Scheduling with Machine Learning

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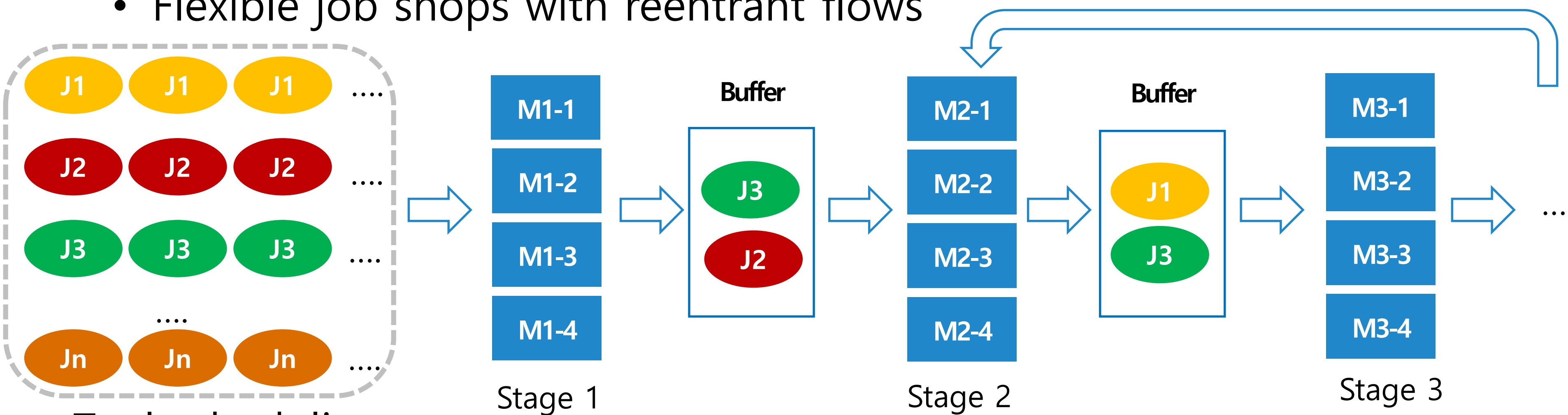
Scheduling with Machine Learning

- Scheduling is field of study concerned with optimal allocation of resources, over time, to a set of tasks.
  - Semiconductor/LCD, steel, automotive, battery, biopharmaceutical
- Machine learning approaches are used for scheduling in manufacturing, such as determining weights of dispatching rules, assigning jobs to machines, etc.

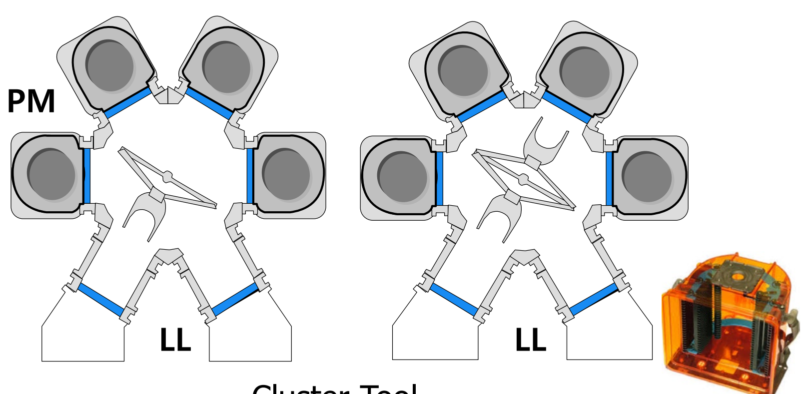
Sources:
https://spectrum.ieee.org/chips-act-of-2022
https://www.howden.com/en-gb/industries/industrial/metal-processing/steel-making
https://inc42.com/buzz/ril-ola-electric-rajesh-exports-pli-scheme-pacts-ev-battery-manufacturing/
https://www.europeanpharmaceuticalreview.com/news/173809/trends-in-biopharma-contract-manufacturing-2022/

Semiconductor Manufacturing

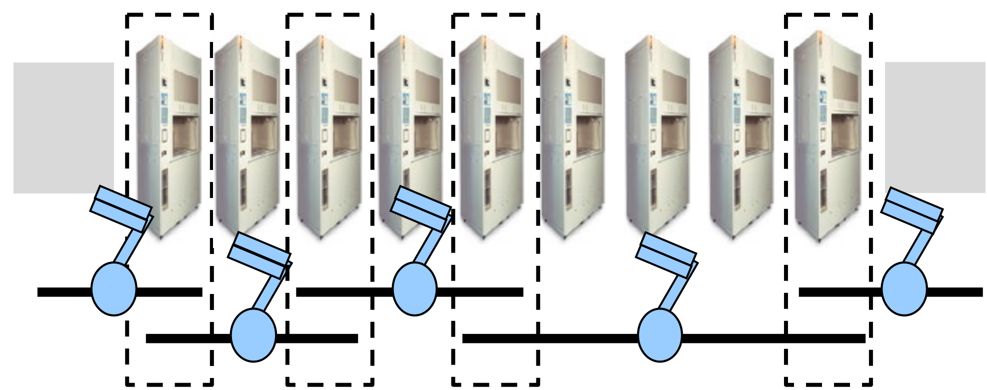
- Scheduling problems in semiconductor manufacturing
  - Production scheduling
    - Flexible job shops with reentrant flows



