My very own experience in solving optimization problems

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Automated tools vs Optimization

- Shift from “manual” to “automated tool” is seen as the holy grail
  - Underlying problem can be tough
- Optimization seen as cherry on the cake… but the cake is needed first
- Optimization expert needs to educate the customer about “optimization potential/capabilities” for managing expectations
- Very often customers do not know what they want to optimize
  - Possibly conflicting objectives
- Optimization can unleash considerable potential savings

- Optimization may threaten jobs. No-optimization may threaten entire companies

Optimization development phases

1. Discovery
   – Understanding the revenue and costs drivers, size of the problem
   – Define the problem, its constraints, its objective function(s)

30%

2. Designing and implementing an optimization model/algorithm
   – All models are wrong but some are useful (cit. George Box)
   – Understand necessary assumptions/approximations

10%

3. Integrating with existing IT system / workflow
   – Fetching and preparing input to optimization model/algorithm
   – Feeding back the (sub) optimal solution

30%

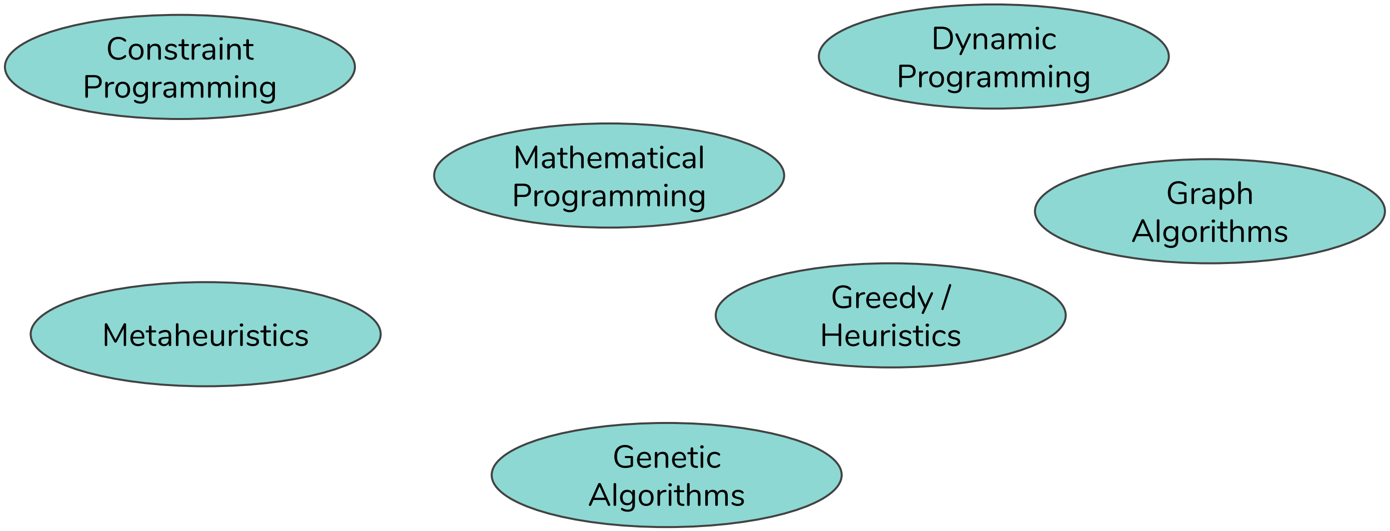
4. Testing – Verifying constraint satisfaction, hypothesis, etc...

30%

Business case/model needs to be defined!!!

Optimization technologies

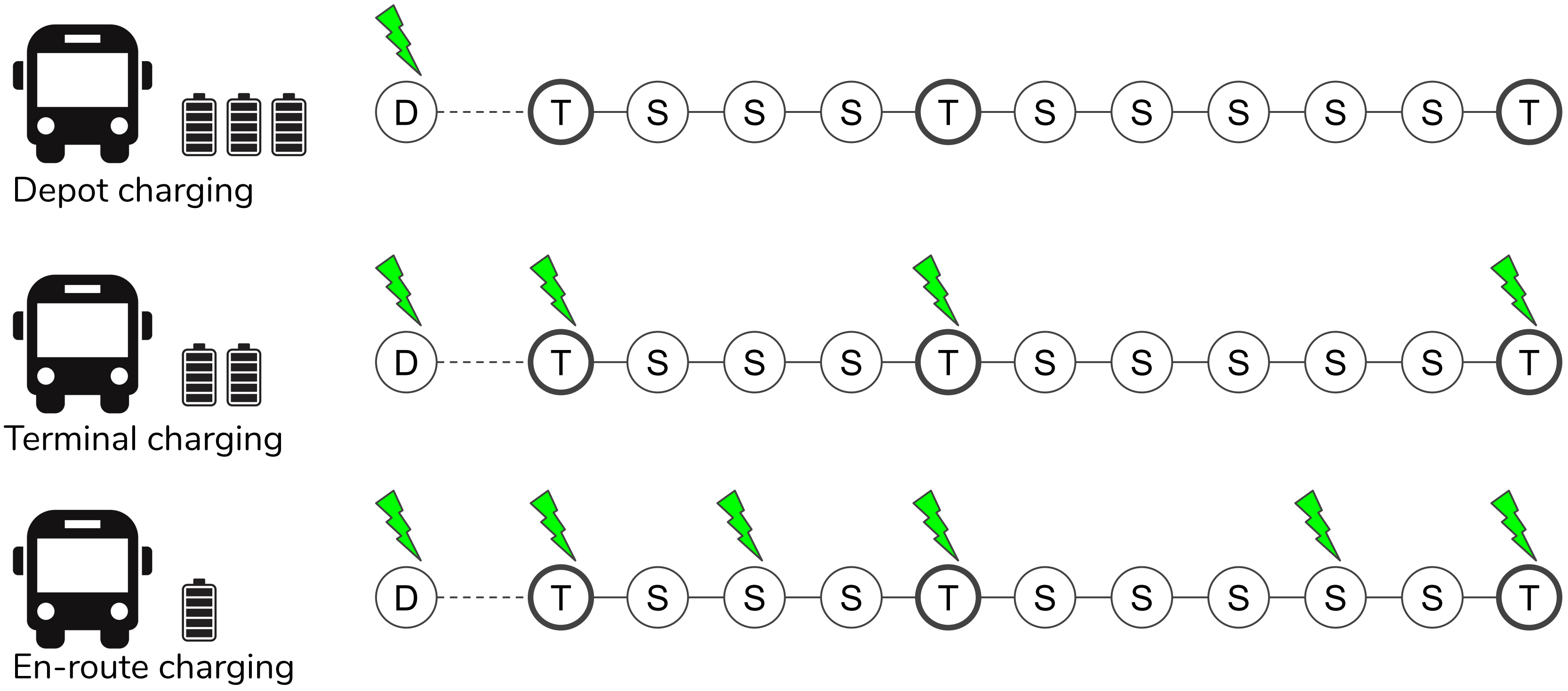
An incomplete list for discrete optimization



