

The University Examination Timetabling Problem with Uncertain Timeslot Capacity: A Two-stage Stochastic Programming Approach

Sara Ceschia¹, Daniele Manerba², Andrea Schaerf¹,
Eugenia Zanazzo¹, Roberto Zanotti²

¹University of Udine (Italy),

²University of Brescia (Italy)

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Uncapacitated Examination Timetabling (UETT, 1996)

- **Data:**

- ▶ enrolment matrix (exams \times students)
- ▶ no rooms

- **Constraint:**

- ▶ no exams with students in common in the same period

- **Objective:**

- ▶ Students should have exams at a minimum distance
- ▶ *Proximity costs:*
distances ≤ 5 are penalized with “exponential” weights (\times student)

Capacitated Examination Timetabling (CETT)

- **Data:**

- ▶ enrolment matrix (exams \times students)
- ▶ number of rooms available

- **Constraint:**

- ▶ no exams with students in common in the same period

- **Objective:**

- ▶ Students should have exams at a minimum distance
- ▶ *Proximity costs:*
distances ≤ 5 are penalized with "exponential" weights (\times student)

CETT: IP formulation

Input data

- T : timeslots, E : exams, S : students
- $n_{e,e'}$: number of students enrolled both in exam e and e'
- $[e, e'] \in C$: set of pairs of exams in conflict ($n_{e,e'} > 0$)
- B : number of available rooms

Decision variables

$$y_{e,t} := \begin{cases} 1 & \text{if exam } e \in E \text{ is scheduled on timeslot } t \in T \\ 0 & \text{otherwise} \end{cases}$$

$$u_{e,e'}^i := \begin{cases} 1 & \text{if exams } [e, e'] \in C \text{ are scheduled at distance } i = 1, \dots, 5 \\ 0 & \text{otherwise} \end{cases}$$

CETT: IP formulation

$$\min \sum_{i=1}^5 \sum_{[e,e'] \in C} 2^{(5-i)} n_{e,e'} u_{e,e'}^i \quad (1)$$

subject to

$$\sum_{t=1}^T y_{e,t} = 1 \quad e \in E \quad (2)$$

$$y_{e,t} + y_{e',t} \leq 1 \quad [e, e'] \in C, t = 1, \dots, T \quad (3)$$

$$y_{e,t} + y_{e',t+i} \leq 1 + u_{e,e'}^i \quad [e, e'] \in C, i = 1, \dots, 5, t = 1, \dots, T - i \quad (4)$$

$$\sum_{e \in E} y_{e,t} \leq B, \quad t = 1, \dots, T \quad (5)$$

$$y_{e,t} \in \{0, 1\} \quad e \in E, t = 1, \dots, T \quad (6)$$

$$u_{e,e'}^i \in \{0, 1\} \quad [e, e'] \in C, i = 1, \dots, 5.$$

Uncertainty in timeslot capacity

After the exam calendar is released, **unexpected events** may occur



some **rooms** are **no longer available** in some periods



the original schedule is **unfeasible!**

Stochastic CETT under uncertain timeslot capacity

Stochastic CETT under uncertain timeslot capacity

$\tilde{B}_t(\xi)$:= stochastic variable representing the loss of capacity of scheduled exams,
with ξ random vector

$$\min_{\mathbf{y}, \mathbf{u}, \xi} \sum_{i=1}^5 \sum_{[e, e'] \in C} 2^{(5-i)} n_{e, e'} u_{e, e'}^i$$

subject to

$$\sum_{t=1}^T y_{e, t} = 1 \quad e \in E$$

$$y_{e, t} + y_{e', t} \leq 1 \quad [e, e'] \in C, t = 1, \dots, T$$

$$y_{e, t} + y_{e', t+i} \leq 1 + u_{e, e'}^i \quad [e, e'] \in C, i = 1, \dots, 5, t = 1, \dots, T - i$$

$$\sum_{e \in E} y_{e, t} \leq B - \tilde{B}_t(\xi), \quad t = 1, \dots, T$$

$$y_{e, t} \in \{0, 1\} \quad e \in E, t = 1, \dots, T$$

$$u_{e, e'}^i \in \{0, 1\} \quad [e, e'] \in C, i = 1, \dots, 5.$$

Two-stage Stochastic Programming paradigm

First stage

- prescheduling of exams to timeslots

Second stage: recourse actions

- rescheduling an exam to a **later** timeslot
- relocate an exam to a **spot-market** room in the same timeslot