  - Tool scheduling
    - Robot sequencing problem



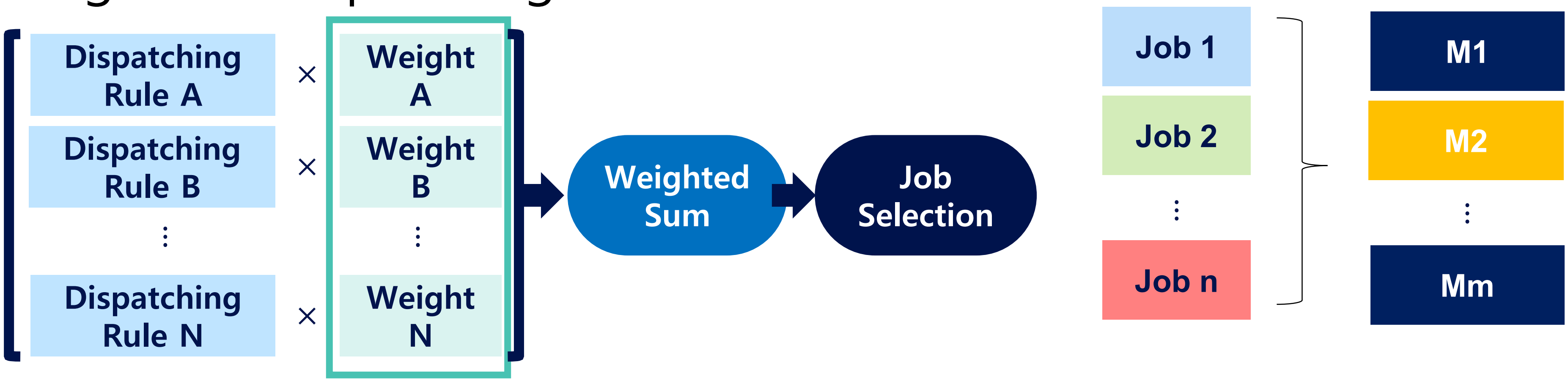
Cluster Tool



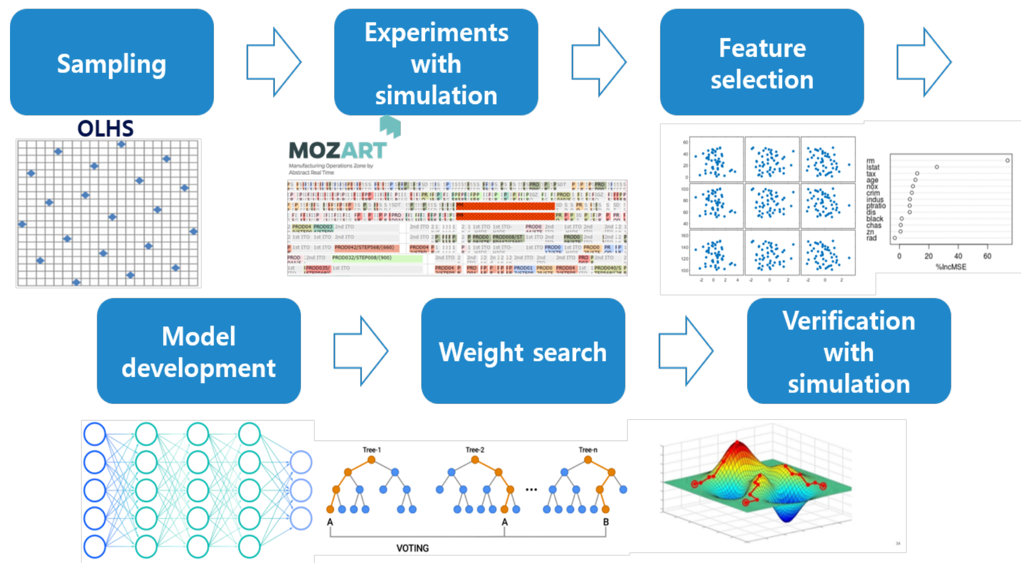
Wet Station

Semiconductor Manufacturing

- Weights of dispatching rules



- Dispatching rules
  - SPT, LPT, EDD, etc
- Weights of dispatching rules between 1 and 100,000
- How to obtain an optimal weight set?
  - (SPT, LPT, EDD) = (1, 10, 100)
  - Model development
    - Input – factory state, dispatching rule weights
    - Output – KPI



Source:
https://www.ibm.com/uk-en/cloud/learn/neural-networks
https://blog.tensorflow.org/2021/05/introducing-tensorflow-decision-forests.html

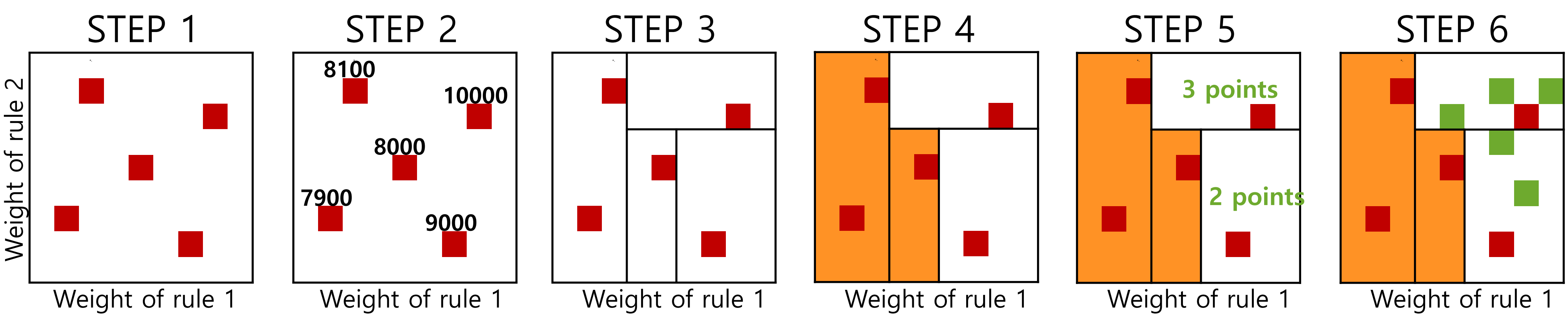
Semiconductor Manufacturing

- Weights of dispatching rules

Input: Initial sample size
Number of iterations
Key performance indicator (KPI)

Repeat: Steps 2 ~ 6
Output: **The best weight set**

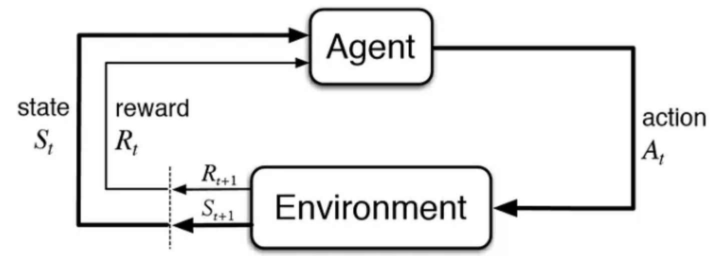
1. Initial Sampling	2. KPI Evaluation	3. Search Space Segmentation	4. Segment Elimination	5. Sampling Size Determination	6. Weight Set Generation
▪ Sample initial weight sets with OLHS	▪ Obtain KPI with each weight set	▪ Segment the search space of weights	▪ Eliminate several segments	▪ Assign sampling number for each segment based on KPI	▪ Generate weight sets using information of the best weight set

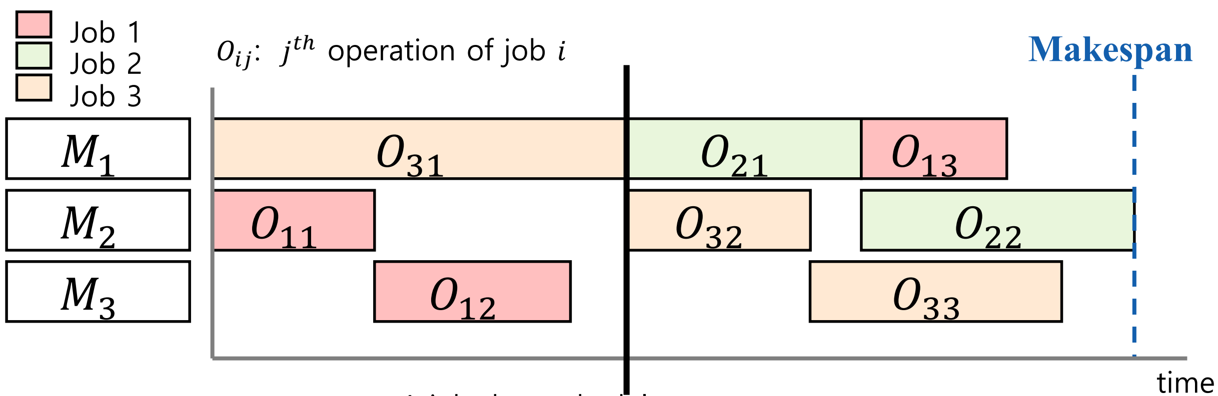


J.-H. Lee, Y. Kim, Y. B. Kim, B.-H. Kim, G.-H. Jung, and H.-J. Kim*, "A sequential search method of dispatching rules for scheduling of LCD manufacturing systems," *IEEE Transactions on Semiconductor Manufacturing*, vol. 33, no. 4, pp. 496-503, 2020.

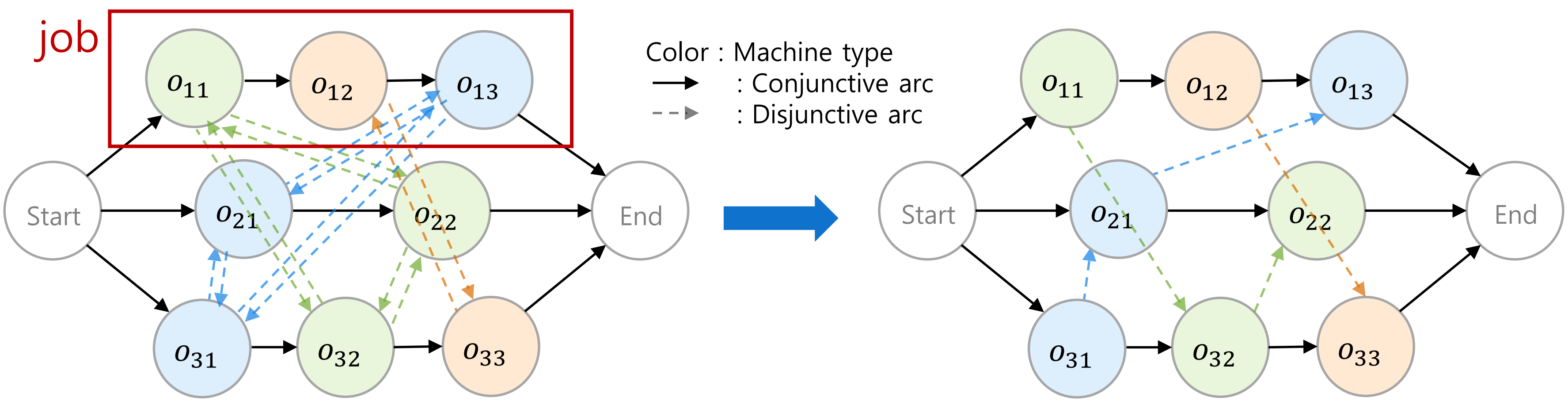
Semiconductor Manufacturing

- Job shop scheduling
  - Reinforcement learning is often used.
    - State, Action, Reward





