Data centric approach for supply chain optimization

Tatsushi Nishi

Associate Professor

Osaka University

Outline of this talk

- Research Introduction
- Cell-based heuristic algorithm for Capacitated Multi-commodity Network Design Problem
- Simultaneous Optimization of Product Configuration and Supply Chain Planning Considering Customer's Participation in Product Design
- Machine Learning Approach Identification of objective function for Scheduling Problems

Introduction to Osaka University

Mathematical Science for Social Systems
Department of Systems Innovation
Graduate School of Engineering Science
Osaka University

bachelor students: 15,358
master students : 4,691
doctor students : 3,165
Total students : 23,214
International students: 2,480

Professors : 942
Associate Prof. : 1014
Assistant Prof. : 1151
Non-academic staff : 3113

Total staffs : 6,654

3 main campus

- Toyonaka campus
- Suita campus
- Minoo campus

Introduction of Engineering Science

Toyonaka campus (450000m^2)

School of Engineering

School of Science

School of Engineering Science

More basic than Engineering

Mathematical Science Department

- Finance and Insurance
- Data Science
- Mathematical Model

System Mathematics Research Group

Center for Mathematical Modeling
And Data Science, Osaka University

Brief Introduction: Associate Prof. Tatsushi Nishi

PhD Degree in Kyoto University (Chemical Engineering)

Assistant Professor of Okayama University (Electrical Engineering)

Associate Professor of Osaka University from 2006 (Mathematical Science for Social Systems)

March 2014-2017, Visiting Professor of Beijing University of Chemical Technology

June-Sept 2015, Visiting Professor of University of Hamburg, Germany

Research areas: system optimization, automation, supply chain planning and scheduling, combinatorial optimization, multi-robot control, public transport, process systems engineering

Courses taught: discrete optimization, graph theory operations research, intelligent mathematical programming

Associate Editor of IEEE Transactions on Automation Science and Engineering 2012- (Impact factor: 2.428 (2015), 2.162 (2014), 3.667 (2017))

Conference Editorial Board of IEEE ICRA (top robotics conference)

Our team

- Scheduling

  public transport, railway crew scheduling, airline scheduling
  transportation, routing, logistics, production scheduling

- Supply chain optimization

  production planning, supplier selection, revenue management,
  contract decision, quantity discounts or volume discounts

- Discrete event systems

  Petri nets, timed automata, modeling, optimization, automated guided
  vehicles, deadlock avoidance, Petri net decomposition technique

Collaboration with industries

- Semiconductor factory automation

  Control of automated guided vehicles for transportation

  Scheduling of cluster tool for silicon wafer production

- Railway scheduling automation

  railway crew scheduling in Japan Railway
  train-set scheduling with maintenance constraints
  shift scheduling

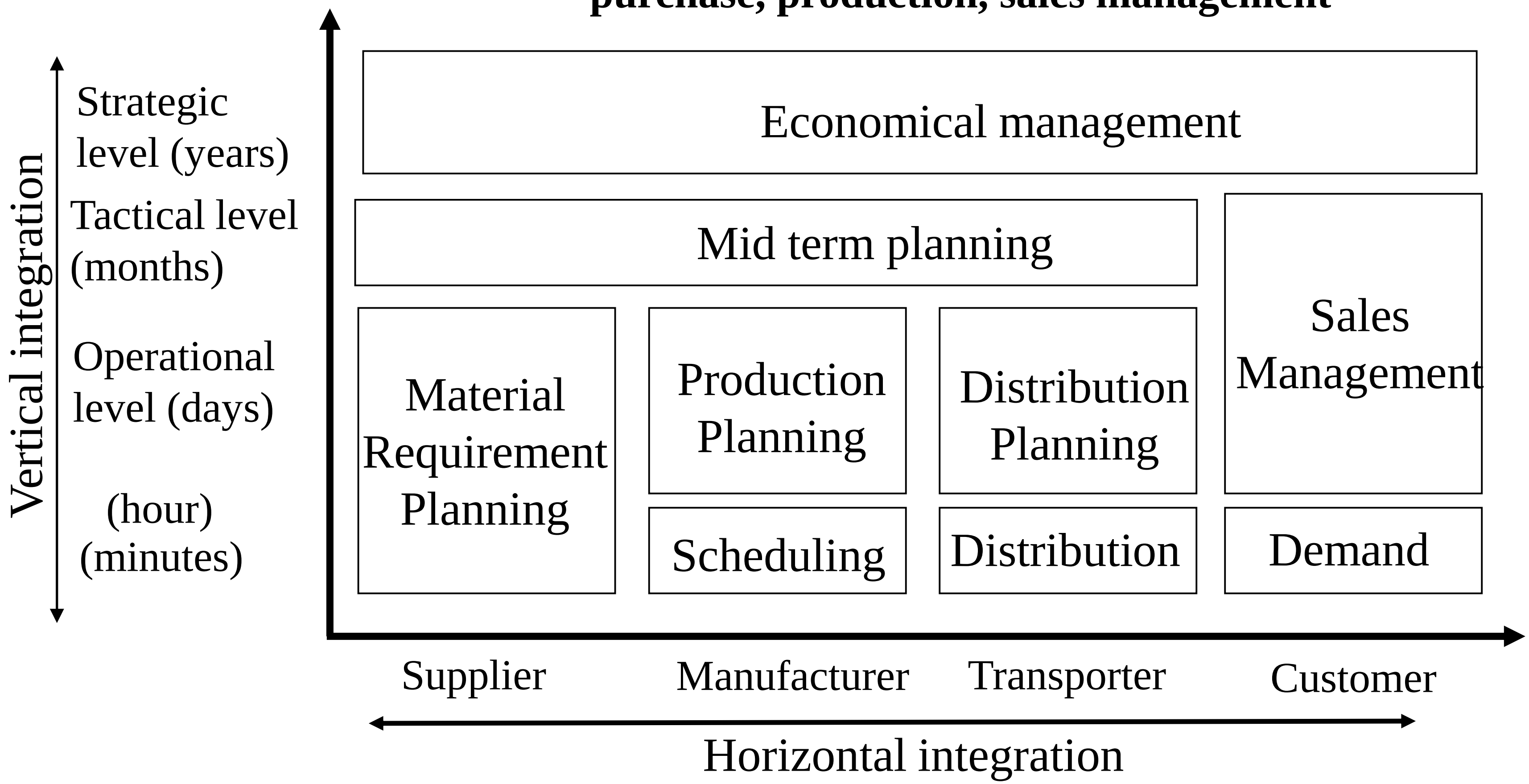
- Petroleum chemical industry automation

  International ship scheduling for crude oil transportation

  Transportation network design

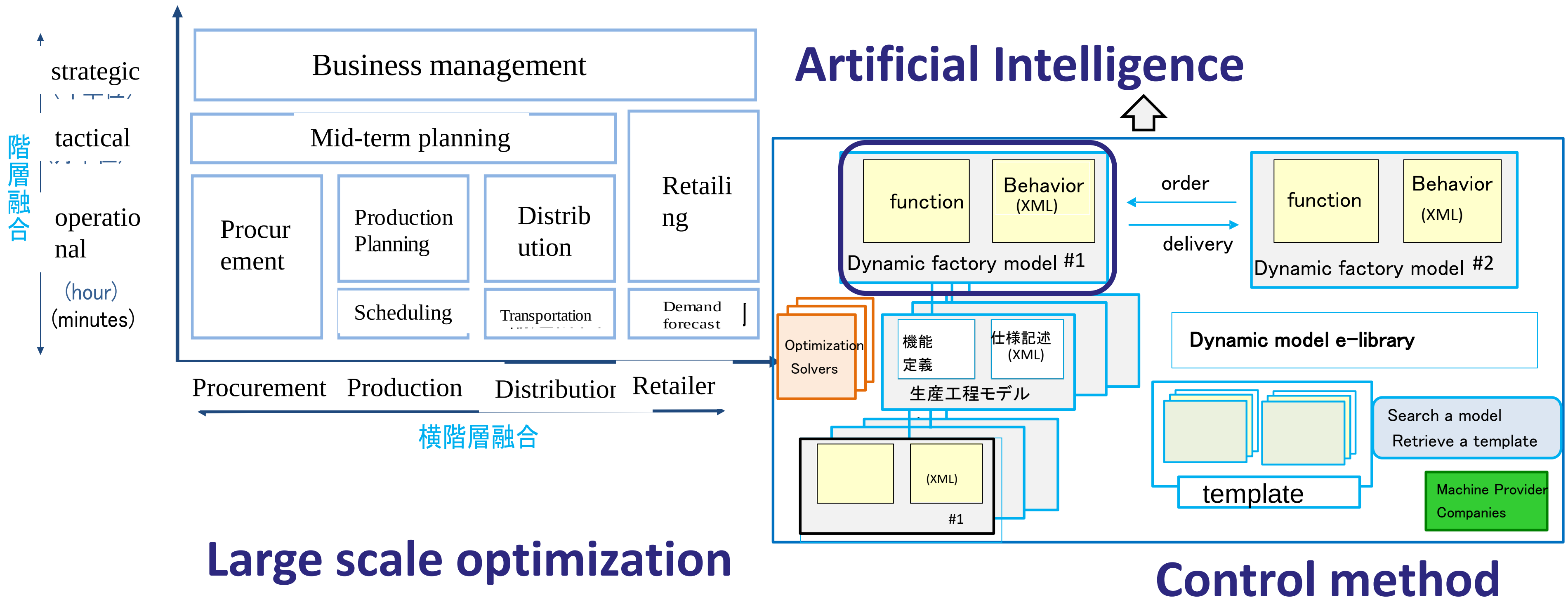
Supply chain optimization

Supply chain management: integrated optimization of material purchase, production, sales management



Single machine ⇨ Single factory ⇨ Multi factory ⇨ Multi company

Dynamic Model Construction Platform for Collaboration and Optimization among Enterprises in Smart Supply Chains



Research

- Real time data extraction and analysis
  Visualization, cloud computing, manufacturing control loop

Novelty

- Game theoretical approach for real time optimization of equilibrium solution
- Standardization of protocols (ISO), common resources for electrical-catalog

Lagrangian Relaxation and Cut Generation

Lagrangian relaxation for production scheduling

Relax machine capacity constraints

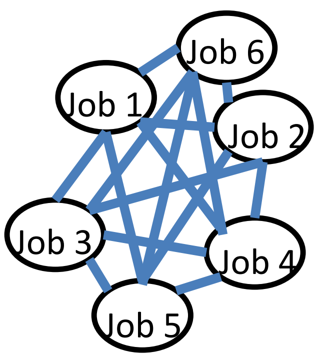
Decomposition into each single job-level subproblem (Luh et al. 1994)

Lagrangian relaxation with cut generation

Additional constraints are imposed to the related problem to derive better lower bound

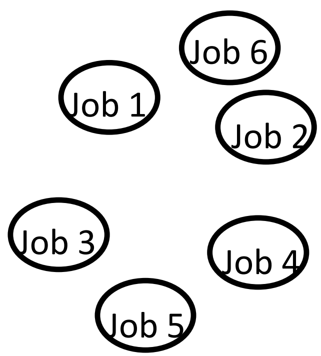
We developed a novel dynamic programming recursion with tree structure

