

# Assignment problem for MAS

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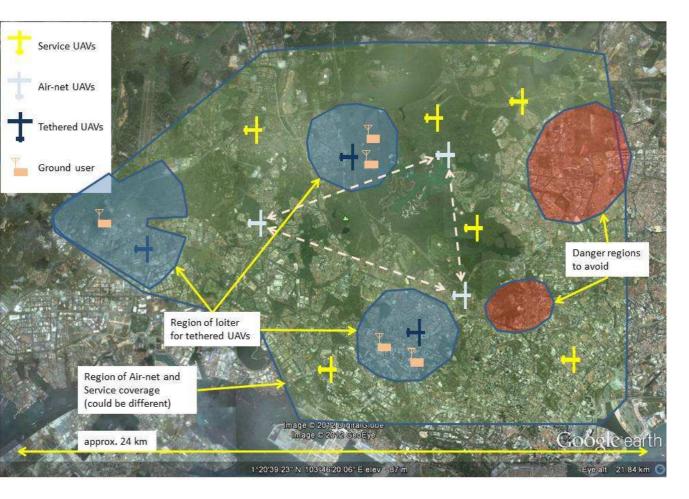
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#### Introduction

The pool of UAVs would loiter above the area of operations and await service requests. Upon receiving a request, the best-suited UAV is deployed to provide the service to the user. At the end of serving the request, the UAV would return to the pool to serve another request:



#### Request info:

- Locations
- Number UAVs
- Time windows
- Duration

## Introduction

Formulation of the problem statement in dynamical form.

Reducing the dynamical optimization problem to static one.

Comparison of the proposed adaptive method with classical LP methods.

Simulation model

# Dynamical assignment (objectives)

$$J_1(x) = \sum_{t=0}^{\nu} x_{ij}(t)(h_i - 2t_{ij}) \to \max_{x_{ij}(t), t=0, \Delta, 2\Delta, \dots, \nu}$$

$$a_i(t + \Delta) = a_i(t) - \sum_{j=1}^{l} x_{ij}(t) + \sum_{j=1}^{l} x_{ij}(t + \Delta - h_i), i = 1, ..., k;$$

$$b_j(t + \Delta) = b_j(t) - \sum_{i=1}^k x_{ij}(t - h_i + t_{ij}) + \sum_{i=1}^k x_{ij}(t - t_{ij}), \ j = 1, ..., l;$$

$$a_i(t) + \sum_{j=1}^{l} x_{ij}(t) = a_i, \ i = 1, ..., k;$$
  $b_j(t) + \sum_{i=1}^{k} x_{ij}(t - t_{ij}) = b_j, \ j = 1, ..., l.$ 

- 1. The total service time for multiple zones
- 2. The total number of UAVs "circles":  $J_2(x) = \sum_{t=0}^{\nu} x_{ij}(t)$
- 3. The total unobservable time for multiple zones:  $J_3(x) = H J_1(x)$

# ynamical assignment (constraints)

$$J_1(x) = \sum_{t=0}^{\nu} x_{ij}(t)(h_i - 2t_{ij}) \to \max_{x_{ij}(t), t=0, \Delta, 2\Delta, \dots, \nu}$$

$$a_i(t + \Delta) = a_i(t) - \sum_{j=1}^{l} x_{ij}(t) + \sum_{j=1}^{l} x_{ij}(t + \Delta - h_i), i = 1, ..., k;$$

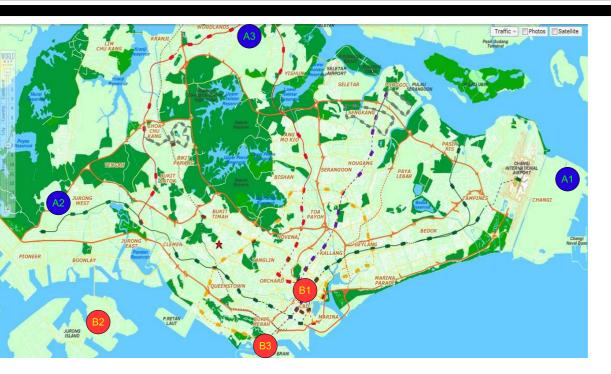
$$b_j(t+\Delta) = b_j(t) - \sum_{i=1}^k x_{ij}(t-h_i+t_{ij}) + \sum_{i=1}^k x_{ij}(t-t_{ij}), \ j=1,...,l;$$

