Data Analytics and Optimization for Smart Industry

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Outline

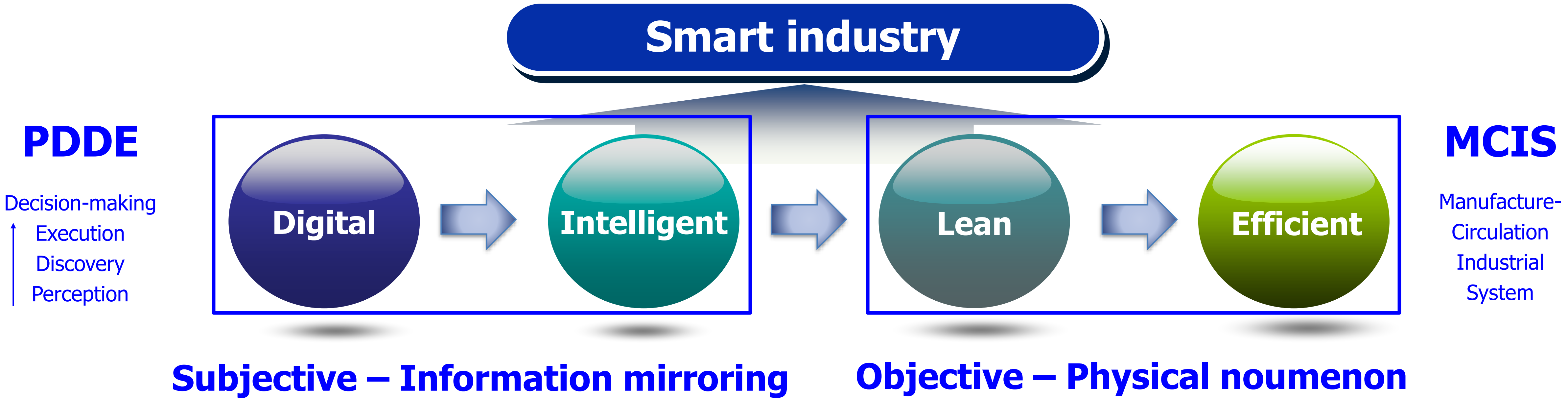
- Data Analytics and Optimization (DAO)
- MCIS-E Production-Logistics-Energy Optimization with Feedback
- PDDE-based Quality Analytics and Dynamic Optimization
- MCIS Environmental Analytics and Optimization

Outline

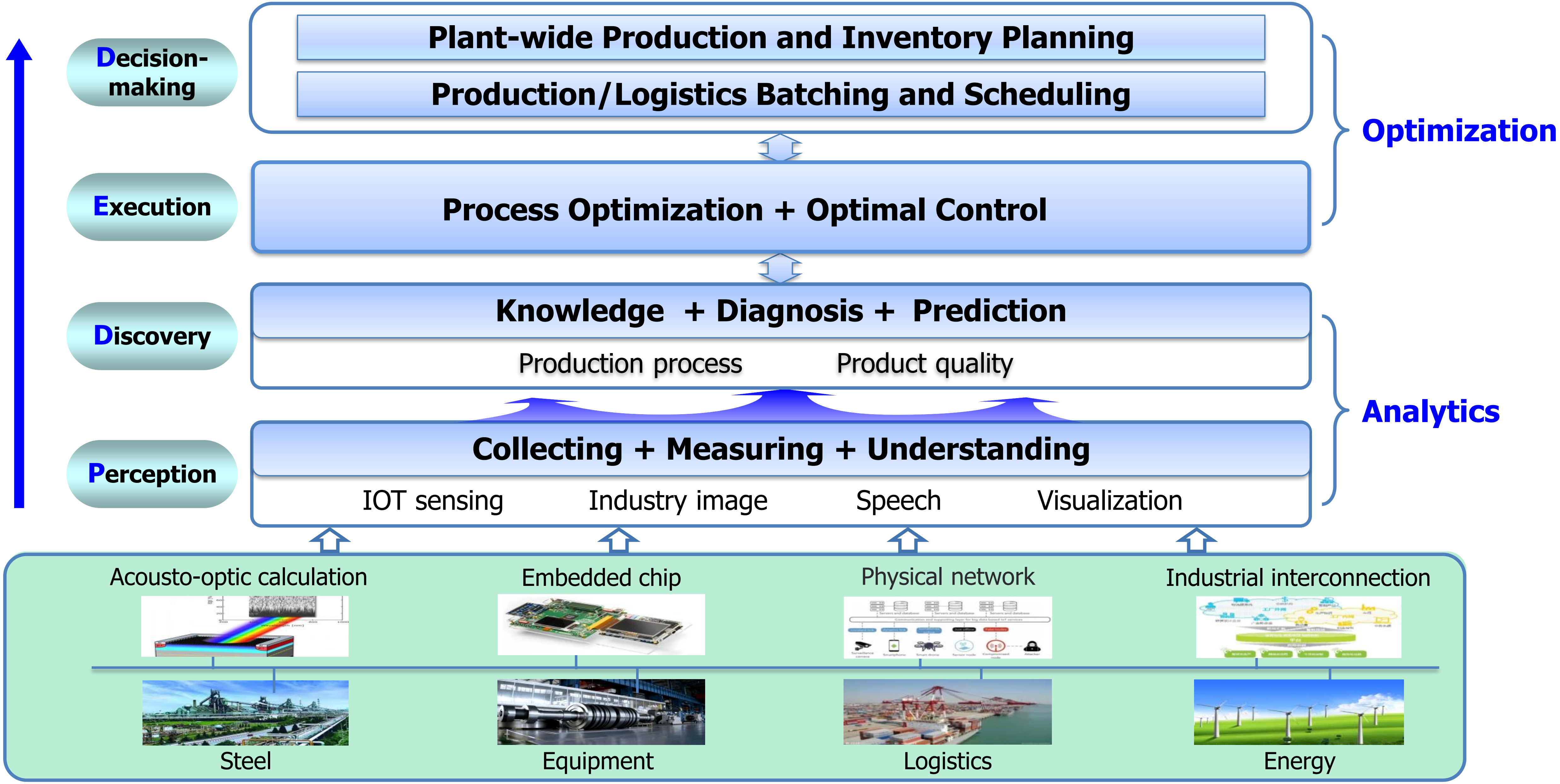
- **Data Analytics and Optimization (DAO)**
- MCIS-E Production-Logistics-Energy Optimization with Feedback
- PDDE-based Quality Analytics and Dynamic Optimization
- MCIS Environmental Analytics and Optimization

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.

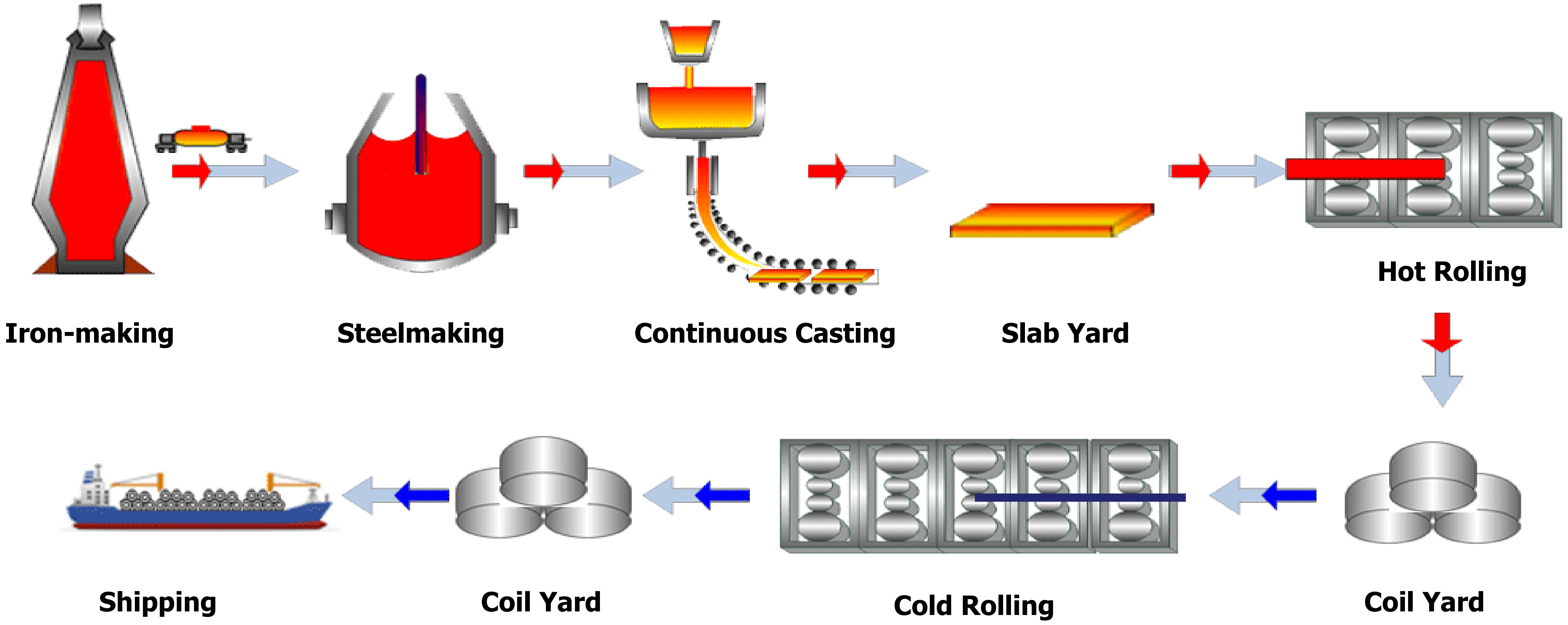


1. Data Analytics and Optimization



1. Data Analytics and Optimization — Steel Production Process

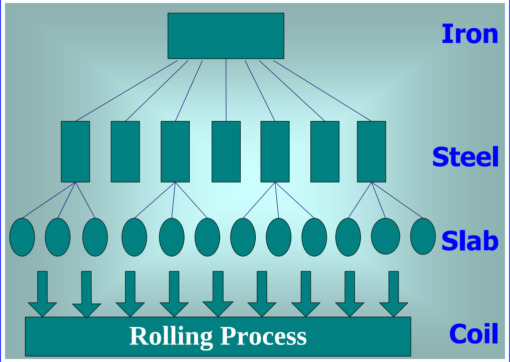
Features: continuous and discrete production, huge devices, high-temperature operations, massive consumption of energy and resource



1. Data Analytics and Optimization

- **New Characteristics**
  - **Complex physical and chemical processes**
  - **Large variety and low volume products**
  - **Complicated logistics structure**

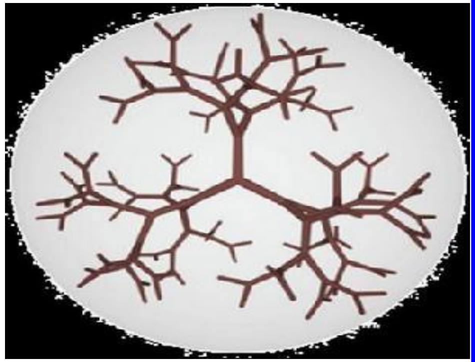
Complicated Production Process



Large Variety and Low Volume

Huge Chemical Equipment

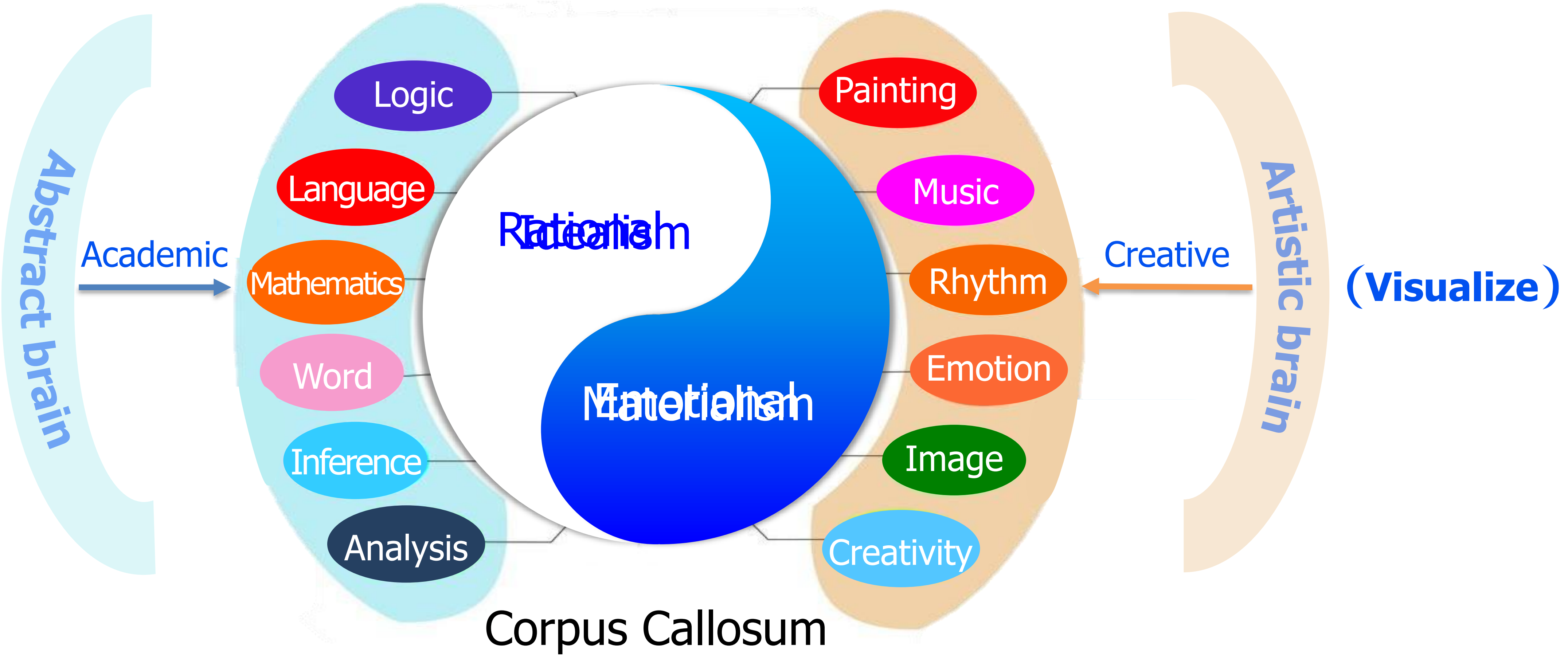
Complicated Logistics Structure



1. Data Analytics and Optimization — DAO based System Modeling

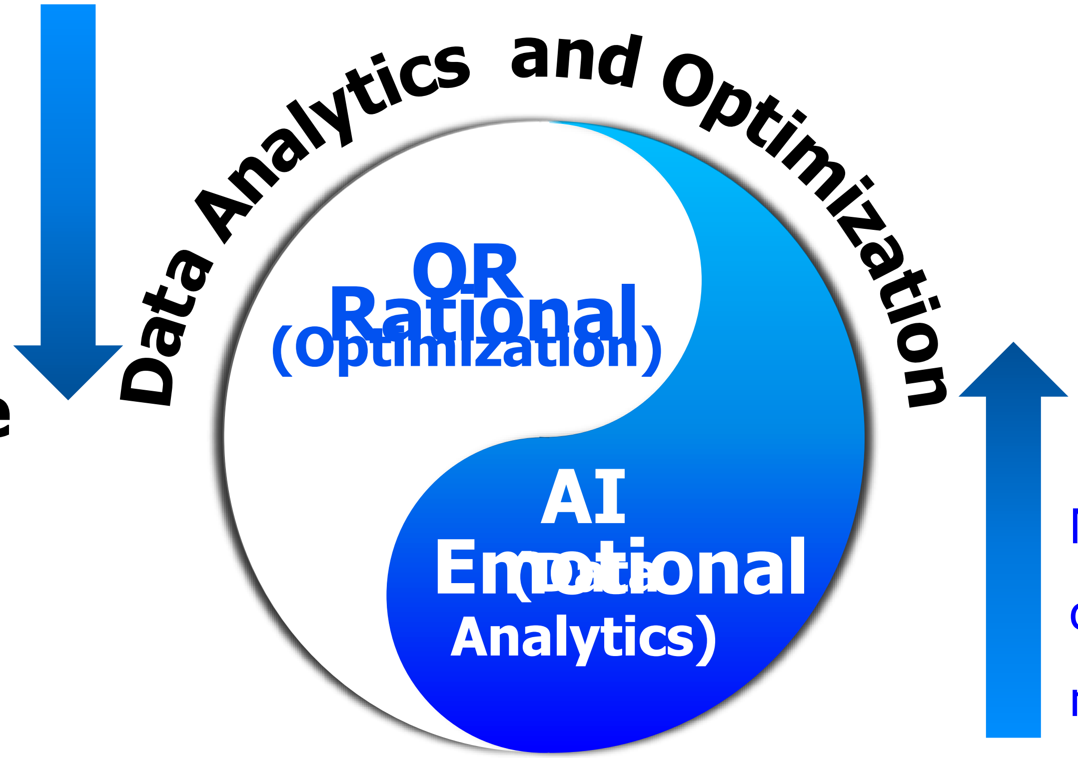
❖ Perceptual cognition is the basis of rational cognition; and rational cognition is the sublimation of perceptual cognition, which are unified in practice.

Left brain-Rational → Comprehension ← Right brain-Emotional



1. Data Analytics and Optimization — DAO based System Modeling

Data Analytics and Optimization (DAO)



Music expresses something that cannot be described in words neither can be silenced.

—— Victor Hugo

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**)

1. 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)

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

$s.t.$

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

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

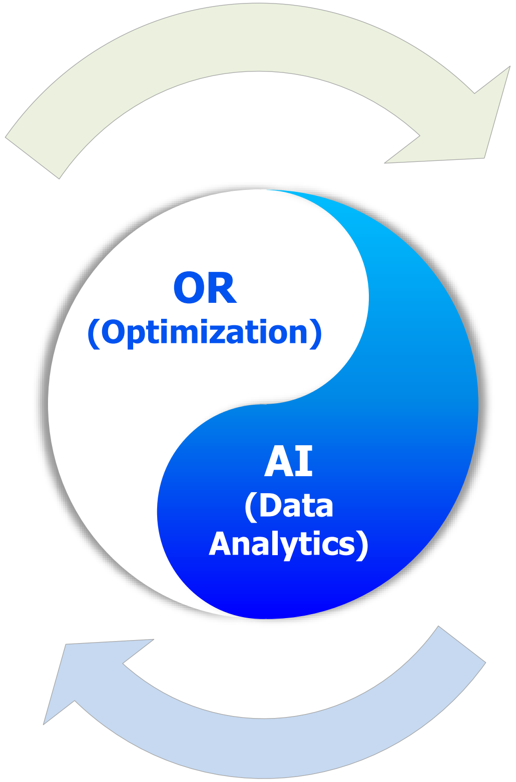
$$\sum_{k\in O_j} Y_{kkj} = 1 \qquad \text{for } j\in P$$

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

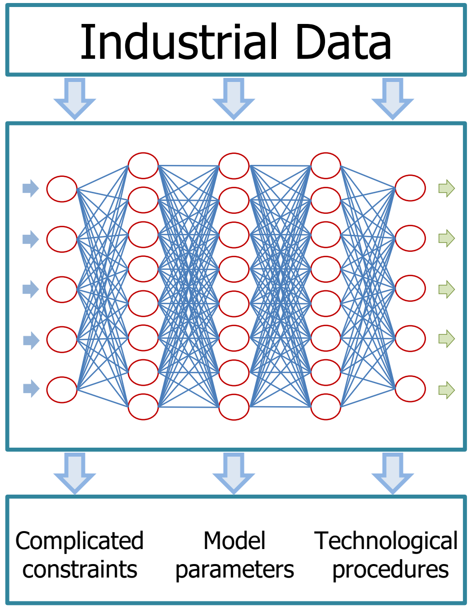
$$X_{ij} = \sum_{k\in O_j\cap R_i} Y_{ikj} \qquad \text{for } j\in P,\ i\in O_j$$

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

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



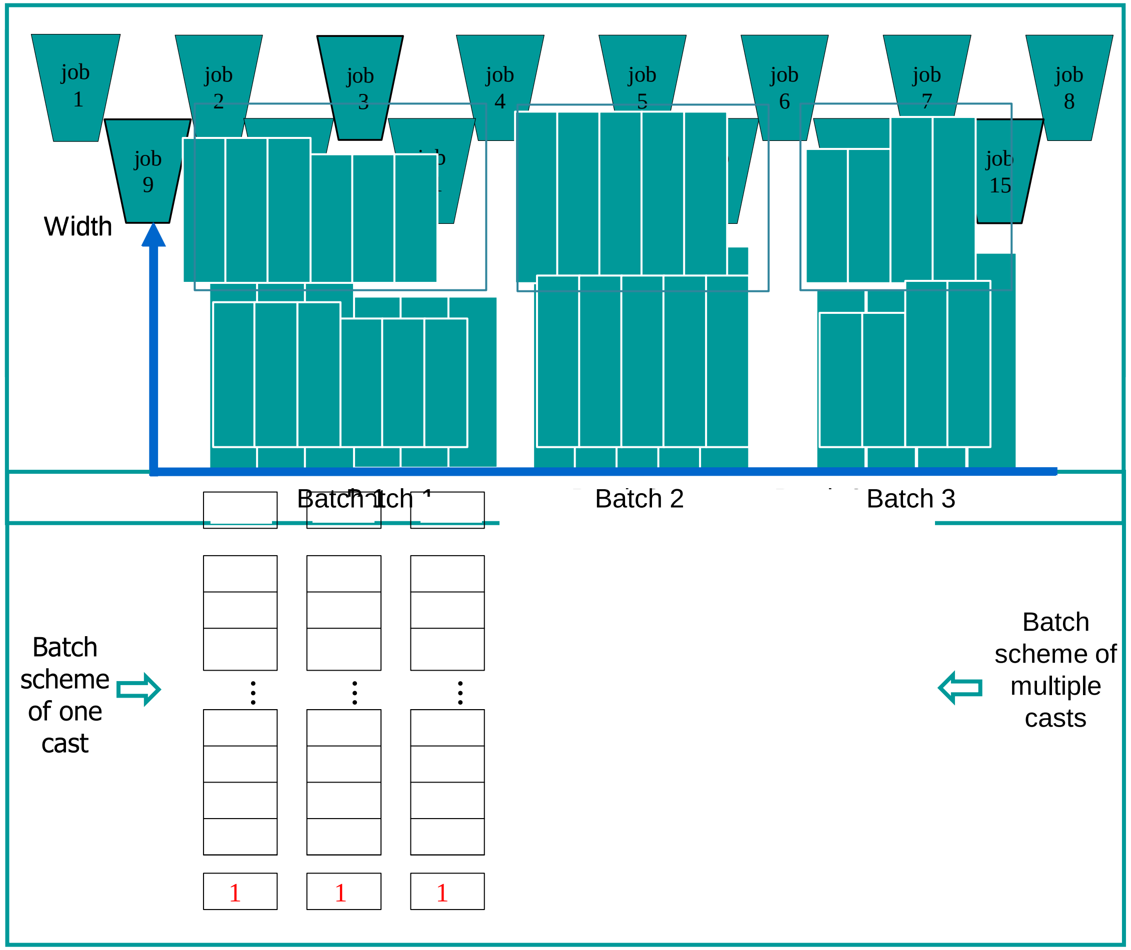
Data Analytics (AI)



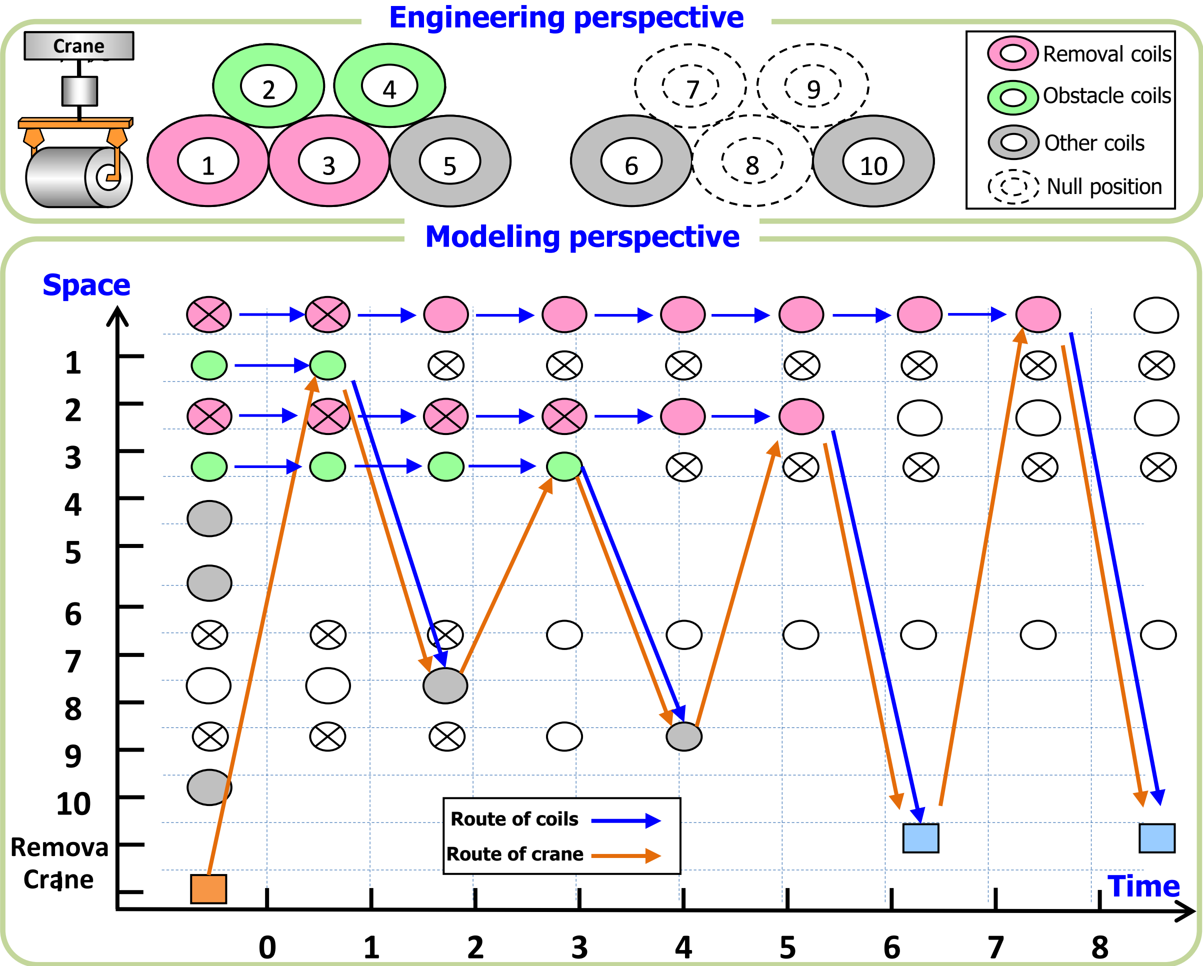
L. Tang, Y. Meng. Data analytics and optimization for smart industry. ***Frontiers of Engineering Management***, 2021, 8(2): 157-171. (**Best Paper Award for 2014~2023**)

1. Data Analytics and Optimization — DAO based System Modeling

Production: Set-packing Modeling



Logistics: Space-time Network Flow Modeling



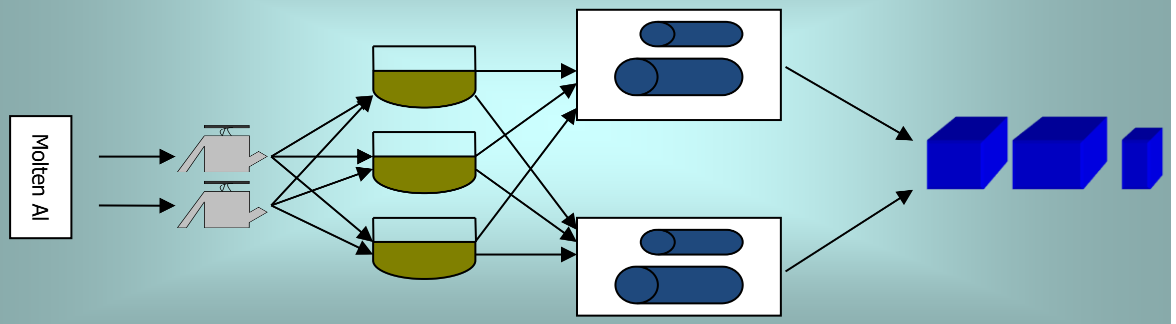
L. Tang, G. Wang, Z. Chen. Integrated charge batching and casting width selection at Baosteel. ***Operations Research***, 2014, 62(4): 772-787.

