#### Multi-skilled workforce management

#### Murat Firat

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Seminar, Information Systems Group, TU/e

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#### Outline

Scheduling problem description State-of-art approaches Further scheduling topics Scheduling and Information Systems

#### Scheduling problem description

Motivation Basic concepts Complexity

#### State-of-art approaches

ALNS approach Local search approach FMM approach Computational Results

#### Further scheduling topics

Stability in multi-skilled workforce assignments Scheduling multi-skilled workforce with varying performances Pilot workforce planning of an airline company in Turkey

#### Scheduling and Information Systems

Scheduling and Business Process Analysis Scheduling and Artificial Intelligence

Motivation Basic concepts Complexity

# Motivation for advanced scheduling

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#### Advanced scheduling in France Télécom

Steadily increasing number of services.

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#### Advanced scheduling in France Télécom

- Steadily increasing number of services.
- Employing more than 10<sup>5</sup> technicians.

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  - to be more competitive
  - to limit the growth of the technician group

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# Basic concepts in scheduling data

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#### Scheduling data of France Télécom

• Given a set  $J = \{j_1, j_2, \dots\}$  of tasks with

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- Given a set  $J = \{j_1, j_2, \dots\}$  of tasks with
  - Precedence relations, *priority classes*, outsourcing options

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- Given a set  $J = \{j_1, j_2, \dots\}$  of tasks with
  - Precedence relations, *priority classes*, outsourcing options
  - Skill requirements

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Motivation Basic concepts Complexity

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- Our mission

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  - Outsource some tasks

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  - Skills with hierarchical levels
- Our mission
  - Outsource some tasks
  - Schedule all tasks on a day-to-day basis
  - Minimize the weighted makespan

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#### Scheduling data of France Télécom

More on Skills:

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#### Scheduling data of France Télécom

More on Skills:

• Skill categories/domains:  $D = \{d_1, d_2, \dots\}$ .

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#### Scheduling data of France Télécom

More on Skills:

- Skill categories/domains:  $D = \{d_1, d_2, \dots\}$ .
- *Hierarchical* skill levels:  $L = \{l_0, l_1, \dots\}$ .

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More on Skills:

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- *Hierarchical* skill levels:  $L = \{l_0, l_1, ... \}$ .
- Skills of technician t are denoted by  $Sk_t \in \{0, 1\}^{|L| \times |D|}$

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More on Skills:

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- Skills of technician t are denoted by  $Sk_t \in \{0, 1\}^{|L| \times |D|}$
- ▶ Skill requirements of task *j* are denoted by  $Rq_i \in \mathbb{Z}^{|L| \times |D|}$

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#### Scheduling data of France Télécom

Consider |D| = |L| = 3 such that

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#### Scheduling data of France Télécom

Consider |D| = |L| = 3 such that • Technicians  $t_1$  and  $t_2$  with *skills*   $d_1 \quad d_2 \quad d_3 \quad d_1 \quad d_2 \quad d_3$  $Sk_{t_1} = \begin{pmatrix} l_0 \\ l_1 \\ l_2 \end{pmatrix} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{bmatrix}, Sk_{t_2} = \begin{pmatrix} l_0 \\ l_1 \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 \\ 0 & 1 & 1 \\ 0 & 1 & 0 \end{bmatrix}$ 

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## Scheduling data of France Télécom

Consider |D| = |L| = 3 such that Technicians t<sub>1</sub> and t<sub>2</sub> with skills  $d_1$   $d_2$   $d_3$  $Sk_{t_{1}} = \begin{matrix} h_{0} \\ h_{1} \\ h_{2} \end{matrix} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{matrix} \end{bmatrix}, Sk_{t_{2}} = \begin{matrix} h_{0} \\ h_{1} \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 \\ 0 & 1 & 1 \\ 0 & 1 & 0 \end{bmatrix}$ Tasks j<sub>1</sub> and j<sub>2</sub> with skill requirements  $d_1$   $d_2$   $d_3$  $Rq_{j_{1}} = \begin{matrix} h_{0} \\ h_{1} \\ h_{2} \end{matrix} \begin{bmatrix} 1 & 2 & 2 \\ 1 & 1 & 1 \\ 1 & 0 & 0 \end{matrix} \end{bmatrix}, Rq_{j_{2}} = \begin{matrix} h_{0} \\ h_{1} \\ h_{2} \end{matrix} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 0 \\ 1 & 1 & 0 \end{matrix} \end{bmatrix}$ 

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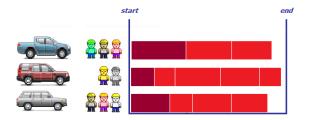
# Scheduling data of France Télécom

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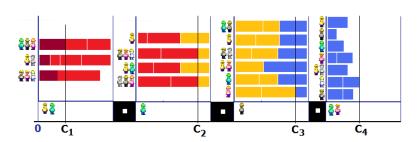
#### A workday schedule



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#### A complete schedule



The schedule cost is the weighted makespan:  $\sum_{i} w_i C_i$ .

