Effective Integration of Theory and Practice

Michael F. Gorman
Department of MIS, OM, DSC
University of Dayton
Spotlight on Advanced Research and Scholarship
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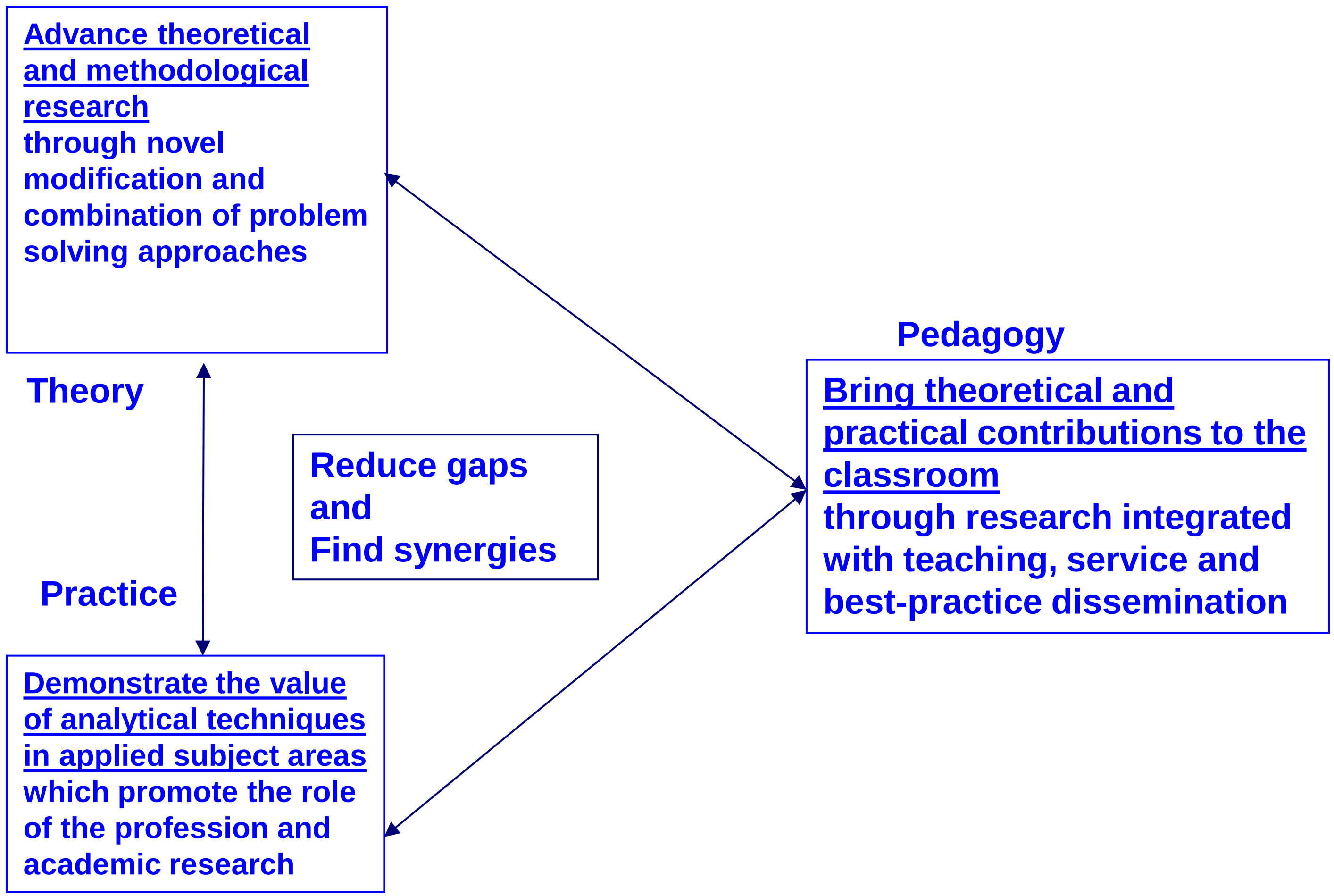
Presentation Overview

