Prognostics-based Scheduling to Extend a Platform Useful Life under Service Constraint

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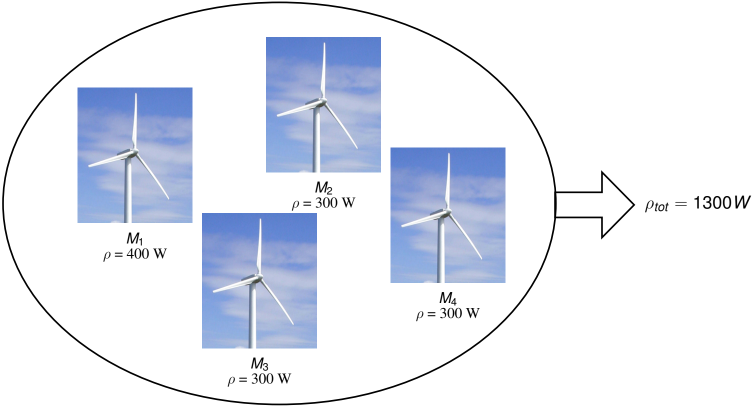
1. State of the art

Production scheduling

- Heterogeneous, independant, parallel machines
- Production based on a customer demand



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Maintenance

- Wear and tear on machines
- Only one global maintenance allowed

$\Longrightarrow$ Production horizon maximization before maintenance

1. State of the art

Maintenance

- Optimization of maintenance strategies
- Gathering of maintenance tasks
- Kovacs et al.: MIP model to optimize maintenance scheduling
  ["Scheduling the maintenance of wind farms for minimizing production loss", 18th IFAC World Congress, 2011 – European Project ReliaWind]
- Besnard et al.: opportunistic maintenance to minimize costs
  ["An optimization framework for opportunistic maintenance of offshore wind power system", IEEE Powertech, 2009]
- Dietl et al.: matching of cutting tools time to failure on a transfer line
  ["An operating strategy for high-availability multi-station transfer lines", Int. J. of Automation and Computing, 2006, 2, p.125 - 130]

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$\Longrightarrow$ Production horizon maximization

Operating conditions

$\Longrightarrow$ Consideration of many running profiles

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Operating conditions

- Variable-speed machines: control of time used by jobs on machines
  - Trick: single and multiple machine variable-speed scheduling

    ["Scheduling multiple variable-speed machines", Operations Research, 1994, 42, p.234-248]
  - Dietl et al.: derating of cutting tools by reducing the cutting speed

    ["An operating strategy for high-availability multi-station transfer lines", Int. J. of Automation and Computing, 2006, 2, p.125 - 130]

- Voltage/Frequency scaling
  - Kimura et al.: energy consumption reducing without impacting performance

    ["Empirical study on reducing energy of parallel programs using slack reclamation by dvfs in a power-scalable high performance cluster", IEEE Int. Conf. on Cluster Computing, Barcelona, 2006]
  - Semeraro et al.: microprocessor's performance and energy efficiency maximization

    ["Energy-efficient processor design using multiple clock domains with dynamic voltage and frequency scaling", HPCA, Cambridge, 2002]

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$\Longrightarrow$ Consideration of many running profiles

$\Longrightarrow$ Taking real wear and tear into consideration (and not average life)

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Prognostics and Health Management (PHM)

- Machine monitoring
- Remaining Useful Life (*RUL*) value depending on past and future usage

1. State of the art

Prognostics and Health Management (PHM)

- Maintenance scheduling based on actual health state
- Haddad et al.: maintenance optimization under availability requirement

  ["A real options optimization model to meet availability requirements for offshore wind turbines", MFPT, Virginia, 2011]
- Vieira et al.: maintenance scheduling based on health limits

  ["New variable health threshold based on the life observed for improving the scheduled maintenance of a wind turbine", 2nd IFAC Workshop on Advanced Maintenance Engineering, 2012]
- Balaban et al.: rover maintenance optimization and mission duration extension

  ["A mobile robot testbed for prognostic-enabled autonomous decision making", Annual Conference of the Prognostics and Health Management Society, 2011]

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Prognostics and Health Management (PHM)