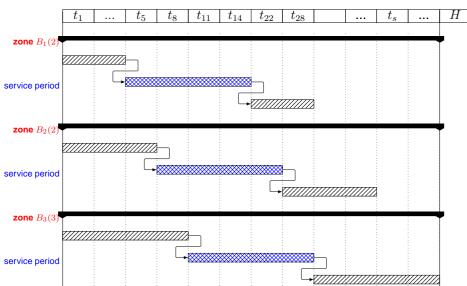
$$a_i(t) + \sum_{j=1}^{l} x_{ij}(t) = a_i, i = 1, ..., k;$$
  $b_j(t) + \sum_{i=1}^{k} x_{ij}(t - t_{ij}) = b_j, j = 1, ..., l.$ 

The number of UAYs at  $A_i$  and at  $B_j$  at the next moment  $t + \Delta$  is composed by:

- UAVs at the previous moment t
- UAVs that are returned during the period  $[t,t+\Delta]$
- →UAVs were send to zones at the moment t
- UAV working at zone at moment t with sufficient flight h;
- UAVs that are reached zone in  $[t, t + \Delta];$ 
  - UAVs that should leave

#### Static case





$$F = \sum_{i=1}^{k} \sum_{j=1}^{l} c_{ij} x_{ij} \to \min_{x_{ij}}$$

$$\sum_{i=1}^{k} x_{ij} = b_j, \quad j = 1, 2, ..., l$$

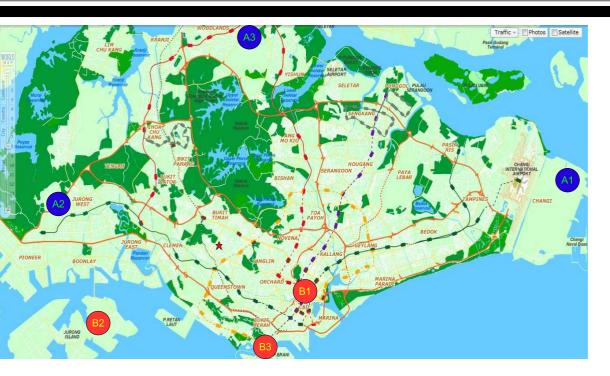
$$\sum_{j=1}^{l} x_{ij} = a_i, \quad i = 1, 2, ..., k$$

$$\sum_{j=1}^{k} a_i = \sum_{j=1}^{l} b_j, x_{ij} \ge 0, x_{ij} \in \mathbb{N}.$$

Time "windows":

$$t_{B_1}^f = t_5, \quad t_{B_1}^l = t_8;$$
 $t_{B_2}^f = t_{11}, \quad t_{B_2}^l = t_{14};$ 
 $t_{B_3}^f = t_{22}, \quad t_{B_3}^l = t_{28}.$ 

#### Static case



The most of methods include the following basic steps:

- **9** To find initial plan  $x_{ij}$ ;
- Check optimality condition for that plan;
- Construct the improved plan in case of nonoptimality.

$$F = \sum_{i=1}^{k} \sum_{j=1}^{l} c_{ij} x_{ij} \to \min_{x_{ij}}$$

$$\sum_{i=1}^{k} x_{ij} = b_j, \quad j = 1, 2, ..., l$$

$$\sum_{j=1}^{l} x_{ij} = a_i, \quad i = 1, 2, ..., k$$

$$\sum_{i=1}^{k} a_i = \sum_{j=1}^{l} b_j, x_{ij} \ge 0, x_{ij} \in \mathbb{N}.$$

#### Matrix model



$$F = c^T x \to \max$$

$$Bx = a$$

$$f_{*i} \le x_i \le f_i^*,$$

$$i = 1, 2, ..., k, k + 1, ..., k + r.$$

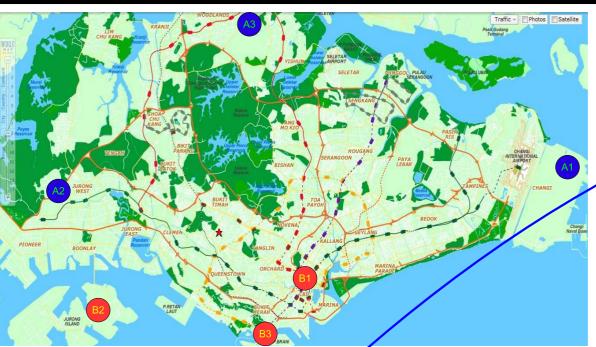
$$I = \{1, 2, ..., m\}, \quad J = \{1, 2, ..., k+r\}, \quad x = (x_1, ..., x_{k+r}) = x(J) = (x_j, j \in J),$$