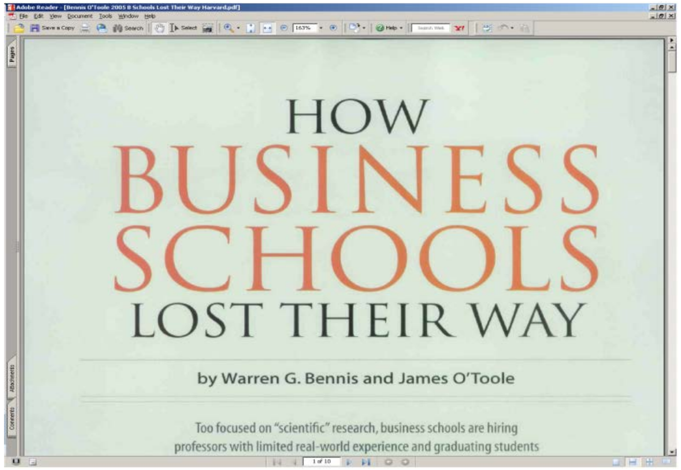
- **Integration of Theory and Practice - Motivation**
- **Case Studies in the Integration of Theory and Practice**
  - **CSX Railroad Equipment Distribution**
  - **Hub Group Intermodal Load Acceptance and Routing**
- **Best Practices in the Integration of Theory and Practice**

The Intersection of Theory, Practice & Pedagogy



Importance of the integration of theory and practice

- **Tests assumptions of theoretical models**
- **Proves the value of technical content and methodologies**
- **Keeps academia relevant to the “real world”**



- **“Though scientific research techniques may require considerable skill in statistics or experimental design, they call for little insight into complex social and human factors and minimal time in the field discovering the actual problems facing managers.”**

CSX Railway Uses Operations Research to Cash in on Optimized Equipment Distribution

How tomorrow moves

Authors: Michael F. Gorman, University of Dayton

Dharma Acharya, David Sellers, CSX Transportation

Executive Presenters: Michael Ward, Alan Blumenfeld, CSXT

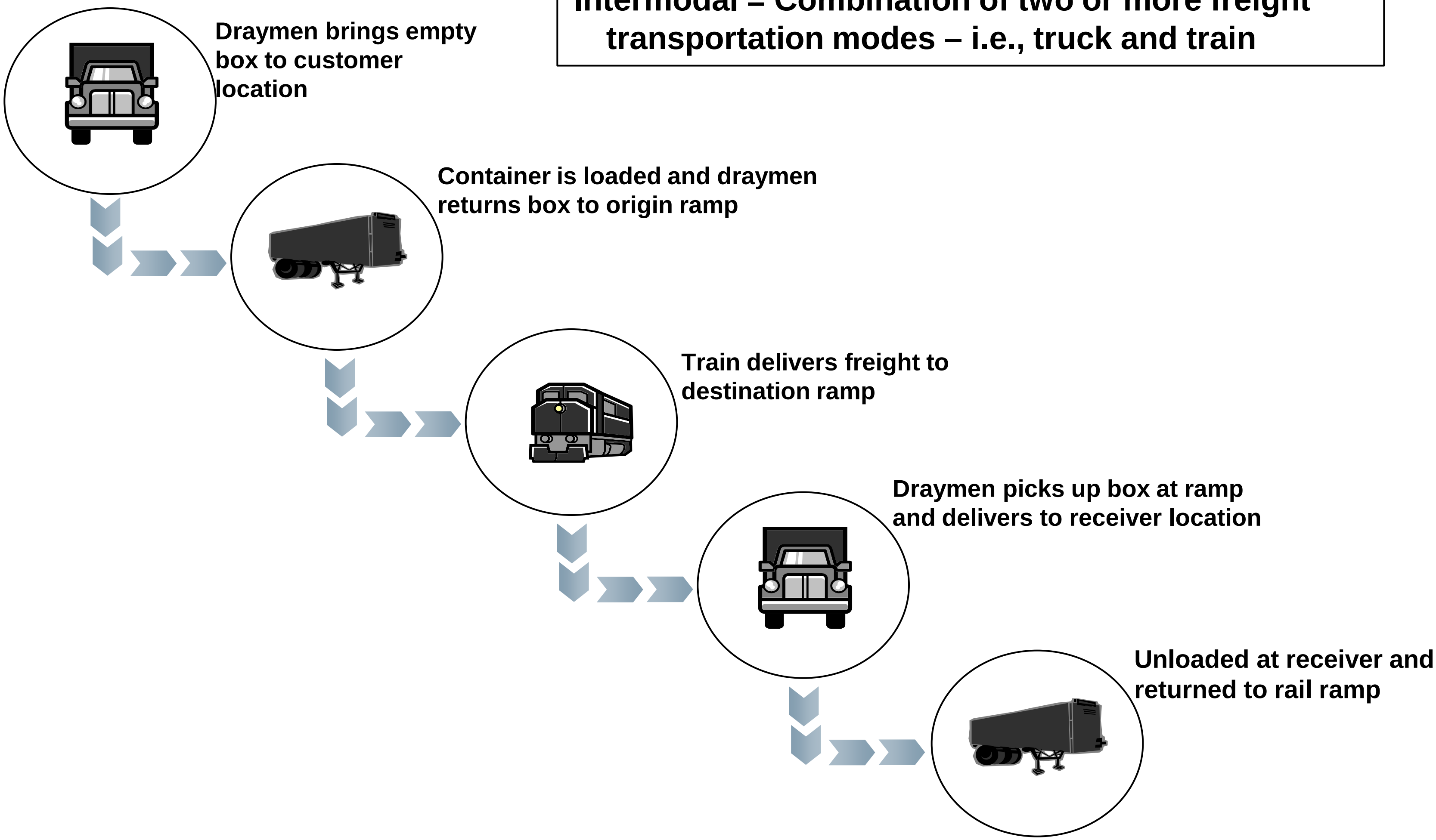
Hub Group Implements a Suite of Tools to Improve its Operations

