Vehicle Routing – Tank Sizing Optimization under Uncertainty: MINLP Model and Branch-and-Refine Algorithm

Fengqi You

Ignacio E. Grossmann

Jose M. Pinto

Chemical Engineering
Carnegie Mellon

PRAXAIR

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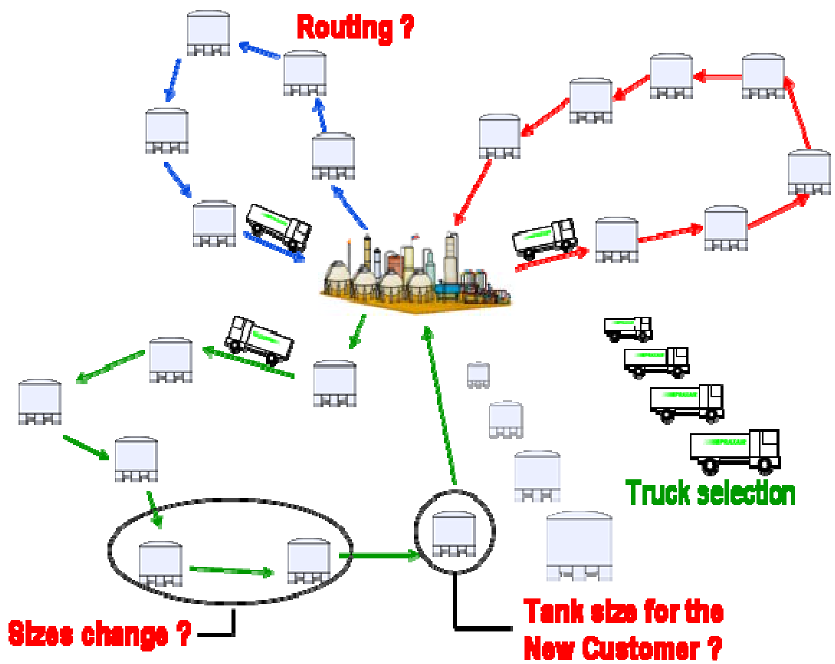
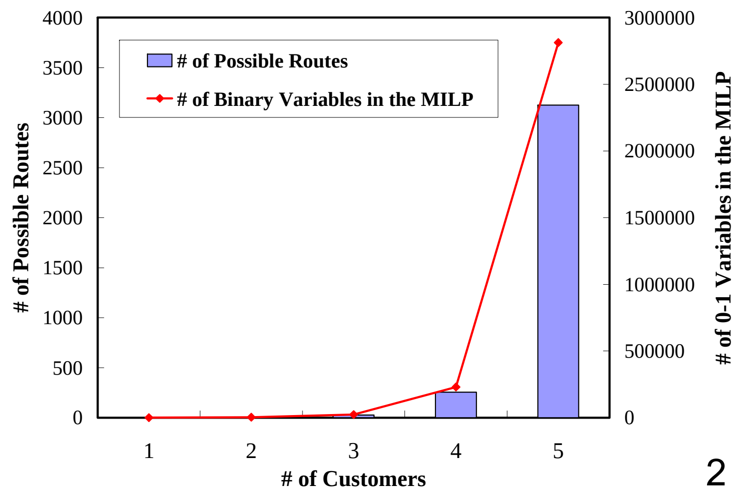
Vehicle Routing – Tank Sizing Problem

- **Tank Sizing**
  - Tank installation, upgrade & downgrade
  - Several available discrete tank sizes
  - Safety stock optimization for uncertainty
- **Vehicle Routing**
  - Several available truck sizes
  - Routing and timing decisions
- **Integration**
  - Tradeoff: operating cost vs. capital cost
  - Capture the effects of customer synergies and truck availability
  - Integration requires to solve "extended" routing problem for long term (e.g. years)
  - Integrated MILP model is **very large**





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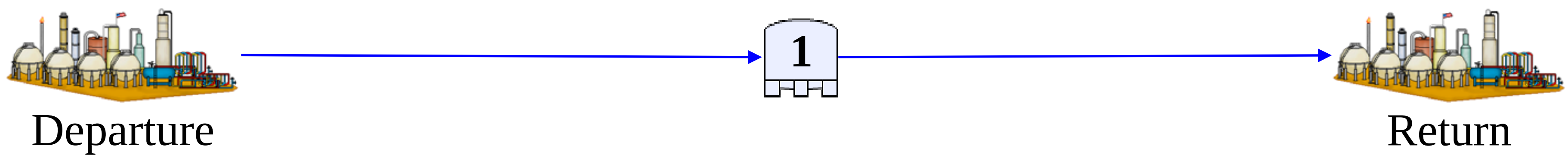
Complexity – 1 customer case



- **1 possible route**, **912 binary variables** in the MILP model for integrating tank sizing and vehicle routing
  - 3-year horizon, 4 available truck sizes, 6 available tank sizes

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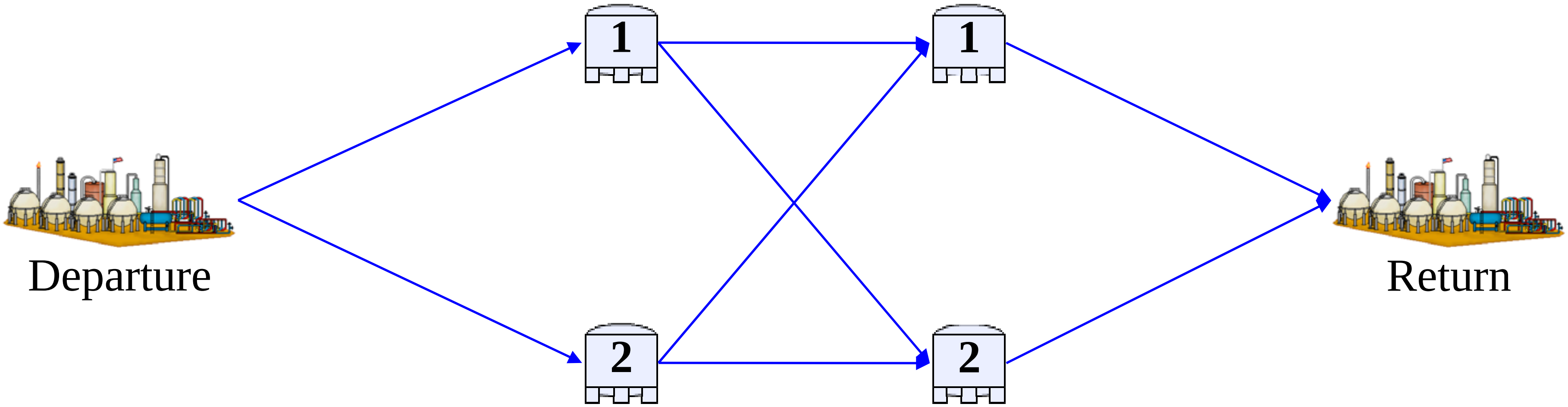
Complexity – 2 customer case



- **4 possible route**, **3,624 binary variables** in the MILP model for integrating tank sizing and vehicle routing
  - 3-year horizon, 4 available truck sizes, 6 available tank sizes

