EXPLAIN: EXPlainable and Learning production & logistics by Artificial INtelligence

Vinnova Strategiska Innovationsprogrammet Produktion2030 (SIP) Utlysning 13

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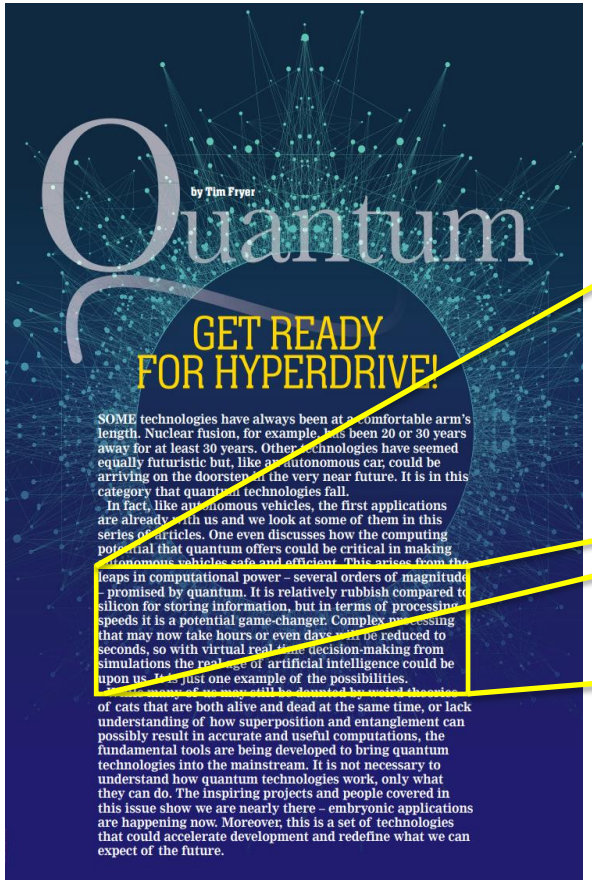
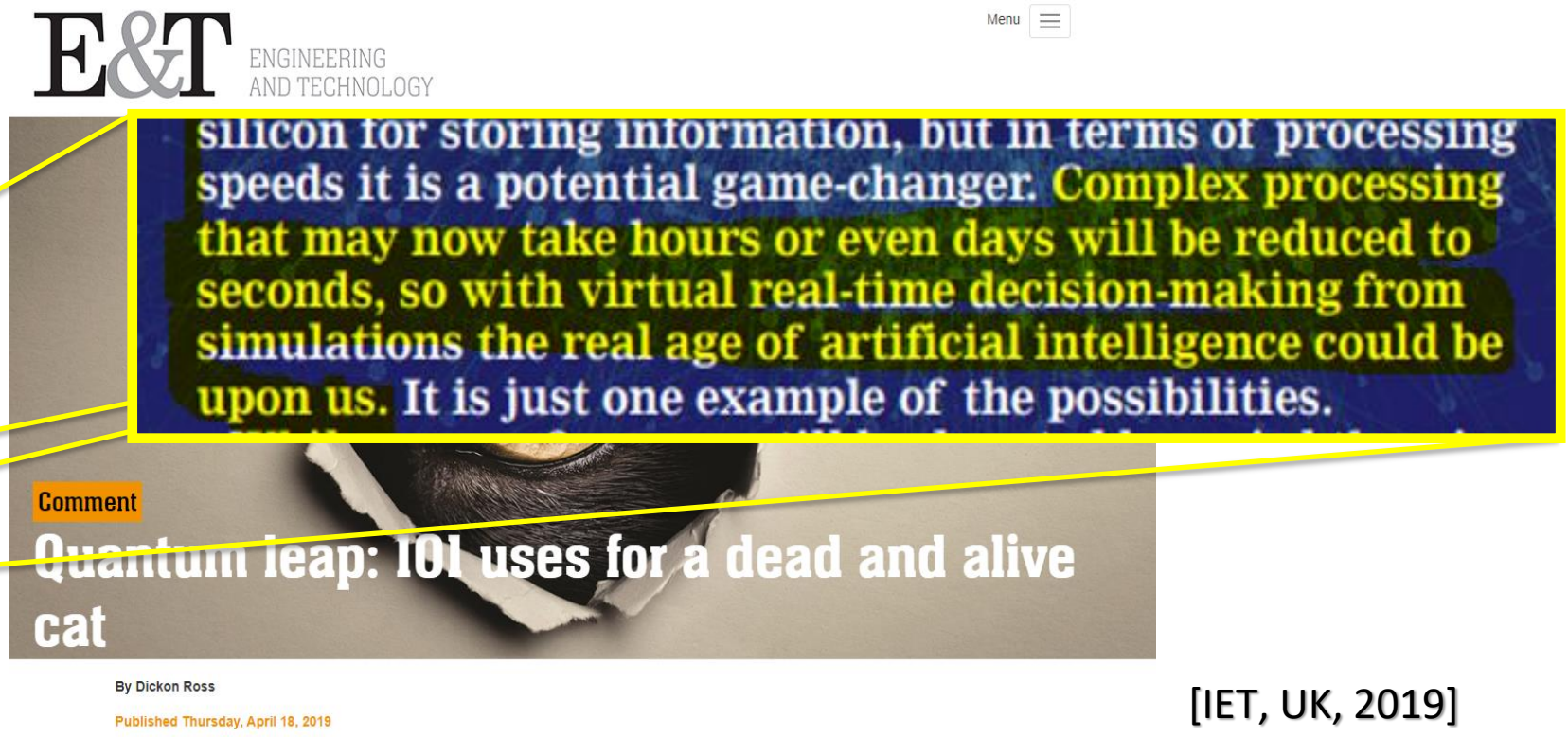
HUVUDMAN: Teknikföretagen

GRUNDARE: swerea swedish research, KTH, The Swedish Production Academy, CHALMERS

Med stöd från VINNOVA Sveriges innovationsmyndighet, Energimyndigheten, FORMAS, Strategiska innovationsprogram

The ”Real Age of AI”





[IET, UK, 2019]

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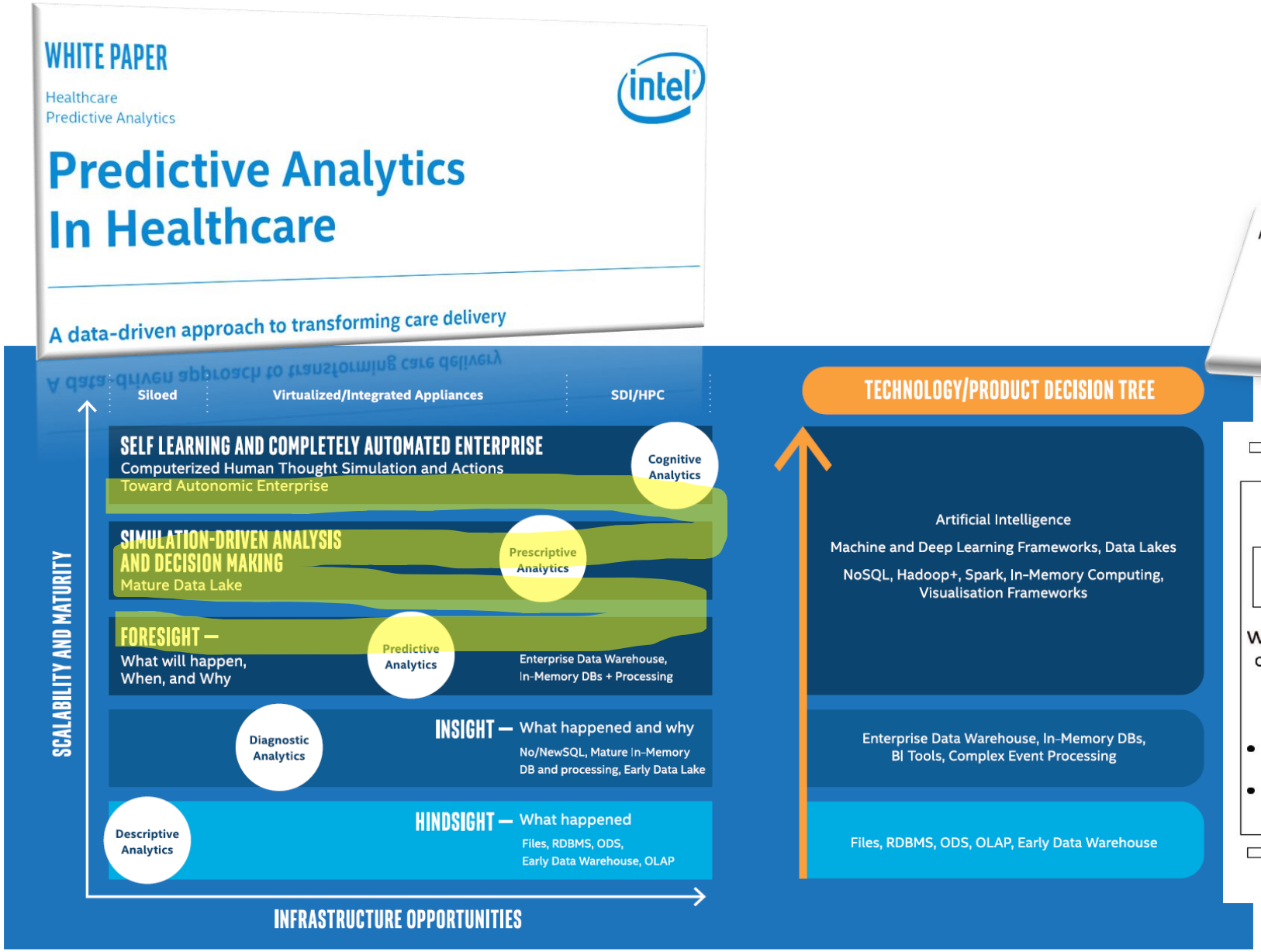