Two-stage SP formulation: First stage problem

$$\min_{\mathbf{y}, \mathbf{u}} \sum_{i=1}^5 \sum_{[e, e'] \in C} 2^{(5-i)} n_{e, e'} u_{e, e'}^i + \mathbb{E}_{\xi}[Q(\mathbf{y}, \mathbf{u}, \xi)] \quad (7)$$

subject to

Constraints (2)–(6)

$\mathbb{E}_{\xi}[Q(\mathbf{y}, \mathbf{u}, \xi)] :=$ expectation of the **recourse function** Q , i.e. the optimal solution value of the *second stage problem*

Two-stage SP formulation: Second stage problem

After the realization of the uncertainty:

$$\tilde{y}_{e,t} := \begin{cases} 1 & \text{if exam } e \in E \text{ is } \mathbf{rescheduled} \text{ on timeslot } t \in T \\ 0 & \text{otherwise} \end{cases}$$

$$\tilde{u}_{e,e'}^i := \begin{cases} 1 & \text{if exams } [e, e'] \in C \text{ are } \mathbf{rescheduled} \text{ at distance } i = 1, \dots, 5 \\ 0 & \text{otherwise} \end{cases}$$

$$\tilde{w}_{e,t} := \begin{cases} 1 & \text{exam } e \text{ is relocated to a } \mathbf{spot-market} \text{ room in timeslot } t \in T \\ 0 & \text{otherwise} \end{cases}$$

Two-stage SP formulation: Second stage problem

$$Q(\mathbf{y}, \mathbf{u}, \xi) = \min_{\tilde{\mathbf{y}}, \tilde{\mathbf{u}}, \tilde{\mathbf{w}}} \underbrace{\sum_{i=1}^5 \sum_{[e, e'] \in C} 2^{(5-i)} n_{e, e'} \tilde{u}_{e, e'}^i}_{\text{second stage distances}} + \underbrace{\alpha \sum_{e \in E} \sum_{t=1}^T \frac{n_e}{2} (|\tilde{y}_{e, t} - y_{e, t}| - \tilde{w}_{e, t})}_{\text{rescheduled exams}} + \underbrace{\beta \sum_{e \in E} \sum_{t=1}^T n_e \tilde{w}_{e, t}}_{\text{spot-market room}}$$

Recourse actions' constraints:

$$y_{e, t} \leq \sum_{t'=t}^T \tilde{y}_{e, t'} + \tilde{w}_{e, t} \quad e \in E, t = 1, \dots, T$$

Deterministic equivalent formulation

Approximate the behavior of the random variables through a finite set Ω of **future scenarios**, each occurring with a **probability** p^ω .

$$\begin{aligned}
 \min_{\mathbf{y}, \mathbf{u}, \tilde{\mathbf{y}}, \tilde{\mathbf{u}}, \tilde{\mathbf{w}}} \quad & \underbrace{\sum_{i=1}^5 \sum_{[e,e'] \in C} 2^{(5-i)} n_{e,e'} u_{e,e'}^i}_{\text{first stage distances}} + \sum_{\omega \in \Omega} p^\omega \left[\underbrace{\sum_{i=1}^5 \sum_{[e,e'] \in C} 2^{(5-i)} n_{e,e'} \tilde{u}_{e,e'}^{i,\omega}}_{\text{second stage distances}} + \right. \\
 & \left. + \underbrace{\alpha \sum_{e \in E} \sum_{t=1}^T \frac{n_e}{2} (|\tilde{y}_{e,t}^\omega - y_{e,t}| - \tilde{w}_{e,t}^\omega)}_{\text{rescheduled exams}} + \underbrace{\beta \sum_{e \in E} \sum_{t=1}^T n_e \tilde{w}_{e,t}^\omega}_{\text{spot-market room}} \right]
 \end{aligned}$$

subject to

...

