



# ODS2023

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*Efficient Last-Mile Delivery using UAVs: A  
Variational Inequality Approach for Optimizing  
Supply Chain Management*

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G. Colajanni, P. Daniele, A. Nagurney, *Centralized Supply Chain Network Optimization with UAV-based Last Mile Deliveries*, Transportation Research Part C, to appear.

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# E-COMMERCE

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## Companies



## Companies



## Customers

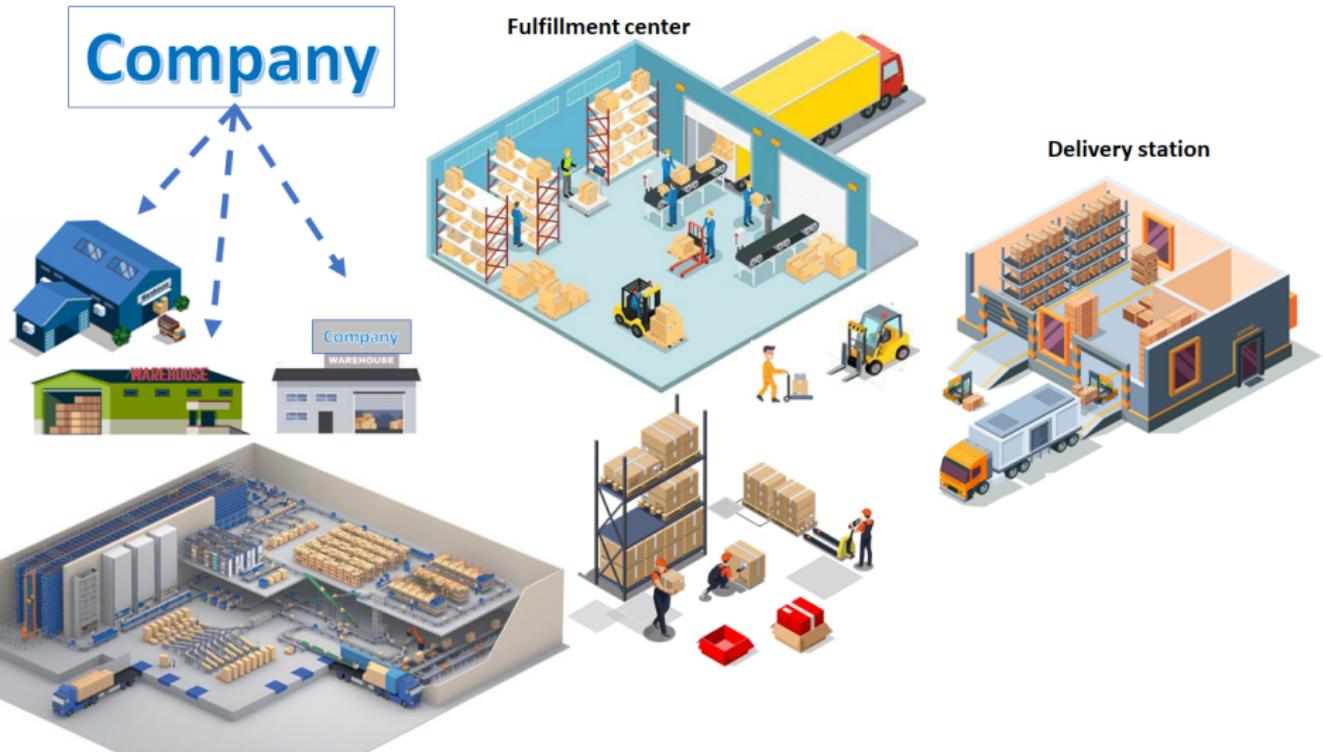


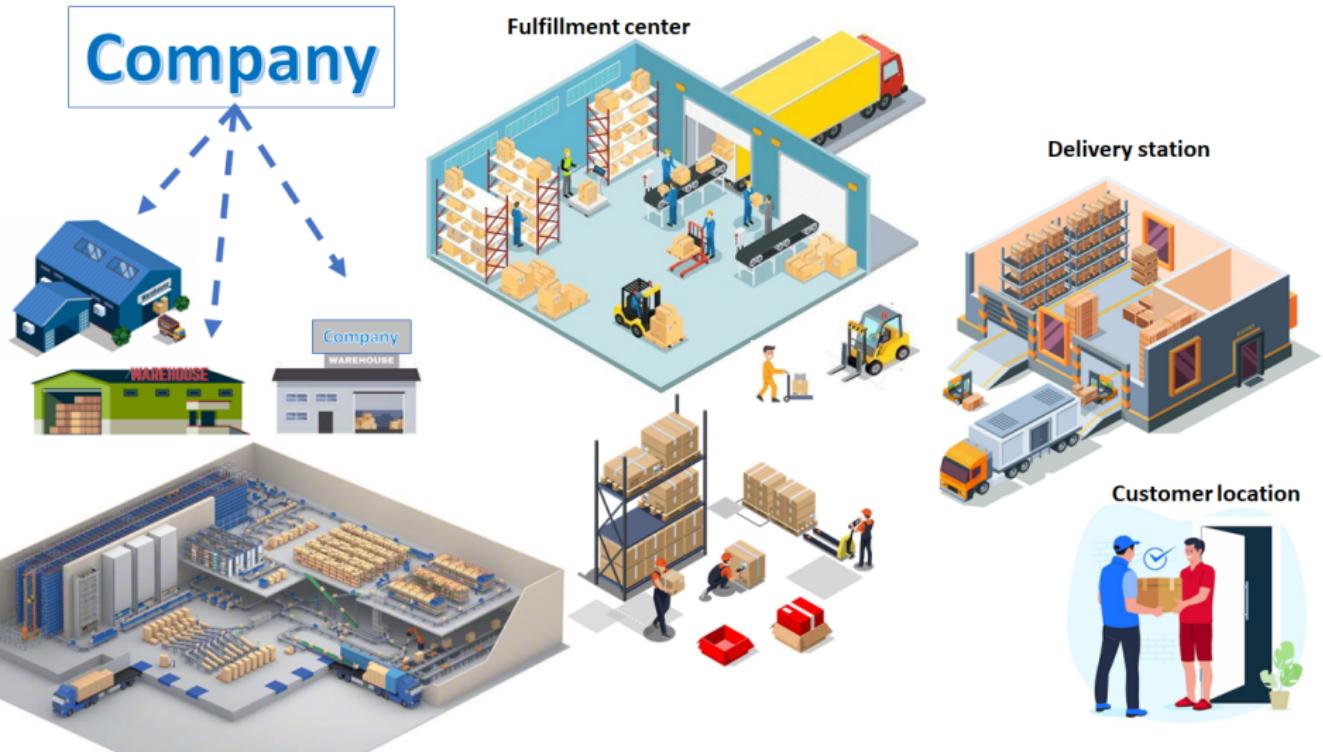














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## Limitations:

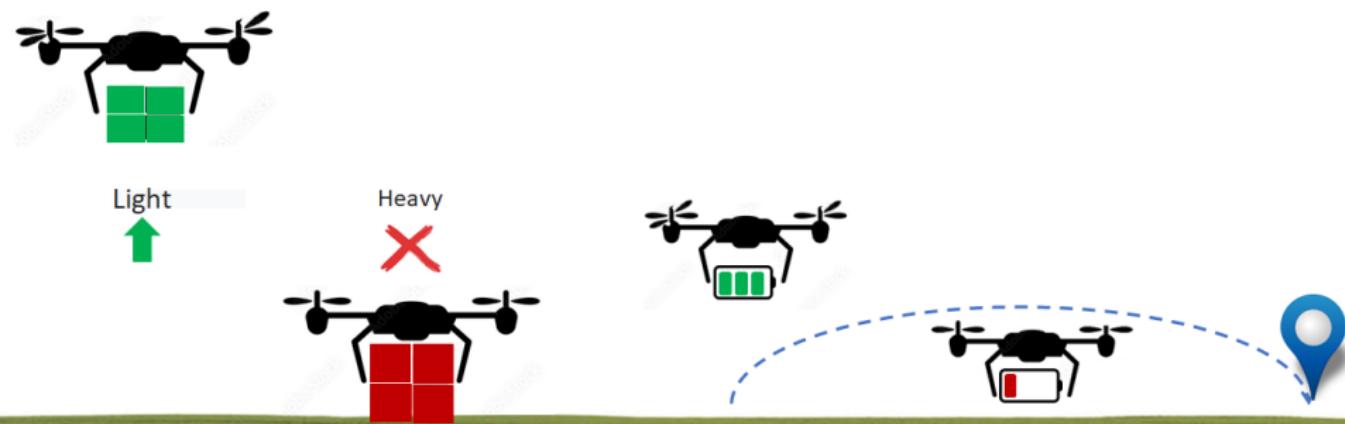
### Weight



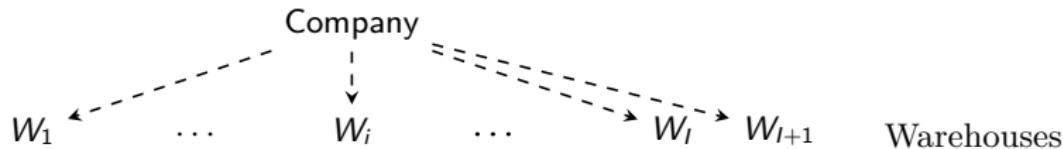
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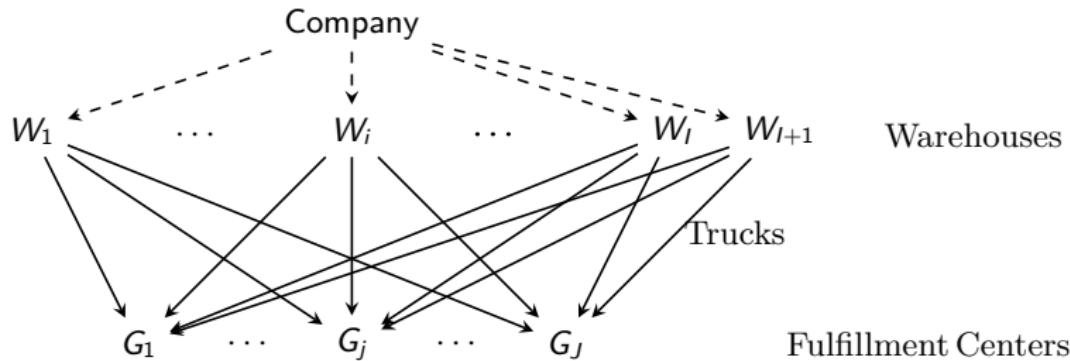
Weight

