

# Impact of Different Strategies on Route Utilization and Airlines Cost:

## *Multi-agent Simulation and Evolutionary Computation*

Progress Report on:  
Parametric Games

Guillermo Calderón-Meza (Ph.D. Student)  
Lance Sherry (Ph.D.)

May 2009

Interim Report: NASA NNA07CN32A  
Analysis of NGATS Sensitivity to Gaming



CENTER FOR AIR TRANSPORTATION SYSTEMS RESEARCH



# Acknowledgments

## **NASA (Provided funding NASA NNA07CN32A)**

María Consiglio, Brian Baxley, Kurt Neitzke

## **Sensis**

George Hunter, Huina Gao

## **Flight Profits**

Randal Kelly

## **CATSR/GMU**

Maricel Medina-Mora, John Ferguson, Keith Sullivan,  
George Donohue, John Shortle, Rajesh Ganesan, Kenneth De  
Jong

## **Metron Aviation**

Norm Fujisaki, Terry Thompson

## **FAA**

2 Joe Post, Tony Diana

# Outline

1. Research objectives & observations
2. Context & definitions
3. Previous work
4. Method, behaviors & assumptions
5. Results experiments: #0 (equal strategies), #1 (single objective) & #2 (multi objective)
6. Conclusions
7. Future work

