Data Analytics and Optimization in Steel Industry

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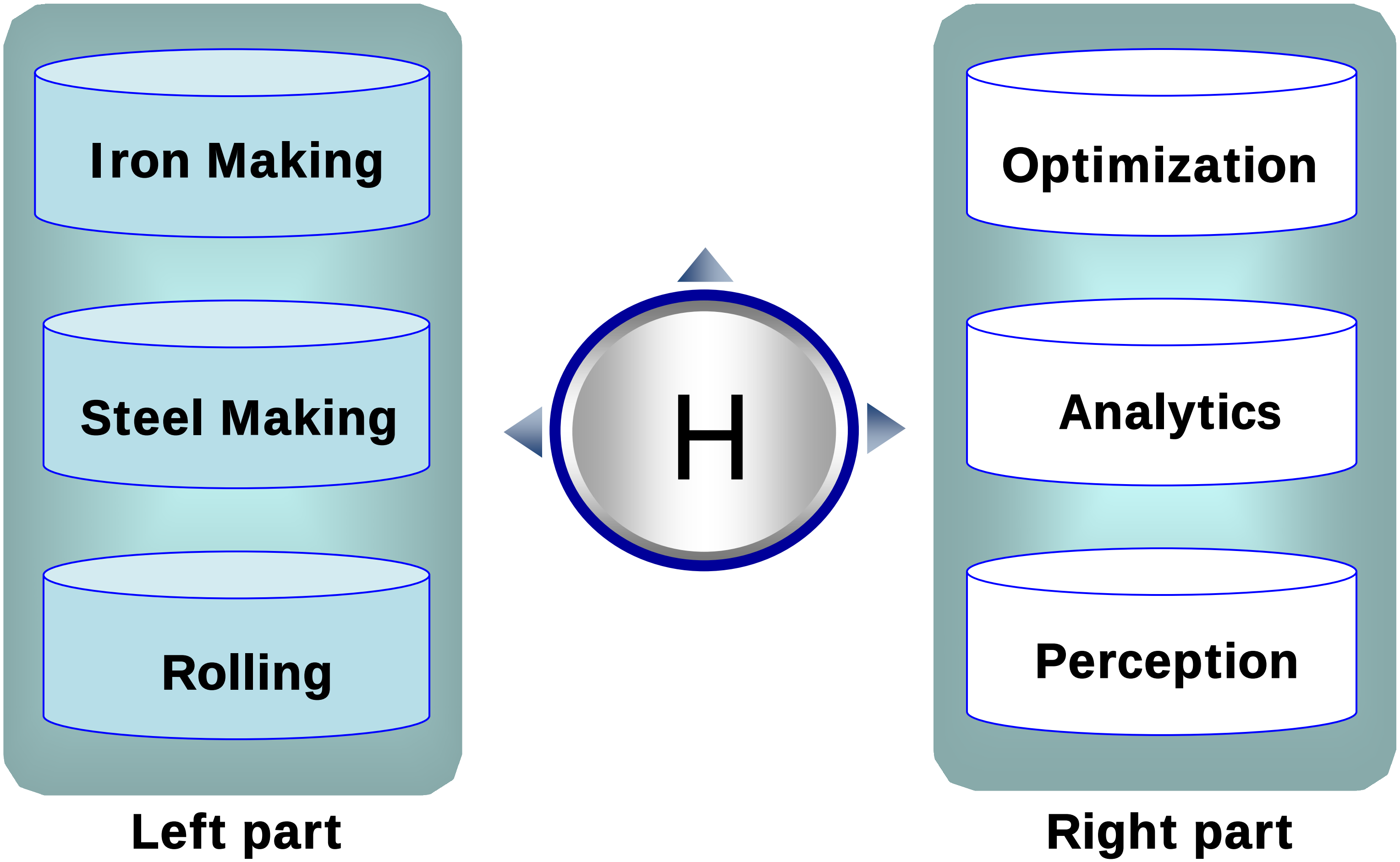
About Northeastern University– basic information

- Founded in 1923, a key university directly affiliated to MOE
- 985, 211, Double First Class Project
- Over **46, 000** students: 29931 undergraduates
  12166 master degree students
  3986 doctoral students
- **2688** faculty members: 538 professors
- **4 Campuses**： Nanhu Campus, Hunnan Campus,
  Qinhuangdao Campus , East Campus

About Northeastern University– Main Direction

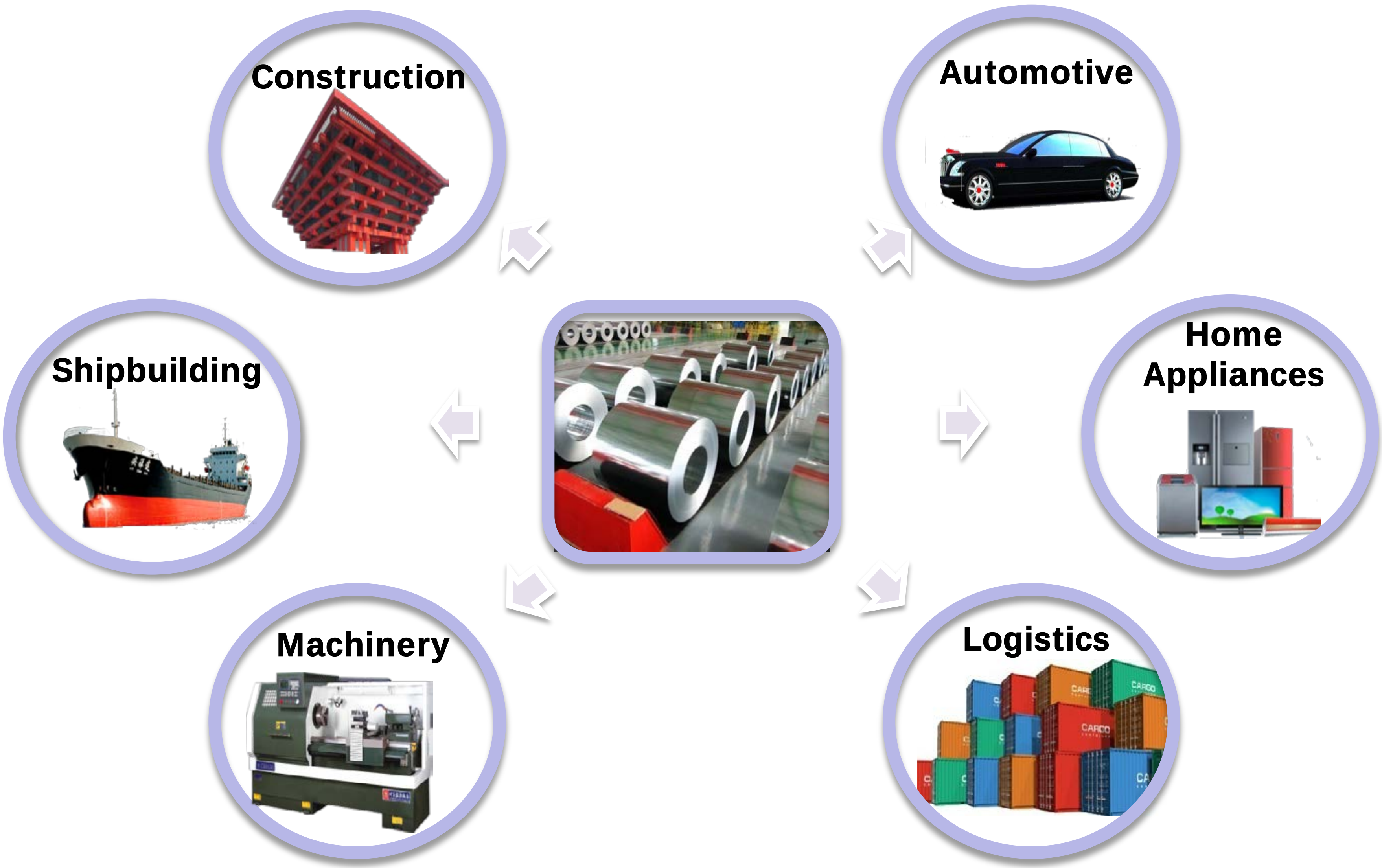
H plan: a interdisciplinary development plan involving two main disciplinary groups of Northeastern University.



Outline

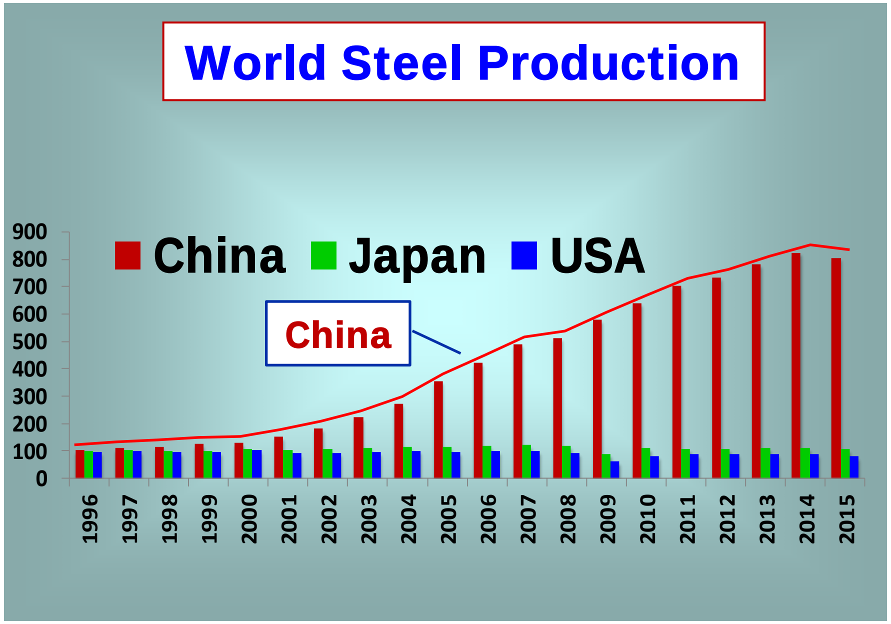
- **Research Background**
- System Modeling and Optimization Method
- Production Scheduling
- Logistics Scheduling
- Energy Optimization
- Data Analytics

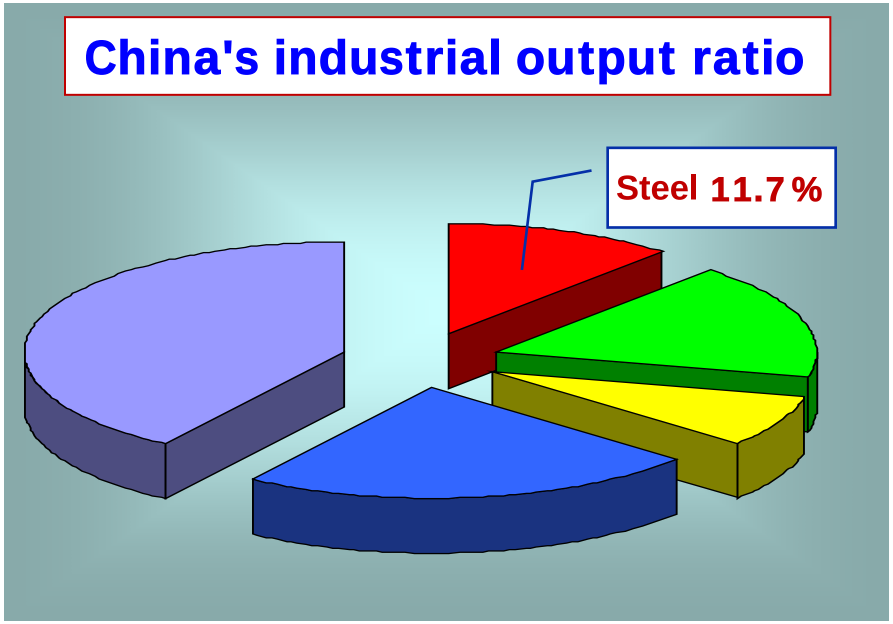
1. Research Background —— Steel is a Key Driver of the World's Economy



1. Research Background —— China is the Largest Steel Producer

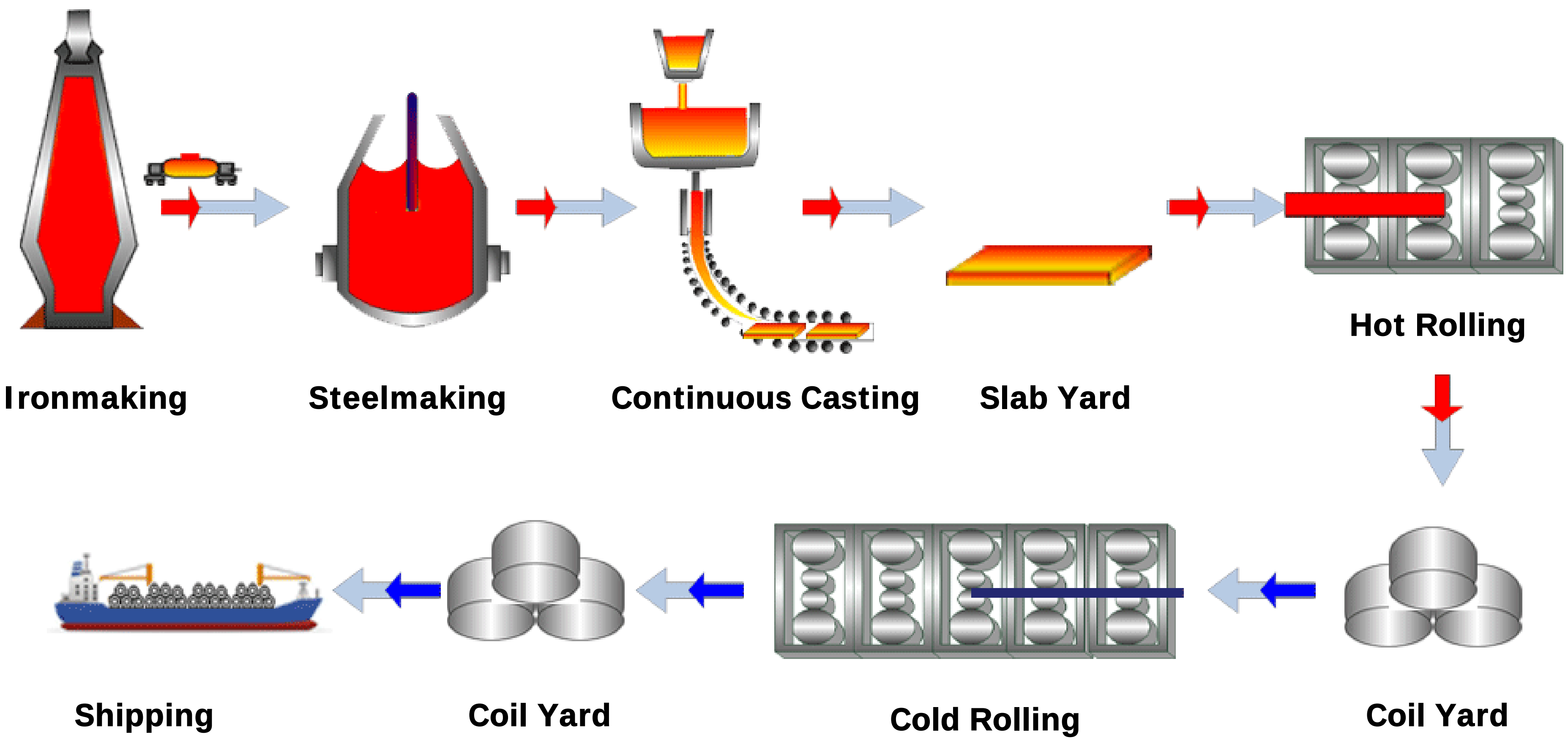
- China has been the largest steel producer in the world for the last twenty consecutive years
- In 2018, China's steel output has reached 928 million tons, accounting for 51.3 percent of the world's steel output
- Steel industry has been one of the pillar industries in China’s national economy



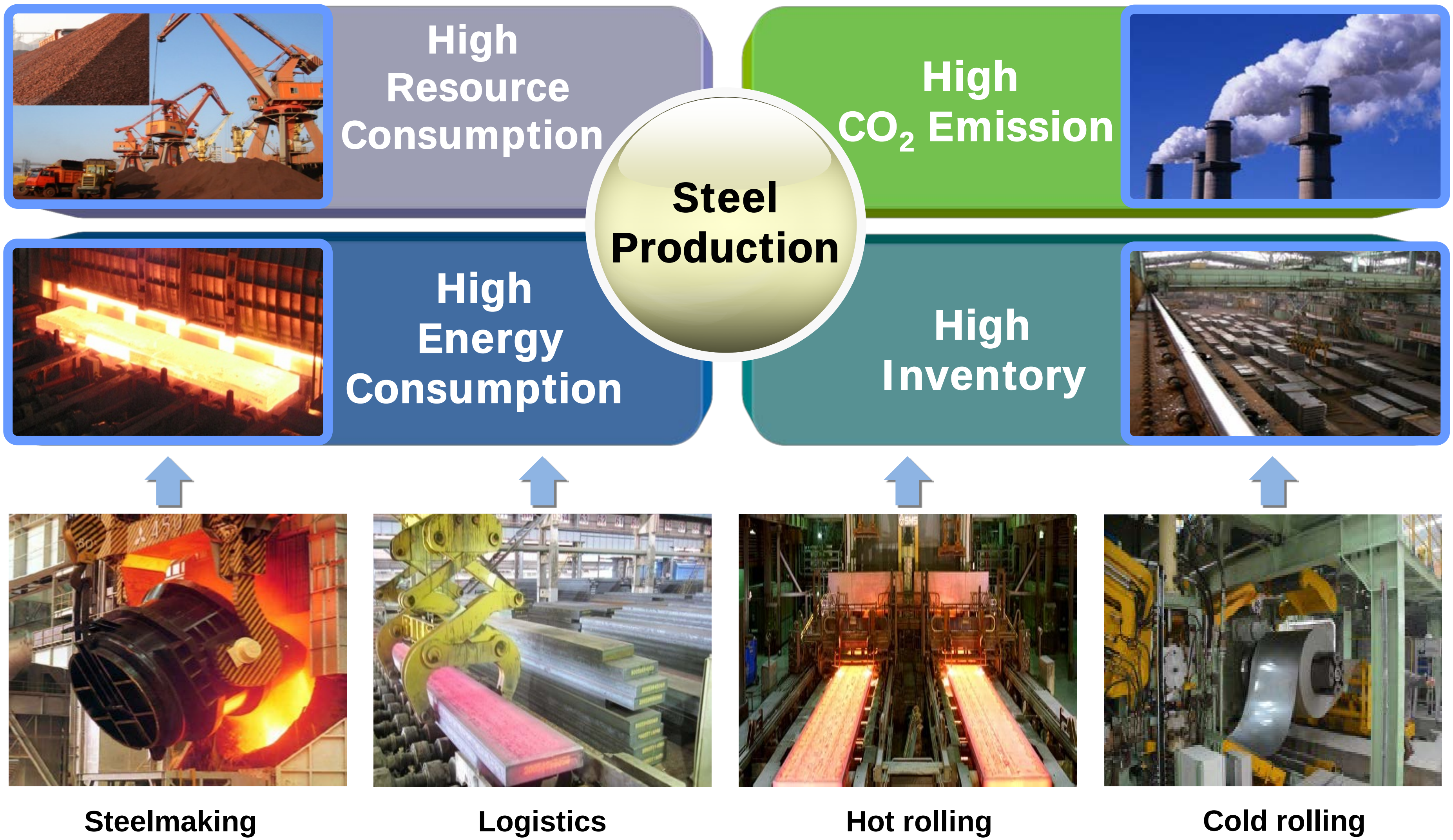


1. Research Background —— Steel Production Process

Features: continuous and discrete production, huge devices, high-temperature operation, mass consumption of energy and resource.

