"A Matheuristic for a Customer Assignment Problem in Direct Marketing"

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Problem Description

Business context:

A telecommunications company runs multiple direct marketing campaigns targeting different customer segments. Campaign managers define offers, target products, and campaign-specific constraints, while central management sets global constraints such as budgets.

A central unit manually assigns customers to activities, ensuring compliance with all constraints and avoiding excessive customer contact. However, with millions of customers and hundreds of activities, the process results in hundreds of millions of conflict constraints.

Due to the size of the problem and the lack of existing suitable heuristics, a tailored heuristic approach is required.

Problem Description

- **Input:**
  - **I**: set of customers
  - **J**: set of activities
  - $\mathbf{e_{ij}}$: expected profit when customer i is assigned to activity j
  - $\mathbf{q_{ij}}$: response probability
  - $\mathbf{c_j}$: cost of activity j
  - Start and end dates of campaigns
  - Scheduled days of each activity
  - Business constraints
  - Customer-specific constraints
- **Objective:**
  - Assign customers to activities to **maximize** total expected profit, subject to the given constraints

Problem Description

Business constraints:

- Minimum assignment (soft constraint)
- Maximum assignment
- Budget
- Minimum sales (soft constraint)
- Maximum sales (soft constraint)

Customer-specific constraints:

- Minimum contact (soft constraint)
- Maximum contact
- Conflict constraints

Comparison with other combinatorial optimization problems

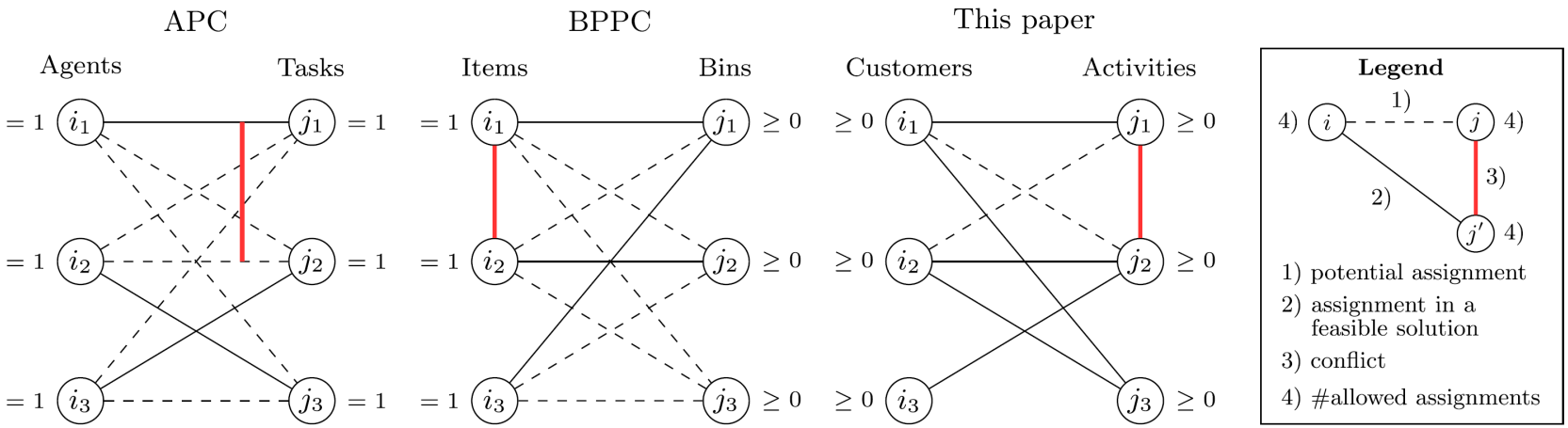


Fig. 2. Conflict constraints in more general combinatorial optimization problems.

Mixed Binary Linear Program (Notations)

- $\mathbf{I}$: Set of customers
- $\mathbf{J}$: Set of activities
- $\mathbf{e_{ij}}$: Expected profit when customer i is assigned to activity j
- $\mathbf{q_{ij}}$: Response probability of customer i for activity j
- $\mathbf{c_j}$: Cost associated with activity j
- $\mathbf{x_{ij}} \in \{0, 1\}$: Decision variable indicating whether customer i is assigned to activity j
- $\mathbf{I_j}$: Set of customers eligible for activity j
- $\mathbf{J_i}$: Set of activities for which customer i is eligible
- α, β, γ, δ: Penalty constants for the respective soft constraints
- z_I^a, z_I^s, $z_I^{\bar{s}}$, z_I^m: Slack variables for the minimum assignment, minimum sales, maximum sales, and minimum contact constraints, respectively
- $\mathbf{J_I^a}$, $\mathbf{J_I^{\bar{a}}}$, $\mathbf{J_I^b}$, $\mathbf{J_I^s}$, $\mathbf{J_I^{\bar{s}}}$, $\mathbf{J_I^m}$, $\mathbf{J_I^{\bar{m}}}$: Subsets of activities associated with each constraint type
- $\mathbf{b_I^a}$, $\mathbf{b_I^s}$, $\mathbf{b_I^{\bar{s}}}$, $\mathbf{b_I^m}$, $\mathbf{b_I^{\bar{m}}}$: Bounds for the respective constraints

Mixed Binary Linear Program

$$(1) \quad \max \sum_{j \in J} \sum_{i \in I_j} e_{ij} x_{ij} - \left(\alpha \sum_{l=1}^{n_a} z_l^a + \beta \sum_{l=1}^{n_s} z_l^s + \gamma \sum_{l=1}^{n_{\bar{s}}} z_l^{\bar{s}} + \delta \sum_{i \in I} \sum_{l=1}^{n_m} z_{il}^m \right) \quad \textbf{s.t.}$$

(2)	$\sum_{j \in J_l^a} \sum_{i \in I_j} x_{ij} + z_l^a \geq b_l^a$	(Min assignment)	$z_l^a \in [0, b_l^a]$
(3)	$\sum_{j \in J_l^{\bar{a}}} \sum_{i \in I_j} x_{ij} \leq b_l^{\bar{a}}$	(Max assignment)	
(4)	$\sum_{j \in J_l^b} \sum_{i \in I_j} c_j x_{ij} \leq b_l^b$	(Budget)	
(5)	$\sum_{j \in J_l^s} \sum_{i \in I_j} q_{ij} x_{ij} + z_l^s \geq b_l^s$	(Min sales)	$z_l^s \in [0, b_l^s]$
(6)	$\sum_{j \in J_l^{\bar{s}}} \sum_{i \in I_j} q_{ij} x_{ij} - z_l^{\bar{s}} \leq b_l^{\bar{s}}$	(Max sales)	$z_l^{\bar{s}} \in [0, \bar{q}]$
(7)	$\sum_{j \in J_l^m \cap J_i} x_{ij} + z_{il}^m \geq b_l^m$	(Min contact)	$z_{il}^m \in [0, b_l^m]$
(8)	$\sum_{j \in J_l^{\bar{m}} \cap J_i} x_{ij} \leq b_l^{\bar{m}}$	(Max contact)	
(9)	$x_{ij_1} + x_{ij_2} \leq 1$	(conflict)	