second stage constraints replicated for **each scenario** $\omega \in \Omega$

Impact of uncertainty: settings

Instances:

- 20 instances
- $E = 10$, $T = 7$, $S = 38-77$, $B = 2$
- $\tilde{B}_t \sim \mathcal{N}(\mu = 0, \sigma = 2)$
- $|\Omega| = 20$ scenarios

SP indicators:

- **Stochastic Loss (SL)**: penalty loss in the provisional schedule (first stage) by using SP instead of a deterministic model
- **Value of the Stochastic Solution (VSS)**: penalty saving by using an SP approach instead of a deterministic model
- **Expected Value of the Perfect Information (EVPI)**: how much we would be willing to pay for not having uncertain data

Tool: Gurobi v.11.0.3

Value of the Stochastic Solution (VSS)

- The VSS (Birge, 1982) represents the potential benefit from solving the stochastic program over solving a deterministic program in which expected values have replaced random parameters.
- The higher the VSS, the more critical the use of the two-stage SP model for examination timetabling is.

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$$VSS[\%] = 100 \cdot \frac{EEV - z_{DEP}^*}{z_{DEP}^*}$$

- ▶ z_{DEP}^* is the optimal solution of the DEP formulation;
- ▶ EEV is the expectation over all the scenarios of implementing at the first stage the optimal solution of the so-called *expected value* problem (EV), i.e., the SCETT_B formulation in which all the random variables are substituted by their mean values.

Expected Value of the Perfect Information (EVPI)

- The *EVPI* (Dempster, 1982) represents the value, averaged over all the future scenarios, obtainable if one could completely forecast the realization of the uncertainties.
- It can be interpreted as the value we would be willing to pay for perfect information on future events.

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$$EVPI[\%] = 100 \cdot \frac{z_{DEP}^* - WS}{z_{DEP}^*}$$

- ▶ z_{DEP}^* is the optimal solution of the DEP formulation;
- ▶ WS is the value of the so-called *wait-and-see* solution, i.e., the mean of the optimal solution value of the DEP solved separately for each scenario;

Impact of uncertainty: validation results

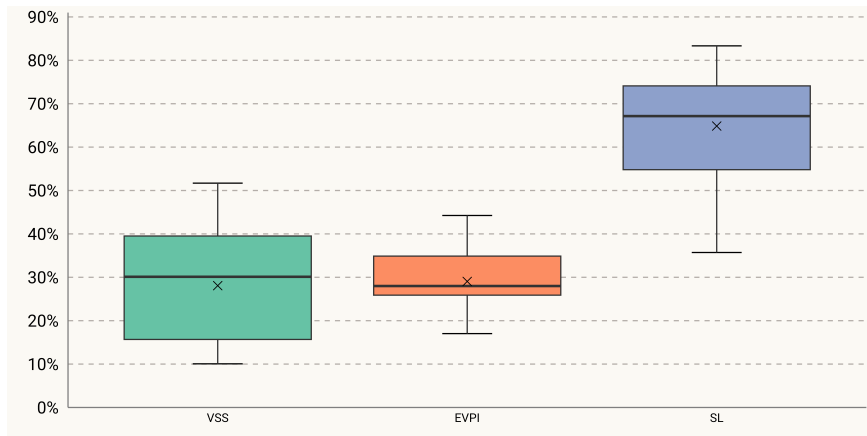


Figure: Percentage values of VSS, EVPI, and SL over all the benchmark instances.

