set of directed physical links. Let $P_{ij} = \{p_{ij}^k\}$ denote the set of all the paths from i to j, where p_{ij}^k denote the kth path from i to j and $i, j \in V$. A link l on the kth path from i to j will be referred to as $l \in \{p_{ij}^k\}$. We also use $\{x_{ij}^k\}$ to denote the rate of flow on the kth path from i to j, x_l to denote the rate of flow on link $l \in E$, and d_{ij} to denote the traffic demand from i to j. The capacity of link $l \in E$ is $c_l > 0$.

Based on the above discussion, the Load Balancing (i.e., LB) optimization problem can be formulated as follows:

Minimize:

$$\sum_l f(x_l) \tag{66}$$

Subject to:

$$x_l = \sum_{i,j:i \neq j} \sum_{k:l \in p_{ij}^k} x_{ij}^k \tag{67}$$

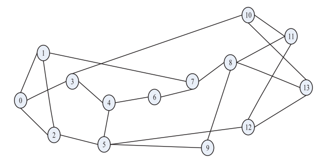
$$x_l \leq c_l \forall l \in E \tag{68}$$

$$\sum_k x_{ij}^k = d_{ij} \quad \forall i, j \neq i \tag{69}$$

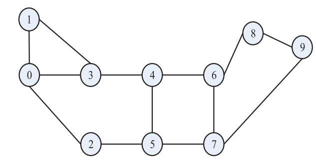
where $f(.)$ represents the congestion link cost. In this paper, we assume that $f(.)$ is a convex, continuous and non-decreasing function of x_l. Using such a cost function in the optimization objective will penalize high link utilization and balance the load in the networks. More specifically, a queueing theory style congestion cost function such as $f(x_l)$=$x_l/(c_l$-$x_l)$ is usually adopted for this purpose, as it has the desired properties of being convex, continuous and non-decreasing with x_l. In addition, by using this congestion cost function, the link that had higher load (or utilization) will have a higher cost than the links with a lower load, so that traffic will be distributed uniformly in the network in the optimal solution.

2) Energy Efficiency Model: While the load balancing problem usually assumes that the congestion cost function of each link is a convex, continuous and non-decreasing function of the amount of traffic carried by the link, there are two popular models that relate power consumption to traffic load: *speed scaling* and *powering down*. In the former model, the processing (or transmission) speed of a network element is adjusted (and accordingly, the corresponding energy consumption also varies) according to the carried traffic load. In the latter model, one tries to turn down any elements carrying no traffic load at all to save energy.

We focus on the speed scaling model in this case study because it is more realistic. In addition, the powering down model focuses on optimizing an individual element in isolation [19], but we want to examine optimization problems that arise in a network consisting of multiple network elements. In particular, we assume that the energy consumption in the network can all be represented in terms of the energy consumption of the links, which can be characterized by energy curve $g(x_l)$. The goal of energy efficiency is to minimize the total energy cost of all the links in the network. Accordingly, the Energy Efficiency (i.e., EE) optimization problem can be formulated as follows:



(a) NSFNET topology



(b) Abilene topology

Fig. 2. Simulation topology.

Minimize:

$$\sum_l g(x_l) \tag{70}$$

Subject to: Eq. (67-69)

Note that, the energy curve is often modeled by a polynomial function $g(x_l)$=$\mu_l x_l^\alpha$, where μ_l and α are device specific parameters. For example, the value of the α is 1.11, 1.66, and 1.62 for Intel PXA 270, a TCP offload engine, and Pentium M 770, respectively [20]. Accordingly, we will set α to be 1.5 in the case study of the paper.