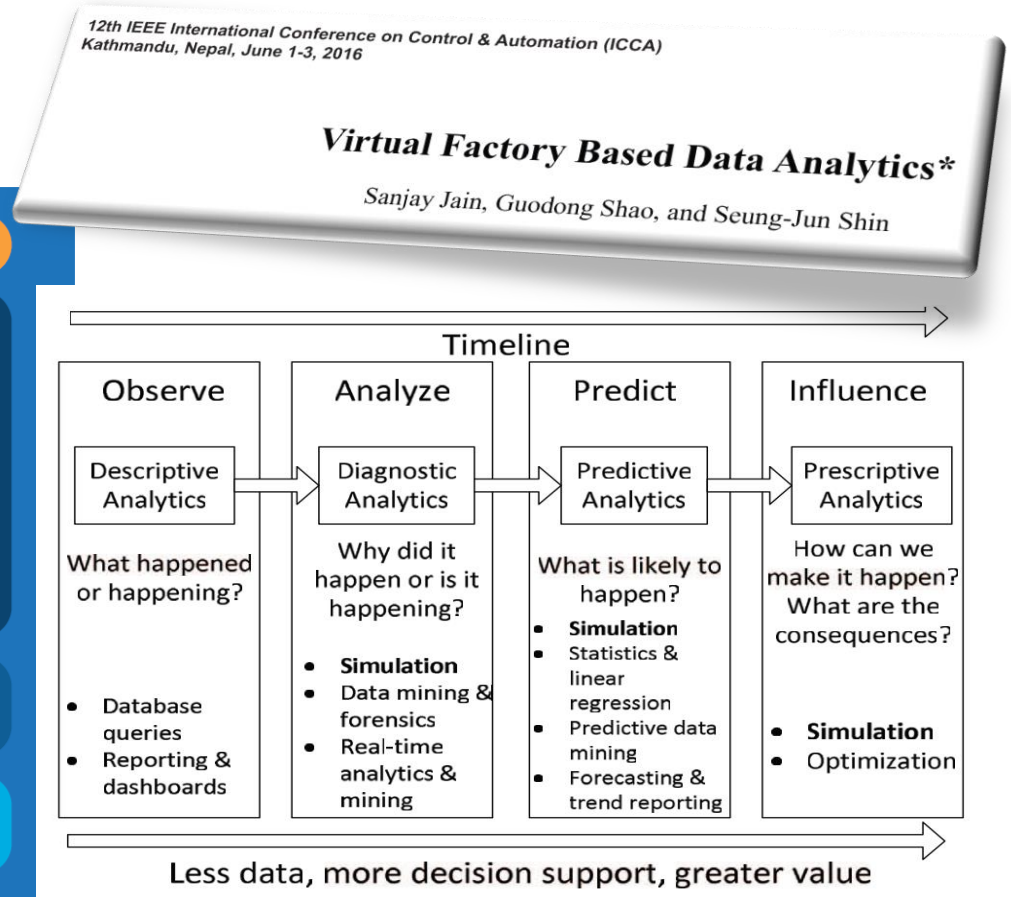

Figure 1: Stages of analytics maturity and associated technologies

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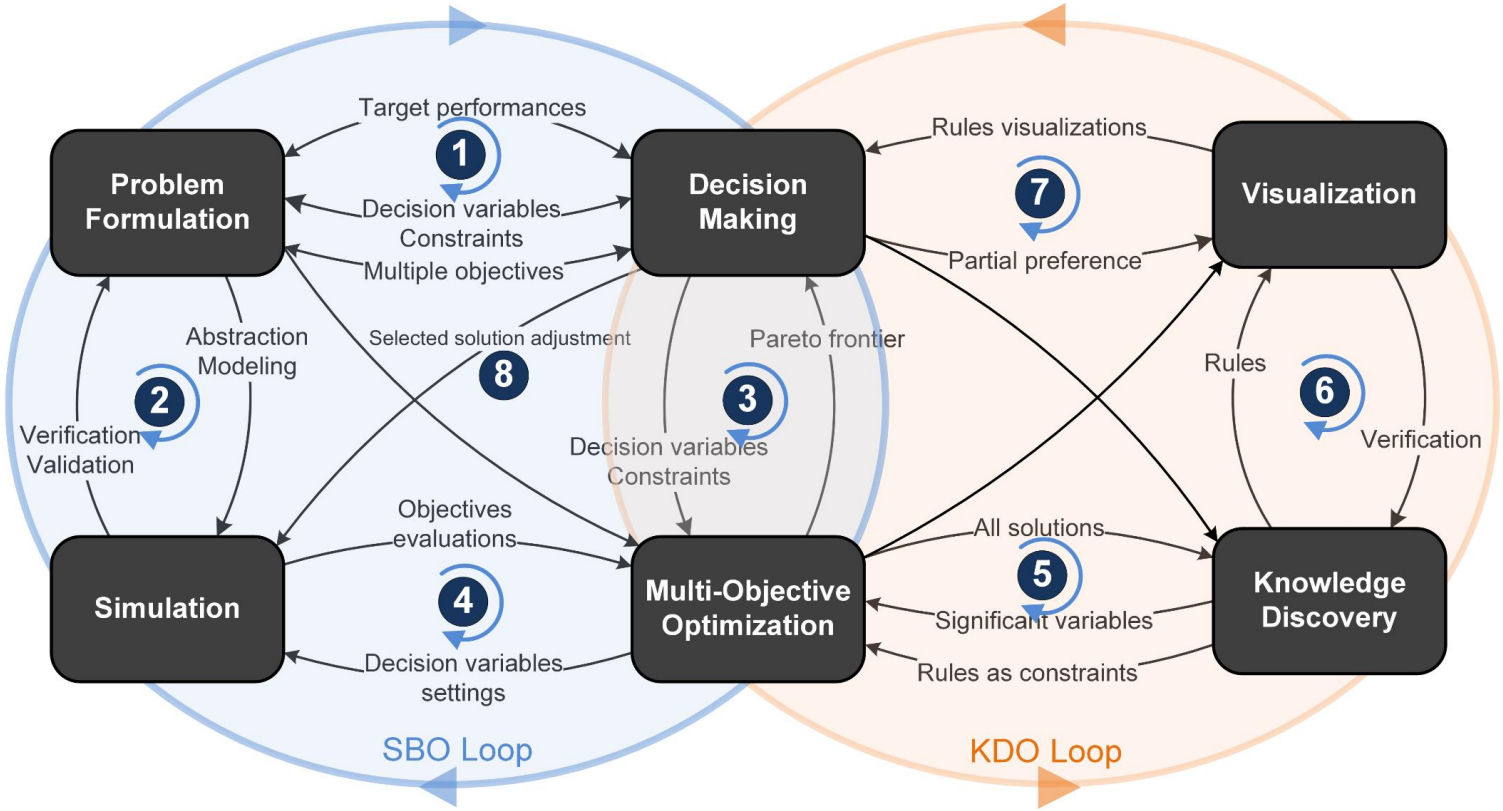
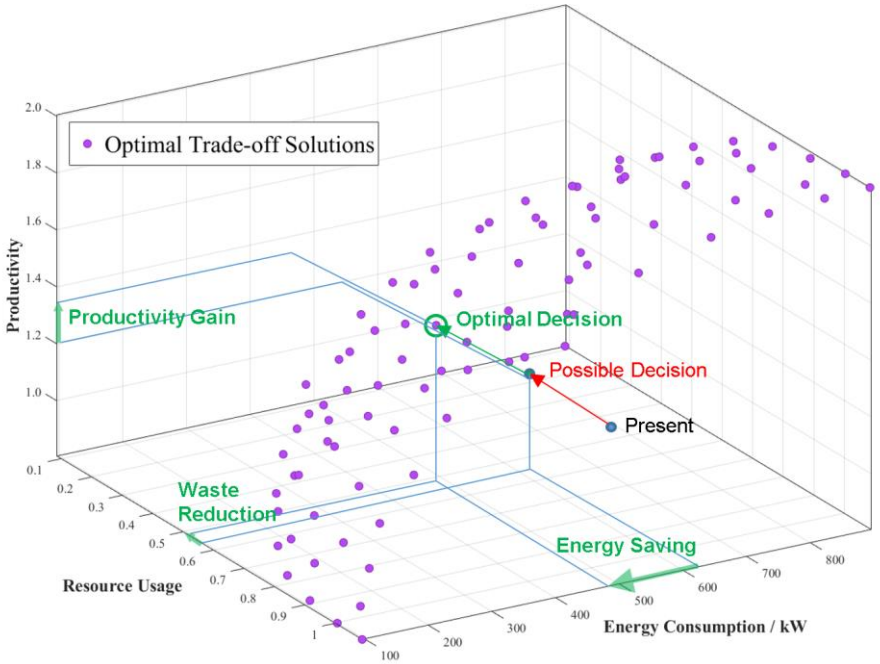
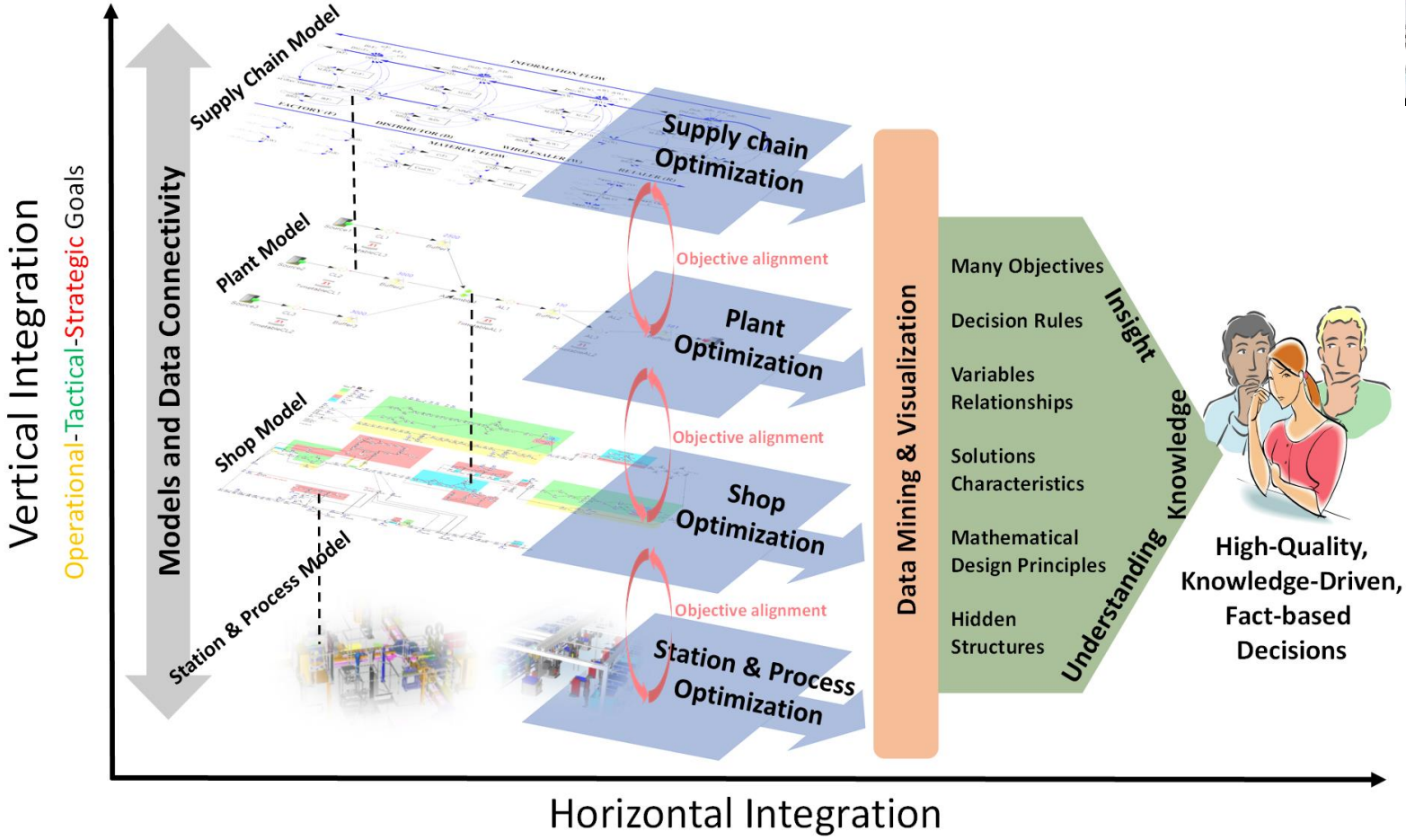
An interactive and iterative methodology that integrates simulation, optimization, knowledge discovery, visualization and decision making, i.e., Knowledge-Driven Optimization (KDO)