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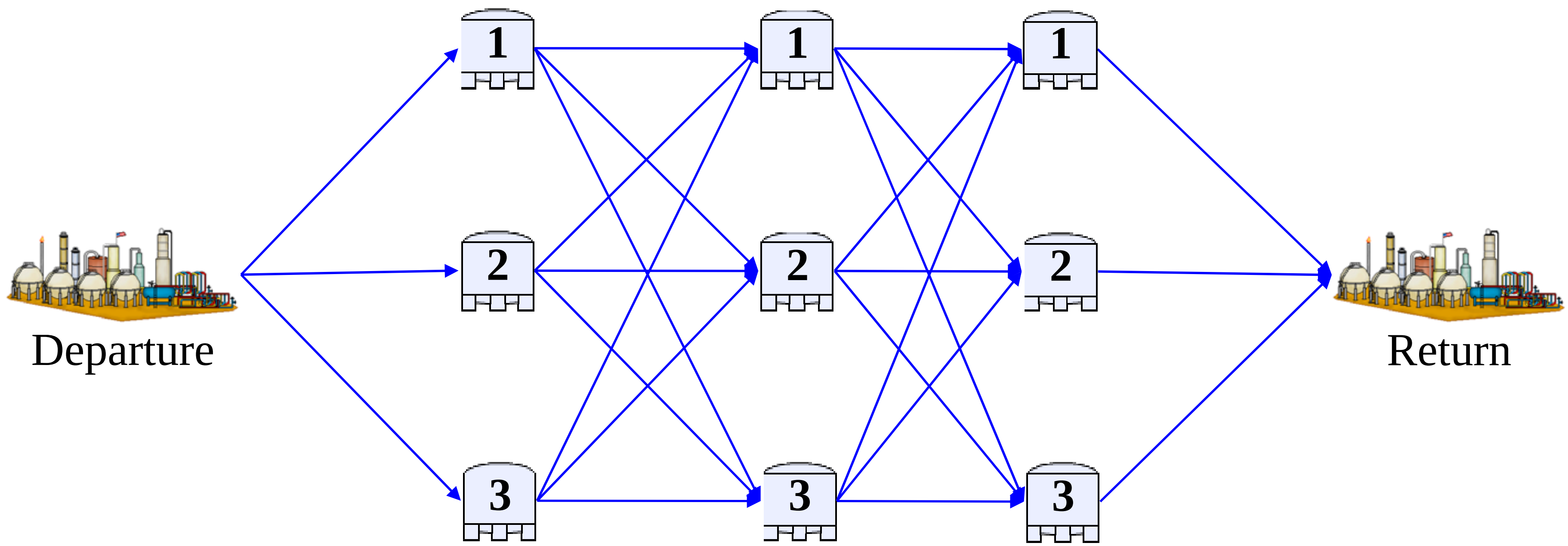
Complexity – 3 customer case



- **27 possible route**, **24,336 binary variables** in the MILP model for integrating tank sizing and vehicle routing
  - 3-year horizon, 4 available truck sizes, 6 available tank sizes

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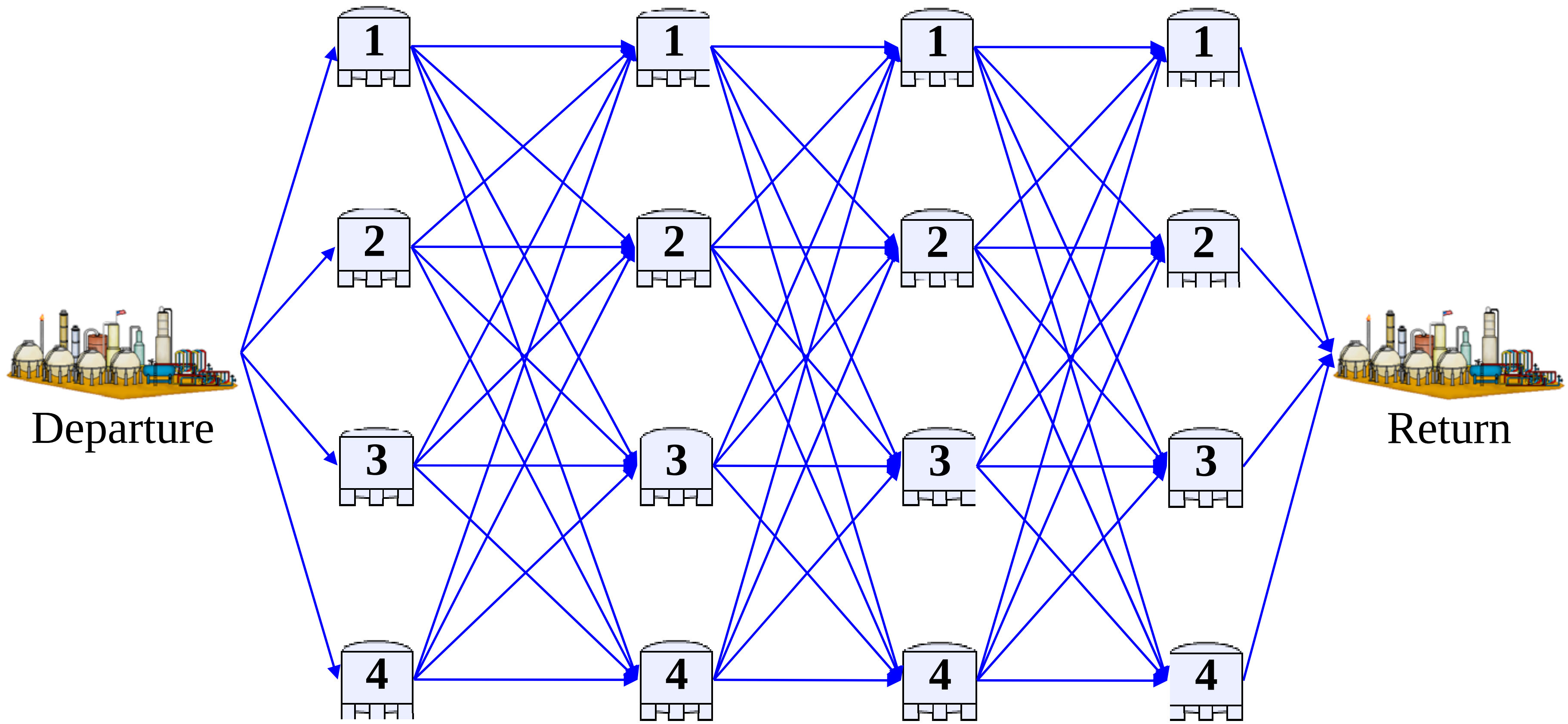
Complexity – 4 customer case



- **256 possible route**, **230,448 binary variables** in the MILP model for integrating tank sizing and vehicle routing
  - 3-year horizon, 4 available truck sizes, 6 available tank sizes

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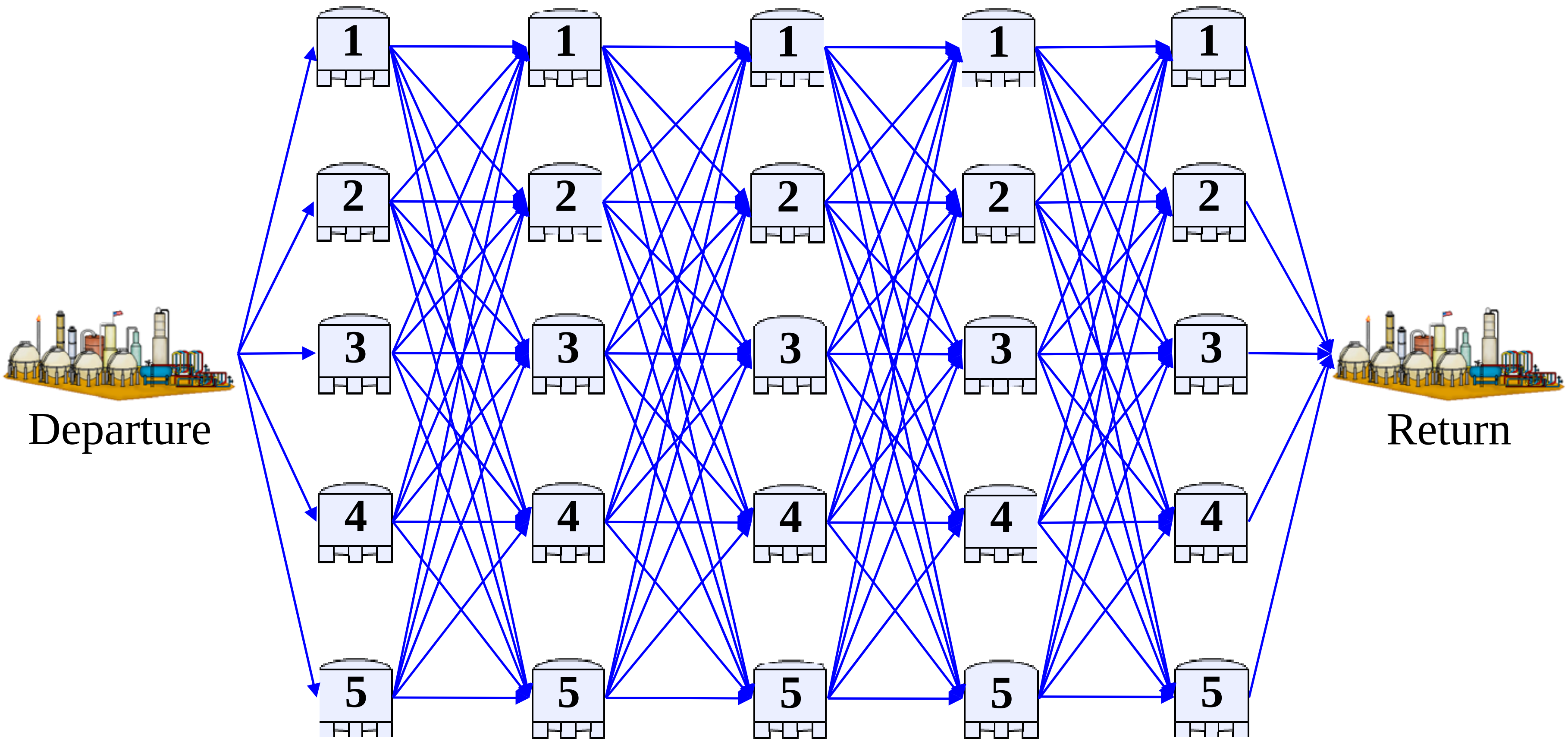
Complexity – 5 customer case