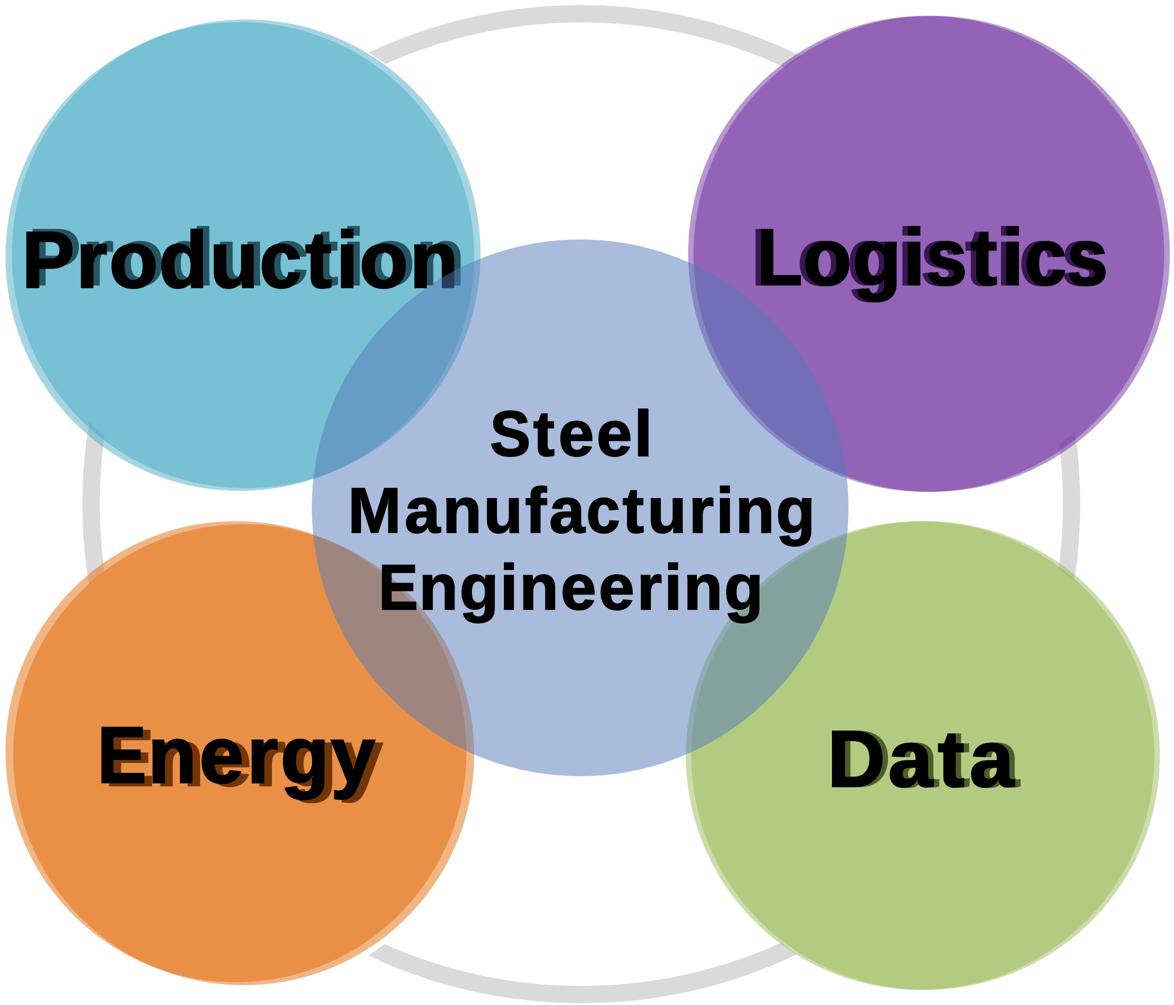


1. Research Background —— Challenges Faced by Steel Industry



Data Analytics and Optimization

1. Research Background —— Analytics and Optimization in Steel Industry



Outline

- Research Background
- **System Modeling and Optimization Method**
- Production Scheduling
- Logistics Scheduling
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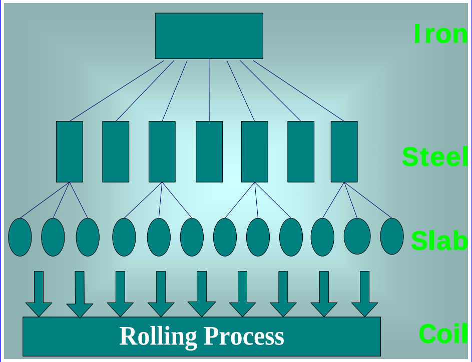
- Data Analytics

2. System Modeling and Optimization Method

New Characteristics

- Complex physical and chemical process
- Large variety and low volume products
- Complicated logistics structure

Complicated Production Process



Large Variety and Low Volume

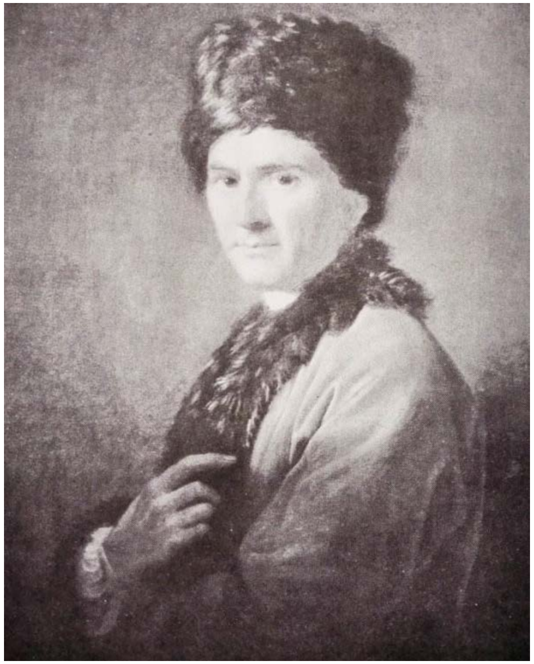
Huge Chemical Equipment

Complicated Logistics Structure

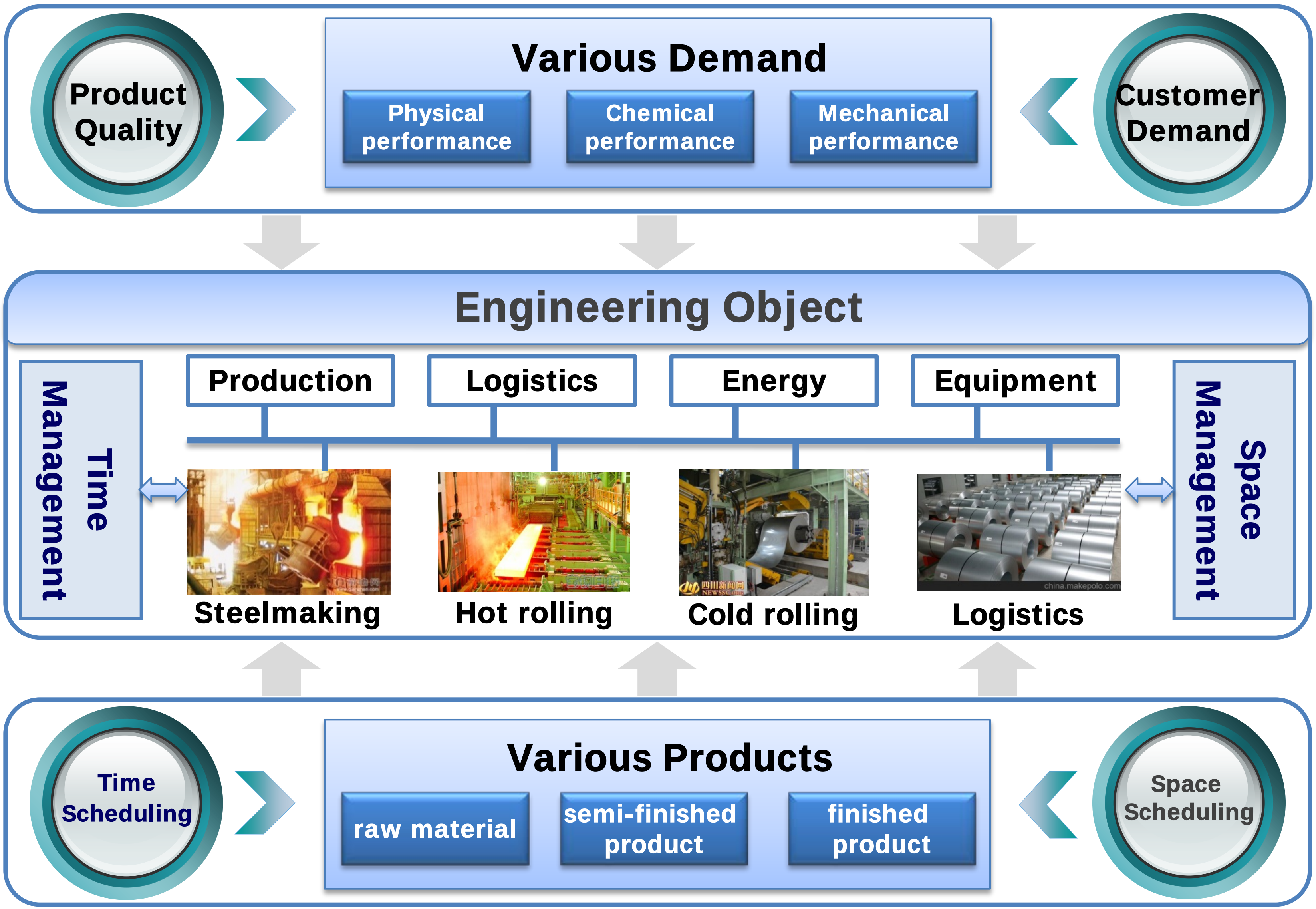
System Modeling

Jean-Jacques Rousseau:

The art of musicians does not lie in depicting images directly, but in placing the mind in the emotions that these objects can create in the mind.



2. System Modeling and Optimization Method — System Modeling



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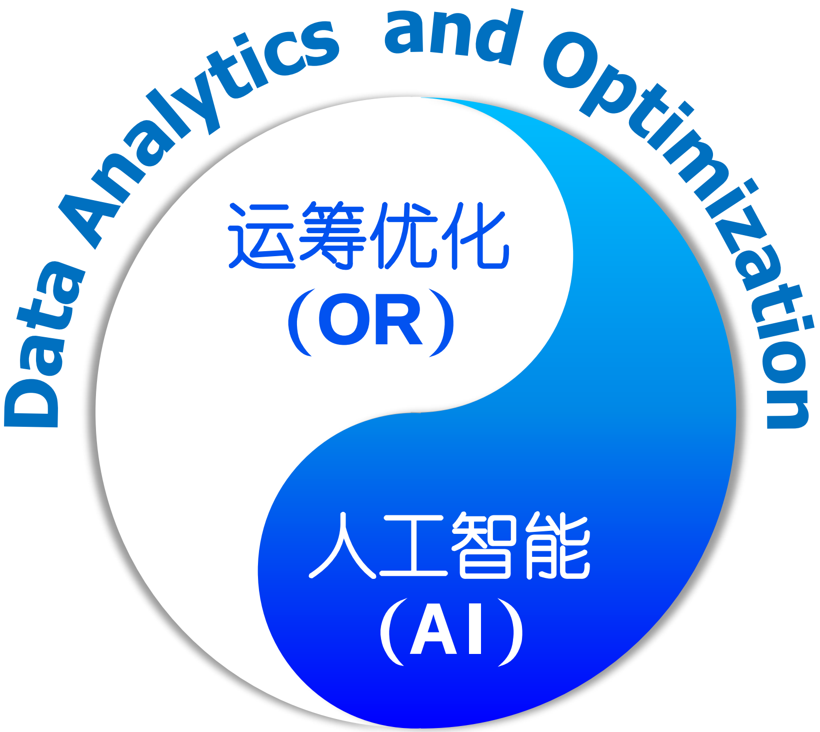


DAO

- A system modeling method combining mathematical optimization and data analytics is proposed. The mathematical integer programming model for production scheduling is established, and complementary part is carried out through data analytics.

Mathematical Modeling

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

$s.t.$

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

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

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

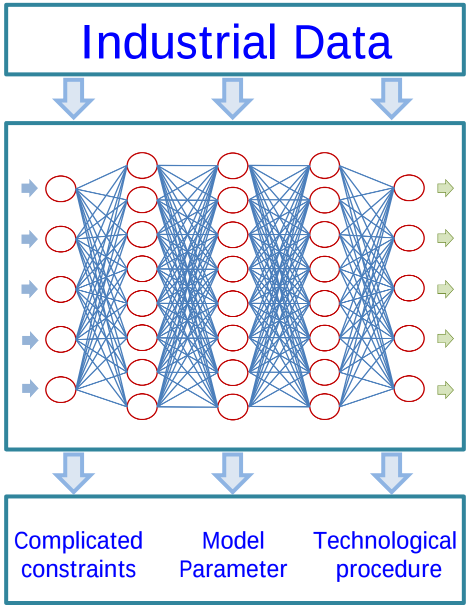
$$Y_{ikj} \le Y_{kkj} \qquad \text{for } j \in P,\ k \in O_j,\ i \in O_j \cap R_k$$

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

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

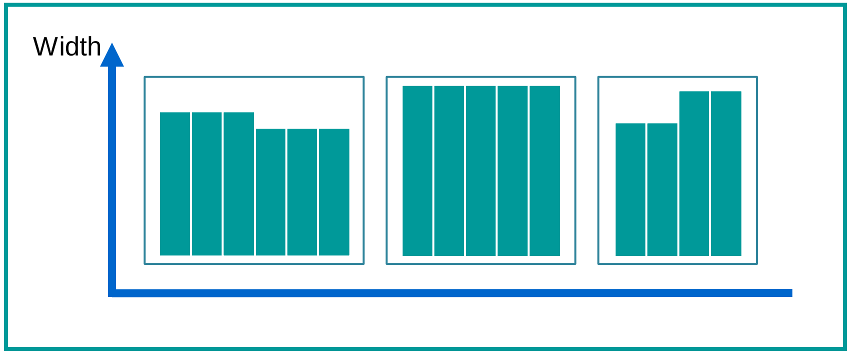
$$Y_{ikj} \in \{0,1\} \qquad \text{for } j \in P,\ k \in O_j,\ i \in O_j \cap R_k$$

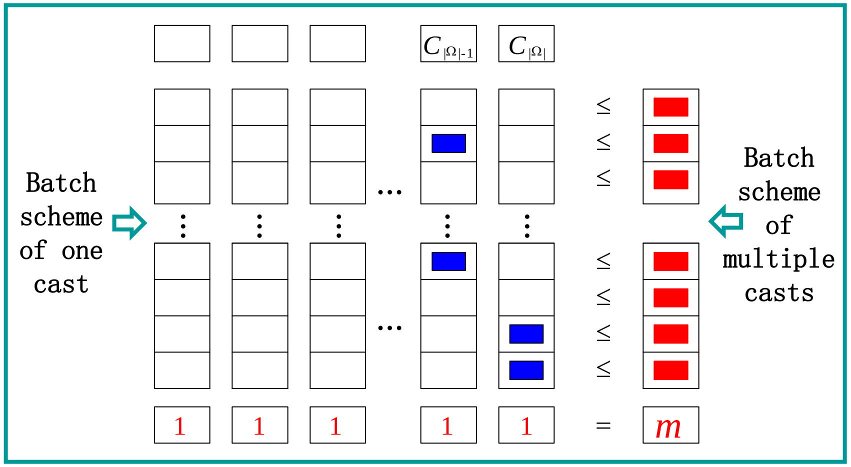
Data Analytics



Set-Packing modeling

- The problem is transformed into the optimization combination of multiple batch schemes of jobs, and the Set-Packing model is established;
- A batch scheme of jobs is defined as an element, which includes the combination of jobs;
- The sub-problems are to describes the generation rules of batch schemes of jobs;
- Effectively reduce the number of variables and constraints and improve the solving efficiency of the model.



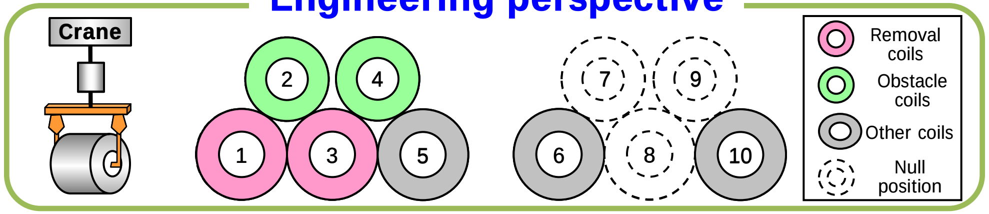


L. Tang, G. Wang. Integrated charge batching and casting width selection at Baosteel. *Operations Research*, 2014, 62(4): 772-787.

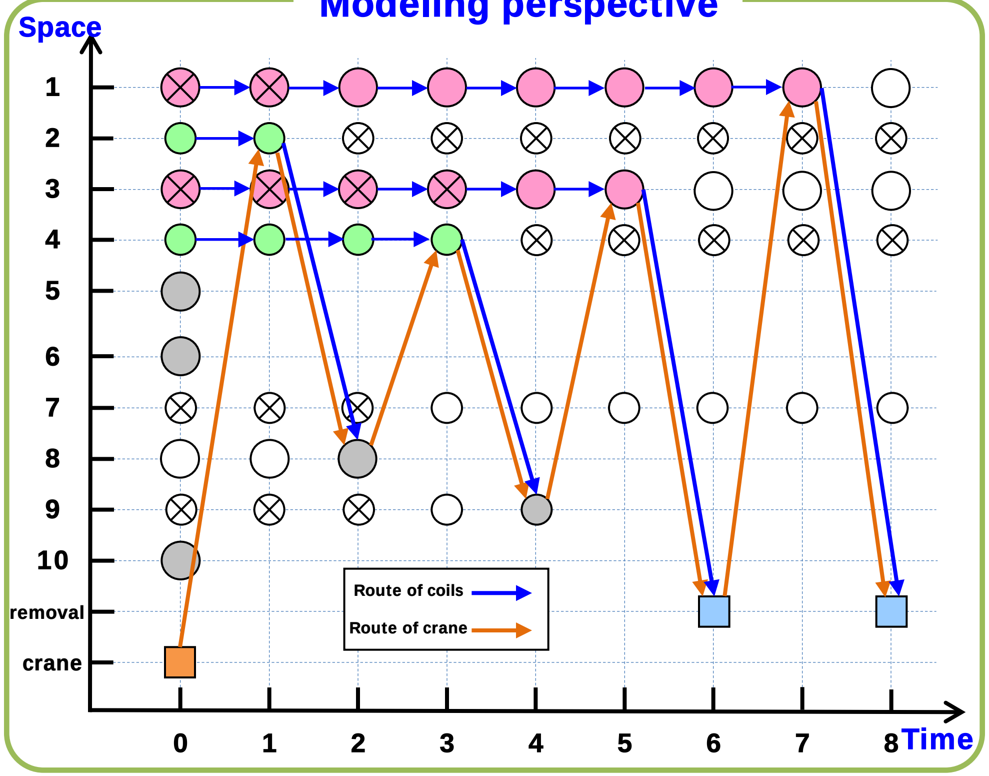
Space-time network flow modeling

- The space-time is discretized into grid and depicted based on network graph. Each node represents a location, each edge indicates a crane's move between two locations in a stage;
- The spatial location includes all the locations in the storage area and the entry, exit and initial location of the crane;
- The scheduling of task sequence is transformed into the allocation of crane movement in stages, and an event-based space-time network model is established.

