

# Some Mathematical Programming Issues in DEA

01302170 埼玉大学 刀根 薫 TONE Kaoru

## 1 Introduction

In this paper, we will analyze the equivalence of the original ratio form fractional program for the CCR model and the derived linear program under the semi-positive data set assumption. Then, the uniqueness issues of the solutions will be discussed in detail.

## 2 Fractional Program with Semipositive Data Set

$$(FP_o) \max \theta = \frac{u y_o}{v x_o} \quad (1)$$

$$st. \quad \frac{u y_j}{v x_j} \leq 1 \quad (j = 1, \dots, n) \quad (2)$$

$$v \geq 0, \quad u \geq 0. \quad (3)$$

$$(LP_o) \max \theta = u y_o \quad (4)$$

$$st. \quad v x_o = 1 \quad (5)$$

$$u Y \leq v X, \quad v \geq 0, \quad u \geq 0. \quad (6)$$

$$(DLP_o) \min \theta \quad (7)$$

$$st. \quad \theta x_o = X \lambda + s_x \quad (8)$$

$$y_o = Y \lambda - s_y \quad (9)$$

$$\lambda \geq 0, \quad s_x \geq 0, \quad s_y \geq 0 \quad (10)$$

**Definition 1 (Semi-positive Data Set)**  $x_j$  and  $y_j$  ( $j = 1, \dots, n$ ) are nonnegative and nonzero.

### 2.1 When $DMU_o$ has no Slacks

If a  $DMU_o$  has an optimal max-slack solution ( $\theta = \theta^*, \lambda = \lambda^*, s_x^* = 0, s_y^* = 0$ ), then, by the strong theorem of complementarity, there exists a positive optimal solution  $(v^*, u^*)$  to  $(LP_o)$  and it holds

$$v^* X \geq u^* Y > 0.$$

Thus, for  $(v^*, u^*)$ , the ratio form

$$\frac{u^* y_j}{v^* x_j}$$

has a definite value for every DMU. Therefore, for  $DMU_o$ ,  $(LP_o)$  is equivalent to  $(FP_o)$ .

### 2.2 When $DMU_o$ has Slacks

If  $DMU_o$  has an optimal max-slack solution with  $s_x^* \neq 0$  and/or  $s_y^* \neq 0$ , we replace  $(FP_o)$  with

$$(\overline{FP}_o) \max \frac{u y_o}{v_o x_o} \quad (11)$$

$$\text{subject to } \frac{u y_j}{v x_j} \leq 1 \quad (\forall j) \quad (12)$$

$$v \geq \epsilon e, \quad u \geq \epsilon e, \quad (13)$$

where  $e$  is a row vector with all elements equal to 1 and the symbol  $\epsilon$  represents the infinitesimal (small) positive number. Thus, the fractional terms in  $(\overline{FP}_o)$  have definite values by the semipositivity assumption on  $X$ .

The derived  $(\overline{LP}_o)$  and  $(\overline{DLP}_o)$  turn out to have the added constraint  $v \geq \epsilon e, \quad u \geq \epsilon e$  and the objective  $\min \theta - \epsilon(e s_x + e s_y)$ , respectively. Since  $\epsilon$  is infinitesimally small,  $(\overline{DLP}_o)$  has the same optimal max-slack solution  $(\theta^*, \lambda^*, s_x^*, s_y^*)$  with  $(DLP_o)$ . For a feasible solution  $(\bar{v}, \bar{u})$  for  $(\overline{LP}_o)$ , the optimality conditions are:

$$\text{if } s_{x_j}^* > 0, \text{ then } \bar{v}_j = \epsilon$$

and

$$\text{if } s_{y_j}^* > 0, \text{ then } \bar{u}_j = \epsilon.$$

As  $\epsilon$  approaches zero, the  $(\bar{v}, \bar{u})$  converges to an optimal solution  $(v^*, u^*)$  of  $(LP_o)$  as its limit.

Thus, it can be concluded that we are solving the following *supremum* (sup) programming problem  $(SP_o)$  in the *positive* orthant of  $(v, u)$ , instead of  $(FP_o)$ .

$$(SP_o) \sup \frac{u y_o}{v_o x_o} \quad (14)$$

$$\text{subject to } \frac{u y_j}{v x_j} \leq 1 \quad (j = 1, \dots, n) \quad (15)$$

$$v > 0, \quad u > 0. \quad (16)$$

## 3 On the Uniqueness of the Solutions

$$\text{Phase I Objective } \min \theta \quad (17)$$

$$\text{Phase II Objective } \max \omega = w_x s_x + w_y s_y$$

### 3.1 General Scheme of LP Computation

The LP problem ( $DLP'_0$ ) can be formulated as:

$$\text{Phase I objective } \min z_1 = c\mathbf{x} \quad (18)$$

$$\text{Phase II objective } \min z_2 = d\mathbf{x} \quad (19)$$

$$\text{subject to } A\mathbf{x} = \mathbf{b} \quad (20)$$

$$\mathbf{x} \geq \mathbf{0}. \quad (21)$$

Let a submatrix  $B$  of  $A$  be an optimal basis for Phase II LP and  $R$  be the nonbasic part of  $A$ .