- **5^5 = 3,125 possible route**, **2,812,560 binary variables** in the MILP model for integrating tank sizing and vehicle routing
  - 3-year horizon, 4 available truck sizes, 6 available tank sizes

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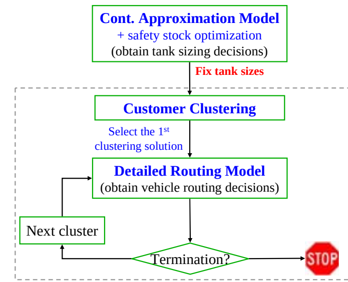
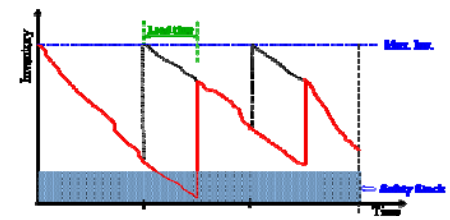
Modeling Challenges

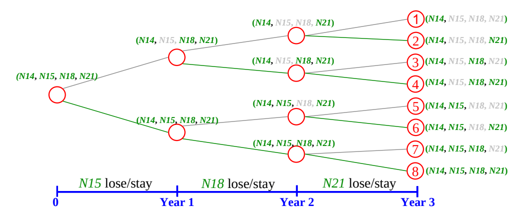
- How to effectively integrate tank sizing with vehicle routing?
  - Continuous approximation (CA) approach
    - tradeoff capital and operating cost in the strategic level
    - reduce most integer variables with some nonlinearities



- How to optimize the safety stocks for **demand uncertainty**?
  - Employ stochastic inventory model
  - Integrate safety stock optimization with tank sizing



- How to model the **uncertainty of adding/losing customers**?
  - Multi-stage (or two-stage) stochastic programming
  - A network structure for each scenario in each year



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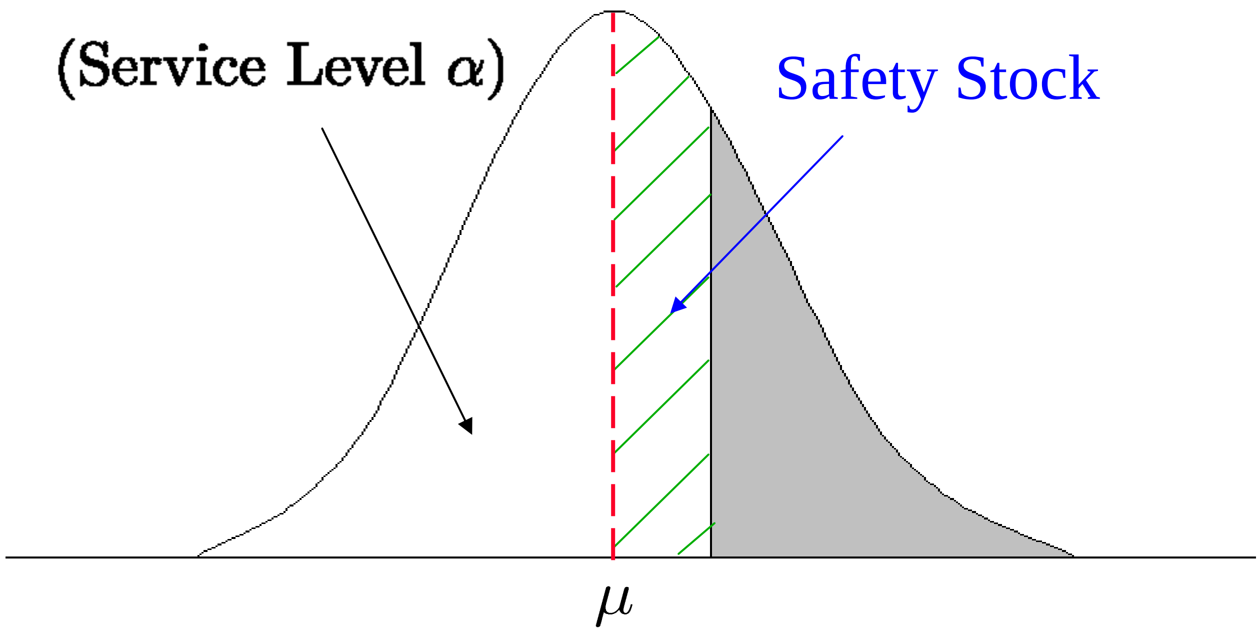
Optimal Safety Stock Level

$D \sim N(\mu, \sigma^2) \Rightarrow$ Safety Stock $= \boxed{z_\alpha \sigma}$, $P(z \leq z_\alpha) = \alpha$ **(Service Level)**

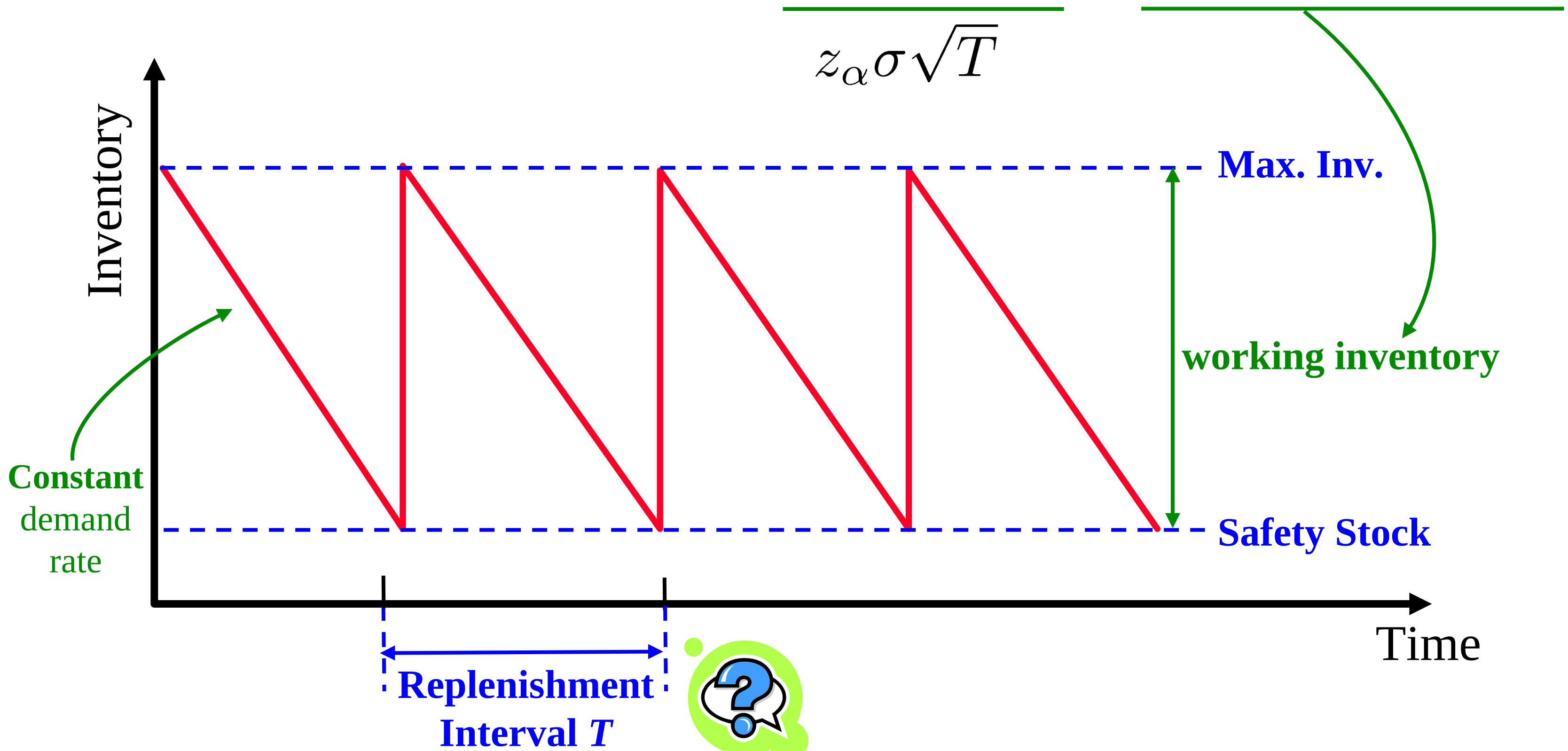
Lead time = *T* $\Rightarrow D \sim N(T \cdot \mu, T \cdot \sigma^2) \Rightarrow$ $\boxed{\text{Safety Stock} = z_\alpha \sigma \sqrt{T}}$