T. Nishi et al. Lagrangian relaxation with cut generation for hybrid flowshop scheduling problems to minimize the total weighted tardiness (2010) Computers and Operations Research, IF:2.962 (cited in scopus 39 times)



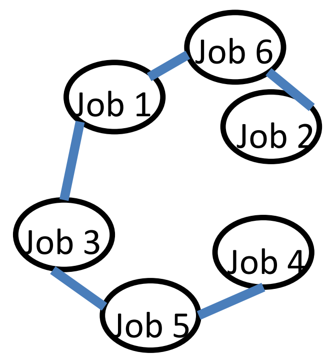
Original problem

$O(H^M)$



Ordinary Lagrangian Relaxation

$O(MH)$



Cut generation with tree structure

$O(MH + 2p_{max}|C_i|)$

Logic-based Benders decomposition with CMU

Master problem

$$\min \ f(x, y)$$

$$\text{s. t. } \ \color{red}{\overline{C}_1(x), \overline{C}_2(x), \ldots, \overline{C}_k(x)}$$

$$x \in D_x$$

$$\xrightarrow{\ \bar{x}\ }$$

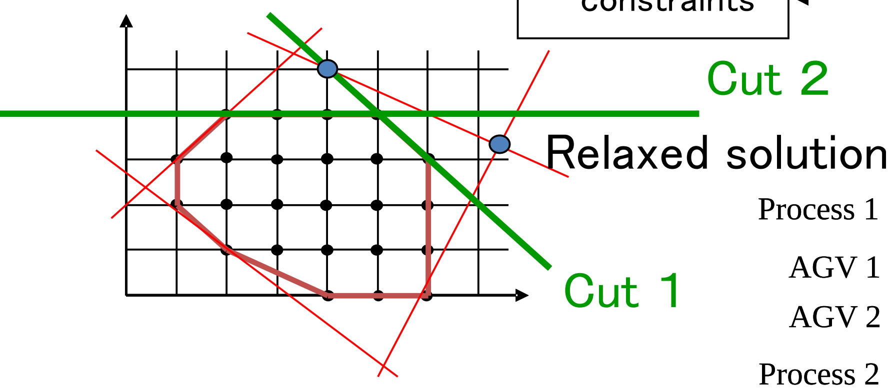
Subproblem

$$\min \ f(\bar{x}, y)$$

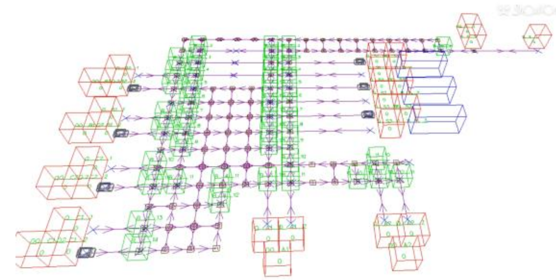
$$\text{s. t. } \ C(\bar{x}, y)$$

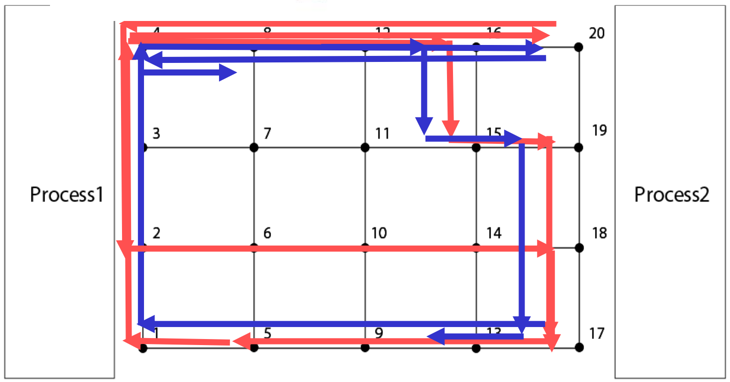
$$y \in D_y$$

Cut generation constraints



Logic-based Benders (Hooker, 1994)





2 Process 2 AGVs

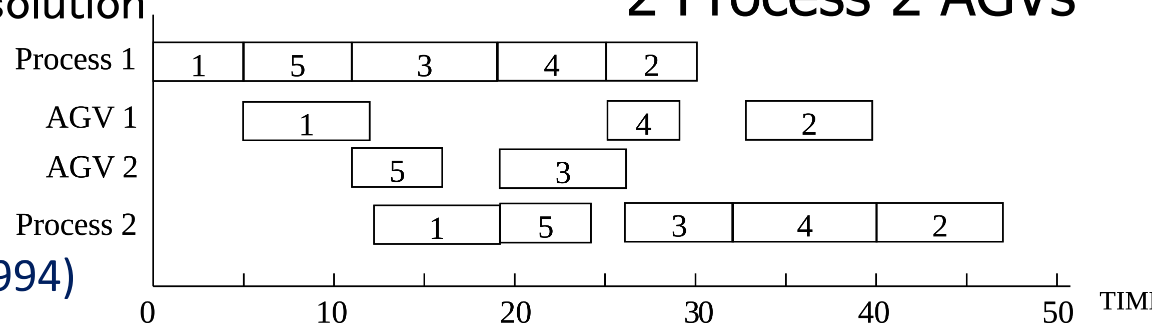
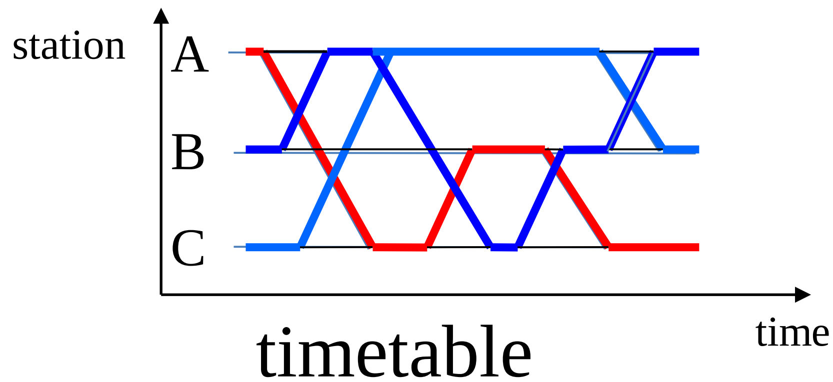


Fig.1 Gantt Chart

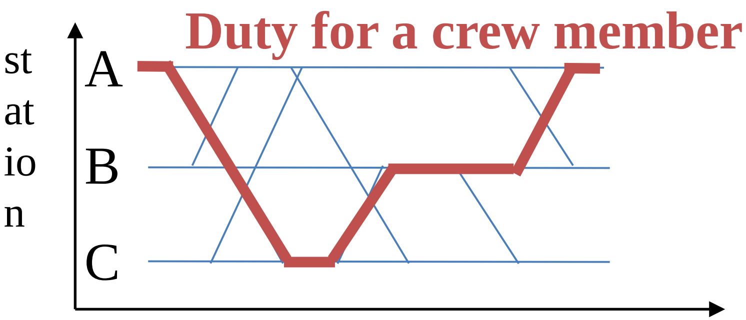
T. Nishi, Y. Hiranaka, I. Grossmann, A bilevel decomposition algorithm for simultaneous production scheduling and conflict-free routing for automated guided vehicles Computers and Operations Research, IF:2.962 (cited 42 times in scopus)

Optimization in Public Transport with Prof. Voss

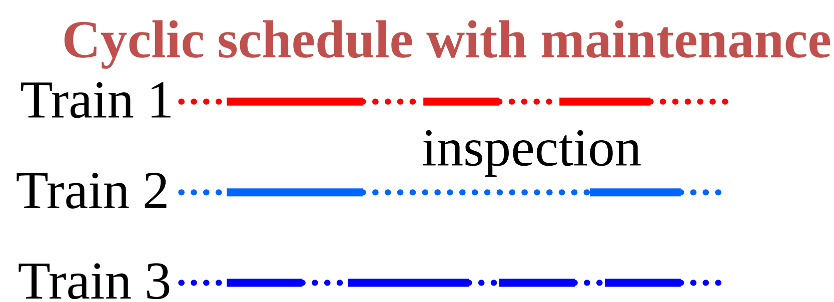
Railway crew scheduling



Railway rolling stock planning

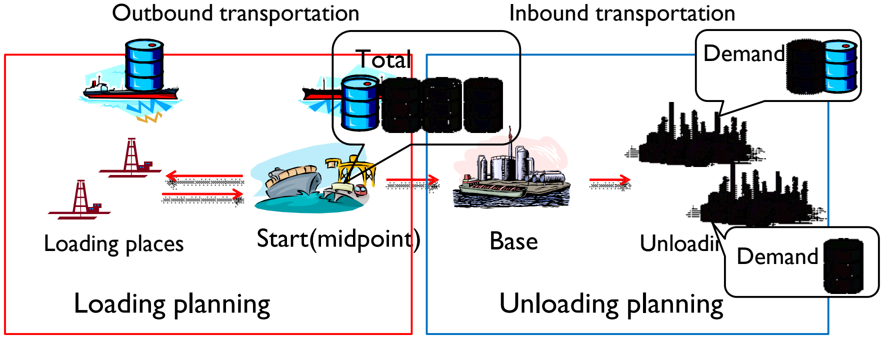


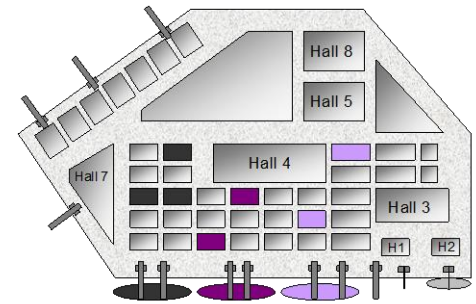
Heuristics for Mathematical Programming Based Railway Crew Scheduling, Awarded by Scheduling Society of Japan



T. Nishi et al., A Combined Column Generation and Heuristics for Railway Short-Term Rolling Stock Planning with Regular Inspection Constraints, Computers and Operations Research, IF:2.962 (2017)

Matheuristic and Logistic Optimization



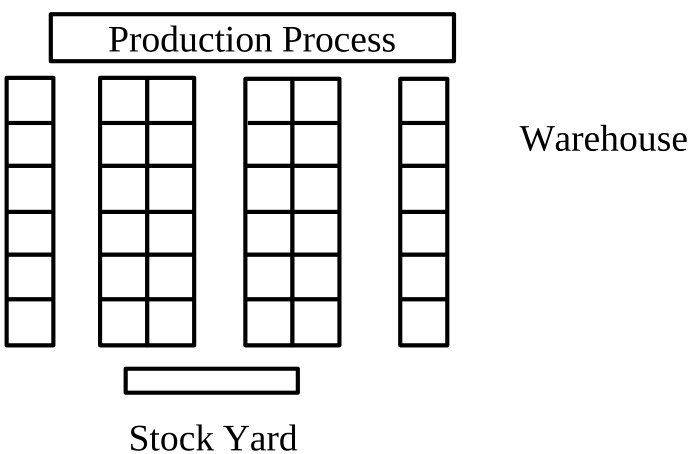


Split-delivery vehicle routing problem

T. Nishi, T. Izuno, Column generation approach to Ship scheduling problems for international crude oil Transportation Comp. Chem. Engng. (2014), IF: 3.113