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# How hard is to solve our scheduling problem?

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#### Theoretical result

Theorem 1 Technician scheduling problem of France Télécom is NP-Hard in the strong sense.<sup>1</sup>

<sup>1</sup>Stable multi-skill workforce assignments, Fırat, M., Hurkens, C., Laugier, A., 2014, Annals of OR.

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## Benchmark instances<sup>2</sup>

|      | Data set A |     |   |   | Data set B |     |    |   | Data set X |     |    |   |
|------|------------|-----|---|---|------------|-----|----|---|------------|-----|----|---|
| Ins. | <i>T</i>   | J   | D | L | <i>T</i>   | J   | D  | L | <i>T</i>   | J   | D  | L |
| 1    | 5          | 5   | 3 | 2 | 20         | 200 | 4  | 4 | 60         | 600 | 15 | 4 |
| 2    | 5          | 5   | 3 | 2 | 30         | 300 | 5  | 3 | 100        | 800 | 6  | 6 |
| 3    | 7          | 20  | 3 | 2 | 40         | 400 | 4  | 4 | 50         | 300 | 20 | 3 |
| 4    | 7          | 20  | 4 | 3 | 30         | 400 | 40 | 3 | 70         | 800 | 15 | 7 |
| 5    | 10         | 50  | 3 | 2 | 50         | 500 | 7  | 4 | 60         | 600 | 15 | 4 |
| 6    | 10         | 50  | 5 | 4 | 30         | 500 | 8  | 3 | 20         | 200 | 6  | 6 |
| 7    | 20         | 100 | 5 | 4 | 100        | 500 | 10 | 5 | 50         | 300 | 20 | 3 |
| 8    | 20         | 100 | 5 | 4 | 150        | 800 | 10 | 4 | 30         | 100 | 15 | 7 |
| 9    | 20         | 100 | 5 | 4 | 60         | 120 | 5  | 5 | 50         | 500 | 15 | 4 |
| 10   | 15         | 100 | 5 | 4 | 40         | 120 | 5  | 5 | 40         | 500 | 15 | 4 |

<sup>2</sup> Technicians and interventions scheduling for telecommunications, France Télécom R&D, Orange Labs.

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#### What about formulating as a MILP model?

An experimentation<sup>3</sup> reports

After 24-hour computation time, instances A3 and A4 could not be solved by CPLEX 11, leaving optimality gaps 20% and 15% respectively.

<sup>3</sup>Scheduling technicians and tasks in a telecommunication company, Cordeau, J. F., Laporte, G., Pasin F., Ropke, S., 2010, Journal of Scheduling = -??

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# State-of-art approaches to our scheduling problem

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Adapted Large Neighborhood search <sup>4</sup>

• A construction heuristic for initial schedule:

<sup>4</sup>Scheduling technicians and tasks in a telecommunication company, Cordeau, J. F., Laporte, G., Pasin F., Ropke, S., 2010, Journal of Scheduling. → <

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### Adapted Large Neighborhood search <sup>4</sup>

- A construction heuristic for initial schedule:
  - Construct teams for seed tasks..

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### Adapted Large Neighborhood search <sup>4</sup>

- A construction heuristic for initial schedule:
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### Adapted Large Neighborhood search <sup>4</sup>

- A construction heuristic for initial schedule:
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- Modifying the current schedule:

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### Adapted Large Neighborhood search <sup>4</sup>

- A construction heuristic for initial schedule:
  - Construct teams for seed tasks..
  - Criteria for seed tasks: Criticality, difficulty, similarity.
- Modifying the current schedule:
  - Choose a destroy and a repair method.

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- A construction heuristic for initial schedule:
  - Construct teams for seed tasks..
  - Criteria for seed tasks: Criticality, difficulty, similarity.
- Modifying the current schedule:
  - Choose a destroy and a repair method.
  - ► Accepting a new schedule: Use simulated annealing criterion.

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  - Update scores of destroy and repair methods.

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- A construction heuristic for initial schedule:
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- Modifying the current schedule:
  - Choose a destroy and a repair method.
  - Accepting a new schedule: Use simulated annealing criterion.
  - Update scores of destroy and repair methods.
- Within timelimit: Make restarts of the schedule modification.

