Data Analytics and Optimization for Manufacture-Circulation Industrial System

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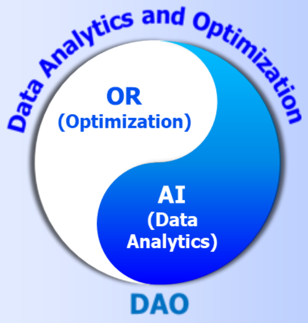
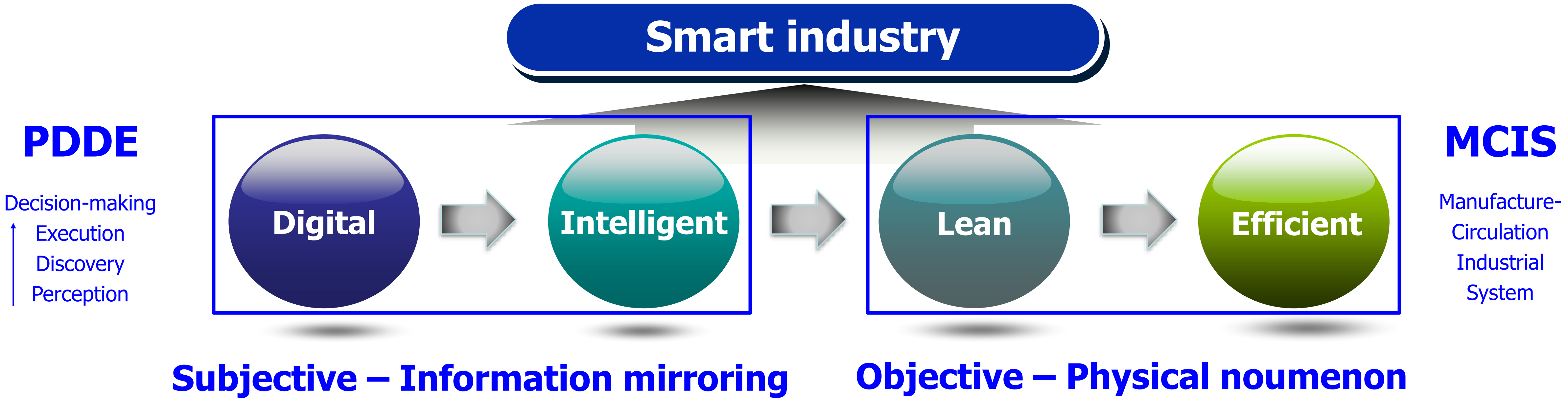
Outline



- **DAO-based PDDE System Technology (H)**
- **Data Analytics and Optimization for Material Science (V)**
- **RDMS-based Quality Analytics and Dynamic Optimization (S)**
- **Full-dimension Organic Management System (E)**
- **DAO & LLM based Design and Simulation for MCIS (M)**

Smart industry

Taking the cyber-physical systems realized by the Internet of Things as carrier, sensors are used to collect on-site perceived data through the network. According to the obtained data, data analytics technology is used to accurately understand, measure, diagnose and forecast the production, logistics and energy flow processes. On this basis, optimal decisions are made on production planning, scheduling, operation and control to realize the intelligent ability of factories.



Data Analytics and Optimization

Systems optimization is not only the key fundamental theory of complex decision-making, but also the core of industrial intelligence, as well as the heart and engine of data analytics.

Decision-making

- Many decision-making problems can be formulated as the following optimization problem:

$$\begin{array}{ll} \max & \mathbf{c}^{\mathrm{T}}\mathbf{x} \\ \textit{subject to} & A\mathbf{x} \leq b \\ & \mathbf{x} \geq \mathbf{0} \\ & \mathbf{x} \in \mathbb{Z}^n \end{array}$$

Data analytics

- Many machine learning problems can be formulated as the following optimization problem:

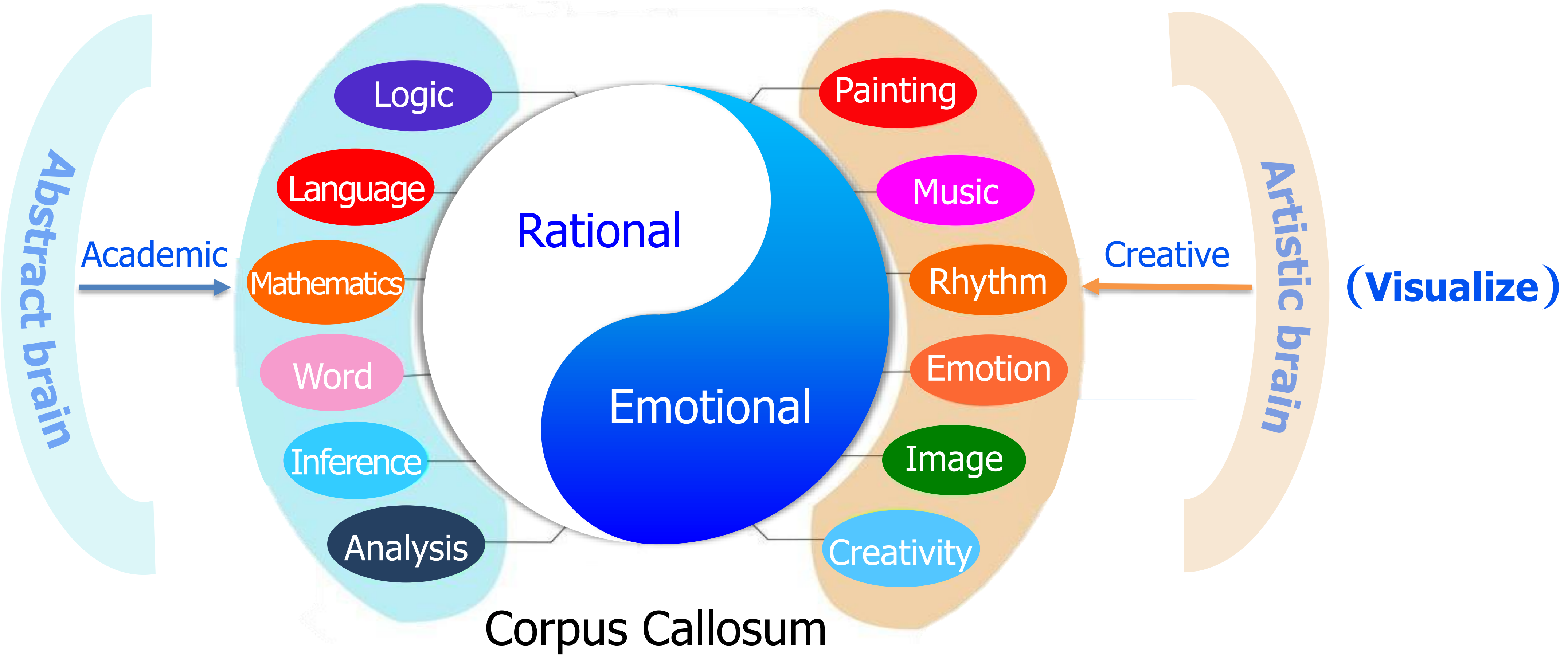
$$\begin{array}{ll} \min\limits_{x} & f(x) \\ \textit{subject to} & g(x) \leq 0 \\ & h(x) = 0 \\ & x \in \Omega \end{array}$$

K. P. Bennett and E. Parrado-Hernández. The interplay of optimization and machine learning research, ***Journal of Machine Learning Research***, 2006, 7: 1265-1281.

Data Analytics and Optimization — DAO based System Modeling

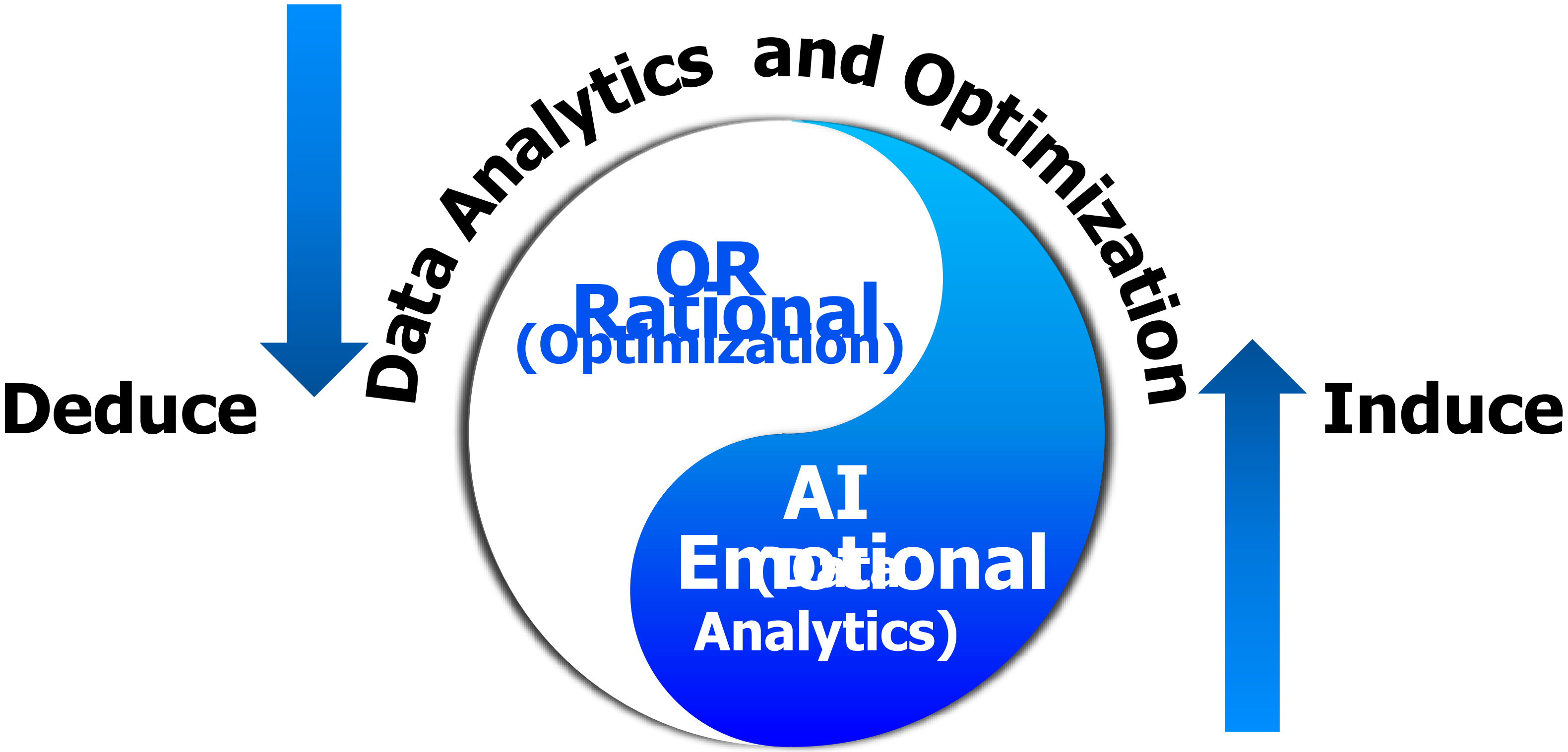
- Perceptual cognition is the basis of rational cognition; and rational cognition is the sublimation of perceptual cognition, which are unified in practice.

Left brain-Rational → Comprehension ← Right brain-Emotional



Data Analytics and Optimization — DAO based System Modeling

Data Analytics and Optimization (DAO)



Brain-inspired Intelligence

L. Tang, Y. Meng. Data analytics and optimization for smart industry. ***Frontiers of Engineering Management***, 2021, 8(2): 157-171.
(**Best Paper Award for 2014~2023**)

Data Analytics and Optimization — DAO based System Modeling

- Mathematical modeling is used to formulate the identifiable and quantifiable parts of the production, logistics and energy optimization problems. Meanwhile, data analytics supplements the mathematical model for constructing the parts that are hardly to model and forming the parameters of the model.

DAO based System Modeling

Optimization (OR)

$$\text{Max } Z = \sum_{j\in P}\sum_{i\in O_j} F_i X_{ij} - \sum_{j\in P}\sum_{i\in O_j}\Big(C_{1ij}X_{ij} + \sum_{k\in O_j\cap R_i} C_{2ik}Y_{ikj}\Big)$$

s.t.

$$\sum_{j\in Q_i} X_{ij} \le 1 \qquad \text{for } i\in N$$

$$\sum_{i\in O_j} h_i X_{ij} \le H \qquad \text{for } j\in P$$

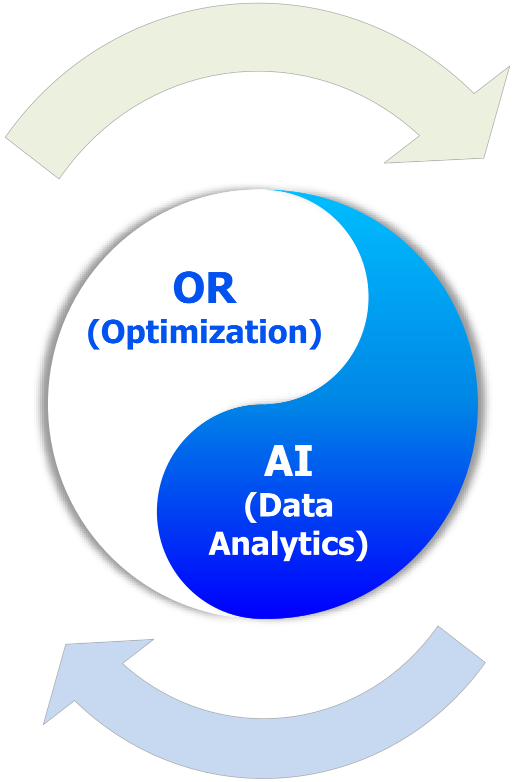
$$\sum_{k\in O_j} Y_{kkj} = 1 \qquad \text{for } j\in P$$

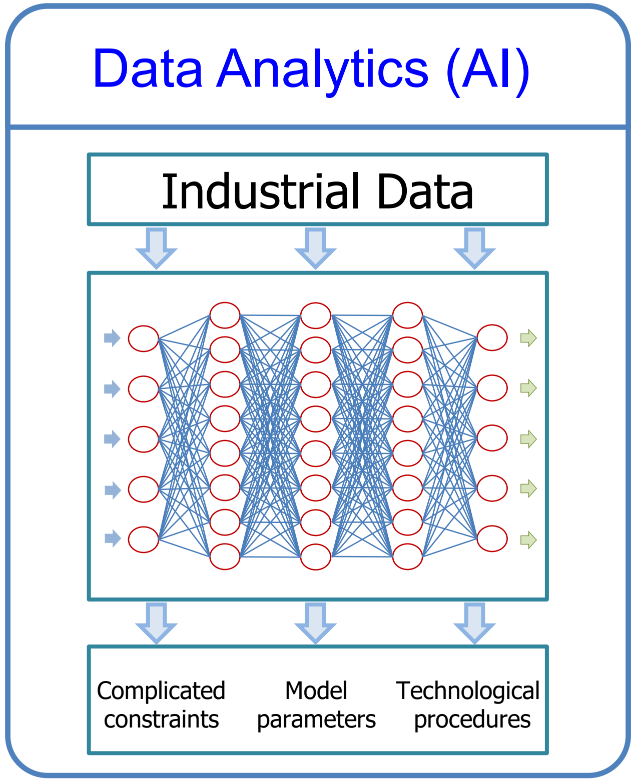
$$Y_{ikj} \le Y_{kkj} \qquad \text{for } j\in P,\ k\in O_j,\ i\in O_j\cap R_k$$

$$X_{ij} = \sum_{k\in O_j\cap R_i} Y_{ikj} \qquad \text{for } j\in P,\ i\in O_j$$

$$X_{ij} \in \{0,1\} \qquad \text{for } j\in P,\ i\in O_j$$

$$Y_{ikj} \in \{0,1\} \qquad \text{for } j\in P,\ k\in O_j,\ i\in O_j\cap R_k$$





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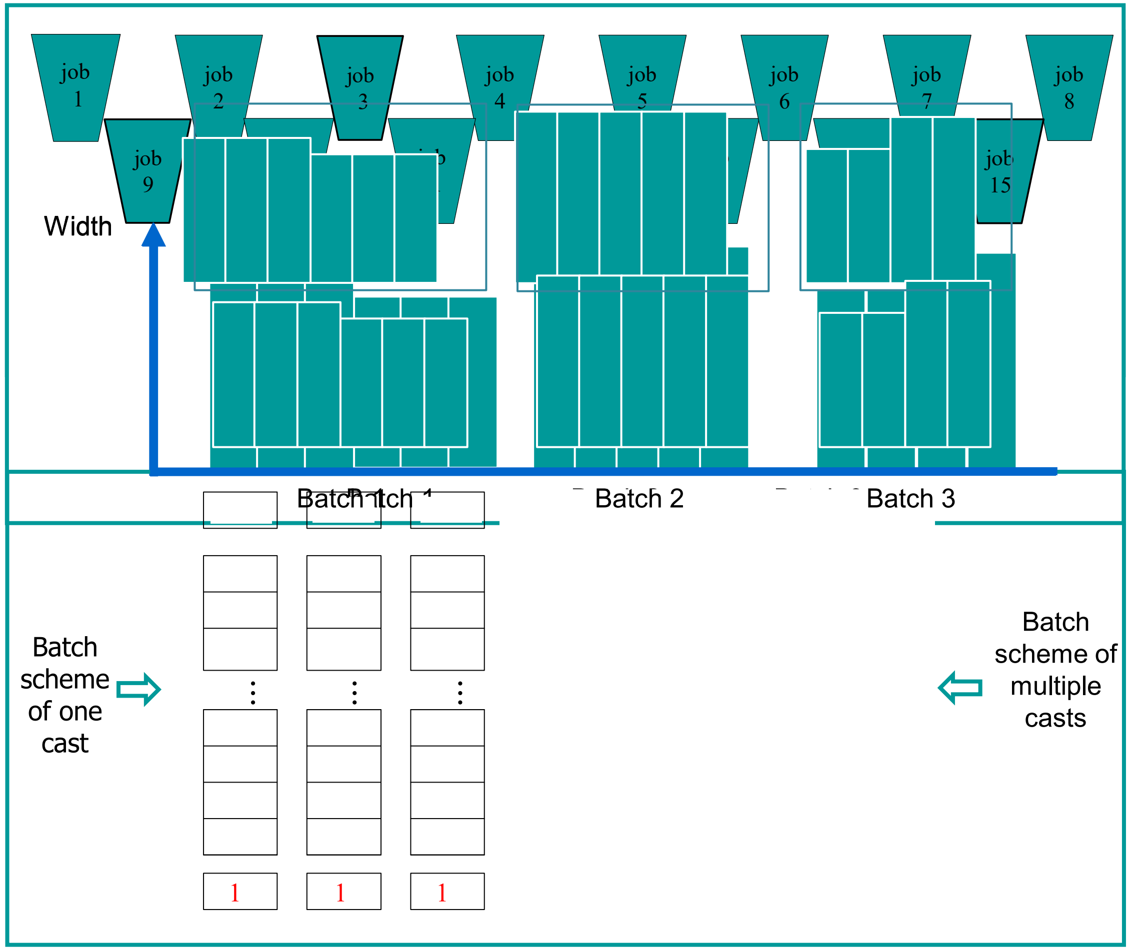
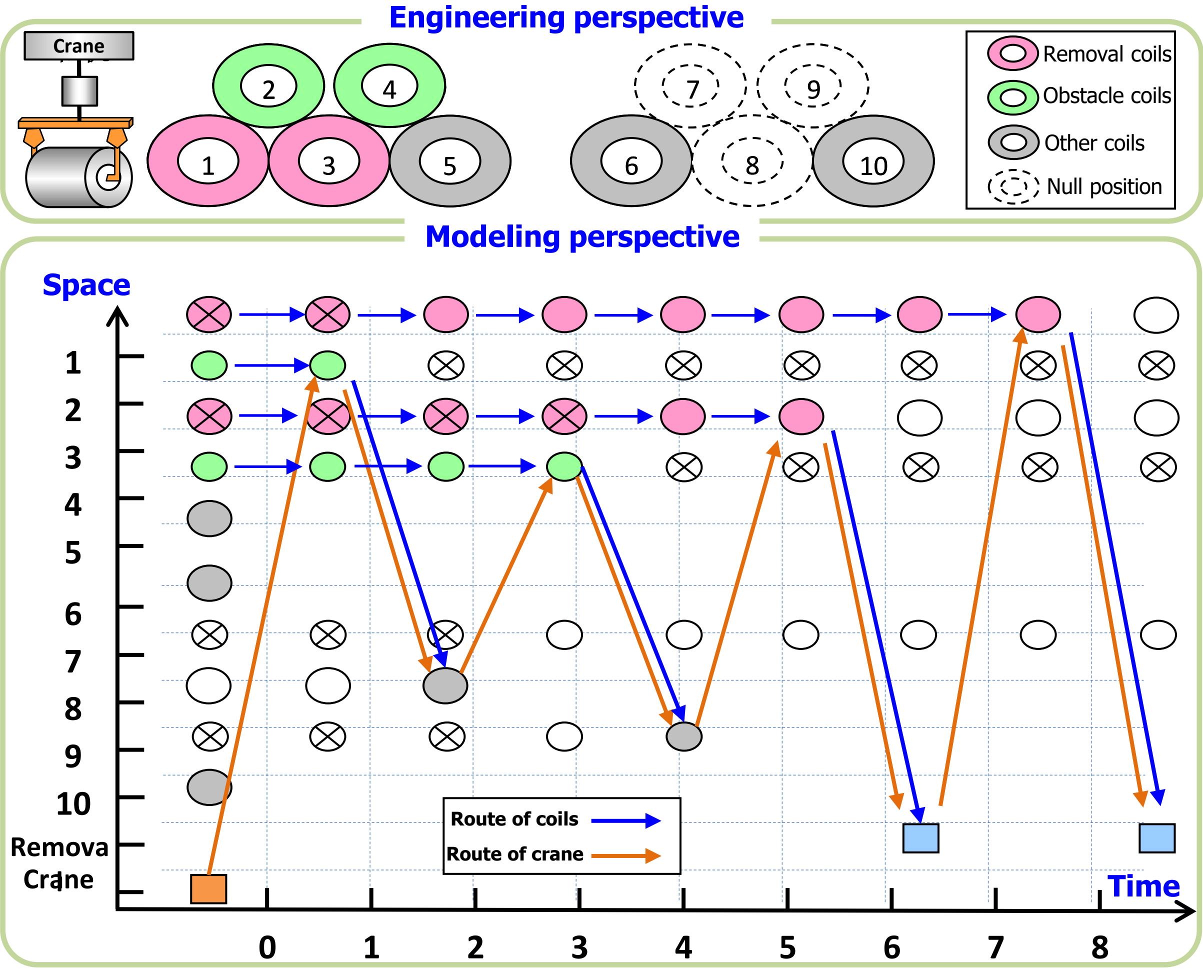
Data Analytics and Optimization — DAO based System Modeling

Production: Set-packing Modeling



Logistics: Space-time Network Flow Modeling



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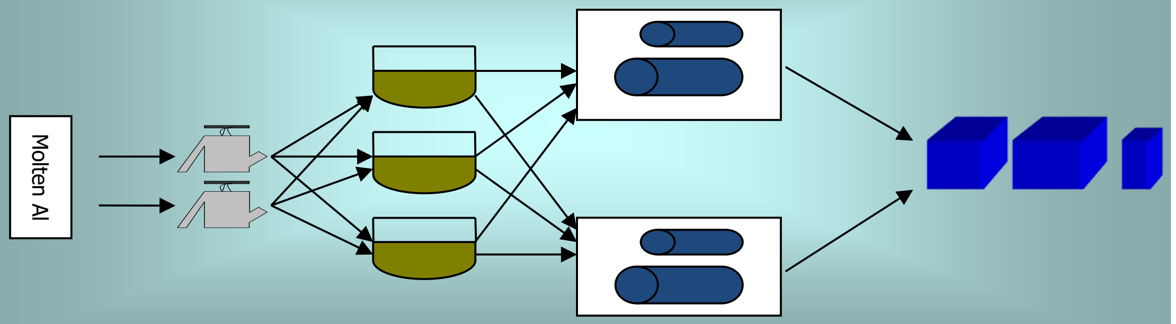
D. Sun, L. Tang, R. Baldacci, Z. Chen. A decomposition method for the group-based quay crane scheduling problem. ***INFORMS Journal on Computing***, 2024, 36(2): 305-704.

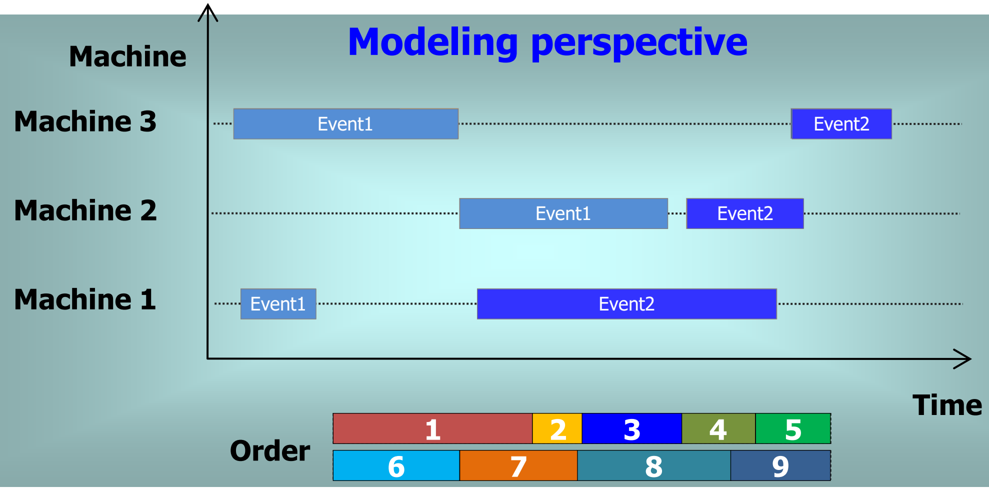
Data Analytics and Optimization — DAO based System Modeling

Energy: Continuous-time Modeling

Engineering perspective



Modeling perspective

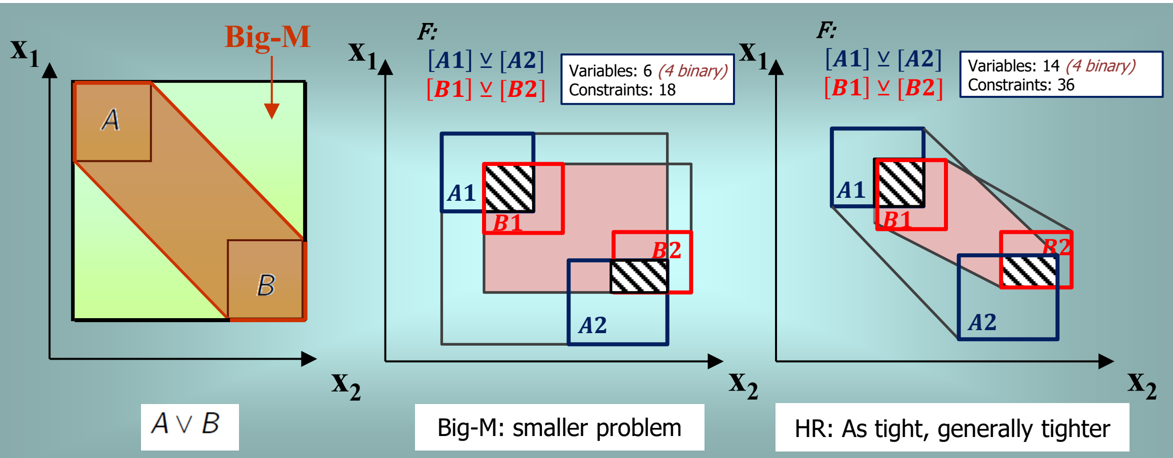


Information: Generalized Disjunctive Programming

$$\min z = f(x) + \sum_{k \in K} c_k$$

$$s.t. \quad g(x) \leq 0 \qquad \Omega(Y) = True$$

$$\bigvee_{i \in D_k} \begin{bmatrix} Y_{ik} \\ r_{ik}(x) \leq 0 \\ c_k = \gamma_{ik} \end{bmatrix} \qquad \begin{array}{l} x^{lo} \leq x \leq x^{up} \\ x \in \mathbb{R}^n, c_k \in \mathbb{R}^1, \\ Y_{ik} \in \{True, False\} \end{array}$$



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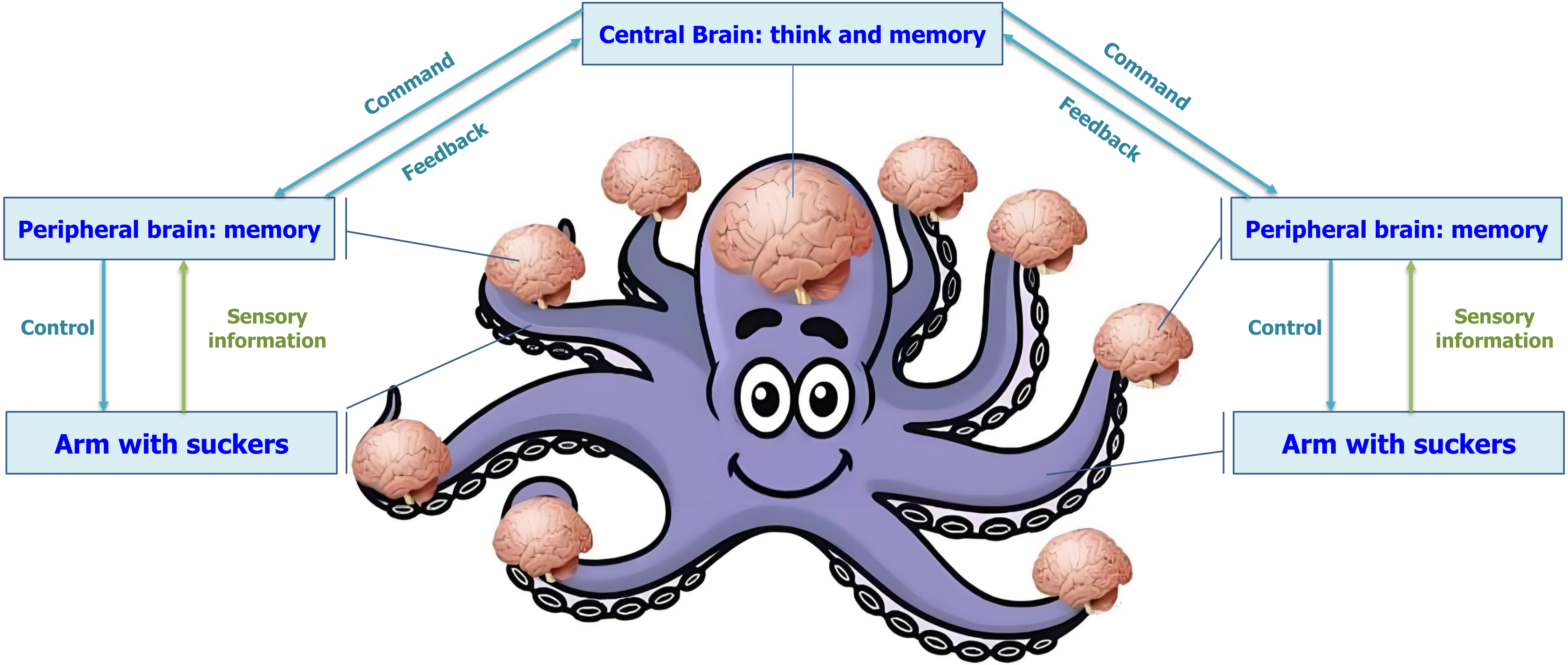
I.E. Grossmann, F. Trespalacios. Systematic modeling of discrete-continuous optimization models through generalized disjunctive programming. ***AIChE***, 2013, 59(9): 3276 - 3295

Data Analytics and Optimization — DAO based Solution



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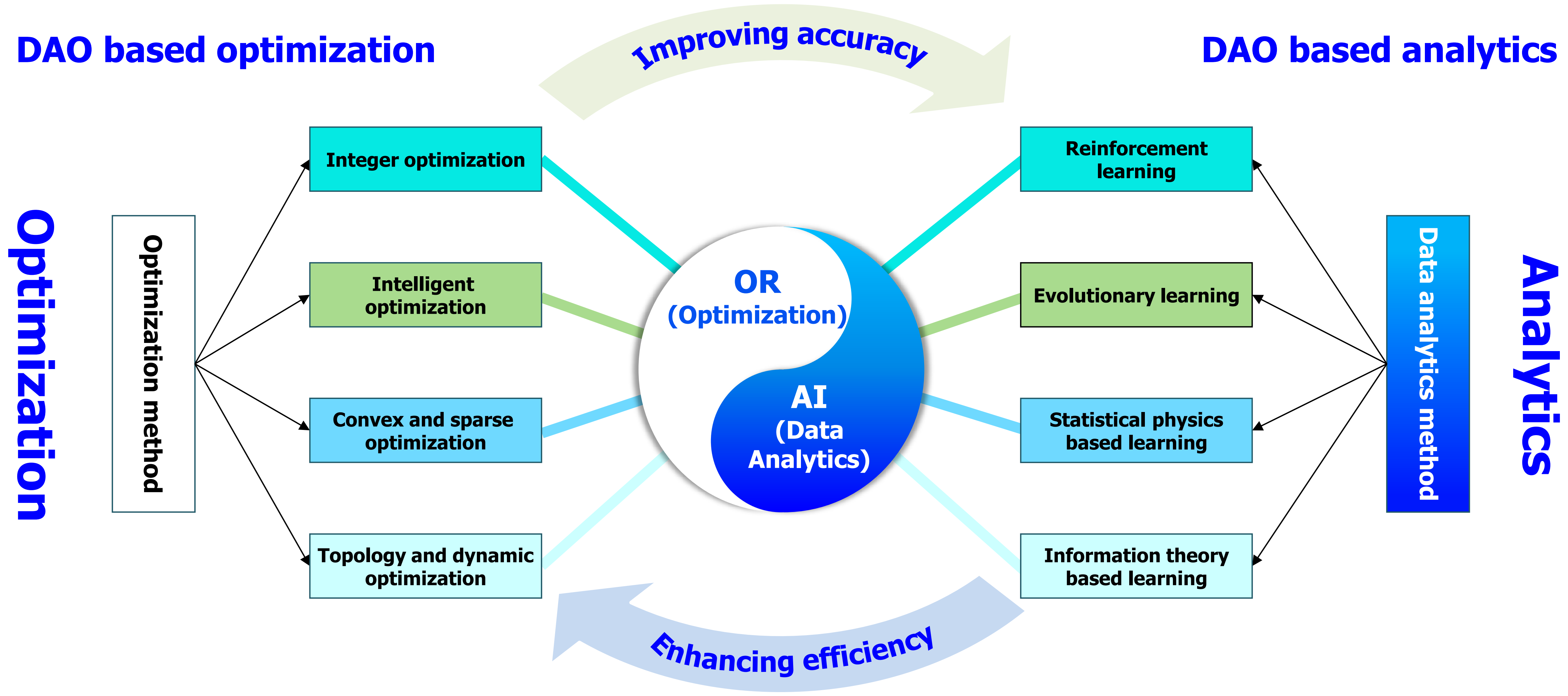

DAO based Octopus-topology Solution

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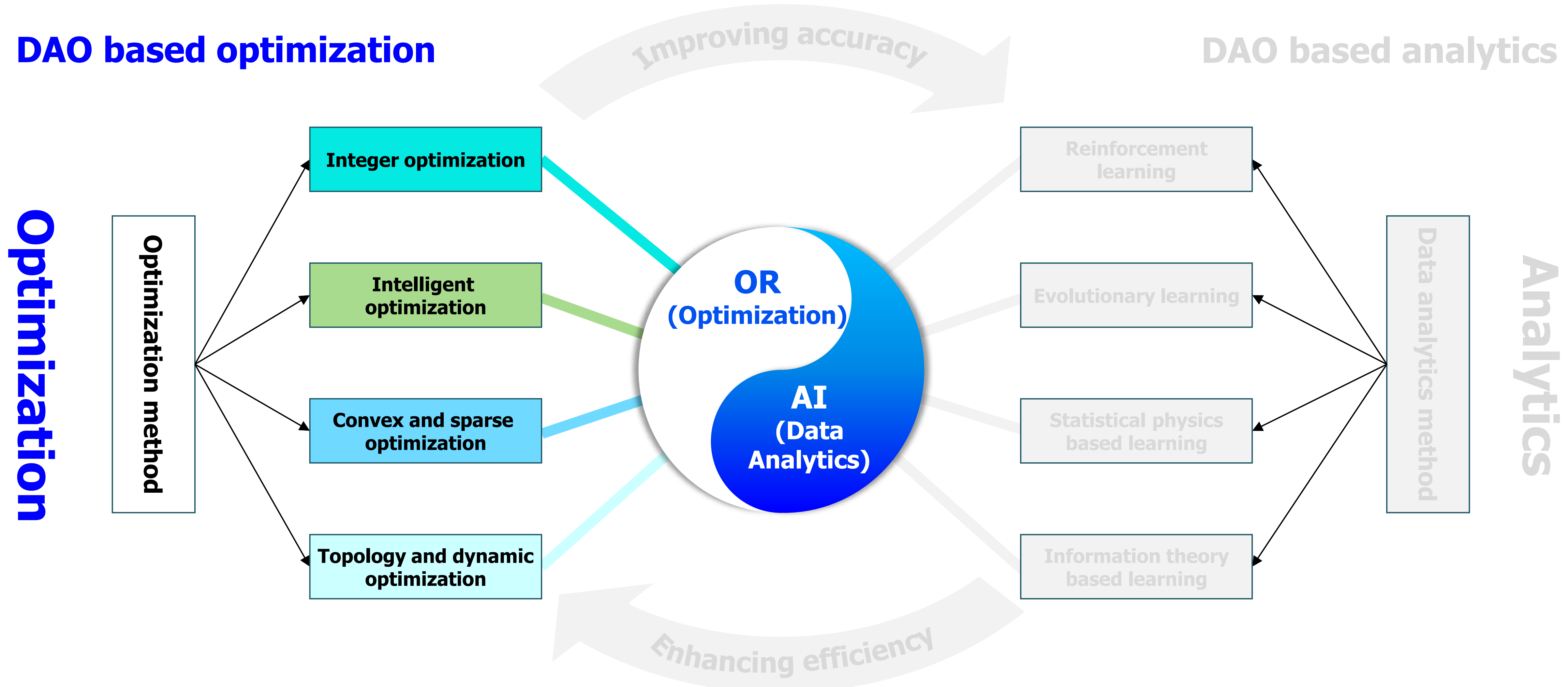

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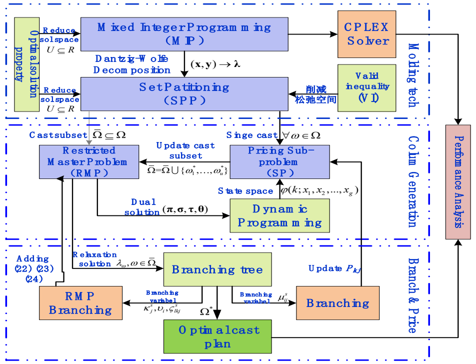
Data Analytics and Optimization — DAO based Solution

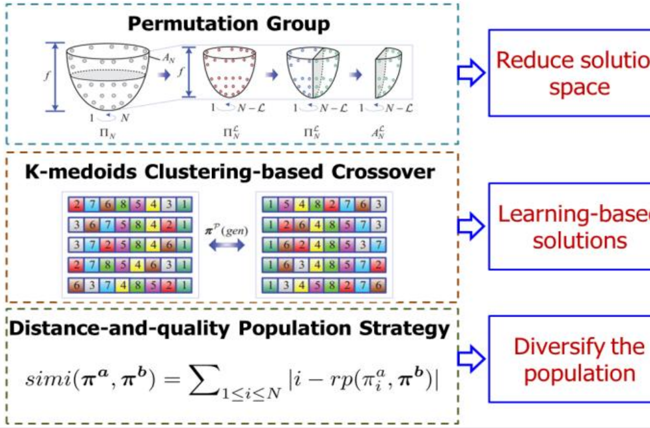
Integer optimization

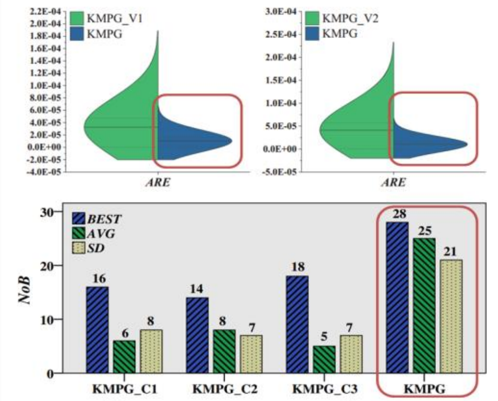
- A Branch & Price approach is proposed based on set packing model.
- Discover the trapezoidal feature of the cost structure and construct a new low-dimensional dynamic programming algorithm, which overcomes the high-dimensional feature of the conventional dynamic programming algorithm.
- Propose a multi-layer branching strategy with sub-problem structure.
- For the first time, it realizes the optimal solving of the same kind of problem.