Michael F. Gorman, Ph.D.
University of Dayton

Wagner Award Presentation
San Diego INFORMS
October, 2009

1) Background
Five Stages of Intermodal Transportation

Intermodal = Combination of two or more freight transportation modes – i.e., truck and train



2) Operations Research Modeling
The need for OR in Hub's changing environment

- **Previous decision rules:**
  - **<u>Load acceptance</u>: Take all profitable moves**
  - **<u>Load routing</u>: Take lowest cost (available) route and equipment**

- **With a fixed fleet, these rules leads to missed profitable loads, and undesirable situations with routing**

- **Change in philosophy:**
  - **<u>Load Acceptance:</u>**
    Not all profitable moves are good moves:
    - **Repositioning costs, Opportunity costs**
  - **<u>Load Routing:</u>**
    "Network view" rather than a "one way" view of each load
    - **Lowest "one way" cost does not lead to lowest network cost**

3) Real Time Optimization
Project Scope Constraints

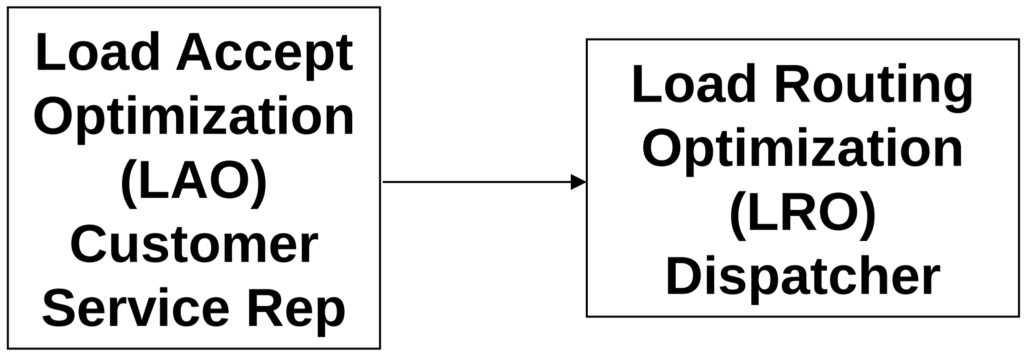
- **We wanted to take a conservative approach to an aggressive project – <u>It is not enough to just be "right"…</u>**
  - **Relatively small company**
  - **Relatively new to OR-based DSS**

- **To reduce project disruption, risk and cost, we applied these constraints to our approach:**

  - **<u>Organizational:</u>**
    - **Business Process cannot change**
    - **Marketing-centric Customer Service Representative (CSR) and Operations-centric Dispatcher responsibilities cannot change**

  - **<u>Technological:</u> optimization technology must fit within Hub's existing production system Transaction Processing System (TPS) interface and data structures**
    - **In particular – "transactional", one-at-a-time order processing (both acceptance and dispatching)**

