

**ON MAXIMAL FLOW PROBLEM IN A TRANSPORTATION
NETWORK WITH A BUNDLE**

TAKASHI KOBAYASHI

Faculty of Engineering, University of Tokyo

(Received June 1, 1967)

Abstract

The author reduces the maximal flow problem in a transportation network with a bundle, which is a subset of its arcs and associated with a capacity, to a parametric programming problem. The latter is related to one of the usual transportation network problems, and a primal-dual algorithm for solving it is shown. This approach is very similar to Jewell's for the critical path analysis in a project with a divisible activity.

1. Introduction

Berge [1] presented the maximal flow problem in a transportation network with bundles as one of special problems of maximal flow. Bundle implies a subset of arcs of the network and is associated with a capacity.

The author reduces the maximal flow problem in a network with a bundle to a parametric programming problem which is related to one of the usual transportation network problems, and shows a primal-dual

algorithm for solving the latter. It is very similar to Jewell's algorithm [4] used for the critical path analysis in a project with a divisible activity.

2. Mathematical Formulations of Problems

Let A denote the set of directed arcs, ordered pairs of nodes, of a transportation network with n nodes: 1 (the source), 2, \dots , $n-1$, n (the sink). We shall consider the case when A consists of a bundle B whose capacity is C and its complement \bar{B} , each arc (i, j) of which is associated with capacity C_{ij} . We define $P(i)$ and $S(i)$ for node i as follows:

$$P(i) = \{j | (j, i) \in A\},$$

$$S(i) = \{j | (i, j) \in A\}.$$

Then, a mathematical formulation of the original problem is obtained:

$$\begin{aligned} & \text{Maximize } \mu, \\ & \text{subject to} \\ & \sum_{j \in S(i)} x_{ij} - \sum_{j \in P(i)} x_{ji} = \begin{cases} \mu, & \text{for } i=1, \\ 0, & \text{for } i \neq 1, n, \\ -\mu, & \text{for } i=n, \end{cases} \\ & C_{ij} \geq x_{ij} \geq 0 \quad \text{for } (i, j) \in \bar{B}, \\ & x_{ij} \geq 0 \quad \text{for } (i, j) \in B, \\ & \sum_{(i, j) \in B} x_{ij} \leq C. \end{aligned}$$

Here, we shall introduce a parameter λ and consider a parametric programming problem:

$$\begin{aligned} & P|\lambda \quad \text{Maximize } \{\lambda\mu - \sum_B x_{ij}\}, \\ & \text{subject to} \\ & \sum_{j \in S(i)} x_{ij} - \sum_{j \in P(i)} x_{ji} = \begin{cases} \mu, & \text{for } i=1, \\ 0, & \text{for } i \neq 1, n, \\ -\mu, & \text{for } i=n, \end{cases} \\ & C_{ij} \geq x_{ij} \geq 0 \quad \text{for } (i, j) \in \bar{B}, \\ & x_{ij} \geq 0 \quad \text{for } (i, j) \in B. \end{aligned}$$

The relations between the solutions of two problems are given by

the followings.

Theorem 1. Let (μ^*, X^*) be an optimal solution of $P|\lambda$ for some positive λ . If $\sum_B x_{ij}^* = C$, it is also optimal to the original problem.

Proof. (μ^*, X^*) is a feasible solution of the original since $\sum_B x_{ij}^* \leq C$. Let (μ, X) be an optimal solution of the original. Then, (μ, X) is a feasible solution of $P|\lambda$. Hence,

$$\lambda\mu^* - \sum_B x_{ij}^* \geq \lambda\mu - \sum_B x_{ij}.$$

$$\text{So, } \lambda\mu^* \geq \lambda\mu + \sum_B x_{ij}^* - \sum_B x_{ij} = \lambda\mu + (C - \sum_B x_{ij}) \geq \lambda\mu.$$

As $\lambda > 0$, $\mu^* \geq \mu$. Therefore, (μ^*, X^*) is an optimal solution of the original problem.

Theorem 2. For λ greater than $|B|$, the number of elements of B , an optimal solution of $P|\lambda$, (μ^*, X^*) is also optimal to the original problem if $\sum_B x_{ij}^* < C$.

Proof. Obviously, (μ^*, X^*) is a feasible solution of the original. Assume that it is not optimal. Then, there exists a path from node 1 to node n , $(i_1=1, i_2, \dots, i_{m-1}, i_m=n)$, such that

- 1) $(i_k, i_{k+1}) \in B$,
- 2) $(i_k, i_{k+1}) \in \bar{B}$ and $x_{i_k i_{k+1}}^* < C_{i_k i_{k+1}}$, or
- 3) $(i_{k+1}, i_k) \in A$ and $x_{i_{k+1} i_k}^* > 0$.