Engineering perspective

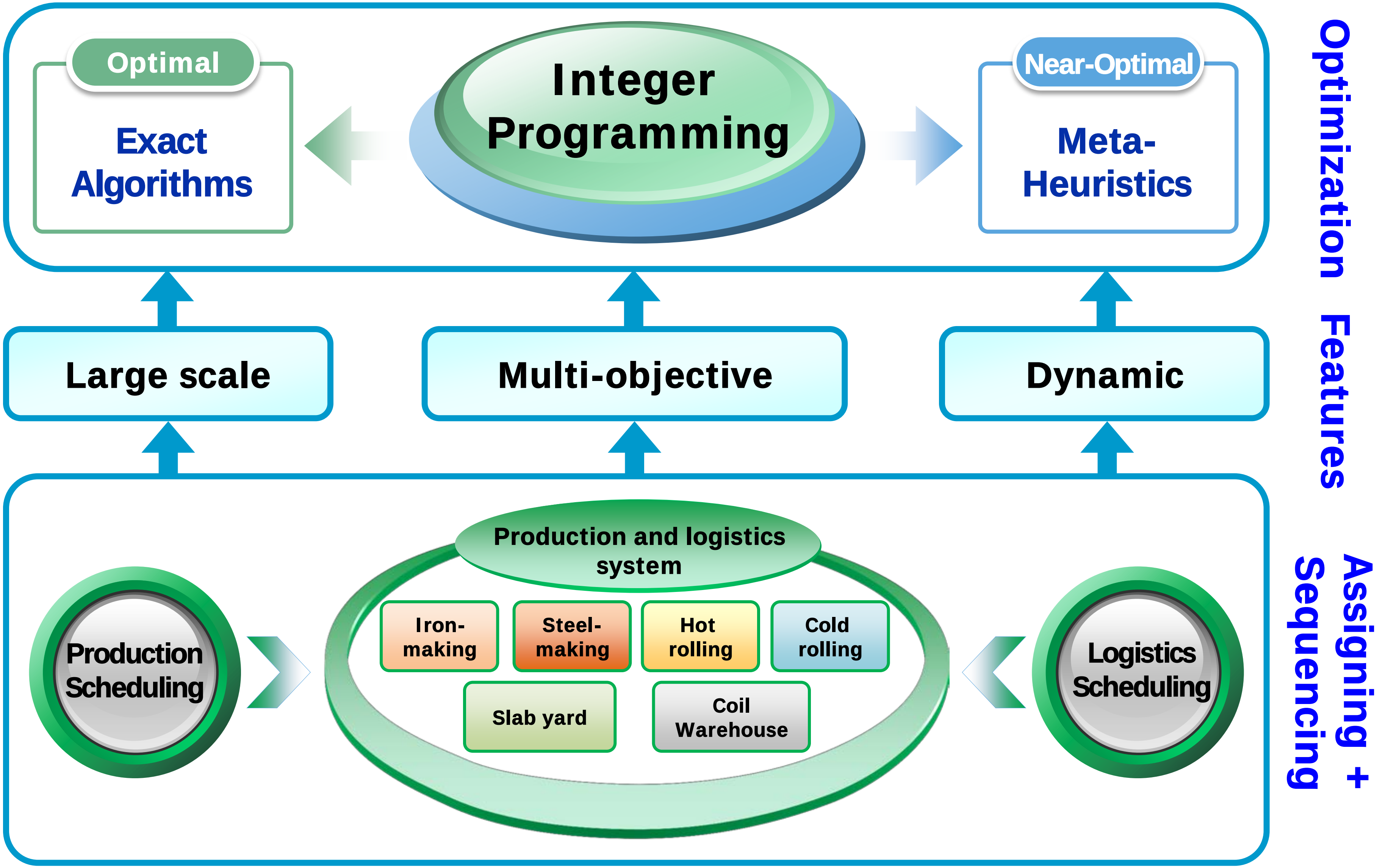


Modeling perspective



Y. Yuan and L. Tang. Novel time-space network flow formulation and approximate dynamic programming approach for the crane scheduling in a coil warehouse. *European Journal of Operational Research*, 2017, 262(2): 424-437.

2. System Modeling and Optimization Method — Optimization Method



Data Analytics and Optimization

2. System Modeling and Optimization Method —Exact Algorithms

Benders Decomposition Algorithm

Various Valid Inequalities

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

⇨ Improving lower bound

Combinatorial Benders Cuts

$$\text{MILP\_CB} := \begin{cases} \mathbf{A\_MILP}_{\text{LP}} \\ \upsilon(\mathbf{A\_MILP}_{\text{LP}}) \leq \text{UB}-\varepsilon \end{cases}$$

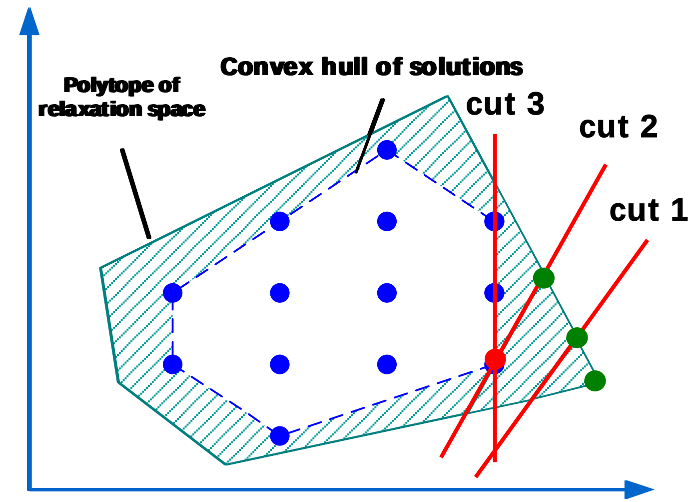
⇨ Accelerating convergence

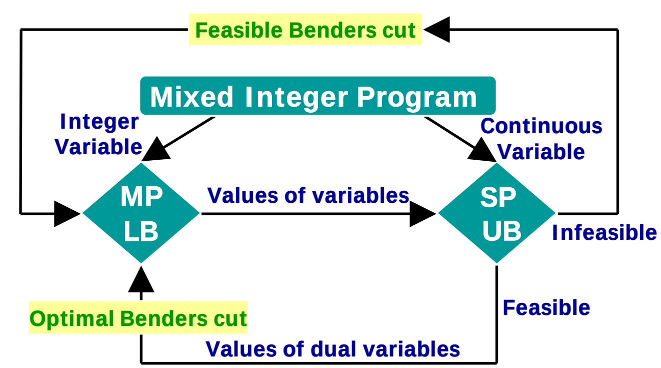
Variable Reduction

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

⇨ Reducing search space

Structure





L. Tang, D. Sun and J. Liu. Integrated storage space allocation and ship scheduling problem in bulk cargo terminals. *IIE Transactions*, 2016, 48(5): 428-439. (**Featured Article**)

Outer Approximation Algorithm (OA)

Multi-generation Cuts

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

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

⇨ Accelerating convergence

Partial Surrogate Cuts

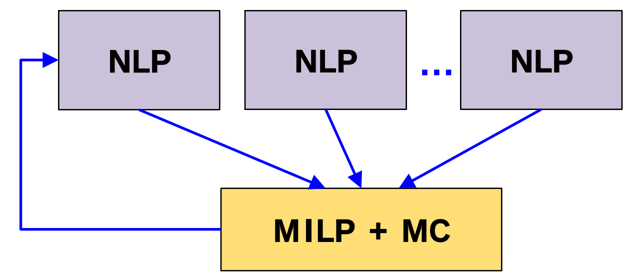
$$\left(\lambda^k\right)^T \cdot \left[Hy + Dw + g(\mathrm{v}^k)\right] - \left(\mu^k\right)^T A_2 \left(v - \mathrm{v}^k\right) \leq 0$$

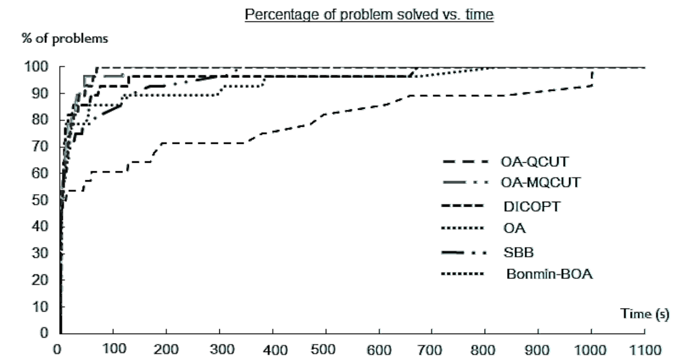
⇨ Tightening lower bound

Hybrid Strategy of OA and GBD

⇨ Improving efficiency

Structure



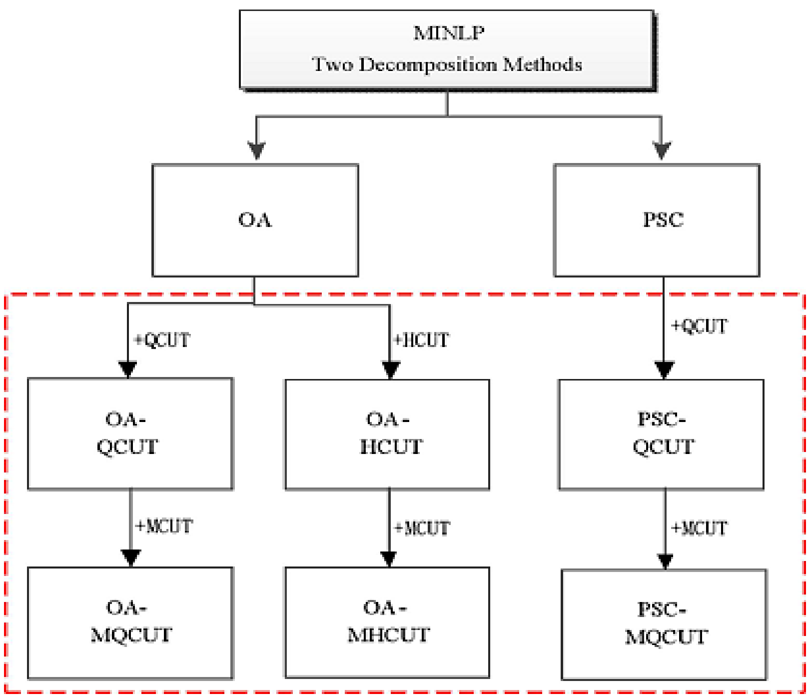


L. Su, L. Tang and I.E. Grossmann. Computational strategies for improved MINLP algorithms. *Computers & Chemical Engineering*, 2015, 75: 40-48.

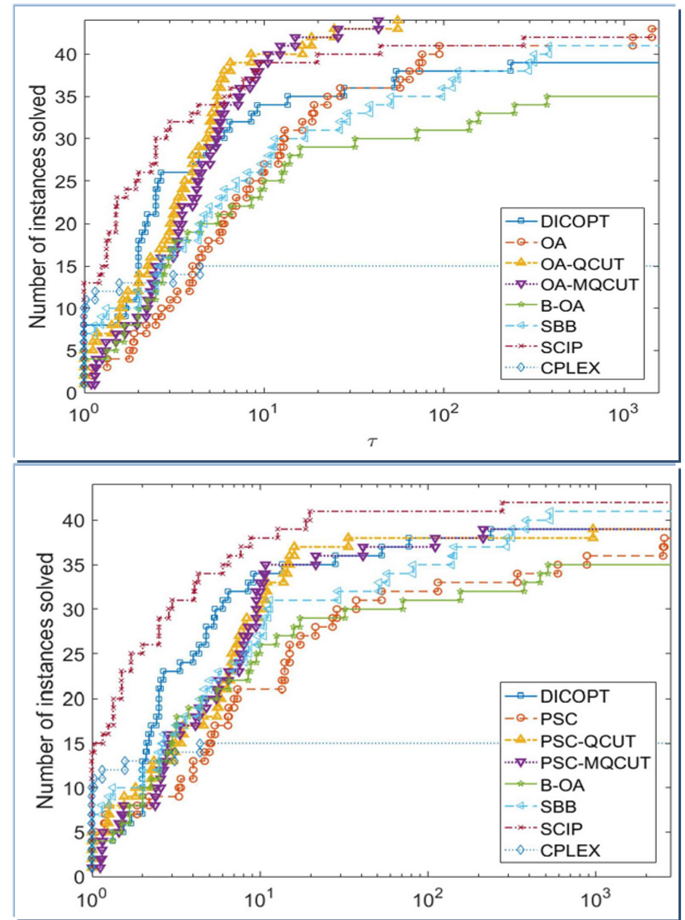
2. System Modeling and Optimization Method —Exact Algorithms

OA Algorithm with Quadratic Cuts

- Integrate the strategies of scaled quadratic cuts with multi-generation cuts for Outer Approximation



Performance



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.

2. System Modeling and Optimization Method — MetaHeuristics

Hybrid Multi-objective Evolutionary Algorithm

Incorporating the Concepts of Personal Best and Global Best ⇒ Avoiding local optimum

Multiple Crossover Operators to Update the Population ⇒ Increasing robust

Propagating Mechanism ⇒ Improving diversity

Performance

Problems	*HMOEA* $\tilde{x}_{IQR}$	*AbYSS* $\tilde{x}_{IQR}$	*SMPSO* $\tilde{x}_{IQR}$	*NSGA-II* $\tilde{x}_{IQR}$	*SPEA2* $\tilde{x}_{IQR}$	
ZDT1	1.572e-04 $_{4.0e-05}$	1.852e-04 $_{4.0e-05}$	1.170e-04 $_{3.5e-05}$	2.203e-04 $_{4.6e-05}$	2.198e-04 $_{2.9e-05}$	+
ZDT2	7.568e-05 $_{1.4e-05}$	1.022e-04 $_{5.4e-05}$	5.012e-05 $_{4.3e-06}$	1.598e-04 $_{4.5e-05}$	1.783e-04 $_{4.5e-05}$	+
ZDT3	7.012e-05 $_{1.2e-05}$	1.670e-04 $_{2.3e-05}$	7.555e-05 $_{2.9e-05}$	1.852e-04 $_{2.2e-05}$	1.114e-04 $_{2.3e-05}$	+
ZDT4	1.502e-04 $_{4.5e-05}$	4.599e-04 $_{3.6e-04}$	1.507e-04 $_{4.5e-05}$	4.079e-04 $_{2.4e-04}$	5.770e-04 $_{3.8e-04}$	−
ZDT6	1.374e-02 $_{1.8e-02}$	4.236e-04 $_{1.2e-05}$	4.630e-05 $_{1.6e-02}$	6.773e-04 $_{1.2e-04}$	1.325e-03 $_{2.5e-04}$	+
Kursawe	1.407e-03 $_{1.7e-04}$	1.411e-03 $_{1.7e-04}$	1.754e-03 $_{2.7e-04}$	1.667e-03 $_{1.9e-04}$	1.416e-03 $_{1.4e-04}$	−
Deb2	6.497e-04 $_{9.3e-05}$	7.445e-04 $_{1.5e-01}$	6.561e-04 $_{1.4e-04}$	6.757e-04 $_{1.2e-04}$	8.720e-04 $_{4.9e-02}$	+
Kita	1.973e-03 $_{7.7e-03}$	4.479e-03 $_{2.4e-02}$	1.768e+00 $_{3.6e-02}$	7.527e-03 $_{2.7e-02}$	4.747e-03 $_{1.6e-02}$	+
Constr	4.292e-04 $_{3.8e-05}$	4.346e-04 $_{3.3e-05}$	2.703e-02 $_{5.7e-04}$	4.630e-04 $_{3.8e-05}$	4.931e-04 $_{3.5e-05}$	−
DTLZ1	1.959e-03 $_{3.7e-02}$	2.316e-03 $_{3.5e-02}$	2.549e-03 $_{7.1e-04}$	4.239e-03 $_{2.9e-02}$	6.471e-02 $_{1.8e-01}$	+
DTLZ2	3.461e-03 $_{1.7e-03}$	7.151e-04 $_{7.2e-05}$	3.743e-03 $_{8.9e-04}$	1.354e-03 $_{2.5e-04}$	1.273e-03 $_{2.3e-04}$	+
DTLZ3	5.843e-01 $_{1.1e+00}$	7.216e-01 $_{5.9e-01}$	4.589e-03 $_{1.6e+00}$	8.271e-01 $_{6.5e-01}$	1.594e+00 $_{1.8e+00}$	+
DTLZ4	4.705e-03 $_{2.5e-03}$	4.853e-03 $_{4.4e-04}$	5.707e-03 $_{4.6e-04}$	5.018e-03 $_{4.5e-04}$	4.820e-03 $_{1.4e-03}$	+
DTLZ5	3.231e-04 $_{8.8e-05}$	2.692e-04 $_{3.7e-05}$	2.304e-04 $_{3.8e-05}$	4.510e-03 $_{7.2e-05}$	3.066e-04 $_{4.9e-05}$	+
DTLZ6	4.807e-04 $_{3.2e-05}$	8.250e-02 $_{2.2e-02}$	4.816e-04 $_{3.4e-05}$	1.318e-01 $_{2.0e-02}$	1.230e-01 $_{1.4e-02}$	−
DTLZ7	3.778e-03 $_{1.2e-03}$	1.591e-03 $_{1.3e-03}$	5.226e-03 $_{1.2e-03}$	3.417e-03 $_{8.2e-04}$	3.738e-03 $_{1.5e-03}$	+
Viennet	9.930e-03 $_{1.8e-03}$	1.123e-02 $_{2.3e-03}$	1.104e-02 $_{2.4e-03}$	1.128e-02 $_{2.6e-03}$	1.319e-02 $_{1.8e-03}$	+
Viennet2	8.851e-04 $_{5.2e-04}$	9.217e-04 $_{5.3e-04}$	9.068e-04 $_{5.0e-04}$	7.753e-04 $_{5.3e-04}$	8.618e-04 $_{3.0e-04}$	−
Viennet3	3.150e-04 $_{1.1e-04}$	6.367e-04 $_{3.2e-04}$	4.578e-04 $_{2.8e-04}$	5.153e-04 $_{1.3e-04}$	6.225e-04 $_{2.2e-04}$	+
Viennet4	1.795e-03 $_{7.8e-04}$	1.568e-03 $_{7.3e-04}$	2.116e-01 $_{2.0e-02}$	2.274e-03 $_{1.1e-03}$	2.752e-03 $_{5.6e-04}$	−
LZ09_F6	9.915e-02 $_{2.8e-01}$	1.236e+00 $_{1.4e+00}$	3.820e+00 $_{2.4e+00}$	1.165e+00 $_{1.2e+00}$	2.735e-01 $_{5.7e-01}$	+
Binh4	5.696e-03 $_{7.6e-04}$	6.171e-02 $_{3.4e-04}$	1.142e+01 $_{5.0e+02}$	6.116e-02 $_{4.3e-04}$	6.204e-02 $_{3.9e-04}$	+
Tamaki	3.716e-03 $_{3.6e-04}$	3.847e-03 $_{3.0e-04}$	7.333e-01 $_{0.0e+00}$	3.766e-03 $_{4.4e-04}$	2.551e-03 $_{3.5e-04}$	+

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

2. System Modeling and Optimization Method — MetaHeuristics

Improved Differential Evolution Algorithm for Dynamic Scheduling

Incremental Mechanism for Initial Population Generation ⇒ Improving efficiency

Real-coded Matrix Representation ⇒ Avoiding invalid solutions

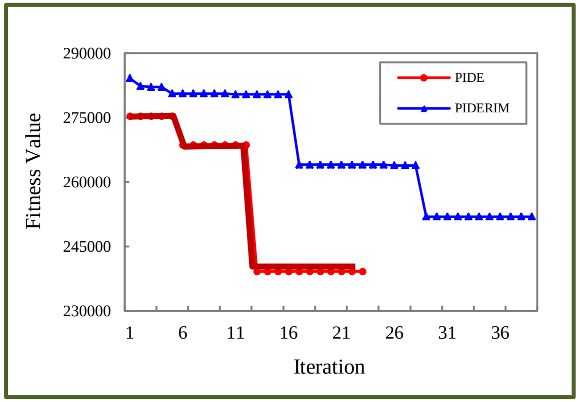
$$\mathbf{A} = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1S} \\ a_{21} & a_{22} & \cdots & a_{2S} \\ \vdots & \vdots & \ddots & \vdots \\ a_{N1} & a_{N2} & \cdots & a_{NS} \end{pmatrix}$$

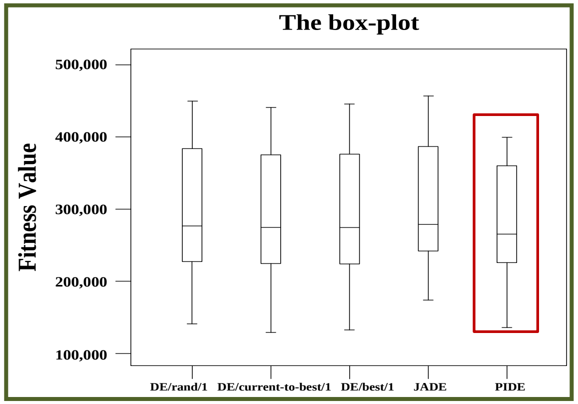
Randomly Mutation Operator ⇒ Expanding search space

$$\mathbf{v}_{i,g} = \mathbf{x}_{i,g} + F(\mathbf{x}_{r1,g} - \mathbf{x}_{r2,g})$$

$$+F(\mathbf{x}^{M}_{best,g} - \mathbf{x}_{i,g}) + F(\mathbf{x}_{r3,g} - \hat{\mathbf{x}}_{r4,g}) + F(\mathbf{x}^{M}_{r5,g} - \mathbf{x}^{M}_{r6,g})$$

Performance





Algorithm has a fast convergence speed

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.