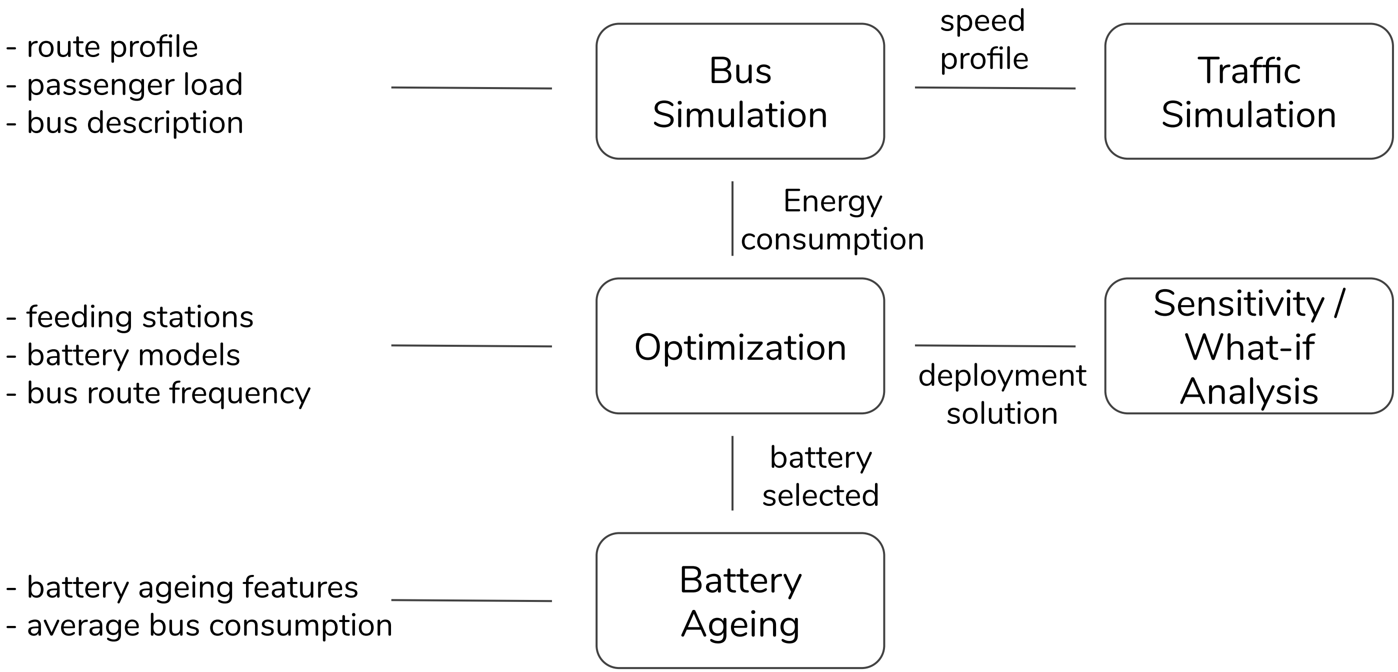
E-bus deployment optimization

Electrical buses - the TOSA case

E-bus technologies



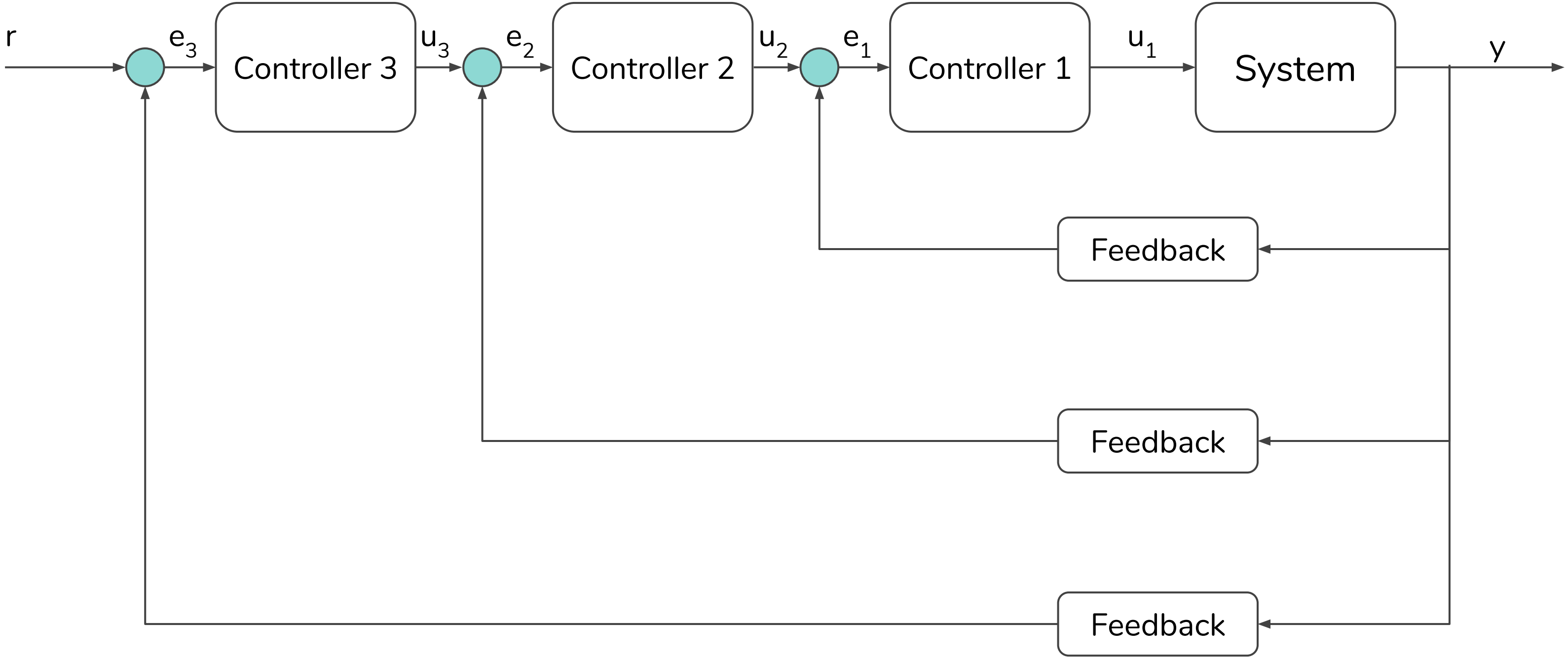
myTOSA



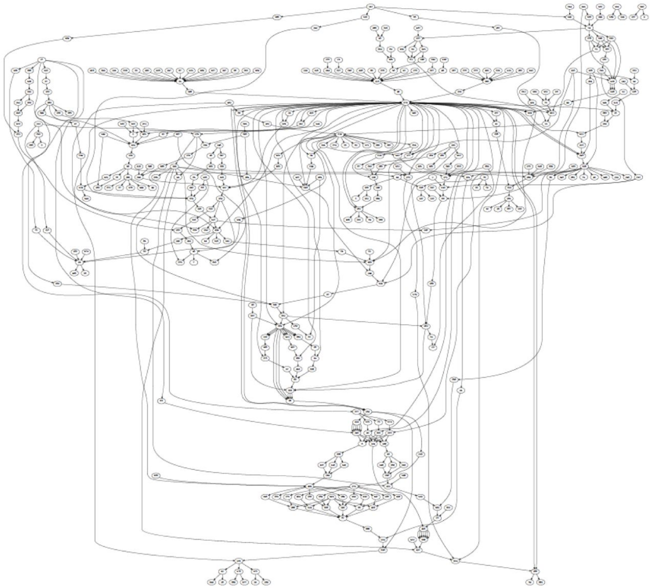
- route profile
- passenger load
- bus description
Bus Simulation
speed profile
Traffic Simulation
Energy consumption
- feeding stations
- battery models
- bus route frequency
Optimization
deployment solution
Sensitivity / What-if Analysis
battery selected
- battery ageing features
- average bus consumption
Battery Ageing