Where $\bar{q} = \sum_{i \in I} \sum_{j \in J} q_{ij}$

Matheuristic Overview

- Instead of modeling individual customer assignments, **the matheuristic solves a model for groups of customers**
- It **incorporates customer-specific constraints** at the group level, enabling the group-level solution to be efficiently transformed into a near-optimal customer-level assignment
- A single parameter controls the **trade-off** between **solution quality** and **running time**
- The approach follows **four steps**:
  1. Group customers by common eligibility
  2. Cluster groups based on expected profit
  3. Solve a group-level linear program
  4. Iteratively assign individual customers

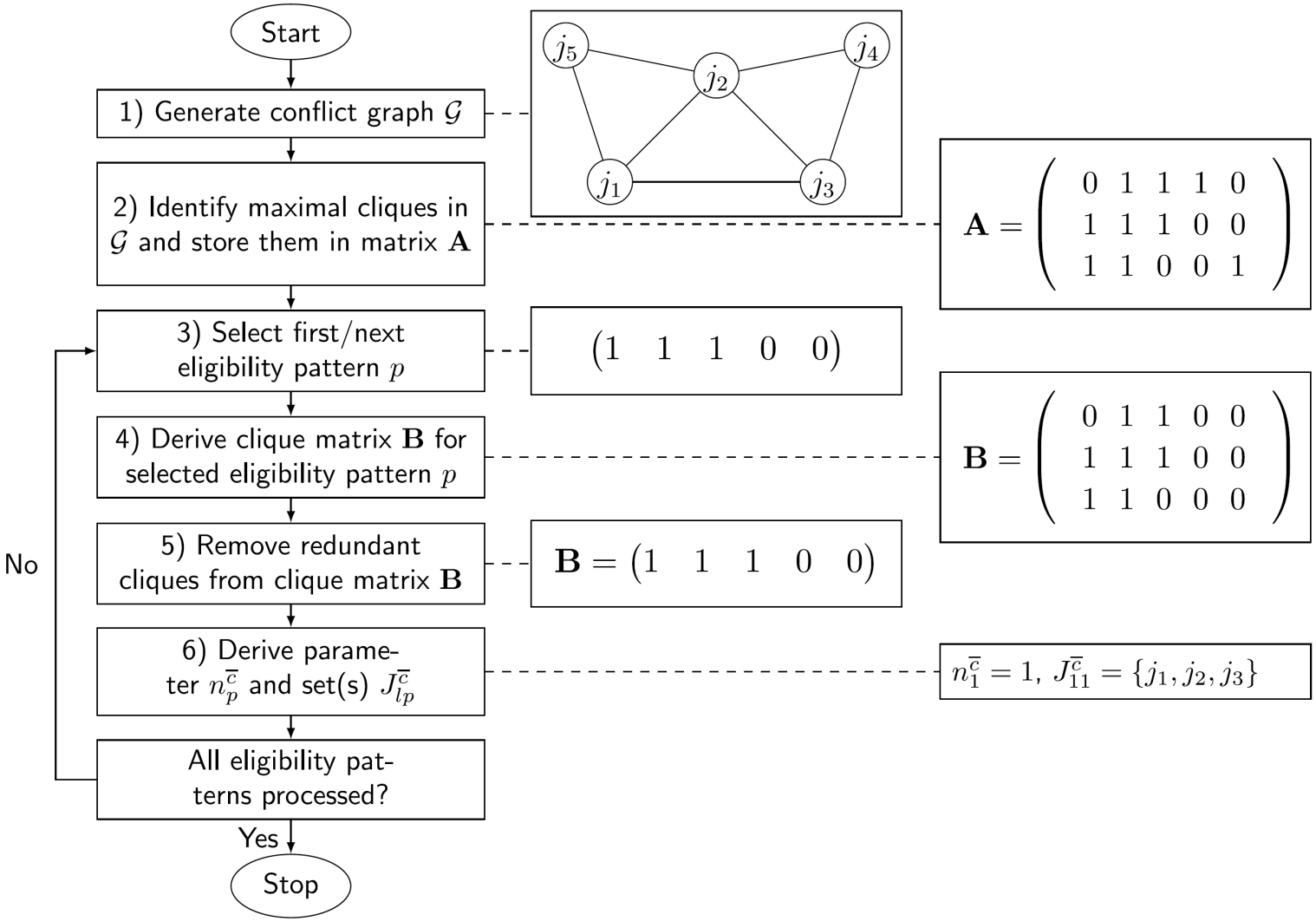
Matheuristic: Step 1 - Grouping by Eligibility Patterns

- Customers are grouped based on their **eligibility pattern p**, indicating the set of activities they are eligible for
- Eligibility pattern is a binary vector (e.g., `[1, 0, 1]`), where '1' indicates eligibility for the activity
- Customers sharing the same pattern are placed in the same group
- **Grouping is essential** as it:
  - Simplifies the **decomposition strategy**
  - Ensures customers in the same group are affected by the **same conflicts**
  - Allows **enforcing customer-specific constraints** later
- In practice, the number of eligibility patterns is much smaller than the number of customers, keeping the approach efficient

Matheuristic: Step 2 - Clustering subgroups

- Each group is divided into up to **k** subgroups
- Customers in the same subgroup have **similar expected profits** for eligible activities
- **Input matrix**: rows are customers, columns are eligible activities, values are expected profits
- **Mini-batch k-means** algorithm is used for efficiency and scalability
- Increasing k leads to smaller and more homogeneous subgroups
- Parameter k allows controlling the **trade-off** between **solution quality** and **computational time**

Preprocessing Technique



Preprocessing: Redundant Cliques Removal (step 5)