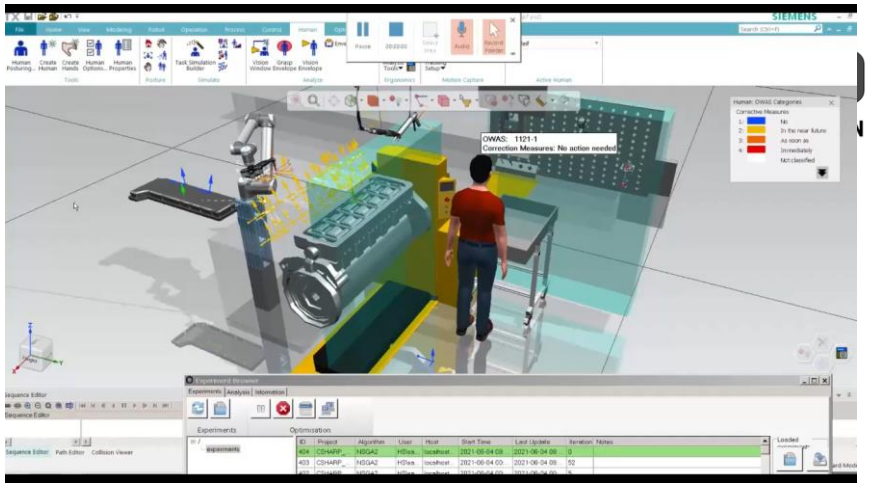


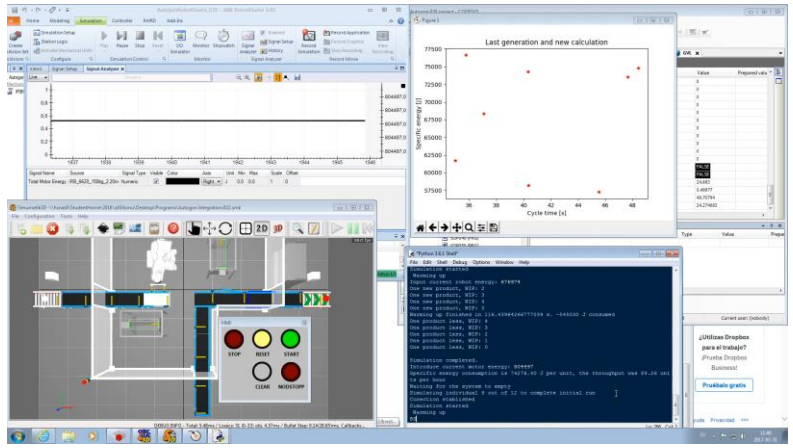


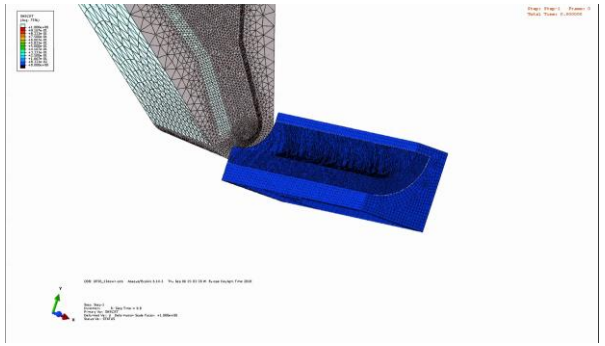
- Bandaru, S., Ng, A.H.C. and Deb, K. (2017). Data Mining Methods for Knowledge Discovery in Multi-Objective Optimization: Part A & B. *Expert Systems with Applications*, Vol. 70, 119-159.
- Ng, A.H.C., Bandaru, S. and Frantzén, M. (2016). Innovative Design and Analysis of Production Systems by Multi-objective Optimization and Data Mining. *Procedia CIRP*, 50, 665-671.

