




Incorporating Stochastic Models and
Stochastic Information Within Traffic Flow
Management Systems



Speaker:

Avijit Mukherjee
University of Maryland, College Park


Outline

- 
- A decorative horizontal bar with a repeating pattern of red, black, and yellow segments.
- Introduction
 - Background on stochastic models for Ground Delay Programs
 - Static vs. dynamic models
 - Recent work on dynamic model for GDP planning
 - Capacity scenarios and scenario tree
 - Experimental results
 - Application under CDM
 - Extension to enroute capacity problem → DFW corner post problem
 - Graphically explain the decision making process
 - Experimental results
 - Concluding remarks
 - Complexities associated with practical implementation
 - Future research

Sources of Uncertainty in Traffic Flow Management

- Demand (uncertain departure/arrival times)
- Capacity (forecast uncertainty)
- Control actions traffic managers may take
- Effects of coordination and timing of inter-related activities

Mitigating Uncertainty

- 
- A decorative horizontal bar with a repeating pattern of red, black, and yellow segments.
- Reduce uncertainty by *improving information quality*.
 - Create plans that “*hedge against*” *multiple possible future outcomes*.
 - Create flexible systems that can *dynamically react to changing conditions*.

NEXTOR Research on Uncertainty in ATM

-
- Uncertainty in airport capacity
 - Richetta and Odoni (1993, and 1994)
 - Ball et al. (1999, 2003)
 - Wilson (2002)
 - Inniss and Ball (2001)
 - Mukherjee and Hansen (2003)
 - Liu et al. (2005)
 - Demand uncertainty
 - Vossen et al (2002)
 - Willemain (2002)
 - Enroute airspace capacity
 - Nilim et al. (2002, 2004)
 - Mukherjee and Hansen (2004)

Research on Stochastic Ground Holding Problem

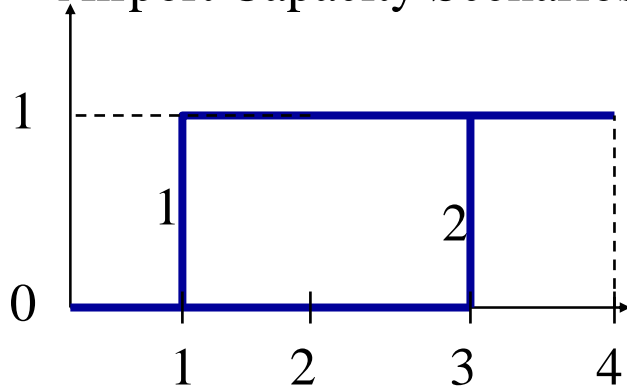
- Static Stochastic Optimization Models
 - Richetta and Odoni (1993)
 - Ball et al.(2003)
 - Considers multiple scenarios of airport capacity profile along with their probability of occurrence
 - Interesting properties of the IP formulation
 - Can be applied repeatedly → “partially” dynamic

Research on Stochastic Ground Holding Problem

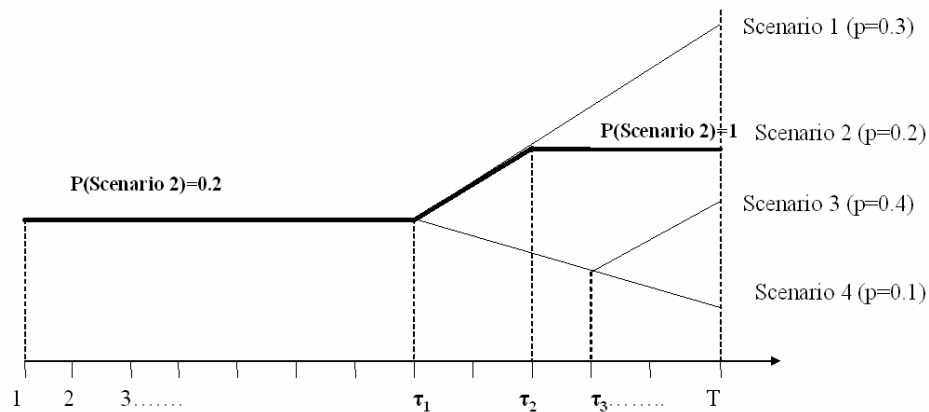
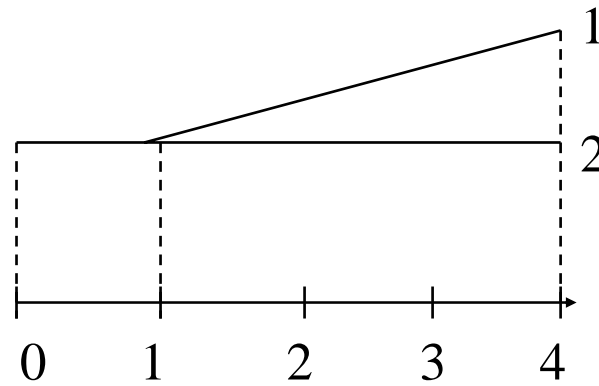
- (Partially) Dynamic Stochastic Optimization Model: Richetta and Odoni (1994)
 - Plans GDP in stages → utilizes updated information on capacity
 - Unable to revise ground delays once they are assigned, even if the flight hasn't departed. However, this increases predictability of flight departure times.
- Dynamic Stochastic Optimization Model: Mukherjee and Hansen (2003)
 - Capacity scenarios and scenario tree
 - Utilizes updated information on capacity to revise ground delays of flights
 - Can incorporate non-linear measures of ground delay

