

**HYBRID OPERATIONAL STRATEGIES for
REAL-TIME FLEET MANAGEMENT:
APPLICATION to LOAD ASSIGNMENT AND
SEQUENCING in TRUCKLOAD TRUCKING**

Hani S. Mahmassani

**THE MARYLAND TRANSPORTATION INITIATIVE
UNIVERSITY OF MARYLAND**

Motivation

*The Transportation System
is carrying 11 billion tons
of freight valued at \$7
trillion annually.*



©Tom Pavia

*Trucking industry occupies 5% GDP, accounts for 81 % shipping cost
International trade has grown from the equivalent of 13 percent of the GDP in
1990 to 27 percent today.*

*Freight will double in the next 20 years, straining our highways, ports and border
gateways.*

**Even slight improvements in the operating efficiency in the trucking industry
would greatly contribute to the overall economy**

Motivation

Demand side motivation

- Many transportation systems operate in a *highly dynamic* environment, characterized by considerable *stochasticity* and *unpredictability*, to serve customers demanding more exacting service levels
- Customer-responsive, made-to-order manufacturing systems
 - Inventory to retail sales ratio over total business: 1.53 (Jan, 1993), 1.44 (Jan, 1998) 1.37 (Dec. 2002)
 - E-commerce retail sales: \$14,334 million (2002), 1.6% out of total retail sales

Supply side

- Availability of real-time information
 - Automatic Vehicle Location (AVL) system
 - Two-way communication system

Potential of these technologies remains vastly underutilized.

INFORMATION AND TELECOMMUNICATION TECHNOLOGY (ICT)

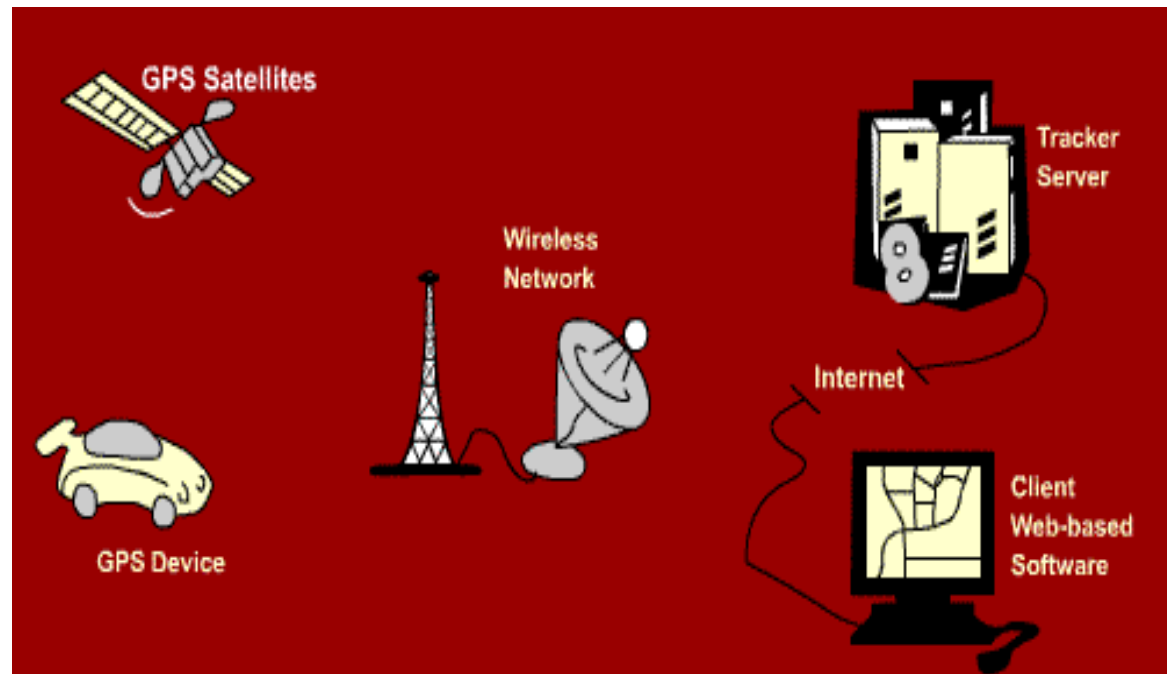
Permeating the world of Transportation Systems through:



- Adoption as tool for better system management
(ATMS, Fleet Management...)
- Ubiquitous availability of mobile information devices to users

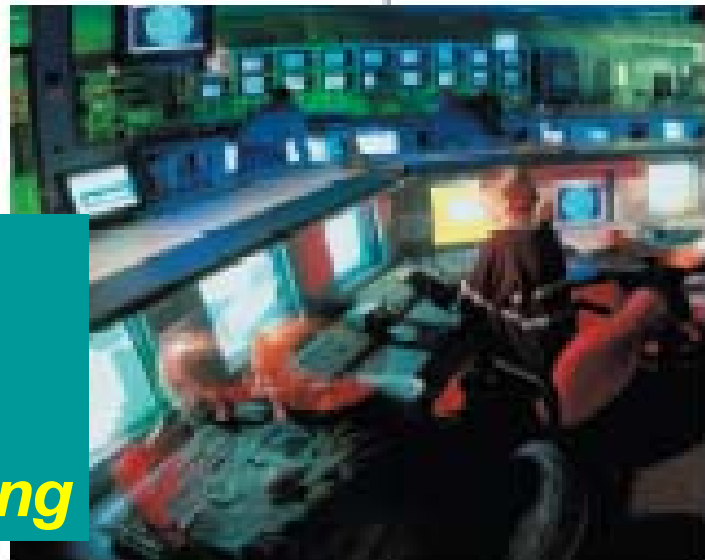
Key enabling technologies:

- *Location via wireless-assisted GPS*
- *Georeferencing via accurate GIS mapping*





The OmniTRACS® Mobile Communications System



**Satellite-based mobile asset tracking and communication:
Tool for truck fleet management and freight tracking**

OmniTRACS®
Satellite Mobile Communications System



Homeland Security

Electronic Payment Services through RFID Tags: m-commerce



e-Drive

Drive-thru
fast food,
gasoline,
car wash, etc



ICT (ctd...)

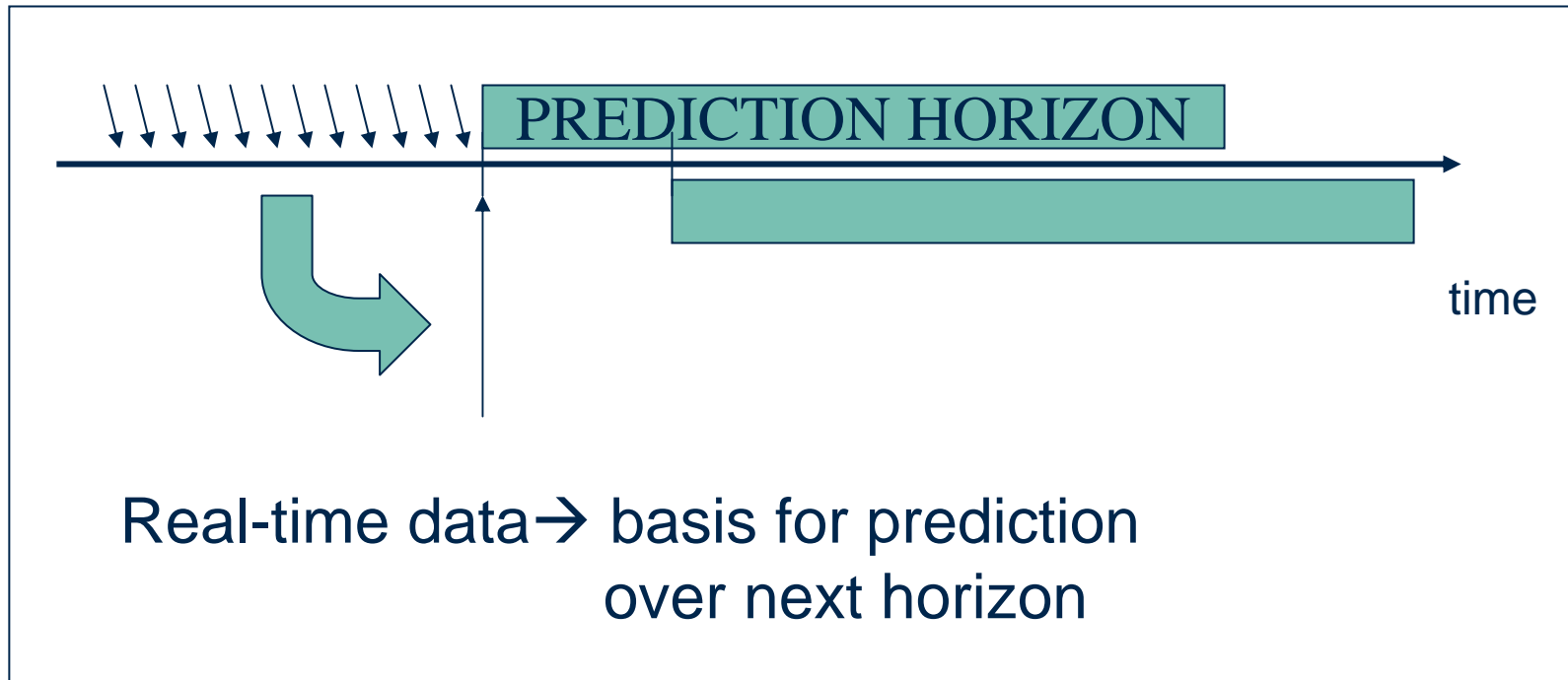
- # Detectors, sensors of traffic activity
 - State measurement
 - # Transaction logs: AVI, EDI
 - # Convergence of voice and data, location (GPS) and wireless telecom devices (CDMA, GSM): handsets and PDA's as probes or diaries
 - # Internet transaction records: activity participation, e- and m-commerce
- *Explosion of real-time information* on system state



