VF-KDO
VIRTUAL FACTORIES WITH KNOWLEDGE-DRIVEN OPTIMIZATION
POWERED BY UNIVERSITY OF SKÖVDE, SWEDEN

SMC2026, Digital Manufacturing

Human-Machine Co-Learning for Sustainable & Resilient Decision-Making in the AI Era:

A Virtual Factories with Knowledge-Driven Optimization Approach (2018-2026)

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Industrial Engineering & Management (IndTek), Uppsala University
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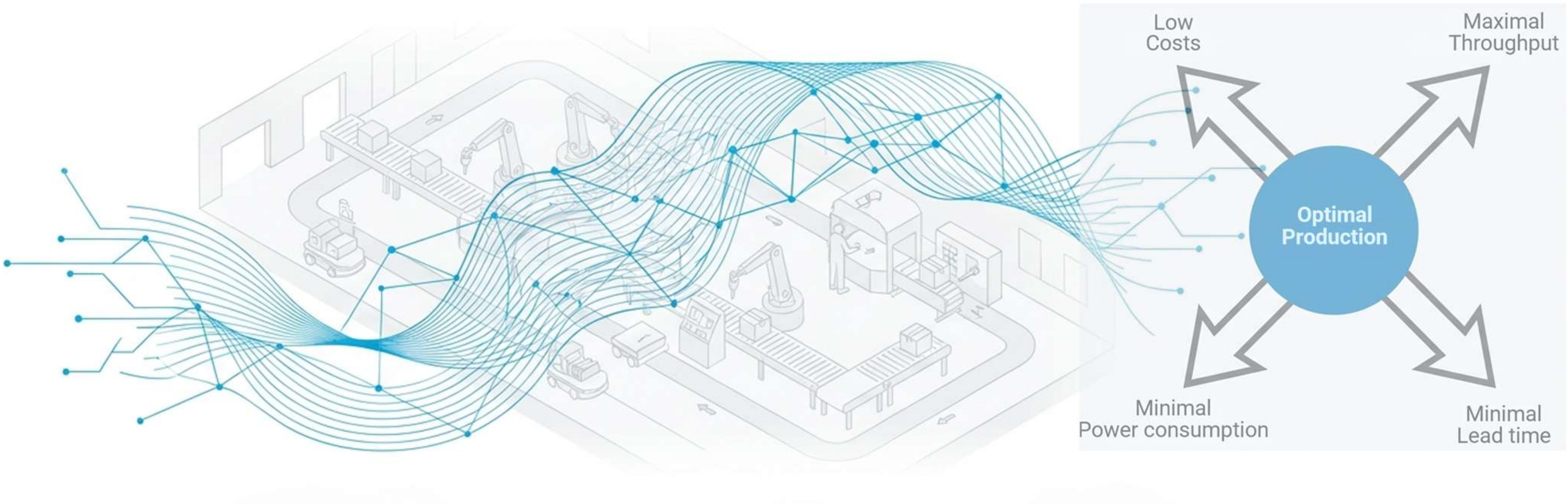
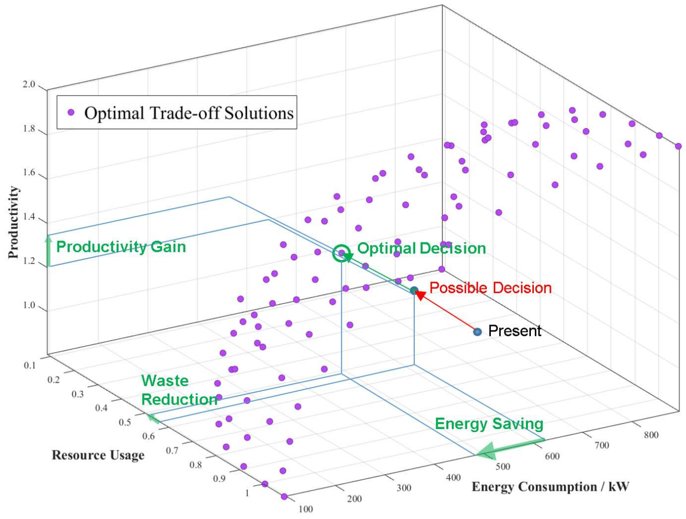

Low
Costs
Maximal
Throughput
Optimal
Production
Minimal
Power consumption
Minimal
Lead time

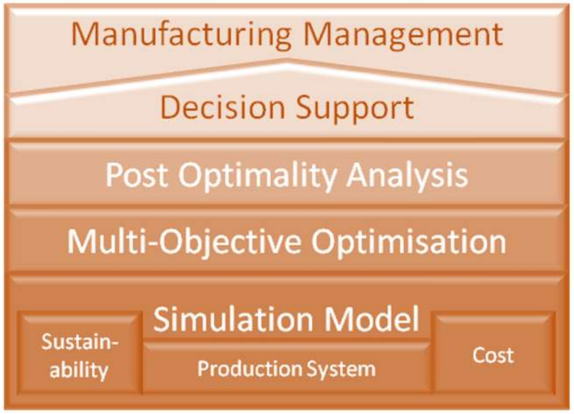

Optimal Trade-off Solutions
Productivity
2.0
1.8
1.6
1.4
1.2
1.0
Productivity Gain
Optimal Decision
Possible Decision
Present
Waste
Reduction
Energy Saving
Resource Usage
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
Energy Consumption / kW
100
200
300
400
500
600
700
800

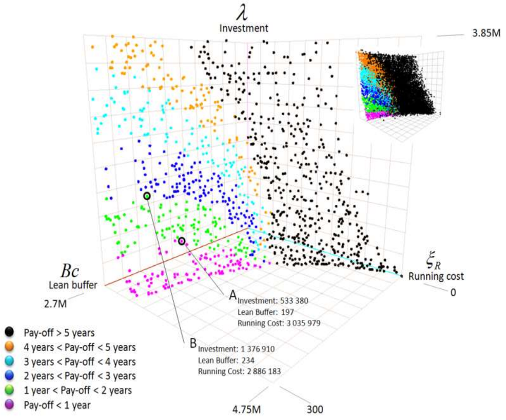
Simulation-Based Optimization (SBO) + Data Mining = Decision Support

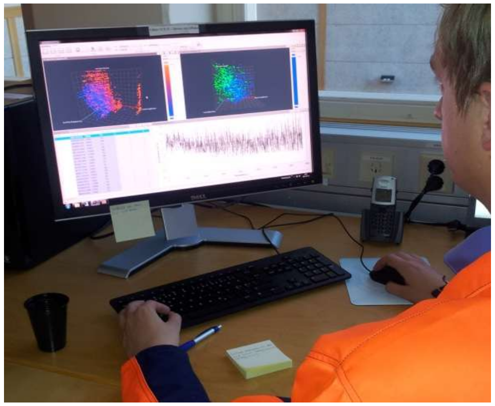
VF-KDO

By generating massive datasets through realistic simulation and mining them for patterns, we identify constraints and improvement actions automatically.

Led to a Volvo Car Technology (Manufacturing) Award 2013


Manufacturing Management
Decision Support
Post Optimality Analysis
Multi-Objective Optimisation
Simulation Model
Sustain-ability
Production System
Cost






VOLVO

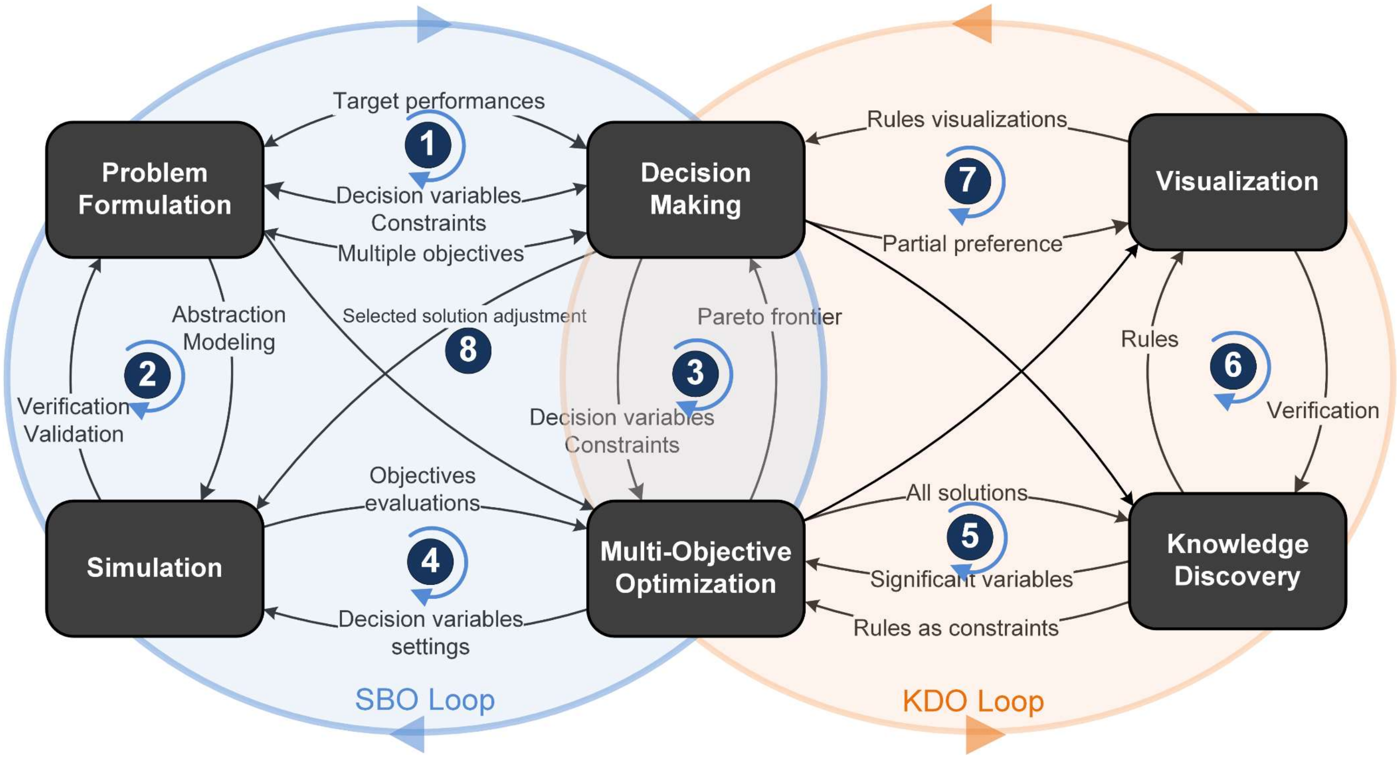
VOLVO CARS
TECHNOLOGY AWARD
RESEARCH, PRODUCT DEVELOPMENT & MANUFACTURING

2013

Amos H.C. Ng
Holistic Simulation Optimization

- Pehrsson, L., Ng, A.H.C. and Bernedixen, J. (2016). Automatic Identification of Constraints and Improvement Actions in Production Systems using Multi-Objective Optimization and Post-Optimality Analysis. *International Journal of Manufacturing Systems,* 39, 24-37.
- Dudas, C., Ng, A.H.C., Pehrsson, L. and Boström, H. (2014). Integration of data mining and multi-objective optimization for decision support in production system development. *International Journal of Computer Integrated Manufacturing*, Vol. 27, Issue 9, 824-839.
- Pehrsson, L., Ng, A.H.C. and Stockton, D.J. (2013). Industrial Cost Modelling for Multi-Objective Optimisation of Production Systems. *International Journal of Computer and Industrial Engineering*, Vol. 66, Issue 4, 1036-1048.

Knowledge-Driven Optimization 2017



Problem Formulation

Decision Making

Visualization

Simulation

Multi-Objective Optimization

Knowledge Discovery

1 Target performances; Decision variables, Constraints, Multiple objectives

2 Abstraction Modeling; Verification Validation

3 Pareto frontier; Decision variables, Constraints

4 Objectives evaluations; Decision variables settings

5 All solutions; Significant variables; Rules as constraints

6 Rules; Verification

7 Rules visualizations; Partial preference

8 Selected solution adjustment

SBO Loop

KDO Loop

Report Series / Department of
Computer & Systems Sciences 14-002

Stockholm
University

Learning from Multi-Objective
Optimization of Production
Systems

A method for analyzing solution sets from multi-objective optimization

Catarina Dudas

Bandaru, S., Ng, A.H.C. and Deb, K. (2017) Data mining Methods for Knowledge Discovery in Multi-objective Optimization: Part A – Survey, Part B – New Developments and Applications. *Expert Systems with Applications* Vol. 70, 119-159.

One of the most important paradigmatic transitions characterizing Industry 5.0 is the shift of focus from technology-driven progress to a thoroughly human-centric approach.