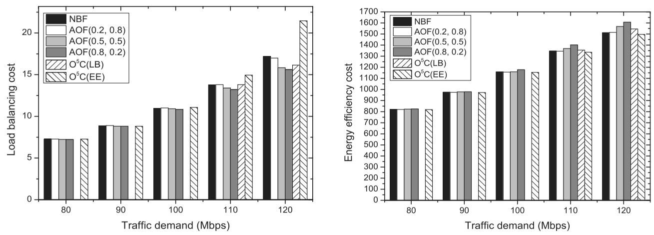
3) Simulation Results: To approve the efficiency of our framework, simulation experiments are performed on NSFNET topology (14 nodes, 21 links) and Abilene topology (10 nodes, 13 links) (shown in Fig. 2). Each link of two networks is bidirectional and the capacity of each link is 1000Mbps. We randomly choose one third of all node pairs generating traffic. The traffic demand between node pair is random with a uniform distribution $U[80, 120]$Mbps. To route the traffic in the network, we find two link-disjoint shortest routes between each node pair. We set the energy curve of link l to be $g(x_l) = 0.01(x_l)^{1.5}$, which means μ_l=0.01.

In the simulation, we compare our proposed Nash Bargaining Framework (NBF) with Aggregate Objective Function (AOF) and Optimizing One Objective with Other Objective as Constraint (O^5C). AOF and O^5C are both traditional multi-objective optimization methods, and we have summarized them in the Section I. We specially note that since each objective may have a different order of magnitude in the case, to guarantee fairness between load balancing and energy efficiency, we construct a new objective for AOF:

$$\alpha * EE_{best} * LB + \beta * LB_{best} * EE \tag{71}$$

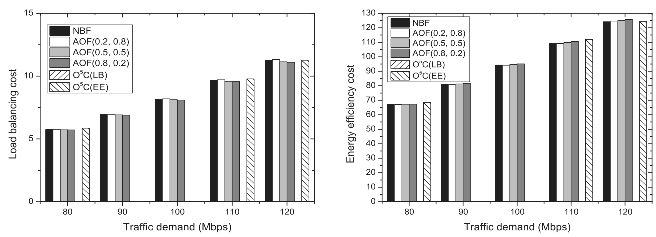
where α represents load balancing weight, β represents energy efficiency weight, α+β=1; LB and EE represents the load balancing objective (see in Eq. (66)) and energy efficiency objective (see in Eq. (70)), respectively; EE_{best} and LB_{best} represents the optimal result of energy efficiency model and load balancing model, respectively. For AOF, we consider different values of (α, β), including: AOF(0.2, 0.8), AOF(0.5, 0.5) and AOF(0.8, 0.2). For O^5C, we first optimize LB with the constraint $EE <$ 0.95*EE_{worst}, and we call it as O^5C(LB). Second, we optimize EE with the constraint $LB <$ 0.95*LB_{worst}, and we call it as O^5C(EE). From Eq. (11) and Eq. (13), we calculate the worst case cost of LB and EE.

Fig. 3 and Fig. 4 shows simulation results for NSFNET and Abilene, respectively. From the two figures we can see that load balancing cost and energy efficiency cost of each method



(a) load balancing cost (b) energy efficiency cost

Fig. 3. Simulation results for NSFNET.



(a) load balancing cost (b) energy efficiency cost

Fig. 4. Simulation results for Abilene.

both increase with the increase of traffic demand. We specially note that in some scenarios there is no feasible solution for O^{5}C method. Thus the corresponding column bar is not plotted in the figure. For AOF, with the increase of load balancing (or energy efficiency) weight, the corresponding load balancing (or energy efficiency) cost would decrease, but energy efficiency (or load balancing) cost would increase. This means that AOF can improve performance of one objective while sacrificing performance of the other. The biggest problem of AOF is to set appropriate weight. More specifically, if we use the same weights for the two objectives (i.e., AOF(0.5, 0.5)), the fairness cannot be guaranteed as two objectives have significantly different orders of magnitude and different sizes of optimization space. For O^{5}C, it is difficult to set threshold value for the corresponding constraint since no one knows the desired specific performance. In some scenarios, unsuitable threshold value often results in no feasible solution to the problem. In our proposed NBF, we set appropriate threat point to derive Pareto-efficient and fair solution. Each objective achieves a equal proportional performance improvement over optimization space.