“Cyclic” Inventory-Routing

- Key Assumption: each customer is replenished in a “cyclic” way with interval T

- Required tank size ≥ max. inv. = Safety Stock + demand rate× T



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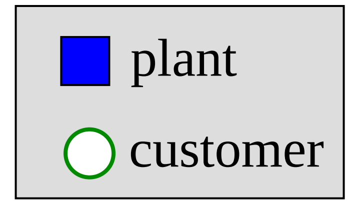
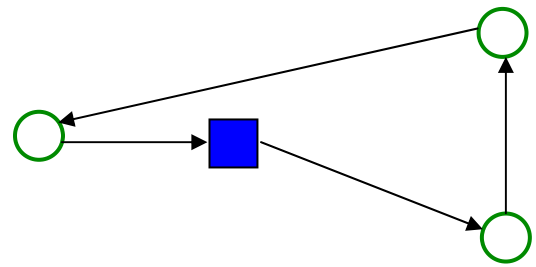
Routing & Replenishment in CAM

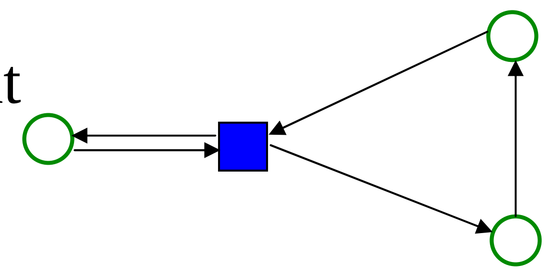
- $T = R$ / (ave. speed)
  - T - replenishment interval
  - R - minimum distance to visit all the customers in a cluster once
  - Average travelling speed is known

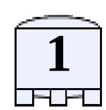


- If only one trip for each replenishment
  - R = **TSP** distance of the cluster & plant



- If allowing multiple trips for replenishment
  - R = ?





CAM for Capacitated Routing Problems*

- Bounds for minimum routing distance ***R***

$$R \approx 2\lceil \frac{n}{q} \rceil r + (1 - \frac{1}{q}) \cdot \text{TSP}$$

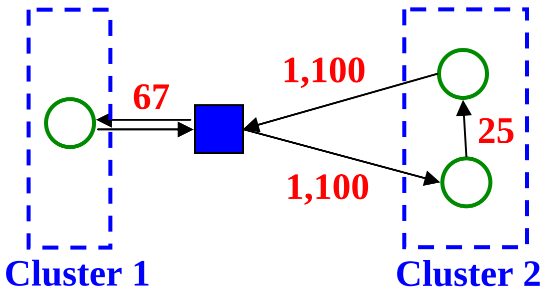
  - *n* – number of customers in the cluster
  - *q* – capacity, max. number of customers that can be visited in one trip
  - *r* – average distance from customers to the plant
  - TSP – traveling salesman distance to visit all customers once

- Examples
  - Cluster 1: *q*=1, TSP=0, *r* = 67

    $2\lceil \frac{n}{q} \rceil r + (1 - \frac{1}{q}) \cdot \text{TSP} = 2r = 2 \times 67 = \boxed{134\text{km}}$

  - Cluster 2: *q*=1, same as Cluster 1, $R = \boxed{4,400\text{km}}$
  - Cluster 2: *q*=2, TSP=50, *r* = 1,100

    $2\lceil \frac{n}{q} \rceil r + (1 - \frac{1}{q}) \cdot \text{TSP} = 2r + \frac{\text{TSP}}{2} = \boxed{2,225\text{km}}$



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* *M Haimovich, AHG Rinnooy Kan, "Bounds and heuristics for CRP", Math. of Oper. Res., 1985, 10(4), 527-541*

Decomposition Method

Tank sizing decisions for 1st stage (int. var.);

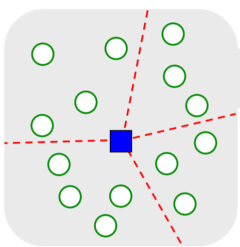
Routing decisions for 2nd stage (cont. var.)

Min. total **expected** cost

Cont. Approximation Model
+ safety stock optimization
(obtain tank sizing decisions)

Stochastic **MINLP**
avoid int. var. in the 2nd stage recourse

Fix tank sizes
Safety stock



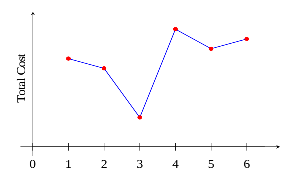
Customer Clustering

Select the 1st cluster

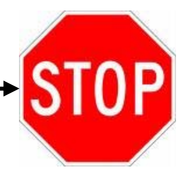
Deterministic Routing Model
(obtain vehicle routing decisions)

Solve the **MILP** problem for each scenario and each year, **separately**

Next clustering soln.



Termination?



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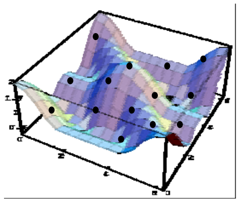
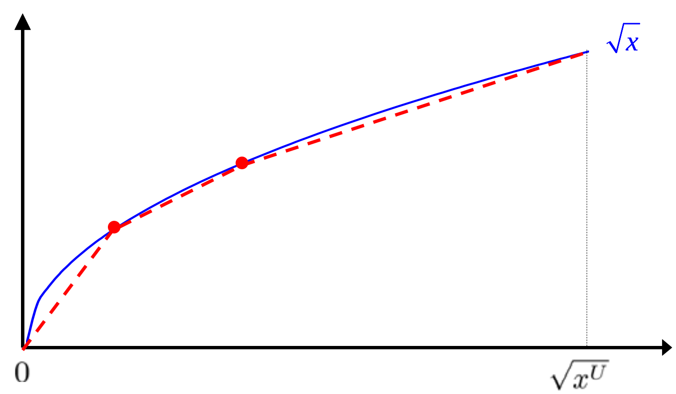
Each scenario has a network structure in each year, problem size increases as scenarios increase

Computational Challenge

- How to **globally optimize the stochastic non-convex MINLP** ?
  - Nonlinearities from continuous approximation and stochastic inventory