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.

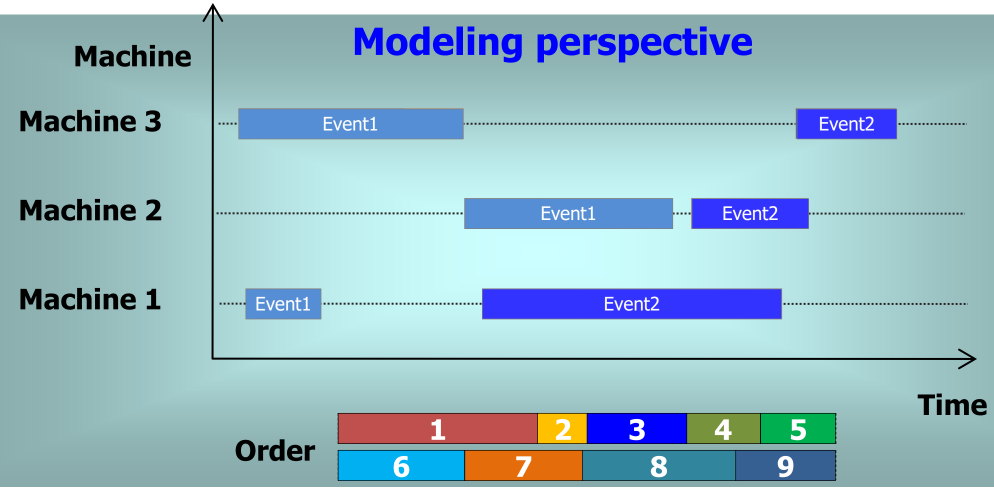
1. Data Analytics and Optimization — DAO based System Modeling

Energy: Continuous-time Modeling

Engineering perspective



Modeling perspective

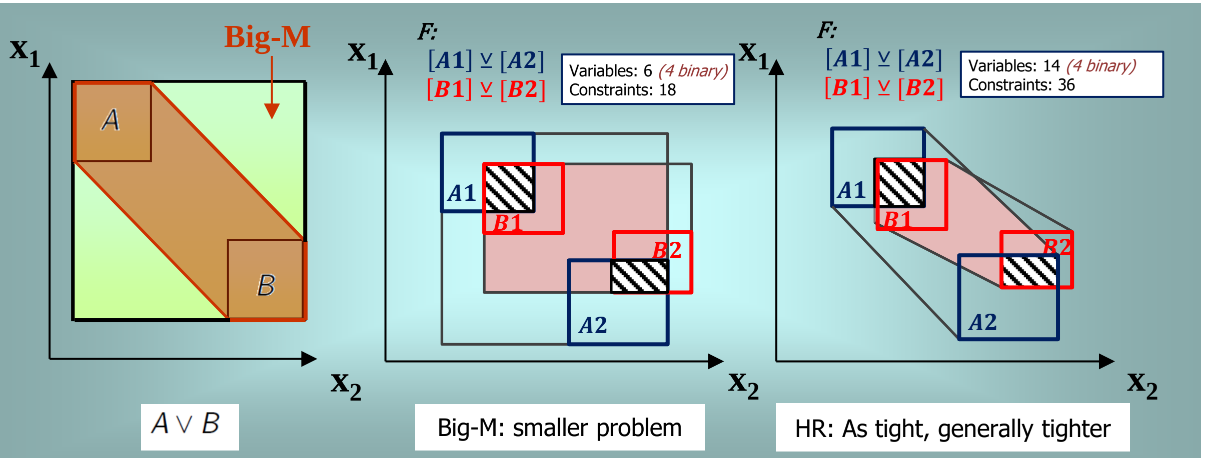


Information: Generalized Disjunctive Programming

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

$$\text{s.t.} \quad g(x) \le 0 \qquad \Omega(Y) = True$$

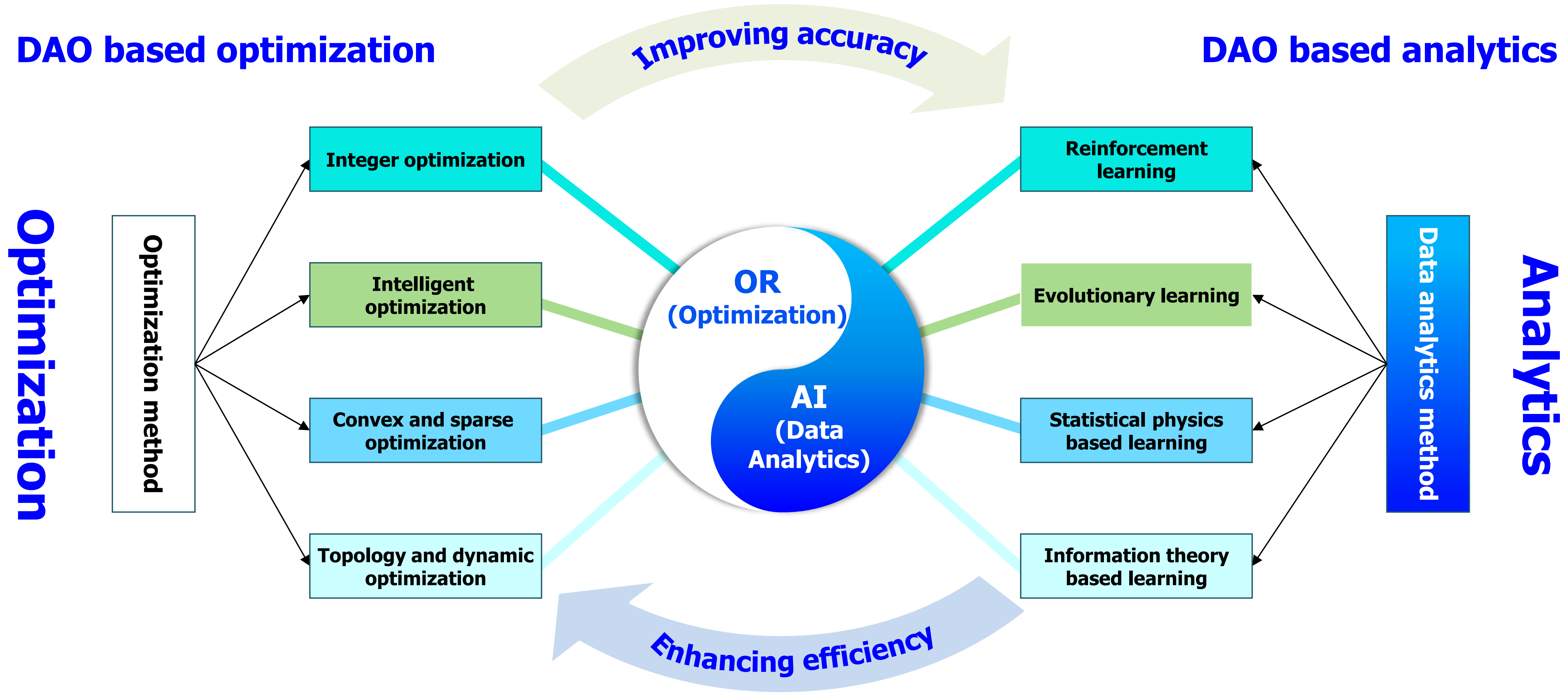
$$\bigvee_{i \in D_k} \begin{bmatrix} Y_{ik} \\ r_{ik}(x) \le 0 \\ c_k = \gamma_{ik} \end{bmatrix} \qquad \begin{array}{l} x^{lo} \le x \le x^{up} \\ x \in \mathbb{R}^n, c_k \in \mathbb{R}^1, \\ Y_{ik} \in \{True, False\} \end{array}$$



Q. Guo, L. Tang, J. Liu, S. Zhao. Continuous-time formulation … in aluminium industry. ***International Journal of Production Research***, 2021, 59(10): 3169-3184.

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

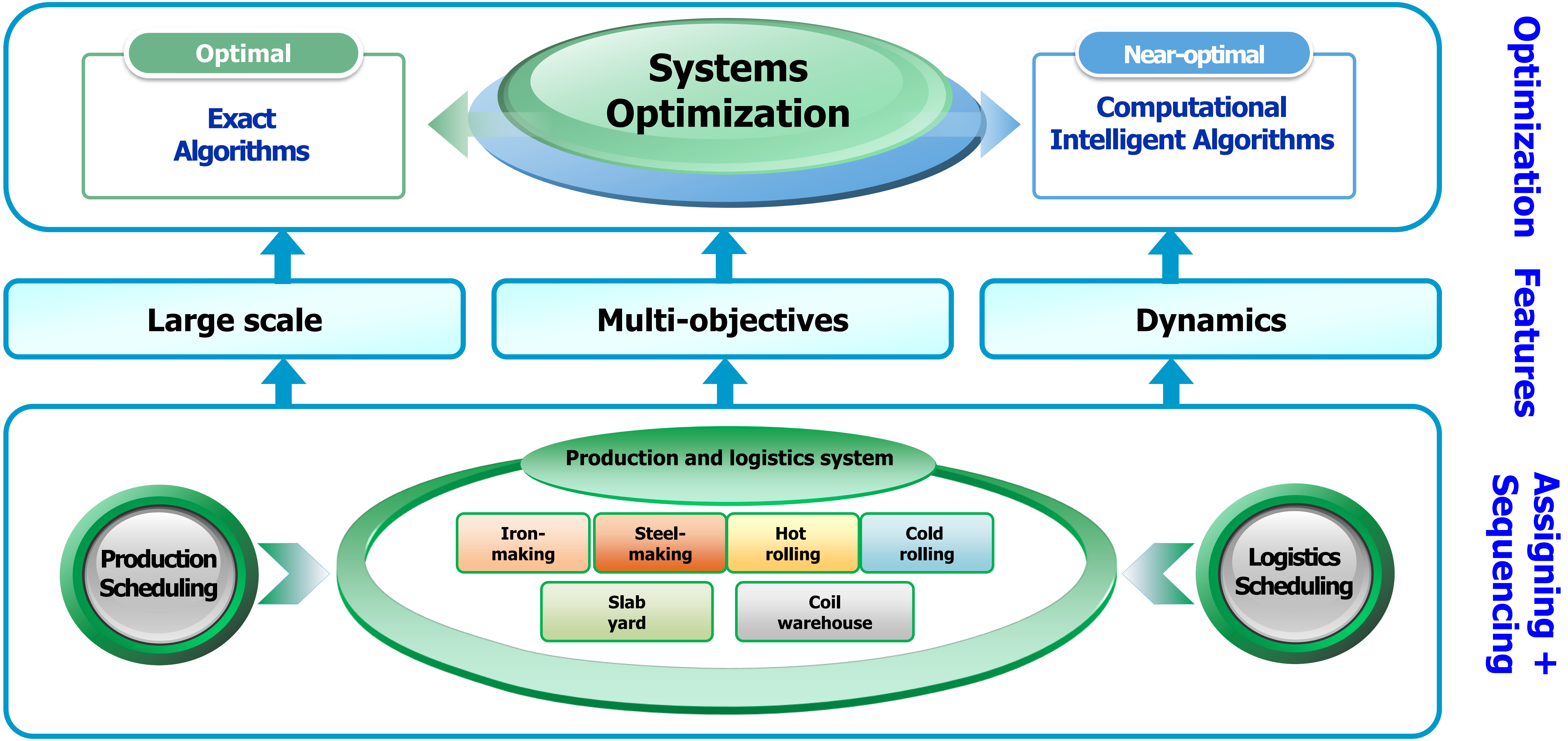
1. Data Analytics and Optimization — DAO based Solution



DAO based Octopus-topology Solution

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**)

1. Data Analytics and Optimization — DAO based Solution



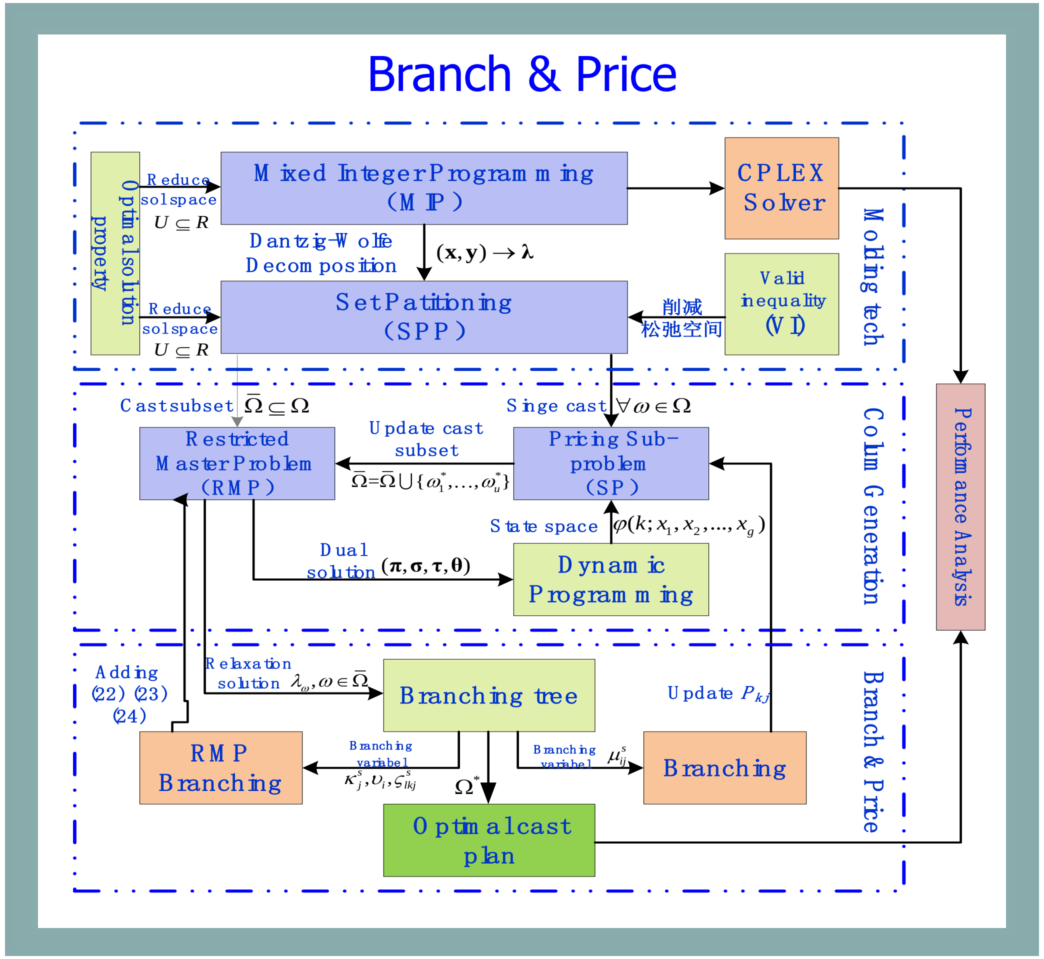
1. Data Analytics and Optimization — DAO based Solution

Integer Optimization Methods and Improvement

Algorithm	Branch & Price	LR/Benders Decomposition	Outer Approximation (OA)	Branch & Cut
Feature	Integer programs with block diagonal structure	Mixed integer linear programs	Mixed integer nonlinear programs	Pure integer programs
Theory	Multilayer branching strategy; Low dimension DP	Multiple cuts; Valid inequality; Variable reduction	Multiple linear cuts; Quadratic cuts	Model tightening; Valid inequality; Variable reduction
Performance	Superior to commercial optimization software CPLEX in performance	Superior to traditional Benders in performance	Superior to traditional OA and commercial optimization software in performance	Superior to commercial optimization software CPLEX in performance

Integer Optimization — Branch & Price

- 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.



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

Integer Optimization — Lagrangian Relaxation

- The coupling/complex constraint is relaxed into the objective function by Lagrangian multiplier, thus decouple and decompose the full problem into several independent sub-problems.
  - **Decomposition**: batch decoupling strategy, stage-based decomposition
  - **Dual problem solution**: hybrid backward and forward dynamic programming

$$z_{SC} = \min \sum_{j=1}^{n} c_j x_j$$

$$\boxed{s.t. \sum_{j=1}^{n} a_{ij} x_j \geq 1, \quad i = 1,2,\cdots,m,}$$

$$x_j \in \{0,1\}, \quad j = 1,2,\cdots,n.$$

Multiplier relaxation →

$$z_{LRSC}(\lambda) = \min \sum_{j=1}^{n} c_j x_j + \sum_{i=1}^{m} \lambda_i (1 - \sum_{j=1}^{n} a_{ij} x_j)$$

$$s.t. \quad x_j \in \{0,1\}, j = 1,2,\cdots,n,$$

$$\lambda \geq 0.$$

↓ decomposition

$$z_{LRSC}(\lambda) = \min \sum_{j=1}^{n} d_j x_j + \sum_{i=1}^{m} \lambda_i$$

$$s.t. \quad x_j \in \{0,1\}, j = 1,2,\cdots,n,$$

$$\lambda \geq 0.$$

← solve subproblems optimally

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

↑ Lower bound

L. Tang, H. Xuan, J. Liu. A new Lagrangian relaxation algorithm for hybrid flowshop scheduling to minimize total weighted completion time. ***Computers & Operations Research***, 2006, 33(11): 3344-3359.

Benders Decomposition Algorithm

Various Valid Inequalities

$$\sum_{j \in I \setminus \{i\}} u_{ij} \neq \sum_{j \in I \setminus \{i'\}} u_{i'j} \qquad \sum_{(r,s) \in G_i} y_{irs} \leq 0$$

⇨ Improve lower bound

Combinatorial Benders Cuts

$$\mathrm{MILP\_CB} := \left\{ \begin{array}{c} \mathbf{A\_MILP}_{\mathrm{LP}} \\ \upsilon(\mathbf{A\_MILP}_{\mathrm{LP}}) \leq \mathrm{UB} - \varepsilon \end{array} \right.$$

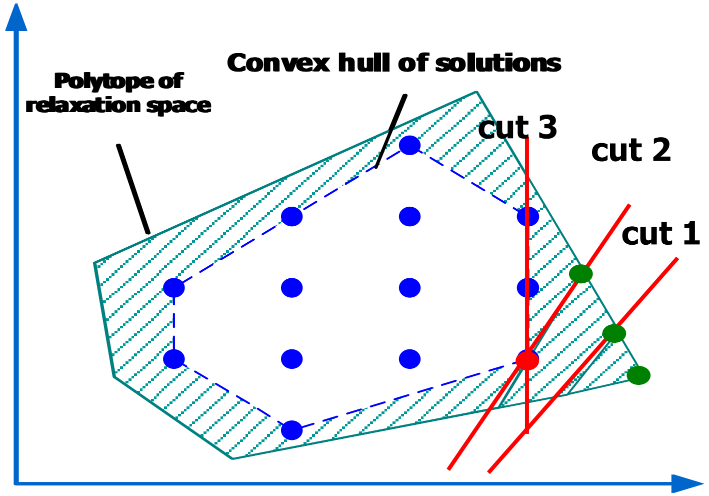
⇨ Accelerate convergence

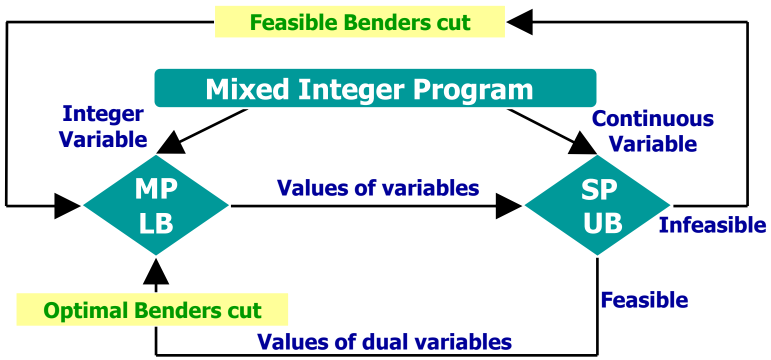
Variable Reduction

$$v[\boldsymbol{MP}^k(\boldsymbol{IR})] > UB \qquad v[\boldsymbol{MP}^k{}_{LP}(\boldsymbol{IR})] > UB$$

⇨ Reduce search space

Structure





1. Data Analytics and Optimization — DAO based Solution

Outer Approximation(OA) Algorithm

Multi-generation Cuts

$$\alpha \ge f(x^k) + h^T \cdot y + (\lambda^k)^T \cdot (g(x^k) + H \cdot y) + (\mu^k)^T \cdot (A \cdot x^k + E \cdot y - b) \qquad k \in KFS$$

$$(\lambda^k)^T \cdot (g(x^k) + H \cdot y) + (\mu^k)^T \cdot (A \cdot x^k + E \cdot y - b) \le 0 \qquad k \in KIS$$

⇨ Accelerate convergence

Partial Surrogate Cuts

$$(\lambda^k)^T \cdot [Hy + Dw + g(\mathrm{v}^k)] - (\mu^k)^T A_2 (v - \mathrm{v}^k) \le 0$$

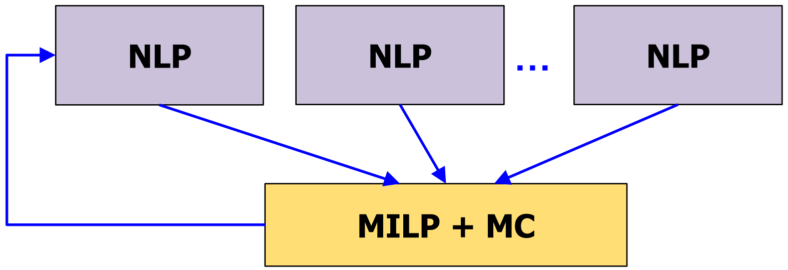
⇨ Tighten lower bound

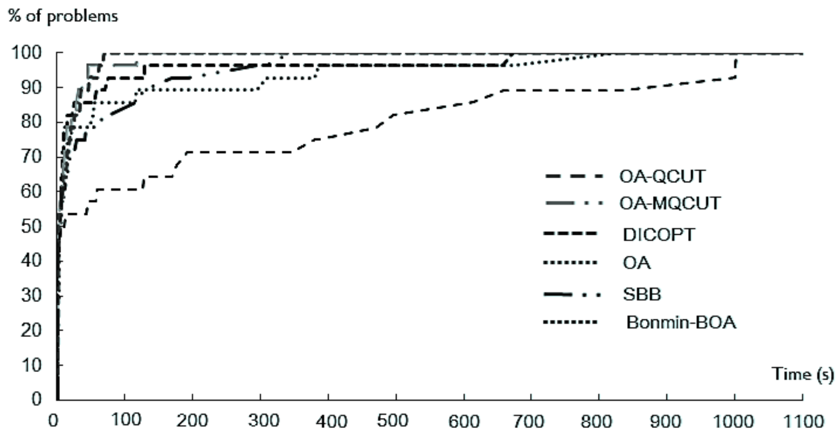
Hybrid Strategy of OA and GBD

Scaled Quadratic Cuts with Multi-generation Cuts

⇨ Improve efficiency

Structure

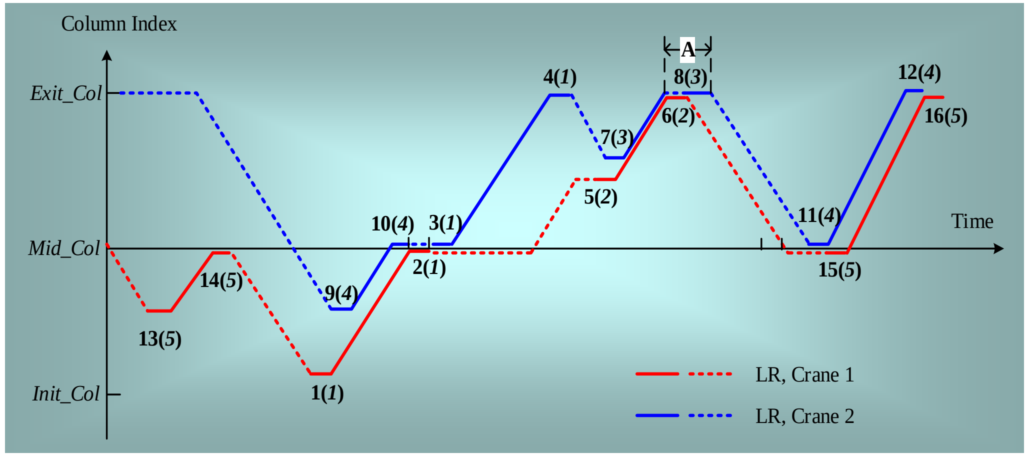




L. Su, L. Tang and I.E. Grossmann. Computational strategies for improved MINLP algorithms. *Computers & Chemical Engineering*, 2015, 75: 40-48.
L. Su, L. Tang, D. E. Bernal, I. E. Grossmann. Improved quadratic cuts for convex mixed-integer nonlinear programs. *Computers & Chemical Engineering*, 2018, 109: 77-95.

Integer Optimization — Branch & Cut

- Branch & Cut is developed.
- The model tightening technique is proposed based on the reformulation with compact lower bound.
- A series of valid inequalities (e.g., subtour elimination) is used to accelerate the convergence of the algorithm.
- Variable reduction
- The algorithm can solve the real scale problems to optimal, and is superior to CPLEX in performance.



Instance	CPLEX sol	CPLEX time (s)	CPLEX Gap (%)	B&C sol	B&C time (s)	B&C number of cuts
1	47	5.273	0	47	2.902	4
2	82	123.225	0	82	73.586	10
3	92	232.270	0	92	55.427	8
18	432	85.099	0	432	73.554	4
19	460	248.010	0	460	81.979	26
20	73	3.978	0	73	3.728	12
Avg		142.119	0		70.180	30

X. Cheng, L. Tang and P.M. Pardalos. A Branch-and-Cut algorithm for factory crane scheduling problem. ***Journal of Global Optimization***, 2015, 63(4): 729-755.