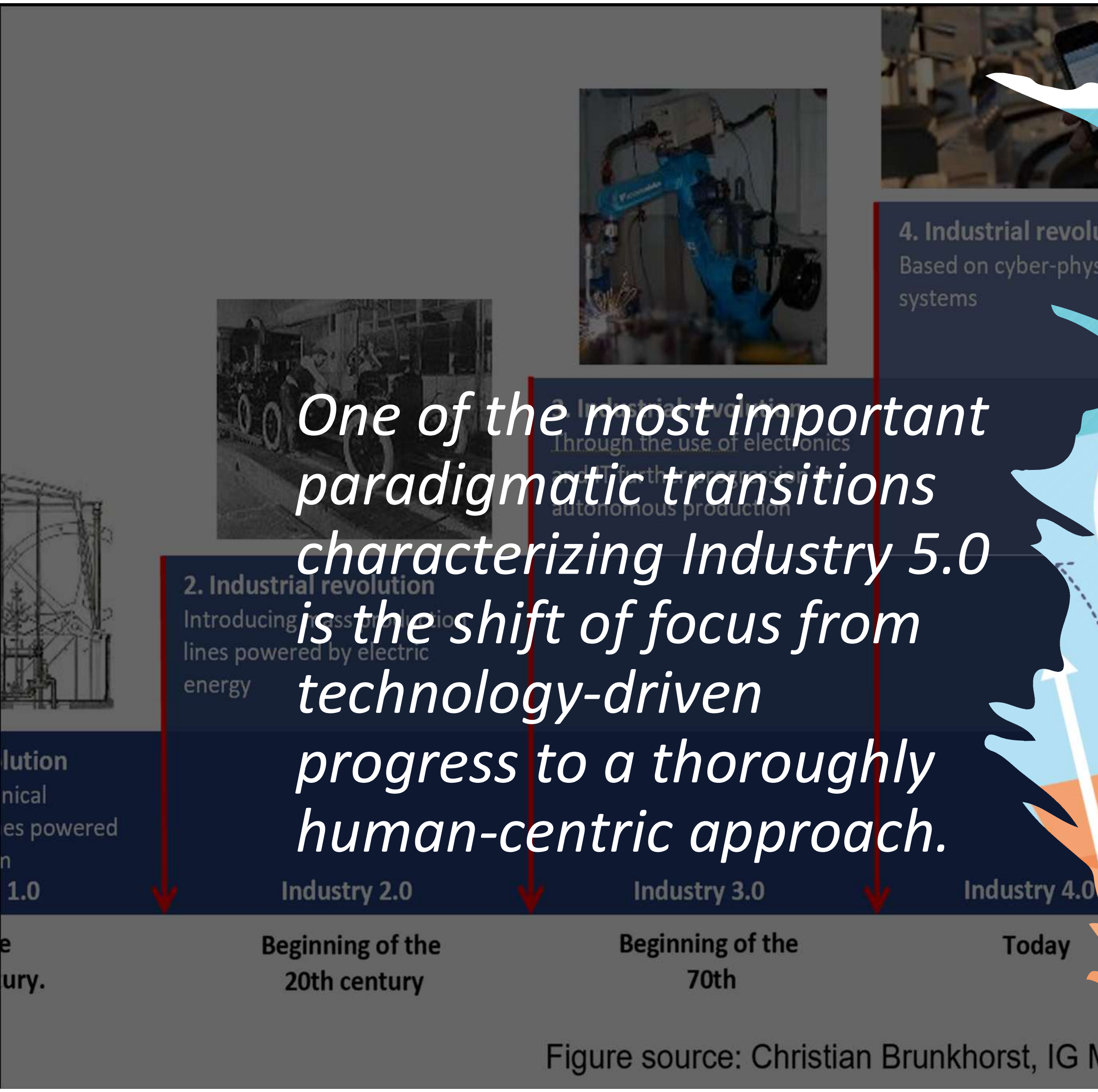


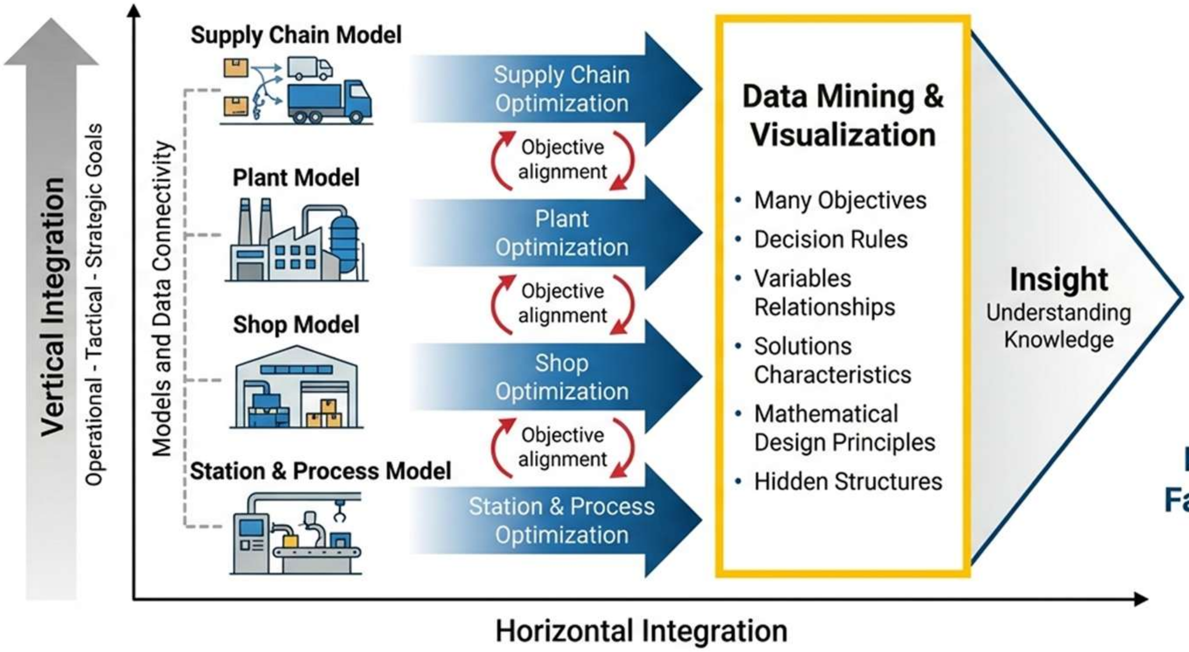
Figure source: Christian Brunkhorst, IG Metall

European Commission

Industry 5.0

Towards a sustainable, human-centric and resilient European industry

Multi-level, Multi-disciplinary & Many-objective



Vertical Integration

Operational - Tactical - Strategic Goals

Models and Data Connectivity

Supply Chain Model

Plant Model

Shop Model

Station & Process Model

Supply Chain Optimization

Objective alignment

Plant Optimization

Objective alignment

Shop Optimization

Objective alignment

Station & Process Optimization

Data Mining & Visualization

- Many Objectives
- Decision Rules
- Variables Relationships
- Solutions Characteristics
- Mathematical Design Principles
- Hidden Structures

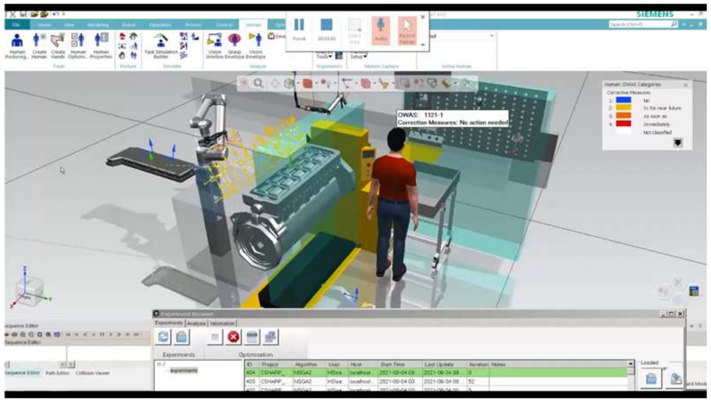
Insight

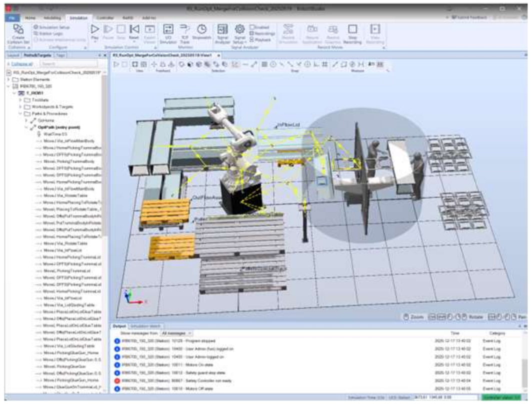
Understanding

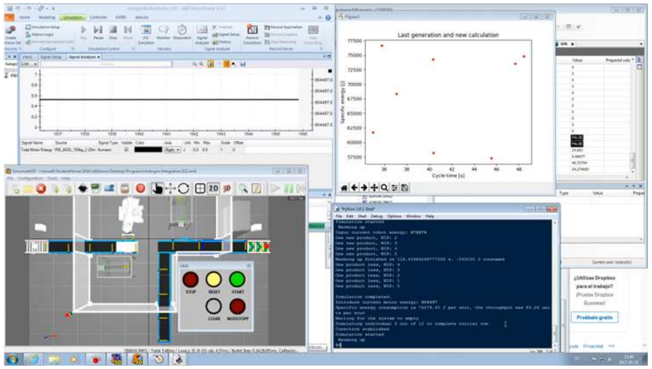
Knowledge

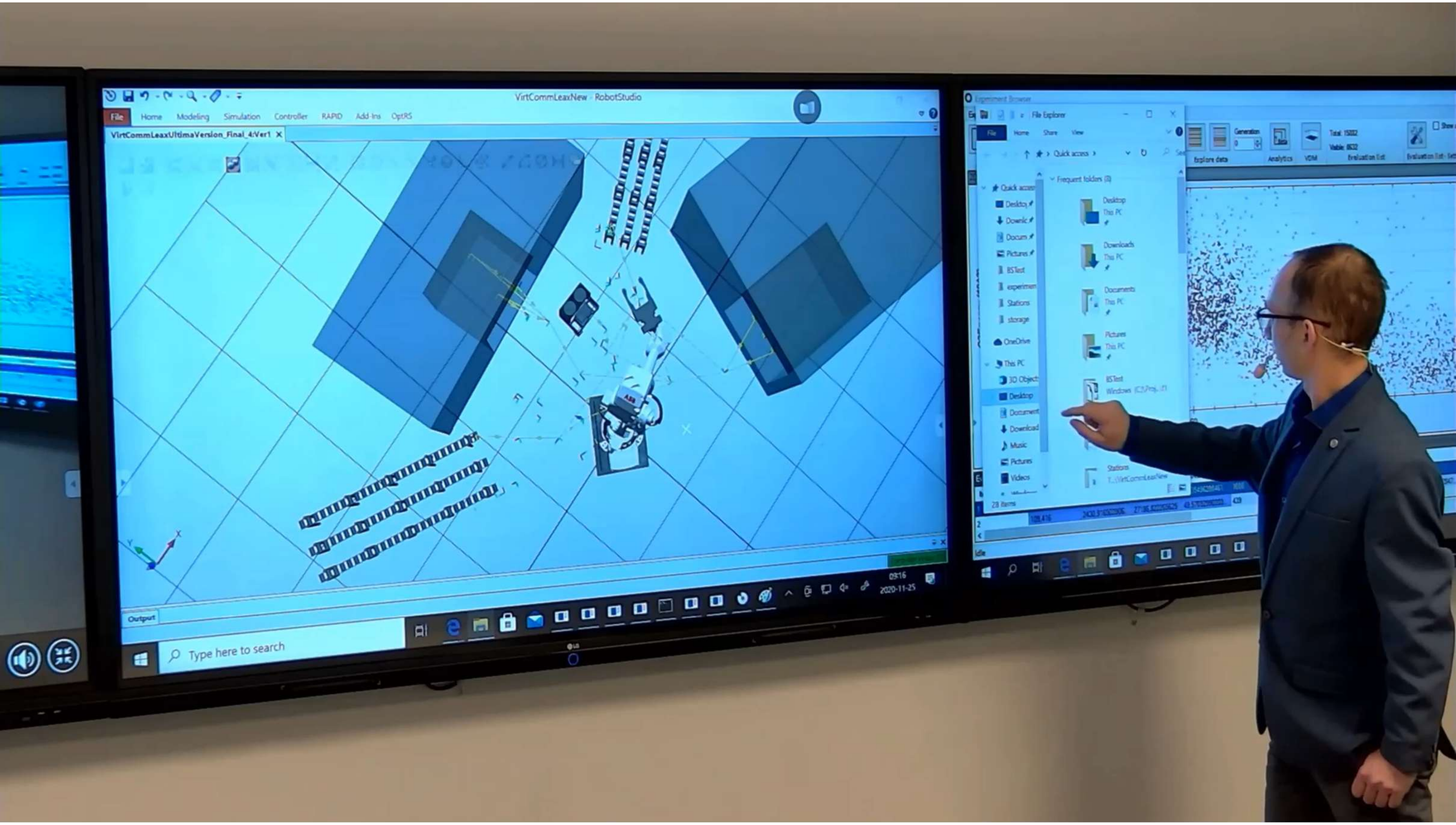
Horizontal Integration

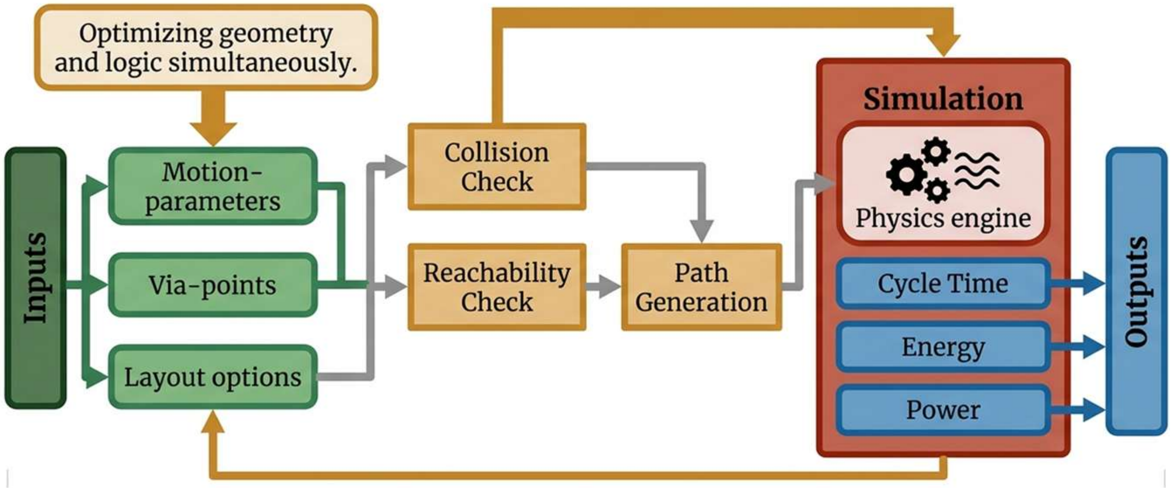
High-Quality, Knowledge-Driven, Fact-based Decisions








VirtCommLeaxNew - RobotStudio
File
Home
Modeling
Simulation
Controller
RAPID
Add-Ins
OptRS
VirtCommLeaxUltimaVersion_Final_4:Ver1
Output
Type here to search
09:16
2020-11-25
Experiment Browser
File Explorer
Share
View
Quick access
Frequent folders (8)
Desktop
Downloads
Documents
Pictures
BSTest
Stations
OneDrive
This PC
3D Objects
Music
Videos
28 items
Explore data
Generation
Analytics
VDM
Evaluation list
Idle



Optimizing geometry and logic simultaneously.