Scenarios and Scenario Tree

Airport Capacity Scenarios

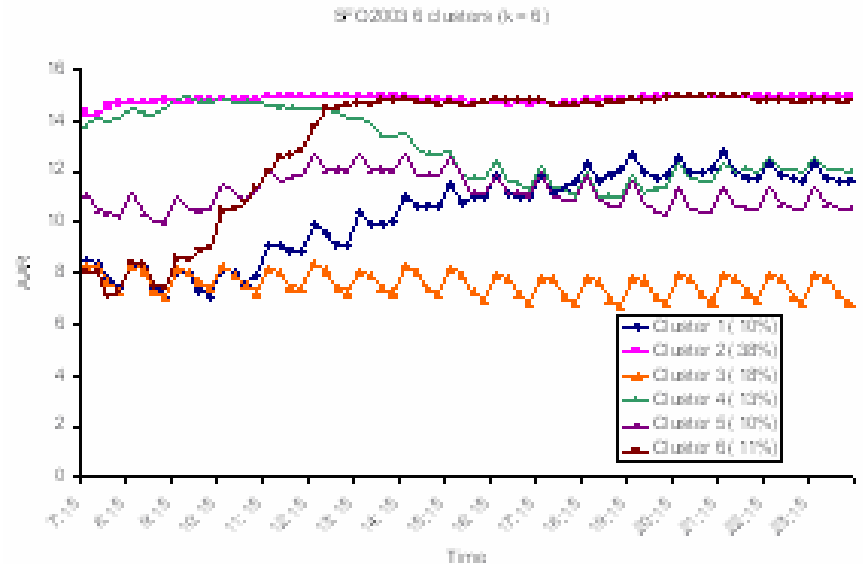


Scenarios Tree




Scenario “Tree” Doesn’t Grow

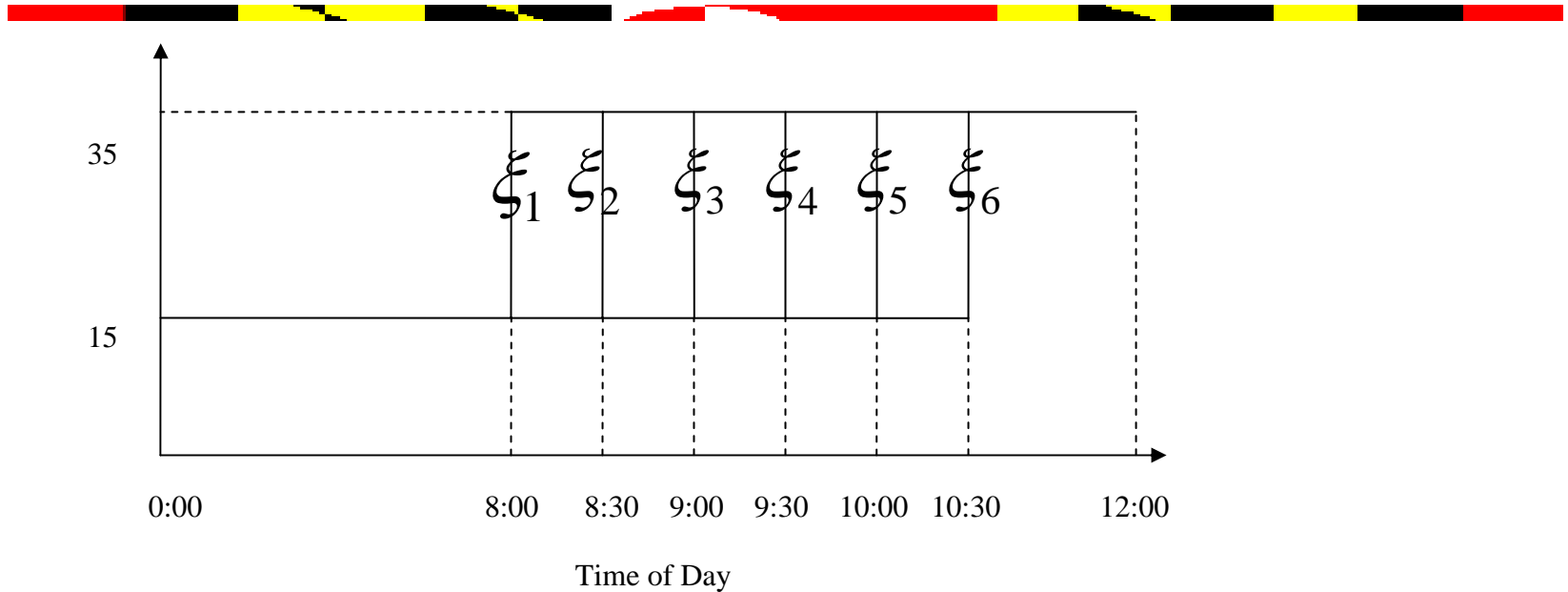
- Can be constructed based on probabilistic weather forecasts
- Can be obtained by performing statistical modeling of historical data on actual airport capacity (Liu et al., 2005)



Experimental Results

- 
- A decorative horizontal bar composed of alternating segments of red, black, and yellow.
- Applied to Dallas Fort Worth Intl. Airport (DFW)
 - 351 flights
 - Six capacity scenarios
 - Four cases of varied model parameters
 - Results compared with that from existing stochastic models (Ball et al 2003, Richetta-Odoni, 1994)