2. System Modeling and Optimization Method — MetaHeuristics

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

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

Self-adaptive selection

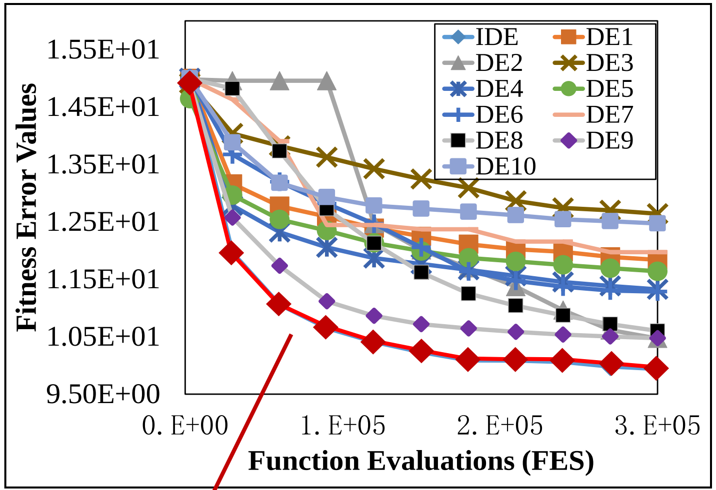
Perturbations with Small Probability

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

Global search

Performance

Algorithms	Dimension of Benchmark Functions								
	10-D			30-D			50-D		
	-	=	+	-	=	+	-	=	+



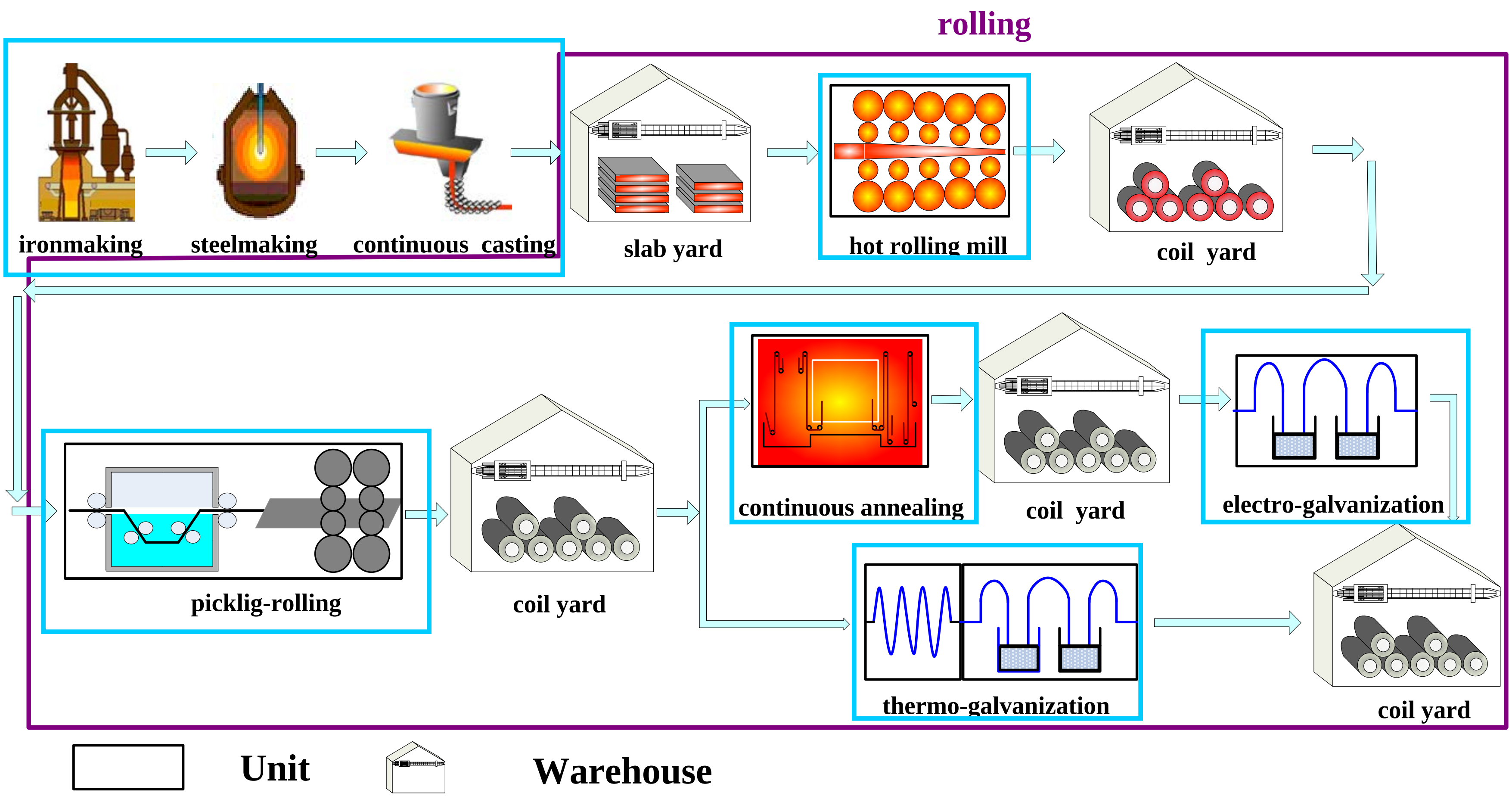
Experimental demonstrate the algorithm's outstanding performance

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.

Outline

- Research Background
- Optimization Modeling and Method
- **Production Scheduling**
- Logistics Scheduling
- Energy Optimization
- Data Analytics

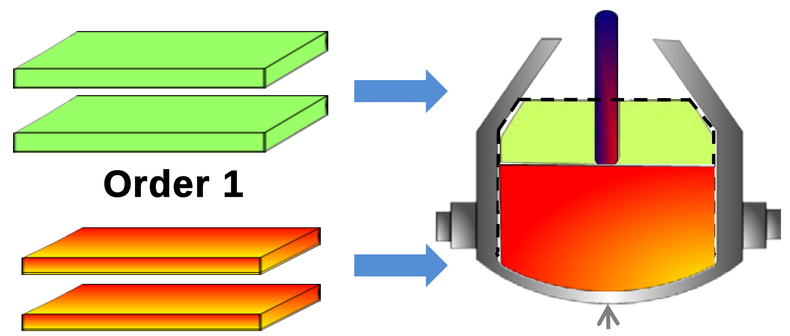
3. Production Scheduling —— Steel Production



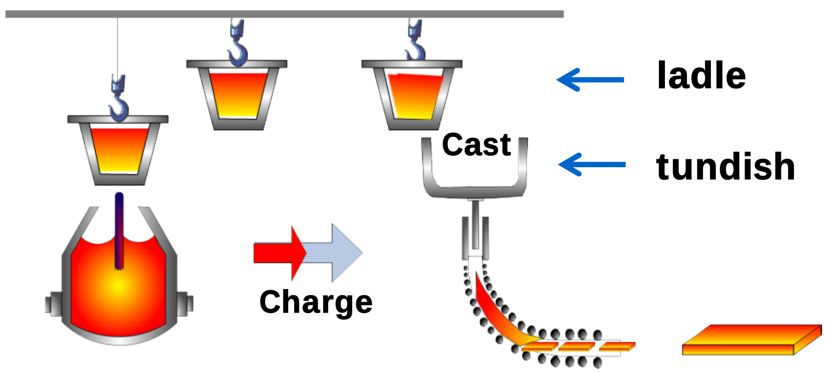
Production: Ironmaking / Steelmaking / Hot rolling / Cold Rolling

3. Production Scheduling —— Steelmaking Stage

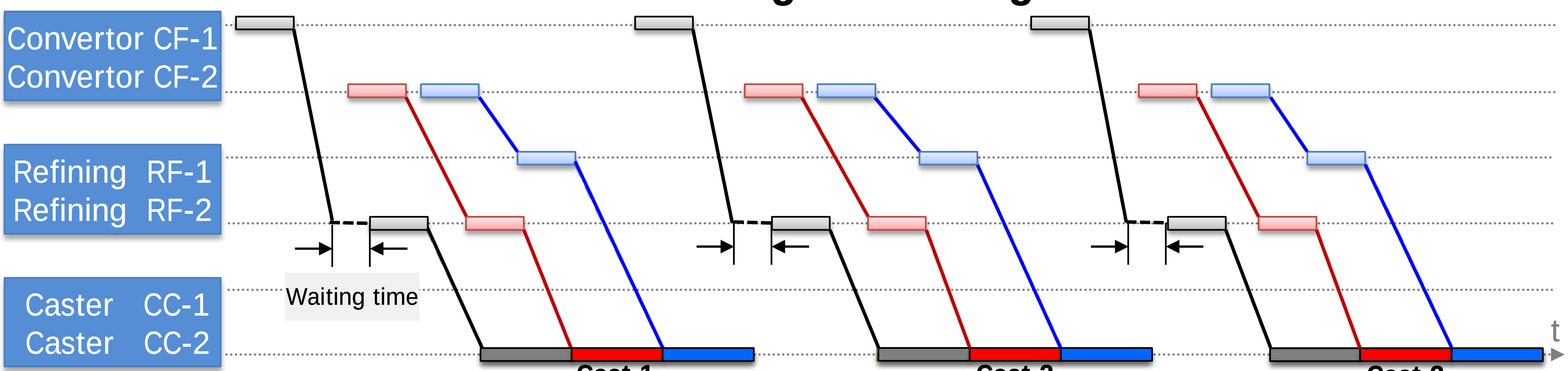
Charge Batching



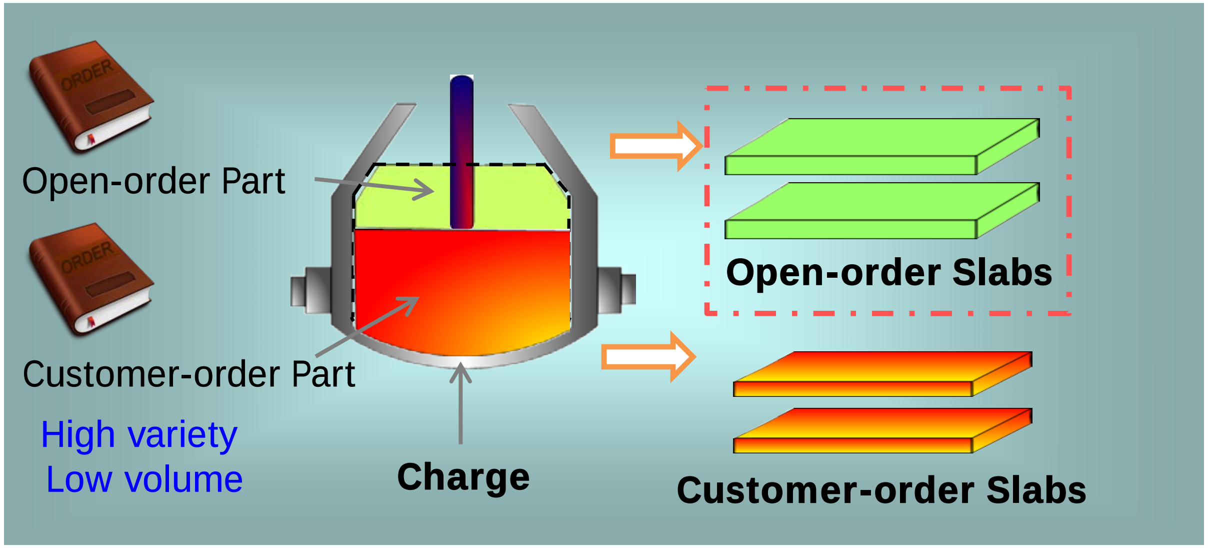
Cast Batching



Steelmaking Scheduling

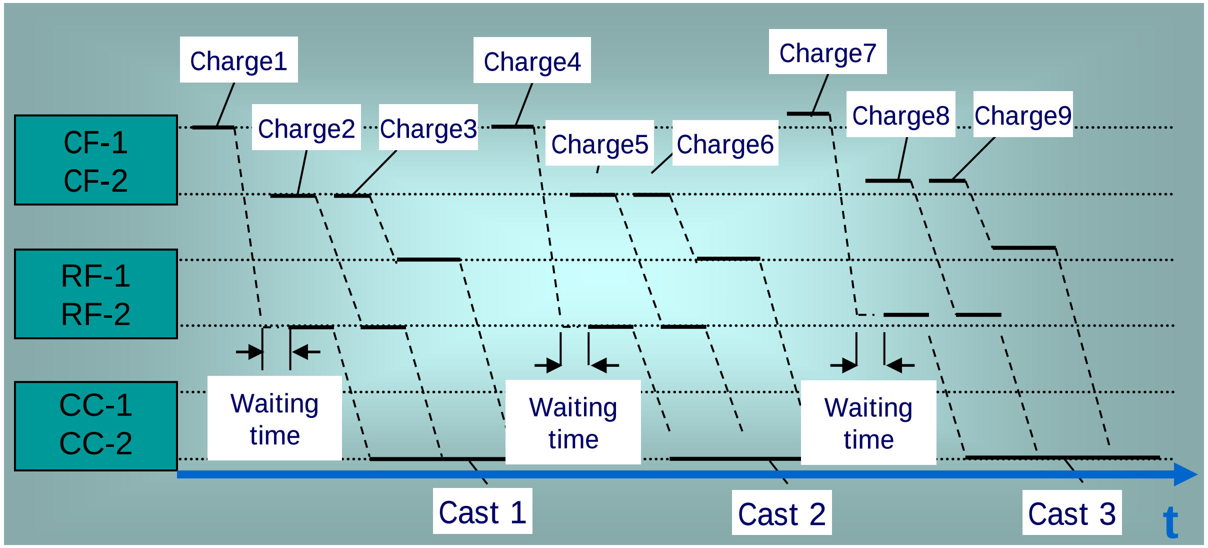


3. Production Scheduling —— Charge Batching of Steelmaking



Group all the slabs of different customer orders into batches

p-median clustering with capacity and additional technical constraints

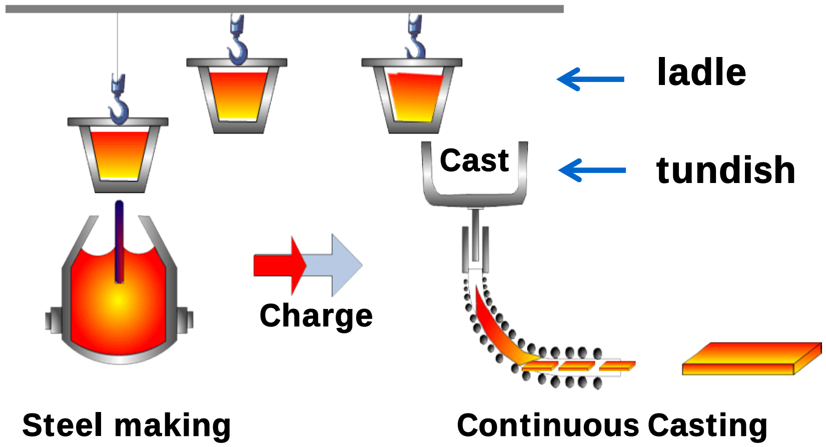


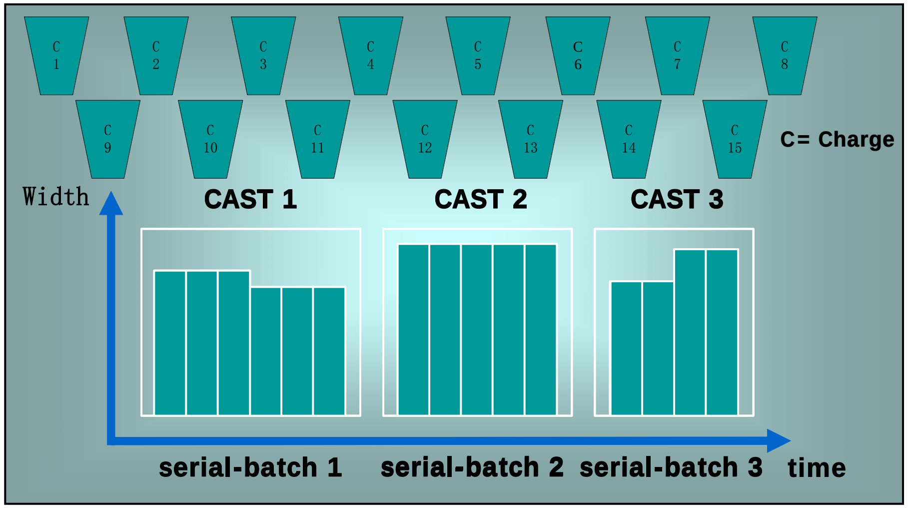
- Minimize assignment cost
- Minimize open-order slabs
- Minimize unfulfilled cost of order

- 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.

3. Production Scheduling —— Cast Batching of Steelmaking





Decisions

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

Objective

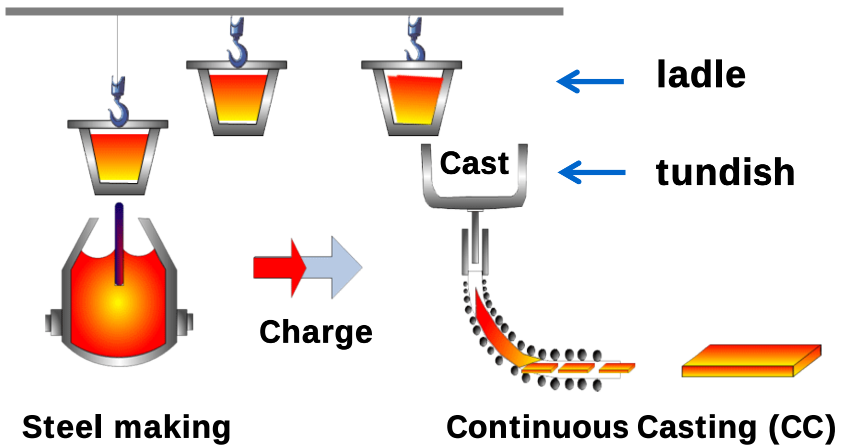
- Maximize tundish utilization
- Minimize total grade switch and width switch cost

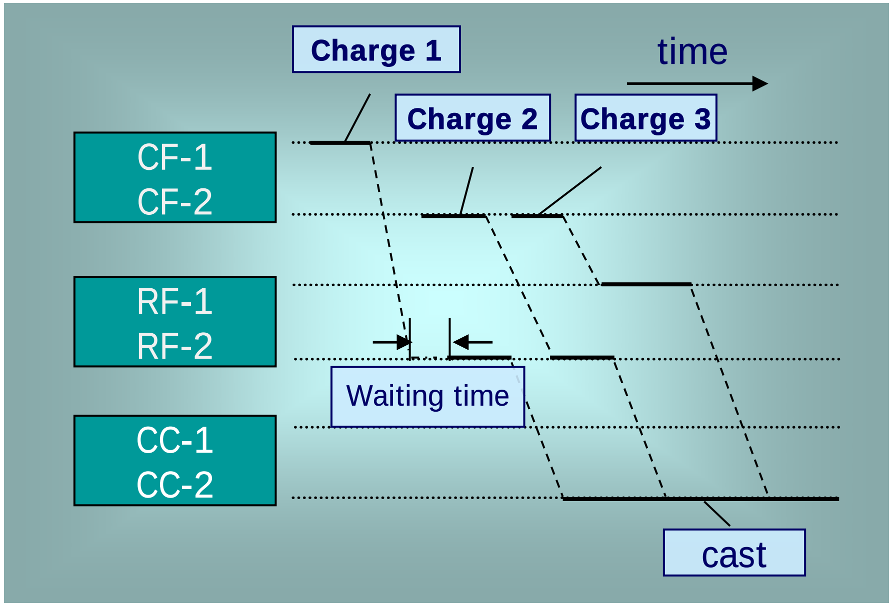
Constraints

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

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

3. Production Scheduling —— Steelmaking Scheduling





Just-in-time idea

Solve machine conflicts in (SCC) production scheduling based on JIT idea

Four-level scheduling

- Level 1: cast sequences on the casters
- Level 2: sub-scheduling
- Level 3: rough scheduling
- Level 4: elimination of machine conflicts

Beneficial effects

- Improve productivity of large devices
- Shorten waiting-time between operations
- Cut down production costs

L. Tang, J. Liu, A. Rong, Z. Yang. A mathematical programming model for scheduling steelmaking-continuous casting production. *European Journal of Operational Research*, 2000, 120(2): 423-435.