Real-Time Info for Operational Decisions

Predictive Approaches:

Optimize for forecast demands



Real-Time Info for Operational Decisions

Reactive Approaches:
Optimize for realized, known demands



Real-Time Info for Operational Decisions

HYBRID APPROACHES:

Optimize for Predicted Conditions

React to deviations from forecast conditions

→ requires logic

for checking, identifying deviations
triggering action: plan modification,
rapid response, etc...

APPLICATIONS:

Traffic network management– route guidance, traffic control

Real-time fleet operations – truck dispatching, load acceptance and assignment

TYPICAL REACTIONS TO UNCERTAINTY IN TRANSPORTATION PLANNING DECISIONS

IGNORE: project single deterministic future (point forecasts based on plugging in mean values of all variables)

PROVIDE **RANGES** (ad hoc or statistical confidence intervals)

CONSTRUCT **ALTERNATIVE SCENARIOS** (reflecting different exogenous event realizations, e.g. economy, land use...)

FORMULATE **A PRIORI STRATEGY** (actions conditioned on alternative realizations)

ARTICULATE **ADAPTIVE PROCESS**

WAIT AND SEE: Reactive attitude

ABANDON PLANNING ALTOGETHER: Why bother?

"Life is uncertain, eat dessert first"

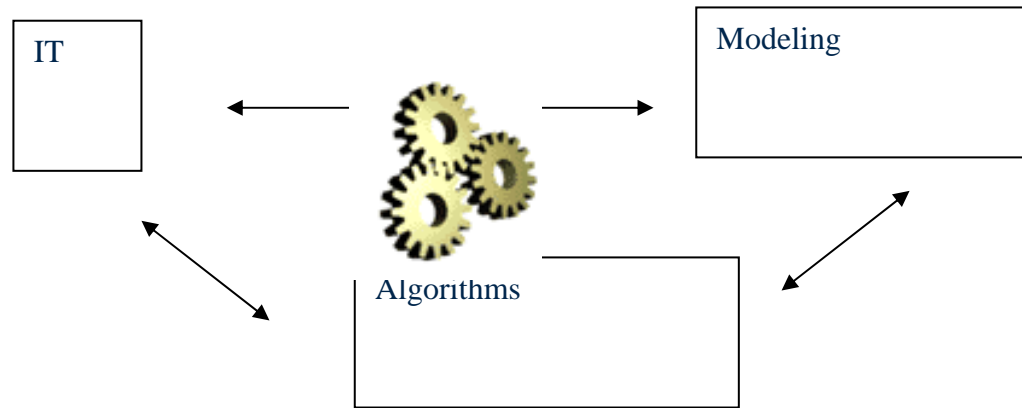
Some Issues in Real-Time Operational Decisions

1. **Value of additional information:** wait to know more about future loads, vs. act now with known demands
2. **Value of prediction,** and how to incorporate uncertain future conditions in objective function
3. **Greedy** (myopic, local) decisions vs. **global** solution quality under uncertain future demands
4. **Robustness of current decisions vis-à-vis forecast errors**

Issues in Real-Time Operational Decisions (ctd.)

5. How good should current solution be for future forecast demands when recourse is available?
6. Trade-off between effort to obtain optimal solution for uncertain predicted demands vs. more frequent updates.
7. Decision to reject known demand to reserve capacity for higher-revenue future demand (yield management).
8. How to evaluate solution quality of dynamic decision stream—benchmark? Hindsight not fair standard.

Classes of problems



OR community needs greater awareness of IT considerations

Algorithmic Approaches

FOR VERY LARGE SCALE CONSTRAINED LOGISTICS/ROUTING PROBLEMS

Develop solutions which are

implementable

robust

scalable

flexible (add constraints as needed)

planning tools – for very large scale problems (10-20k customers)

scheduling tools – can update plans, executable in real-time

EVALUATION OF DECISION PROCESS PERFORMANCE

How to evaluate solution quality of dynamic decision stream?

Criteria—

Must include some sense of computational resources (IT) and responsiveness

Benchmark?

Hindsight not fair standard.

Compare to known simple rules/algorithms

Fair comparisons?

Evaluation in simulation framework (test bed)

Test problems/benchmarking: role of consortia, industry, professional societies

Problem Statement

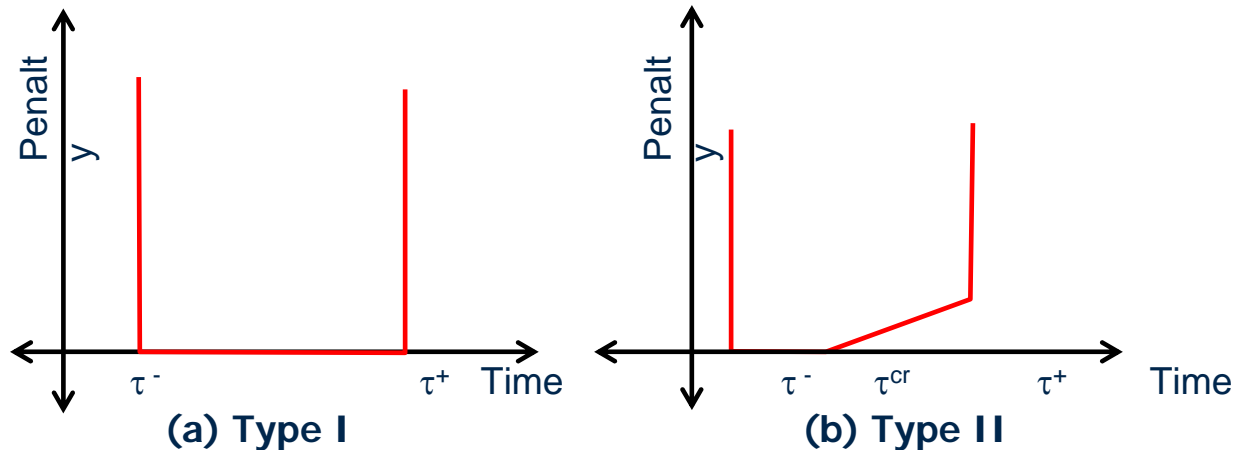
- # The principal focus of this work is to find good and computationally efficient ways, in which a commercial vehicle fleet operations manager can take advantage of real-time information to serve dynamically requested time-sensitive demands for **truckload** pickup and delivery service.