Inputs

Motion-parameters

Via-points

Layout options

Collision Check

Reachability Check

Path Generation

Simulation

Physics engine

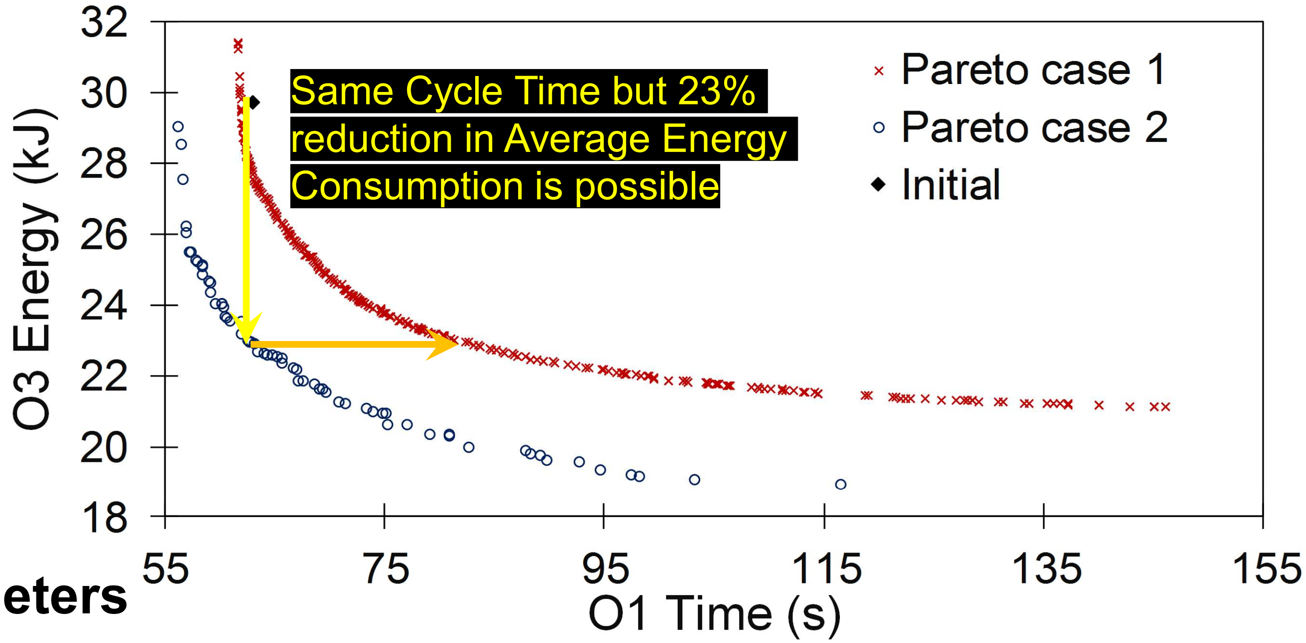
Cycle Time

Energy

Power

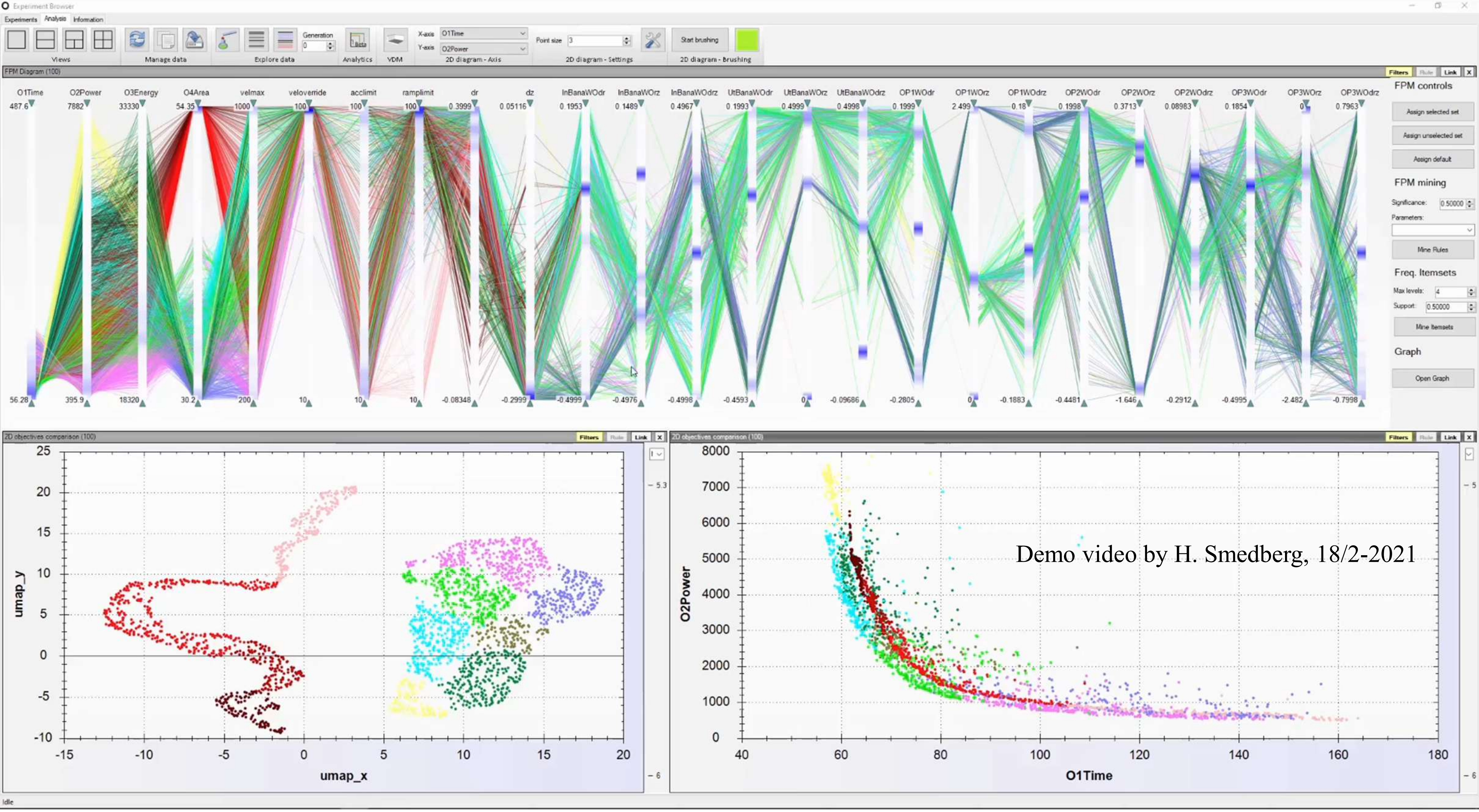
Outputs

Schmidt, B., Ng, A.H.C. and Seger, M. Integration of Realistic Simulation and Multi-objective Optimization for Energy-efficient Robot Cell. To be submitted to *IEEE Transactions on Automation Systems Engineering.*



Same Cycle Time but 23% reduction in Average Energy Consumption is possible

Robotic Cell Optimization with and without layout parameters

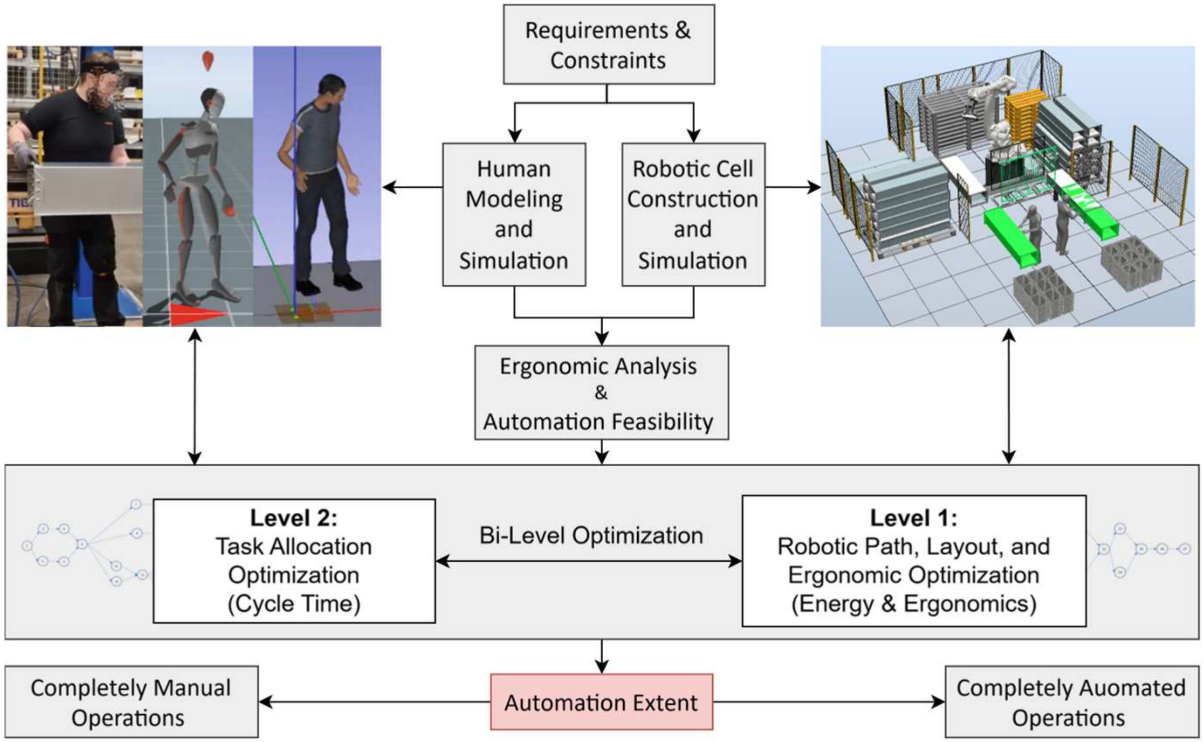


Demo video by H. Smedberg, 18/2-2021

Bi-level, Ergonomic-Robotic (Human-Robot) Multi-Objective Load Balancing

SKANDIA ELEVATOR

ABB



Requirements & Constraints

Human Modeling and Simulation

Robotic Cell Construction and Simulation

Ergonomic Analysis & Automation Feasibility

Level 2: Task Allocation Optimization (Cycle Time)

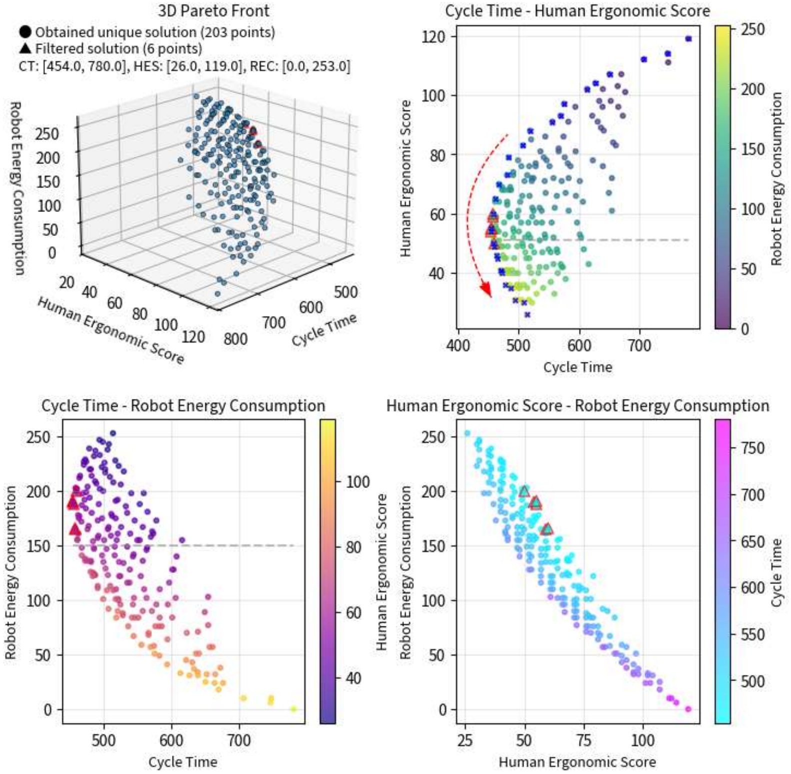
Bi-Level Optimization

Level 1: Robotic Path, Layout, and Ergonomic Optimization (Energy & Ergonomics)