1. Data Analytics and Optimization — DAO based Solution

Differential Evolution with an Individual–dependent Mechanism

Individual–dependent Parameters Setting

$$F_i = randn(\frac{i}{NP}, 0.1) \quad CR_i = randn(\frac{i}{NP}, 0.1)$$

⇨ Self-adaptive allocation

Individual–dependent Mutation Operator

$$DI = \frac{1}{N}\sqrt{\sum_{i=1}^{N}\left\|x_i - \frac{1}{N}\sum_{j=1}^{N}x_j\right\|^2} \quad DF = \frac{1}{N}\sqrt{\sum_{i=1}^{N}\left(f(x_i) - \frac{1}{N}\sum_{j=1}^{N}f(x_j)\right)^2}$$

⇨ Self-adaptive selection

Perturbations with Small Probability

$$d = L + rand(0,1) * (U - L)$$

⇨ Global search

L. Tang, Y. Dong and J.Y. Liu. Differential evolution with an individual–dependent mechanism. ***IEEE Transactions on Evolutionary Computation***, 2015, 19(4): 560-574 . (**ESI Highly Cited Paper, IF: 14.3**)

Improved Differential Evolution Algorithm for Dynamic Scheduling

Incremental Mechanism for Initial Population Generation

⇨ Improve efficiency

Real-coded Matrix Representation

$$\mathbf{A} = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1S} \\ a_{21} & a_{22} & \cdots & a_{2S} \\ \vdots & \vdots & \ddots & \vdots \\ a_{N1} & a_{N2} & \cdots & a_{NS} \end{pmatrix}$$

⇨ Avoid invalid solutions

Randomly Mutation Operator

$$\mathbf{v}_{i,g} = \mathbf{x}_{i,g} + F(\mathbf{x}_{r1,g} - \mathbf{x}_{r2,g}) + F(\mathbf{x}^M_{best,g} - \mathbf{x}_{i,g}) + F(\mathbf{x}_{r3,g} - \mathbf{x}_{r4,g}) + F(\mathbf{x}^M_{r5,g} - \mathbf{x}^M_{r6,g})$$

⇨ Expand search space

L. Tang, Y. Zhao and J.Y. Liu. An improved differential evolution algorithm for practical dynamic scheduling in steelmaking-continuous casting production. ***IEEE Transactions on Evolutionary Computation***, 2014, 18(2): 209-225. (**IF: 14.3**)

Hybrid Multi-objective Evolutionary Algorithm

Incorporating the Concepts of Personal Best and Global Best

⇨ Avoid local optimum

Multiple Crossover Operators to Update the Population

⇨ Increase robustness

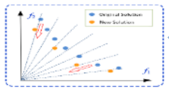
Propagating Mechanism

⇨ Improve diversity

L. Tang and X. Wang. A hybrid multiobjective evolutionary algorithm for multiobjective optimization problems. ***IEEE Transactions on Evolutionary Computation***, 2013, 17(1): 20-45. (**IF: 14.3**)

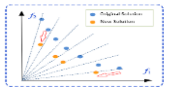
MOEA/D with Neighborhood-based Knowledge Transfer for Multiobjective Multitask Optimization (MTEA/D-DN)

Gray Relation Analysis



$$r(Y, X_i) = \frac{1}{n}\sum_{k=1}^{n}\zeta(k)$$

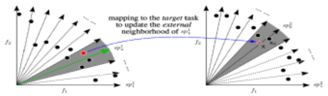
$$\zeta(k) = \frac{\min_{i=1}^{m}\min_{k=1}^{n}\Delta_i(k) + \rho \times \max_{i=1}^{m}\max_{k=1}^{n}\Delta_i(k)}{\Delta_i(k) + \rho \times \max_{i=1}^{m}\max_{k=1}^{n}\Delta_i(k)}$$



⇨ Knowledge mining

Dual Neighbor-hoods

Inner neighborhood



External neighborhood

⇨ Knowledge transfer

Achievement Scalarizing Function

$$u^{ASF}(\mathbf{F}(\mathbf{x}); \mathbf{w}) = \max_{i=1}^{m} \frac{1}{w_i}|f_i(\mathbf{x}) - z_i^*|$$

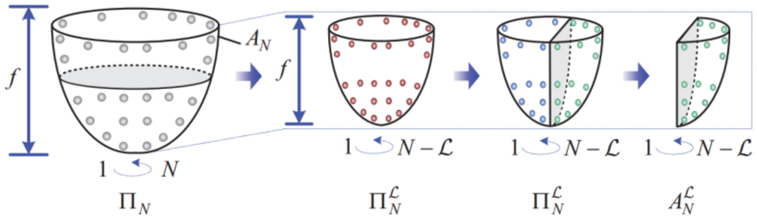
⇨ Individual set update strategy

X. Wang, Z. Dong, L. Tang, and Q. Zhang. Multiobjective multitask optimization - neighborhood as a bridge for knowledge transfer. ***IEEE Transactions on Evolutionary Computation***, 2023, 27(1): 155-169. (**ESI Highly Cited Paper, IF: 14.3**)

1. Data Analytics and Optimization — DAO based Solution

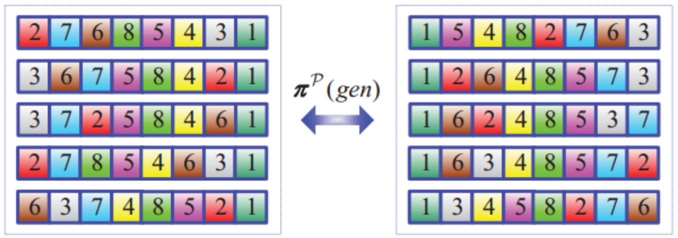
K-medoids Memetic Permutation Group Algorithm

Permutation Group



Reduce solution space

K-medoids Clustering-based Crossover



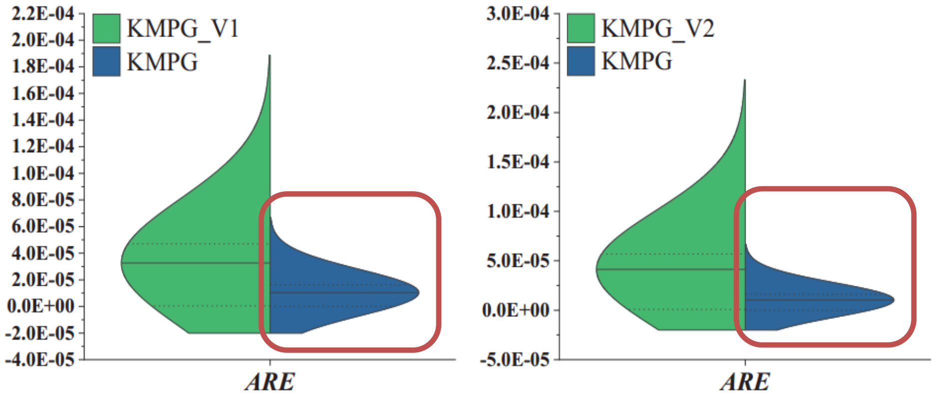
Learning-based solutions

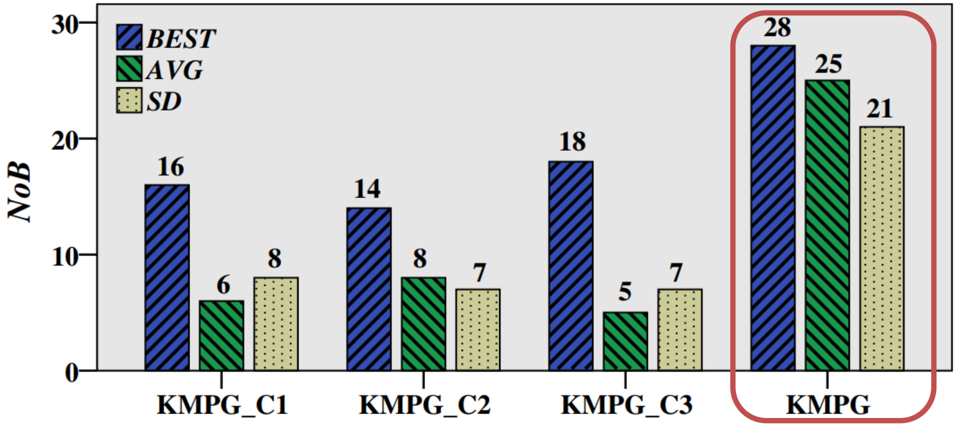
Distance-and-quality Population Strategy

$$simi(\boldsymbol{\pi}^a, \boldsymbol{\pi}^b) = \sum_{1\le i\le N} |i - rp(\pi_i^a, \boldsymbol{\pi}^b)|$$

Diversify the population

Performance





The KMPG outperforms the state-of-the-art methods.

L. Tang, Z. Li and J. Hao. Solving the single row facility layout problem by k-medoids memetic permutation group. ***IEEE Transactions on Evolutionary Computation***, 2023, 27(2): 251-265. (**IF: 14.3**)

Outline

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- **MCIS-E Production-Logistics-Energy Optimization with Feedback**
- PDDE-based Quality Analytics and Dynamic Optimization
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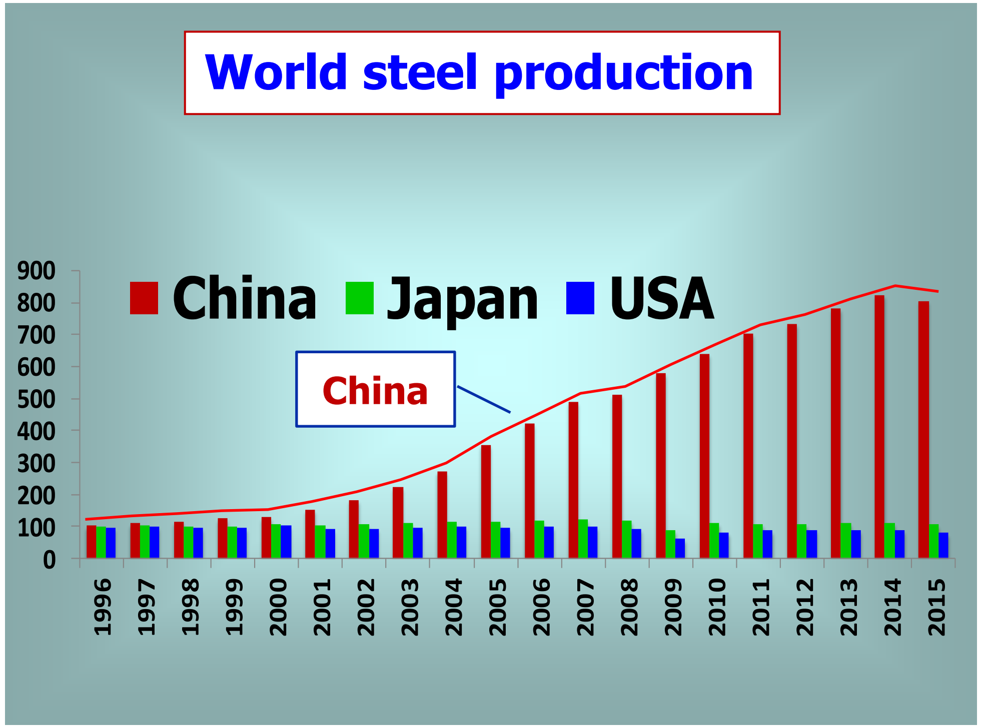
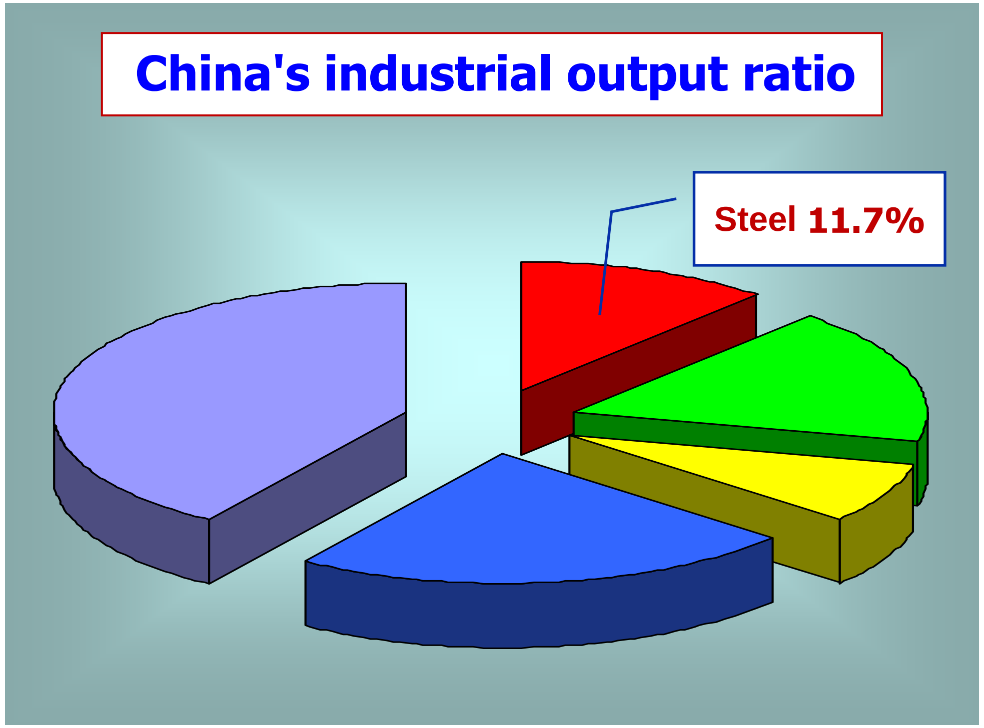
China is the Largest Steel Producer

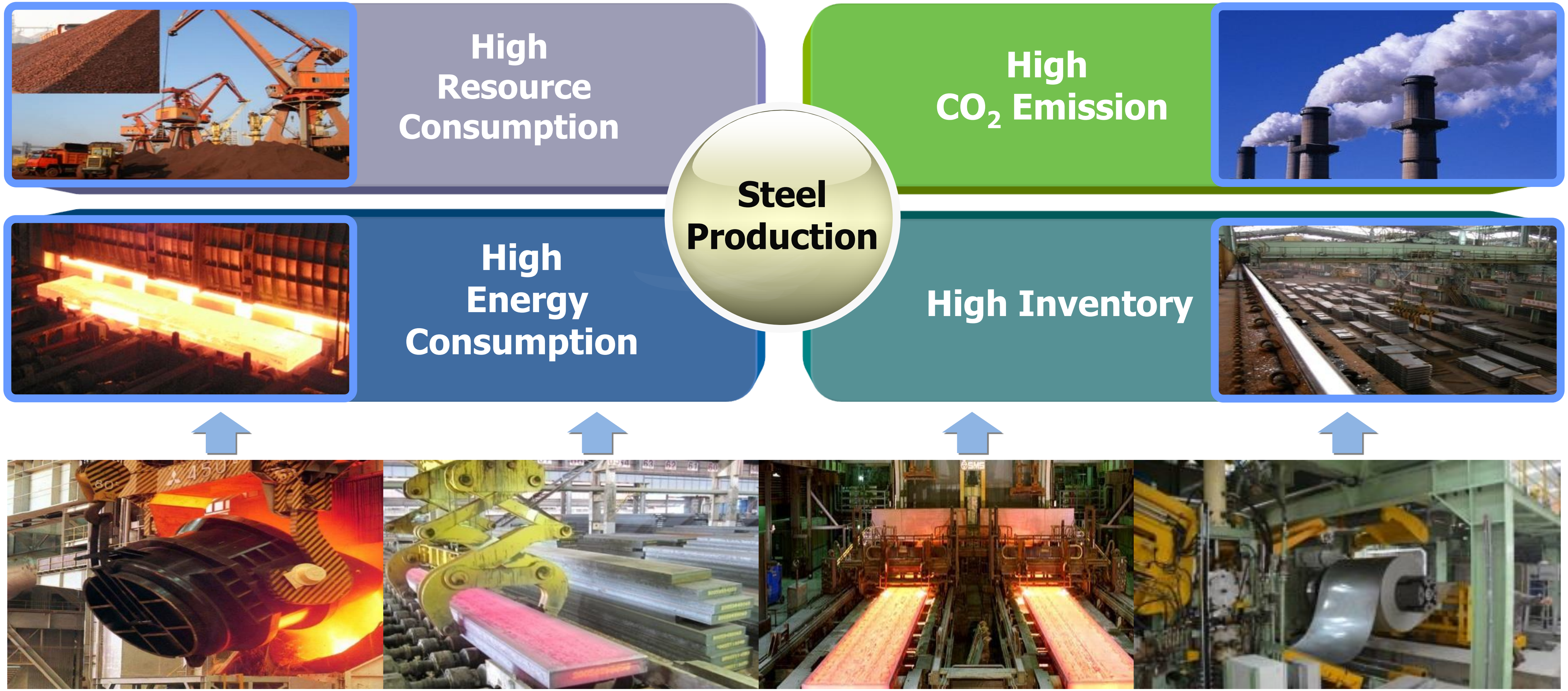
- China has been the largest steel producer in the world for the last twenty consecutive years.
- In 2022, China's steel output has reached about 1.013 billion tons, accounting for about 53.93% of the world's steel output.
- Steel industry has been one of the pillar industries in China’s national economy.





2. MCIS-E Production-Logistics-Energy Optimization with Feedback

Challenges Faced by Steel Industry



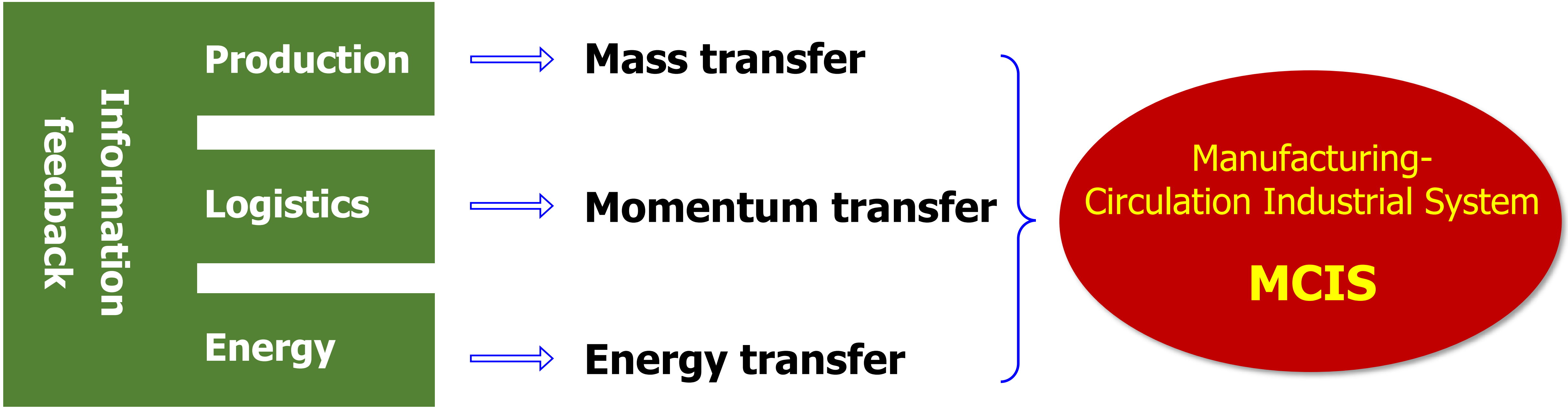
Steelmaking

Logistics

Hot rolling

Cold rolling

Triple transfer and one feedback (MCIS-E)



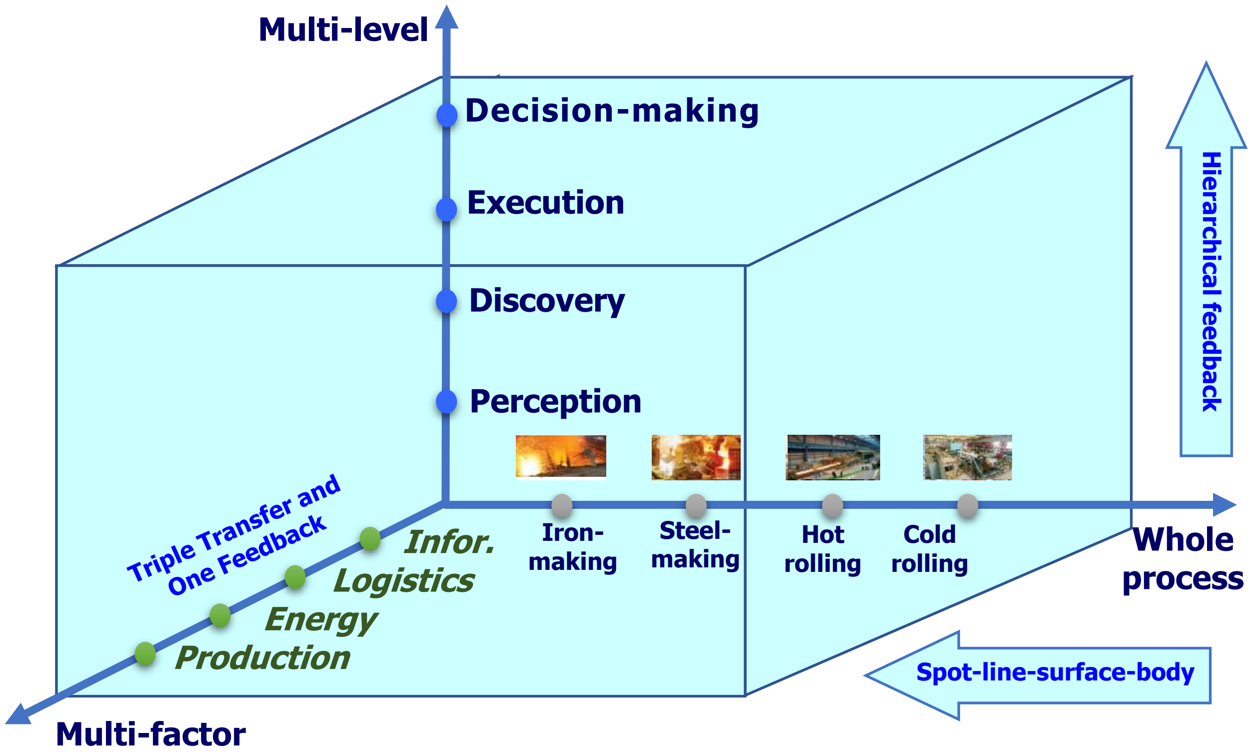
E (*ECO-System*) = Production + Logistics + Energy + Information

Triple Transfer and One Feedback (MCIS-E)

Circulation Element

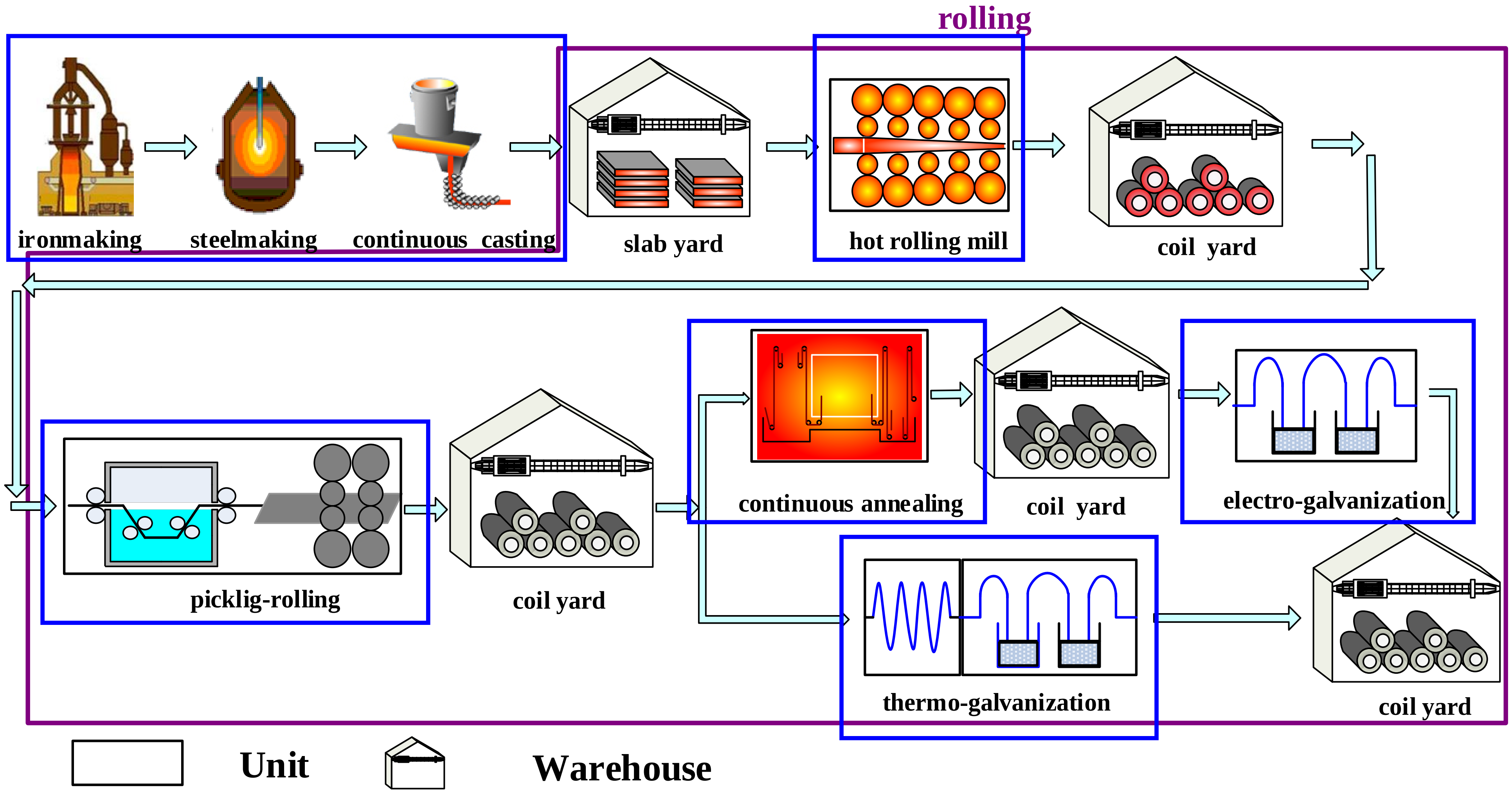
Production	⇨	**Mass transfer**
Logistics	⇨	**Momentum transfer**
Energy	⇨	**Energy transfer**
Information	⇨	**Information feedback**