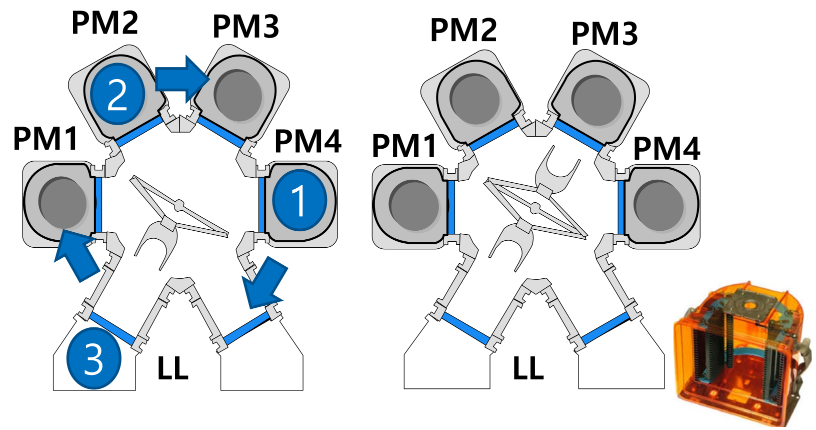
< A job shop schedule >

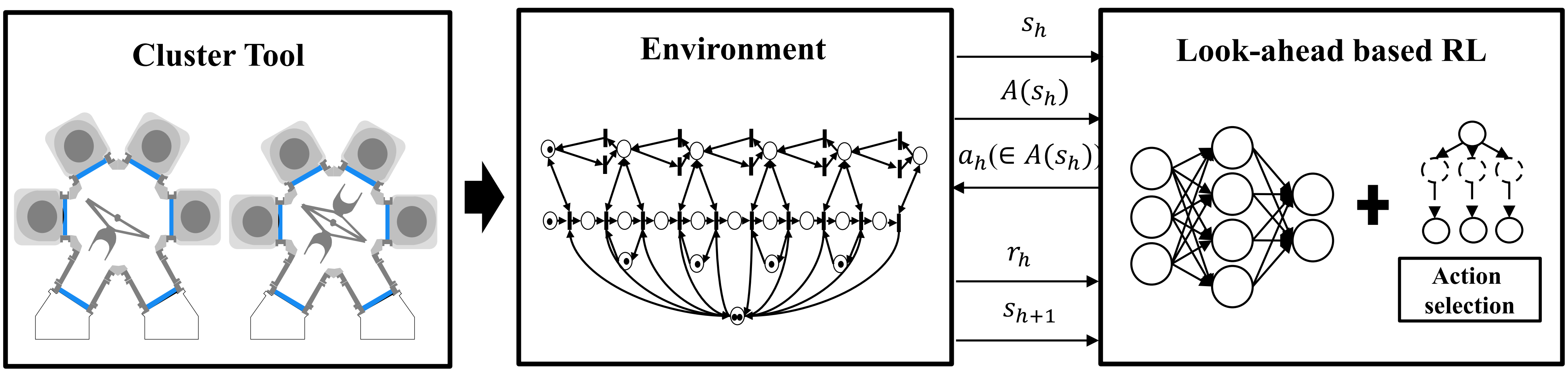


Source: https://towardsdatascience.com/reinforcement-learning-101-e24b50e1d292

Semiconductor Manufacturing

- Cluster tool scheduling
  - Multiple processing modules (PMs), a material handling robot, and loadlocks (LL)
  - Wafers need to be processed in PMs in sequence.
    - Diverse wafer flows
  - Robot task sequence
    - Systematic analysis for cyclic scheduling
  - Reinforcement learning is applied for noncyclic scheduling with diverse products.



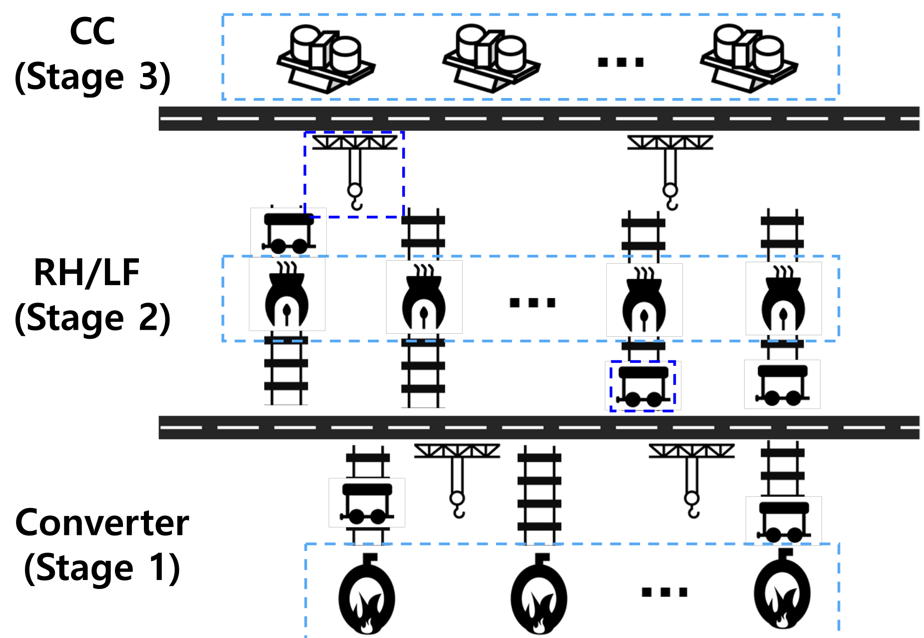


J.-H. Lee and H.-J. Kim*, "Reinforcement learning for robotic flow shop scheduling with processing time variations," *International Journal of Production Research*, vol. 60, no. 7, pp. 2346-2368, 2022.

Steel Manufacturing

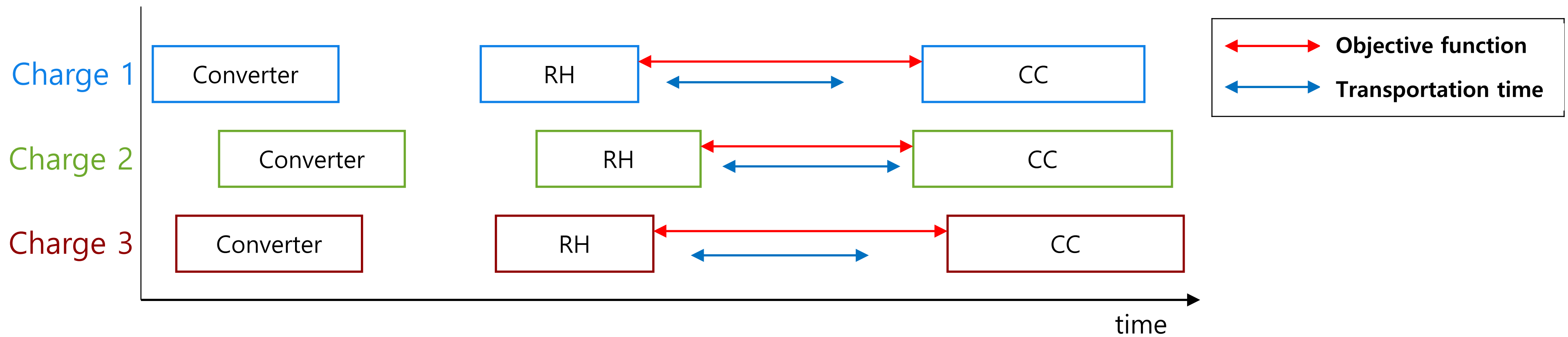
- Scheduling problems in steelmaking process
  - When charges arrive at the converter, engineers assign them to one of machines (RH (Ruhrstahl-Heraues) or LF (Ladle Furnace)).
  - RH and LF machines often require maintenance operations.
  - It is required to improve performance and assist engineers simultaneously.