Multi-level, Multi-disciplinary & Many-objective









Why does AI need simulation?

- AI needs a lot of high-quality training data which can be too expensive (or simply infeasible) to gather from the real system/equipment. Simulations and Digital Twins can provide a safe and cheaper environment for training the AI algorithms.

Why do Digital Twins need AI?

- By definition, AI/ML provides the analytics capability for controlling the real counterpart of the digital twin.

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Four Crucial Questions

- Where come the “data” used to train the algorithms?
  - Without quality (historical and “future”) data, AI does not work
- What are our (Human) values and goals?
- What do we want to achieve with intelligent machines? Are we building intelligent machines to assist or replace humans?
- Is the understanding for the machine or for humans?

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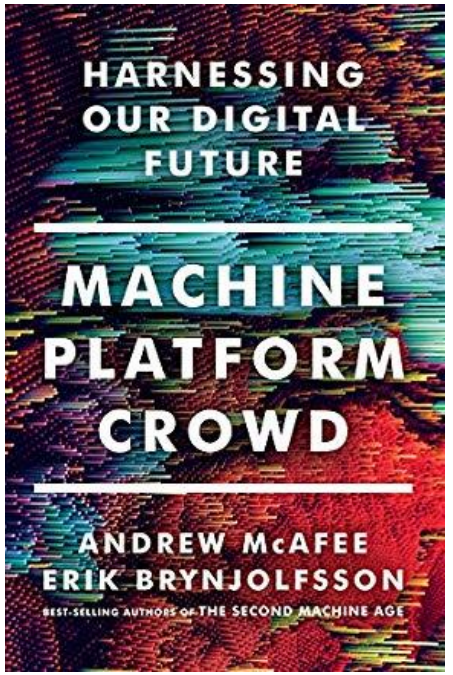
"…the best chess player
in the world is neither
man nor machine…

… but both – a team of computer-assisted chess players is still able to defeat any chess playing machines (68%)"

[McAfee and Brynjolfsson 2017]



*"We've **decided** **it's more about building a better human-machine combination** than it is about building a machine where we will be lucky if it wants us around as a household pet."*

[Rosalind Picard, Founder of the MIT Media Lab. Affective Computing Research, in a 2012 interview]

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- In a lot of early work in AI, humans explicitly devised an algorithm to solve a particular problem. *In more recent AI, they do not. Instead, they devise a general learning algorithm, which then "learns" a solution to the problem.*
Often the human developers don't know an explicit algorithm for solving the problem and don't know how the system arrives at its conclusions.

[John C. Lennox (2020) 2084, p. 21]

The distinction between **explanation** and **understanding** is very important.
Understanding in science is a deep experience going beyond mere predictive power or the currently fashionable notion of algorithmic compressibility.

[John C. Polkinghorne (1994), The Faith of a Physicist: Reflections of a Bottom-Up Thinker, p.36]

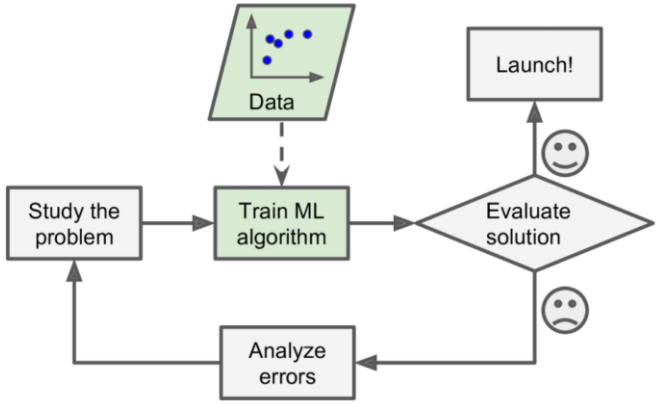


Figure 1-2. Machine Learning approach

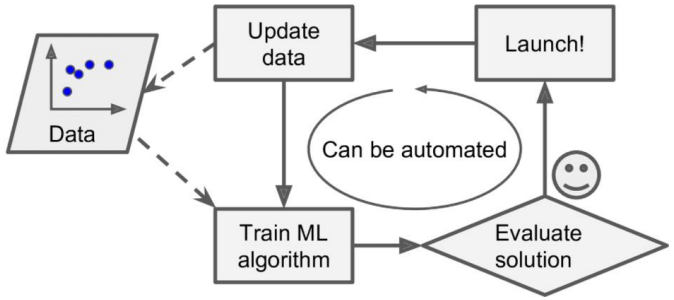
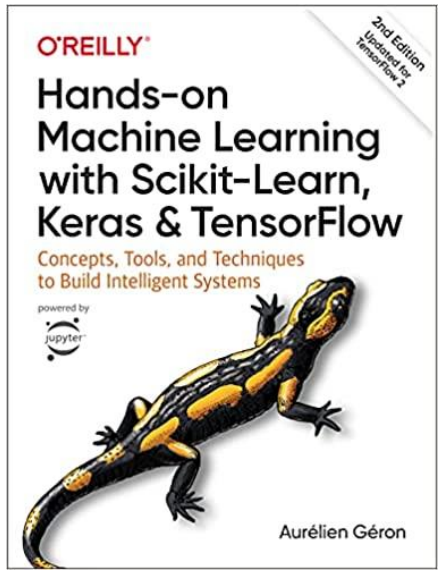


Figure 1-3. Automatically adapting to change



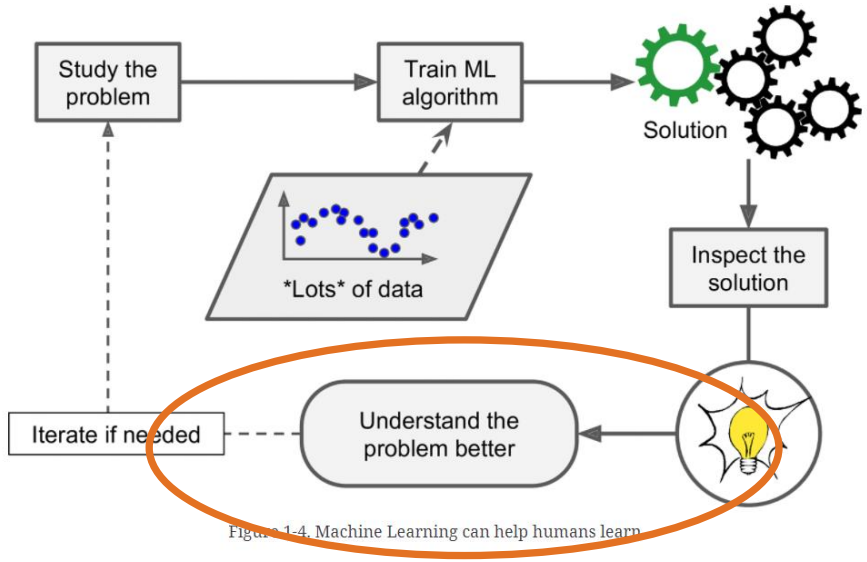


Figure 1-4. Machine Learning can help humans learn

EXPlainable and Learning production & logistics by Artificial Intelligence <EXPLAIN>

Koordinator: Uppsala Universitet

Aim & Objectives:

The overall aim of the EXPLAIN project is to increase the profitability, sustainability, and competitiveness of the Swedish manufacturing industry. The project conducts research and development of a new generation of interactive and **innovative fusion of virtual production modeling methods and machine learning algorithms for decision-making support** and increasing knowledge and competence within the production systems lifecycle. EXPLAIN will target cases on production planning and control with humans-in-the-loop, wherein complex multi-criteria decisions are to be made, including energy and resource efficiency.