*Collaborative research with Patrick Jaillet (MIT)
Recent doctoral research of Yongin Kim (UT-Austin);
previously with Amelia Regan (now at UC-Irvine);
Currently with Miguel Figliozzi and Ricardo Giesen*

Problem Context

- Demand information is revealed on a continuous basis as the scheduled routes and/or the solution procedures are executed
- Real-time information (location, status of vehicles) is available to a dispatcher and the dispatcher can control all the activities of vehicles in real-time
- Demand information: origin, destination, time-windows (earliest & latest pickup time) and demand type
- No en-route load swap
- Substitutable homogeneous demands vs. multiple demand classes
- Constant speed
- Short-haul demands relative to their time-windows allowing tour schedule with several legs

Time-Windows



- Constraint representing the time sensitivity of the demand; limits the fleet's capacity to accept requested demands
- Type I (hard): no penalty is charged if a demand is picked up at any time within the specified time frame
- Type II (soft): if the demand is picked up after the "critical time" τ^{cr} , a penalty proportional to the amount of **lateness** ($\tau^{cr} \sim$ pickup time) is assessed.
- The width of these time-windows is relatively large compared to the average haul-length so as to construct a routing schedule with multiple legs

Background Review

Classical problems

- TSP (Traveling Salesman Problem)
- VRP (Vehicle Routing Problem)

Stochastic/Dynamic Vehicle Routing problems

- Stochastic & Static
 - Stewart and Golden (1983), Berman and Simchi-Levi (1989)
 - Incorporates uncertainty explicitly into a model
- Probabilistic TSP
 - Jaillet (1985, 1988), Bertsimas et al. (1990)
- Review of Dynamic VRP
 - Psaraftis (1988), Golden and Assad (1986), Dejax and Crainic (1987), Powell, Jaillet, and Odoni (1995)

Review: Solution Approaches

Stochastic approaches

- Incorporates uncertainty explicitly into *a priori* model: Powell (1986,1987, 1988,1996), Frantzeskakis and Powell (1990) Powell & Frantzeskakis(1994), Bertsimas and Van Ryzin (1991, 1993)

Fast local *online* operation

- Easy to implement and fast computation time
- Regan, Mahmassani and Jaillet (1995, 1996a, 1996b, 1997, 1998); Kim, Mahmassani and Jaillet (2000,2001); Powell, Towns and Marar (2000); Larssen and Madsen (2003).

Review: Solution Approaches

Sophisticated Static Procedure

- Seek local optimum routing schedule
- Yang, Jaillet, and Mahmassani (2000, 2002)
- Powell, Snow, and Cheung (2000)

Meta-heuristics

- Tabu search
 - Badeau, Guertin, Gendreau & Potvin (1997), Gendreau, Guertin, Potvin & Taillard (1999), Ichoua, Gendreau and Potvin (2000)
- Genetic Algorithm
 - Jung and Haghani (2000): static pickup-and delivery with TW
- Simulated Annealing
 - Chiang and Russell (1996) : static VRPTW

Objectives of Fleet Management

- # To maximize profit while managing service quality within acceptable level
- # Profit: earned revenue - required cost
 - Revenue: proportional to the haul-length (and demand type) and managed through a load-acceptance decision
 - Cost: fixed and variable costs.
 - Fixed cost: fleet size is fixed
 - Variable operating cost: loaded and **empty movements**
- # Service quality:
 - **Response time**: demand arrival ~ customer receives the acceptance/ rejection decision
 - **Wait time** (arrival of a demand ~ pickup time), **Lateness** (*critical* pickup time ~ actual pickup time in type II time-window)

Formal Definition

Single class of service (homogeneous demands):

Find Policy π that maximizes

$$V^* = \max_{\pi \in \Pi} \sum_{i, A_i < T} D_i^\pi (R_i - \beta(\varphi_i^\pi + l_i))$$

D_i^π the decision of whether to accept ($D_i^\pi = 1$) or reject ($D_i^\pi = 0$) the requested demand i under policy π

φ_i^π transportation cost (distance) required to serve load i

R_i reward from load i , which is proportional to the loaded distance (l_i) and price rate (r) such that $R_i = r \times l_i$.

β transportation cost per unit distance.

Formal Definition

Two classes of service (two demand classes: priority vs. regular):

Find Policy π that maximizes

$$V''^* = \max_{\pi \in \Pi} \sum_i^{A_i < T} D_i^\pi (R_i - \beta(\varphi_i^\pi + l_i) - \gamma l_i \xi_i (\delta_i^\pi - \tau_i^{cr})^+)$$

ξ_i demand class ($\xi_i=1$ regular demand, $\xi_i=0$ priority demand)

τ^{cr} critical time

γ scaling parameter

Decisions: dispatcher responsibility

Acceptance vs. Rejection Decision

- Permanent decision that should be made in a short time
- Critical to the revenue of the company
- Depends on characteristics of the requested demand as well as those of the existing demands in the system queue
- Complete assessment of the feasibility and the expected profit of a demand in real-time is extremely hard

Assignment/Scheduling

- Assign an accepted demand to a vehicle ('s routing schedule)
- Can be modified (reassignment) with updated information
- Routing schedule governs the operating cost of the fleet
- [It is not necessary to inform the drivers of this decision until a driver completes his/her current job, except for en-route diversion decisions]

Basic Solution Approach

- # To solve the successive local problems as close to optimality as possible
 - Myopic optimality
 - Even a local snapshot problem defined with a set of trucks and known accepted and unserved demands, is in most cases too large to solve optimally in a short time
 - Develop dynamic operation policies determining how to set up local problems and how to apply the solutions of the local problems to the dispatching system in a dynamic context
 - Apply fast acceptance decision policies on the dynamically requested demands

MIP Formulation

- # K trucks ($1, \dots, K$) and their N known demands at the decision instant
- # node k ($1 \leq k \leq K$) represents truck k
- # node $K+i$ ($1 \leq i \leq N$) corresponds to demand i .

The objective function

- # To find the least-cost set of cycles that involve all nodes

Decision variables

- # x_{uv} : binary decision variable ($u, v = 1, \dots, K+N$) to indicate whether arc (u, v) is connected
- # δ_i continuous variable to represent the pickup time.
- # $\omega_i = (\delta_i - \tau^{cr}_i)^+$ denote **lateness** of demand i

MIP Formulation

Parameters

- τ_i^-, τ_i^+ represent the earliest and latest pickup time of demand i
- τ_i^{cr} critical pickup time of demand i ,
- v^k , time at which truck k becomes available,
- d_{ij} distance from demand i 's destination to demand j 's origin
- d_{oi}^k distance from truck k 's updated location to demand i 's origin
- l_i loaded distance of demand i .
- ξ_i type of demand i ; 0: priority demand, 1: regular demand
- γ penalty parameter
- ρ scale parameter for rejection decision
- M, B large constant

Local Snapshot problem Formulation I

$$\min \sum_{k=1}^K \sum_{i=1}^N d_{0i}^k x_{k,K+i} + \sum_{i=1}^N (\rho l_i x_{K+i,K+i} + \sum_{j=\{1,..,N\}, j \neq i} d_{ij} x_{K+i,K+j})$$

subj to

$$\sum_{v=1}^{K+N} x_{uv} = 1 \quad \forall u = 1, \dots, K + N \quad (1)$$

$$\sum_{v=1}^{K+N} x_{vu} = 1 \quad \forall u = 1, \dots, K + N \quad (2)$$

$$x_{uv} = 0,1 \quad \forall u, v = 1, \dots, K + N \quad (3)$$

$$-\sum_{k=1}^K (d_{0i}^k + v^k) x_{k,K+i} + \delta_i \geq 0 \quad \forall i = 1, \dots, N \quad (4)$$

$$(l_i + d_{ij}) x_{K+i,K+i} - M x_{K+i,K+j} - \delta_i + \delta_j \geq -M + l_i + d_{ij} \quad \forall i, j = 1, \dots, N \quad (5)$$

$$\tau_i^- \leq \delta_i \leq \tau_i^+ \quad \forall i = 1, \dots, N \quad (6)$$

Formulation II

$$\text{Min} \sum_{k=1}^K \sum_{i=1}^N d_{0i}^k x_{k,K+i} + \sum_{i=1}^N (\rho l_i x_{K+i,K+i} + \sum_{j=\{1,..,N\}, j \neq i} d_{ij} x_{K+i,K+j}) + \gamma \sum_{i=1}^N l_i \omega_i$$

subj to

$$\sum_{v=1}^{K+N} x_{uv} = 1 \quad \forall u = 1, \dots, K + N \quad (1)$$

$$\sum_{v=1}^{K+N} x_{vu} = 1 \quad \forall u = 1, \dots, K + N \quad (2)$$

$$-\sum_{k=1}^K (d_{0i}^k + v^k) x_{k,K+i} + \delta_i \geq 0 \quad \forall i = 1, \dots, N \quad (3)$$

$$(l_i + d_{ij}) x_{K+i,K+i} - M x_{K+i,K+j} - \delta_i + \delta_j \geq -M + l_i + d_{ij} \quad \forall i, j = 1, \dots, N \quad (4)$$