From Fig. 3 and Fig. 4, we also find that two objectives have different optimization spaces. For example, when traffic load is $U[100]$Mbps in NSFNET, the best case cost of load balancing is 11.0943 while the worst case cost is 12.1918; the best case cost of energy efficiency is 1170 while the worst case cost is 1228. This means that the optimization space of energy efficiency is much larger than that of load balancing in the case study scenario. Thus in NBF we set the threat point to be (12.1918, 1228) to derive a fair solution. Fig. 5 shows the Pareto frontier and NBF solution for the scenario. From Fig. 5, we can see that the fair solution derived by NBF is close to the optimal result for both load balancing and energy efficiency.

Table I and Table II further shows Ratio of Optimization Performance Improvement (ROPI) for NSFNET and Abilene,

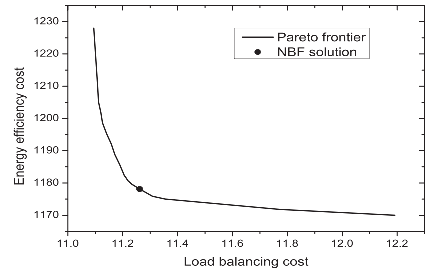


Fig. 5. Pareto frontier and NBF solution in NSFNET.

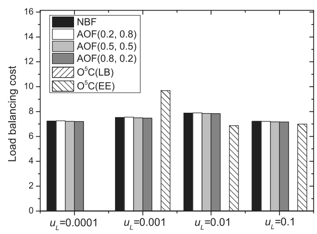
TABLE I
ROPI VS TRAFFIC DEMAND FOR NSFNET

Mbps	80	90	100	110	120
NBF	(0.7350, 0.7350)	(0.8163, 0.8163)	(0.8470, 0.8470)	(0.8735, 0.8735)	(0.8867, 0.8867)
AOF(0.2,0.8)	(0.5557, 0.8453)	(0.7130, 0.8258)	(0.7681, 0.8714)	(0.7658, 0.8833)	(0.7881, 0.8616)
AOF(0.5,0.5)	(0.9069, 0.3697)	(0.9654, 0.5126)	(0.8731, 0.7833)	(0.9139, 0.6064)	(0.9607, 0.4553)
AOF(0.8,0.2)	(0.9984, 0.0139)	(0.9804, 0.4265)	(0.9802, 0.3529)	(0.9802, 0.3529)	(0.9961, 0.1569)
O^{5}C(LB)	–	–	–	(0.7670, 0.8241)	(0.9125, 0.6299)
O^{5}C(EE)	(0.4314, 0.8837)	(0.7833, 0.6350)	(0.7005, 0.8958)	(0.3284, 0.9874)	(0.1675, 0.9983)

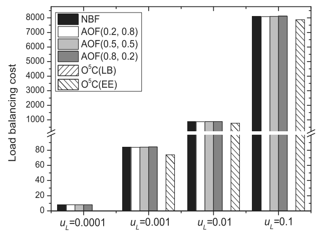
TABLE II
ROPI VS TRAFFIC DEMAND FOR ABILENE

Mbps	80	90	100	110	120
NBF	(0.7350, 0.7350)	(0.8163, 0.8163)	(0.8470, 0.8470)	(0.8735, 0.8735)	(0.8867, 0.8867)
AOF(0.2,0.8)	(0.5557, 0.8453)	(0.7130, 0.8258)	(0.7681, 0.8714)	(0.7658, 0.8833)	(0.7881, 0.8616)
AOF(0.5,0.5)	(0.9069, 0.3697)	(0.9654, 0.5126)	(0.8731, 0.7833)	(0.9139, 0.6064)	(0.9607, 0.4553)
AOF(0.8,0.2)	(0.9984, 0.0139)	(0.9804, 0.4265)	(0.9802, 0.3529)	(0.9802, 0.3529)	(0.9961, 0.1569)
O^{5}C(LB)	–	–	–	(0.7670, 0.8241)	(0.9125, 0.6299)
O^{5}C(EE)	(0.4314, 0.8837)	(0.7833, 0.6350)	(0.7005, 0.8958)	(0.3284, 0.9874)	(0.1675, 0.9983)

