Real-Time Management of the Berth Allocation Problem with Stochastic Arrival and Handling Times

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Contents

Motivation

- High level of uncertainty in port operations due to weather conditions, mechanical problems etc.
  - Disrupt the normal functioning of the port
  - Require quick real time action.

- Very few studies address the problem of real time recovery in port operations

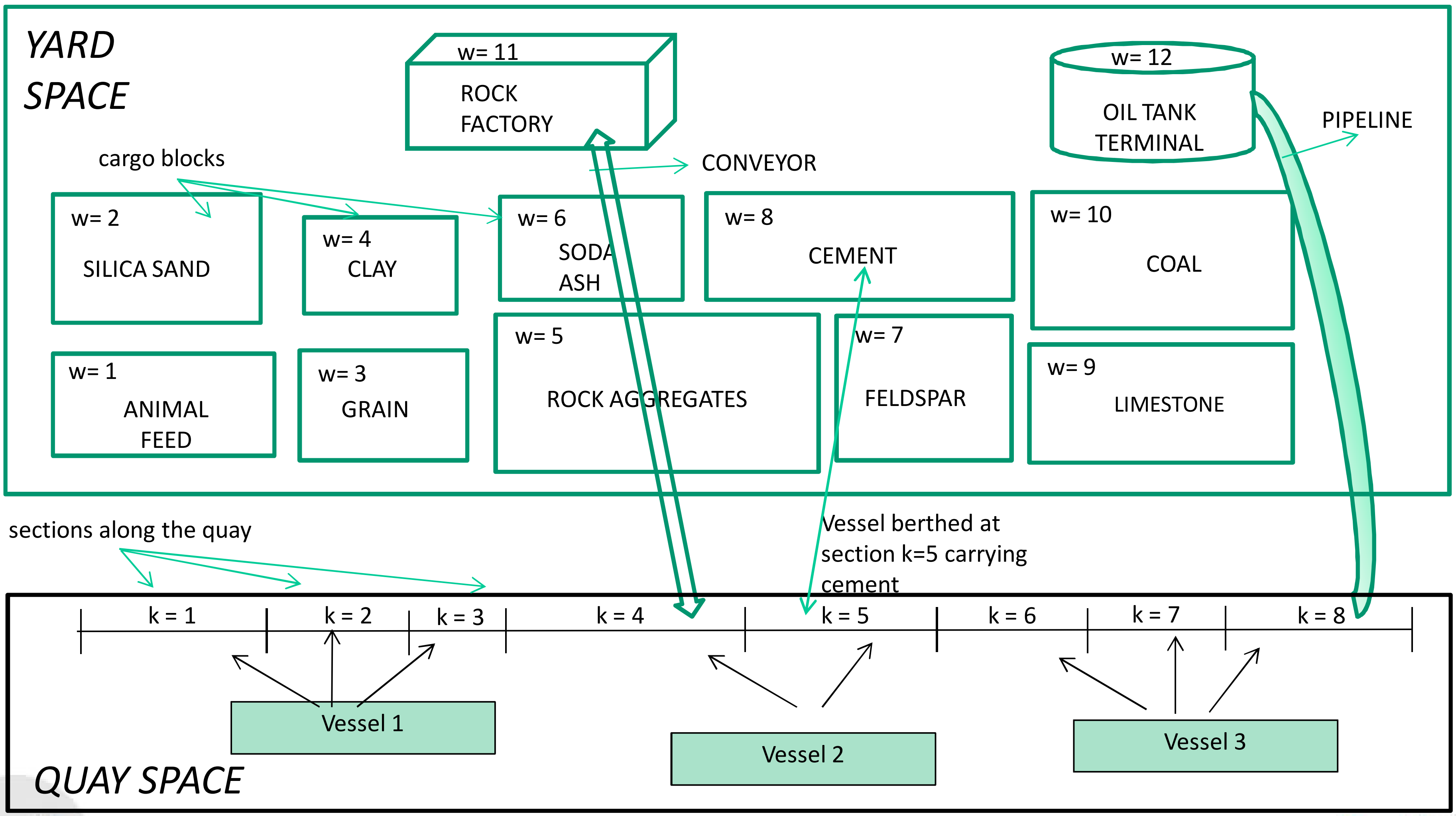
- Our research problem derives from the realistic requirements at the SAQR port, Ras Al Khaimah, UAE where there is a high degree of uncertainty in the vessel arrival and handling times.

Research Objectives

- Develop methodologies to react to disruptions in real time.

- For a given baseline berthing schedule, minimize the total realized costs of the updated schedule as actual arrival and handling time data is revealed in real time.

Schematic Diagram of a Bulk Terminal



How to Determine the Baseline Schedule ?

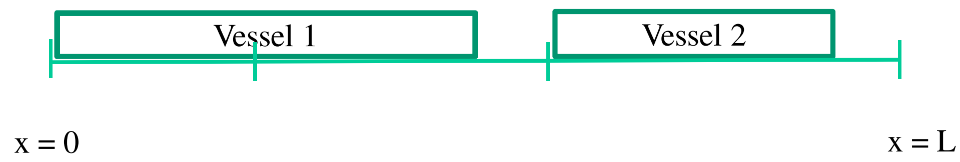
- Any feasible berthing assignment and schedule of vessels along the quay respecting the spatial and temporal constraints on the individual vessels

- **Best case**: Optimal solution of the deterministic berth allocation problem (without accounting for any uncertainty in information)

Deterministic BAP: Problem Definition

- **Find**
  - Optimal assignment and schedule of vessels along the quay (without accounting for any uncertainty)
- **Given**
  - **Expected arrival times** of vessels
  - **Estimated handling times** of vessels dependent on cargo type on the vessel (the relative location of the vessel along the quay with respect to the cargo location on the yard) and the number of cranes operating on the vessel
- **Objective**
  - Minimize total service times (waiting time + handling time) of vessels berthing at the port
- **Results**
  - Near optimal solutions obtained using set partitioning method or heuristic based on squeaky wheel optimization for instances containing up to 40 vessels

GSPP Formulation: A simple example



- $|N| = 2$, $|M| = 3$, $|H| = 3$
- Vessel 1 cannot occupy section 3 as it does not have conveyor facility, vessel 2 arrives at time t = 1
- Feasible assignment matrix:

Vessel 1	1	1	0	0
Vessel 2	0	0	1	1
Section 1 , Time 1	1	0	0	0
Section 1, Time 2	1	1	1	0
Section 1, Time 3	0	1	1	0
Section 2, Time 1	1	0	0	0
Section 2, Time 2	1	1	1	1
Section 2, Time 3	0	1	1	1
Section 3, Time 1	0	0	0	0
Section 3, Time 2	0	0	0	1
Section 3, Time 3	0	0	0	1

GSPP Model Formulation

Objective Function:

$$\min \sum_{p \in P} (d_p \lambda_p + h_p \lambda_p)$$

Constraints:

$$\sum_{p \in P} (A_{ip} \lambda_p) = 1 \qquad \forall i \in N$$

$$\sum_{p \in P} (b_p^{st} \lambda_p) \leq 1 \qquad \forall s \in M, \forall t \in H$$

d_p : *delay in service associated with assignment* $p \in P$

h_p : *handling time associated with assignment* $p \in P$

λ_p : binary parameter, equal to 1 if assignment $p \in P$ is part of the optimal solution

Real Time Recovery in Berth Allocation Problem

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Problem Definition: Real time recovery in BAP

- **Objective:** For a given baseline berthing schedule, minimize the total realized costs as data (arrival times and handling times of vessels) is revealed in real time.