$$c = (c_1, ..., c_{k+r}) = c(J) = (c_j, j \in J), \quad a = \{a_i, ..., a_m\} = a(I) = (a_i, i \in I)$$

$$f^* = (d_1^*, ..., d_{k+r}^*) = f^*(J) = (f_j^*, j \in J), \quad f_* = (d_{1*}, ..., d_{(k+r)*}) = f_*(J) = (f_{j*}, j \in J),$$

$$B = \begin{pmatrix} b_{11} & \dots & b_{1(k+r)} \\ \dots & \dots & \dots \\ b_{m1} & \dots & b_{m(k+r)} \end{pmatrix} = B(I,J) = \begin{pmatrix} b_{i,j}, & i \in I, \\ & j \in J \end{pmatrix}$$

#### Matrix model



$$F = c^T x \rightarrow \max$$

$$Bx = a$$

$$f_{*i} \le x_i \le f_i^*,$$

$$i = 1, 2, ..., k, k + 1, ..., k + r.$$

Denote by  $X = \{x \in R^{k+r} : Bx \neq a, f_* \le x \le f^* \}$ 

 $\forall x \in X$  are called the feasible points, and the set X- is admissible set.

 $x^o \in X$  optimal solution if the objective function achieves the maximal value at this point.

From index set I of matrix B(I,J) select  $\forall$  subset  $I_{supp}$ ,

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Then by pair

$$K_{supp} = \{I_{supp}, J_{supp}\}$$

$$B_{supp} = B(I_{supp}, J_{supp})$$

From index set I of matrix B(I,J) select  $\forall$  subset  $I_{supp}$ , From index set J of matrix B(I,J) select  $\forall$  subset  $J_{supp}$ .  $\Downarrow$  the number  $|I_{supp}| = |J_{supp}|$ 

Then by pair

$$K_{supp} = \{I_{supp}, J_{supp}\} - Support$$

$$B_{supp} = B(I_{supp}, J_{supp}) - Support \ matrix(\det B_{supp} \neq 0)$$

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What does the support means physically?

Then by pair

$$K_{supp} = \{I_{supp}, J_{supp}\} - Support$$

$$B_{supp} = B(I_{supp}, J_{supp}) - Support \ matrix(\det B_{supp} \neq 0)$$

Introduce the vector ("the intensity of pump") z = Bx, where

$$B = \begin{pmatrix} B_{supp} & B_{supp,N} \\ B_{N,supp} & B_{N,N} \end{pmatrix}$$

$$B_{supp} = B(I_{supp}, J_{supp}),$$

$$B_{supp,N} = B(I_{supp}, J_N), B_{N,supp} = B(I_N, J_{supp})$$

$$B_{N,N} = B(I_N, J_N), I_N = I \setminus I_{supp}.$$

then support components  $z(I_{supp})$  of vector z:

$$z_{supp} = B_{supp} x_{supp} + B_{supp,N} x_N$$

$$\downarrow since \det B_{supp} \neq 0$$

$$x_{supp} = B_{supp}^{-1} z_{supp} + B_{supp}^{-1} B_{supp,N} x_N$$

support component of the feasible point  $x_{supp} = x(J_{supp})$ 

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 components  $z(I_{supp})$  of vector  $z$ :

$$B_{N,N} = B(I_N, J_N), \ I_N = I \setminus I_{supp}.$$

then support components  $(I_{supp})$  of vector z:

$$z_{supp} = B_{supp} x_{supp} + B_{supp,N} x_N$$

$$\Downarrow$$
 since  $\det B_{supp} \neq 0$ 

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non-support component of the feasible point  $x_N=x(J_N)$ 



Support- is pair of indices sets  $K(I_{supp}, J_{supp})$ , such that:

 $\forall z_{supp}$ 

 $\forall x_N$ 

 $\Downarrow$  we can find the support component  $x_{supp}$  of  $\forall$  feasible point $x=(x_{supp},x_N)$  such that :

$$z_{supp} = B_{supp} x_{supp} + B_{supp,N} x_N$$

holds.