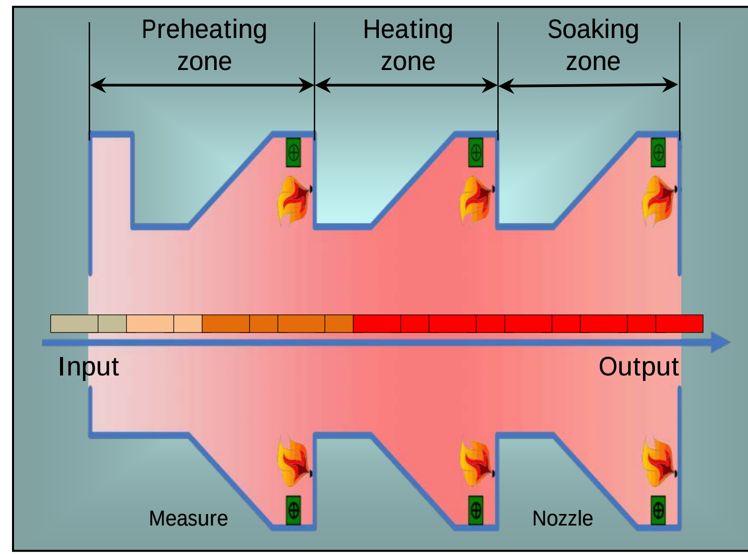
3. Production Scheduling —— Semi-continuous Batch Scheduling

Characteristics of Semi-Continuous Batching Scheduling

Classical Batching Machine Scheduling	Handle several jobs simultaneously	The new Semi-Continuous Batching Machine Scheduling
Begin and finish processing together		Enter and leave the machine one by one
The same batch begin processing at the same time		Respective start time
The same completion time		Respective completion time

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 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.

3. Production Scheduling —— Hot Rolling Scheduling

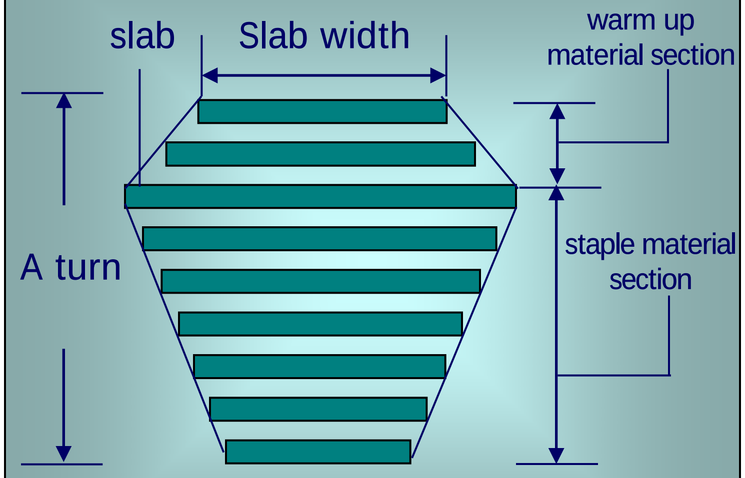
Decisions	Objective
Sequence of adjacent jobs to be processed	Minimize the total changeover costs

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

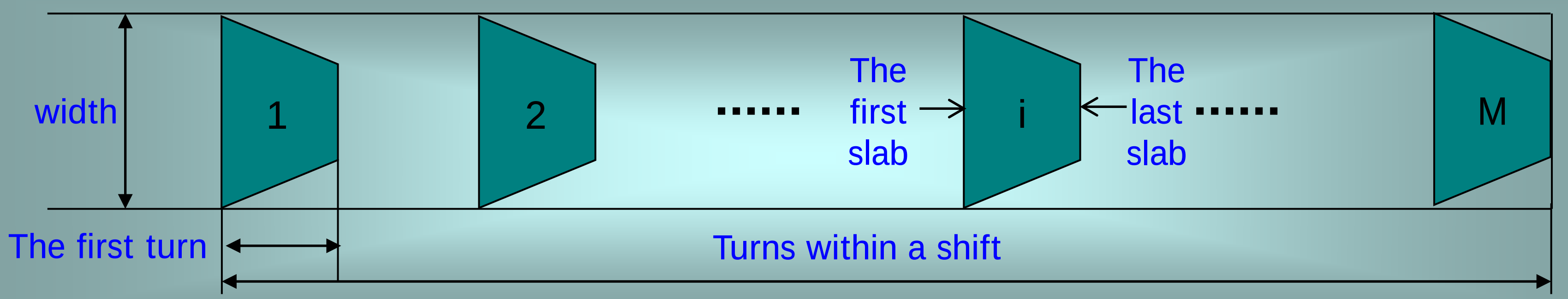
Subject to $\sum_{i=1}^{N+M} X_{ij} = 1, \quad j \in \{1, 2, ..., N+M\}$

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

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



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.

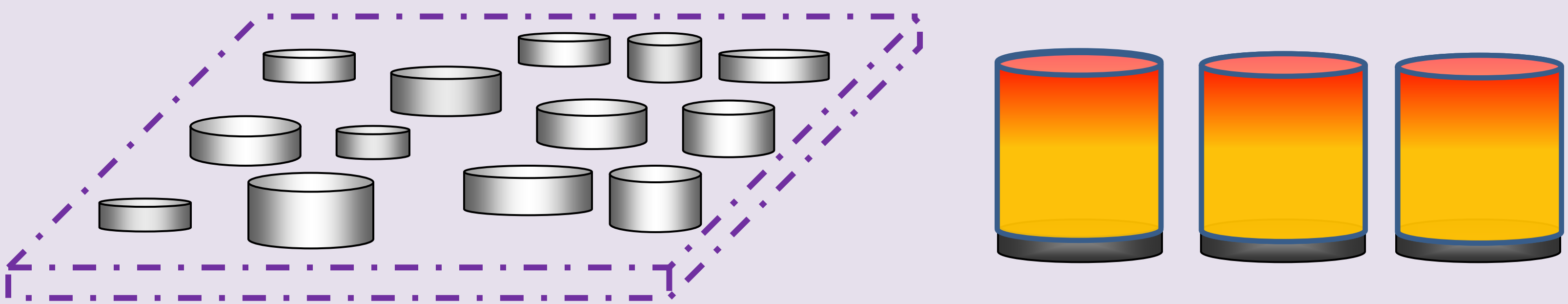
3. Production Scheduling —— Cold Rolling Scheduling

Maximize Reward

Minimize Mismatching cost

Equipment Constraints

Matching Constraints



Form batches for each empty furnace

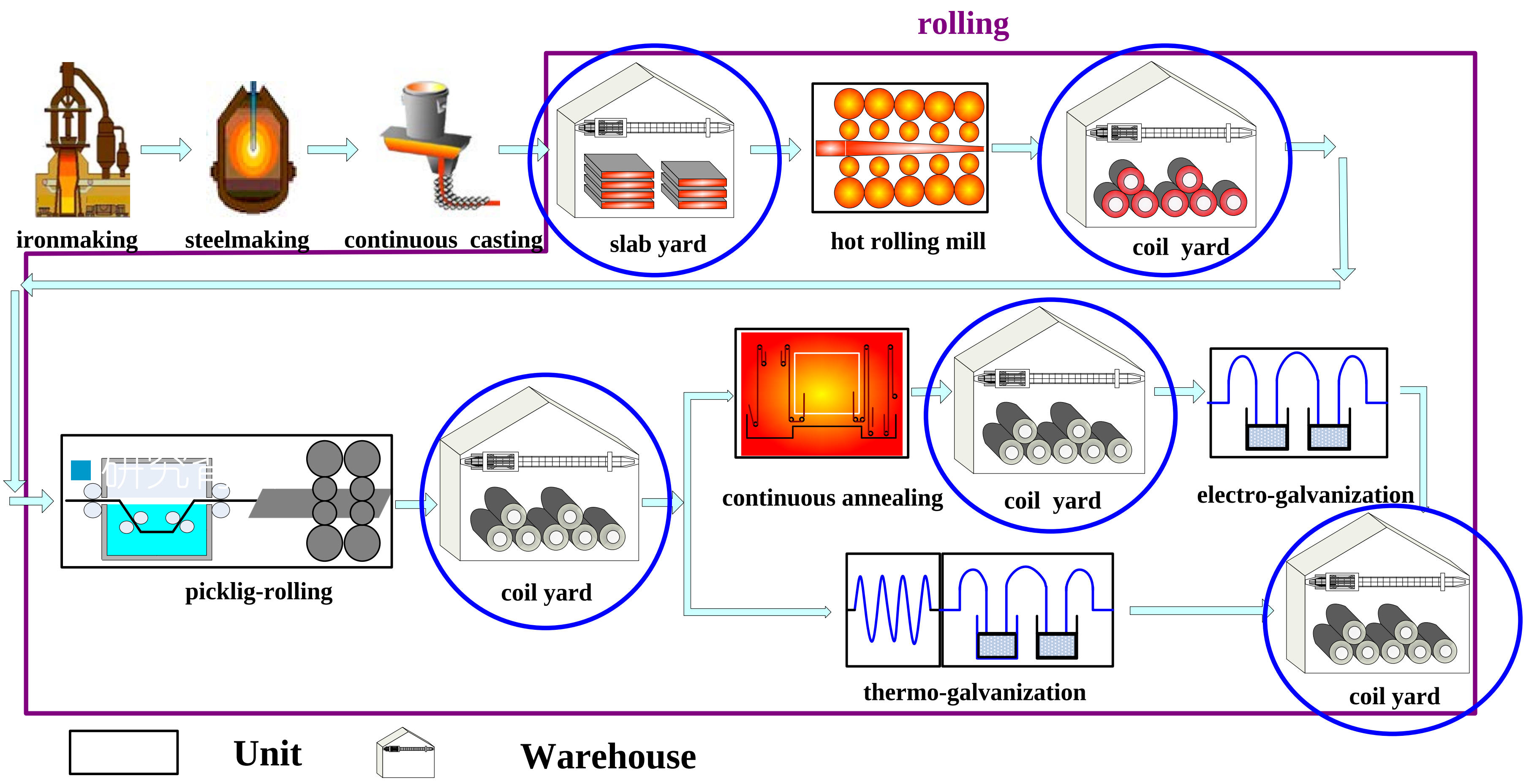
Select a median coil for each batch

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.

Outline

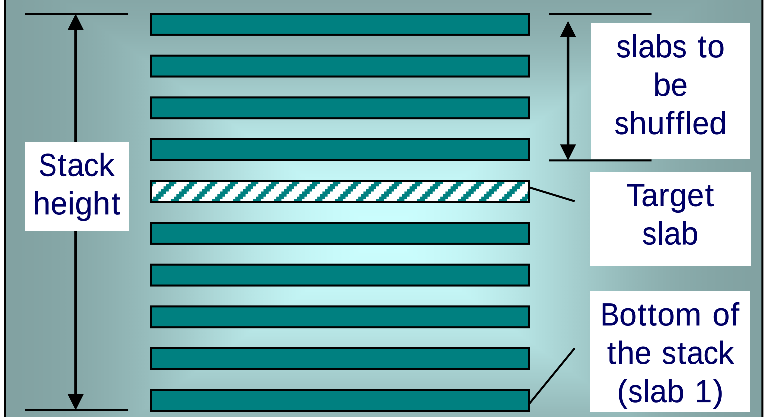
- Research Background
- Optimization Modeling and Method
- Production Scheduling
- **Logistics Scheduling**
- Energy Optimization
- Data Analytics

4. Logistics Scheduling —— Logistics in Steel Plant

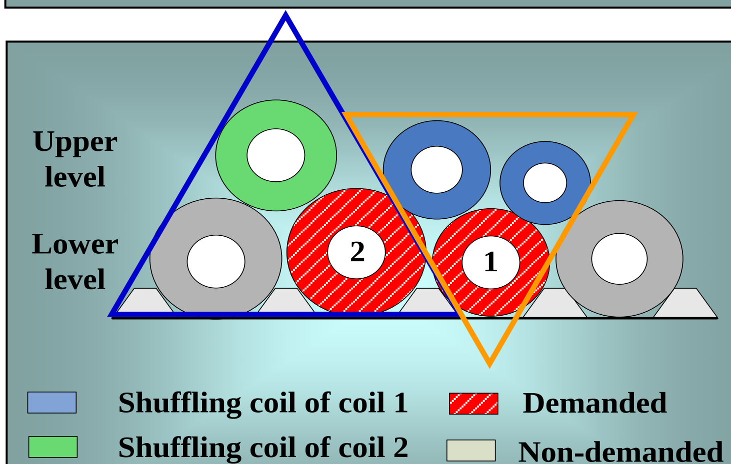


Logistics: Loading(Un) / Transportation / Shuffling / Storage / Stowage

4. Logistics Scheduling —— Shuffling



The structure of a slab stack



The structure of a coil stack

Shuffling Problems in Steel Plants

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

Decisions

Suitable storage positions for shuffled items

Objective

Minimize shuffling and crane traveling

For general case

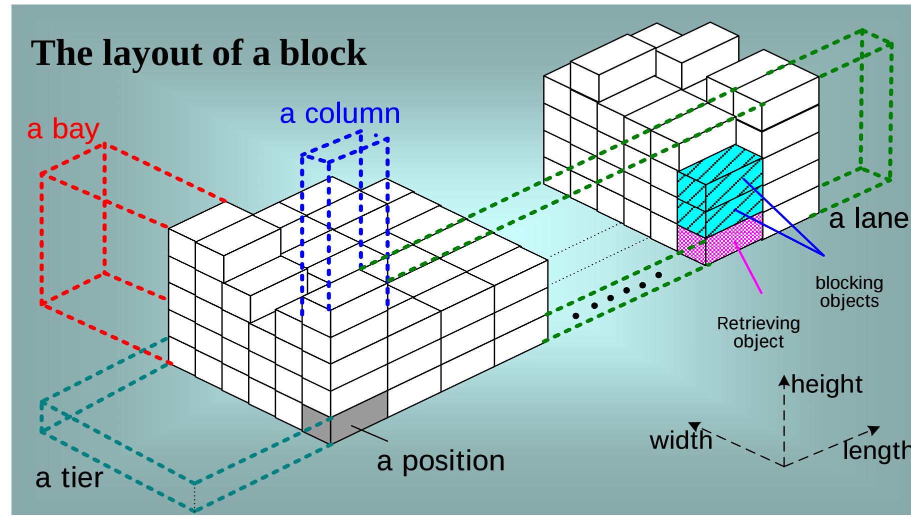
Greedy heuristic

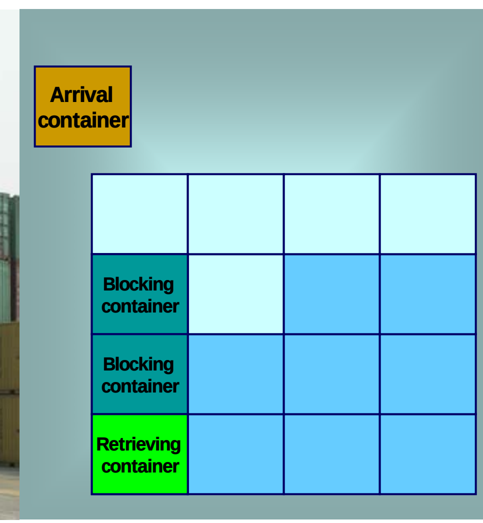
For special cases

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.

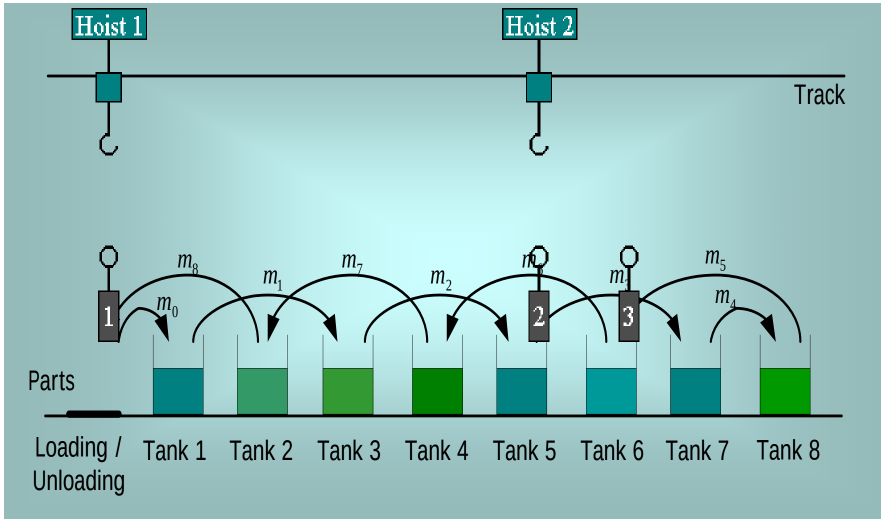
- For statistic and dynamic reshuffling problem, an improved mathematical formulation and a simulation model are established, respectively；
- Five polynomial time heuristics and their extended versions are proposed and analyzed theoretically；
- The proposed heuristic outperforms existing methods.

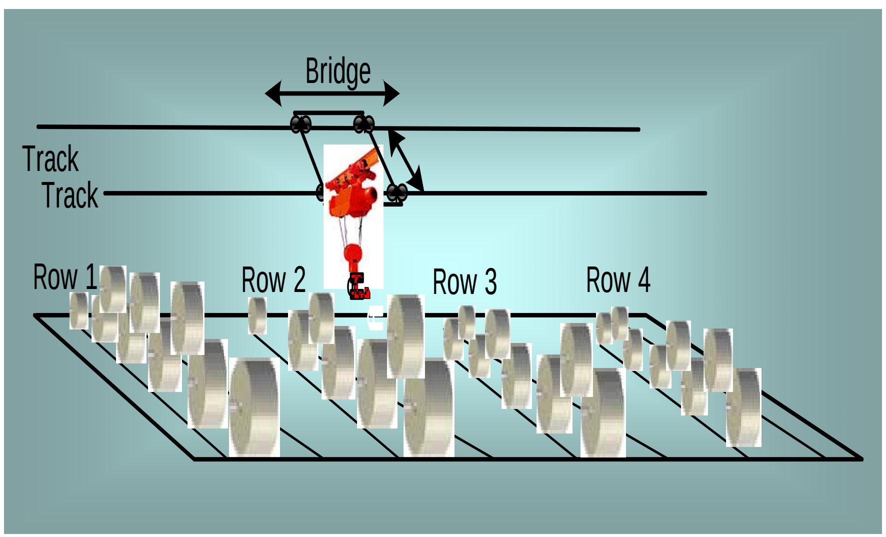




L. Tang, W. Jiang, J.Y. Liu, Y, Dong. Research into container reshuffling and stacking problems in container terminal yards. *IISE Transactions*, 2015, 47(7): 751-766. (**IISE Transactions Best Applications Paper Award**).