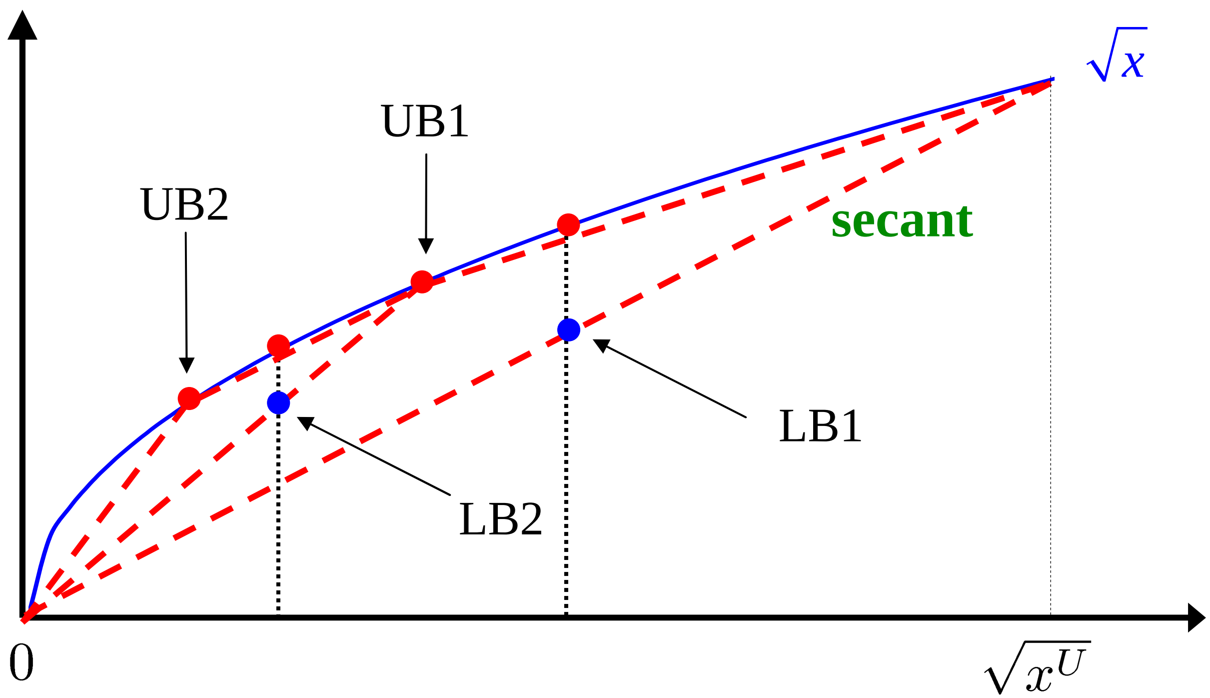


    - Continuous approximation: multi-linear terms (each term is the product of binary variables and at most one continuous variable) – exact linearization
    - Stochastic inventory: square root terms in the safety stock constraints
  - After reformulation, the *only* nonlinearities in the MINLP are the square root terms in the safety stock constraints $Safety_{n,y,s} \geq z_{\alpha} \cdot \sigma_{n,y}\sqrt{LT_{ci,y,s}},\ \forall n \in N_{ci}, y, s$
  - *Property*: If we replace the square root terms in the safety stock constraints with piecewise linear under-estimators, the solution of the resulting MILP problem provides a global lower bound of the MINLP.



Branch-and-Refine Algorithm

- Global Optimization for MINLPs with *only* Univariate Concave Terms
  - Piece-wise linear approximation (MILP) provides **global** lower bounds
  - Feasible solutions provide upper bounds – solving a reduced MINLP
  - Increasing the number of pieces as iteration number increases



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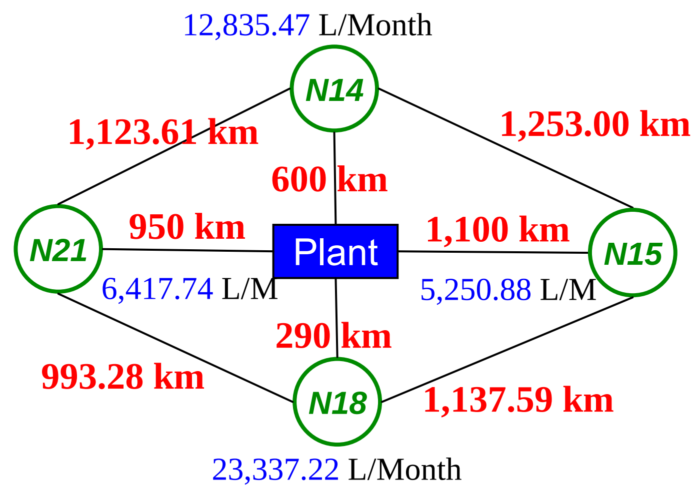
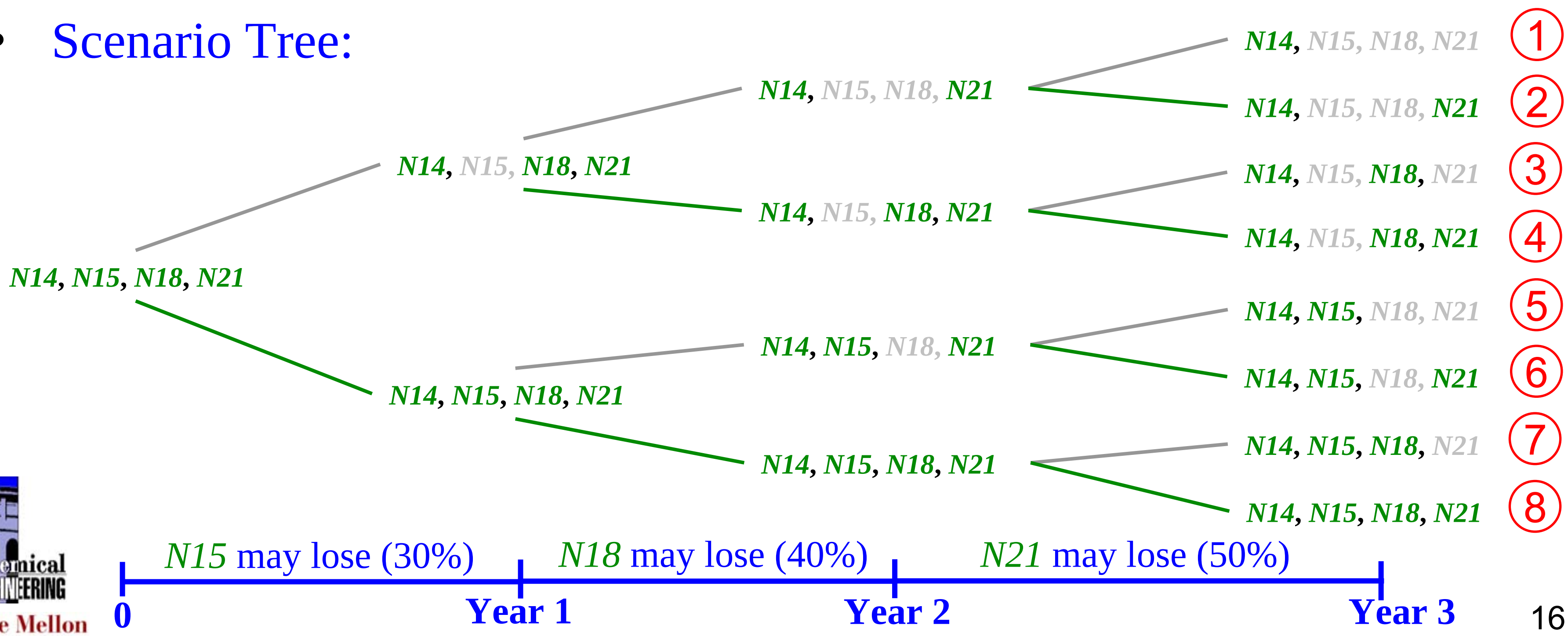
3 Existing Customer and 1 New Customer

- **Example 1:** 3-year planning horizon
  - 4 customers, 6 tank sizes, 6 types of trucks
    - *N14* will not lose by the end of Year 3
    - *N15* may lose in Year 1 with 30% chance
    - *N18* may lose in Year 2 with 40% chance
    - *N21* may lose in Year 3 with 50% chance



- Scenario Tree:



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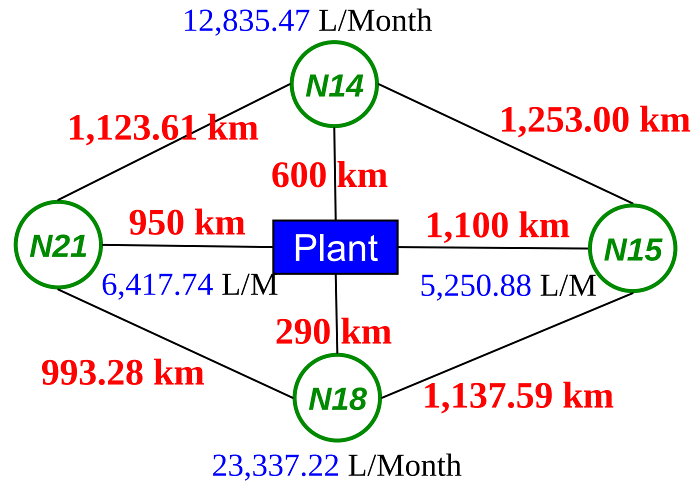