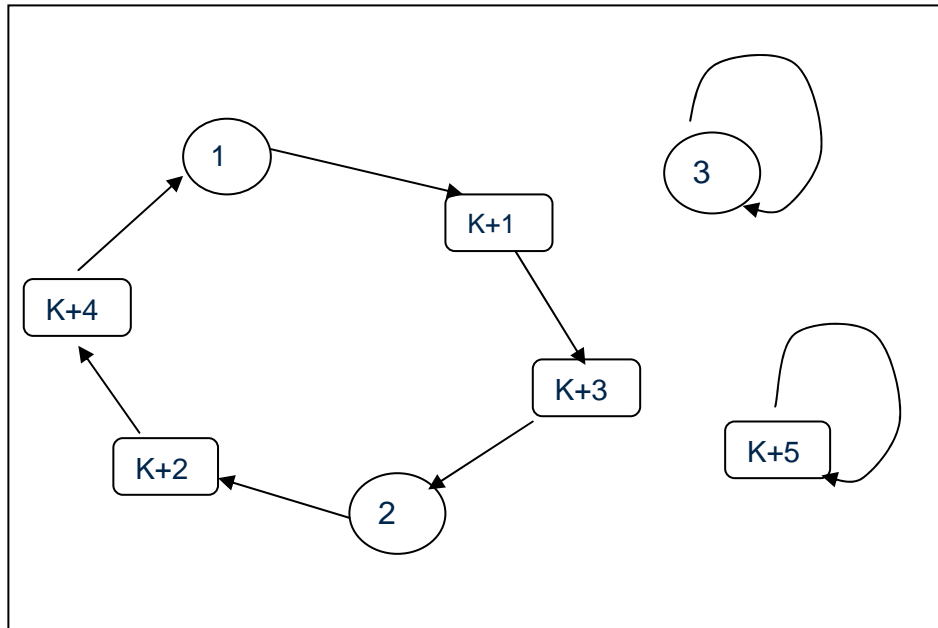
$$B+ \omega_i - \delta_i \geq B \xi_i - \tau_i^{cr} \quad \forall i = 1, \dots, N \quad (5)$$

$$\omega_i \geq 0 \quad \forall i = 1, \dots, N \quad (6)$$

$$x_{uv} \in \{0,1\} \quad \forall u, v = 1, \dots, K + N \quad (7)$$

$$\tau_i^- \leq \delta_i \leq \tau_i^+ \quad \forall i = 1, \dots, N \quad (8)$$

Example



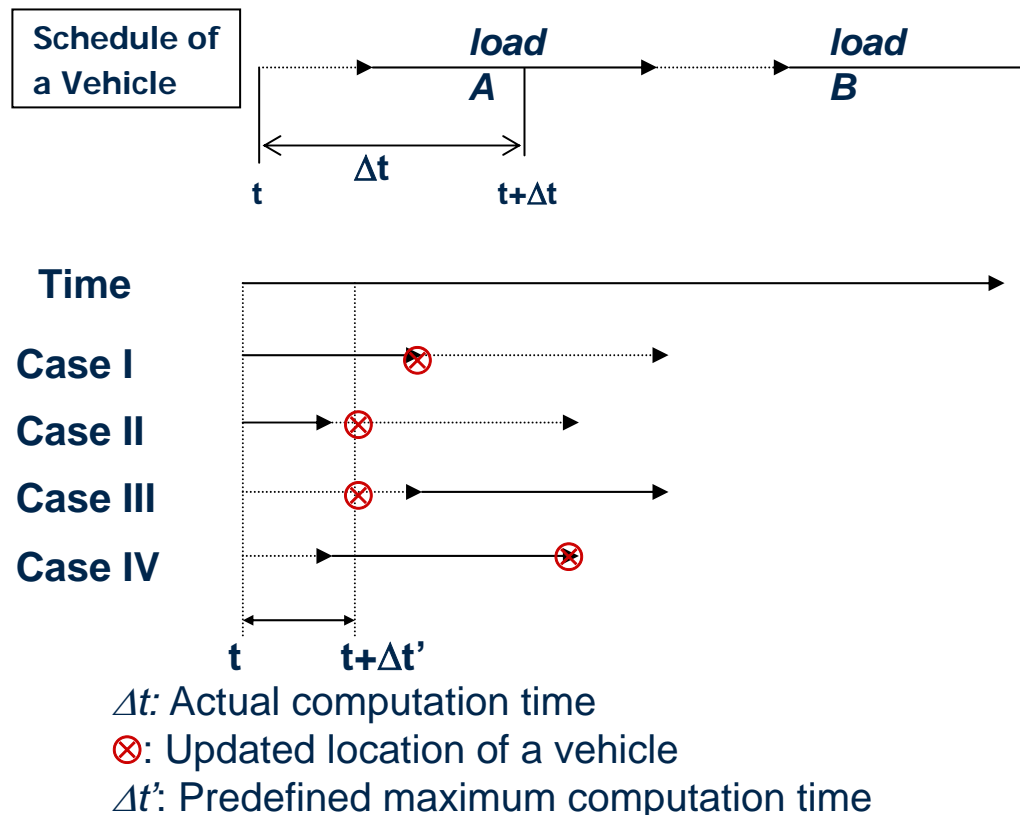
- A cycle consisting of 1, K+1, K+3, 2, K+2, K+4, 1
 - Veh 1 serves demands 1 and 3 sequentially
 - Veh 2 serves demands 2 and 4
- A cycle with one vehicle node (3): veh 3 is idle
- A cycle with one demand node (K+5): the demand is rejected

Hybrid Dynamic Decision Approach

- # Combine a Heuristic local rule and Optimization-based routing
- # Heuristic local rule (acceptance/rejection and initial assignment)
 - Provides fast response time and feasible schedule
 - Whenever a request is received,
find the minimum cost sequence of demands (including the newly requested demand) *for each truck individually*
 - Compare these costs across the entire fleet to identify the feasible vehicle-load assignment with the minimum additional cost
 - Assign the new demand to this vehicle allowing re-sequencing
- # Optimization-based routing (reassignment)
 - Long computation time but produces an optimal solution for defined local snapshot problem
 - Utilize the MIP models
 - Re-optimize the initial schedule before the next demand comes in

Local Problem Setting

- When a local snapshot problem is set up, execution time of the solution algorithm needs to be considered (due to intervening fleet vehicle movement that will occur before completion of the decision process)



Evaluation

- # Use a simulation framework for the evaluation of proposed policies in comparison with benchmark policies.
- # Simulation Framework
 - Discrete-event simulation framework
 - Some policies explicitly take into account the end of the real (wall-clock) computation time of a solution procedure as one of the simulation events that update the system state
 - The simulation time cannot get ahead of the real-world time
- # Benchmark
 - The simple heuristic approach (Regan et al., 1996a)
 - RAPID-SL (Resource Allocation procedure for the Integrated Dynamic Assignment Problem-Single Label) by Powell, Snow, & Cheung (2000)

Selected Results in various problem settings



5 10 15 20 25 30 35 40 45 50 55 60 65 70 75 80 85 90 95 100 105 110 115 120

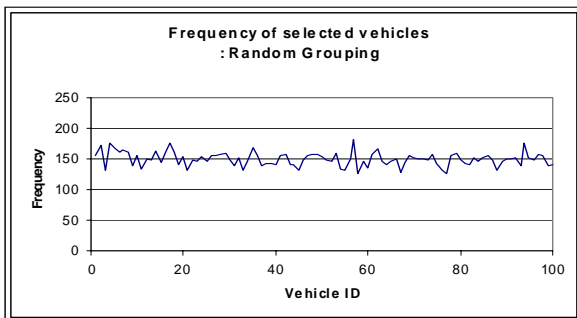
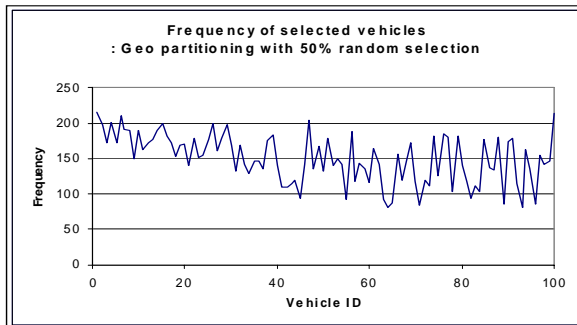
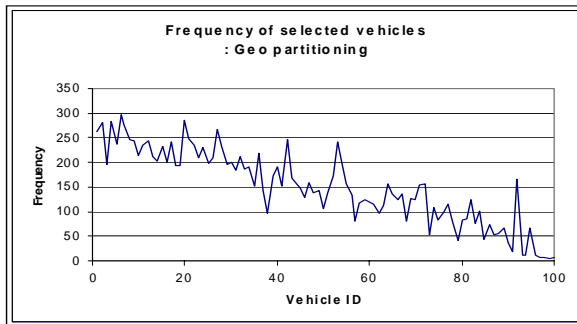
Large fleet problem: Partitioning

- Problem specification
 - Moderate demand arrival rate is assumed
 - Large fleet : 100 vehicles
- Apply the hybrid two-phase strategy whenever a new demand arrives
 - Initial Assignment : local heuristic rule for a initial schedule & acceptance decision
 - Reassignment : Optimization-based procedure to improve the schedule
- Due to the large size fleet, only a subset of vehicles and their associated demands are selected as candidates for the reassignment
- How should the high potential candidates be identified and selected ?