Scenarios, Scenario Tree, and Cost Ratio



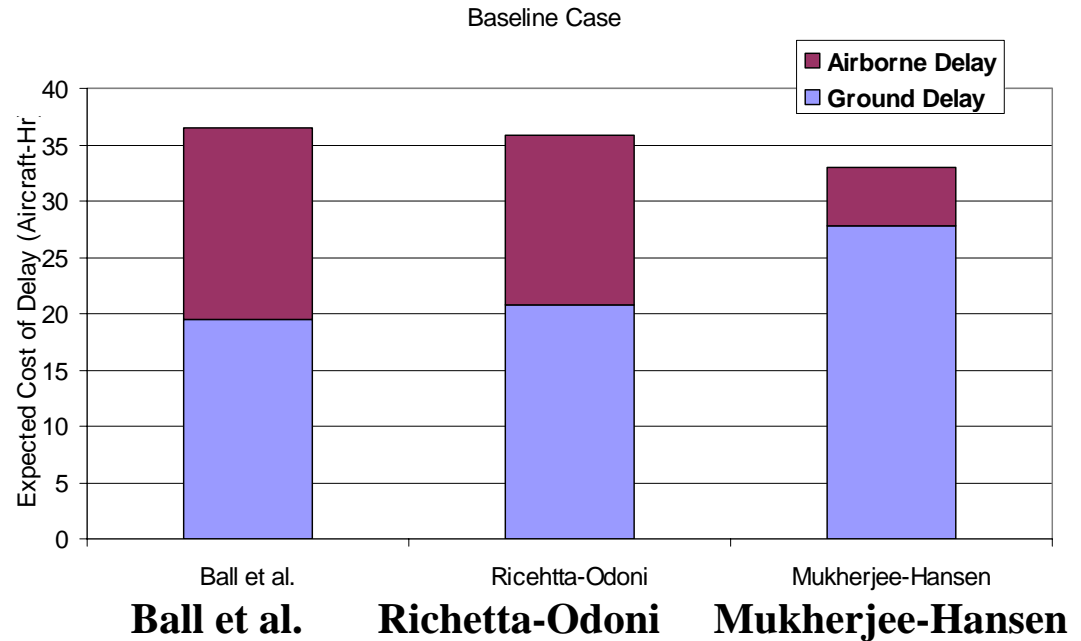
Probability Mass Function

$$P\{\xi_1\} = 0.4; P\{\xi_2\} = 0.2; P\{\xi_3\} = 0.1; P\{\xi_4\} = 0.1; P\{\xi_5\} = 0.1; P\{\xi_6\} = 0.1$$

$$\text{Cost Ratio } \lambda = 3$$

Results

- Due to low cost ratio, airborne delays are faced in all models
- Dynamic Model
 - Less total expected cost
 - Ground delays more severe
 - Less airborne delays
- Delay reduction compared to Static Model
 - 10% in Dynamic Model
 - 2% in Richetta-Odoni