Dynamic berth allocation

T. Nishi et al. , A dynamic programming-based Matheuristic for the dynamic berth allocation problem Annals of Operations Research (2018), IF 1.864



	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
Crew 1	Roster 1	Roster 2		Holiday	Holiday	Roster 6	Holiday
Crew 2	Roster 5			Roster 1	Holiday	Roster 2	
Crew 3	Roster 3	Roster 4	Roster 2		Roster 6	Holiday	Holiday
Crew 4	Holiday	Roster 5			Holiday	Roster 3	Roster 1
Crew 5	Roster 2		Holiday	Holiday	Roster 3	Roster 4	Roster 6

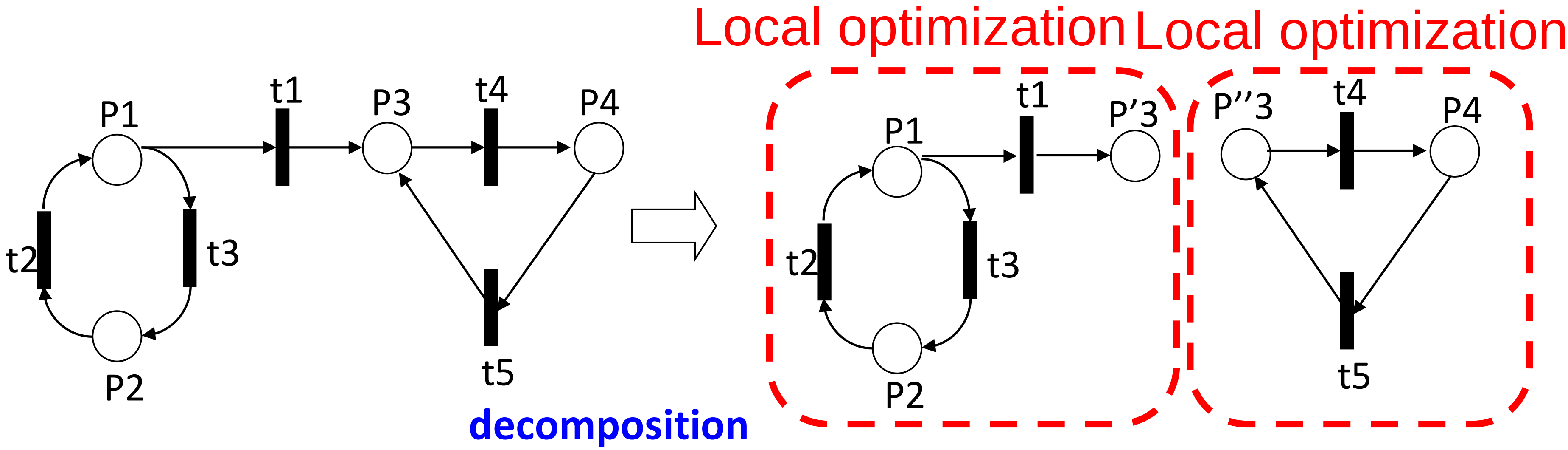
Simultaneous Optimization of Production Planning Warehouse Layout

G. Zhang, T. Nishi, et al., Omega (2017)
IF: 4.311, Most Downloaded Omega Article (2017)

Airline Crew Rostering Optimization

T. Doi, T. Nishi, S. Voss, European Journal of Operational Research (2018), IF: 3.428
EJOR Editors' Choice Article, June 2018

Petri net decomposition approach



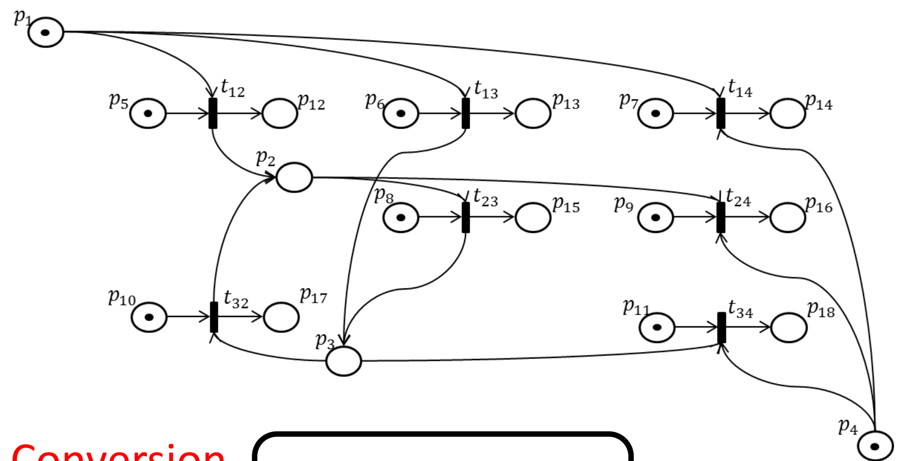
Decomposable condition

- The objective function J is represented by the summation for each of subnet.
- The final making is not specified for the duplicated places.

General Conversion of IP into Petri nets

New Approach for Discrete Optimization

$$
\begin{aligned}
&\min c^T x + d^T y \\
&\text{s.t. } B_1 x + C_1 y = b_1 \\
&\qquad B_2 x + C_2 y \leq b_2 \\
&\qquad B_3 x + C_3 y \geq b_3 \\
&\qquad\quad x \in \{0,1\}^n \\
&\ y \geq 0, y \in Z^n
\end{aligned}
$$



Integer Programming → **Conversion** → Petri net model

Petri net model ↓ **Reachability Analysis** ↓ Valid Inequalities

Valid Inequalities → **Conversion** → Original IP + Valid Inequalities

Structural analysis is conducted via Petri net representation and reachability analysis

T. Nishi, A. Kodama, Petri net representation of 0-1 integer linear programming problems, Information Sciences (2017) (IF: 4.305)

Cell-based Heuristic Algorithm for Capacitated Multi-commodity Network Design Problem

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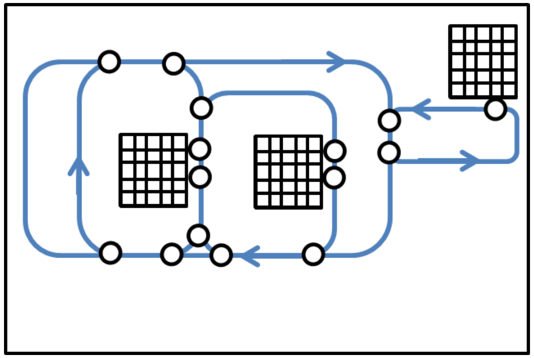
Outline

1. Introduction
2. Dynamic Multi-commodity Network Design Problem
3. Cell-based Heuristic Algorithm
4. Improvement of Performance
5. Computational experiments
6. Summary and conclusion

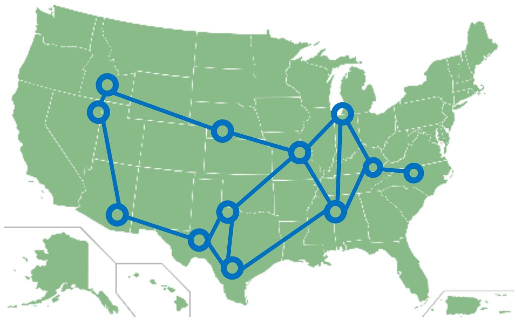
Introduction

Networked System

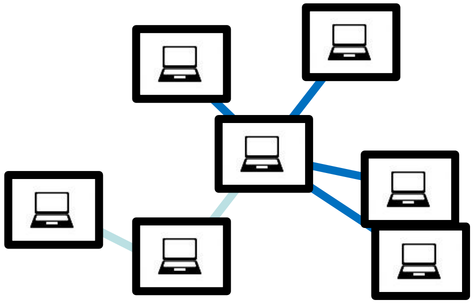
Connectivity is important for social systems



Layout design in warehousing



Transportation systems



Communication systems

Society 5.0 promotes connection between people and physical world via Internet of Things. Network design is a significant issue.

Conventional Network Design Problem

Network design problem

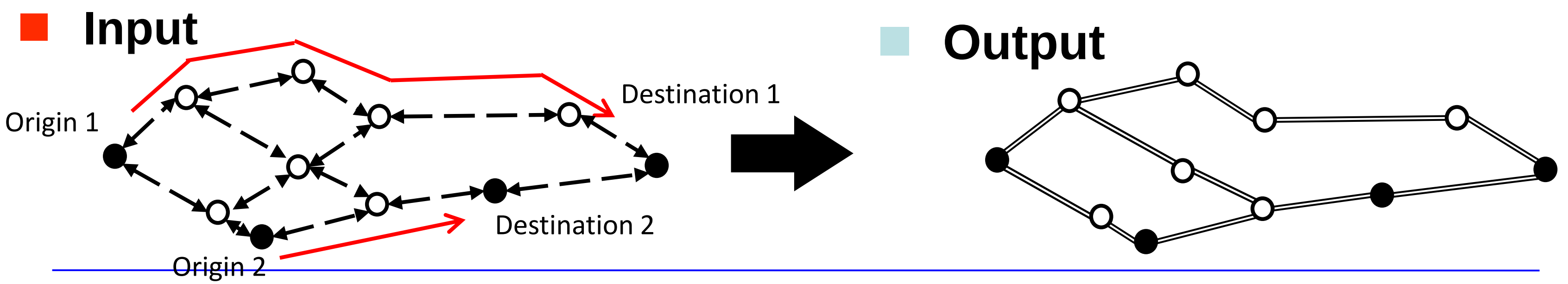
- Determine a network structure (graph and flow) to minimize total costs

Input
- Candidate of graph $G = (N, A)$
- Origin and destination

Output
- Derived graph $G' = (N', A')$
- Flow quantity from origin to destination

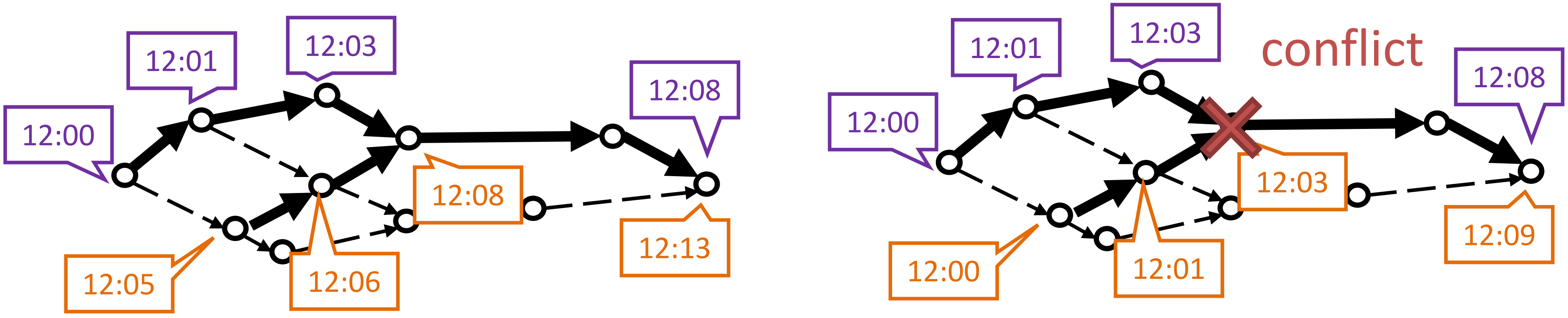
Multi-commodity Network Design Problem (Magnanti, 1984)

- To determine the selection of arcs and flow of commodities. Commodities are routed from its origin to destination satisfying total capacity constraints.