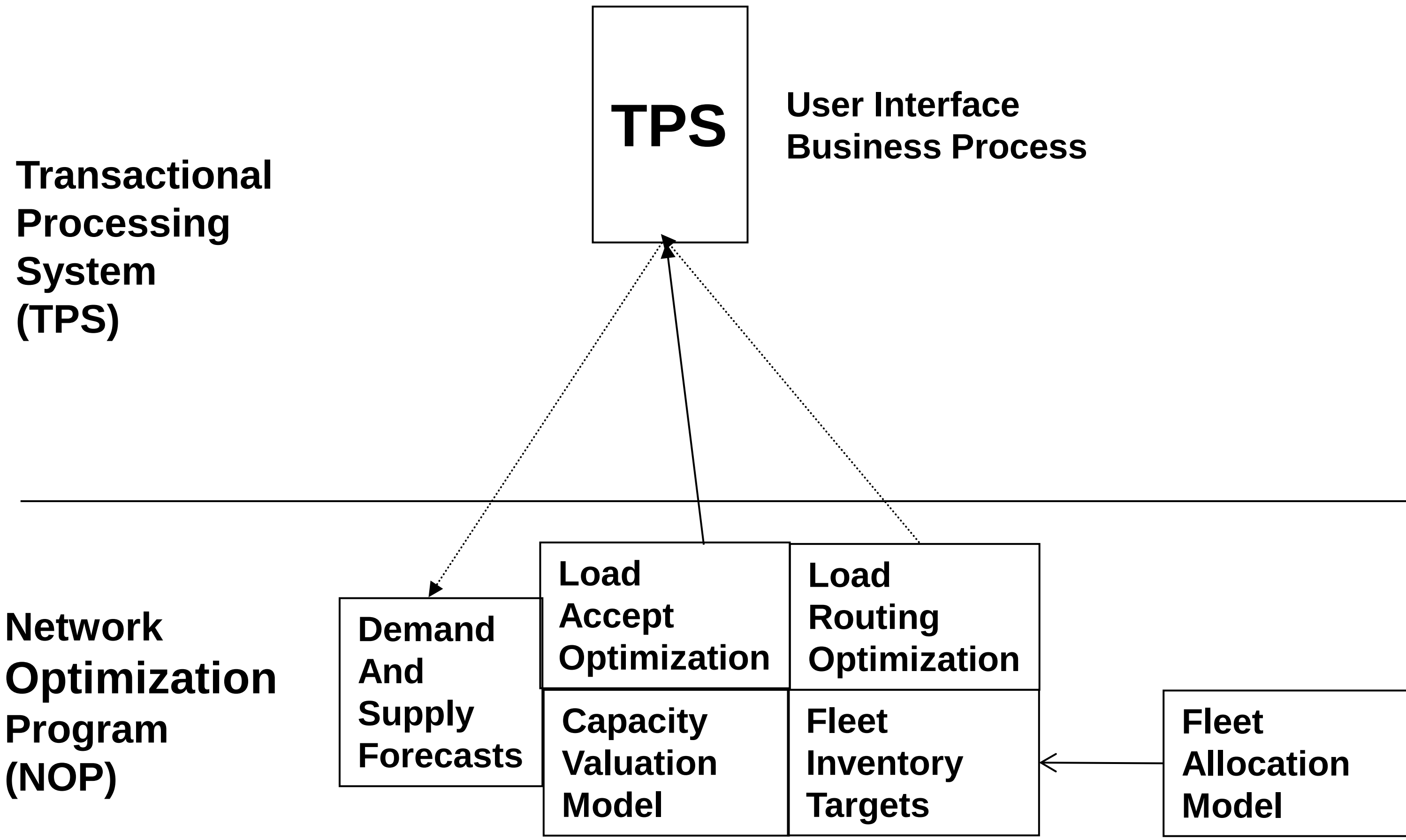
3) Real Time Optimization – Organization and Process
Load Accept and Routing Decisions are Sequential



<u>First,</u> the Load Acceptance decision (Marketing Decision)
– Should Customer Service Representative (CSR) accept a tendered load?
To maximize contribution of scarce resources

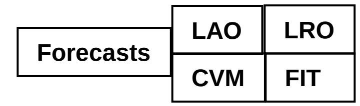
<u>Second,</u> the Load Routing decision (Operating Decision)
– Which equipment/railroad should dispatcher choose?
To minimize cost, given a set of accepted loads

3) Real Time Optimization: Technological TPS/NOP Architecture Overview and Information Flow