4. Logistics Scheduling —— Crane Scheduling





Crane scheduling problem

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

Decisions

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)

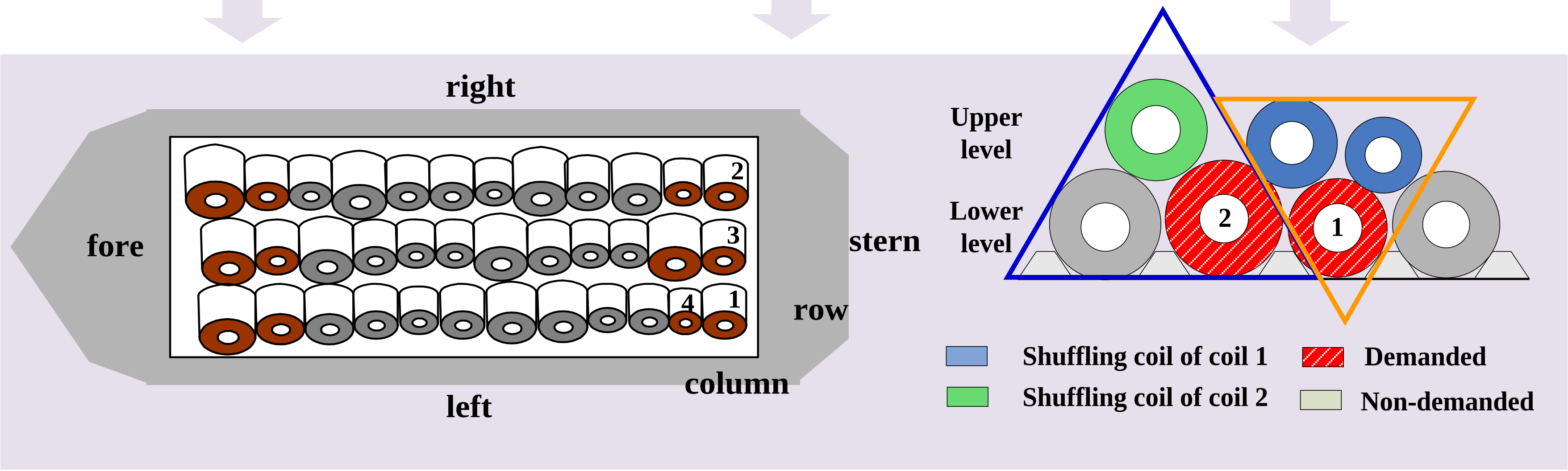
L. Tang, X. Xie, J. Liu. Crane scheduling in a warehouse storing steel coils. ***IIE Transactions***, 2014, 46(3): 267-282

4. Logistics Scheduling —— Ship Stowage Planning

Minimize the moment imbalance

Minimize the shuffling

Minimize the dispersion of coils for the same destination



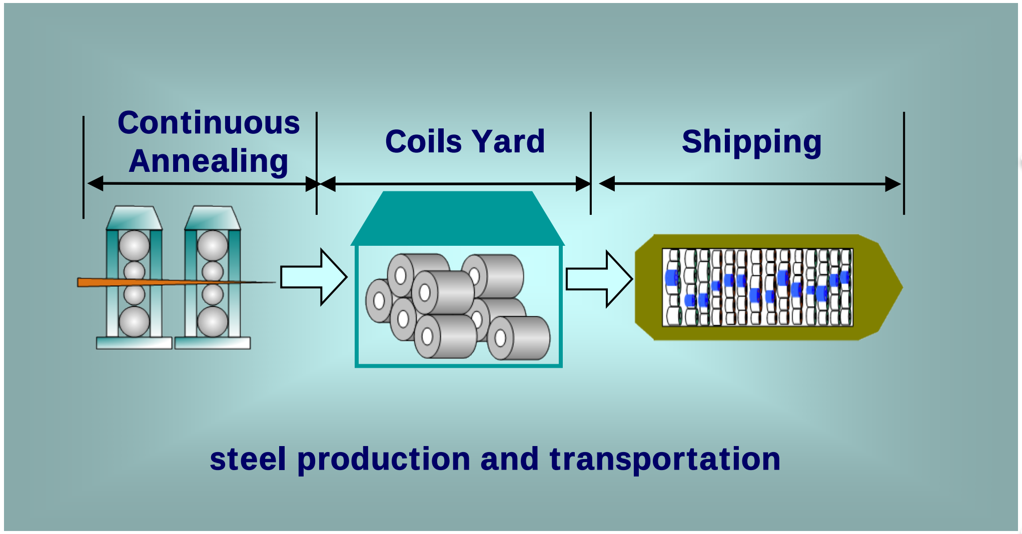
Structural constraints

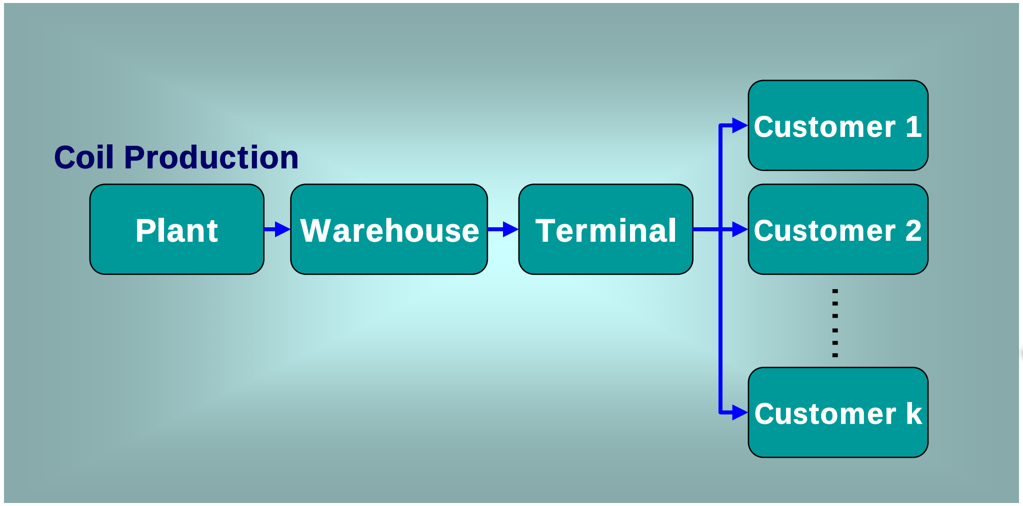
Weight restriction constraints

Operational constraints

L. Tang, J. Liu. 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. Logistics Scheduling —— Coordinated Scheduling





Integrated production, inventory, and delivery problem

Complexity Analysis

- Case 1: order delivery is splittable
- Case 2: order delivery is non-splittable

Most General Problems

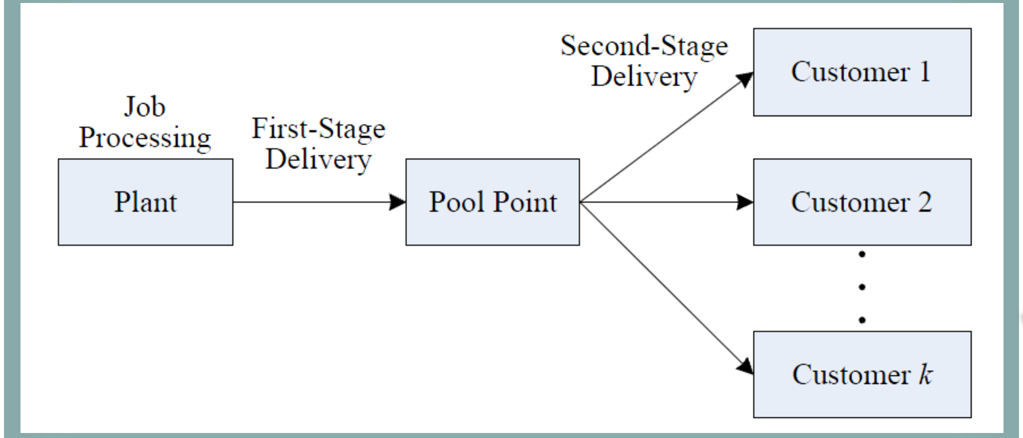
- No approximation algorithms exist with a constant worst-case ratio
- Combined column generation and tabu search heuristic algorithms

F. Li, Z.L. Chen, L. Tang. Integrated production, inventory and delivery problems: complexity and algorithms. *INFORMS Journal on Computing*, 2017, 29(2): 232-250.

4. Logistics Scheduling —— Coordinated Scheduling

Integrated Production & Two-Stage Distribution Scheduling

- Obtain a joint schedule of job processing at the plant and two-stage shipping
- Optimize a performance measure that takes into account both delivery timeliness and total transportation costs



Offline problems involving a single production line

- Optimal dynamic programming algorithms

Offline problems involving multiple production lines

- Fast heuristics
- Worst-case & asymptotic performance

Online problems

- Online algorithms
- Competitive ratios analytics

L. Tang, F. Li, Z.L. Chen. Integrated scheduling of production and two-stage delivery of make-to-order products: offline and online algorithms. *INFORMS Journal on Computing*, 2019, 31(3):493-514.

Outline

- Research Background
- Optimization Modeling and Method
- Production Scheduling
- Logistics Scheduling
- **Energy Optimization**
- Data Analytics

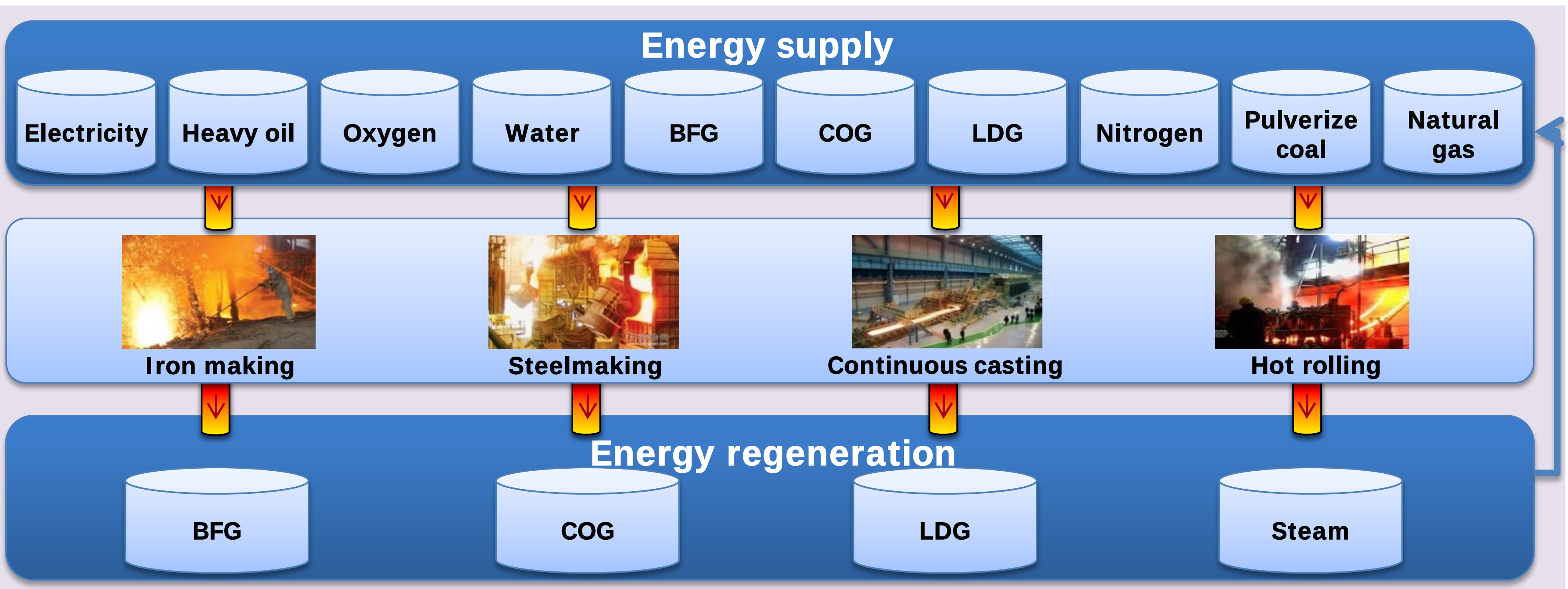
5. Energy Optimization

Goal

- Determine energy purchased and secondary energy generated
- Minimize total energy cost

Challenges

- Frequent change of production environment
- Unstable ratio of energy consumption and regeneration



5. Energy Optimization —— Dynamic Energy Allocation

Objectives

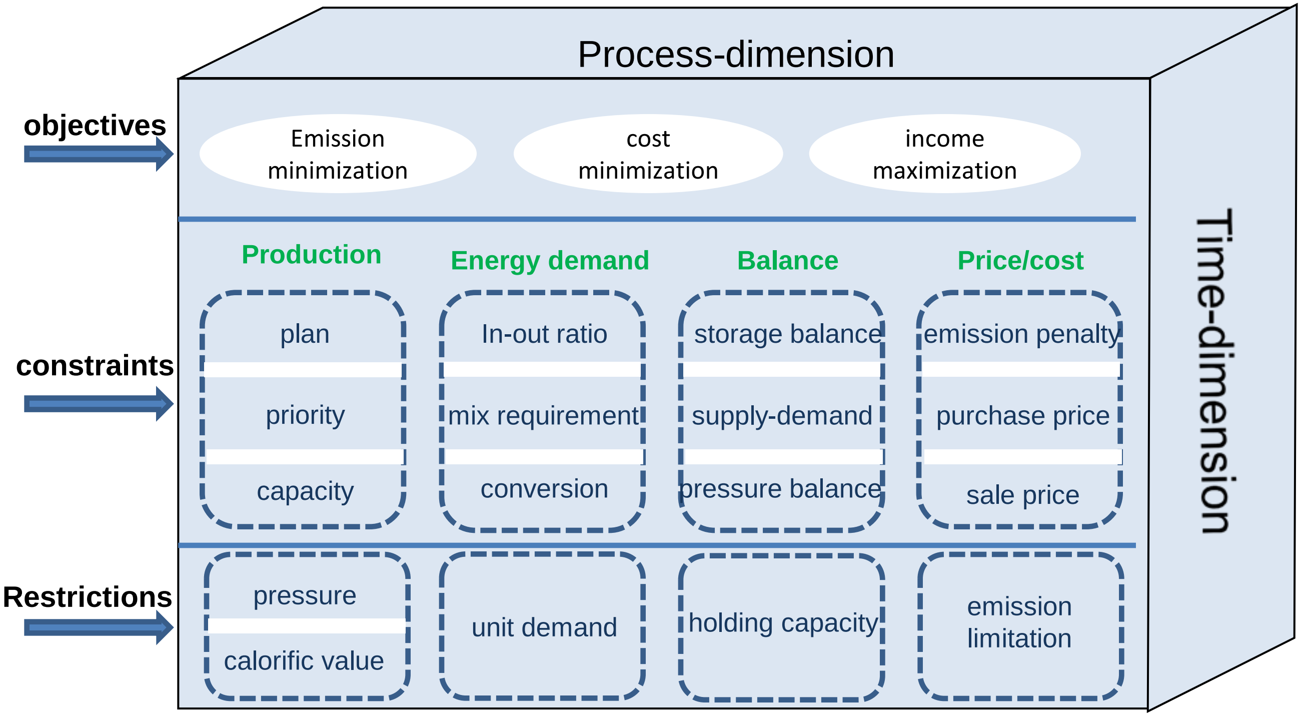
- Minimizing emission
- Minimizing cost
- Maximizing income

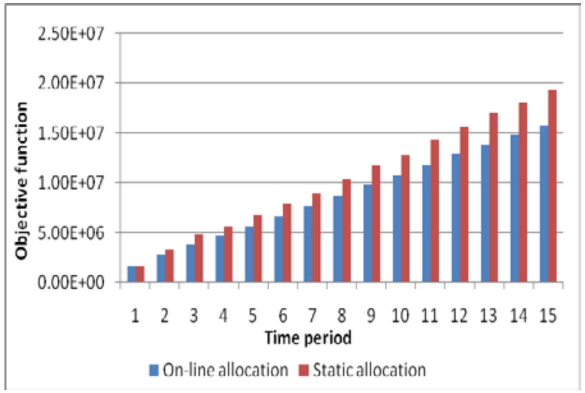
Constraints

- Production
- Balance
- Demand
- Price

ADP Algorithm

Accomplish dynamic energy allocation



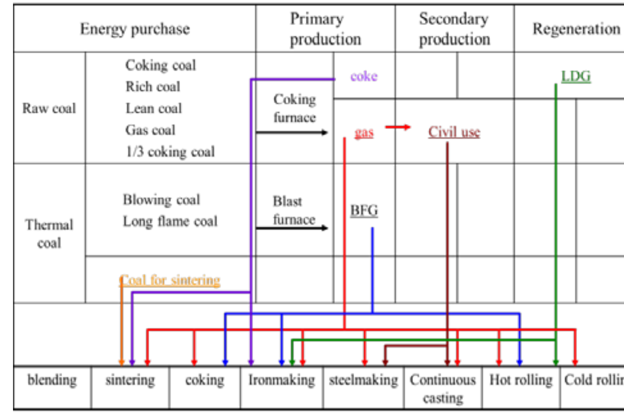


❖ The proposed energy allocation method shows obvious superiority in effectiveness and stability than static method.

5. Energy Optimization —— Comprehensive Scheduling of Gas System

Comprehensive scheduling of gas system

- **Determine**: mixing plan of BFG, COG, LDG
- **Goal**: maximize value flow by controlling heat value



Minimizing emission | **Minimizing supply shortage**

Objectives : $Min\ Z = \sum_j \sum_t c_j^F F_{jt} + c^Q \sum_t \sum_i Q_{ti}$

$$\alpha_{il2} x_{tij1} = \alpha_{il1} x_{tij2} \quad \sum_l x_{ijtl} \le \sum_l e_{ilt} A_{ilj}$$

$$\alpha_{il3} x_{tij1} = \alpha_{il1} x_{tij3}$$

$$\alpha_{il3} x_{tij2} = \alpha_{il2} x_{tij3} \quad \sum_l e_{ilt} = 1$$

$$\sigma_{it} = \Omega_{it} - \sum_j \sum_l (b_j \cdot x_{ijtl})$$

$$Q_{it} = Max\{\ 0, \sigma_{it}\ \}$$

$$O_{ijt} = f_{ij} \cdot S_{it}$$

$$\delta_{tj} = \sum_i O_{ijt} + \left(H_{j,t-1} - H_j^0\right) - \sum_i \sum_l x_{ijtl}$$

$$H_{jt} = Min\left\{\max\left\{\delta_{jt} + H_j^0, H_j^0\right\}, H_j^1\right\}$$

$$H_j^0 \le H_{jt} \le H_j^1$$

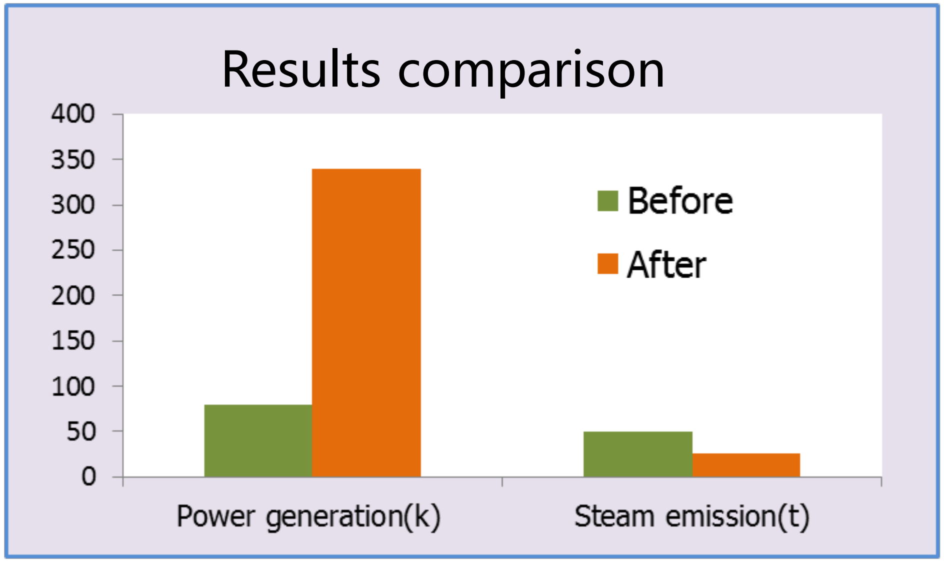
$$\phi_j^0 \le \sum_i O_{ijt} \le \phi_j^1 \qquad \phi_j^0 \le \sum_i x_{ijt} \le \phi_j^1$$

Gas mixing ratio constraints | **Capacity & demand constraints** | **Pipeline balance, flow, holding constraints**

5. Energy Optimization —— Steam Scheduling

Steam scheduling by coordination 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

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

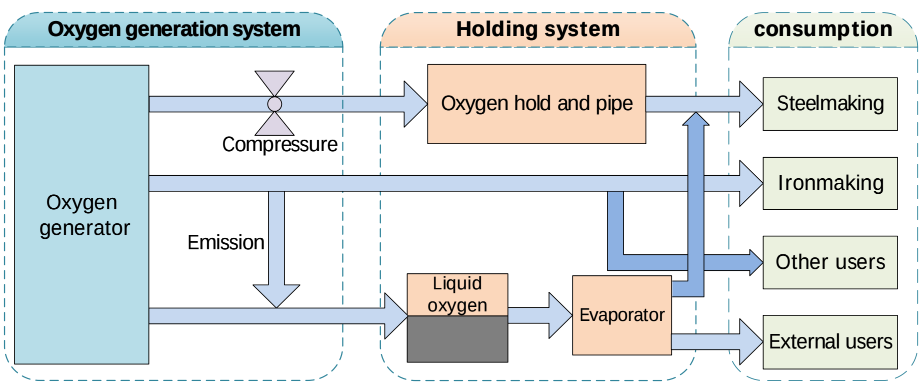
5. Energy Optimization —— Oxygen Scheduling

Task

Dynamically balance and optimization 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