respectively. ROPI represents the performance improvement in the whole optimization space. The calculation of ROPI is shown Eq. (72), which comes from Eq. (14) of *Definition 2*. The bigger value of ROPI means the better optimization effect. For each item of the two tables, the first value of bracket is ROPI of load balancing, and the second one is ROPI of energy efficiency. The item "_" denotes no feasible solution. The ROPI value of the two tables is calculated from load balancing cost and energy efficiency cost shown in Fig. 3 and Fig. 4. As a relative value, ROPI can more clearly reflect the fairness and effectiveness of optimization result. From the two tables we can see that for NBF two ROPI values of each item are both equal and at least bigger than 0.73. This means that the two objectives get the same percentage of performance improvement over its optimization space. That is to say, ROPI values of NBF satisfy *Definition 2*. For the method of AOF and O^{5}C, the two values of ROPI have significant difference. The performance improvement of one objective is at expense of the other. In conclusion, a fair and effective solution is difficult to obtain by using the

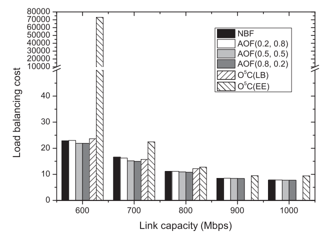


(a) load balancing cost

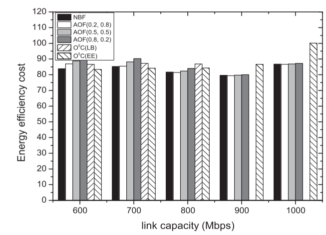


(b) energy efficiency cost

Fig. 6. simulation results with variation of μ_l for NSFNET.



(a) load balancing cost



(b) energy efficiency cost

Fig. 7. simulation results with variation of link capacity for NSFNET.

TABLE III
ROPI WITH VARIATION OF μ_l FOR NSFNET

μ_l	0.0001	0.001	0.01	0.1
NBF	(0.7625, 0.7625)	(0.7724, 0.7724)	(0.7641, 0.7641)	(0.8414, 0.8414)
AOF(0.2,0.8)	(0.6044, 0.8317)	(0.6027, 0.8939)	(0.6192, 0.8370)	(0.6410, 0.7484)
AOF(0.5,0.5)	(0.8934, 0.4880)	(0.8753, 0.6458)	(0.8972, 0.4955)	(0.9119, 0.3995)
AOF(0.8,0.2)	(0.9836, 0.2380)	(0.9778, 0.3089)	(0.9868, 0.2507)	(0.9854, 0.1874)
O^5C(LB)	–	–	–	–
O^5C(EE)	–	(0.8102, 0.7719)	(0.5519, 0.7589)	(0.4581, 0.6897)

TABLE IV
ROPI WITH VARIATION OF LINK CAPACITY FOR NSFNET

Mbps	600	700	800	900	1000
NBF	(0.9430, 0.9430)	(0.8453, 0.8453)	(0.8405, 0.8405)	(0.7418, 0.7418)	(0.7526, 0.7526)
AOF(0.2,0.8)	(0.9346, 0.6199)	(0.7839, 0.8275)	(0.7207, 0.8966)	(0.6676, 0.7896)	(0.6778, 0.7634)
AOF(0.5,0.5)	(0.9878, 0.3804)	(0.9528, 0.4608)	(0.8614, 0.7275)	(0.9527, 0.3807)	(0.9232, 0.4508)
AOF(0.8,0.2)	(0.9988, 0.2795)	(0.9953, 0.1593)	(0.9797, 0.3182)	(0.9896, 0.2300)	(0.9872, 0.2192)
O^5C(LB)	(0.9687, 0.6278)	(0.9069, 0.6125)	(0.7771, 0.7637)	–	–
O^5C(EE)	(0.6573, 0.9993)	(0.2027, 0.9947)	(0.4687, 0.9137)	(0.8548, 0.6298)	(0.7043, 0.8728)

