

# Exam scheduling at United States Military Academy West Point

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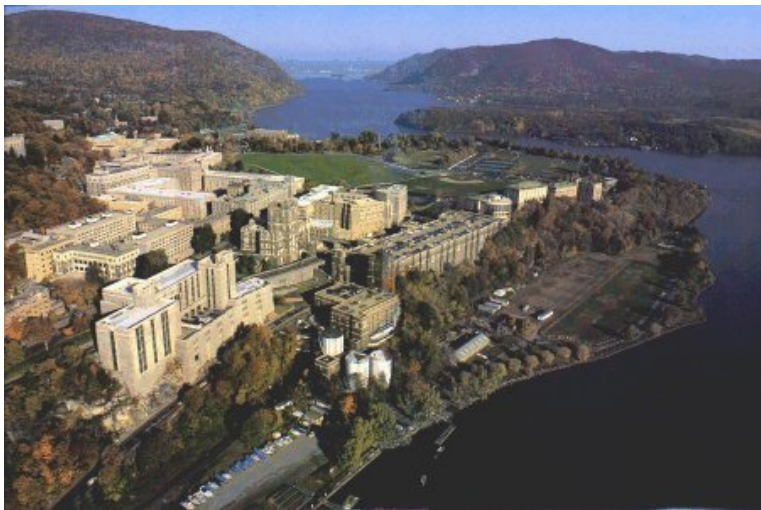
# Agenda

- 1 The Examination Timetabling Problem (ETP) at USMA West Point
- 2 Algorithm
- 3 Implementation in GAMS
- 4 Computational results
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# About USMA



Source: <http://www.usma.edu>

# The ETP at USMA

- More than 21 000 term end exams need to be scheduled to a fixed number of 11 time slots
- Each cadet can only attend one exam per period (hard constraint)
- Number of periods is not sufficient to generate clash-free schedule
- Some courses will therefore need an extra exam version called makeup exam

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# Current objectives at USMA

- Makeups also used for improving other objectives at USMA
  - Multiple objectives like minimizing number of makeups or minimizing the violations of various soft constraints
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## Two formulations for the ETP

- Hierarchical approach: separate objective function for each objective
  - Modules solved successively
- A linear and nonlinear IP model were formulated for each objective of the ETP
- Linear model is iteratively decomposed into smaller subproblems each solved using CPLEX
- Nonlinear model solved with local search based solver: *LocalSolver*

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## Two formulations for the ETP

- Linear version of the constraints to ensure that no cadet takes more than one exam per period:

$$\sum_{r \in \mathcal{R}_c} xy_{c,r,p} \leq 1 \quad \forall c, p \quad (1)$$

$$x_{c,r,m} + y_{r,m,p} - 1 \leq xy_{c,r,p} \quad \forall c, r, m, p \quad (2)$$

'1': base exam

'2': makeup exam

- Nonlinear version:

$$\sum_{r \in \mathcal{R}_c} \max(0, y_{r, '1', p} - \sum_{\substack{m2 \in \mathcal{R}M_r \\ m2 \geq 2}} x_{c,r,m2}) + \sum_{r \in \mathcal{R}_c} \sum_{\substack{m2 \in \mathcal{R}M_r \\ m2 \geq 2}} x_{c,r,m2} \cdot y_{r,m2,p} \leq 1 \quad \forall c, p \quad (3)$$

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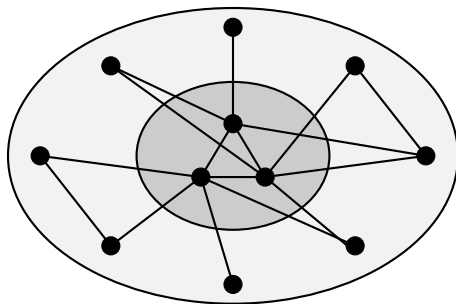
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# Decomposition strategies