Expected Results:

The EXPLAIN project brings into a paradigm that emphasizes the **human-machine co-learning** through transferability of preferences/values and knowledge between human and machine within a multi-objective (productivity and sustainability) optimization context and hence will provide a unique, long-term contribution to knowledge-driven industry in Sweden. Fully in-line with other worldwide Learning Factories efforts, the human-machine symbiosis framework proposed can in the long-term increase the sustainability and competitiveness of the Swedish manufacturing industry.

Projektparter: AstraZeneca, HITACHI ABB, KTH Vetenskap och Konst, Mainly AI, RI.SE, SCANIA, SECO

Projekttid: 2021-04-15 – 2024-04-14

Budget: 12 774 000 kr (bidrag från Vinnova 6 Mkr)

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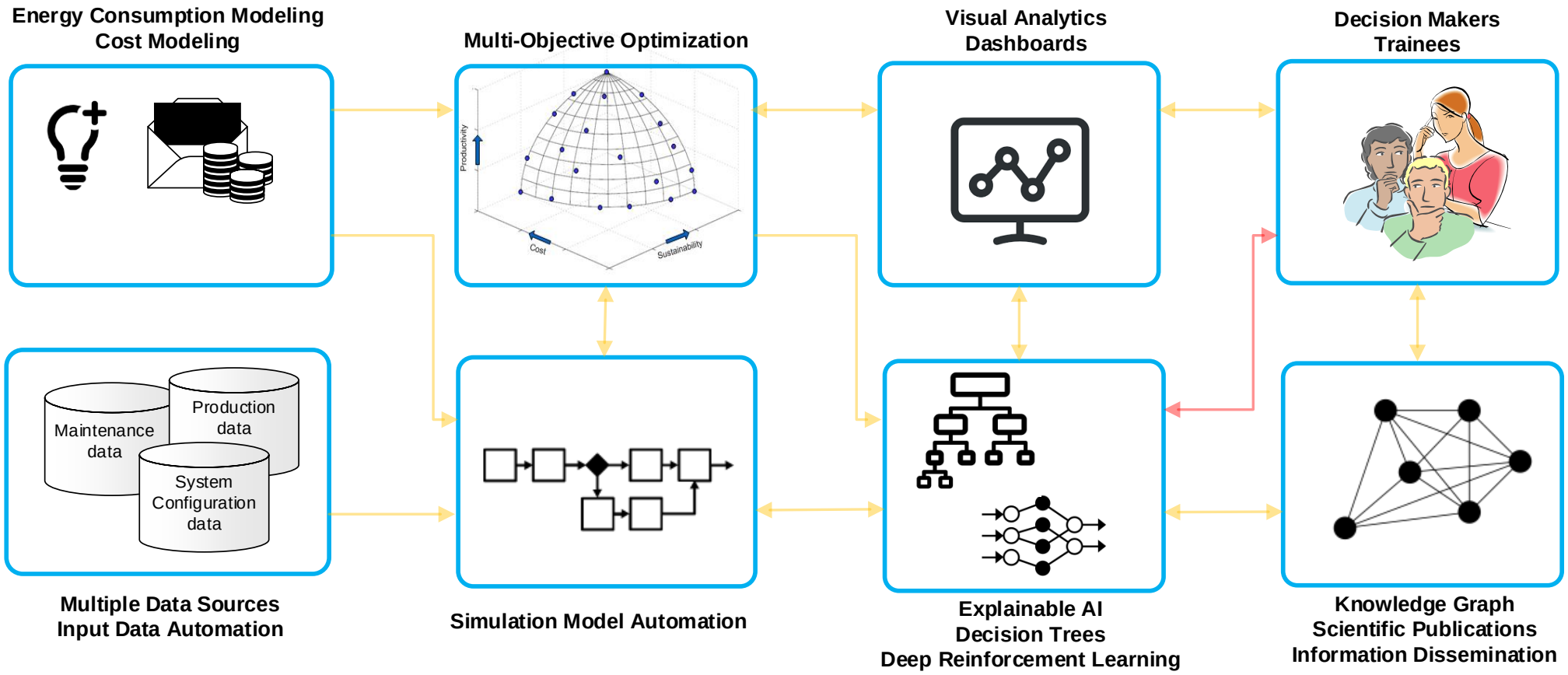
Conceptual Framework



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Consortium and Keywords

- **Uppsala University** IndTek: **Multi-Objective and Explainable AI/ML**, Process Mining technologies
- **KTH** Södertälje: automatic model generation and sustainability modeling
- **AstraZeneca** Södertälje: simulation modeling and optimization
- **Hitachi-ABB** Ludvika: Process Mining; simulation-based optimization
- **MainlyAI** Stockholm: SME supplying an AI operational platform, **Miranda**
- **Scania** Södertälje: sustainability, HMI, energy modelling & optimization
- **SECO Tools** Fagersta: **AI-based production scheduling and human learning**
- **RISE** Mölndal: sustainability modeling and knowledge dissemination