We can realize the support general constraints Bx = z

using Support (namely support component  $x_{supp}$  of feasible point)

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 $\forall x_N$ 

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holds.

The pair 
$$(x, K_{supp})$$
 - support feasible (SF) point  $\forall x, \forall K_{supp}$ 

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holds.

Let  $(x, K_{supp})$  arbitrary SF point.

Consider another feasible point  $\bar{x}$ .

We set  $\Delta x = \bar{x} - x$  and calculate the increment of the objective value:

$$\Delta F(x) = c^T \bar{x} - c^T x = c^T \Delta x$$

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↓ construct the convenient formula for increment calculation.

Consider the support components of the "intensity vector"  $z_{supp}$  on two feasible points:

 $\boldsymbol{x}$ 

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↓ component form of formula for increment calculation.

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$$c^{T} \Delta x = c_{supp}^{T} (B_{supp}^{-1} \Delta z_{supp} - B_{supp}^{-1} B_{supp,N} \Delta x_{N}) + c_{N}^{T} \Delta x_{N} =$$

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Complete vectors  $u_{supp}^T$  and  $\Delta_N^T$  by components:

$$u_N = u(J_N) = 0$$
  
$$\Delta_{supp}^T = c_{supp}^T - c_{supp}^T B_{supp}^{-1} B_{supp} = 0$$



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#### Vector of potentials

#### Vector of estimates

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$$u(I) = (u(I_{supp}), u(I_N)) = (u_{supp}, 0)$$
  $\Delta(J) = (\Delta(J_{supp}, \Delta(J_N))) = (0, \Delta_N)$ 

$$\Delta F(x) = u_{supp}^{T} \Delta z_{supp} + \Delta_{N}^{T} \Delta x_{N} = \sum_{i \in I_{supp}} u_{i} \Delta z_{i} + \sum_{j \in J_{N}} \Delta_{j} \Delta x_{j}$$

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reduced gradient of the cost function by z

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reduced gradient of the cost function by x

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Complete vectors  $u_{supp}^T$  and  $\Delta_N^T$  by components:

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Since  $\Delta = c - B^T u \implies$ , it easy to see that we can get  $\Delta$  from c by correction  $B^T u$  which depends on general constraints. And correcting multiplier u constructed with Support help.



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Since  $\Delta = c - B^T u \implies$ , it easy to see that we can get  $\Delta$  from c by correction  $B^T u$  which depends on general constraints. And correcting multiplier u constructed with help of support.

 $\Delta$  - is support gradient of the cost function

# **Optimality criteria**

Let x be a feasible point.

Question: is it optimal point?

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Use the support  $K_{supp}$  and calculate the support gradient.

# **Optimality criteria**

Let x be a feasible point.

For the optimality of a feasible point x it is sufficient and, in the case of non-degeneracy of SF-point  $\{x, K_{supp}\}$ , also necessary, that the following conditions:

$$\begin{cases} u_i \leq 0 \text{ for } z_i = a_{*i}, \\ u_i \geq 0 \text{ for } z_i = a_i^*, \\ u_i = 0 \text{ for } a_{*i} \leq x_i \leq a_i^*, i \in I_{supp}; \end{cases}$$

$$\begin{cases} & \Delta_j \geq 0 \text{ for } x_j = f_{*j}, \\ & \Delta_j \leq 0 \text{ for } x_j = f_j^*, \\ & \Delta_j = 0 \text{ for } f_{*j} \leq x_j \leq f_j^*, \ j \in J_N \end{cases}$$

Independent variables:

$$x_j, \qquad j \in I_N$$

Dependent variables:

$$x_j, \quad j \in J_{supp}$$

Independent variables:

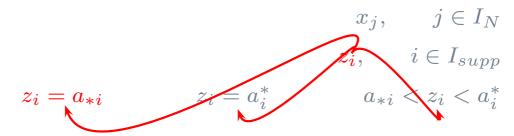
$$x_j, \quad j \in I_N$$
 $z_i, \quad i \in I_{supp}$ 

Dependent variables:

$$x_j, \quad j \in J_{supp}$$

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#### Independent variables:

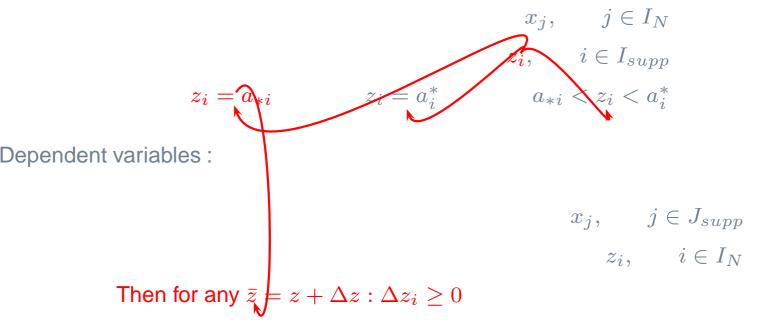


#### Dependent variables:

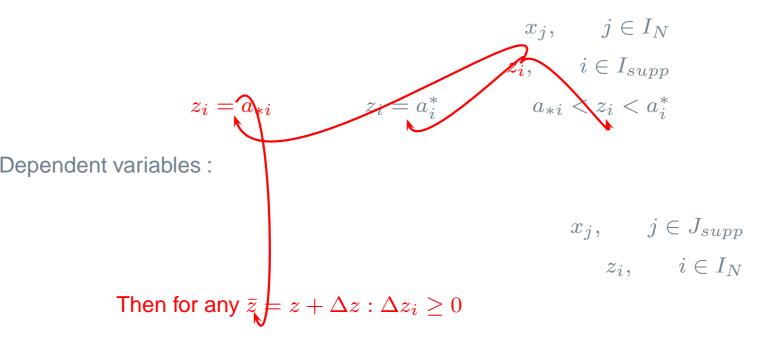
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#### Independent variables:

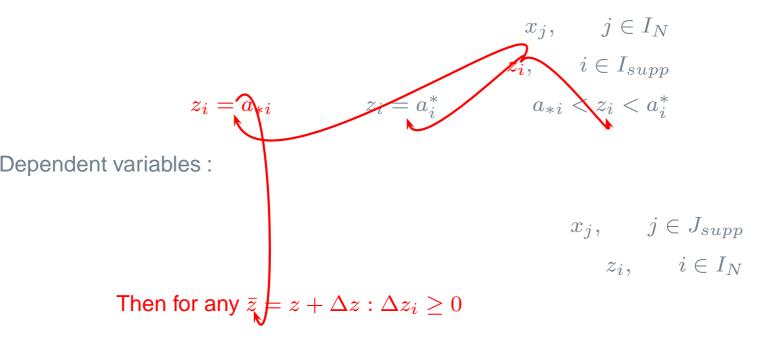


#### Independent variables:



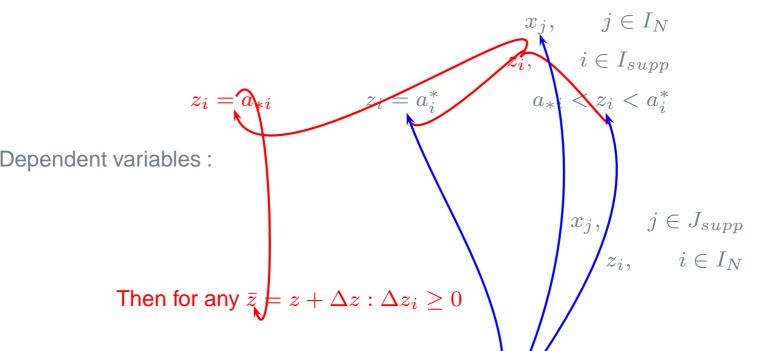
In this case by optimality criteria  $\Rightarrow u_i \leq 0$  holds.

#### Independent variables:



 $\Downarrow$  Hence the variation of the  $z_i$  can not increase the value of the cost function (since  $u_i \Delta z_i \leq 0$ )

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By analogy can be explained the signs of other variables in optimality criteria.