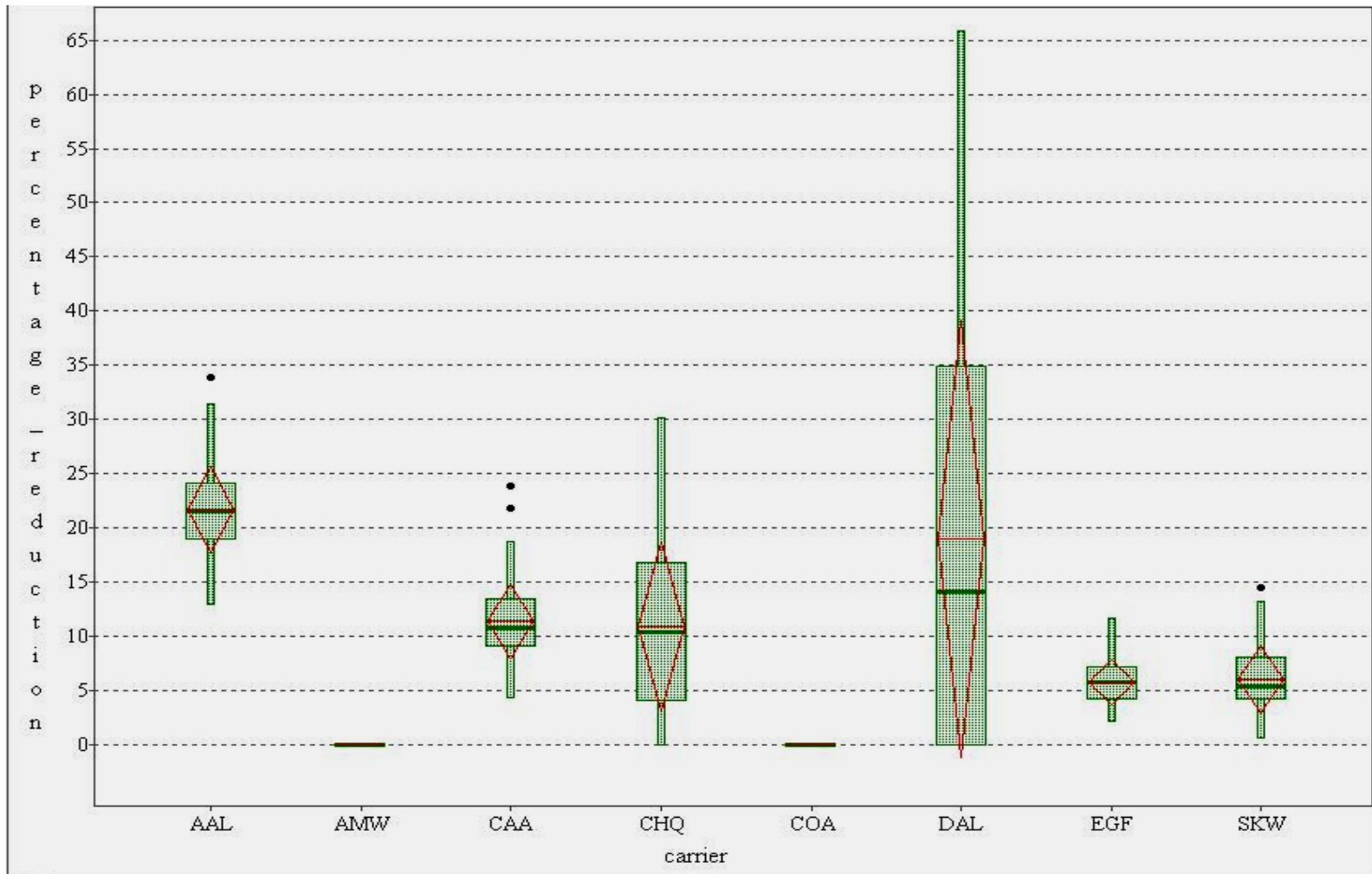


Application in CDM

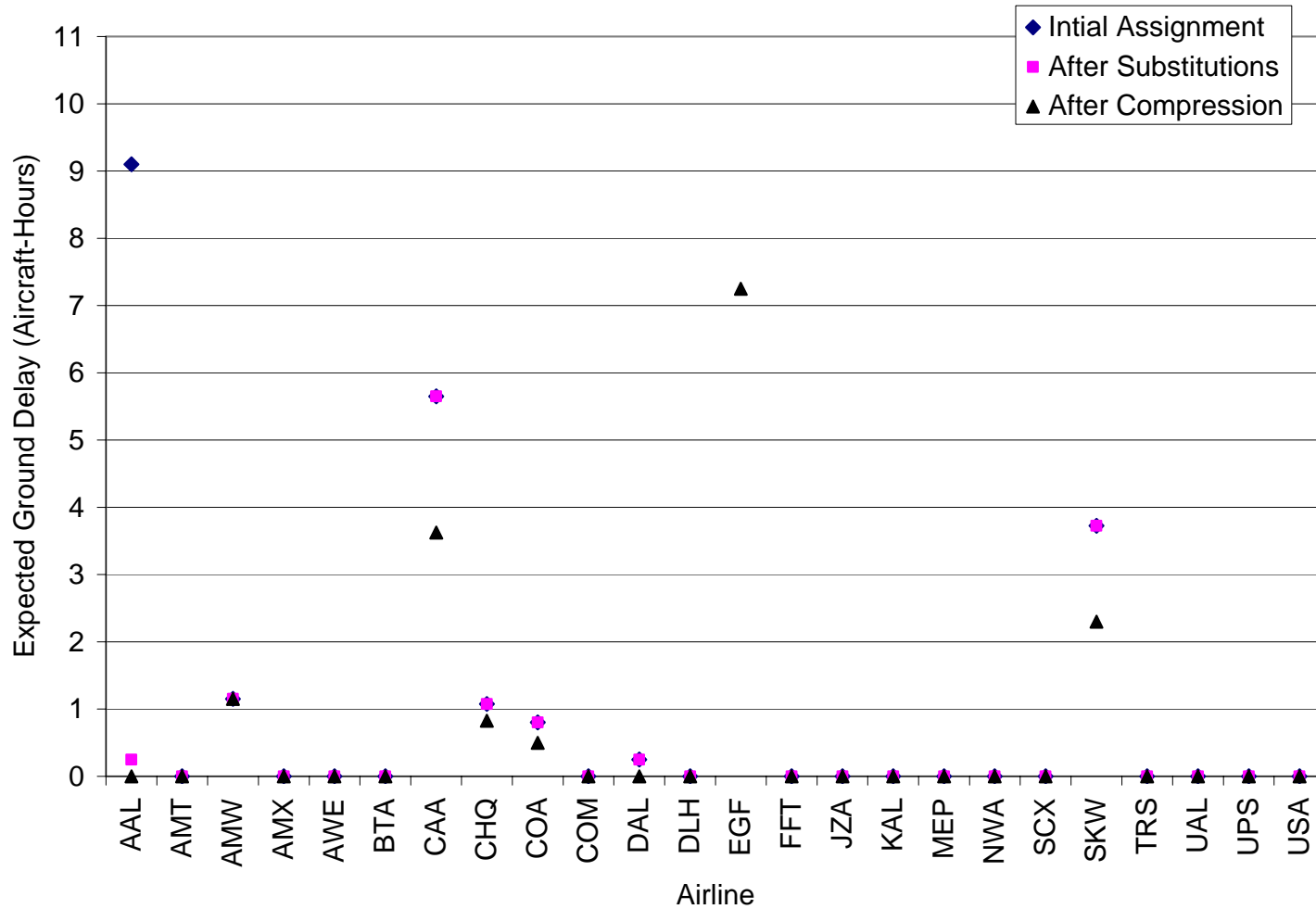
- Dynamic substitution model that can be used by individual airlines to perform scenario-contingent substitutions
 - Airlines cannot exceed the number of slots (during any hour) assigned to them in the initial stage (by the GH model)
 - While making substitutions, airlines must not violate the coupling constraints that account for limited information on airport capacity in future time periods
- Dynamic compression model that can be used by the FAA
 - An optimization model that works like the Compression Algorithm currently used by the FAA
 - Vacant slots (due to cancellations) are utilized by making substitutions, and priority is given to canceling airline
 - No flight is assigned a later slot than it currently owns → Everyone is better off