Dynamic Multi-Commodity Network Design Problem (DMCND)

Commodities are routed over a time horizon.



- Dynamics of commodities (conflicts and jams) are represented.

→ More exact network design can be achieved.

Connectivity

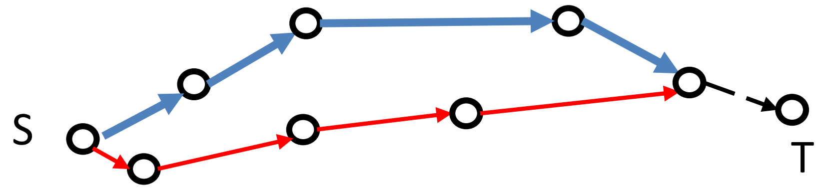
- Most of real-world network has connectivity between their origin and destination -> Connectivity of the selected arcs is important

Conventional works on DMCND

Few works have been developed for DMCND.

- Hall et al. (2007) developed a greedy algorithm for S-T path which has conflicts in dynamic commodities when the distance is equal.

→ Problem is not general



- Conversion of DMCMD into time-space network

→ Network size issues

Our objective

✓ Formulation of dynamic multi−commodity network design problem

✓ Effective local search algorithm

Dynamic Multi-Commodity Network Design Problem (DMCND)

Performance indices

- Quickest flow : Minimize the sum of total time to reach destination
- Maximum flow : Maximize the total flow quantity
- Minium cost flow : Mimimize the total costs
  fixed costs + transportation costs

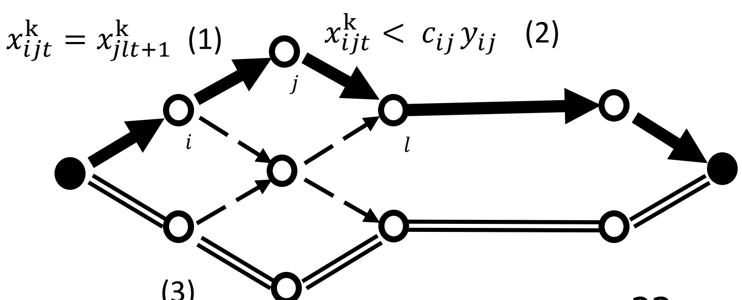
■ Input

- $G = (N, A, K)$
- (demand q^k, origin o_k, destination d_k)
- Capacity of arc $c_{i,j}$
- Fixed costs $m_{i,j}$, transportation cost $l_{i,j}$
- Time periods $\mathrm{T} = \{0,1,\dots\}$

■ Output

- **Designed network $G' = (N', A')$**
- Selection of arcs $y_{i,j} \in \{0,1\}$
- Flow quantity $x^k{}_{i,j,t} \in \mathbb{R}$

1. Flow conservation constraints
2. Arc capacity constraints
3. Connectivity constraint of the selected arcs

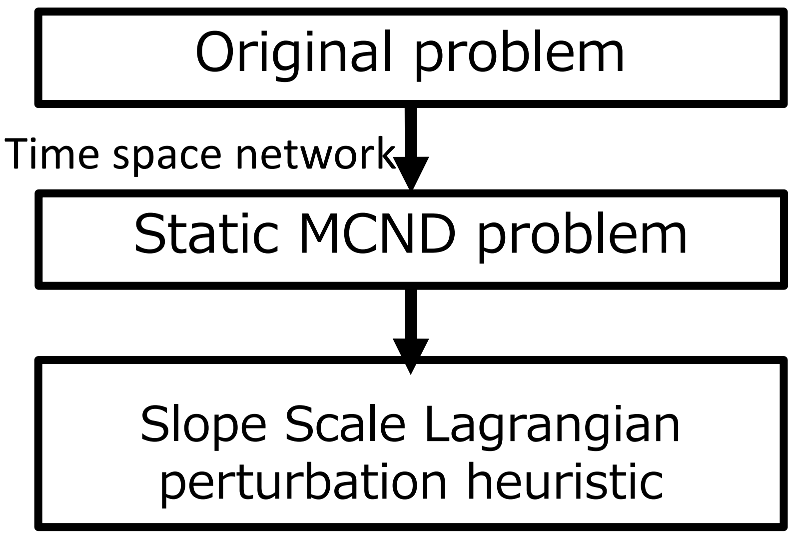


Two-stage heuristic algorithm

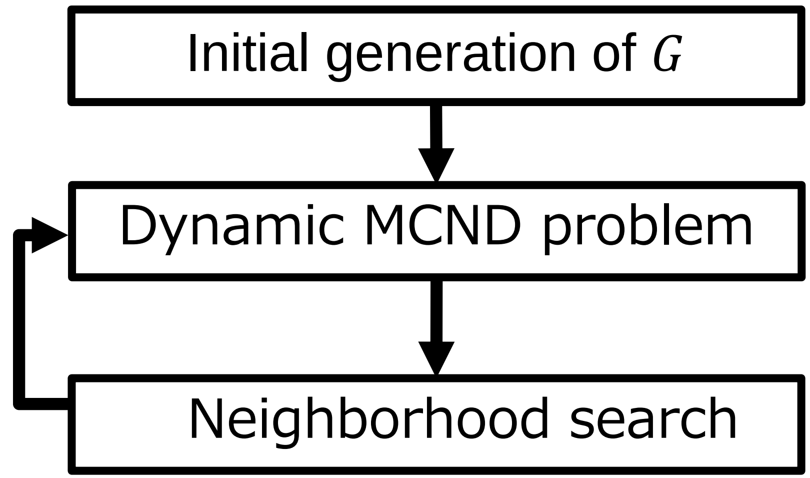
Four dimensions of x_{ijt}^{k} and binary $y_{i,j} \in \{0{,}1\}$ are too huge for computations.
For only x_{ijt}^{k} → Dynamic multi-commodity flow is an LP problem.

We propose a neighborhood search which repeats the generation of the selection of arcs and LP for multi-commodity flow problem.

Conventional method



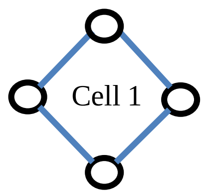
Proposed method



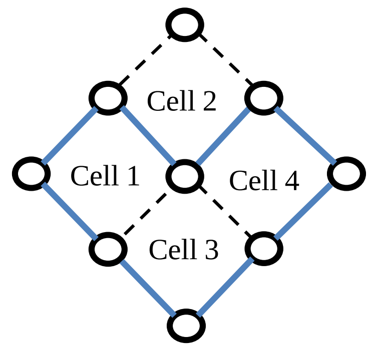
Cell-based heuristics

Introduction of concept of cells

Search space for the selection of arcs is too huge
⇒Cell is defined as minimal set of arcs which constitutes a loop.

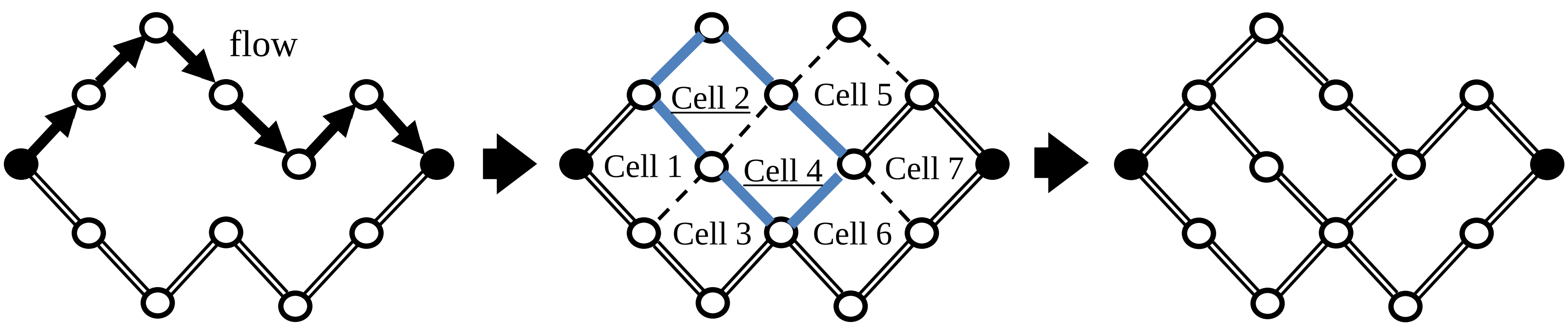


Single cell



k-neighborhood

Neighborhood search with K-neighborhood cell



Current selection of arcs

2-cells $\{c_2, c_4\}$

Neighborhood using 2-cells

Cell-based heuristic algorithm

Properties of K-neighborhood cells

Proposition 1. All selection of arcs can be represented by cells.

→ An optimal solution can be represented by cell-based neighborhood.

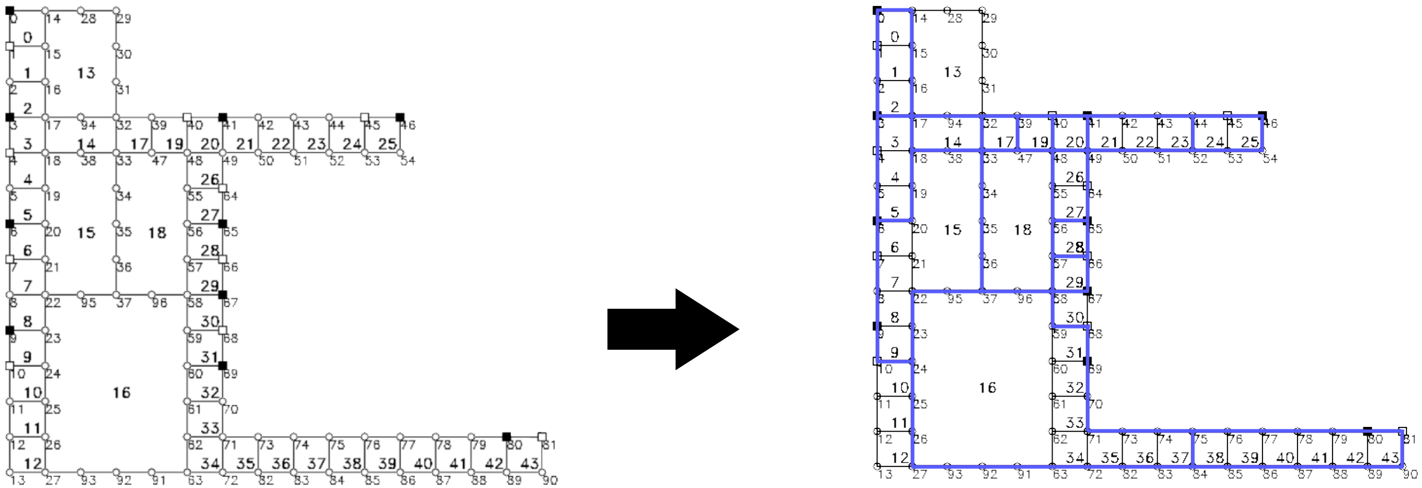
Proposition 2. Cell-based neighborhood solutions always satisfy connectivity.

