Load Balance vs Energy Efficiency in Traffic Engineering: A Game Theoretical Perspective

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***Abstract*—In this paper, we study the tradeoff between two important traffic engineering objectives: load balance and energy efficiency. Although traditional commonly used multi-objective optimization methods can yield a Pareto efficient solution, they need to construct an aggregate objective function (AOF) or model one of the two objectives as a constraint in the optimization problem formulation. As a result, it is difficult to achieve a fair tradeoff between these two 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 in order 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. In addition, the insights from this work are also useful for achieving a fair tradeoff in other multi-objective optimization problems.**

***Index Terms*—Traffic Engineering; Load Balance; Energy Efficiency; Nash Bargaining; Multi-Objective Optimization.**

I. INTRODUCTION

Many objectives exist in network traffic engineering [1-7], such as minimizing E2E (end to end) delay or hop count, maximizing throughput, balancing link load, and reducing total energy consumption. Most of these objectives are conflicting with each other, in that improving one objective hurts the other. How to achieve a tradeoff between such conflicting objectives is an interesting problem in network traffic engineering. In this paper, we focus on achieving a fair tradeoff between two important traffic engineering objectives: load balance and energy efficiency.

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. 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 balance (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 aggregate objective function (AOF), such as the well-known weighted linear sum of the objectives. 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 not only have different performance metrics representing different dimensions of interest (e.g., load balance and energy efficiency), but also have different scales or orders of magnitude. Note that Lagrange 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 in traffic engineering, 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.

To derive a fair tradeoff among multiple objectives in traffic engineering, e.g., load balance and energy efficiency, we propose a framework based on Nash bargaining to jointly optimize both objectives and guarantee the fairness between them. We treat the objectives of load balance and energy efficiency as two virtual game players who are negotiating the solution of traffic engineering. 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 mechanism which can not only guarantee an agreement, but also achieve a fair tradeoff.

The rest of the paper is organized as follows. Section II briefly describes the related work. Section III and Section IV present the commonly used models for load balance and energy efficiency, respectively. After that, we analyze the fair tradeoff problem in detail and describe the motivation for using Nash bargaining to

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solve the problem in Section V. In Section VI, we propose a method to achieve a fair tradeoff between load balance and energy efficiency, and determine the initial (and subsequent) threat points which can induce a fair solution. We also present a case study of our method in Section VII and conclude our paper in Section VIII. Due to the space limits, some proofs and technical details are omitted from this version and can be found (online) in [20].

II. RELATED WORK

In the past decades, a lot of works have been done on the traffic engineering in networks. Some have focused on traffic load balance [1-4], while others have tried to minimize the energy consumption [5-7]. Load balance can be realized by optimizing the link weight in the OSPF network [2] or by configuring LSPs (label-switched path) in MPLS networks [10]. None of such works, however, considered reducing the energy consumption in the network. On the other hand, recent works in [5] and [11] pursued energy efficiency, but neither of them considered load balance as an objective. To the best of our knowledge, there is no existing work on traffic engineering that pursues both load balance and energy efficiency simultaneously.

To deal with multiple objectives, the commonly used traditional multi-objective optimization approach [9] creates an AOF or treats one of the objectives as the primary objective and expresses all other (secondary) objectives as constraints of the optimization problem. Though both of these methods can yield a Pareto efficient solution, it is difficult to select the appropriate weights when constructing the AOF or to determine the appropriate performance threshold values to be used in the constraints for the secondary objectives. As a result, a fair tradeoff among the objectives cannot be achieved.

Game theory is a useful tool to solve many network optimization problems. There are an increasing number of researchers who apply it to address routing issues in multilayer network [12-14], cooperation (or competition) among multiple autonomous systems [4], and content provider selection [15]. To the best of our knowledge, there has been no existing work which has analyzed the tradeoff between multiple objectives of a single operator in a game theoretic perspective, let alone any work on achieving fair tradeoff between load balance and energy efficiency.

The work which is most similar to our work is the Nash arbitration scheme [17]. In this scheme, an AOF having the same form as that in Nash bargaining was introduced to derive the optimization solution. But it approached the problem mostly from a multi-objective optimization perspective while we will approach it from a game theoretic perspective in this paper. In addition, it has been proved that the solution of Nash arbitration depends on the threat value of each objective and an objective that is the farthest away from its threat value tends to improve most significantly [16]. However, it neither showed how the threat value affects the outcome of the optimization, nor how to set the threat values.

III. LOAD BALANCE MODEL

In this section, we describe the network model and formulate the standard load balance optimization problem.

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

The goal of load balance is to enhance the network performance by reducing congestion and improving scalability. In practice, network operators control routing either by changing OSPF link weights [2] or by establishing MPLS label-switched paths [10]. The latter one is assumed in our model. It is not only because it is optimal, i.e. it gives the routing with minimum congestion cost, but also due to the fact that it can be realized easily by routing protocols that use MPLS tunneling.