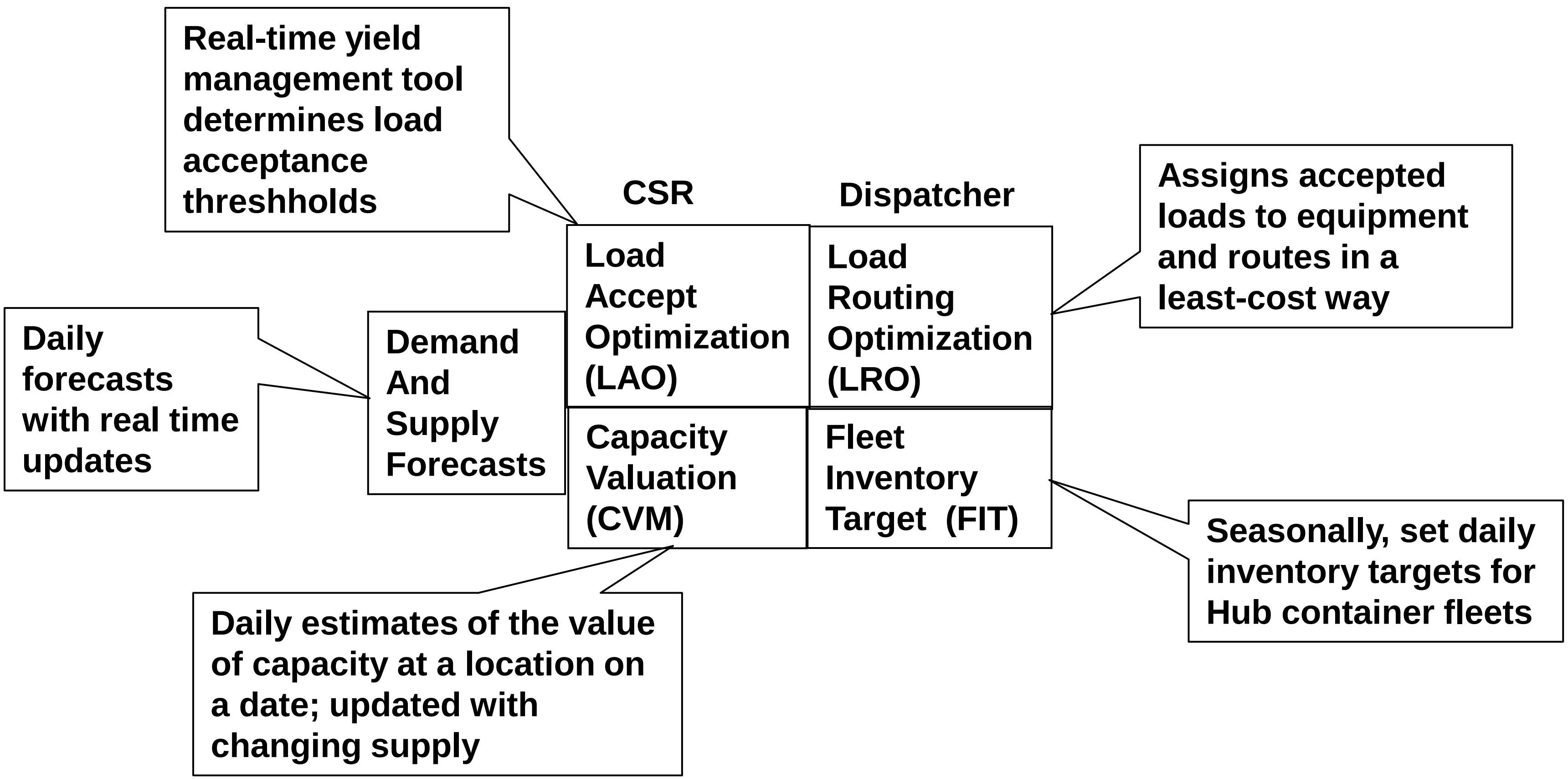


Data passed from TPS to NOP Forecast Modules
Results of decision modules passed back to TPS for display

3) Real Time Optimization Modeling Component Overview



Network Optimization Program (NOP) suite of integrated tools



Tight integration between decision modules assure consistency.
LAO and LRO interact directly with TPS system, CSR and dispatcher.

3.1) Daily Supply and Demand Forecasts

- **Demand Forecast:**
  - Two week horizon of daily orders
  - Time-series based statistical demand forecast
  - Hundreds of estimated equations
  - Aggregate forecast of smaller lanes so that all demand is forecasted
- **Distribution of forecast errors is critical to model success**
  - Probabilistic projections of each demand level used in expected value decision making
- **Rolling horizon – forecast for each day in the horizon is updated each day to reflect new information, re-estimated forecast equations**

3.2) CVM Detail

- **Capacity Valuation Model – CVM**
  - Establishes the value of an additional unit of capacity
  - Output is Capacity Valuation Curve (CVC) – relationship between expected margin and capacity
- **Capacity Valuation Curve (CVC) depends on**
  - Demand Forecast and forecast error distribution
  - Margin distribution of market segments and ODs out of an origin

CVM Algorithm Overview:

- **Step 1: Marginal Expected Valuation Calculation**
  - Calculate Marginal Expected Profit (MEP) for all possible forecast levels
- **Step 2: Opportunity Ranking Algorithm**
  - Hierarchically rank fractional loads
  - Recombine fractional loads into whole loads