Geographical Partitioning

- To exploit the schedule of previous decision epoch rather than to totally re-optimize the schedule
- The local problem (location & status and associated schedule of vehicles) at the previous decision epoch is similar to the current decision epoch
 - New load, served demands during the inter-arrival time
- Initial assignment changes only one vehicle's schedule
- Select **close neighboring** vehicles (and their demands)– to the winner of the initial assignment-- as candidates for reassignment
- Rationale is that close vehicles offer good possibility of reducing overall cost by swapping or resequencing their demands
- Candidate vehicles for reassignment are selected on basis of **geographic proximity** with simple feasibility check

Frequency Of Selected Vehicles



- Geographic partitioning shows good performance in local sense; big improvement from the initial schedule
- However, it shows poor performance from global perspective
- Culprit: it tends to select vehicles with long task queues
- Biased selection in the geographic partitioning misses the opportunity of reassigning demands to diverse vehicles
- Balanced selection can be achieved by combination with random selection (hybrid partitioning)

Dynamic Control

- Congested conditions with high arrival rates produce large local problems
- Cutting the size at some critical point can avoid extremely long computation time.
- The loads, whose future scheduled pickup times are earlier than the time criterion are removed from the candidate pool.
- Cut-off criterion increases gradually until the reassignment pool size decreases to its predefined point.

Numerical Results

| Strategy | Empty distance [mile] | Lateness (min) | Comp. time [sec] | # of candidate demands for Phase II | Violation (%) |
|-----------------------------|-----------------------|----------------|--------------------|-------------------------------------|---------------|
| Initial assignment only | 11.75 | 117.7 | 2.06 ± 0.25 | | 3.4 |
| Random Partitioning | 8.70 | 104.4 | 5.04 ± 18.59 | 20.6 | 6.8 |
| Geographic | 8.91 | 112.8 | 66.47 ± 140.22 | 28.7 | 28.4 |
| Hybrid Partitioning | 8.46 | 104.2 | 4.3 ± 11.01 | 20.8 | 6.6 |
| Dynamic hybrid partitioning | 8.43 | 104.95 | 3.47 ± 7.02 | 20.4 | 5.9 |

Summary

- # A proximity measure is developed to identify high potential vehicles
- # Geographic partitioning using this measure misses opportunity for reassigning demands to diverse vehicles
- # Hybrid partitioning strategy, which selects a portion of the candidates by 'geographic partitioning' and the remainder through 'random partitioning', is proposed
- # This strategy performs well with respect to the computation time and empty distance
- # Dynamic problem size control is very effective in reducing not only the average computation time but also its variance

Comparison with RAPID-SL

- # Based on Powell, Snow, and Cheung (2000)
- # Integer mathematical formulation, which contains subtour constraints and highly nonlinear constraints
- # The algorithm eliminates the nonlinear constraints and relaxes the subtour constraints
- # a pure network problem is solved repeatedly to eliminate subtours by penalizing the arcs in the subtours using dual variables
- # Since the algorithm does not completely eliminate the subtours, we developed two dynamic implementation strategies
 - Strategy I rejects the demands in the subtours at every decision epoch
 - Strategy II keeps the demands in the subtour until the time-window of a demand allows
- # Even though it is not guaranteed that these dynamic implementation strategies are efficient with respect to the computation time, the quality of the solution is comparable

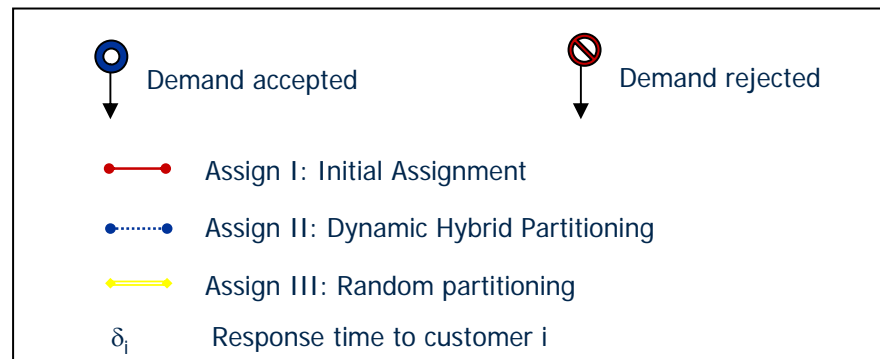
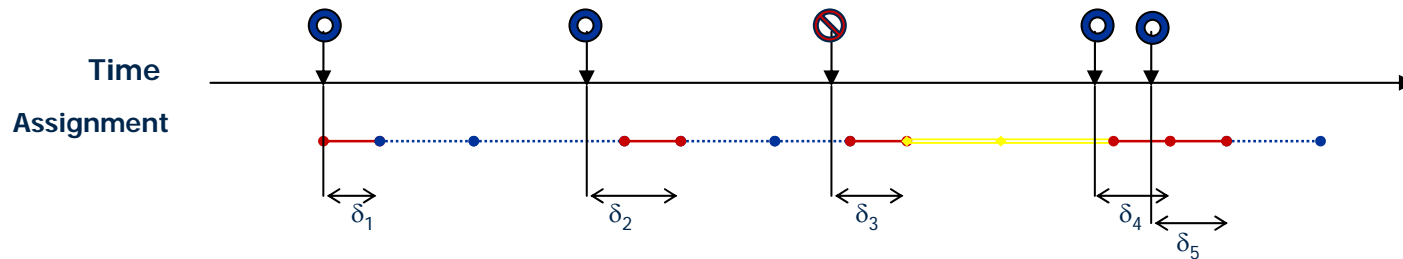
Comparison with *RAPID-SL*

| | Inter arrival time/veh = 90min | | | Inter arrival time/ veh = 60 min | | |
|-----------------------|-----------------------------------|-----------------|-----------------|-------------------------------------|-----------------|-----------------|
| | TPD | RAPID-SL | | TPD | RAPID-SL | |
| | | I | II | | I | II |
| Total Empty Time | 159.3 | 139.8 | 151.0 | 184.6 | 134.8 | 144.6 |
| Total Loaded Time | 1033.5 | 957.1 | 986.9 | 960.7 | 907.4 | 935.5 |
| Total Idle Time | 488.5 | 551.2 | 506.4 | 186.0 | 194.6 | 160.1 |
| Total Empty Distance | 7965 | 6990 | 7548 | 9232 | 6740 | 7231 |
| Total Loaded Distance | 51676 | 47855 | 49346 | 48034 | 45372 | 46776 |
| # of served demands | 1000 | 895 | 952 | 935 | 836 | 897 |
| Profit | \$28,016 | \$26,164 | \$26,786 | \$24,999 | \$24,743 | \$25,347 |

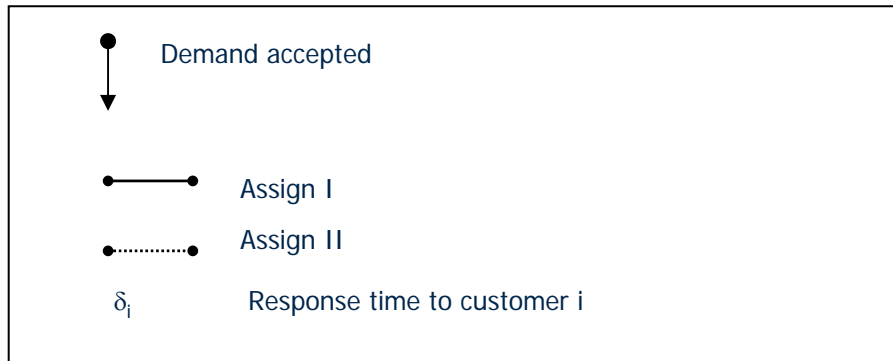
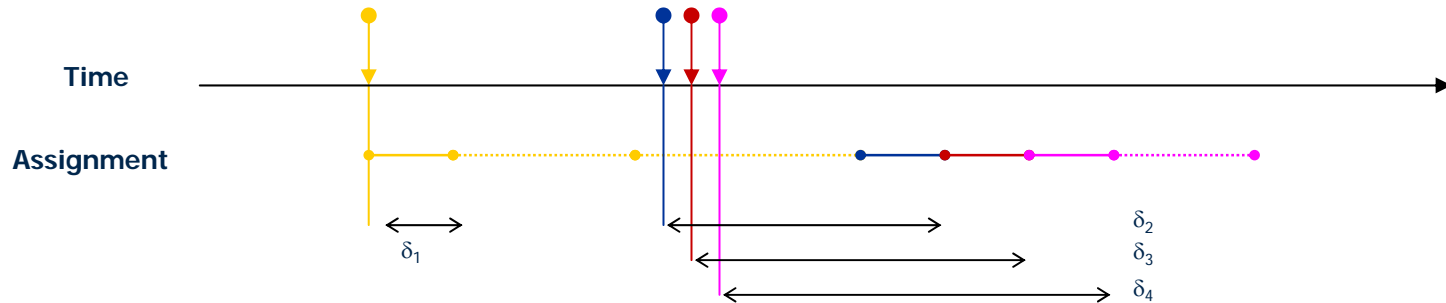
Over-saturated demand situation