Optimal deployment of control solutions

Multirate control systems



Context



Hardware
- SoC (2 cores + FPGA)

Problem Definition

- *Set of homogeneous resources R*
- Set of *cyclic applications* $A = \{a_0, \dots, a_{n-1}\}$
  - with fixed priority $prio(a_0) > \dots > prio(a_{n-1})$
  - *with different periods* $\lambda_{i+1} = \eta_i \lambda_i \quad (\lambda_{max} = \lambda_{n-1})$
- Apps composed from *activities* $V_i = \{x_j^i\}$
  - with fixed duration $d(x_j^i)$
  - and precedences $x_j^i \prec x_k^i$

Objective function

Minimize makespan of a_0 then a_1 then …

$$\min lexico(makespan(a_0), \dots, makespan(a_{n-1}))$$

Experimental evaluation - CP

	Avg #act	MRC	T&E	DJ
Real 1 (η_{tot} = 36)	2353	5	521	496
Real 2 (η_{tot} = 2000)	177646	159	1827187	2468504

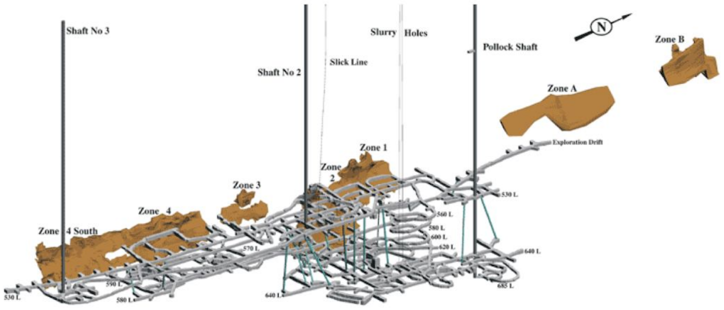
Solution time (ms)

	MRC	T&E	DJ
Real 1 (η_{tot} = 36)	14.9	27.4	29.25
Real 2 (η_{tot} = 2000)	34.4	1258.3	1253.8

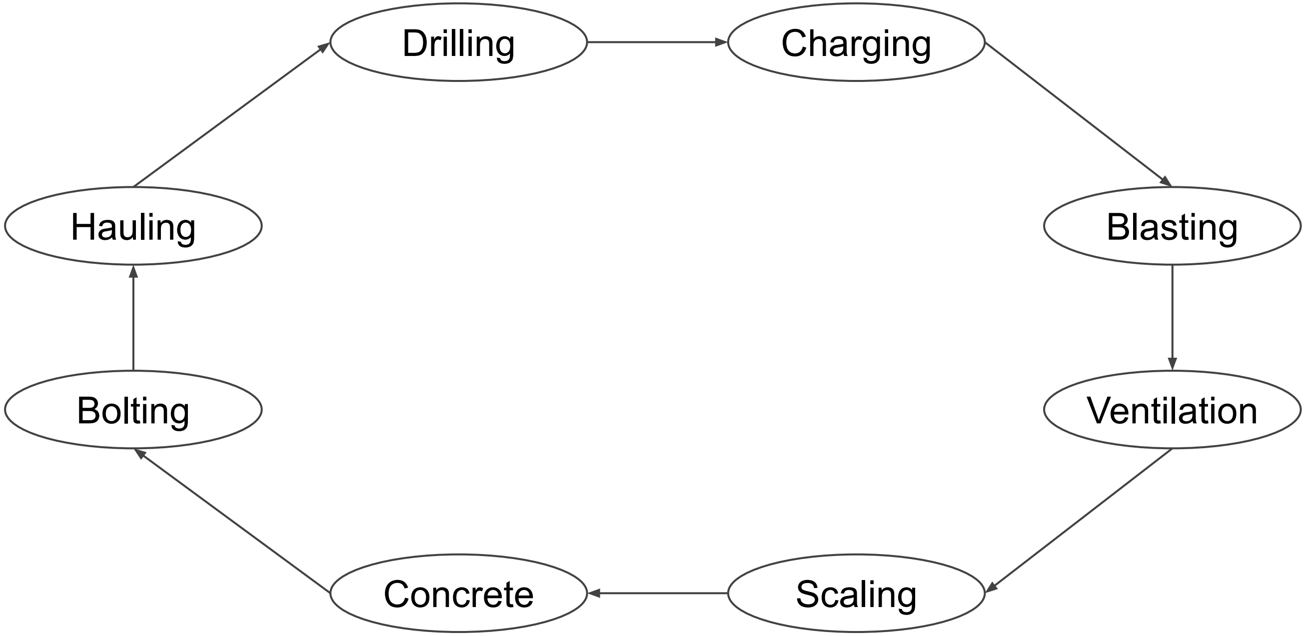
Memory Consumption (MB)