3.2) CVM Step One Algorithm: Marginal Expected Profit Algorithm

Forecasts	LAO	LRO
	CVM	FIT

Step 1: Calculate the marginal expected profit in a lane (as in Table 2 in the text)

```
For all origins, i, do:

    For j = 1 to m                                        ! all destinations from the origin

        CDF = 0

        For u =  F(i, j) + e(i,j,1) to F(i, j) + e(i,j,n) ! all forecast levels for the lane

          For k = 1 to K                                  ! all market segments

            InvCDF(i, j, u, k)  = 1 – CDF

            MEP(i, j, u, k) = InvCDF(i, j, u, k) • P(i, j, k)  ! Marginal Expected Profit

            JP(i, j, u, k) = ρ(i,j,k) • ε(i,j,u)          ! joint probability

            CDF = CDF + JP(i, j, u, k)

          Next k                                          ! market segment

        Next u                                            ! forecast unit

    Next j                                                ! destination from origin

End.
```

3.2) CVM Step Two Algorithm: Opportunity Ranking Algorithm

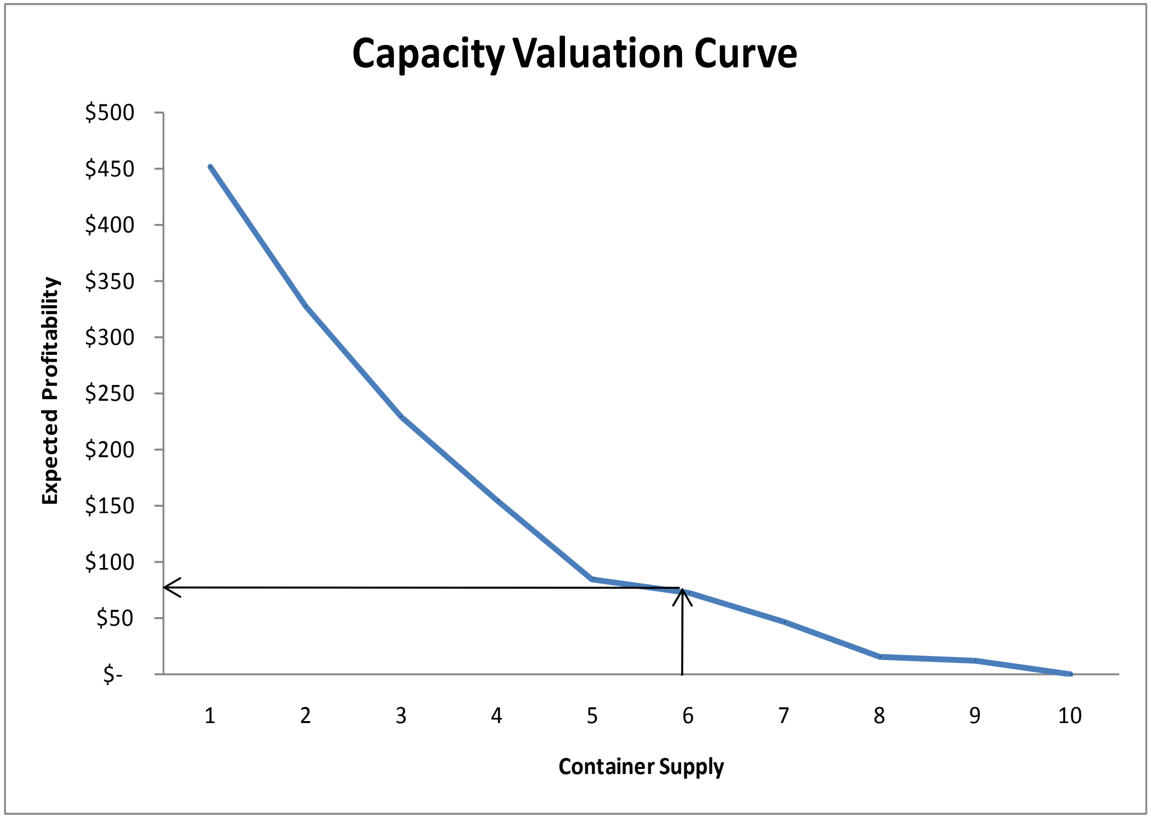
Step 2: Rank the opportunities by expected profit and calculate their whole unit equivalent

(as in Table 3 in the text)

```
For all origins, i, do:
    Sort all data by MEP(i, j, u, k)
    Create index r, on all arrays           ! blends all destinations, markets, forecast levels
      CL = 0
      for r = 1 to m • k • n                ! all destinations, market class, fcst levels
          Unit = 0
          Do while INT(CL) = INT(CL + Unit) ! haven't crossed whole unit of capacity
              Unit = Unit + ρ(r)
              EP = EP + MEP(r) • ρ(r)       ! weighted sum
          End do
          CapUnit = INT(CL+Unit)            ! Nearest whole capacity unit
          CVC(CapUnit) = EP/Unit            ! weighted avg; full unit equivalent
          CL = CL + Unit                    ! next whole capacity unit
       Next r
```