Branch & Price



Intelligent optimization



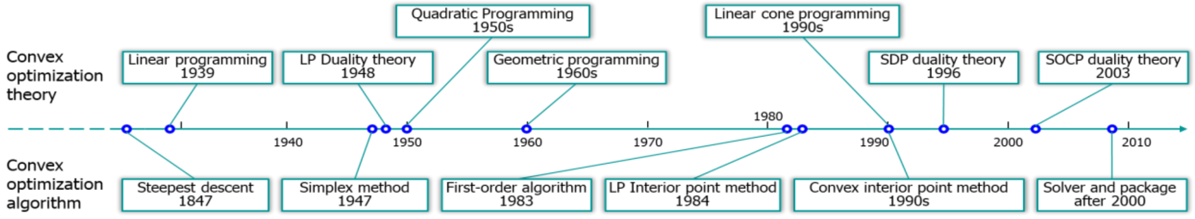


Convex and sparse optimization

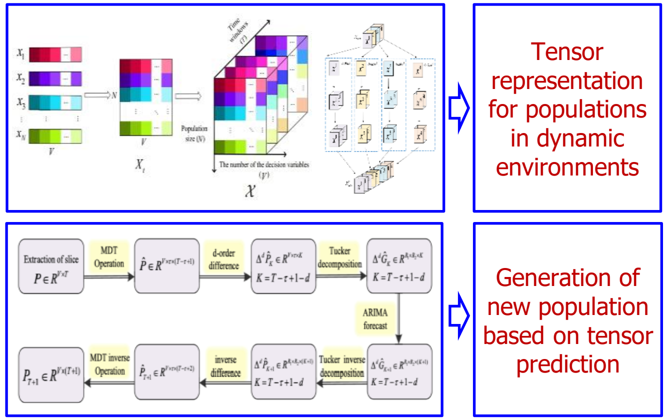
A general convex optimization problem is

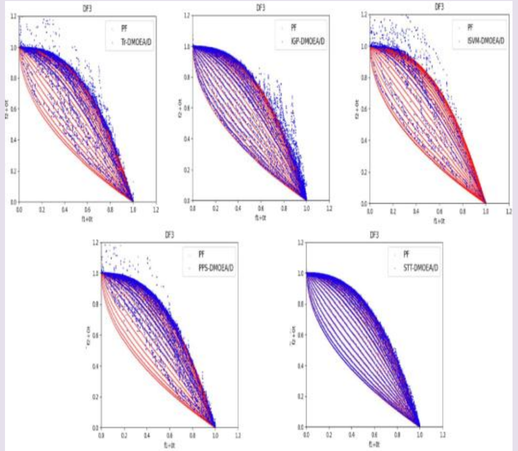
$$
\begin{aligned}
\min \quad & f_0(x) \\
s.t. \quad & f_i(x) \le 0, i = 1,2,\ldots,m \\
& h_i(x) = 0, i = 1,2,\ldots,p
\end{aligned}
$$

where $f_0, f_1, \ldots, f_m : \mathrm{R}^n \to \mathrm{R}$ are convex functions and $h_1, h_2, \ldots, h_p : \mathrm{R}^n \to \mathrm{R}$ are affine.



Topology and dynamic optimization





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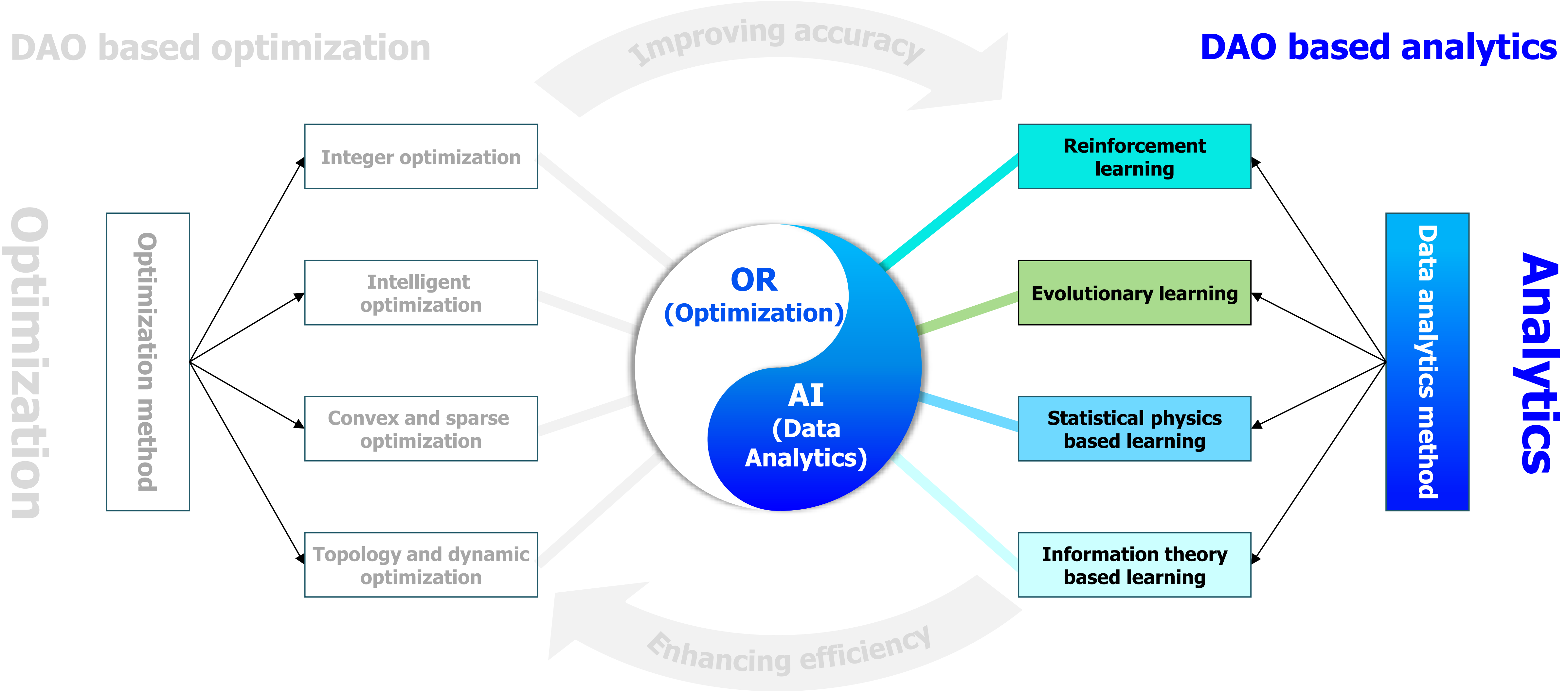
L. Tang, T. Li, Y. Meng, J. Liu. Searching in symmetric solution space ... *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2025. (**IF: 18.6**)
L. Tang, Z. Li and J. Hao. Solving the single row facility layout ... permutation group. *IEEE Transactions on Evolutionary Computation*, 2023, 27(2): 251-265. (**IF: 12**)
X. Wang, Y. Zhao, L. Tang and X. Yao. MOEA/D with spatial-temporal ... multiobjective optimization. *IEEE Transactions on Evolutionary Computation*, 2025, 29(3): 764-778.

Data Analytics and Optimization — DAO based Solution



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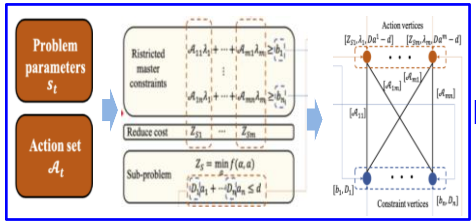
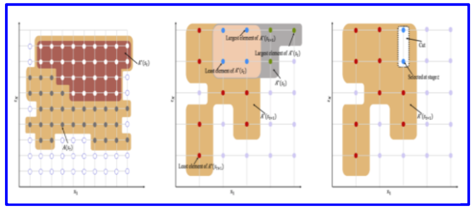
Data Analytics and Optimization — DAO based Solution

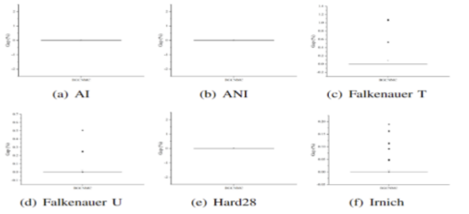
Reinforcement learning



Column generation based Markov decision process

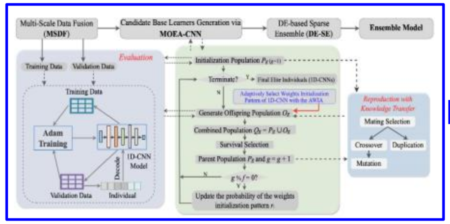


Monotonicity cut based on supermodularity



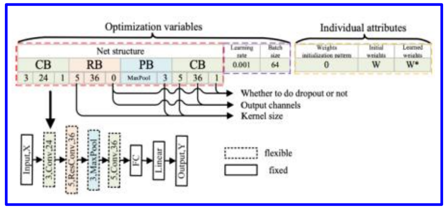
alg 1 \ alg 2	RG	FG	FFD	BGCN	BGCNMC	PTR	HRL-GPN	RRMCTS
RG	-	4	8	4	2	10	11	11
FG	7	-	8	3	3	9	11	11
FFD	1	3	-	3	1	7	11	11
BGCN	7	5	8	-	3	9	11	11
BGCNMC	6	8	9	5	-	10	11	11
PTR	1	0	1	0	1	-	11	11
HRL-GPN	2	2	2	2	2	2	-	4
RRMCTS	2	2	2	2	2	2	9	-

Evolutionary learning

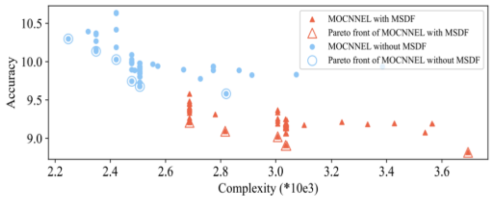


Multi-objective evolutionary ensemble learning framework

Category	Method	R^2 Best	R^2 $Mean_{\pm St.dev}$	ARE Best	ARE $Mean_{\pm St.dev}$	RMSE Best	RMSE $Mean_{\pm St.dev}$
Single learner	BPNN [45]	6.22e-1	$5.26e\text{-}1_{\pm 5.41e-2}(+)$	1.42e-2	$1.62e\text{-}2_{\pm 8.79e-4}(+)$	11.62e+0	$13.15e{+}0_{\pm 8.92e-1}(+)$
	1D-CNN [33]	7.06e-1	$6.26e\text{-}1_{\pm 4.96e-2}(+)$	1.32e-2	$1.44e\text{-}2_{\pm 7.64e-4}(+)$	10.17e+0	$11.66e{+}0_{\pm 7.85e-1}(+)$
Traditional ensemble method	Adaboost_1D-CNN [46]	7.46e-1	$6.69e\text{-}1_{\pm 3.77e-2}(+)$	1.27e-2	$1.38e\text{-}2_{\pm 6.92e-4}(+)$	9.64e+0	$10.98e{+}0_{\pm 7.70e-1}(+)$
	Bagging_1D-CNN [47]	7.32e-1	$6.51e\text{-}1_{\pm 4.83e-2}(+)$	1.26e-2	$1.37e\text{-}2_{\pm 6.89e-4}(+)$	9.71e+0	$11.27e{+}0_{\pm 8.72e-1}(+)$
	RF [6]	7.56e-1	$6.81e\text{-}1_{\pm 4.91e-2}(+)$	1.17e-2	$1.30e\text{-}2_{\pm 6.60e-4}(+)$	9.31e+0	$10.77e{+}0_{\pm 8.94e-1}(+)$
Powerful ensemble learning method	MO_SELM [21]	6.40e-1	$5.47e\text{-}1_{\pm 4.35e-2}(+)$	1.49e-2	$1.61e\text{-}2_{\pm 5.64e-4}(+)$	11.66e+0	$12.85e{+}0_{\pm 7.44e-1}(+)$
	NSDE_EL_ANN [8]	7.15e-1	$5.64e\text{-}1_{\pm 8.22e-2}(+)$	1.41e-2	$1.64e\text{-}2_{\pm 1.61e-3}(+)$	10.59e+0	$12.57e{+}0_{\pm 1.20e+0}(+)$
	MOSNE-EFS [18]	7.06e-1	$6.48e\text{-}1_{\pm 3.45e-2}(+)$	1.26e-2	$1.35e\text{-}2_{\pm 4.09e-4}(+)$	9.99e+0	$10.92e{+}0_{\pm 5.36e-1}(+)$
	CNE [49]	6.97e-1	$5.80e\text{-}1_{\pm 5.56e-2}(+)$	1.25e-2	$1.40e\text{-}2_{\pm 7.62e-4}(+)$	9.88e+0	$12.38e{+}0_{\pm 1.13e+0}(+)$
	EF [9]	7.59e-1	$6.96e\text{-}1_{\pm 3.61e-2}(+)$	1.19e-2	$1.30e\text{-}2_{\pm 5.72e-4}(+)$	9.43e+0	$10.52e{+}0_{\pm 7.28e-1}(+)$
	MOENE-EFS [3]	7.25e-1	$5.85e\text{-}1_{\pm 6.03e-2}(+)$	1.34e-2	$1.55e\text{-}2_{\pm 7.58e-4}(+)$	10.40e+0	$12.28e{+}0_{\pm 8.51e-1}(+)$
Our method	MOCNNEL-MSDF	7.74e-1	$7.18e\text{-}1_{\pm 3.22e-2}$	1.16e-2	$1.25e\text{-}2_{\pm 5.72e-4}$	9.19e+0	$10.13e{+}0_{\pm 6.63e-1}$

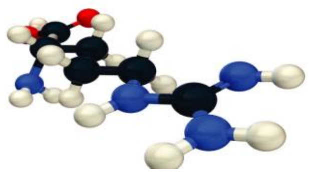


Network architecture encoding and learning based crossover

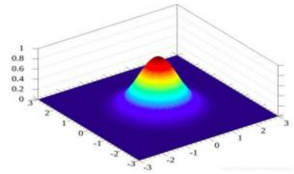


Statistical physics based learning

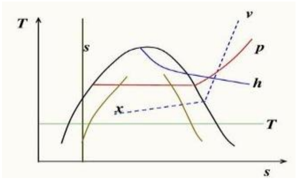
- Based on the theory of statistical physics, the correlation is established between the movement of a large number of microscopic particles and the characteristics of macroscopic behaviors, corresponding microscopic particles to data, and macroscopic behaviors to knowledge, and an explainable learning model with parameters with physical meaning is constructed.



Microscopic



Statistical distribution



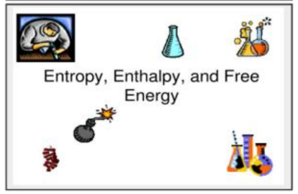
Macroscopic

Information theory based learning

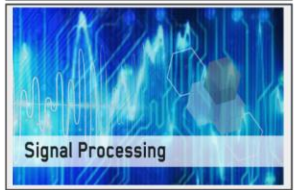
- Several important concepts related to information theory are always presented in machine learning: information entropy, information gain, information gain ratio, etc.
- The applications of information theory in machine learning are mainly in the construction of loss functions, the construction of models, and the research of deep learning interpretability.

Coding Theory

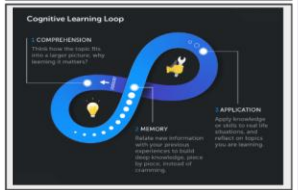
Entropic-Enthalpy Learning



Signal Processing



Cognitive Learning



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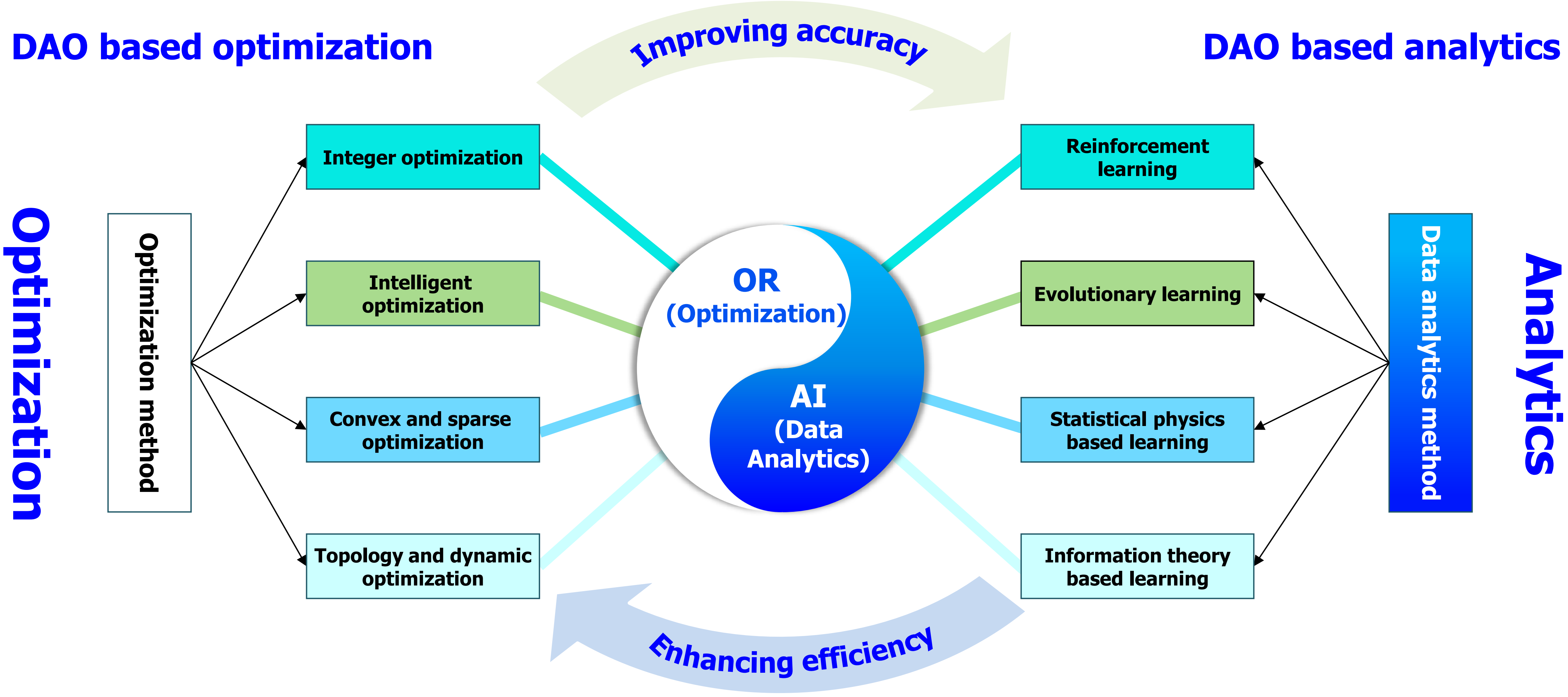
X. Wang, J. Zhang, L. Tang, Y. Liu. Evolutionary direction learning with multivariate Gaussian probabilistic model for multiobjective optimization. ***IEEE Transactions on Evolutionary Computation***, 2025.

Data Analytics and Optimization — DAO based Solution



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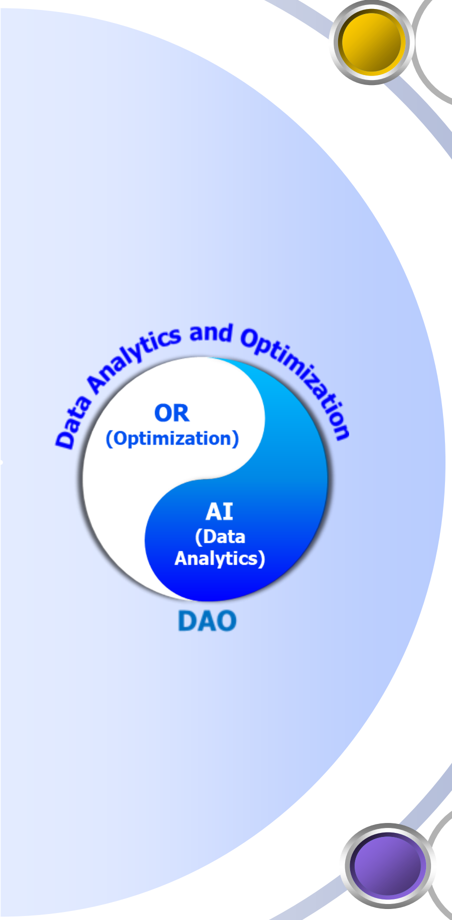

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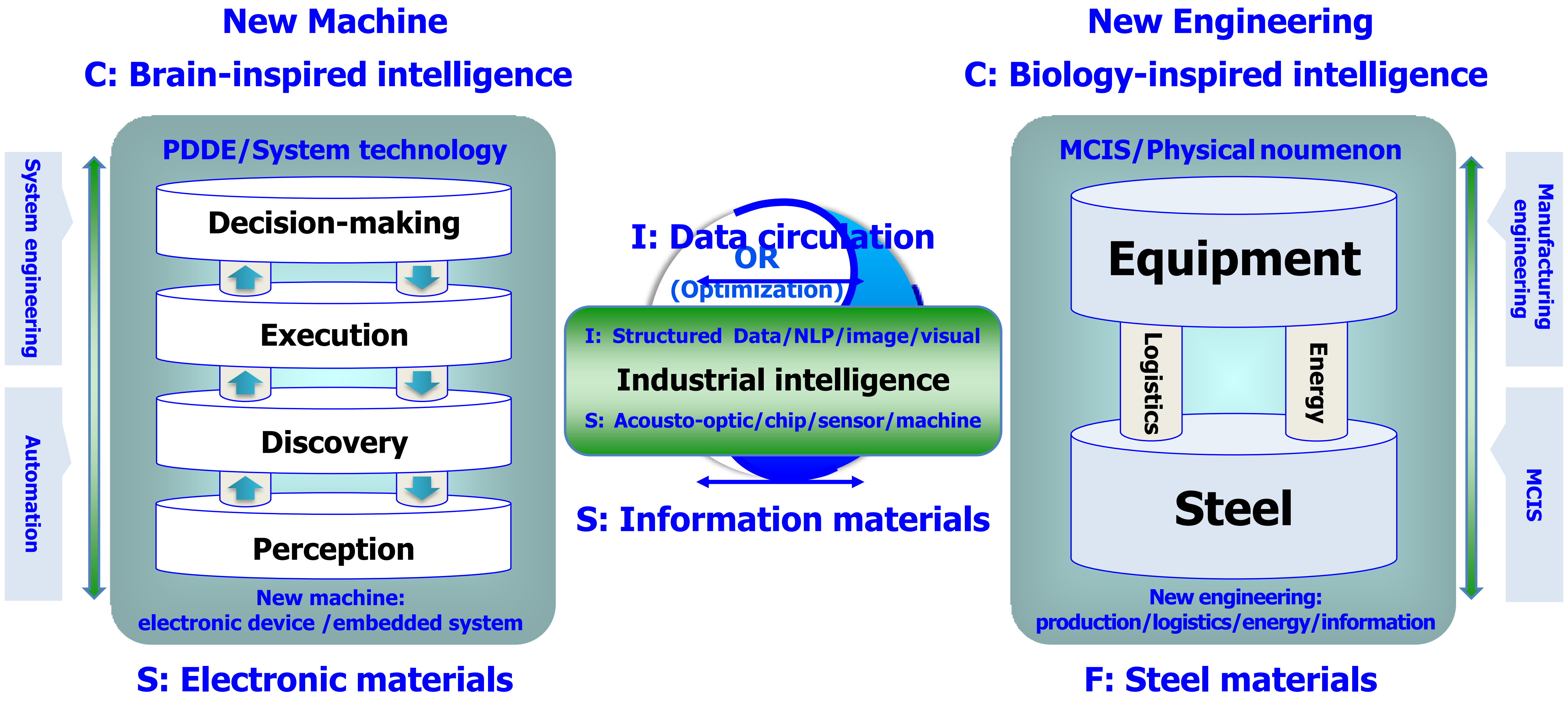
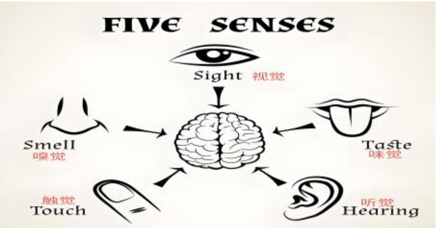


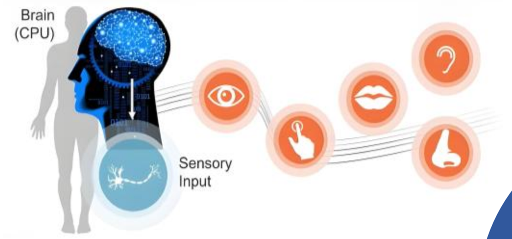
H = *Hierarchy* + *Human* = Brain-inspired intelligence (PDDE) + Industrial intelligence (SI) + Biology-inspired intelligence (MCIS)

1. DAO-based PDDE System Technology (H)

Perception (P)

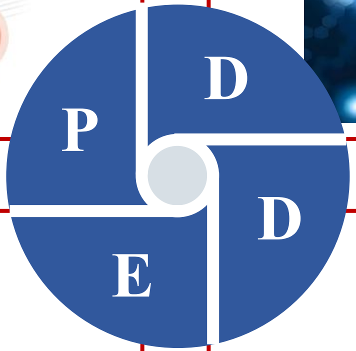
- The origin of cognition, sensory systems (such as vision, hearing, touch, and taste) convert external stimuli into neural signals via receptors





Discovery (D)

- Signals are transmitted to association cortex (e.g., prefrontal and parietal), combined with memory and experience for integration and cognitive modeling

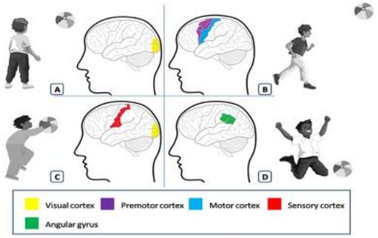


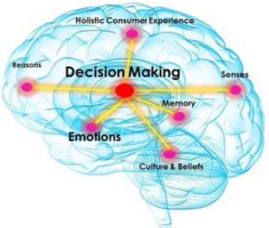
Execution (E)

- Motor cortex transforms decisions into action commands, basal ganglia regulate initiation, force and coordination, with feedback via thalamus

Decision (D)

- Decision-making involves cooperation of multiple neural systems, with synaptic connections in cortical circuits supporting learning and task decision





1. DAO-based PDDE System Technology (H)

Full-dimension Organic System Intelligence

P
D
D
E

P D D E

Industrial intelligence

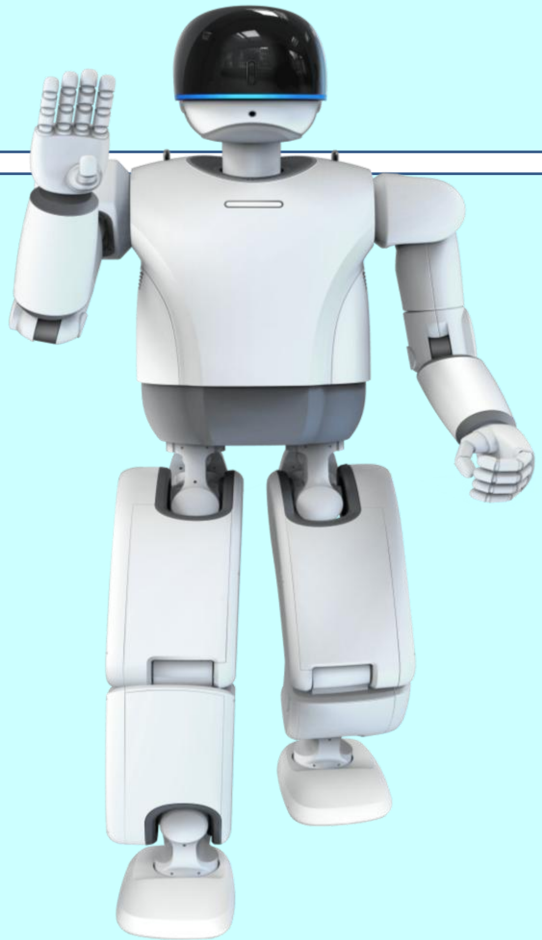
Industrial intelligence

Triple transfer and one feedback

Triple transfer and one feedback

Brain

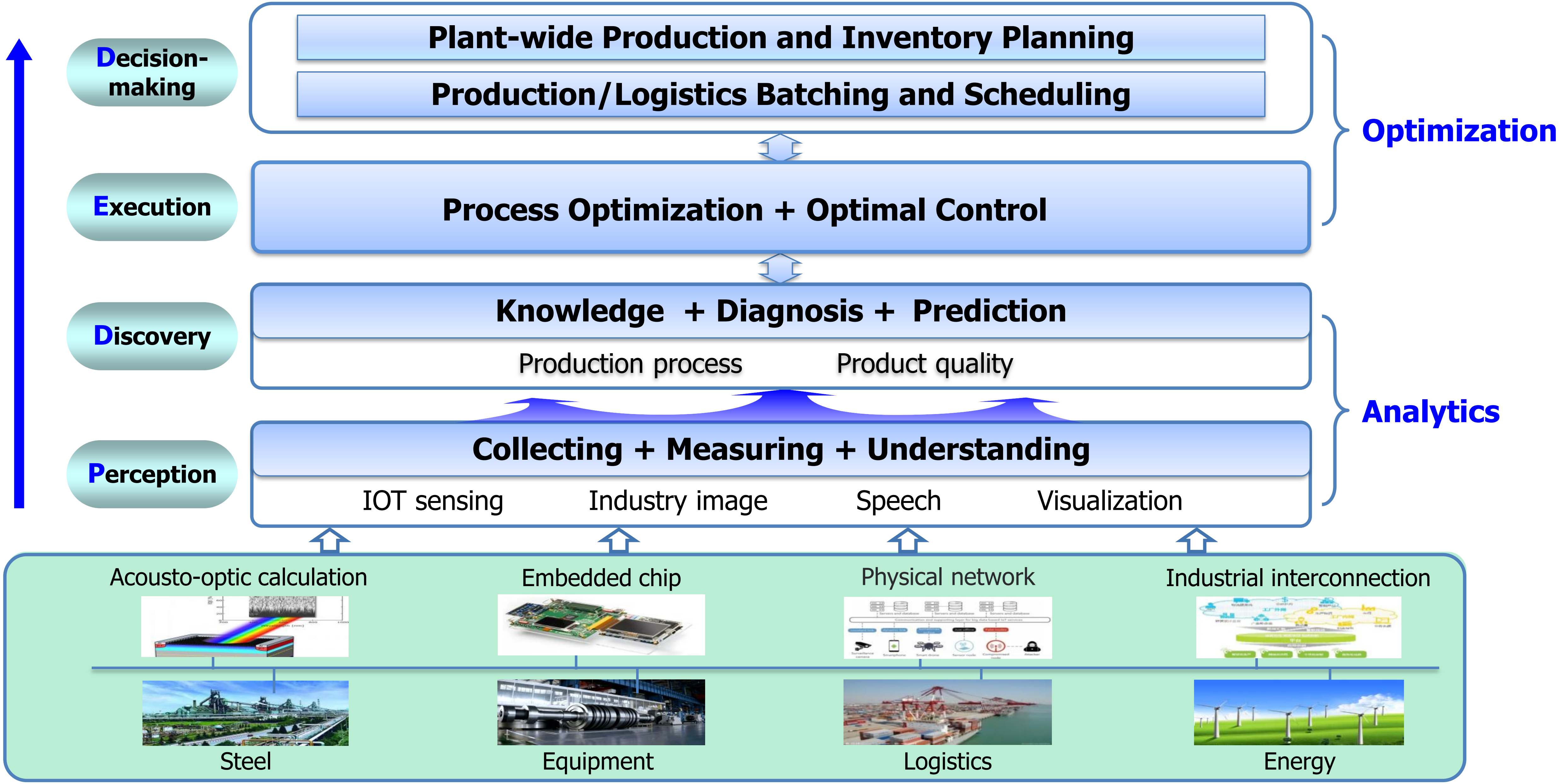
Body



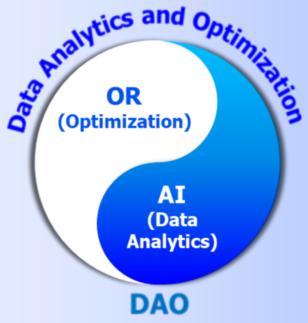
P
D
D
E

M
C
I
S

1. DAO-based PDDE System Technology (H)

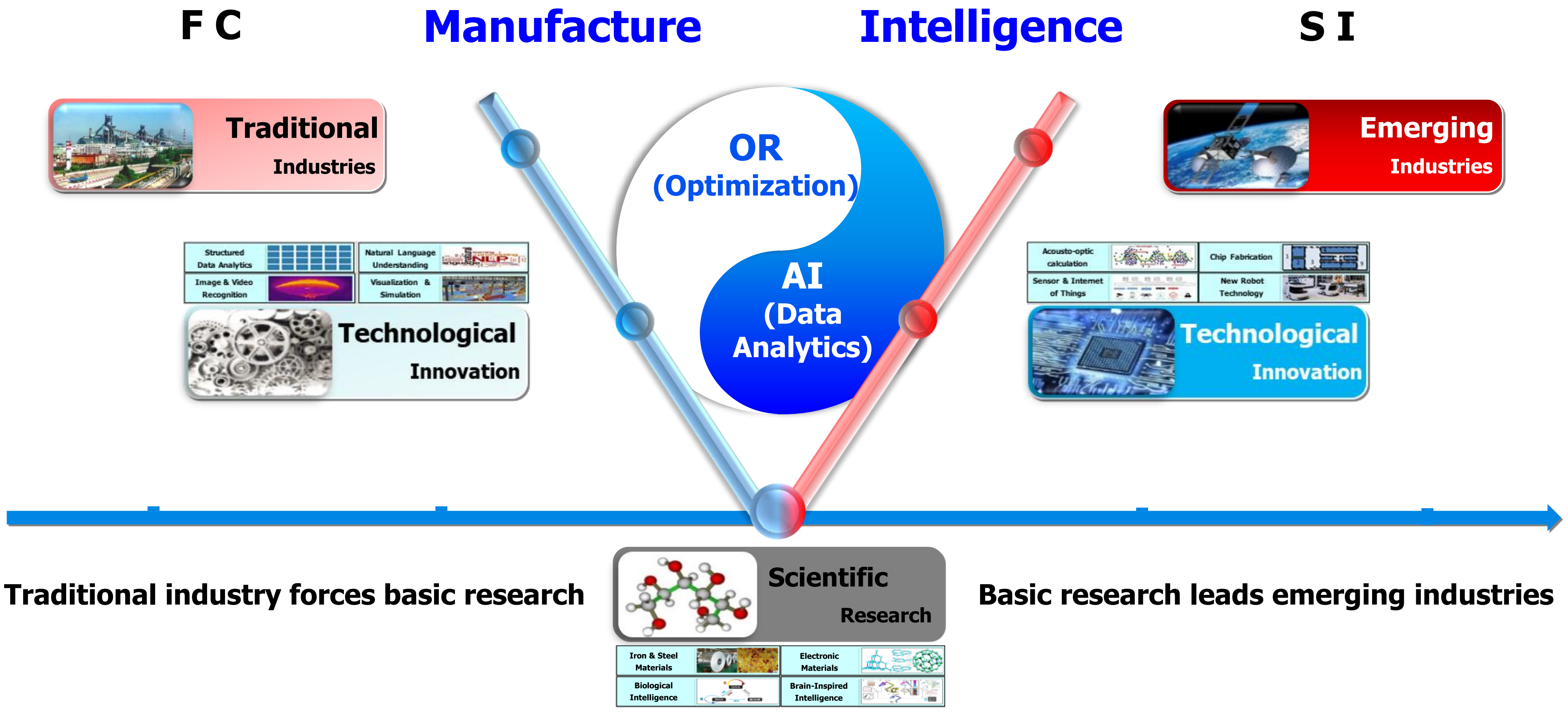


Outline



- DAO-based PDDE System Technology (H)
- **Data Analytics and Optimization for Material Science (V)**
- RDMS-based Quality Analytics and Dynamic Optimization (S)
- Full-dimension Organic Management System (E)
- DAO & LLM based Design and Simulation for MCIS (M)

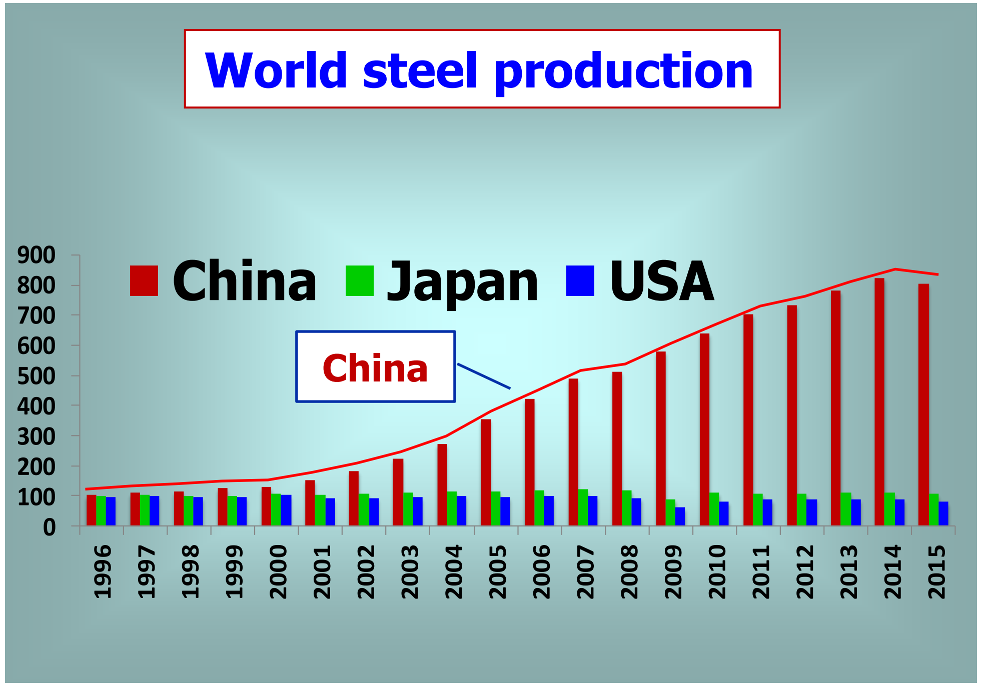
2. Data Analytics and Optimization for Material Science (V)

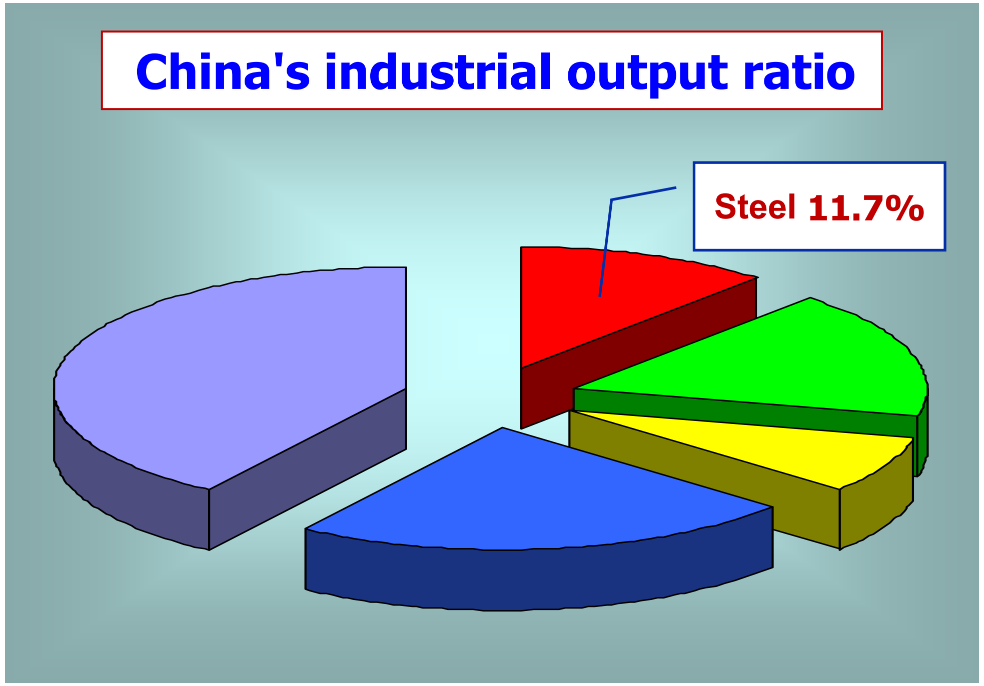


V （*Valley*） = Engineering + Technology + Science

2. Data Analytics and Optimization for Material Science (V)

- China has been the largest steel producer in the world for the last twenty consecutive years.
- In 2024, China's steel output has reached about 1.005 billion tons, accounting for about 53.3% of the world's steel output.
- Steel industry has been one of the pillar industries in China’s national economy.