- This amounts to solving an optimization problem at time instant t with the following objective function:

$$\min \quad Z_t = Z_{1t} + Z_{2t} + Z_{3t}$$

$$Z_{1t} = \sum_{i \in N_t^u} (m'_i - a_i^t + h_i^t(k'))$$

Service cost of unassigned vessels

$$Z_{2t} = \sum_{i \in N_t^u} (c_1 | b_i(k') - b_i(k) | + c_2 \mu_i | e'_i - e_i |)$$

Cost of re-allocation of unassigned vessels

$$Z_{3t} = \sum_{i \in N_o^t} (c_3 w'_i)$$

Berthing delays to vessels arriving on-time

Problem Definition: Real time recovery in BAP

- Key arrival disruption pattern in real time
  - For each vessel $i \in N$, we are given an expected arrival time A_i which is known in advance.
  - The expected arrival time of a given vessel may be updated $|F|$ times during the planning horizon of length $|H|$ at time instants t_{i1}, t_{i2}...t_{iF} such that

    $$0 \leq t_{i1} < t_{i2} < t_{i3} \ldots t_{i(F-1)} < t_{iF} < a_i$$

    where a_i is the actual arrival time of the vessel, and the corresponding arrival time update at time instant t_{iF} is A_{iF} for all $i \in N$.
- Actual handling time of a vessel is revealed at the time instant when the handling of the vessel is actually finished

Modeling the Uncertainty

- **Uncertainty in arrival times**
  - Based on the data sample, arrival times are modeled using a discrete uniform distribution. Actual arrival time a_i of vessel i lies in the range $[A_i\text{-}V, A_i\text{+}V]$, where A_i is the expected arrival time of vessel i at the start of the planning horizon.
  - At any given time instant t in the planning horizon, the following 3 cases arise
    - Case I : vessel i has arrived and the actual arrival time a_i is known
    - Case II : the vessel hasn't arrived yet but the expected arrival time A_i is known
    - Case III : neither the actual nor the expected arrival time is known at time instant t, then the arrival time estimate a_i^t at time instant t is such that $a_i^t \in [t, A_i + V]$, and is determined from the following equation

$$\text{Prob } (a_i \leq a_i^t) = \rho_a$$

Since the arrival time of vessel i is assumed to be uniformly distributed,

$$a_i^t = t + \rho_a (A_i + V - t)$$

Modeling the Uncertainty

- **Uncertainty in handling times**
  - Handling times are modeled using a discrete truncated exponential distribution. Actual handling time $h_i(k)$ of vessel *i* berthed at starting section *k* lies in the range $[H_i(k), \gamma H_i(k)]$, where $H_i(k)$ is the estimated (deterministic) handling time of vessel *i* berthed at starting section *k*
  - At any given time instant *t* in the planning horizon, the following 3 cases arise
    - Case I : the handling of vessel *i* berthed at starting section *k'* is finished, then the actual handling time $h_i(k')$ is known
    - Case II : the vessel is being handled at time instant *t,* thus the actual berthing position *k'* of the vessel is known, but the actual handling time is unknown. The handling time estimate $h_i^t(k')$ at time instant *t* is given by

$$\text{Prob}\ (h_i(k') \le h_i^t(k')) = \rho_h$$

    - Case III : the vessel is not assigned yet, in which case the handling time of the vessel at time instant *t* for any berthing position *k* is given by

$$\text{Prob}\ (h_i(k) \le h_i^t(k)) = \rho_h$$

Since the handling times follow a truncated exponentially distribution,

$$h_i^t(k) = -1/\lambda \ln(e^{-\lambda h_{iL}^t(k)} - \rho_h(e^{-\lambda h_{iL}^t(k)} - e^{-\lambda h_{iU}^t(k)}))$$

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Solution Algorithms

- **Re-Optimization Based Recovery Algorithm**
  - Re-optimize the berthing schedule of all unassigned vessels using set-partitioning method every time there is a **disruption**
    - arrival time of any vessel is updated and it deviates from its previous expected value.
    - handling of any vessel is finished and it deviates from the estimated value
  - Uncertainty in the unknown arrival and handling times provided as input parameters is modeled as discussed earlier
  - Berthing assignment of all vessels that have already been assigned to the quay is considered frozen and unchangeable
- **Smart Greedy Recovery Algorithm**
  - Assign an incoming vessel to the quay as soon as berthing space is available, at or after the estimated berthing time of the vessel (as per the baseline schedule)
  - The vessel is assigned to the section(s) at which **the total realized cost of all the unassigned vessels** at that instant is minimized by modeling the uncertainty in unrevealed arrival and handling times, as discussed earlier
    - To determine the total realized cost to assign a given vessel at a given set of section(s), all other unassigned vessels are assigned to the estimated berthing sections as per the baseline schedule

Benchmark Solutions

- **Ongoing Practice at the Port: Greedy Recovery Algorithm**
  - Assign the vessels as they arrive as soon as berthing space is available, at or after the estimated berthing time of the vessel (as per the baseline schedule)
  - Any given vessel is assigned at those set of sections where the realized cost of assigning it is minimized. Thus no need to model uncertainty in future arrival and handling times
  - Closely represents the ongoing practice at the port