# Maximum principle

The optimality condition can be rewritten in maximum principle form.

by intensity vector z:

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$$u_i z_i = \max_{a_{*i} \le \zeta_i \le a_i^*} u_i \zeta_i \quad i \in I_{supp}$$

$$\Delta_j x_j = \max_{f_{*j} \le \omega_j \le f_j^*} \Delta_j \omega_j \quad j \in J_N$$

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$$u_i z_i = \max_{a_{*i} \le \zeta_i \le a_i^*} u_i \zeta_i - \varepsilon_{zi} \quad i \in I_{supp}$$

$$\Delta_j \chi_j = \max_{f_{*j} \le \omega_j \le f_j^*} \Delta_j \omega_j - \varepsilon_{xj} \quad j \in J_N$$

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$$\varepsilon_{zi} = u_i (\xi_i - z_i) \quad i \in I_{supp}$$

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$$c^{T}x^{o} - c^{T}x^{\varepsilon} \leq \max_{a_{*} \leq \bar{z}_{supp} \leq a^{*}, } c^{T}(\bar{x} - x^{\varepsilon}) = a_{*} \leq \bar{z}_{supp} \leq a^{*},$$

$$f_{*} \leq x_{N} \leq f^{*}$$

$$= \beta(x^{\varepsilon}, K_{supp}) \leq \varepsilon = \sum_{i \in I_{supp}} \varepsilon_{zi} + \sum_{j \in J_{N}} \varepsilon_{xj}.$$

Consider the SF point  $\{x, K_{supp}\}$  and corresponding vector  $z, u, \Delta$  then the  $\varepsilon - maximum$  condition is:

For a feasible point x to be  $\epsilon$ -optimal it is sufficient that there exists a support  $K_{supp}$  such that

$$\beta(x, K_{supp}) \le \epsilon.$$

by vector z:

$$u_i z_i = \max_{a_{*i} \le \zeta_i \le a_i^*} u_i \zeta_i - \varepsilon_{zi} \quad i \in I_{supp}$$
$$\varepsilon_{zi} = u_i (\xi_i - z_i) \quad i \in I_{supp}$$

$$\Delta_{j}\chi_{j} = \max_{f_{*j} \leq \omega_{j} \leq f_{j}^{*}} \Delta_{j}\omega_{j} - \varepsilon_{xj} \quad j \in J_{N}$$
$$\varepsilon_{xj} = \Delta_{j}(\chi_{j} - x_{j}) \quad j \in J_{N}$$

- lacksquare Select the initial support  $Q_{supp}$ 
  - a)Calculate the coefficients  $\mu_i$ ;
  - b) Construct the matrix and check the support criteria:

$$G_{supp} = \left(g_{si}, s \in I_{\Sigma supp}, i \in I_{\Delta supp}\right)$$

$$g_{si} = \sum_{k \in I_{\Delta(i)} \cup I_{\Sigma(s)}} \mu_k a_{ik}, s \in I_{\Sigma supp}, i \in_{\Delta supp}.$$

The collection  $Q_{supp} = \{I_{\Delta supp}, I_{\Sigma supp}\}$  is called the support of the network S if  $|I_{\Delta supp}| = |I_{\Sigma supp}|$  and  $\det G_{supp} \neq 0$ .

- Support flow  $\{z, Q_{supp}\}$
- Verify the optimality criteria for the support flow
- m arphi Changing the flow z o ar z
- lacksquare The second part of the iteration  $Q_{supp} 
  ightarrow \overline{Q}_{supp}$
- **●** Complete iteration  $\{z, Q_{supp}\} \rightarrow \{\bar{z}, \bar{Q}_{supp}\}$
- The suboptimality estimation



- ullet Select the initial support  $Q_{supp}$
- **Support flow**  $\{z, Q_{supp}\}$

formed by the flow z, corresponding to the initial admissible input flow

$$z = \{x_i, i \in I_{\Delta}; x_{ij}, (i, j) \in U_*; f\}.$$

- Verify the optimality criteria for the support flow
- lacksquare Changing the flow  $z 
  ightarrow ar{z}$
- lacksquare The second part of the iteration  $Q_{supp} 
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- ullet Select the initial support  $Q_{supp}$
- **Support flow**  $\{z, Q_{supp}\}$
- Verify the optimality criteria for the support flow

a)Calculate the potencials  $y_i$  and estimation  $\Delta$ ;