- ⌘ Problem setting:
 - Large fleet: 100 vehicles
 - Over-saturated demand condition
- ⌘ Develop and apply a dynamic adaptive dispatching (*DAD*) policy to utilize computation resources fully while keeping customer's response time within acceptable limits
- ⌘ Develop a filtering procedure (acceptance decision process), which improves the system's efficiency by providing greater opportunity for reassignment of existing routes

Dynamic Adaptive Dispatching (*DAD*)



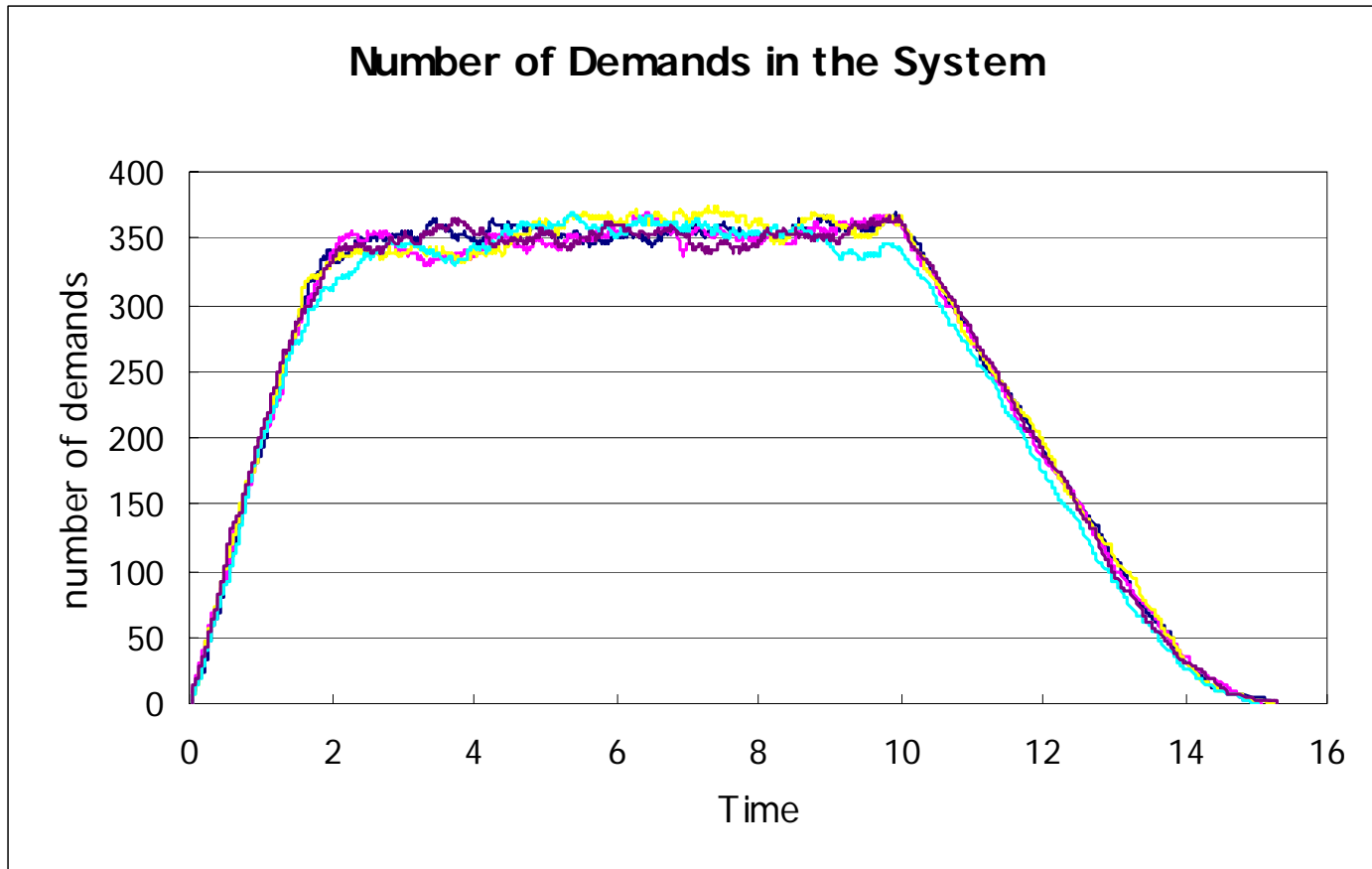
Worst-case Response Time



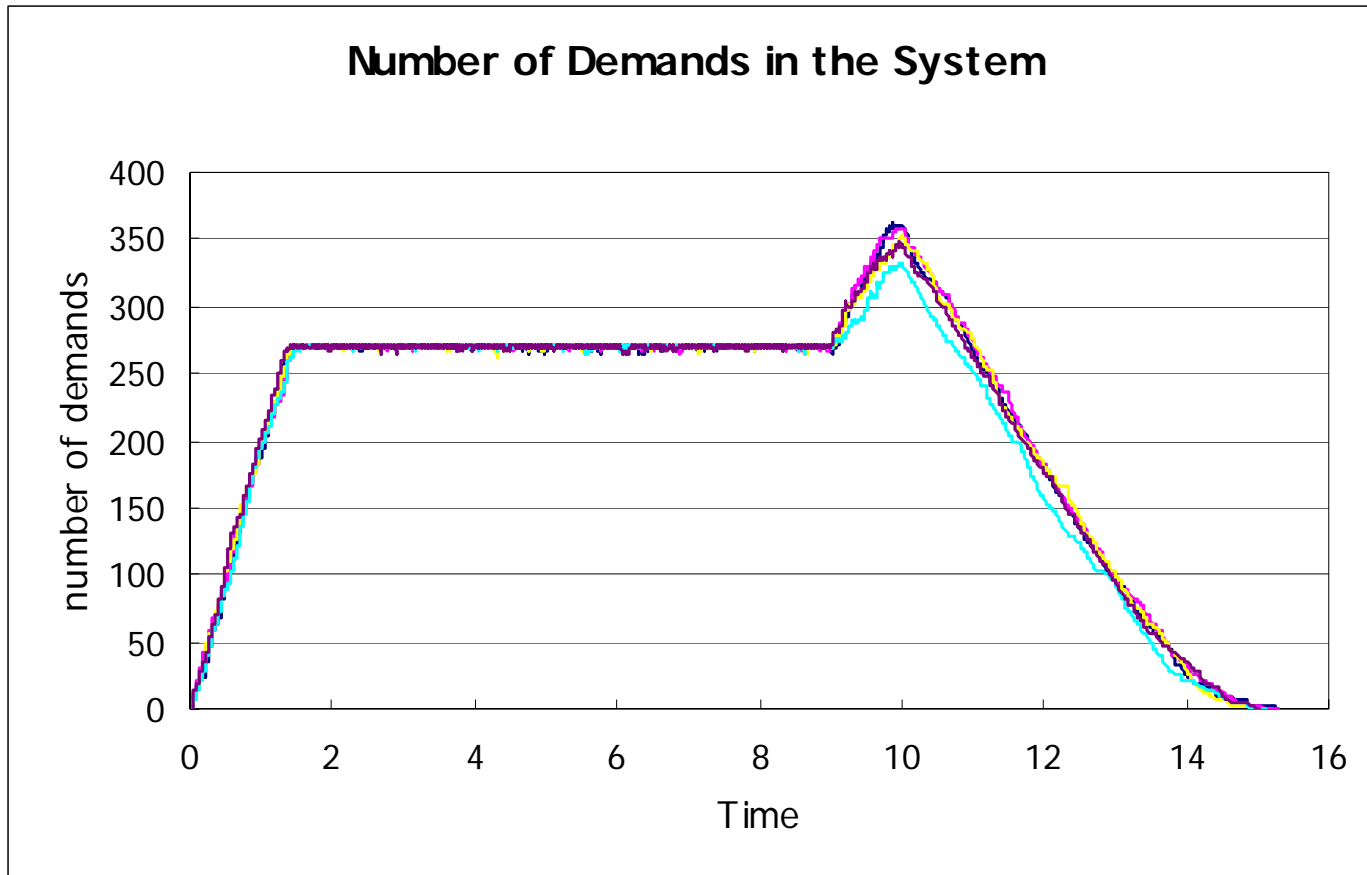
Filtering Process

- ✦ Filtering controls the total number of demands in the system
- ✦ Whenever a new demand arrives, count the number of demands
 - If the number is below a predefined threshold, apply Assign I
 - O.w. the demand is rejected outright
- ✦ Due to the time-windows of demands, the number of demands in the queue of the system is limited
- ✦ **Holding capacity:** the maximum number of demands waiting for service in the system
- ✦ High arrival rate causes the 'holding capacity' to completely fill up with the accepted demands
- ✦ When the 'holding capacity' is full, it is difficult to find reassignment opportunities because there is not enough room for swapping and re-sequencing existing demands
- ✦ The filtering only limits the number of demands in the queue, not the number of served demands in a day.

Before Filtering



After Filtering



Intelligent Acceptance Decision

- # An intelligent acceptance decision process (*AddCost*) is applied in combination with the filtering process
- # The *Assign /* procedure provides a measure to characterize the potential of new demand
 - Additional cost due to the new demand
- # A new demand is accepted
 - If the additional cost is less than a certain level
 - And, the total # of demands in the system is less than the filtering threshold

Performance of Algorithms

| | Profit | | # of served demands | | Lateness [min] | | Response time [sec] | | Worst case response time [sec] |
|------------|--------------------|---------------|---------------------|--------------|----------------|-------------|---------------------|-------------|--------------------------------|
| | | | | | | | | | |
| TPD | \$18,250.60 | <i>390.74</i> | 1073.00 | <i>19.03</i> | 161.3 | <i>0.64</i> | 5.44 | <i>4.15</i> | 39.51 |
| DAD | \$18,964.06 | <i>270.50</i> | 1075.80 | <i>14.87</i> | 160.72 | <i>0.69</i> | 6.62 | <i>2.99</i> | 22.7 |
| Filter 270 | \$20,077.76 | <i>475.62</i> | 1051.80 | <i>21.78</i> | 125.89 | <i>0.92</i> | 2.97 | <i>2.88</i> | 16.18 |
| AddCost | \$20,981.28 | <i>436.89</i> | 1087.20 | <i>18.73</i> | 121.20 | <i>2.01</i> | 3.04 | <i>2.76</i> | 18.36 |

Summary

- # This policy applies various assignment techniques adaptively depending on the state of the system
- # *DAD* provides opportunities to improve a schedule by re-optimizing existing routes while keeping the response time within a tolerable range
- # A filtering process controls the number of waiting jobs in the system below the 'holding capacity', which provides room for effective reassignment
- # Additional improvement can be attained by combining this filtering process with an intelligent acceptance decision rule, which utilizes the information obtained from *Assign I* procedure

Load Acceptance Decision with Priority Demand

- Problem setting
 - Large fleet
 - Over-saturated demand situation
 - Two types of delivery service
- Priority customers are time sensitive and requires express on-time delivery service
 - They are willing to pay a premium for on-time, earlier delivery
 - Relatively narrow, Type I time-window
- Regular customers are more sensitive to price, and request the low-price flexible service