Triple Transfer and One Feedback



2. MCIS-E Production-Logistics-Energy Optimization with Feedback

Steel Production

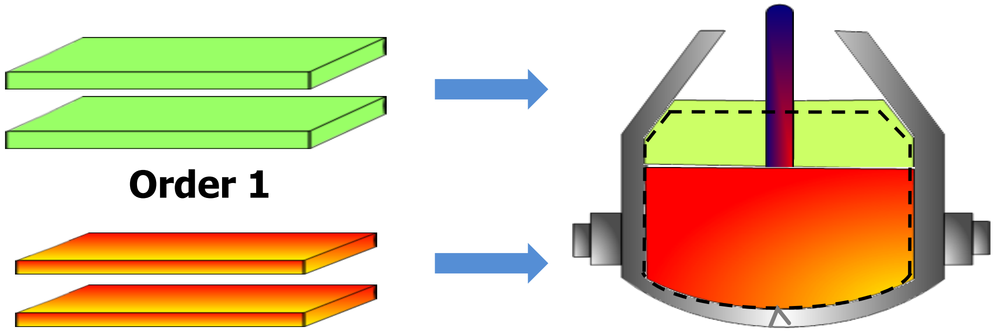


Production: Iron-making/Steelmaking/Hot Rolling/Cold Rolling

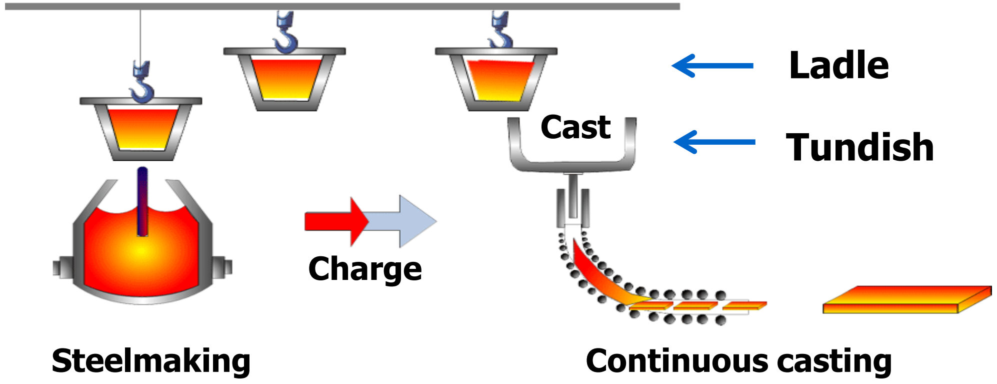
2. MCIS-E Production-Logistics-Energy Optimization with Feedback

Production Scheduling

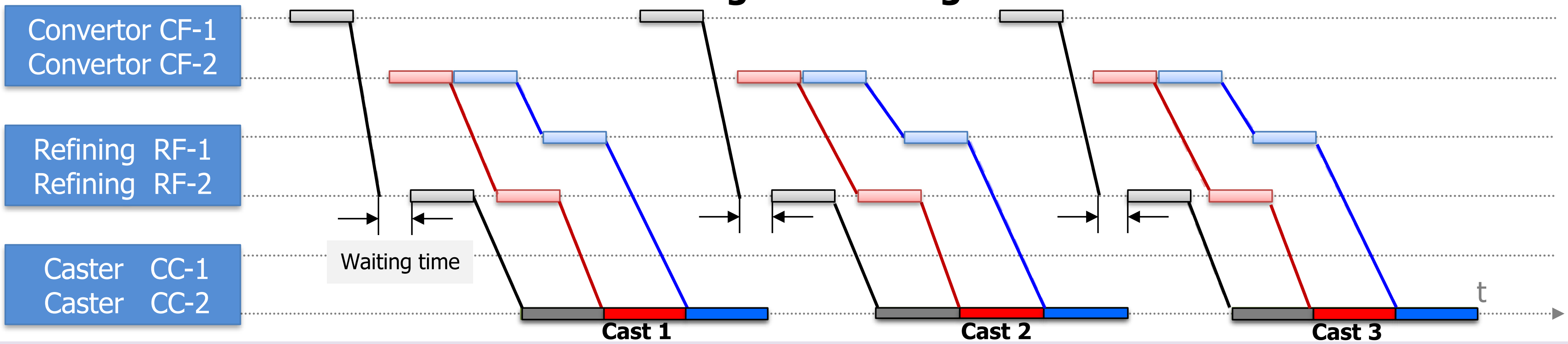
Charge Batching



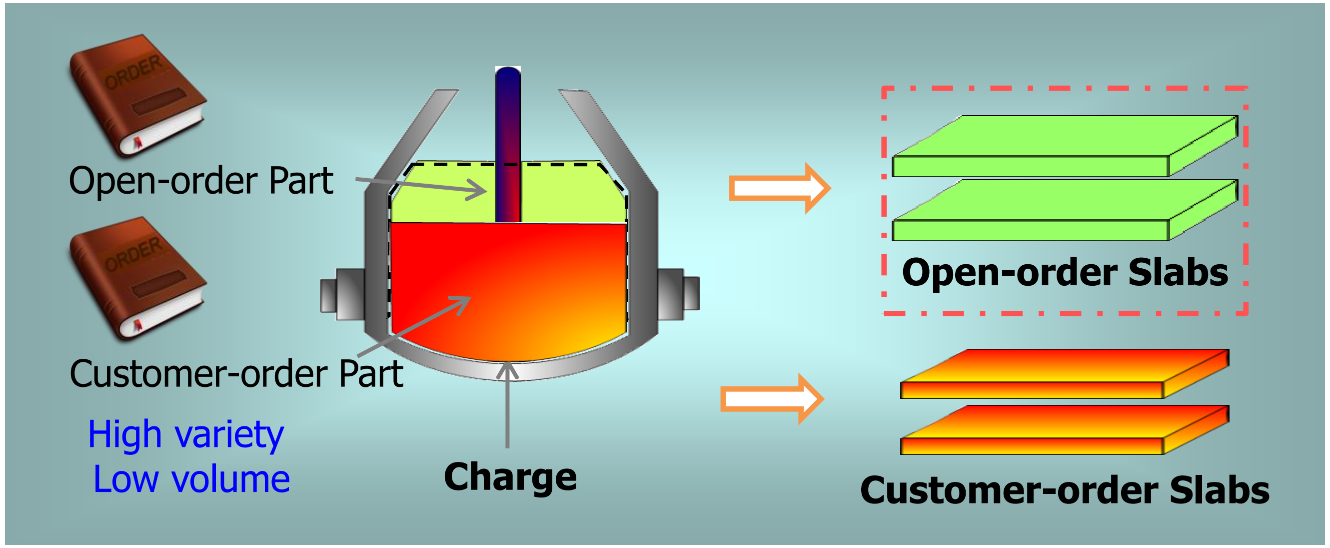
Cast Batching



Steelmaking Scheduling

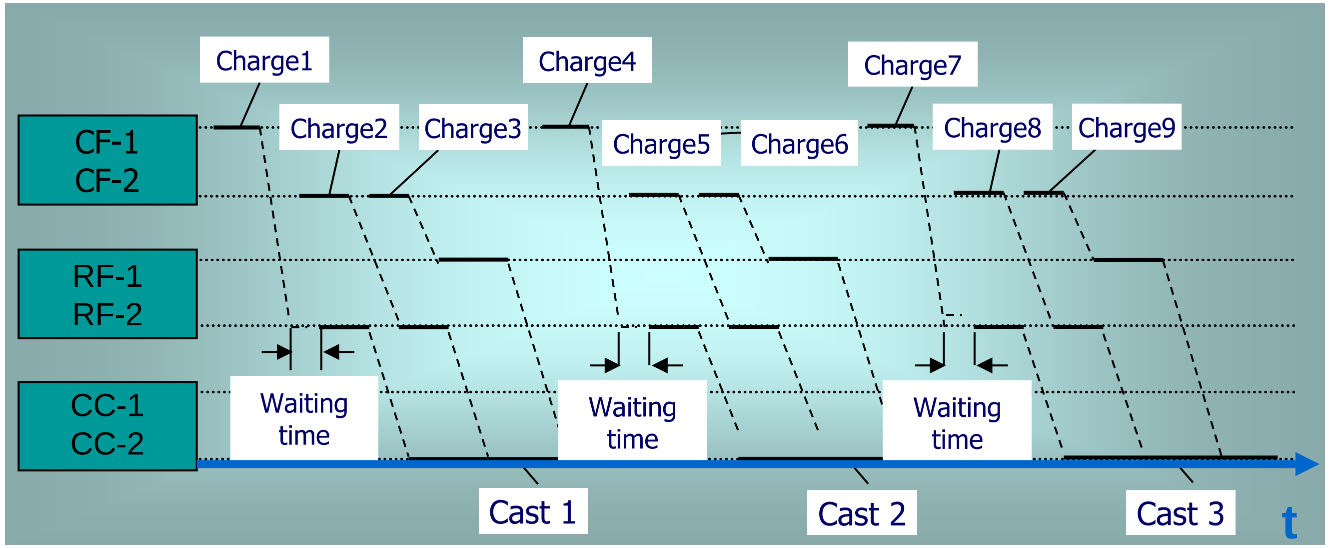


2. MCIS-E Production-Logistics-Energy Optimization with Feedback



Group all the slabs of different customer orders into batches

p-median clustering
with capacity and additional technical constraints

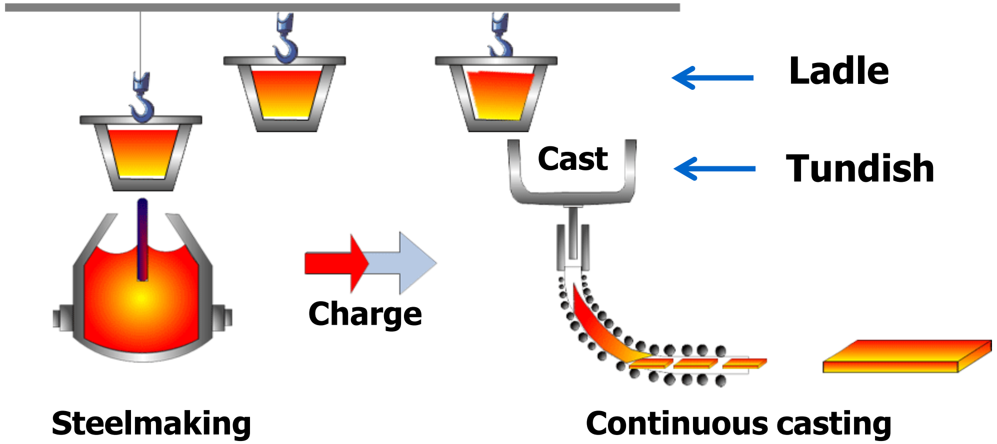


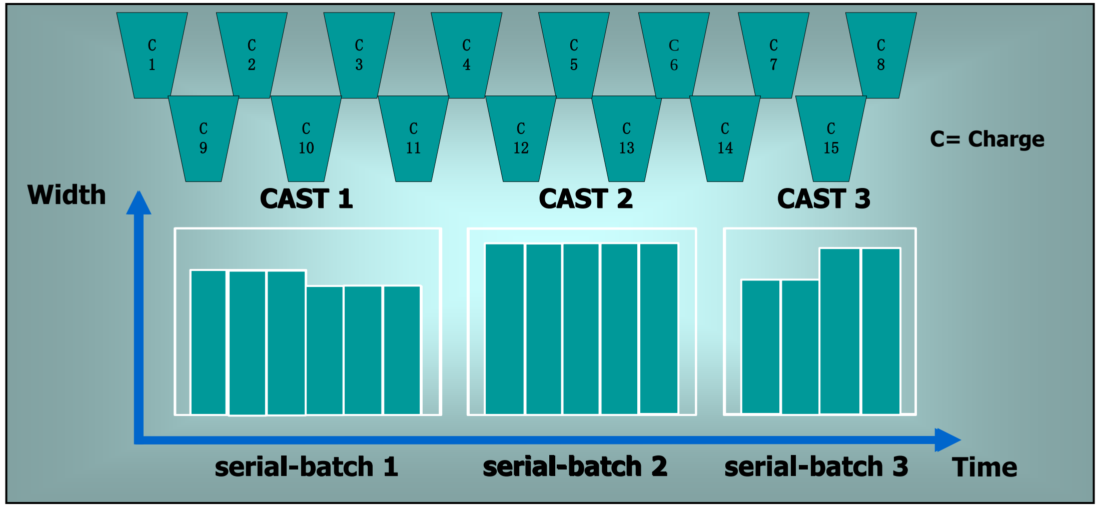
- Minimize assignment cost
- Minimize open-order slabs
- Minimize unfulfilled cost of order

- 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.

2. MCIS-E Production-Logistics-Energy Optimization with Feedback





Decisions

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

Objectives

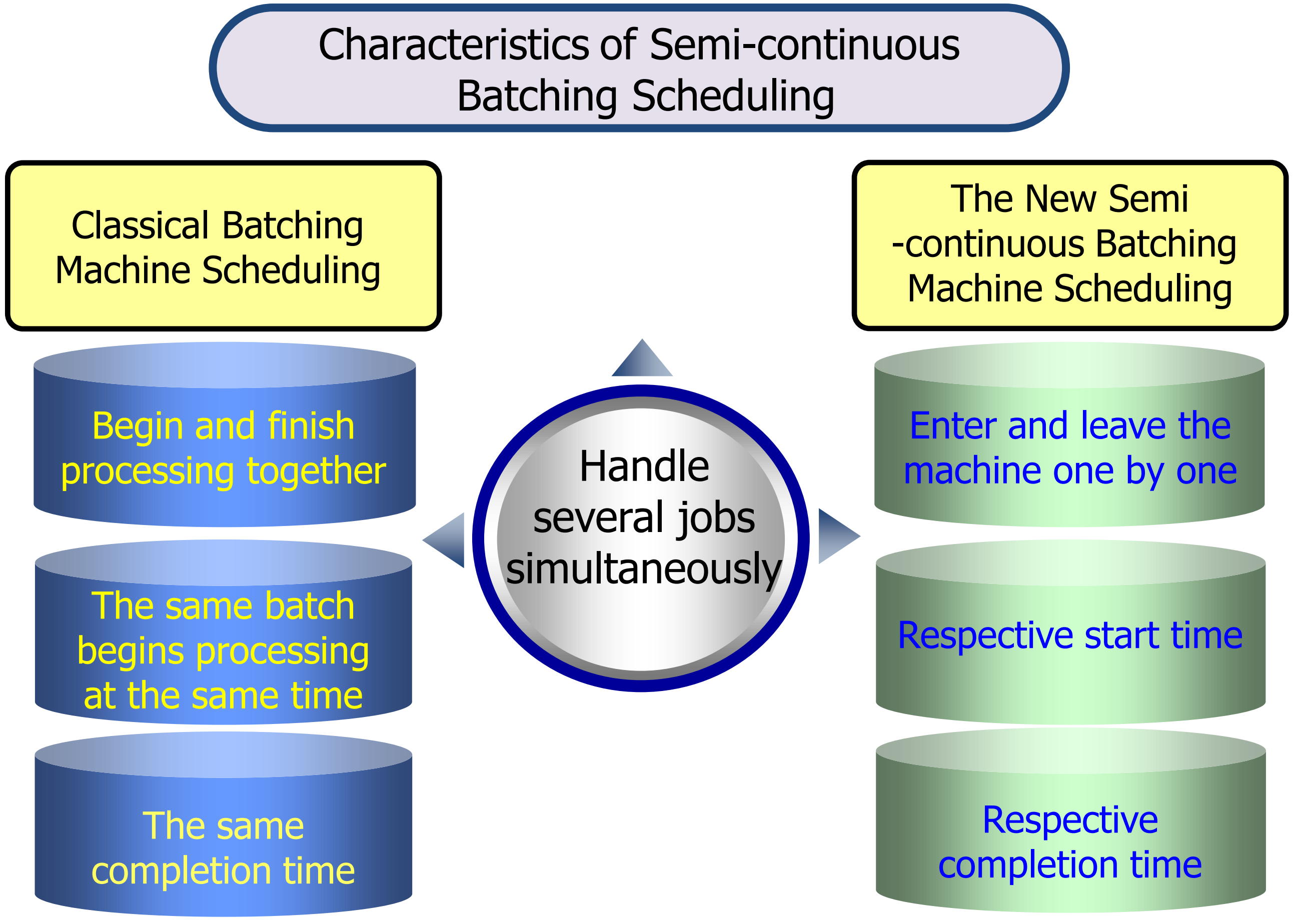
- Maximize tundish utilization
- Minimize total grade switch and width switch cost

Constraints

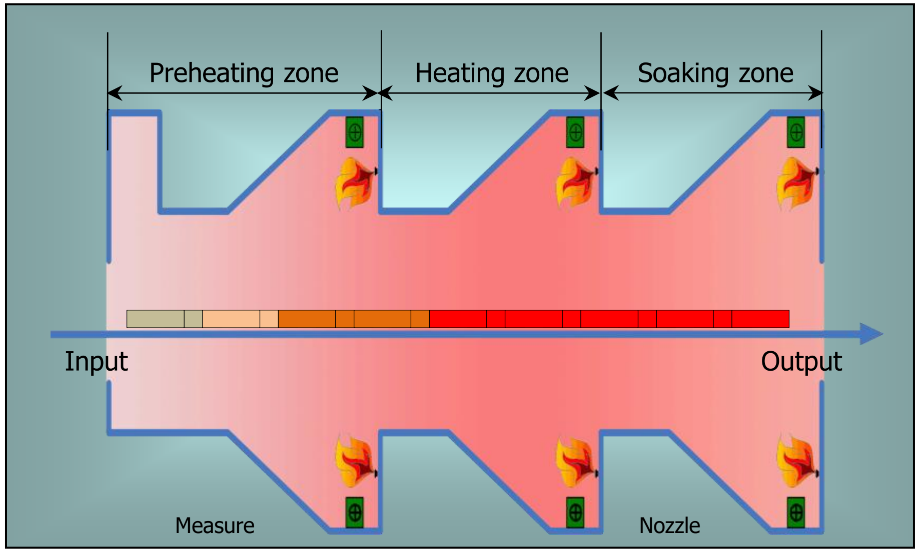
- Grade switch constraint
- Width switch constraint
- Lifespan of tundish

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

2. MCIS-E Production-Logistics-Energy Optimization with Feedback



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



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

The heating process of tube-billets in heating furnace

2. MCIS-E Production-Logistics-Energy Optimization with Feedback

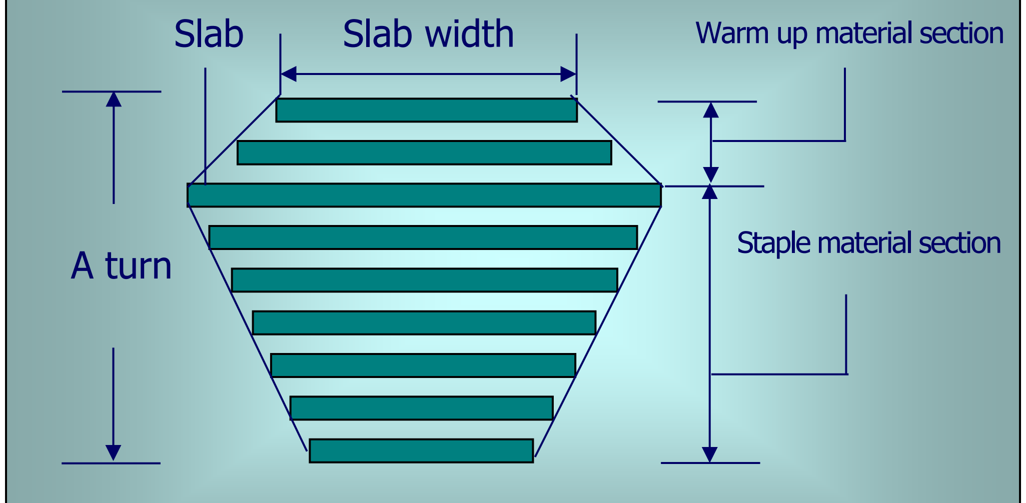
Decision	Objective
Sequence of adjacent jobs to be processed	Minimize the total changeover costs

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

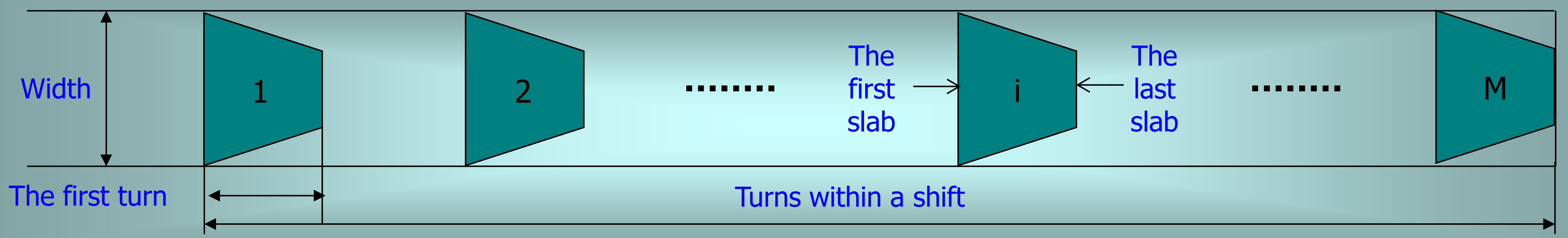
$$\text{Subject to} \sum_{i=1}^{N+M} X_{ij} = 1, \qquad j \in \{1, 2, \ldots, N+M\}$$

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

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

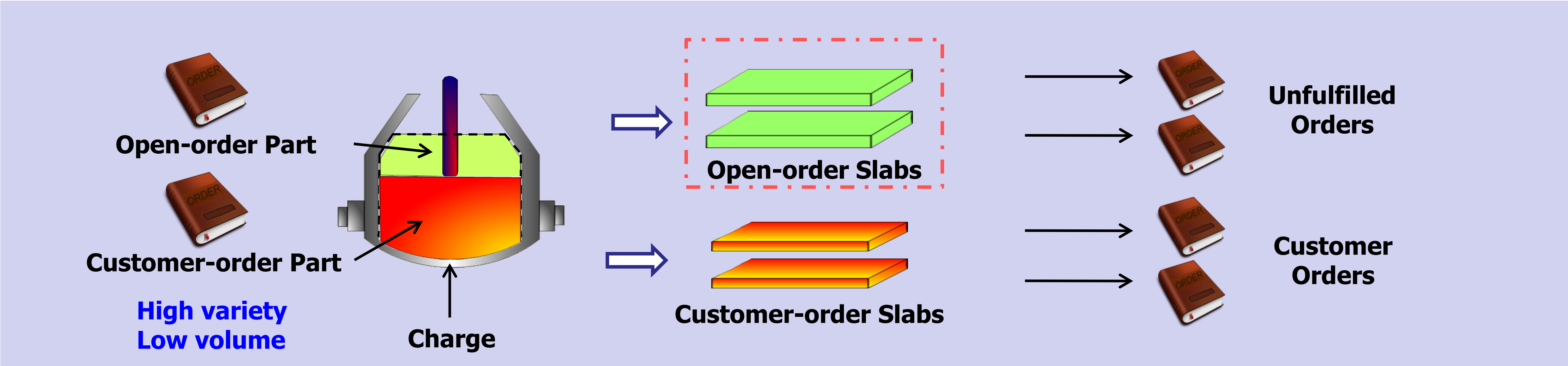


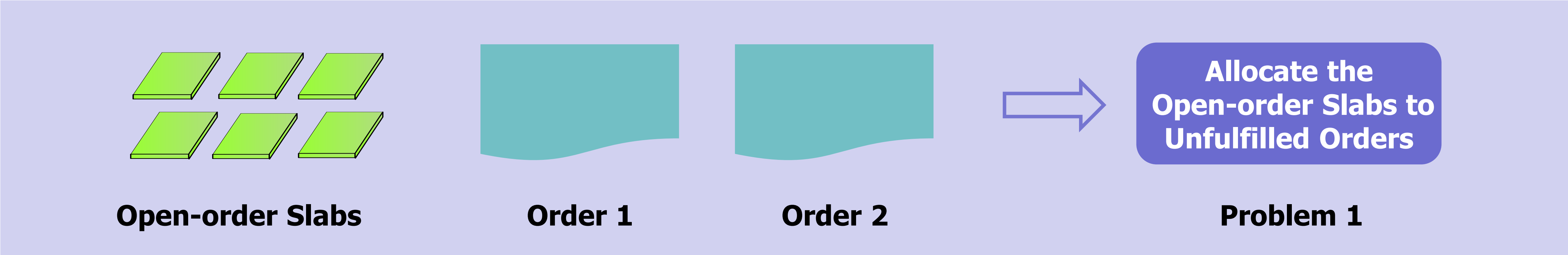
Structure and components of a turn



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.

2. MCIS-E Production-Logistics-Energy Optimization with Feedback





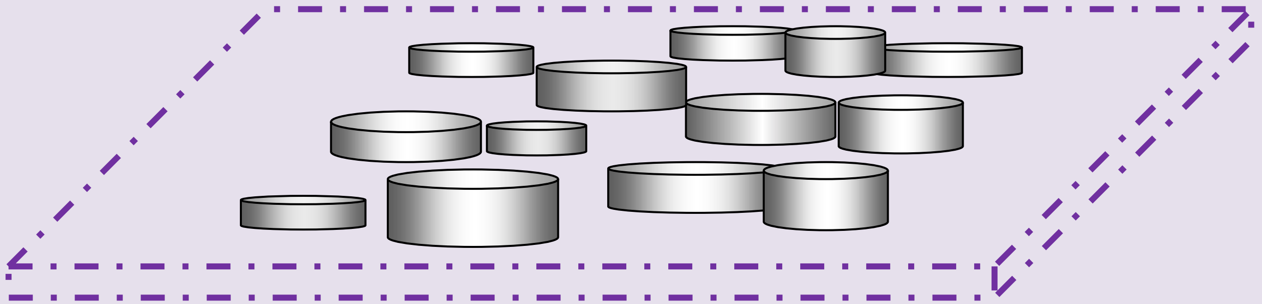
2. MCIS-E Production-Logistics-Energy Optimization with Feedback

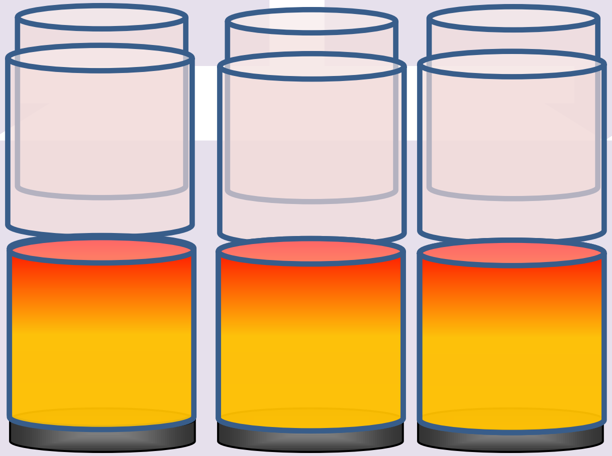
Maximize the Reward

Minimize the Mismatching Cost

Equipment Constraints

Matching Constraints





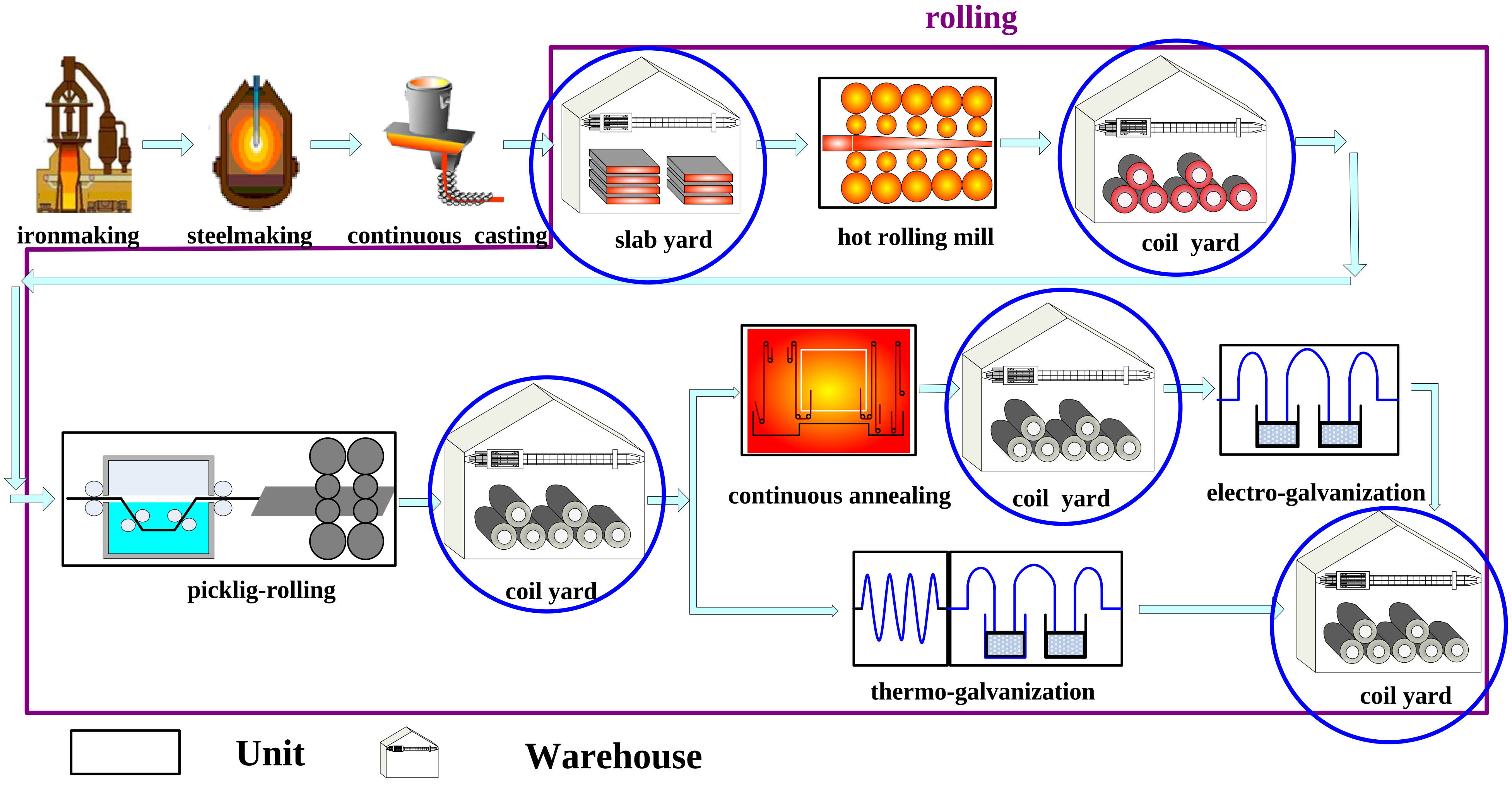
Form batches for each empty furnace

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.