  - Issues
    - Engineers have different preferences.
    - Hard to obtain some data, especially for the maintenance operations
  - Proposed approach
    - MILP + ML
    - MILP for improving the performance with limited information
    - ML for assisting engineers



Steel Manufacturing

- Scheduling problems in steelmaking process
  - MILP model
    - Objective function
      - Maximize the average time each charge spends between RH/LF and CC



    - Decision variables

Variables	Definitions
X_{isk}	1, if machine k is allocated to charge i in stage s. 0, otherwise.
B_{is}	Start time of charge i in stage s
Z_{iskt}	1, if charge i is the tth process of machine k in stage s. 0, otherwise.
SL_i	Time that charge i spends between RH and CC
WL_k	Workload of machine k
OL_{kt}	1, if machine k processes special charges in $t-1$th and tth processes. 0, otherwise.
TU_{kt}	1, if machine k uses a transfer car successively in $t-1$th and tth processes. 0, otherwise.
NMT_{kt}	1, if there is enough time for the maintenance before the machine k's tth process. 0, otherwise.

Steel Manufacturing

- Scheduling problems in steelmaking process
  - MILP model
    - Constraints

No.	Constraints	
(1)	$B_{is} + p_{is} + t_{kl} \leq B_{i,ns(i,s)} + M \times (2 - X_{isk} - X_{i,ns(i,s),k})$	$\forall\, i \in I, s \in S - \{CC\}, k \in K, l \in K$
(2)	$B_{is} + p_{is} + a_k \leq B_{jw} + M \times (2 - Z_{iskt} - Z_{j,w,k,t+1})$	$\forall\, i,j \in I, i \neq j, s, w \in S, k \in K,$ $t = 1, \dots, n-1$
(3)	$\sum_{k \in K_i^s} X_{isk} = 1$	$\forall\, s \in S, i \in I^s$
(4)	$B_{i,CF} = f_{i,CF}, X_{i,CF,k_i^{CF}} = 1$	$\forall\, i \in I$
(5)	$B_{i,CC} = f_{i,CC}, X_{i,CC,k_i^{CC}} = 1$	$\forall\, i \in I$
(6)	$SL_i = B_{i,CC} - (B_{i,RF1} + p_{i,RF1})$	$\forall\, i \in I^{RF1}$
(7)	$lb_{SL} \leq SL_i$	$\forall\, i \in I$
(8)	$SL_i \leq ub_{SL}$	$\forall\, i \in I$

(1): Flow constraints of each charge

(2): Machine conflicts & Minimum idle time (for the logistics)

(3): Machine allocations

(4)-(5): Converter and CC are given

(6)-(8): Time between RH and CC (objective function)

Steel Manufacturing

- Scheduling problems in steelmaking process
  - ML approach

			1st stage	3rd stage			1st stage		2nd stage		3rd stage	
	No.	Type	Converter	Cont. Caster	2nd refining code	Assignment	1st start	1st end	2nd start	2nd end	3rd start	3rd end
Already assigned	1	AAA	3	2	D	1RH	0:00	0:30	0:40	1:00	1:10	1:30
	2	BBB	2	3	E	2RH	0:10	0:40	0:50	1:10	1:20	1:40
	3	CCC	1	4	F	3RH	0:20	0:50	1:00	1:20	1:30	1:50
	4	DDD	3	1	G	LF	0:30	1:00	1:10	1:30	1:40	2:00
	5	AAA	2	2	H	1RH	0:40	1:10	1:20	1:40	1:50	2:10
	6	BBB	1	3	D	2RH	0:50	1:20	1:30	1:50	2:00	2:20
	7	CCC	3	4	E	3RH	1:00	1:30	1:40	2:00	2:10	2:30
	8	DDD	2	1	F	LF	1:10	1:40	1:50	2:10	2:20	2:40
	9	AAA	1	2	G	LF+1RH	1:20	1:50	2:00	2:20	2:30	2:50
	10	BBB	3	3	H	1RH	1:30	2:00	2:10	2:30	2:40	3:00
Current	11	CCC	2	4	D		1:40	2:10			2:50	3:10
Queue	12	DDD	1	1	E		1:50	2:20			3:00	3:20
	13	AAA	3	2	F		2:00	2:30			3:10	3:30
	14	BBB	2	3	G		2:10	2:40			3:20	3:40
	15	CCC	1	4	H		2:20	2:50			3:30	3:50
	16	DDD	3	1	D		2:30	3:00			3:40	4:00
	17	AAA	2	2	E		2:40	3:10			3:50	4:10
	18	BBB	1	3	F		2:50	3:20			4:00	4:20
	19	CCC	3	4	G		3:00	3:30			4:10	4:30
	20	DDD	2	1	H		3:10	3:40			4:20	4:40

<An example of real data>

- Descriptions of basic features

① Characteristics: Special charges, Low carbon

② Secondary refining code: A set of candidate machines

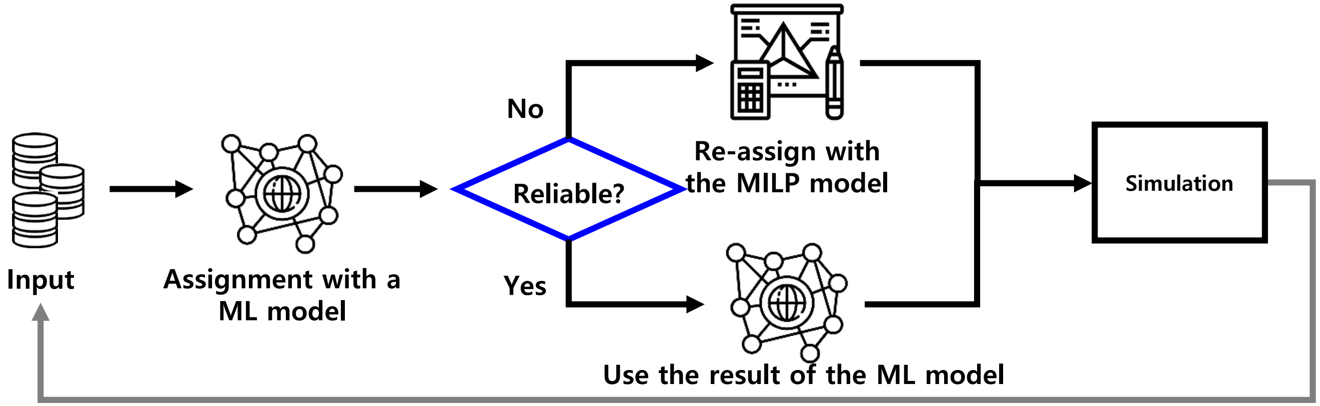
③ Converter, Continuous caster: Machines of 1st and 3rd stages