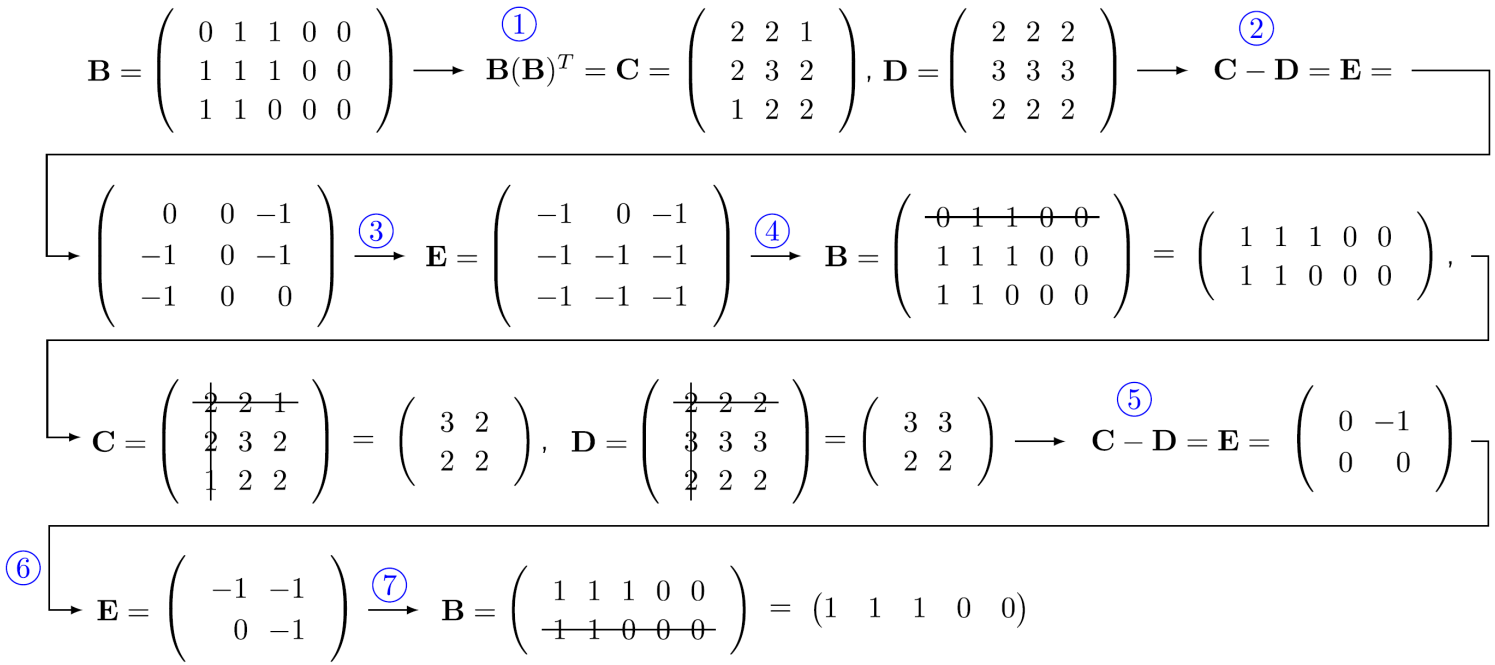


Fig. 7. Example for removing cliques from the binary matrix **B** that are a subset of another clique.

Matheuristic: Step 3 - Linear Program (Notations)

- $\mathbf{G}$: Subgroups determined in step 2
- $\mathbf{P}$: Eligibility patterns
- $\mathbf{x_{gj}} \in [0, o_g]$: Decision variables. Number of customer of group g assigned to activity j
- $\mathbf{o_g}$: Number of customers in group g
- $\mathbf{J_g}$: Activities for which customers in group g are eligible
- $\mathbf{J^c_{lp}}$: Activities associated with constraint $l = 1, ..., n^c_p$ which ensures conflict rules for groups with eligibility pattern p
- $\mathbf{\bar{e}_{gj}}$: Average expected profit of customers of group g when assigned to activity j
- $\mathbf{\bar{q}_{gj}}$: Average response probability of customers of group g when assigned to activity j
- $\mathbf{z^m_{gl}}$: Slack variable of group g for minimum contact rule

Matheuristic: Step 3 - Linear Program

$$(15)\quad \max \sum_{g\in G}\sum_{j\in J_g} \bar{e_{gj}} x_{gj} - \left(\alpha \sum_{l=1}^{n_a} z_l^a + \beta \sum_{l=1}^{n_s} z_l^s + \gamma \sum_{l=1}^{n_{\bar{s}}} z_l^{\bar{s}} + \delta \sum_{g\in G}\sum_{l=1}^{n_m} z_{gl}^m \right) \quad \textbf{s.t.}$$

(16)	$\sum_{g\in G}\sum_{j\in J_l^a\cap J_g} x_{gj} + z_l^a \geq b_l^a$	(Min assignment)	$z_l^a \in [0, b_l^a]$
(17)	$\sum_{g\in G}\sum_{j\in J_l^{\bar{a}}\cap J_g} x_{gj} \leq b_l^{\bar{a}}$	(Max assignment)	
(18)	$\sum_{g\in G}\sum_{j\in J_l^b\cap J_g} c_j x_{gj} \leq b_l^b$	(Budget)	
(19)	$\sum_{g\in G}\sum_{j\in J_l^s\cap J_g} \bar{q_{gj}} x_{ij} + z_l^s \geq b_l^s$	(Min sales)	$z_l^s \in [0, b_l^s]$
(20)	$\sum_{g\in G}\sum_{j\in J_l^{\bar{s}}\cap J_g} \bar{q_{gj}} x_{ij} - z_l^{\bar{s}} \leq b_l^{\bar{s}}$	(Max sales)	$z_l^{\bar{s}} \in [0, \bar{q}]$
(21)	$\sum_{j\in J_l^m\cap J_g} x_{gj} + z_{gl}^m \geq o_g b_l^m$	(Min contact)	$z_{gl}^m \in [0, o_g b_l^m]$
(22)	$\sum_{j\in J_l^{\bar{m}}\cap J_g} x_{gj} \leq o_g b_l^{\bar{m}}$	(Max contact)	
(23)	$\sum_{j\in J_{lp}^c} x_{gj} \leq o_g$	(Conflict)	