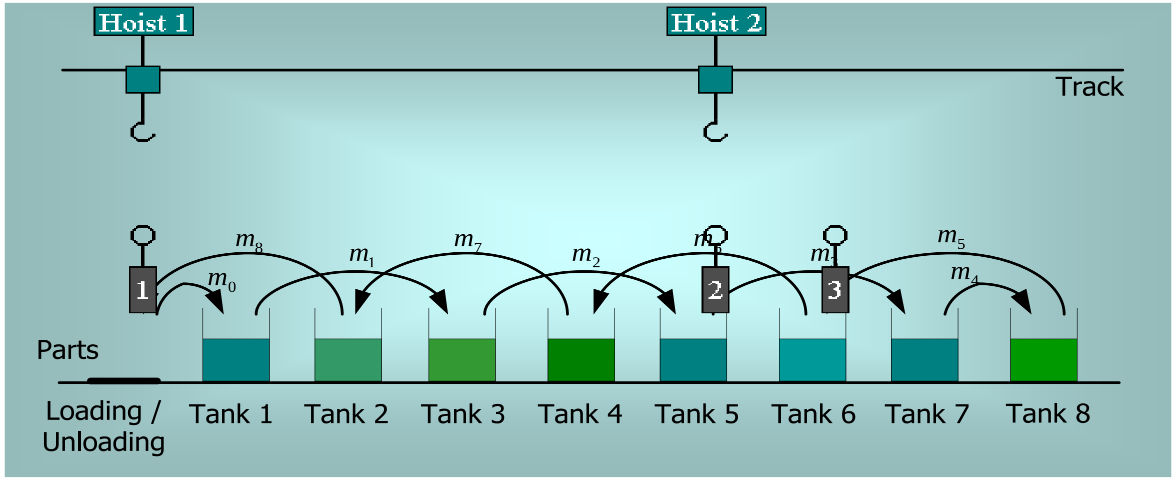
2. MCIS-E Production-Logistics-Energy Optimization with Feedback

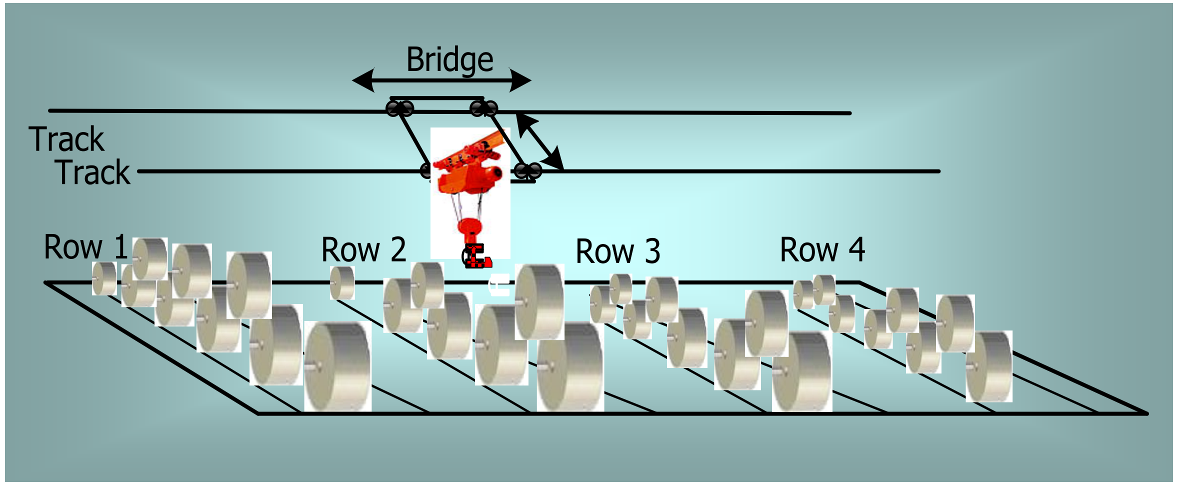
Logistics in Steel Plant



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

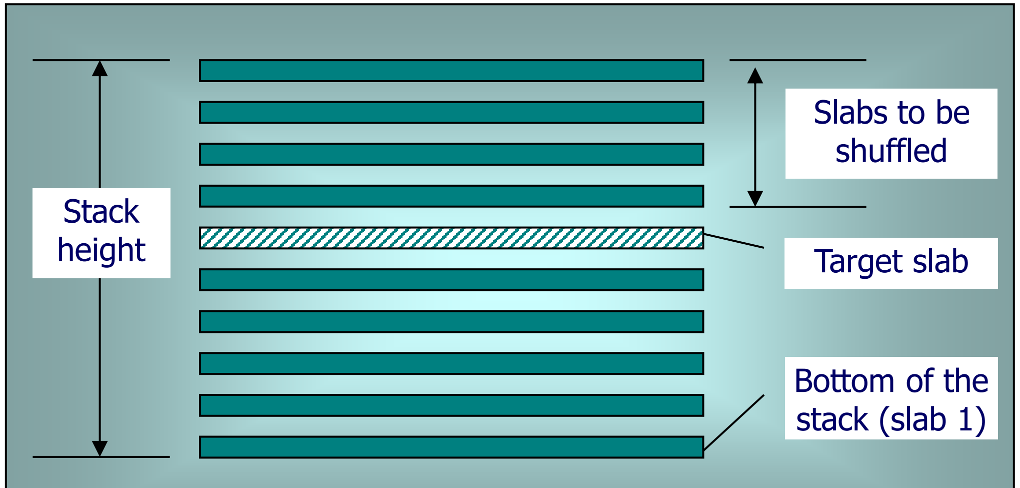
Heuristic algorithm & worst-case analysis

For special cases

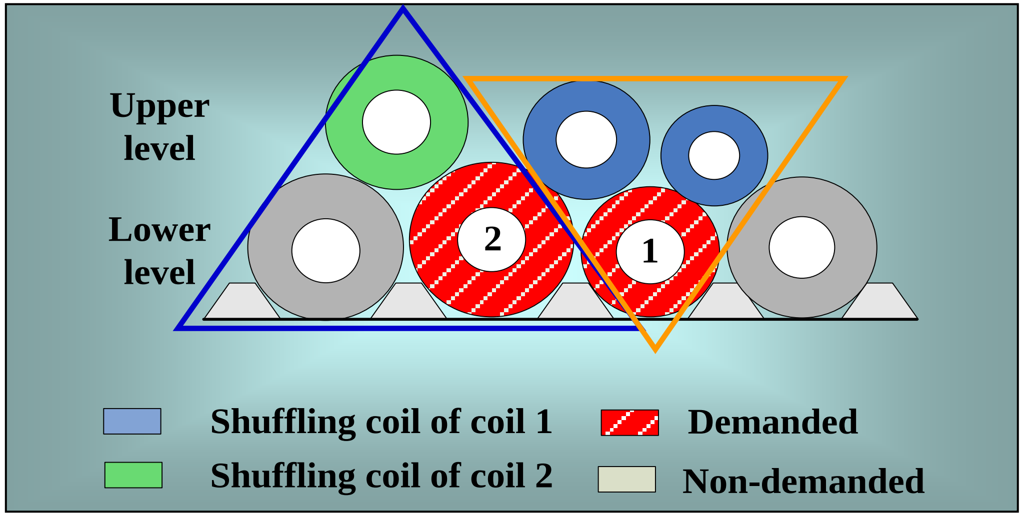
Polynomial algorithms (optimal solutions)

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

2. MCIS-E Production-Logistics-Energy Optimization with Feedback



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

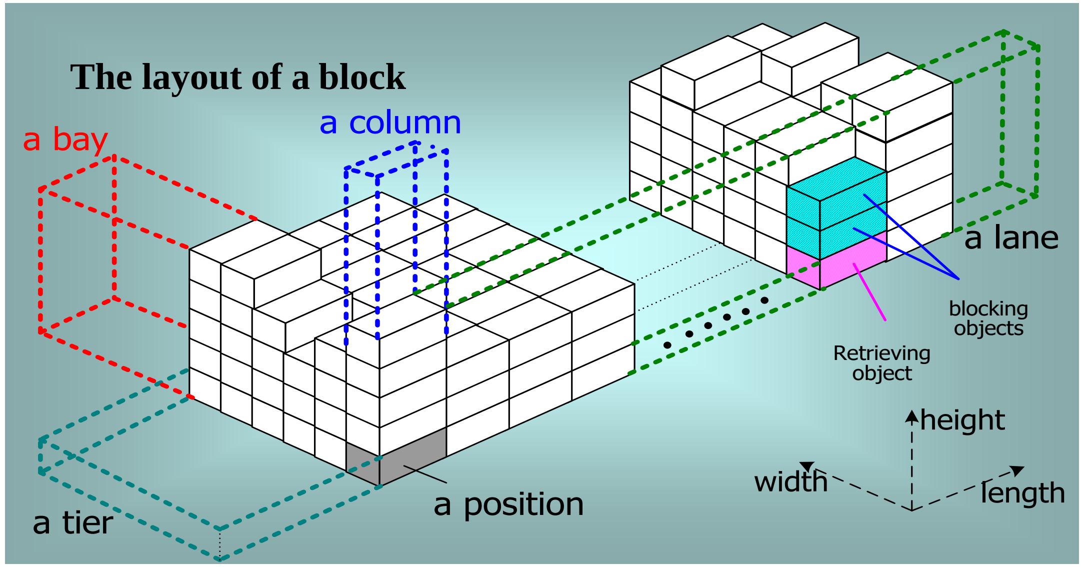
For special cases

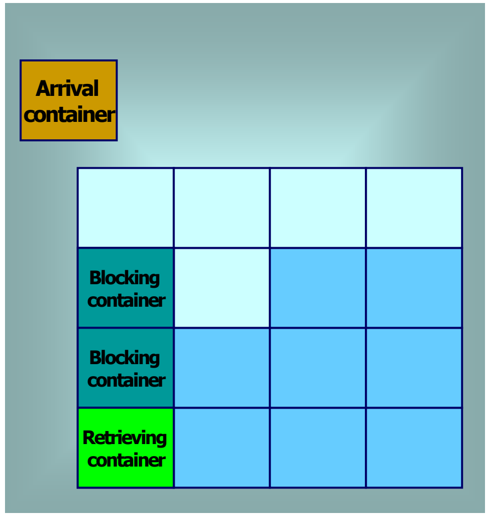
Polynomial algorithms (optimal solutions)

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

2. MCIS-E Production-Logistics-Energy Optimization with Feedback

- 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.





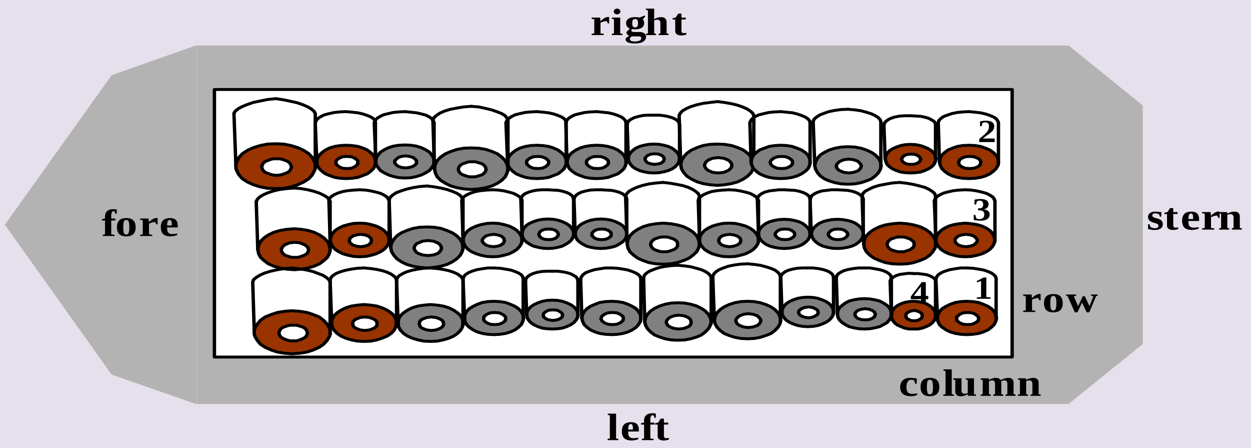
L. Tang, W. Jiang, J. Liu, Y. Dong. Research into container reshuffling and stacking problems in container terminal yards. ***IISE Transactions***, 2015, 47(7): 751-766. (***IISE Transactions*** **Best Applications Paper Award**)

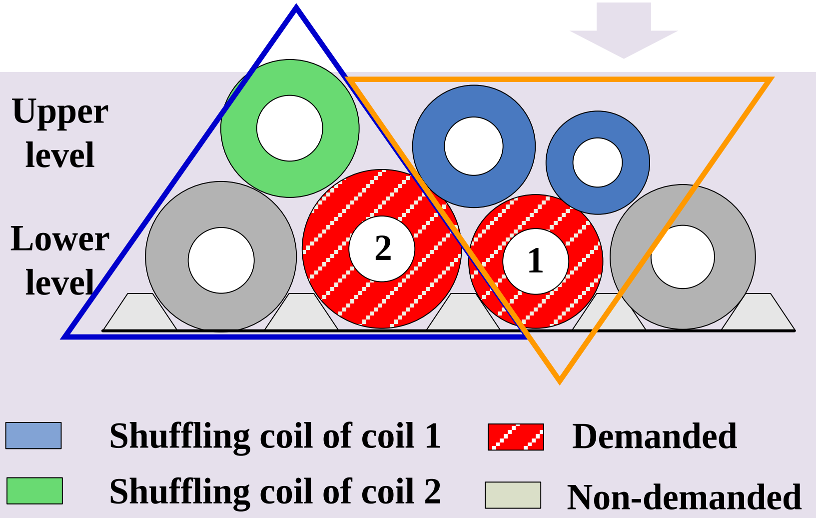
2. MCIS-E Production-Logistics-Energy Optimization with Feedback

Minimize the moment imbalance

Minimize the shuffling

Minimize the dispersion of coils for the same destination





Structural constraints

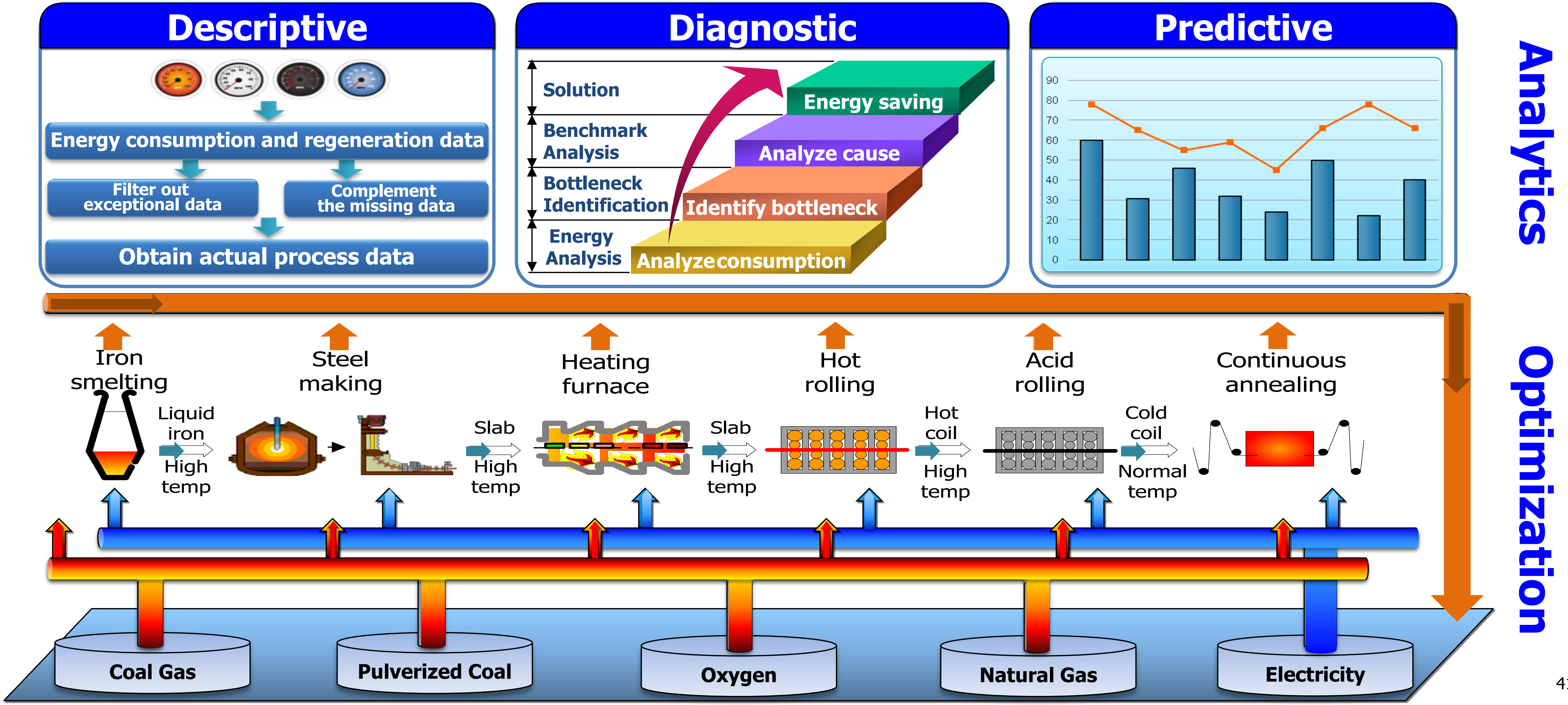
Weight restriction constraints

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.

2. MCIS-E Production-Logistics-Energy Optimization with Feedback

Energy Scheduling



2. MCIS-E Production-Logistics-Energy Optimization with Feedback

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

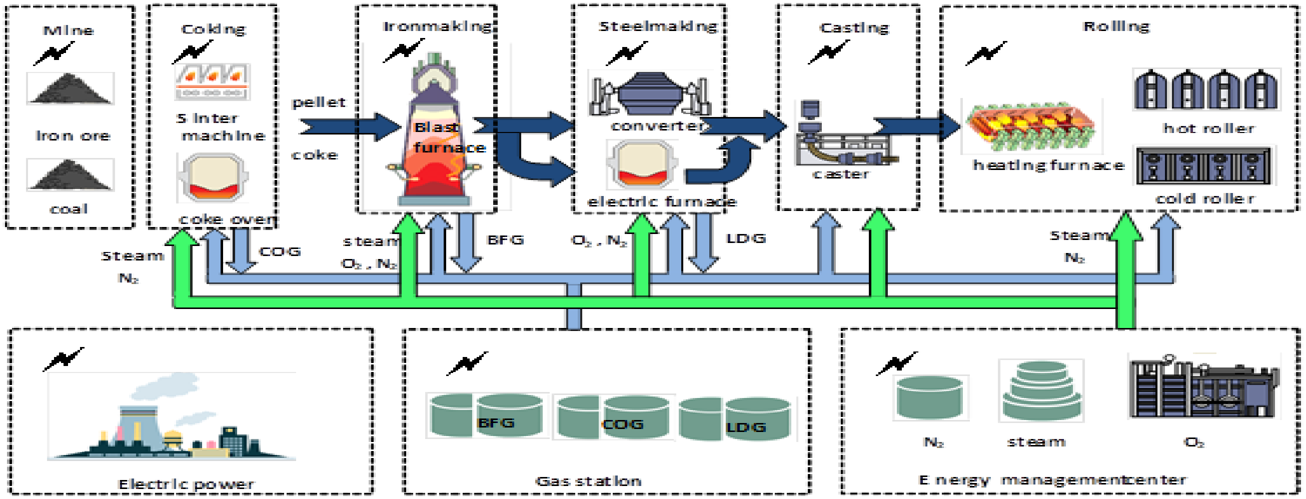
$$\sum_i x_i + w \le \sum_i y_i + z + \left(H - H^0\right)$$

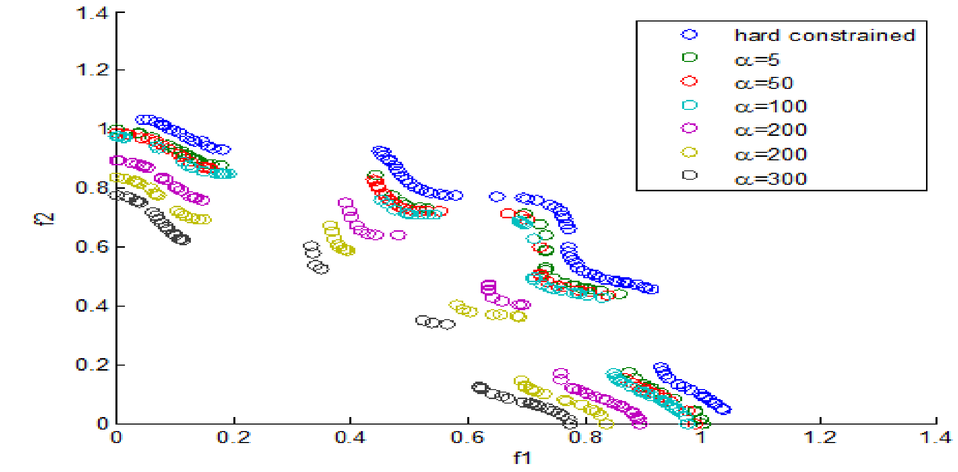
$$y_i \le \theta_i^1 p_i, i = 1, 2, \ldots, I$$

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

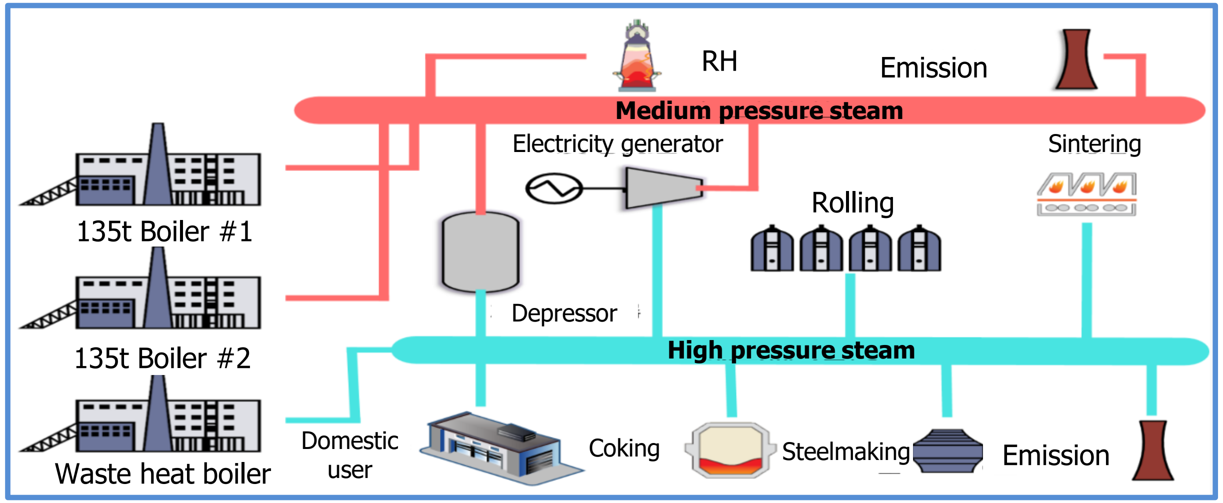




Steam scheduling

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

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

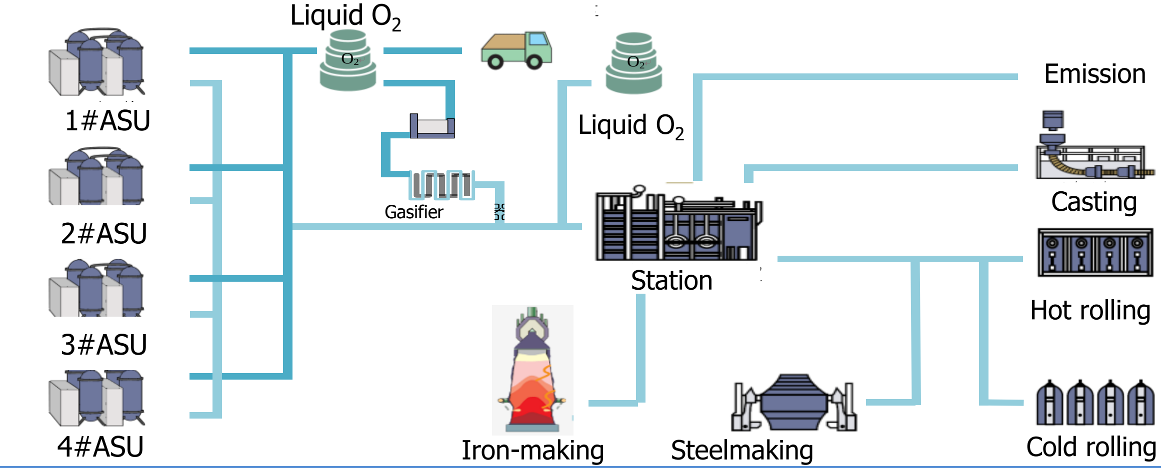
Oxygen scheduling

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

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

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

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

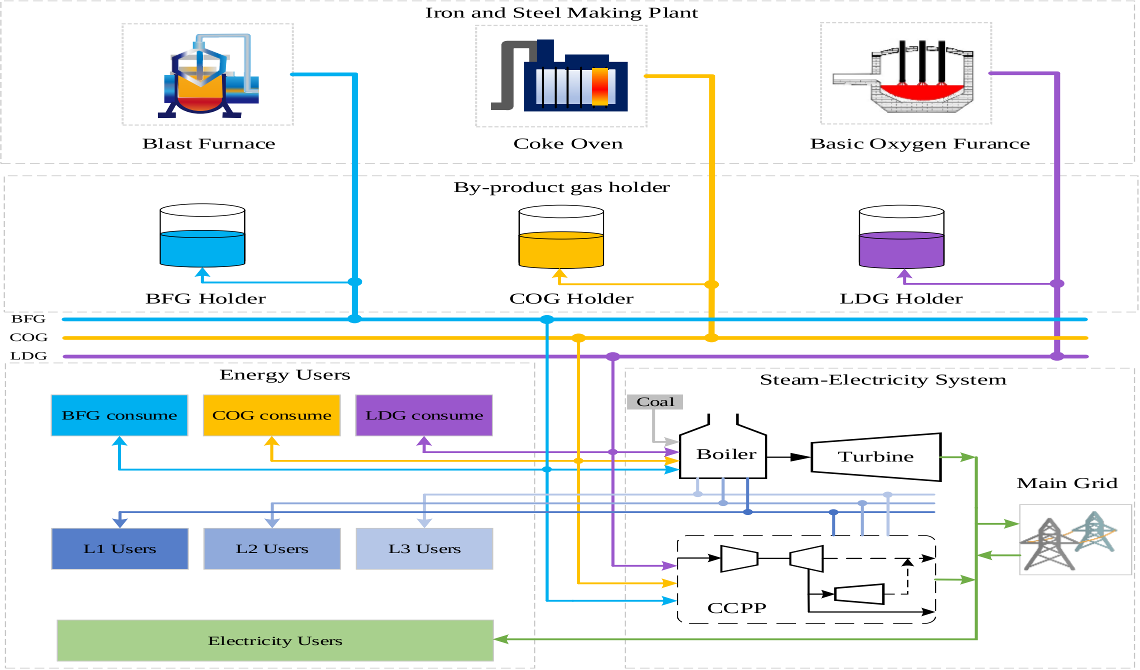
G. Che, Y. Zhang, L. Tang, S. Zhao. A deep reinforcement learning based multi-objective optimization for the scheduling of oxygen production system in integrated iron and steel plants. *Applied Energy*, 2023, 345: 121332.