3.2) CVC Illustration

Forecasts	LAO	LRO
	CVM	FIT



The CVC captures the diminishing marginal value of container capacity as capacity increases.
In this example, supply of 6 has CV=$72.30

3.3) Load Acceptance Optimization (LAO) Overview of Methodology

- **Load Acceptance Optimization maximizes the anticipated value of a tendered load against other future potential loads at that origin**

- **Accept a tendered load if: <u>Load Value >= Acceptance Threshold:</u>**

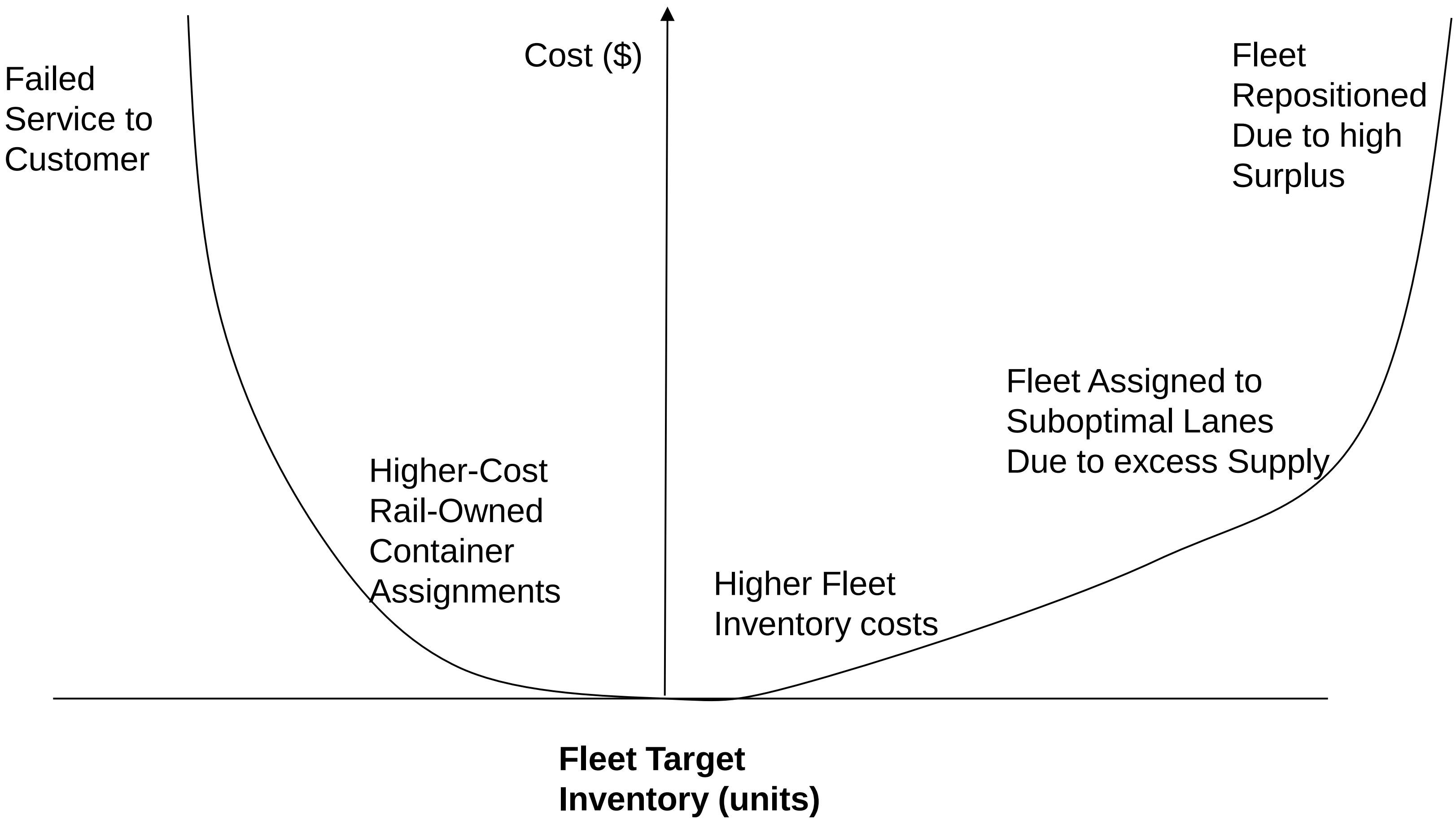
Tendered Load Profitability + Expected Destination Value
>=
Origin Load Value + Average Destination Value

- **Captures the opportunity costs of accepting a customer order as determined by the CVC**

- **Includes the future potential created by the accepted load at the load's destination, as compared to other loads' future potential**

3.4) Target Inventory Setting
Cost of Deviation from Target Inventory

Forecasts	LAO	LRO
	CVM	FIT



We establish a fleet inventory target and estimate a cost of deviation from that target.