AOF and O^5C method.

$$ROPI(Obj) = \frac{Obj_{worst} - s_{Obj}}{Obj_{worst} - Obj_{best}} \tag{72}$$

Intuitively, for the energy curve function $\mu_l x_l^{1.5}$, the value of μ_l would affect the magnitude of energy efficiency cost. We evaluate the impact of μ_l on the two objectives. The simulation topology is NSFNET. We assume that traffic demand between node pair is $U[80]$Mbps and the capacity of bidirectional link is 1000Mbps. Fig. 6 shows simulation results for NSFNET with variation of μ_l. Table III shows the corresponding ROPI. In Fig. 6, with the increase of μ_l, load balancing cost has little change, but energy efficiency cost dramatically increases to higher magnitude. From Table III, we can see that our proposed NBF can derive a fair and efficient solution even when the value of μ_l increases from 0.0001 to 0.1.

Since load balancing cost is effected by link capacity, we evaluate the impact of link capacity on the two objectives. The simulation topology is NSFNET. We assume that traffic demand between node pair is $U[80]$Mbps and the energy curve is $0.01x_l^{1.5}$. Fig. 7 shows simulation results for NSFNET with variation of link capacity. Table IV shows the corresponding ROPI. In Fig. 7, with the increase of link capacity, load balancing cost obviously decreases, but energy efficiency cost has little change. From Table III, we can see that our proposed NBF performs best in terms of fairness and efficiency among all methods.

B. *Energy Efficiency for Multi-domain Networks*

Inter-domain traffic engineering is widely used in current Internet which is operated by multiple Internet Service Providers (ISPs). Usually, each ISP can only determine the traffic routing in the domain operated by itself and optimize its own objective, such as energy efficiency and load balancing. However, how to arrange the inter-domain traffic may greatly impact the performance of all the neighboring domains, and different domains may require different inter-domain routing method. Accordingly, the framework proposed in this paper is suitable to negotiate an inter-domain routing method that is fair for all the neighboring domains. In this section, we will show how to apply our framework into the inter-domain traffic engineering with the objective energy efficiency.

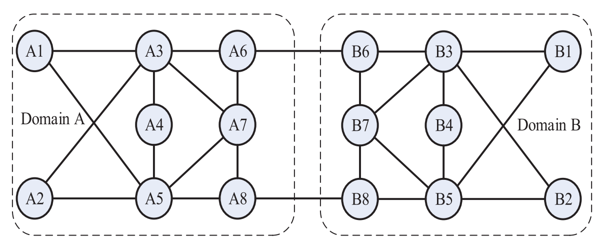


Fig. 8. Sample network with two routing domains.

1) Network Model: For simplicity, we consider the network shown in Fig. 8. There are two domains in the network and connected by two inter-domain links. We assume that the energy consumed by the inter-domain links is spread half to each domain. Therefore, the energy consumption of each domain can be calculated by

$$\sum_{l \in domain\_i} g(x_l) + \frac{1}{2} \sum_{l \in inter\_domain\_links} g(x_l) \tag{73}$$

where $i \in \{A, B\}$ is the index of each domain.

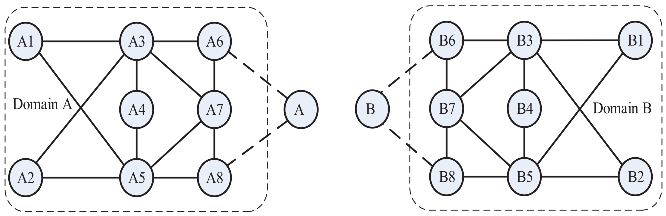


Fig. 9. Sample network with virtual nodes.