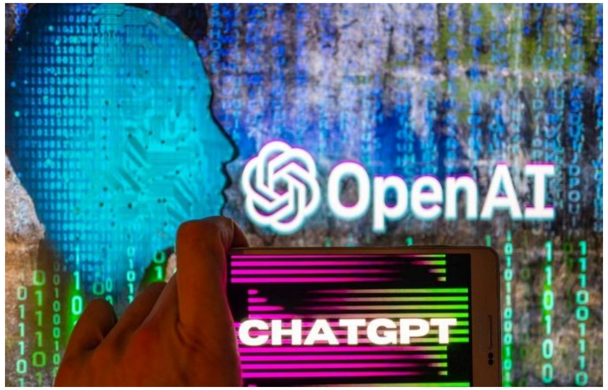


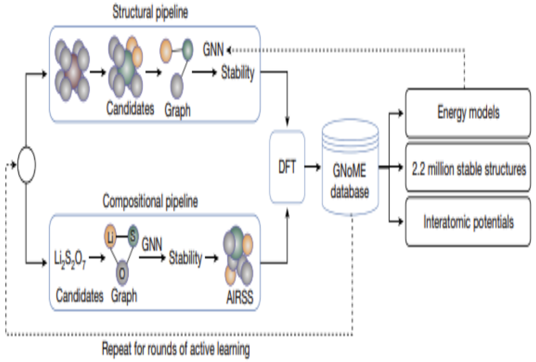


2. Data Analytics and Optimization for Material Science (V) — Large Language Model

Material Discovery

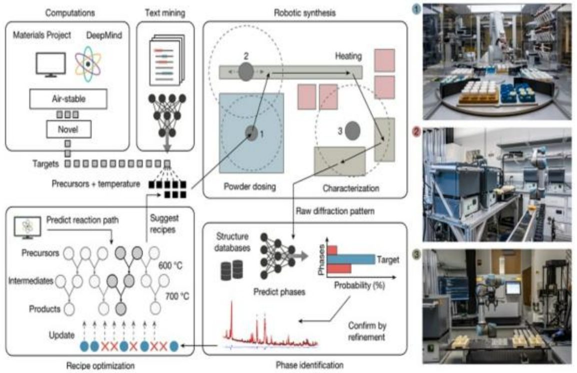
- **Model Overview:** The GNoME model developed by the Google DeepMind team has achieved remarkable results in materials science.
- **Crystalline Structure Discovery:** Based on the large language model, it has found the number of crystalline structures over 45 times than history.
- **Stability Prediction Efficiency:** The discovery rate of material stability prediction has increased by 30% compared to previous studies.





Material Synthesis

- **Platform Overview:** A-Lab is an autonomous platform designed to bridge the gap between computational material screening and experimental realization.
- **Experimental Capability:** A-Lab is able to decide for itself how to synthesize the target material, conducting 355 experiments in 17 days.
- **Synthesis Efficiency:** It successfully synthesized 41 of 58 compounds, which remarkably enhanced the synthesis efficiency.

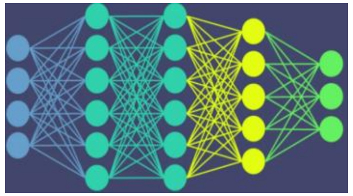


Merchant, A., Batzner, S., Schoenholz, S.S. et al. Scaling Deep Learning for Materials Discovery. *Nature*, 2023, 624: 80–85.
Szymanski, N.J., Rendy, B., Fei, Y. et al. An autonomous laboratory for the accelerated synthesis of novel materials *Nature*, 2023, 624: 86–91.

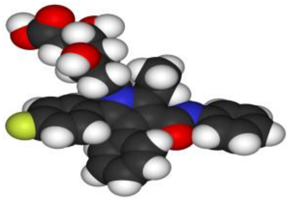
2. Data Analytics and Optimization for Material Science (V) — Steel Material

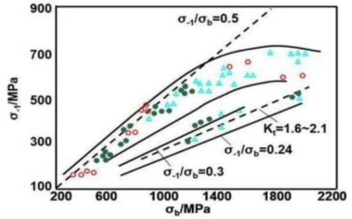
Material Design

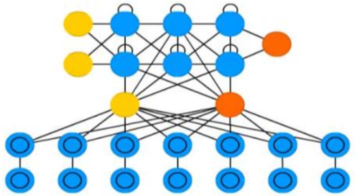
- Metallurgical equipment: Topology-optimized steel design enhances metallurgical equipment performance and durability.
- Logistics equipment: Topology-driven lightweight steel enhances logistics equipment performance.
- Energy equipment: Steel material based on data-driven and mechanical model ensures energy equipment safety.

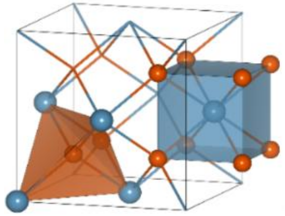


Fully Connected Network



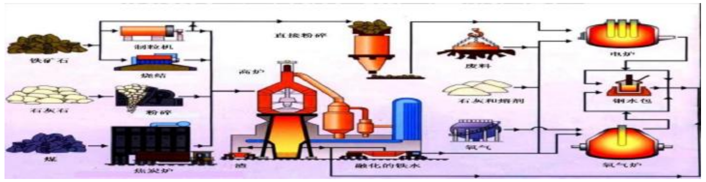




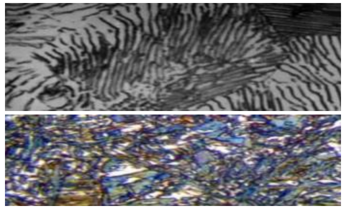


Process Design

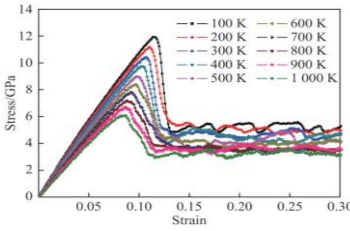
- Process design: Precise process control enables superior material performance and functionality.
- Analytics model: The material analytics model serves as the basis for process optimization. It is built using mechanism and data-driven model.
- Dynamic optimization: Model parameters are optimized by a dynamic multi-objective evolutionary algorithm.



Steelmaking process



Metallurgical organization



Mechanical properties

2. Data Analytics and Optimization for Material Science (V) — Steel Material

Steel Material Design and Optimization Software System

Si:0.2

Component search | Advanced Search | New material design | Performance prediction

Component

Brand	C/%	Si/%	Mn/%	P/%	S/%
X70	0.45-0.65	0.1-0.25	0.18-0.25	0-0	0-0.002
X60	0.06-0.12	0.15-0.4	1.2-1.6	0-0	0-0.02

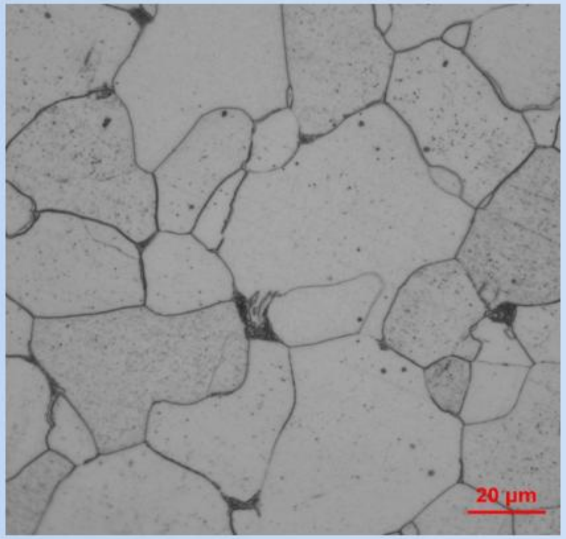
Process

Brand	Furnace Time/…	Thickness/mm	Width/mm	Pouring …
X70	190	12	857	1220±20
X60	200	12	857	1240±30

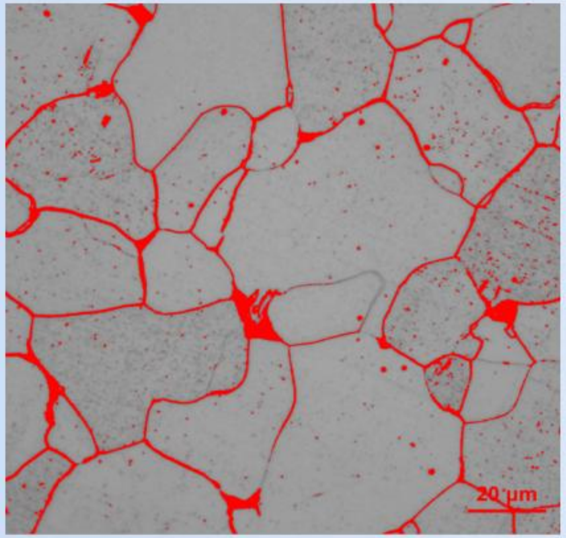
Performance

Yield Strength/Mpa	308.0
Tensile Strength/Mpa	450.0
Elongation/%	30.0
Impact Performance	—
Drop Weight Test Performance	—
Surface Decarburization Layer	—
Surface Roughness	—

Image segmentation of crystal grain



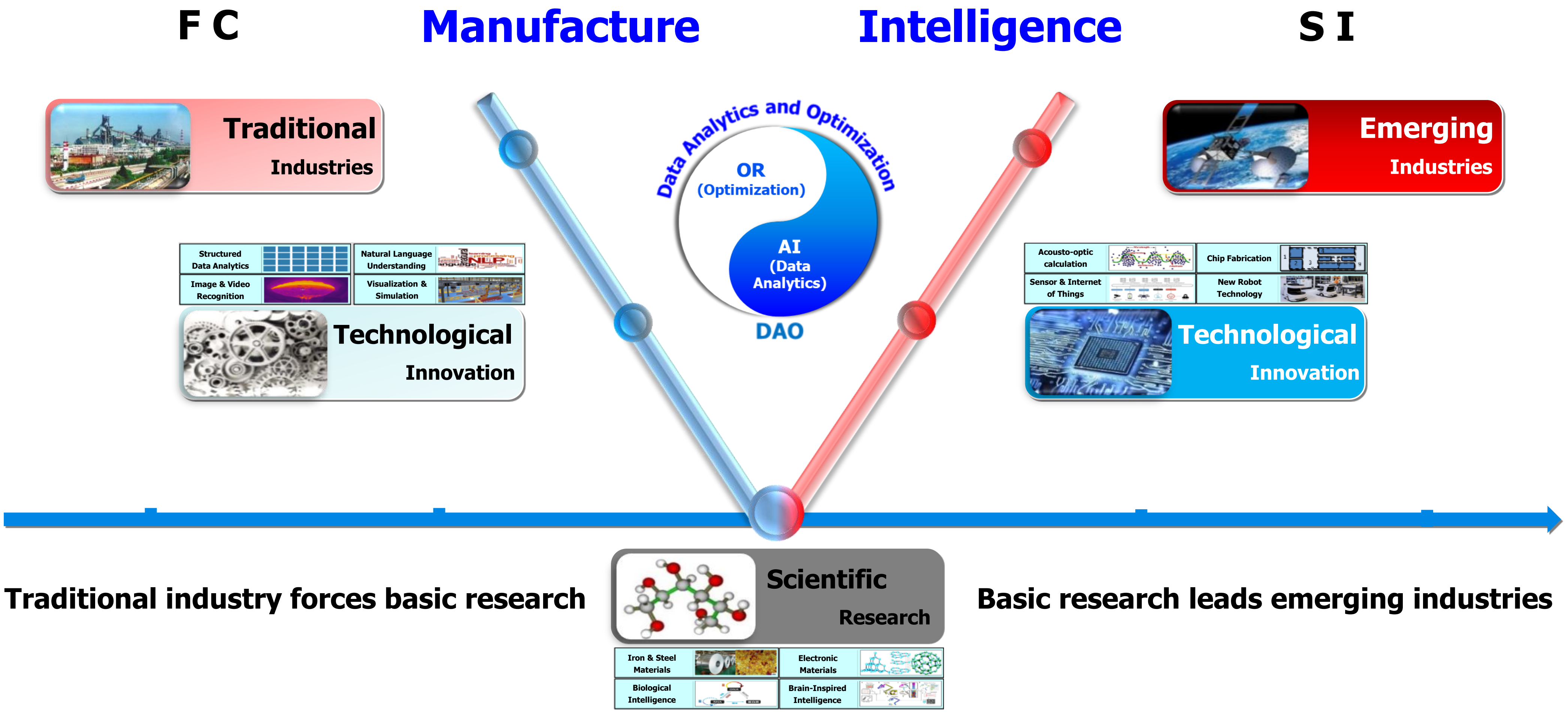
Identify the original image



Crystal granularity: 4.5

Metallographic organization	Ferrite & Precipitates
Crystal granularity	4.5
Component segregation	—
Triangle	—
Inclusion A	—
Inclusion B	—
Inclusion C	—
Inclusion D	—

2. Data Analytics and Optimization for Material Science (V)

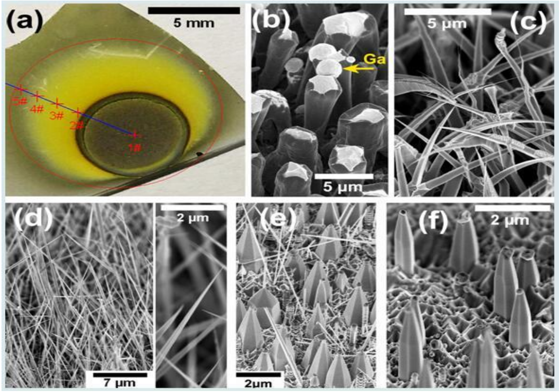


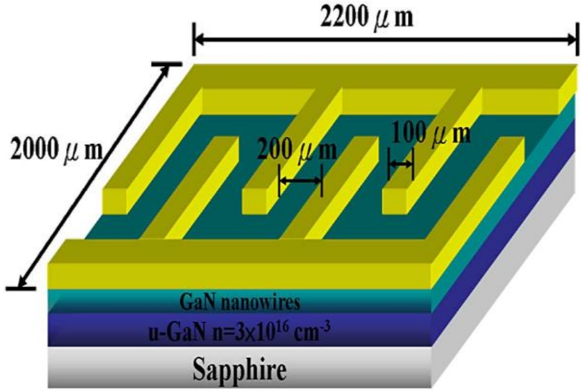
V (*Valley*) = Engineering + Technology + Science

2. Data Analytics and Optimization for Material Science (V) — Information Material

Material Design

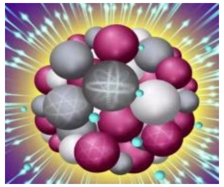
- **Sensing, storage, communication and computing**: new semiconductor materials realize high-precision control and optimization of industrial process.
- **New acousto-optic materials, energy and environmental materials**: design new materials to optimize energy conversion efficiency.
- **New machines**: development of smart and bionic materials for new robot body structures and smart chips for new robot brains.

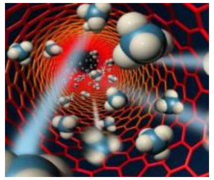


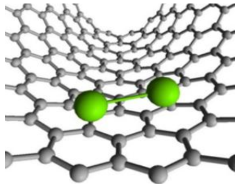


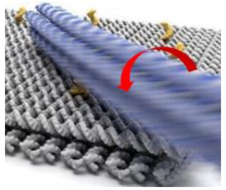
Atom Manufacturing

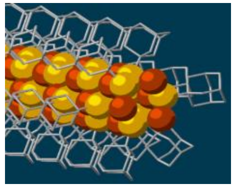
- **In situ sensing**: a multimodal in situ observation platform achieves the interfacial atomic coordination evolution and defect nucleation mechanisms.
- **Precise control**: atomic manufacturing requires the ultimate delicate manipulation technology to achieve the precise manipulation of atoms.
- **Operation optimization**: optimizing the atomic deposition path improves the precision of atomic fabrication manipulation by combining with DAO .


Atomic primitives


In situ control


Assembly devices


Intelligent moving parts


Assembly engineering

2. Data Analytics and Optimization for Material Science (V) — Information Material

Information Material Design and Optimization Software System

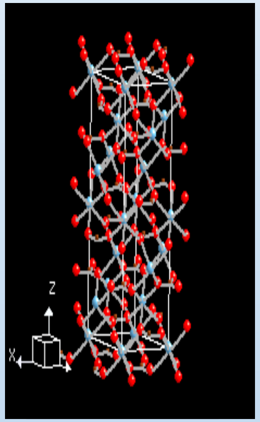
Reset | Component design | Performance Prediction | Structural Modeling

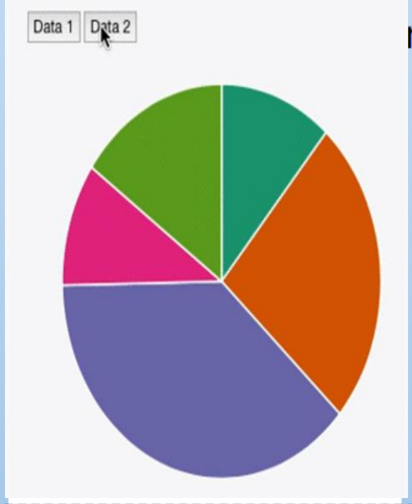
Crystal Model Setting

Element Selection	Element Doping	Doping Number
Ga	Si	1
O	P	2
Si	N	1
	Cl	1

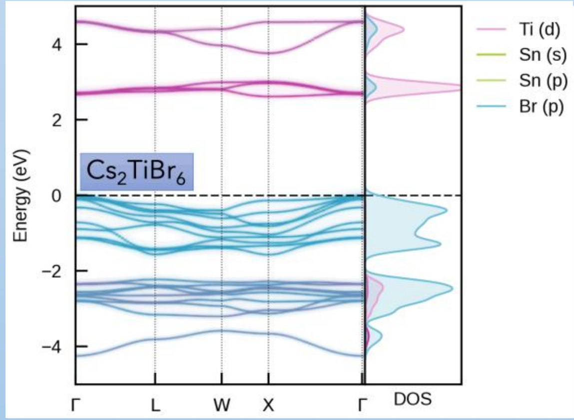
Structural Modeling

Site	Element	Wyckoff Symbol	X	Y	Z
Ga1	Ga	4i	m	0.0904	0
O1	O	4i	m	0.1674	0
O2	O	4i	m	0.1721	0
Ga2	Ga	4i	m	0.3414	0
O3	O	4i	m	0.5043	0

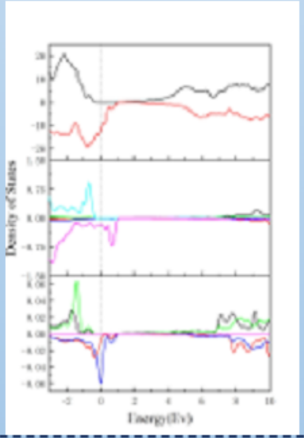


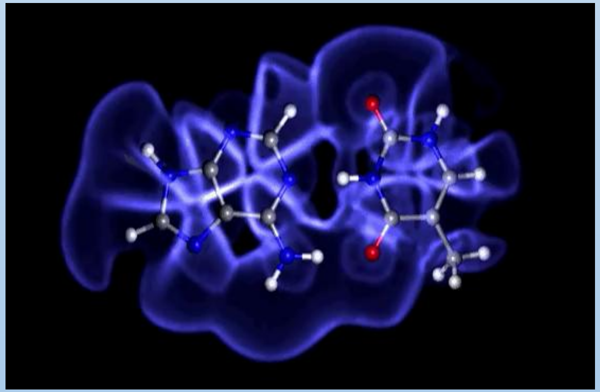


rmance Prediction



Optimization Results

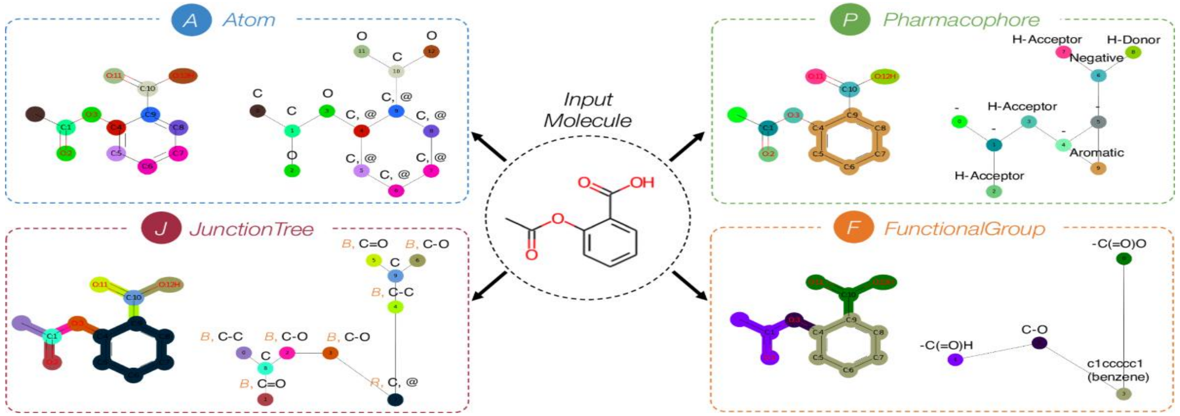




2. Data Analytics and Optimization for Carbon Science (V)

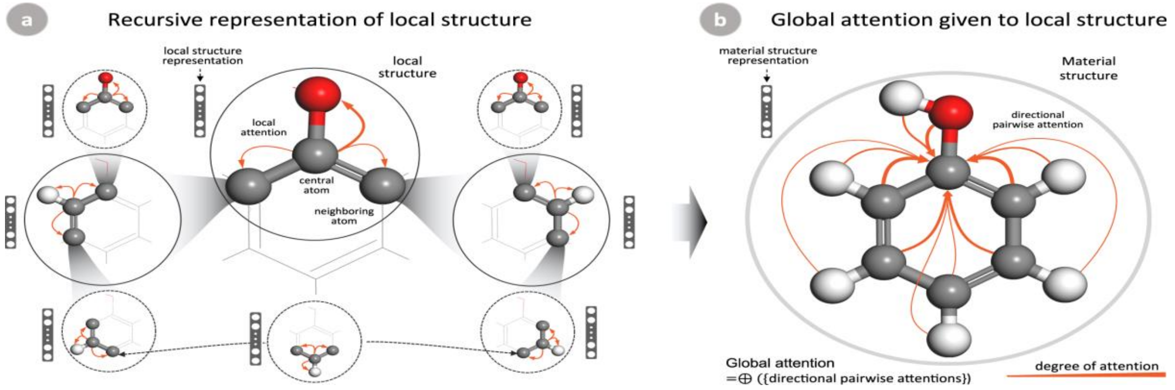
Chemistry Graph

- Molecular Graph: providing a framework for predicting the macroscopic properties of complex carbon systems from their atomic connectivity.
- Carbon Genetic: the connection relationship between atoms determines the properties and behavior of carbon molecules.
- Performance Prediction: understanding structure-property relationship for carbon-based substances like CO_2, CH_4, and chemicals.

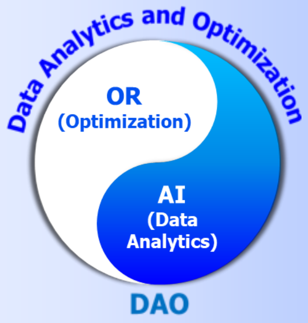


Stereochemical Topology

- 3D Chemistry Topology: The chemical properties of carbon-based substances arise from the combined effect of its structure and topology, especially the topology of graphs embedded in three-dimensional space.
- Synthesis Optimization: facilitating the synthesis of carbon chemicals, the preparation of carbon materials, and the design of carbon capture and conversion materials.



Outline

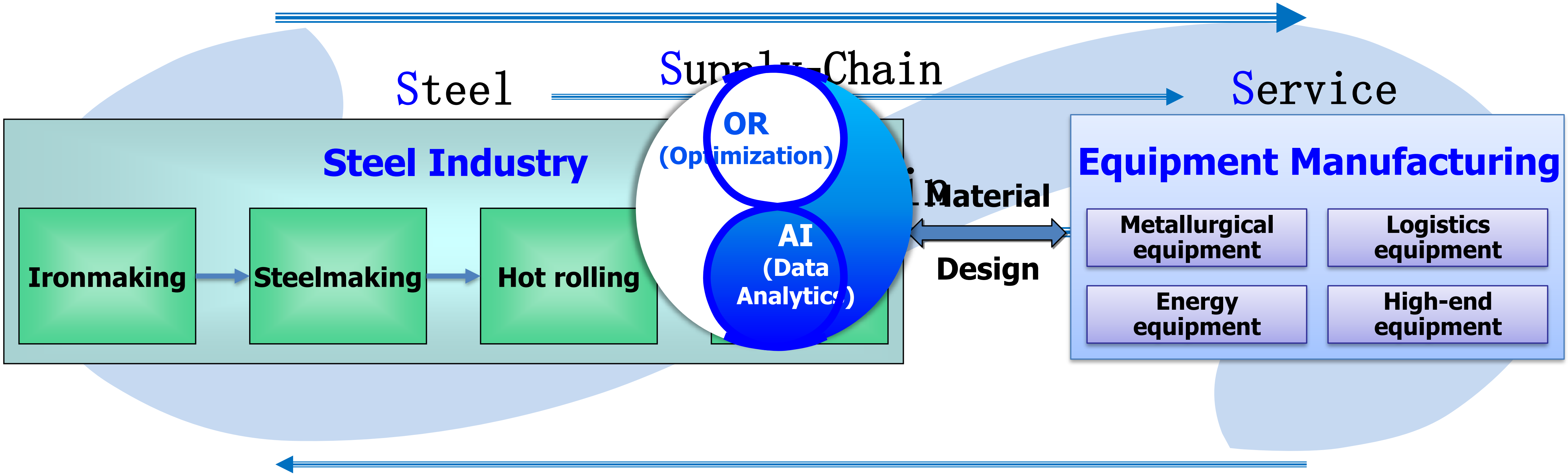


- DAO-based PDDE System Technology (H)
- Data Analytics and Optimization for Material Science (V)
- **RDMS-based Quality Analytics and Dynamic Optimization (S)**
- Full-dimension Organic Management System (E)
- DAO & LLM based Design and Simulation for MCIS (M)

3. RDMS-based Quality Analytics and Dynamic Optimization (S)

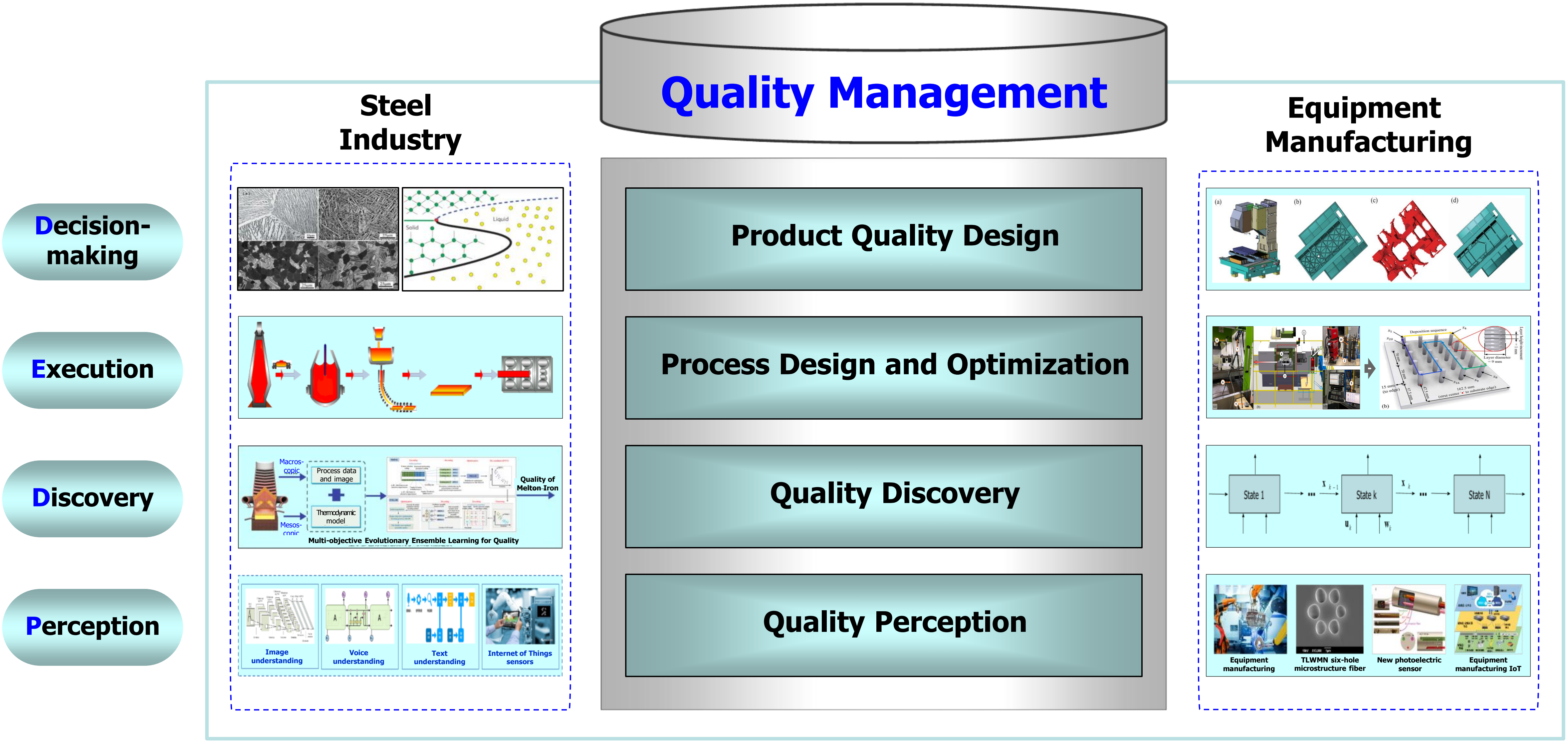
RDMS： Raw Material - Device - Machine - Systems

Pushed forward from the source by technology



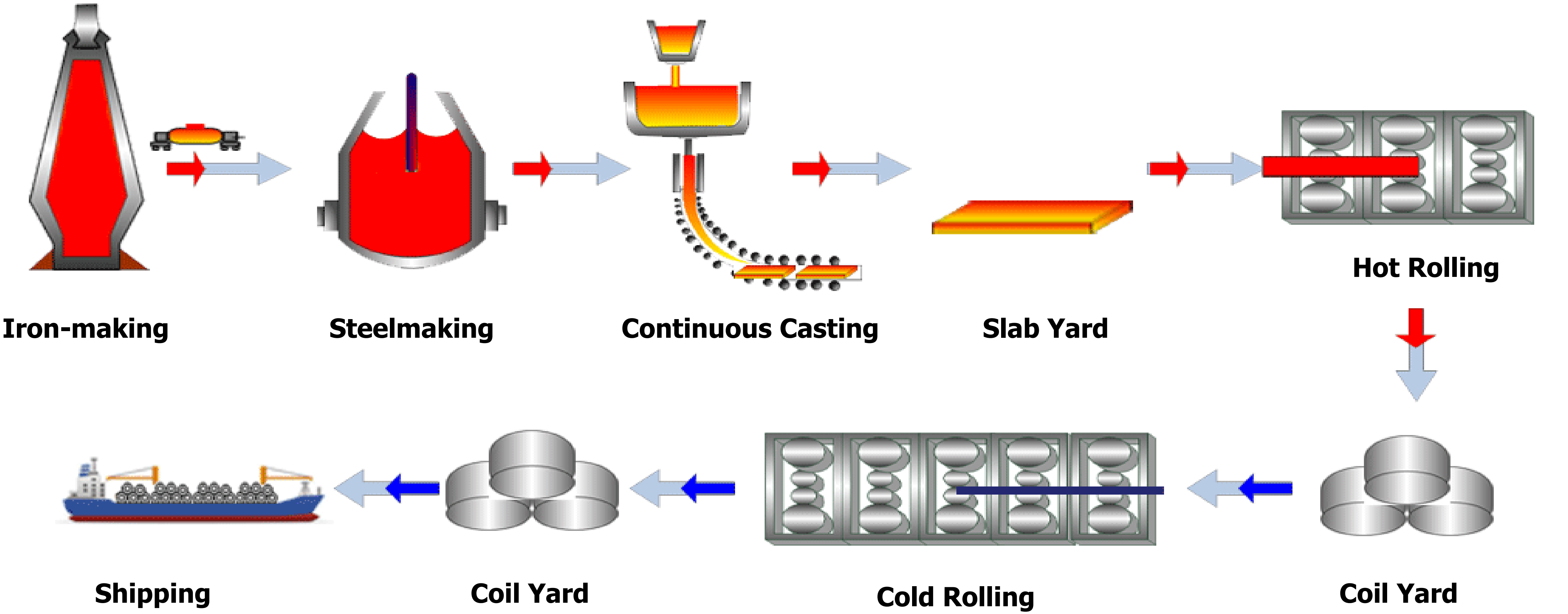
Demand-driven with precision

3. RDMS-based Quality Analytics and Dynamic Optimization (S) — PDDE



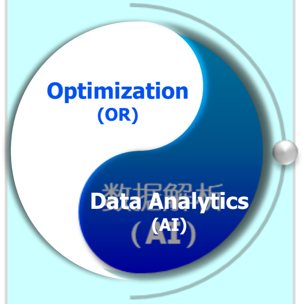
3. RDMS-based Quality Analytics and Dynamic Optimization (S)

Features: continuous and discrete production, huge devices, high-temperature operations, massive consumption of energy and resource



3. RDMS-based Quality Analytics and Dynamic Optimization (S) — Quality Perception

Fusion of Multi-dimensional Intelligent Technologies



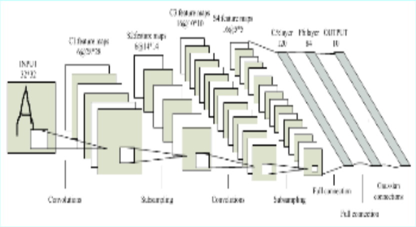
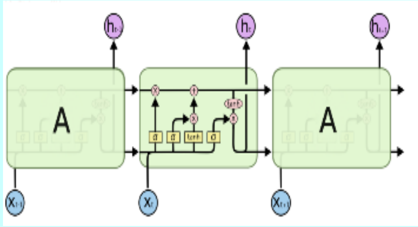
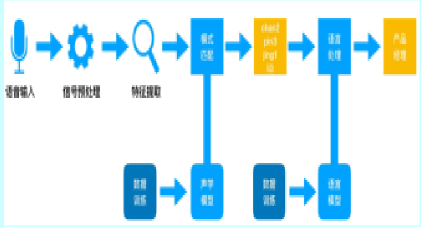


Image understanding



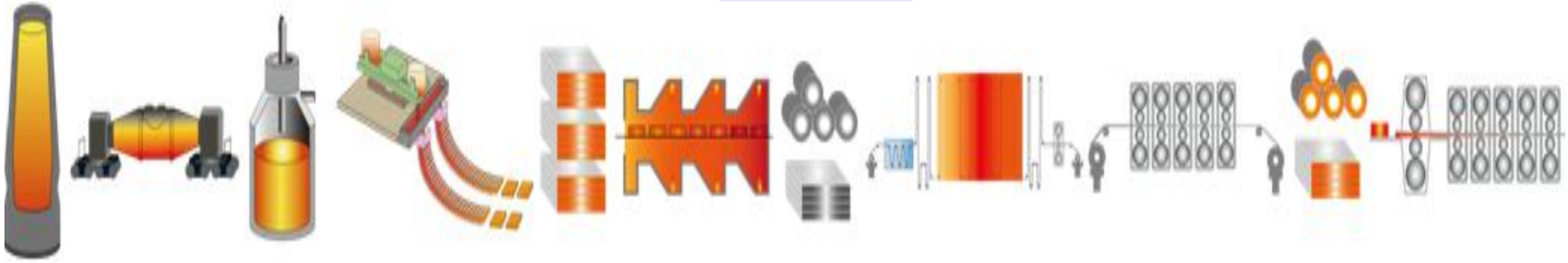
Voice understanding



Text understanding

Internet of Things sensor

Industrial intelligence



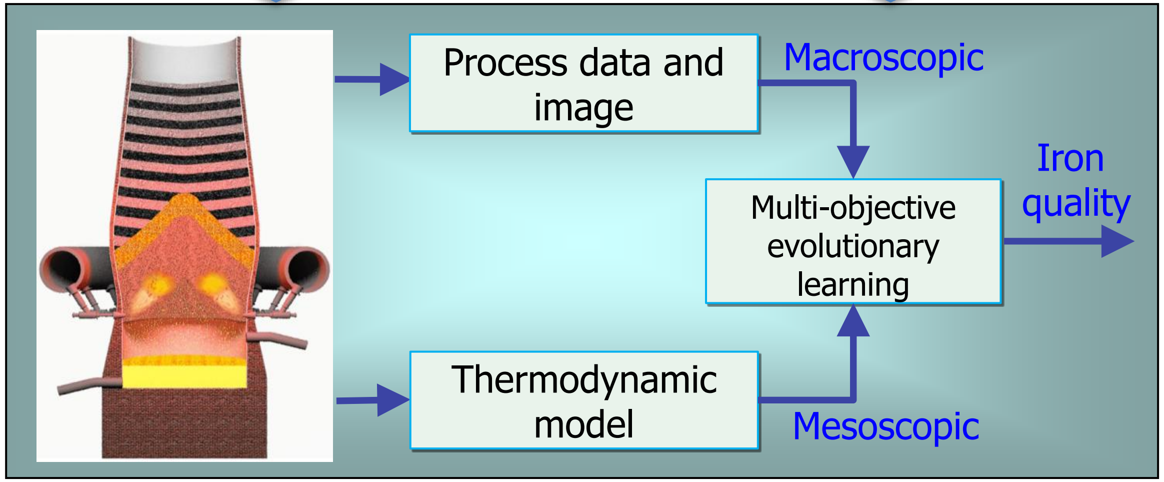
Industrial process

3. RDMS-based Quality Analytics and Dynamic Optimization (S) — Quality Discovery

Case 1: Iron Quality Prediction

Multi-objective Evolutionary Ensemble Learning

Fusion of thermodynamic model (meso) and process data (macro)	⇨	**Sub-learner based on fusion of meso and macro data**
Multi-objective evolutionary algorithm	⇨	**Evolving the structure and parameters of ensemble model**



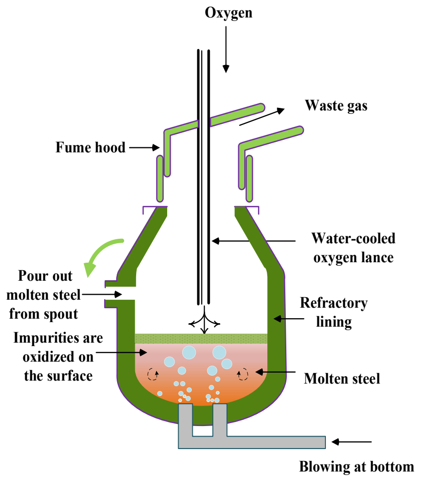
Case 2: Steel-making Dynamic Prediction

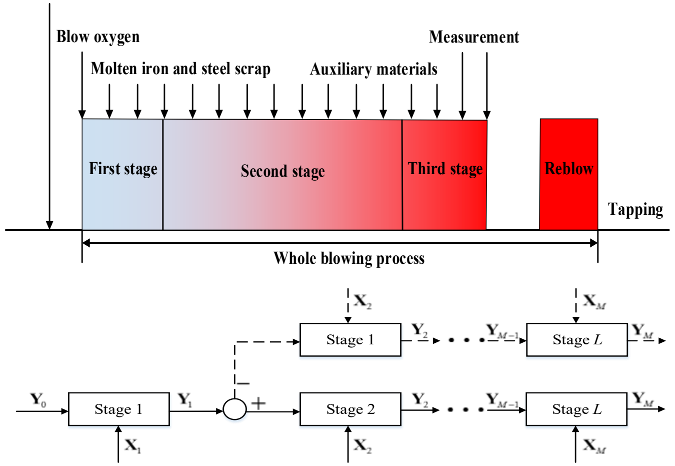
Challenges

- Continuous prediction requirement
- Unstable performance of single model
- Dynamic adjustment requirement

Dynamic analytics method

- Multi-stage modeling strategy
- Dynamic model with feedback
- Hybrid kernel function
- Differential evolution algorithm





X. Wang, T. Hu, and L. Tang. A multiobjective evolutionary nonlinear ensemble learning …. *IEEE Transactions on Neural Networks and Learning Systems*, 2022, 33(5): 2080-2093.
C. Liu, L. Tang, J. Liu, Z. Tang. A dynamic analytics method based on multistage modeling for a BOF steelmaking process. *IEEE Transactions on Automation Science and Engineering*, 2019, 16(3): 1097-1109.
X. Wang, Y. Wang, L. Tang, Q. Zhang. Multiobjective ensemble learning with multiscale data for product quality prediction in iron and steel industry. *IEEE Transactions on Evolutionary Computation*, 2024, 28(4): 1099-1113.