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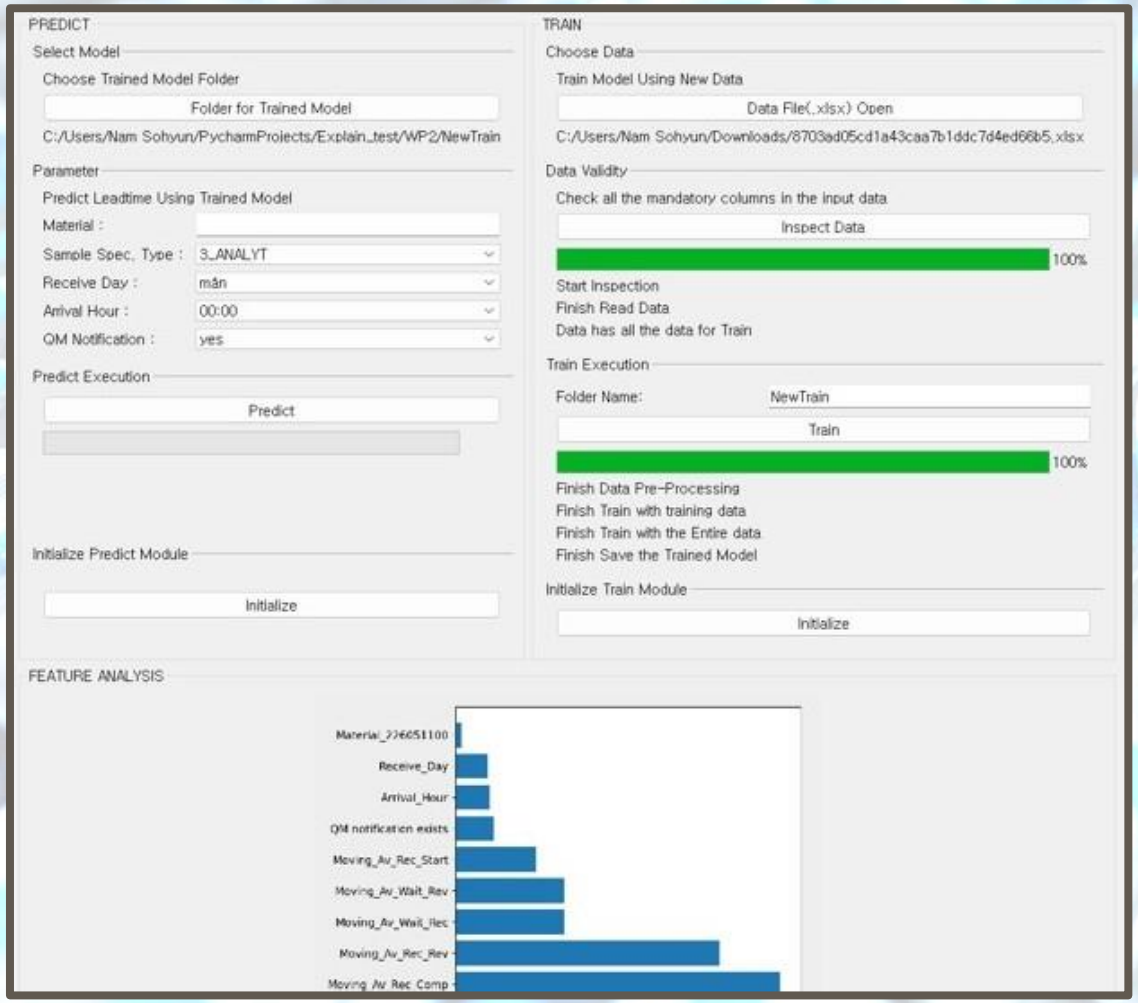
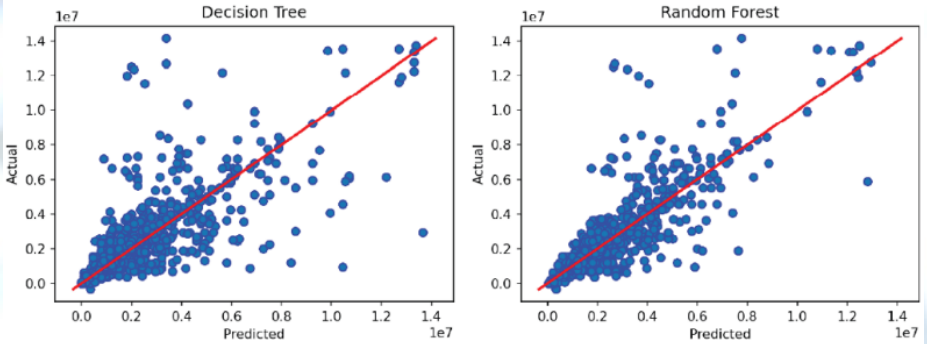
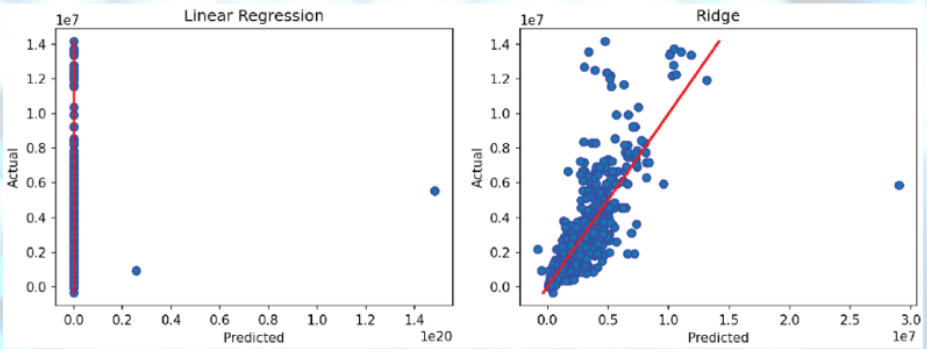
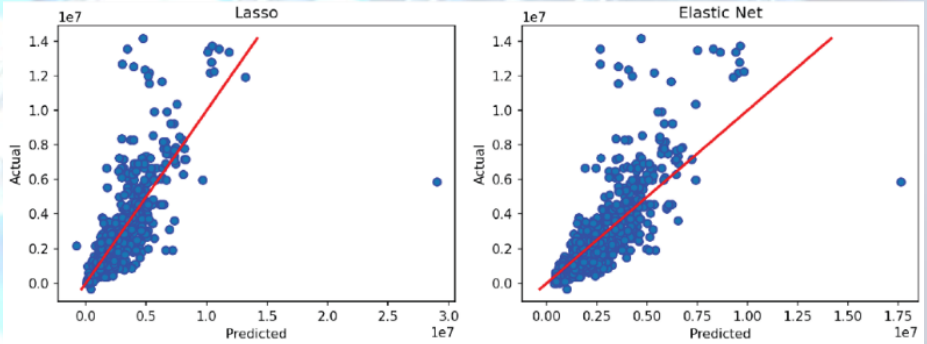
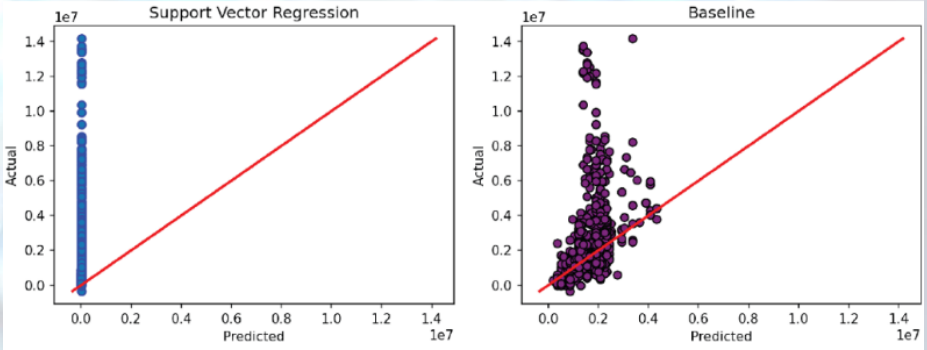
A Predictive Analytics Tool for AstraZeneca









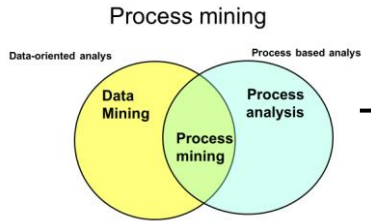


A Production Scheduling Case of Seco Tools

Expected Research Outcomes:

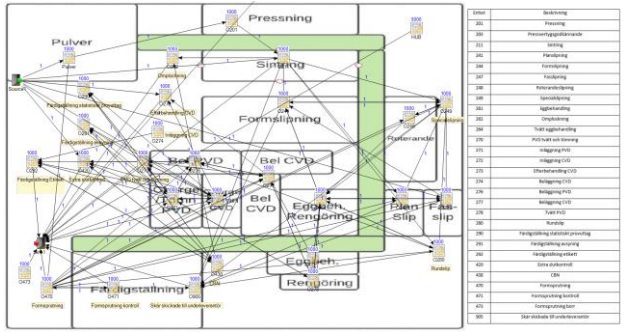
- **Digital Twin Based Bottleneck Analysis**
- **Human learning on optimal dispatching/batching rules.**
- **Optimal, Real-Time AI decision-making, especially on uncertain production scenarios.**

Company databases

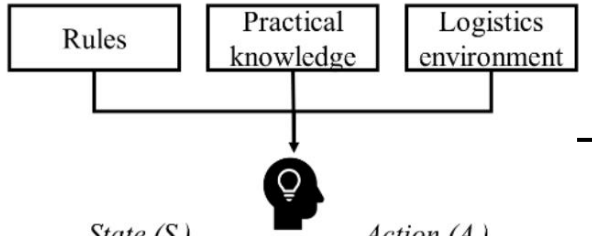


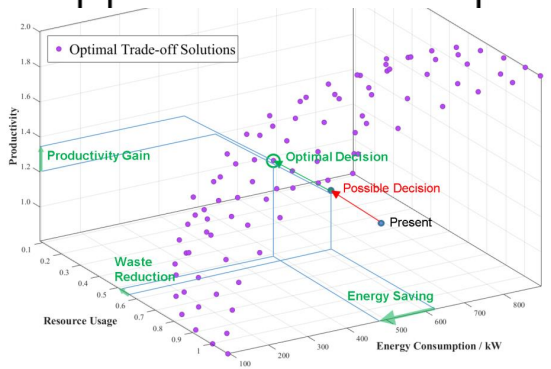
Automated model generation

Digital Twin



SMO-based AI training





Optimal rules for human learning

AI for real-time decisions (fast)

Optimal solutions (slow)

- Applying ML-enabled MOO algorithms:
  - *f1 = Max. (Effective utilization)*
  - *f2=Max. (Energy effectiveness)*
  - *f3=Min. (Tardiness)*

Automated bottleneck analysis

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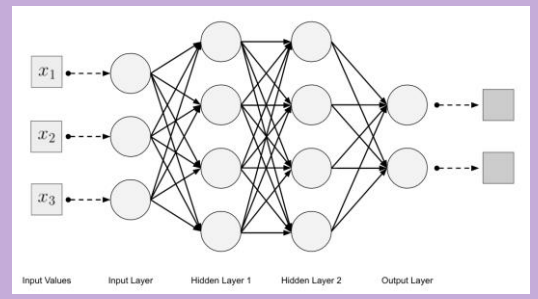
Deep Reinforcement Learning for Oven Scheduling