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

Outline

- Research Background
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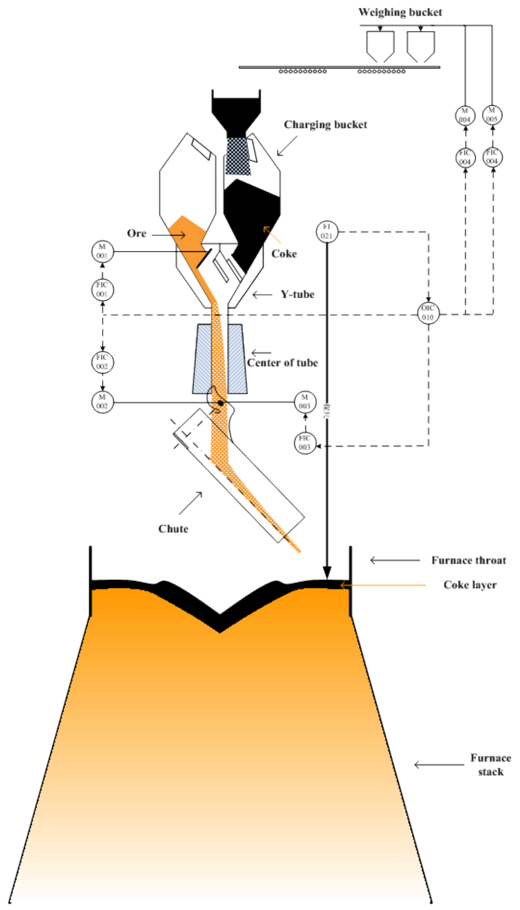
- **Data Analytics**

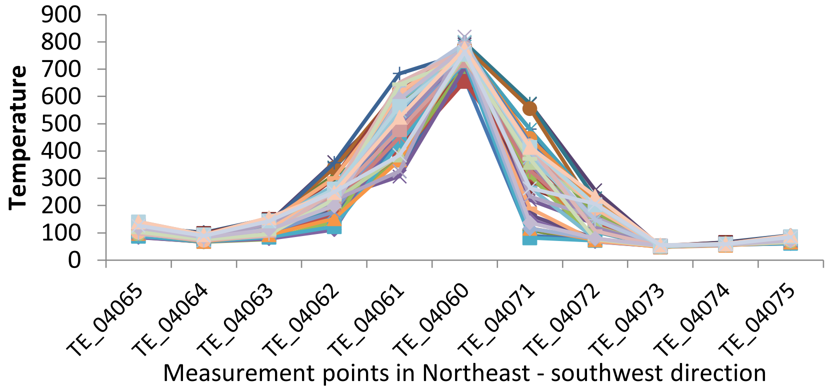
6. Data Analytics

Case 1. Prediction of Burden Distribution

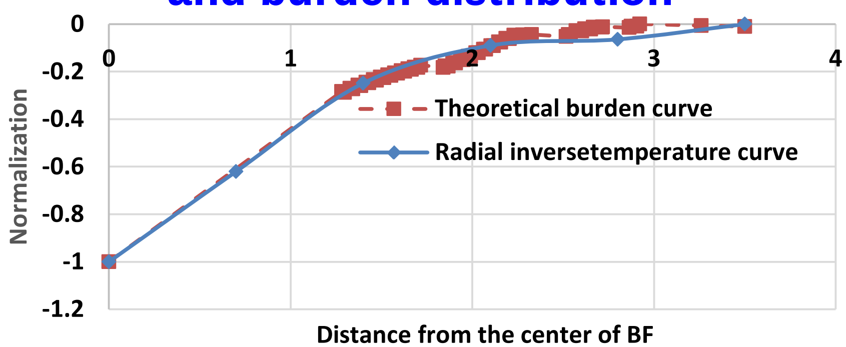
Burden distribution



Temperature of the burden surface

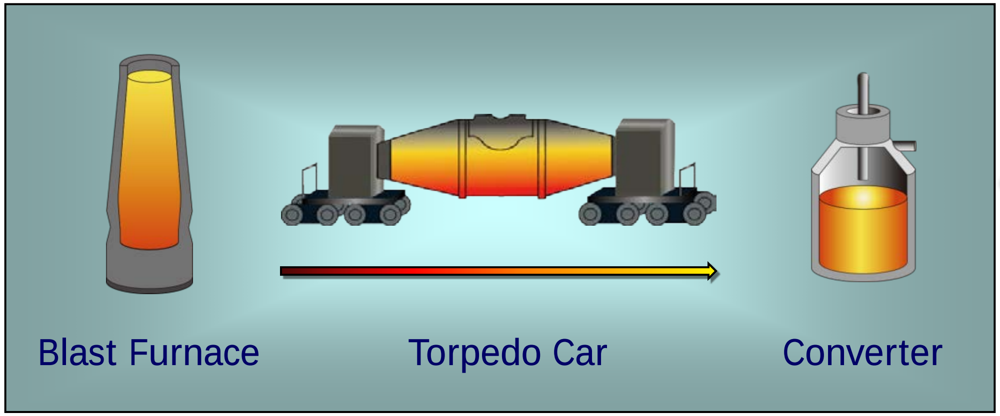


The relationship between temperature and burden distribution



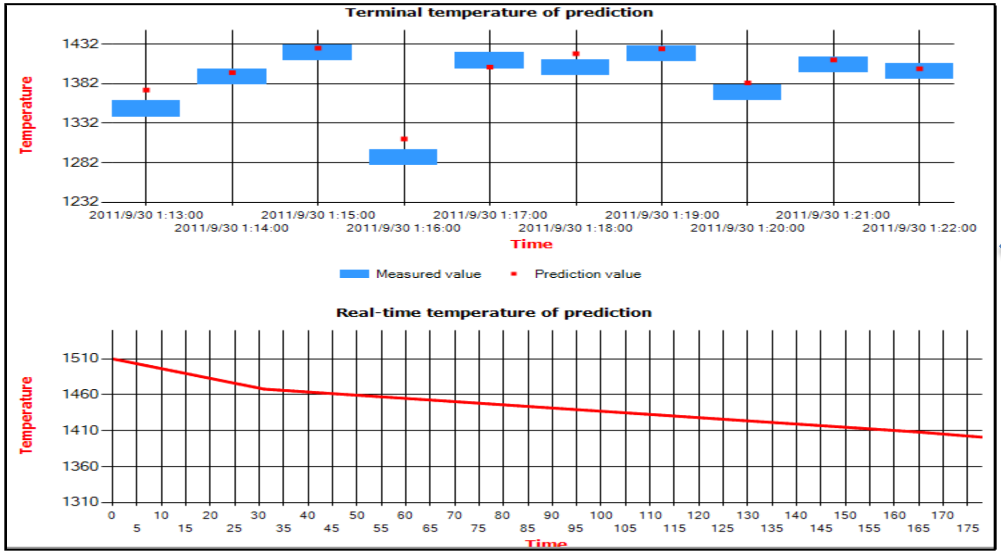
6. Data Analytics

Case 2. Temperature Prediction of Molten Iron in Transportation



Task

Predict the temperature of molten iron in transportation process from blast furnace stage to converter stage

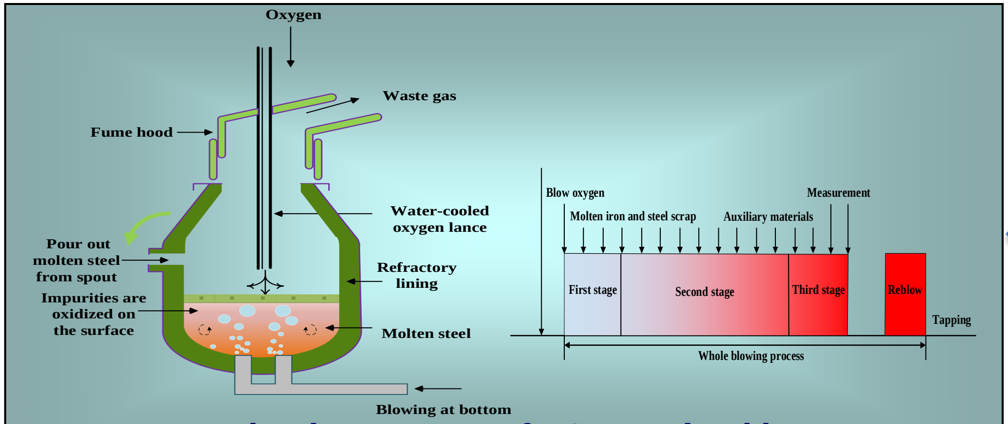


Prediction based on multi-model

- Multiple regression model
- Multiple LSSVM modeling based on estimation of distribution algorithm
- Hybrid modeling based on Kalman filter

6. Data Analytics

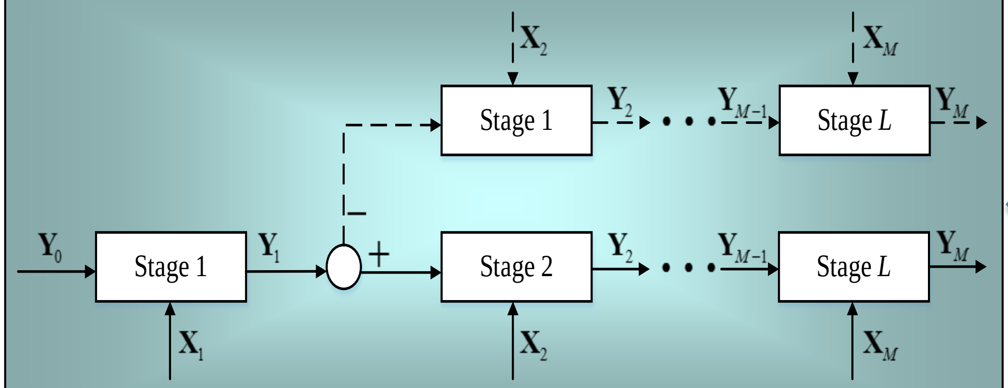
Case 3. Dynamic Prediction of BOF Steelmaking Process



Production process of BOF steelmaking

Challenges

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



Principle of multi-stage modeling in BOF steelmaking process

Dynamic analytics method

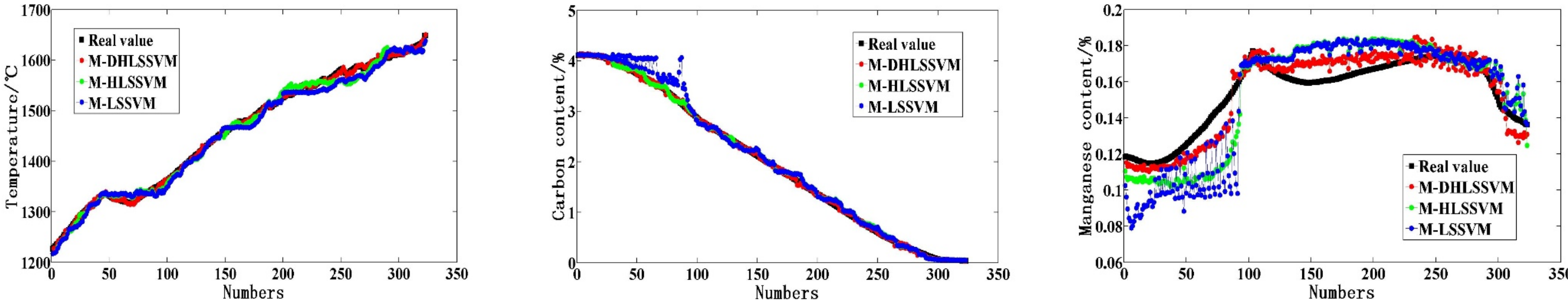
- Multi-stage modeling strategy
- Dynamic model with feedback
- Hybrid kernel function
- Differential evolution algorithm

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 .

6. Data Analytics

Case 3. Dynamic Prediction of BOF Steelmaking Process

Data sets	Indexes	SVR	RVM	KELM	DSAE	M-DHLSSVM
T	RMSE	2.27E+01	1.26E+01	1.55E+01	1.13E+01	**4.00E+00**
	MAPE(%)	1.35E+00	**1.47E-01**	8.29E-01	5.96E-01	2.12E-01
	MAXE (℃)	5.08E+01	1.60E+02	6.34E+01	4.62E+01	**1.56E+01**
C	RMSE	9.99E-02	4.03E-01	1.45E-01	8.51E-02	**3.94E-02**
	MAPE(%)	1.53E+01	2.37E+01	2.29E+01	1.26E+01	**3.45E+00**
	MAXE (%)	2.00E-01	3.05E+00	7.73E-01	4.20E-01	**1.28E-01**
Mn	RMSE	3.00E-02	5.88E-02	1.25E-02	**9.09E-03**	9.73E-03
	MAPE(%)	2.05E+01	3.71E+01	7.82E+00	**5.30E+00**	6.47E+00
	MAXE (%)	5.06E-02	1.27E-01	2.64E-02	2.51E-02	**2.22E-02**
Si	RMSE	1.11E-01	1.38E-01	6.71E-02	9.78E-02	**2.72E-02**
	MAPE(%)	5.21E+02	2.87E+01	6.87E+02	3.61E+02	**1.77E+01**
	MAXE (%)	4.47E-01	6.78E-01	2.87E-01	3.23E-01	**1.25E-01**
S	RMSE	1.31E-03	3.46E-03	6.22E-04	6.94E-04	**3.83E-04**
	MAPE(%)	3.17E+01	9.14E+01	1.72E+01	2.26E+01	**9.53E+00**
	MAXE (%)	2.62E-03	7.85E-03	1.77E-03	2.01E-03	**1.21E-03**
P	RMSE	7.98E-03	1.28E-02	7.77E-03	9.73E-03	**4.67E-03**
	MAPE(%)	1.08E+01	4.00E+01	1.25E+01	1.37E+01	**8.21E+00**
	MAXE (%)	**1.66E-02**	5.59E-02	2.34E-02	2.38E-02	**1.93E-02**
No. of Best		**1/18**	**1/18**	**0/18**	**2/18**	**14/18**

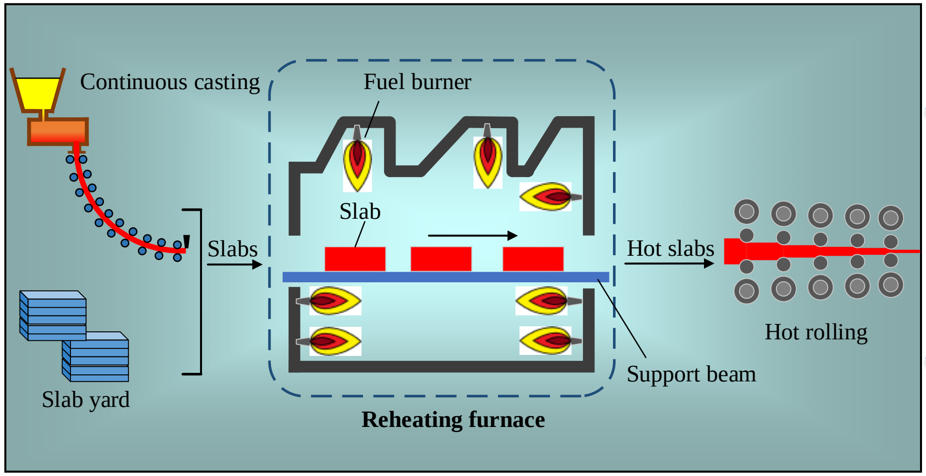


(a) T (b) C (c) Mn

Dynamic prediction results by M-LSSVM, M-HLSSVM and M-DHLSSVM.

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 .

Case 4. Temperature Prediction of Reheat Furnace

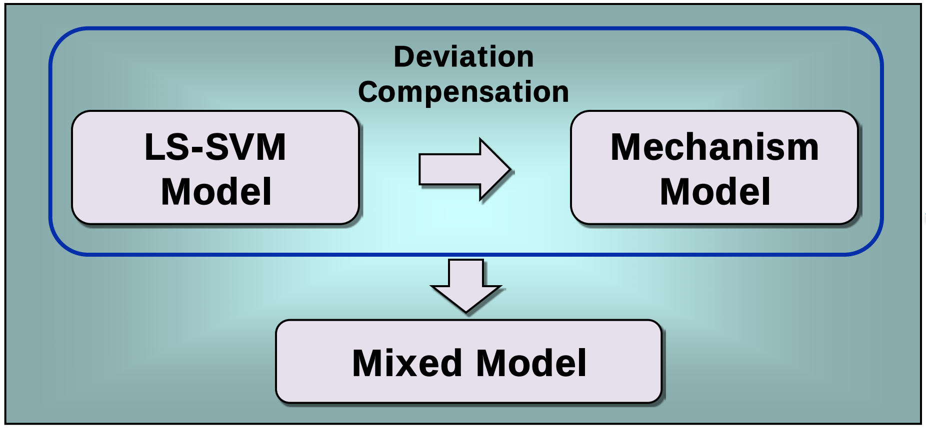


Features of Heating Process

- Dynamic
- Non-linear

Mechanism Model

- Difficult to obtain
- Obvious prediction error



Mechanism Model

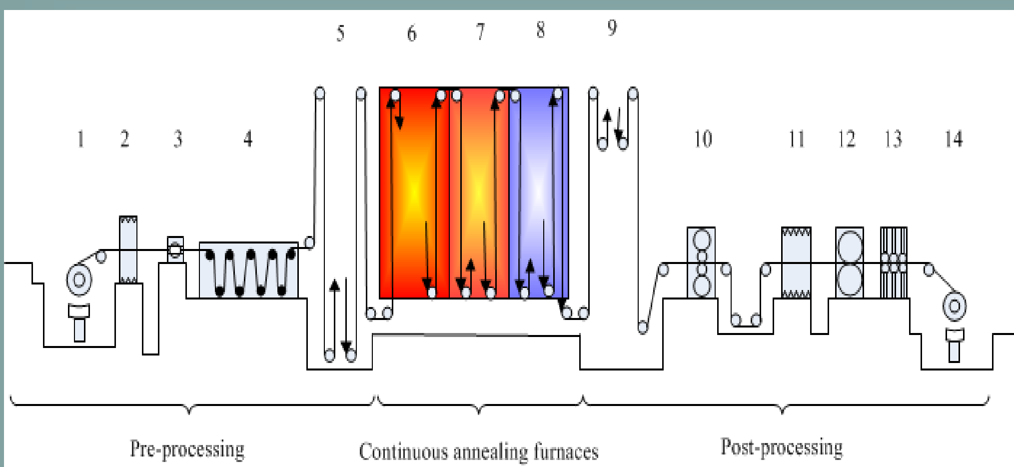
- LS-SVM is used to compensate for the prediction deviation of the slab temperature
- Significantly improve the model prediction accuracy

6. Data Analytics

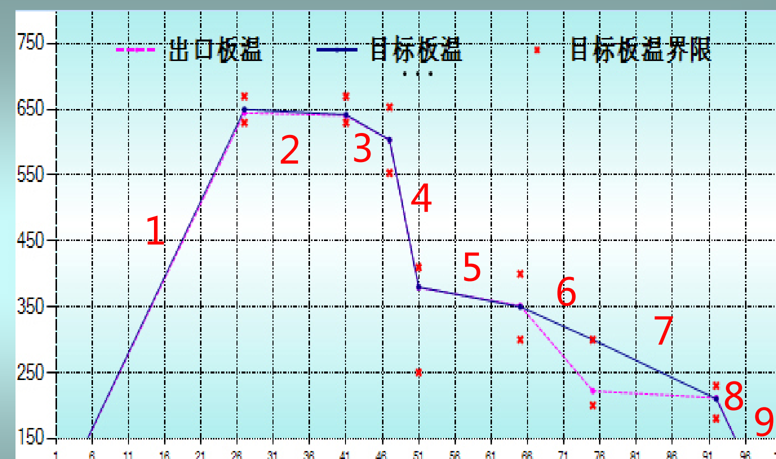
Case 5. Strip Quality Analytics of Continuous Annealing

Difficulties in current production process modeling

- Production process is very complex
- Exact mechanism model is not available
- Dimensions of data are more than 30
- Dimensions of data are strongly correlated