Intra-Airline Substitution Benefits

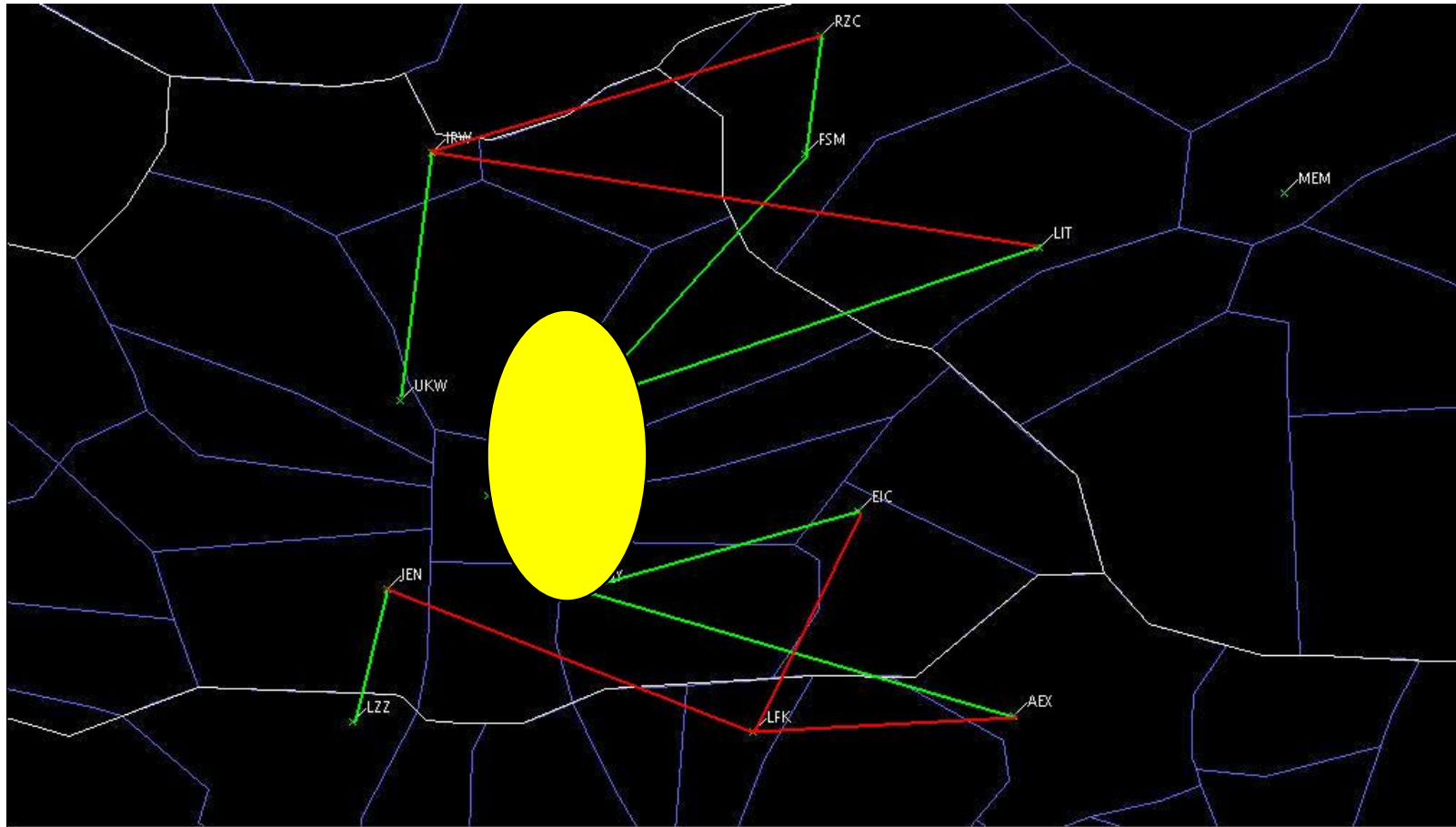
Percentage Reduction of Delay Cost



Benefits from Compression

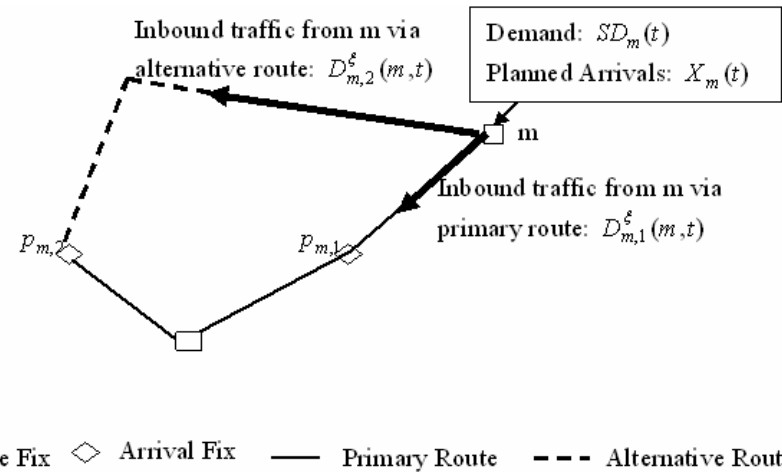


Enroute Airspace Capacity Problem

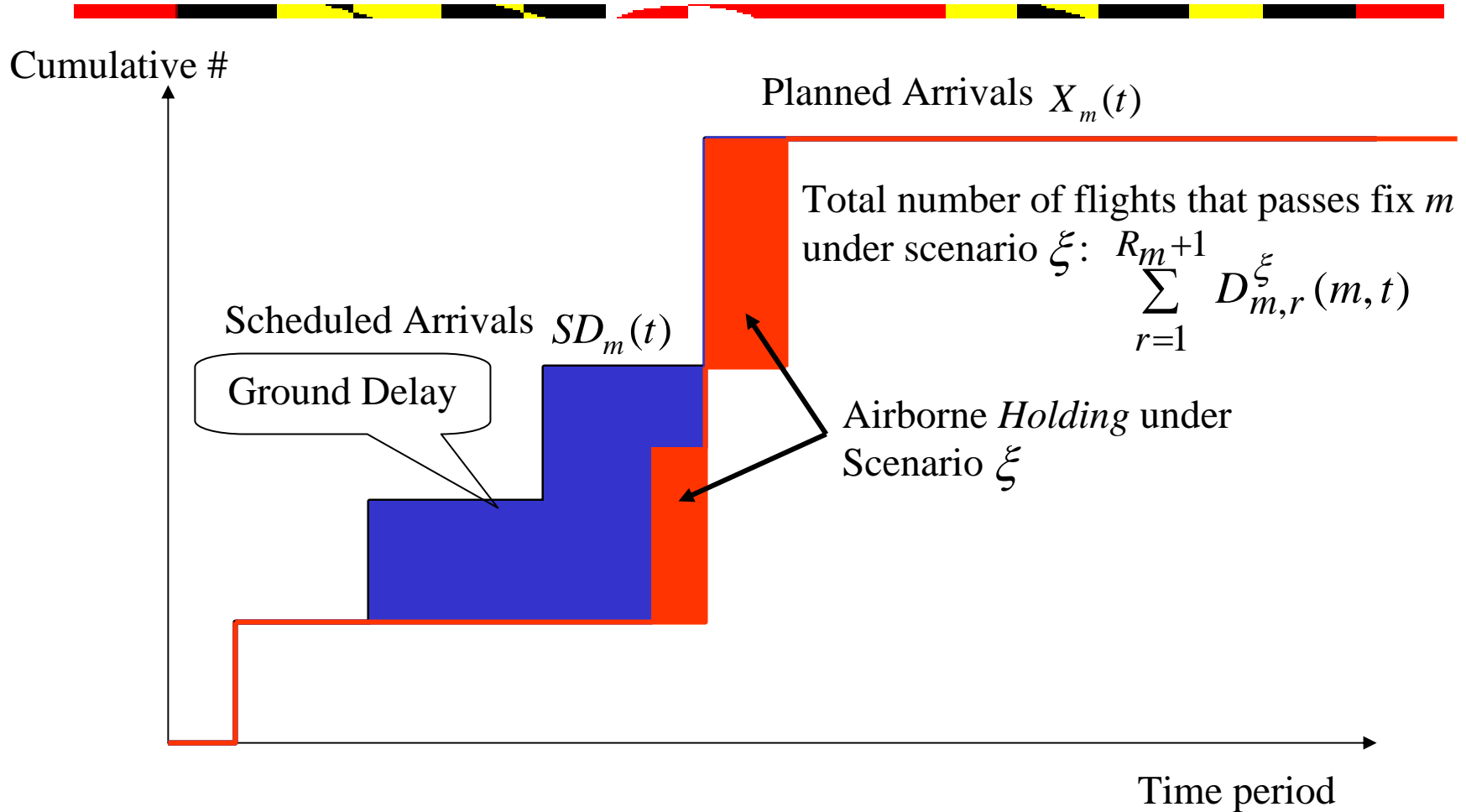


Model Formulation

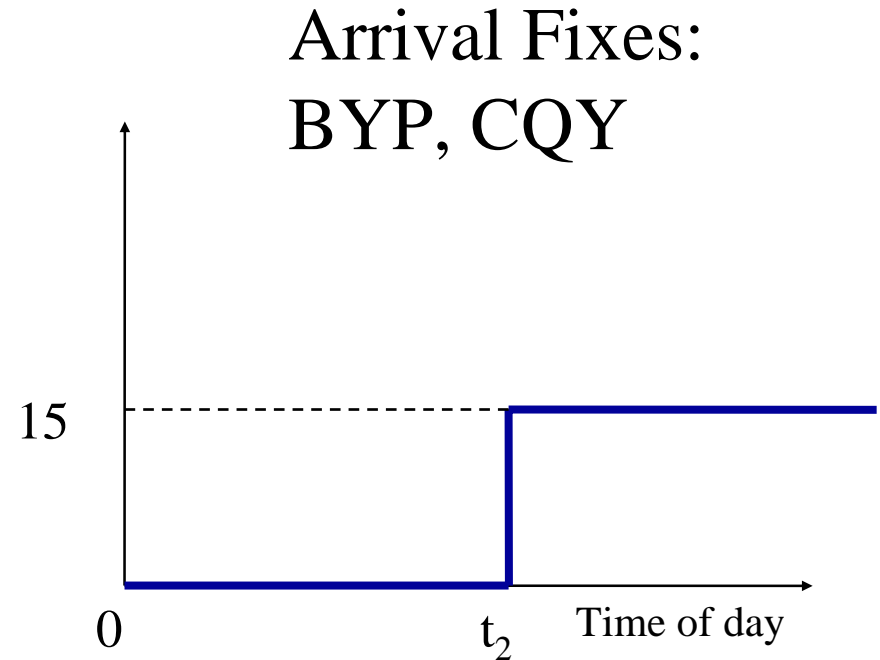
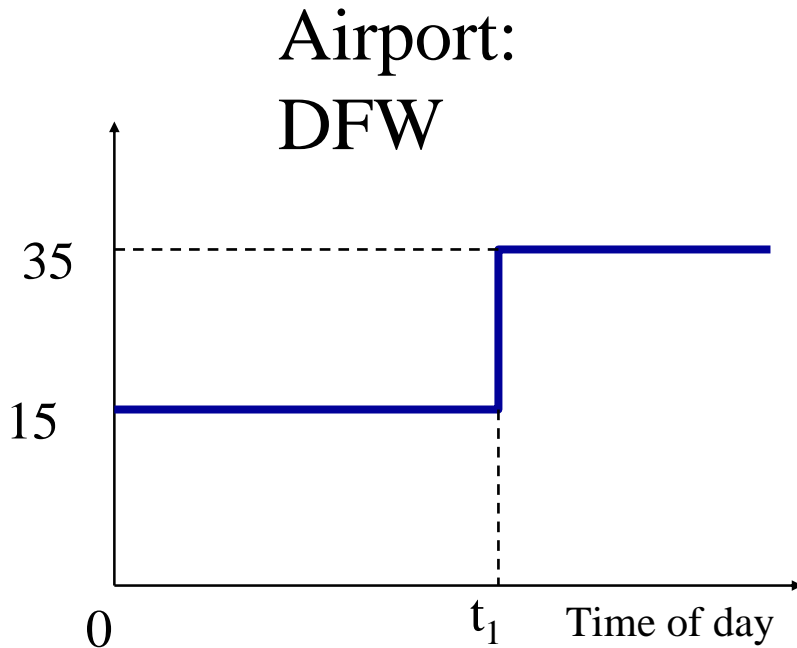
- Input:
 - Scheduled demand
 - Capacity scenarios and scenario tree
 - Set of enroute fixes where rerouting can occur and the available routes
- Main Decision Variables
 - Planned arrivals at enroute fixes where flights may be rerouted
 - Cumulative count of flights inbound via available routes



Delay Calculations