 - Employ wider type II time-windows where a penalty is charged in proportion to the amount of the overtime

General Revenue Management

$$D^*(\Gamma_t^\pi, Q_t^\pi, j) = \begin{cases} 1 & \text{if demand } j \text{ is feasible} \\ & \text{and } R_j > E\left[\sum_{i: A_j < A_i < T} D_i^\pi (R_i - \beta(\varphi_i^\pi + l_i) - \gamma \xi_i l_i (\delta_i^\pi - \tau_i)^+) \middle| \Gamma_t^\pi, Q_t^\pi \right] - \\ & E\left[\sum_{i: A_j < A_i < T} D_i^\pi (R_i - \beta(\varphi_i^\pi + l_i) - \gamma \xi_i l_i (\delta_i^\pi - \tau_i)^+) \middle| \Gamma_t^\pi, \bar{Q}_t^\pi \right] \\ 0 & \text{if demand } j \text{ is not feasible} \\ & \text{or } R_j \leq E\left[\sum_{i: A_j < A_i < T} D_i^\pi (R_i - \beta(\varphi_i^\pi + l_i) - \gamma \xi_i l_i (\delta_i^\pi - \tau_i)^+) \middle| \Gamma_t^\pi, Q_t^\pi \right] - \\ & E\left[\sum_{i: A_j < A_i \leq T} D_i^\pi (R_i - \beta(\varphi_i^\pi + l_i) - \gamma \xi_i l_i (\delta_i^\pi - \tau_i)^+) \middle| \Gamma_t^\pi, \bar{Q}_t^\pi \right] \end{cases}$$

- It is extremely difficult to estimate the expected total profit with respect to the future demands under a given situation
- The acceptance decision policy for this dynamic fleet management problem should be able to make a decision in a short time, and should take into account the system state upon arrival of a load.

Feasibility Index based Acceptance Decision

- The 'Feasibility Index' (FI) characterizes the system state upon arrival of a regular demand arrival in terms of an approximate expected number of vehicles that can serve an unrealized (future) priority demand.
- Assumptions
 - The time-window width of a priority demand is known in advance.
 - The arrival time of a priority demand is same as the time that FI is estimated
 - The estimation process exploits an insertion heuristic method to explore the feasible routing schedule involving the future priority demand.
 - The FI estimation process involves probabilistic information about haul-length and the empty distance to serve it.
 - Haul-length: use the *pdf* obtained from historical data
 - Empty distance: a threshold (β) (mean + σ from historical data) is pre-specified representing the maximum allowable empty distance required to serve a demand

Feasibility Index

$$FI(t | \Gamma_t^\pi, Q_t^\pi) = \sum_{k=1}^{k=K} FI(k | \Gamma^\pi(k, t), q^{k, \pi}(t))$$

$$FI(k | \Gamma^\pi(k, t), q^{k, \pi}(t)) =$$

$$\left\{ \begin{array}{l} \text{if } s^{k, \pi} = 1 \text{ (loaded)} \\ \quad \max(\{ FI(k, (q_i^{k, \pi}, q_{i+1}^{k, \pi})), \text{ for } i = 1, \dots, I - 1 \}, FI(k, q_I^{k, \pi})) \\ \text{if } s^{k, \pi} = 2 \text{ (empty)} \\ \quad \max(FI(k, q_1^{k, \pi}), \{ FI(k, (q_i^{k, \pi}, q_{i+1}^{k, \pi})), \text{ for } i = 1, \dots, I - 1 \}, FI(k, q_I^{k, \pi})) \\ \text{if } s^{k, \pi} = 3 \text{ (idle)} \\ \quad FI(k) \end{array} \right.$$

where I represents queue length ($I = q^{k, \pi}(t)$), and for notational simplicity current time t is omitted

$$FI(k, (q_i^{k, \pi}, q_{i+1}^{k, \pi})) = FI^T(k, (q_i^{k, \pi}, q_{i+1}^{k, \pi})) * FI^L(k, (q_i^{k, \pi}, q_{i+1}^{k, \pi}))$$

Feasibility Index

- # Location based Feasibility Index($FI^L(k)$)
 - A vehicle can serve a requested demand only if the vehicle can reach the origin of the requested demand within min (time-window width, β) considering updated vehicle location

- # Time-window based Feasibility Index ($FI^T(k)$)
 - $FI^T(k, (a,b)) = \Pr\{S(a,b) > \eta + \beta\}$
 - $S(a,b) = TO(b) - TD(a) + \min\{(-TO(b)), (-TO(c))\}$
 - $S(a,b)$: maximum space-time room between demands **a** and **b**
 - $TO(j)$: scheduled time at the origin of load j
 - $TD(j)$: scheduled time at the destination of load j
 - η : a random variable representing haul-length