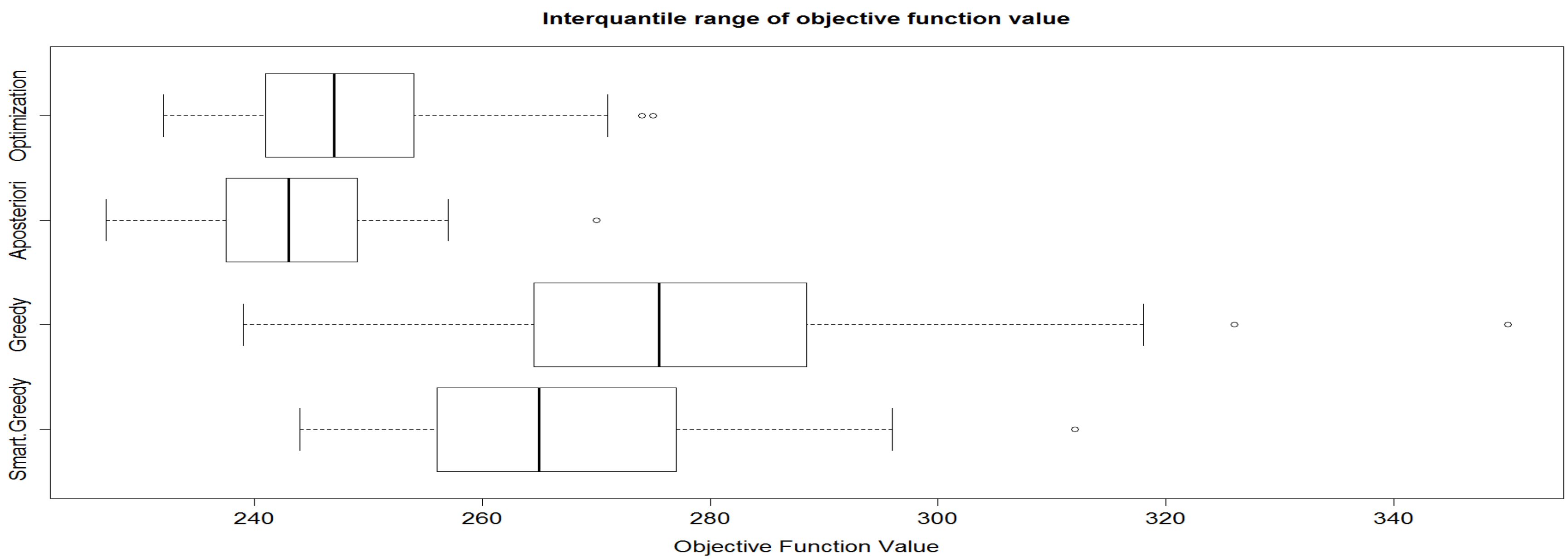
- **Best Solution : Aposteriori Optimization Approach**
  - Re-solve the problem of real time recovery once all the unknown data is revealed at the end of the planning horizon
  - Problem of real time recovery reduces to solving the deterministic berth allocation problem with the objective function to minimize total realized cost of the schedule
  - Provides a lower bound to the minimization problem of real time recovery we are interested in solving

Arrival Disruption Scenario

	ETA									
Vessel 0:	19	22(2)	21(4)	24(5)	22(6)	24(7)	23(8)	23(9)	23(22)	**ATA**:23
Vessel 1:	3	**ATA**:6								
Vessel 2:	4	7(3)	6(4)	6(5)	**ATA**:7					
Vessel 3:	14	16(2)	10(3)	12(4)	**ATA**:11					
Vessel 4:	18	23(9)	**ATA**:22							
Vessel 5:	12	13(7)	**ATA**:12							
Vessel 6:	0	5(2)	**ATA**:4							
Vessel 7:	0	**ATA:**-4								
Vessel 8:	0	**ATA**:3								
Vessel 9:	11	**ATA**:7								

Computational Results

- *Low Stochasticity, mildly congested scenario*
- $|N|$=10 vessels, $|M|$= 10 sections, $c_1 = c_3 = 1.0$, $c_2 = 0.002$, U= 4 hours, $V = 5$, $\gamma = 1.1$, $\rho_a = \rho_h = 0.95$

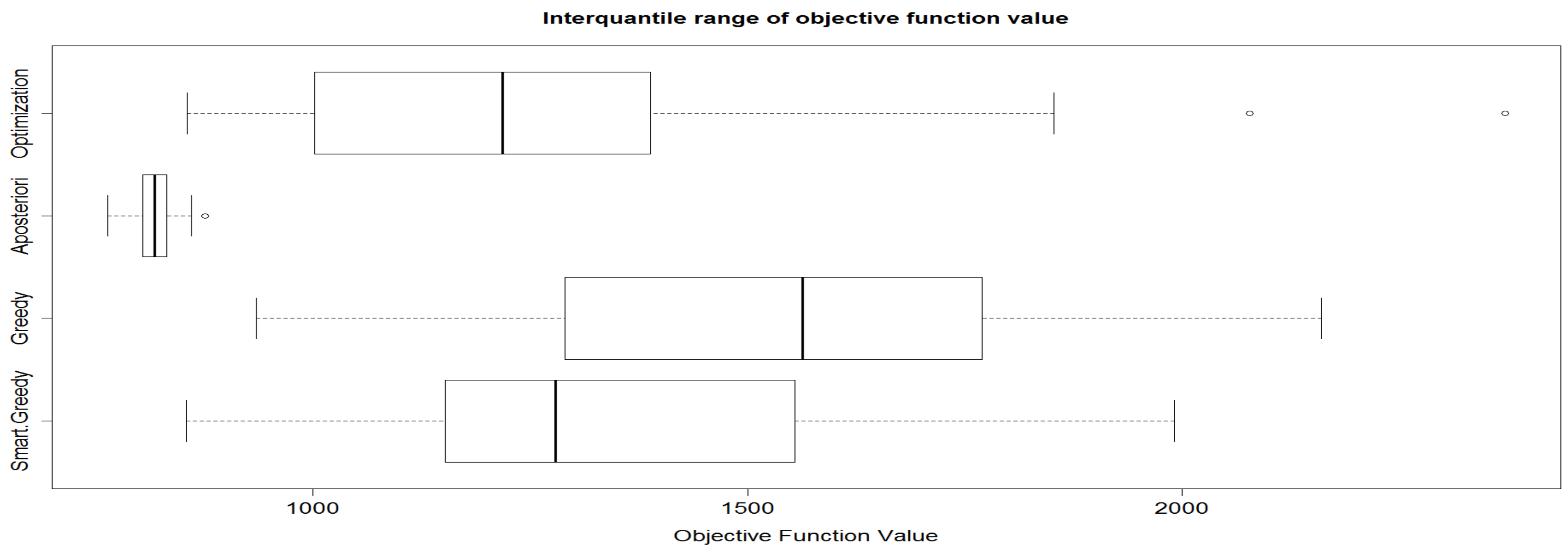


- Mean Gap with respect to the aposteriori optimization solution

Greedy Approach	Optimization based Approach	Smart Greedy Approach
13.75%	1.78%	9.53%