Capacity Scenarios



$$t_1 \text{ and } t_2 \in \{8:00, 8:30, 9:00, 9:30, 10:00\}$$

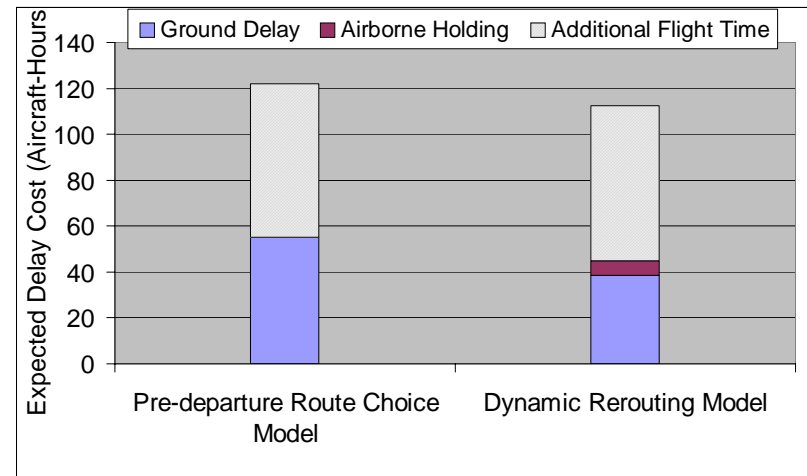
$5 * 5 (=25)$ scenarios

Experimental Case

- All scenarios equally likely
- Cost ratio 1:3

Results

- Rerouting results in additional flight time
- Overall delay cost in dynamic model 9% less than static model
- Ground delay in Dynamic RR model 30% less than Static model
- *Loss due to imperfect information:*
 - 13% less in dynamic model



Summary

-
- Mitigating uncertainty
 - Improve the quality of information
 - Hedge against possible outcomes
 - Need to incorporate decision support models that address uncertainty in ATM
 - Compatibility with Collaborative Decision Making is a necessary criteria
 - Models/algorithms needs to be simple and transparent in order to be implemented in practice
 - Dynamically adjusting plans in response to changing conditions and updated information is key to making the system more efficient

Work in Progress

- Develop realistic scenarios and scenario trees from past data
 - Cluster analysis of airport capacity profiles
 - Challenges in practical implementation: Identifying branching
- How to incorporate weather forecasts providing new capacities and probability of occurrence?
 - Compare the performance of dynamic model with static model applied repeatedly



Questions?