Iterative Algorithm

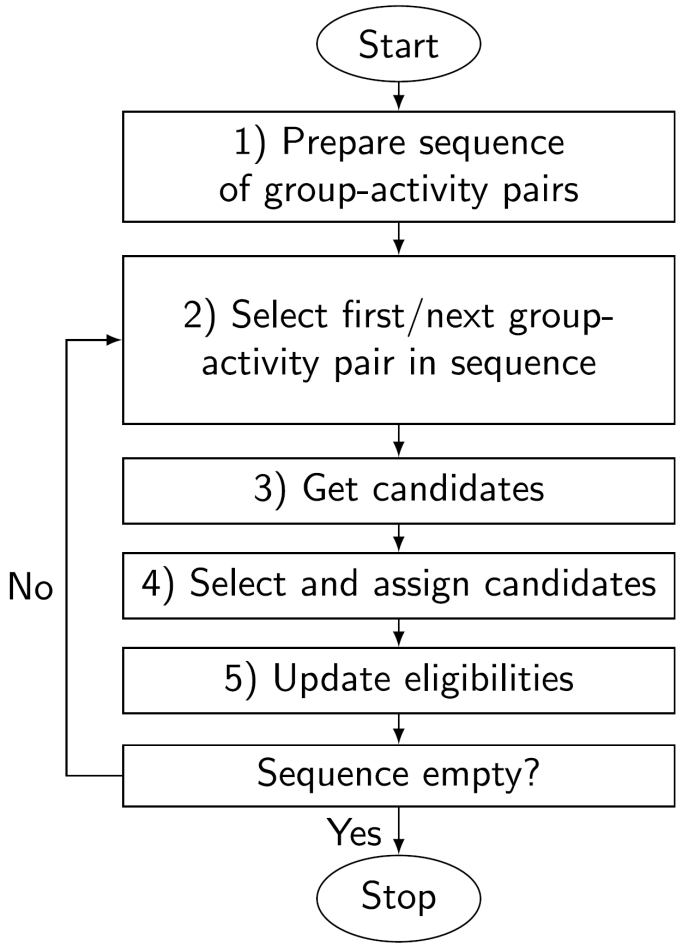


Fig. 4. Flowchart of the iterative algorithm.

Alternative MBLP

- **Goal:** Reduce number of conflict constraints by using conflict sets for subgroups
- **Conflict Constraint Formulation:**

$$(26) \quad \sum_{j \in J_{lp}^{c}} x_{ij} \leq 1 \quad \text{for all } i \in I_p,\ l = 1, \ldots, n_c^p$$

- **Benefits:**
  - Fewer constraints than original MBLP
  - Tighter LP relaxation
  - More scalable for larger instances
- **Conclusion:** Effective alternative to original MBLP, preserving feasibility while improving computational efficiency

Datasets Overview

Generated Instances:

- **GS (Small)**: up to 20,000 customers and 75 activities
- **GM (Medium)**: up to 200,000 customers and 125 activities
- *GL (Large)*: up to 1,000,000 customers and 175 activities

Real-World Instances:

- *RL (Large)*: up to 1.4M customers and 385 activities
- *RVL (Very Large)*: over 2M customers and 295 activities

Note: Focus is on **GS** and **GM** instances due to computational limits
Datasets vary in terms of **eligibility fraction** and **number of eligibility patterns**

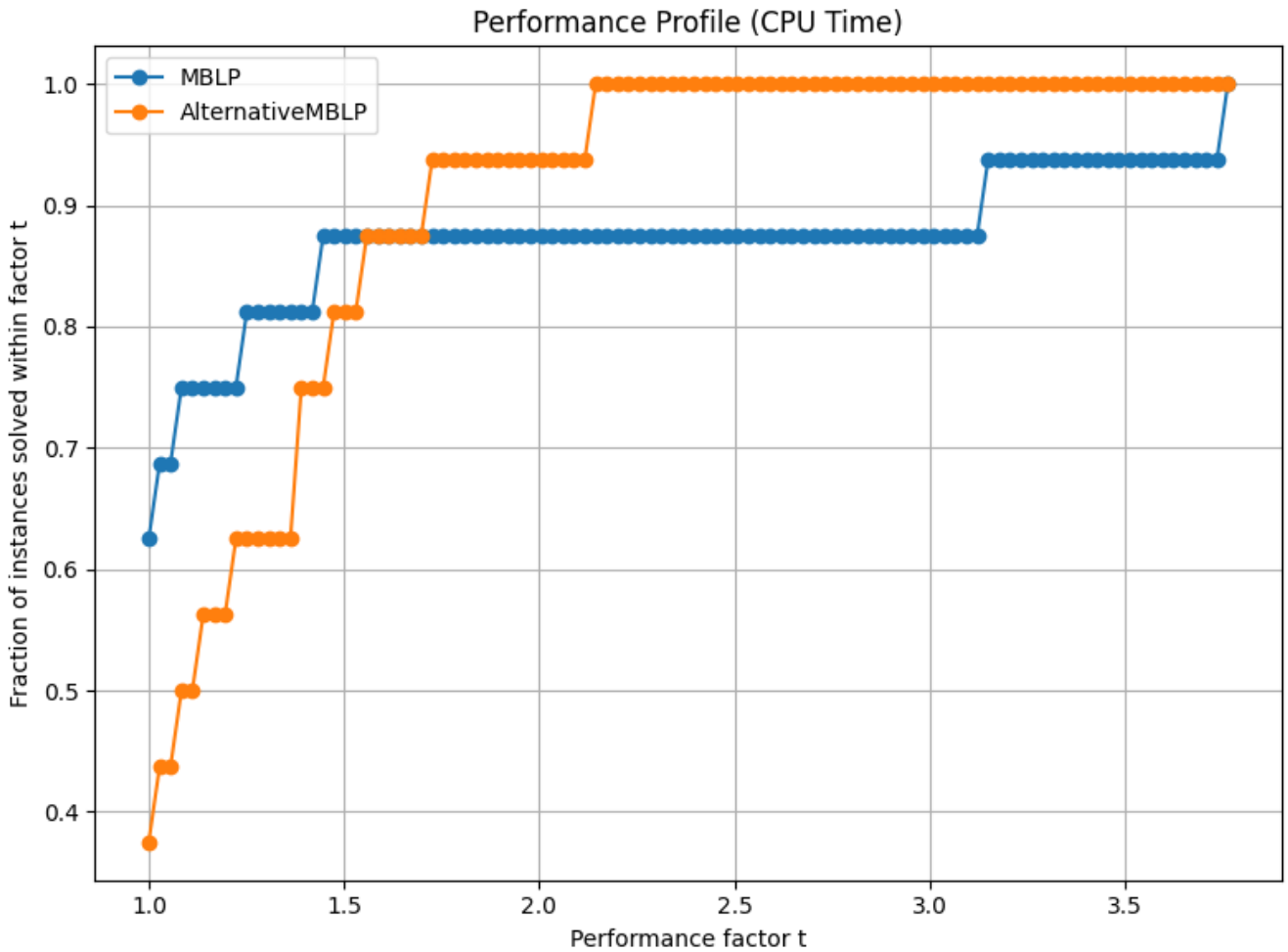
Experimental Setup

- **Operating System:** Windows 11
- **Processor:** Intel Core i7-12700KF (12th Gen) @ 3.61 GHz
- **Memory:** 32 GB RAM
- **Solver:** Gurobi 11.0
- **Programming Language:** Python 3.12
- **Time Limit:** 30 minutes (company requirement)
- **Matheuristic parameter k:** Default $k = 20$, tested with varying k
- **Penalty constants $\alpha, \beta, \gamma, \delta$:** Set to maximum expected profit
- **Note:** Import/export time excluded as identical across models