2. MCIS-E Production-Logistics-Energy Optimization with Feedback

Integrated Multi-Energy Scheduling

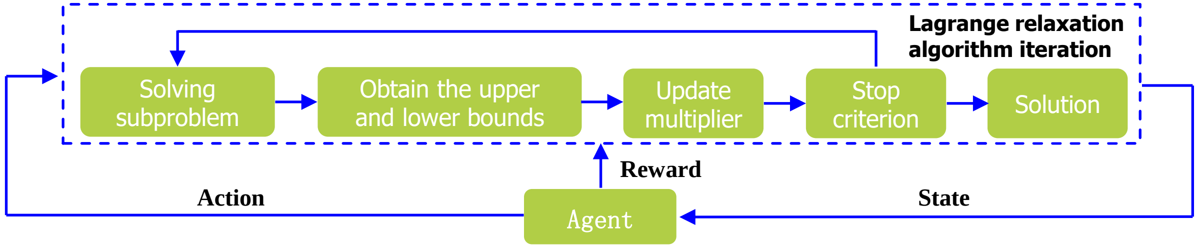
❖ Research Background

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 scheduling period.



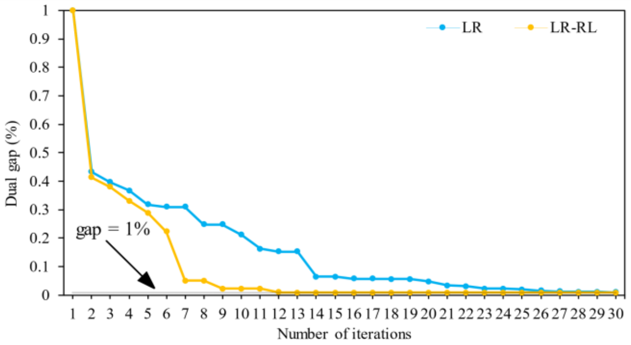
❖ Reinforcement Learning Based Improved Lagrangian Relaxation Algorithm

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



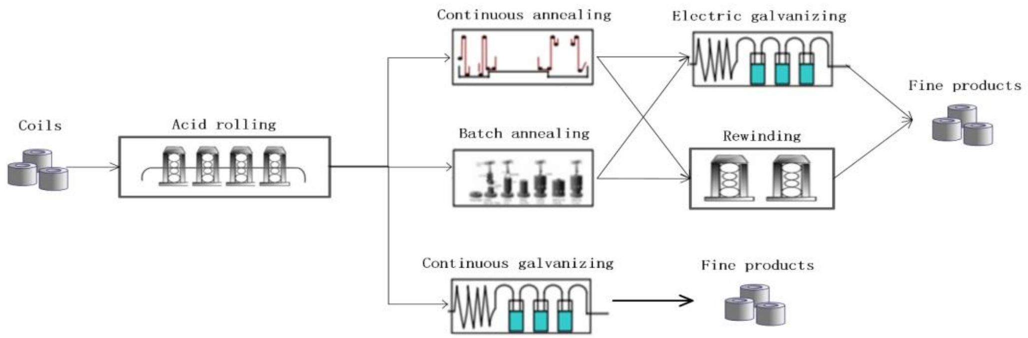
Algorithm dual gap comparison

C. Miao, S. Zhao, L. Tang, J. Liu, Y. Zhang. A Reinforcement Learning Based Lagrangian Relaxation Algorithm for Multi-Energy Allocation Problem in Steel Enterprise. *Computers & Chemical Engineering*, 2024. (Revision)

Integrated Scheduling of Production and Energy

❖ Research Background

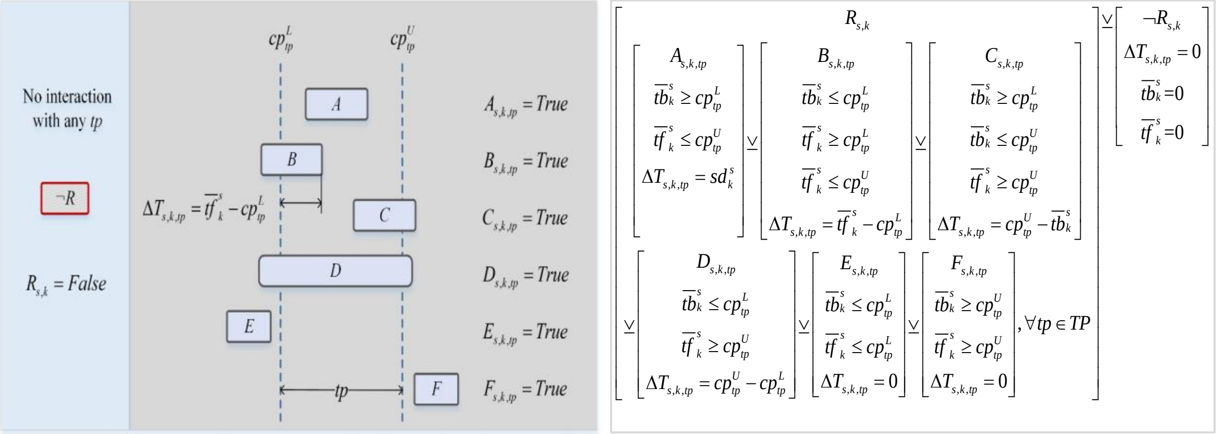
Cold rolling in steel production is a typical power intensive process. Steel companies can take advantage of processing flexibility to make better use of electric power, and thus reduce the energy cost.



The integrated scheduling problem of the rolling sector with consideration of energy consumption under time-of-use electricity prices was proposed to optimize the coordination of production and electricity consumption, and minimize the typical production costs.

❖ MINLP modeling with generalized disjunctive programming constraints

Based on a continuous time representation, the MINLP/GDP model was formulated with nonlinear and disjunctive constraints, and then reformulated as a tight MILP model through hull reformulation and exact linearization.

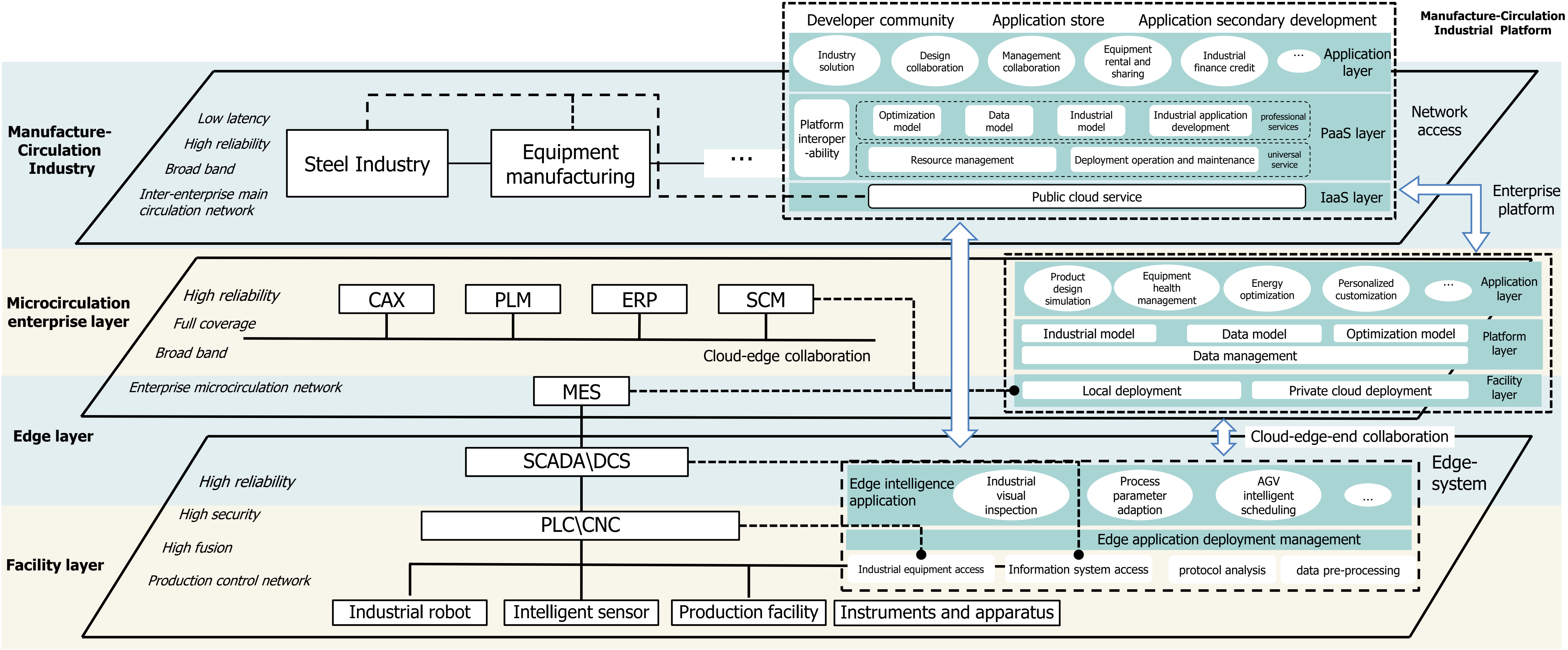


GDP is used to formulate the possible interactions of a time slot with a constant time period

S. Zhao, I. E. Grossmann, L. Tang. Integrated scheduling of rolling sector in steel production with consideration of energy consumption under time-of-use electricity prices. ***Computers & Chemical Engineering***, 2018, 111:55-65

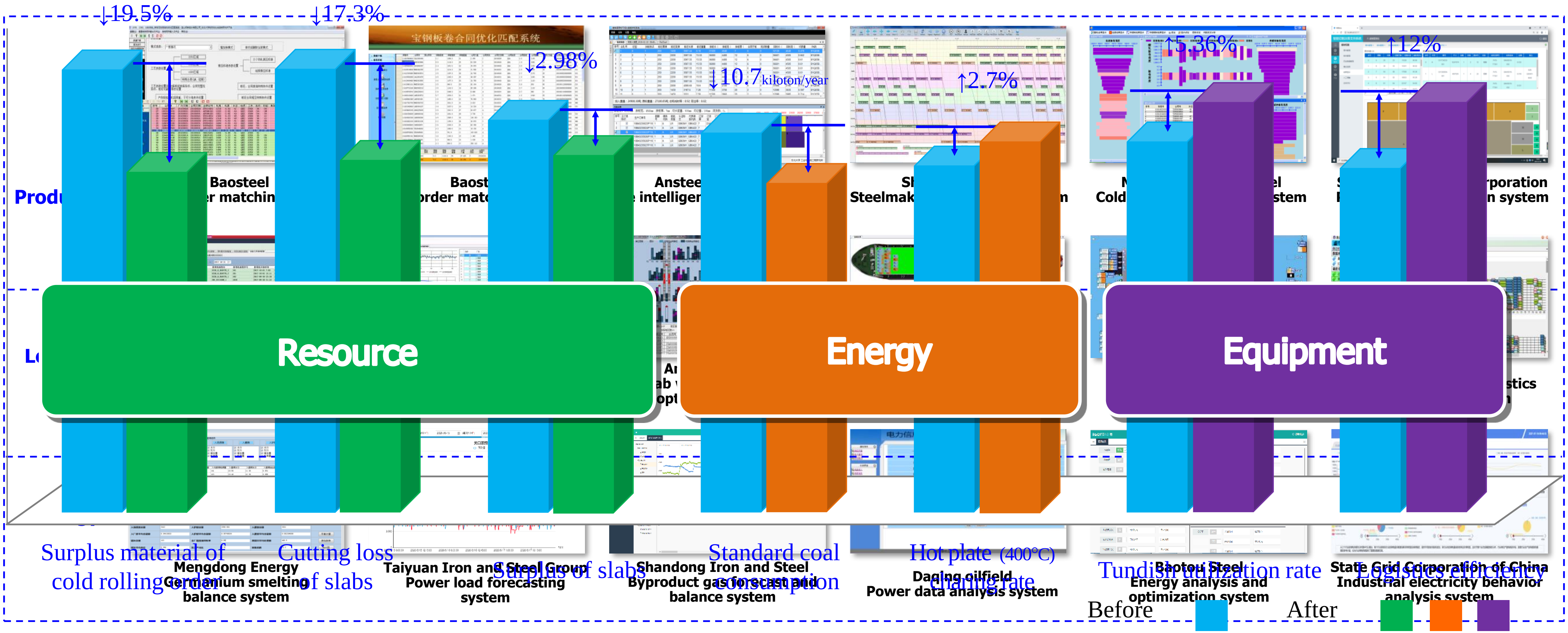
2. MCIS-E Production-Logistics-Energy Optimization with Feedback

Information Feedback



2. MCIS-E Production-Logistics-Energy Optimization with Feedback

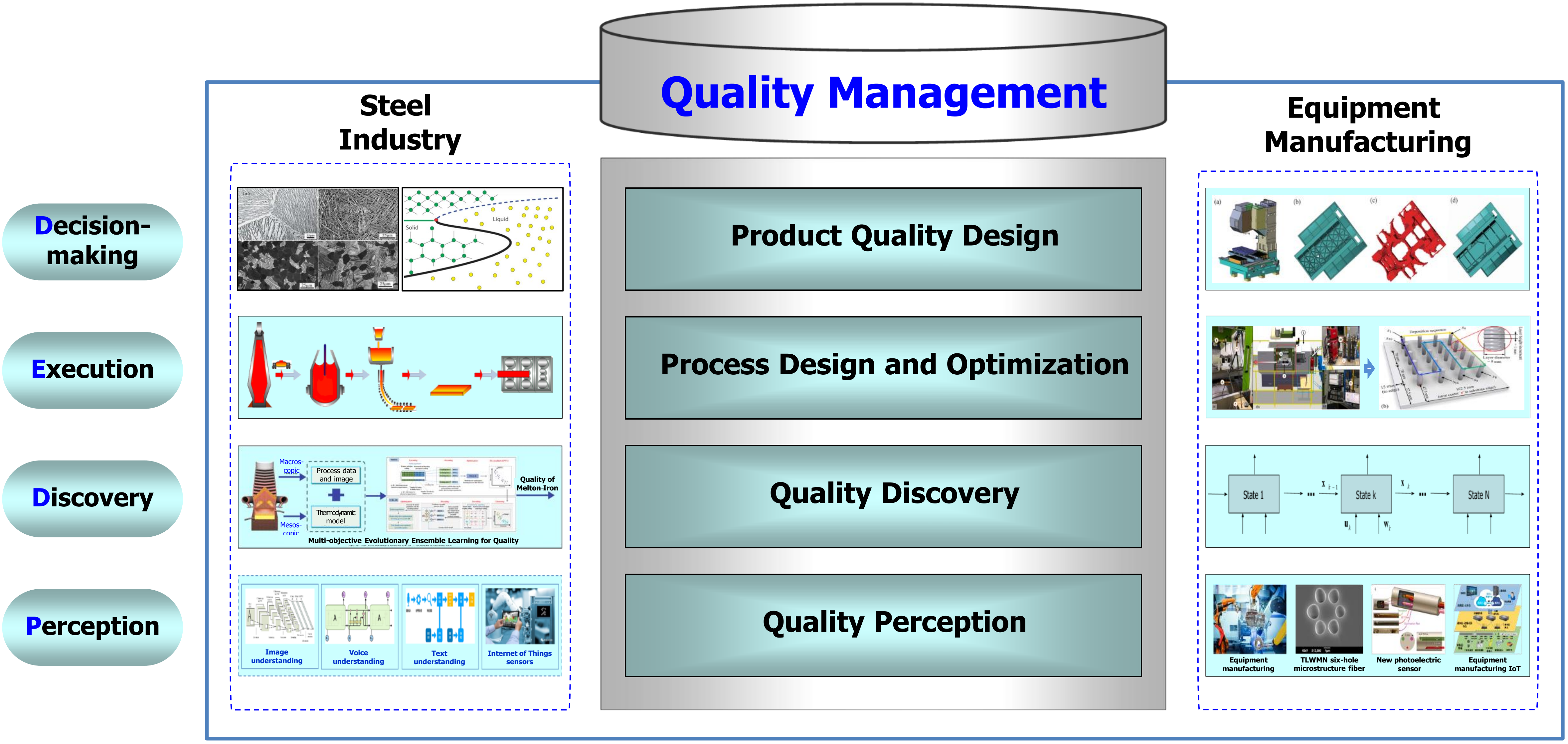
❖ A series of manufacturing optimization software systems are developed which have been successfully applied to more than 40 enterprises in steel, equipment manufacturing, logistics, and energy industries.



Outline

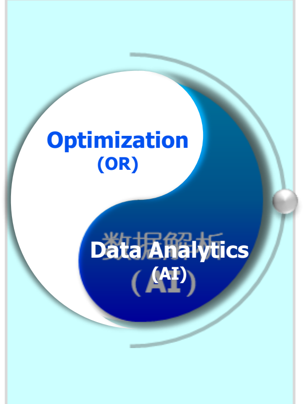
- Data Analytics and Optimization (DAO)
- MCIS-E Production-Logistics-Energy Optimization with Feedback
- **PDDE-based Quality Analytics and Dynamic Optimization**
- MCIS Environmental Analytics and Optimization

3. PDDE-based Quality Analytics and Dynamic Optimization — PDDE



3. PDDE-based Quality Analytics and Dynamic Optimization — Quality perception (P)

Fusion of Multi-dimensional Intelligent Technologies



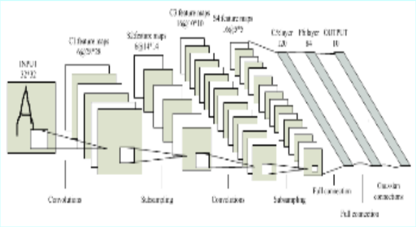
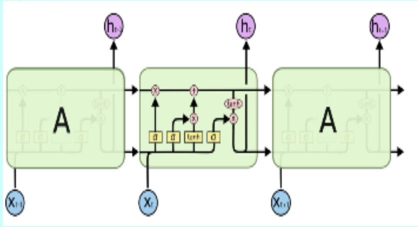
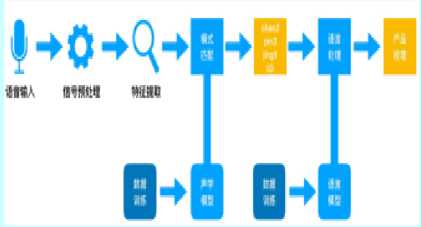


Image understanding



Voice understanding



Text understanding

Internet of Things sensor

Industrial intelligence

Industrial process

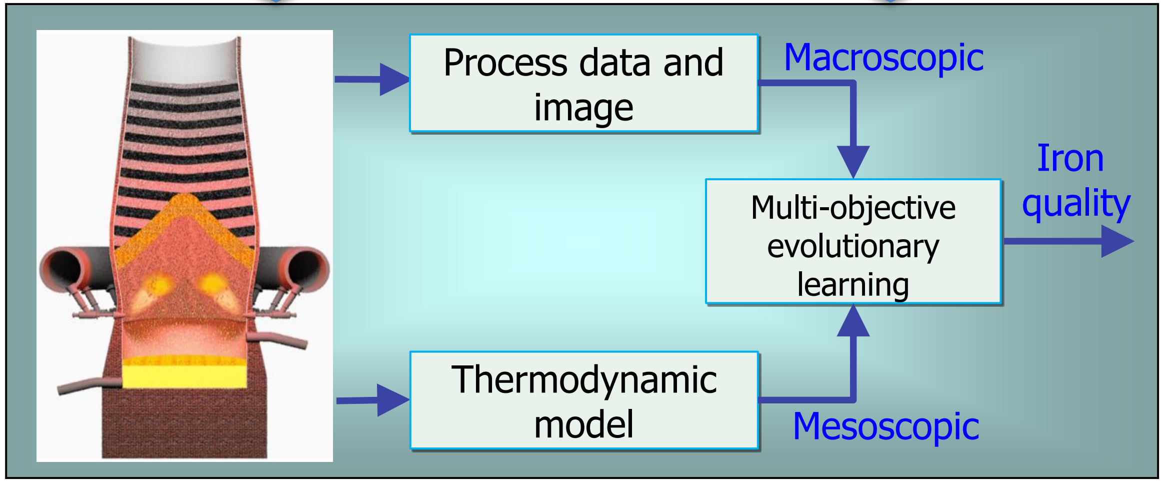
3. PDDE-based Quality Analytics and Dynamic Optimization — Quality discovery (D)

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**



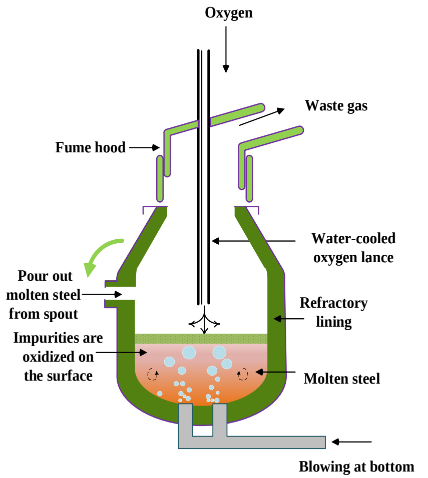
Case 2: Steel-making Dynamic Prediction

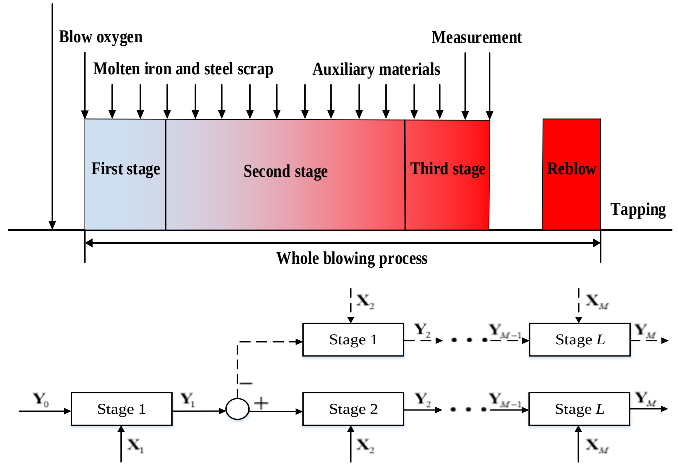
Challenges

- 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.