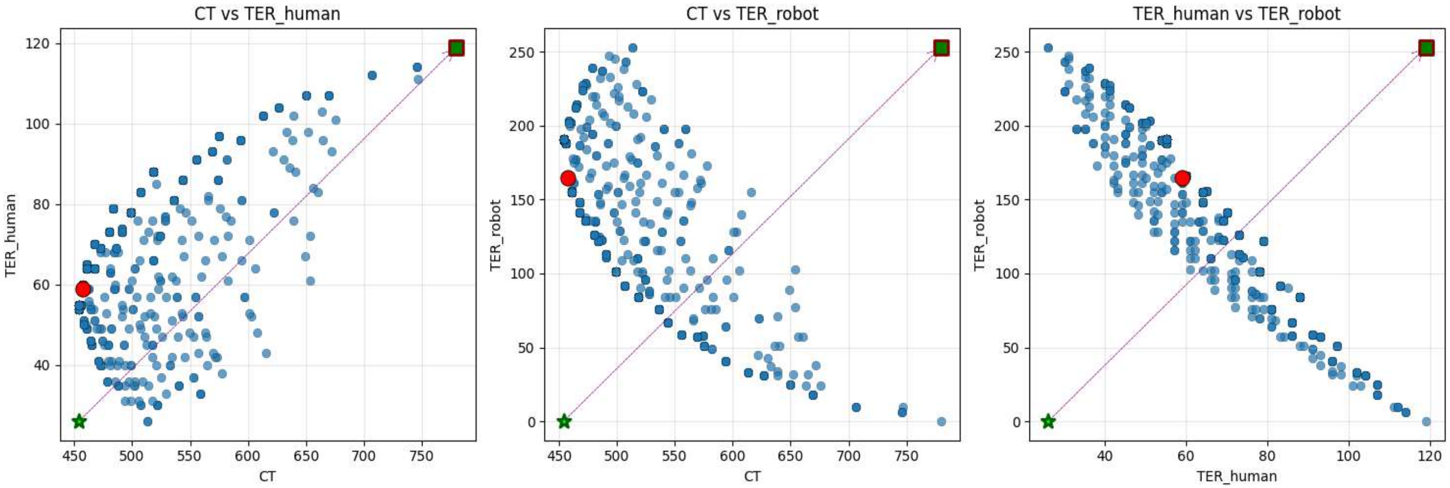
Completely Manual Operations

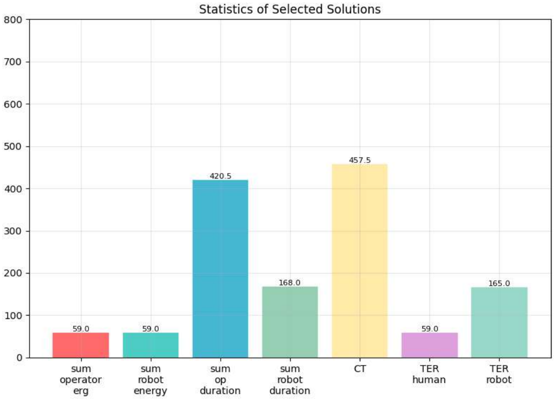
Automation Extent

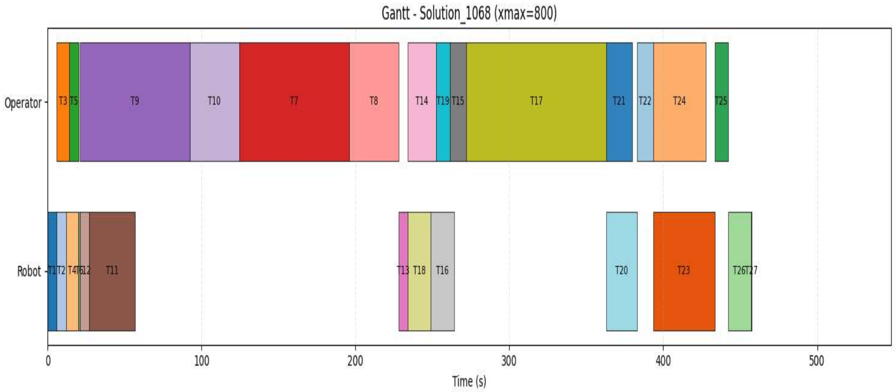
Completely Auomated Operations

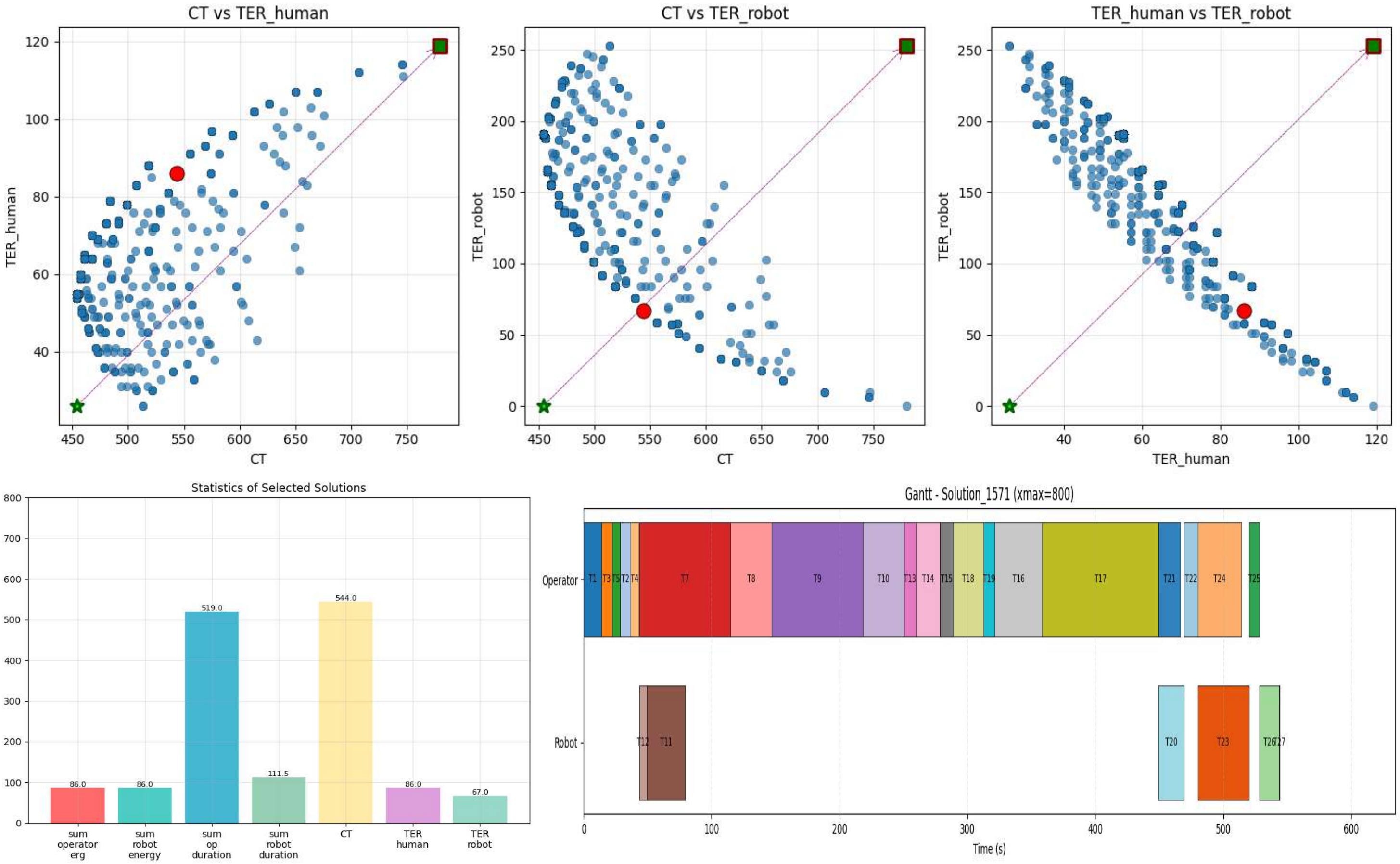


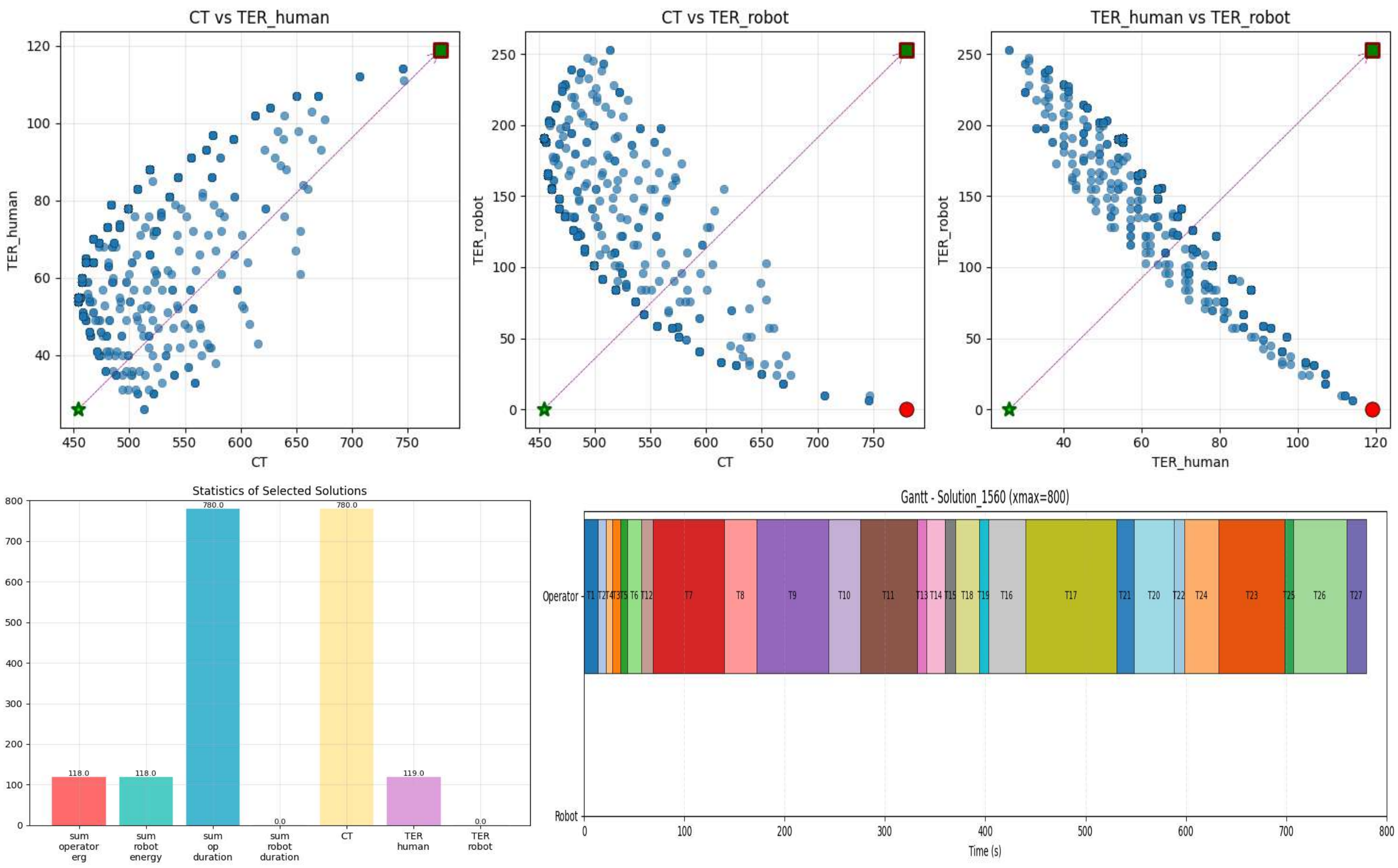
Fu, S et al. (2026). Multi-disciplinary Optimization for Designing Human-Robot Collaborated Work-Cell for Low-Volume and High-Variant Production. *Swedish Production Symposium* 2026 (to appear).


CT vs TER_human
TER_human
CT
120
100
80
60
40
450
500
550
600
650
700
750
CT vs TER_robot
TER_robot
CT
250
200
150
100
50
0
450
500
550
600
650
700
750
TER_human vs TER_robot
TER_robot
TER_human
250
200
150
100
50
0
40
60
80
100
120

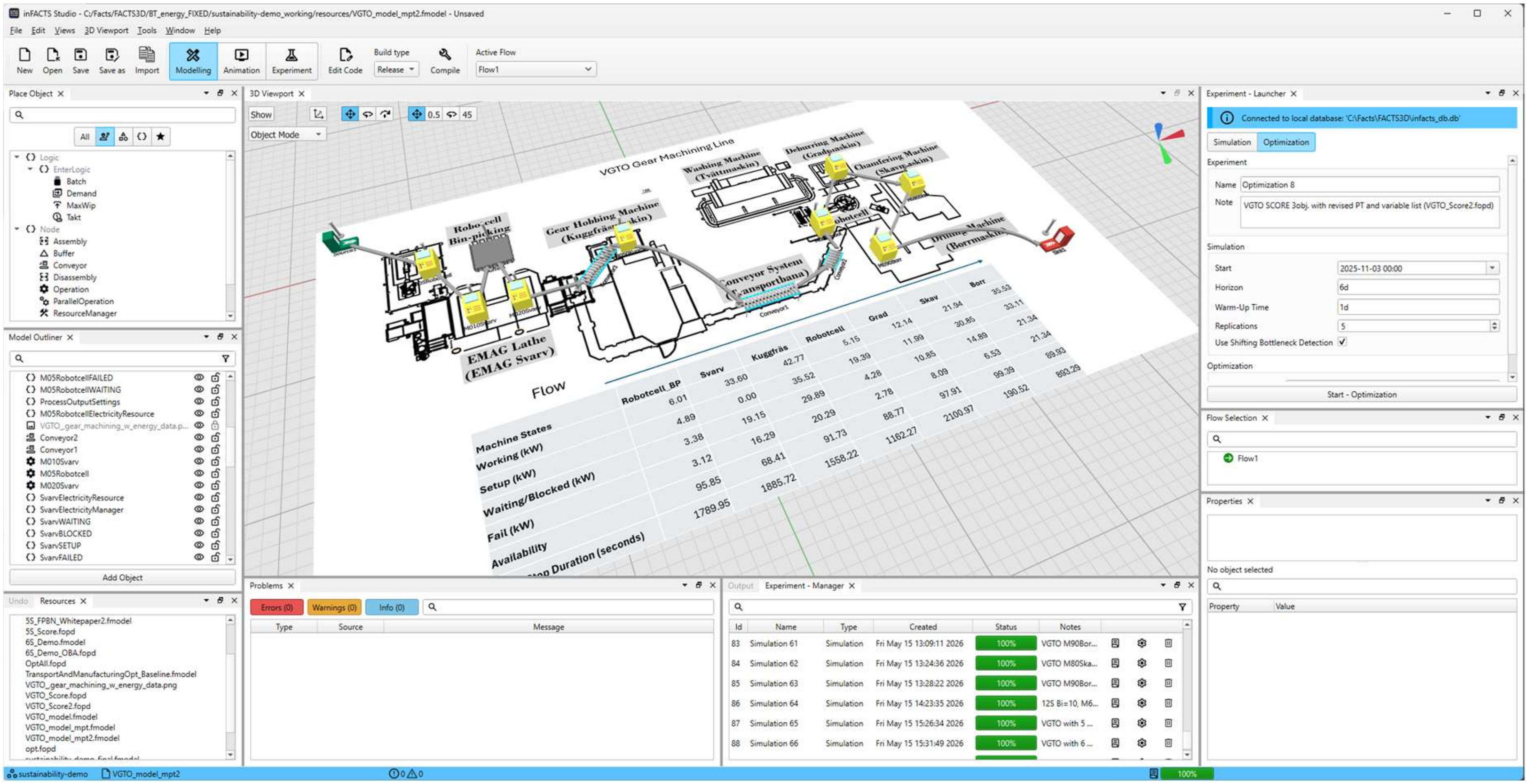

Statistics of Selected Solutions
800
700
600
500
400
300
200
100
0
59.0
59.0
420.5
168.0
457.5
59.0
165.0
sum operator erg
sum robot energy
sum op duration
sum robot duration
CT
TER human
TER robot


Gantt - Solution_1068 (xmax=800)
Operator
Robot
T3
T5
T9
T10
T7
T8
T14
T19
T15
T17
T21
T22
T24
T25
T1
T2
T4
T6
T12
T11
T13
T18
T16
T20
T23
T26
T27
0
100
200
300
400
500
Time (s)


CT vs TER_human
TER_human
CT
120
100
80
60
40
450
500
550
600
650
700
750
CT vs TER_robot
TER_robot
CT
250
200
150
100
50
0
TER_human vs TER_robot
TER_robot
TER_human
40
60
80
100
120
Statistics of Selected Solutions
800
700
600
500
400
300
200
100
0
86.0
86.0
519.0
111.5
544.0
86.0
67.0
sum operator erg
sum robot energy
sum op duration
sum robot duration
CT
TER human
TER robot
Gantt - Solution_1571 (xmax=800)
Operator
Robot
T1
T3
T5
T2
T4
T7
T8
T9
T10
T13
T14
T15
T18
T19
T16
T17
T21
T22
T24
T25
T12
T11
T20
T23
T26
T27
0
100
200
300
400
500
600
Time (s)


CT vs TER_human
TER_human
CT
120
100
80
60
40
450
500
550
600
650
700
750
CT vs TER_robot
TER_robot
CT
250
200
150
100
50
0
TER_human vs TER_robot
TER_robot
TER_human
40
60
80
100
120
Statistics of Selected Solutions
800
700
600
500
400
300
200
100
0
118.0
118.0
780.0
0.0
780.0
119.0
0.0
sum operator erg
sum robot energy
sum op duration
sum robot duration
CT
TER human
TER robot
Gantt - Solution_1560 (xmax=800)
Operator
Robot
T1
T2
T4
T3
T5
T6
T12
T7
T8
T9
T10
T11
T13
T14
T15
T18
T19
T16
T17
T21
T20
T22
T24
T23
T25
T26
T27
Time (s)
0
100
200
300
400
500
600
700
800

A Gear Machining Line



Machine States	Robotcell_BP	Svarv	Kuggfräs	Robotcell	Grad	Skav	Borr
Working (kW)	6.01	33.60	42.77	5.15	12.14	21.94	35.53
Setup (kW)	4.89	0.00	35.52	19.39	11.99	30.85	33.11
Waiting/Blocked (kW)	3.38	19.15	29.89	4.28	10.85	14.89	21.34
Fail (kW)	3.12	16.29	20.29	2.78	8.09	6.53	21.34
Availability	95.85	68.41	91.73	88.77	97.91	99.39	89.93
…top Duration (seconds)	1789.95	1885.72	1558.22	1162.27	2100.97	190.52	893.29

Experiment - Launcher

Connected to local database: 'C:\Facts\FACTS3D\infacts_db.db'

Simulation | Optimization

Experiment

Name: Optimization 8

Note: VGTO SCORE 3obj. with revised PT and variable list (VGTO_Score2.fopd)

Simulation

Start: 2025-11-03 00:00

Horizon: 6d

Warm-Up Time: 1d

Replications: 5

Use Shifting Bottleneck Detection ☑

Optimization

Start - Optimization

Flow Selection

Flow1

Experiment - Manager

Id	Name	Type	Created	Status	Notes
83	Simulation 61	Simulation	Fri May 15 13:09:11 2026	100%	VGTO M90Bor...
84	Simulation 62	Simulation	Fri May 15 13:24:36 2026	100%	VGTO M80Ska...
85	Simulation 63	Simulation	Fri May 15 13:28:22 2026	100%	VGTO M90Bor...
86	Simulation 64	Simulation	Fri May 15 14:23:35 2026	100%	12S Bi=10, M6...
87	Simulation 65	Simulation	Fri May 15 15:26:34 2026	100%	VGTO with 5 ...
88	Simulation 66	Simulation	Fri May 15 15:31:49 2026	100%	VGTO with 6 ...