3. RDMS-based Quality Analytics and Dynamic Optimization (S) — Quality Discovery

Case 3: Temp. Prediction of Reheat Furnace

Features of heating process

- Dynamic and nonlinear
- Difficult to obtain mechanism model
- Obvious prediction error with mechanism model

Analytics method

- LS-SVM is used to compensate for the prediction deviation of the slab temperature
- Significantly improve the model prediction accuracy

Deviation Compensation

LS-SVM Model → **Mechanism Model**

↓

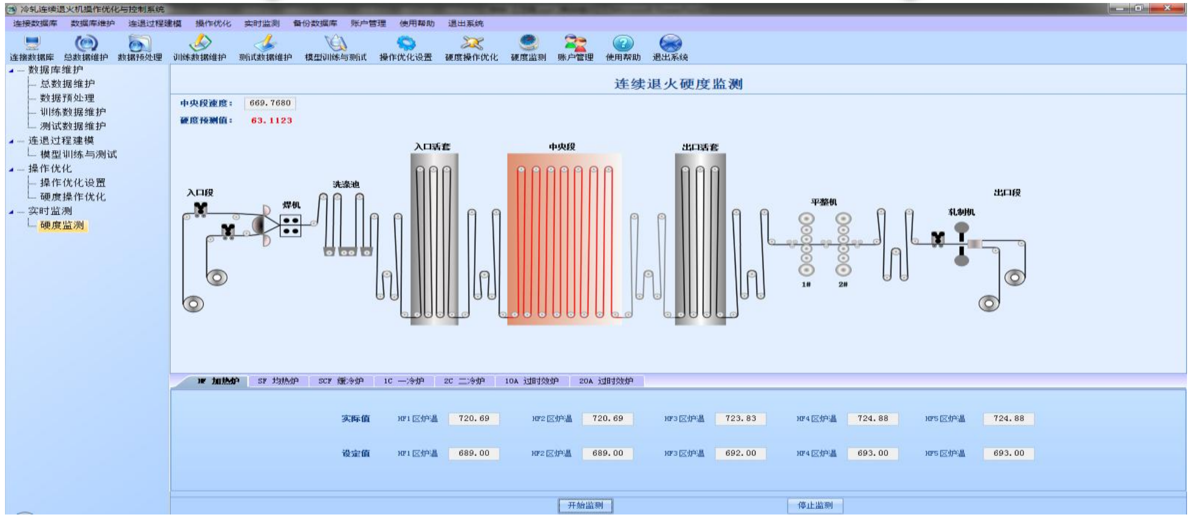
Mixed Model

Case 4: Strip Quality Analytics

Multi-objective Ensemble Learning

Least square support vector machine (LSSVM) ⇒ **Sub-learner in the ensemble learning**

Multi-objective evolutionary algorithm ⇒ **Evolving the ensemble learning model**



X. Wang, Y. Wang, L. Tang, Q. Zhang. Multiobjective ensemble learning with multiscale data for product quality prediction in iron and steel industry, ***IEEE Transactions on Evolutionary Computation***, 2024, 28(4): 1099-1113.
X. Wang, Y. Wang, L. Tang. Strip hardness prediction in continuous annealing using multiobjective sparse nonlinear ensemble learning …. ***IEEE Transactions on Automation Science and Engineering***, 2022, 19(3): 2397-2411.

3. RDMS-based Quality Analytics and Dynamic Optimization (S) — Product Quality Design

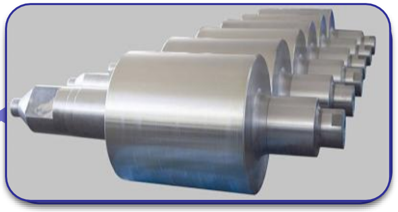
Material Production
(Raw Material)

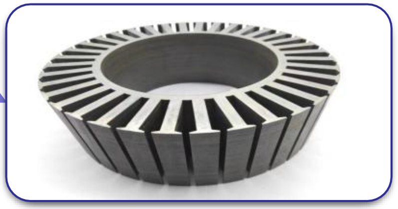
Key Components
(Device)

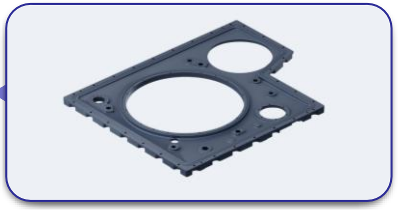
Equipment Manufacturing
(Machine)

Industrial Systems
(Systems)

Steel Materials





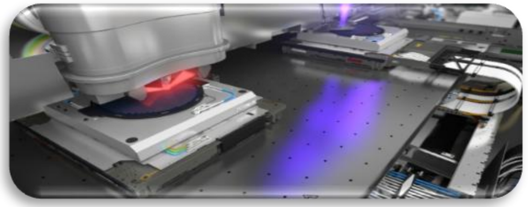


Metallurgical Equipment

Logistics Equipment

Energy Equipment

Information Equipment



Design / Synthesis

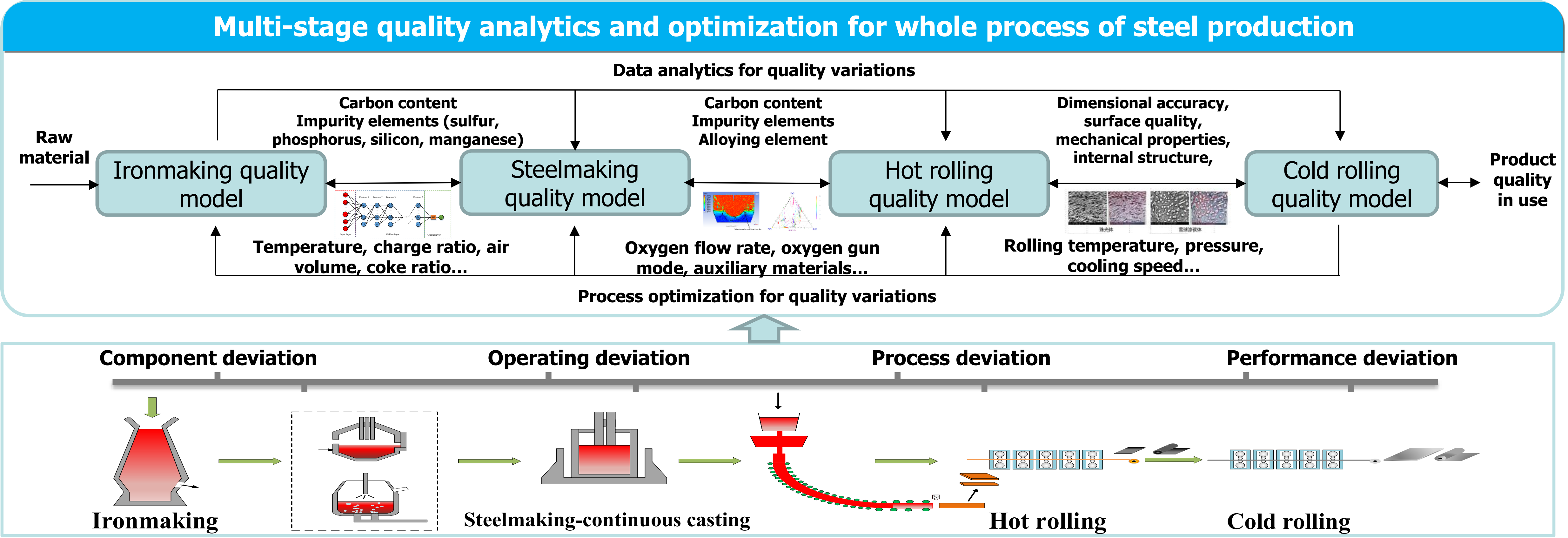
Forging / Processing

Machining / Assembly

Service / Maintenance

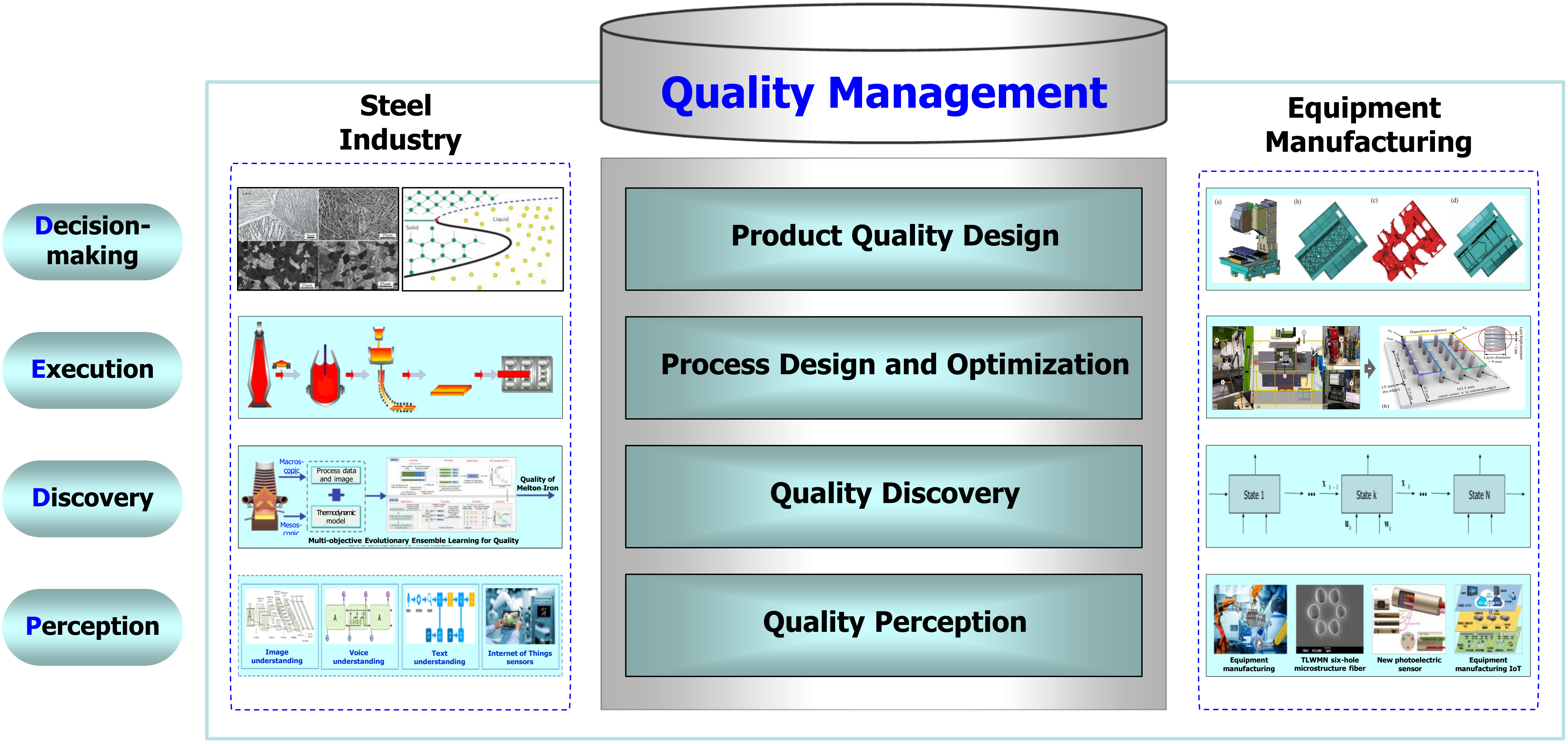
3. RDMS-based Quality Analytics and Dynamic Optimization (S)—Process Design and Optimization

- Steel production is a highly complex and multi-stage process, and the interaction and quality transfer between the various links directly affect the quality of the final product. Therefore, the quality control of each process cannot be carried out in isolation, but should be coordinated in the whole process, which can effectively identify and eliminate accumulated quality deviations and ensure that the final product meets the design requirements.



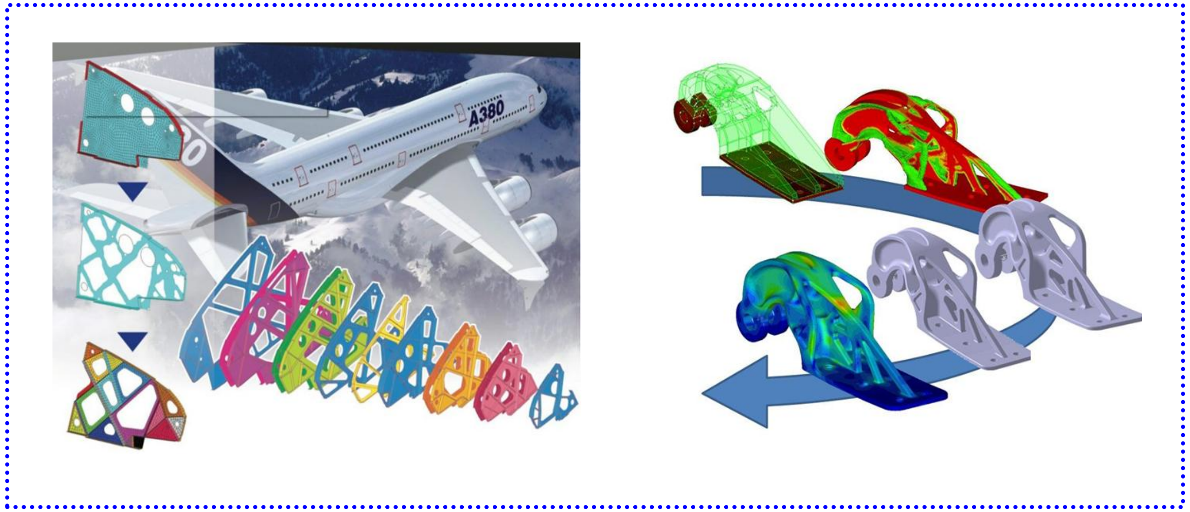
C. Liu, L. Tang, K. Zhang and X. Xu. Multiobjective evolutionary learning for multitask quality prediction problems in continuous annealing process. ***IEEE Transactions on Neural Networks and Learning Systems***, 2024.

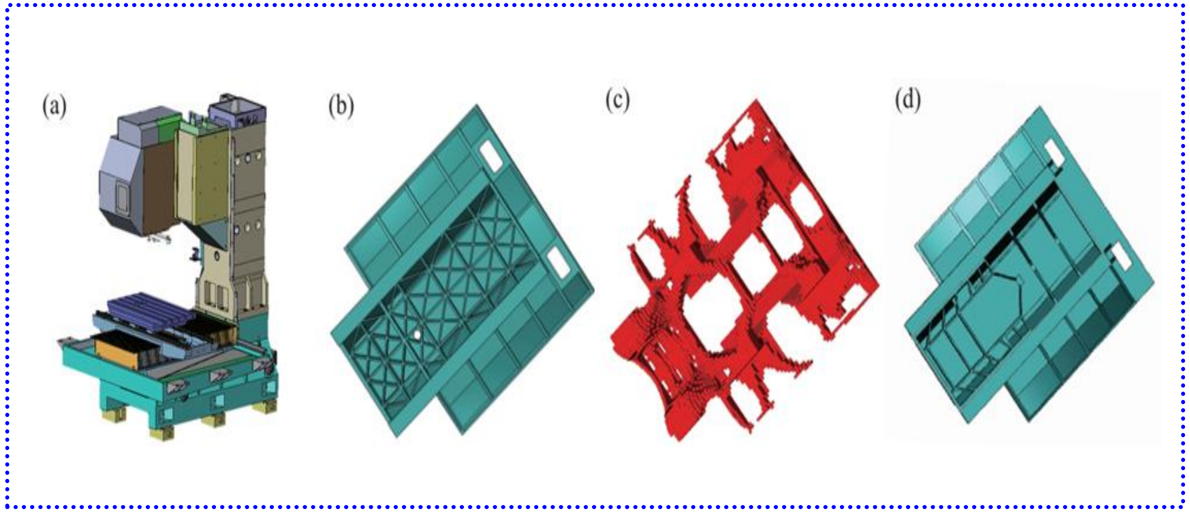
3. RDMS-based Quality Analytics and Dynamic Optimization (S) — PDDE



3. RDMS-based Quality Analytics and Dynamic Optimization (S) — Product Quality Design

- **Topology optimization:** optimization design method for equipment manufacturing products, integrating structural mechanics and optimization methods. Through optimizing spatial distribution of materials, structural configuration and component size, it can obtain the optimal structural form from multiple structural design schemes to achieve weight reduction, cost reduction and performance improvement for aviation, automotive and other products.
- **Quality design:** topology optimization for design important structural parts in equipment, such as machine base, beam of forging machine, tooling structures for aircraft etc.



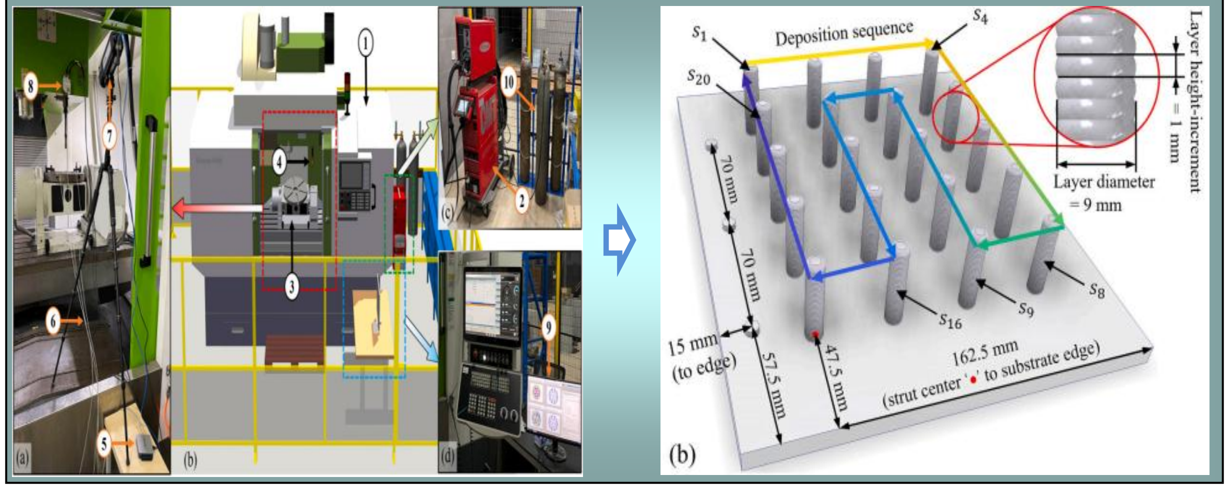


3. RDMS-based Quality Analytics and Dynamic Optimization (S)—Process Design and Optimization

Process Optimization in Manufacturing

Multi-objective process optimization

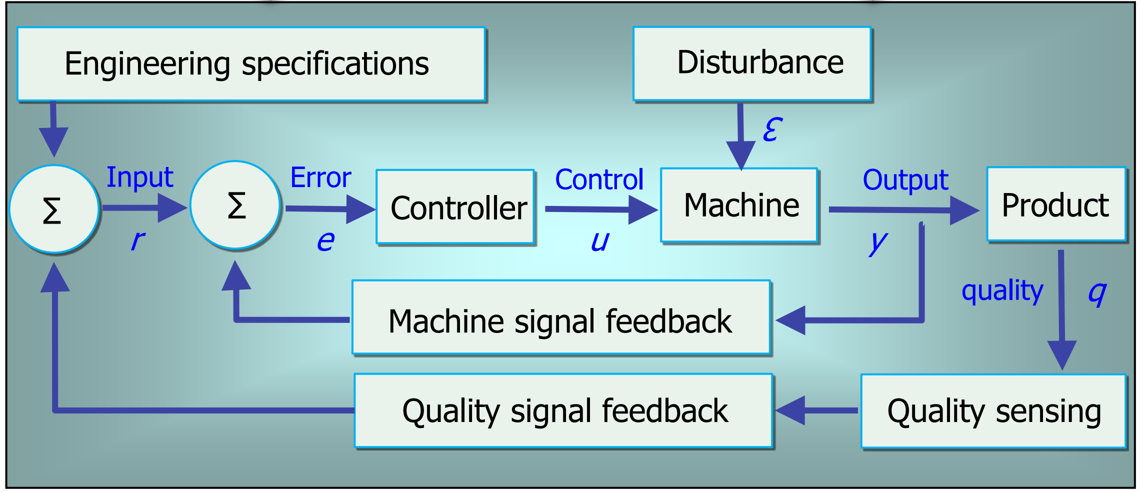
Multi-objective optimization for product quality	⇨	**Improve product performance, life, reliability, maintainability, and safety**
Operation parameters for process optimization	⇨	**Adjust machining speed, pressure, angle, depth, and shears**



In-process Quality Improvement (IPQI)

IPQI-enhanced automation

Engineering-driven data fusion for quality improvement	⇨	**Advanced statistical and machine learning methods and optimization methods**
IPQI methodologies for assembly, machining, and forming	⇨	**Integrate causation-based models and optimization algorithms**



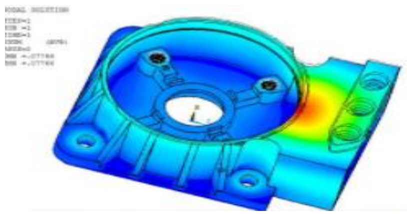
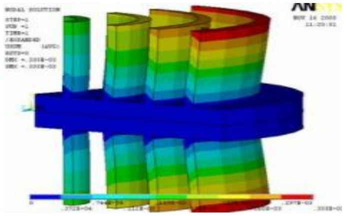
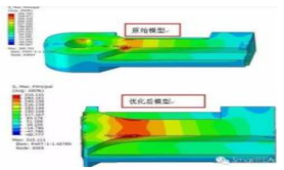
J. J. Shi. In-process quality improvement: Concepts, methodologies, and applications. ***IISE Transactions***, 2023, 55(1): 2-21.

Z. P. Yu, Z. X. Pan, D. H. Ding, et. al. Strut formation control and processing time optimization for wire arc additive manufacturing of lattice structures. ***Journal of Manufacturing Processes***, 2022, 79: 962-974.

❖ Fusion modeling for multistage manufacturing process

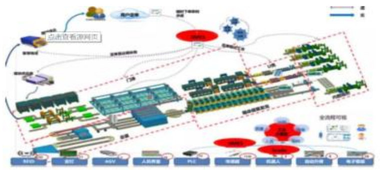
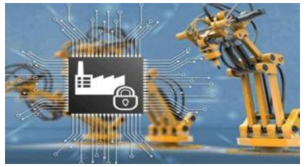
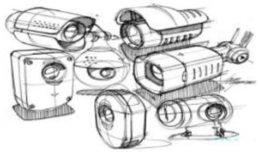
Product Design

-Quality representation
-Critical features
-Tolerance design

Process Design

-Relationship between workpiece and tool
-Machine layout
-Process sequences

	Linear mechanism model	**Nonlinear data model**
Datum Error	$\mathbf{x}_k \to A_{k-1}\mathbf{x}_{k-1}$	$\mathbf{x}_k \to g_1(\mathbf{x}_{k-1})$
Fixture Error	$\mathbf{x}_k \to B_{k-1}\mathbf{u}_k$	$\mathbf{x}_k \to g_2(\mathbf{u}_k)$
Machine Error		
Overall Error	$\mathbf{x}_k = A_{k-1}\mathbf{x}_{k-1} + B_{k-1}\mathbf{u}_k + \mathbf{w}_k$	$\mathbf{x}_k = g_1(\mathbf{x}_{k-1}) + g_2(\mathbf{u}_k) + \mathbf{w}_k$
Observation	$\mathbf{y}_k = C_k\mathbf{x}_k + \mathbf{v}_k$	$\mathbf{y}_k = g_3(\mathbf{x}_k) + \mathbf{v}_k$

J Shi. Stream of Variation Modeling and Analysis for Multistage Manufacturing Processes. ***CRC Press***, 2006.
J V Abellan-Nebot, J Liu, F R Subirón, J. Shi. State space modeling of variation propagation in multistation machining processes considering machining-induced variations. ***ASME. J. Manuf. Sci. Eng.,*** 2012, 134(2): 021002.
A Wang, J Shi, J. Holistic modeling and analysis of multistage manufacturing processes with sparse effective inputs and mixed profile outputs. ***IISE Transactions***, 2020, 53(5): 582–596.

Quality Perception

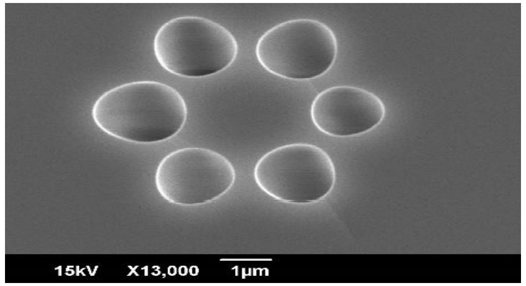
❖ In view of complex conditions and key links in the equipment manufacturing process, industrial intelligent chips and embedded systems are developed, special micro-nano sensors/intelligent photoelectric sensors with high sensitivity are developed, and sensors are interconnected with equipment through the Internet of Things, so as to achieve highly reliable deep intelligent perception of key process parameters that are difficult to measure in the equipment manufacturing process.

❖ Types of fault perception in equipment manufacturing process:

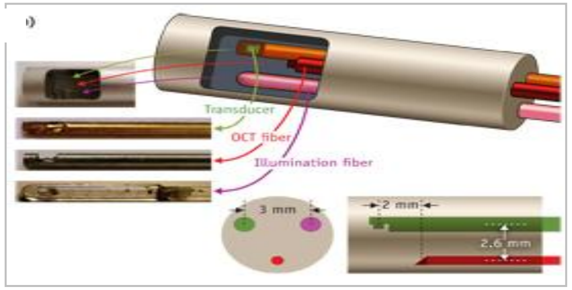
1. Wear fault, i.e., the equipment wear degree
2. Structural faults, e.g., cracks, wear, corrosion, imbalance
3. Parametric faults, e.g., fluid vortex, resonance, overheating, improper fit tightness
4. Failure of poor operation and maintenance

Demand-driven → New materials → Smart sensing → Embedded system → Industrial interconnection

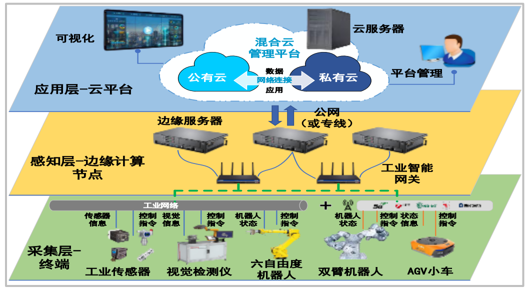
Equipment manufacturing process



TLWMN six-hole microstructure fiber



New photoelectric sensor



Equipment manufacturing IoT

3. RDMS-based Quality Analytics and Dynamic Optimization (S)

D

Decision-making: Through topology and multi-objective optimization, optimize the topology structure and performance of structural components of equipment to realize weight and cost reduction, and performance enhancement of aircraft, automotive and other products.

E

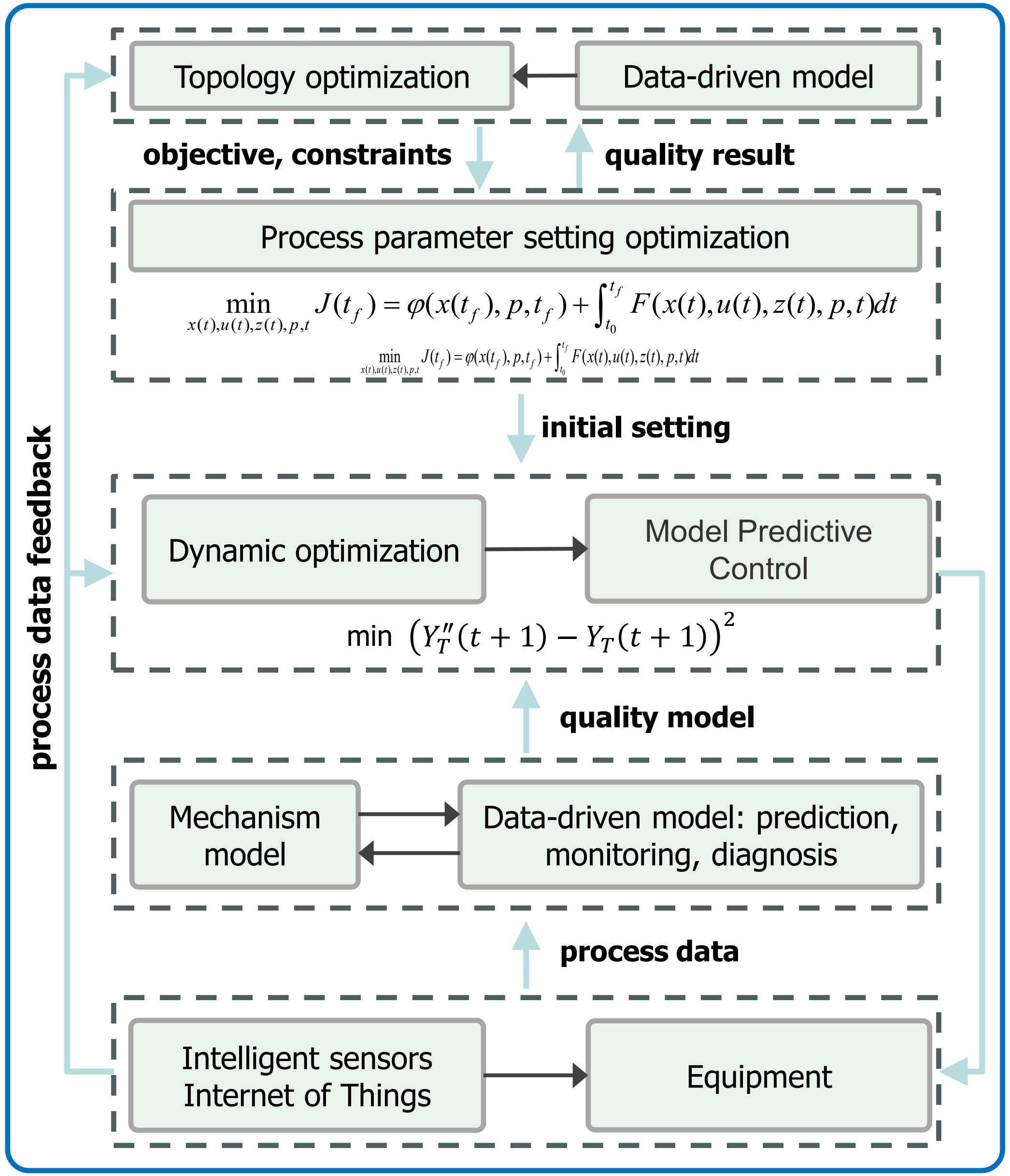
Execution: Based on the quality discovery models, the dynamic operation optimization of the production process is carried out with evolutionary algorithms to dynamically get the best parameter settings to achieve the expected product quality requirements of equipment.

D

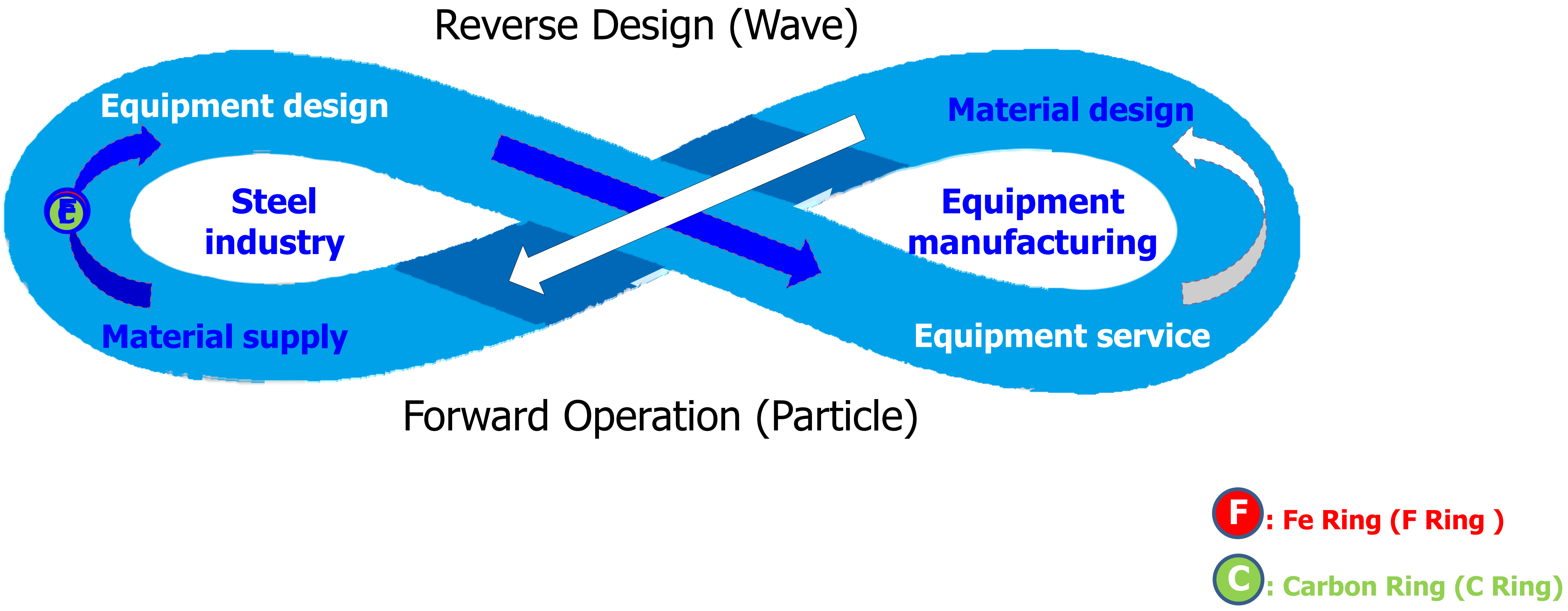
Discovery: Through multi-source data fusion for manufacturing process, it provides common models for product quality prediction, and monitoring; together with multi-objective evolutionary learning methods, it achieves consistency and stability of product quality.

P

Perception: Through the development of high sensitivity special intelligent sensors and taking use of the Internet of Things, it realizes the intelligent and reliable measurement of the key process parameters in the equipment manufacturing process.