A Progressive Hedging approach (Rockafellar and Wets, 1991)

- 1 Relax non-anticipativity constraints in a Lagrangian fashion
- 2 Decompose the Lagrangian problem by scenarios
- 3 Solve each mono-scenario problem independently
- 4 Compare first-stage schedules and calculate a *Temporary Global Solution* (TGS)
- 5 According to the differences between first-stage schedules over the scenarios, update Lagrangian penalties and re-iterate from 3 until a *global consensus* is met

Convergence proved only for convex programs, but



PH can be used as a heuristic convergence framework

Problem reformulation

Let:

- $y_{e,t}^\omega$ as a copy of the first stage variable $y_{e,t}$ relative to scenario $\omega \in \Omega$
- $u_{e,e'}^{i,\omega}$ as a copy of the first stage variable $u_{e,e'}^i$ relative to scenario $\omega \in \Omega$
- $\bar{y}_{e,t}$ as the *Reference Solution* (RS) decisions.

$$\min_{\mathbf{y}^\omega, \mathbf{u}^\omega, \tilde{\mathbf{y}}, \tilde{\mathbf{u}}, \tilde{\mathbf{w}}, \bar{\mathbf{y}}} \sum_{\omega \in \Omega} p^\omega \left[\underbrace{\sum_{i=1}^5 \sum_{[e,e'] \in C} 2^{(5-i)} n_{e,e'} (u_{e,e'}^{i,\omega} + \tilde{u}_{e,e'}^{i,\omega})}_{\text{distances}} + \underbrace{\alpha \sum_{e \in E} \sum_{t=1}^T \frac{n_e}{2} (|\tilde{y}_{e,t}^\omega - y_{e,t}^\omega| - \tilde{w}_{e,t}^\omega)}_{\text{rescheduled exams}} + \underbrace{\beta \sum_{e \in E} \sum_{t=1}^T n_e \tilde{w}_{e,t}^\omega}_{\text{spot-market room}} \right] \quad (8)$$

Non-anticipativity constraints:

$$y_{e,t}^\omega - \bar{y}_{e,t} = 0 \quad e \in E, t = 1, \dots, T, \omega \in \Omega$$

Augmented Lagrangian relaxation

- Relaxing non-anticipativity constraints the model is **separable per scenario**
- Let $\lambda_{e,t}^\omega$ be the Lagrangian multiplier for each non-anticipativity constraint,
- ρ be a penalty factor for the associated quadratic term added to speed up convergence

$$\mathcal{L}(\bar{\mathbf{y}}, \boldsymbol{\lambda}, \rho) := \min_{\mathbf{y}^\omega, \mathbf{u}^\omega, \tilde{\mathbf{y}}, \tilde{\mathbf{u}}, \tilde{\mathbf{w}}} \sum_{\omega \in \Omega} p^\omega \left[\sum_{i=1}^5 \sum_{[e,e'] \in C} 2^{(5-i)} n_{e,e'} (u_{e,e'}^{i,\omega} + \tilde{u}_{e,e'}^{i,\omega}) + \right. \\ \left. + \alpha \sum_{e \in E} \sum_{t=1}^T \frac{n_e}{2} (|\tilde{y}_{e,t}^\omega - y_{e,t}^\omega| - \tilde{w}_{e,t}^\omega) + \beta \sum_{e \in E} \sum_{t=1}^T n_e \tilde{w}_{e,t}^\omega + \right. \\ \left. + \underbrace{\sum_{e \in E} \sum_{t=1}^T \lambda_{e,t}^\omega (y_{e,t}^\omega - \bar{y}_{e,t}) + \frac{\rho}{2} \sum_{e \in E} \sum_{t=1}^T (y_{e,t}^\omega - \bar{y}_{e,t})^2}_{\text{Lagrangian terms}} \right]$$

The overall Lagrangian problem can be decomposed per scenario in $|\Omega|$ sub-problems.