Based on the above discussion, the traffic engineering for load balance can be formulated as follows:

$$\begin{aligned} \text{minimize} \quad & \sum_l f_l(x_l) && (1) \\ \text{subject to} \quad & x_l = \sum_{i,j:i\neq j} \sum_{k:l\in p^k_{ij}} x^k_{ij}, \quad \forall\, l \in E \\ & x_l \le c_l \quad \forall\, l \in E \\ & \sum_k x^k_{ij} = d_{ij} \quad \forall\, i, j \neq i \end{aligned}$$

where $f_l(\cdot)$ represents the congestion cost of link $l \in \boldsymbol{E}$. In this paper, we assume that $f_l(\cdot)$ 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 $f_l(x_l)=x_l/(c_l-x_l)$ 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 margin cost than the links with a lower load, so that traffic will be distributed uniformly in the network in the optimal solution.

IV. ENERGY EFFICIENCY MODEL

While the load balance 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* [6] and *powering down* [5, 7]. 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 paper because it is more realistic. In addition, the powering down model focuses on optimizing an individual element in isolation [5], 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 $g_l(x_l)$. The goal of traffic engineering to achieve energy efficiency is thus to minimize the total energy cost of all the links in the network. Accordingly, the optimization problem can be formulated as follows:

$$\text{minimize} \quad \sum_{l} g_l(x_l) \qquad (2)$$

$$\text{subject to} \quad x_l = \sum_{i,j:i\neq j}\sum_{k:l\in p_{ij}^k} x_{ij}^k, \quad \forall\, l \in E$$

$$x_l \le c_l \quad \forall\, l \in E$$

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

The energy curve is often modeled by a polynomial function $g_l(x_l)= \mu_l x_l^{\alpha}$, 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 [8].

V. Problem Analysis

In this section, we will analyze the desirable properties of the solution obtained by our method and explain why the Nash bargaining framework is suitable to our problem. For each of the optimization problems in (1) and (2), x_l in the objective function can be substituted based on the first equation (constraint), so $f_l(\cdot)$ and $g_l(\cdot)$ can be treated as a function of $x=\{x^k{}_{ij}\}$. From now on, we also use $f_l(x)$ and $g_l(x)$ to denote the cost function of load balance and energy efficiency for link l.

A. Desirable Properties

a. Pareto efficiency: In our problem, the two objectives (load balance and energy efficiency) are pursued by one operator, so that the solution x^* should not be worse than any solution x for both objectives, i.e. there exist no feasible solution x such that $\sum_{l\in E} f_l(x) < \sum_{l\in E} f_l(x^*)$ and $\sum_{l\in E} g_l(x) < \sum_{l\in E} g_l(x^*)$. It also means that the solution of our method should lie on the Pareto frontier (See Definition 5) and hence no other solution can improve at least one player's performance without hurting the performance of the other one.

b. Fairness: Load balance and energy efficiency 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 x_{LB} and x_{EE} be the solutions to the optimization problems (1) and (2) respectively, then we define the best case and worst case load balance cost to be

$$LB_{best} = \sum_{l\in E} f_l(x_{LB}) \text{ and } LB_{worst} = \sum_{l\in E} f_l(x_{EE})$$

respectively. Similarly, we define the best case and worst case costs of energy efficiency to be

$$EE_{best} = \sum_{l\in E} g_l(x_{EE}) \text{ and } EE_{worst} = \sum_{l\in E} g_l(x_{LB})$$

respectively.

Definition 2: Assume that s_{LB} and s_{EE} are the objective values of load balance and energy efficiency corresponding to a solution that achieves some tradeoffs between the two, then the solution is fair if and only if it satisfies the following equation:

$$\frac{LB_{worst} - s_{LB}}{LB_{worst} - LB_{best}} = \frac{EE_{worst} - s_{EE}}{EE_{worst} - EE_{best}}.$$

Definition 2 means that in the solution with a fair tradeoff, both the load balance and energy efficiency objectives 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.

B. Why Nash Bargaining

The key idea of our work is to find a performance 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.

VI. Trading off Load Balance against Energy Efficiency Using Nash Bargaining

In this section, we realize the tradeoff between load balance and energy efficiency 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 (3) 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_{LB} and a_{EE} be some chosen threat values of load balance and energy efficiency, respectively. The Nash bargaining solution can be derived by the following optimization problem:

$$\text{maximize} \quad (a_{LB} - \sum_{l\in E} f_l(x_l))(a_{EE} - \sum_{l\in E} g_l(x_l)) \qquad (3)$$

$$\text{subject to} \quad x_l = \sum_{i,j:i\neq j}\sum_{k:l\in p_{ij}^k} x_{ij}^k, \quad \forall\, l \in E$$

$$x_l \le c_l \quad \forall\, l \in E$$

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

$$\sum_{l\in E} f_l(x_l) \le a_{LB}$$

$$\sum_{l\in E} g_l(x_l) \le a_{EE}$$

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 (3)). To analyze such a game in more depth, we first have the following definition.