By selecting a sufficiently small positive number ϵ and putting

$$\mu = \mu^* + \epsilon,$$

$$x_{ij} = \begin{cases} x_{ij}^* + \epsilon, & \text{if } (i, j) \text{ is a forward arc of the path (Case 1 or 2),} \\ x_{ij}^* - \epsilon, & \text{if } (i, j) \text{ is a reverse arc of the path (Case 3),} \\ x_{ij}^*, & \text{otherwise,} \end{cases}$$

we can make (μ, X) a feasible solution of $P|\lambda$. Then, we have

$$\lambda\mu - \sum_B x_{ij} \geq \lambda(\mu^* + \epsilon) - \sum_B (x_{ij}^* + \epsilon) = \lambda\mu^* - \sum_B x_{ij}^* + (\lambda - |B|)\epsilon > \lambda\mu^* - \sum_B x_{ij}^*,$$

which contradicts that (μ^*, X^*) is optimal to $P|\lambda$. Hence, (μ^*, X^*) is optimal to the original. The proof is completed.

From the theorems above, we may solve a parametric programming problem $P|\lambda$, instead of solving the original directly. $P|\lambda$ is one of the problems related to the following transportation network flow problem:

$$\begin{aligned}
 D^*|\mu \quad & \text{Minimize } \left\{ \sum_B x_{ij} \right\}, \\
 \text{subject to} \quad & \sum_{j \in S(i)} x_{ij} - \sum_{j \in P(i)} x_{ji} = \begin{cases} \mu & \text{for } i=1, \\ 0 & \text{for } i \neq 1, n, \\ -\mu & \text{for } i=n, \end{cases} \\
 & C_{ij} \geq x_{ij} \geq 0 \quad \text{for } (i, j) \in B, \\
 & x_{ij} \geq 0 \quad \text{for } (i, j) \in B.
 \end{aligned}$$

Note that μ is a parameter here.

According to Kurata's formulations [5], we shall introduce the dual problem of $P|\lambda$ (called $D|\lambda$), the restricted one based on (v) , which is a part of an optimal solution of $D|\lambda$, (v, t) (called $RP|\lambda(v)$), and the restricted one based on (X) , an optimal solution of $D^*|\mu$ (called $RP^*|\mu(X)$).

$$\begin{aligned}
 D|\lambda \quad & \text{Minimize } \left\{ \sum_B C_{ij} t_{ij} \right\}, \\
 \text{subject to} \quad & v_n - v_1 = \lambda, \\
 & \left. \begin{aligned} t_{ij} &\geq 0, \\ v_i - v_j + t_{ij} &\geq 0, \end{aligned} \right\} \text{ for } (i, j) \in \bar{B}, \\
 & v_i - v_j \geq -1, \quad \text{for } (i, j) \in B.
 \end{aligned}$$

$$\begin{aligned}
 RP|\lambda(v) \quad & \text{Maximize } \mu, \\
 \text{subject to} \quad & \sum_{j \in S(i)} x_{ij} - \sum_{j \in P(i)} x_{ji} = \begin{cases} \mu & \text{for } i=1, \\ 0 & \text{for } i \neq 1, n, \\ -\mu & \text{for } i=n, \end{cases} \\
 & x_{ij} = 0 \quad \text{if } (i, j) \in \bar{B} \text{ and } v_i - v_j > 0, \\
 & C_{ij} \geq x_{ij} \geq 0 \quad \text{if } (i, j) \in \bar{B} \text{ and } v_i - v_j = 0, \\
 & x_{ij} = C_{ij} \quad \text{if } (i, j) \in \bar{B} \text{ and } v_i - v_j < 0, \\
 & x_{ij} = 0 \quad \text{if } (i, j) \in B \text{ and } v_i - v_j > -1, \\
 & x_{ij} \geq 0 \quad \text{if } (i, j) \in B \text{ and } v_i - v_j = -1,
 \end{aligned}$$

where (v) is a part of an optimal solution of $D|\lambda, (v, t)$.

$$\begin{aligned}
 & RP^*|\mu(X) && \text{Maximize } \lambda, \\
 & \text{subject to} && v_n - v_1 - \lambda = 0, \\
 & && v_i - v_j \geq 0 \text{ if } (i, j) \in \bar{B} \text{ and } x_{ij} = 0, \\
 & && v_i - v_j = 0 \text{ if } (i, j) \in \bar{B} \text{ and } C_{ij} > x_{ij} > 0, \\
 & && v_i - v_j \leq 0 \text{ if } (i, j) \in \bar{B} \text{ and } x_{ij} = C_{ij}, \\
 & && v_i - v_j \geq -1 \text{ if } (i, j) \in B \text{ and } x_{ij} = 0, \\
 & && v_i - v_j = -1 \text{ if } (i, j) \in B \text{ and } x_{ij} > 0,
 \end{aligned}$$

where (X) is an optimal solution of $D^*|\mu$.

The following theorems are proved by Kurata's propositions.