Underground mining fleet optimization

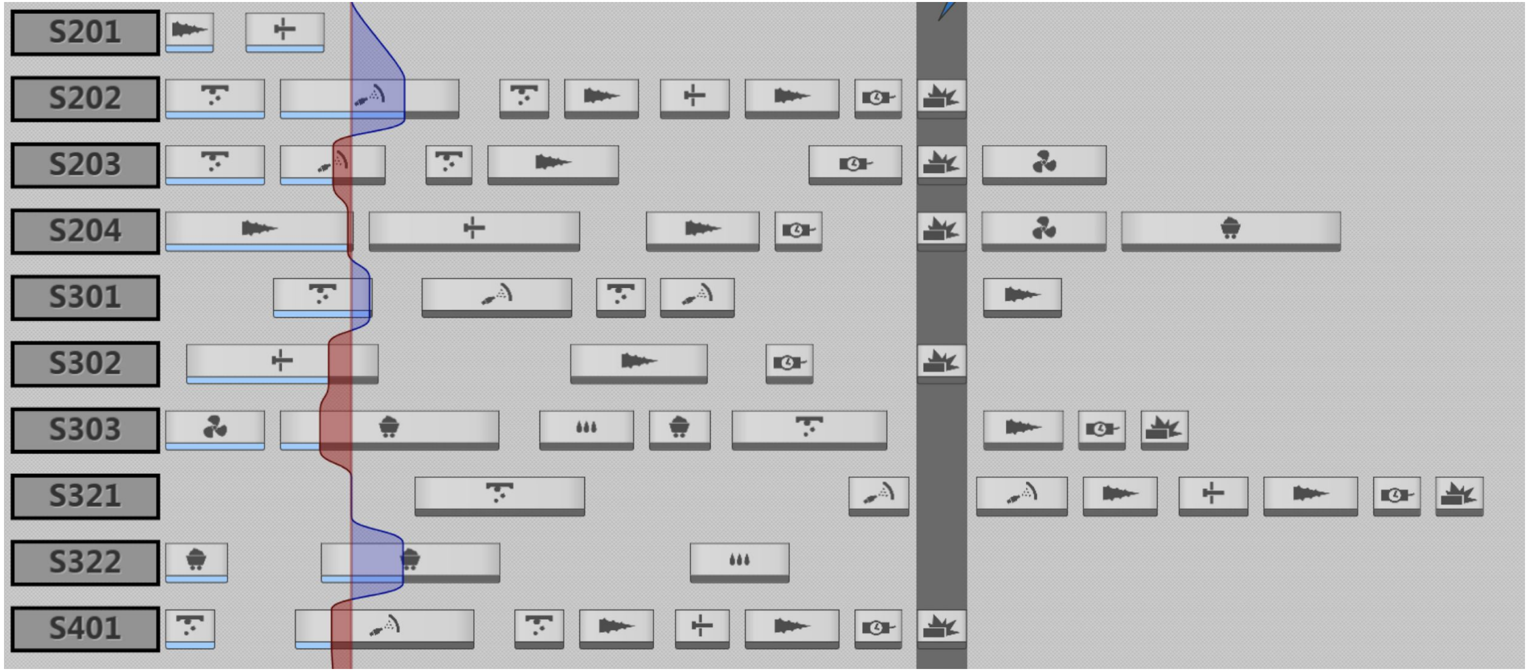
Underground Mine



Undeground mining operations



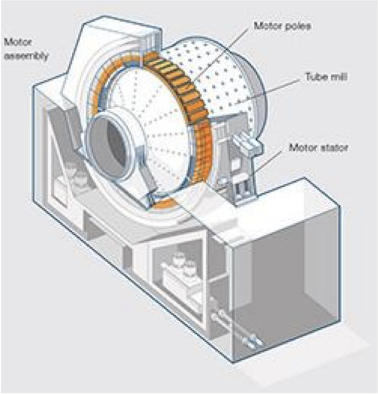
Automated Cyclic Scheduling



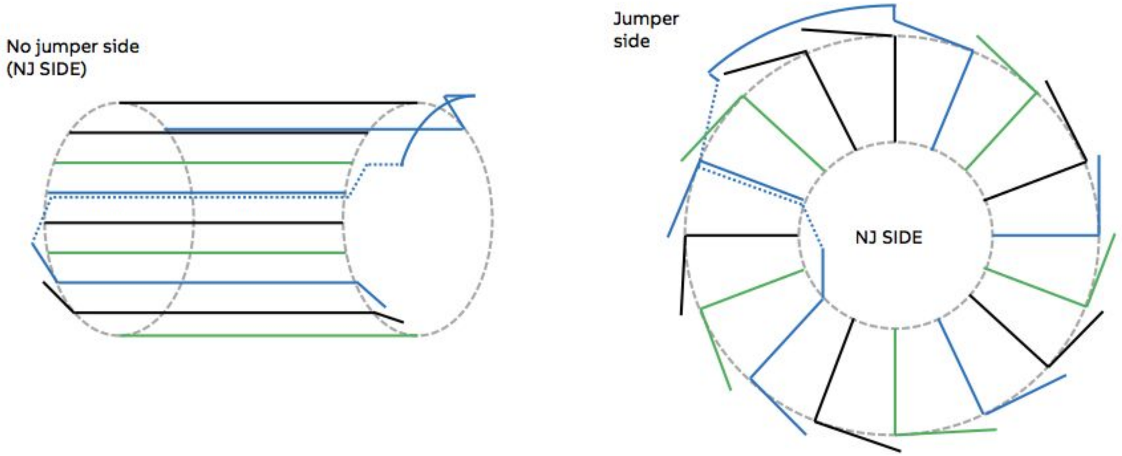
Stator Winding Design Optimization

Gearless Mill Drives

Stator



Main Intuition



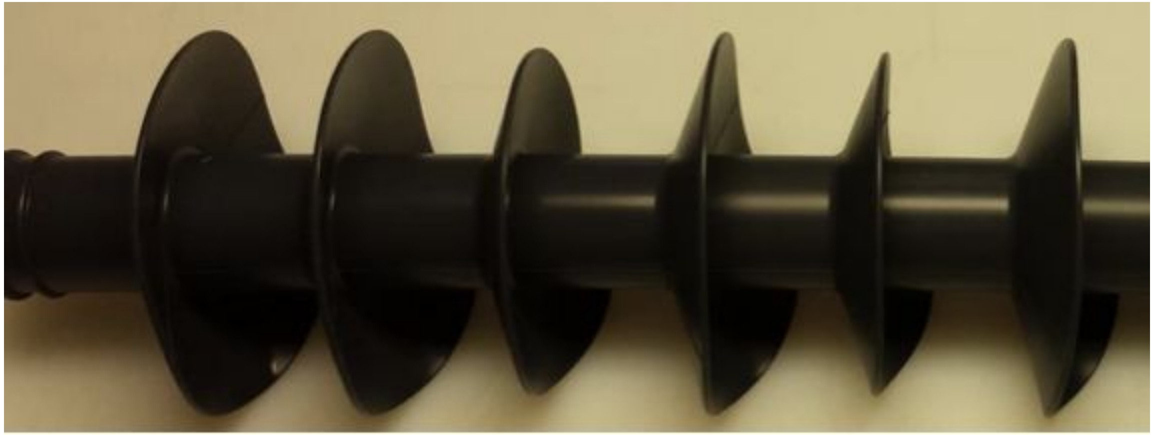
Different approaches

	Decomposed MIP+CP				Decomposed MIP				MIP			
n_s	t (μ)	t (σ)	Obj_{CP}	%Sol	t (μ)	t (σ)	$\frac{Obj}{Obj_{CP}}$	%Sol	t (μ)	t (σ)	$\frac{Obj}{Obj_{CP}}$	%Sol
102	4.4	1.0	12.18	100%	2.4	1.2	100.0%	100%	177.6	112.2	98.2%	90%
264	28.6	28.7	23.57	100%	26.0	28.9	100.0%	95%	340.7	2.0	101.7%	5%
384	23.2	19.5	25.39	100%	19.4	19.4	99.9%	95%	342.1	3.2	-	0%
480	42.0	35.6	32.34	100%	38.8	34.8	100.1%	100%	339.8	2.2	-	0%
576	65.0	33.4	43.56	70%	60.4	32.7	99.8%	30%	341.2	2.4	-	0%

Optimal Stock Sizing in a Cutting Stock Problem with Stochastic Demands

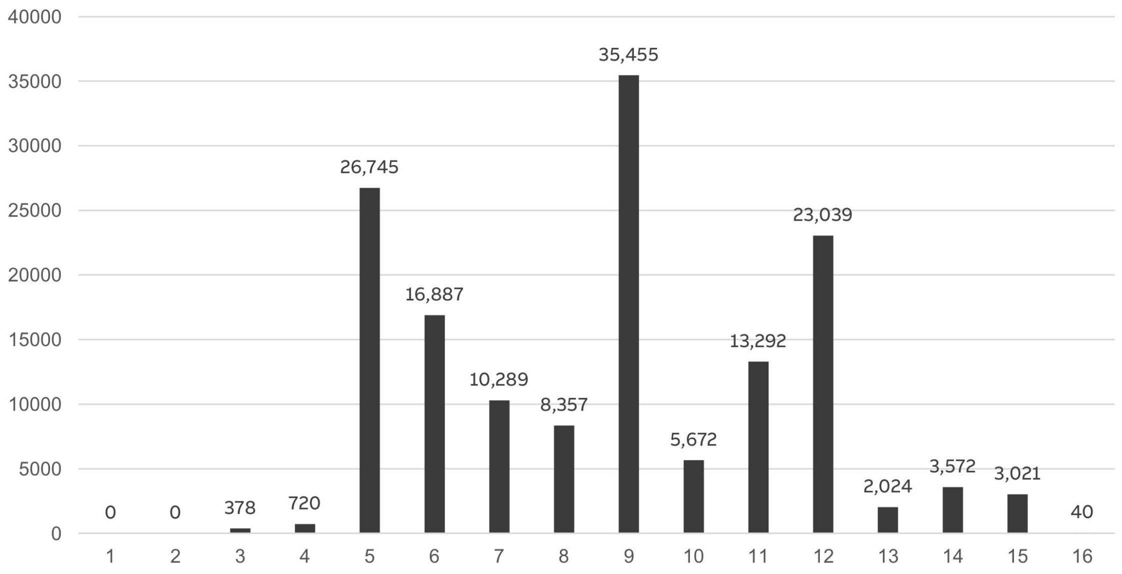
Case Study 1

Production of plastic pieces



Initial Input

- A mold creates a piece with 16 discs
- Orders in year 2018



Discovery Phase

- What are the cost drivers?
    - Total time of production, waste, total plastic used, overproduction, cutting costs
- Is there a possibility to build a new mold?
- Will different molds have the same yield?
- Will different molds have the same throughput?
- Are the production requirements constant or they may vary on subsequent years (i.e. stochastic)?
- Is the yield of the cutting procedure constant?