The nondegenerate support flow  $\{z, Q_{supp}\}$  is optimal iff:

$$\Delta_{i} \geq 0 \quad at \quad x_{i} = d_{*i}; \quad \Delta_{i} \leq 0 \quad at \quad x_{i} = d_{i}^{*}$$

$$\Delta_{i} = 0 \quad at \quad d_{*i} < x_{i} < d_{i}^{*}, \quad i \in I_{\Delta nsupp}$$

$$\Delta_{ij} \geq 0 \quad at \quad x_{ij} = d_{*ij}, \quad \Delta_{ij} \leq 0 \quad at \quad x_{ij} = d_{ij}^{*};$$

$$\Delta_{ij} = 0 \quad at \quad d_{*ij} < x_{ij} < d_{ij}^{*}, \quad (i, j) \in U_{nsupp}.$$

- lacksquare Changing the flow z o ar z
- lacksquare The second part of the iteration  $Q_{supp} 
  ightarrow \overline{Q}_{supp}$
- Complete iteration  $\{z, Q_{supp}\} \rightarrow \{\bar{z}, \bar{Q}_{supp}\}$
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- Select the initial support  $Q_{supp}$
- **Support flow**  $\{z, Q_{supp}\}$
- Verify the optimality criteria for the support flow
- Changing the flow  $z \to \bar{z}$

$$\overline{z} = z + \theta_0 \Delta z,$$

where the improvement direction is  $\theta_0$ , and

$$\Delta z = (\Delta x_i, \ i \in I_{\Delta}; \ \Delta x_{ij}, \ (i,j) \in U_*; \ \Delta f)$$

- lacksquare The second part of the iteration  $Q_{supp} 
  ightarrow \overline{Q}_{supp}$
- Complete iteration  $\{z, Q_{supp}\} \rightarrow \{\bar{z}, \bar{Q}_{supp}\}$
- The suboptimality estimation



- lacksquare Select the initial support  $Q_{supp}$
- Support flow  $\{z, Q_{supp}\}$
- Verify the optimality criteria for the support flow
- Changing the flow  $z 
  ightarrow ar{z}$
- The second part of the iteration  $Q_{supp} \to \overline{Q}_{supp}$ This are realized on the basis of dual theory.
- Complete iteration  $\{z, Q_{supp}\} \rightarrow \{\bar{z}, \bar{Q}_{supp}\}$
- The suboptimality estimation

- lacksquare Select the initial support  $Q_{supp}$
- **Support flow**  $\{z, Q_{supp}\}$
- Verify the optimality criteria for the support flow
- lacksquare Changing the flow  $z 
  ightarrow ar{z}$
- lacksquare The second part of the iteration  $Q_{supp} 
  ightarrow \overline{Q}_{supp}$
- Complete iteration  $\{z, Q_{supp}\} \rightarrow \{\bar{z}, \bar{Q}_{supp}\}$

 $\downarrow \downarrow$ 

Here the iteration of the optimization method is complete.

The suboptimality estimation

- lacksquare Select the initial support  $Q_{supp}$
- **Support flow**  $\{z, Q_{supp}\}$
- Verify the optimality criteria for the support flow
- Changing the flow  $z 
  ightarrow ar{z}$
- lacksquare The second part of the iteration  $Q_{supp} 
  ightarrow \overline{Q}_{supp}$
- Complete iteration  $\{z,Q_{supp}\} \rightarrow \{\bar{z},\bar{Q}_{supp}\}$
- The suboptimality estimation

The suboptimality estimation of the new support flow is

$$eta(\overline{z},\overline{Q}_{supp}) =$$

$$(1 - \theta_0)\beta(z, Q_{supp}) + v_0\sigma_{i_{(1)}} + \sum_{k=1}^{\nu-1} v_k(\sigma_{i_{k+1}} - \sigma_{i_{(k)}})$$

$$\leq \beta(z, Q_{supp}).$$

## Short summary

#### Comparison of the proposed adaptive method with classical LP methods.

- The basic "instrument" of the adaptive method support quite flexible react on a different situation during the solution process.
- Simplex methods start from a specified basis. The support lets us satisfy the general constraints initially and later.
- Nonsupport (nonbasic) variables need not be zero—they may have any value satisfying the bounds.
- The adaptive method allows to use any priory information about feasible solution.

- The new principle used on iteration of the adaptive method.
- The method equipped with stop criteria.
- The primal adaptive method significantly uses the ideas of the dual theory.(dual step in second procedure)
- The dual adaptive method is much more effective then traditional dual simplex methods due to the long step rule.
- ....provide sensitivity analisys

By these reasons the method called adaptive since its properties of using the all the initial and current information for effective construction of suboptimal feasible solution.

### The end

#### Thank you!