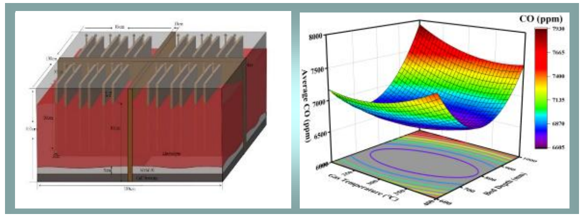
Wave-Particle Duality Quantum Holographic Quality Management (S)

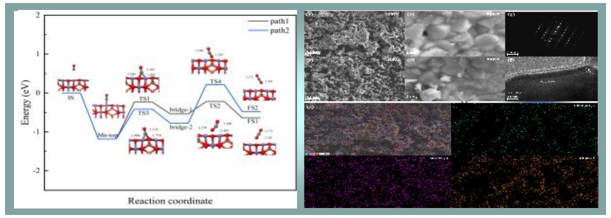


3. RDMS-based Quality Analytics and Dynamic Optimization (S) – Carbon Reduction

Process Design Optimization (D)

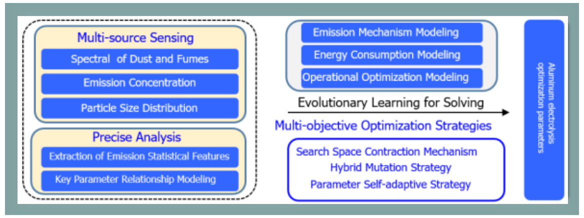
- Optimize the ingredient sourcing to achieve low/zero-carbon manufacturing. Optimal design the production process and develop advanced technologies for energy conservation and carbon reduction.

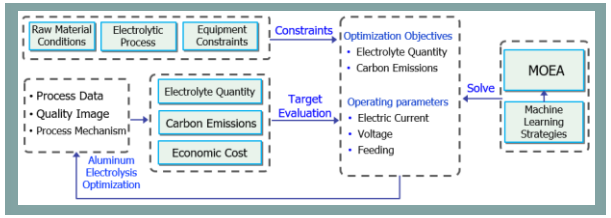




Real-time Process Optimization (E)

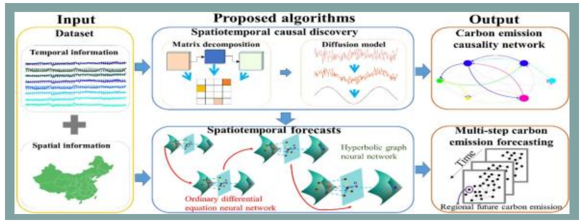
- Develop carbon emissions models considering key process parameters. Propose dynamic multi-objective optimization of operating parameters considering dynamic changes in energy consumption and carbon emissions.

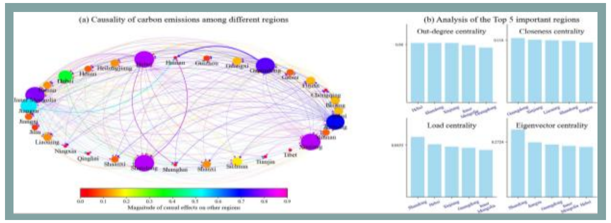




Discovery of Carbon Emission Patterns (D)

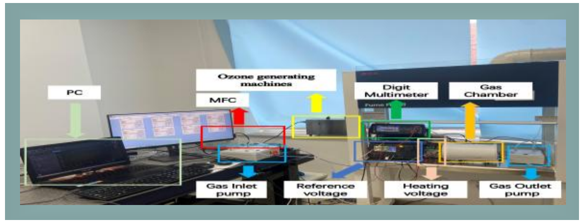
- The mechanism and data fusion method is proposed to analyze multi-source data patterns, identify carbon emission hotspots and anomalies, enabling full-process, multi-dimensional emission discovery.

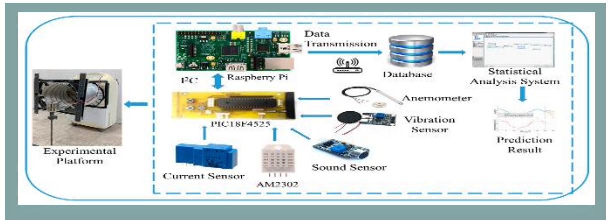




Perception of Carbon Footprint (P)

- System perception technology uses structured data, text, voice, images, and sensors for accurate, real-time, stable acquisition and monitoring of carbon emission data across various sources and processes.





3. RDMS-based Quality Analytics and Dynamic Optimization (S) – Carbon Reduction

The value chain is shifting from low-end to high-end

Carbon Reduction

- Ingredient Optimization
- Process Optimization
- Efficiency Enhancement
- Hydrogen Metallurgy

Carbon Capture

- Chemisorption
- Physisorption
- Membrane Separation
- Electrochemistry

Carbon Conversion

- Information Material
- Energy Conversion
- Carbon Mineralization
- Biological Utilization

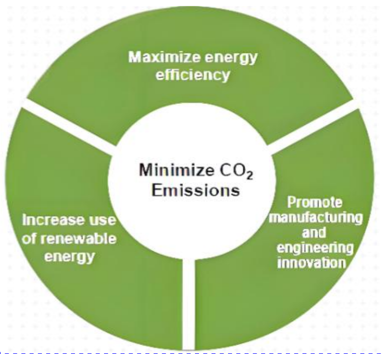
Process-driven upstream integration

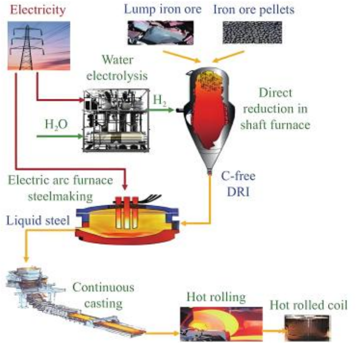
Demand-pulled precision guidance

3. RDMS-based Quality Analytics and Dynamic Optimization (S) – Carbon Reduction

Carbon Reduction

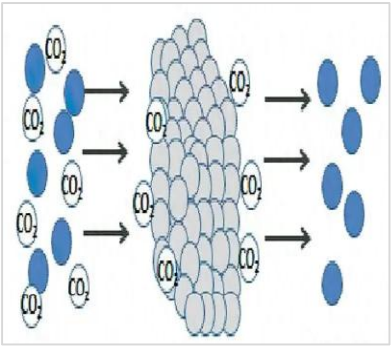
- **Extreme energy efficiency:** energy saving and improving energy utilization efficiency.
- **Resource recycling:** expanding the scale of waste recycling and reduce resource consumption.
- **Carbon substitution:** accelerating the using of low-carbon energy, such as, hydrogen metallurgy.

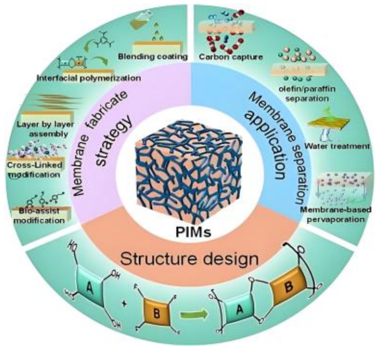




Carbon Capture

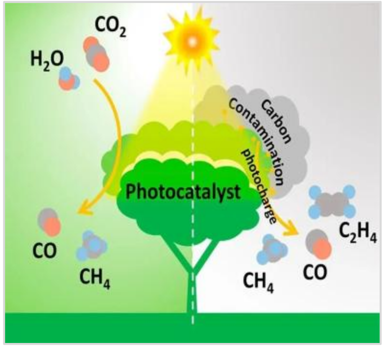
- **Physical adsorption:** using MOFs, activated carbon, molecular sieve materials to capture CO_2.
- **Chemical absorption:** using materials such as ammonia and calcium oxide to absorb CO_2.
- **Membrane separation:** using selective polymer membranes, to separate CO_2.

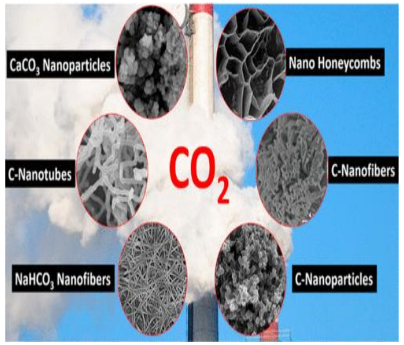




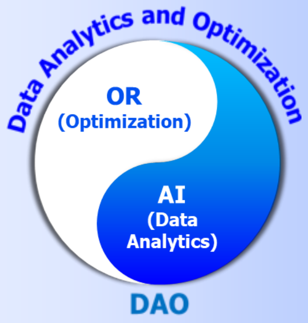
Carbon Conversion

- **Energy conversion:** Photocatalytic and electrocatalytic technologies enable the conversion of CO_2 into energy carriers such as syngas, methanol, and jet fuel.
- **Carbon material preparation:** converting CO_2 into key materials like diamond semiconductors for electronics manufacturing.





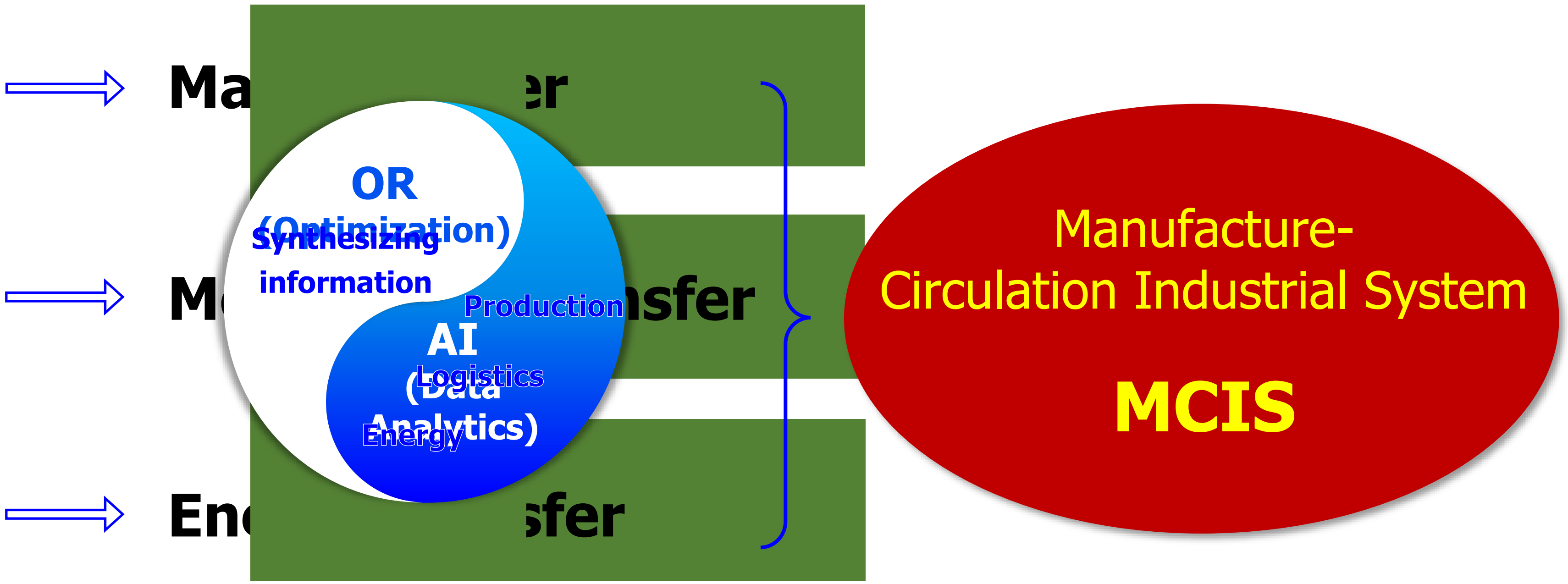
Outline



- DAO-based PDDE System Technology (H)
- Data Analytics and Optimization for Material Science (V)
- RDMS-based Quality Analytics and Dynamic Optimization (S)
- **Full-dimension Organic Management System (E)**
- DAO & LLM based Design and Simulation for MCIS (M)

4. Full-dimension Organic Management System (E)

Manufacture-Circulation Industrial System (ECO-System, abbreviated as E)



E (*ECO-System*) = Production + Logistics + Energy + Information

4. Full-dimension Organic Management System (E)

Challenges Faced by Steel Industry

High Resource Consumption

High CO_2 Emission

Steel Production

High Energy Consumption

High Inventory

Production

Logistics

Energy

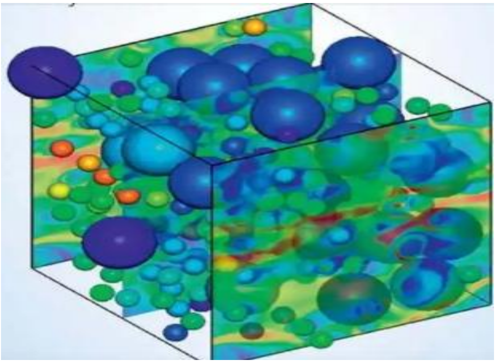
Data

4. Full-dimension Organic Management System (E)

➢ **New Characteristics**

- **Complex physical and chemical processes with multiphase production**
- **Large variety and low volume products, as well as large equipment**
- **Complicated logistics structure, as well as break down type production structure**

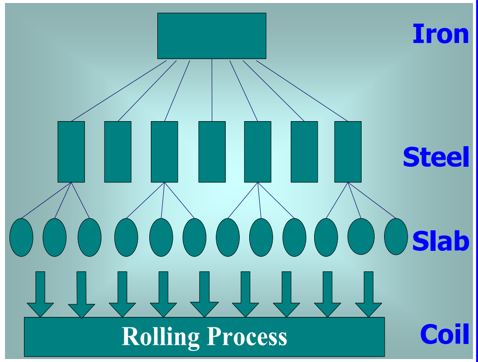
Complicated Production Process



Large Variety and Low Volume

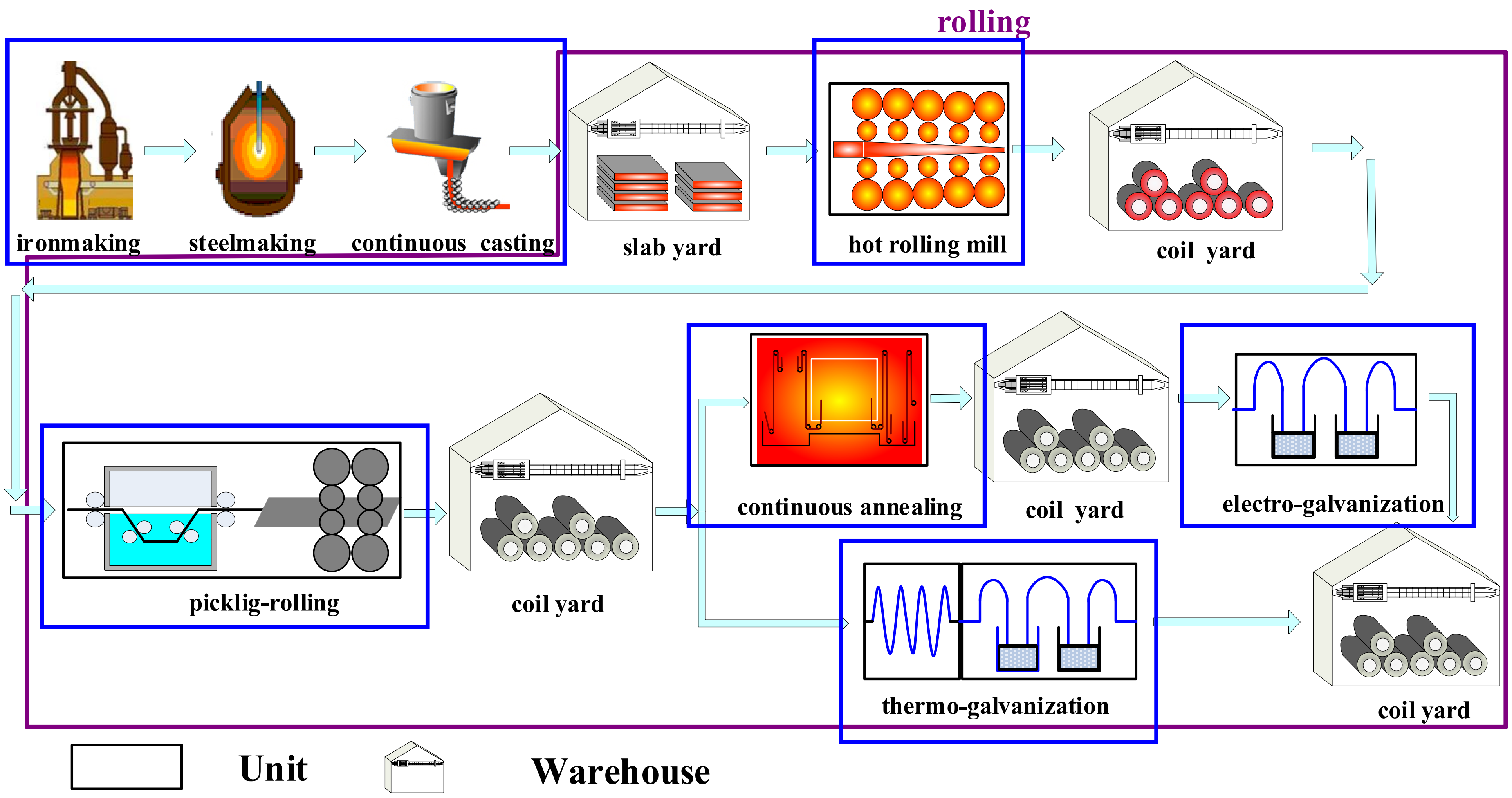
Huge Chemical Equipment

Complicated Logistics Structure



4. Full-dimension Organic Management System (E)

Steel Production

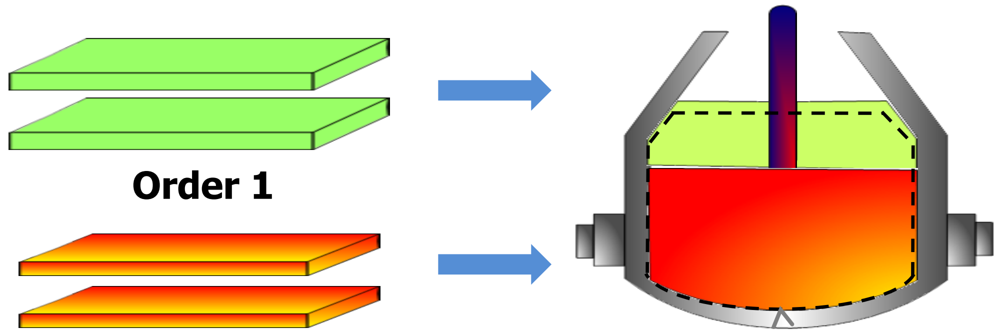


Production: Iron-making/Steelmaking/Hot Rolling/Cold Rolling

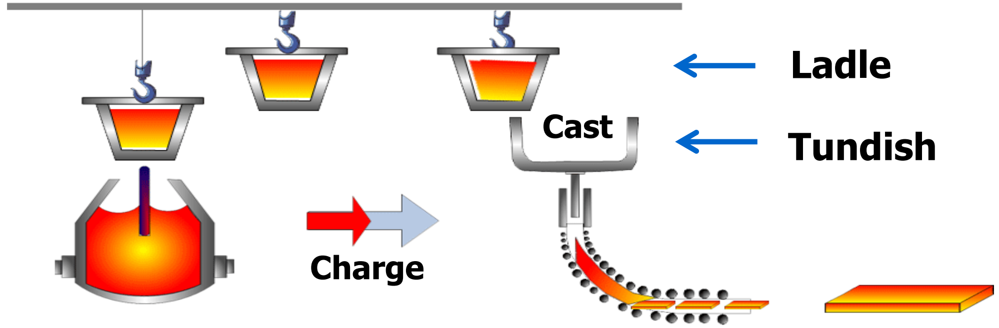
4. Full-dimension Organic Management System (E)

Production Scheduling

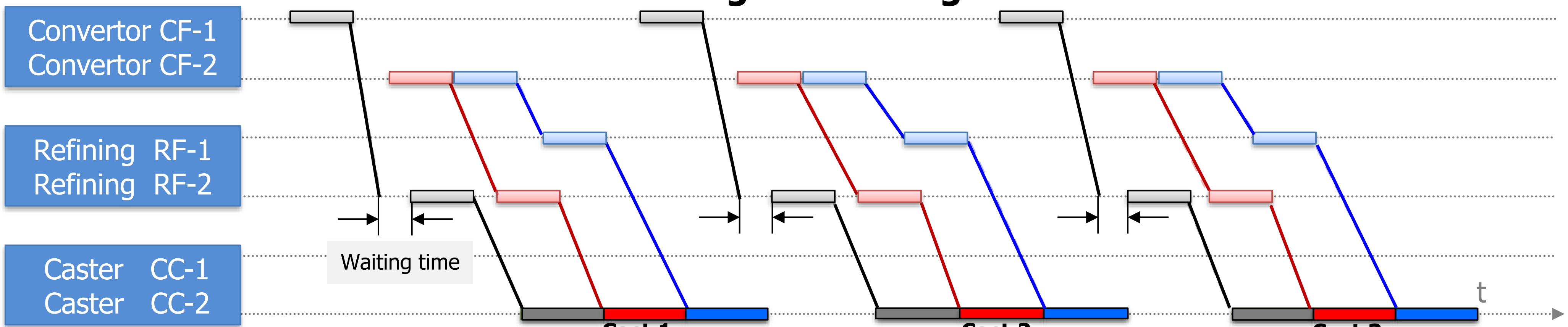
Charge Batching



Cast Batching

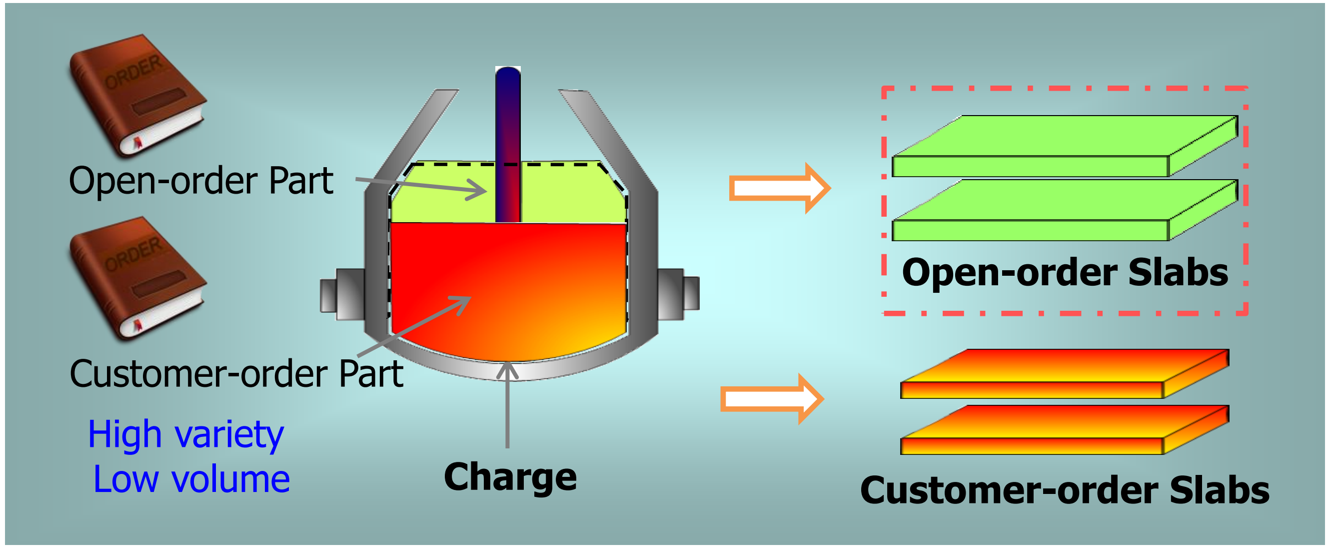


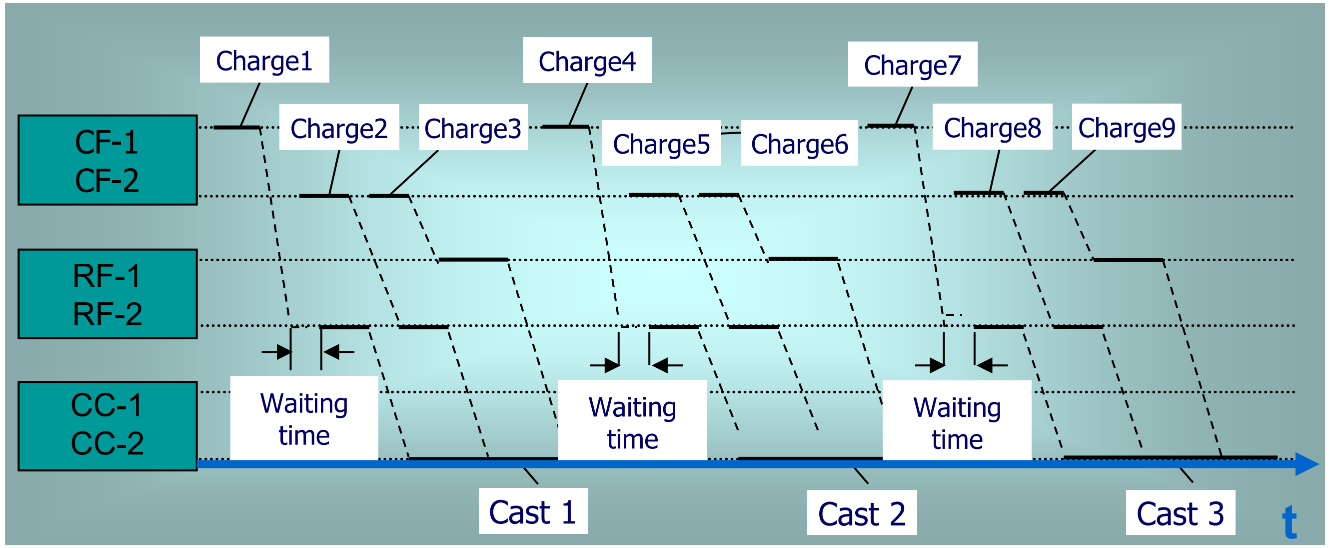
Steelmaking Scheduling



L. Tang, G. Wang, J. Liu, J. Liu. A combination of Lagrangian … steelmaking and continuous-casting production. ***Naval Research Logistics***, 2011, 58(4): 370-388.
L. Tang, G. Wang, Z. Chen. Integrated charge batching and casting width selection at Baosteel. ***Operations Research***, 2014, 62(4): 772-787.

4. Full-dimension Organic Management System (E) — Production Optimization





Group all the slabs of different customer orders into batches

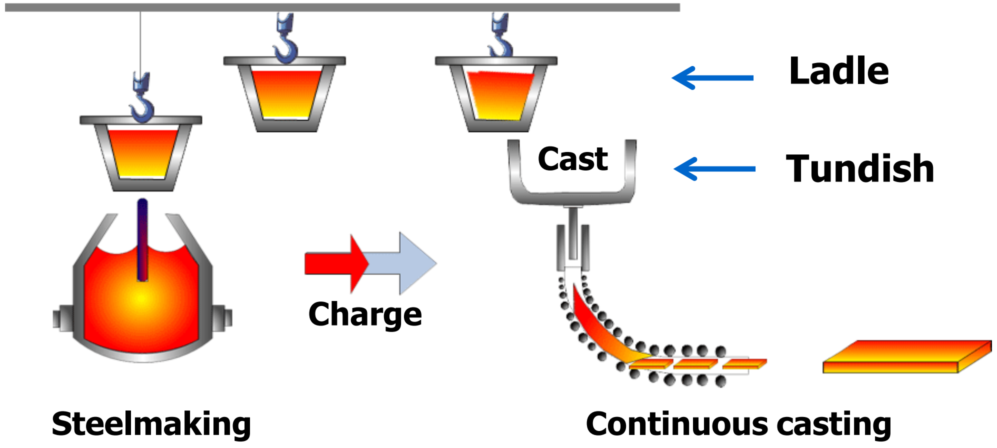
p-median clustering with capacity and additional technical constraints

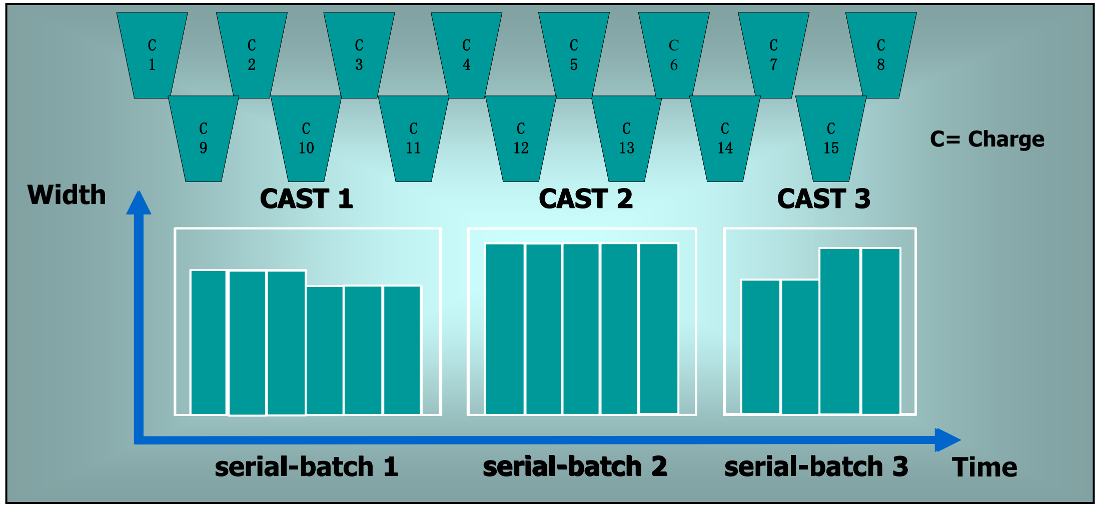
- Minimize assignment cost
- Minimize open-order slabs
- Minimize unfulfilled cost of order

- Lagrangian relaxation
- Column generation

L. Tang, G. Wang, J. Liu, J. Liu. A combination of Lagrangian relaxation and column generation for order batching in steelmaking and continuous-casting production. ***Naval Research Logistics***, 2011, 58(4): 370-388.

4. Full-dimension Organic Management System (E) — Production Optimization





Decisions

- Batch and sequence charges to form casts for the given tundishes
- Select a casting width for each charge in a cast

Objectives

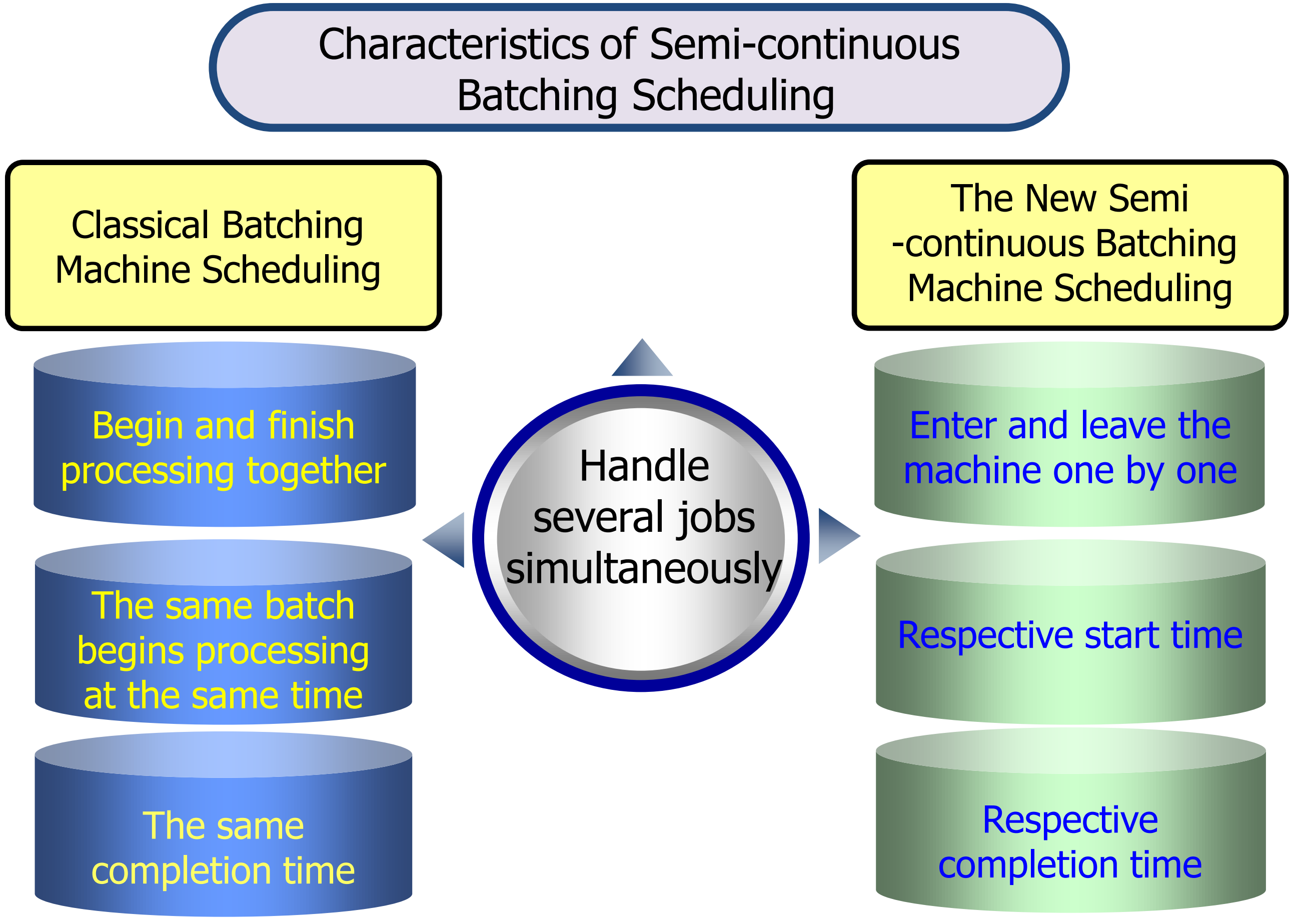
- Maximize tundish utilization
- Minimize total grade switch and width switch cost

Constraints

- Grade switch constraint
- Width switch constraint
- Lifespan of tundish

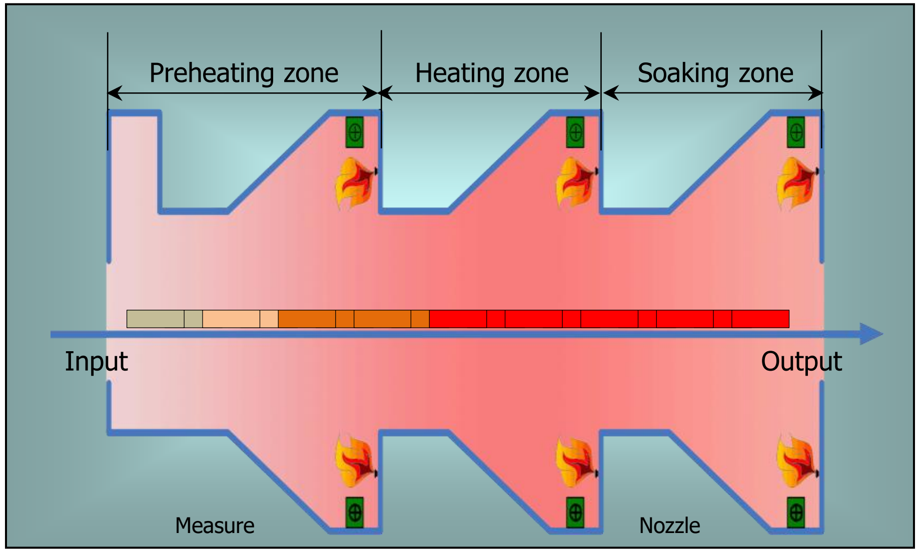
L. Tang, G. Wang, Z. Chen. Integrated charge batching and casting width selection at Baosteel. ***Operations Research***, 2014, 62(4): 772-787.

4. Full-dimension Organic Management System (E) — Production Optimization



Traditional batching machines are mainly divided into three types:
(1) burn-in (2) fixed batch (3) serial batching

- A new kind of batch scheduling
- We analyze the semi-continuous batch scheduling problem, and present the optimal algorithm.