Computational Results

- *Low Stochasticity, highly congested scenario*
- $|N|$=25 vessels, $|M|$= 10 sections, $c_1 = c_3 = 1.0$, $c_2 = 0.002$, U= 4 hours, V = 5, $\gamma = 1.1$, $\rho_a = \rho_h = 0.95$



- Mean Gap with respect to the aposteriori optimization solution

Greedy Approach	Optimization based Approach	Smart Greedy Approach
86.85 %	48.06 %	63.68 %

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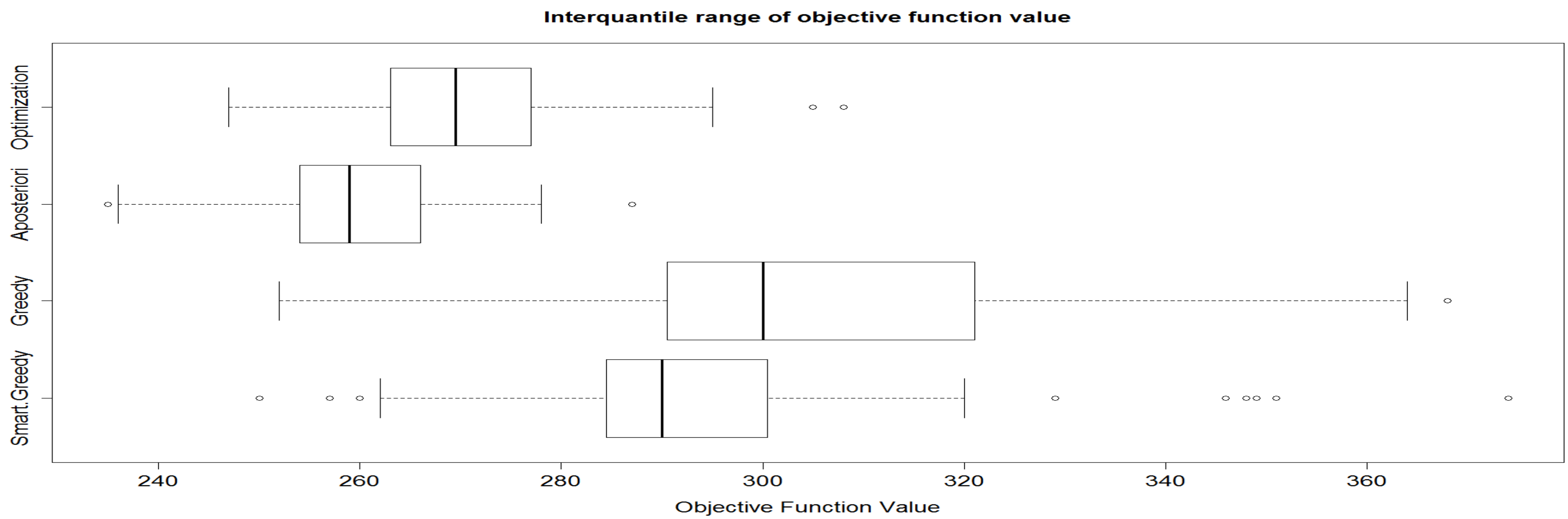
Computational Results

- *High Stochasticity, mildly congested scenario*
- $|N|$=10 vessels, $|M|$= 10 sections, $c_1 = c_3$ = 1.0, c_2 = 0.002, U= 4 hours, V = 10, γ = 1.2, $\rho_a = \rho_h$= 0.95



- Mean Gap with respect to the aposteriori optimization solution

Greedy Approach	Optimization based Approach	Smart Greedy Approach
17.70 %	4.11 %	13.27 %

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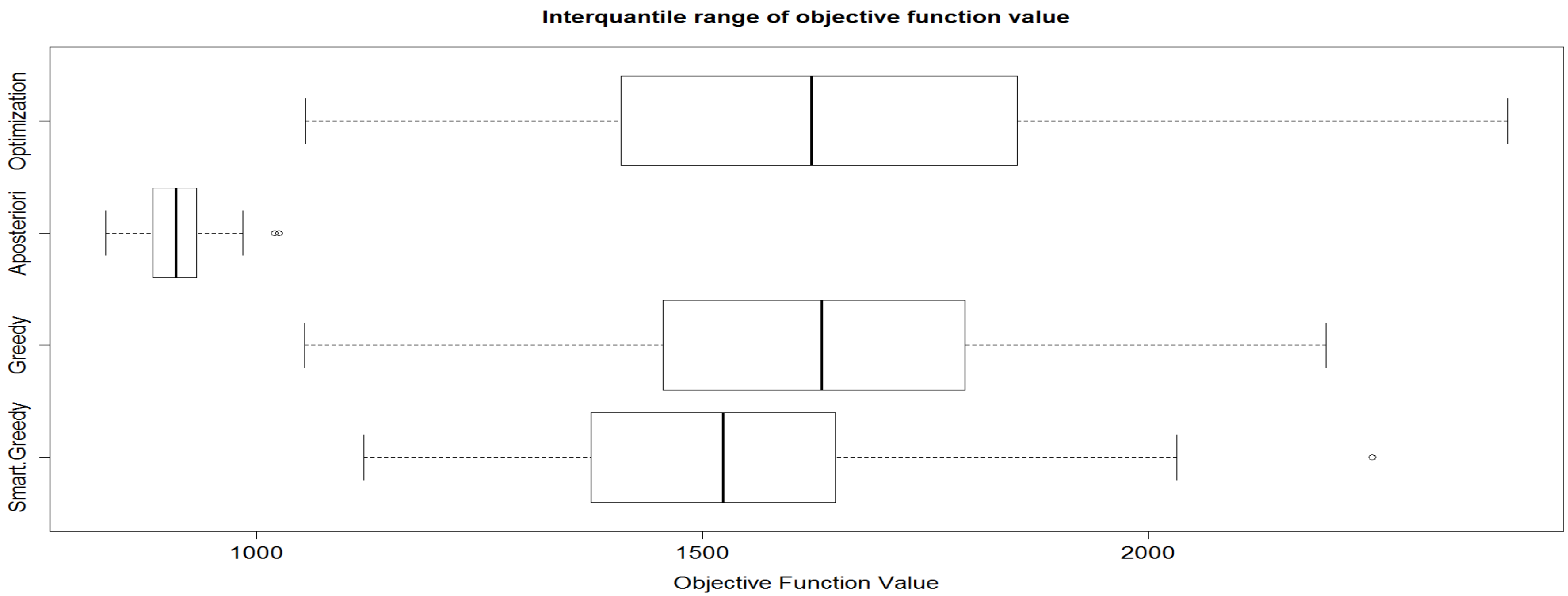
Computational Results

- *High Stochasticity, highly congested scenario*

- $|N|$=25 vessels, $|M|$= 10 sections, $c_1 = c_3 = 1.0$, $c_2 = 0.002$, U= 4 hours, $V = 10$, $\gamma = 1.2$, $\rho_a = \rho_h = 0.95$



- Mean Gap with respect to the apriori optimization solution

Greedy Approach	Optimization based Approach	Smart Greedy Approach
77.57 %	78.41 %	68.88 %

Conclusions and Future Work

- Modeling the uncertainty in future vessel arrival and handling times can significantly reduce the total realized costs of the schedule, in comparison to the ongoing practice of re-assigning vessels at the port.