3. PDDE-based Quality Analytics and Dynamic Optimization — Quality discovery (D)

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**

↓

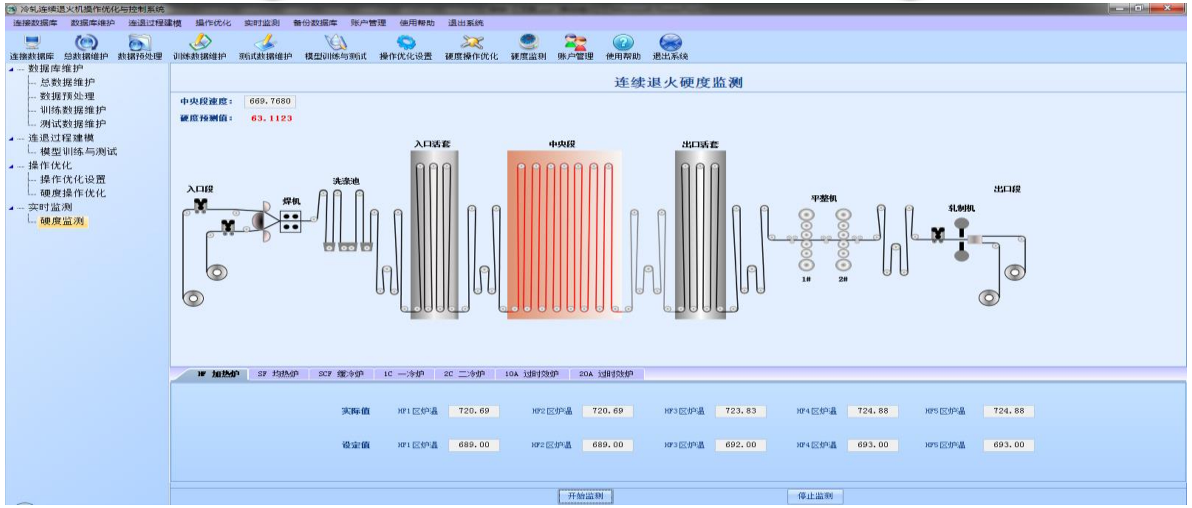
Mixed Model

Case 4: Strip Quality Analytics

Multi-objective Ensemble Learning

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

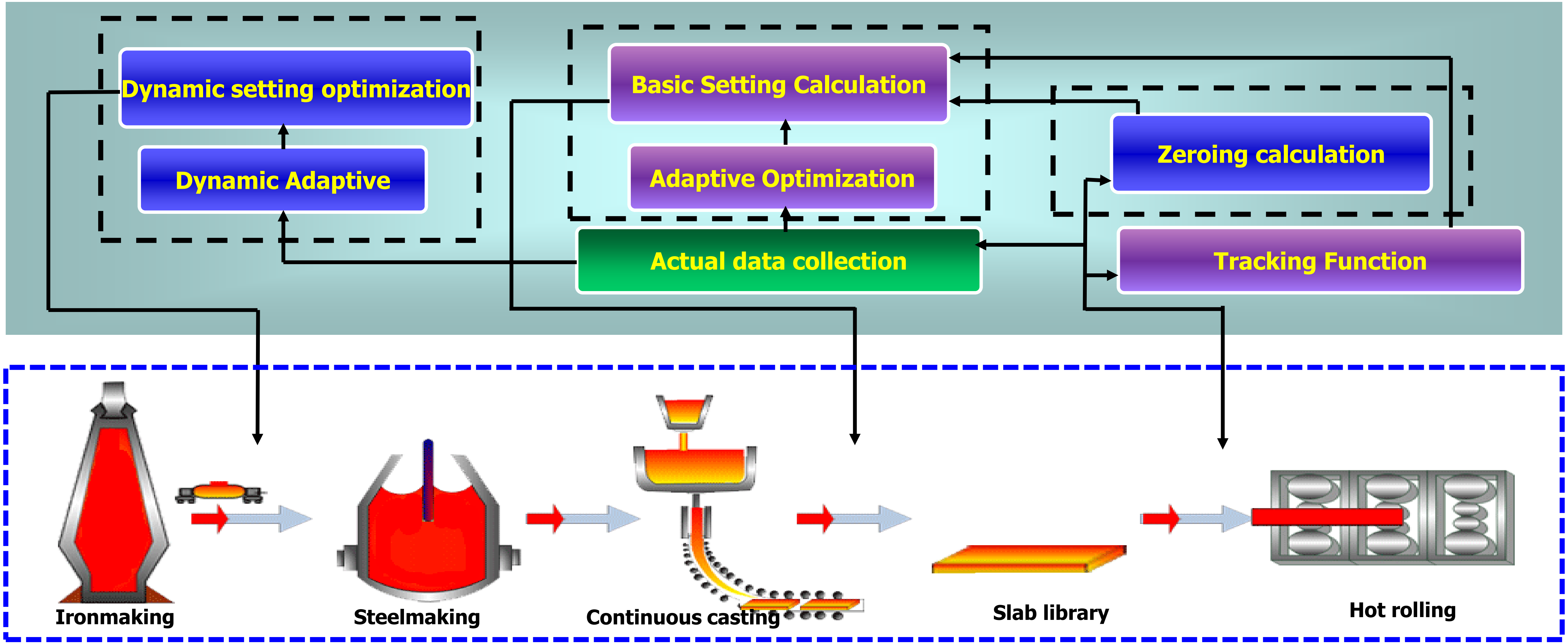
Multi-objective evolutionary algorithm ⇨ **Evolving the ensemble learning model**



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.

Quality analytics and optimization for production process



Significance: Improve product quality and economic efficiency, reduce energy consumption, and make the production process in optimized operating state.

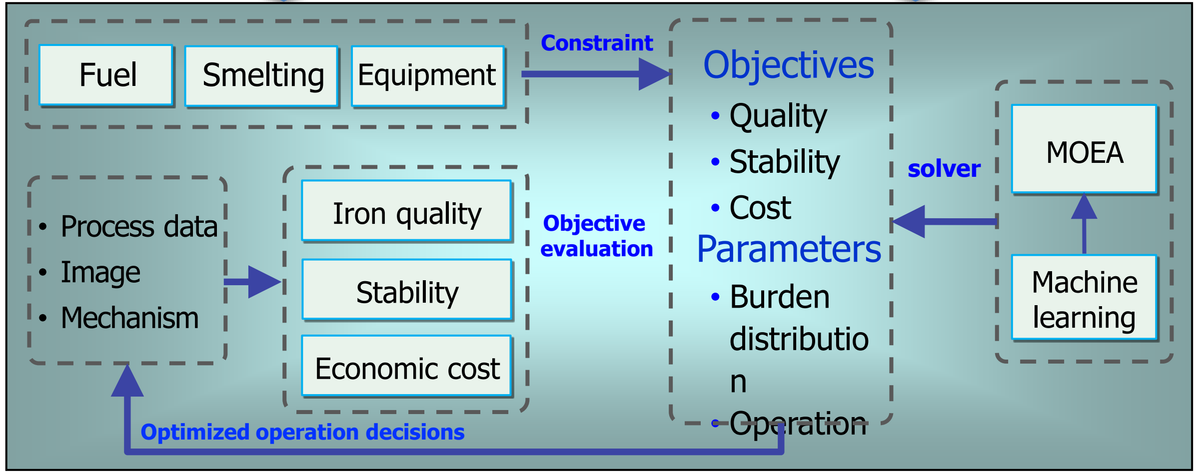
3. PDDE-based Quality Analytics and Dynamic Optimization — Process design and optimization (E)

Multi-objective Process Optimization for Iron-making

Multi-objective Process Optimization based on Learning

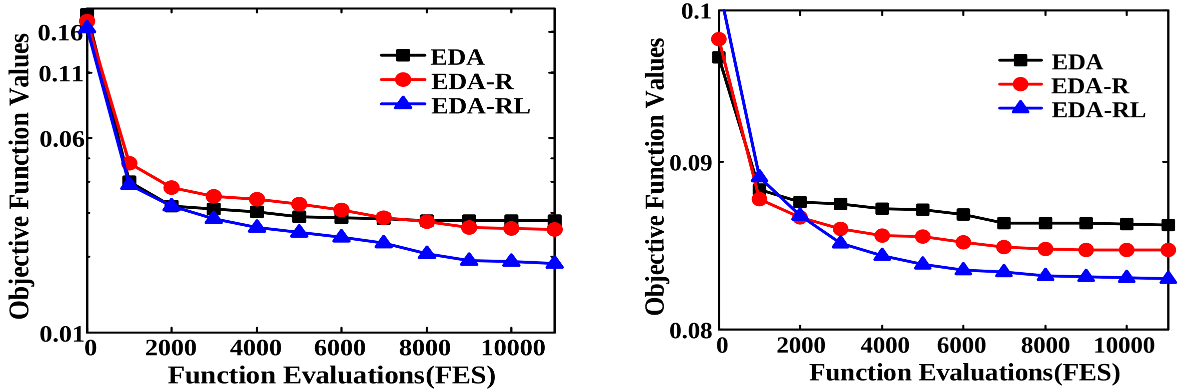
Mechanism-data fusion model for iron quality ⇨ **DAO-based multi-objective process optimization model**

Multi-objective evolutionary algorithm based on learning ⇨ **Optimal setting for key operation parameters**



Process Optimization for Steel-making

Challenges	Dynamic analytics method
● Black-box model ● High temperature ● Large number of variables	● EDA with a hybrid distribution model ● Resampling ● Local improvement



The convergence curves of EDA, EDA-R and EDA-RL

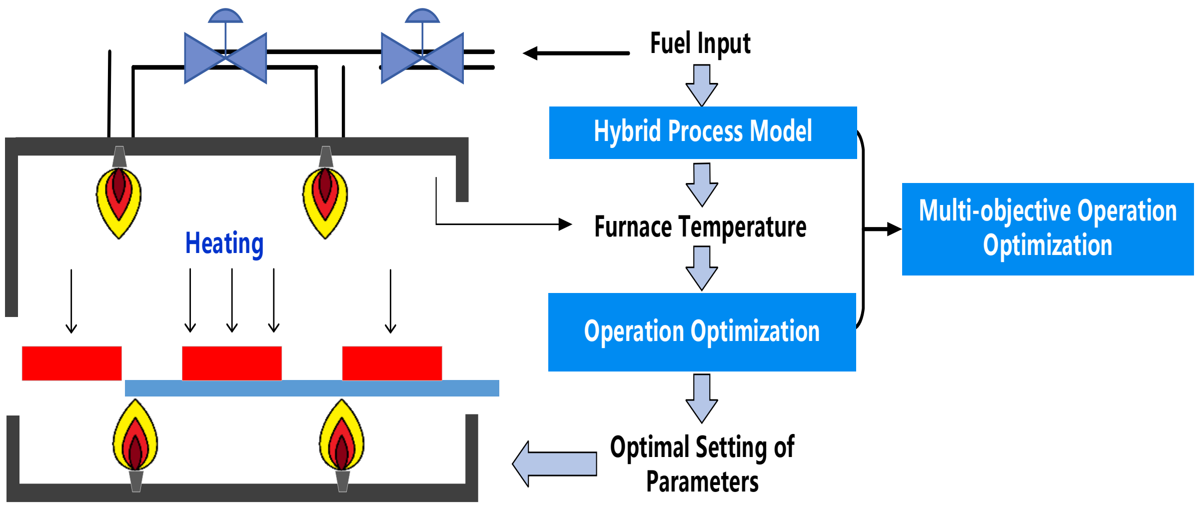
L. Tang, C. Liu, J. Liu, X. Wang. An estimation of distribution algorithm with resampling and local improvement for an operation optimization problem in steelmaking process. ***IEEE Transactions on Systems, Man, and Cybernetics: Systems***, 2020.

3. PDDE-based Quality Analytics and Dynamic Optimization — Process design and optimization (E)

Multi-objective Process Optimization for Hot Rolling

Multi-objective Evolutionary Algorithm Based on Reinforcement Learning

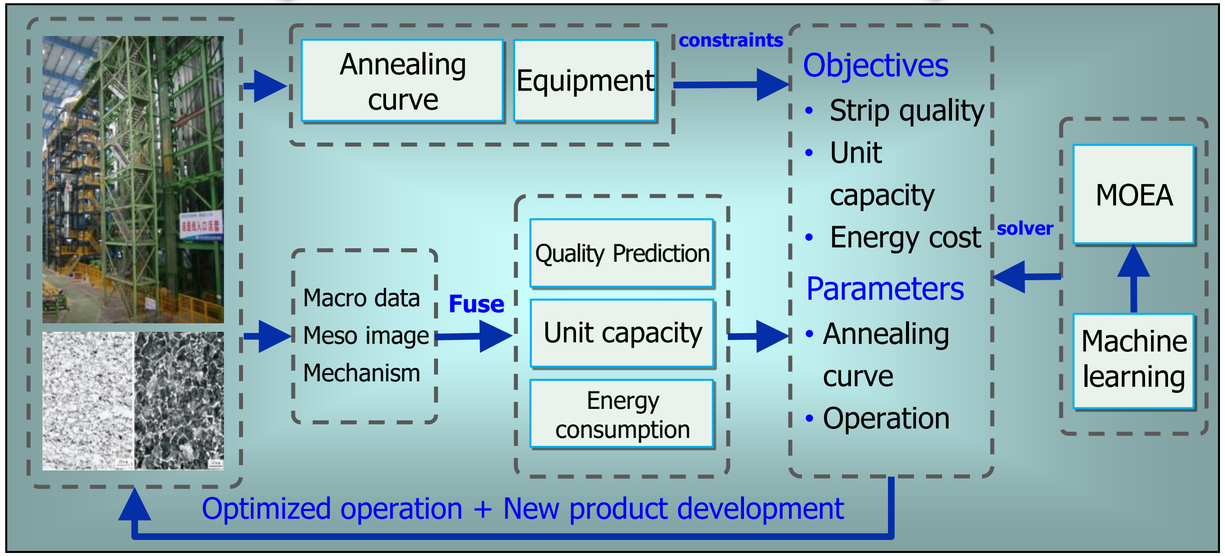
- **DAO-based modeling method for the reheating furnace** ⇨ **Multi-objective process optimization model**
- **Multi-objective evolutionary algorithm based on DQN** ⇨ **Optimal setting of operation parameters in the furnace**



Multi-objective Process Optimization for Colding Rolling

Multi-objective Evolutionary Algorithm Based on Machine Learning

- **Multi-objective ensemble learning model of strip quality** ⇨ **DAO-based multi-objective process optimization model**
- **Multi-objective evolutionary algorithm based on learning** ⇨ **Optimal setting of operation parameters and new product**



3. PDDE-based Quality Analytics and Dynamic Optimization — Product quality design (D)

Material Production

Steel material

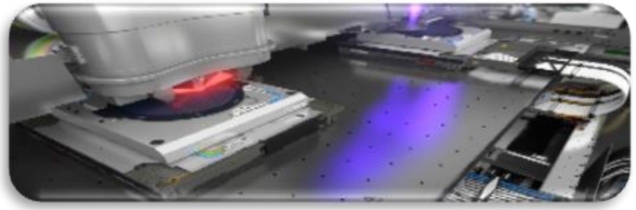
Design and Processing

Equipment Manufacturing

- Metallurgical equipment
- Logistics equipment
- Energy equipment
- High-end equipment

Machining and Assembling

Industrial System

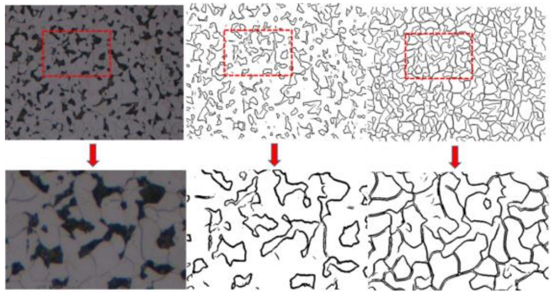


Operation and Maintenance

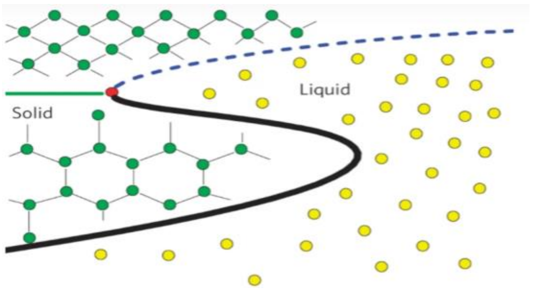
3. PDDE-based Quality Analytics and Dynamic Optimization — Product quality design (D)

Material Discovery

- **Microstructure**: In steel smelting process, metallographic organization identification is a critical step. The idea of fusing neural network and optimal control model is proposed, which is combined with fractal theory to solve the problem. Ultimately, a quantitative analysis of the metallographic organization is achieved.
- **Topological phase transition**: In steel industrial production, process parameters determine the organization properties. A material structure prediction model based on thermodynamic model and topological phase transition is constructed from the mesoscopic viewpoint to realize dynamic regulation and optimization of material structure.



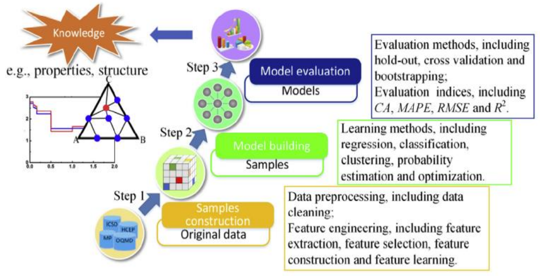
Microstructures



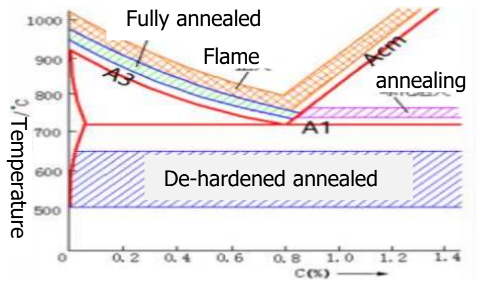
Topological phase transition

Material Design

- **Material design**: From the mesoscopic view of steel materials, the mapping relationship between material composition, structure, and properties is established based on networks and multi-objective evolutionary methods, with synergistic control and optimization of steel property design and material selection for new material design.
- **Process design**: In response to steel performance requirements, the integration of mechanism and deep learning model is applied. A differential evolutionary algorithm is used to dynamically adjust the steelmaking process parameters to control and optimize the metallurgical organization.



Material design



Process design

Outline

- Data Analytics and Optimization (DAO)
- MCIS-E Production-Logistics-Energy Optimization with Feedback
- PDDE-based Quality Analytics and Dynamic Optimization
- **MCIS Environmental Analytics and Optimization**

4. MCIS Environmental Analytics and Optimization

Enterprise

A tree

A single enterprise material transformation

basic unit

Industry

A forest

Homogeneous enterprise similar products

a whole collection

System

An Eco-system

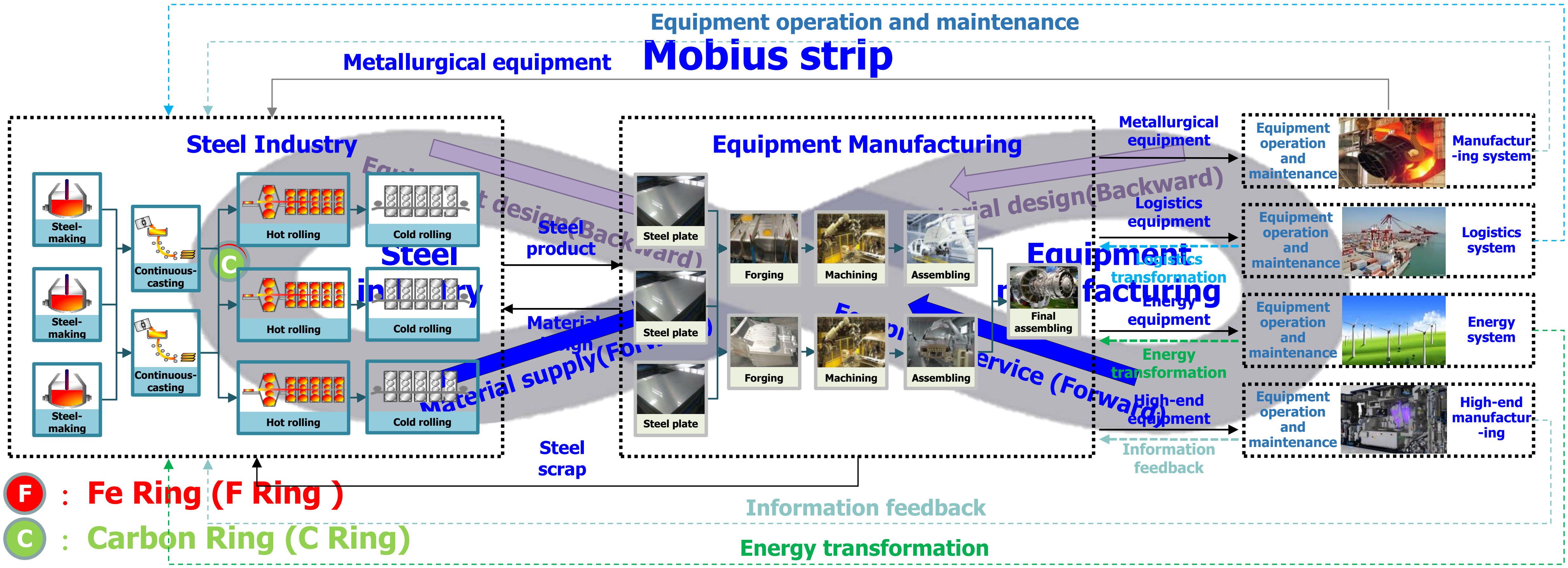
Heterogeneous enterprise elements connection

ecosystem

4. MCIS Environmental Analytics and Optimization

MCIS from Steel Industry to Equipment Manufacturing (F Ring)

- The steel industry provides important raw material for equipment manufacturing, and the metallurgical equipment, logistics equipment, energy equipment and high-end equipment produced by equipment manufacturing serve the steel industry, forming a manufacture-circulation industrial system (MCIS) with Northeastern characteristics of the modern industrial system.



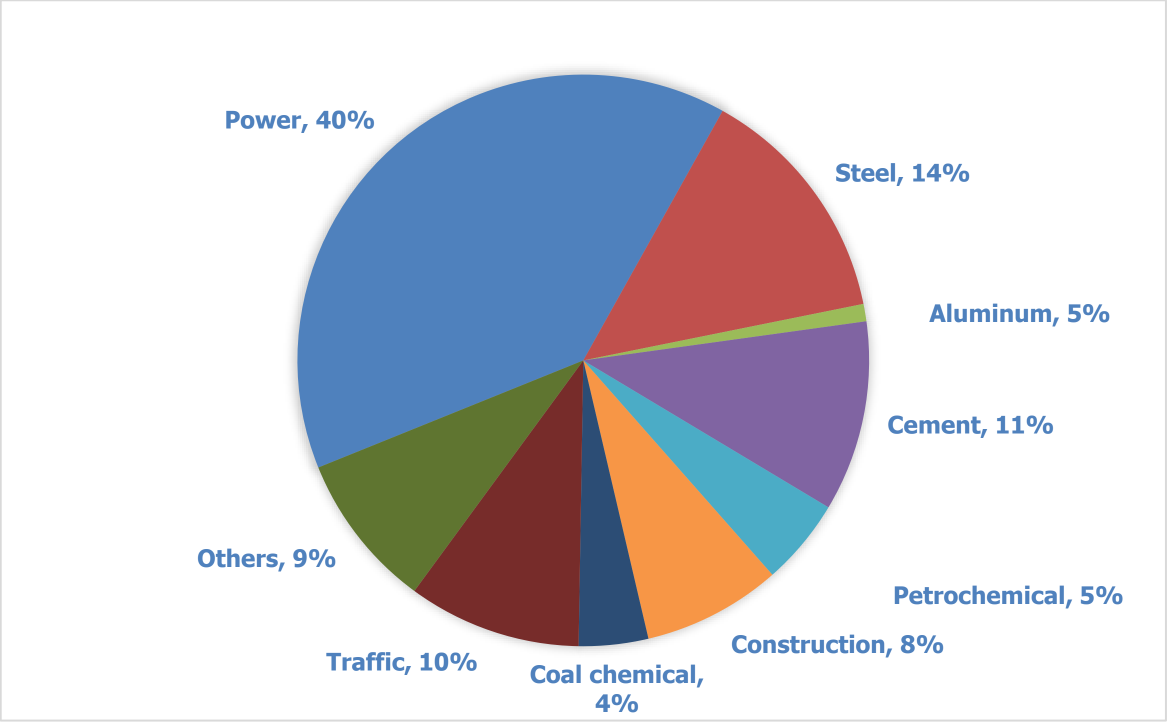
F : Fe Ring (F Ring)

C : Carbon Ring (C Ring)

Carbon Emissions of Steel Industry

- In 2023, China's CO_2 emissions is approximately 12.6 billion tons. Power, steel, aluminum, cement, petrochemical, and coal chemical, as well as two fields including transportation and construction cover over 90% of the country's total CO_2 emissions.
- Over the decade from 2011 to 2020, the average growth rates of the value added by domestic manufacturing and crude steel production were 7.9% and 5.1%, respectively, providing stable support for the high-quality development of China's manufacturing industry.
- The global steel industry accounts for approximately 7% of the total emissions from the energy system, making it the manufacturing sector with the highest carbon emissions, primarily stemming from the use of fossil fuels.

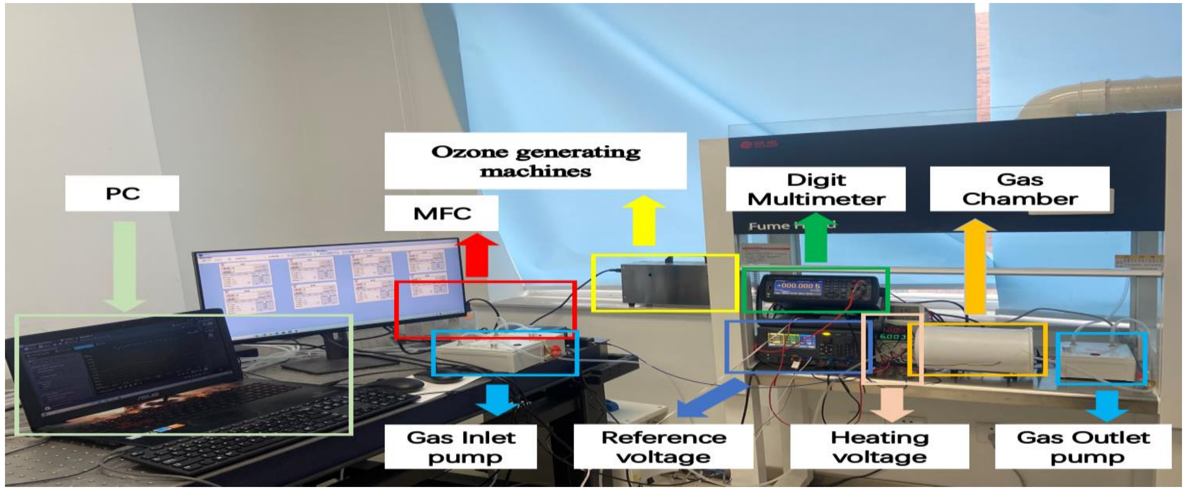
- The CO_2 emissions from the steel industry account for about 14% of total industrial CO_2 emissions in China, with approximately 2 tons of greenhouse gases emitted per ton of steel produced, of which 90% originates from the pre-iron and ironmaking.



4. MCIS Environmental Analytics and Optimization

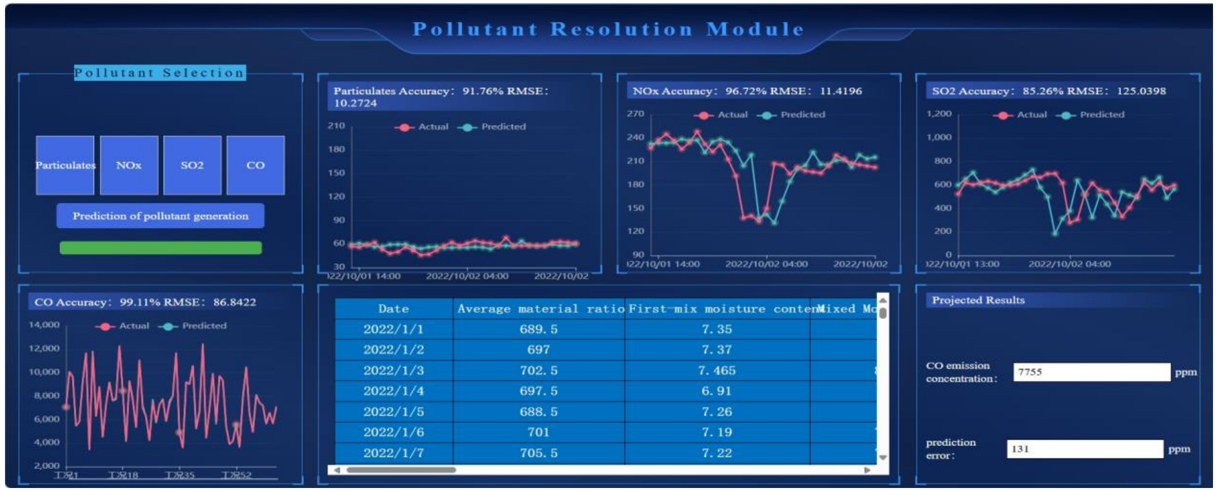
Environment Perception

- **Background**: steel production involves multiple processes, pollutants, and carbon emissions. Extreme conditions affect data accuracy and stability. Representing pollutant and carbon information in a single modal feature is difficult.
- **Perception method**: fusion perception technology uses structured data, text, voice, and images for accurate, real-time, and stable acquisition of pollution and carbon emission data. Multi-source data mining enables feature fusion, enhancing prediction reliability.