In summary, the energy efficiency model of each domain $i \in \{A, B\}$ can be formulated as

$$minimize \sum_{l \in domain\_i} \mu_l x_l^{1.5} + \sum_{l \in inter\_domain\_links} \frac{\mu_l x_l^{1.5}}{2} \tag{74}$$

subject to Eq. (67-69)

2) How to Derive Threat Value: When applying our framework to derive a fair solution, the most important is to find the threat value for each domain. As discussed in Theorem 3, in order to get a fair solution, we should set the threat value of each domain as its worst performance. According to the Definition 1, the worst performance of a domain is associated with the best performance of the other domain, i.e. determine the inter-domain traffic routing based on the optimal solution of the other domain. Therefore, the key point of applying our framework is how to get the best performance of each domain.

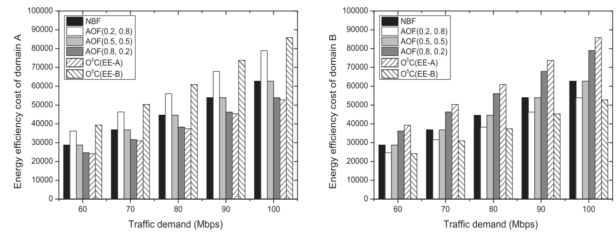
To this end, we should optimize the energy efficiency of each domain. Consider the fact that the performance of each domain is independent on the traffic routing in the other domain, we introduce a virtual node for each domain and treat it as the sink of all the inter-domain flows as shown in Fig. 9. The energy consumption on the links connecting edge node and the virtual node (say them as virtual links) is the same as half of the energy consumption on the inter-domain links. And then, we optimize the energy efficiency through an intra-domain global optimization. After we get the intra-domain solution, the traffic on the virtual links is associated with the traffic on the inter-domain links. With this inter-domain traffic routing, we can derive the worst performance of the other domain which should be set as the threat value.

3) Simulation Results: To approve the efficiency of our framework, simulation experiment is performed on the sample network (shown in Fig. 8). Each link of the network is bidirectional and without loss of generality, we assume that the capacity of each link is 1000Mbps. The traffic demand is random with a uniform distribution $U[60, 100]$Mbps between each inter-domain node pair. To route the traffic in the network, we find two link-disjoint shortest routes between each node pair. We set the energy curve of link l to be $g(x_l) = 0.01(x_l)^{1.5}$.

In the simulation, we still compare our proposed NBF with AOF and O^{5}C. Since the two objectives are both energy efficiency cost in the case, we can directly use weighted linear sum of two objectives for AOF:

$$\alpha * EE(A) + \beta * EE(B) \tag{75}$$

where α represents energy efficiency weight for domain A, β represents energy efficiency weight for domain B,



(a) energy efficiency cost for domain A (b) energy efficiency cost for domain B

Fig. 10. simulation results for sample network of two domains.

TABLE V
ROPI VS TRAFFIC DEMAND FOR SAMPLE NETWORK OF TWO DOMAINS

Mbps	60	70	80	90	100
NBF	(0.7292, 0.7292)	(0.7292, 0.7292)	(0.7292, 0.7292)	(0.7293, 0.72923)	(0.7385, 0.7385)
AOF(0.2,0.8)	(0.3015, 0.9643)	(0.3012, 0.9646)	(0.3012, 0.9645)	(0.3012, 0.9645)	(0.3012, 0.9645)
AOF(0.5,0.5)	(0.7294, 0.7291)	(0.7292, 0.7294)	(0.7292, 0.7293)	(0.7293, 0.7293)	(0.7292, 0.7293)
AOF(0.8,0.2)	(0.9646, 0.3011)	(0.9644, 0.3014)	(0.9644, 0.3013)	(0.9645, 0.3012)	(0.9644, 0.3014)
O^{5}C(EE-A)	(0.9949, 0.1193)	(0.9946, 0.1193)	(0.9947, 0.1193)	(0.9947, 0.1193)	(0.9947, 0.1193)
O^{5}C(EE-B)	(0.1193, 0.9946)	(0.1193, 0.9948)	(0.1193, 0.9948)	(0.1193, 0.9947)	(0.1193, 0.9948)

$\alpha+\beta=1$; $EE(A)$ and $EE(B)$ represents the energy efficiency objective for domain A and domain B (see in Eq. (74)), respectively. For AOF, we consider different values of (α, β), including: AOF(0.2, 0.8), AOF(0.5, 0.5) and AOF(0.8, 0.2). For O^{5}C, we first optimize $EE(A)$ with the constraint $EE(B) < 0.95{*}EE(B)_{worst}$, and we call it as O^{5}C(EE-A). Second, we optimize $EE(B)$ with the constraint $EE(A) < 0.95{*}EE(A)_{worst}$, and we call it as O^{5}C(EE-B). From Eq. (11) and Eq. (13), we calculate the worst case cost of $EE(A)$ and $EE(B)$.