- The optimization based recovery algorithm outperforms the heuristic based smart greedy recovery algorithm, but is computationally more expensive.

- Limitation: The re-optimization based algorithm that involves updating the entire schedule in the event of disruptions is more sensitive to the increase in problem size and stochastic variability, as compared to the smart greedy approach.

- As part of future work, we are developing a robust formulation of the berth allocation problem with a certain degree of anticipation of variability in information.

Thank you!

Literature Review

- Very scarce literature on dealing with uncertainty in operations in container terminals . To the best of our knowledge, no literature on bulk ports.

- OR literature related to BAP under uncertainty in container terminals:

  - **Pro-active Robustness:** Plan with a certain degree of anticipation of variability in information.

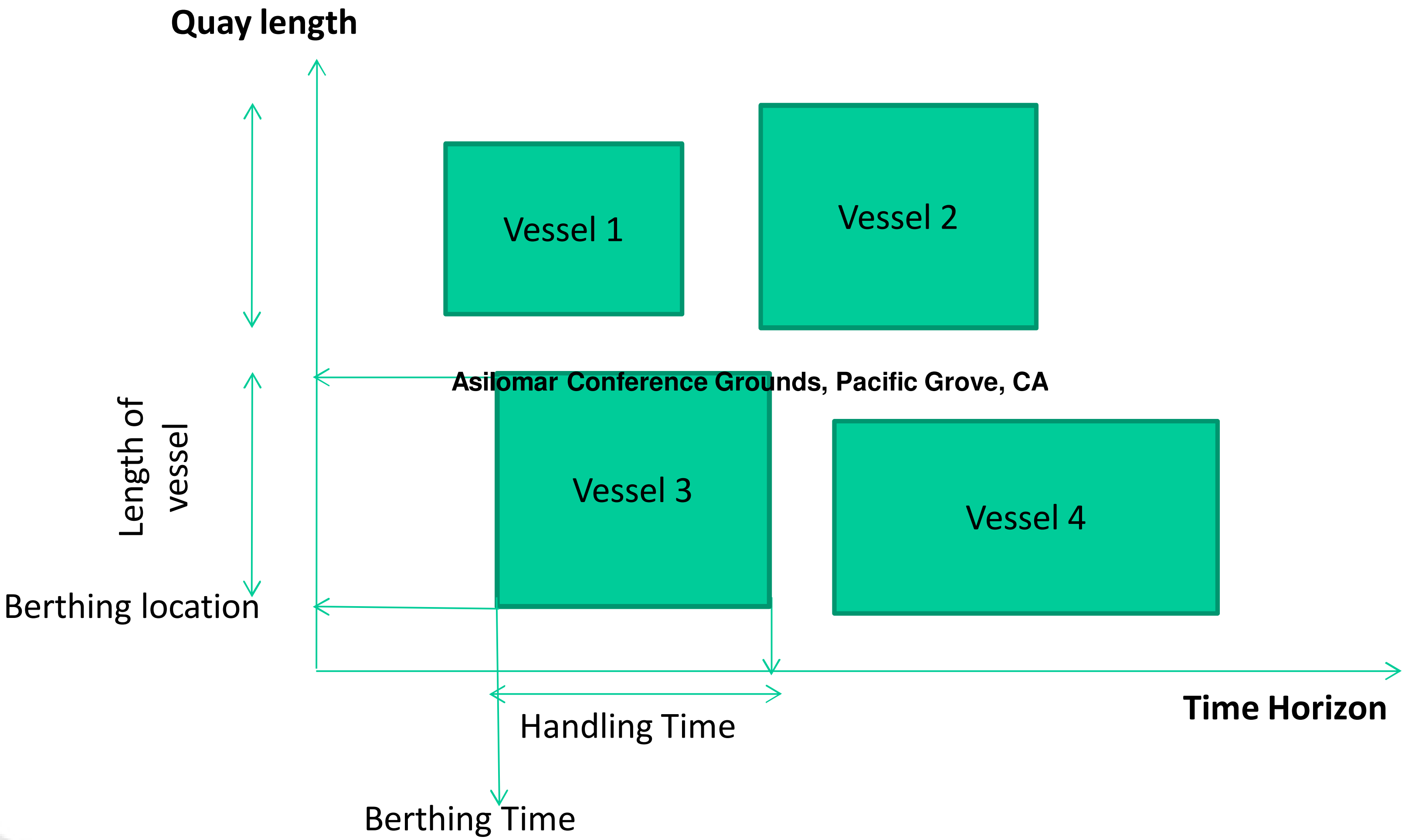
    - Stochastic programming approaches used by Zhen et al. (2011), Han et al. (2010).

    - Define surrogate problems i.e. for a given level of service, maximize buffer times or minimize expected delays: Moorthy and Teo (2006), Zhen and Chang (2012), Xu et al. (2012, Hendriks et al. (2010)