AI Agent

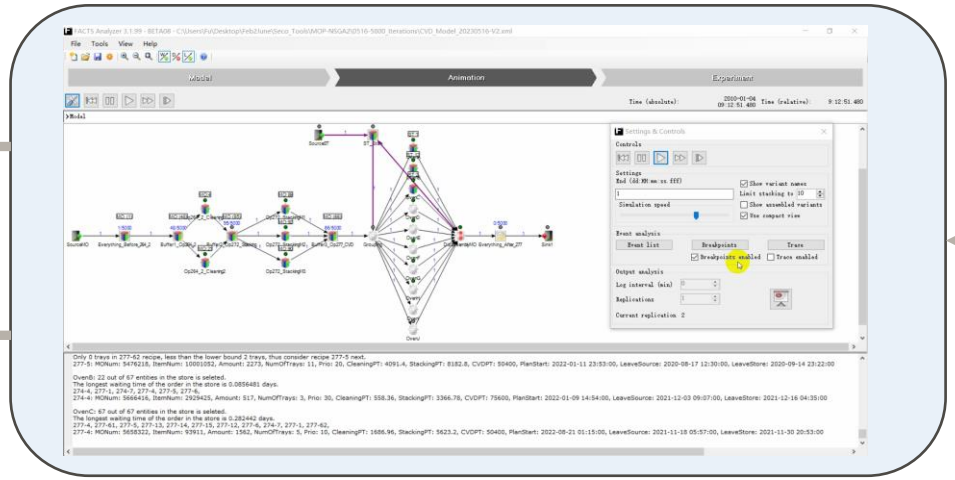


Control real-world ovens after training

State (not in SBO)

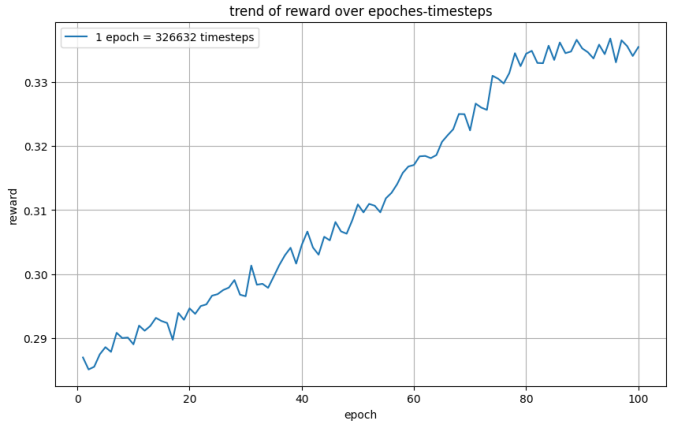
$Reward = f(Utilization, Occupation)$

Action



Training Environment = Simulation

Training Results



Max. $f(Utilization, Occupation)$ will directly optimize energy efficiency

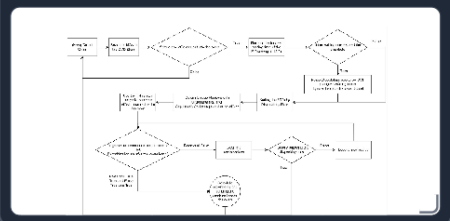
SCANIA SECO PRODUKTION2030

DRL & Simulation Based Optimization Workflow Comparison

Data/Heuristic from Production

Control Logic of the Ovens

logic figure



CSV: Recipe-Oven data

demo data

Recipe	OvenA	OvenB	OvenC	OvenD	OvenE	OvenF	OvenG	OvenH	OvenI	OvenJ
274-2	1	1	1	1	0	0	0	1	0	1
274-3	1	1	1	1	0	0	0	1	0	1
274-4	1	1	1	1	1	1	1	1	0	1
274-b1	1	0	0	0	0	0	0	1	0	1

CSV: Cutting tools' facts info data

demo data

ItemNum	Recipe	AmountPerTray	CleaningPTPerUnit	StackingPTPerUnit	OVENPT
3234700	277-4	460	0.0002	0.0009	14
10103063	277-15	227	0.0003	0.002	13.5
2486571	277-6	227	0.0003	0.0009	12
8596	277-4	323	0.0002	0.0009	14

CSV: Manufacturing Order data

demo data

MONum	ItemNum	Prio	Amount	PlanStart	LeaveSource	LeaveStore
5072007	2000821	10	2479	1/12/2022 18:59	12/17/2021 6:58	1/11/2022 21:35
5072205	3002707	10	1698	1/18/2022 13:03	12/17/2021 6:44	1/11/2022 23:20
5072572	2807371	10	2823	1/27/2022 10:39	12/20/2021 13:52	1/11/2022 23:27
5071198	3272759	10	783	1/15/2022 20:01	12/14/2021 13:56	1/12/2022 0:56

Discrete Event Simulation Model

Model Building Material Processor

- running logic
- recipe-oven information
- tools' facts information
- model building material

Manufacturing Order Processor

- historical order
- Switch: Input Manufacturing Order Type
- manufacturing orders
- real time order
- synthetic order generator

Synthetic Order Generator

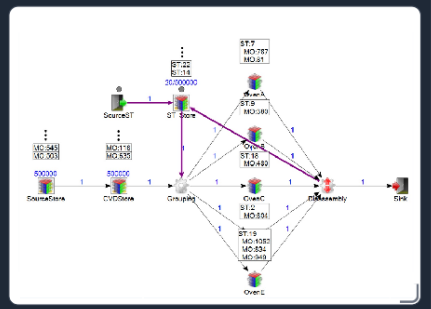
- historial data
- Generator Para.: nr_of_toall_required_MO
- Generator Para.: mean_MO_per_day
- Generator Para.: std_MO_per_day
- synthetic order generator

Dispatching Rules Processor

- dispatching rule
- Rule_OA
- Rule_OB
- Rule_OC
- Rule_OD
- Rule_OE

FACTS Analyzer Simulation Model

- Model Para.: min_oven_capacity
- Model Para.: MO_max_waiting_days
- Model Para.: strict_disptch
- Model Building Material
- Input: manufacturing orders



- Model Para.: ovens' dispatching rules
- Output: objectives
- Output: state information

Optimization Engine

Optimization Engine

- Optimization algorithm (NSGA-II/PSO...)
- Decision Space Settings
- kargs
- Objective value of previous decision candidate
- Next decision candidate

DRL Agent

DRL Agent

- DRL algorithm (DQN/PPO/A2C...)
- Customized Environment
- learning_rate
- exploration_fraction
- kargs
- input_state_info
- DRL action
- reward

DRL Reward Function

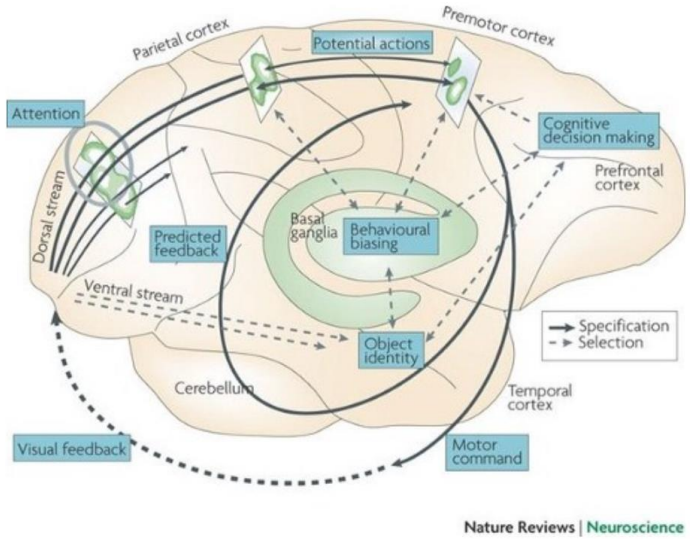
- objectives till previous step
- state info
- reward