$\Longrightarrow$ Use of prognostics results: *RUL*

$\Longrightarrow$ **Prognostics-based scheduling**

2. Problem statement

Problem data

- m independant machines (M_j)
- n running profiles (N_i)
- PHM monitoring $\rightarrow (\rho_{i,j}, RUL_{i,j})$

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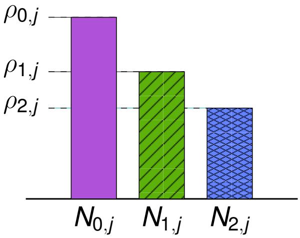

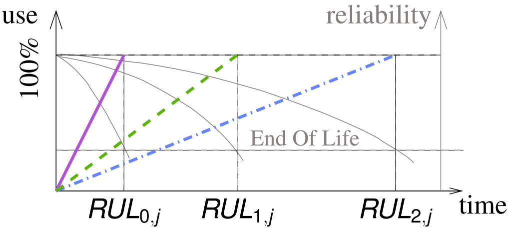

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Constraints

- No *RUL* overrun
- Mission fulfillment: constant demand in terms of throughput (σ)

Objective

- To fulfill total throughput requirements as long as possible
  MAXK($\sigma \mid \rho_{i,j} \mid RUL_{i,j}$)

- Time discretization ($T = K \times \Delta T, 1 \leq k \leq K$)

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Motivating example

M_2

$N_0 = (\rho_0 = 300W, RUL_0 = 1u.t.)$
$N_1 = (\rho_1 = 100W, RUL_1 = 2u.t.)$

M_1

$N_0 = (\rho_0 = 400W, RUL_0 = 1u.t.)$
$N_1 = (\rho_1 = 125W, RUL_1 = 3u.t.)$

M_4

$N_0 = (\rho_0 = 300W, RUL_0 = 1u.t.)$
$N_1 = (\rho_1 = 100W, RUL_1 = 2u.t.)$

M_3

$N_0 = (\rho_0 = 300W, RUL_0 = 1u.t.)$
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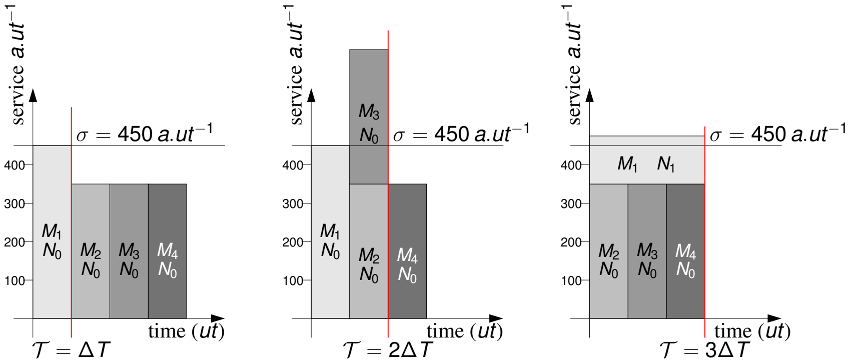
2. Problem statement