The proposed algorithm can be strengthened by the following components.

1. Intensification of search using flow information.
2. Redundant arc elimination
3. Subtour elimination
4. Network size reduction
5. Variable neighborhood search

Application to guide path layout design of Automated Guided Vehicles

The layout design of AGV systems |N|=101,|A|=371

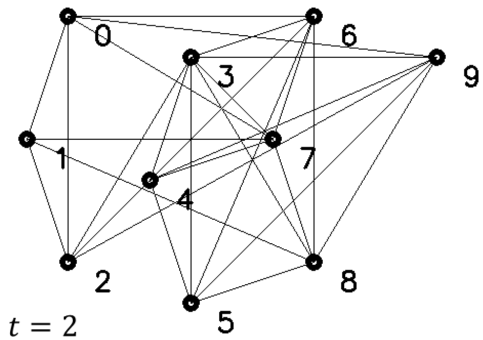


	General purpose solver (CPLEX)		Proposed method	
demand	Time [s]	Obj [-]	Time [s]	Obj [-]
28	75.8	26189	269.7	27709
78	10801.9	132378	1122.6	141599
88	-	-	2423.7	191011

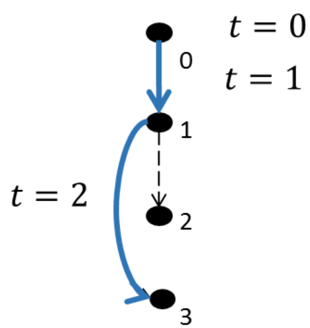
- CPLEX requires more than 10000 sec.
- The proposed method derive a solution with 1000 sec with 7% gap

Application to general graph structure

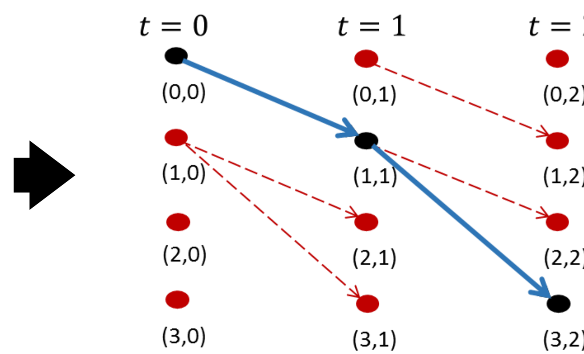
Improvement of cell based heuristics to general graph structure



Reduction of time-space network



Problem size
$=|A||T-1||K|$
$=3*2*1$

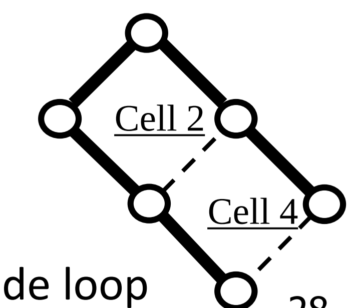


Reduced size
=2

Some unreachable arcs for each time period are eliminated by backward and forward calculations

Variable size of neighborhood

Variable neighborhood depending on the search times



Partially opened outside loop

Computational experiments

Benchmark instance for capacitated fixed cost multi-commodity network design problem (Gendron and Crainic, 1994)

			General purpose solver (CPLEX)		Proposed method		Ant Colony Optimization		Slope Scaling and Lagrangean Perturbation	
|M|	|N|	|A|	Time [s]	Objective value	Time [s]	Objective value	Time [s]	Objective value	Time [s]	Objective value
10	10	90	2.44	1014	40.9	1227	65.1	1014	316.6	1113
10	10	56	0.95	1213	37.9	1325	68.4	1213	226.9	1213
25	10	90	3.78	2922	91.9	3140	200.9	2927	497.4	2927
100	20	204	–	–	381	17892	–	–	–	–

Summary and conclusion

We have proposed a cell-based heuristic for dynamic multi-commodity network design problem.

The proposed heuristic utilizes the cell-based arc selection and multi-commodity flow problem repeatedly. The performance is strengthened by variable neighborhood search and intensification of search.

The effectiveness of the proposed method is confirmed from computational experiments.

Simultaneous Optimization of Product Configuration and Supply Chain Planning Considering Customer's Participation in Product Design

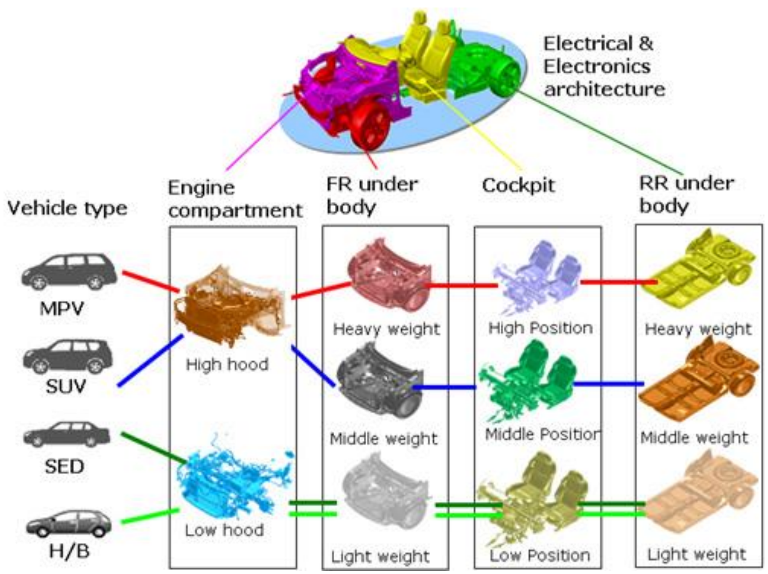
Takuya Tsuboi and Tatsushi Nishi
Graduate School of Engineering Science
Osaka University, Japan

Introduction

Mass Customization = Mass Production + Customization

- **Modular Production:** Produce a large number of modules and manufacture a variety of products by assembling them

→ Electric appliance, Computer, Car, Bike , Shoes, Clothes…



Ex: Nissan Common Module Family

- ✓ There are main four modules: Engine compartment, Cockpit, Front underbody and Rear underbody
- ✓ Each module has appropriate variations
- ➢ A variety of vehicles can be designed by assembling these modules

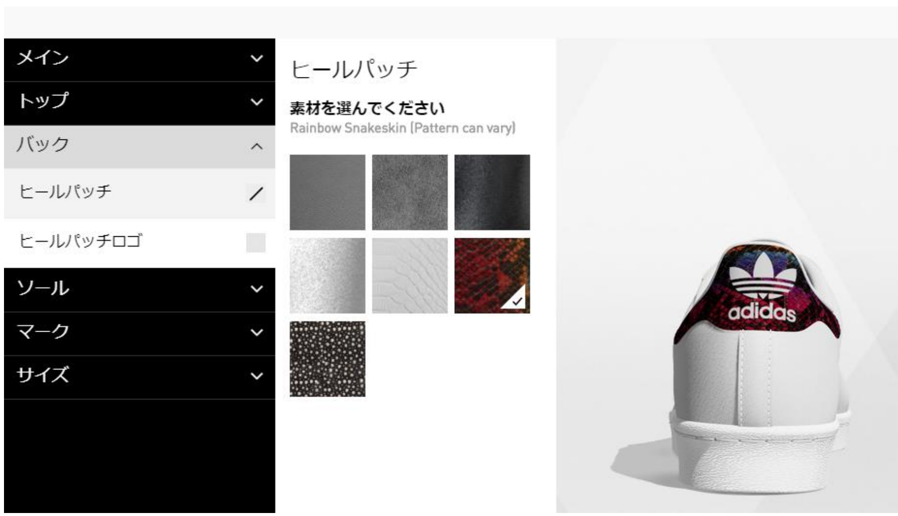
http://www.Nissanglobal.com/EN/NEWS/2012/_STORY/120227-01-e.html

Customer's participation in product design

Conventional :Product configuration is determined by manufacturer

Introduction online self-customization service

Now: Customer can determine product configuration



Shoes customization on "miadidas"
(adidas) "https://shop.adidas.jp/miadidas/"

Bike customization on "Built Own Your Bike"
(HARLEY DAVIDSON)
"https://www.harley-davidson.com/us/en/tools/bike-builder/index.html"

Introduction

■ Challenges in Mass Customization

- Product configuration : Selection of products and modules
  Configurations of products

- Supply chain planning : Operation of facilities, Selection of suppliers
  Production products, Inventory, Distribution

<u>Simultaneous optimization of product configuration and supply chain planning</u>

- Customer's participation in product design (e.g. Online self-customization)

<u>Optimization model considering customer's preferences and purchasing behavior</u>

- Fluctuated costs and demands

<u>Dynamic(multi-period) optimization model</u>

Introduction

■ Conventional works

- Product configuration (PC) problem
  - ✓ Maximization customer utility model (Frutos et al, 2004)
  - ✓ Consumer choice rule (Cao et al. 2012)

    Consider customer purchasing behavior

- Supply chain planning (SCP) problem

  Facility location, Supplier selection …

integrated

- Simultaneous optimization of PC and SCP
  - ✓ Comparison two-phase model and integrated model (Khalf et al. 2010)

    Single period, Cost minimization only

  - ✓ Stackelberg model (Yang et al. 2015)