<sup>4</sup>Scheduling technicians and tasks in a telecommunication company, Cordeau, J. F., Laporte, G., Pasin F., Ropke, S., 2010, Journal of Scheduling **a** 

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High-Performance local search heuristic<sup>5</sup>

Obtain an initial schedule using a greedy algorithm

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High-Performance local search heuristic<sup>5</sup>

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- Modify the schedule with 31 predefined moves:

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- Obtain an initial schedule using a greedy algorithm
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### High-Performance local search heuristic<sup>5</sup>

- Obtain an initial schedule using a greedy algorithm
- Modify the schedule with 31 predefined moves:
  - Swapping technicians randomly.
  - Swapping tasks randomly within a day, between days.
  - Other 28 sophisticated moves.

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High-Performance local search heuristic<sup>5</sup>

- Obtain an initial schedule using a greedy algorithm
- Modify the schedule with 31 predefined moves:
  - Swapping technicians randomly.
  - Swapping tasks randomly within a day, between days.
  - Other 28 sophisticated moves.
- Some bookkeeping for maintaining precedence relations.

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### Flexible Matching Model (FMM) Approach<sup>6</sup>

General properties:

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### Flexible Matching Model (FMM) Approach<sup>6</sup>

General properties:

Constructing day schedules one by one.

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## Flexible Matching Model (FMM) Approach<sup>6</sup>

General properties:

- Constructing day schedules one by one.
- Initializing a day schedule with one-task team loads.

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## Flexible Matching Model (FMM) Approach<sup>6</sup>

General properties:

- Constructing day schedules one by one.
- Initializing a day schedule with one-task team loads.
- Inserting more tasks into day schedule possibly by

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## Flexible Matching Model (FMM) Approach<sup>6</sup>

General properties:

- Constructing day schedules one by one.
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- Inserting more tasks into day schedule possibly by
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# Flexible Matching Model (FMM) Approach<sup>6</sup>

General properties:

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  - merging teamloads

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# Flexible Matching Model (FMM) Approach<sup>6</sup>

General properties:

- Constructing day schedules one by one.
- Initializing a day schedule with one-task team loads.
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  - merging teamloads
  - reshuffling technicians of a team

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# Flexible Matching Model (FMM) Approach<sup>6</sup>

General properties:

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  - merging teamloads
  - reshuffling technicians of a team
  - initializing a new team

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# Flexible Matching Model (FMM) Approach<sup>6</sup>

General properties:

- Constructing day schedules one by one.
- Initializing a day schedule with one-task team loads.
- Inserting more tasks into day schedule possibly by
  - extending teamloads
  - merging teamloads
  - reshuffling technicians of a team
  - initializing a new team
- The above decisions are simultaneously made by a flexible Matching model!

<sup>&</sup>lt;sup>6</sup>An improved MIP-based approach for a multi-skill workforce scheduling problem, Fırat., M., Hurkens, C., 2012, Journal of Scheduling.

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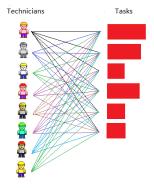
# Initial Matching Model (IMM)

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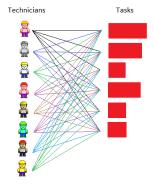
#### IMM: Bipartite Graph



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#### IMM: Matching constraints

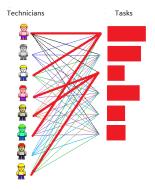


- Technicians match to at most one task.
- Tasks can be matched to any #technicians
- Technicians matched to one task should cumulatively meet skill requirements
- Objective: Maximize weighted sum of matched tasks.

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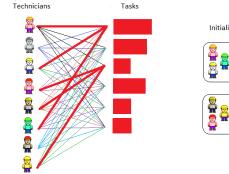
#### IMM: Matching solution



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#### IMM: Initialized teams



Initialized Teams





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#### FMM Approach

Matching weights of tasks are sum of the following criteria

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### FMM Approach

Matching weights of tasks are sum of the following criteria

processing time

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### FMM Approach

Matching weights of tasks are sum of the following criteria

- processing time
- coverage

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### FMM Approach

Matching weights of tasks are sum of the following criteria

- processing time
- coverage
- min-tech

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### FMM Approach

Matching weights of tasks are sum of the following criteria

- processing time
- coverage
- min-tech
- hardness

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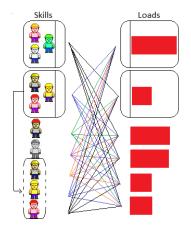
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# Flexible Matching Model (FMM)

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#### FMM: Bipartite Graph

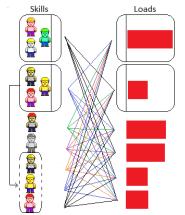


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#### FMM: Matching skills or loads of teams



- Either the skill or the load of a team can be matched in a solution.

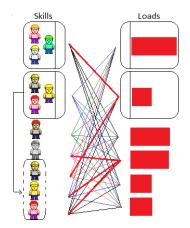
- Matching of the skill of a team results in extension of the load of that team.

- Matching of the load of a team results in releasing the conditionally available technicians of that team.

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#### FMM: Matching solution

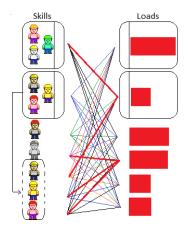


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#### FMM: Extended day schedule



#### Extended day schedule





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ALNS approach Local search approach FMM approach Computational Results

#### Computational Results: Set A

| Instance | FMM   | (%) | Cordeau | (%) | EsGaNo | (%)  | BEST* | LB    |
|----------|-------|-----|---------|-----|--------|------|-------|-------|
| A1       | 2340  | 0.0 | 2340    | 0.0 | 2340   | 0.0  | 2340  | 2310  |
| A2       | 4755  | 0.0 | 4755    | 0.0 | 4755   | 0.0  | 4755  | 2100  |
| A3       | 11880 | 0.0 | 11880   | 0.0 | 11880  | 0.0  | 11880 | 11340 |
| A4       | 13452 | 0.0 | 13452   | 0.0 | 14040  | 4.4  | 13452 | 10680 |
| A5       | 29355 | 1.8 | 29355   | 1.8 | 29400  | 1.9  | 28845 | 26940 |
| A6       | 20055 | 6.7 | 18795   | 0.0 | 18795  | 0.0  | 18795 | 17640 |
| A7       | 30960 | 1.4 | 30540   | 0.0 | 30540  | 0.0  | 30540 | 28672 |
| A8       | 17355 | 2.6 | 17700   | 4.6 | 20100  | 18.8 | 16920 | 16216 |
| A9       | 28280 | 3.4 | 27692   | 1.3 | 27440  | 0.3  | 27348 | 25558 |
| A10      | 39300 | 2.6 | 38636   | 0.9 | 38460  | 0.4  | 38296 | 36992 |
| Average  |       | 1.8 |         | 0.9 |        | 2.6  |       |       |

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ALNS approach Local search approach FMM approach Computational Results

#### Computational Results: Set B

| Instance   | FMM   | (%)  | Cordeau | (%)  | EsGaNo | (%)  | BEST* | LB    |
|------------|-------|------|---------|------|--------|------|-------|-------|
| B1         | 34575 | 2.0  | 37200   | 9.7  | 33900  | 0.0  | 33900 | 31875 |
| B2         | 16755 | 5.6  | 17070   | 7.6  | 16260  | 2.5  | 15870 | 14280 |
| B3         | 16275 | 1.7  | 18015   | 12.6 | 16005  | 0.0  | 16005 | 13965 |
| B4         | 23925 | 0.6  | 23775   | 0.0  | 24330  | 2.3  | 23775 | 16800 |
| B5         | 88920 | 0.3  | 117540  | 32.5 | 88680  | 0.0  | 88680 | 79530 |
| B6         | 28785 | 5.1  | 27390   | 0.0  | 27675  | 1.0  | 26955 | 24180 |
| B7         | 31620 | 0.0  | 33900   | 7.2  | 36900  | 16.7 | 31620 | 25290 |
| <b>B</b> 8 | 35520 | 10.4 | 33240   | 3.4  | 36840  | 14.6 | 32160 | 31890 |
| B9         | 28080 | 0.0  | 29760   | 6.0  | 32700  | 16.5 | 28080 | 25680 |
| B10        | 35040 | 1.0  | 35640   | 1.7  | 41280  | 19.0 | 34680 | 32370 |
| Average    |       | 2.7  |         | 8.1  |        | 7.3  |       |       |

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ALNS approach Local search approach FMM approach Computational Results

#### Computational Results: Set X

| Instance | FMM    | (%) | Cordeau | (%)  | EsGaNo | (%)  | BEST*  | LB     |
|----------|--------|-----|---------|------|--------|------|--------|--------|
| X1       | 146220 | 0.0 | 159300  | 8.9  | 180240 | 23.3 | 146220 | 136680 |
| X2       | 7740   | 6.6 | 8280    | 14.0 | 8370   | 15.3 | 7260   | 5700   |
| X3       | 48720  | 0.0 | 50400   | 3.4  | 50760  | 4.2  | 48720  | 36060  |
| X4       | 64600  | 0.0 | 66780   | 3.4  | 68960  | 6.7  | 64600  | 58230  |
| X5       | 144750 | 0.0 | 157800  | 9.0  | 178560 | 23.4 | 144750 | 130995 |
| X6       | 9690   | 2.2 | 9900    | 4.4  | 10440  | 10.1 | 9480   | 6150   |
| X7       | 32040  | 0.0 | 47760   | 49.1 | 38400  | 19.9 | 32040  | 25410  |
| X8       | 23220  | 0.0 | 24060   | 3.6  | 23800  | 2.5  | 23220  | 17600  |
| X9       | 122700 | 0.0 | 152400  | 24.2 | 154920 | 26.3 | 122700 | 98805  |
| X10      | 120300 | 0.0 | 140520  | 16.8 | 152280 | 26.6 | 120300 | 87210  |
| Average  |        | 0.9 |         | 13.7 |        | 15.8 |        |        |

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### Further scheduling topics

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#### Stability in multi-skilled workforce assignments

The notion of stability in workforce assignments is defined<sup>7</sup>.

<sup>7</sup>Stable multi-skill workforce assignments, Fırat, M., Hurkens, C., Laugier, A., 2014, Annals of OR.

<sup>8</sup>A Branch-and-Price algorithm for stable multi-skill workforce assignments with hierarchical skills, Fırat, M., Briskorn, D., Laugier, A., 2016, EJOR

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### Stability in multi-skilled workforce assignments

- The notion of stability in workforce assignments is defined<sup>7</sup>.
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## Scheduling multi-skilled workforce with varying performances<sup>9</sup>

Scheduling by taking a dynamic view of human performance.

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## Scheduling multi-skilled workforce with varying performances<sup>9</sup>

- Scheduling by taking a dynamic view of human performance.
- It is shown how the scheduling problem can be constructed from business process knowledge.

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# Scheduling multi-skilled workforce with varying performances<sup>9</sup>

- Scheduling by taking a dynamic view of human performance.
- It is shown how the scheduling problem can be constructed from business process knowledge.
- The types of nodes in process trees matched with the notion of scheduling concepts.

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# Scheduling multi-skilled workforce with varying performances $^{9}$

- Scheduling by taking a dynamic view of human performance.
- It is shown how the scheduling problem can be constructed from business process knowledge.
- The types of nodes in process trees matched with the notion of scheduling concepts.
- The problem is formulated as an MIP model to conduct computational experimentation.

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#### Pilot workforce planning of an airline company in Turkey

An aggregated planning problem of pilot in a one-year horizon.

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#### Pilot workforce planning of an airline company in Turkey

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- Demands for every aircraft type are to be met.

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#### Pilot workforce planning of an airline company in Turkey

- An aggregated planning problem of pilot in a one-year horizon.
- Demands for every aircraft type are to be met.
- Dynamic skills of pilots with trainings.
- Advise a pilot employment plan to human resource department.

Scheduling and Business Process Analysis Scheduling and Artificial Intelligence

### Scheduling and Information Systems

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Scheduling and Business Process Analysis Scheduling and Artificial Intelligence

#### Precision in scheduling data

Setup times

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#### Precision in scheduling data

Setup times

▶ are the components of scheduling data due to real-life issue.

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#### Precision in scheduling data

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Scheduling and Business Process Analysis Scheduling and Artificial Intelligence

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Scheduling and Business Process Analysis Scheduling and Artificial Intelligence

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- possibly one topic that may integrate Scheduling and Business Process Analysis

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#### Scheduling and Artificial Intelligence

Exact algorithms

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#### Scheduling and Artificial Intelligence

Exact algorithms

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Exact algorithms

- are smart enumerations methods
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#### Scheduling and Artificial Intelligence

Exact algorithms

- are smart enumerations methods
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- usually decomposes scheduling problem into sub-problems

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- there are more than one criteria to deal with

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- the sub-problems are usually finding "good" objects

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Scheduling and Business Process Analysis Scheduling and Artificial Intelligence

#### Scheduling and Artificial Intelligence

Exact algorithms

- are smart enumerations methods
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- usually decomposes scheduling problem into sub-problems
- there are more than one criteria to deal with
- the sub-problems are usually finding "good" objects
- defining adaptively how an object is "good" is crucial

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### Thanks

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