ROBOPROX

Scheduling, Discrete Optimization and Decision-Making

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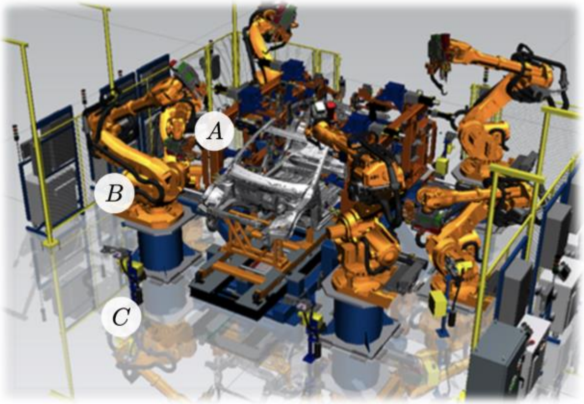
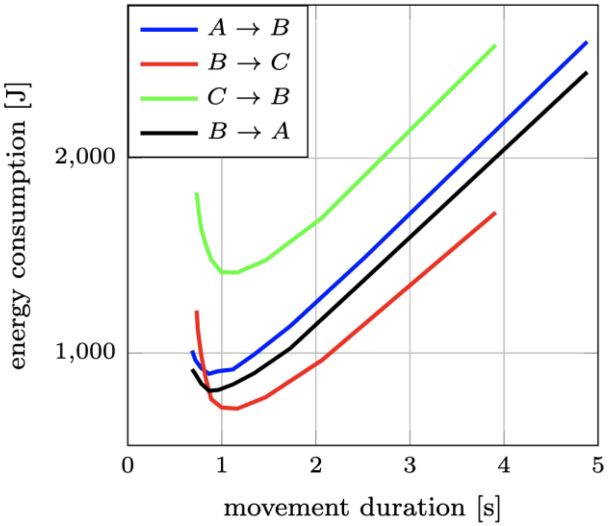
Robotics and Advanced Industrial Production
CZ.02.01.01/00/22_008/0004590

RA11: Scheduling, Discrete Optimization and Decision-Making



- Two groups:
  - G11: Industrial Informatics Department, CIIRC
  - G16: VŠB TUO

- RO 11.1 - **High-performance algorithms for the novel extensions of production scheduling problems** (G11: Hanzálek, Šůcha, Rohaninejad)
- RO 11.2 - **Uncertainty and machine learning in discrete optimization** (G11: Hanzálek, Šůcha, Novák)
- RO 11.3 - **Effective Decision-Making for Long-term autonomy** (G11: Chrpa)
- RO 11.4 - **Metaheuristic methods application for large scale, high dimensional data** (G16: Snášel, Nowaková)
- RO 11.5 - **Optimization of energy consumption and production** (G11: Šůcha, Hanzálek)



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RA11 people: G11 - CIIRC

prof. Zdeněk Hanzálek (PI)

doc. Přemysl Šůcha (ex. TT)

doc. Lukáš Chrpa (ex. TT)

Antonín Novák (PD)

Mohammad Rohaninejad (PD)

Vilém Heinz (PhD student)

Josef Grus (PhD student)

Adam Kollarčík (PhD student)

+3 positions (acquiring)

RA11 people: G16 - VŠB TUO

prof. Václav Snášel (GL)

Jana Nowaková (ex. TT)

Swagatam Das (ex. T)

Vojtěch Uher (PD)

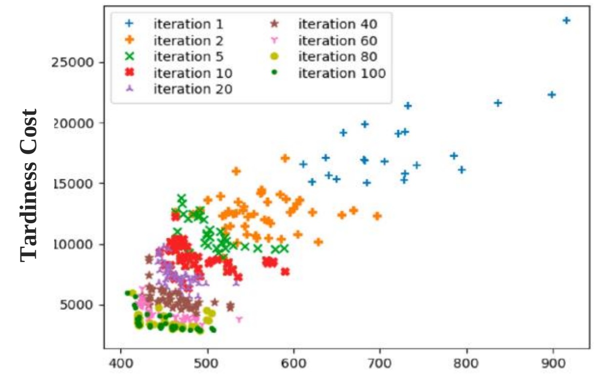
Lingping Kong (PD)

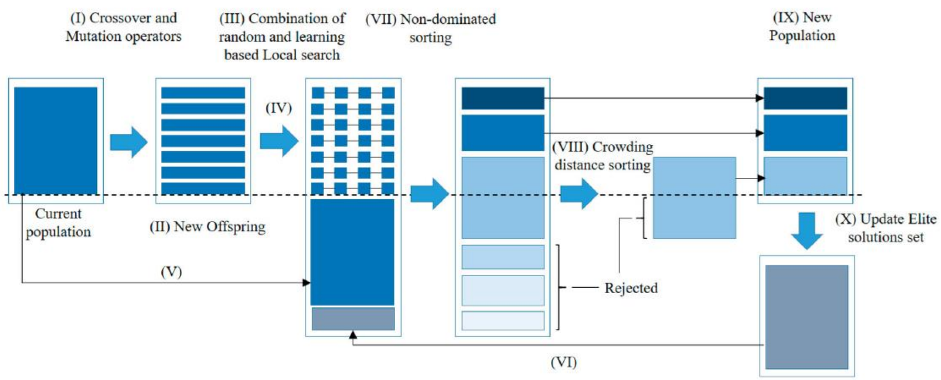
Meenu Singh (PD)

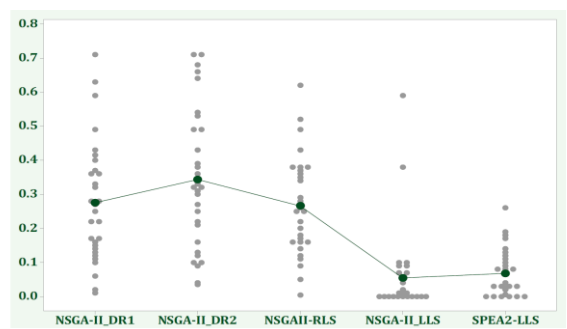
+2 positions (acquiring)

RO 11.1: High-performance algorithms for the novel extension of production scheduling problems

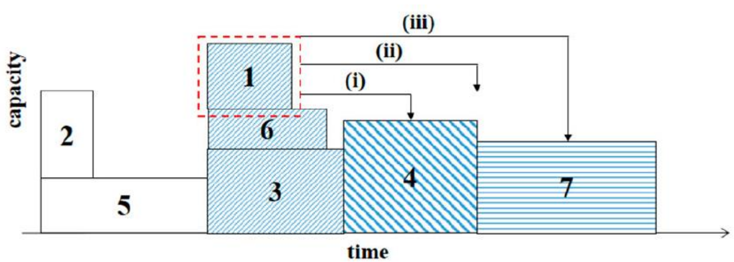
- Investigating bi-objective scheduling problem to minimize **Makespan** and the **Total Tardiness Cost** in an additive manufacturing system.
- Developing an efficient approach by combining the NSGA-II algorithm and a self-adaptive local search.







Set Coverage Index



Mohammad Rohaninejad, Reza Tavakkoli-Moghaddam, Behdin Vahedi-Nouri, Zdeněk Hanzálek & Shadi Shirazian. *A hybrid learning-based meta-heuristic algorithm for scheduling of an additive manufacturing system consisting of parallel SLM machines.* IJPR 2022.

RO 11.1: High-performance algorithms for the novel extension of production scheduling problems

- **What we will aim for:**
  - Identifying Critical Scheduling Areas (CSA) brought by the new manufacturing paradigms
    - Exploring the characteristics, complexity, and mathematical formulation of CSAs for example *vertical and Horizontal Integration, Flexible Production Environments, Real-Time Scheduling* etc.
  - Developing solution algorithms according to opportunities and threats brought by the CSAs.
    - Threats eg. *Higher Complexity or Time-Sensitive Decision Making*
    - opportunities eg. *Leveraging Big Data*
- **International collaboration:**
  - Prof. Armand Baboli (National Institute of Applied Sciences of Lyon, France)
- **Cooperation with other RAs:**
  - Jan Zeman - RO 4.2: Designing suitable heuristics for assembly plan optimization
  - Dušan Knop – RO 12.4: Identifying of the problems from practice and designing new algorithms

RO 11.2: Uncertainty and machine learning in discrete optimization

Distributionally robust optimization (DRO)

$$\min_{\pi \in \Pi} \max_{\mathbb{P} \in \mathcal{D}} \mathbb{E}_{\mathbb{P}} \left[g(\boldsymbol{\pi}, \tilde{\boldsymbol{p}}) \right]$$

- $\tilde{\boldsymbol{p}}$ follows an **unknown** probabilistic distribution $\mathbb{P}$
- but we assume that $\mathbb{P}$ belongs to a set of distributions $\mathcal{D}$ (ambiguity set)
- it turns out to be a generalization of both RO and SP frameworks

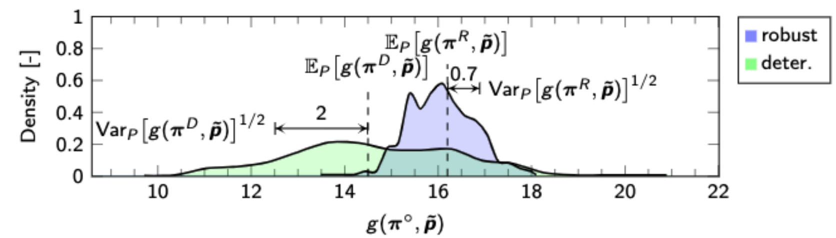
Observation

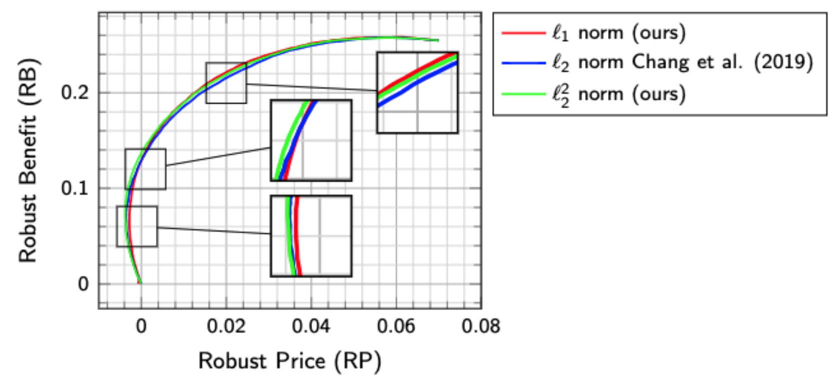
The problem can be equivalently expressed as

$$\text{DR-PTFT}(\ell_2) \equiv \min_{\boldsymbol{\pi} \in \boldsymbol{\Pi}} \boldsymbol{\pi}^\intercal \hat{\boldsymbol{\mu}} + \gamma_1 \left\| \hat{\boldsymbol{\Sigma}}^{1/2} \boldsymbol{\pi} \right\|_2,$$

where $\hat{\boldsymbol{\Sigma}}^{1/2} = \boldsymbol{V} \boldsymbol{D}^{1/2} \boldsymbol{V}^{-1}$ and $\| \cdot \|_2$ is ℓ_2 norm.

- Reformulation of distributionally robust scheduling problem into its deterministic variant + regularization term in the objective
- Complexity characterization for independent jobs in terms of the lp norm: some are polynomial, some pseudopolynomial
- Nearly identical trade-offs between the stability of the solution and its cost





Antonin Novak, Andrzej Gnatowski and Premysl Sucha. *Distributionally robust scheduling algorithms for total flow minimization on parallel machines using norm regularizations.* EJOR 2022.

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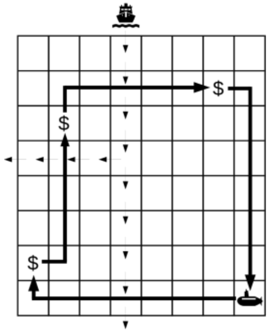
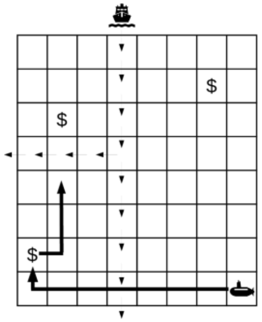
RO 11.2: Uncertainty and machine learning in discrete optimization

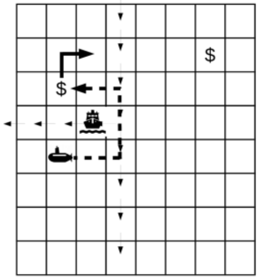
- **What we will aim for:**
  - Study trade-offs between computational complexity and modelling efficiency in distributionally robust optimization.
    - In which cases does the increased complexity of uncertainty model translate to better protection from undesired realizations? Sweet spots for applications?
  - Develop surrogate and automated data-driven models of discrepancy-based ambiguity sets.
    - Exact solution of simplified model vs. heuristic solution with complex uncertainty model.
  - Role of ML for approximation of weakly NP-hard problems.
  - Enhancing CP solvers with ML exploration strategies.
- **International collaboration:**
  - Dr. Andrzej Gnatowski, Prof. Wojciech Bozejko, (Wroclaw University of Technology)
  - Prof. Alessandro Agnetis (Universita di Siena, Italy)
- **Cooperation with other RAs:**
  - D. Knop – RO 12.4: fixed-parameter tractability for stochastic optimization problems
  - M. Janota - RO 12.3: learning from solutions & synthesis of uncertainty models
  - D. Henrion – RO 3.2: efficient LMI representations and solution methods for data-driven ambiguity sets

RO 11.3: Effective decision-making for long-term autonomy

- **Planning and Acting for longer-term goals in dynamic environments**
  - Safe planning and acting in dynamic environments [1]
  - Generating *eventually applicable* plans in dynamic environments [2]
  - Balancing deliberative (planning) and reactive (e.g. rule-based acting) reasoning in dynamic or adversarial environments [3]







[1] Lukás Chrpa, Jakub Gemrot, Martin Pilát: *Planning and Acting with Non-Deterministic Events: Navigating between Safe States.* AAAI 2020: 9802-9809

[2] Lukás Chrpa, Martin Pilát, Jakub Med: *On Eventual Applicability of Plans in Dynamic Environments with Cyclic Phenomena.* KR 2021: 184-193

[3] Lukás Chrpa, Martin Pilát, Jakub Gemrot: *Planning and acting in dynamic environments: identifying and avoiding dangerous situations.* Journal of Experimental and Theoretical Artificial Intelligence 34(6): 925-948 (2022)

RO 11.3: Effective decision-making for long-term autonomy

- **What we aim for**
  - Formalize the concept of *planning against nature* [1]
  - Investigate under what circumstances we can generate safe or robust plans/policies
    - Investigate the concept of action reversibility [2]
  - Investigate how effectively deliberative (e.g. planning) and reactive (e.g. MCTS) techniques can be combined in dynamic environments
  - Validate the methods in real/realistic scenarios (e.g. in robotic systems)
- **International Collaboration**
  - Mauro Vallati, University of Huddersfield
  - Erez Karpas, Technion
  - Wolfgang Faber and Martin Gebser, University of Klagenfurt
- **Intended Cooperation within the Project**
  - RA6 (L. Přeučil, M. Kulich)
  - RA7 (R. Babuška)

[1] Lukás Chrpa, Erez Karpas: *On Verifying Linear Execution Strategies in Planning Against Nature*, ICAPS 2024 (to appear)

[2] Jakub Med, Lukás Chrpa, Michael Morak, Wolfgang Faber: *Weak and Strong Reversibility of Non-Deterministic Actions: Universality and Uniformity*, ICAPS 2024 (to appear)

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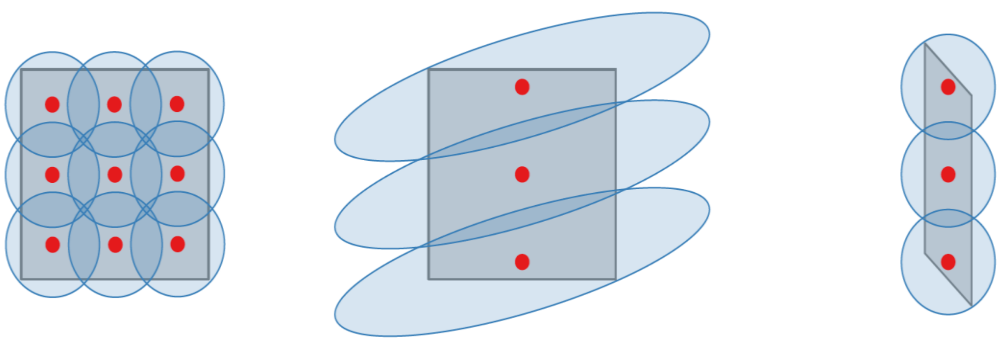
RO 11.4: Metaheuristic methods application for large scale, high dimensional data

1.1. Definition. We define the Lipschitz matrix analogously to the Lipschitz constant. Given a domain $\mathcal{D} \subset \mathbb{R}^m$, the scalar Lipschitz constant $L \in \mathbb{R}_+$ defines a set of *scalar Lipschitz functions*, denoted by $\mathcal{L}(\mathcal{D}, L)$, that satisfy

$$\mathcal{L}(\mathcal{D}, L) := \{f : \mathcal{D} \to \mathbb{R} \ : \ |f(\mathbf{x}_1) - f(\mathbf{x}_2)| \leq L\|\mathbf{x}_1 - \mathbf{x}_2\|_2, \ \mathbf{x}_1, \mathbf{x}_2 \in \mathcal{D}\}. \quad (1.1)$$

The *Lipschitz matrix* changes this definition, moving the constant L inside the norm and promoting it to a matrix $\mathbf{L} \in \mathbb{R}^{m \times m}$. This defines the *matrix Lipschitz functions*

$L = 1$, $\mathcal{D} = [-1, 1]^2$ $\quad$ $\mathbf{L} = \begin{bmatrix} 1/4 & 0 \\ -1/4 & 1 \end{bmatrix}$, $\mathcal{D} = [-1, 1]^2$ $\quad$ $\mathbf{L} = \begin{bmatrix} 1/4 & 0 \\ -1/4 & 1 \end{bmatrix}$, $\mathcal{D} = \mathbf{L}[-1, 1]^2$



$$d_{\mathbf{L}}(\mathbf{x}, \mathbf{y}) := \|\mathbf{L}(\mathbf{x} - \mathbf{y})\|_2, \qquad \mathbf{x}, \mathbf{y} \in \mathcal{D}.$$

- Lipschitz matrix: a generalization of the scalar Lipschitz constant for functions with many inputs. Among the Lipschitz matrices compatible with a particular function, we choose the smallest such matrix in the Frobenius norm to encode the structure of this function.
- Application for Expensive Optimization Problems.

Abhishek Kumar, Swagatam Das, Lingping Kong, **Václav Snášel**: *Self-Adaptive Spherical Search With a Low-Precision Projection Matrix for Real-World Optimization.* IEEE Trans. Cybern. 53(7): 4107-4121 (2023).

Abhishek Kumar, Swagatam Das, **Václav Snášel**: *Efficient Three-Stage Surrogate-Assisted Differential Evolution for Expensive Optimization Problems*, submitted.

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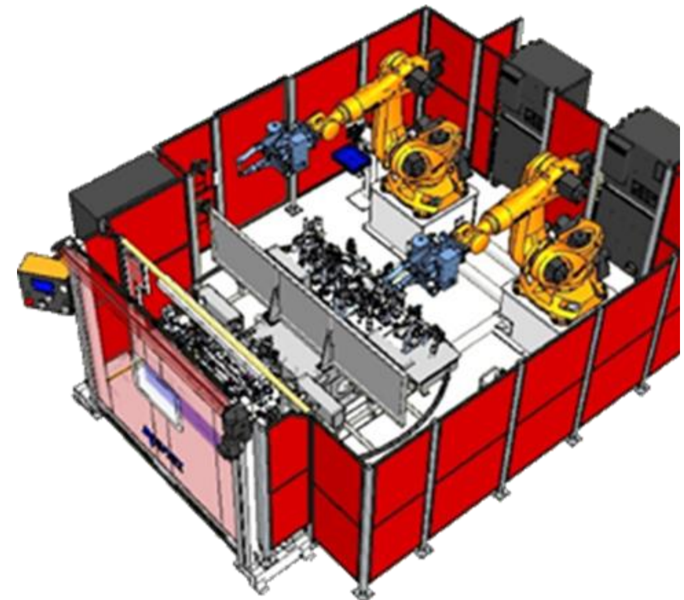
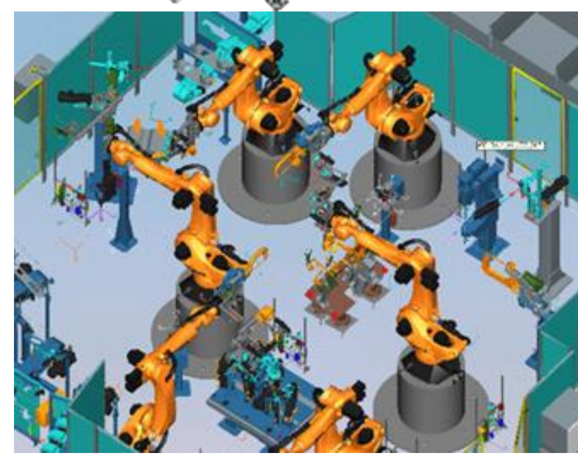
RO 11.4: Metaheuristic methods application for large scale, high dimensional data

- **What we will aim for:**
  - with Examples of typical/interesting results (most likely achieved before Roboprox but relevant to the Objective) to make it more illustrative
  - develop new surrogate models (and develop the recent ones) for more effective and faster solving real problems using new hyper-spherical models with automatically self-adaptive control parameters of the optimization task,
    - taking into account the complexity of the real application from the beginning,
    - Be able to test the algorithms in real-world application.
  - Our work could be divided into three steps
    - development of metaheuristic methods with an emphasis on adaptive model search,
    - verification of the developed metaheuristic methods in real applications, e.g., energy-efficient planning and reasoning,
    - use of the developed methods in large-scale data as a basis for decision support systems.
- **International collaboration:**
  - Varun Ojha, New Castle University, UK
  - Ponnuthurai Nagaratnam Suganthan, Nanyang Technological University, Singapore
  - Millie Pant, Indian Institute of Technology
- **Cooperation with other RAs:**
  - Prepared for cooperation with all RA and RG in all RO.

RO 11.5: Optimization of energy consumption and production





- Robotic cells - Production rate is the main KPI, **energy efficiency is disregarded**
- Current situation:
  - use **maximal speed** of movement
  - does not guarantee the maximum production rate
  - negative impact on energy consumption
- Solution:
  - optimized from the **global point of view**
  - synergy with a **digital twin**
  - Results (savings):
    - Škoda: energy **20%**
    - Blumenbecker: cycle time **4-9%**, energy **10-20%**
    - Continental: energy **26%**

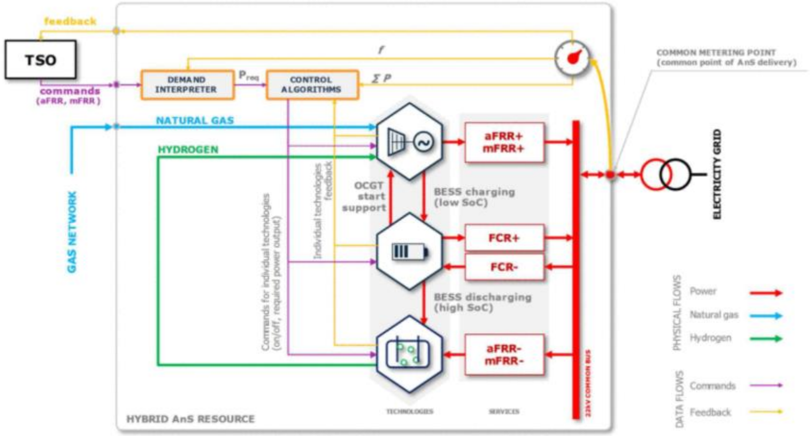
RO 11.5: Optimization of energy consumption and production

- Optimization of **energy production** (**anscillary services**)

- Control of a **virtual power plant** (VPP)
  - 6 Aeroderivative Gas Turbines (Lockheed C-130 Hercules)
  - the largest battery system in ČR (20MWh)

- Tasks:
  - design **robust optimization** algorithms to control the VPP (uncertain demand)
  - design **machine learning models** to improve the control

- Cooperation with O. Mamula
- International: prof. B. Maenhout (U Ghent)



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RA11: Industrial collaborations

- **Porsche Engineering:** automated cone slalom, lane-keeping assistant demonstrator
- **Blumenbecker Prag:** Process Simulate extension for energy optimization of industrial robots
- **Continental:** implementation of energy optimization of industrial robots
- **Škoda Auto:** EV routing algorithm, kick-activated opening of the trunk
- **Eaton:** code generation platform for safety controller, AC motor bearing health prediction
- **PPL:** simulation and optimization of hub-depot parcel transport
- **ČEZ:** analysis and improving mathematical models for profit optimization
- **ST Microelectronics:** algorithm for analog integrated circuit placement

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