    Customer utility maximization and Cost minimization

    Single period, Not consider customer purchasing behavior

Introduction

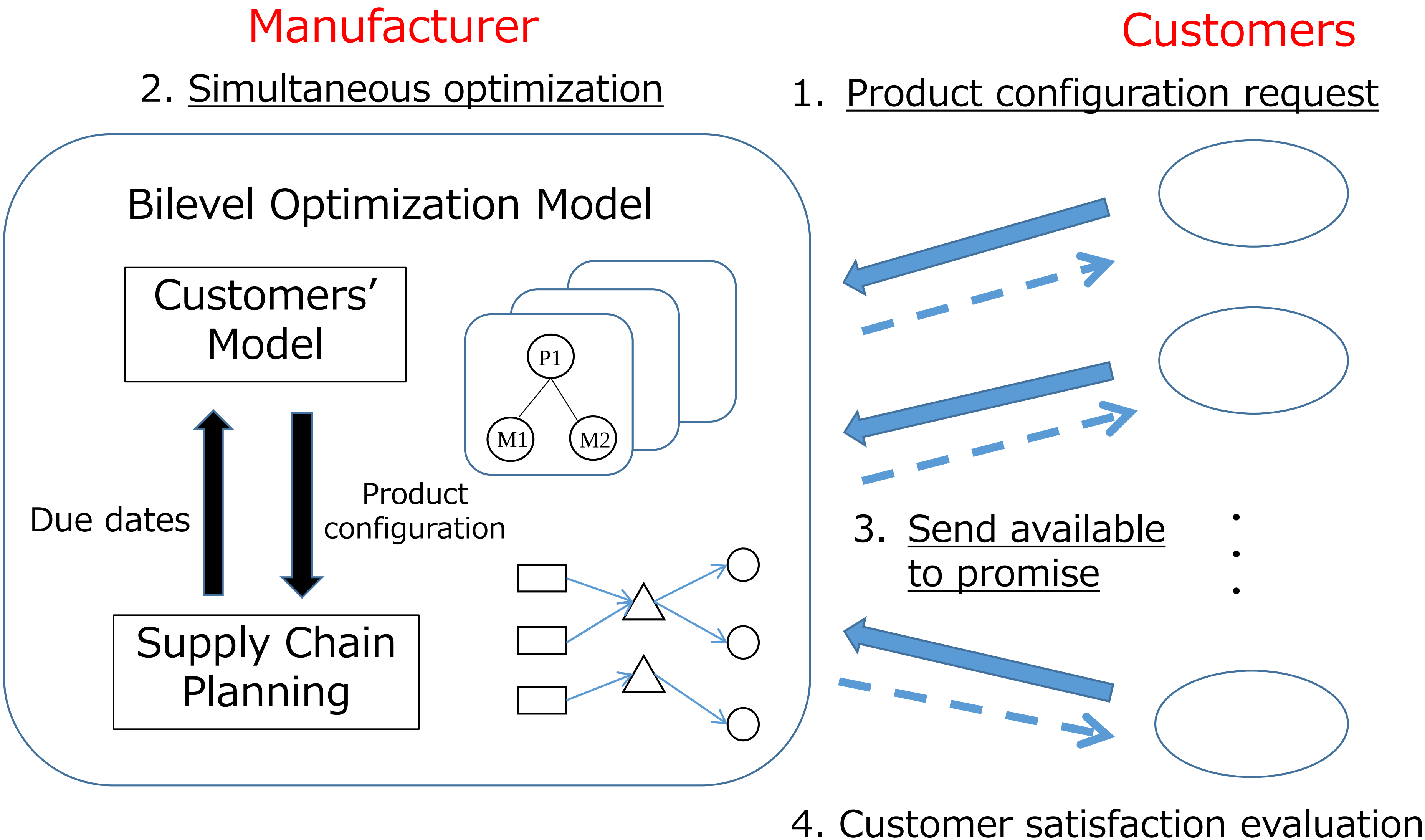
■ Our research

- We formulate new multi-period model for mass customization
  - Simultaneous optimization of PC and SCP
  - Customer model based on customer purchasing behavior
  - Delayed demand satisfaction

- We optimize both customer satisfaction and total profit by Game theoretical approach
  - Leader：Manufacturer, Follower: Customers
  - Leader：Customer, Follower: Manufacturer

- We reformulate Bilevel problem into single-level problem and obtain an exact Stackelberg equilibrium

Production system and interaction between manufacturer and customers

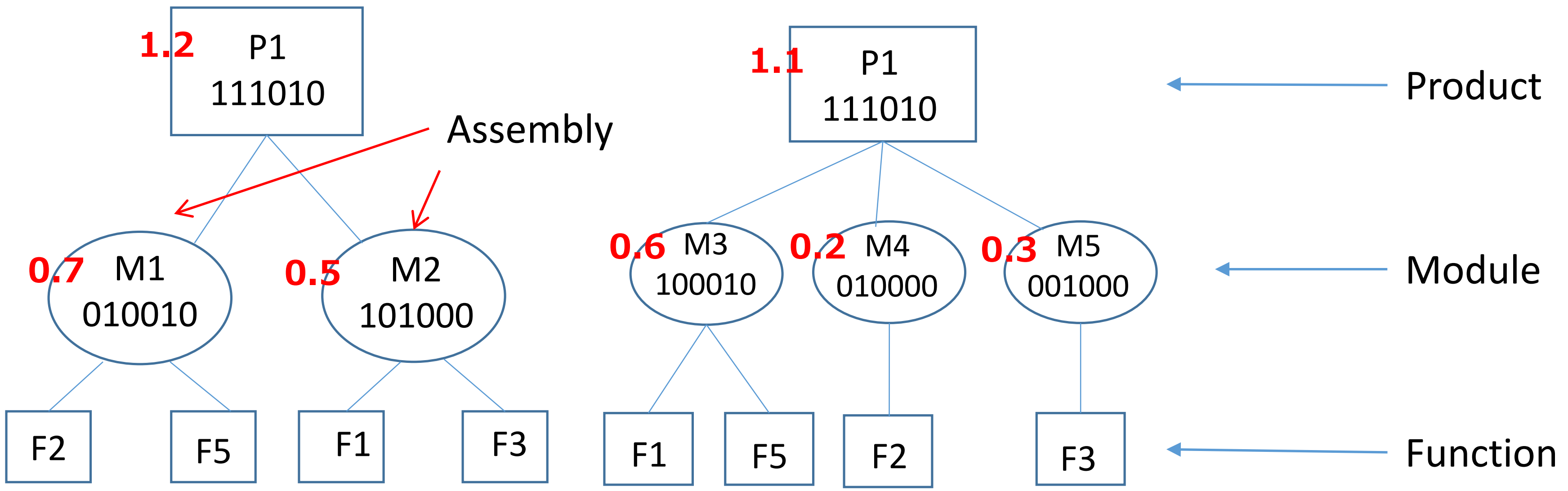


Problem definition

- Product and module definition

✓ The module is a part of product and it has several functions
✓ Each product can be manufactured by assembling some modules selected from candidate modules

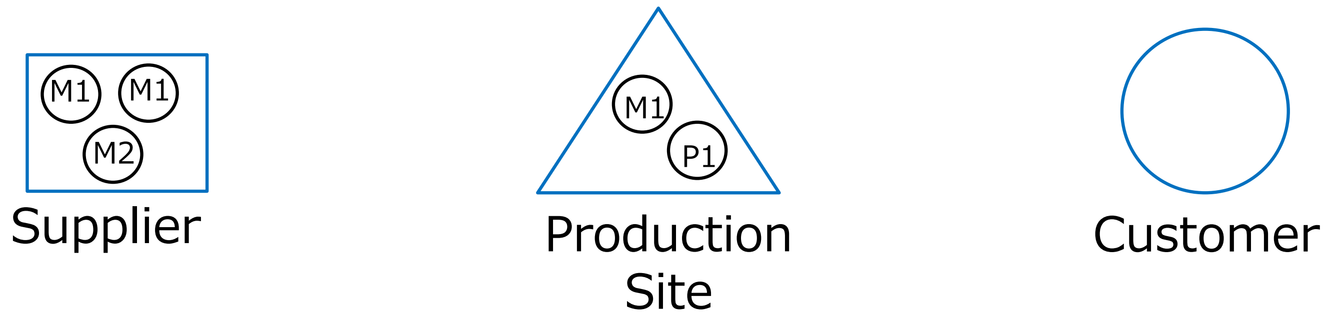
Ex: Alternative two configurations for product 1



Problem definition

- Supply chain planning is to determine the production volume of the products and the procurement volume of modules , the operation of production sites and the selection of suppliers

  - ✓ Modules are supplied by suppliers and transported to production sites
  - ✓ Products are manufactured by assembling some modules at production site
  - ✓ Products are directly sold to customers
  - ✓ Modules are stocked as inventories



Stackelberg model between customers and manufacturer

Customers: to maximize own satisfaction
Manufacturer: to maximize total profit

Different decision makers

Derive the equilibrium solution by Game theoretical approach

- We propose Bilevel optimization model that the manufacturer predicts customers' purchasing behavior and maximize total profit

■ Stackelberg model

Leader — Manufacturer

Followers — Customer1 | Customer 2 | … | Customer K

Formulation of Bilevel problem

<u>Bilevel programming problem between customers and manufacturer (BP)</u>

max (TP) ← Manufacturer's objective function

s.t. $Constraints\ (1) - (13)$ ← Manufacturer's constraints

max (TU_k) ← Customer's objective function

s.t. $Constraints\ (14_k) - (16_k)$ ← Customer's constraints

Bilevel programming problem can not be solved directly ⇨

- Iterative optimization
- Single-level reformulation
- Nested evolutionally algorithm ···

- In this model, the follower's optimization problem is a LP

✓ Reformulate BP into a single-level programming problem

Reformulation method

Duality Theorem	:	In LP, if either P or D has a finite optimal value, then so does the other, the optimal values coincide, and optimal solutions to both P and D exist.

- Transform the followers' optimization problems to some constraints based on duality theorem

- Remove the objective functions of followers from BP and add two kinds of constraint to BP

1. Dual optimality condition ($\rightarrow$ the optimality of lower-level problem)
2. Dual feasibility condition ($\rightarrow$ the feasibility of lower-level problem)

Proposition : Reformulated SP is equivalent to original BP

Reformulation

- Reformulation Bilevel programming problem to Single-level programming problem

Bilevel programming problem(BP)

$$\begin{aligned} \max\ & F(x) \\ \text{s.t.}\ & G(x) \le 0 \\ & \quad \max\ f(x) \\ & \quad \text{s.t.}\ g(x) \le 0 \end{aligned}$$

Add new constraints
based on duality theorem

Single-level programming problem(SP)

$$\begin{aligned} \max\ & F(x) \\ \text{s.t.}\ & G(x) \le 0 \\ & H(x) \le 0 \end{aligned}$$

The reformulated single-level problem can be solved by general-purpose solver

Computational results

▪Stackelberg equilibrium between the manufacturer and multiple customers

	Ins 1(T=3)	Ins 2(T=3)	Ins 3(T=4)	Ins 4(T=3)	Ins 5(T=4)
Total profit	1197.75	2681.13	5315.89	6240.17	9184.77
Cus. 1 satisfaction	331.64	338.21	603.85	541.51	563.54
Cus. 2 satisfaction	343.59	335.51	510.51	632.25	515.40
Cus. 3 satisfaction	-	381.25	527.46	540.81	525.71
Cus. 4 satisfaction	-	-	-	502.43	599.56
Cus. 5 satisfaction	-	-	-	-	467.88
Computation time(s)	25.13	119.61	1619.60	4857.80	(36346.15)

(Problem size : $|\mathrm{P}| = 4, |\mathrm{M}| = 9, |\mathrm{I}| = 3, |\mathrm{J}| = 1, \rho = 1\ or\ 2$)