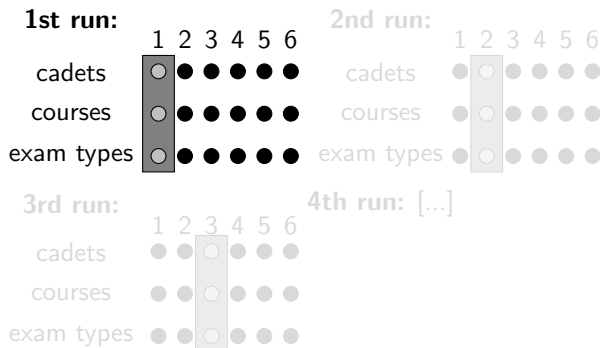
## Decomposition based on vertex degree



group 1
  group 2
  course  
 — common cadets

# Decomposition strategies

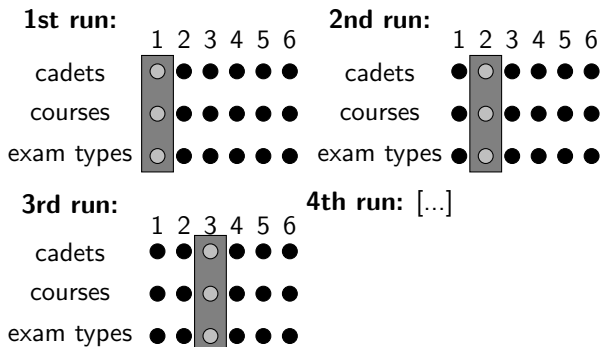
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- fixed binary variables
- binary variables to be optimized
- currently considered group

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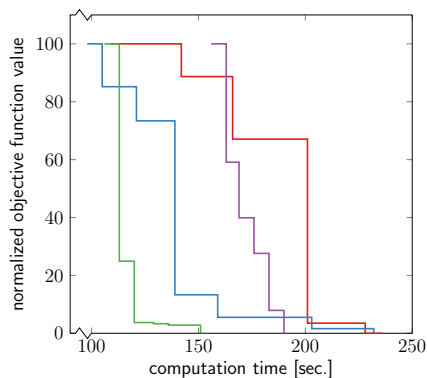
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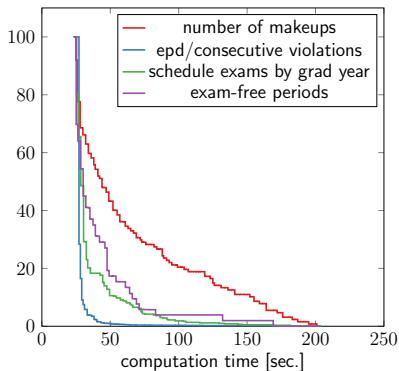
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# Solving the ETP

Qualitative trend of the objective function value over time for the two solution methods