- **Size of the problem?**

Actual Problem

Decision variables

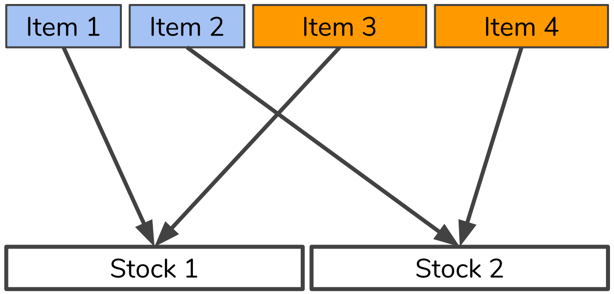
- Which investment to build a set of molds to use subject to stochastic production requirements
- Which cutting patterns to use subject to given production requirements

Objective function

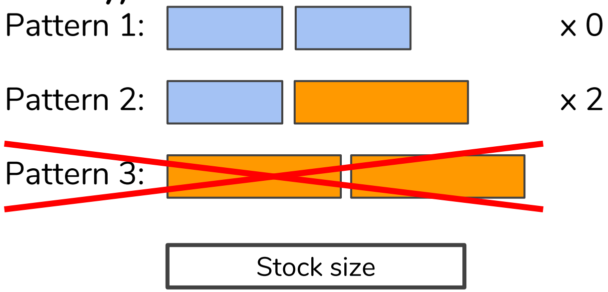
- Minimize: Waste, Over-production, Number of cuts

Models for operational optimization

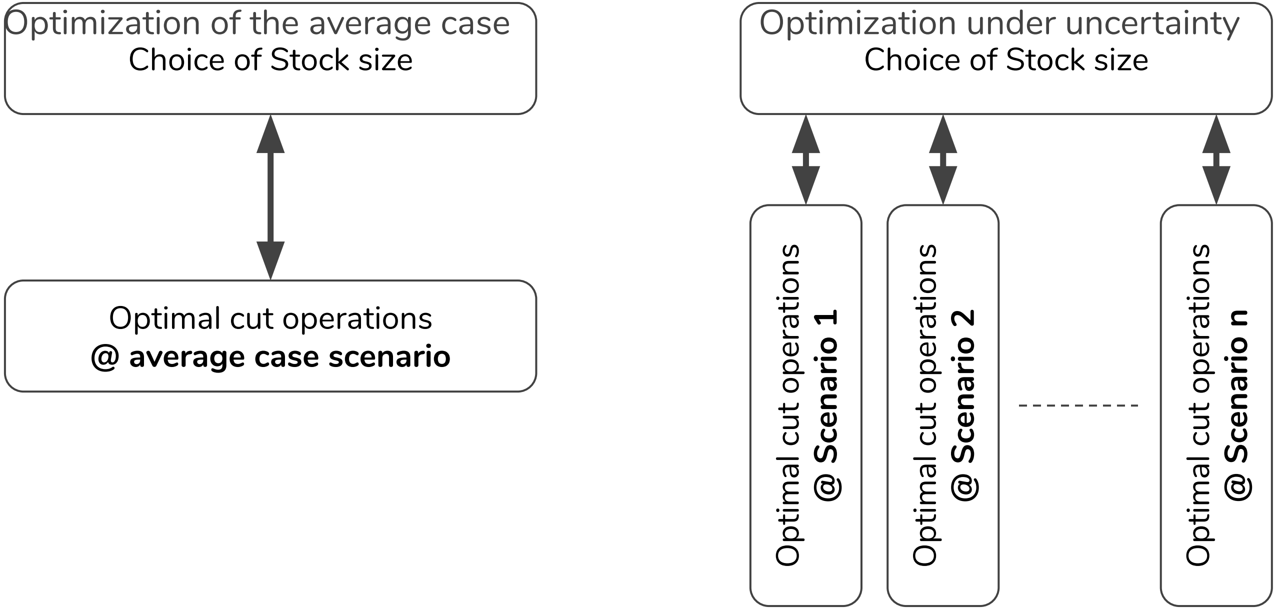
Item-based formulation (Kantorovich)



Pattern-based formulation (Gilmore & Gomory)



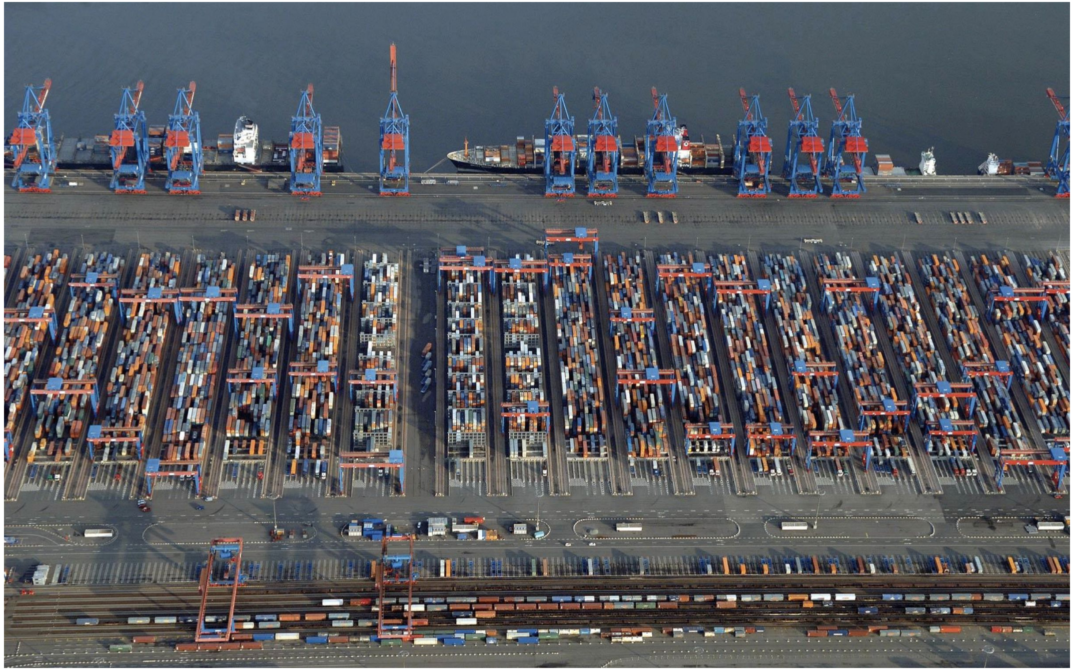
High level model for (stochastic) planning