Motivating example

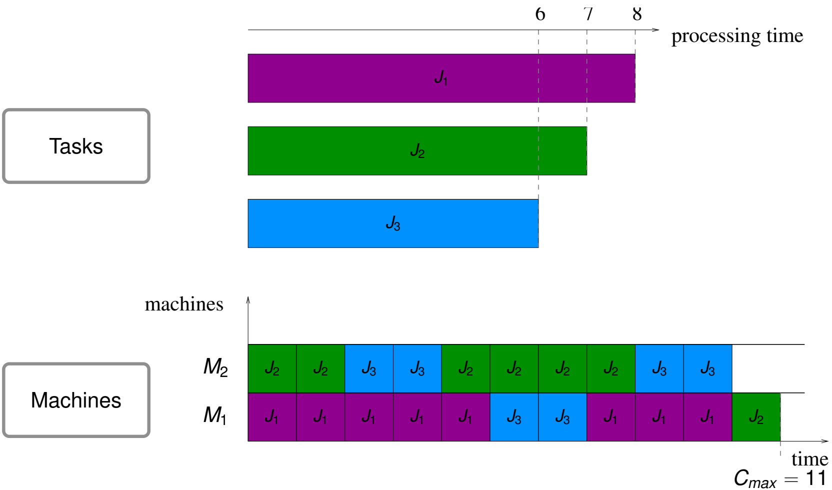


Complexity map

	Homogeneous machines	Heterogeneous machines
1 running profile	$\rho_{i,j} = \rho$ $\text{MAXK}(\sigma \mid \rho \mid RUL_j)$ $\Longrightarrow$ polynomial	$\rho_{i,j} = \rho_j$ $\text{MAXK}(\sigma \mid \rho_j \mid RUL_j)$ $\Longrightarrow$ NP-complete
n running profiles	$\rho_{i,j} = \rho_i$ $\text{MAXK}(\sigma \mid \rho_i \mid RUL_{i,j})$ $\Longrightarrow$?	$\rho_{i,j} = \rho_{i,j}$ $\text{MAXK}(\sigma \mid \rho_{i,j} \mid RUL_{i,j})$ $\Longrightarrow$ NP-complete

3. Complexity results – $(\rho_{i,j} = \rho,\ N = 1)$

Optimal LRPT schedule for $P_q \,|\, prmp \,|\, C_{max}$ [Pinedo1995]



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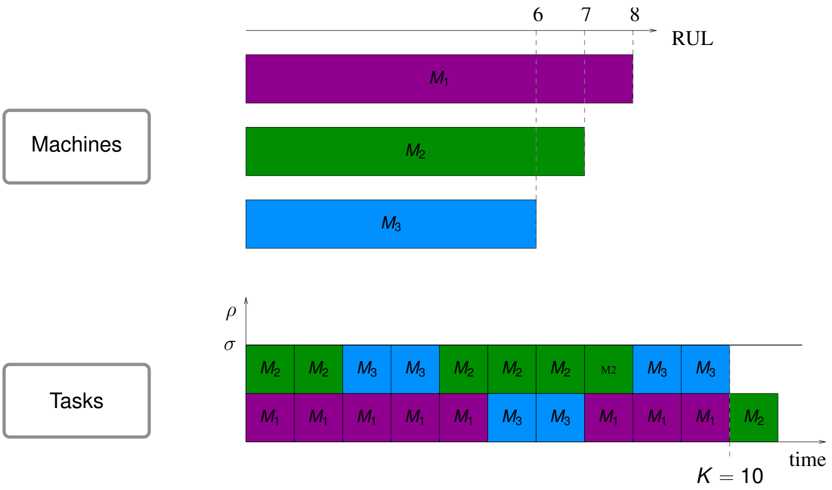
Optimal LRUL schedule for MAXK$(\sigma \mid \rho \mid RUL_j)$



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4. Optimal approach

Binary Integer Linear Program (BILP)

$a_{i,j,k} = 1$ if machine M_j is used with running profile N_i during period k,
0 otherwise

$$\begin{cases} \forall k,\ \forall j,\ \sum_{i=0}^{n-1} a_{i,j,k} \leq 1 & \text{(machines)} \\ \forall j,\ \sum_{i=0}^{n-1} \frac{\sum_{k=1}^{K} a_{i,j,k} \times \Delta T}{RUL_{i,j}} \leq 1 & (RUL) \\ \forall k,\ \sum_{j=1}^{m} \sum_{i=0}^{n-1} a_{i,j,k} \times \rho_{i,j} \geq \sigma & \text{(service)} \end{cases}$$

- Binary search to find maximal value of k

$\Longrightarrow$ Limited to small instances: $\approx$ 5 machines, 2 running profiles, 20 time periods

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5. Sub-optimal resolution

Polynomial time heuristics

Basic heuristics

- Assignment of machines to reach the demand σ as long as possible
- Selection of one running profile for each machine and each time period

- H–LRF: Largest *RUL* First
- H–HOF: Highest Output First
- H–DP: Dynamic Programming based

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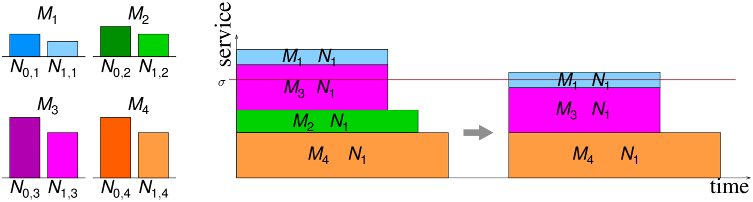