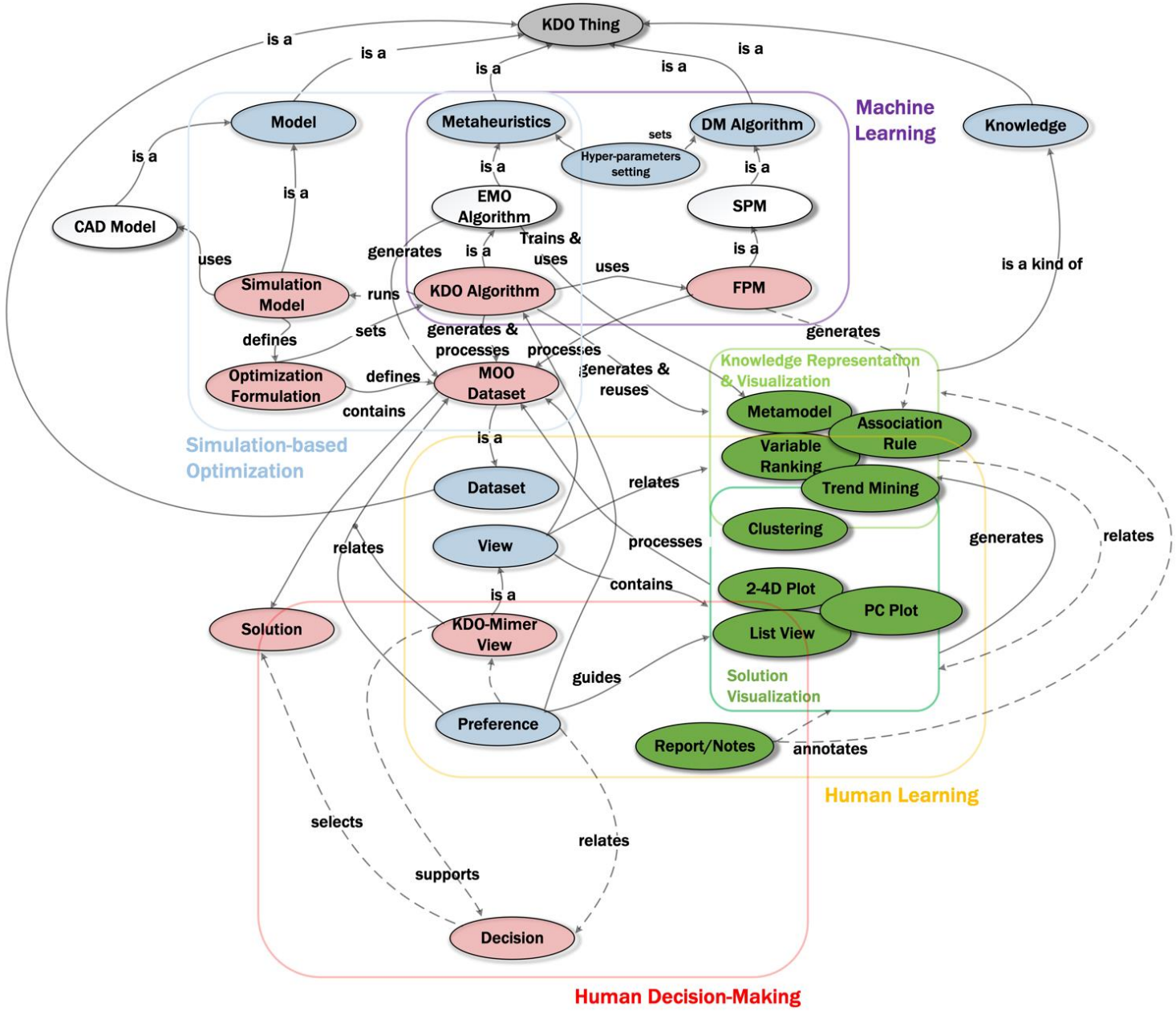
Dispatching Rule Processor

- SBO Candidate (Replication-Wise)
- Switch: SBO or DRL
- DRL Action (Step-Wise)
- Oven Rule

An Ontology

"It is well known that the decision-making process results from communication between the prefrontal cortex (working memory) and hippocampus (long-term memory). However, there are other regions of the brain that play essential roles in making decisions, but their exact mechanisms of action still are unknown."
Moghadam et al. 2019
An Algorithmic Model of Decision Making in the Human Brain





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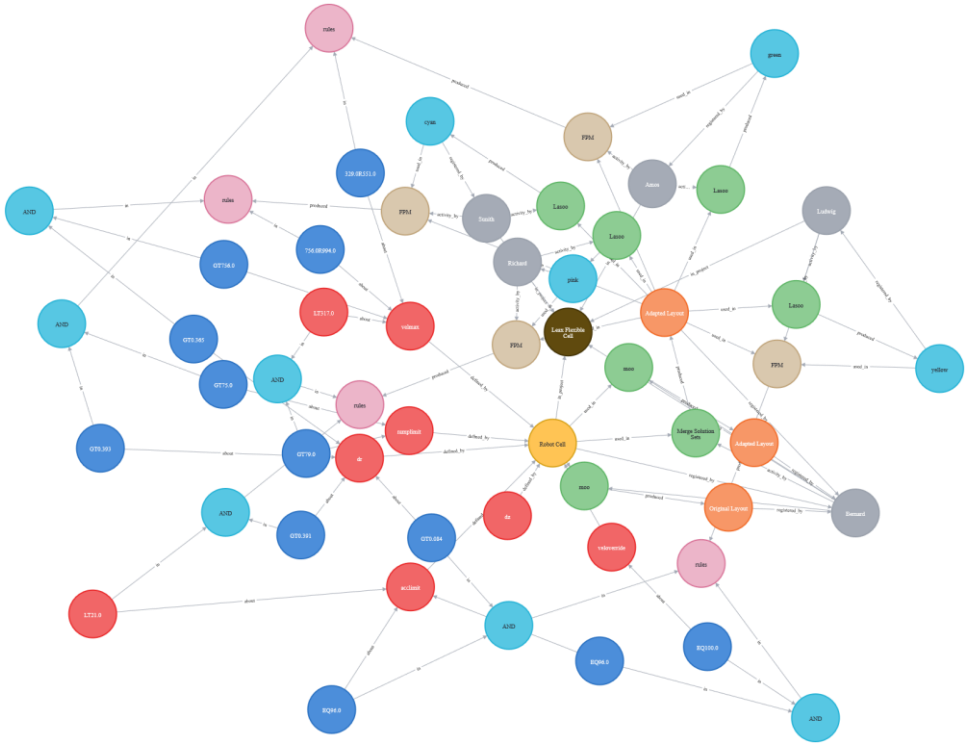
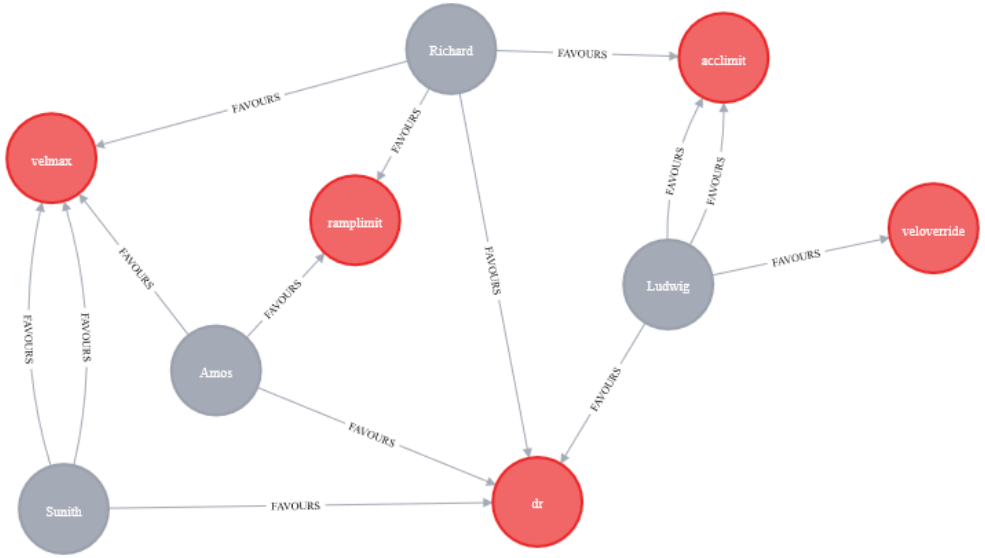
Converting Structured Group Decision Support Activities to Graph Database Queries (Active Research started 2023Q3)

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



Extracting which DM favours which design variables from the KDO data



Key group decision support features aimed by VF-KDO research - transparency, traceability and information sharing to enable:

- *effective communication channels that encourage open and honest dialogue among stakeholders;*
- *diversity of thought and minimize the impact of groupthink.*

Conclusion & Current Work:

Some good results, but not yet there!

- We have demonstrated Deep Reinforcement Learning (DRL) models trained with data-driven, online simulation produce comparable results as multi-objective optimization in industrial scheduling problems that maximize oven utilization, minimize tardiness and energy consumption.
- The research hypothesis is that DRL and high-level AI can be more robust than simple simulation-based optimization in handling anomality/uncertainty that can be embedded in the simulation during training and we are testing it with the EXPLAIN and other company cases.
- We will demonstrate the VF-KDO Knowledge Graph prototype next time!