Definition 3: A *threat value game* is a tuple $\boldsymbol{G}=(N, (A_i)_{i\in\{LB,EE\}}, (c_i)_{i\in\{LB,EE\}})$, where

- A_i is the set of available strategies for player $i\in\{LB,EE\}$. In our model, $A_{LB}=[LB_{best}, LB_{worst}]$ and $A_{EE}=[EE_{best}, EE_{worst}]$. We use a_i to denote a special strategy for player *i*.
- c_i is the cost for player $i\in\{LB,EE\}$. The value of c_i depends on the solution of optimization problem (3).

The threat value can also be treated as the performance threshold of each player to sign the agreement. If there exist no feasible solution to (3) (which means no agreement can be achieved), $c_i=\infty$ for each player. Otherwise,

$$c_{LB}^{*}=\sum_{l\in E} f_l(x^{*}) \text{ and } c_{EE}^{*}=\sum_{l\in E} g_l(x^{*})$$

where $x^{*}=\{x^{k}{}_{ij}{}^{*}\}$ is the solution of (3).

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

Definition 4: Let *S* be the set of all the possible cost pairs for two players. We say that the cost pair $(a_{LB}, a_{EE})\in S$ is dominated by $(a'_{LB}, a'_{EE})\in S$ iff:

- $a_{LB}\geqslant a'_{LB}$ and $a_{EE}\geqslant a'_{EE}$
- $a_{LB}>a'_{LB}$ or $a_{EE}>a'_{EE}$

Definition 5: 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 1: Every point (a_{LB}, a_{EE}) in Pareto frontier is a Nash equilibrium point in the threat value game.

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 in (3) 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 $(a^{(k)}{}_{LB}, a^{(k)}{}_{EE})$ denote the threat point during the k^{th}-iteration, and $x^{(k)}$ be the optimal solution to (3) corresponding to threat point $(a^{(k)}{}_{LB}, a^{(k)}{}_{EE})$,. We assume that each player updates its threat value during the k^{th}-iteration as a function of its current threat value ($a^{(k)}{}_{LB}$ for player *LB* and $a^{(k)}{}_{EE}$ for player *EE*) and the optimal solution to (3) ($x^{(k)}$). Therefore, we have,

$$a_{LB}^{(k+1)}=h_{LB}(a_{LB}^{(k)}, x^{(k)}) \tag{4.1}$$

$$a_{EE}^{(k+1)}=h_{EE}(a_{EE}^{(k)}, x^{(k)}) \tag{4.2}$$

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

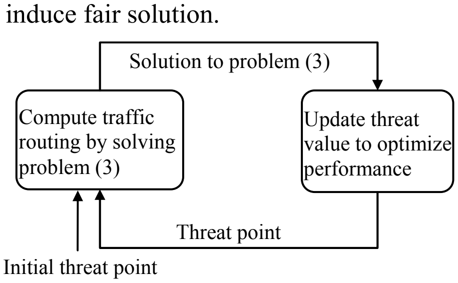

Fig.1 Procedure of repeated threat value game

Theorem 2: If the cost function of both load balance and energy efficiency, i.e. $f_l(\cdot)$ and $g_l(\cdot)$ for all $l\in E$, are continuous, then the threat point of problem (3) (LB_{worst}, EE_{worst}) will yield a fair solution.

Theorem 2 gives an initial threat point which can yield a fair tradeoff between load balance and energy efficiency. Such a threat point is easy to determine as it corresponds to the worst-case performance of load balance and energy efficiency, 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 $(a^{(k)}{}_{LB}, a^{(k)}{}_{EE})$ denote the threat point during the k^{th}-iteration and $x^{(k)}$ be the optimal solution to (3), we initialize the threat point at $(LB_{\text{worst}}, EE_{\text{worst}})$ and constraint the threat value updating of each player to satisfy

$$a_{LB}^{(k+1)}\geq a_{LB}^{(k)}-\frac{a_{LB}^{(k)}-\sum_{l\in E} f_l(x^{(k)})}{2}=\frac{1}{2}(a_{LB}^{(k)}+\sum_{l\in E} f_l(x^{(k)})) \tag{5.1}$$

$$a_{EE}^{(k+1)}\geq a_{EE}^{(k)}-\frac{a_{EE}^{(k)}-\sum_{l\in E} g_l(x^{(k)})}{2}=\frac{1}{2}(a_{EE}^{(k)}+\sum_{l\in E} g_l(x^{(k)})) \tag{5.2}$$

With the above two constraints, each player can only claim to occupy half of the performance gap between its threat value and its cost corresponding to the solution of (3).