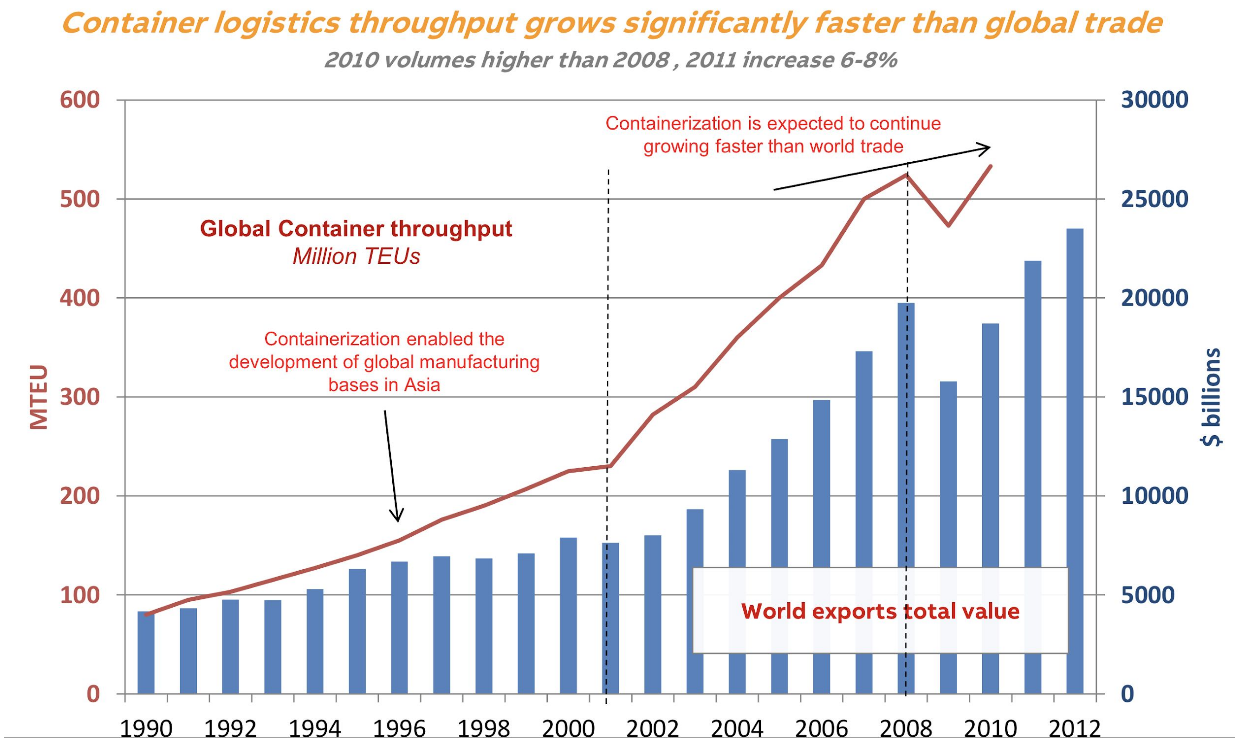
Container Terminal Optimization

Case Study 2

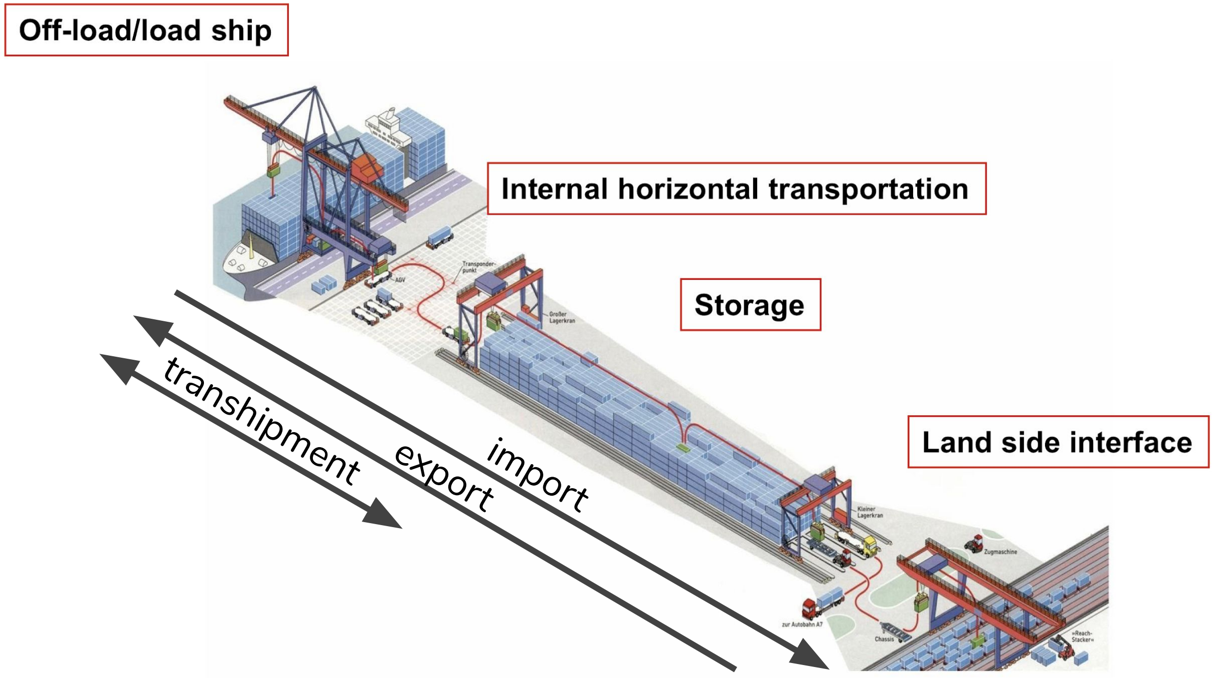
Container Terminal



Container Trade Growth

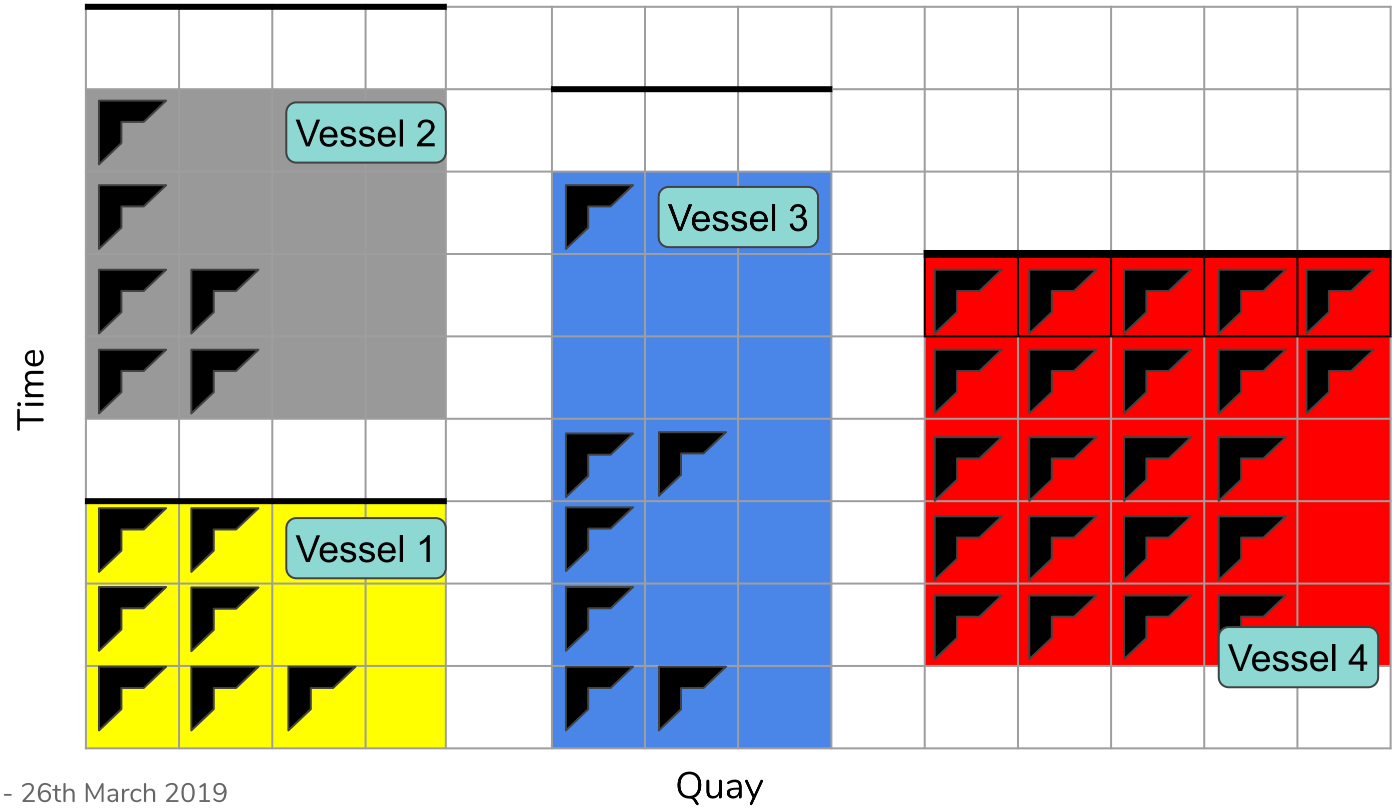


End-loaded terminal operations

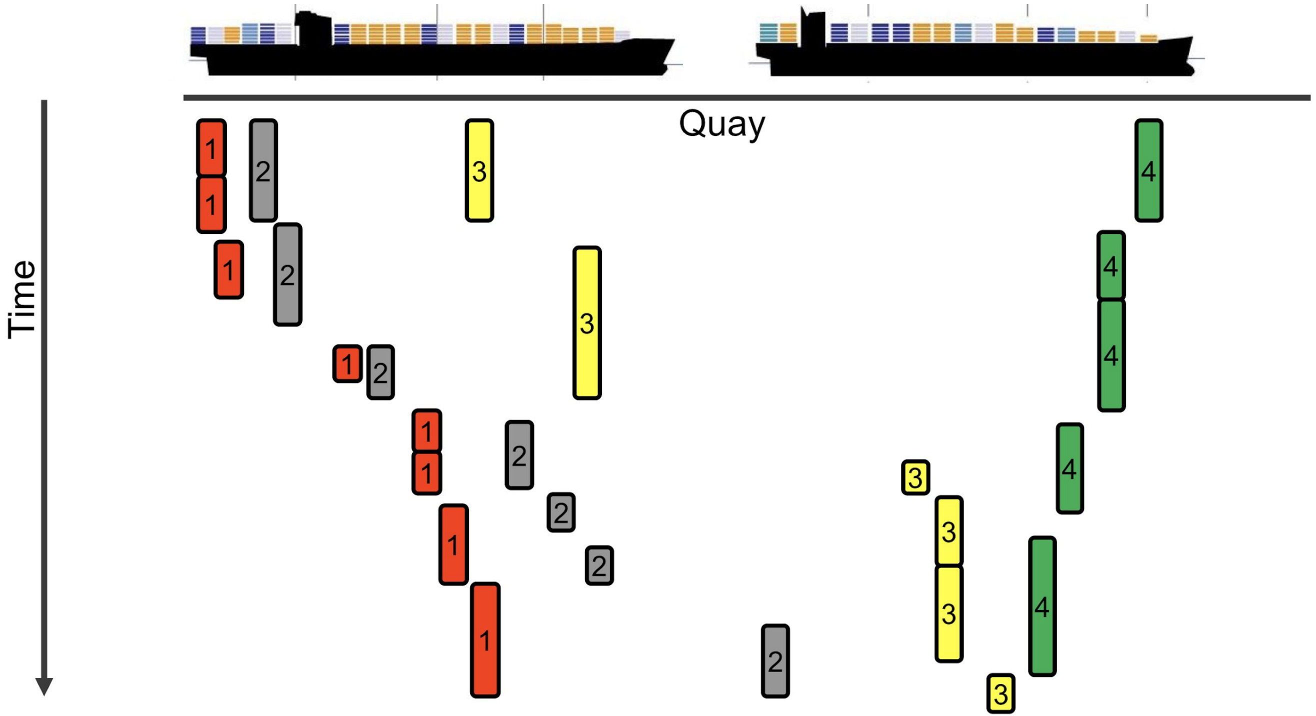


Discovery Phase

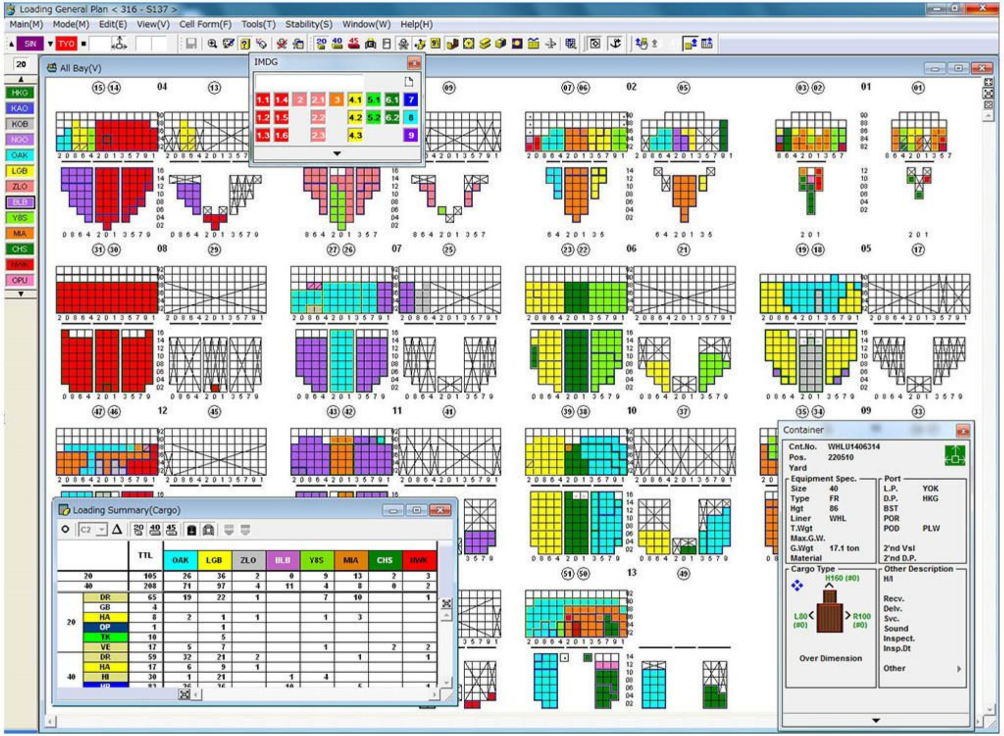
Berth Crane and Allocation



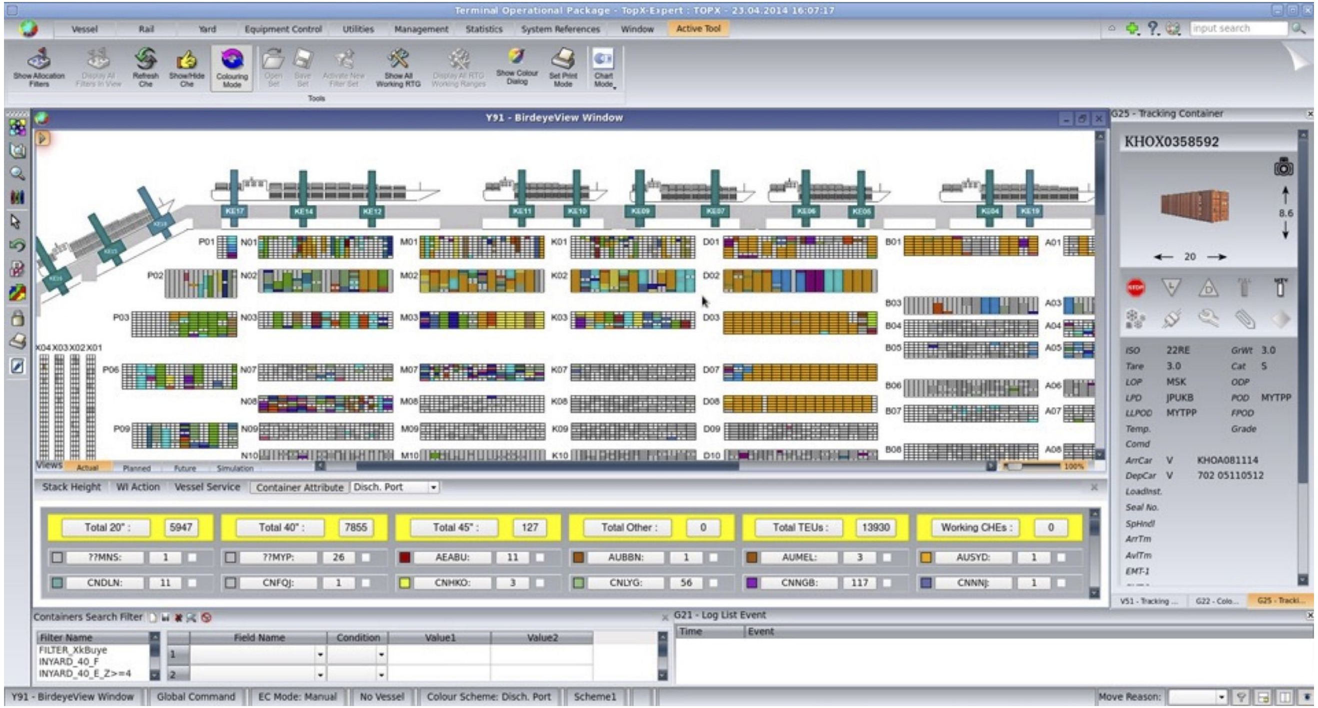
Quay Crane Allocation and Scheduling