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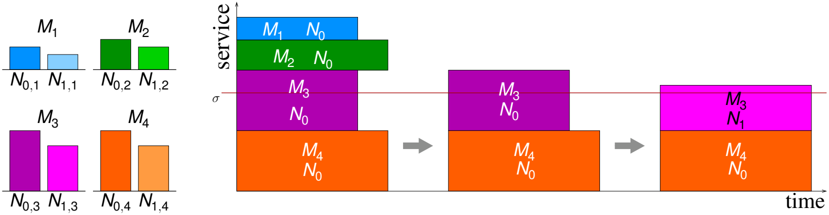


5. Sub-optimal resolution

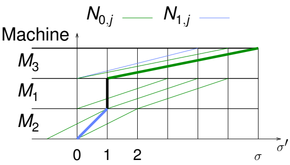
Polynomial time heuristics – H–DP: Dynamic Programming based

- Knapsack-like algorithm for each period
- Two criteria:
  - Crit.1: overproduction minimization
  - Crit.2: number of machines minimization

$$ov_i(\sigma', j) = OV(\sigma' - \rho_{i,j}, j-1) + \rho_{i,j} \text{ with } 0 \leq i \leq n-1$$

$$OV_i(\sigma', j) = \begin{cases} ov_i(\sigma', j) \text{ if } ov_i(\sigma', j) \geq \sigma' \\ +\infty \text{ otherwise} \end{cases}$$

$$OV(\sigma', j) = \min\left(OV(\sigma', j-1), \min_{0 \leq i \leq n-1} OV_i(\sigma', j)\right)$$



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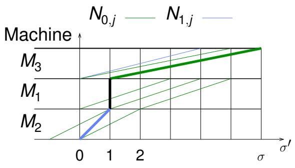

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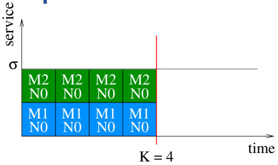
Enhancement: repair module

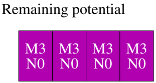
- Revision of the schedules obtained with basic heuristics
- Use of available machines

5. Sub-optimal resolution

Polynomial time heuristics – Repair module

- H–DP schedule





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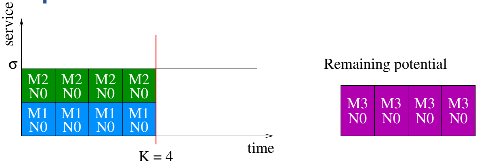
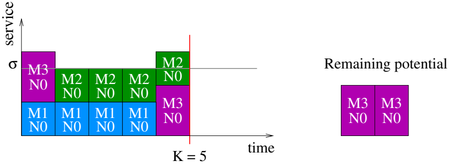
- H–DP schedule



- H–DP-R Step 1



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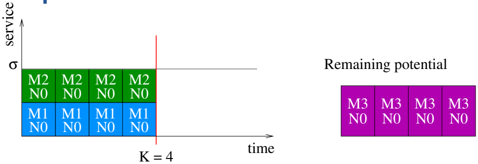
- H–DP schedule



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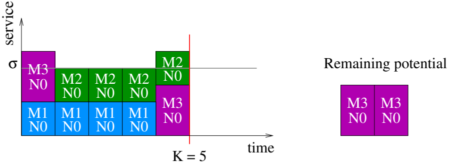
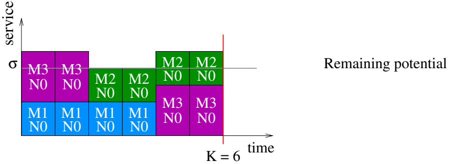


- H–DP-R Step 2



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- Use of available machines

¤ H–LRF-R, H–HOF-R, H–DP-R

6. Results

Simulations

- Validation of heuristics on random problem instances
- Consideration of an increasing output $Q_{i,j} = \rho_{i,j} \times RUL_{i,j}$ with ρ such that:

$$Q_{0,j} > Q_{1,j} > \ldots > Q_{n-1,j}$$

$$\text{with} \;\; \rho_{0,j} > \rho_{1,j} > \ldots > \rho_{n-1,j}$$

$$\text{and} \;\; RUL_{0,j} < RUL_{1,j} < \ldots < RUL_{n-1,j}$$

- Constant demand $\sigma_k = \sigma$, with:

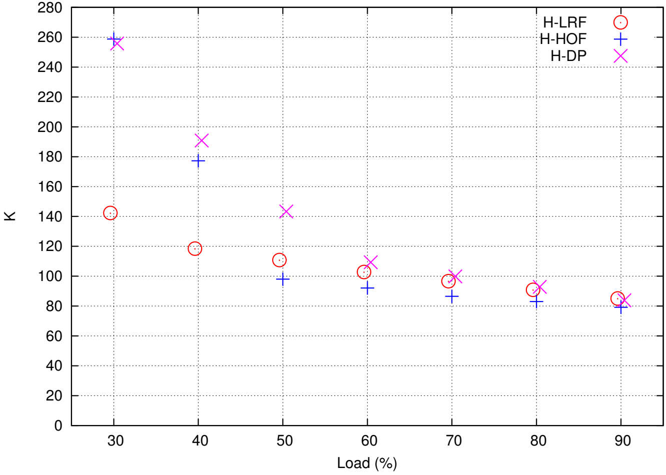
$$\sigma = \alpha \times \sum_{1 \leq j \leq m} \rho_{max,j}$$

$$\text{with} \;\; 30\% \leq \sigma \leq 90\%$$

- Average value of 20 instances with same parameters values

6. Results

Comparison of basic heuristics (n=5, m=25)



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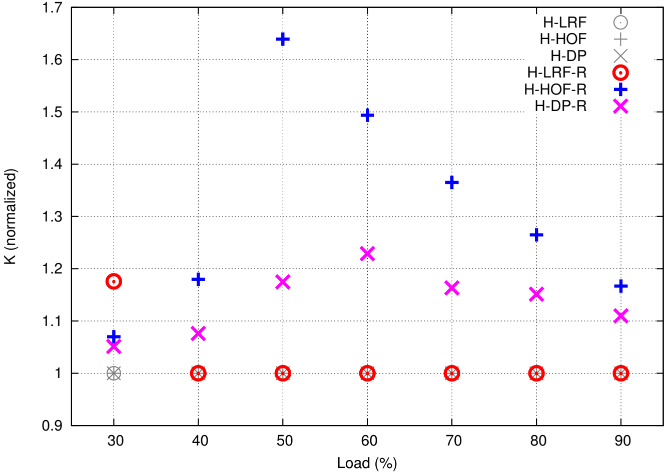
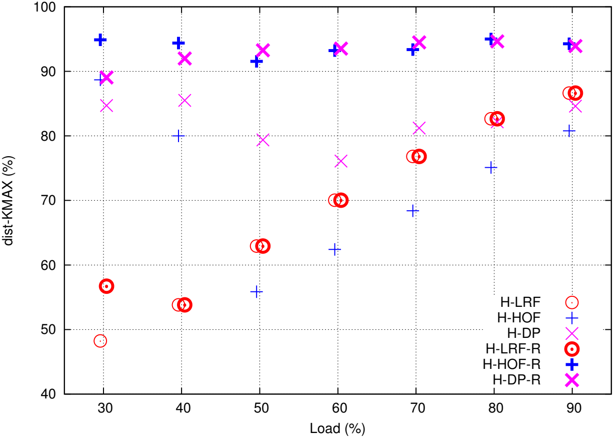
Rate improvement of the repair module (n=5, m=25)



6. Results

Comparison to an upper bound(n=5, m=25)

$$\text{KMAX} = \left\lfloor \sum_j \max_i \left(\rho_{i,j} \times RUL_{i,j}\right) / \sigma \right\rfloor$$



7. Conclusion

Adressed problem: maximizing the production horizon under service constraint

- Scheduling using prognostics results (*RUL*)
- Use of several running profiles
- Extension of a platform operational time
- Efficient sub-optimal heuristics (6% from upper bound)

Future work

- Continuous use of machines (fuel cells)
- Consideration of maintenance tasks within schedules (steady-state scheduling)

Thank you for your attention

Any questions ?