④ Top charge: First charge of a cast

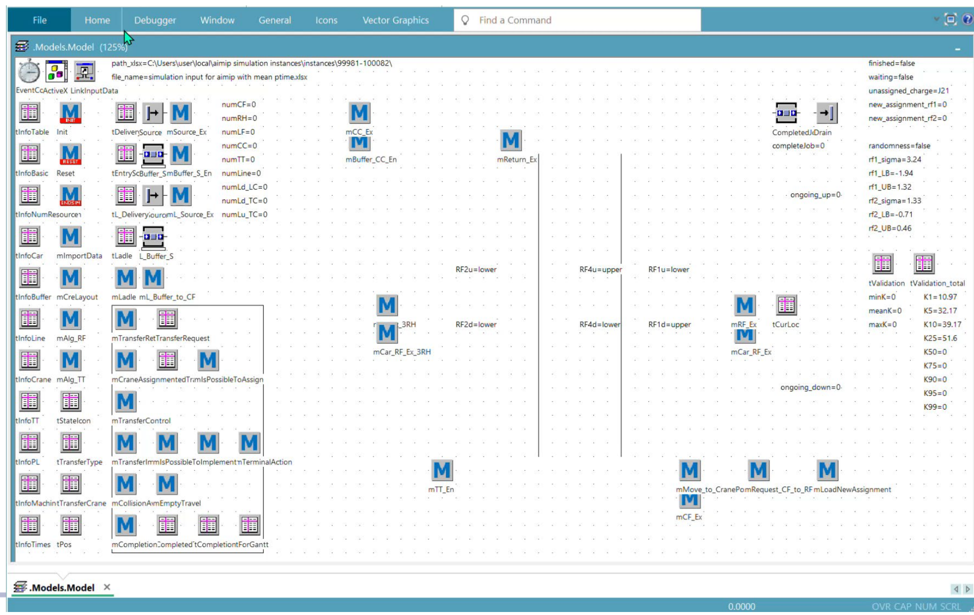
⑤ More features…

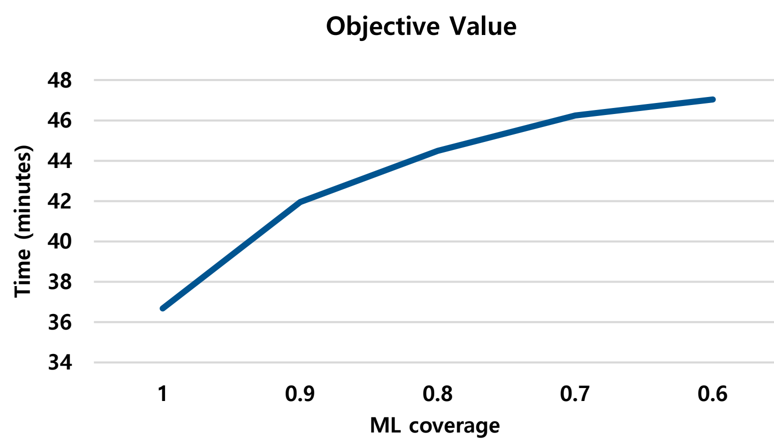
Steel Manufacturing

- Scheduling problems in steelmaking process
  - MILP+ML model



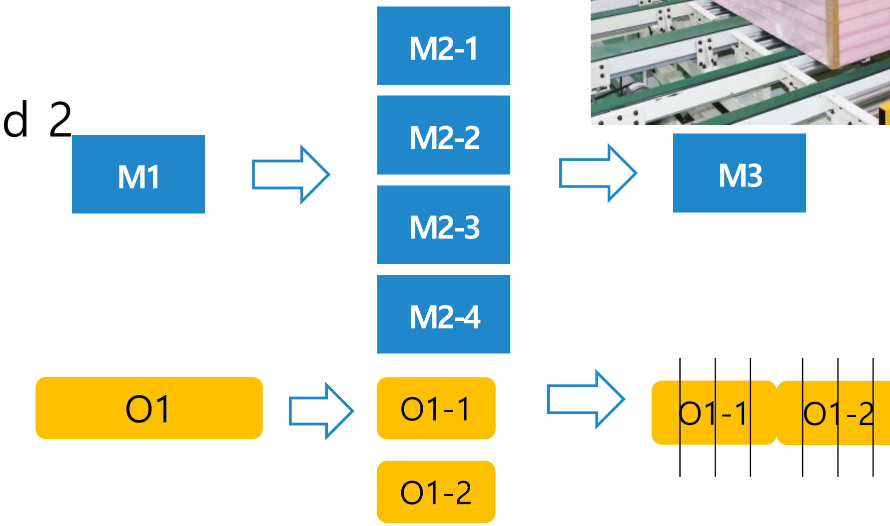
	Accuracy	Macro F1
KNN	0.5563	0.5059
AdaBoost	0.5594	0.5531
Ridge Regression	0.6459	0.5166
SVM	0.6678	0.6438
Logistic Regression	0.6735	0.6475
Random Forest	0.7468	0.6580
Multi-Layer Perceptron	0.7723	0.7006
Gradient Boosting	0.8105	0.7285
XGBoost	0.8213	0.7417
CatBoost	0.8451	0.7691
LightGBM	0.8492	0.7561
LSTM	0.9173	0.8144
GRU	**0.9664**	**0.9530**

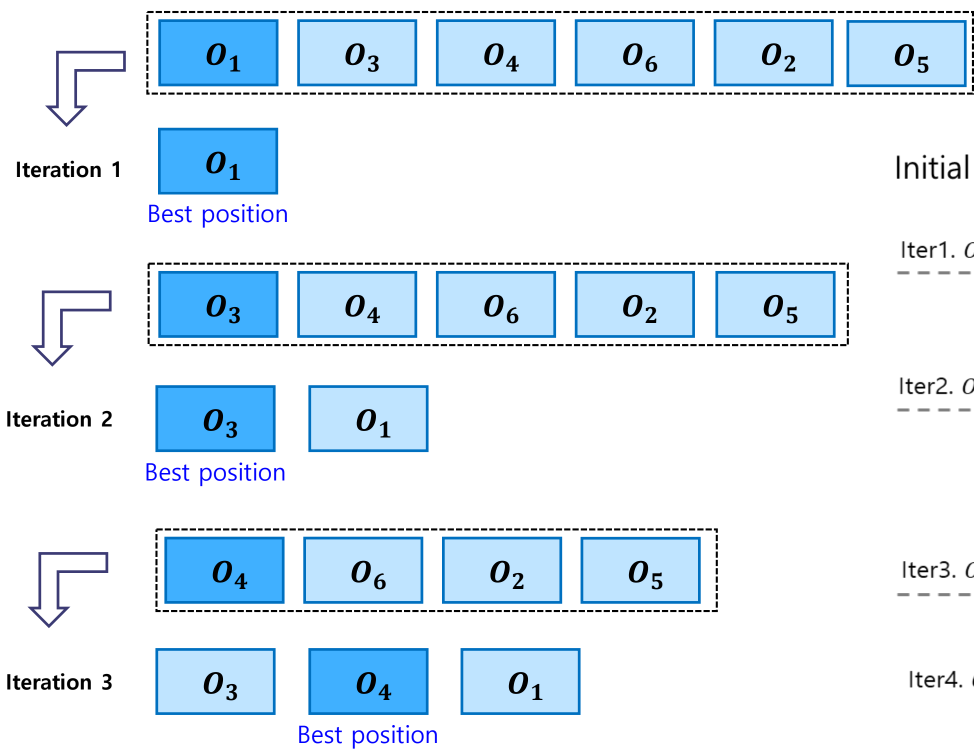


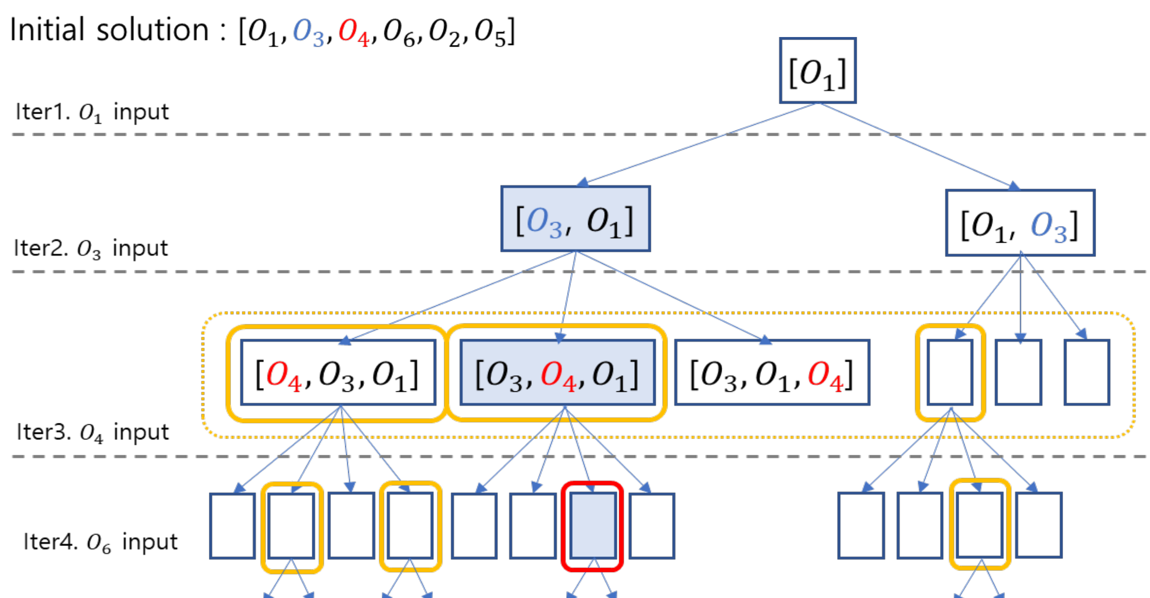


Insulation Manufacturing

- Hybrid flow shop scheduling
  - Foaming → Curing → Cutting
  - No waiting time between stages 1 and 2
  - No buffer between stages 2 and 3
  - Tardiness + Makespan
  - NEH based algorithm