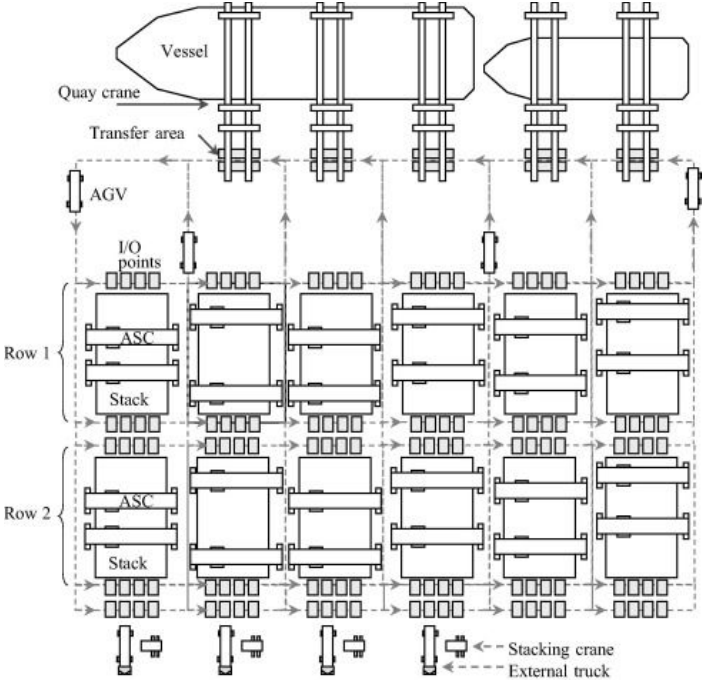
Stowing sequence and allocation



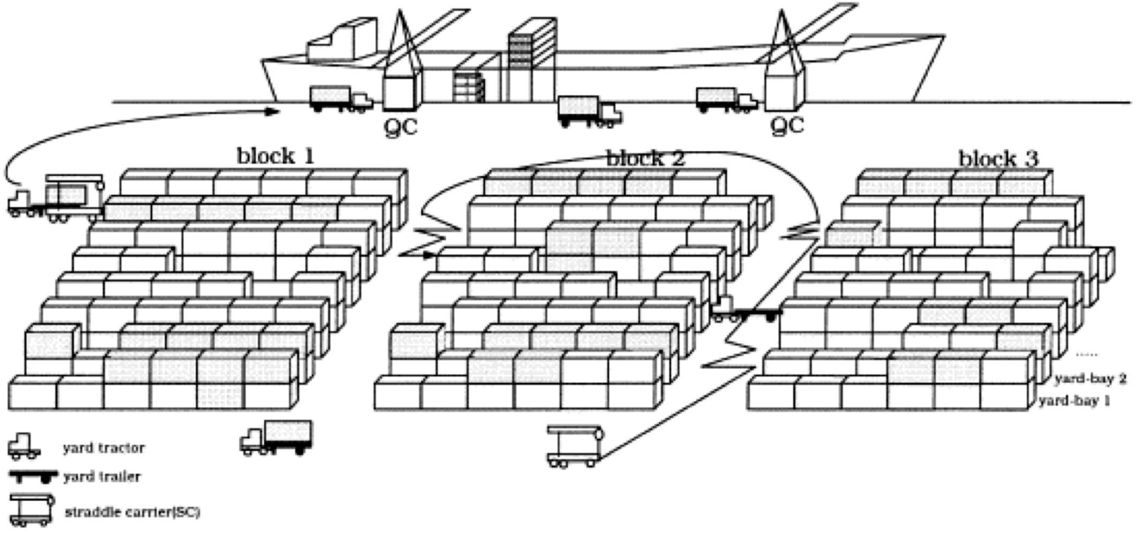
Yard Management / Planning



Automated Stacking Cranes



Horizontal Transportation



Conclusions

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- Real challenge is understanding domain-specific knowledge and translate it into abstractions and mathematical formulations
- Getting access to data is key
  - Baseline for comparing optimized solution vs current solution
  - Understanding problem features and size
- Educate the customer about
  - Optimization potentials (setting expectations right)
  - Trade-off between performance vs quality
- Fail fast
  - Short feedback cycle with customer
  - Post-processing tool for verifying solution (better if customer developed)
- Technology mastery is required to understand strengths and weaknesses of each technology and figure out which technology is suited for which problem