Fig. 10 shows simulation results for sample network of two domains. Table V shows the corresponding ROPI. For each item of Table V, the first value of bracket is ROPI of energy efficiency for domain A, and the second one is ROPI of energy efficiency for domain B. We can see that in NBF a solution with fair tradeoff is derived and energy efficiency of each domain get the same percentage of performance improvement. For the method of AOF and O^{5}C, the performance improvement of energy efficiency for two domains has significant difference. This is because the two methods improve energy efficiency of one domain by sacrificing energy efficiency of the other. Thus a fair solution cannot be derived by the two methods.

In addition, we also calculate the overall energy efficiency cost of two domains. By Global Optimization (GO), we can get the optimal overall energy efficiency cost. Fig. 11 shows overall energy efficiency cost for sample network of two domains. From the figure, we can see that our proposed NBF is most close to the result of GO in all multi-objective optimization methods. There is only 0.1% gap between the two optimization results in average. It means that our proposed NBF can derive a fair tradeoff between two domains while guaranteeing optimization performance.

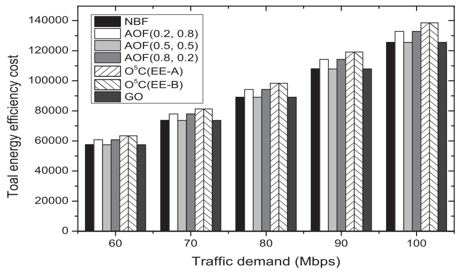


Fig. 11. Overall energy efficiency cost for sample network of two domains.

VII. Conclusion

In this paper, we have studied how to achieve a fair tradeoff in multi-objective optimization problem for green network routing. Different from the traditional methods which either construct an aggregate objective function (AOF) or treat one of the objectives as a constraint of the problem, we have analyzed such a problem from a game theoretic perspective. More specifically, we have treated the two objectives as two virtual players in a so-called threat value game, who negotiate with each other in order to achieve an agreement under the Nash bargaining framework. In such a game, each player can announce its threat value to optimize its performance and our analysis have shown that the number of Nash equilibriums can be infinite and each player determines its threat value will prevent an agreement, so as to induce an infinite cost to both of them. To avoid such an undesirable outcome, we have designed a mechanism that can not only reach an agreement but also lead to a fair tradeoff between two objectives. In addition, it is very easy to find all the initial threat points which can be used to get the fair tradeoff solution in our framework. We implement our framework into two multi-objective optimization cases for network green routing. The first case is load balancing and energy efficiency optimization for intra-domain routing, and the second one is the energy efficiency optimization of two domains for inter-domain routing. Simulation results approve the fairness and efficiency of our proposed framework.

References

[1] A. P. Sokolov *et al.*, “Probabilistic forecast for 21st century climate based on uncertainties in emissions (without policy) and climate parameters,” MIT, Cambridge, MA, USA, MIT Global Change Program Report No. 169, Jan. 2009.

[2] P. Leisching and M. Pickavet, “Energy footprint of ICT: Forecasts and network solutions,” in *Proc. Workshop Energy Footprint ICT; Forecast Netw. Solutions*, San Diego, CA, USA, Mar. 2009.

[3] J. Chabarek, J. Sommers, P. Barford, C. Estan, D. Tsiang, and S. Wright, “Power awareness in network design and routing,” in *Proc. IEEE INFOCOM*, Apr. 2008, pp. 457–465.