Theorem 3. (μ, X) is a feasible solution of $RP|\lambda(v)$ if and only if it is an optimal solution of $P|\lambda$.

Theorem 4. Let (λ, v) be an optimal solution of $RP^*|\mu(X)$, and $t_{ij} = \max(v_j - v_i, 0)$ for $(i, j) \in \bar{B}$.

Then, 1) (v, t) is optimal to $D|\lambda$, and

2) (μ, X) is a feasible solution of $RP|\lambda(v)$ and also an optimal one of $P|\lambda$.

The next theorem is available when we wish to get an optimal solution for a special value of C .

Theorem 5. Let (μ_1, X_1) and (μ_2, X_2) be both optimal solutions of $P|\lambda$. Then, for $0 < \theta < 1$, $[\theta\mu_1 + (1-\theta)\mu_2, \theta X_1 + (1-\theta)X_2]$ is also optimal to $P|\lambda$.

3. Algorithm

Since it is easily seen that $(X=O)$ is an optimal solution of $D^*|\mu=0$, we start with $\mu=0, X=O$, and continue to solve $RP^*|\mu(X)$, or $RP|\lambda(v)$ alternatively until it occurs that $\lambda > |B|$ or that $\sum_B x_{ij} \geq C$. The flow chart of the algorithm is shown in Fig. 1.

To solve $RP^*|\mu(X)$, Iri's θ matrix method [3] is applicable, and the procedure for solving $RP|\lambda(v)$ given its feasible solution can be constructed similarly as the usual maximal flow labeling procedure [2]. Here, it is very useful that an optimal solution of $RP|\lambda(v)$ is a feasible solu-

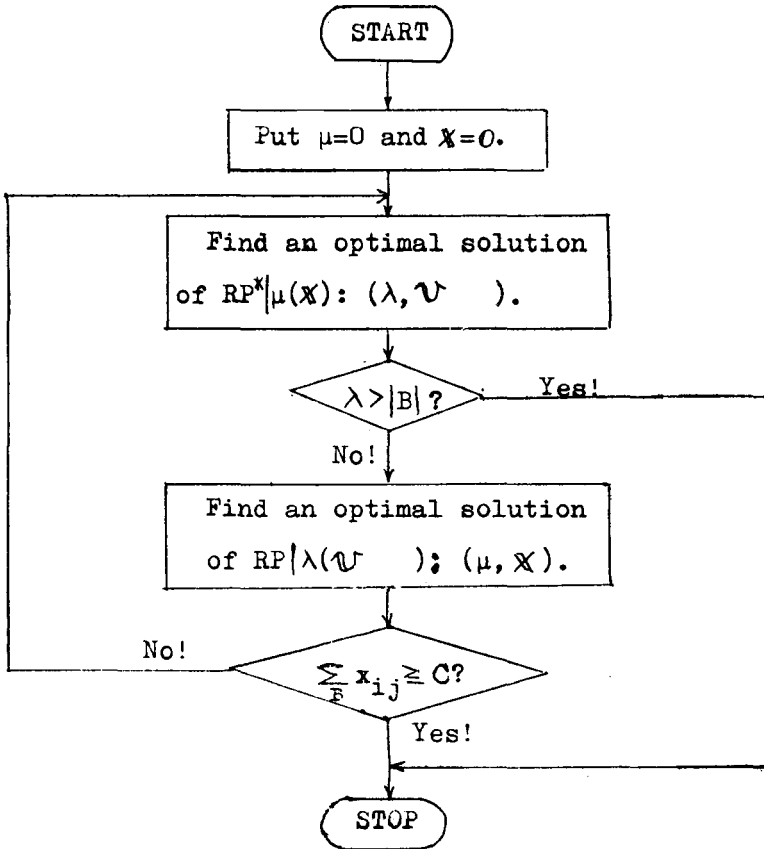


Fig. 1.

tion in the next step (Theorem 4). Details of these procedures are deleted.

4. Remarks

In a network with two or more bundles, it is much difficult to solve the problem by this approach.

It is advisable that the labeling procedure and θ matrix method are programmed in more general forms so as to be applied to the transportation network problem, the critical path method, and some other problems to arise.

Acknowledgement

The author is deeply grateful to Dr. M. Iri for his suggestion of the problem.

REFERENCES

- [1] C. Berge and A. Ghouila-Houri, *Programming, Games and Transportation Networks* (English Translation), Methuen, 1965.
- [2] L.R. Ford and D.R. Fulkerson, *Flows in Networks*, Princeton University Press, 1962.
- [3] M. Iri, "A New Method of Solving Transportation- Network Problems," *JORSJ*, 3, (1960). 27-87
- [4] W.S. Jewell, "Divisible Activities in Critical Path Analysis," *JORSA* 13, (1965) 747-760.
- [5] R. Kurata, "Primal Dual Method of Parametric Programming and Iri's Theory on Network Flow Problems," *JORSJ*, 7, (1965) 104-144.