Backup Slides

Decision Variables

$$X_{f,t}^q = \begin{cases} 1 & \text{if flight } f \text{ is planned to arrive by the end of} \\ & \text{time period } t \text{ under scenario } q; \\ 0 & \text{otherwise} \end{cases}$$

$$\boxed{q \in \Theta, f \in \Phi, t \in \{Arr_f..T+1\}}$$

$$Y_{f,t}^q = \begin{cases} 1 & \text{if flight } f \text{ is released for departure by the end of} \\ & \text{time period } t \text{ under scenario } q; \\ 0 & \text{otherwise} \end{cases}$$

$$\boxed{q \in \Theta, f \in \Phi, t \in \{Dep_f..T+1\}}$$

$$W_{f,t}^q = \begin{cases} X_{f,t+Arr_f-Dep_f}^q & \text{if } t + Arr_f - Dep_f \leq T \\ 1 & \text{otherwise} \end{cases}$$

$W_{f,t}^q$ = number of aircraft subject to airborne queuing delay at time t for one or more time periods, under scenario q

Objective Function

$$\text{Min} \sum_{q \in \{1..Q\}} P_q \times \left\{ \left[\sum_{f \in \{1..F\}} \sum_{t=Arr_f}^{T+1} (t - Arr_f) \times (X_{f,t}^q - X_{f,t-1}^q) \right] + \lambda \times \sum_{t=1}^T W_t^q \right\}$$

Constraints

Decision variables are non decreasing

$X_{f,t}^q - X_{f,t-1}^q \geq 0; \forall f \in \Phi, q \in \Theta, t \in \{Arr_f..T+1\}$
Number of flights that land during any time period, under different scenarios, must be less than or equal to the scenario specific airport arrival capacity during that time

$$W_{t-1}^q - W_t^q + \sum_{f \in \Phi} \left(X_{f,t}^q - X_{f,t-1}^q \right) \leq M_t^q; \quad t \in \{1..T+1\}, q \in \Theta$$

Feasibility Conditions

$$W_0^q = W_{T+1}^q = 0$$

$$X_{f,T+1}^q = 1 \quad \forall f \in \Phi, q \in \Theta$$

Coupling constraints impose the condition that as long as two or more scenarios are possible, the decisions on flight release time must be same under all those scenarios

$$Y_{f,t}^{S_1^i} = \dots = Y_{f,t}^{S_k^i} = \dots = Y_{f,t}^{S_{N_i}^i}; \quad f \in \Phi, t \in \{1..T\}; S_k^i \in \Omega_i : N_i \geq 2 \text{ and } o_i \leq t \leq \mu_i$$

Dynamic Substitution Model

Airline-specific objective function:

$$z = \sum_{f \in F_a} \sum_{\xi \in \Theta} P\{\xi\} \times \sum_{t=Arr_f}^{T+1} c(f, t - Arr_f) \times (X_{f,t}^{\xi} - X_{f,t-1}^{\xi})$$

Key Constraints:

The number of planned arrivals of an airline cannot exceed the number of slots assigned to the airline from the initial assignment (dynamic GH model)

$$\sum_{f \in F_a} (X_{f,t}^{\xi} - X_{f,t-1}^{\xi}) \leq v_{a,t}^{\xi}; \quad \forall t \in \Gamma, \xi \in \Theta$$

Coupling (or non-anticipativity) constraints:

$$Y_{f,t}^{S_1^i} = \dots = Y_{f,t}^{S_k^i} = \dots = Y_{f,t}^{S_{N_i}^i}; \quad \forall f \in F_a, t \in \Gamma, S_k^i \in \Omega_i : N_i \geq 2 \text{ and } o_i \leq t \leq \mu_i$$

Dynamic Compression Model

Objective Function

$$\min z = \sum_{\xi \in \Theta} P\{\xi\} \times \left(\sum_{a \in A} (1 + can_a) \times \sum_{f \in F_a} \sum_{t=Arr_f}^{T+1} (t - Arr_f) (X_{f,t}^{\xi} - X_{f,t-1}^{\xi}) \right)$$

Key Constraints

No flight can be assigned a later arrival slot under any scenario, than what it owns after airline substitutions

$$\sum_{t=Arr_f}^{T+1} t \times (X_{f,t}^{\xi} - X_{f,t-1}^{\xi}) \leq \rho_f^{\xi}; \quad \forall f \in G, \xi \in \Theta$$

Constraints Continued

Scenario-specific airport capacity constraints

$$\sum_{f \in G} (X_{f,t}^{\xi} - X_{f,t-1}^{\xi}) + W_{t-1}^{\xi} - W_t^{\xi} \leq M_t^{\xi}; \quad \forall t \in \Gamma, \xi \in \Theta$$

Amount of scenario-specific airborne holding during any time period must not exceed the corresponding values from initial assignment

$$W_t^{\xi} \leq \hat{W}_t^{\xi}; \quad \forall t \in \Gamma, \xi \in \Theta$$

Coupling constraints

$$Y_{f,t}^{S_1^i} = \dots = Y_{f,t}^{S_k^i} = \dots = Y_{f,t}^{S_{N_i}^i}; \quad \forall f \in G, t \in \Gamma, S_k^i \in \Omega_i : N_i \geq 2 \text{ and } o_i \leq t \leq \mu_i$$