[4] L. Chiaraviglio, M. Mellia, and F. Neri, “Minimizing ISP network energy cost: Formulation and solutions,” *IEEE/ACM Trans. Netw.*, vol. 20, no. 2, pp. 463–476, Apr. 2012.

[5] M. Zhang, C. Yi, B. Liu, and B. Zhang, “GreenTE: Power-aware traffic engineering,” in *Proc. 18th IEEE Int. Conf. Netw. Protocols*, Kyoto, Japan, Oct. 2010, pp. 21–30.

[6] B. Addis, A. Capone, G. Carello, and L. G. Gianoli, “Energy management through optimized routing and device powering for Greener communication networks,” *IEEE/ACM Trans. Netw.*, vol. 22, no. 1, pp. 313–325, Feb. 2014.

[7] A. P. Bianzino, C. Chaudet, F. Larroca, D. Rossi, and J.-L. Rougier, “Energy-aware routing: A reality check,” in *Proc. IEEE Globecom Workshop Green Commun.*, Miami, FL, USA, Dec. 2010, pp. 1422–1427.

[8] S. Lee, P. Tseng, and A. Chen, “Link weight assignment and loop-free routing table update for link state routing protocols in energy-aware internet,” *Future Gener. Comput. Syst.*, vol. 28, no. 2, pp. 437–445, 2012.

[9] R. E. Steuer, *Multiple Criteria Optimization: Theory, Computation, and Application*. Hoboken, NJ, USA: Wiley, 1986, ISBN 0-471-8846-X.

[10] K. Rzadca, J. Yong, and A. Datta, “Multi-objective traffic engineering for data center networks,” *Comput. Netw.*, vol. 65, no. 2, pp. 167–182, 2014.

[11] G. Athanasiou, K. Tsagkaris, and P. Vlacheas, “Multi-objective traffic engineering for future networks,” *IEEE Commun. Lett.*, vol. 16, no. 1, pp. 101–103, Jan. 2012.

[12] A. Eira, J. Santos, and J. Pedro, “Multi-objective design of survivable flexible-grid DWDM networks,” *IEEE/OSA J. Opt. Commun. Netw.*, vol. 6, no. 3, pp. 326–339, Mar. 2014.

[13] B. Sanso and H. Mellah, “On reliability, performance and internet power consumption,” in *Proc. Int. Workshop Des. Reliable Commun. Netw.*, 2009, pp. 259–264.

[14] K. Rzadca, J. Yong, and A. Datta, “Multi-objective optimization of multicast overlays for collaborative applications,” *Comput. Netw.*, vol. 54, no. 12, pp. 1986–2006, 2010.

[15] J. F. Nash, “The bargaining problem,” *Econometrica*, vol. 28, no. 2, pp. 155–162, 1950.

[16] M. D. Davis, *Game Theory: A Nontechnical Introduction*. New York, NY, USA: Dover, 1983.

[17] M. Grant and S. Boyd. *CVX Users Guide for CVX Version 1.22*, 2012 [Online]. Available: http://cvxr.com/cvx/cvx_usrguide.pdf.

[18] S. Secci, K. Liu, K. Rao, and B. Jabbari, “Resilient traffic engineering in a transit-edge separated internet routing,” in *Proc. IEEE Int. Conf. Cpmmun.*, 2011, pp. 1–6.

[19] M. Andrews, A. F. Anta, L. Zhang, and W. Zhao, “Routing for energy minimization the speed scaling model,” in *Proc. 29th IEEE Conf. Comput. Commun.*, 2010, pp. 1–9.

[20] “Enhanced Intel speed step technology for the Intel Pentium M processor,” Intel White Paper 201170-001, 2004.

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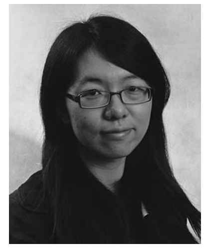

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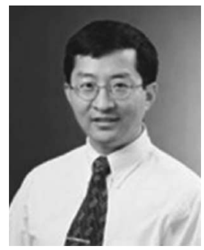

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