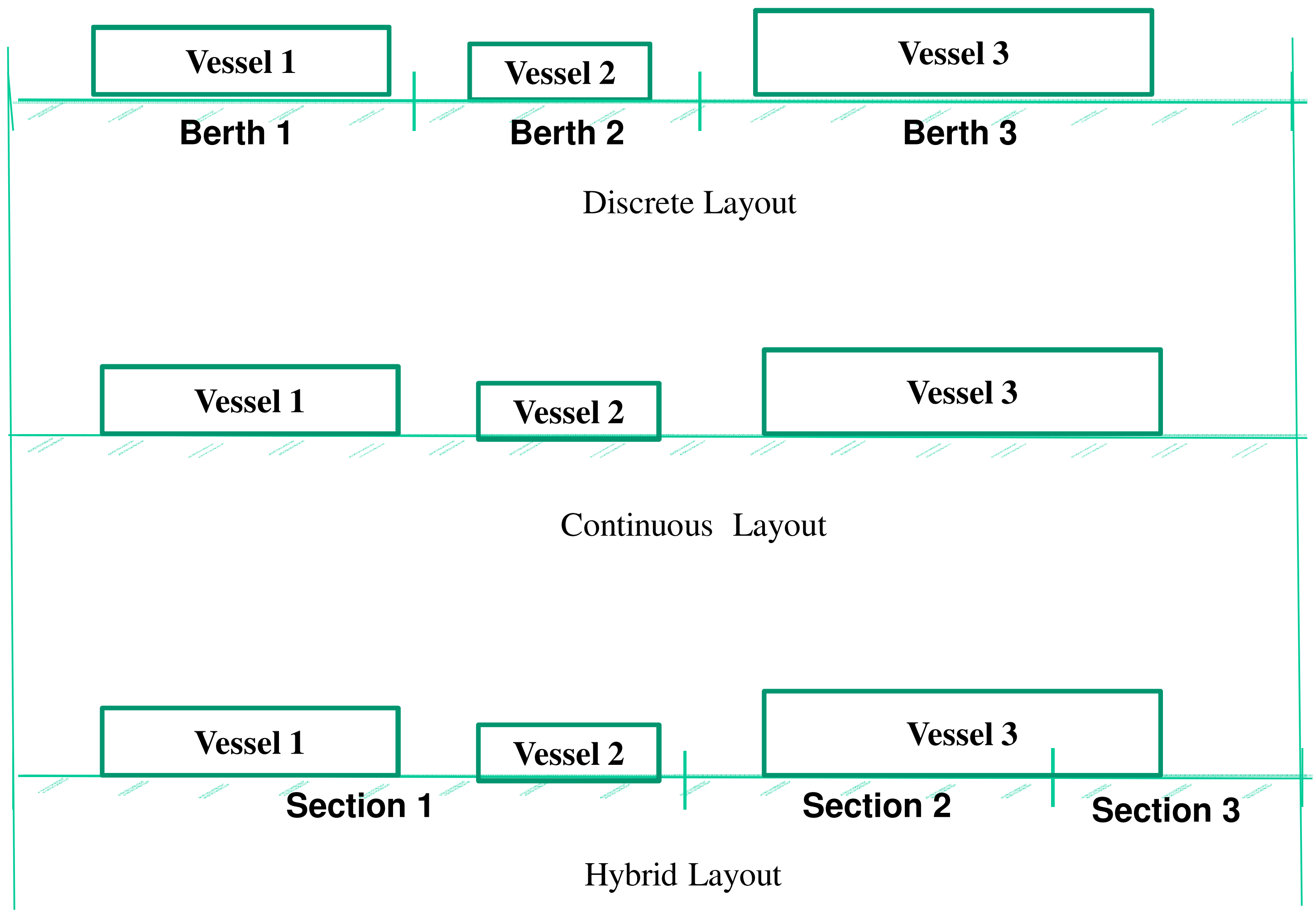
  - **Reactive approach or disruption management :** Reacting to disruptions in real time

    - Zeng et al.(2012) and Du et al. (2010) propose reactive strategies based on simple rules of thumb or local rescheduling heuristics.

BAP Solution



Discretization



MILP Model

Objective Function

$$\min \sum_{i \in N} (m_i - A_i + c_i)$$

Decision variables:

m_i starting time of handling of vessel $i \in N$;

c_i total handling time of vessel $i \in N$;

MILP Model

Dynamic vessel arrival constraints

$$m_i - A_i \geq 0 \qquad \forall i \in N,$$

Non overlapping constraints

$$\sum_{k \in M} (b_k s_k^j) + B(1 - y_{ij}) \geq \sum_{k \in M} (b_k s_k^i) + L_i \qquad \forall i, j \in N, i \neq j,$$

$$m_j + B(1 - z_{ij}) \geq m_i + c_i \qquad \forall i, j \in N, i \neq j,$$

$$y_{ij} + y_{ji} + z_{ij} + z_{ji} \geq 1 \qquad \forall i, j \in N, i \neq j,$$

MILP Model

Section covering constraints

$$\sum_{k \in M} s_k^i = 1 \qquad \forall i \in N,$$

$$\sum_{k \in M} (b_k s_i^k) + L_i \leq L \qquad \forall i \in N,$$

$$\sum_{l \in M} (d_{ilk} s_l^i) = x_{ik} \quad \forall i \in N, \forall k \in M,$$

Draft Restrictions

$$(d_k - D_i) x_{ik} \geq 0 \qquad \forall i \in N, \forall k \in M,$$

MILP Model

Determination of Handling Times

- Given an input vector of unit handling times for each combination of cargo type and section along the quay
- Specialized facilities (conveyors, pipelines etc.) also modeled as cargo types
- All sections occupied by the vessel are operated simultaneously

$$c_i \geq h_k^w p_{ilk} Q_i s_l^i \qquad \forall i \in N, \forall k \in M, \forall l \in M, \forall w \in W_i$$

Q_i quantity of cargo to be loaded on or discharged from vessel *i*

h_k^w handling time for unit quantity of cargo $w \in W$ and vessel berthed at section $k \in M$;

p_{ilk} fraction of cargo handled at section $k \in M$ when vessel *i* is berthed at starting section $l \in M$

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GSPP Model

- Used in context of container terminals by Christensen and Holst (2008)

- Generate set P of columns, where each column $p \in P$ represents a feasible assignment of a single vessel in both space and time

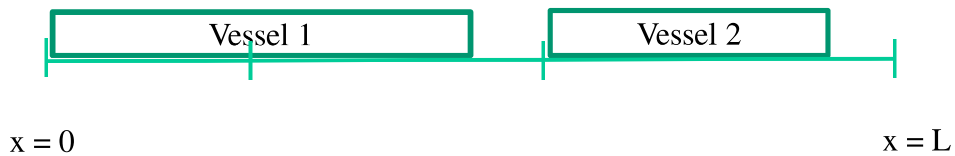
- Generate two matrices

  - Matrix A = (A_{ip}) ; equal to 1 if vessel $i \in N$ is the assigned vessel in the feasible assignment represented by column $p \in P$

  - Matrix B = (b_p^{st}) ; equal to 1 if section $s \in M$ is occupied at time $t \in H$ in column $p \in P$

Note: Assume integer values for all time measurements

GSPP Formulation: A simple example



- $|N| = 2$, $|M| = 3$, $|H| = 3$
- Vessel 1 cannot occupy section 3 owing to spatial constraints (does not have conveyor facility), vessel 2 arrives at time t = 1
- Constraint matrix P has 4 feasible assignments:

Vessel 1	1	1	0	0
Vessel 2	0	0	1	1
Section 1 , Time 1	1	0	0	0
Section 1, Time 2	1	1	1	0
Section 1, Time 3	0	1	1	0
Section 2, Time 1	1	0	0	0
Section 2, Time 2	1	1	1	1
Section 2, Time 3	0	1	1	1
Section 3, Time 1	0	0	0	0
Section 3, Time 2	0	0	0	1
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GSPP Model Formulation

Objective Function:

$$\min \sum_{p \in P} (d_p \lambda_p + h_p \lambda_p)$$

Constraints:

$$\sum_{p \in P} (A_{ip} \lambda_p) = 1 \qquad \forall i \in N$$

$$\sum_{p \in P} (b_p^{st} \lambda_p) \leq 1 \qquad \forall s \in M, \forall t \in H$$

d_p : *delay in service associated with assignment* $p \in P$

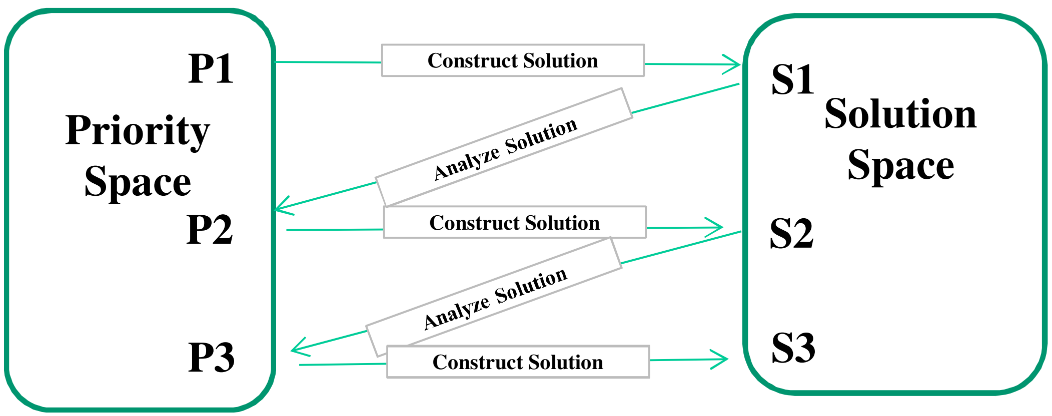
h_p : *handling time associated with assignment* $p \in P$

λ_p : binary parameter, equal to 1 if assignment $p \in P$ is part of the optimal solution

SWO Heuristic Approach

- Introduced by Clements (1997), typically successful in problems where it is possible to quantify the contribution of each single problem element to the overall solution quality

- Construct/ Analyze/ Prioritize: Solution generated at each successive iteration is constructed and analyzed, results of analysis used to generate a new priority order



- Moves in search space are motivated by the weak performing elements and not the overall objective function value

SWO Heuristic Approach

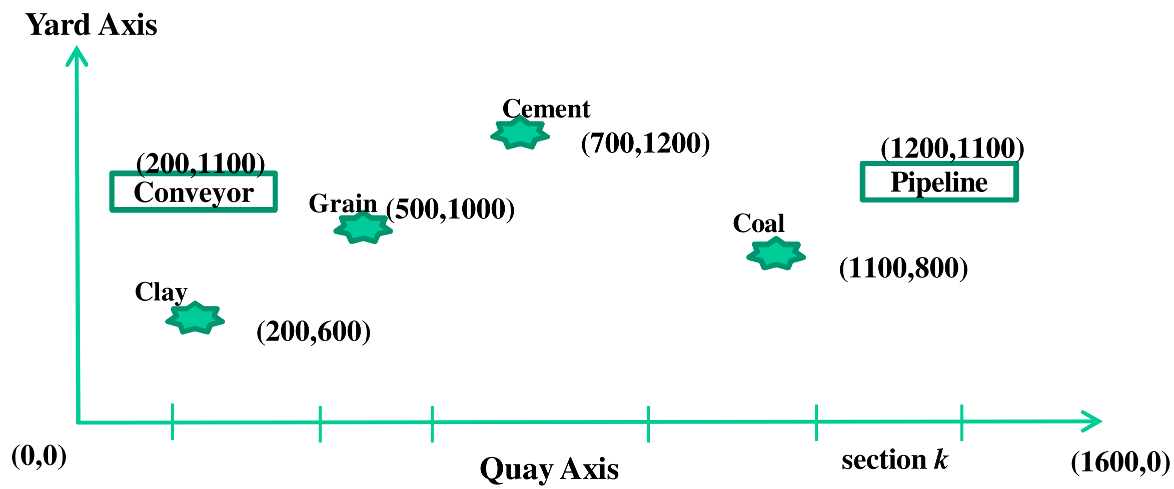
- **Construction heuristic**: Returns a feasible berthing assignment for given priority order of vessels
- **Initial Solution**: First-Cum-First-Served ordering based on arrival times of vessels
- **Algorithm**: In each successive iteration, a new priority order is constructed based on the service quality measure of each berthing vessel in the previous solution
  - Service time of the vessel in the solution found in the last iteration
  - Deviation of service time of vessel from the minimum service time possible for that vessel (zero delay + minimum handling time)
  - Sum of service times of the vessel in all iterations completed so far!
- If a priority order is already evaluated, introduce randomization by swapping two or more vessels, until we obtained a priority order that has not been evaluated so far
- Algorithm terminates after a preset number of iterations and best solution is selected as the final solution

Generation of Instances

- Instances based on data from SAQR port with quay length of 1600 meters and vessel lengths in the range 80-260 meters.

- Generate 6 instances sizes with $|N|$ = 10, 25 and 40 vessels, and $|M|$ = 10 and 30 sections, with 9 instances for each instance size.

- Handling times generated for 6 cargo types.