Running SCORE with three objectives using an inFACTS simulation model

Export MOO solution data to Mimer for clustering

Rule extraction on the preferred cluster using FPM

Scale: ☑ Text: ☑

Levels

Max: 3

Significance

Min: 0.787

Unselected significance

Max: 0.322

Sig/UnSig

Min: 10.921

imp_M070Grad_Improve
sig: 100.00
unsig: 30.83

imp_M080Skav_Improve
unsig: 32.80

imp_M060Robot_Improv
sig: 100.00
unsig: 49.67

imp_M090Borr_Improve
sig: 100.00
unsig: 54.51

imp_M090Borr_Improve
sig: 100.00
unsig: 57.88

imp_M05Robotcell_Impr
sig: 86.67
unsig: 36.22

imp_M070Grad_Improve
imp_M080Skav_Improve
imp_M090Borr_Improve
sig: 100.00
unsig: 8.21

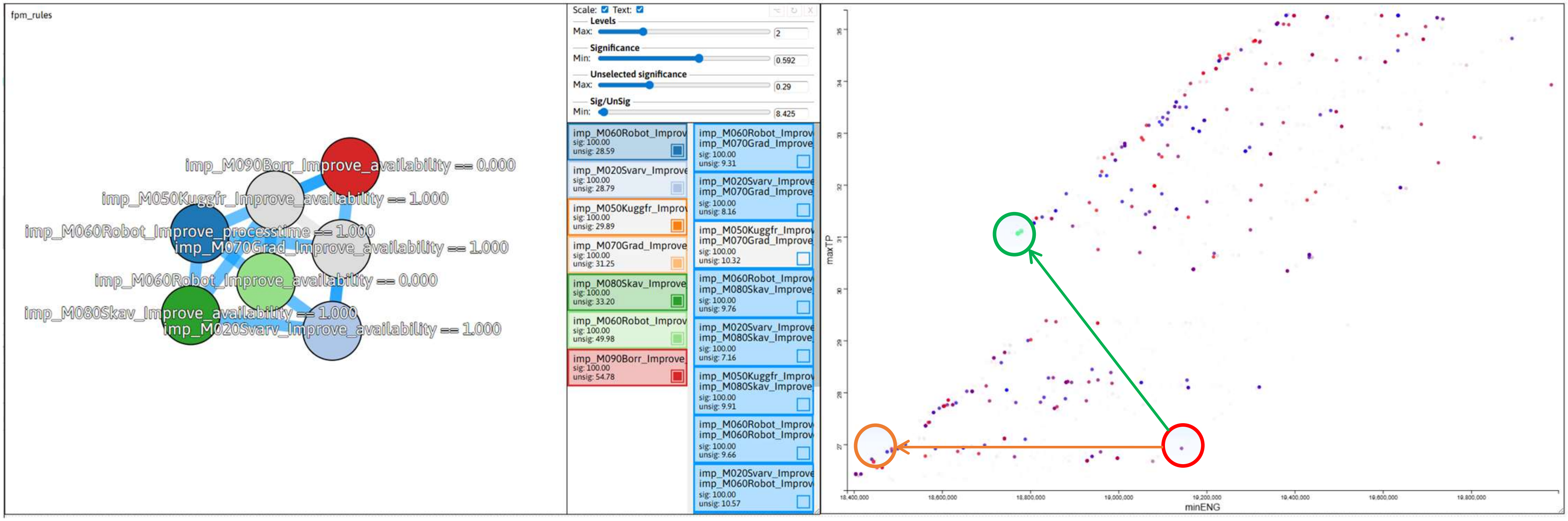
imp_M070Grad_Improve
imp_M060Robot_Improv
imp_M090Borr_Improve
sig: 100.00
unsig: 6.90

imp_M080Skav_Improve
imp_M060Robot_Improv
imp_M090Borr_Improve
sig: 100.00
unsig: 7.91

imp_M070Grad_Improve
imp_M090Borr_Improve
imp_M090Borr_Improve
sig: 100.00
unsig: 5.19

imp_M080Skav_Improve
imp_M090Borr_Improve
imp_M090Borr_Improve
sig: 100.00
unsig: 7.71

imp_M060Robot_Improv
imp_M090Borr_Improve
imp_M05Robotcell_Impr
sig: 86.67
unsig: 7.81



Scale: ☑ Text: ☑

Levels
Max: 2

Significance
Min: 0.592

Unselected significance
Max: 0.29

Sig/UnSig
Min: 8.425

imp_M060Robot_Improv
sig: 100.00
unsig: 28.59

imp_M020Svarv_Improve
sig: 100.00
unsig: 28.79

imp_M050Kuggfr_Improv
sig: 100.00
unsig: 29.89

imp_M070Grad_Improve
sig: 100.00
unsig: 31.25

imp_M080Skav_Improve
sig: 100.00
unsig: 33.20

imp_M060Robot_Improv
sig: 100.00
unsig: 49.98

imp_M090Borr_Improve
sig: 100.00
unsig: 54.78

imp_M060Robot_Improv
imp_M070Grad_Improve
sig: 100.00
unsig: 9.31

imp_M020Svarv_Improve
imp_M070Grad_Improve
sig: 100.00
unsig: 8.16

imp_M050Kuggfr_Improv
imp_M070Grad_Improve
sig: 100.00
unsig: 10.32

imp_M060Robot_Improv
imp_M080Skav_Improve
sig: 100.00
unsig: 9.76

imp_M020Svarv_Improve
imp_M080Skav_Improve
sig: 100.00
unsig: 7.16

imp_M050Kuggfr_Improv
imp_M080Skav_Improve
sig: 100.00
unsig: 9.91

imp_M060Robot_Improv
imp_M060Robot_Improv
sig: 100.00
unsig: 9.66

imp_M020Svarv_Improve
imp_M060Robot_Improv
sig: 100.00
unsig: 10.57

Final insight:

- *Improving 4 variables lead to 20% improve in productivity without the requirement of increasing energy consumption.*
- *Reducing energy by 2.5% to keep the current throughput is possible.*

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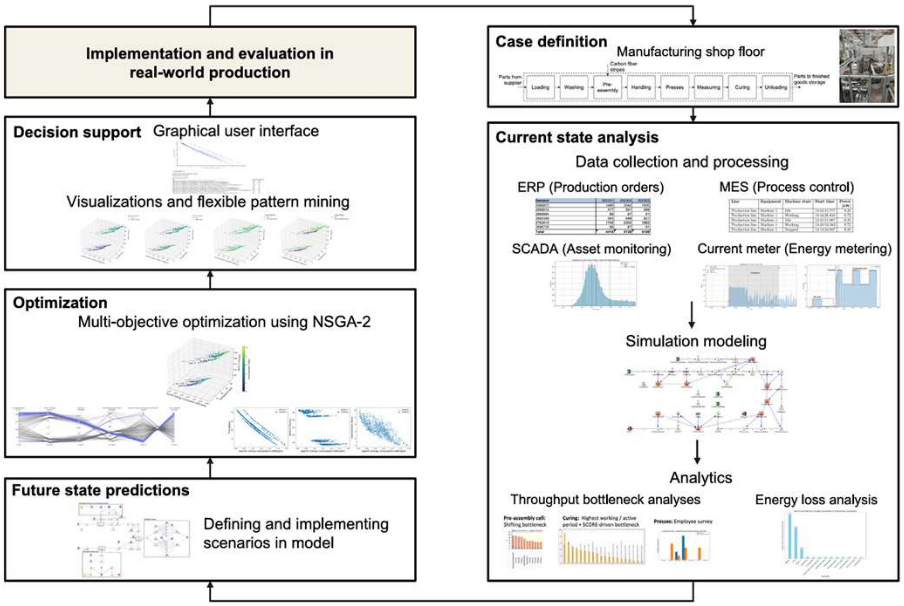
journal homepage: www.elsevier.com/locate/jmansys

Technical paper

Optimizing energy efficiency and productivity in industrial manufacturing: A simulation-based optimization approach with knowledge discovery

Thomas Schmitt [a,b,*], Sergi Olives Juan [a,b], Kaveh Amouzgar [b], Lars Hanson [c], Matías Urenda Moris [b]

[a] Scania CV AB, Global Industrial Development, Södertälje, 151 38, Sweden
[b] Uppsala University, Department of Civil and Industrial Engineering, Division of Industrial Engineering & Management, Uppsala, 752 37, Sweden
[c] University of Skövde, School of Engineering Science, Skövde, 541 28, Sweden



Implementation and evaluation in real-world production

Decision support Graphical user interface

Visualizations and flexible pattern mining

Optimization

Multi-objective optimization using NSGA-2

Future state predictions

Defining and implementing scenarios in model

Case definition Manufacturing shop floor

Current state analysis

Data collection and processing

ERP (Production orders)

MES (Process control)

SCADA (Asset monitoring)

Current meter (Energy metering)

Simulation modeling

Analytics

Throughput bottleneck analyses

Energy loss analysis

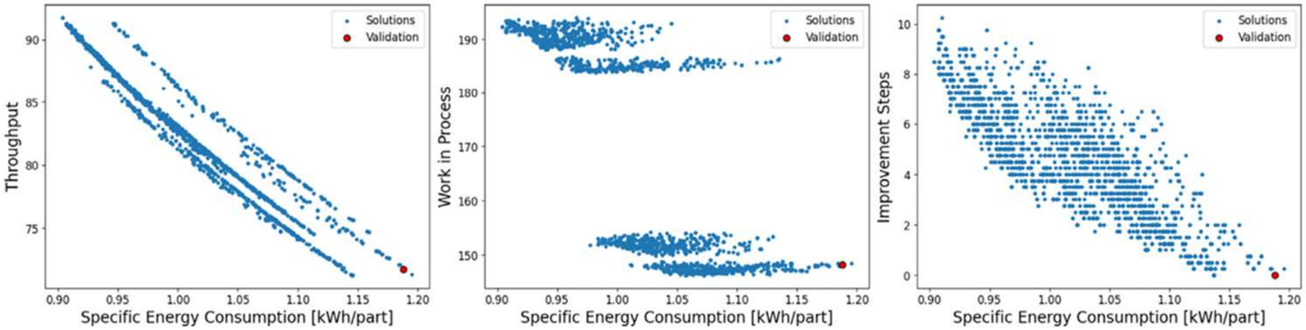
$$E_{\text{total}} = \sum_{i=1}^{n} E_i$$

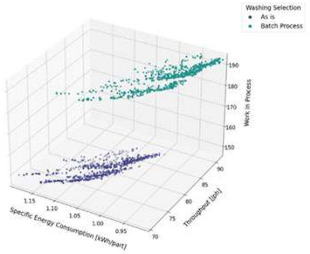
where:

$$E_i = P_{\text{process},i} \cdot T_{\text{process},i} + P_{\text{idle},i} \cdot T_{\text{idle},i} + P_{\text{transitional},i} \cdot T_{\text{transitional},i}$$

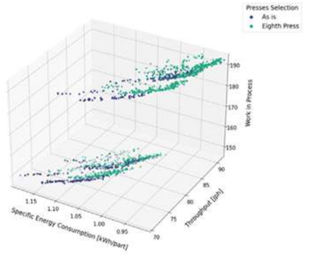
The variables are defined as follows:

- E_{total}: Total energy consumption of the entire production line.
- E_i: Total energy consumption of machine i.
- n: Total number of machines in the production line.
- $P_{\text{idle},i}$, $P_{\text{process},i}$, $P_{\text{transitional},i}$: Power consumption during idle, processing, and transitional states for machine i.
- $T_{\text{idle},i}$, $T_{\text{process},i}$, $T_{\text{transitional},i}$: Corresponding time durations for machine i.

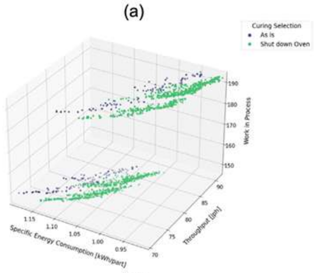




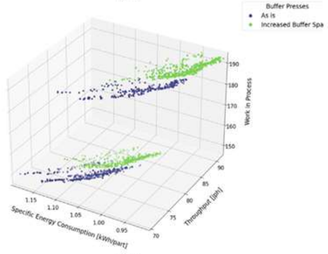
(a)



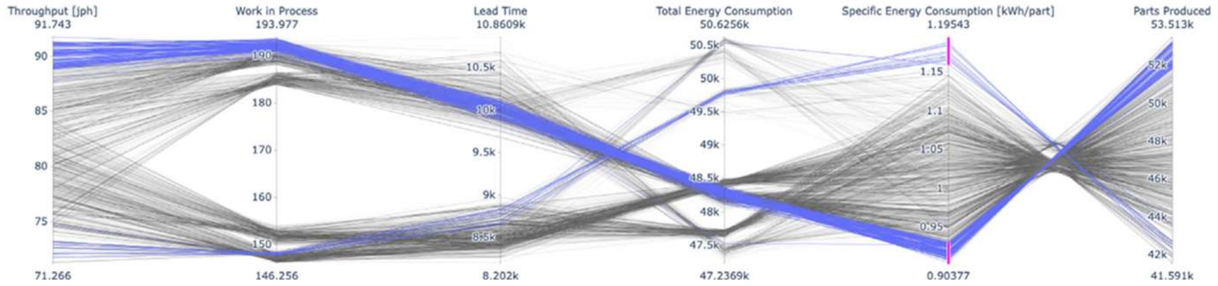
(b)

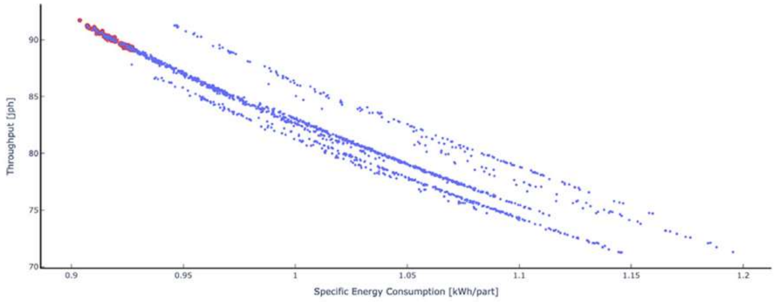


(c)



(d)



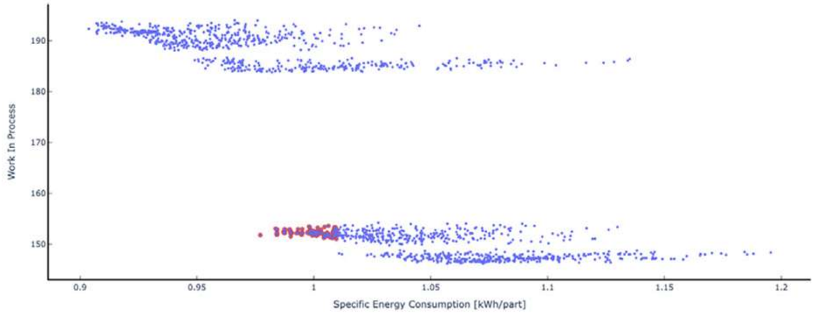


Mean Specific Energy Consumption [kWh/part]: 0.91 (-23.08%)

Mean Work In Process: 191.94 (29.55%)

Mean Throughput [jph]: 90.54 (26.22%)

Rules	Selected (%)	Unselected (%)
Buffer_Presses_10.0, CuringSelection_2.0, PressesSelection_2.0, Presses_CT_< 166.478, WashingSelection_2.0	100	14.66
Buffer_Presses_10.0, CuringSelection_2.0, Curing_Availability_> 83.128, PressesSelection_2.0, Presses_CT_< 166.478, WashingSelection_2.0	97.48	11.38
Buffer_Presses_10.0, CuringSelection_2.0, PreassemblyRobot_CT_< 19.285, PressesSelection_2.0, Presses_CT_< 166.478, WashingSelection_2.0	96.54	2.51
Buffer_Presses_10.0, CuringSelection_2.0, Curing_Availability_> 83.128, PreassemblyRobot_CT_< 19.285, PressesSelection_2.0, Presses_CT_< 166.478, WashingSelection_2.0	94.03	1.54
Buffer_Presses_10.0, CuringSelection_2.0, Defect_Rate_< 0.08455, PressesSelection_2.0, Presses_CT_< 166.478, WashingSelection_2.0	86.79	4.17
Buffer_Presses_10.0, CuringSelection_2.0, Curing_Availability_> 83.128, Defect_Rate_< 0.08455, PressesSelection_2.0, Presses_CT_< 166.478, WashingSelection_2.0	85.22	3.78
Buffer_Presses_10.0, CuringSelection_2.0, Defect_Rate_< 0.08455, PreassemblyRobot_CT_< 19.285, PressesSelection_2.0, Presses_CT_< 166.478, WashingSelection_2.0	83.33	0.46
Buffer_Presses_10.0, CuringSelection_2.0, Curing_Availability_> 83.128, Defect_Rate_< 0.08455, PreassemblyRobot_CT_< 19.285, PressesSelection_2.0, Presses_CT_< 166.478, WashingSelection_2.0	81.76	0.39
Buffer_Presses_10.0, CuringSelection_2.0, PressesSelection_2.0, Presses_CT_< 166.478, Presses_MTTR_> 69.35, WashingSelection_2.0	69.5	13.23
Buffer_Presses_10.0, CuringSelection_2.0, Curing_Availability_> 83.128, PressesSelection_2.0, Presses_CT_< 166.478, Presses_MTTR_> 69.35, WashingSelection_2.0	68.87	10.07