Acceptance decision policy

$$D^*(\Gamma_t^\pi, Q_t^\pi, j) = \begin{cases} 1 & \text{if } \xi_j = 0, \text{ and demand } j \text{ is feasible} \\ & \text{or} \\ & \xi_j = 1, \text{ and demand } j \text{ is feasible, and } FI(t|\Gamma_t^\pi, \bar{Q}_t^\pi) \geq FI^* \\ 0 & \text{if demand } j \text{ is not feasible} \\ & \text{or} \\ & FI(t|\Gamma_t^\pi, \bar{Q}_t^\pi) < FI^* \end{cases}$$

■ FI^* : threshold (optimal FI)

Numerical Results

6.25% of priority demand

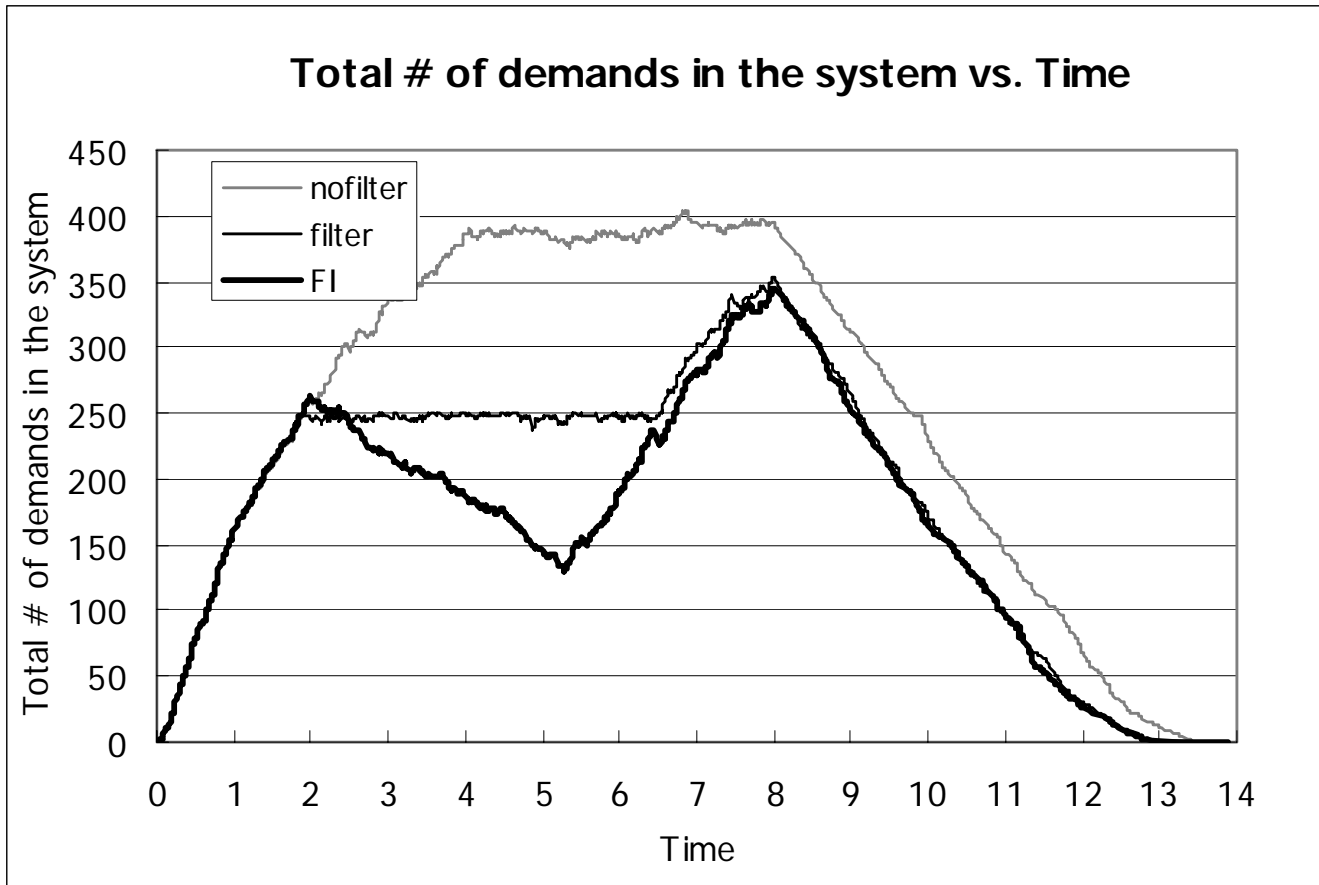
| Acceptance decision policy | Total Revenue (std.) | Total Cost (std.) | Over Time Cost (std.) | Total Profit (std.) | Total # of Served Demands (std.) | # of served Priority demands (std.) |
|------------------------------|----------------------|-------------------|-----------------------|---------------------|----------------------------------|-------------------------------------|
| Feasibility based acceptance | \$56,663 | \$32,312 | \$5,340 | \$19,011 | 896.8 (70.9%) | 25.8 (33.4%) |
| | (618) | (229) | (363) | (849) | (13.2) | (3) |
| Simple Filtering | \$57,295 | \$31,937 | \$1,249 | \$24,109 | 920.8 (72.8%) | 35.2 (45.6%) |
| | (412) | (449) | (205) | (484) | (10.1) | (5) |
| FI | \$59,879 | \$31,820 | \$979.2 | \$27,080 | 897.2 (70.9%) | 66.3 (85.6%) |
| | (460) | (184) | (168) | (453) | (11.2) | (7) |

Numerical Results

25% of Priority demands

| Acceptance decision policy | Total Revenue (std.) | Total Cost (std.) | Over Time Cost (std.) | Total Profit (std.) | Total # of Served Demands (std.) | # of served Priority demands (std.) |
|------------------------------|----------------------|-------------------|-----------------------|---------------------|----------------------------------|-------------------------------------|
| Feasibility based acceptance | \$60,712 | \$32,485 | \$4,920 | \$23,307 | 900.2 (71.1%) | 102.8 (33.1%) |
| | (572) | (223) | (232) | (492) | (6.3) | (4.5) |
| Simple Filtering | \$61,622 | \$31,483 | \$1,267 | \$28,872 | 903.8 (71.4%) | 139.8 (45.1%) |
| | (910) | (655) | (302) | (335) | (16.5) | (7.7) |
| FI | \$68,829 | \$30,038 | \$352 | \$38,438 | 850.6 (67.2%) | 267.2 (86.1%) |
| | (1090) | (535) | (98) | (804) | (13.2) | (11.2) |

Numerical Results



Summary

- # Two classes of service are introduced corresponding to various customer requirements
- # Feasibility Index(FI)-based acceptance decision policy is proposed
- # FI represents the probability that a carrier can accept and serve a future (still unrealized) priority demand based on the current system state in terms of the expected number of vehicles that can serve the load
- # FI policy improves the total profit significantly particularly when more priority demands are requested

Conclusion

- Partitioning strategies provide a solution approaches to a problem managing a large fleet of vehicles
- **Dynamic Adaptive Dispatching** improve a schedule by re-optimizing existing routes while keeping the response time within a tolerable range
- Various real-time acceptance/ rejection decision policies are developed corresponding to a range of demand situations
- A simulation framework is developed in order to evaluate the effectiveness of developed policies,
- A simple local heuristic approach (Regan, 1997) and RAPID-SL (Powell, Snow, & Cheung, 2000) algorithm are coded and implemented in this simulation framework as benchmark policies

Future and ongoing research

- Consider multiple pickups and deliveries
 - For less-than truckload delivery
 - Truck capacity constraints
- Consider variable travel times
 - Due to unpredictable events such as network congestion and/or accidents
 - In urban area, travel time between two points varies significantly and affects the system performance (city logistics); combine with traffic simulation/prediction DTA systems (DYNASMART-X).
- Evaluation of carrier strategies in auction marketplace (Figliozzi)
- Extension to real-time inventory routing problems (Giesen)

Thank you Q & A



and management services with 3PL support transportation trading and
services with 3PL support transportation trading and management serv
support transportation trading and management services with 3PL support trans
transportation trading and management services with 3PL support transportation
trading and management services with 3PL support transportation trading and
management services with 3PL support transportation trading and management ser

About Us

Products & Services

News &
Events

FAQ

Contact Us

- ▶ Management
- ▶ History
- ▶ Partners

- ▶ TrantisLink
- ▶ TrantisTracker



[Try our online software demo](#)

[Member Login](#)

[Join Trantis](#)

[Client Center](#)

Conceptual Diagram