The heating process of tube-billets in heating furnace

L. Tang, Y. Zhao. Scheduling a single semi-continuous batching machine. ***Omega***, 2008, 36(6):992-1004.

4. Full-dimension Organic Management System (E) — Production Optimization

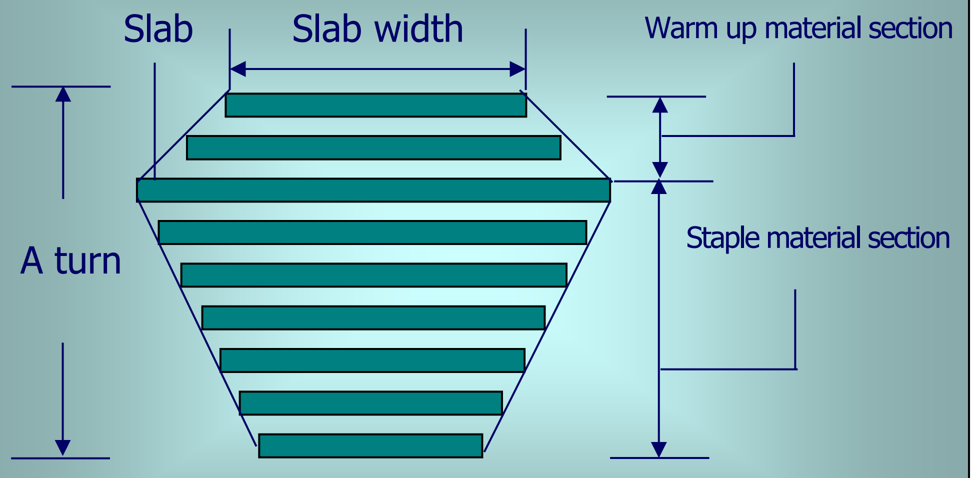
Decision	Objective
Sequence of adjacent jobs to be processed	Minimize the total changeover costs

$$\text{Minimize} \sum_{i=1}^{N+M} \sum_{j=1}^{N+M} C_{ij} X_{ij}$$

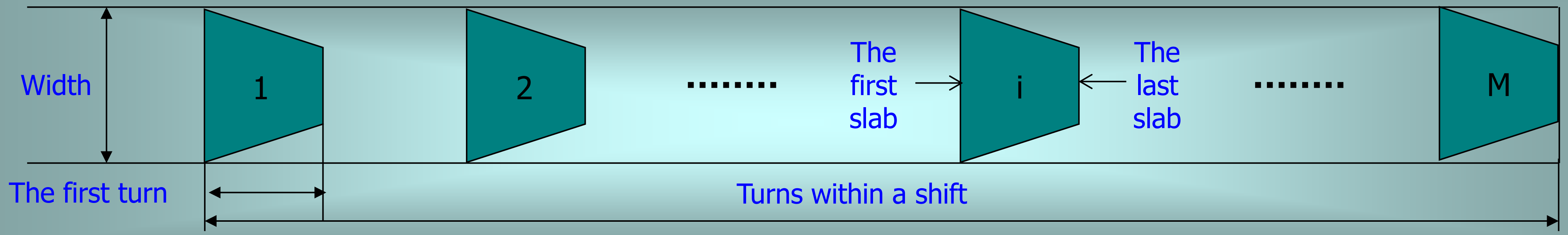
$$\text{Subject to} \sum_{i=1}^{N+M} X_{ij} = 1, \qquad j \in \{1, 2, ..., N+M\}$$

$$\sum_{j=1}^{N+M} X_{ij} = 1, \qquad i \in \{1, 2, ..., N+M\}$$

$$\sum_{i \in S} \sum_{j \in S \setminus \{i\}} X_{ij} \le |S| - 1, \quad S \subset \{1, ..., N+M\}, \quad 2 \le |S| \le N+M-2$$

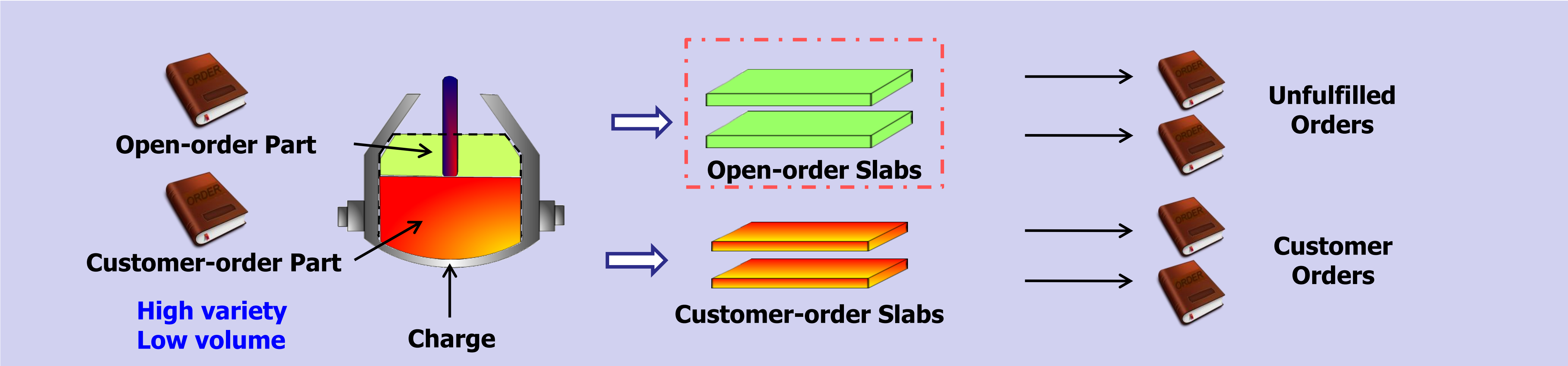


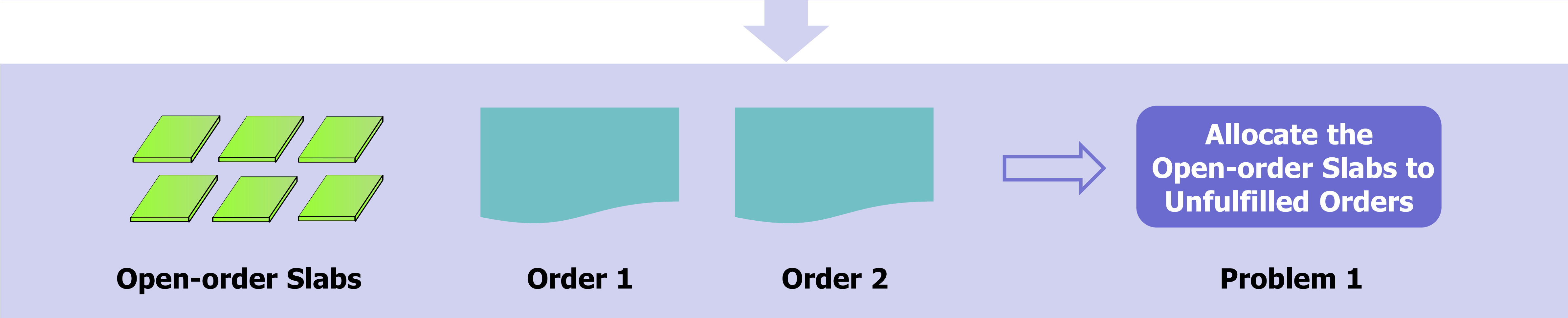
Structure and components of a turn



L. Tang, J. Liu, A. Rong, Z. Yang. A multiple traveling salesman problem model for hot rolling scheduling in Shanghai Baoshan Iron & Steel Complex. ***European Journal of Operational Research***, 2000, 124(2): 267-282.

4. Full-dimension Organic Management System (E) — Production Optimization





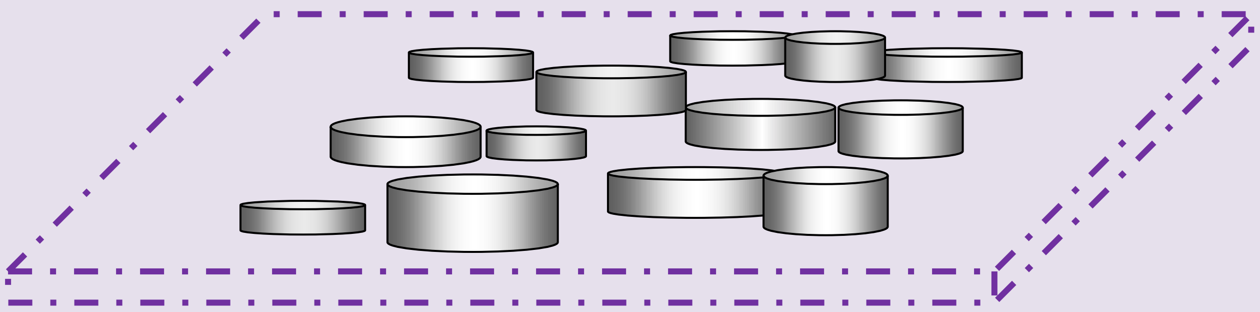
4. Full-dimension Organic Management System (E) — Production Optimization

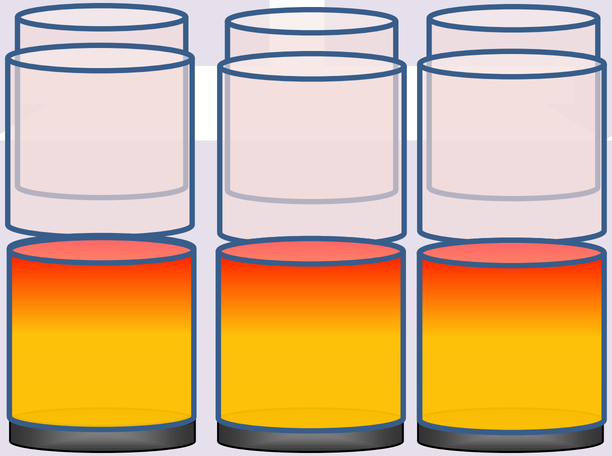
Maximize the Reward

Minimize the Mismatching Cost

Equipment Constraints

Matching Constraints



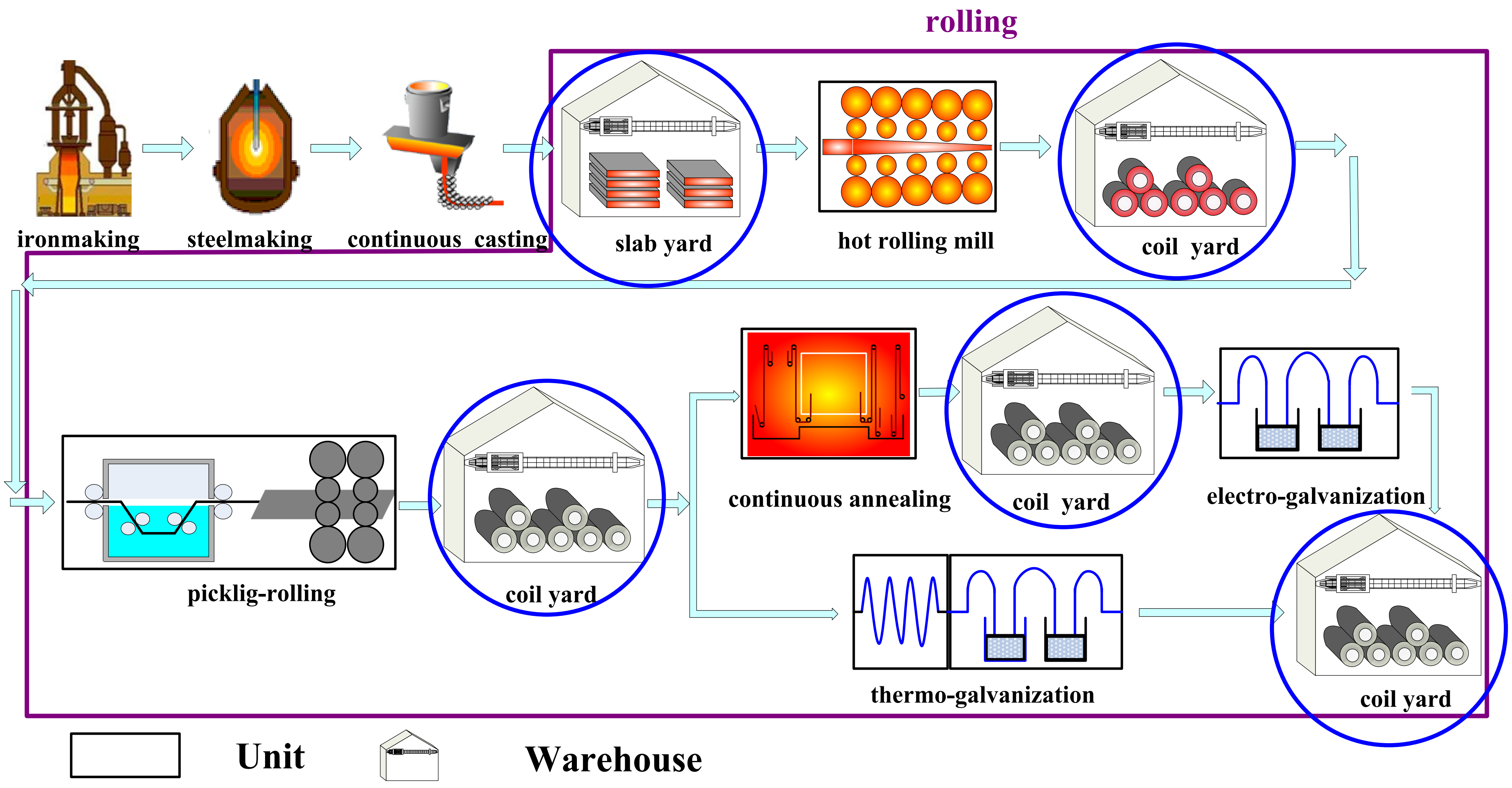


Form batches for each empty furnace

Select a median coil for each batch

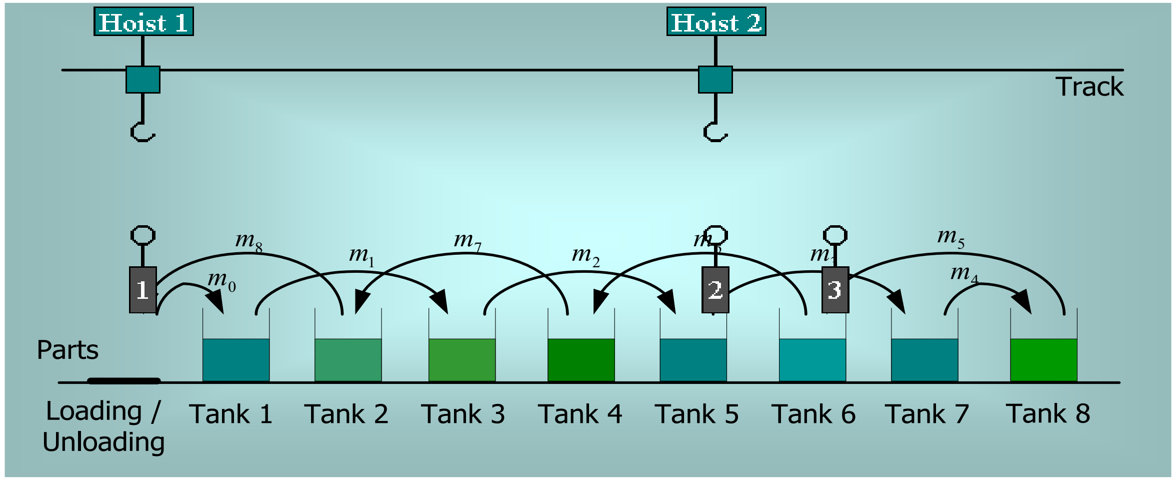
L. Tang, Y. Meng, Z. Chen, J. Liu. Coil batching to improve productivity and energy utilization in steel production. ***Manufacturing & Service Operations Management***, 2016, 18(2): 262-279.

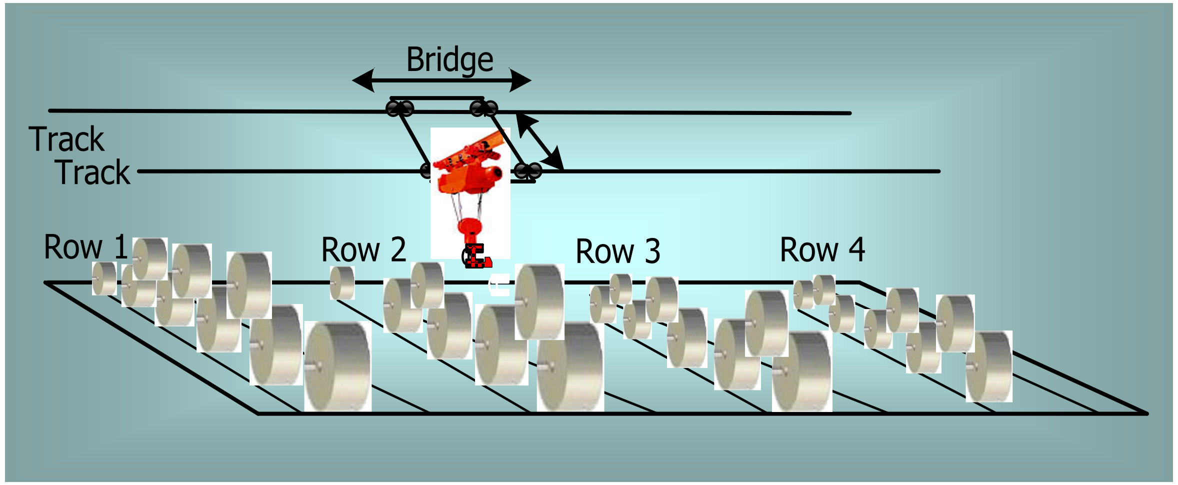
Logistics in Steel Plant



Logistics: Loading/Transportation/Shuffling/Storage/Stowage

Logistics Scheduling





Crane scheduling problem

Determines the transportation sequence for all demanded coils and shuffled position for each blocking coil.

Decision

Retrieval sequence of the target coils and shuffled positions for blocking coils

Objective

Minimize the time by which the retrieval of all target coils is completed

For general case

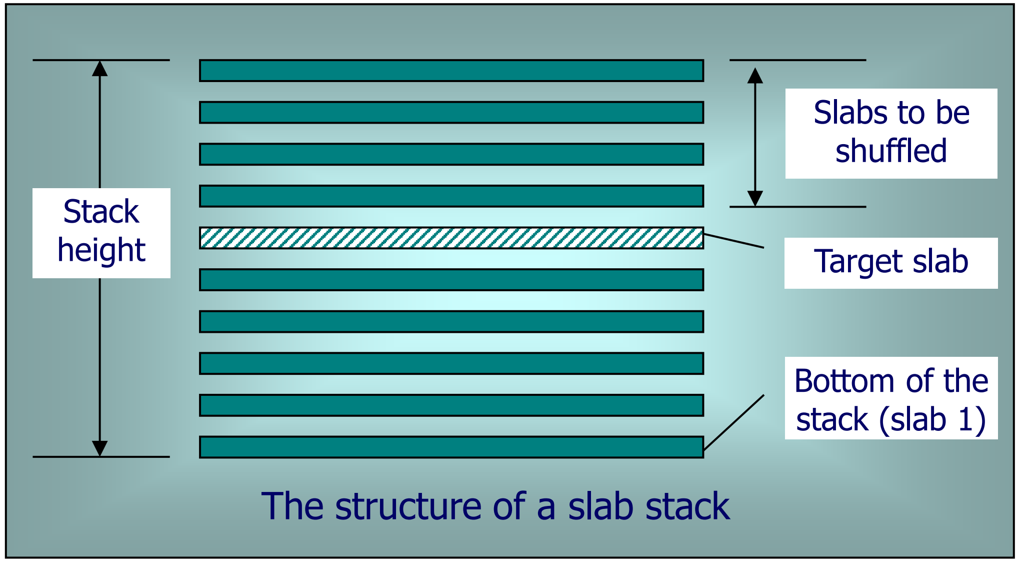
Heuristic algorithm & worst-case analysis

For special cases

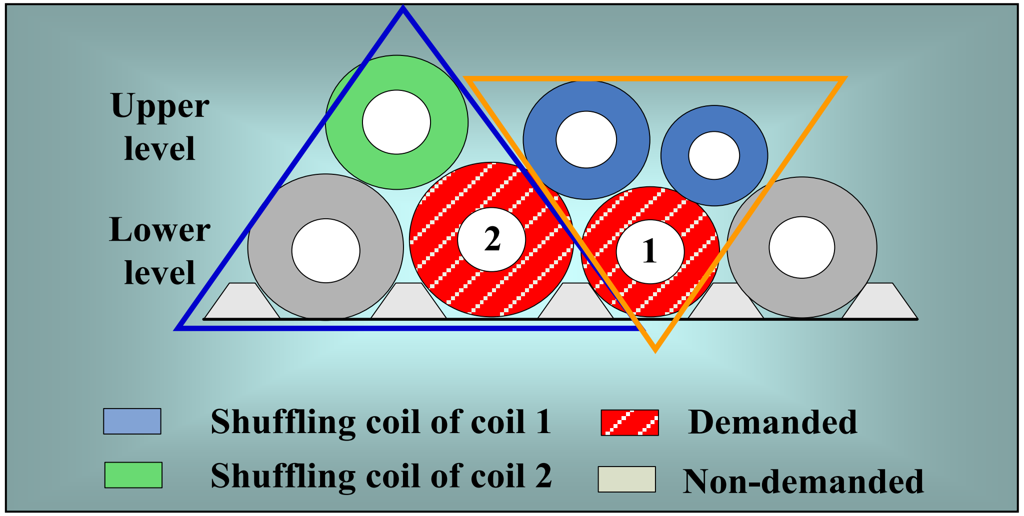
Polynomial algorithms (optimal solutions)

L. Tang, X. Xie, J. Liu. Crane scheduling in a warehouse storing steel coils. ***IISE Transactions***, 2014, 46(3): 267-282.

4. Full-dimension Organic Management System (E) — Logistics Optimization



The structure of a slab stack



Shuffling problem in steel plants

Assign a storage slot for each shuffled item during retrieving all target items in the given sequence

Decision

Suitable storage positions for shuffled items

Objective

Minimize shuffling and crane traveling

For general case

Greedy heuristics

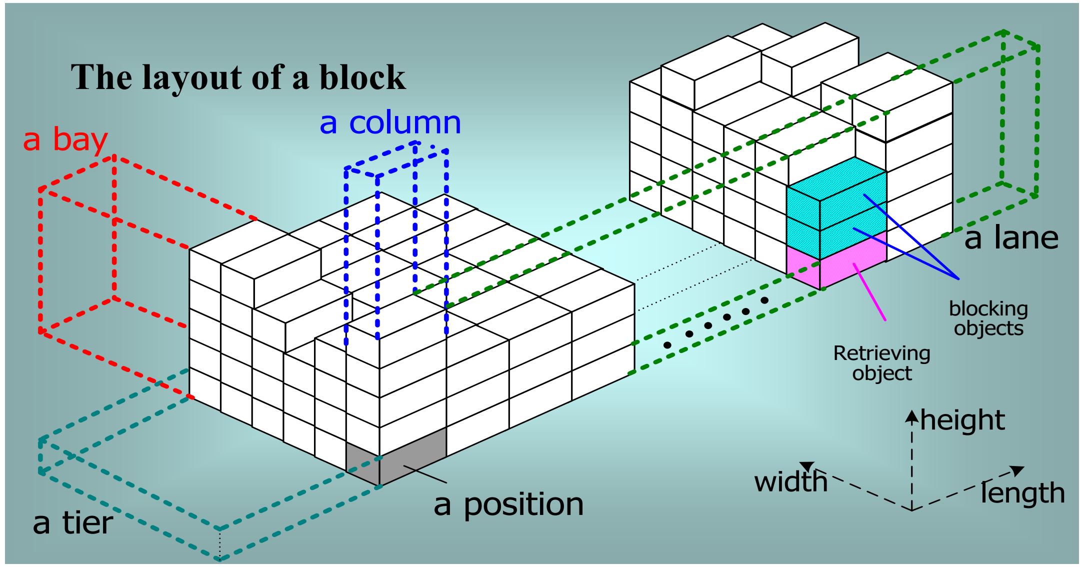
For special cases

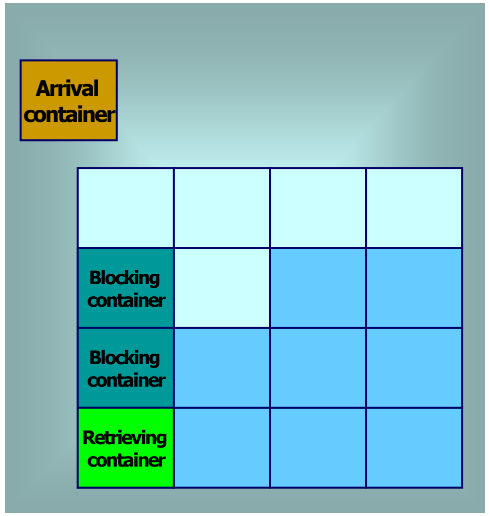
Polynomial algorithms (optimal solutions)

L. Tang, R. Zhao, J. Liu. Models and algorithms for shuffling problems in steel plants. ***Naval Research Logistics***, 2012, 59(7): 502-524.

4. Full-dimension Organic Management System (E) — Logistics Optimization

- For statistic and dynamic reshuffling problem, an improved mathematical formulation and a simulation model are established.
- Five polynomial time heuristics and their extended versions are proposed and analyzed theoretically.
- The proposed heuristics outperforms existing methods.



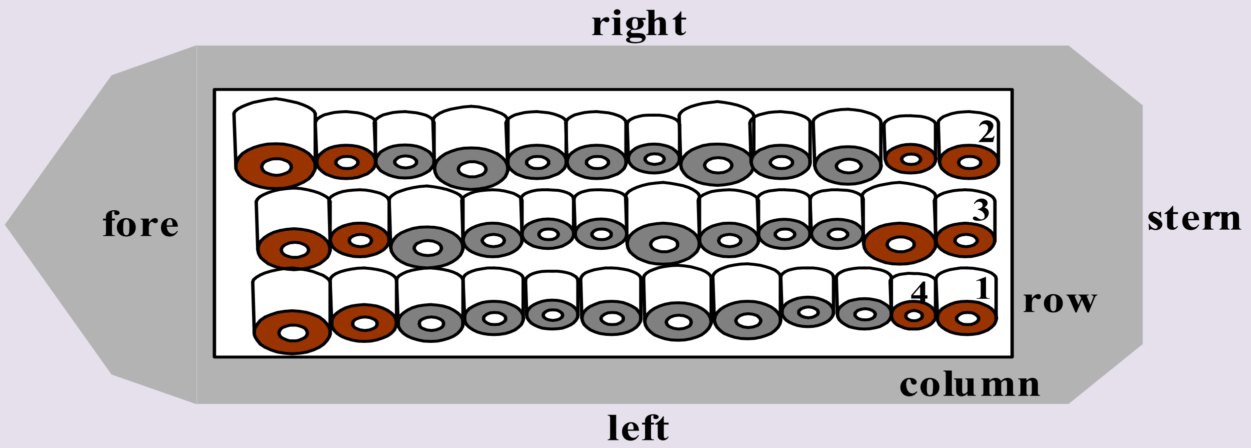


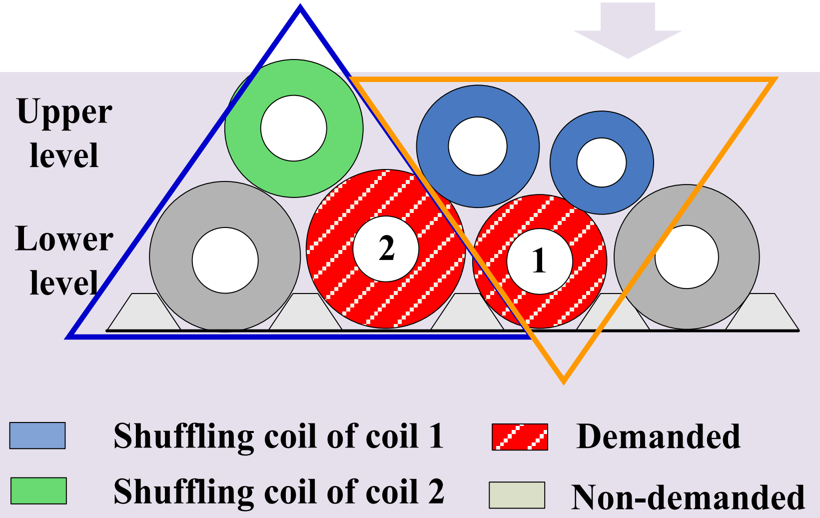
4. Full-dimension Organic Management System (E) — Logistics Optimization

Minimize the moment imbalance

Minimize the shuffling

Minimize the dispersion of coils for the same destination





Structural constraints

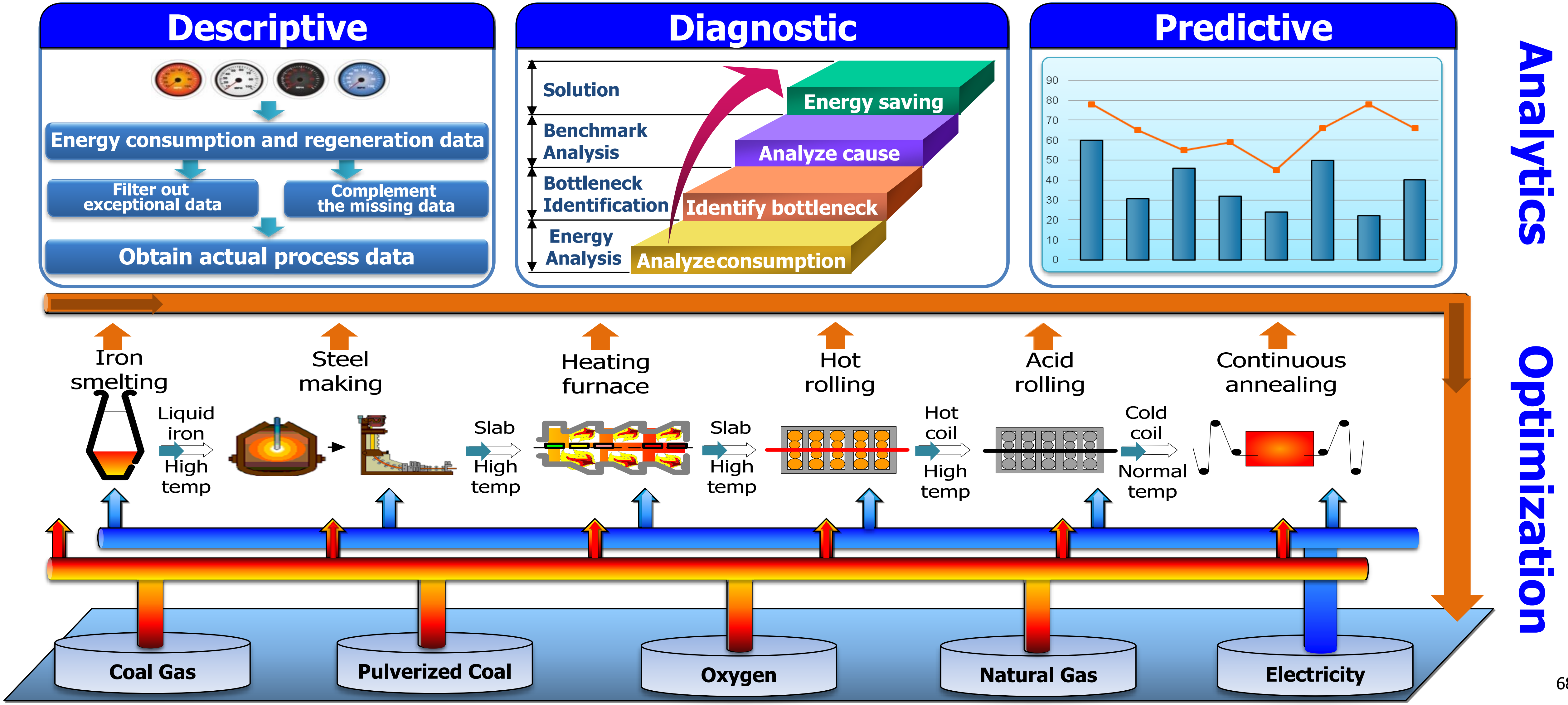
Weight restriction constraints

Operational constraints

L. Tang, J. Liu, et al. Modeling and solution for the ship stowage planning Modeling and solution for the ship stowage planning problem of coils in the steel industry. ***Naval Research Logistics***, 2015, 62(7): 564-581.

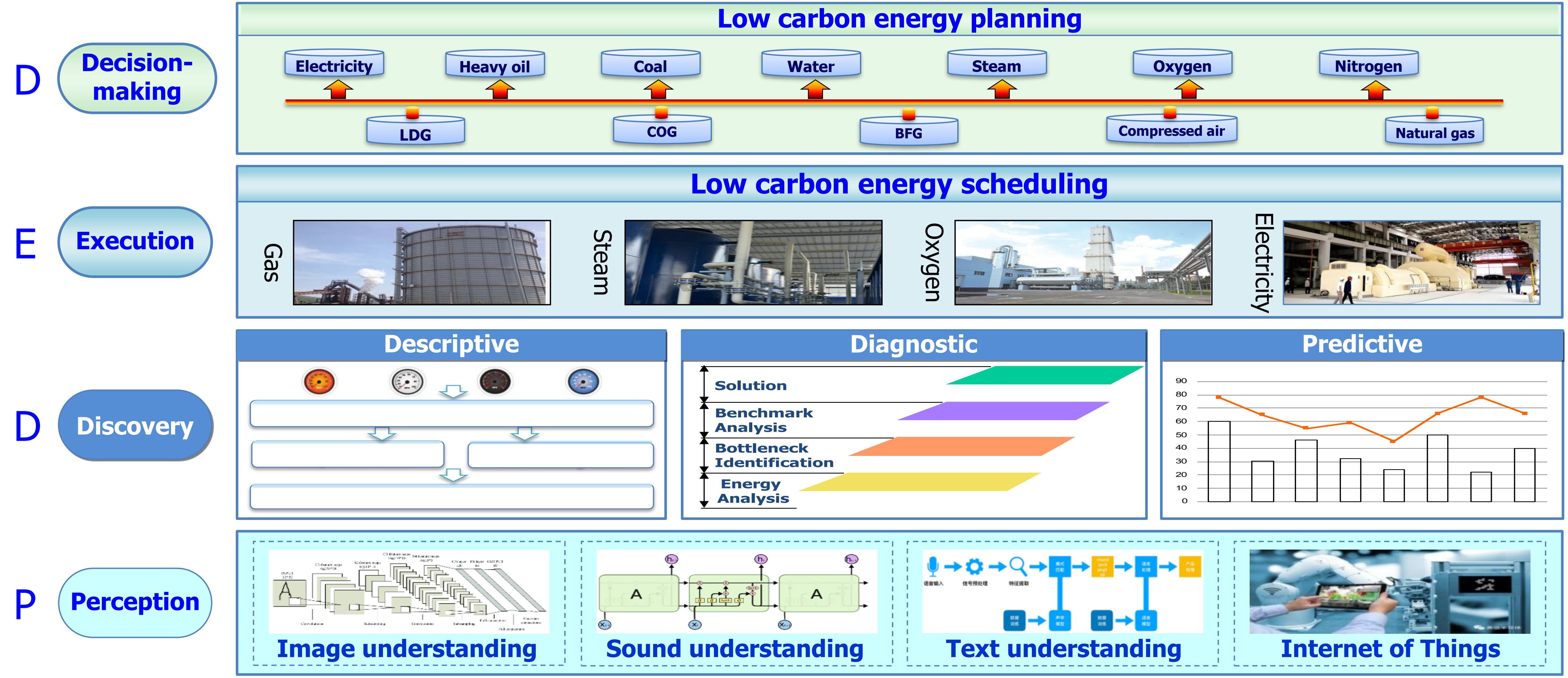
4. Full-dimension Organic Management System (E)

Energy Analytics



4. Full-dimension Organic Management System（E）

Energy Optimization

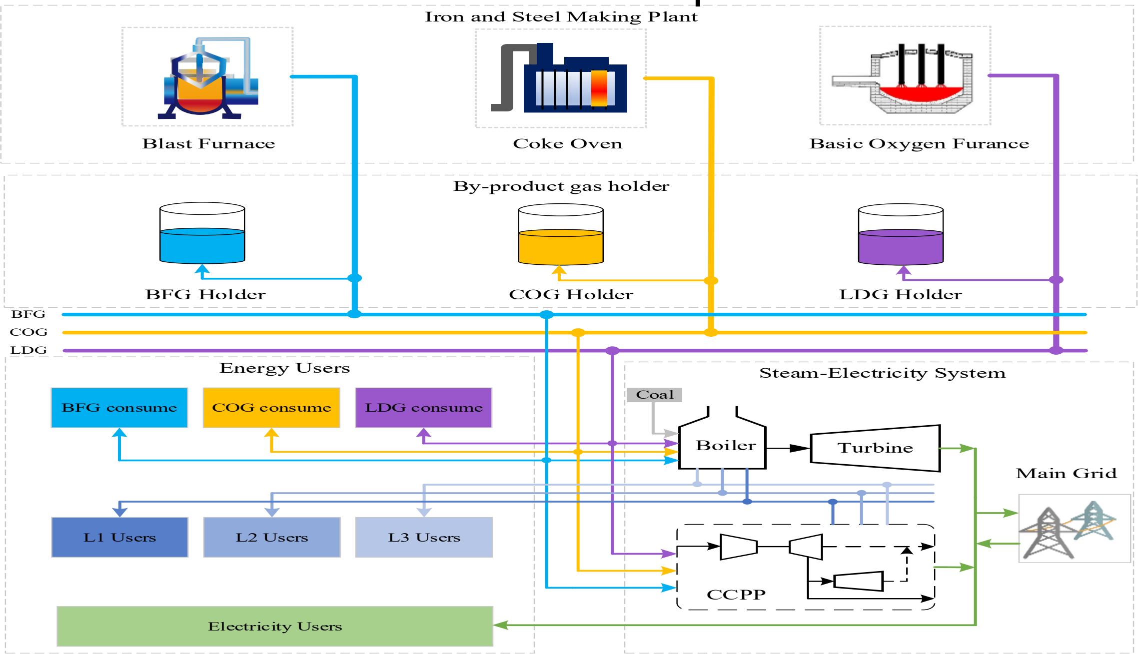


4. Full-dimension Organic Management System (E)

Multi-Energy Planning

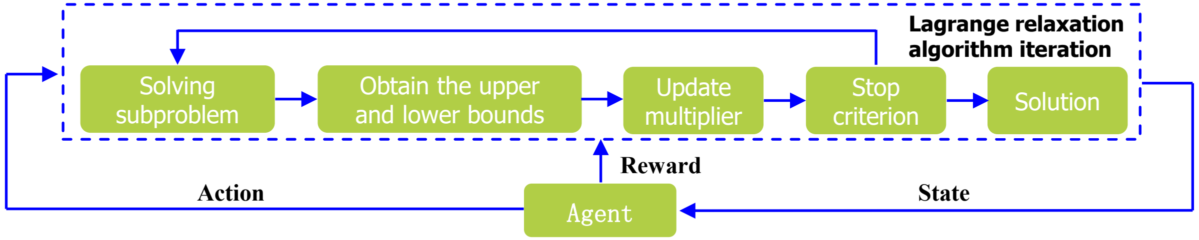
❖ Research Background

In steel enterprises, by-product gases, steam, and electricity constitute a coupled system and the supply and demand balance of all energy carriers is maintained within the allocation period.



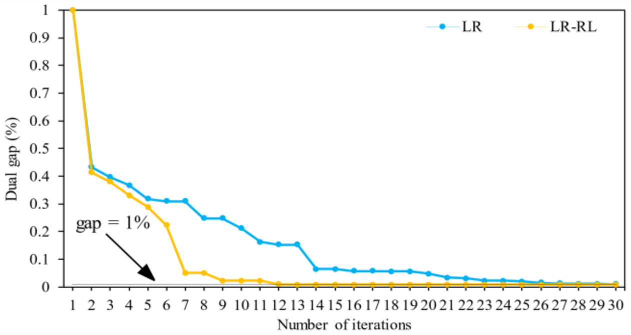
❖ Reinforcement Learning Based Improved Lagrangian Relaxation Algorithm

A reinforcement learning based method for step size update is proposed to dynamically adjust the multipliers Lagrangian relaxation algorithm.



Item	Gurobi Time(s)	Solution Time(s)		Gap(%)	
		LR	RL-LR	LR	RL-LR
1	3.6	6.3	**3.5**	0.8	0.9
2	41.6	20.1	**13.2**	1.4	**0.0**
3	148.5	47.7	**27.2**	1.3	**1.0**
4	420.0	66.3	**48.0**	1.2	**1.0**
5	859.1	127.0	**77.9**	1.7	**0.9**
6	2841.8	207.2	**193.7**	1.5	**1.1**
7	>3600	430.7	**380.8**	1.7	**1.3**
8	>3600	529.8	**409.6**	1.6	**1.2**

The algorithm solves the time comparison



Algorithm dual gap comparison

Miao Chang, Shengnan Zhao, Lixin Tang, Jiyin Liu, Yanyan Zhang. A reinforcement learning based Lagrangian relaxation algorithm for multi-energy allocation problem in steel enterprise. ***Computers & Chemical Engineering***, 2025, 194:108948.

Miao Chang, Lixin Tang, Shengnan Zhao. A Reinforcement Learning-based Lagrangian Decomposition Approach for Energy-Oriented Scheduling Optimization in Steelmaking Process. ***IEEE Transactions on Automation Science and Engineering***, 2025.