Environment Discovery

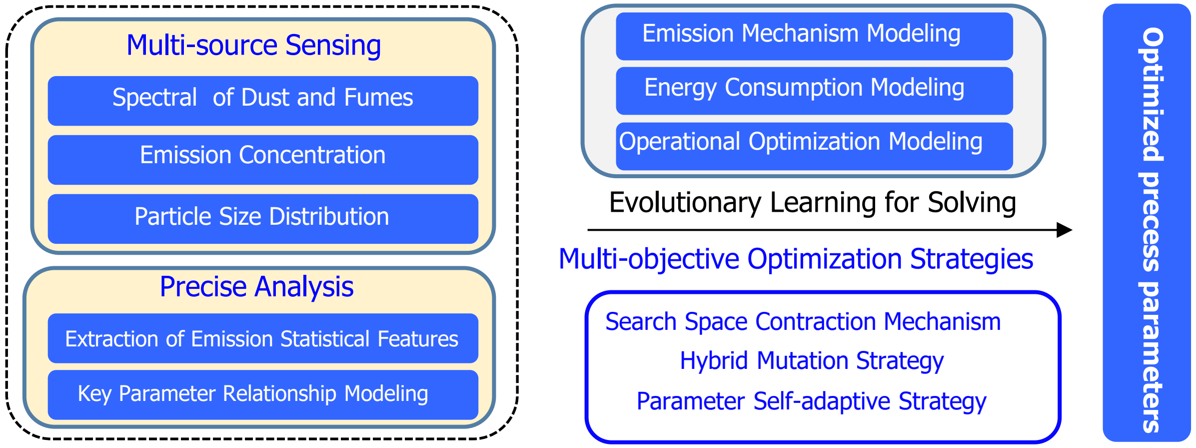
- **Background**: Pollutants, carbon emissions, production processes, output, product quality, energy, and raw material consumption have complex coupling relationships.
- **Discovery method**: mechanism and data fusion method leverages mechanism and data analytics models to analyze multi-source data patterns, identify key pollutant emission areas and abnormal conditions, and obtain pollutant emission characteristics and trend predictions.



4. MCIS Environmental Analytics and Optimization

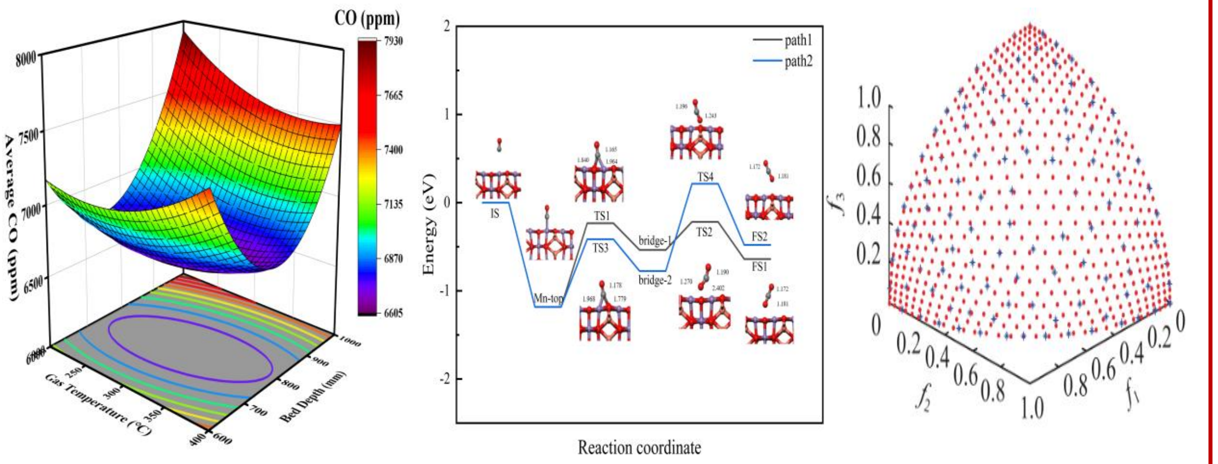
Real-time Process Optimization

- **Background**: The steel industry emits large amounts of CO_x, SO_x, NO_x, etc.. Pollutants, carbon emissions, production processes, output, product quality, energy, and raw material consumption have complex coupling relationships.
- **Process optimization**: Analyze relationship between process control parameters, emissions and energy consumption. Formulate multi-objective process optimization model based on mechanism and multi-modal data to minimize pollutant and carbon emission.



Process Design Optimization

- **Background**: Carrying out full process design and formula optimization from source blockage to end-point treatment is an important guarantee for reducing pollution and carbon emissions.
- **Process Design**: investigate full process optimization design from the systematic point of view to form a pollution and carbon reduction path. Optimize the ingredient scheme to achieve harmless manufacturing of steel materials based on source blockage.

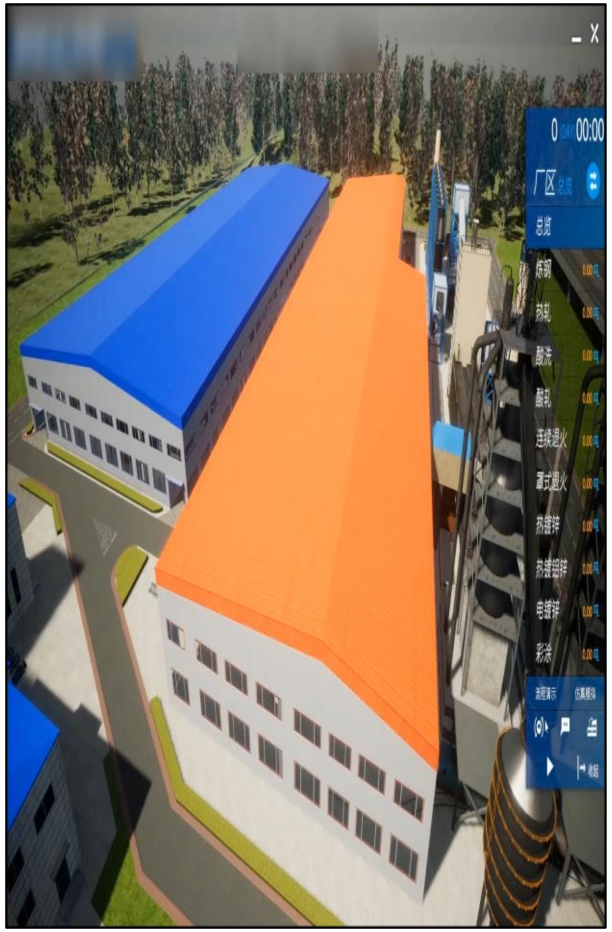


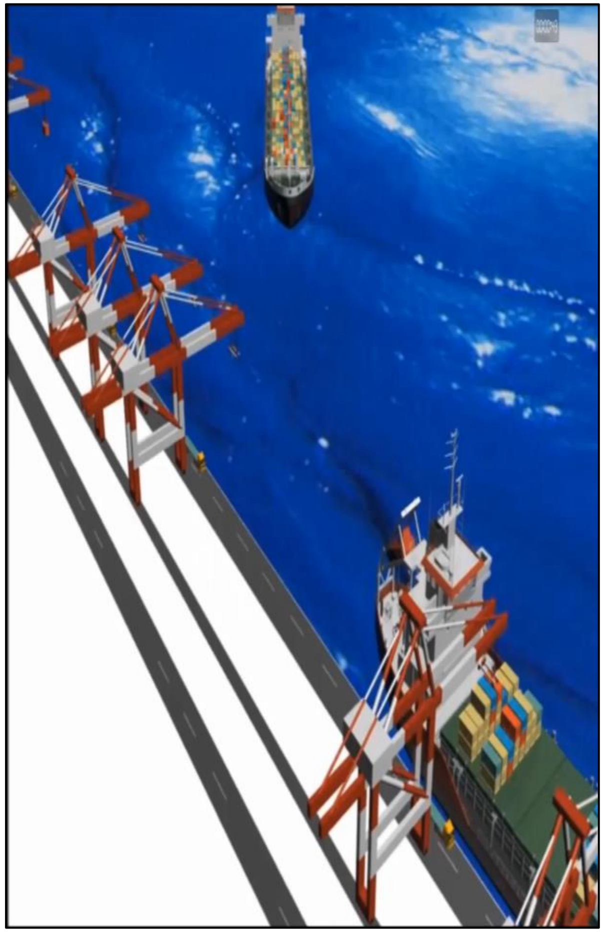
4. MCIS Environmental Analytics and Optimization

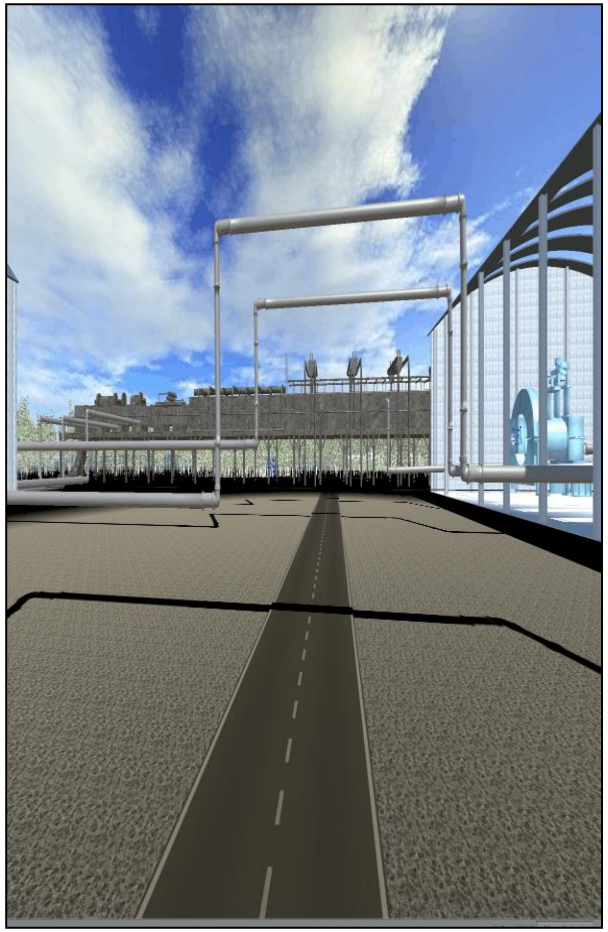
MCIS from Steel Industry to Equipment Manufacturing (F Ring)

4. MCIS Environmental Analytics and Optimization

MCIS from Steel Industry to Equipment Manufacturing (F Ring)



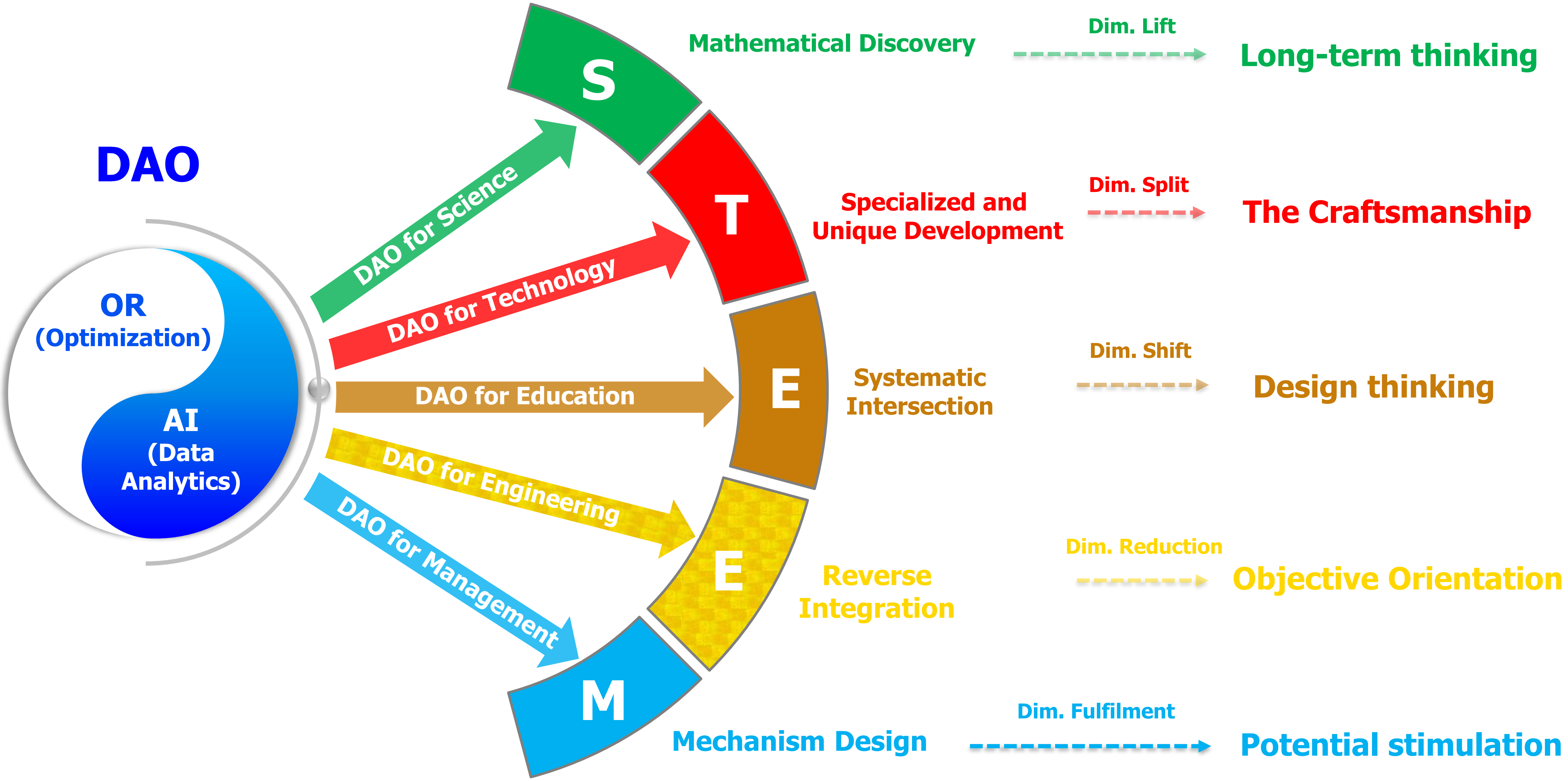


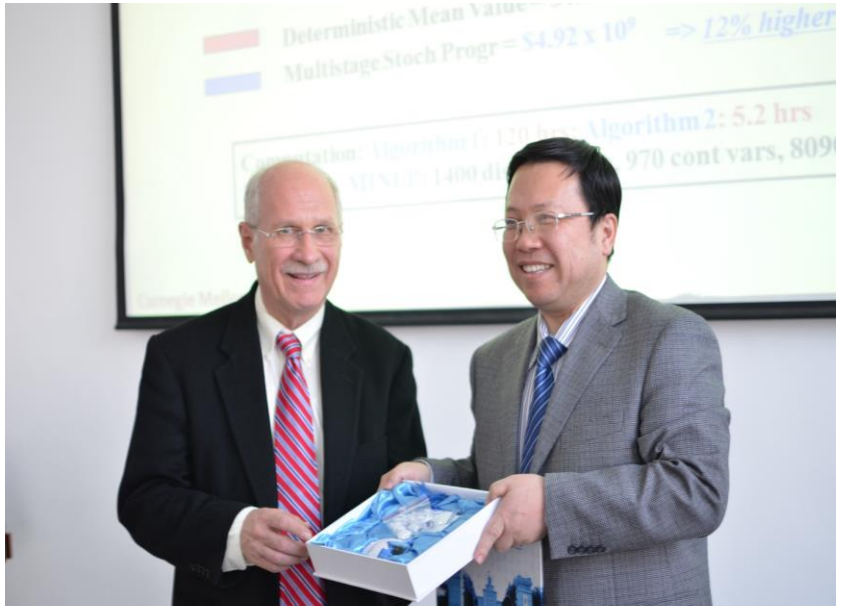


Steel Industry	Equipment Manufacturing	Logistics System	Environment & Energy

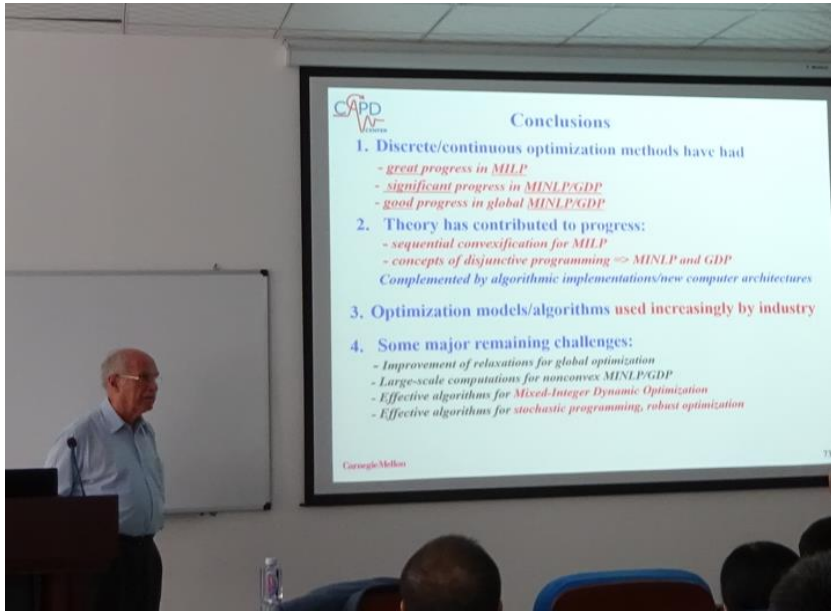

Contribute to Society
Data Analytics and Optimization
OR
AI
D A O
工业智能与系统优化
DAO
国家级前沿科学中心
National Frontiers Science Center
for Industrial Intelligence and Systems Optimization
Rooted in Industry

DAO for STEEM





Professor Ignacio Grossmann visited DAO Lab in 2014 and 2017



President , University of Oxford ~ Louise Richardson

President , Yale University ~ Peter Salovey

President, University of California, Berkeley ~ Carol Christ

President, University of Chicago ~ Robert J Zimmer

President, University of Cambridge ~ Stephen Toope

President, University of California, Los Angeles ~ Gene Block

Vice Provost, Harvard University ~ Mark C. Elliott

President, University of New South Wales, Sydney ~ Ian J Jacobs

Chancellor, University of Warwick, UK ~ Stuart Croft

President, Moscow State University ~ Victor A. Sadovnichiy

President, University of Copenhagen, Denmark ~ Henrik C Wegener

President, ETH Zurich ~ Lino Guzzella

China-Japan University Presidents Forum

China-Japan University Presidents Forum Speech

President, University of Tokyo, Japan ~ FUJII Teruo

Trustee, Tohoku University, Japan ~ UEKI Toshiya

Trustee, Waseda University ~ GEMMA Masahiko

Vice President, Kyoto University ~ KONO Yasuyuki

University of Sydney's Vice-Chancellor Mark Scott AO, etc.

China-Australia University Presidents Forum ~ Keynote

Dean, Engineering and Information Technology, University of Melbourne ~ Thas Nirmalathas

New Zealand ~ Minister for Tertiary Education and Skills

China-New Zealand University Presidents Forum

China-New Zealand University Presidents Forum

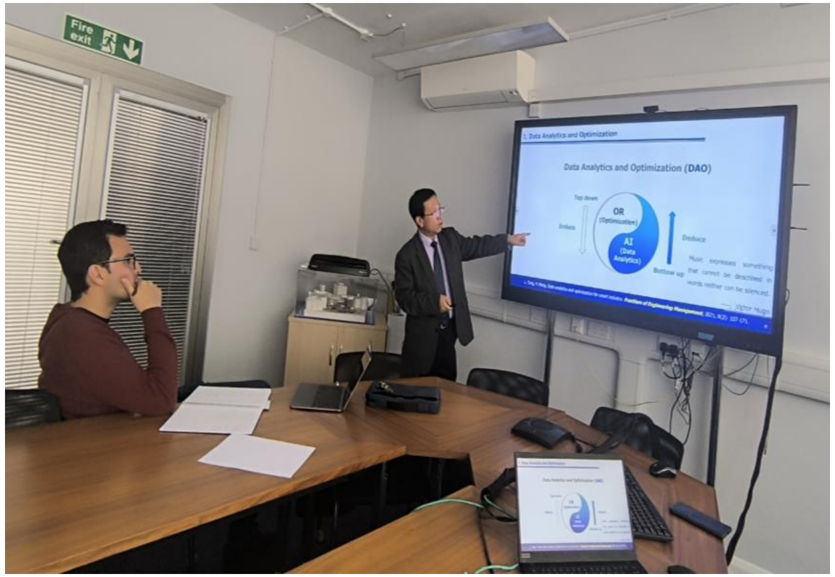
9th Cambridge International Education Seminar, Keynote

University of Cambridge

Cavendish Laboratory, University of Cambridge

9th Cambridge International Education Seminar, Panel

Worcester College, Oxford Certificate Programmes Director



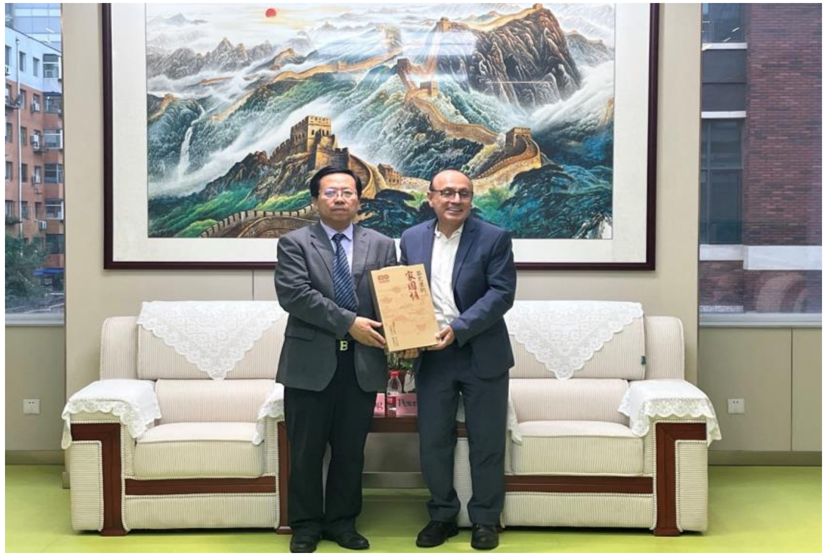
Visit Department of Materials, Oxford University

China-Africa Consortium of Universities Exchange Mechanism Annual Conference ~ Keynote

Harvard University ~ Professor Peter Sicinski

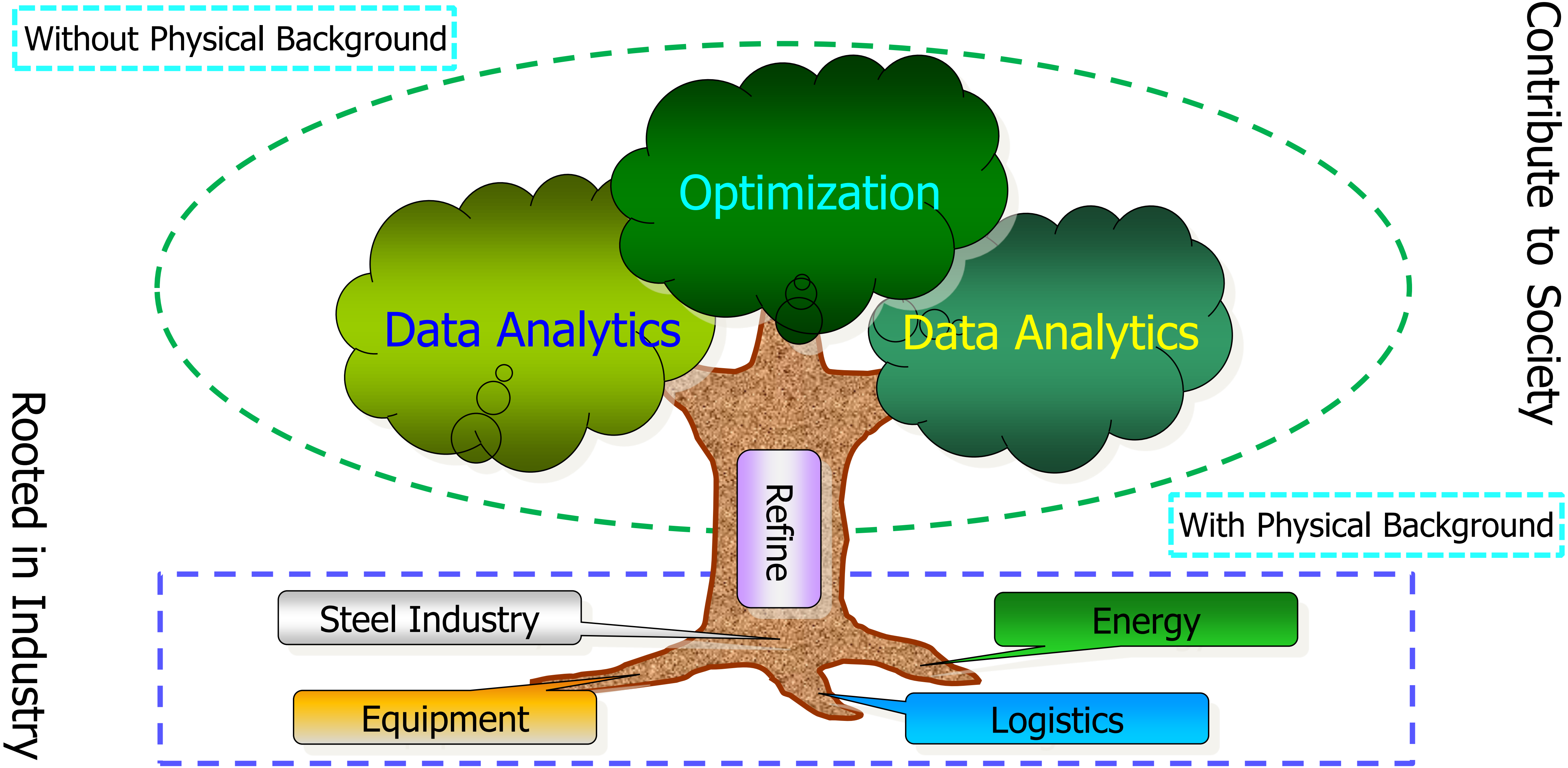
Nobel Prize winner in physics ~ Professor Zhaozhong Ding

China-Africa Consortium of Universities Exchange Mechanism Annual Conference



Harvard University ~ Professor Peter Sicinski

Nobel Prize winner in economics ~ Professor Oliver Hart


Without Physical Background
Contribute to Society
Optimization
Data Analytics
Data Analytics
Refine
With Physical Background
Rooted in Industry
Steel Industry
Energy
Equipment
Logistics