Stackelberg model between customer and manufacturer

Proposal: Bilevel optimization model that prioritize customer's requests and maximize customer satisfaction

- Stackelberg model (Restriction: single customer)

Leader — Customer

↓

Follower — Manufacturer

Bilevel programming problem between customers and manufacturer (BP)

$\max \quad$ (TU) ← Customer's objective function

s.t. $\quad Constraints\ (1)-(6)$ ← Customer's constraints

$\qquad \max \quad$ (TP) ← Manufacturer's objective function

$\qquad$ s.t. $\quad Constraints\ (7)-(16)$ ← Manufacturer's constrains

Computational results

- The influence of delivery delay to supply chain

The coefficient related to product configuration (A) : 1

The coefficient related to delivery delay (B) : 0, 1, 10 ← change

SP(・)	SP(0)	SP(1)	SP(10)
Customer Satisfaction	95.49	91.77	88.53
Product configuration utility	95.49	95.49	88.53
Delivery delay penalty	0	3.72	0
Total profit	-124.69	-129.07	-172.20
Computational time[s]	3.67	6.24	5.28

(Problem size : $|T| = 3, |\mathrm{P}| = 3, |\mathrm{M}| = 8, |\mathrm{I}| = 2, |\mathrm{J}| = 1, \rho = 1$)

Customer purchasing behavior affects product configuration and supply chain planning

Conclusion and Future work

■ Conclusion

- We propose new multi-period model for Simultaneous optimization
  - ➢ Formulate two Bilevel programming problems

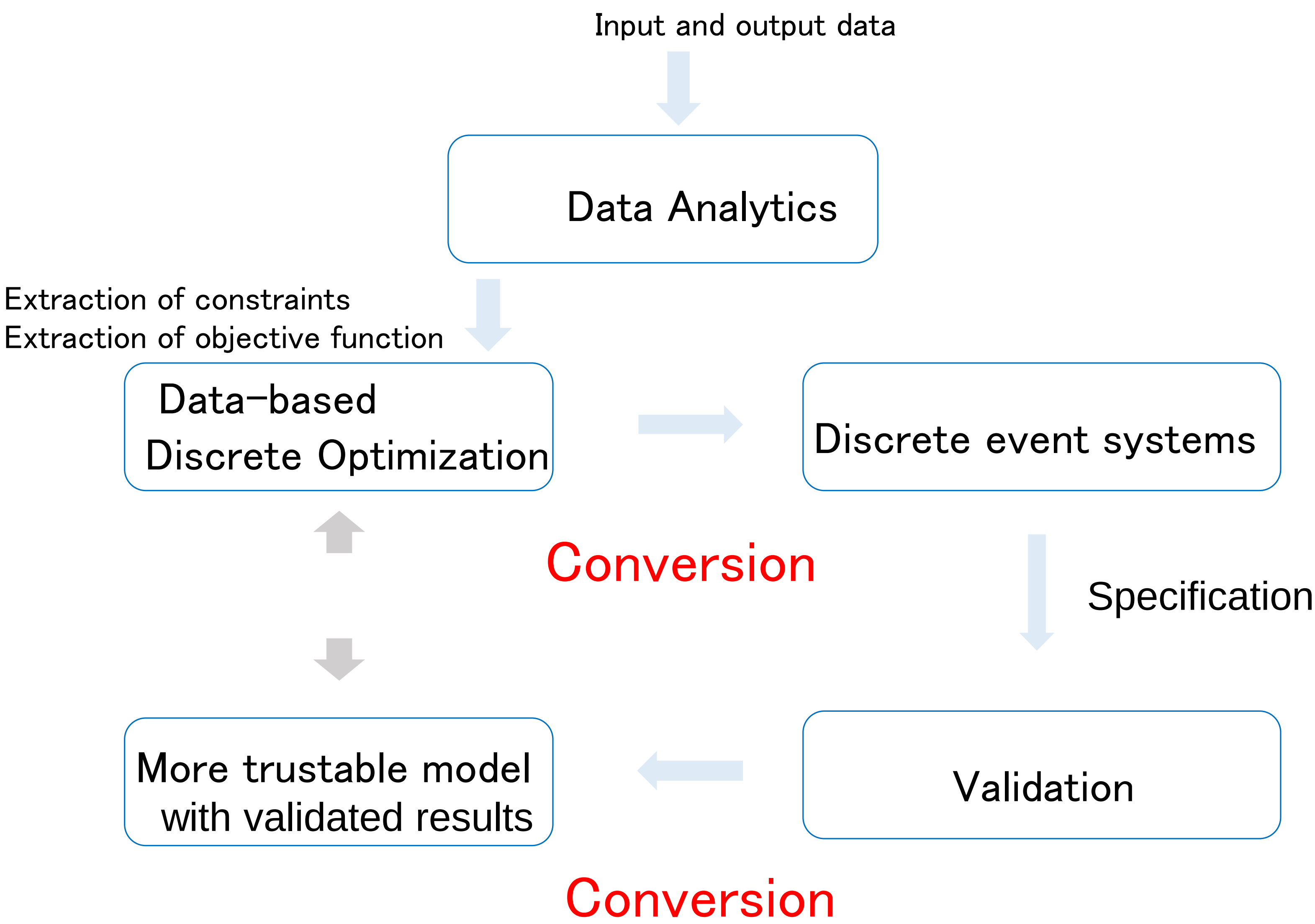
- Reformulation based on duality theorem
  - ➢ The effectiveness of the proposed model is confirmed from computational experiment

■ Future work

- We will develop an effective solution approach

- We will extend supply chain model
  - ➢ Multiple customers are leader, manufacturer is follower

Integration of Data Science, AI and Optimization



Objective

Extract objective function from input and output data of scheduling problems

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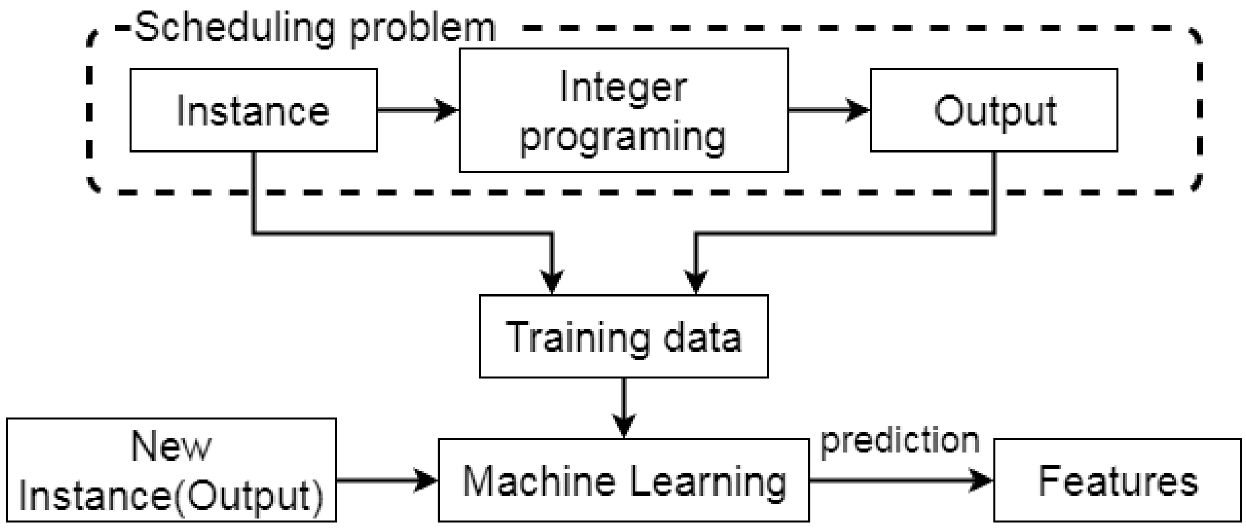


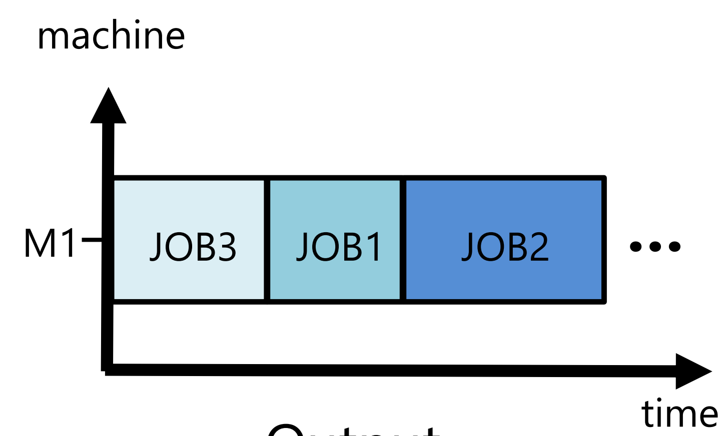
Scheduling Problem

- Single Machine Scheduling Problem

	ω	d	p
JOB1	ω_1	d_1	p_1
JOB2	ω_2	d_2	p_2
JOB3	ω_3	d_3	p_3
⋮	⋮	⋮	⋮

Instanc
e

Integer
programing



Output

ω : weight d : due date p : processing time

Construction of scheduling problems

- Variant of objective functions
  Objective Function : min z

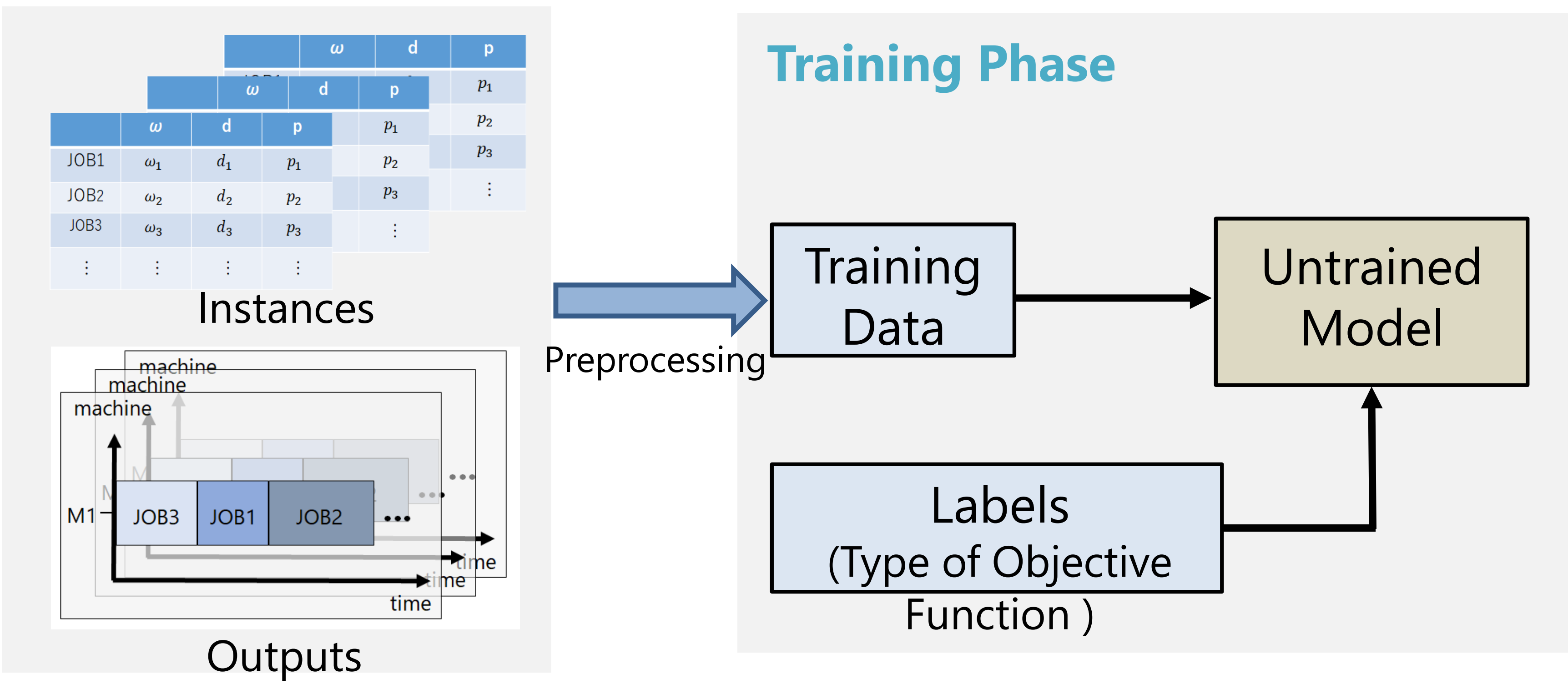
①Weighted Completion Time $z = \sum \omega_i C_i$