- 8 scenarios for two-stage stochastic programming
  - S1 – Y1: *N14*, *N15*, *N18*, *N21*; Y2: *N14*, *N15*, *N18*, *N21*; Y3: *N14*, *N15*, *N18*, *N21*.
  - S2 – Y1: *N14*, *N15*, *N18*, *N21*; Y2: *N14*, *N15*, *N18*, *N21*; Y3: *N14*, *N15*, *N18*, *N21*.
  - S3 – Y1: *N14*, *N15*, *N18*, *N21*; Y2: *N14*, *N15*, *N18*, *N21*; Y3: *N14*, *N15*, *N18*, *N21*.
  - S4 – Y1: *N14*, *N15*, *N18*, *N21*; Y2: *N14*, *N15*, *N18*, *N21*; Y3: *N14*, *N15*, *N18*, *N21*.
  - S5 – Y1: *N14*, *N15*, *N18*, *N21*; Y2: *N14*, *N15*, *N18*, *N21*; Y3: *N14*, *N15*, *N18*, *N21*.
  - S6 – Y1: *N14*, *N15*, *N18*, *N21*; Y2: *N14*, *N15*, *N18*, *N21*; Y3: *N14*, *N15*, *N18*, *N21*.
  - S7 – Y1: *N14*, *N15*, *N18*, *N21*; Y2: *N14*, *N15*, *N18*, *N21*; Y3: *N14*, *N15*, *N18*, *N21*.
  - S8 – Y1: *N14*, *N15*, *N18*, *N21*; Y2: *N14*, *N15*, *N18*, *N21*; Y3: *N14*, *N15*, *N18*, *N21*.

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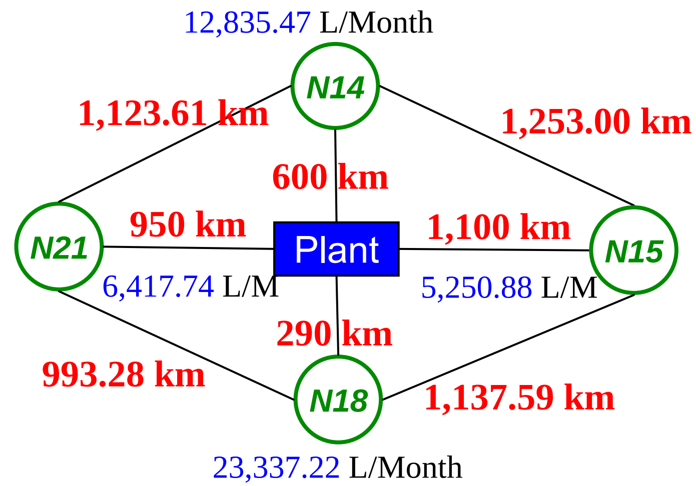
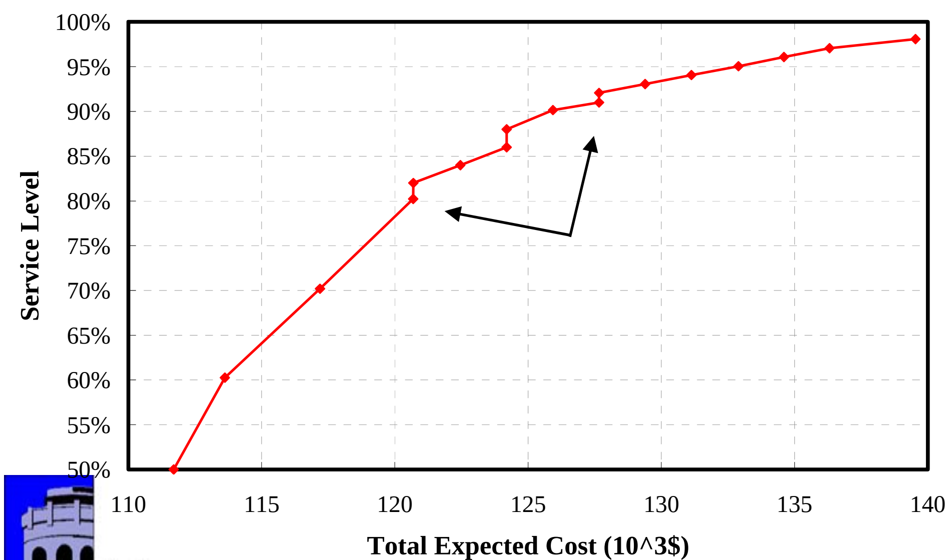
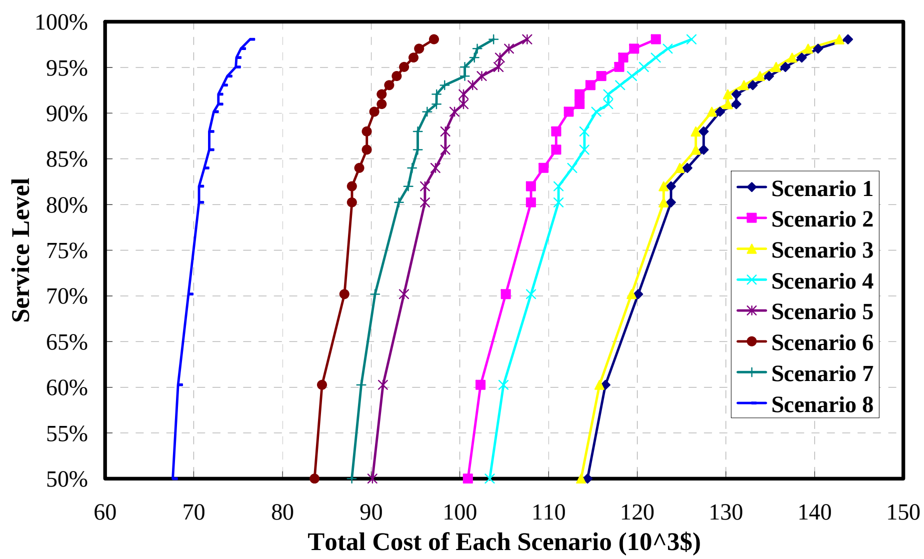
Pareto Curves and Scenario Costs

- CPU Times
  - Directly solved with DICOPT – infeasible
  - Directly solved with BARON – > 7 days
  - B&R algorithm (CPLEX 12 + DICOPT) - 285s for all the 17 instances