Scalability Analysis: MBLP vs MBLP'

Dataset	MBLP							ALTERNATIVE MBLP						
	OFV (100k)	PENALTY (100K)	MIPGAP (%)	CONSTR. (1K)	MEMORY (MB)	CPU (SEC)	STATUS	OFV (100k)	PENALTY (100K)	MIPGAP (%)	CONSTR. (1K)	MEMORY (MB)	CPU (SEC)	STATUS
GS1	**1,3**	0.0 (1)	0.0	34	665	**3.56**	Optimal	**1,3**	0.0 (1)	0.0	**13**	654	6.14	Optimal
GS2	**1,2**	0.0	0.0	176	1330	**8.56**	Optimal	**1,2**	0.0	0.0	**35**	1227	10.29	Optimal
GS3	**0,98**	0.0	0.0	41	695	**3.89**	Optimal	**0,98**	0.0	0.0	**16**	682	8.27	Optimal
GS4	**4,7**	0.0	0.0	182	1507	**9.11**	Optimal	**4,7**	0.0	0.0	**35**	1370	12.61	Optimal
GS5	**1,2**	0.0	0.0	36	1548	**6.79**	Optimal	**1,2**	0.0	0.0	**20**	1551	9.95	Optimal
GS6	**13,3**	0.0	0.0	805	4572	32.32	Optimal	**13,3**	0.0	0.0	**83**	3987	**29.95**	Optimal
GS7	**3,5**	0.2 (1)	0.0	72	1787	**9.22**	Optimal	**3,5**	0.2 (1)	0.0	**29**	1784	14.3	Optimal
GS8	**-16,3**	23.0 (2)	0.0	729	4484	31.67	Optimal	**-16,3**	23 (2)	0.0	**81**	3965	**31.39**	Optimal
GM1	**34,1**	0.0	0.0	1144	14011	**87.62**	Optimal	**34,1**	0.0	0.0	**277**	13413	98.12	Optimal
GM2	**84,7**	0.0	0.0	5918	23481	369.74	Optimal	**84,7**	0.0	0.0	**539**	24162	**259.02**	Optimal
GM3	**24,6**	0.0	0.0	1232	13884	**86.56**	Optimal	**24,6**	0.0	0.0	**287**	12883	118.87	Optimal
GM4	**29,7**	0.0	0.0	5742	22889	250.83	Optimal	**29,7**	0.0	0.0	**534**	23582	**204.42**	Optimal
GM5	**45,3**	0.0	0.0	3138	23997	**232.57**	Optimal	**45,3**	0.0	0.0	**624**	24040	235.72	Optimal
GM6	-149,4	-	-	18118	-	-	Out of Memory	**144,8**	0.0	0.0	**1243**	16982	**2523.54**	Optimal
GM7	**68,4**	0.0	0.0	3264	22819	**249.46**	Optimal	**68,4**	0.0	0.0	**621**	25674	267.28	Optimal
GM8	-	-	-	-	-	-	Out of Memory	**128,3**	0.0	0.0	**1225**	12103	**2800.09**	Optimal

Scalability Analysis: Performance Profile



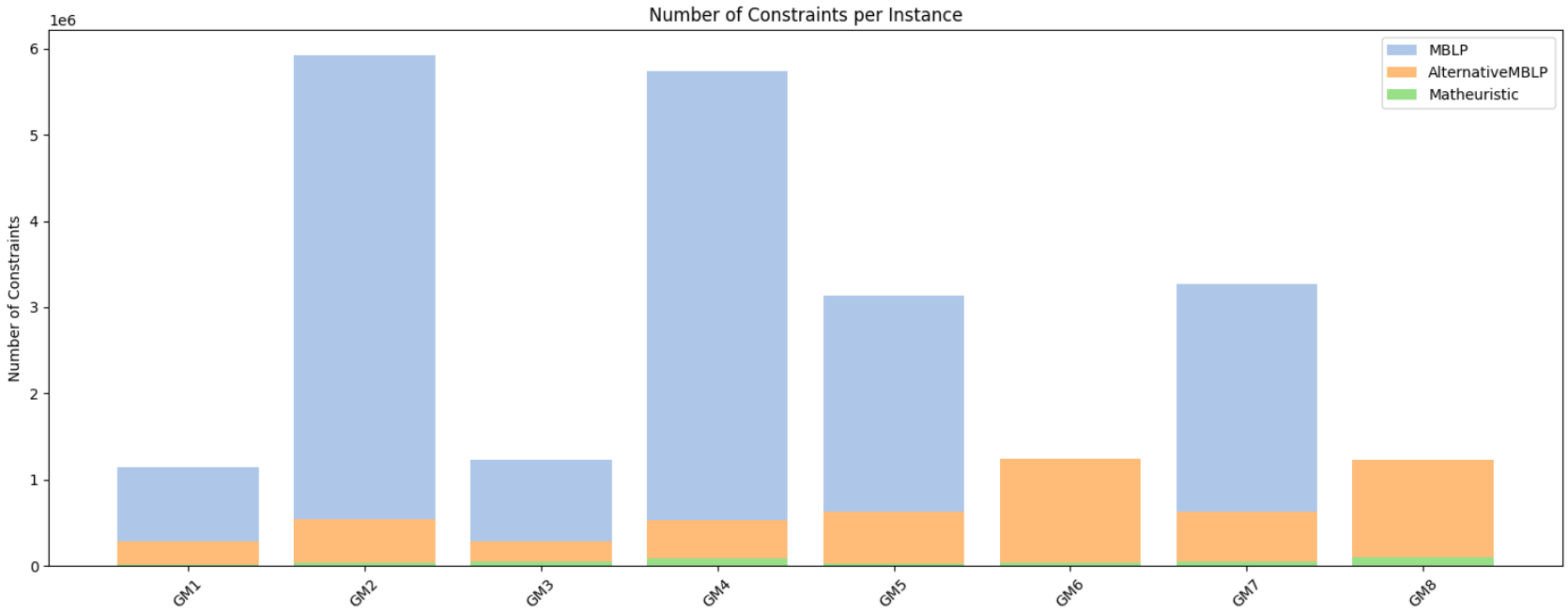
Scalability Analysis: MBLP' vs Matheuristic