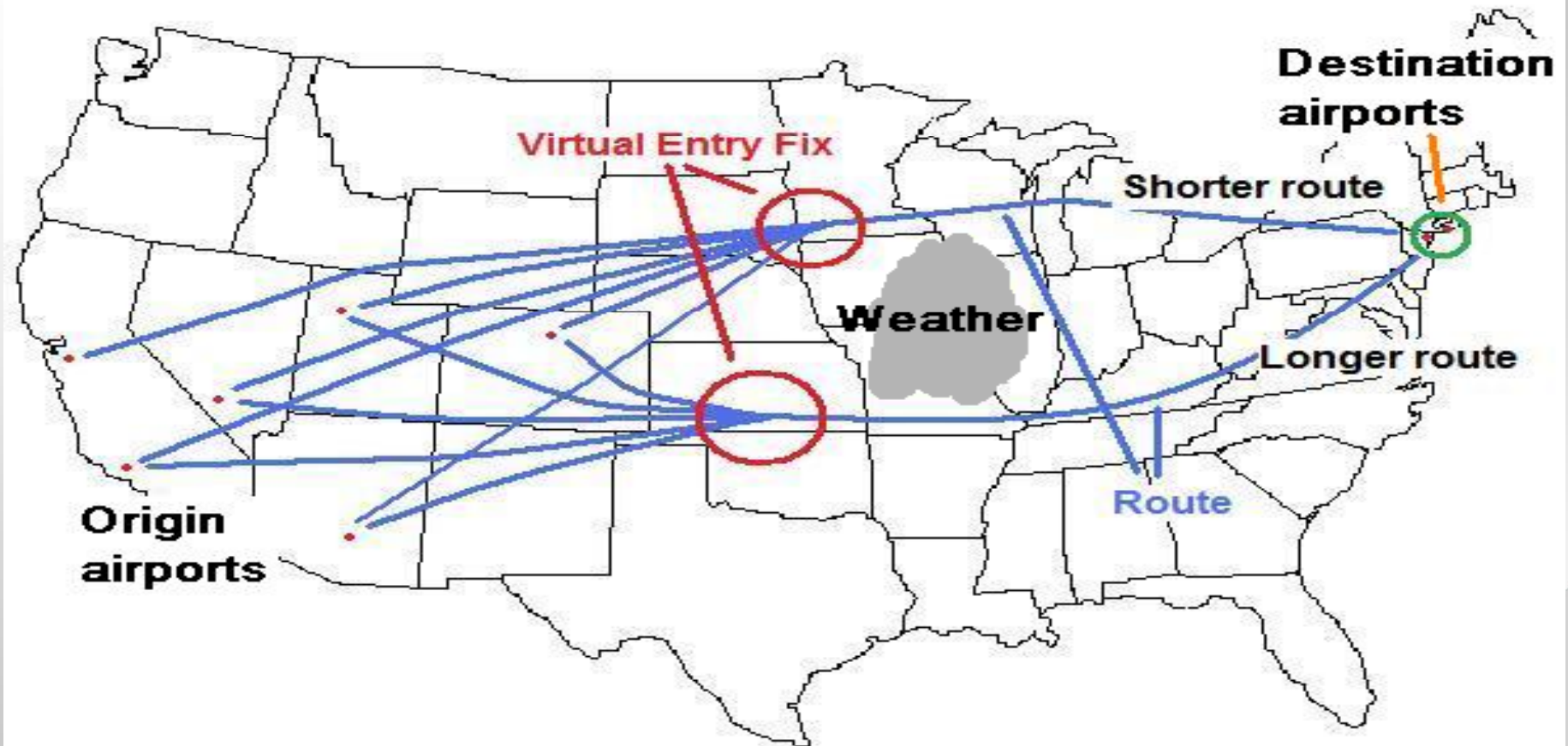
# Research Objectives



- TFM/ATC objectives for *utilization* conflict with airline objective of *profit*
- Evaluate the impact of agent *gaming* in selection of alternate trans-continental routes
  - Cost vs utilization
- *Simulation vs optimization* models
  - Gain knowledge about behavior

- *NextGen* increases capacity & throughput by investing in infrastructure
  - *TFM – SEVEN* – (Klopfenstein, 2007)
  - Re-routing (Wanke & Greenbaum, 2007; Ramamoorthy, Boisvert, Hunter, 2006)
  - System Wide Information Management, *SWIM* (Dieudonne, Crane, Jones, Smith, Remillard, Snead, 2007)
  - *Ribbons / Tubes* - (Kopardekar, Bilimoria, Sridhar, 2007; Yousefi, Donohue, Sherry, 2004)
- Re-routing could result in under-utilization
- Impact on investment if airlines “game” the system?
  - Under-utilized resources?

# Context



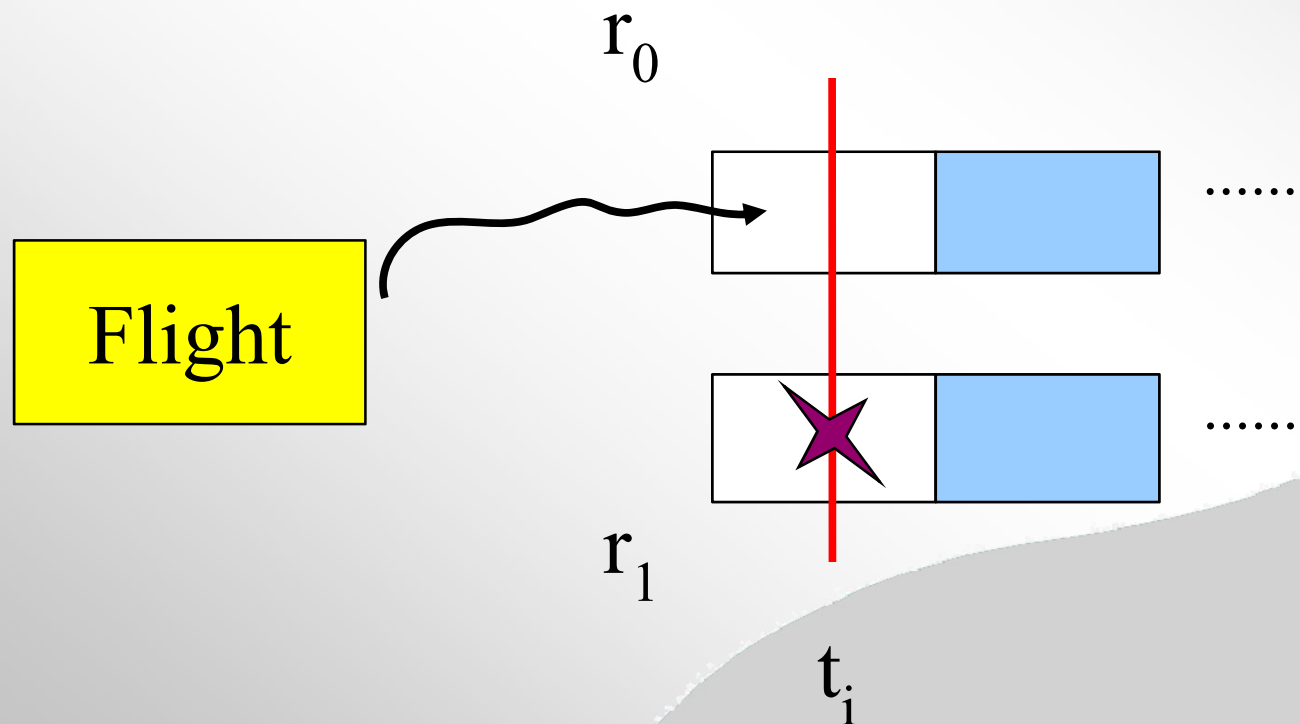
Will airlines use the resources if provided, or will the resources go unused (due to airline preferences) ?