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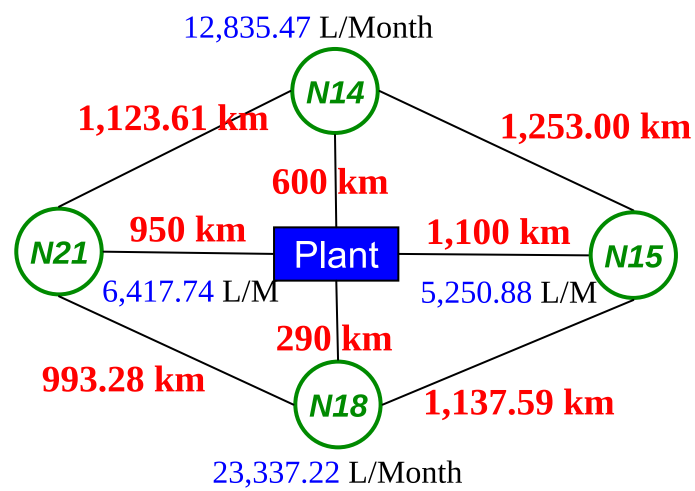
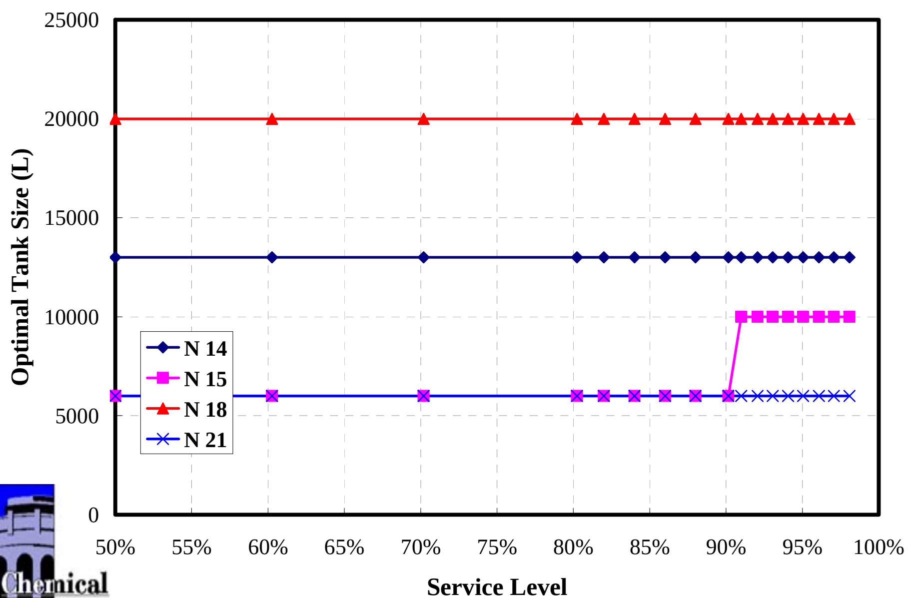
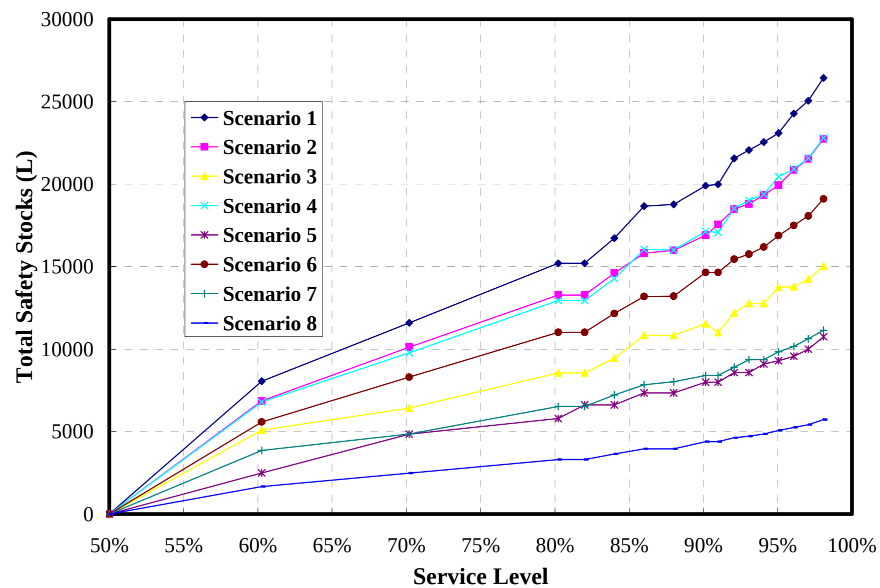
Tank Sizes and Safety Stocks

- Model Statistics
  - MINLP: 288 dis. var., 2,484 cont. var., 4,056 cons.
  - MILP model: 408 dis. var., 2,724 cont. var., 4,344 cons.; Reduced MINLP: 48 dis. var., 2,484 cont. var., 4,056 cons. (5 iter.)







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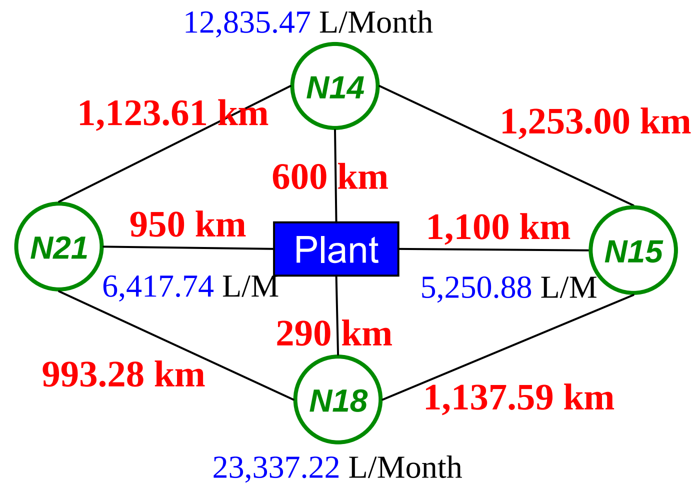
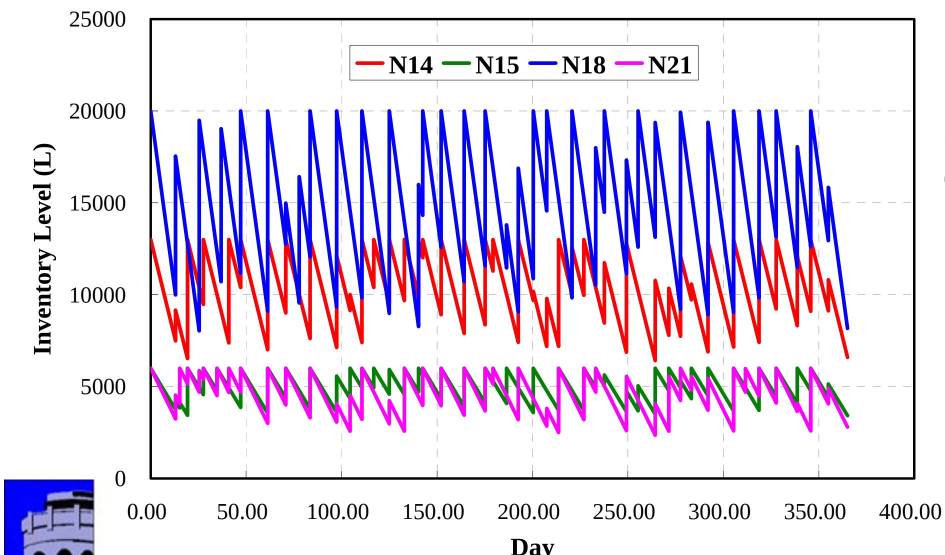
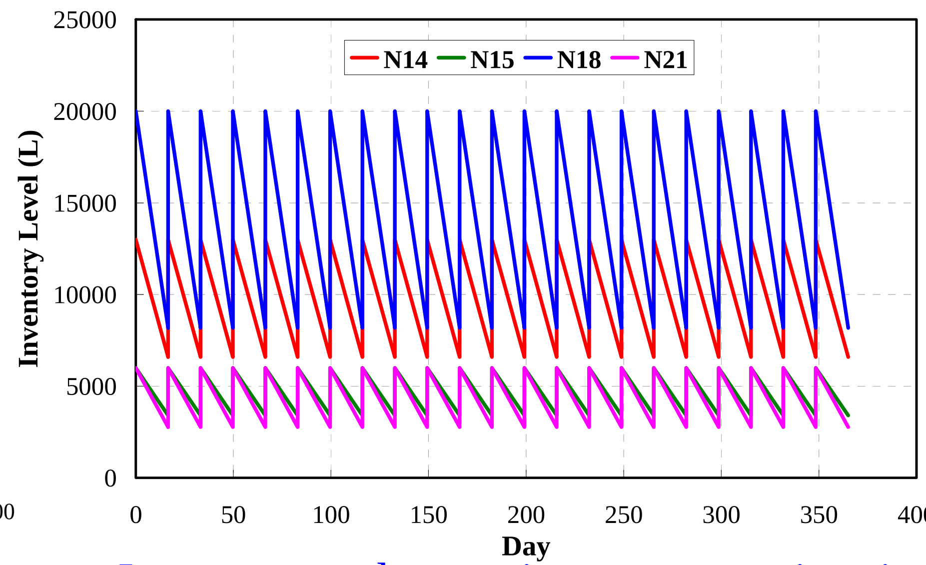
Optimal Routing Decisions

- Scenario 1 at Year 1, 90% Service Level
  - Number of visits:
    - *N14*: 17; *N15*: 17; *N18*: 37; *N21*: 18.
  - Three routes are used:
    - P → *N18* → *N15* → *N14* → *N21* → P.
    - P → *N18* → *N21* → P.
    - P → *N18* → P.