	ALTERNATIVE MBLP							MATHEURISTIC						
	OFV (100k)	PENALTY (100K)	MIPGAP (%)	CONSTR. (1K)	MEMORY (MB)	CPU (SEC)	STATUS	OFV (100k)	PENALTY (100K)	MIPGAP (%)	CONSTR. (1K)	MEMORY (MB)	CPU (SEC)	K
GS1	**1,3**	0.0 (1)	0.0	13	654	6.14	Optimal	1,3	0.0 (1)	0.33	**2**	**45**	**3.19**	20
GS2	**1,2**	0.0	0.0	35	1227	10.29	Optimal	1,2	0.0	0.47	**17**	**466**	**6.52**	100
GS3	**0,98**	0.0	0.0	16	682	8.27	Optimal	0,97	0.0 (1)	0.45	**4**	**87**	**5.26**	20
GS4	**4,7**	0.0	0.0	35	1370	12.61	Optimal	4,7	0.0	0.44	**20**	**618**	**9.35**	60
GS5	**1,2**	0.0	0.0	20	1551	9.95	Optimal	1,2	0.0 (1)	0.14	**1**	**46**	**3.46**	20
GS6	**13,3**	0.0	0.0	83	3987	29.95	Optimal	13,2	0.0	0.66	**24**	**932**	**11.12**	120
GS7	**3,5**	0.2 (1)	0.0	29	1784	14.3	Optimal	3,4	0.2	0.55	**4**	**100**	**5.93**	20
GS8	**-16,3**	23 (2)	0.0	81	3965	31.39	Optimal	-16,4	23.0	0.57	**35**	**1346**	**16.37**	90
GM1	**34,1**	0.0	0.0	277	13413	98.12	Optimal	33,5	0.0	1.69	**17**	**524**	**24.67**	20
GM2	**84,7**	0.0	0.0	539	24162	259.02	Optimal	80,7	0.0	4.69	**32**	**1249**	**33.13**	20
GM3	**24,6**	0.0	0.0	287	12883	118.87	Optimal	24,4	0.0 (1)	0.92	**48**	**1254**	**54.52**	20
GM4	**29,7**	0.0	0.0	534	23582	204.42	Optimal	28,9	0.0 (1)	2.82	**85**	**2954**	**70.33**	20
GM5	**45,3**	0.0	0.0	624	24040	235.72	Optimal	44,5	0.0 (1)	1.77	**19**	**615**	**38.55**	20
GM6	**144,8**	0.0	0.0	1243	16982	2523.54	Optimal	138,8	0.0	4.14	**37**	**1451**	**57.46**	20
GM7	**68,4**	0.0	0.0	621	25674	267.28	Optimal	67,3	0.0 (1)	1.62	**51**	**1483**	**66.47**	20
GM8	**128,3**	0.0	0.0	1225	12103	2800.09	Optimal	121,8	0.0 (1)	5.12	**98**	**4011**	**100.26**	20

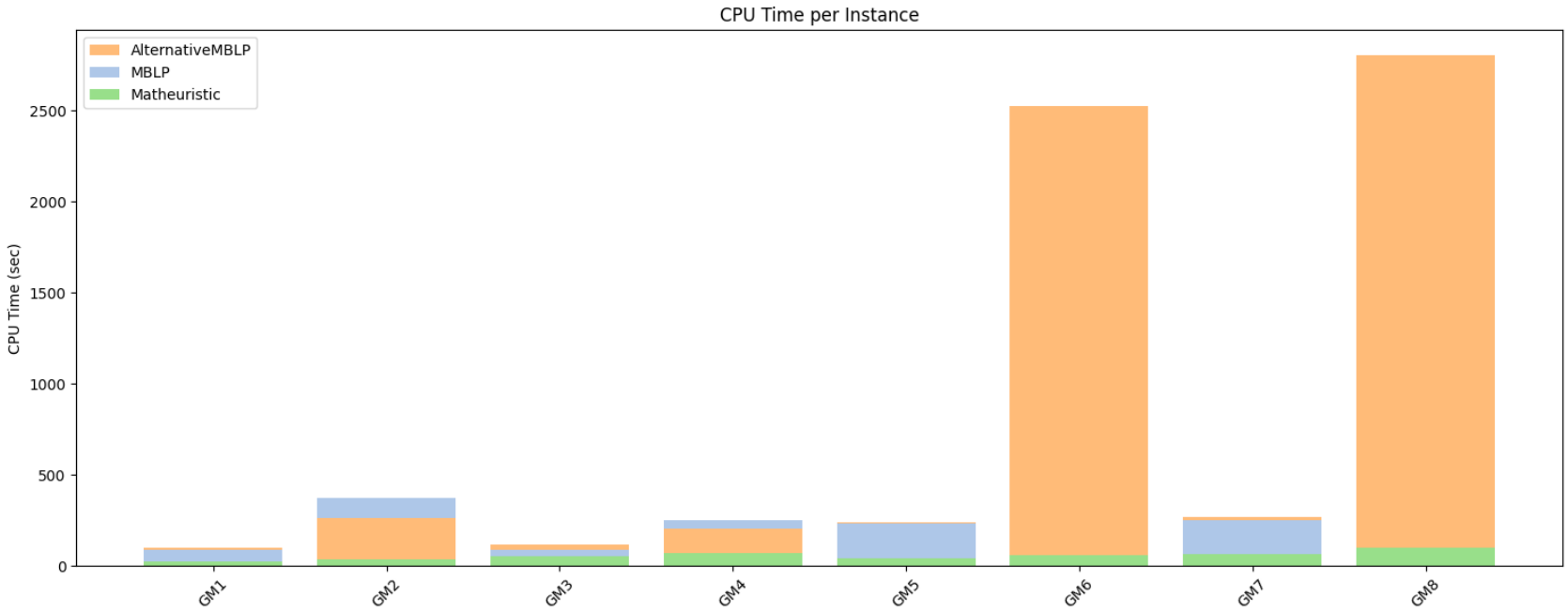
Scalability Analysis: Models Constraints