4. Full-dimension Organic Management System (E)

Gas scheduling

Comprehensive allocation of gas system

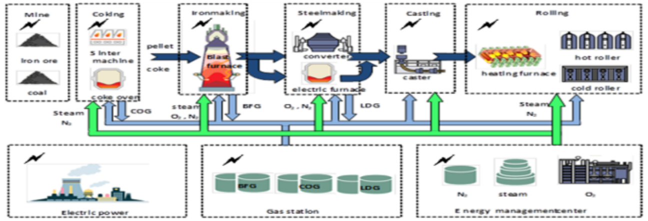
- **Determine**: allocation plan of BFG, COG, LDG
- **Multi-objective:** minimize consumption cost, purchase cost, emission cost, and energy holding cost
- **Solution method:** soft constraint handling NSGA-II

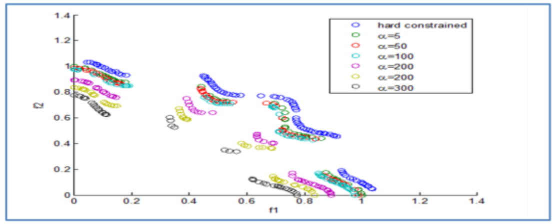
$$\sum_i x_i + w \le \sum_i y_i + z + \left(H - H^0\right)$$
$$y_i \le \theta_i^1 p_i, i = 1, 2, \dots, I$$

Constraint definition

$$\mu(G) = \begin{cases} 0 & G \le \delta \\ 1\text{-}e^{-\left(\frac{G-\delta}{\alpha}\right)} & G > \delta \end{cases}$$

Soft constraint definition

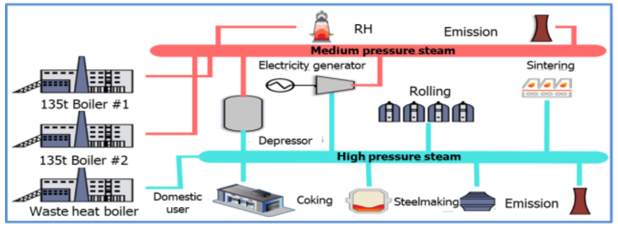




Steam scheduling

Steam scheduling by coordinating demand and electricity generation

User demand → Make full use of excess steam resources ← Electricity generation



Objectives

- Maximize electricity generation upon demand

$$z = \max \sum_t \sum_i \left(u_i + v_i x_{ti,j=1} + w_i R_{ti}\right)$$

Supply capacity constraints

$$a_i^0 < \sum_{j=1}^{4} x_{tij} < a_i^1,\ b_{ij}^0 \le x_{tij} \le b_{ij}^1,\ r_i^0 \le R_{ti} \le \min\left(x_{ti1}, r_i^1\right),\ q_i^0 \le Q_{ti} \le \min\left(x_{ti1}, q_i^1\right)$$
$$x_{tij} = \min\left\{a_i^1, \max\left(a_i^0, S_t^D - \sum_{i \in I_1 \cup I_2 \cup I_3}\left(x_{ti,3} + R_{ti} + Q_{ti}\right)\right)\right\}$$

Fluctuation, safe flow constraints

$$F_t^D = \max\left(0, \sum_i \sum_{j \in J_3}\left(x_{tij} + R_{ti} + Q_{ti}\right) - e^D\right) \quad F_t^Z = \max\left(0, \sum_i x_{tij} - e^Z\right)$$
$$\left|\sum_i \sum_j \left(x_{tij} + R_{ti} + Q_{ti}\right) - \sum_i \sum_{j \in J_3}\left(x_{t-1,ij} + R_{t-1,i} + Q_{t-1,i}\right)\right| \le \delta^D$$

Steam demand constraints

$$\eta^Z \sum_i x_{tij} > S_t^Z \qquad \eta^D \sum_i \sum_j \left(x_{tij} + R_{ti} + Q_{ti}\right) > S_t^D$$

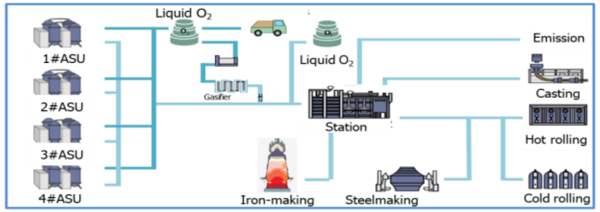
Oxygen scheduling

Task

Dynamically balance and optimize the oxygen system

Supply Modes

- Supplied by oxygen generator
- Supplied by liquid oxygen system



Minimize operating cost of oxygen system

$$Z = \sum_t \sum_{i \in E}\left(c_i \cdot F_{ti} + c_i^A \cdot A_{ti} + c_i^Y \cdot Y_{ti} + \frac{1}{2}\gamma_{ti} \cdot c_i \cdot 0.7 B_i\right)$$

Oxygen generators capacity, operating requirements

$$\left|O_{ti} - O_{t-1,i}\right| \le \beta_{ti}\varepsilon \qquad G_{ti} = G_{t-1,i} + Y_{ti} - D_{ti}, \qquad G_i^0 \le G_{ti} \le G_i^1,$$
$$\gamma_{ti} = \max\left\{0, \left(\beta_{ti} - \beta_{t-1,i}\right)\right\} \qquad d_t = \sum_{i \in E} D_{ti}, \qquad d_t < \sum_{i \in E} G_{t-1,i}$$

Pipeline pressure, fluctuation limitations

$$\left(H_t - H_{t-1}\right) + \sum_{j=1} S_{tj} < \sum_{i \in E} A_{ti} \qquad H^0 \le H_t \le H^1$$
$$\left|\frac{H_t - H_{t-1}}{H_{t-1}}\right| \le \delta \qquad A_{ti} \le \beta_{ti} a_i \qquad A_{ti} < O_{ti}$$

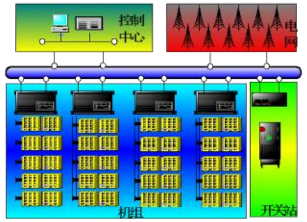
Oxygen demand constraints

$$\sum_j S_{tj} + \sum_{i \in E} Y_{ti} + \left(H_t - H_{t-1}\right) + F_t = \sum_{i \in E} O_{ti}$$

Electricity scheduling

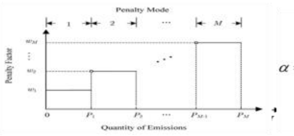
Thermal Generation Scheduling

Running state → Maximize generation profits ← Output level



System modeling

Representation of emission penalty



$$\alpha = \begin{cases} w_1, & \sum_{i=1}^{n}\sum_{t=1}^{T} E_i(x_{it}, u_{it}) \le Q_1 \\ w_m, & Q_{m-1} < \sum_{i=1}^{n}\sum_{t=1}^{T} E_i(x_{it}, u_{it}) \le Q_m \\ w_M, & \sum_{i=1}^{n}\sum_{t=1}^{T} E_i(x_{it}, u_{it}) > Q_{M-1} \end{cases}$$

Lagrangian relaxation

$$z_{SC} = \min \sum_{j=1}^{n} c_j x_j$$
$$\boxed{s.t. \sum_{j=1}^{n} a_{ij} x_j \ge 1,\ i = 1, 2, \cdots, m,}$$
$$x_j \in \{0,1\},\ j = 1, 2, \cdots, n.$$

Relaxation →

$$z_{LRSC}(\lambda) = \min \sum_{j=1}^{n} c_j x_j + \sum_{i=1}^{m} \lambda_i \left(1 - \sum_{j=1}^{n} a_{ij} x_j\right)$$
$$s.t.\quad x_j \in \{0,1\}, j = 1, 2, \cdots, n, \quad \lambda \ge 0.$$

Decomposition ↓

$$z_{LRSC}(\lambda) = \min \sum_{j=1}^{n} d_j x_j + \sum_{i=1}^{m} \lambda_i$$
$$s.t.\quad x_j \in \{0,1\}, j = 1, 2, \cdots, n, \quad \lambda \ge 0.$$

← Sub-problem Optimization

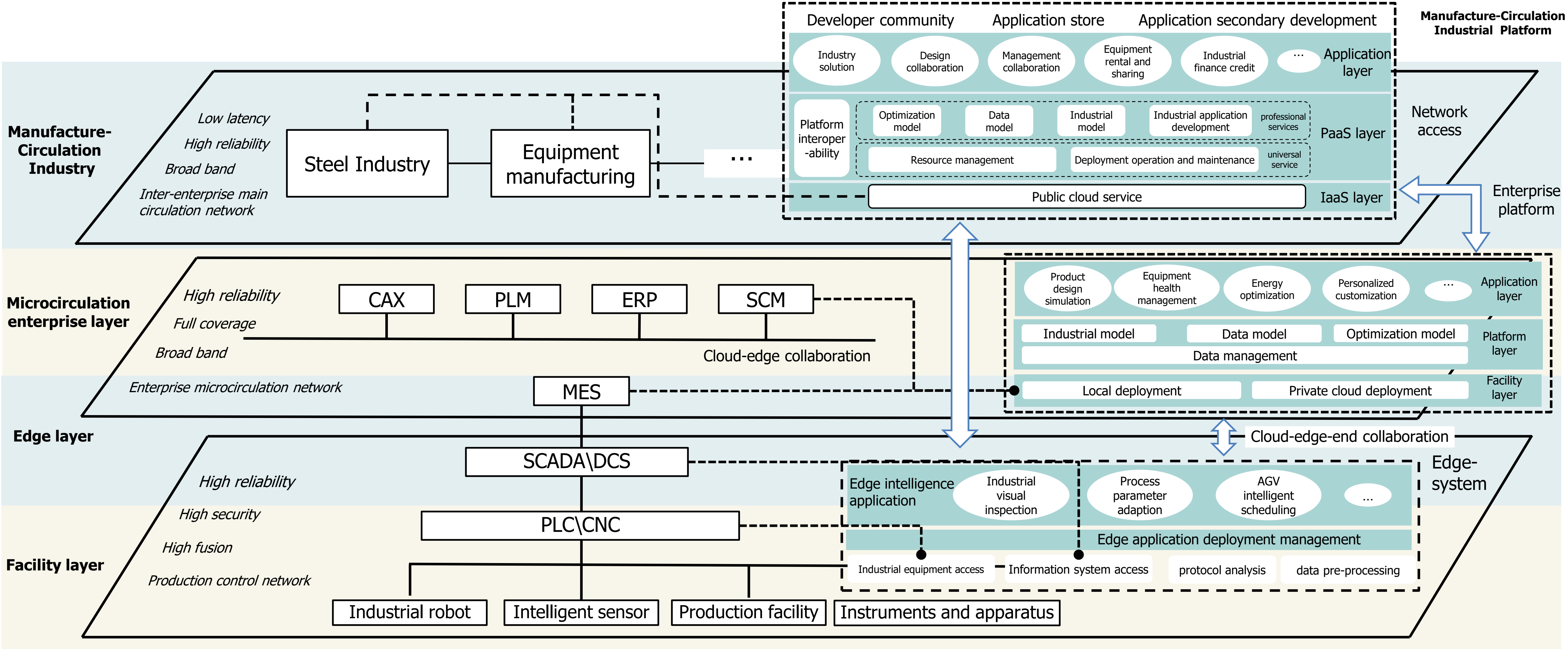
$$\boxed{z_{LRSC}(\lambda) = \sum_{j=1}^{n} d_j x_j^* + \sum_{i=1}^{m} \lambda_i, \quad x_j^* = \begin{cases} 1, & if\ d_j \le 0 \\ 0, & otherwise \end{cases}}$$

Lower bound ↑

Y. Zhang, G. G. Yen, and L. Tang. Soft constraint handling for a real-world multiobjective energy distribution problem. *International Journal of Production Research*, 2020, 58(19): 6061-6077.
G. Che, Y. Zhang, L. Tang, S. Zhao. A deep reinforcement learning based multi-objective optimization … oxygen production system in integrated iron and steel plants. *Applied Energy*, 2023, 345: 121332.
L. Tang, P. Che, J. Wang. Corrective Unit Commitment to an Unforeseen Unit Breakdown. *IEEE Transactions on Power Systems*, 2012, 27(4): 1729-1740.

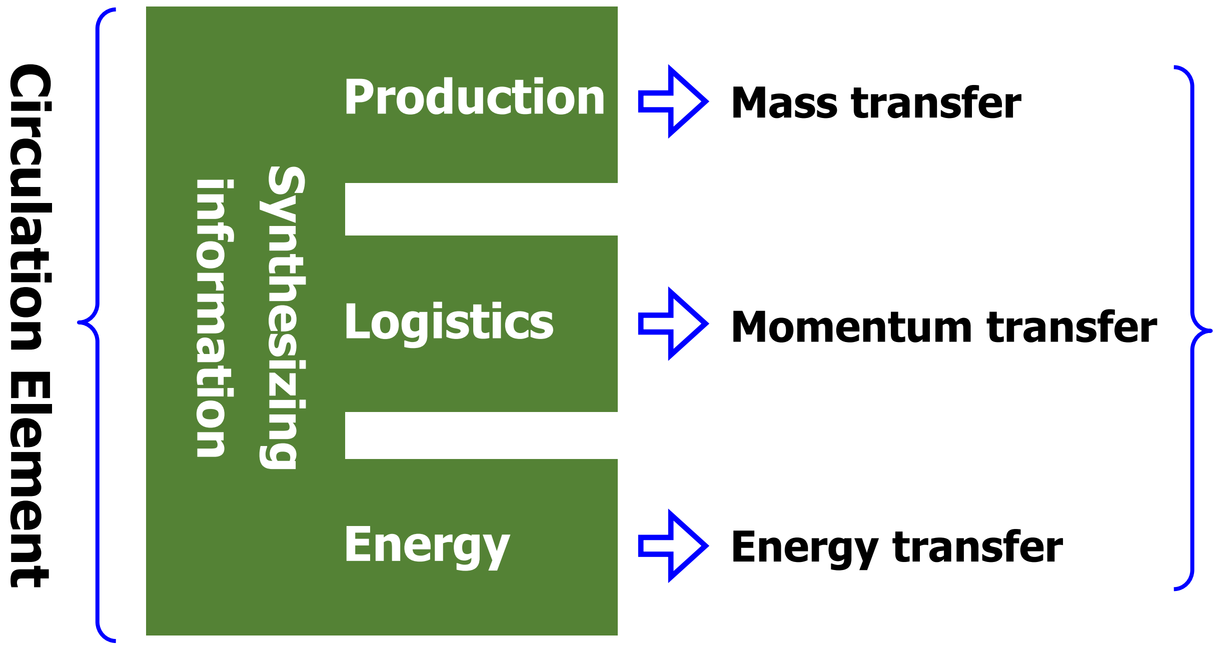
4. Full-dimension Organic Management System（E)

Information Feedback

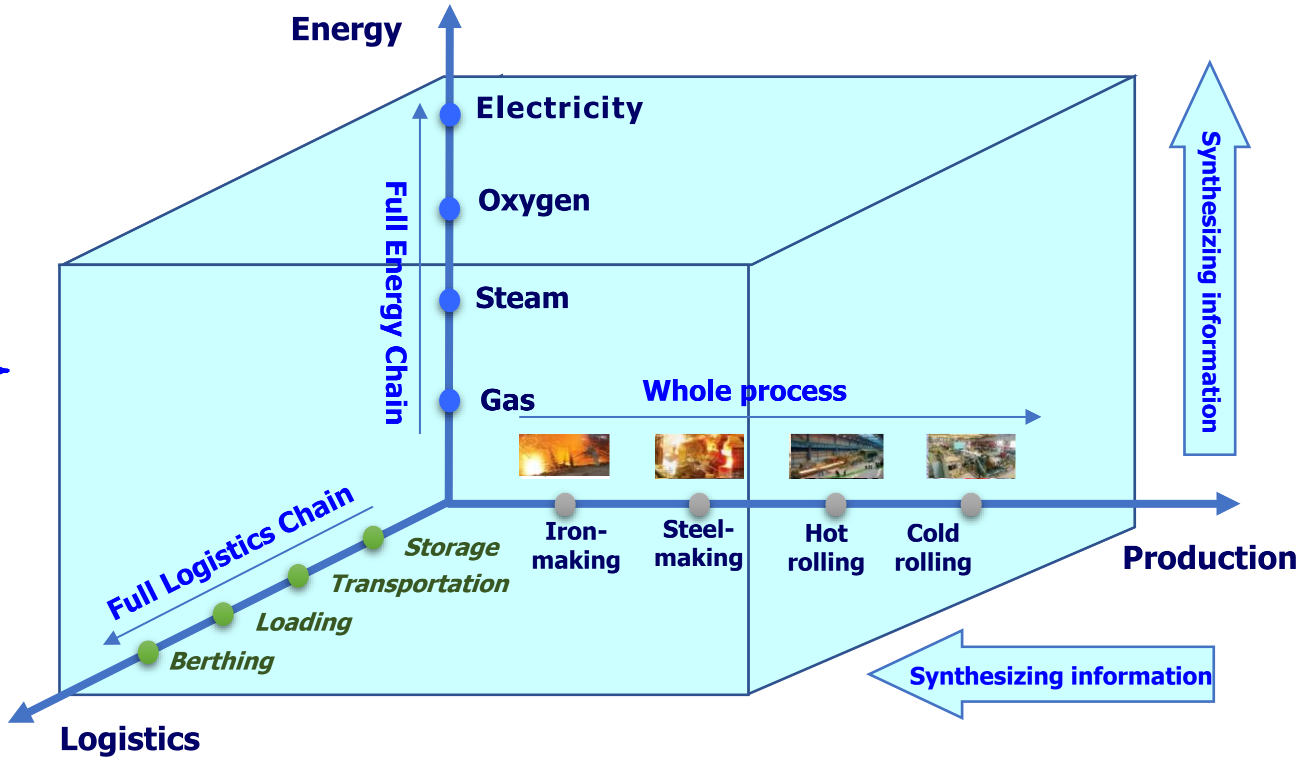


4. Full-dimension Organic Management System （E）

Full-dimension Organic Management System



ECO-System： Physical Strength, Vitality, Momentum, Intelligence



4. Full-dimension Organic Logistics Management System (E)

Game Theory

- Game theory is the study of mathematical models of strategic interactions among rational decision-makers. Industrial organization can be modeled as game problem.
- Basic components include player, state, action, payoff, strategy and equilibrium.

Game

- Non-co. Game ⟷ Cooperative Game
- Static Game ⟷ Dynamic Game

Mechanism Design

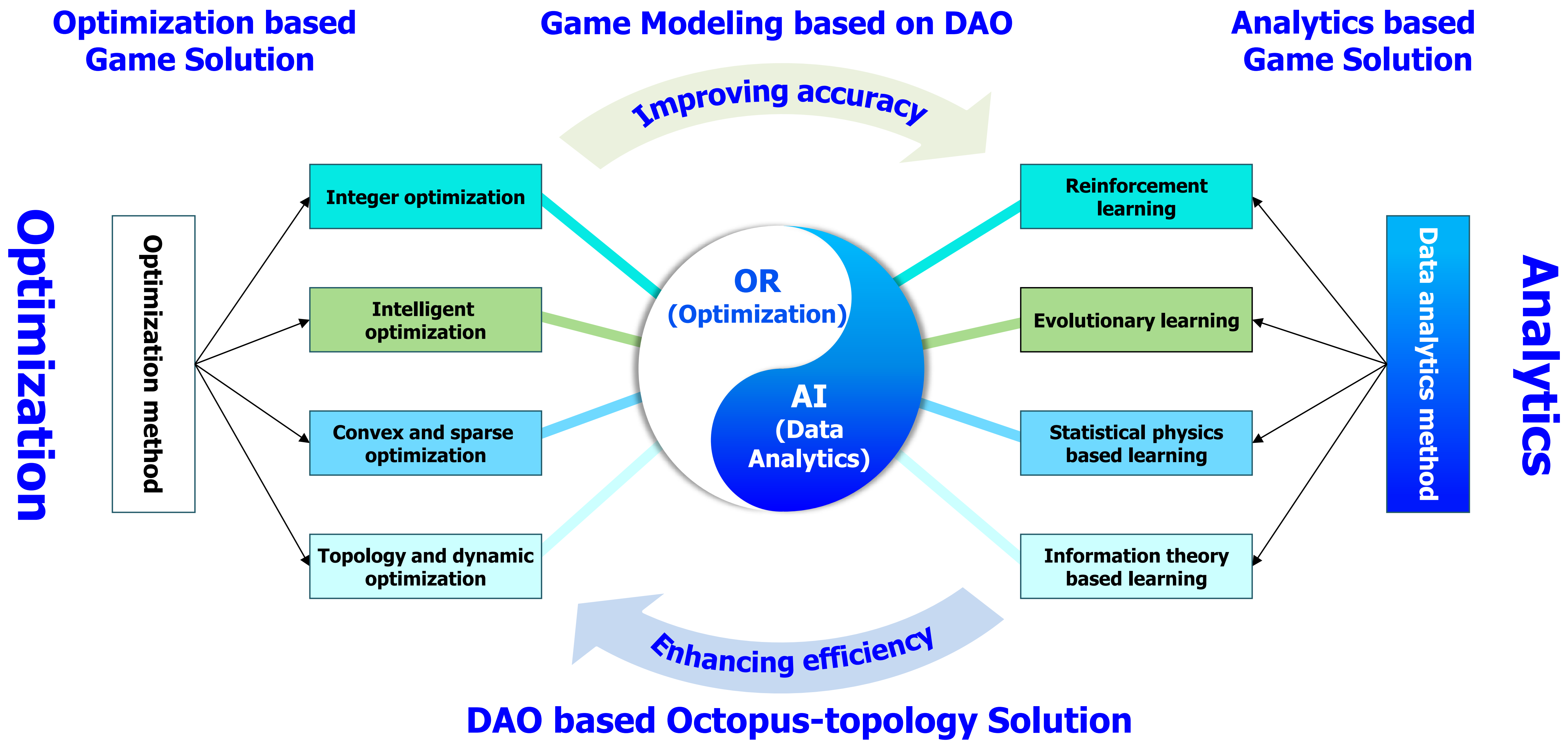
- Mechanism design is an economic framework for understanding how business can achieve optimal outcomes when individual self-interest and incomplete information may get in the way.
- Mechanism design theory is built on the concept of game theory.

Mechanism Design

+

Participant Design

4. Full-dimension Organic Logistics Management System (E)

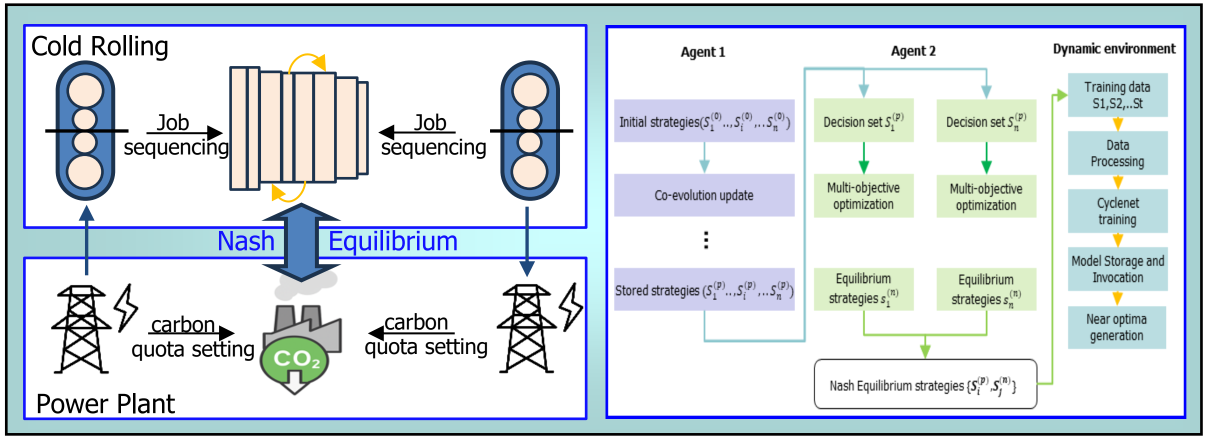


L. Tang, Y. Meng. Data analytics and optimization for smart industry. ***Frontiers of Engineering Management***, 2021, 8(2): 157-171.
(**Best Paper Award for 2014~2023**)

4. Full-dimension Organic Logistics Management System (E) — Production

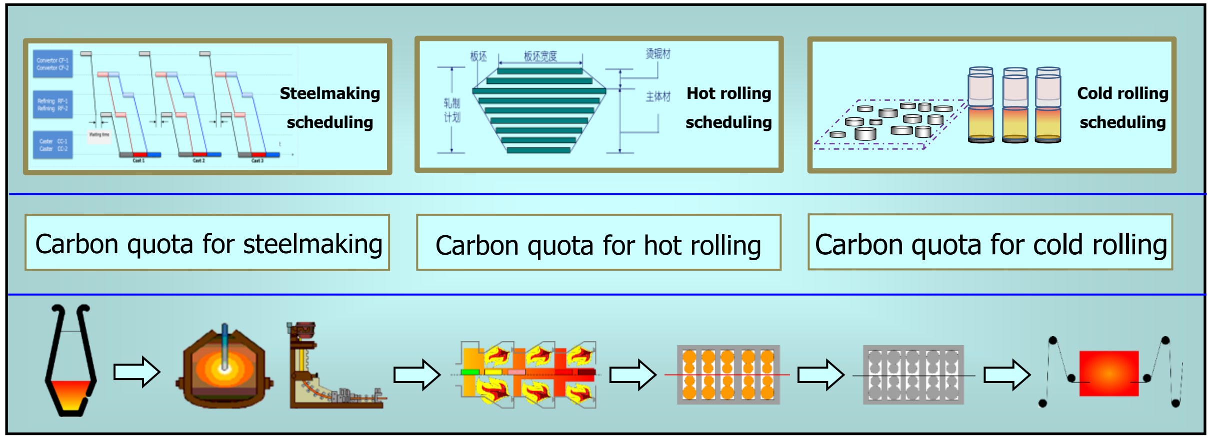
Carbon-aware Production Scheduling Game

- ❖ Game Modeling: the scheduling of cold rolling production and electricity consumption is formulated as non-cooperative game model, which aims to make trade-off between production efficiency and carbon emission.
- ❖ Game Solution: A co-evolutionary algorithm is developed to solve the low-carbon cold rolling scheduling game problem efficiently. Moreover, the solution process is enhanced via Deep CycleNet initialization.



Carbon-aware Integrated Scheduling Game

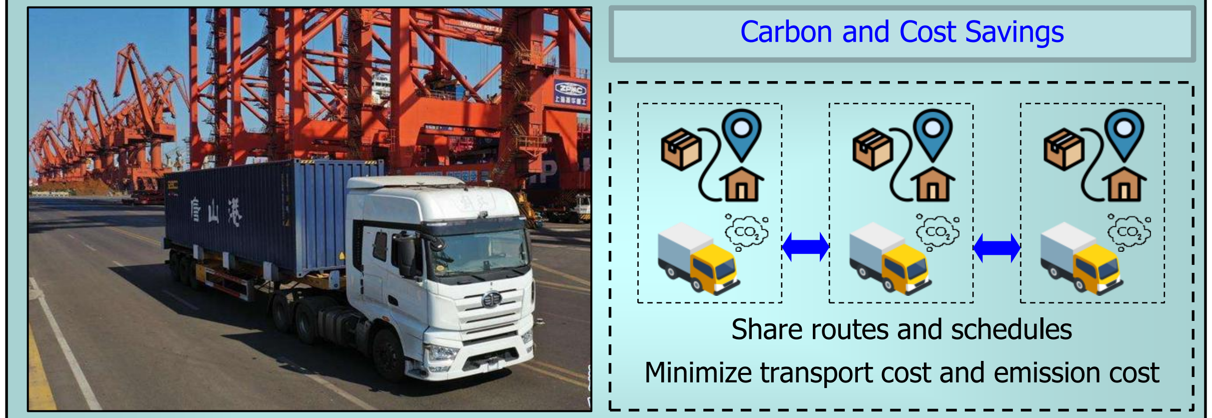
- ❖ Game Modeling: the carbon-aware integrated production scheduling is formulated as cooperative game model. The carbon footprint of whole process production is optimized by forming a grand coalition of all production stages.
- ❖ Solution Methods: A row generation algorithm is developed to solve the cooperative game model of integrated production scheduling. The solving process is accelerated by the reinforcement learning method.



4. Full-dimension Organic Logistics Management System (E) — Logistics

In-port Logistics Game for Carbon Reduction

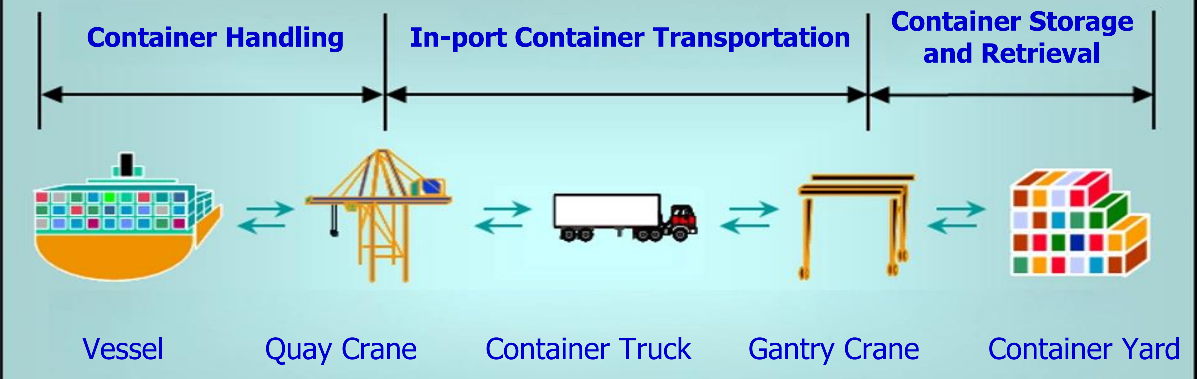
- Game modeling: In container ports, horizontal transport between quays and yards consumes carbon emission. A cooperative game allows trucks to share routes and schedules, reducing empty trips and emissions.
- Game solution: A low-carbon scheduling model minimizes transport and emission costs under time-window constraints. Carbon savings are fairly shared through data-driven optimization for efficient coordination.



Cooperative game mechanism for typical logistics operation

Port-wide Logistics Game for Carbon Reduction

- Game modeling: Container ports are typical logistics systems involving loading, transport, storage, and stacking. A cooperative logistics network integrates operations for low-carbon synergy.
- Game solution: A cooperative game model integrates analytics and integer optimization to compute core allocations of carbon and cost savings. The algorithm improves efficiency for large-scale scheduling.



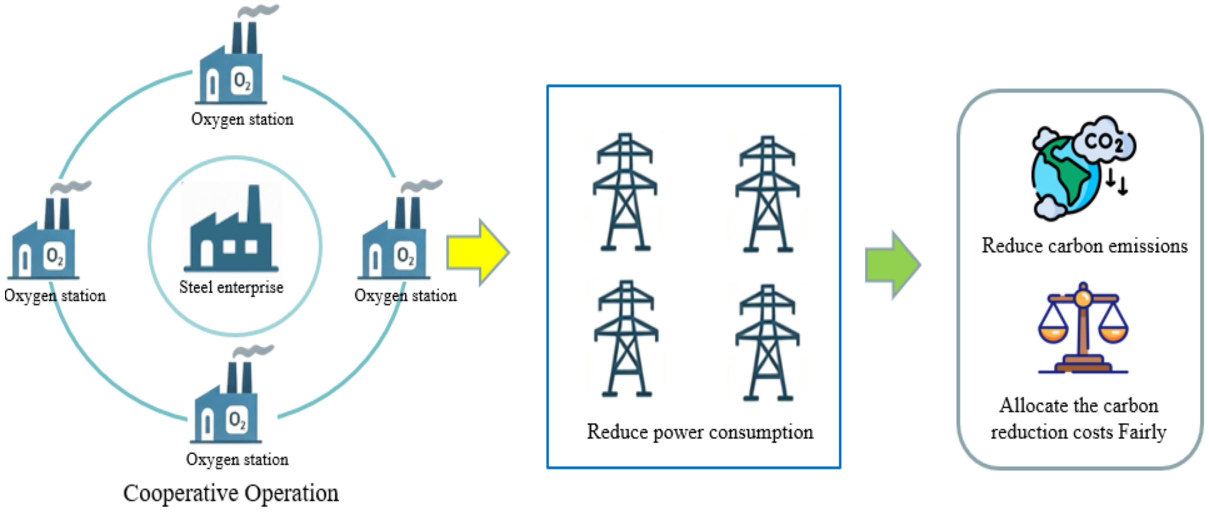
Cooperative game for integrated logistics for carbon reduction

4. Full-dimension Organic Logistics Management System (E) — Energy

Oxygen System Game for Carbon Reduction

❖ Game Modeling: Coordinate multi-unit oxygen operations to reduce system-wide electricity consumption and carbon emissions, with cooperative game ensuring fair carbon cost-sharing.

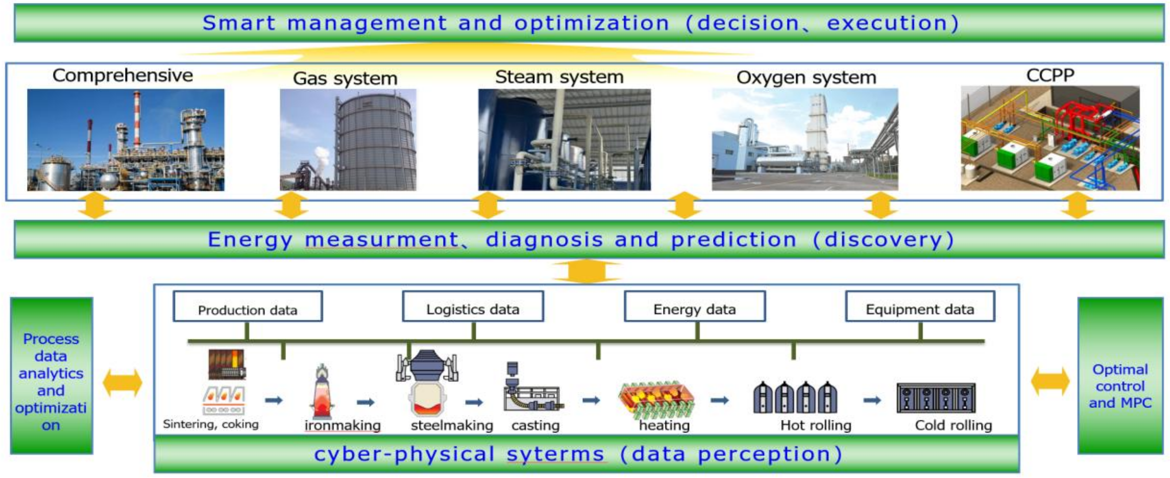
❖ Game Solution: A hybrid row generation-OA algorithm solves the model, quantifying each unit's marginal carbon reduction contribution. Efficiency is enhanced via reinforcement learning and parallel cutting planes.



Integrated Energy Game for Carbon Reduction

❖ Game Modeling: For integrated energy systems, establish non-cooperative game model and design collaborative energy subsystem strategies to balance low-carbon objectives with self-sufficiency.

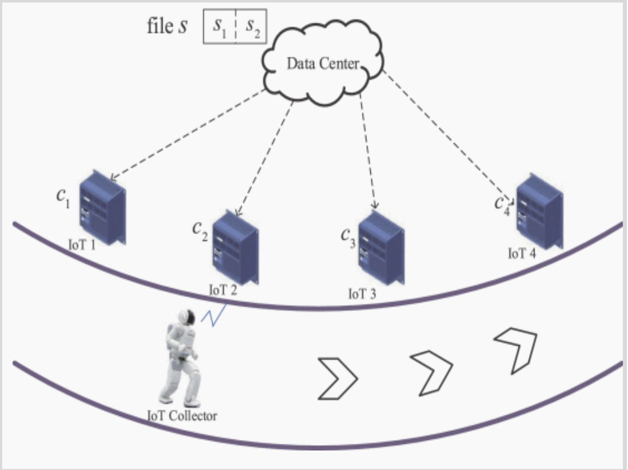
❖ Solution Method: A RL guided conditional variational autoencoder based dynamic multi-objective optimization is established to online solve the model, yielding dynamic game equilibria among multi subjects in each period.

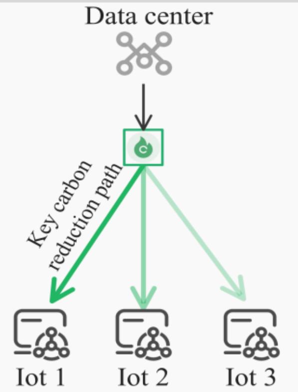


4. Full-dimension Organic Carbon-Reduction System (E) — Information

Low-carbon Mechanism for Edge Computing Nodes

- Game Modeling: Design energy-aware caching at edge nodes to meet power and carbon-intensity constraints, reducing latency, bandwidth, and transmission energy through incentive-driven low-carbon operation.
- Game Solution: A two-stage game-theoretic mechanism coordinates edge–center topology via matching games and optimizes caching through Stackelberg games over backhaul links for low-carbon collaboration.

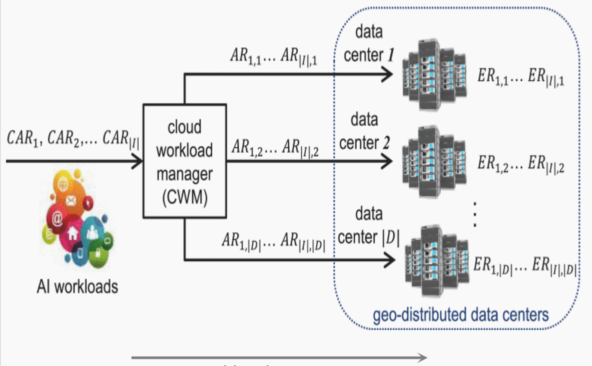




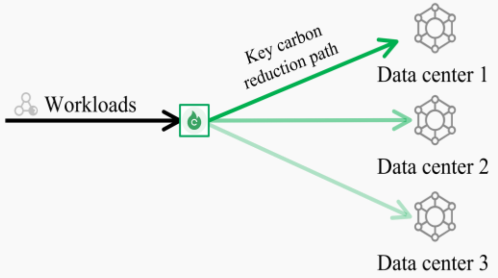
Cache assignment based on carbon reduction intensity

Low-carbon Mechanism for Computing Centers

- Game Modeling: Determine the workload allocation across data centers, considering hardware heterogeneity, dynamic electricity pricing, inter-center data transfer costs, and carbon footprint reduction.
- Game Solution: A Stackelberg game model coordinates workload allocation, where each task type minimizes carbon emissions, and deep reinforcement learning derives strategies toward Nash equilibrium.