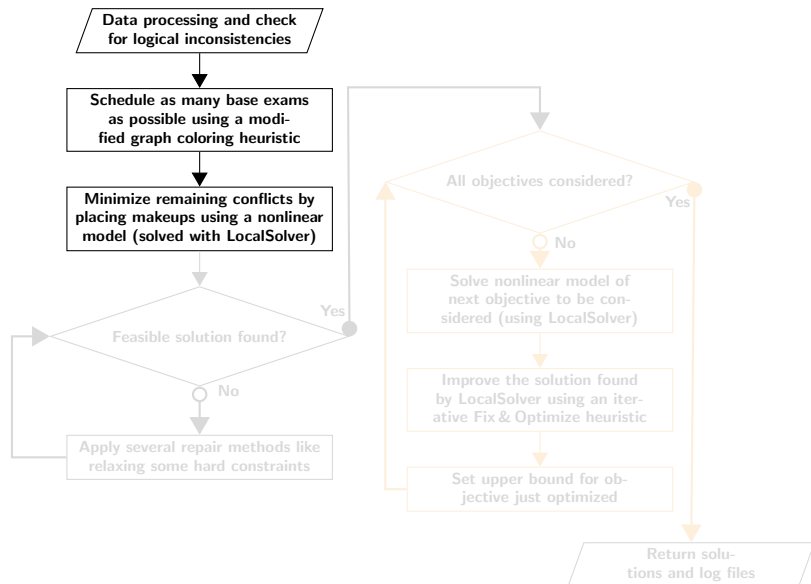


Fix&Optimize heuristic

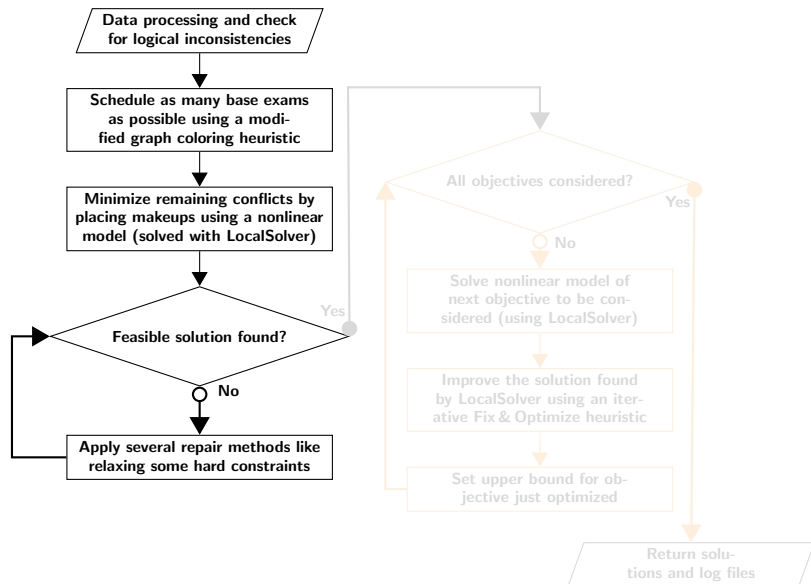


LocalSolver

# The complete algorithm

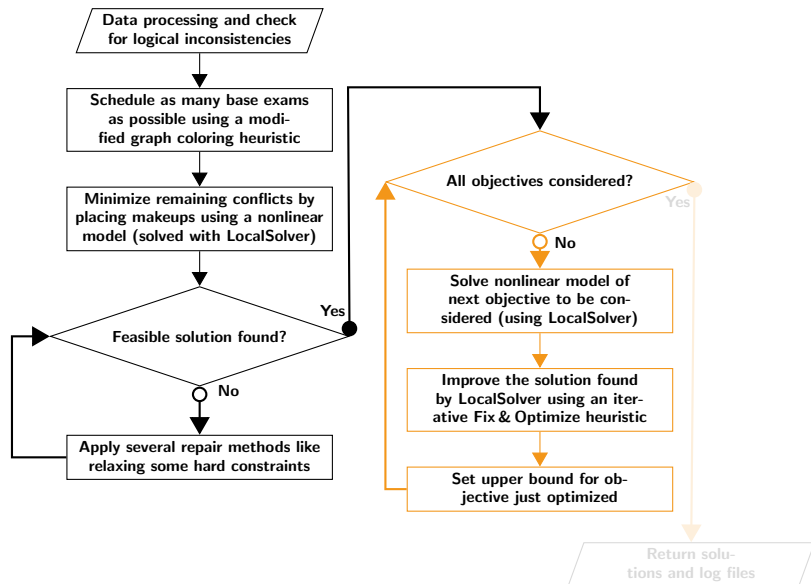


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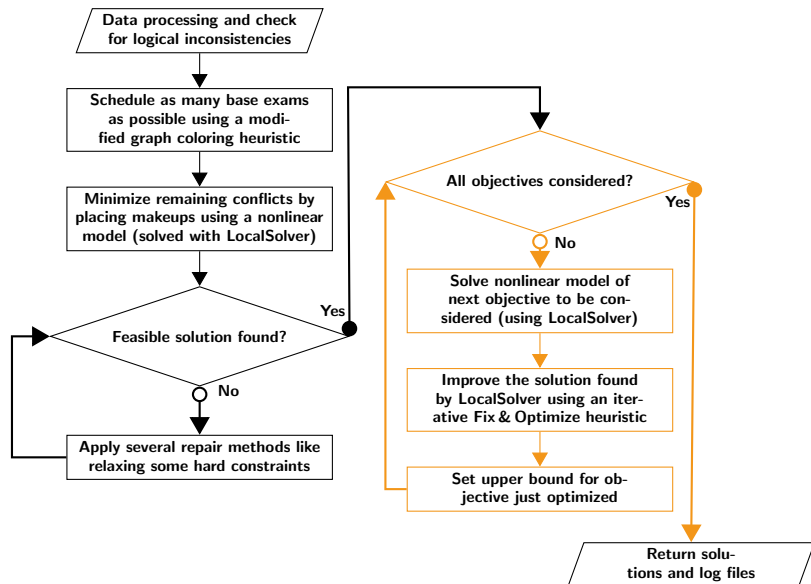




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# Linear model formulation

---

```
noConflicts(c,p)..
```

```
    sum(cr(c,r), xy(cr,p)) =l= 1;
```

```
combineXY(cr(c,r),m,p)..
```

```
    x(cr,m) + y(r,m,p) - 1 =l= xy(cr,p);
```

```
    :
```

```
solve capacity minimizing objMaxCapVio use mip;
```

```
    :
```

```
solve makeup minimizing objMu use mip;
```