Lemma 2: Let x^{*} be the optimal solution of optimization problem (3) associated with threat point (a_{LB}, a_{EE}), then x^{*} is also the optimal solution of problem (3) associated with threat point $(\frac{1}{2}(a_{LB}+\sum_{l\in E} f_l(x^{*})), \frac{1}{2}(a_{EE}+\sum_{l\in E} g_l(x^{*})))$.

Theorem 3: 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.

Corollary 1: Suppose a'_{LB} and a'_{EE} are the performance of load balance and energy efficiency, respectively, derived from solving (3) with (a_{LB}, a_{EE}) as the threat point. If we set the initial threat point at any points on the line connecting (a_{LB}, a_{EE}) and (a'_{LB}, a'_{EE}), we will derive the same solution as if the initial threat point is (a_{LB}, a_{EE}).

Corollary 2: Suppose LB_{fair} and EE_{fair} are the performance of load balance and energy efficiency, respectively, derived from solving (3) with $(LB_{\text{worst}}, EE_{\text{worst}})$ as the threat point. If the initial threat point is set as neither $(LB_{\text{worst}}, EE_{\text{worst}})$ nor any points along the line connecting $(LB_{\text{worst}}, EE_{\text{worst}})$ to (LB_{fair}, EE_{fair}), then the solution will not converge to the fair tradeoff.

Intuitively, this is because starting with a different threat point than $(LB_{\text{worst}}, EE_{\text{worst}})$ 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 $(LB_{\text{worst}}, EE_{\text{worst}})$.

C. Conversion to Convex Optimization Form

The optimization problem (3) 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 4: If the optimization problem (3) is feasible, its solution will be the same as problem (6):

$$\begin{aligned}
\text{maximize} \quad & \log(a_{LB} - t_{LB}) + \log(a_{EE} - t_{EE}) \qquad (6)\\
\text{subject to:} \quad & \text{The constraints in (3)}\\
& t_{LB} \geq \sum_{l \in E} f_l(x_l)\\
& t_{EE} \geq \sum_{l \in E} g_l(x_l)
\end{aligned}$$

Theorem 5: If $f_l(\cdot)$ and $g_l(\cdot)$ are both convex functions, problem (6) is a convex optimization problem.

Theorem 4 and Theorem 5 guarantee the Nash bargaining solution can be solved efficiently.

VII. Case Studies

In this section, we will use our proposed method to realize a fair tradeoff between load balance and energy efficiency in the NSFNET backbone network. All the computations are carried out on a computer with Duo-Core 2.20 GHz intel CPU using CVX1.22 [18].

In NSFNET (The topology of NSFNET and name of each site can be found in [20]), each link is bidirectional and without loss of generality, we assume that the capacity of each link is 45Mbps (such capacity is offered by NSFNET during 1992 and 1995 [19] and was chosen to simplify our computation only). To route the demand in the network, we find two link disjointed routes between each node pairs and assume a 10Mpbs demand between every pair of the six supercomputer sites (SDSCNET, NCSA, CNSF, PSCNET, JVNC and NCAR). In order to show that our method can derive a fair solution even when each objective has a different order of magnitude, we set the congestion cost of link l to be $f_l(x_l)=x_l/(45-x_l)$, while set its energy curve to be $g_l=(x_l/45)^{1.5}$.

In this case study scenario, the best case cost for load balance is 18.3378 while the worst case cost is 2.9597×10^7, which is much worse than the best case. For energy efficiency, the best and worst case costs are 5. 42 and 5.8313, respectively. This means that the optimization space of load balance is much larger than that of energy efficiency.

Note that if the conventional approach based AOF were to be used in this case, one would not know how to set an appropriate weight for each objective. More specifically, if she uses more or less the same weights for the two objectives, the load balance will get much more performance improvement than energy efficiency, because it has a larger optimization space than energy efficiency, which would be unfair to energy efficiency. In short, a fair solution is difficult to obtain by using the AOF method.

In our method, we set the threat point to be (2.9597×10^7, 5.8313) to derive a fair solution. In the solution, the cost of load balance is 261.0334 while the cost of energy efficiency is very close to 5.4200 (the accuracy is to 10^{-4}). This represents that both objectives get 99.999% optimization space.

VIII. Conclusion

In this paper, we have studied how to achieve a fair tradeoff between load balance and energy efficiency in traffic engineering. Different from the traditional multi-objective optimization 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 in 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 load balance and energy efficiency. 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 method.

Although this work focuses on achieving a fair tradeoff between load balance and energy efficiency in traffic engineering, it also provides some useful insights into the other multi-objective optimization problems.

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