Inventory profile from detailed routing



Inventory under continuous approximation

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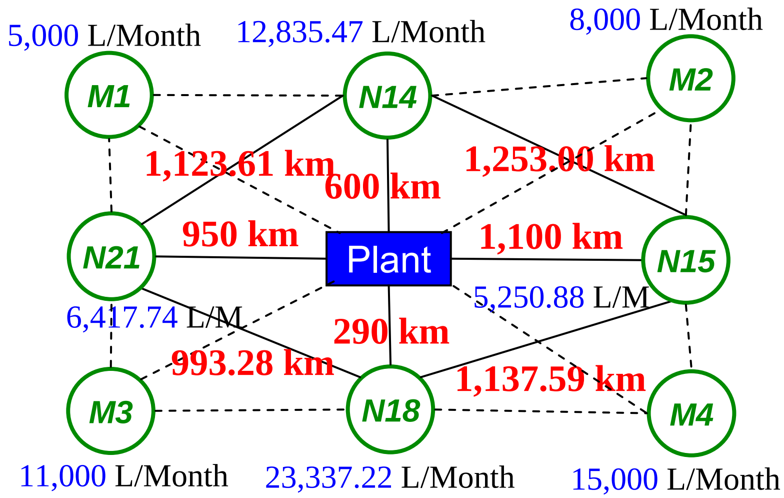
3 Existing, 1 New and 4 potential New

- **Example 2:** 3-year planning horizon
  - 4 existing customers:
    - *N14* will not lose by the end of Year 3
    - *N15* may lose in Year 1 with 30% chance
    - *N18* may lose in Year 2 with 10% chance
    - *N21* may lose in Year 3 with 20% chance



  - 4 new potential customers:
    - *M1* may join in Year 1 with 25% chance, demand is 5,000L/Month
    - *M2* may join in Year 2 with 35% chance, demand is 8,000L/Month
    - *M3* may join in Year 3 with 20% chance, demand is 11,000L/Month
    - *M4* may join in Year 2 with 50% chance, demand is 15,000L/Month
  - 6 available tank size, 4 types of trucks
  - Demands follow normal distribution
  - Consider 40 possible scenarios **(more can be specified)**

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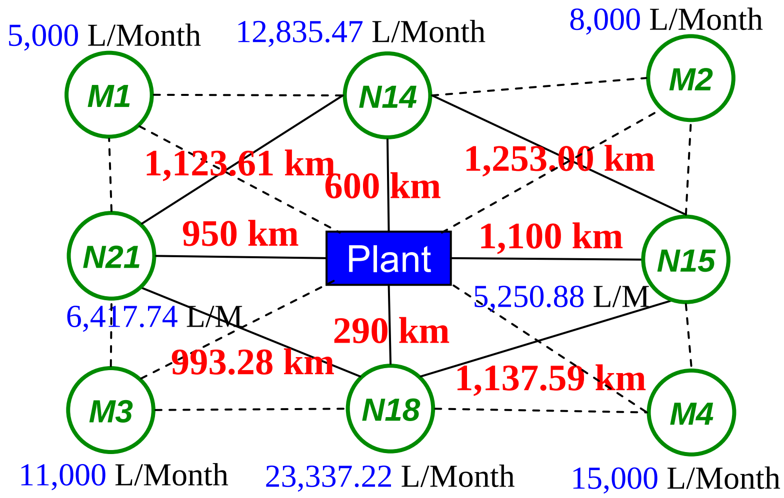
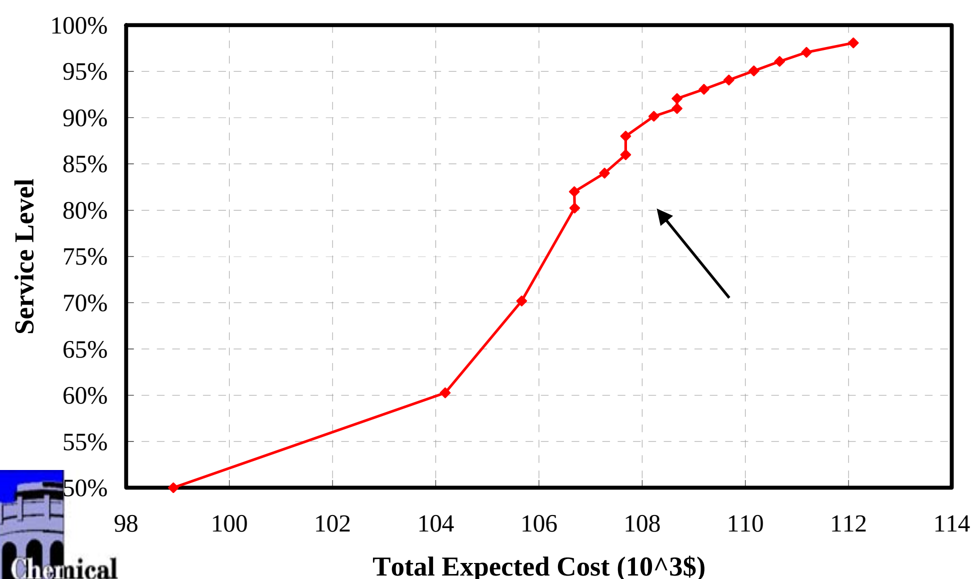
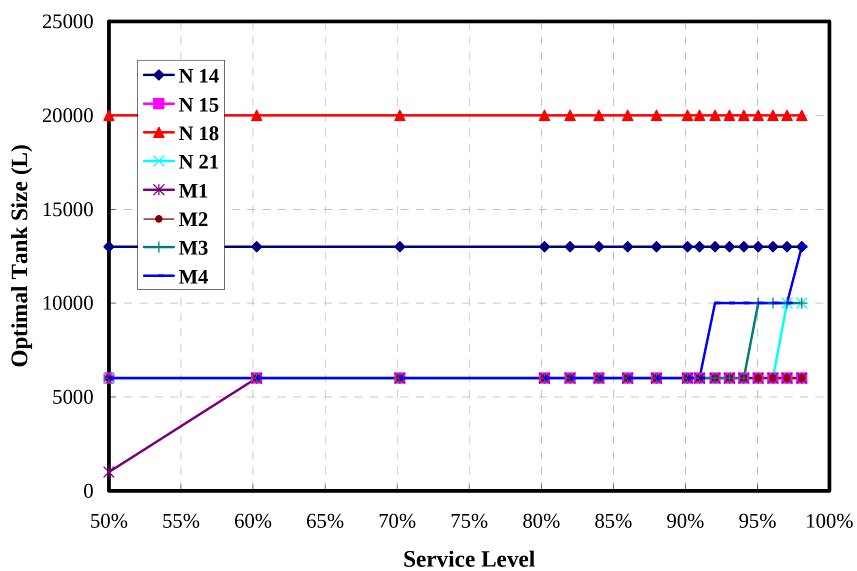
Pareto Curves and Optimal Tank Sizes

- Model Statistics & CPU Times
  - Solved MINLP with BARON – > 7 days
    - 1,296 bin. var., 13,100 con. var., 22,826 cons.
  - B&R algorithm - 1,770s for 17 instances
    - MILP: 2,016 dis. var., 13,820 cont. var., 24,506 cons.; Reduced MINLP: 96 dis. var., 14,300 cont. var., 22,826 cons. (6 iter.)







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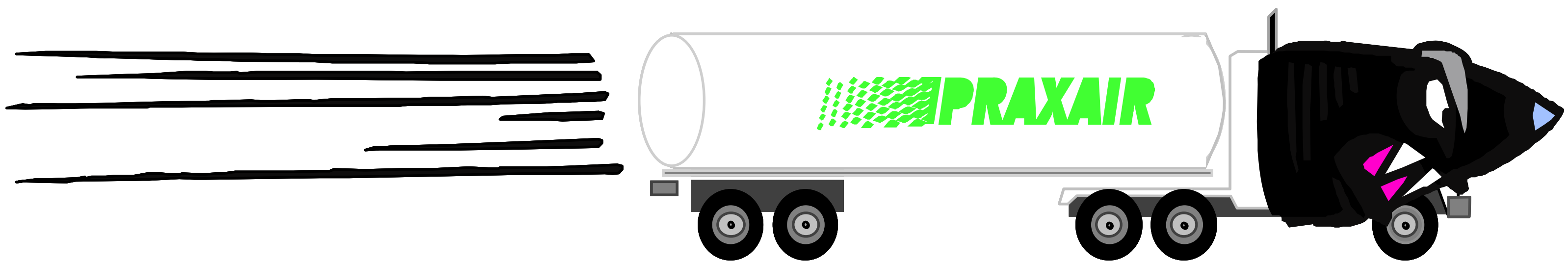
Conclusion / Future Work

- Conclusion
  - Formulate an MINLP model for continuous approximation of large scale vehicle routing – tank sizing problem.
  - Integrate stochastic inventory model with stochastic programming.
  - Propose a branch-and-refine algorithm based on successive piece-wise linear approximation method for global optimization.
- Future Work
  - Improve clustering method.
  - Consider fleet scheduling problem.



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