Dataset	Customers	Activities	Eligibility Fraction	Eligibility Patterns	MBLP	AlternativeMBLP	Matheuristic (conflict constrs.)
GS1	10	50	small (5)	few (50)	34	13	2 (1)
GS2	**10**	**50**	**large (15)**	**few (50)**	**176**	**35**	**3 (2)**
GS3	10	50	small (5)	many (100)	41	16	4 (2)
GS4	**10**	**50**	**large (15)**	**many (100)**	**182**	**35**	**7 (5)**
GS5	20	75	small (5)	few (50)	36	20	1.8 (0.8)
GS6	**20**	**75**	**large (15)**	**few (50)**	**805**	**83**	**4 (3)**
GS7	20	75	small (5)	many (100)	72	29	4 (2)
GS8	**20**	**75**	**large (15)**	**many (100)**	**729**	**81**	**8 (6)**
GM1	100	100	small (5)	few (300)	1144	277	17 (11)
GM2	100	100	small (5)	few (300)	5918	539	32 (26)
GM3	100	100	small (5)	many (800)	1232	287	48 (32)
GM4	**100**	**100**	**large (15)**	**many (800)**	**5742**	**534**	**85 (69)**
GM5	200	125	small (5)	few (300)	3138	624	19 (13)
GM6	**200**	**125**	**large (15)**	**few (300)**	**18118**	**1243**	**37 (31)**
GM7	200	125	small (5)	many (800)	3264	621	51 (35)
GM8	**200**	**125**	**large (15)**	**many (800)**	**- (out of memory)**	**1225**	**98 (82)**

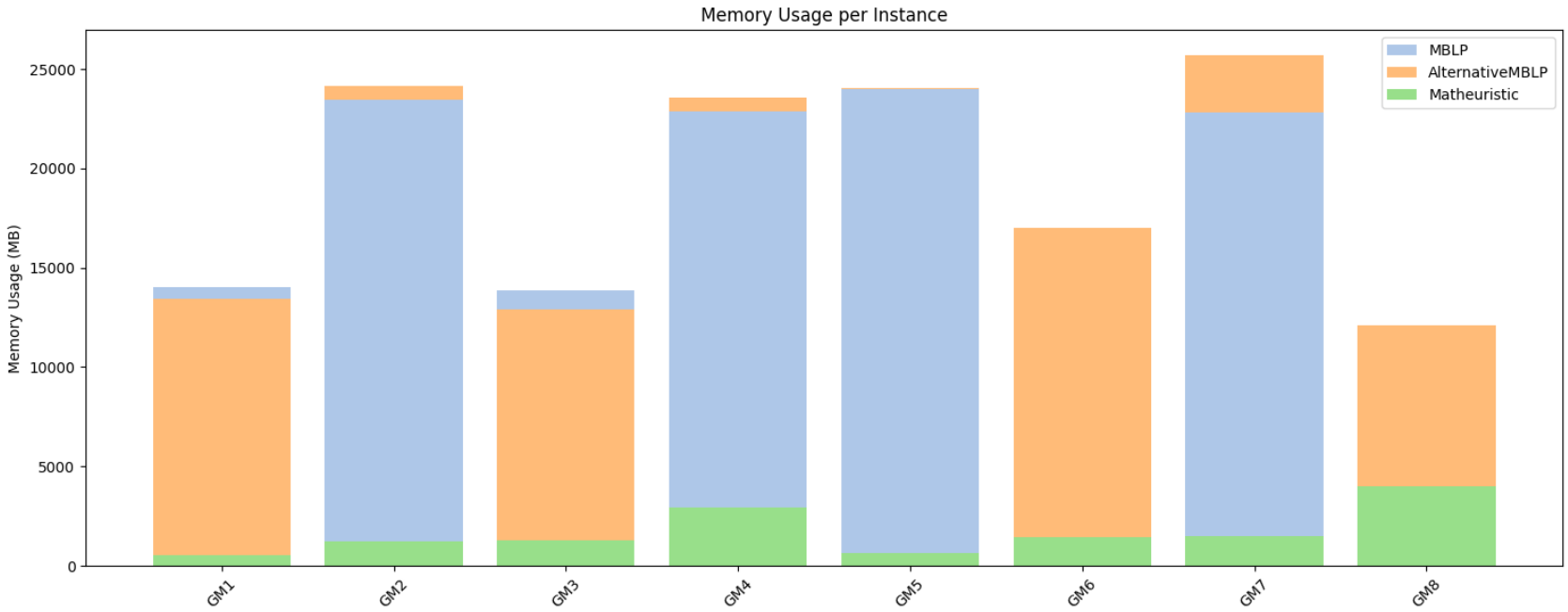
Scalability Analysis: Number of Constraints GM Datasets



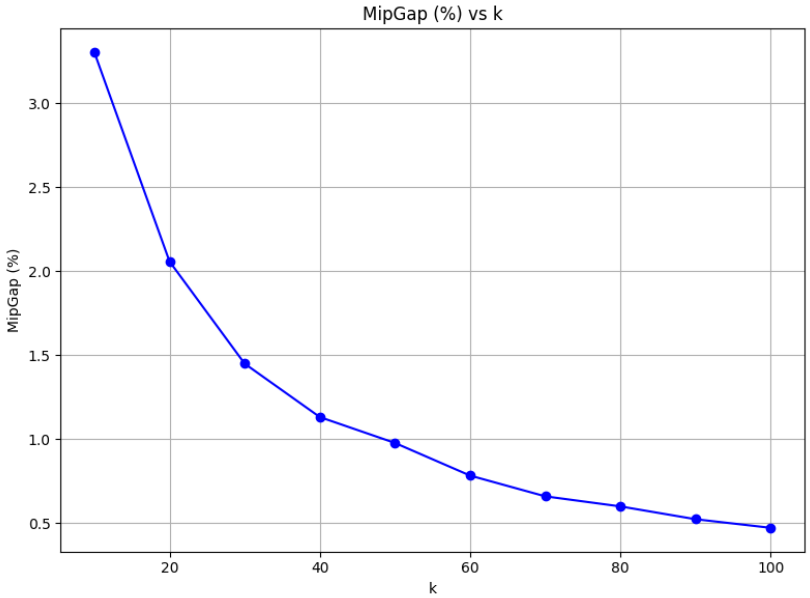
Scalability Analysis: CPU Time (sec) GM Datasets