Problem decomposition

For each scenario $\omega \in \Omega$, the single-scenario Lagrangian sub-problem is:

$$\begin{aligned}
 \mathcal{L}^\omega(\bar{\mathbf{y}}, \boldsymbol{\lambda}, \rho) := & \min_{\mathbf{y}^\omega, \mathbf{u}^\omega, \tilde{\mathbf{y}}, \tilde{\mathbf{u}}, \tilde{\mathbf{w}}} \underbrace{\sum_{i=1}^5 \sum_{[e, e'] \in C} 2^{(5-i)} n_{e, e'} (u_{e, e'}^{i, \omega} + \tilde{u}_{e, e'}^{i, \omega})}_{\text{distances}} \\
 & + \underbrace{\alpha \sum_{e \in E} \sum_{t=1}^T \frac{n_e}{2} (|\tilde{y}_{e, t}^\omega - y_{e, t}^\omega| - \tilde{w}_{e, t}^\omega)}_{\text{rescheduled exams}} + \underbrace{\beta \sum_{e \in E} \sum_{t=1}^T n_e \tilde{w}_{e, t}^\omega}_{\text{spot-market}} \\
 & + \underbrace{\sum_{e \in E} \sum_{t=1}^T \left(\lambda_{e, t}^\omega + \frac{\rho}{2} - \rho \bar{y}_{e, t} \right) y_{e, t}^\omega}_{\text{Lagrangian term}} \quad \cancel{-\lambda_{e, t}^\omega \bar{y}_{e, t} + \frac{\rho}{2} (\bar{y}_{e, t})^2}
 \end{aligned}$$

PH algorithm

```
1: Initialize  $\bar{\mathbf{y}}, \boldsymbol{\lambda}^{(0)} = \mathbf{0}, \rho^{(0)} > 0, \rho_{step} > 1, i \leftarrow 0$ 
2: while  $i \leq \text{max\_iterations}$  do
3:   for each scenario  $\omega \in \Omega$  do
4:     Solve the corresponding subproblem  $\mathcal{L}^\omega(\bar{\mathbf{y}}, \boldsymbol{\lambda}^{(i)}, \rho^{(i)})$ .
     Let  $\mathbf{y}^{\omega(i)}$  be the resulting first stage solution.
5:   end for
6:    $\mathbf{y}_{e,t}^{TGS} \leftarrow \sum_{\omega \in \Omega} p^\omega \mathbf{y}_{e,t}^{\omega(i)}, \quad e \in E, t = 1, \dots, T$  //Calculate a temporary global
     solution (TGS)
7:   if the TGS is integer-valued then
8:     break //Consensus met and optimal solution found
9:   else
10:     $\rho^{(i+1)} \leftarrow \rho_{step} \cdot \rho^{(i)}$  //Update the penalty factor
11:     $\lambda_{e,t}^{\omega(i+1)} \leftarrow \lambda_{e,t}^{\omega(i)} + \rho^{(i)}(\mathbf{y}_{e,t}^{\omega(i)} - \bar{\mathbf{y}}_{e,t}), \quad \forall e \in E, t = 1, \dots, T, \omega \in \Omega$  //Update
     the Lagrangian multipliers
12:     $\bar{\mathbf{y}} \leftarrow \mathbf{y}^{TGS}$  //Update the reference solution
13:   end if
14:    $i \leftarrow i + 1$ 
15: end while
```

Local search-based metaheuristic

- **Search space:**
vector: period for each exam
- **Cost function:**
objective function of the subproblem $\mathcal{L}^\omega(\bar{\mathbf{y}}, \boldsymbol{\lambda}, \rho)$
- **Initial solution:**
reference solution $\bar{\mathbf{y}}$ or the solution found in the previous iteration
- **Neighborhoods:**
 - ▶ **MoveExam:** change the period of an exam in the first stage
 - ▶ **MoveRescheduledExam:** change the period of an exam in the second stage
 - ▶ **MoveExamAndRescheduledExam:** change the period of an exam both in the first and the second stage
- **Simulated Annealing with cutoff** [Bellio et al, 2021]

Conclusions

- Stochastic CETT with Uncertain Timeslot Capacity
- Two-stage Stochastic Programming method with rescheduling and spot-market
- Validation results confirm the impact of uncertainty and the value of using SP
- Progressive Hedging framework that embeds a SA metaheuristics

Current and future work

- Experimental validation and tuning of the PH with different variants
- Sensitivity of analysis of the different weights of the obj
- Extensive experimental campaign on real-size instances

Thanks for your attention!