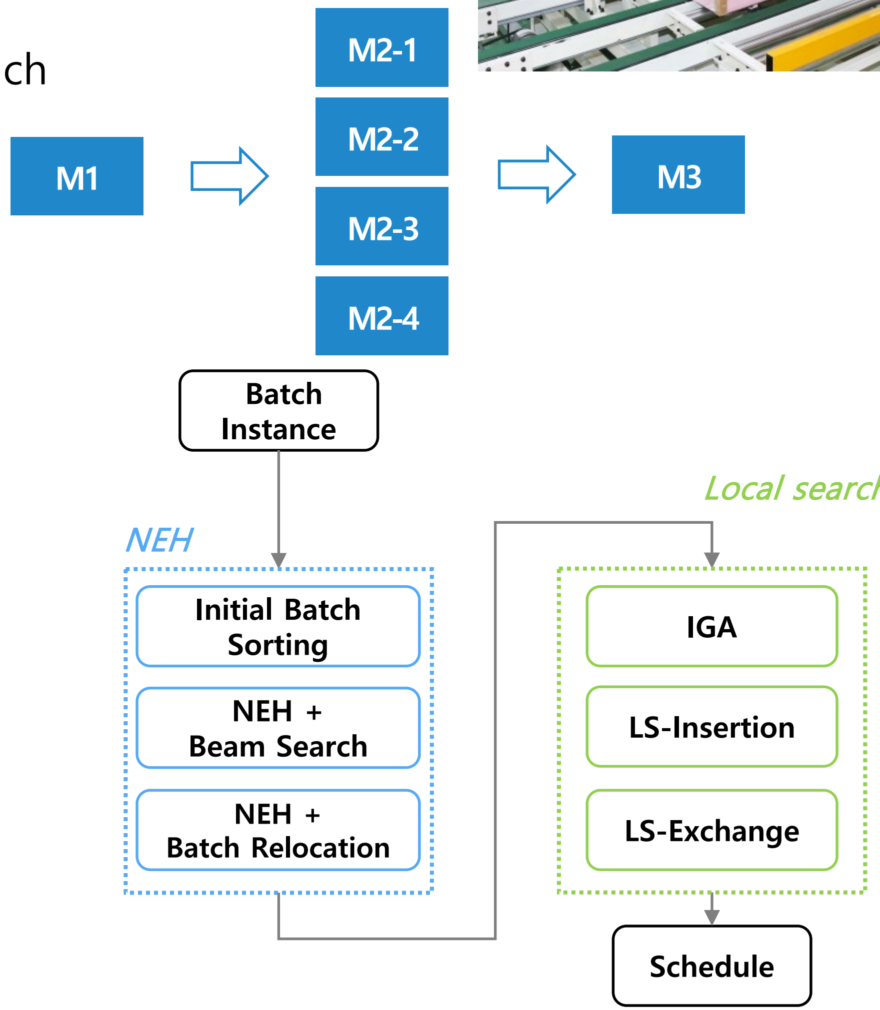


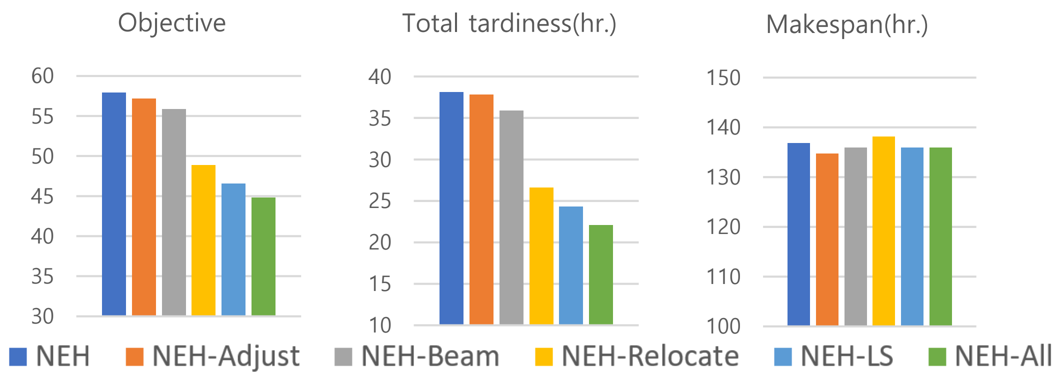


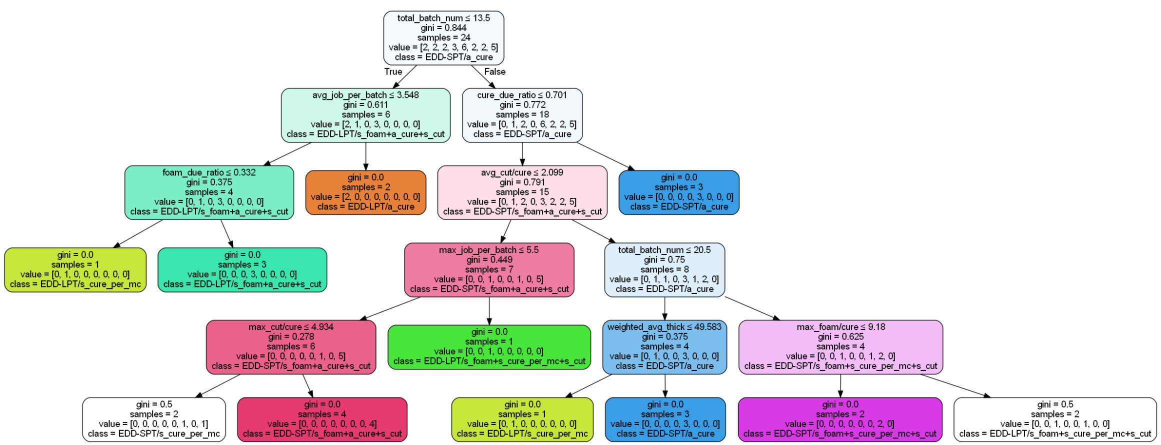
Source: https://weekly.hankooki.com/news/articleView.html?idxno=6791764

Insulation Manufacturing

- Hybrid flow shop scheduling
  - Machine learning for initial sorting
    - Features: due dates, processing times at each stage, factory state, job thickness…
    - Output: ordering rule (EDD, LPT…)