Phase I objective	$\theta^*$	$\mathbf{0}$	$-\bar{c}$
Phase II objective	$-\omega^*$	$\mathbf{0}$	$-\bar{d}$
	$\bar{\mathbf{b}}$	$I$	$B^{-1}R$

#### Definition 2 (Degeneracy)

An optimal basis  $B$  is called

1.  $b$ -nondegenerate if  $\bar{\mathbf{b}} > \mathbf{0}$ , otherwise  $b$ -degenerate,
2.  $c$ -nondegenerate if  $\bar{c} > \mathbf{0}$ , otherwise  $c$ -degenerate, and
3.  $d$ -nondegenerate if  $\bar{d}_j > 0$  for all  $j \in R$  with  $\bar{c}_j = 0$ , and  $d$ -degenerate if for some  $j \in R$ ,  $\bar{d}_j = 0$  and  $\bar{c}_j = 0$ .

### 3.2 The 'c-nondegenerate' Case

In this case, all nonbasic variables have negative simplex criteria in the  $c$ -row of the optimal tableau. Thus,  $x_j$  ( $j \in R$ ) cannot have a positive value in every optimal solution and hence  $((\mathbf{x}^B)^* = \bar{\mathbf{b}}, (\mathbf{x}^R)^* = \mathbf{0})$  is the only optimal solution. In CCR terminology, the optimal solution  $(\theta^*, \lambda^*, \mathbf{s}_x^*, \mathbf{s}_y^*)$  is unique. We will now discuss the  $b$ -degeneracy issue in this case.

(i) When the basis  $B$  is  $b$ -nondegenerate.

In this case, the basis  $B$  is the only optimal basis and both ( $DLP_0$ ) and ( $LP_0$ ) have unique optimal solutions.

(ii) When the basis  $B$  is  $b$ -degenerate.

In this case, we have only one optimal solution  $(\lambda^*, \mathbf{s}_x^*, \mathbf{s}_y^*)$  for ( $DLP_0$ ). However, the optimal solution  $(\mathbf{v}^*, \mathbf{u}^*)$  is not necessarily unique.

### 3.3 The 'c-degenerate but d-nondegenerate' Case

In this case, the optimal basic solution  $(\lambda^*, \mathbf{s}_x^*, \mathbf{s}_y^*)$  corresponds to the unique vertex that maximizes

$\omega = e\mathbf{s}_x + e\mathbf{s}_y$  in the ( $DLP_0$ ) feasible region with  $\theta = \theta^*$ . Thus, the solution is unique. However, this uniqueness depends on the objective function form of Phase II.

### 3.4 The 'c-degenerate and d-degenerate' Case

In this case, the optimal solution  $(\lambda^*, \mathbf{s}_x^*, \mathbf{s}_y^*)$  is seemingly not unique. However, we should be careful in deciding the existence of substantially multiple optimal solutions. For this purpose, we consider a Phase III LP, based on an optimal basis  $B$  and its optimal solution  $(\lambda^*, \mathbf{s}_x^*, \mathbf{s}_y^*)$  for Phase II, as follows.

We maximize the objective function :

$$\eta = \sum_j \lambda_j \quad (j \in R \text{ with } \bar{c}_j = 0 \text{ and } \bar{d}_j = 0) + \sum_j \lambda_j \quad (j \in B \text{ with } \lambda_j^* = 0), \quad (22)$$

subject to the constraints of ( $DLP_0$ ), added by  $\theta = \theta^*$  and  $e\mathbf{s}_x + e\mathbf{s}_y = e\mathbf{s}_x^* + e\mathbf{s}_y^*$ .

Let the optimal value of  $\eta$  be  $\eta^*$ . Then, if  $\eta^* > 0$ , it is found that ( $DLP_0$ ) has multiple optimal solutions. On the other hand, if  $\eta^* = 0$ , then  $(\lambda^*, \mathbf{s}_x^*, \mathbf{s}_y^*)$  is the only one solution of ( $DLP_0$ ).

### 3.5 Summary of the Degeneracy and Uniqueness Issues

Uniqueness and degeneracy are summarized in Table 1 and Table 2, where in Table 2, 'not unique' means 'not necessarily unique'.

Table 1: Degeneracy and Uniqueness in ( $DLP_0$ )

	c-nond.	c-deg.		
		d-nond.	d-deg.	
			$\eta^* = 0$	$\eta^* > 0$
$(\lambda^*, \mathbf{s}^*)$	unique	unique	unique	not unique

Table 2: Degeneracy and Uniqueness in ( $LP_0$ )

	$b$ -nondegenerate	$b$ -degenerate
$(\mathbf{v}^*, \mathbf{u}^*)$	unique	not unique

Reference [1] Charnes, Cooper and Thrall, JPA, 2, 197-237, 1991.