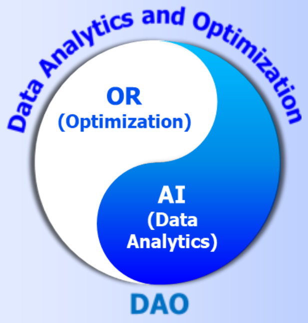


Workload assignment



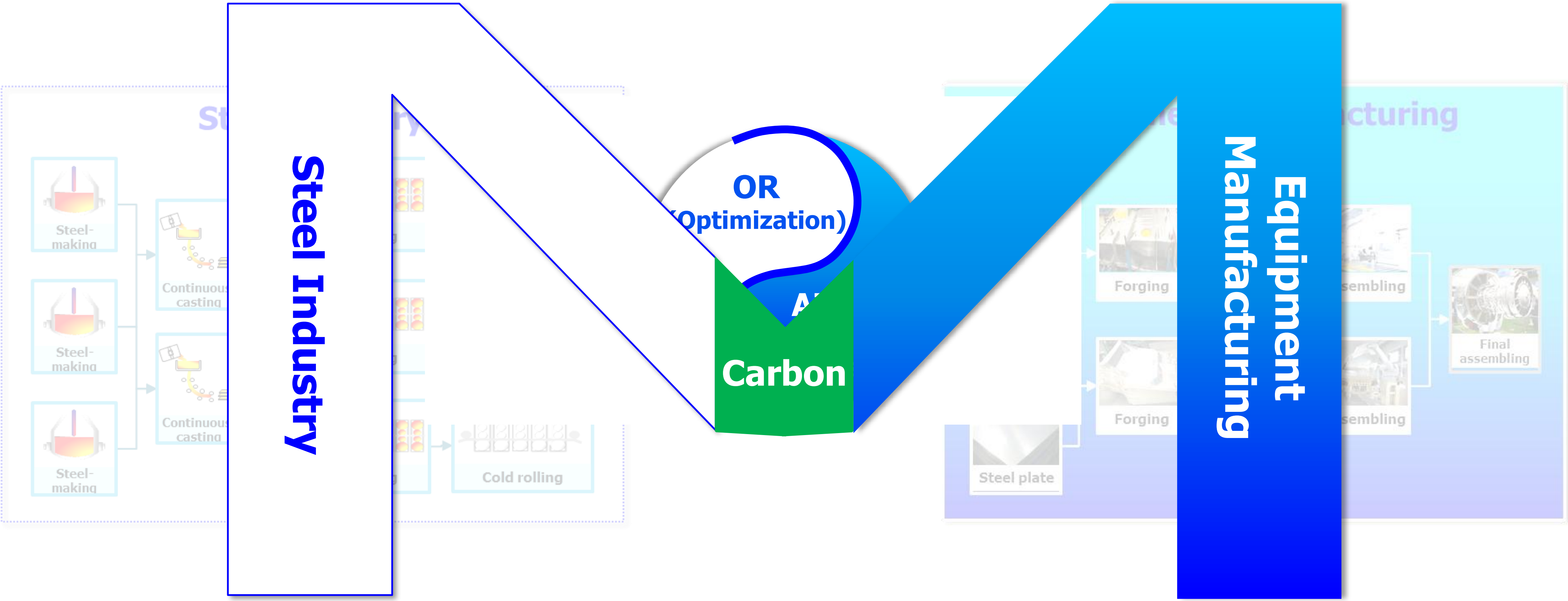
Workload assignment based on carbon reduction intensity

Outline



- DAO-based PDDE System Technology (H)
- Data Analytics and Optimization for Material Science (V)
- RDMS-based Quality Analytics and Dynamic Optimization (S)
- Full-dimension Organic Management System (E)
- **DAO & LLM based Design and Simulation for MCIS (M)**

5. DAO & LLM based Design and Simulation for MCIS (M)



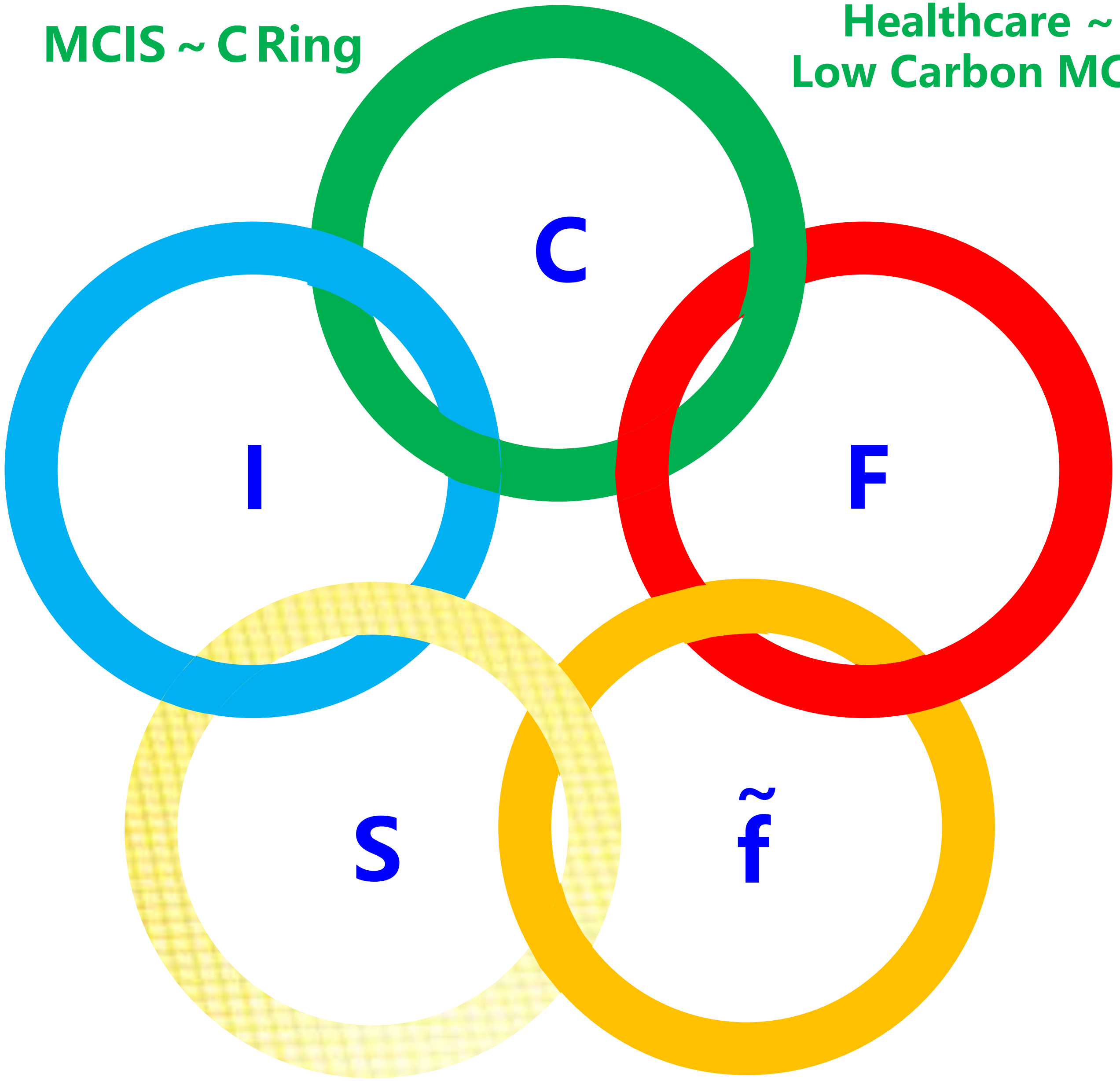
5. DAO & LLM based Design and Simulation for MCIS (M)

Enterprise	Industry	System
		
A tree	**A forest**	**An eco-system**
An enterprise	Homogeneous enterprise	Heterogeneous enterprise

5. DAO & LLM based Design and Simulation for MCIS (M)

MCIS ~ C Ring

Healthcare ~ Low Carbon MCIS



MCIS ~ I Ring

Quantum Intelligence ~ Information MCIS

MCIS ~ F Ring

Steel ~ Machinery Equipment MCIS

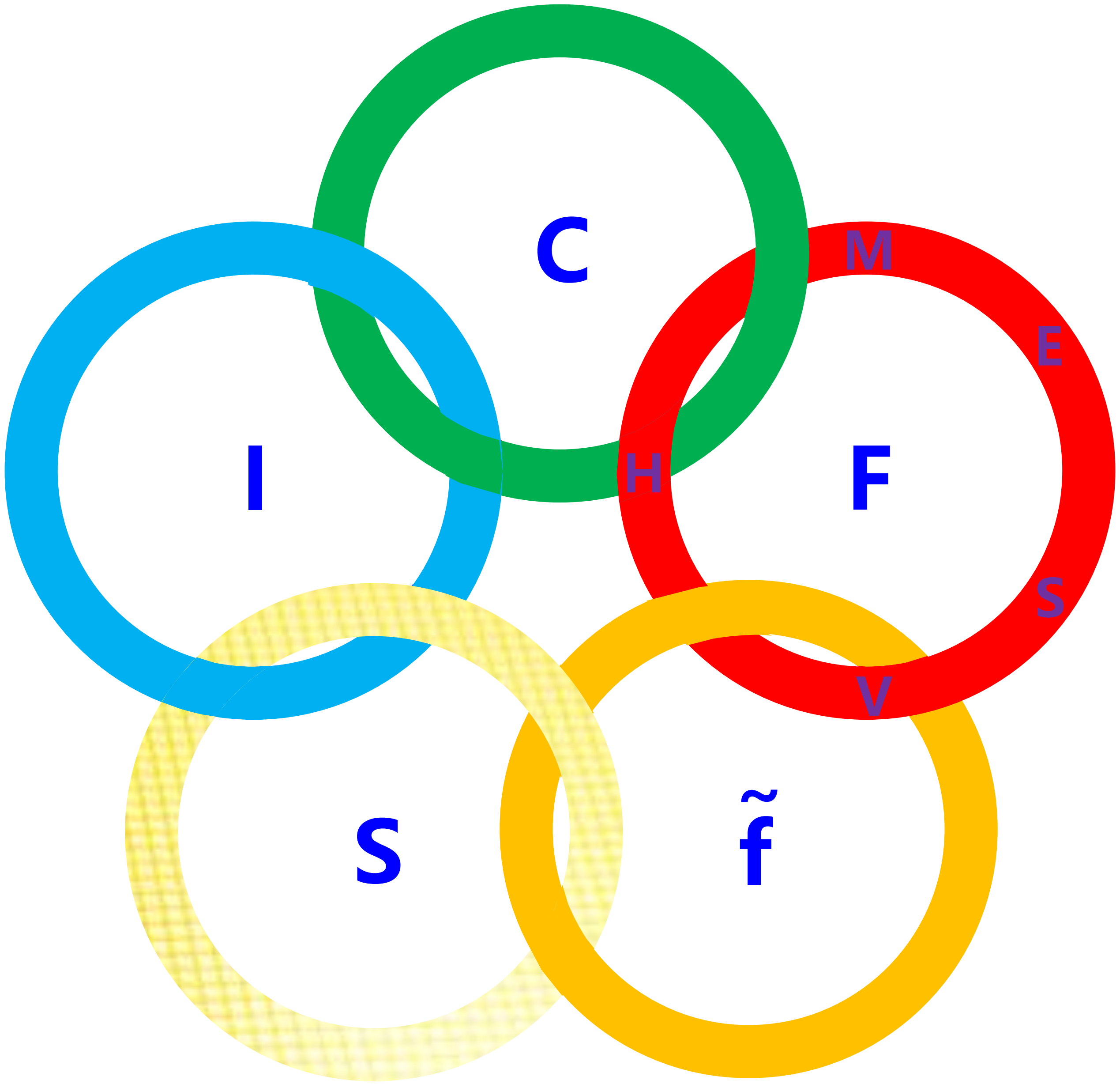
MCIS ~ S Ring

Semiconductor ~ Electronics MCIS

MCIS ~ f̃ Ring

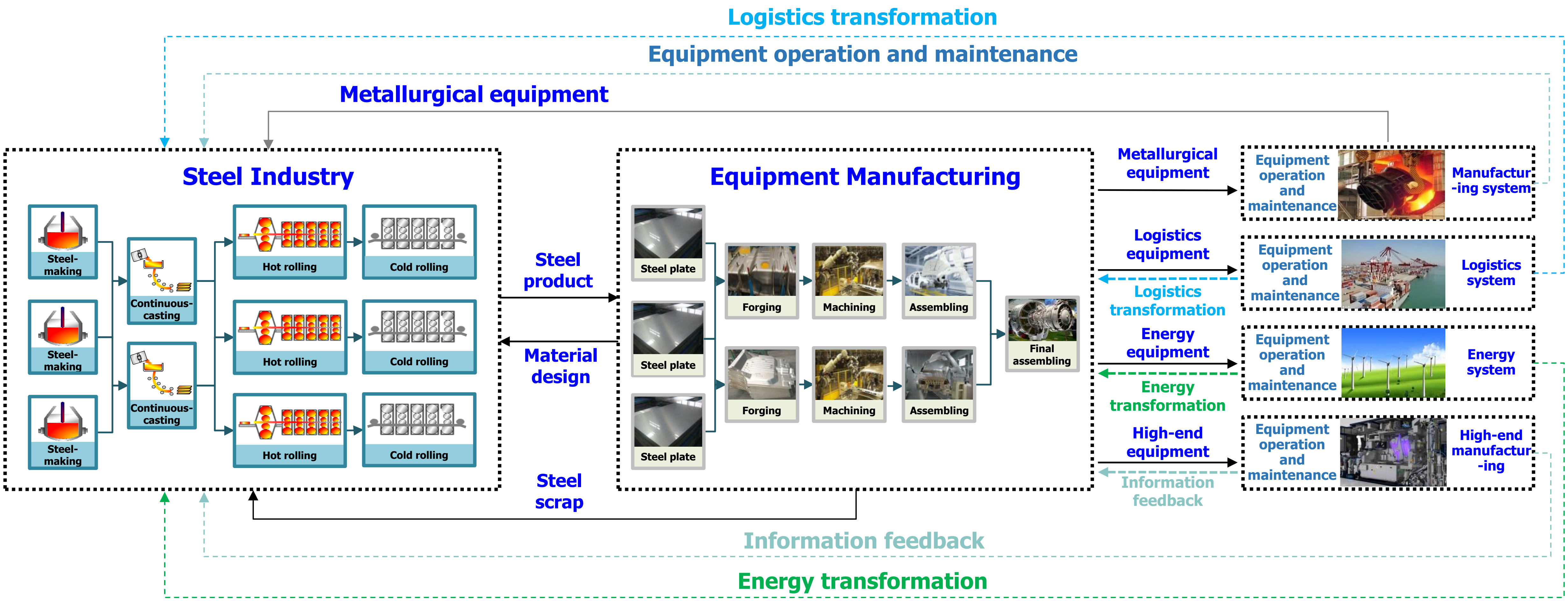
Nonferrous ~ Aviation Equipment MCIS

5. DAO & LLM based Design and Simulation for MCIS (M)



5. DAO & LLM based Design and Simulation for MCIS (M)

MCIS from Steel Industry to Equipment Manufacturing (F Ring)



5. DAO & LLM based Design and Simulation for MCIS (M)

Assortment Planning

- Based on market demand and production capacity, decisions are made regarding the varieties and specifications to be produced, production efficiency is enhanced while meeting diverse demands.

Static Planning

- Based on the customer orders and inventory structure, determine the production volume, inventory, balance production, inventory costs and service levels, and set initial values for the production & inventory systems.

Dynamic Planning

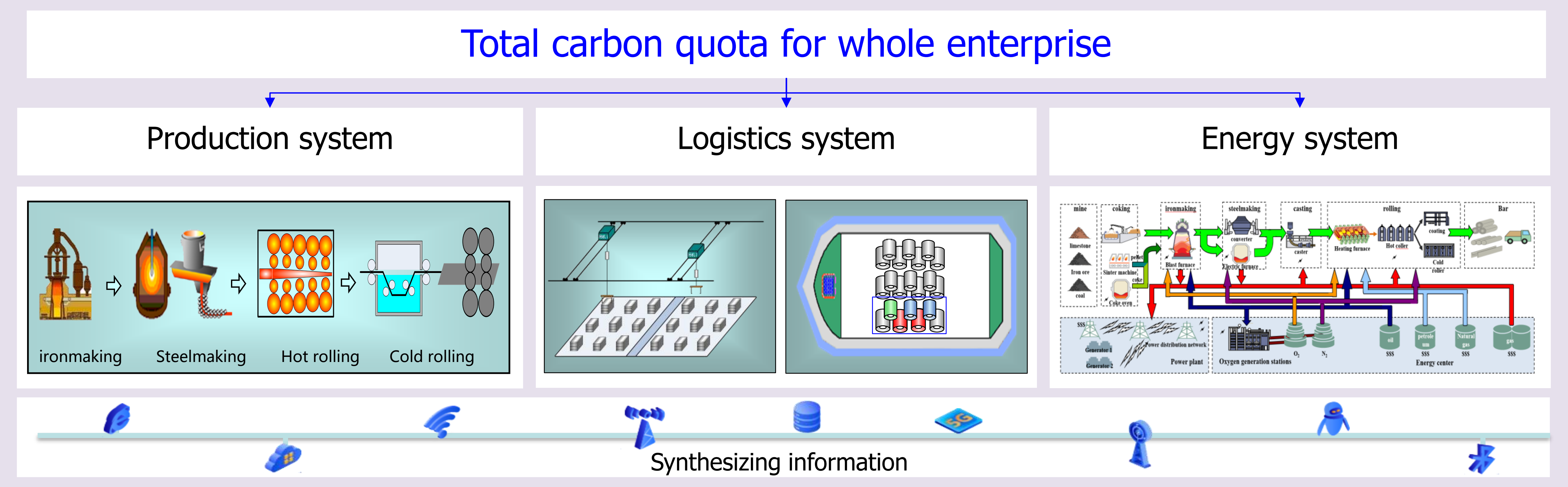
- Taking into account the dynamic changes in supply-demand, by continuously monitoring fluctuations in demand, inventory status, and dynamically adjusting production & inventory strategies, the overall can be enhanced.

Inventory Control

- Based on inventory status, an inventory control model is constructed, and control strategies are designed to ensure that the inventory level remains within a reasonable range, thereby guaranteeing the stability of the system.

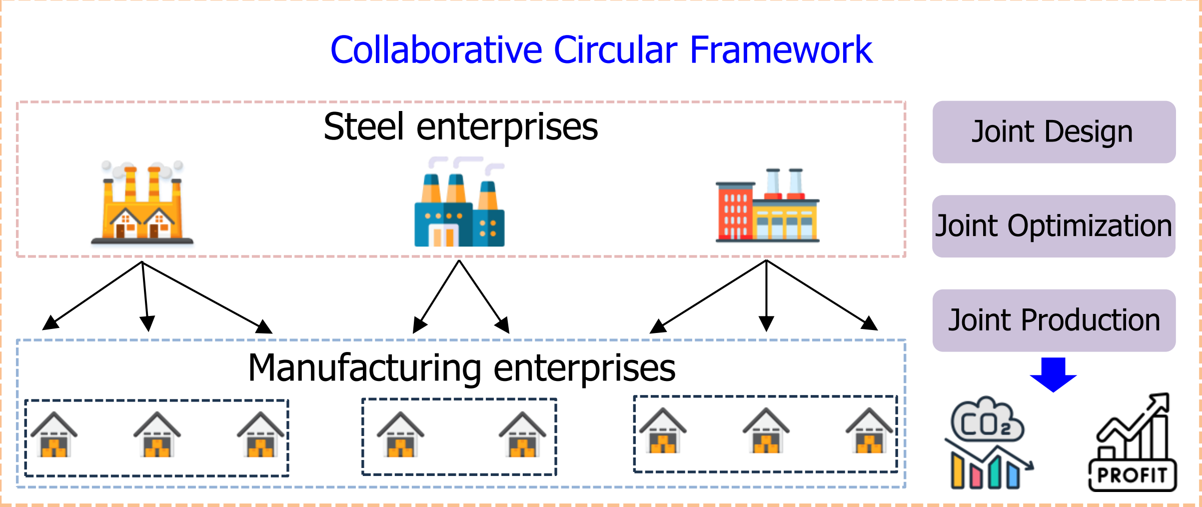
Enterprise-wide carbon quota allocation

- Allocate the enterprise-wide carbon quota to the production, logistics, and energy systems based on their emission reduction potentials, to achieve balanced emission responsibility and coordinated low-carbon operation across the plant.

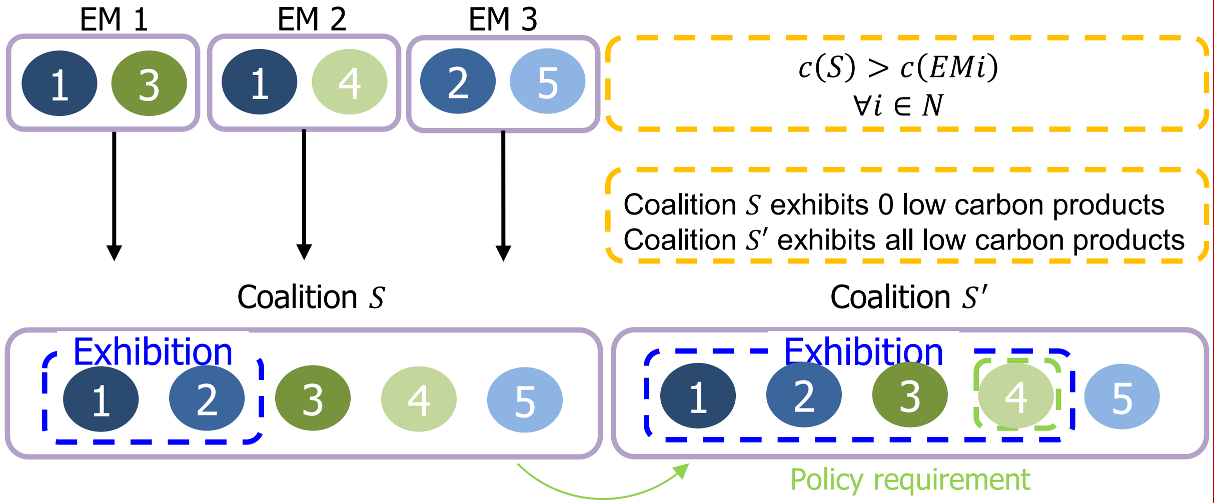


MCIS Carbon Reduction through Cooperation

- For the MCIS, diverse technologies and customized low-carbon steel demands often lead to redundant production and higher emission. A collaborative circular framework enables joint production and low-carbon manufacturing.
- A cooperative game-based profit allocation mechanism ensures fair sharing, while a data-driven core allocation method optimization algorithm enhance efficiency.



- The production and sales process of equipment manufacturers (EM) can be modeled as an assortment optimization model.
- EMs can cooperate to share the assortment they can produce. Policies can encourage cooperation among EMs to avoid duplication of development and promote a wider range of low-carbon products.



Xihua Liu, Shengnan Zhao, Lixin Tang. Carbon Emission Reduction in Manufacture-Circulation Industrial System: An Assortment Optimization Embedded Cooperative Game Theory Method. ***2025 INFORMS Annual Meeting***, Atlanta.

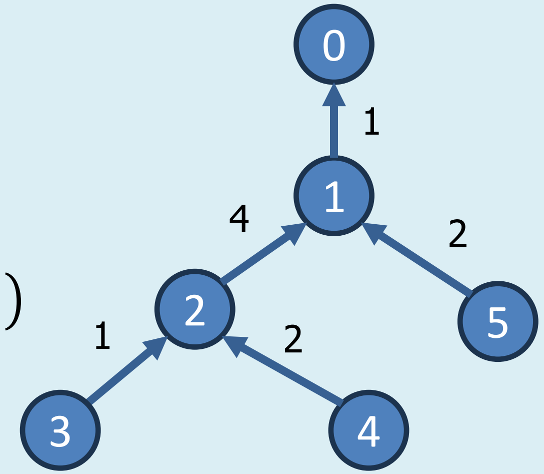
5. DAO & LLM based Design and Simulation for MCIS (M)

Carbon Reduction Game

- The carbon emission problem of fossil fuel supply chain is established as a cooperative game model, and the nucleolar mechanism is proposed to assign the carbon emission responsibility of fossil fuel supply chain.

Nucleolus Allocation

$$\begin{cases} z_i = a(T_{ij}) - z(T_{ij}), \\ if\ z_j \geq a(T_{ij}) - z(T_{ij}) \\ z_i = z_j, if\, z_j \leq a(T_{ij}) - z(T_{ij}) \\ z(N) = c(N). \end{cases}$$



Carbon Reduction Mechanism Design

- The carbon emission reduction in the supply chain can be realized through the information collection of all pollution sources in the supply chain by enterprises, and total carbon tax can be redistributed among enterprises in the supply chain.

1. Enterprise emission reduction

Each firm i in supply chain makes efforts to reduce emissions f_j of the processes j where $i \in N_j$.

2. Responsibility allocation

Total emissions $\sum_{j\in M} f_j$

Allocation $\{\phi_i\}_{i\in N}$

Footprint $\sum_{i\in N} \phi_i = \sum_{j\in M} f_j$

Carbon penalty $p^S \phi_i$

Shapley allocation

Gopalakrishnan S, Granot D, Granot F. Consistent allocation of emission responsibility in fossil fuel supply chains. ***Management Science***, 2021, 67(12): 7637-7668.
Gopalakrishnan S, Granot D, Granot F, et al. Incentives and emission responsibility allocation in supply chains. ***Management Science***, 2021, 67(7): 4172-4190.

5. DAO & LLM based Design and Simulation for MCIS (M)

Mechanism Design and Optimization for Entire Life Cycle Carbon Reduction

Synthesizing information

Production

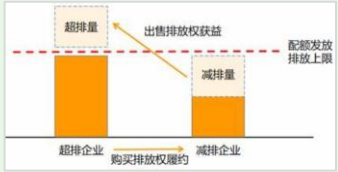
Logistics

Energy

All-dimensional organic management

Mechanism design

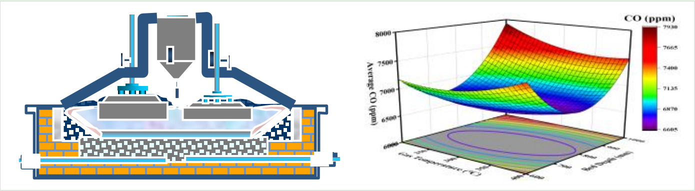
System optimization



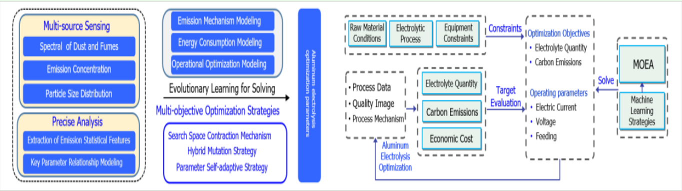
Quota allocation

Carbon sink trading

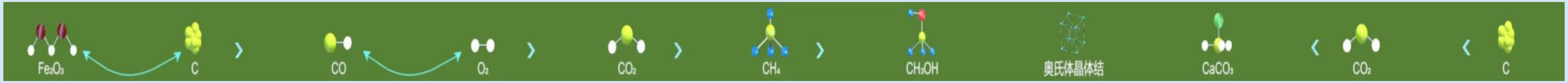
High quality and low carbon technology

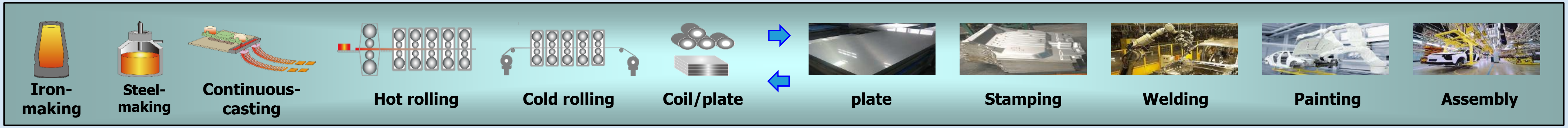


Quality optimization



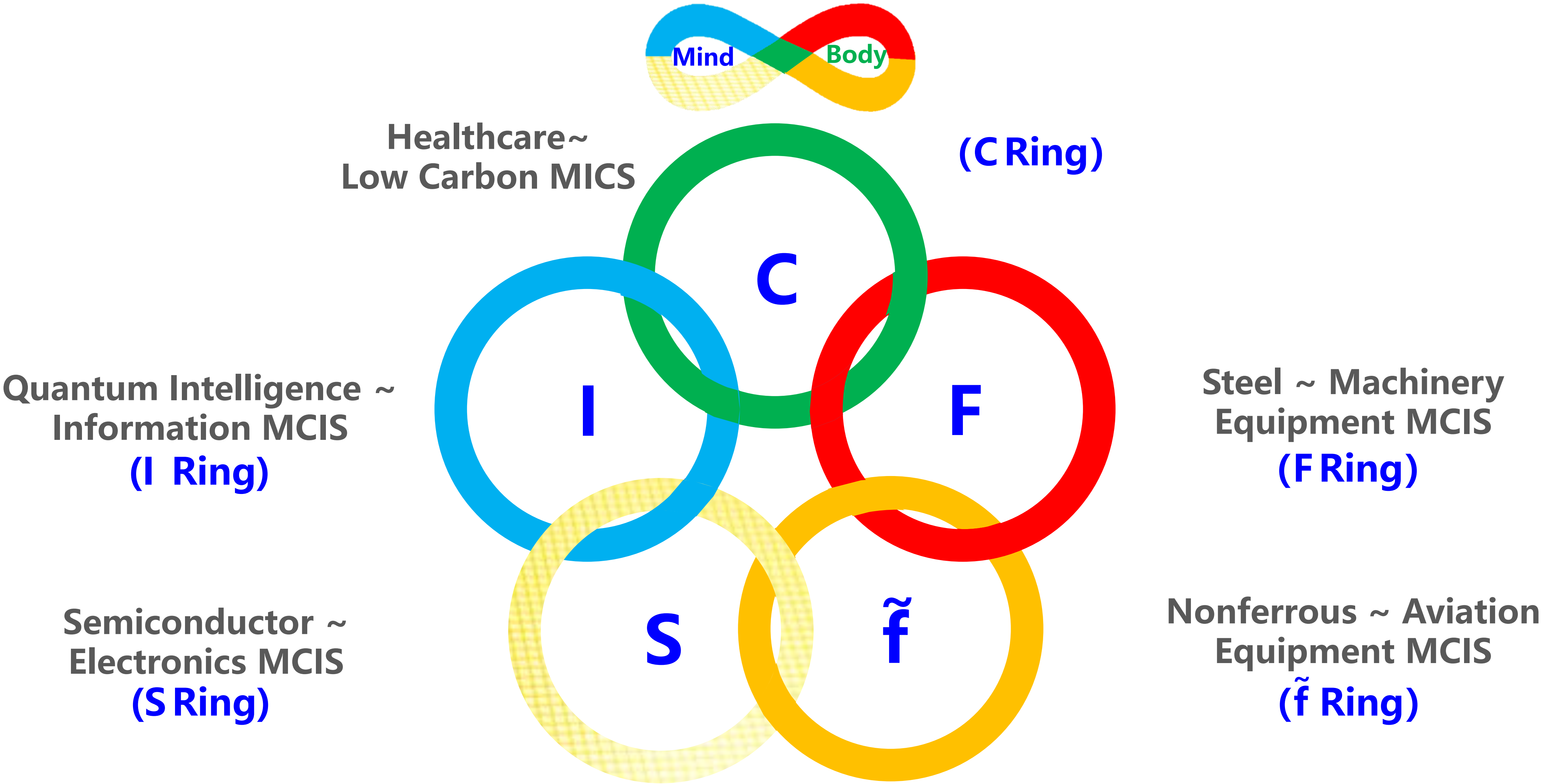
Carbon reduction process





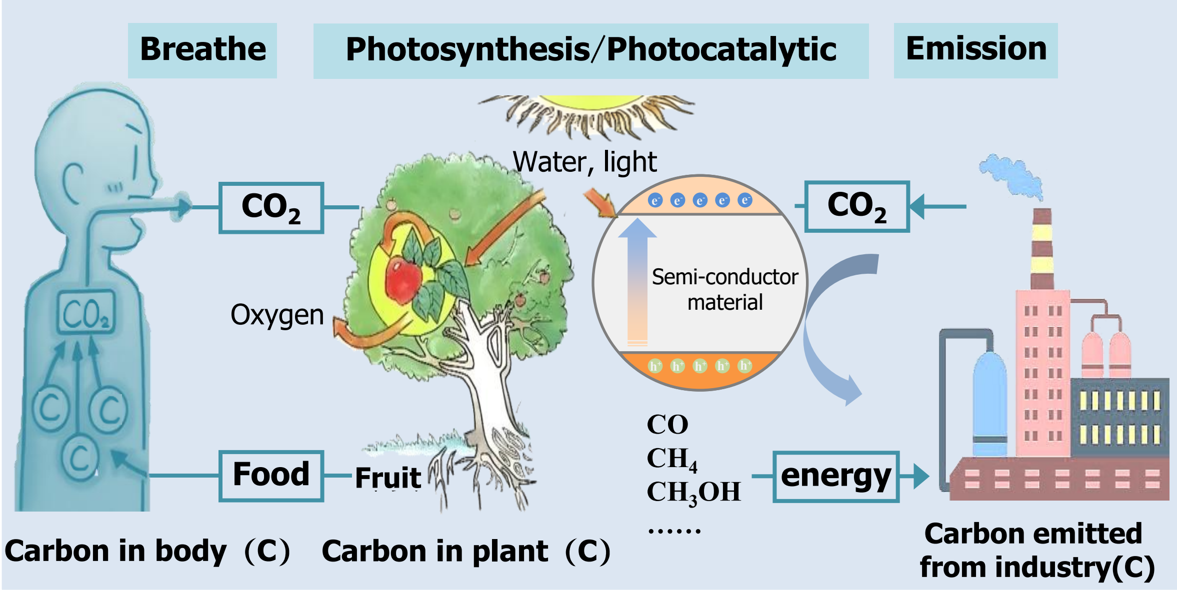
5. DAO & LLM based Design and Simulation for MCIS (M)

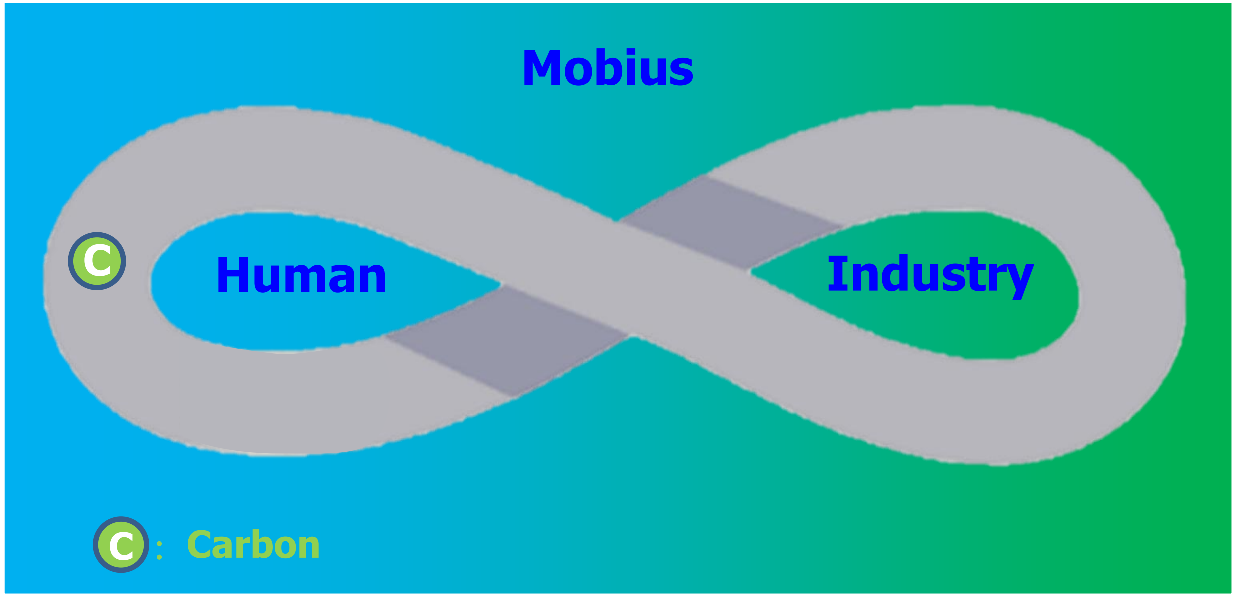
Comprehensive Organic System Intelligence

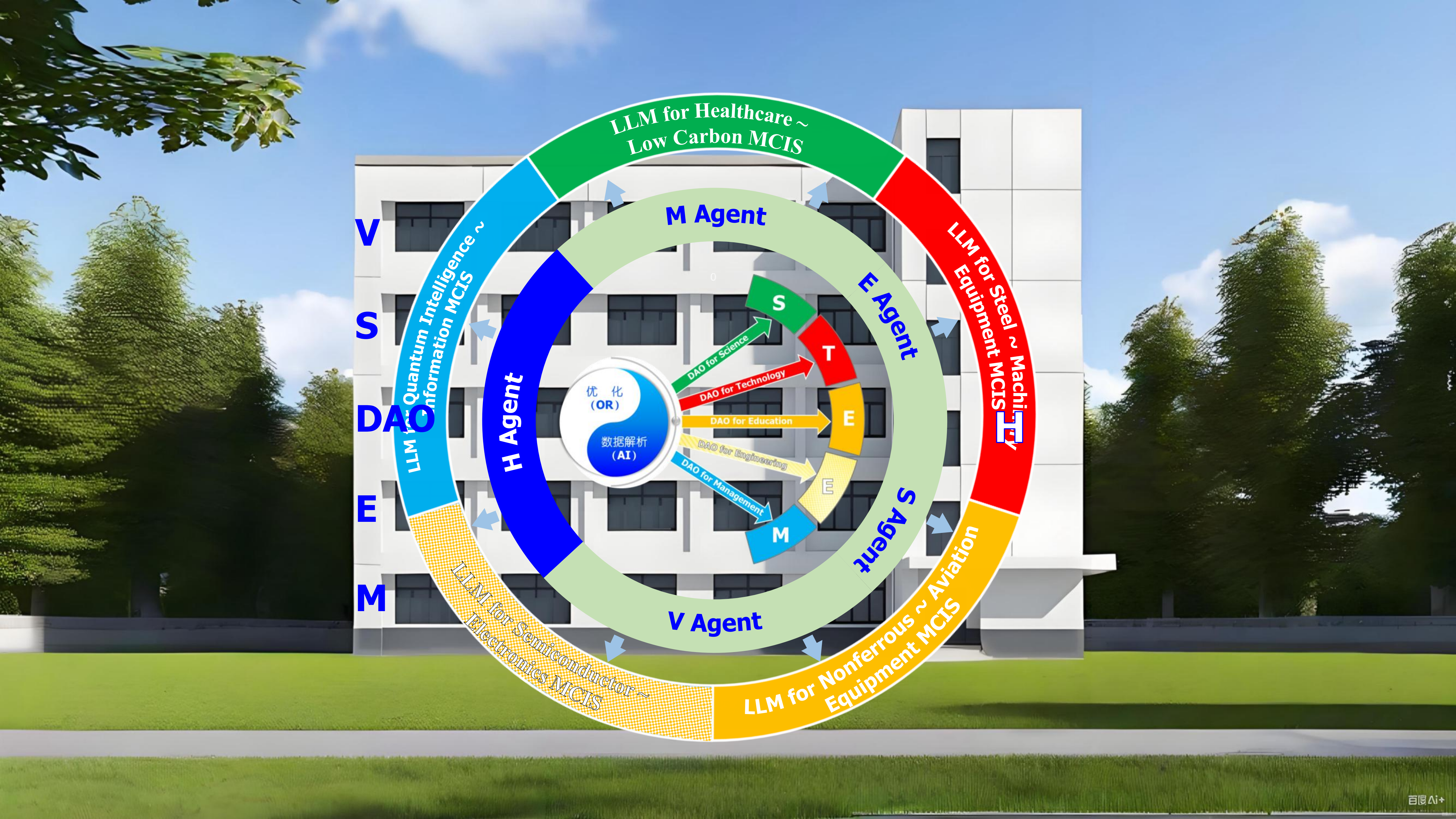


5. DAO & LLM based Design and Simulation for MCIS (M)

- Carbon cycle： Carbon elements store, migrate, exchange, and transform between human body and the natural environment, being essential carriers for material and energy flows
  - Carbon cycle in human body: Humans ingest carbohydrates, which are converted into glucose molecules absorbed by cells. Metabolism enables the carbon cycle within the body, providing the material and energy basis for life activities.
  - Carbon cycle in environment: Humans produce CO2 through respiration, which plants convert into carbohydrates via photosynthesis. These carbohydrates then transfer to humans through the food chain, providing energy and materials.
  - Carbon cycle in industries: Industrial CO2 can be converted through plant photosynthesis and photocatalytic reactions, transforming CO2 into renewable hydrocarbon fuels, providing energy for industry.






LLM for Healthcare ~ Low Carbon MCIS
LLM for Steel ~ Machinery Equipment MCIS
LLM for Nonferrous ~ Aviation Equipment MCIS
LLM for Semiconductor ~ Electronics MCIS
LLM for Quantum Intelligence ~ Information MCIS
M Agent
E Agent
S Agent
V Agent
H Agent
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S
DAO
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H
优 化
（OR）
数据解析
（AI）
DAO for Science
DAO for Technology
DAO for Education
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