3.4) Step 1: Target Inventory Setting

Maximize $OBJ^{*} = HFB_t - \sum_{t=1}^{7} HC \bullet I_t$

Subject to:

$HFB_t = x \bullet (y - FL_t/L_t)^z$ for t = 1…7

$FL_t <= L_t$ for t = 1…7

$I_{t+1} = FR_{t+1} - FL_{t+1} + I_t$ for t = 1…7

$I_t > = 0$ for t = 1…7

In the strategic model, starting inventory is governed by ending inventory to assure repeatability:

$I_1 = I_7 + FR_1 - FL_1$

In the tactical model,

I_1 = some starting value, I_0

$I_7 = I_7$ from the strategic model (recovery), or is unconstrained (reactionary)

3.4) Step 2: Cost of Target Inventory Deviation

For t = 1 to 7

For i = 0 to I_{max} ! possible capacity levels to evaluate

$I_t = i$

Solve model for OBJ(t,i)

DeviationCost = OBJ(t,i) – OBJ^*

Next i

Next t

A Monte Carlo Simulation to estimate the cost of inventory deviation from target.

3.5) Load Routing Optimization Formulation: Integration of all the pieces

Forecasts	LAO	LRO
	CVM	FIT

One-way cost of shipment

FIT Orig/Dest Target inventory

Inventory and Service failure costs

$$\text{Minimize cost} \sum_{i=1}^{N}\sum_{j=1}^{M}\sum_{k=1}^{K}\sum_{t=1}^{T} (C_{ijk} + TI_{ikt}, + TI_{jkt} - CV_{jkt} + Inv_{jkt} + SV_{jkt}) \cdot x_{ijkt} \qquad (1)$$

CVM Estimated Capacity Value at Destination

Subject to:

$$\sum_{k=1}^{K}\sum_{t=1}^{T} x_{ijkt} = D_{ijt} \qquad \text{for all (i,j)} \qquad (2)$$

$$\sum_{j=1}^{M}\sum_{t=1}^{T} x_{ijkt} <= S_{ikt} \qquad \text{for all k, for all i} \qquad (3)$$

4) Financial Benefits

- **Load Routing Optimization – the cost savings Hub has realized averaging $22 per load from improved selection of rail routes.**

- **Based on these savings, the benefit to Hub has been estimated at <u>$11 million in 2008</u> on an expenditure of only $500,000 – a dramatic return of 22 times investment in one year.**

- **Load Accept Optimization – 3 point drop in the percentage of low-value loads handled in 2008 from improved load rejection and better inventory positioning.**

- **Asset utilization – In 2008, Hub realized a 5% improvement in Hub container velocity resulting from better target inventory setting and management - positioning of equipment for the next load.**

What do these successful applications have in common?

- Deep systems integration
  - Current information, ease of use, easily updated
- Deep business process integration
  - Answers when needed, no sooner, no later; at the right level of detail
- Consistent with the Organizational responsibilities
  - Marketing, Operational decisions are related, but separated
- Considerate of organizational operating philosophy and risk tolerance
- Robust with respect to uncertainty
  - Can react quickly to errors of forecast, unplanned events
  - Recognize the problem is constantly changing; so should model
- Big return on investment
  - Makes research possible; proves its value

The void between theory and practice

- **Theory doesn't touch on many of these critical issues.**
  - **There is no "theory of practice"**
- **The model itself is a small part of the solution**
  - **Theoretical models should consider organizational, systems and process implications and integration to be more useful**
- **Simple models with quick answers**
  - **<u>Not</u> complex, detailed models with perfect answers;**
  - **Rather, simple, actionable, workable recommendations**
  - **Do not assume too much of the data or the problem;
do not try to get it perfect, prove optimality, etc.**

- **Applied research such as the case studies shown –**
  - **Test (or contest) the validity of theoretical assumptions**
  - **Show the value of advanced methods in practice,
or when they are not of practical interest**
  - **Provide avenues for high-return theoretical research based on its potential impact in the "real world"**

Thank you!

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