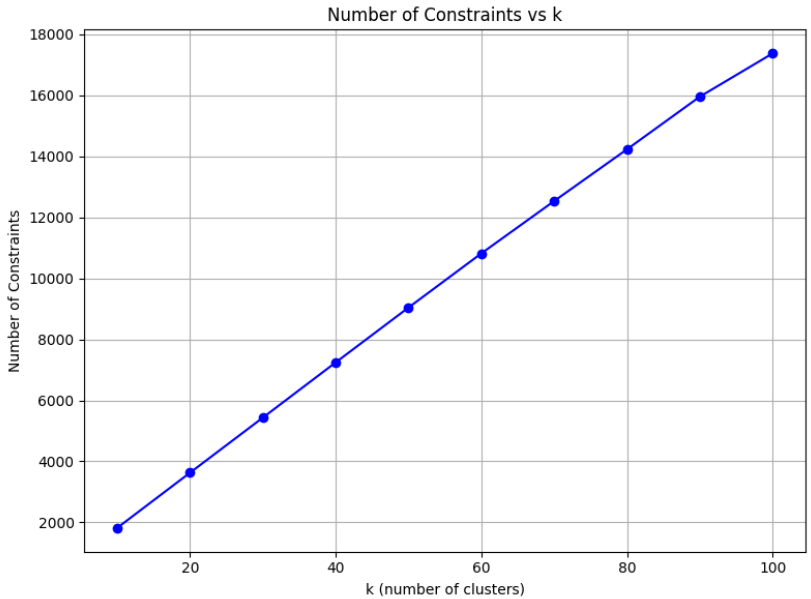
Scalability Analysis: Memory (MB) GM Datasets



Scalability Analysis: k values



MIP Gap vs. k



Number of Constraints vs. k

Matheuristic: Performance Overview

- **Near-optimal solutions** achieved in most cases with $k = 20$
- Increasing k improves solution quality, with a faster-than-linear decrease in the optimality gap
- Penalty costs from slack variables are generally low
- Matheuristic **significantly faster** than the alternative MBLP
- Always stays within the company's time limit, even for very large real-world instances
- Solution quality is **more sensitive to eligibility fraction** than to the number of patterns
- **Scalability is excellent**: maintains high solution quality as instance size grows

Matheuristic Analysis

We now analyze:

- **Impact of Step 5 of the preprocessing technique:**
  Effect of removing redundant subcliques at the group-level on matheuristic performance

- **Impact of the new modeling technique:**
  Effect of the group-level approach to conflict constraints on matheuristic performance

Matheuristic without the New Modeling Technique

Benchmark version of the matheuristic:

- In this version, the matheuristic does not use the new modeling technique for handling conflict constraints
- Conflict constraints are included in the linear program by directly formulating **constraint (9)** of the MBLP at the group level
- The resulting linear program (LP) is defined as:
  - **Objective:** Maximize total expected profit (equation 15)
  - **Subject to:** Constraints (11)–(13), (16)–(22), (24), (25)
  - **Conflict constraints:**

$$x_{gj_1} + x_{gj_2} \leq o_g \quad (g \in G;\ (j_1, j_2) \in T :\ j_1, j_2 \in J_g)$$

- Serves as a baseline to evaluate the impact of the new modeling technique

Matheuristic: new modeling impact

	MATHEURISTIC							MATHEURISTIC WITHOUT NEW MODELING TECHNIQUE						
	OFV (100k)	PENALTY (100K)	MIPGAP (%)	CONSTR. (1K)	MEMORY (MB)	CPU (SEC)	K	OFV (100k)	PENALTY (100K)	MIPGAP (%)	CONSTR. (1K)	MEMORY (MB)	CPU (SEC)	K
GS1	1,3	0.0 (1)	0.33	2	45	3.19	20	0,3	0.8	70.86	4	46	3.3	20
GS2	1,2	0.0	3.15	3	106	3.42	20	-0,6	1.1	105.2	17	114	3.96	20
GS3	0,97	0.0 (1)	0.45	4	87	5.26	20	0,8	0.0 (1)	8.42	9	92	5.5	20
GS4	4,6	0.0	2.13	7	225	6.46	20	3,7	0.0 (1)	19.96	36	244	7.21	20
GS5	1,2	0.0 (1)	0.14	1	46	3.46	20	1,2	0.0 (1)	5.51	2	47	3.71	20
GS6	13	0.0	2.26	4	169	4.81	20	10,8	0.5	18.65	40	195	6.22	20
GS7	3,4	0.2	0.55	4	100	5.93	20	3,1	0.3	10.91	8	104	6.83	20
GS8	-16,6	23.0	1.81	8	322	7.94	20	-18,2	24.9	11.66	72	364	9.92	20
GM1	33,5	0.0	1.69	17	524	24.67	20	26,2	3.3	22.96	69	562	31.55	20
GM2	80,7	0.0	4.69	32	1249	33.13	20	46,9	17.3	44.61	355	1451	47.96	20
GM3	24,4	0.0 (1)	0.92	48	1254	54.52	20	-15,1	35.3	161.16	199	1335	71.81	20
GM4	28,9	0.0 (1)	2.82	85	2954	70.33	20	-84,8	107.3	385.08	915	3486	109.52	20
GM5	44,5	0.0 (1)	1.77	19	615	38.55	20	36,8	1.3	18.72	94	664	51.94	20
GM6	138,8	0.0	4.14	37	1451	57.46	20	58,4	52.2	139.12	543	1770	82.84	20
GM7	67,3	0.0 (1)	1.62	51	1483	66.47	20	50,4	6.4	26.3	262	1600	102.68	20
GM8	121,8	0.0 (1)	5.12	98	4011	100.26	20	58,1	36.1	54.7	1446	4856	169.16	20

Matheuristic: new modeling impact

		Matheuristic	Matheuristic without step 5	Matheuristic without new modeling technique
Number of Constraints	∑ GS	34	294 **(+764%)**	188 **(+452%)**
	∑ GM	387	6507 **(+1581%)**	3883 **(+903%)**
Number of Conflict Constraints	∑ GS	22	282 **(+1181%)**	22
	∑ GM	299	6419 **(+2046%)**	299

- **Step 5** is critical for **reducing** the number of **conflict constraints**
- **Both** Step 5 of the preprocessing and the new modeling technique **drastically reduce the total number of constraints** in the matheuristic

Conclusions

The study addresses a real-world planning problem from a telecommunications company: assigning customers to direct marketing activities while respecting complex business and customer-specific constraints. Existing methods ignore customer-specific constraints and are unsuitable for this problem.

A **matheuristic approach** is developed, which:

- Solves the problem first at a **group level**, then assigns individual customers iteratively
- Introduces **new modeling and preprocessing techniques** to handle customer-specific constraints efficiently

Conclusions

Results:

- The new modeling technique alongside the preprocessing step **drastically reduces the number of constraints** in the model, improving the matheuristic performance
- The matheuristic achieves an **average gap** of only **1.8%** from optimal solutions on generated instances
- Increasing the number of groups further reduces the gap, with minimal impact on runtime
- The method is adopted by the company, improving **sales** by **90%** and campaign **profitability** by around **300%**

Reference and Data

Paper reference:

T. Bigler, M. Kammermann, P. Baumann

"A matheuristic for a customer assignment problem in direct marketing"

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GitHub repository with generated instances:

https://github.com/phil85/customer-assignment-instances