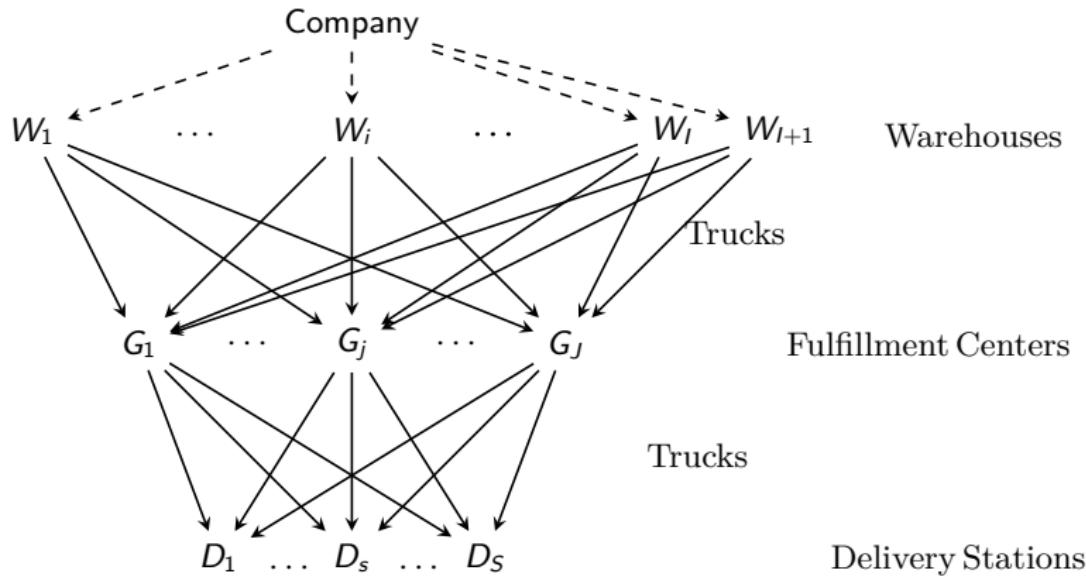
Battery  $\Rightarrow$  Distance

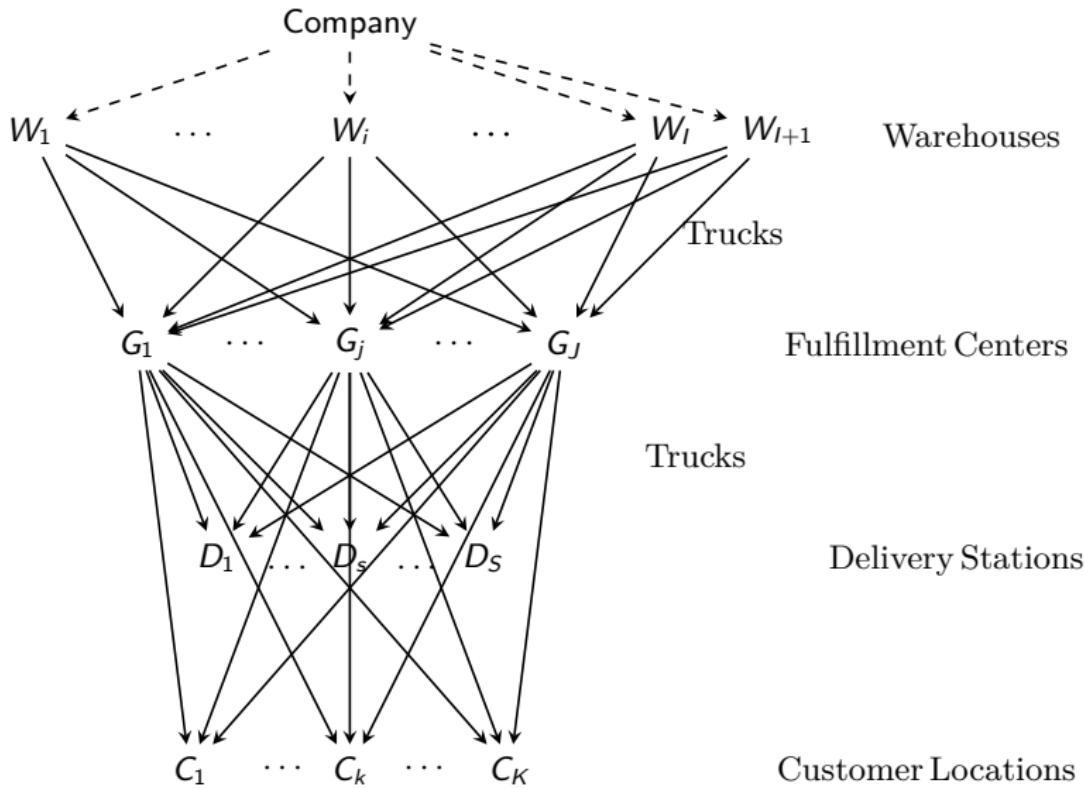


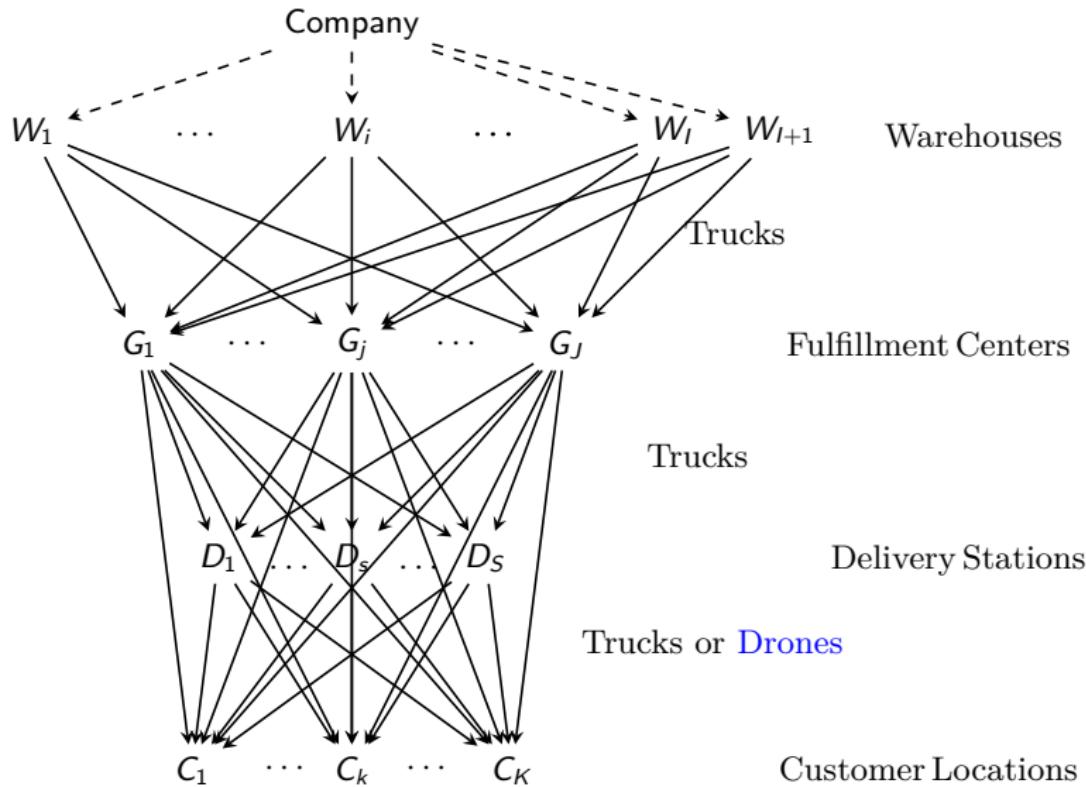
## Company

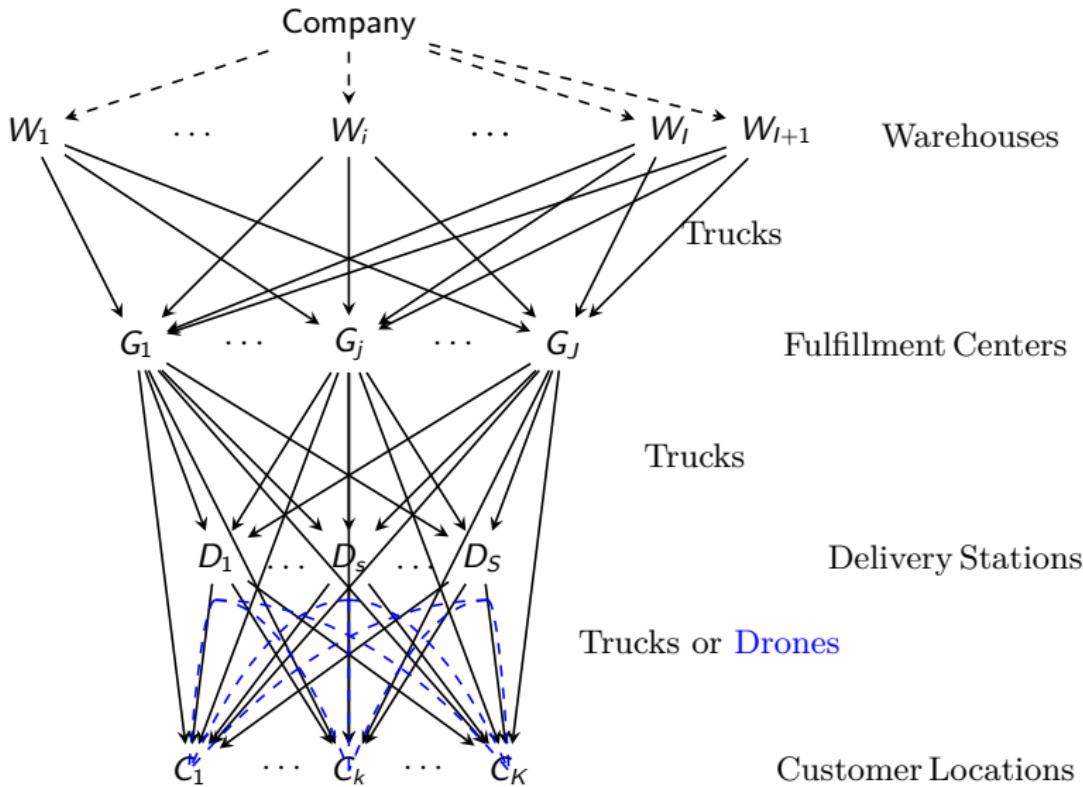




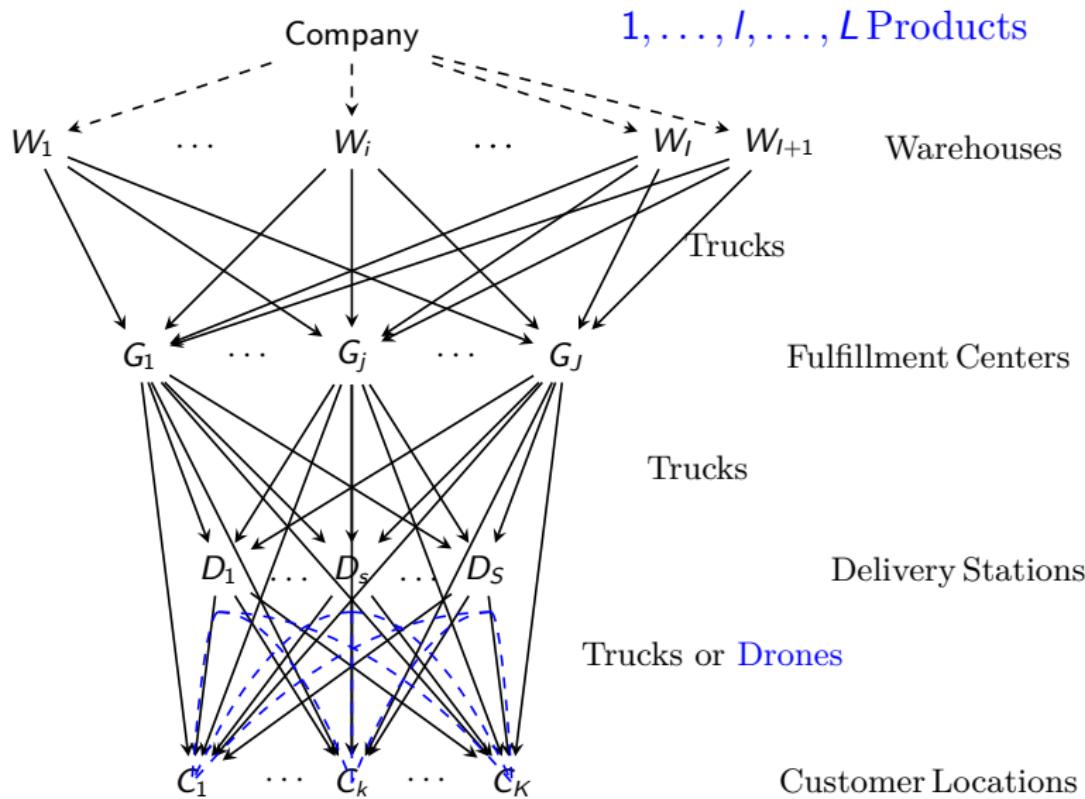




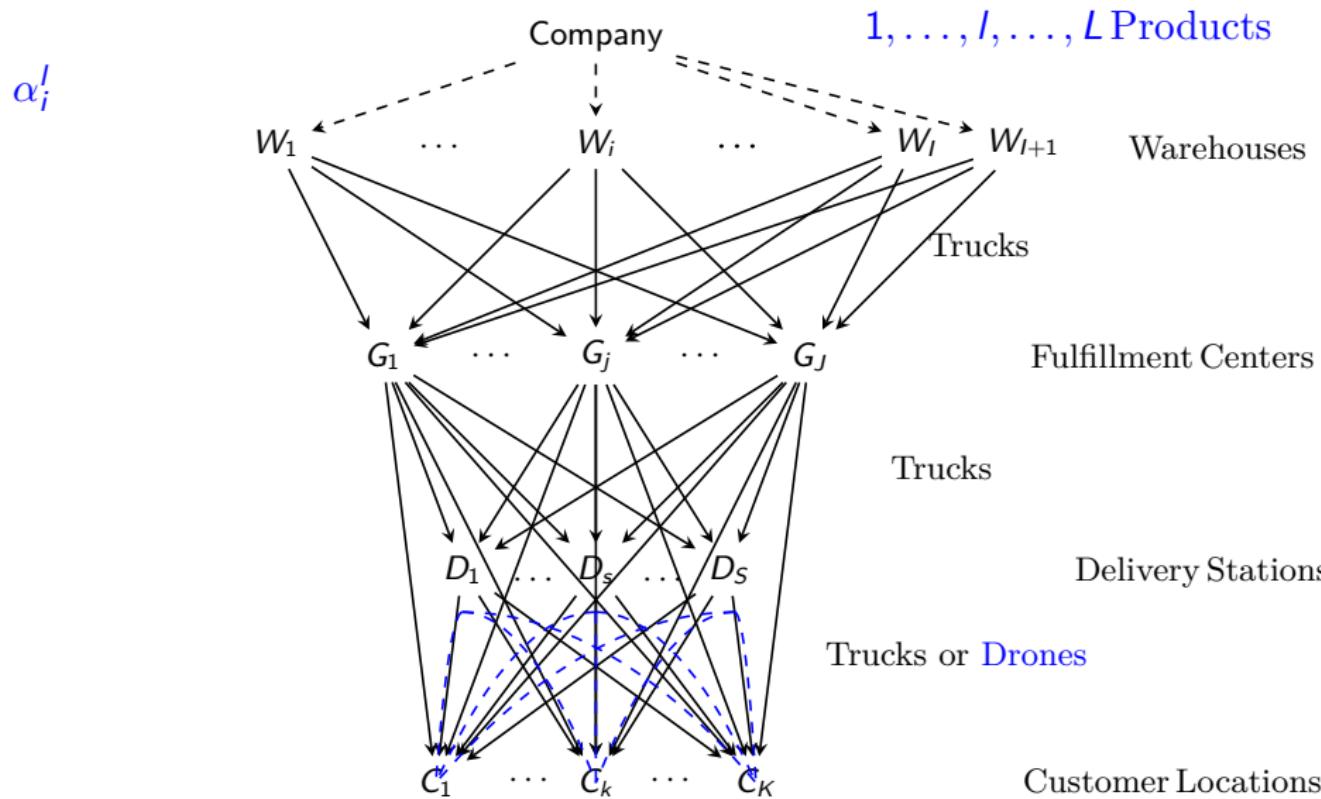




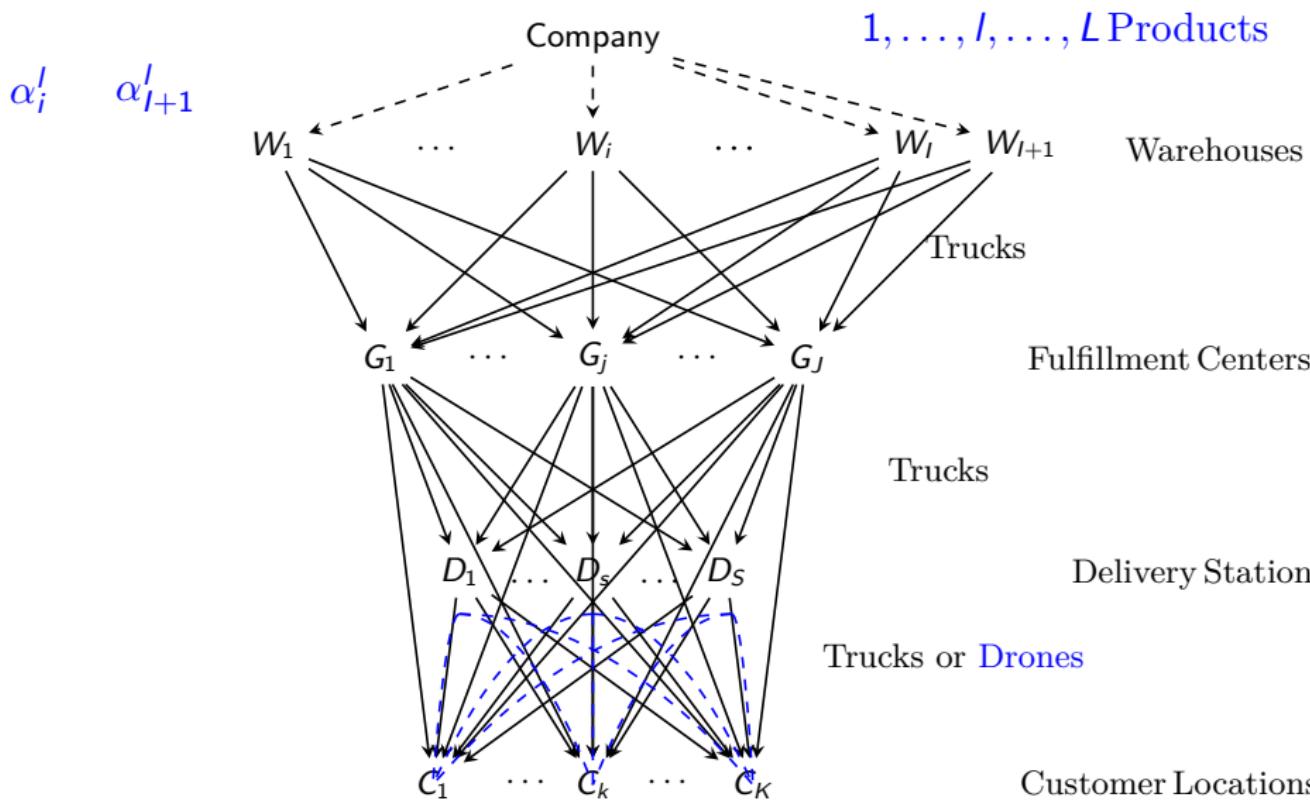
## The variables



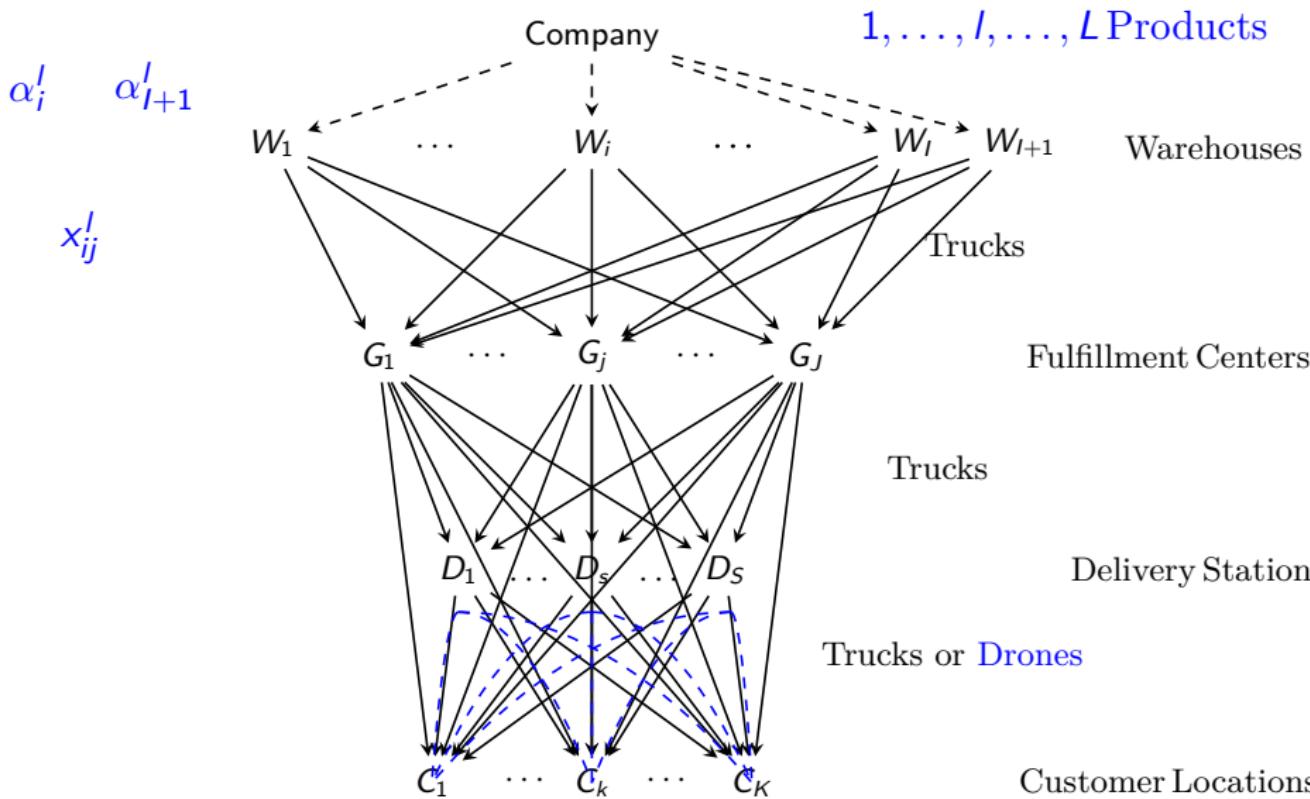
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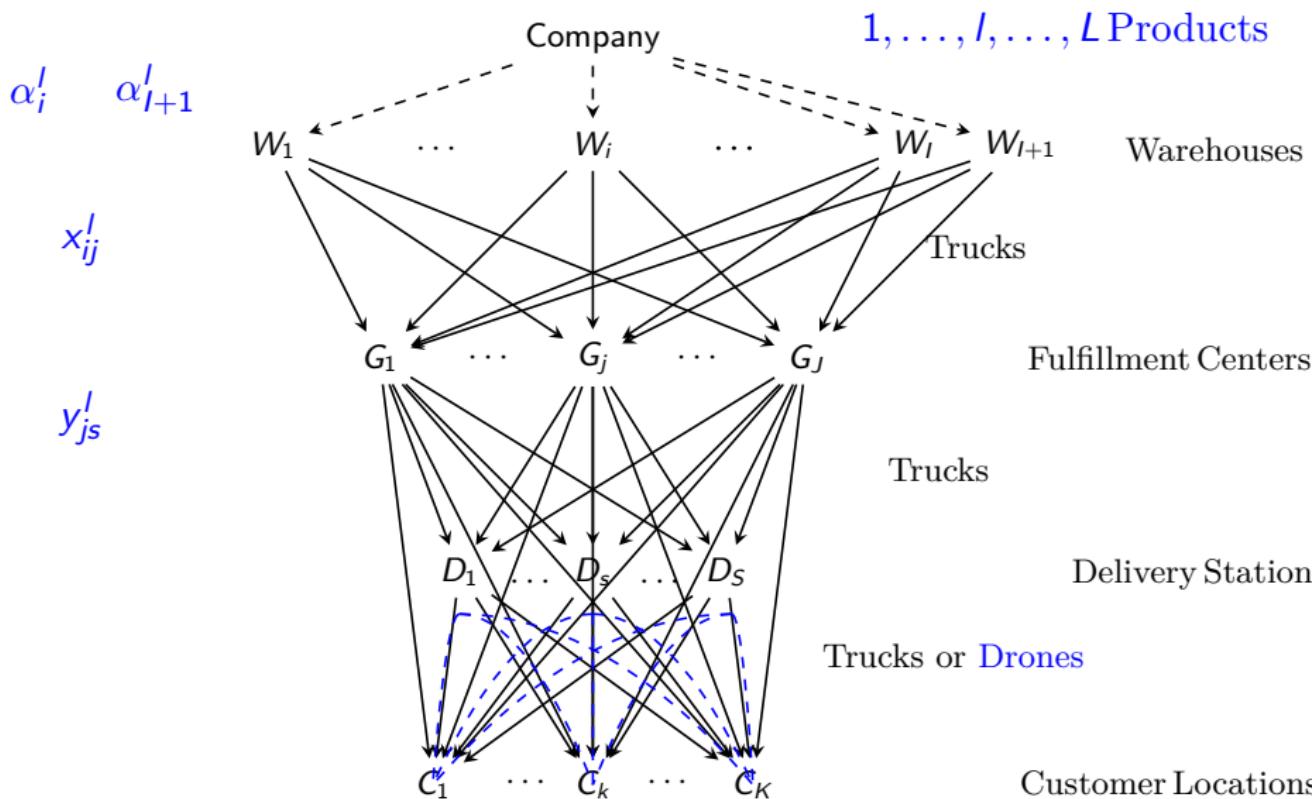
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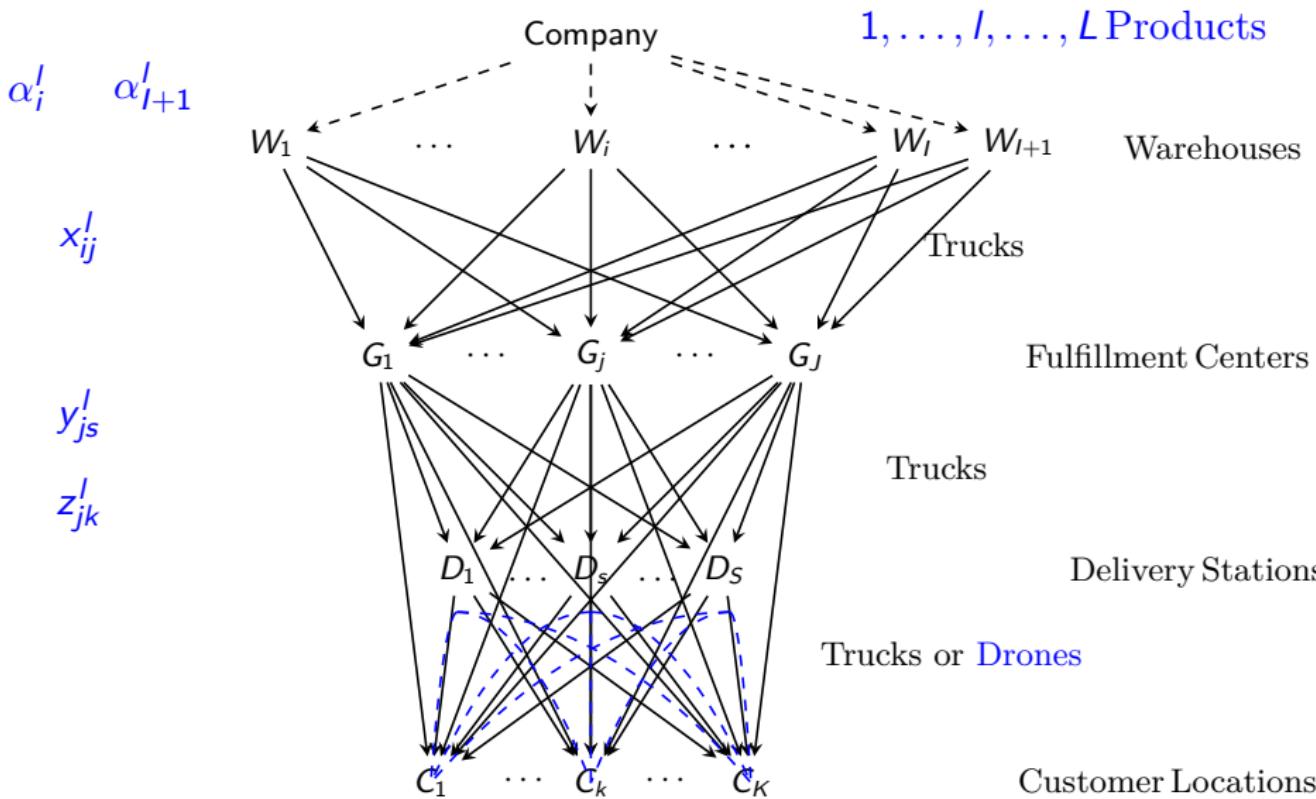
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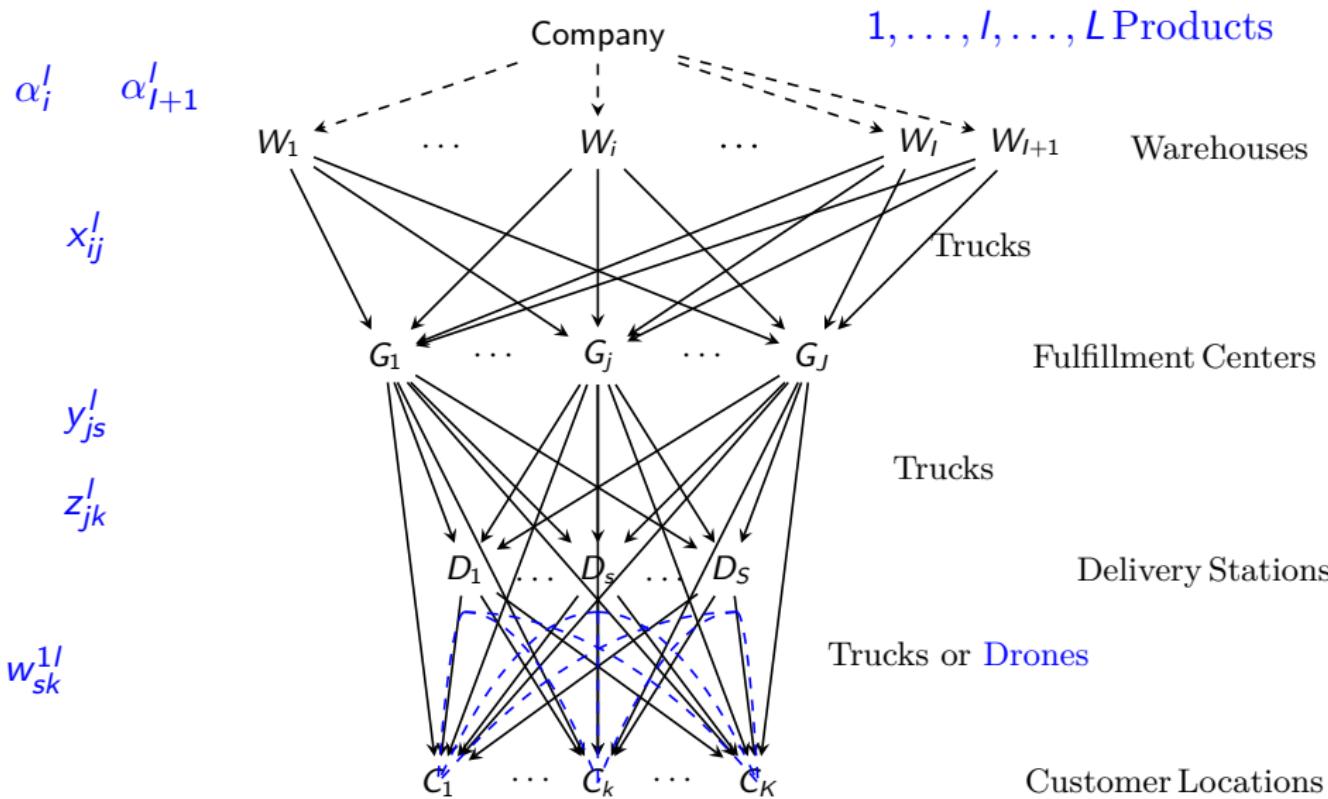
## The variables



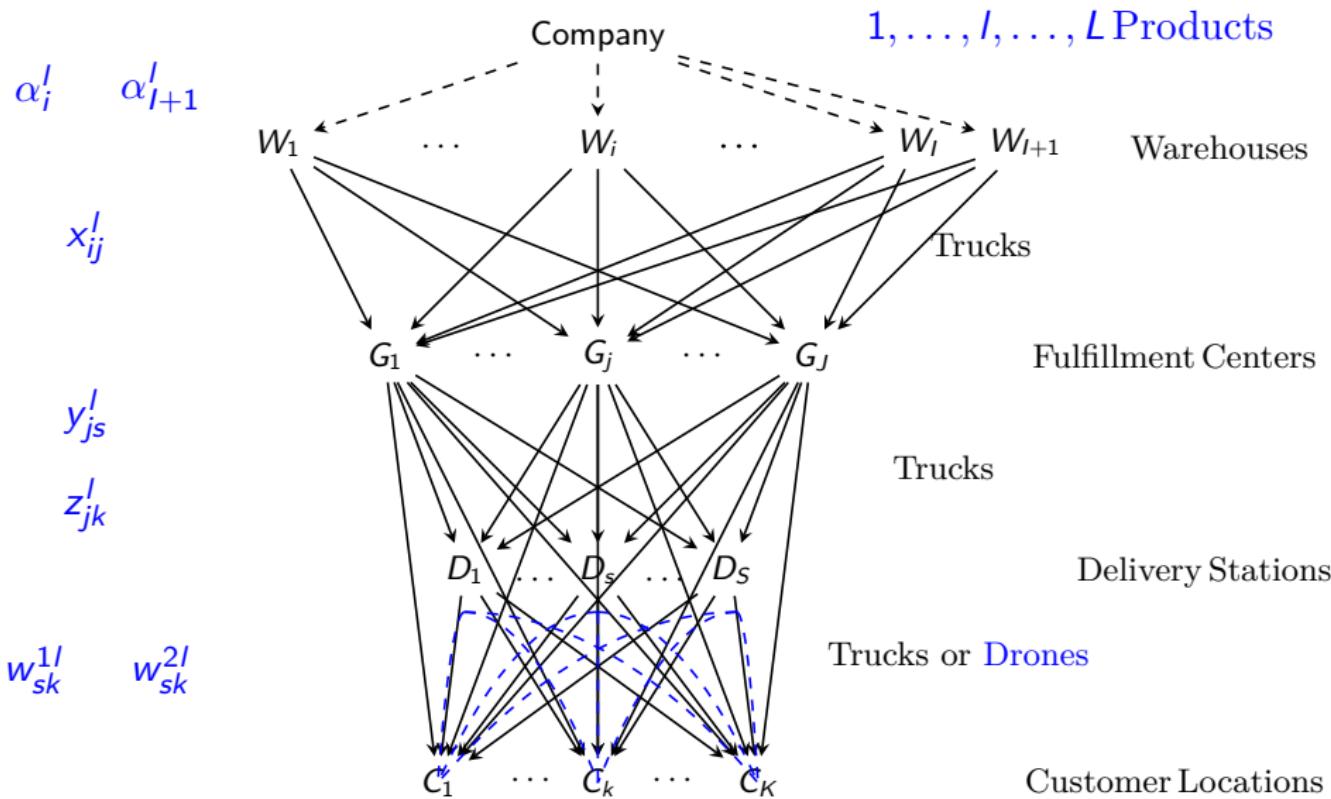
## The variables



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## The variables



## The objective function

$$\max_{\alpha, x, y, z, w^1, w^2} \left\{ \right.$$

(1)

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$$\max_{\alpha, x, y, z, w^1, w^2} \left\{ -c(\alpha, x, y, z, w^1, w^2) \right.$$

(1)

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$$\max_{\alpha, x, y, z, w^1, w^2} \left\{ -c(\alpha, x, y, z, w^1, w^2) - \sum_{l=1}^L \sum_{i=1}^{l+1} \gamma_i^l \alpha_i^l \right.$$

(1)

## The objective function

$$\begin{aligned} \max_{\alpha, x, y, z, w^1, w^2} & \left\{ -c(\alpha, x, y, z, w^1, w^2) - \sum_{l=1}^L \sum_{i=1}^{l+1} \gamma_i^l \alpha_i^l - \sum_{i=1}^{l+1} \sum_{j=1}^J c_{ij}(x_{ij}) \right. \\ & - \sum_{j=1}^J \sum_{s=1}^S \hat{c}_{js}(y_{js}, z_j) - \sum_{j=1}^J \sum_{k=1}^K \bar{c}_{jk}(y_j, z_{jk}) - \sum_{s=1}^S \sum_{k=1}^K \tilde{c}_{sk}^1(w_{sk}^1) \\ & \left. - \sum_{s=1}^S \sum_{k=1}^K \tilde{c}_{sk}^2(w_{sk}^2) \right\} \end{aligned} \tag{1}$$

## The objective function

$$\begin{aligned} \max_{\alpha, x, y, z, w^1, w^2} & \left\{ -c(\alpha, x, y, z, w^1, w^2) - \sum_{l=1}^L \sum_{i=1}^{I+1} \gamma_i^l \alpha_i^l - \sum_{i=1}^{I+1} \sum_{j=1}^J c_{ij}(x_{ij}) \right. \\ & - \sum_{j=1}^J \sum_{s=1}^S \hat{c}_{js}(y_{js}, z_j) - \sum_{j=1}^J \sum_{k=1}^K \bar{c}_{jk}(y_j, z_{jk}) - \sum_{s=1}^S \sum_{k=1}^K \tilde{c}_{sk}^1(w_{sk}^1) \\ & \left. - \sum_{s=1}^S \sum_{k=1}^K \tilde{c}_{sk}^2(w_{sk}^2) + \sum_{l=1}^L \sum_{s=1}^S \sum_{k=1}^K l_{sk} w_{sk}^{2l} \right\} \end{aligned} \tag{1}$$

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$$\begin{aligned} \max_{\alpha, x, y, z, w^1, w^2} & \left\{ -c(\alpha, x, y, z, w^1, w^2) - \sum_{l=1}^L \sum_{i=1}^{l+1} \gamma_i^l \alpha_i^l - \sum_{i=1}^{l+1} \sum_{j=1}^J c_{ij}(x_{ij}) \right. \\ & - \sum_{j=1}^J \sum_{s=1}^S \hat{c}_{js}(y_{js}, z_j) - \sum_{j=1}^J \sum_{k=1}^K \bar{c}_{jk}(y_j, z_{jk}) - \sum_{s=1}^S \sum_{k=1}^K \tilde{c}_{sk}^1(w_{sk}^1) \\ & - \sum_{s=1}^S \sum_{k=1}^K \tilde{c}_{sk}^2(w_{sk}^2) + \sum_{l=1}^L \sum_{s=1}^S \sum_{k=1}^K l_{sk} w_{sk}^{2l} \\ & \left. - \sum_{i=1}^{l+1} c_i^{tr}(\alpha, w^2) - \sum_{s=1}^S c_s^{dr}(w^2) \right\} \end{aligned} \tag{1}$$

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$$\begin{aligned}
 & \max_{\alpha, x, y, z, w^1, w^2} \left\{ -c(\alpha, x, y, z, w^1, w^2) - \sum_{l=1}^L \sum_{i=1}^{l+1} \gamma_i^l \alpha_i^l - \sum_{i=1}^{l+1} \sum_{j=1}^J c_{ij}(x_{ij}) \right. \\
 & - \sum_{j=1}^J \sum_{s=1}^S \hat{c}_{js}(y_{js}, z_j) - \sum_{j=1}^J \sum_{k=1}^K \bar{c}_{jk}(y_j, z_{jk}) - \sum_{s=1}^S \sum_{k=1}^K \tilde{c}_{sk}^1(w_{sk}^1) \\
 & - \sum_{s=1}^S \sum_{k=1}^K \tilde{c}_{sk}^2(w_{sk}^2) + \sum_{l=1}^L \sum_{s=1}^S \sum_{k=1}^K l_{sk} w_{sk}^{2l} \\
 & - \sum_{i=1}^{l+1} c_i^{tr}(\alpha, w^2) - \sum_{s=1}^S c_s^{dr}(w^2) \\
 & \left. + \sum_{l=1}^L \sum_{j=1}^J \sum_{k=1}^K \gamma_{jk}^l z_{jk}^l + \sum_{l=1}^L \sum_{s=1}^S \sum_{k=1}^K \gamma_{sk}^l w_{sk}^{1l} + \sum_{l=1}^L \sum_{s=1}^S \sum_{k=1}^K \gamma_{sk}^l w_{sk}^{2l} \right\} \quad (1)
 \end{aligned}$$

## The constrained optimization model

$$\alpha_i^l \leq Q_i^l, \quad \forall l=1,\dots,L, \forall i=1,\dots,l+1 \quad (2)$$

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$$\sum_{i=1}^{I+1} x_{ij}^l \geq \sum_{s=1}^S y_{js}^l + \sum_{k=1}^K z_{jk}^l, \quad \forall j=1, \dots, J, \forall l=1, \dots, I \quad (4)$$

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$$\sum_{j=1}^J y_{js}^l \geq \sum_{k=1}^K w_{sk}^{1l} + \sum_{k=1}^K w_{sk}^{2l}, \quad \forall s=1, \dots, S, \forall l=1, \dots, L \quad (5)$$

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$$\sum_{j=1}^J z_{jk}^l + \sum_{s=1}^S w_{sk}^{1l} + \sum_{s=1}^S w_{sk}^{2l} = r_k^l, \quad \forall k=1, \dots, K, \forall l=1, \dots, L \quad (6)$$

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$$w_{sk}^{2l} \leq P_l^{dr}, \quad \forall l=1, \dots, L, \forall s=1, \dots, S, \forall k=1, \dots, K \quad (9)$$

## The constrained optimization model

$$\sum_{l=1}^L \sum_{j=1}^J x_{ij}^l \leq W \cdot n_i^{tr}, \quad \forall i=1, \dots, I+1 \quad (7)$$

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$$w_{sk}^{2l} \leq P_l^{dr}, \quad \forall l=1, \dots, L, \forall s=1, \dots, S, \forall k=1, \dots, K \quad (9)$$

$$w_{sk}^{2l} \leq B_{sk}^{dr}, \quad \forall s=1, \dots, L, \forall k=1, \dots, K, \forall l=1, \dots, L \quad (10)$$

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$$w_{sk}^{2l} \leq B_{sk}^{dr}, \quad \forall s=1, \dots, L, \forall k=1, \dots, K, \forall l=1, \dots, L \quad (10)$$

$$\alpha_i^l, x_{ij}^l, y_{js}^l, z_{jk}^l, w_{sk}^{1l}, w_{sk}^{2l} \geq 0$$

$$\forall l=1, \dots, L, \forall i=1, \dots, I+1, \forall j=1, \dots, J, \forall s=1, \dots, S, \forall k=1, \dots, K \quad (11)$$

## Variational Inequality

## Theorem

A vector  $(\alpha^*, x^*, y^*, z^*, w^{1*}, w^{2*}) \in \mathbb{K}$  is an optimal solution to the problem (1)-(11)

if and only if such a vector is a solution to the variational inequality:

Find  $(\alpha^*, x^*, y^*, z^*, w^{1*}, w^{2*}) \in \mathbb{K}$  such that:

$$\begin{aligned} & \sum_{i=1}^{I+1} \sum_{l=1}^L \left[ \frac{\partial c(\alpha^*, x^*, y^*, z^*, w^{1*}, w^{2*})}{\partial \alpha_i^l} + \gamma_i^l + \frac{\partial c_i^{tr}(\alpha^*, w^{2*})}{\partial \alpha_i^l} \right] \times (\alpha_i^l - \alpha_i^{l*}) \\ & + \sum_{i=1}^{I+1} \sum_{j=1}^J \sum_{l=1}^L \left[ \frac{\partial c(\alpha^*, x^*, y^*, z^*, w^{1*}, w^{2*})}{\partial x_{ij}^l} + \frac{\partial c_{ij}(x_{ij}^*)}{\partial x_{ij}^l} \right] \times (x_{ij}^l - x_{ij}^{l*}) \\ & + \sum_{j=1}^J \sum_{s=1}^S \sum_{l=1}^L \left[ \frac{\partial c(\alpha^*, x^*, y^*, z^*, w^{1*}, w^{2*})}{\partial y_{js}^l} + \frac{\partial \hat{c}_{js}(y_{js}^*, z_j^*)}{\partial y_{js}^l} + \frac{\partial \bar{c}_{jk}(y_j^*, z_{jk}^*)}{\partial y_{js}^l} \right] \times (y_{js}^l - y_{js}^{l*}) \\ & + \sum_{j=1}^J \sum_{k=1}^K \sum_{l=1}^L \left[ \frac{\partial c(\alpha^*, x^*, y^*, z^*, w^{1*}, w^{2*})}{\partial z_{jk}^l} + \frac{\partial \hat{c}_{js}(y_{js}^*, z_j^*)}{\partial z_{jk}^l} + \frac{\partial \bar{c}_{jk}(y_j^*, z_{jk}^*)}{\partial z_{jk}^l} - \gamma_{jk}^l \right] \times (z_{jk}^l - z_{jk}^{l*}) \end{aligned}$$

## Variational Inequality

$$\begin{aligned} & + \sum_{s=1}^S \sum_{k=1}^K \sum_{l=1}^L \left[ \frac{\partial c(\alpha^*, x^*, y^*, z^*, w^{1*}, w^{2*})}{\partial w_{sk}^{1l}} + \frac{\partial \tilde{c}_{sk}^1(w_{sk}^{1l*})}{\partial w_{sk}^{1l}} - \gamma_{sk}^l \right] \times (w_{sk}^{1l} - w_{sk}^{1l*}) \\ & + \sum_{s=1}^S \sum_{k=1}^K \sum_{l=1}^L \left[ \frac{\partial c(\alpha^*, x^*, y^*, z^*, w^{1*}, w^{2*})}{\partial w_{sk}^{2l}} + \frac{\partial \tilde{c}_{sk}^2(w_{sk}^{2l*})}{\partial w_{sk}^{2l}} - I_{sk} \right. \\ & \quad \left. + \frac{\partial c_i^{tr}(\alpha^*, w^{2*})}{\partial w_{sk}^{2l}} + \frac{\partial \tilde{c}_s^{dr}(w^{2*})}{\partial w_{sk}^{2l}} - \gamma_{sk}^l \right] \times (w_{sk}^{2l} - w_{sk}^{2l*}) \geq 0 \\ & \forall (\alpha, x, y, z, w^1, w^2) \in \mathbb{K}, \end{aligned} \tag{12}$$

where

$$\mathbb{K} := \left\{ (\alpha, x, y, z, w^1, w^2) \in \mathbb{R}_+^{L[(I+1)+J(I+1)+JS+JK+2SK]} : (2)-(10) \text{ hold} \right\}. \tag{13}$$

## Theorem

*Variational inequality problem (12) admits at least one solution.*

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$VI(F, \mathcal{K})$ : Find  $X^* \in \mathcal{K}$  such that:  $\langle F(X^*), X - X^* \rangle \geq 0, \quad \forall X \in \mathcal{K}.$

## Theorem (Existence)

*If  $\mathcal{K}$  is a compact and convex set and  $F$  is a continuous function on  $\mathcal{K}$ , then variational inequality problem  $VI(F, \mathcal{K})$  admits at least a solution  $X^*$ .*

## Existence and Uniqueness Results

**Theorem**

*Variational inequality problem (12) admits at least one solution.*

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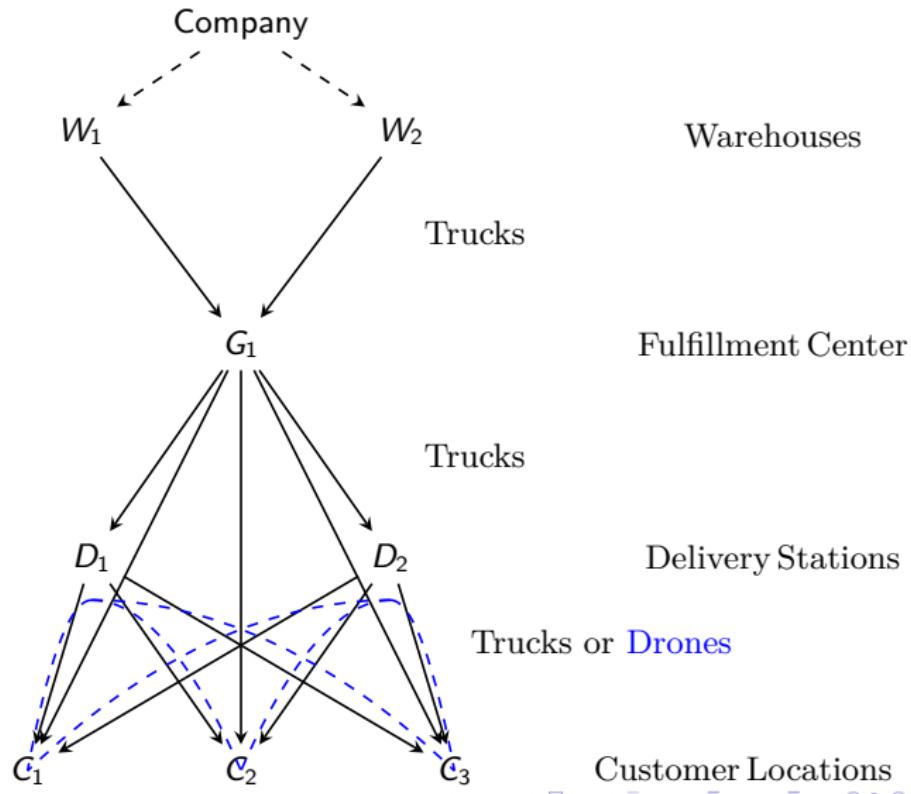
**Theorem (Uniqueness)**

*Under the assumptions of the Existence Theorem, if the function  $F(X)$  in  $VI(F, K)$  is strictly monotone on  $\mathcal{K}$ , that is:*

$$\langle (F(X_1) - F(X_2))^T, X_1 - X_2 \rangle > 0, \quad \forall X_1, X_2 \in \mathcal{K}, X_1 \neq X_2,$$

*then variational inequality (12), admits a unique solution.*

## Simulation Setting



## Simulation Setting

$$c(x) = \beta_1 \cdot x^2 + \beta_2 \cdot x, \quad (14)$$

where  $\beta_1 > 0$  and  $\beta_2 \geq 0$ .

Cost functions	Description	$\beta_1$	$\beta_2$
$c(\alpha, x, y, z, w^1, w^2)$	Handling	0.5	0.5
$c_{ij}(x_{ij})$	Transp. from $W_1$ to $G_1$	0.2	0.2
	Transp. from $W_2$ to $G_1$	0.1	0.1
$\hat{c}_{js}(y_{js}, z_j)$	Transp. from $G_1$ to $D_1$	0.1	0.1
	Transp. from $G_1$ to $D_2$	0.1	0.1
$\bar{c}_{jk}(y_j, z_{jk})$	Transp. from $G_1$ to $C_1$	50	50
	Transp. from $G_1$ to $C_2$	1	1
	Transp. from $G_1$ to $C_3$	50	50
$c_i^{tr}(\alpha, w^2)$	Trucks handling ( $\forall i = 1, 2$ )	0.3	0.3
$c_s^{dr}(w^2)$	UAVs handling ( $\forall s = 1, 2$ )	0.1	0.1

Table: Parameters of the cost functions numerical simulations

## Simulation Setting

Cost functions	Description	$\beta_1$	$\beta_2$
$\tilde{c}_{sk}^1(w_{sk}^1)$	Transp. from $D_1$ to $C_1$ (trucks)	2	2
	Transp. from $D_1$ to $C_2$ (trucks)	8	8
	Transp. from $D_1$ to $C_3$ (trucks)	8	8
	Transp. from $D_2$ to $C_1$ (trucks)	8	8
	Transp. from $D_2$ to $C_2$ (trucks)	9	9
	Transp. from $D_2$ to $C_3$ (trucks)	2	2
$\tilde{c}_{sk}^2(w_{sk}^2)$	Transp. from $D_1$ to $C_1$ (UAVs)	1	1
	Transp. from $D_1$ to $C_2$ (UAVs)	4	4
	Transp. from $D_1$ to $C_3$ (UAVs)	4	4
	Transp. from $D_2$ to $C_1$ (UAVs)	4	4
	Transp. from $D_2$ to $C_2$ (UAVs)	4.5	4.5
	Transp. from $D_2$ to $C_3$ (UAVs)	1	1

Table: Parameters of the cost functions numerical simulations

## Simulation Setting

Parameters	Values
Purchase price	$\gamma_1 = 3$
Production cost	$\gamma_2 = 4$
Incentive for UAVs	$I_{sk} = 2, \forall s = 1, 2, \forall k = 1, 2, 3$
Selling price from $G_j$	$\gamma_{jk} = 149, \forall j = 1, \forall k = 1, 2, 3$
Selling price from $D_s$	$\gamma_{sk} = 150, \forall s = 1, 2, \forall k = 1, 2, 3$
Maximum quantity at $W_1$	$Q_1 = 20$
Maximum quantity at $W_2$	$Q_2 = 10$
Demand from $C_k$	$r_k = 10, \forall k = 1, 2, 3$
Number of trucks at $W_1$	$n_1^{tr} = 4$
Number of trucks at $W_2$	$n_2^{tr} = 5$
Maximum capacity of trucks	$W = 6$
Number of UAVs at $D_1$	$n_1^{dr} = 5$
Number of UAVs at $D_2$	$n_2^{dr} = 5$
Maximum weight (UAV)	$p_d = 4$
Parameter on the weights	$P^{dr} = 30$
Parameter on distances	$B_{sk}^{dr} = 30, \forall s = 1, 2, \forall k = 1, 2, 3$

Table: Parameter values for numerical simulations

## Performed Simulations, Analysis and Comparison of Results

Two main numerical simulations, which focus on:

- S1: a UAV-based last mile network;
- S2: a supply chain without using UAVs.

## Performed Simulations, Analysis and Comparison of Results

Two main numerical simulations, which focus on:

- S1: a UAV-based last mile network;
- S2: a supply chain without using UAVs.

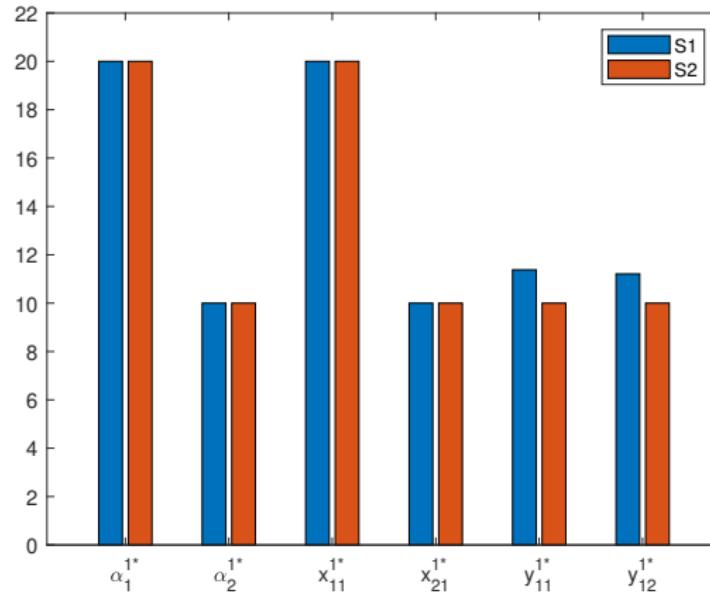
Variables	Optimal solutions	
	S1	S2
$\alpha_i^{I*}$	$i = 1$	20
	$i = 2$	10
$x_{ij}^{I*}$	$i = 1, j = 1$	20
	$i = 2, j = 1$	10
$y_{js}^{I*}$	$j = 1, s = 1$	11.38
	$j = 1, s = 2$	11.21
$z_{jk}^{I*}$	$j = 1, k = 1$	0
	$j = 1, k = 2$	7.41
	$j = 1, k = 3$	0

Variables	Optimal solutions	
	S1	S2
$w_{sk}^{1I*}$	$s = 1, k = 1$	0
	$s = 1, k = 2$	0
	$s = 1, k = 3$	0
	$s = 2, k = 1$	0
	$s = 2, k = 2$	0
	$s = 2, k = 3$	0
$w_{sk}^{2I*}$	$s = 1, k = 1$	7.98
	$s = 1, k = 2$	1.39
	$s = 1, k = 3$	1.92
	$s = 2, k = 1$	1.93
	$s = 2, k = 2$	1.20
	$s = 2, k = 3$	7.99

## Performed Simulations, Analysis and Comparison of Results

Two main numerical simulations, which focus on:

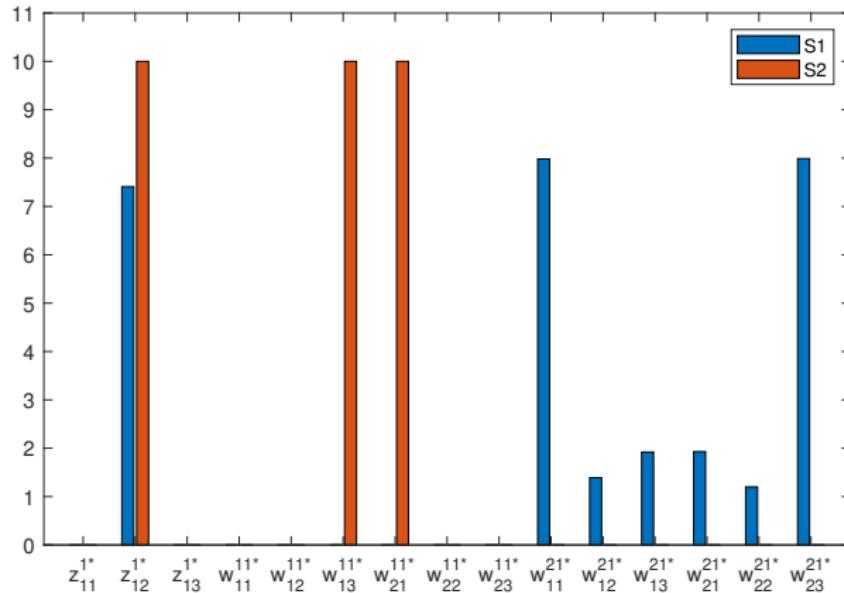
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## Performed Simulations, Analysis and Comparison of Results

Two main numerical simulations, which focus on:

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## Performed Simulations, Analysis and Comparison of Results

$$f^{(S1)}(\alpha^*, x^*, y^*, z^*, w^{1*}, w^{2*}) = 2850.6;$$

$$f^{(S2)}(\alpha^*, x^*, y^*, z^*, w^{1*}, w^{2*}) = 1137.$$

## Performed Simulations, Analysis and Comparison of Results

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$$PC = \left| \frac{\Delta f}{f^{(S1)}(\alpha^*, x^*, y^*, z^*, w^{1*}, w^{2*})} \right| \cdot 100\% = \left| \frac{1713.6}{2850.6} \right| \cdot 100\% = 60.11\%.$$

## Performed Simulations, Analysis and Comparison of Results

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The total GHG emission  $CO_2$  equivalent emissions (expressed as grams, using the EcoTransit World Model online environmental assessment tool):

$$E^{(S1)} = 3.2g, \quad E^{(S2)} = 27.3g.$$

## Additional Configurations

Simulations	$n_1^{dr}$	$n_2^{dr}$	$P^{dr}$	$B_{11}^{dr}$	$B_{12}^{dr}$	$B_{13}^{dr}$	$B_{21}^{dr}$	$B_{22}^{dr}$	$B_{23k}^{dr}$
S1.1	5	5	30	30	30	30	30	30	30
S1.2	5	5	30	0	30	0	30	0	0
S1.3	5	2	30	30	30	30	30	30	30
S1.4	4	2	30	0	30	30	30	0	30
S1.5	5	5	0	30	30	30	30	30	30
S1.6	5	5	0	0	0	0	0	0	0

Table: Main parameters of the additional configurations

## Additional Configurations

	S1.1	S1.2	S1.3	S1.4	S1.5	S1.6
$\alpha_1^*$	20.00	20.00	20.00	20.00	20.00	20.00
$\alpha_2^*$	10.00	10.00	10.00	10.00	10.00	10.00
$x_{11}^*$	20.00	20.00	20.00	20.00	20.00	20.00
$x_{21}^*$	10.00	10.00	10.00	10.00	10.00	10.00
$y_{11}^*$	15.00	14.38	20.05	18.26	15.00	15.00
$y_{12}^*$	15.00	15.62	9.95	11.74	15.00	15.00
$z_{11}^*$	0.00	0.00	0.00	0.00	0.00	0.00
$z_{12}^*$	0.00	0.00	0.00	0.00	0.00	0.00
$z_{13}^*$	0.00	0.00	0.00	0.00	0.00	0.00

Table: Optimal solutions of the additional configurations

## Additional Configurations

	S1.1	S1.2	S1.3	S1.4	S1.5	S1.6
$w_{11}^{1*}$	0.00	1.82	0.33	3.20	6.83	6.83
$w_{12}^{1*}$	0.00	0.66	0.28	0.71	5.00	5.00
$w_{13}^{1*}$	0.00	3.19	0.08	0.24	3.17	3.17
$w_{21}^{1*}$	0.00	0.63	0.17	1.51	3.17	3.17
$w_{22}^{1*}$	0.00	0.62	0.62	0.92	5.00	5.00
$w_{23}^{1*}$	0.00	6.81	1.16	1.30	6.83	6.83
$w_{11}^{2*}$	6.62	0.00	8.15	0.00	0.00	0.00
$w_{12}^{2*}$	5.00	8.72	6.41	8.37	0.00	0.00
$w_{13}^{2*}$	3.38	0.00	4.80	5.75	0.00	0.00
$w_{21}^{2*}$	3.38	7.56	1.35	5.29	0.00	0.00
$w_{22}^{2*}$	5.00	0.00	2.69	0.00	0.00	0.00
$w_{23}^{2*}$	6.62	0.00	3.96	2.71	0.00	0.00

Table: Optimal solutions of the additional configurations



## Sensitivity analysis on the incentive values

	SA1	SA2	SA3	SA4	SA5	SA6	SA7
$I_{sk}$	0	1	2	4	8	16	32

**Table:** Incentive value for each sensitivity analysis configuration

## Sensitivity analysis on the incentive values

	SA1	SA2	SA3	SA4	SA5	SA6	SA7
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Table: Incentive value for each sensitivity analysis configuration

	SA1	SA2	SA3	SA4	SA5	SA6	SA7
$I_{sk}$	0	1	2	4	8	16	32
$W^{(tr)}$	11.95	11.70	11.16	8.66	7.09	0.00	0.00
$W^{(dr)}$	18.05	18.30	18.84	21.34	22.91	30.00	30.00
$I^{(SM)}$	0.00	18.30	37.68	85.34	183.25	480.00	960.00

Table: Sensitivity analysis: amount of product sent via trucks ( $W^{(tr)}$ ) and via drones ( $W^{(dr)}$ ) and incentive for sustainable mobility ( $I^{(SM)}$ )

## Sensitivity analysis on the incentive values

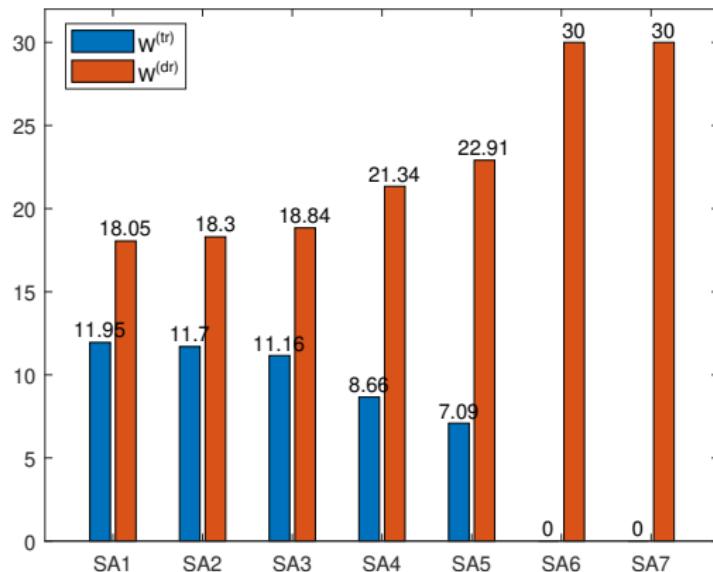


Figure: Total amount of product sent via trucks ( $W^{(tr)}$ ) and via drones ( $W^{(dr)}$ ) in the sensitivity analysis simulations

# Conclusions

- ✓ Centralized supply chain network optimization model that maximizes the total profit obtained by a company that produces and/or outsources production, stores, ships and sells products to customers using a fleet made up of trucks and, in the last mile, also of drones.

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- ✓ Centralized supply chain network optimization model that maximizes the total profit obtained by a company that produces and/or outsources production, stores, ships and sells products to customers using a fleet made up of trucks and, in the last mile, also of drones.
- ✓ Fundamental limitations such as weight limitations, low battery capacities and short delivery ranges.

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- ✓ Detailed numerical simulations that emphasize the advantages of the use of a hybrid fleet for last mile parcel deliveries.

## Further research:

Include green charging stations and landing pads, the use of renewable energy and collection points in the supply chain.

Crowdsourcing delivery.

# Main references

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# Thank you!