---

# Nonlinear model formulation

---

```

ls_assignToPeriod(c,p)..
    sum(cr(c,r), max[0, y(r,'0',p)
                    - sum(rm(r,mx), x(cr,mx))])
+ sum((cr(c,r),mx), x(cr,mx) * y(r,mx,p))
    =l= 1;

    :

solve ls_cadetConflicts minimizing objConflicts use
    minlp;

```

---

# Fix&Optimize heuristic

## Decomposition based on vertex degree

---

```

loop(vdGroup,
* free all variables
  x.lo(cr(c,r),m) = 0;
  x.up(cr(c,r),m) = 1;
  y.lo(rm,p) = 0;
  y.up(rm(r,m),p)$[not prohibit(r,p)] = 1;
* fix all exams of other vdGroups
  y.fx(rm(r,m),p)$[not rSet(vdGroup,r)] = y.l(rm,p);
  solve makeup minimizing objMu use mip;
);

```

---

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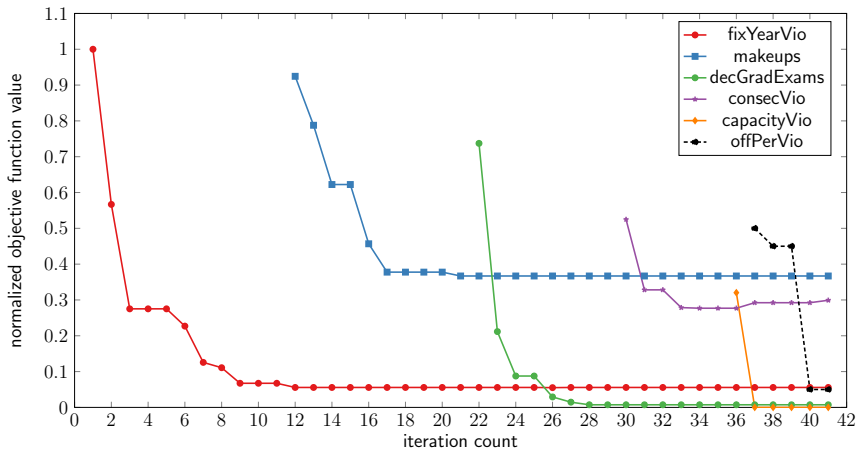
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# Computational results

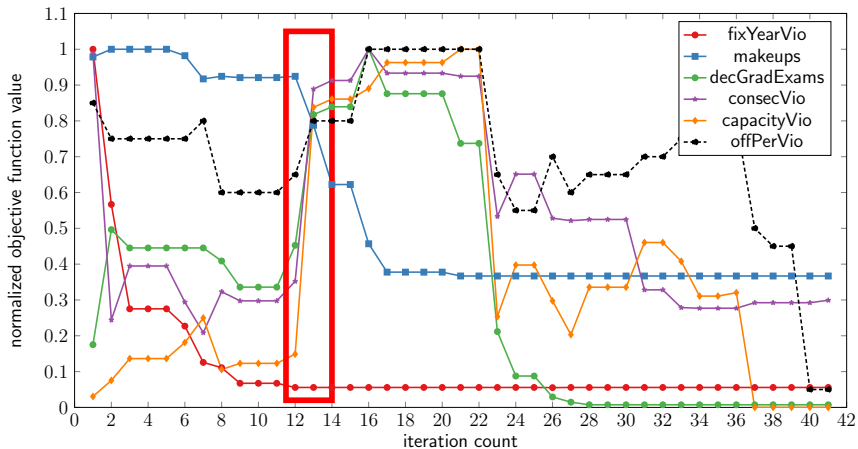
objective functions	F&O	<i>LocalSolver</i>	combination
makeups	114	172	126
epd/consecutive violations	0	25	0
exams for December Graduates	3	0	0
cadet specific exam-free periods	1	1	0
schedule exams by grad year	389	470	425
exam-free periods	330	636	183
capacity violations	0	0	0
computation time [sec.]	1323	(884)	1156



# Overview (normalized)



# Conflicting objectives



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- Algorithm based on decomposition (divide and conquer) as well as local search techniques
- Local search (in particular *LocalSolver*) consistent in finding initial solution (no hard constraints violated)
- Fix&Optimize heuristic for improving solution by exploiting problem structure (MIPs solved using CPLEX)

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- Model formulation in GAMS similar to algebraic notation
- Switching between solvers with one line of code (currently more than 25 solvers supported)
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