# Definitions

- *Airborne cost (flying cost)*
  - Flying 25 nm @ constant speed, same altitude
  - Particular type of aircraft
- *Ground cost (waiting / delay cost)*
  - Waiting (being delayed) 5 min on ground
- *Airline cost (all flights)*
  - Airborne cost
  - Ground cost
- *Aggregated airline cost*
  - Summation across airlines (last step)

# Definitions

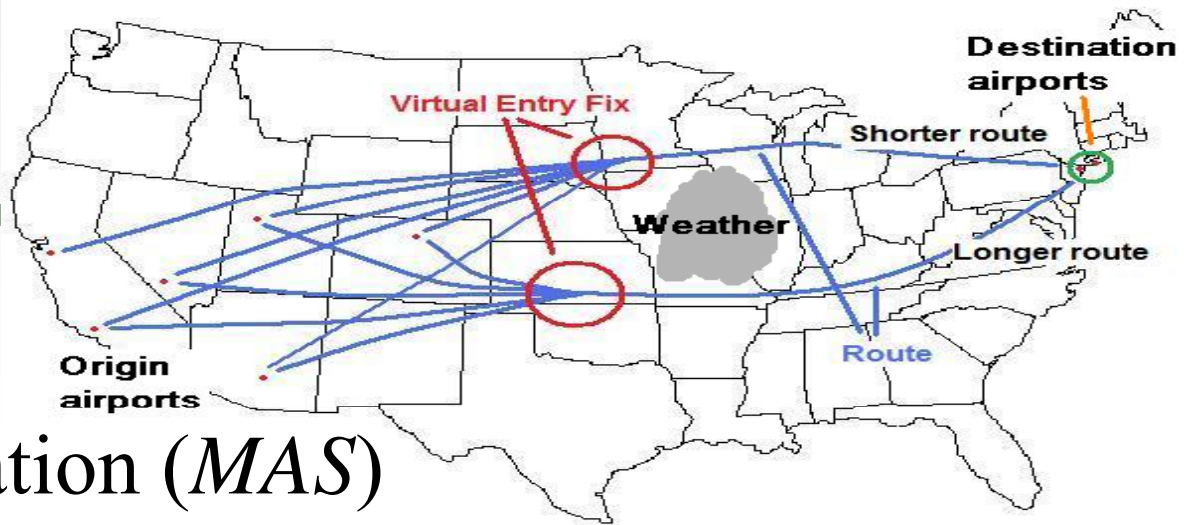
- *Route under-utilization*
  - # of unassigned route slots
  - