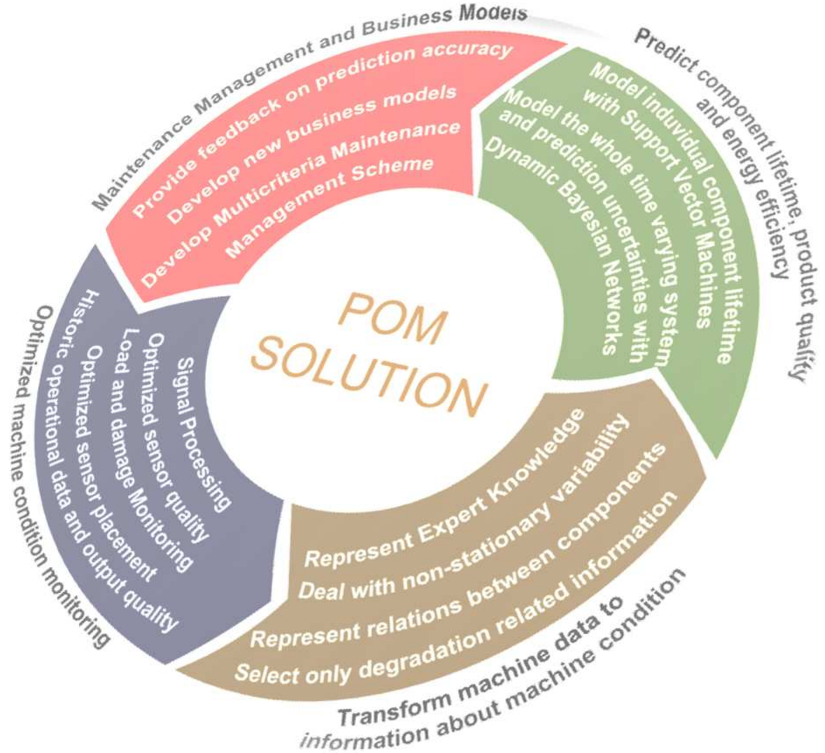


Smart run-time machine modeling

Koen Rutten

KU Leuven, MeBioS

Overview

- Introduction
  - The Concept of Run-Time Modeling
  - EVOP-based methods
- Case Study – Badminton Robot
  - Introduction to the Case
  - Dealing with constraint/multiple objectives
  - Results
  - Conclusions
- Case Study – Bearing Set-Up
  - Introduction to the Case
  - Dealing with non-linear processes, gathering information
  - Conclusions
- General Conclusions

The Concept of Run-Time Modeling

INTRODUCTION

The Concept of Run-Time Modeling

Problem

- **Nowadays: highly complex processes**
  - Non-linearity, non-stationarity, …
- **Complexity of mathematical models**
  - Often impossible to model everything: *Model uncertainty*
- **Offline modeling might require intense effort**
  - Effort = money, personnel, non-standard machine operation, …

Solution

- ***Produce/Generate product/response + information on how to improve the process***
  - Small shifts in operating conditions
  - ***Small steps, "Slower methods"***
  - ***Probability of infeasible results lower***
  - Optimize sequentially during run-time

The Concept of Run-Time Modeling

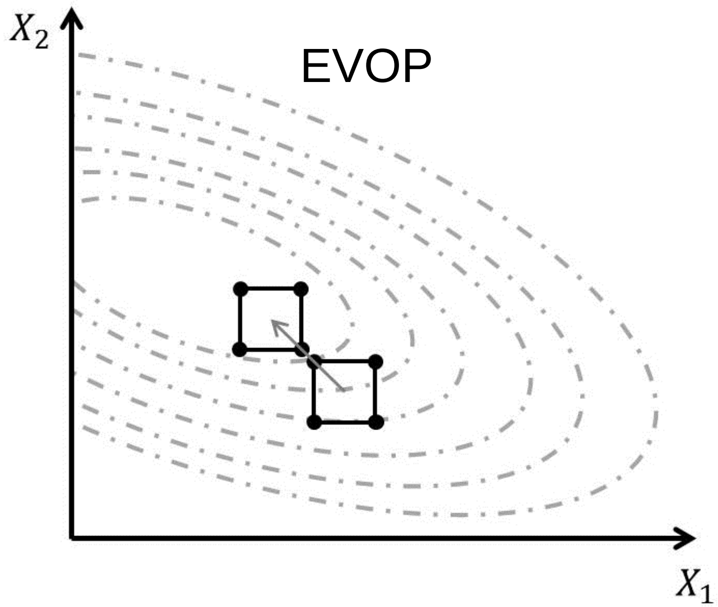
State of process

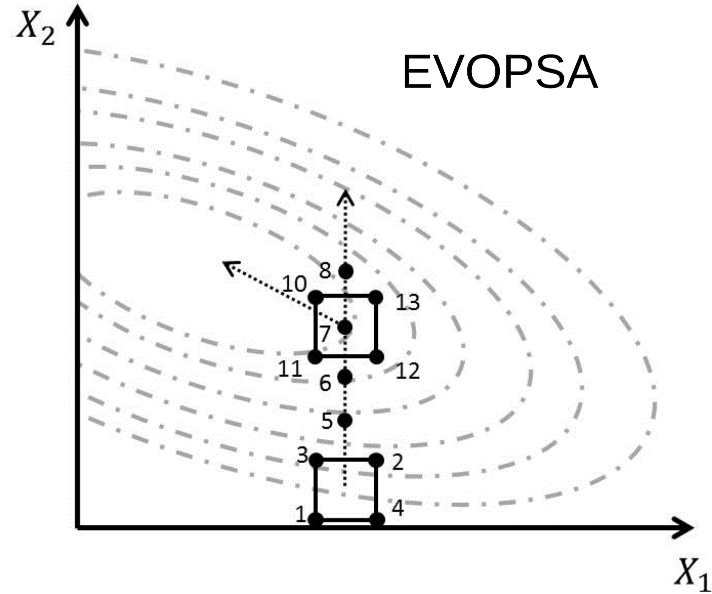
+ **Process usually has acceptable output *but***
  - Sub-optimal performance (“might perform better”)
  - Shifting optimum (“Variations shift the optimum”): impurity of input batches, …
  - Drifting optimum (“Optimum slowly shifts with time”): changing production speeds due to friction, moisture level of environment, …

Goal

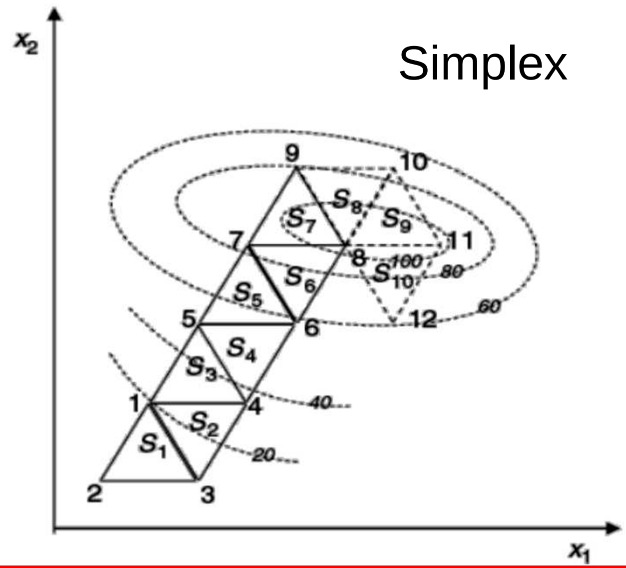
+ **Track the optimum (shifting/drifting)**
  - Try and keep the response steady and acceptable over time
+ **Towards better output efficiency / Finding the optimum (sub-optimal)**
  - Push the operating conditions to a more efficient set of conditions.

Statistics





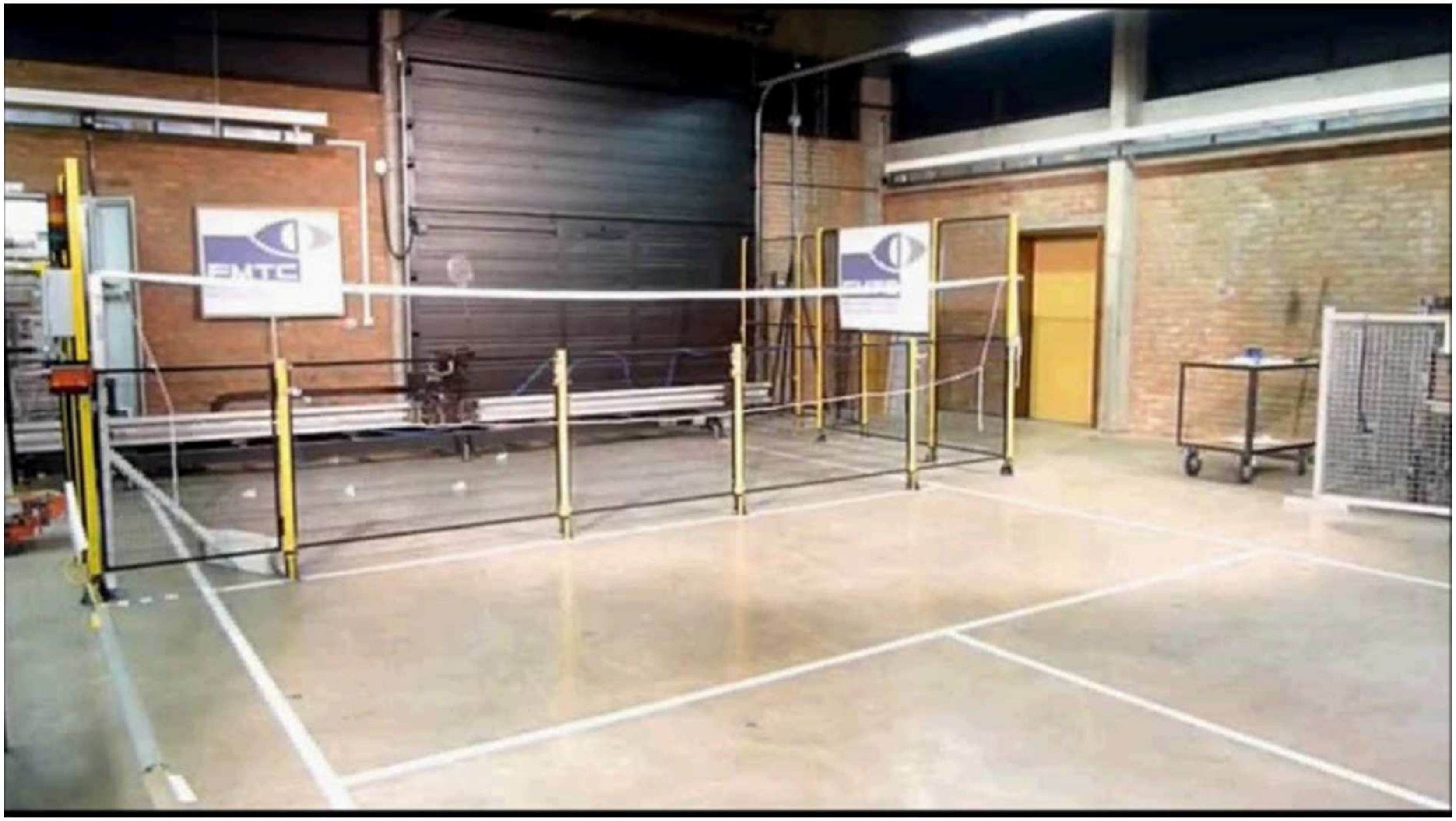
Heuristics



Introduction to the Badminton Robot

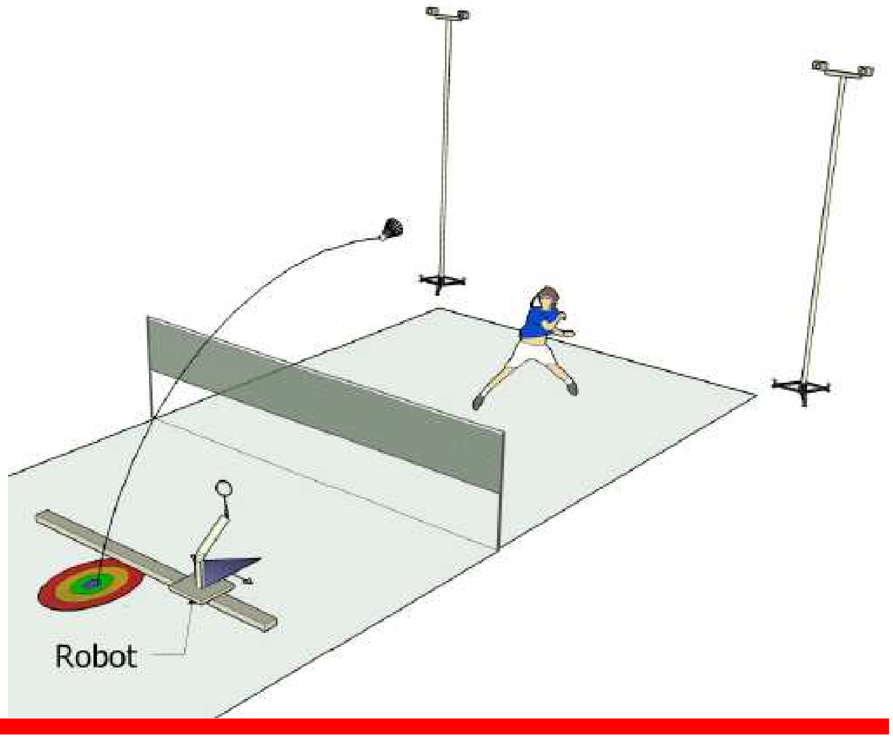
BADMINTON ROBOT

Case Study – The Badminton Robot



Case Study – The Badminton Robot

+ **Linear axis**
  - Main energy consumer
  - 2 control parameters *a*, *v*
+ **PTOS**
  - "As fast as possible"
  - Maximum energy consumed
  - Maximum *a*, *v*
+ **PEOS**
  - Reduce energy
  - *a* , *v* dependant on
    - interception time t_{max}
    - interception reference y_{des}

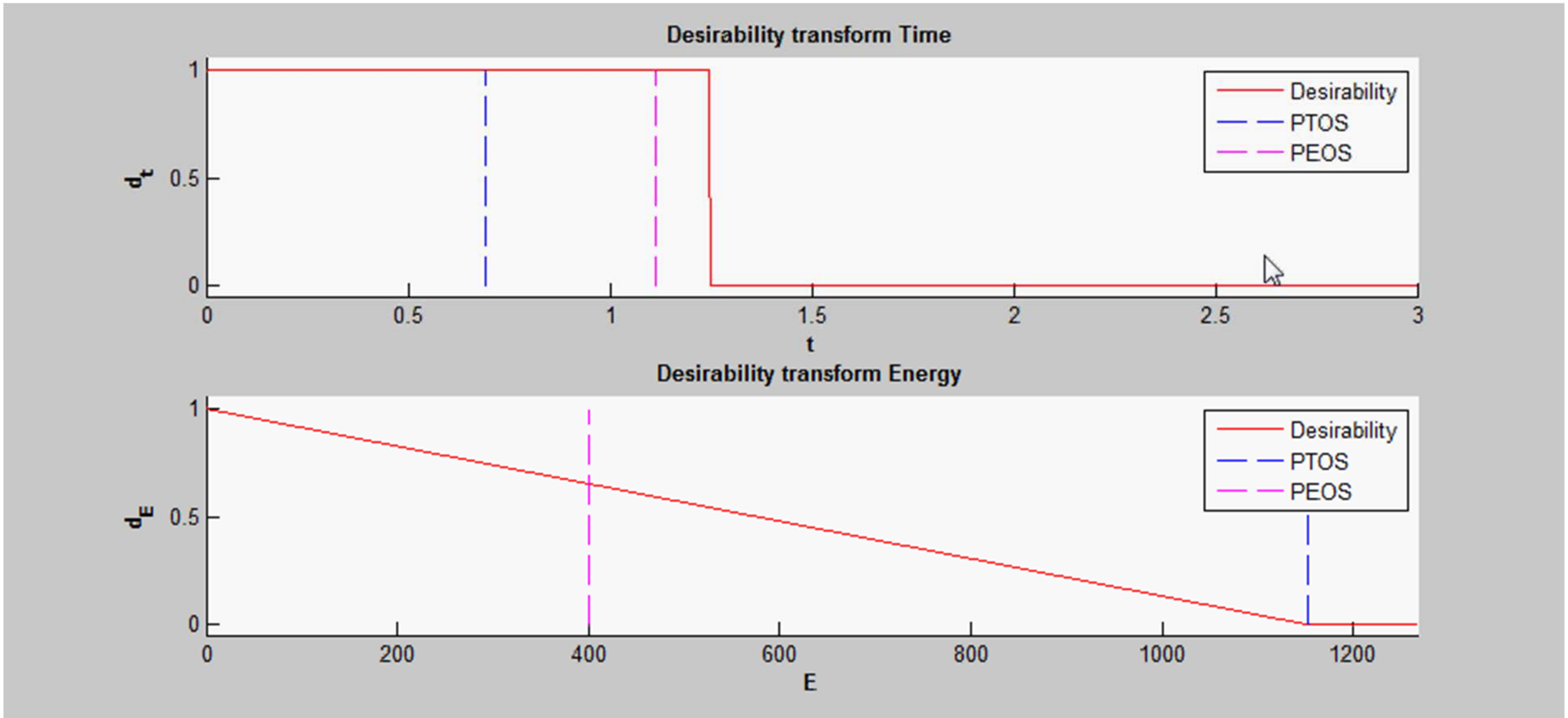


Dealing with Multiple Objectives

+ **Transform objectives into desirabilities d_i**
  - $0 \leq d_i \leq 1$
  - d_i *increases as desirability increases*

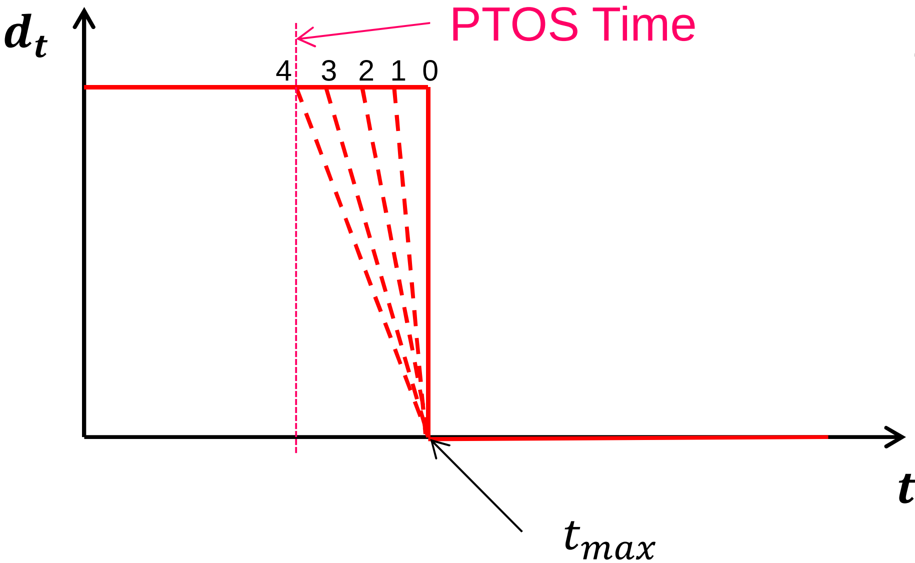
+ **Scale multi-objective to single-objective**
  - Combine individual desirabilities in global desirability
  - Find the best trade-off between responses

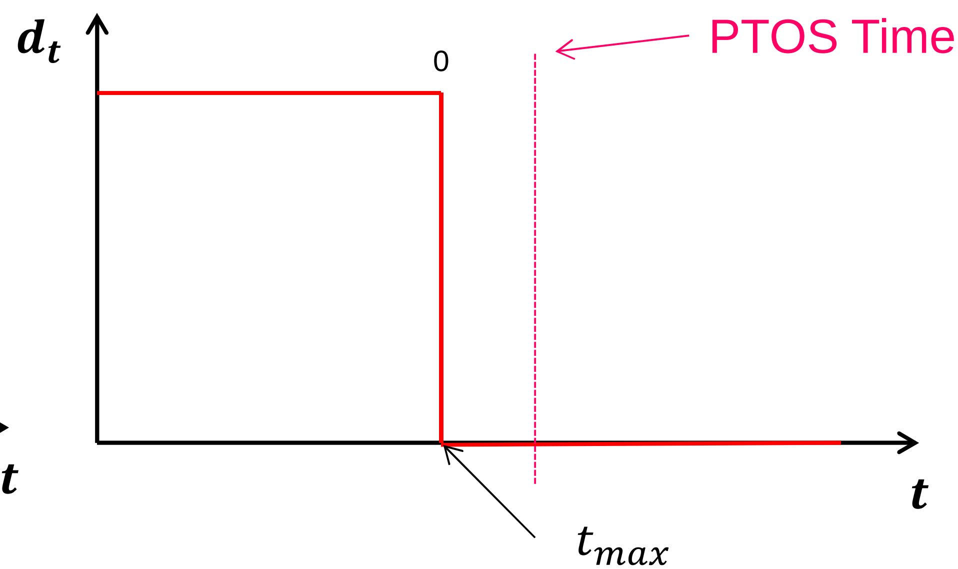
Example of Desirability functions



Optimization Test II - EVOPSA

+ **Select one method, do extensive testing**
  - More restrictive scaling of objectives: Implement several forms of objective function for time





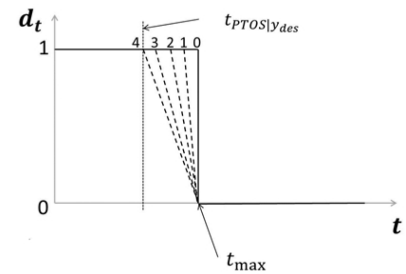
Results

BADMINTON ROBOT

Benchmark Testing

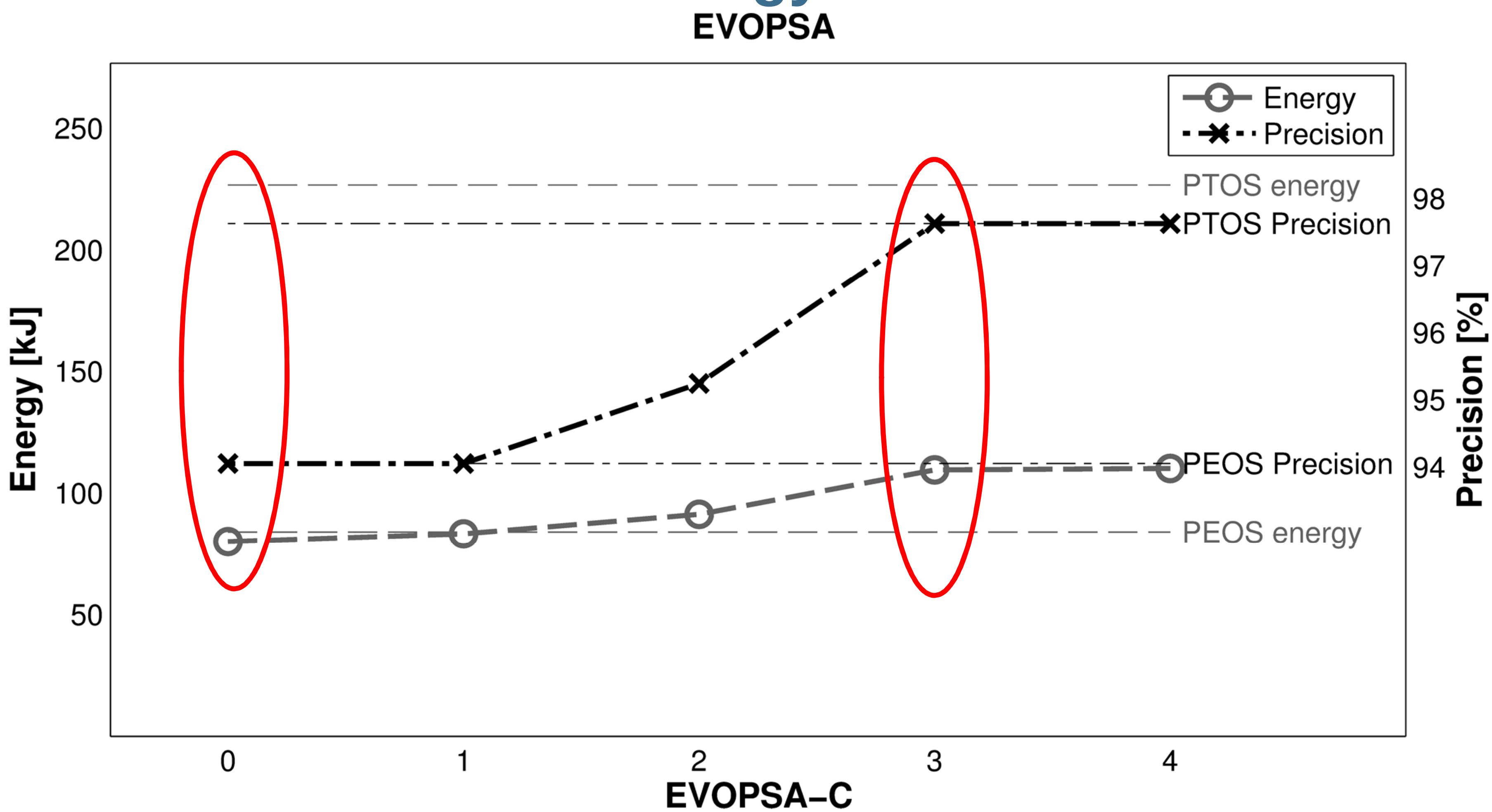
+ **Test during badminton play**
+ **Comparing: exactly the same play for each method**
+ **Impossible for human player**
+ **Prerecorded linear sequence ("Human play") is run through the robot**
    - Measure energy
    - Calculate position error (± 5cm)

Benchmark Results



Method	Consumed Energy ± SD [kJ]	Reduction consumed energy vs. PTOS [%]	Reduction consumed energy vs. PEOS [%]	Precision [%]
PTOS	$\mathbf{226.527 \pm 2.94}$	-	-	97.62
PEOS	$\mathbf{83.782 \pm 0.18}$	*63.02*	-	94.05
EVOPSA-0	$\mathbf{79.823 \pm 0.16}$	64.76	4.73	94.05
EVOPSA-1	$\mathbf{82.982 \pm 0.11}$	63.37	0.95	94.05
EVOPSA-2	$\mathbf{91.091 \pm 0.01}$	59.79	-8.72	95.24
EVOPSA-3	$\mathbf{109.317 \pm 0.1}$	51.74	-30.48	97.62
EVOPSA-4	$\mathbf{109.943 \pm 0.08}$	51.47	-31.22	97.62

Trade-off between Energy and Precision



Conclusions

BADMINTON ROBOT

Conclusions

- **On-line optimization reduces energy consumption by 5%**
- **A more stringent constraint achieves maximum precision (97.62%) with 51.74% reduction in consumed energy compared to previous maximum precision mode**
- **Desirability functions are an easy implementation to deal with multiple objectives and (certain) constraints**

Introduction

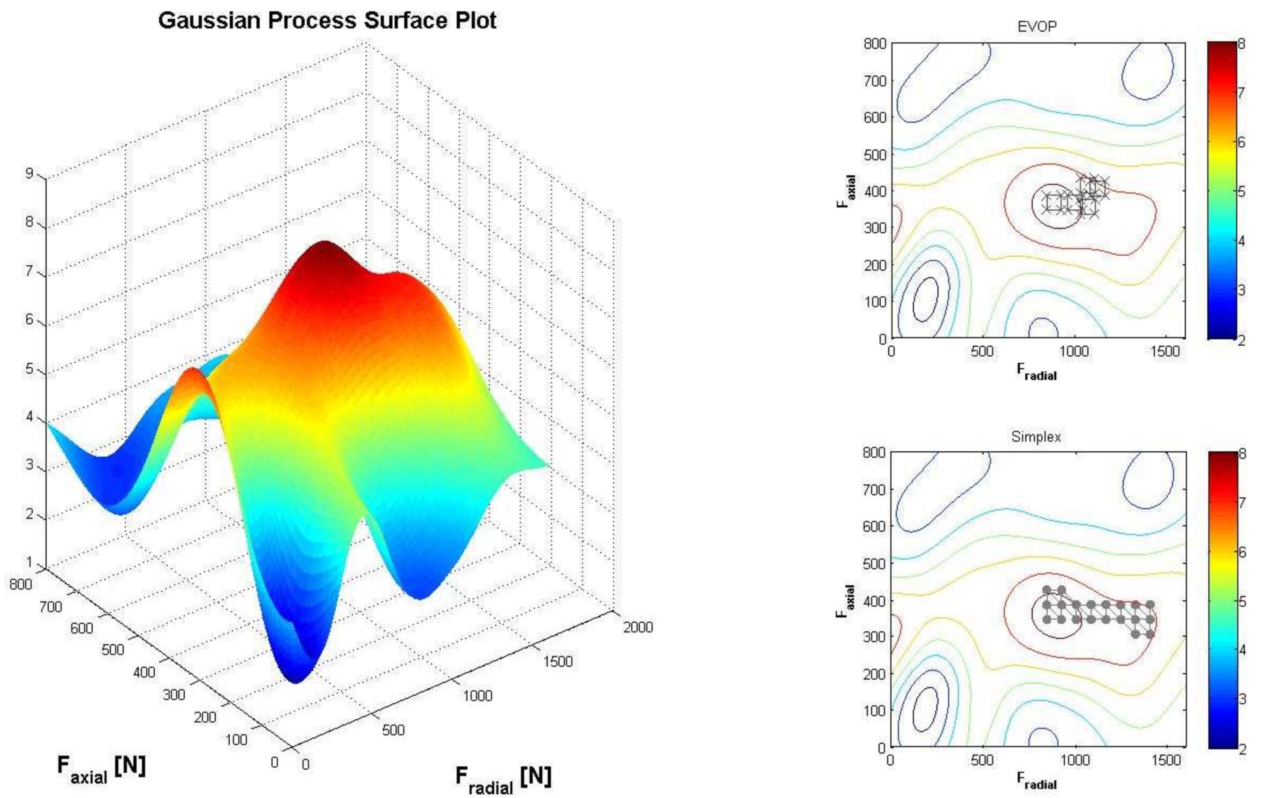
BEARING SET-UP

Bearing Set-Up

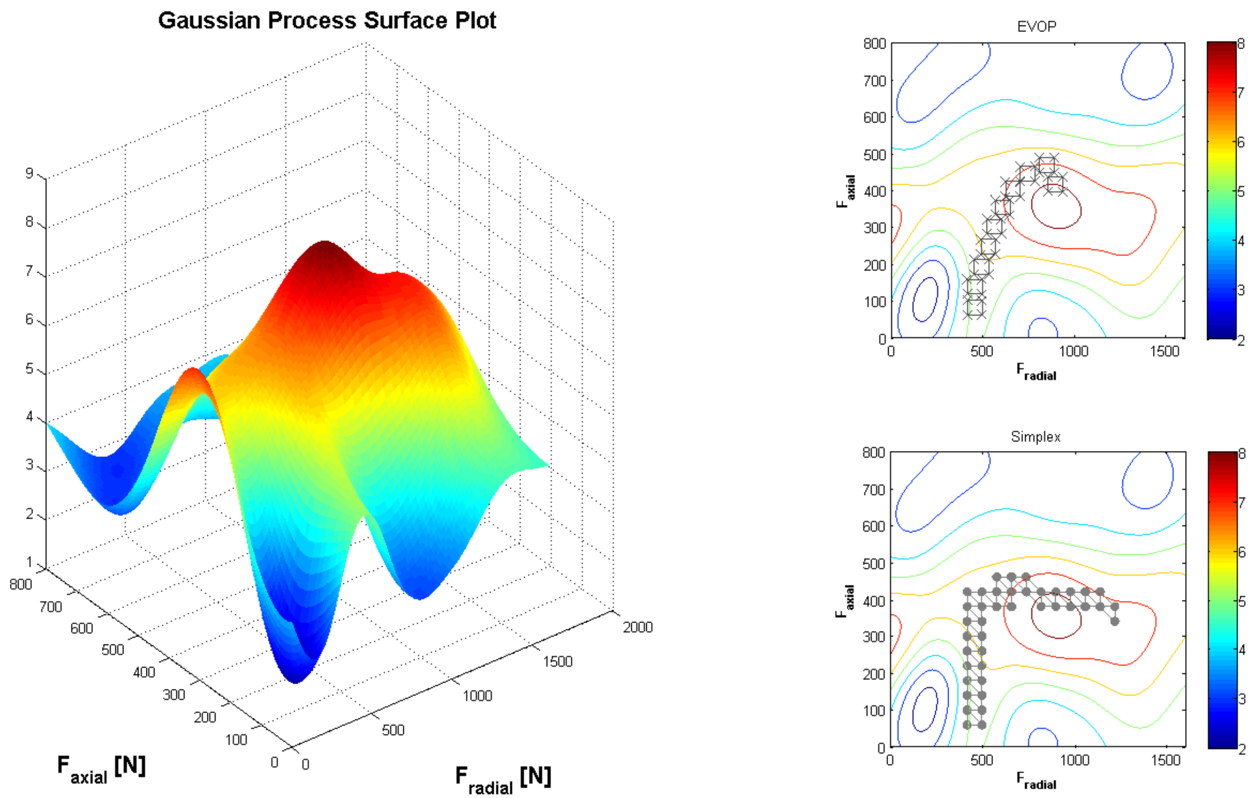
+ **Minimize bearing displacement**
  - Constant rotation speed
  - Constant axial dynamic load
  - Vary static load in dynamic and axial direction to minimize bearing displacement

+ **Lab Set-Up**
  - Demonstrate optimization when there is no knowledge about process
  - Suspected highly non-linear process, classical methods can not deal with this
  - Off-line: Sparse, space-filling designs and Gaussian Process Estimation for rough estimation
  - On-line: Evolutionary Operation and Simplex optimization

Bearing Case – “From expected optimum”



Bearing Case – "Away from expected optimum"



Conclusions

BEARING SET-UP

Conclusions

+ **GP modelling has merits for rough model exploration**
+ **On-line optimization further fine-tunes settings**
+ **Minimum experimentation effort: maximum results**

General Conclusions

CONCLUSIONS

General Conclusions

- **On-line optimization can yield significant cost reductions without disturbing normal operation**
- **Desirability functions can be used to deal with multiple objectives**
- **Major advantage: the process can be run in normal operation**

Questions

Contact

Koen Rutten
BIOSYST – MeBioS
Katholieke Universiteit Leuven
Kasteelpark Arenberg 30, B-3001 Leuven, Belgium
tel: +32(0)16372403
fax: +32(0)16321994
koen.rutten@biw.kuleuven.be