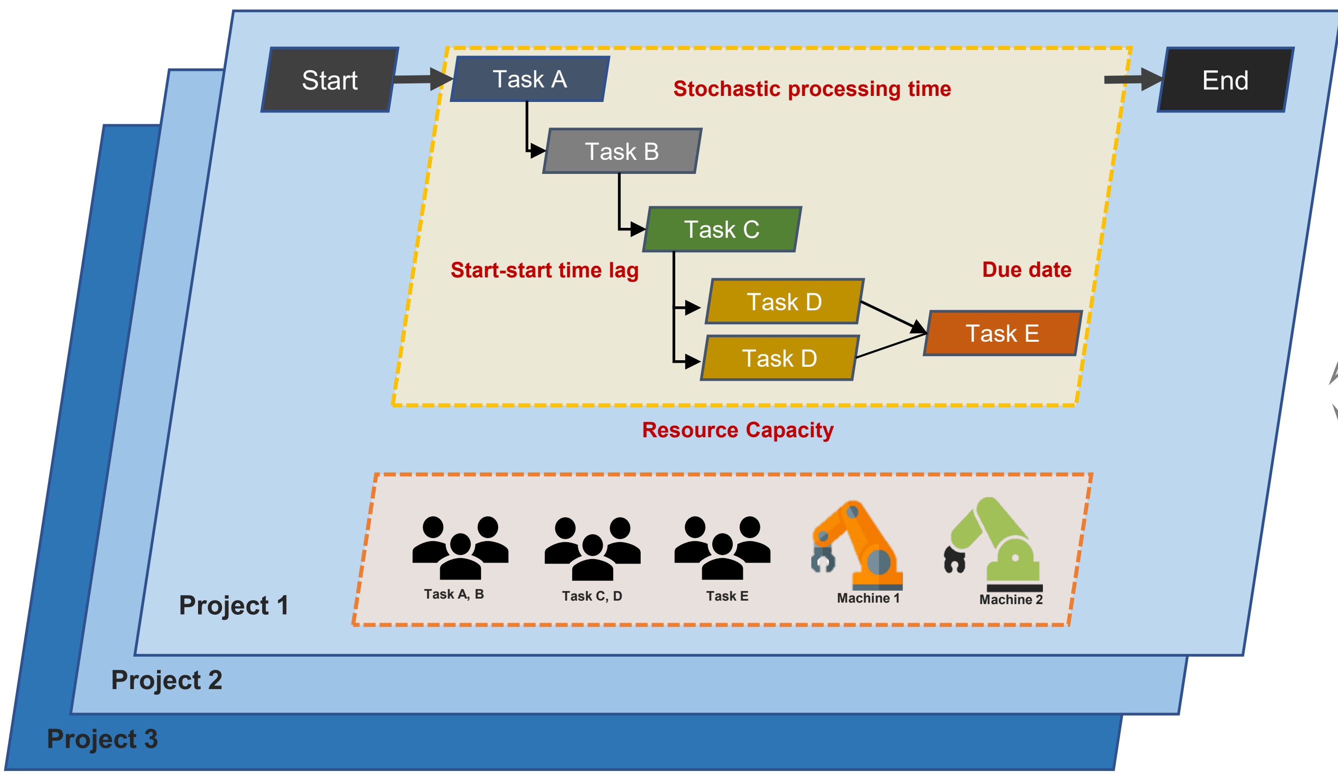




Source: https://weekly.hankooki.com/news/articleView.html?idxno=6791764

Project Scheduling for Shipbuilding

- Project scheduling with reinforcement learning
  - Resource-constrained project scheduling problem
    - Precedence relations, time lags, activity time uncertainty
    - Makespan minimization, resource leveling



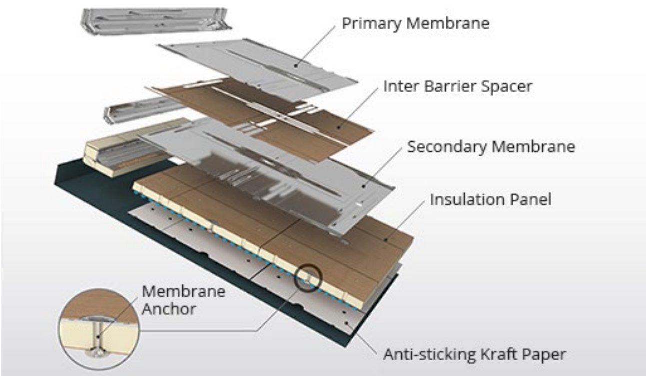
Shipbuilding

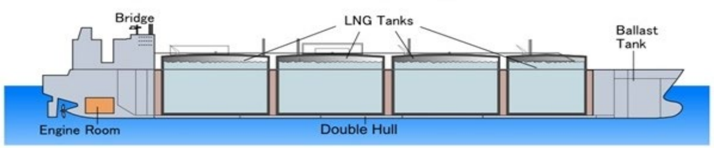
Construction

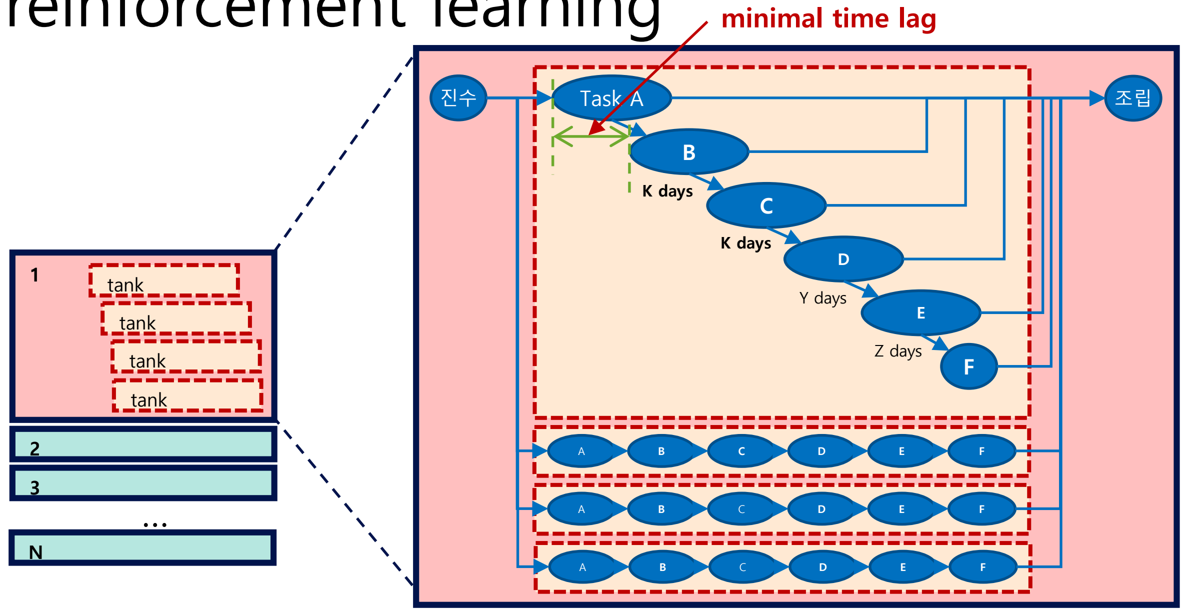
Source: https://blog.bizvibe.com/blog/top-shipbuilding-companies-world
https://www.insidehousing.co.uk/news/news/engie-sells-construction-and-services-arm-to-bouygues-in-6bn-deal-73267

Project Scheduling for Shipbuilding

- Resource leveling with reinforcement learning

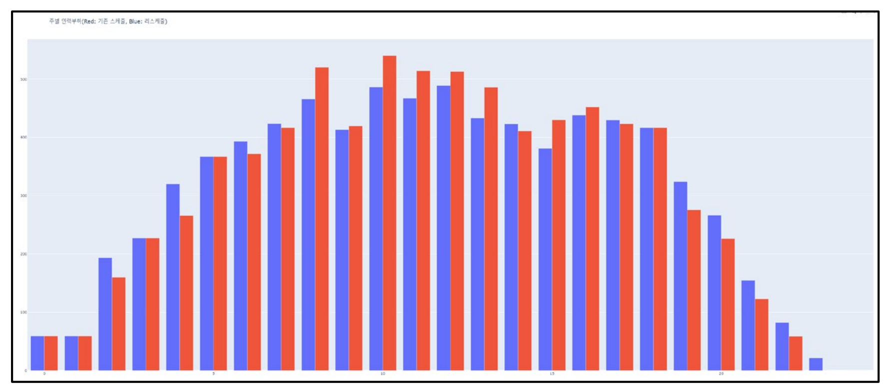






<Algorithm comparison>

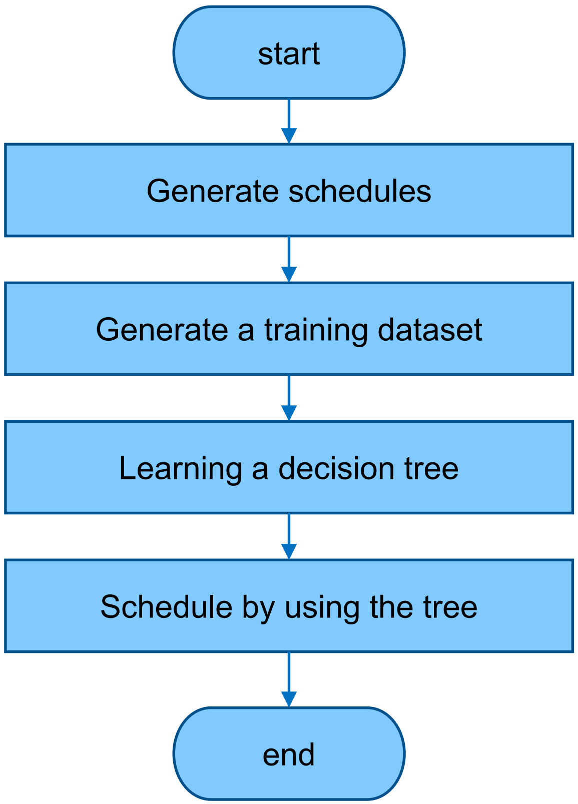
Objective	Time lag extension ratio	Greedy algorithm	Simulated annealing	RL
Std (obj: 175.054)	0.1	168.194	172.307	**160.104**
	0.2	160.500	169.655	**153.702**
	0.3	152.100	163.792	**148.367**