②Weighted Lateness $z = \sum \omega_i L_i$

③Weighted Number of Tardy Jobs $z = \sum \omega_i U_i$

④Maximum Lateness $z = \max_i L_i$

Neural Network



Learning Process for NN

- Preprocessing

JOB1	JOB2	JOB3	…		
ω_1	ω_2	ω_3	…	Ranking	τ_ω
d_1	d_2	d_3	…		τ_d
p_1	p_2	p_3	…		τ_p
$\frac{\omega_1}{p_1}$	$\frac{\omega_2}{p_2}$	$\frac{\omega_3}{p_3}$	…		$\tau_{\omega/p}$
$\frac{\omega_1}{d_1}$	$\frac{\omega_2}{d_2}$	$\frac{\omega_3}{d_3}$	…		$\tau_{\omega/d}$
$\frac{1}{p_1 d_1}$	$\frac{1}{p_2 d_2}$	$\frac{1}{p_3 d_3}$	…		$\tau_{1/pd}$
$\frac{\omega_1}{p_1 d_1}$	$\frac{\omega_2}{p_2 d_2}$	$\frac{\omega_3}{p_3 d_3}$	…		$\tau_{\omega/pd}$
t_1	t_2	t_3	…		τ_t

t : start time

Learning Process for NN

- ②(preprocessing)
  - Spearman's rank correlation coefficient

$$\rho = 1 - \frac{6\sum_{i=1}^{N}\left(\tau_x(i) - \tau_y(i)\right)^2}{N^3 - N}$$

τ_t と τ_ω ⇒ ρ_ω

τ_t と τ_d ⇒ ρ_d

τ_t と τ_p ⇒ ρ_p

τ_t と $\tau_{\omega/p}$ ⇒ $\rho_{\omega/p}$

τ_t と $\tau_{\omega/d}$ ⇒ $\rho_{\omega/d}$

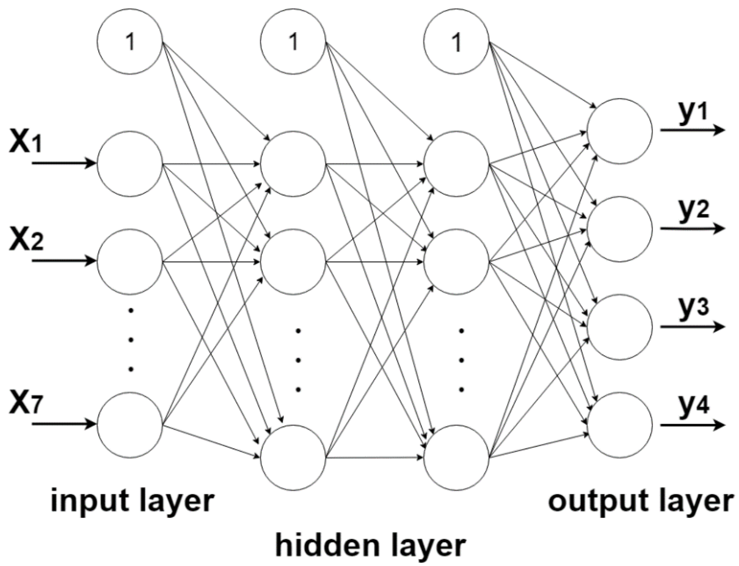
τ_t と $\tau_{1/pd}$ ⇒ $\rho_{1/pd}$

τ_t と $\tau_{\omega/pd}$ ⇒ $\rho_{\omega/pd}$

Learning Neural Network

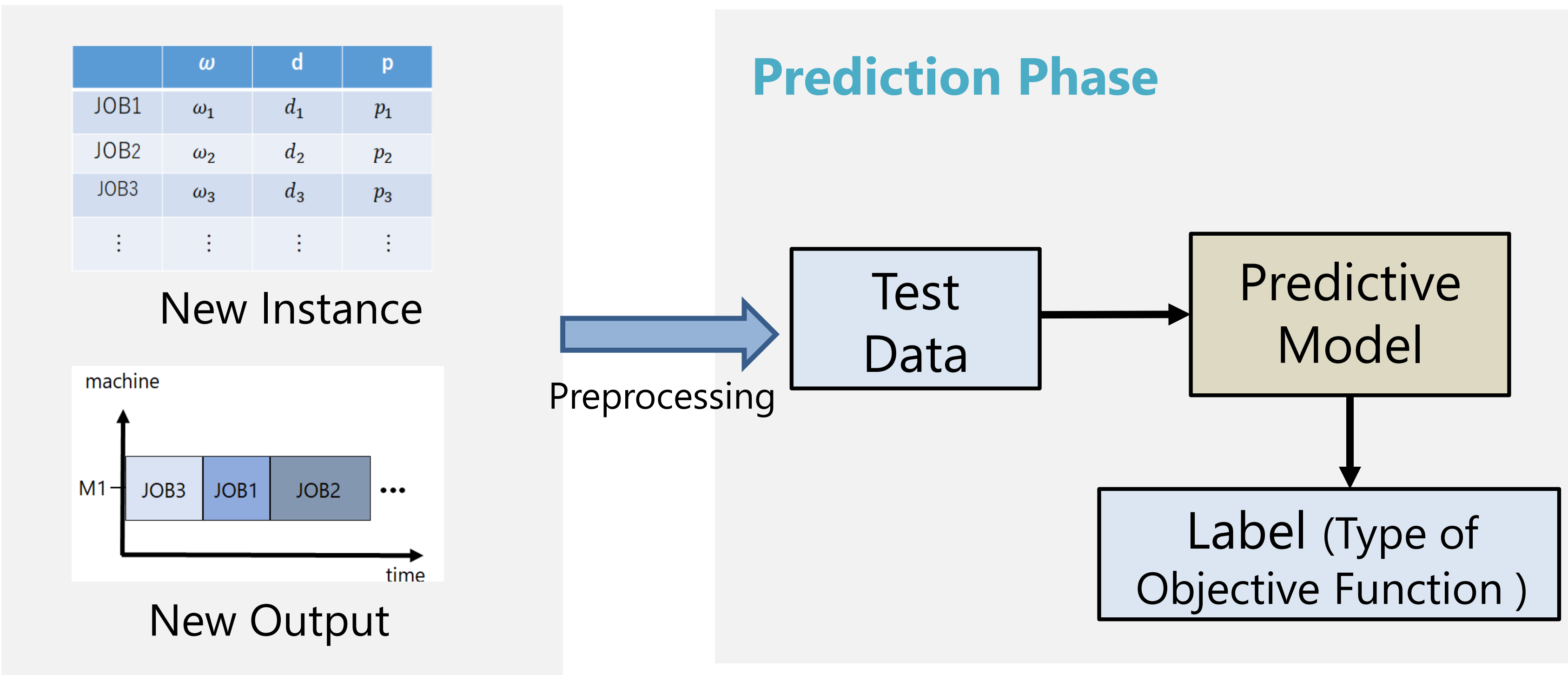
- Three layers Neural Network

$$
\begin{aligned}
x_1 &= \rho_\omega \\
x_2 &= \rho_d \\
x_3 &= \rho_p \\
x_4 &= \rho_{\omega/p} \\
x_5 &= \rho_{\omega/d} \\
x_6 &= \rho_{1/pd} \\
x_7 &= \rho_{\omega/pd}
\end{aligned}
$$



Output value is the percentage of the objective function

Identification of the objective function

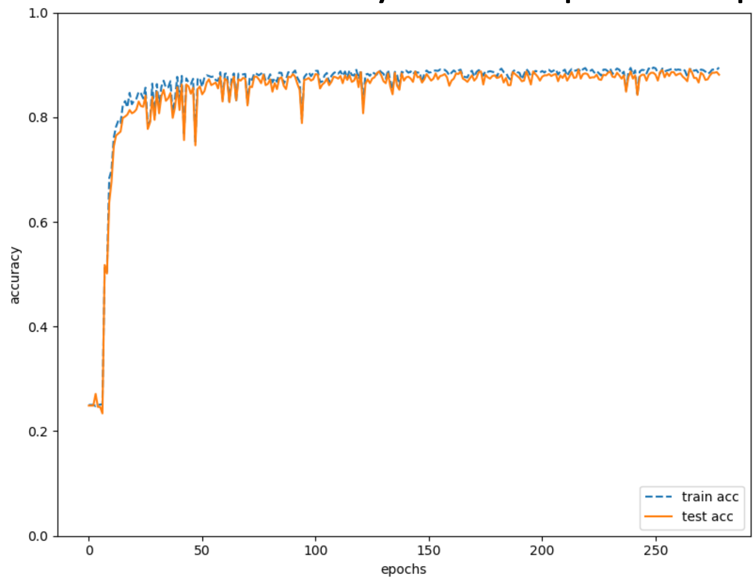


Computational Results

8000 Instances (=2000 × 4)

→ Training Data : 7200, Test Data : 800

Transition of the accuracy with respect to episode



Accuracy for each objective function

Type	Accuracy
1. $\sum \omega_i C_i$	0.95
2. $\sum \omega_i L_i$	0.78
3. $\sum \omega_i U_i$	0.83
4. $\max_i L_i$	0.93
Total	0.88

Future works

1. Application to Parallel Machine Scheduling Problem
2. Improvement of the performance of the neural network
3. Identification of constraints or problem features