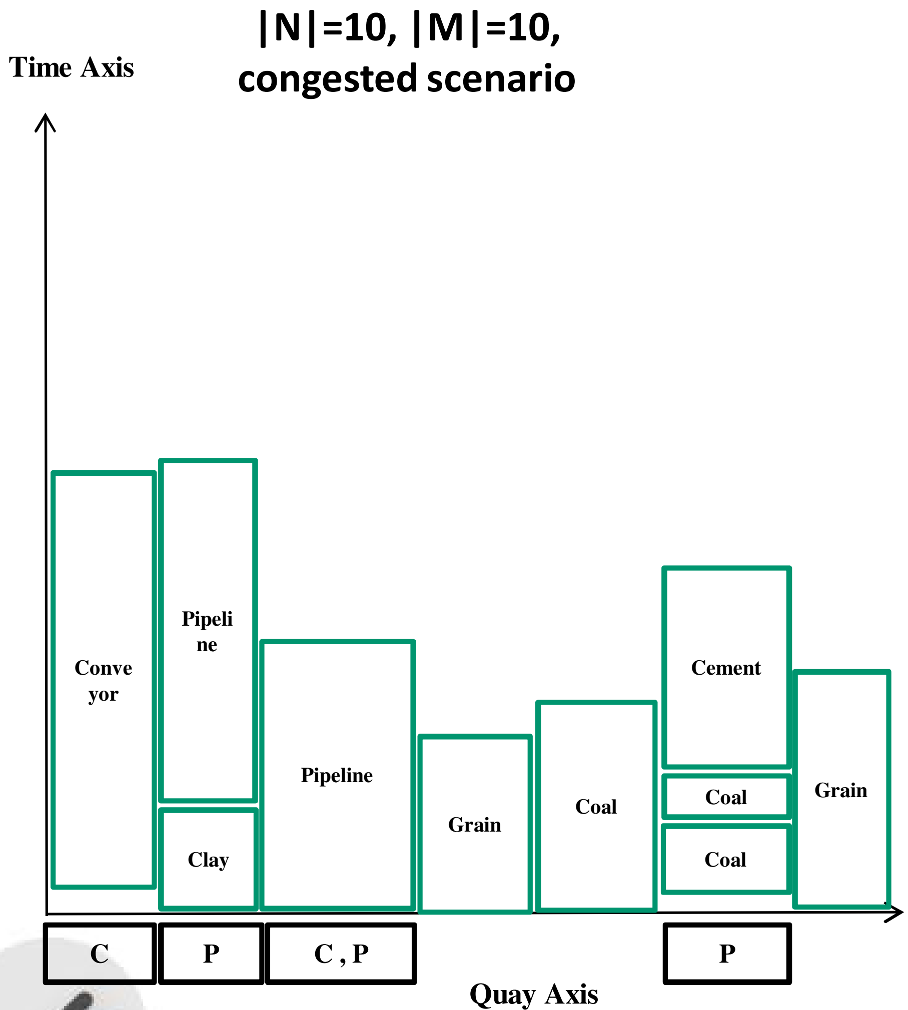


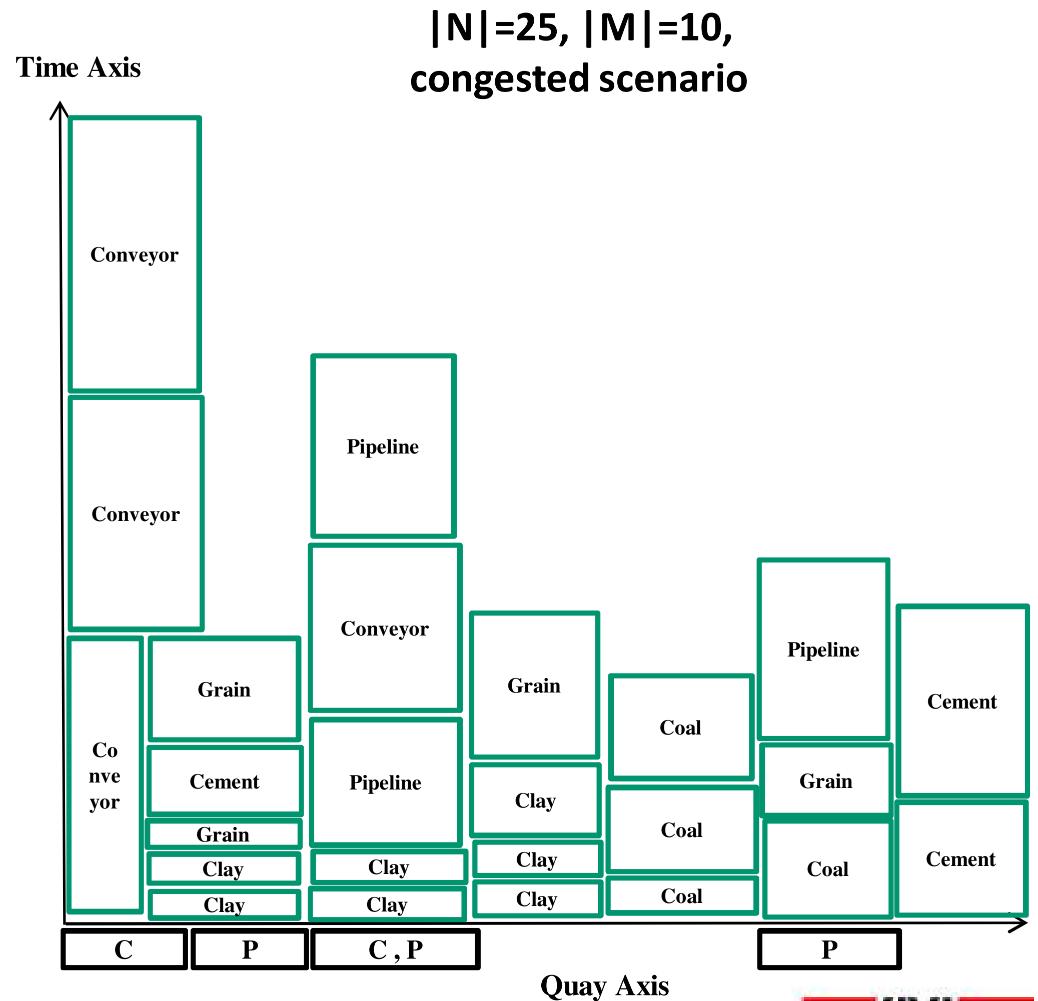
- Drafts of all vessels D_i are less than the minimum draft along the quay.

Computational Results

- Instances based on data from SAQR port
- All tests were run on an Intel Core i7 (2.80 GHz) processor and used a 32-bit version of CPLEX 12.2.
- Results inspired by port data show that the problem is complex !
- MILP formulation fails to produce optimal results for even small instances with $|N|=$ 10 vessels within CPLEX time limit of 2 hours.
- The performance of the GSPP model is quite remarkable!
  - Can solve instances up to $|N| = 40$ vessels
  - Limitations: For larger instances, or longer horizon H solver runs out of memory (use dynamic column generation!)
- Alternate heuristic approach based on squeaky wheel optimization (SWO) performs reasonably well for not so large instances. Optimality gap is less than 10% (with respect to exact solution obtained from GSPP approach) averaged over all tested instances.

Results Analysis





Problem Definition: Real time recovery in BAP

- **Penalty Cost on late arriving vessels:** Impose a penalty fees on vessels arriving beyond the right end of the arrival window, A_i+U_i