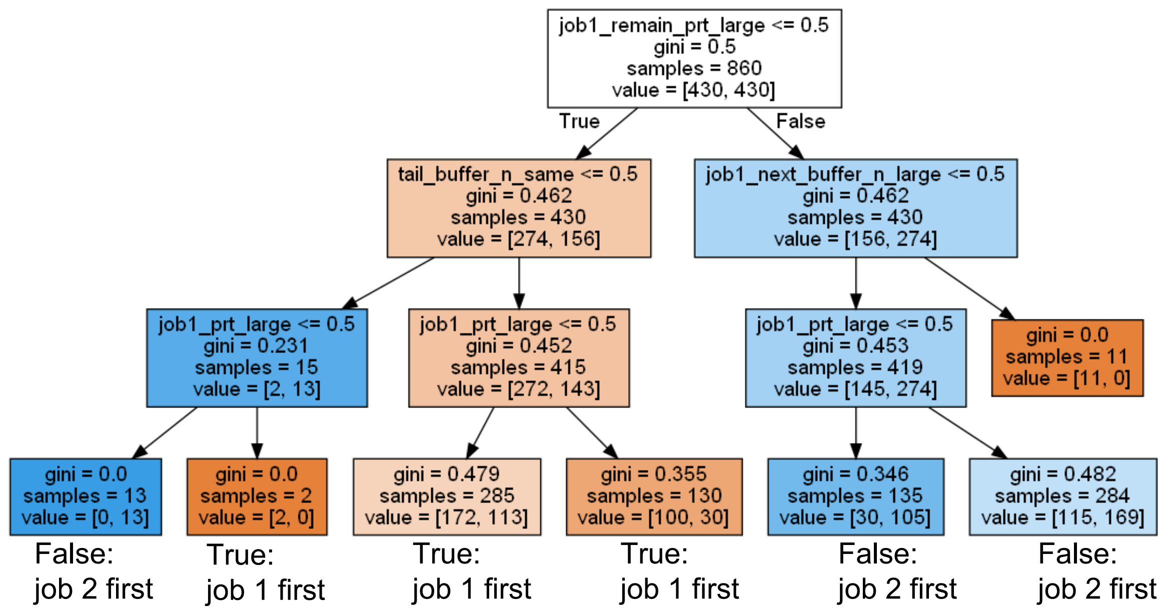
Source: http://www.kclng.co.kr/en/Technology/kc.php
https://blog.samsungshi.com/?page=3

Rule Extraction from Schedule Data

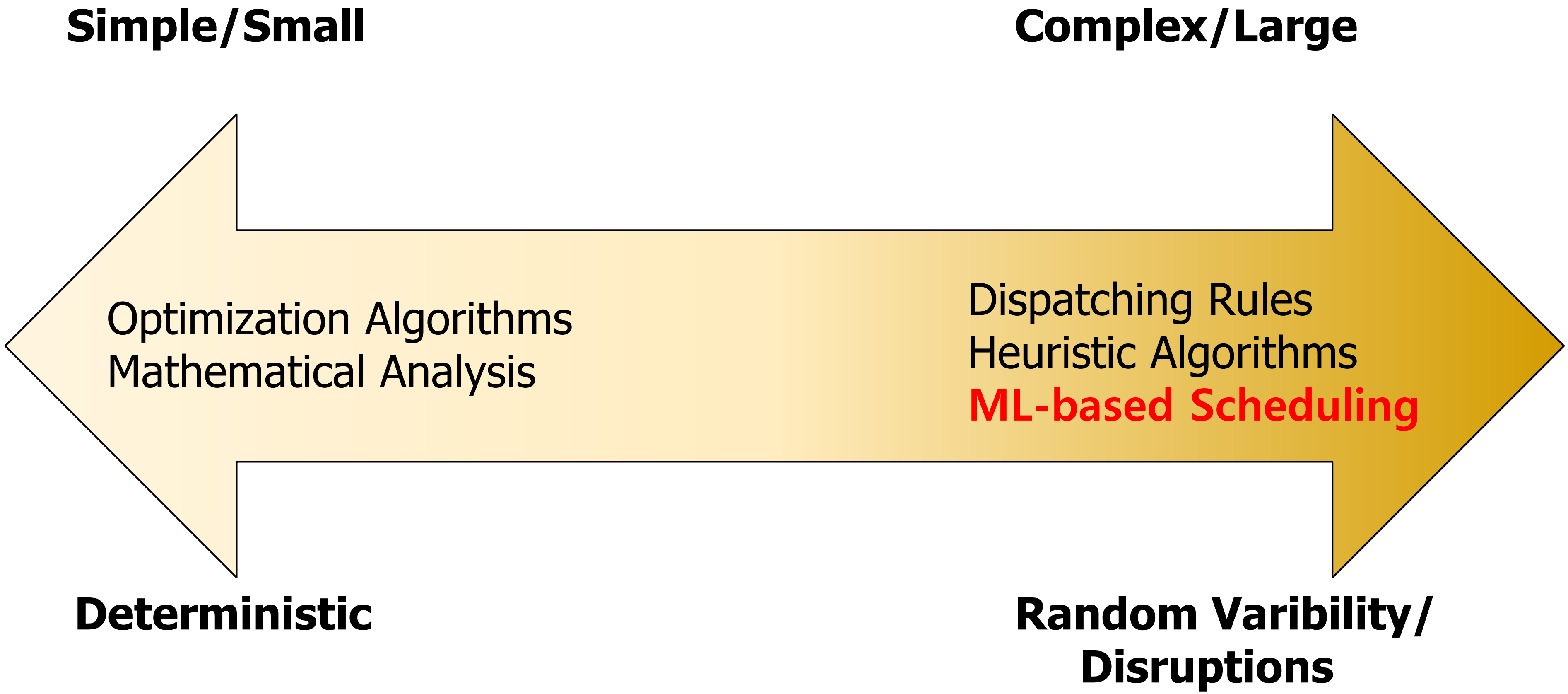
- Rule extraction with a decision tree
  - Olafsson, S., & Li, X. (2010). Learning effective new single machine dispatching rules from optimal scheduling data. International Journal of Production Economics, 128(1), 118-126.



job1 prt > job2 prt	job1 tail prt > job2 tail prt	job1 tail num > job2 tail num	job1 tail machine load > job2 tail load	job 1 first?
True	True	True	False	True
False	False	False	True	False
True	True	False	False	True



Scheduling with ML



Scheduling with ML

- Scheduling with machine learning
  - Imitation learning
  - Solving subproblems with machine learning
  - Parameter selection for scheduling algorithms
  - New dispatching rule working well in a dynamic and unseen environment

	Exact Algorithm	**Meta-heuristic**	**Dispatching rule**	**ML**
Performance	**optimal**	good	**poor**	**?**
Real-time scheduling	X	X	O	O
Dynamic environment	X	X	O	O
Timing control for scheduling	O	O	X	Δ

- ML as one of useful tools for scheduling especially in a dynamic environment

Thank You.

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