Continuous Annealing Process



Annealing Curve

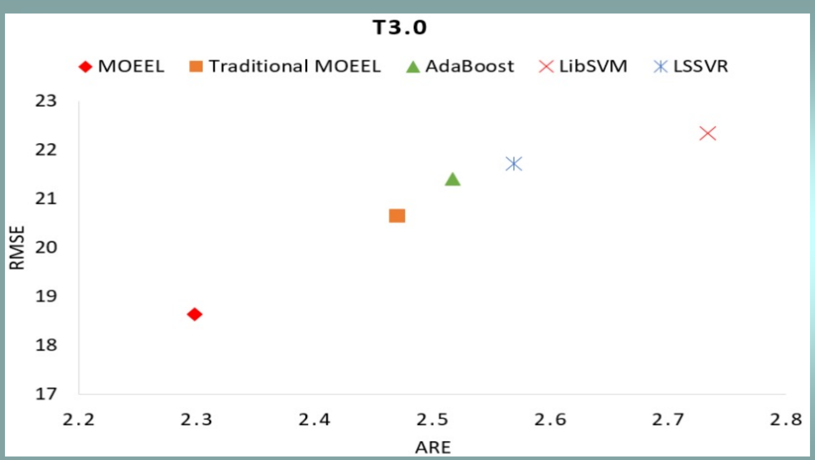
Fluctuations of strip quality have cause great economic loss to the cold rolling mill

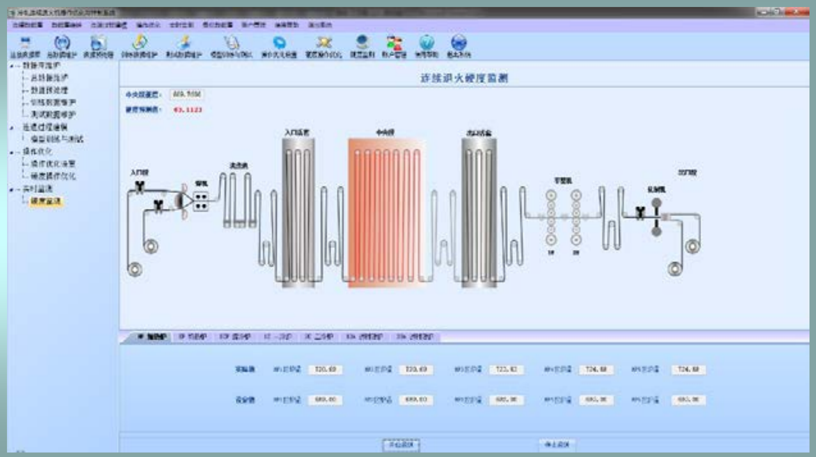
6. Data Analytics

Case 5. Strip Quality Analytics of Continuous Annealing

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**





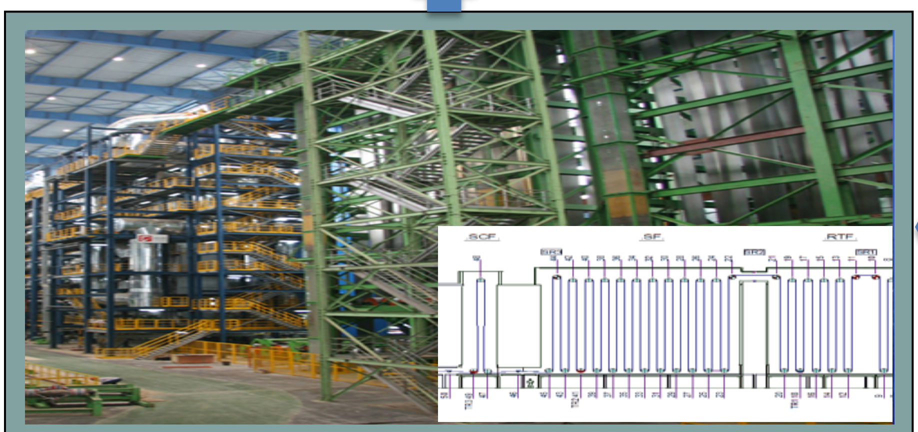
Case 6. Process Monitoring and Diagnosis of Continuous Annealing

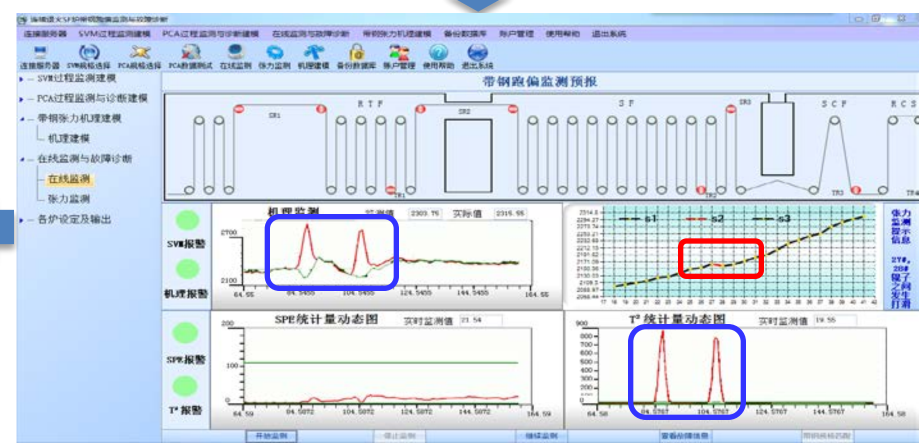
Motivation

- Tension fluctuations
- ⇩ Running deviation
- ⇩ Breakdown of production line

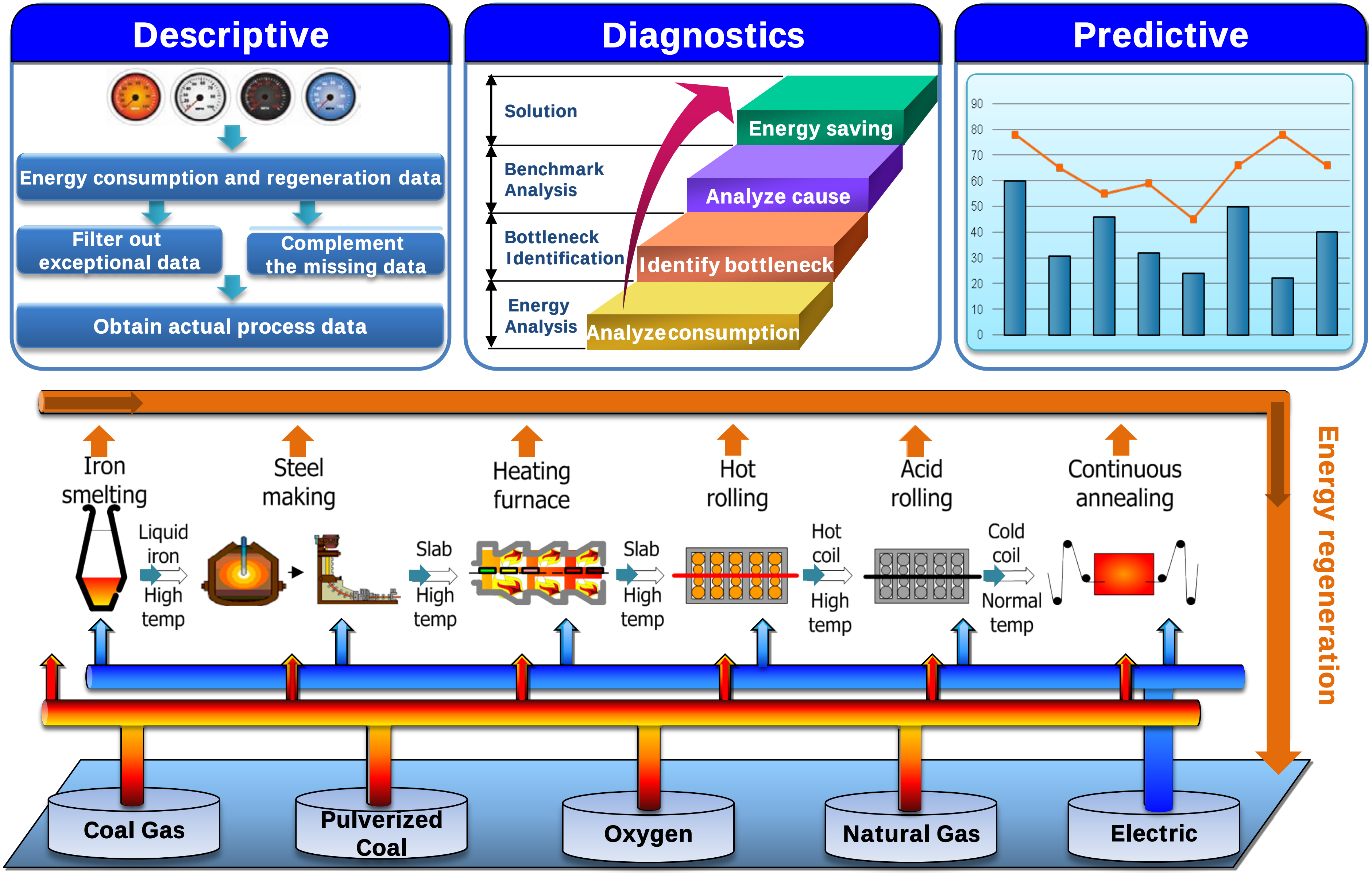
Data Analytics

- **Monitoring Model** ⇨ Monitoring the strip tension
- **Diagnosis Model** ⇨ Locating the roller where the deviation occurs

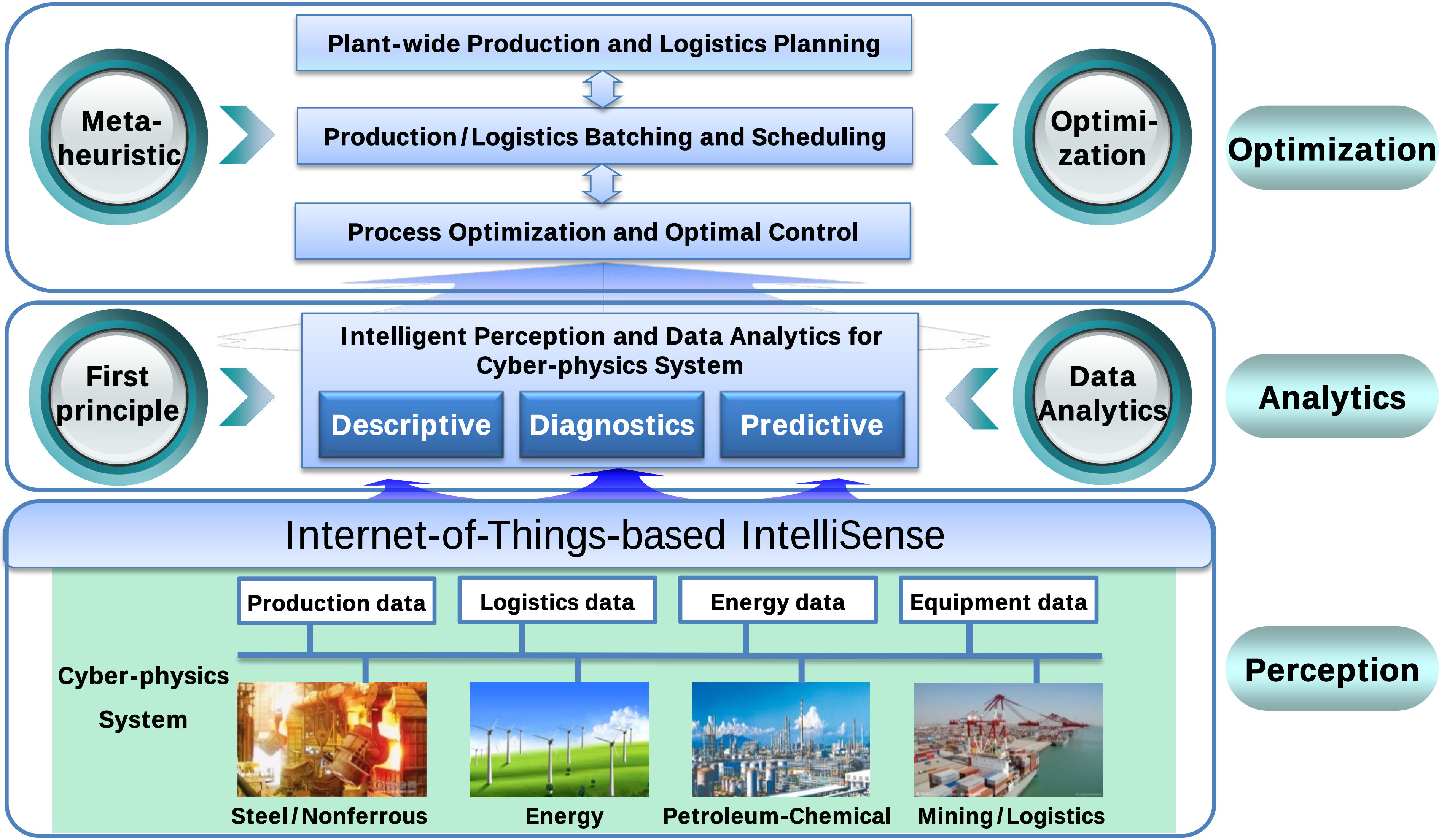




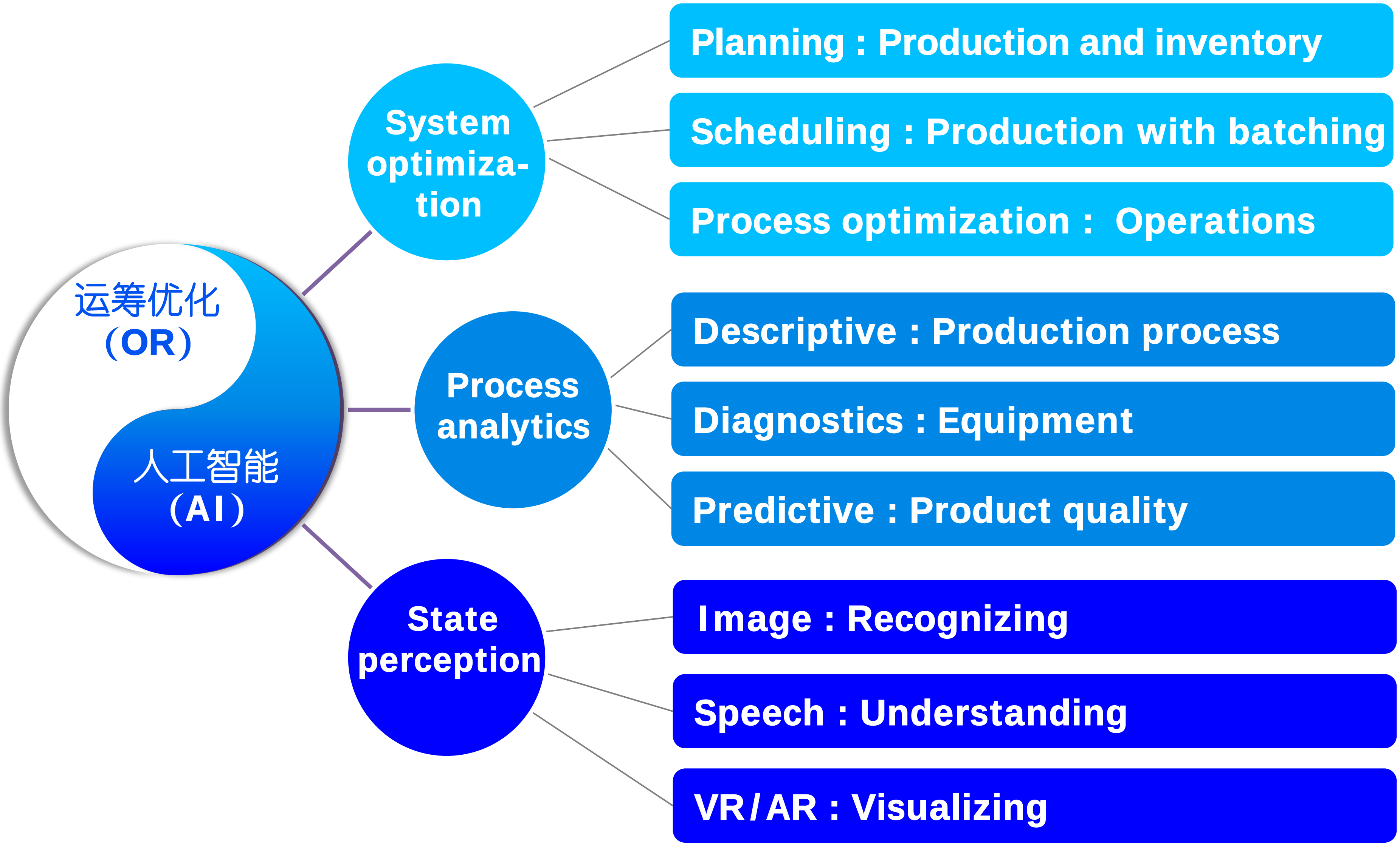
6. Data Analytics —— Energy analytics



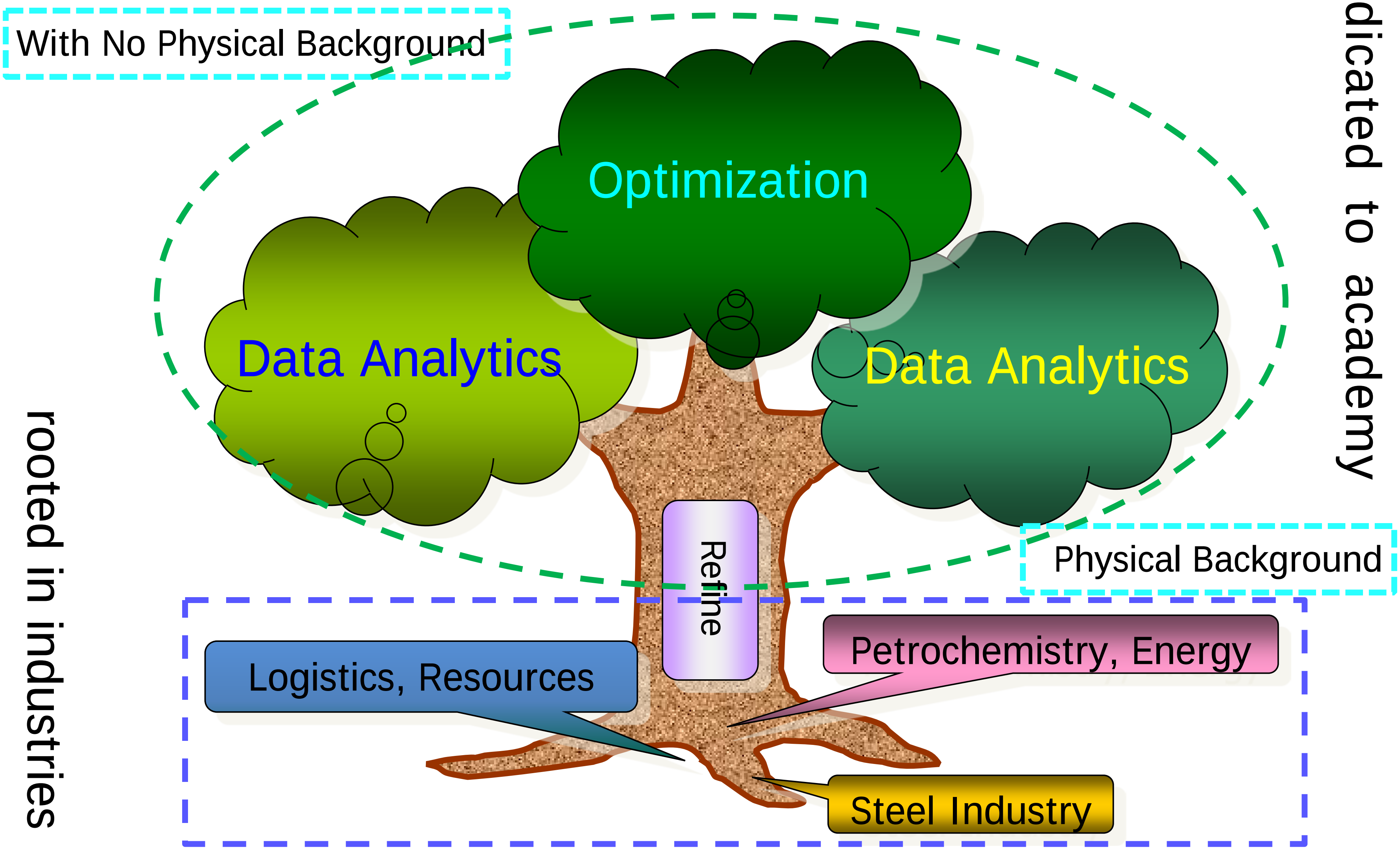
Conclusion and On-going Research



Conclusion and On-going Research



Conclusion and On-going Research



Thank You !

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November 21 2019