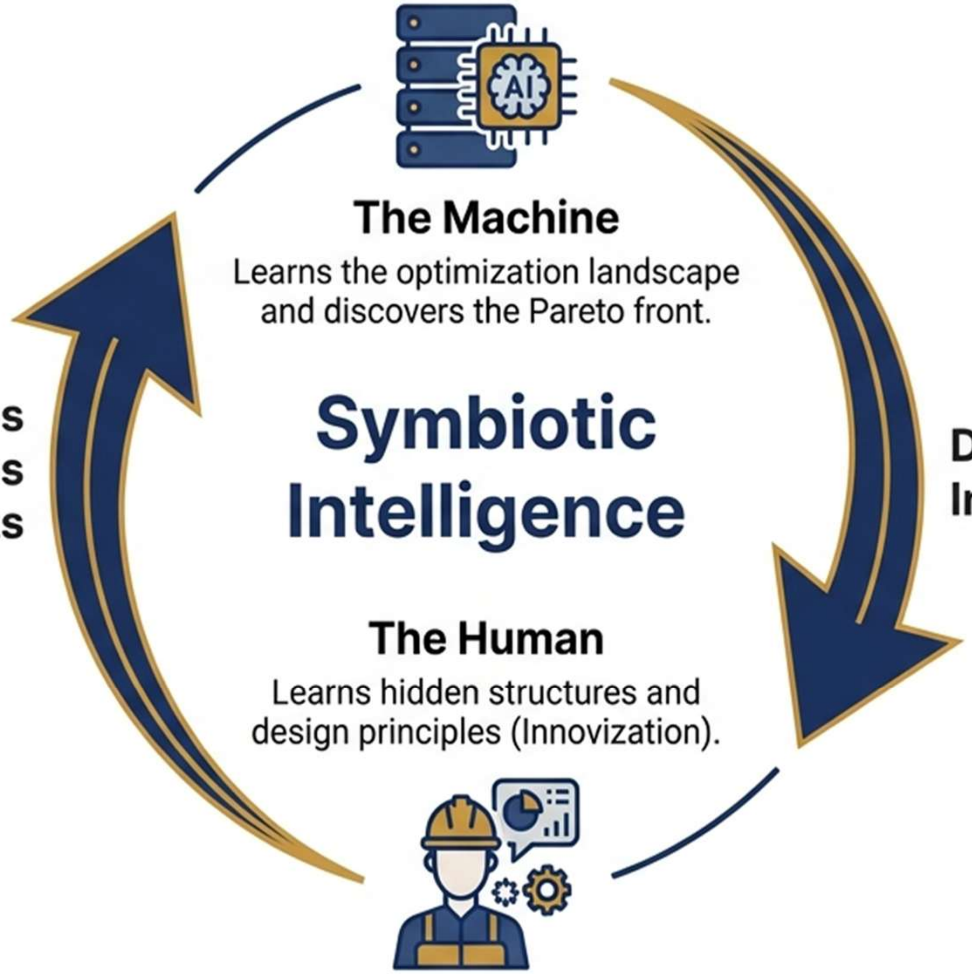
Mean Specific Energy Consumption [kWh/part]: 1.00 (-15.94%)

Mean Work In Process: 152.30 (2.80%)

Mean Throughput [jph]: 82.95 (15.64%)

Rules	Selected (%)	Unselected (%)
Buffer_Presses_10.0, CuringSelection_2.0, WashingSelection_1.0	100	13.29
Buffer_Presses_10.0, CuringSelection_2.0, Presses_CT_< 166.478, WashingSelection_1.0	97.09	9.44
Buffer_Presses_10.0, CuringSelection_2.0, PreassemblyRobot_CT_< 19.285, WashingSelection_1.0	96.12	3.85
Buffer_Presses_10.0, CuringSelection_2.0, Curing_Availability_> 83.128, WashingSelection_1.0	95.15	7.27
Buffer_Presses_10.0, CuringSelection_2.0, PreassemblyRobot_CT_< 19.285, Presses_CT_< 166.478, WashingSelection_1.0	93.2	2.92
Buffer_Presses_10.0, CuringSelection_2.0, Curing_Availability_> 83.128, Presses_CT_< 166.478, WashingSelection_1.0	92.23	5.84
Buffer_Presses_10.0, CuringSelection_2.0, Curing_Availability_> 83.128, PreassemblyRobot_CT_< 19.285, WashingSelection_1.0	91.26	2.21
Buffer_Presses_10.0, CuringSelection_2.0, Curing_Availability_> 83.128, PreassemblyRobot_CT_< 19.285, Presses_CT_< 166.478, WashingSelection_1.0	88.35	1.75
Buffer_Presses_10.0, CuringSelection_2.0, PressesSelection_2.0, WashingSelection_1.0	84.47	8.12
Buffer_Presses_10.0, CuringSelection_2.0, Curing_Availability_> 83.128, PressesSelection_2.0, WashingSelection_1.0	83.5	5.17

Human-Machine Co-Learning



The Machine

Learns the optimization landscape and discovers the Pareto front.

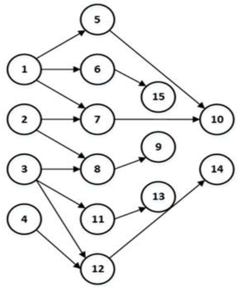
Refines Objectives & Constraints

Symbiotic Intelligence

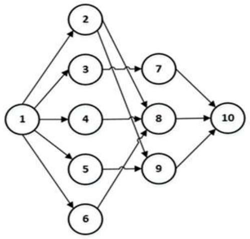
Delivers Insight & Rules

The Human

Learns hidden structures and design principles (Innovization).



(1) Precedence graph for 4cylP



(2) Precedence graph for 4cylD

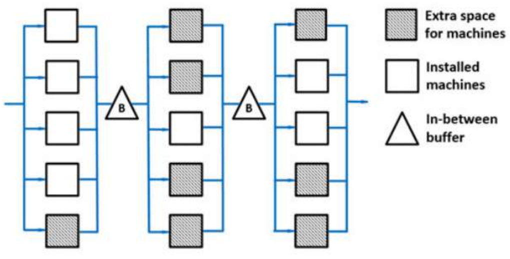


FIGURE 16. Reconfigurable workstations layout.

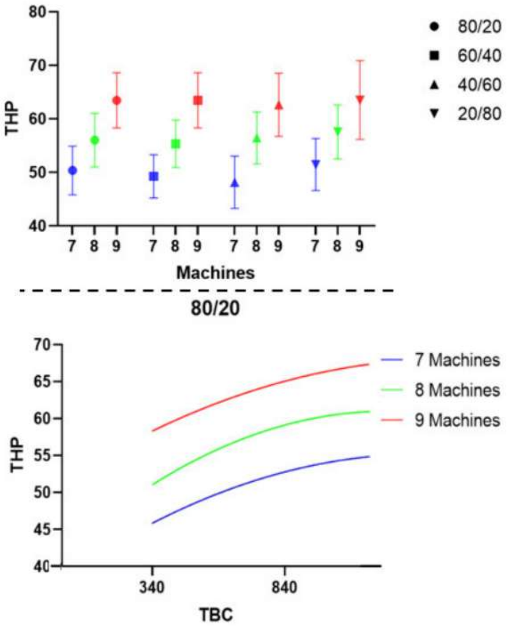
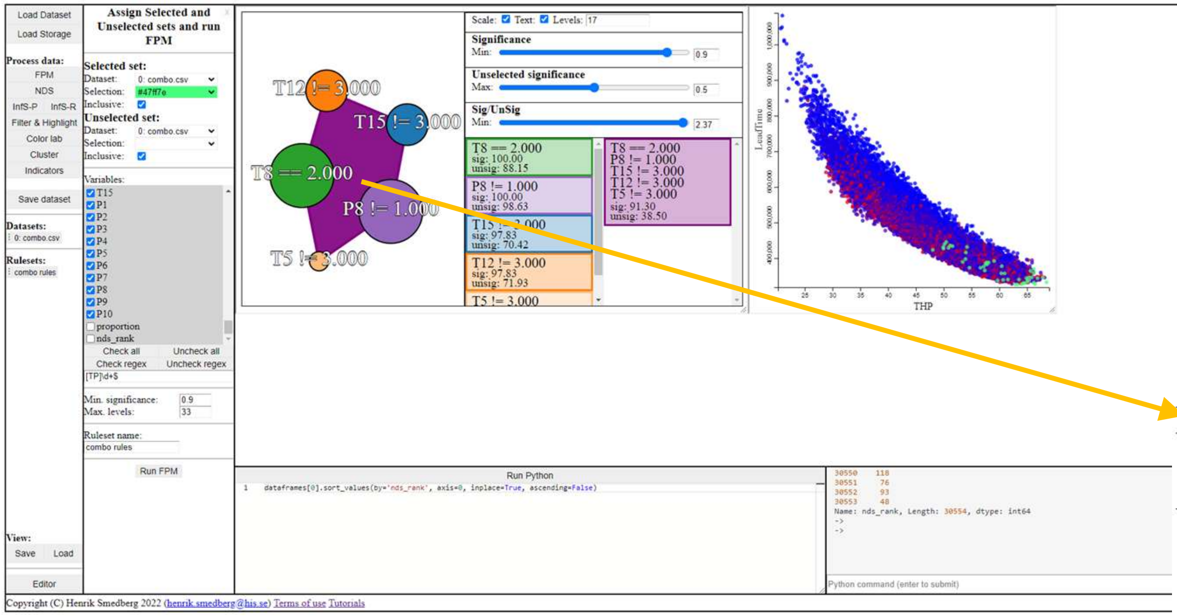


FIGURE 20. THP progression example.



Assign Selected and Unselected sets and run FPM

Selected set:
Dataset: 0: combo.csv
Selection: #47ff7e
Inclusive: ☑
Unselected set:
Dataset: 0: combo.csv
Selection:
Inclusive: ☑

Variables:
☑ T15
☑ P1
☑ P2
☑ P3
☑ P4
☑ P5
☑ P6
☑ P7
☑ P8
☑ P9
☑ P10
☐ proportion
☐ nds_rank

[TP]\d+$

Min. significance: 0.9
Max. levels: 33

Ruleset name: combo rules

Datasets: 0: combo.csv

Rulesets: combo rules

Scale: ☑ Text: ☑ Levels: 17

Significance
Min: 0.9

Unselected significance
Max: 0.5

Sig/UnSig
Min: 2.37

T8 == 2.000
sig: 100.00
unsig: 88.15

P8 != 1.000
sig: 100.00
unsig: 98.63

T15 != 3.000
sig: 97.83
unsig: 70.42

T12 != 3.000
sig: 97.83
unsig: 71.93

T5 != 3.000

T8 == 2.000
P8 != 1.000
T15 != 3.000
T12 != 3.000
T5 != 3.000
sig: 91.30
unsig: 38.50

```
dataframes[0].sort_values(by='nds_rank', axis=0, inplace=True, ascending=False)
```

```
30550    118
30551     76
30552     93
30553     48
Name: nds_rank, Length: 30554, dtype: int64
->
->
```

Python command (enter to submit)

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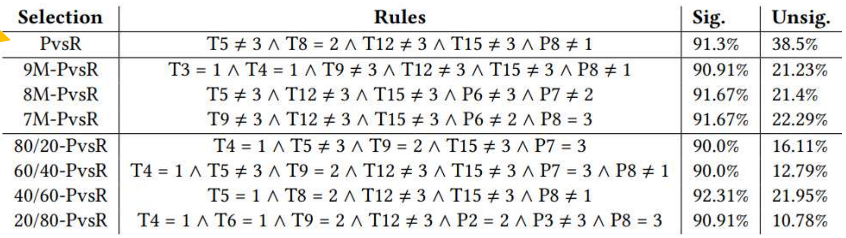


Selection	Rules	Sig.	Unsig.
PvsR	$T5 \neq 3 \wedge T8 = 2 \wedge T12 \neq 3 \wedge T15 \neq 3 \wedge P8 \neq 1$	91.3%	38.5%
9M-PvsR	$T3 = 1 \wedge T4 = 1 \wedge T9 \neq 3 \wedge T12 \neq 3 \wedge T15 \neq 3 \wedge P8 \neq 1$	90.91%	21.23%
8M-PvsR	$T5 \neq 3 \wedge T12 \neq 3 \wedge T15 \neq 3 \wedge P6 \neq 3 \wedge P7 \neq 2$	91.67%	21.4%
7M-PvsR	$T9 \neq 3 \wedge T12 \neq 3 \wedge T15 \neq 3 \wedge P6 \neq 2 \wedge P8 = 3$	91.67%	22.29%
80/20-PvsR	$T4 = 1 \wedge T5 \neq 3 \wedge T9 = 2 \wedge T15 \neq 3 \wedge P7 = 3$	90.0%	16.11%
60/40-PvsR	$T4 = 1 \wedge T5 \neq 3 \wedge T9 = 2 \wedge T12 \neq 3 \wedge T15 \neq 3 \wedge P7 = 3 \wedge P8 \neq 1$	90.0%	12.79%
40/60-PvsR	$T5 = 1 \wedge T8 = 2 \wedge T12 \neq 3 \wedge T15 \neq 3 \wedge P8 \neq 1$	92.31%	21.95%
20/80-PvsR	$T4 = 1 \wedge T6 = 1 \wedge T9 = 2 \wedge T12 \neq 3 \wedge P2 = 2 \wedge P3 \neq 3 \wedge P8 = 3$	90.91%	10.78%

Diaz, C. A. B., Aslam, T., & Ng, A.H.C. (2021). Optimizing Reconfigurable Manufacturing Systems for Fluctuating Production Volumes: A Simulation-Based Multi-Objective Approach. *IEEE Access*, *9*, 144195-144210.

Mathematical and Computational Applications

MDPI

Article

Knowledge-Driven Multi-Objective Optimization for Reconfigurable Manufacturing Systems

Henrik Smedberg [1,*], **Carlos Alberto Barrera-Diaz** [1], **Amir Nourmohammadi** [1], **Sunith Bandaru** [1] **and Amos H. C. Ng** [1,2]

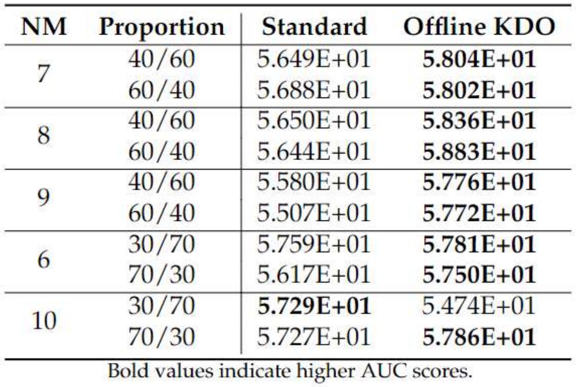
sustainability

MDPI

Article

Enabling Knowledge Discovery in Multi-Objective Optimizations of Worker Well-Being and Productivity

Aitor Iriondo Pascual [1,*], **Henrik Smedberg** [1], **Dan Högberg** [1], **Anna Syberfeldt** [1] **and Dan Lämkull** [2]



NM	Proportion	Standard	Offline KDO
7	40/60	5.649E+01	**5.804E+01**
	60/40	5.688E+01	**5.802E+01**
8	40/60	5.650E+01	**5.836E+01**
	60/40	5.644E+01	**5.883E+01**
9	40/60	5.580E+01	**5.776E+01**
	60/40	5.507E+01	**5.772E+01**
6	30/70	5.759E+01	**5.781E+01**
	70/30	5.617E+01	**5.750E+01**
10	30/70	**5.729E+01**	5.474E+01
	70/30	5.727E+01	**5.786E+01**

Bold values indicate higher AUC scores.

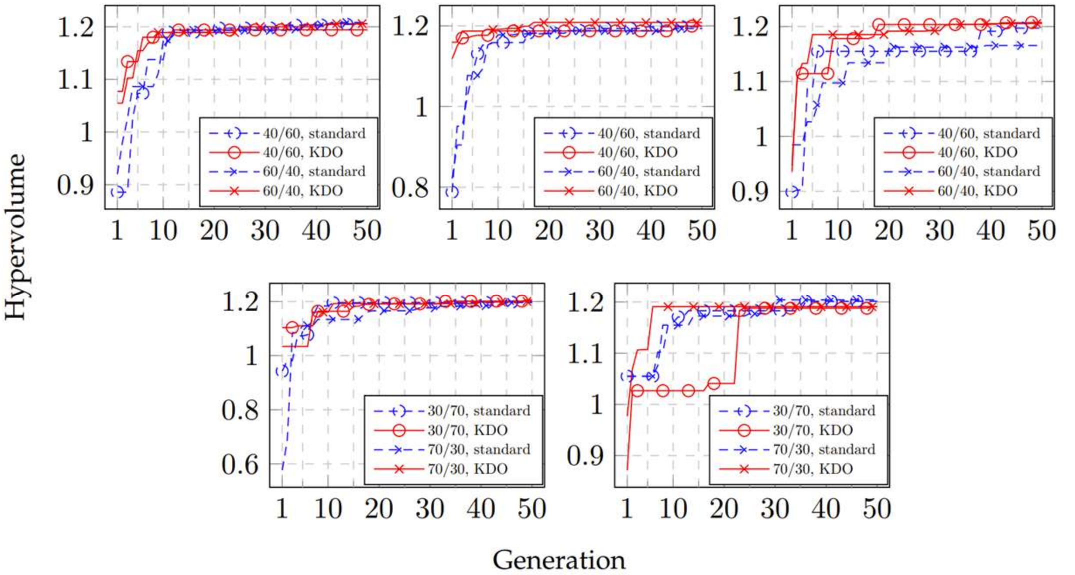
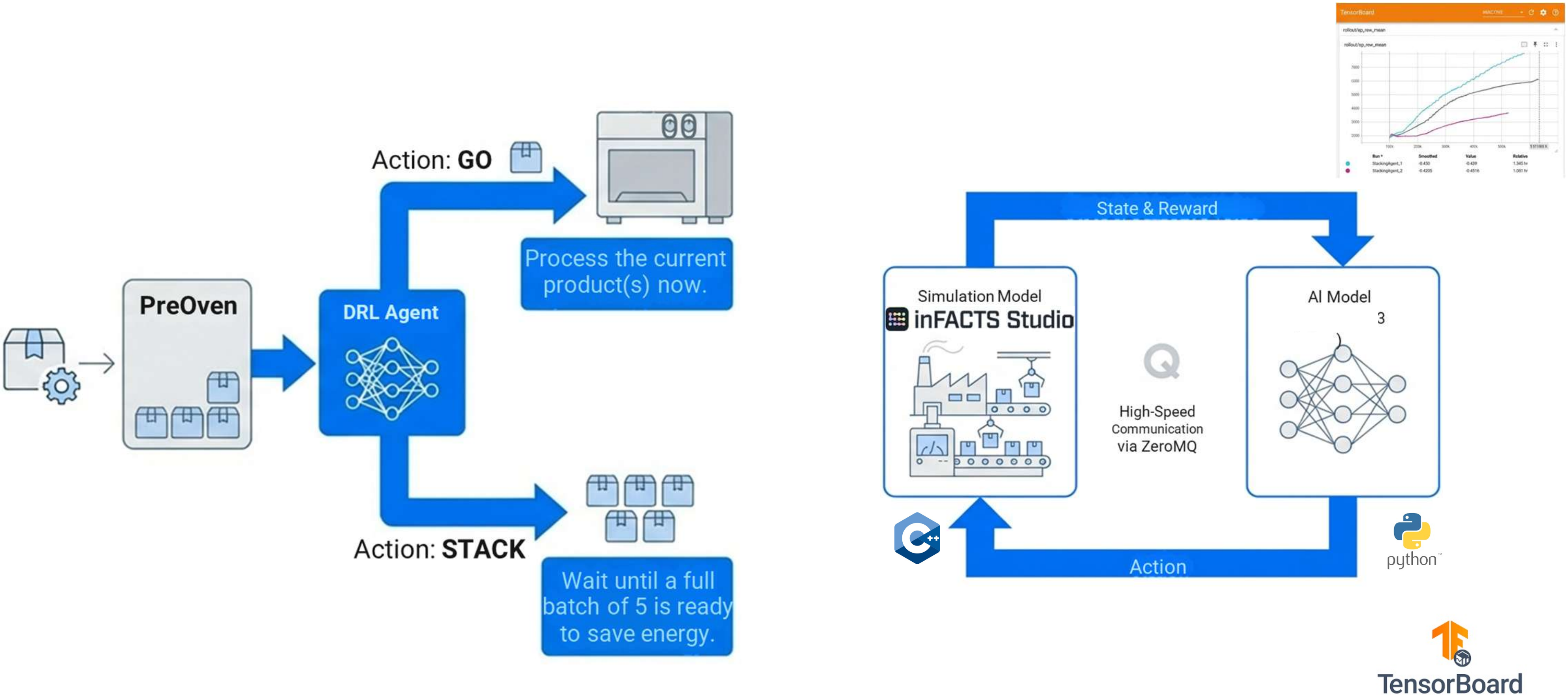
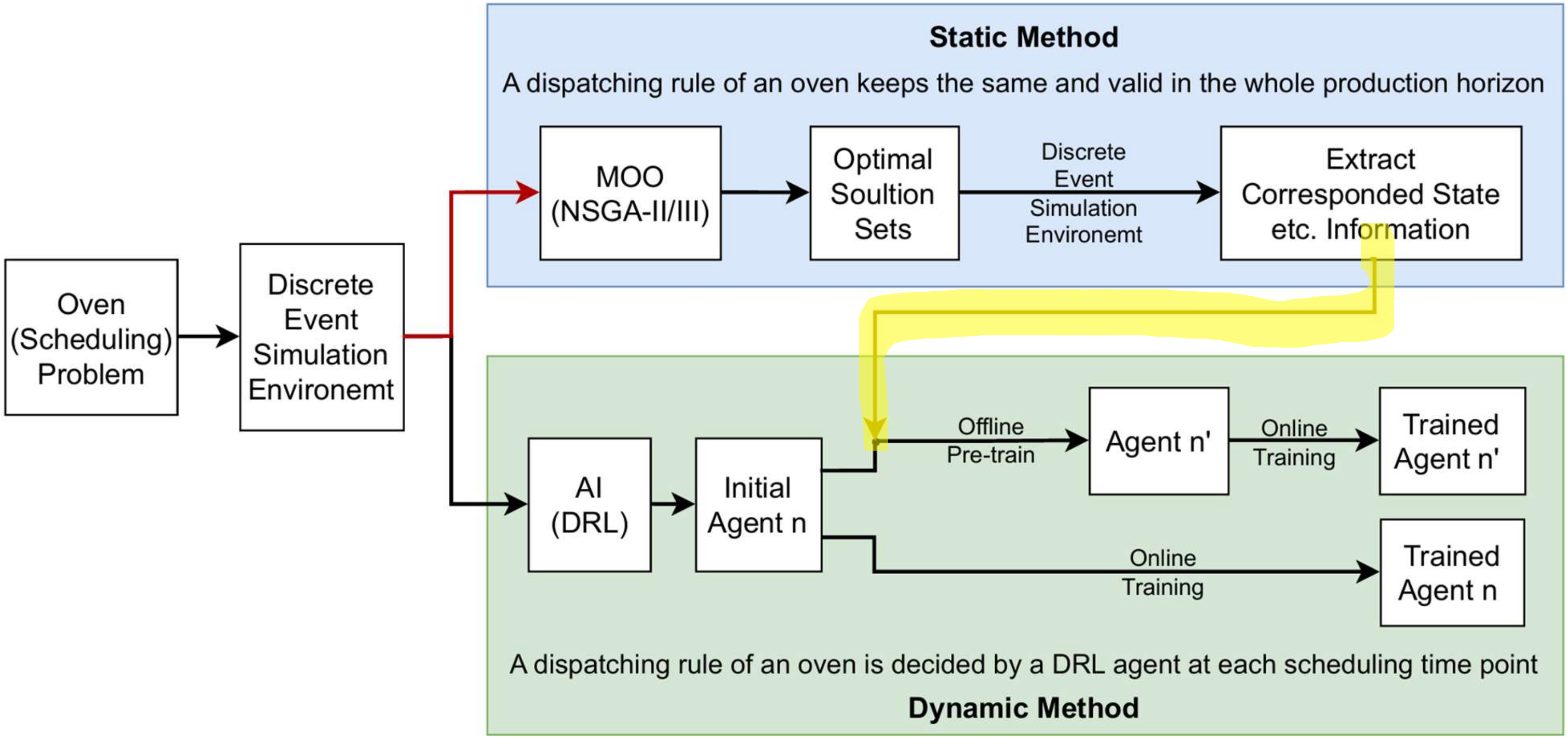
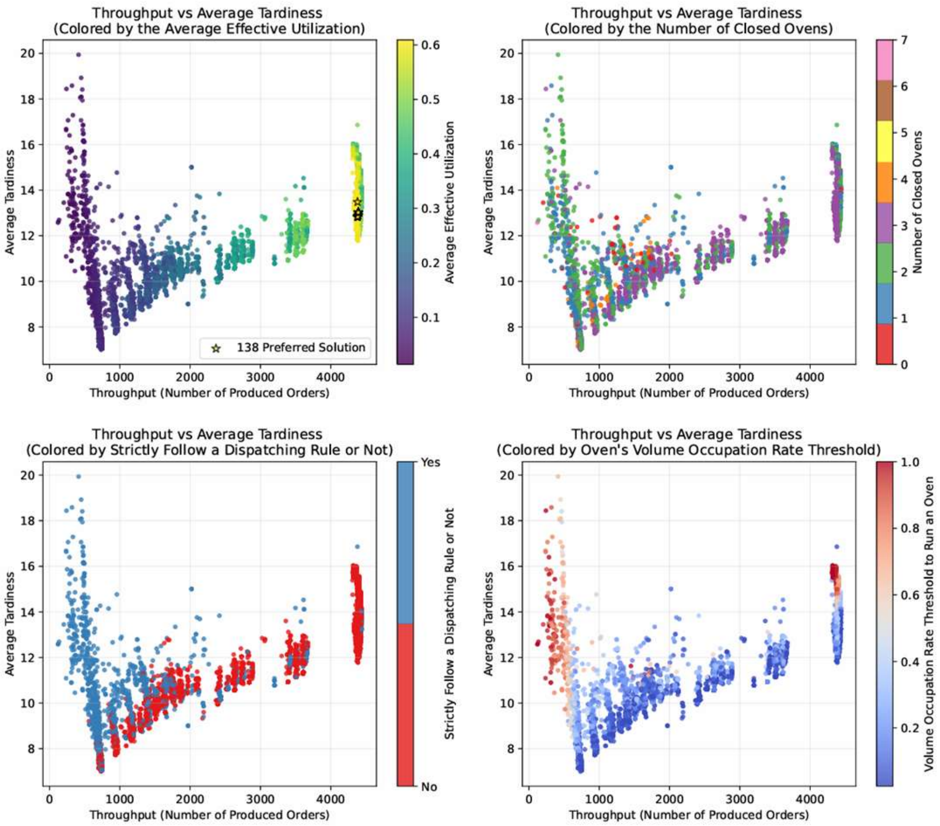


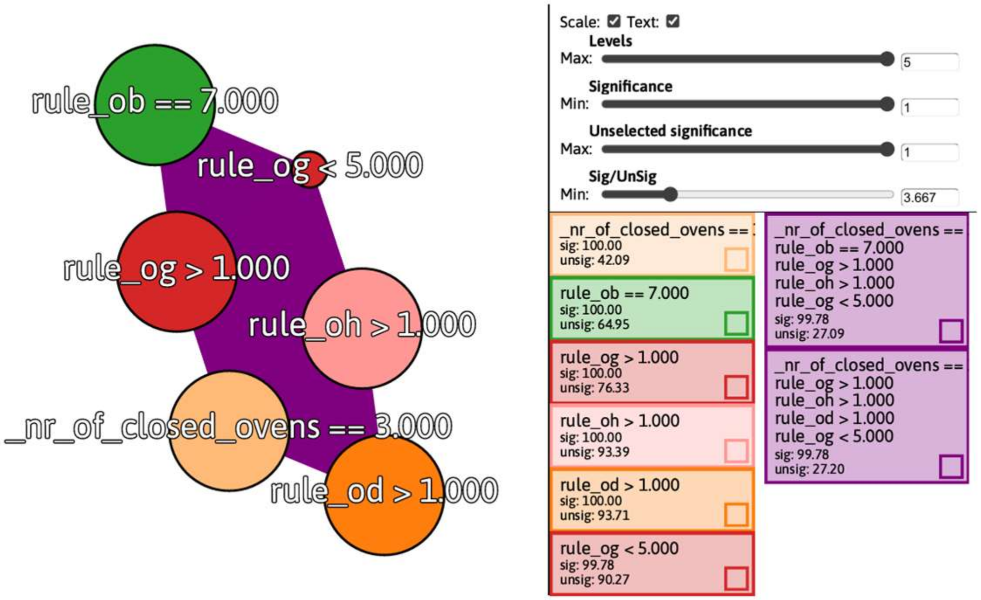
Figure 8. Convergence plots of the scenarios with 7 operators (**top left**), 8 operators (**top center**), 9 operators (**top right**), 6 operators (**lower left**), and 10 operators (**lower right**).



Using Simulation Based Optimization and Deep Reinforcement Learning to Solve Ovens Scheduling Problem in Cutting Tool Manufacturing. To be submitted to *Advanced Engineering Informatics.*


Oven (Scheduling) Problem
Discrete Event Simulation Environemt
Static Method
A dispatching rule of an oven keeps the same and valid in the whole production horizon
MOO (NSGA-II/III)
Optimal Soultion Sets
Discrete Event Simulation Environemt
Extract Corresponded State etc. Information
AI (DRL)
Initial Agent n
Offline Pre-train
Agent n'
Online Training
Trained Agent n'
Online Training
Trained Agent n
A dispatching rule of an oven is decided by a DRL agent at each scheduling time point
Dynamic Method





Scale: ☑ Text: ☑

Levels

Max: 5

Significance

Min: 1

Unselected significance

Max: 1

Sig/UnSig

Min: 3.667

_nr_of_closed_ovens ==
sig: 100.00
unsig: 42.09

rule_ob == 7.000
sig: 100.00
unsig: 64.95

rule_og > 1.000
sig: 100.00
unsig: 76.33

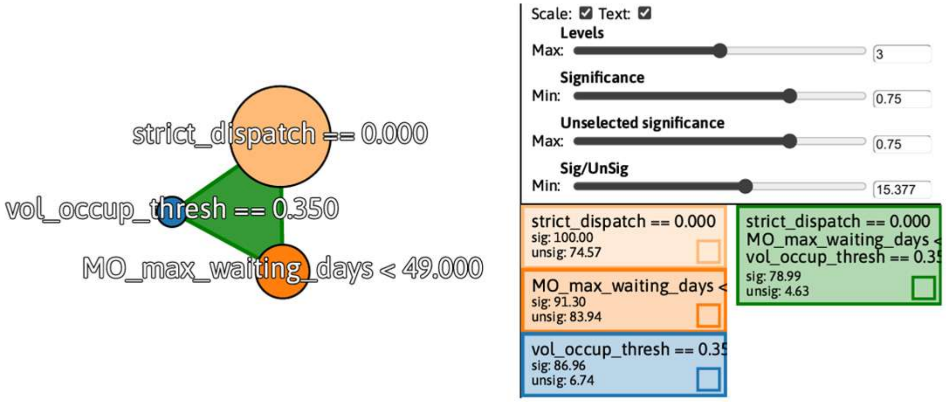
rule_oh > 1.000
sig: 100.00
unsig: 93.39

rule_od > 1.000
sig: 100.00
unsig: 93.71

rule_og < 5.000
sig: 99.78
unsig: 90.27

_nr_of_closed_ovens ==
rule_ob == 7.000
rule_og > 1.000
rule_oh > 1.000
rule_og < 5.000
sig: 99.78
unsig: 27.09

_nr_of_closed_ovens ==
rule_og > 1.000
rule_oh > 1.000
rule_od > 1.000
rule_og < 5.000
sig: 99.78
unsig: 27.20



Scale: ☑ Text: ☑

Levels

Max: 3

Significance

Min: 0.75

Unselected significance

Max: 0.75

Sig/UnSig

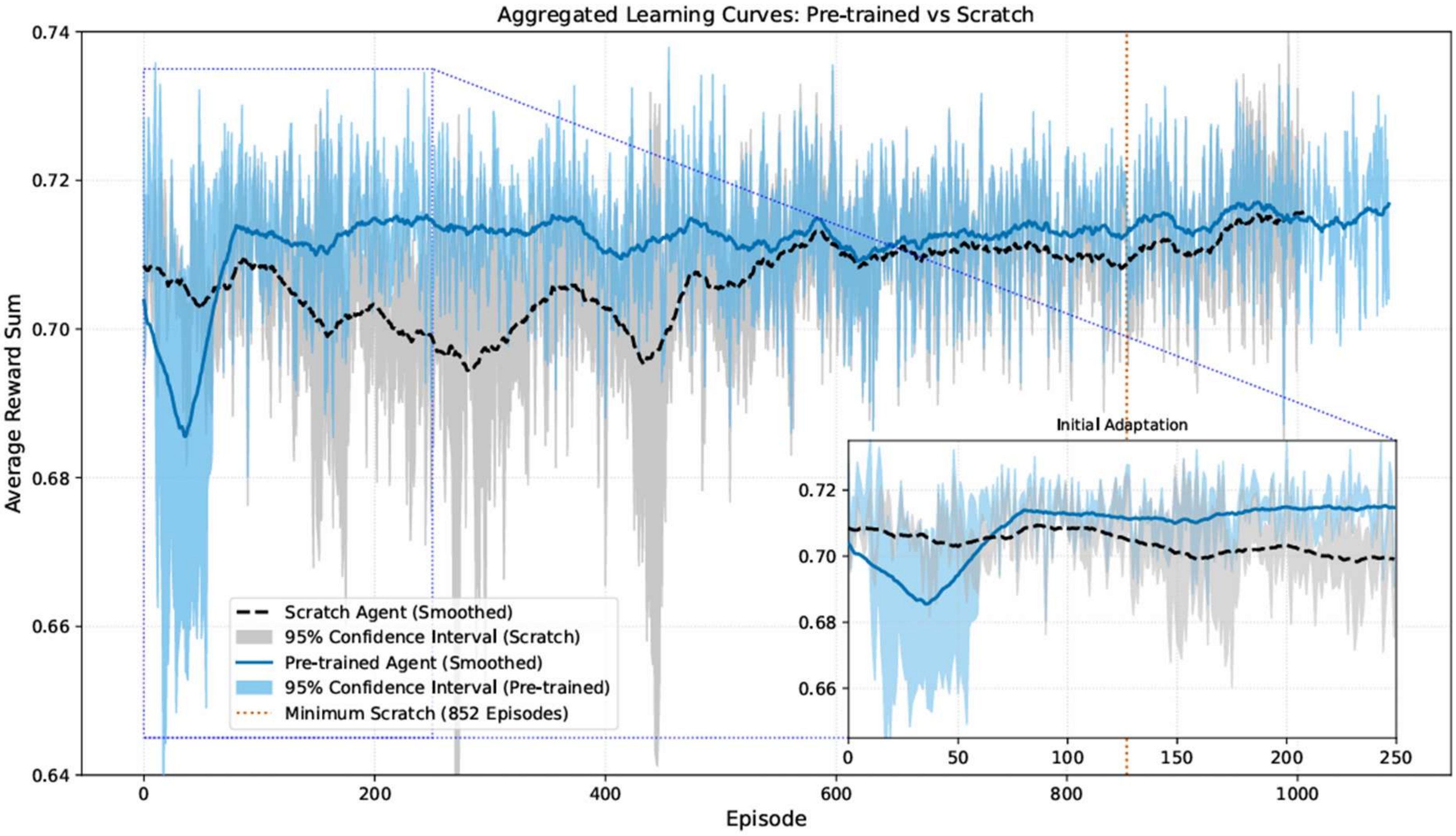
Min: 15.377

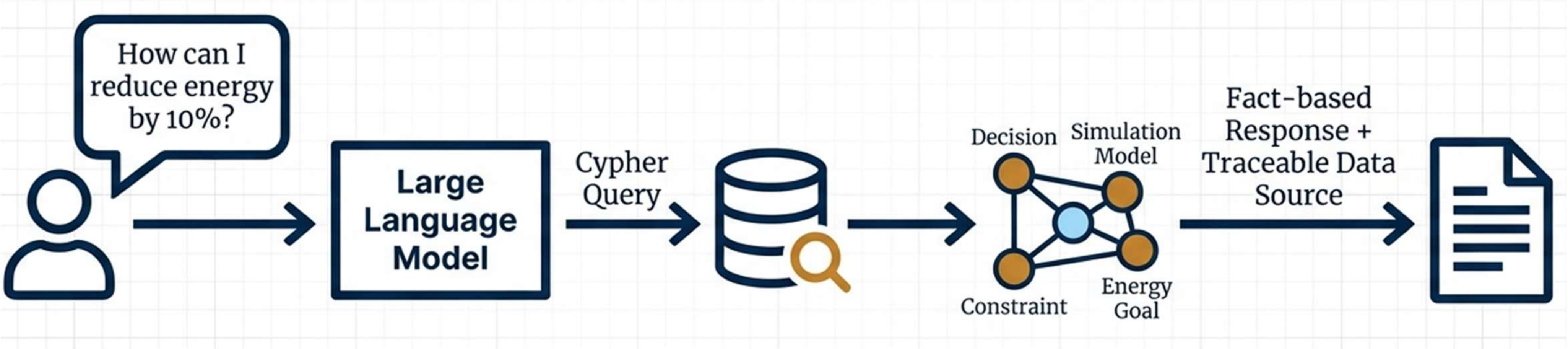
strict_dispatch == 0.000
sig: 100.00
unsig: 74.57

MO_max_waiting_days <
sig: 91.30
unsig: 83.94

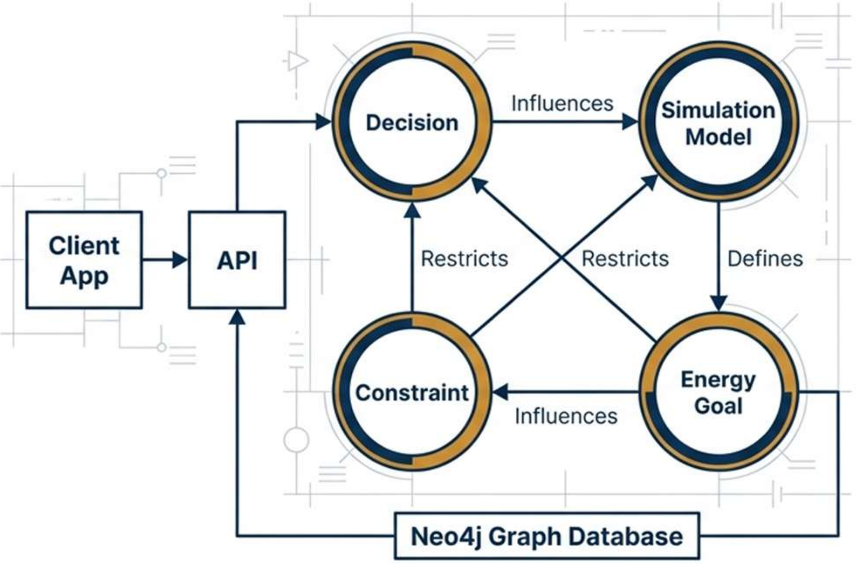
vol_occup_thresh == 0.35
sig: 86.96
unsig: 6.74

strict_dispatch == 0.000
MO_max_waiting_days <
vol_occup_thresh == 0.35
sig: 78.99
unsig: 4.63


Aggregated Learning Curves: Pre-trained vs Scratch
Average Reward Sum
Episode
0.74
0.72
0.70
0.68
0.66
0.64
0
200
400
600
800
1000
Scratch Agent (Smoothed)
95% Confidence Interval (Scratch)
Pre-trained Agent (Smoothed)
95% Confidence Interval (Pre-trained)
Minimum Scratch (852 Episodes)
Initial Adaptation
0.72
0.70
0.68
0.66
0
50
100
150
200
250

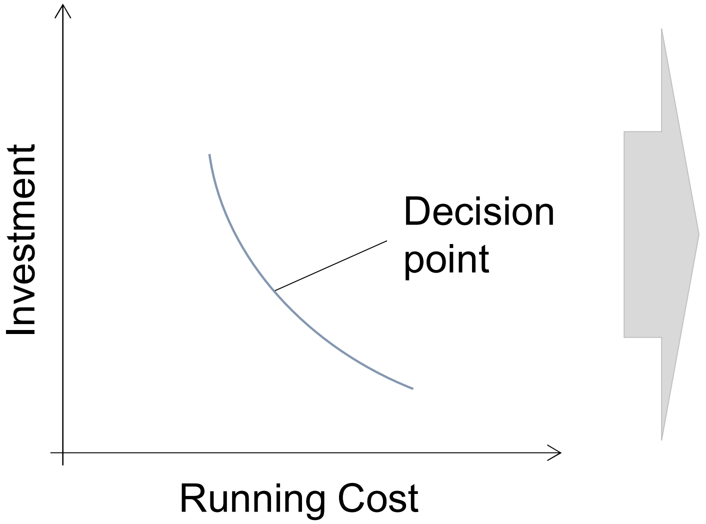


LLM-interface to a Knowledge Graph that links data-model-optimization-knowledge-decision

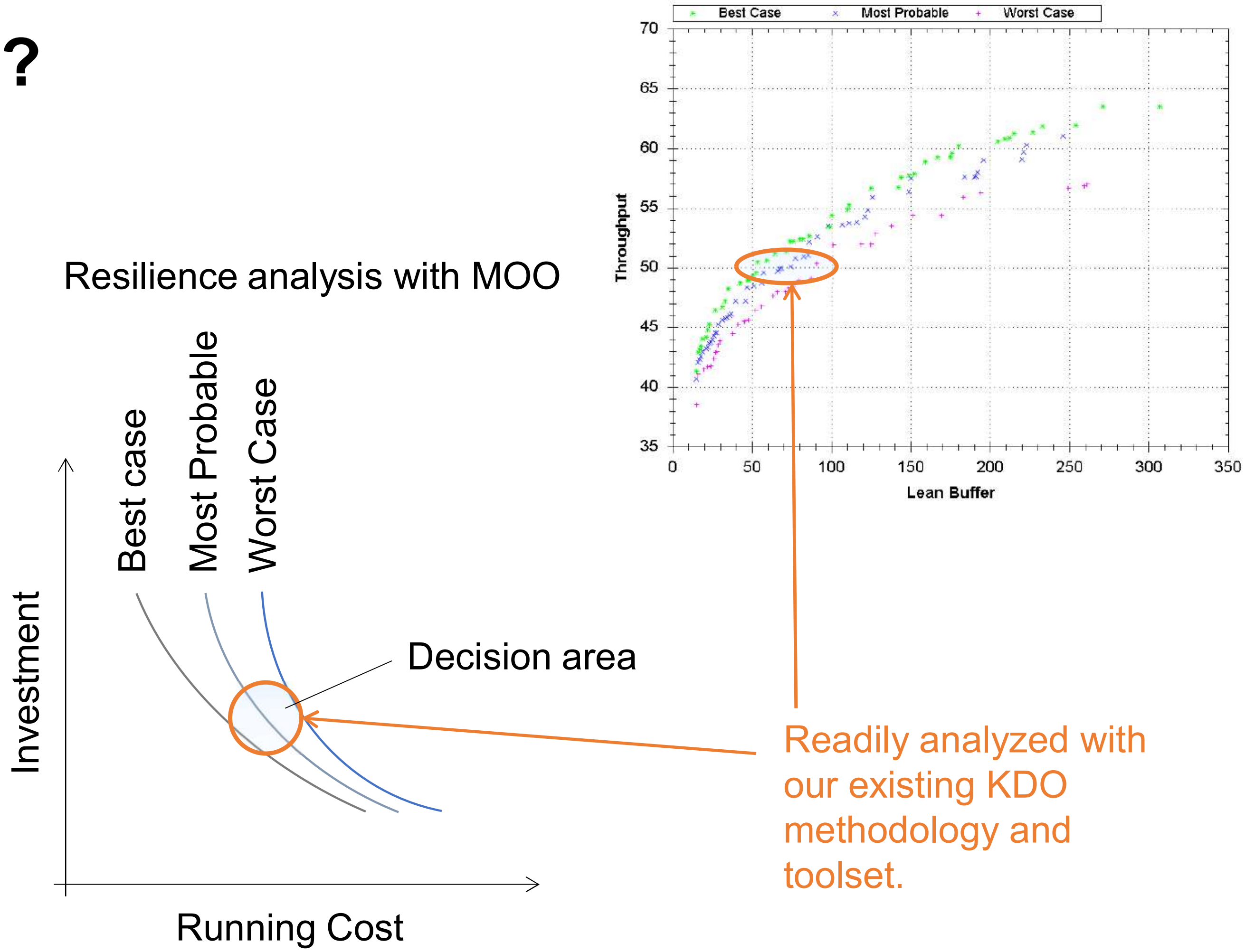


How about Resilience?

Ordinary decision support with MOO



Resilience analysis with MOO



Readily analyzed with our existing KDO methodology and toolset.

Conclusions

- Our proposed VF-KDO approach has advanced to provide an innovative methodology that puts simulation, AI-based multi-objective optimization and knowledge extraction, visualization and storing for sustainable and resilient decision-making support into an integrated human-machine co-learning (HMCoL) framework.
- We are developing an LLM-based interface to graph database for supporting HMCoL through linking data-model-optimization-knowledge-decision for enhancing transparency and traceability in supporting group decision making and learning.
- HMCoL in a multi-objective simulation-based optimization context is relatively new but will gain higher momentum when computing and AI are advancing in a lightning pace – e.g., quantum computing.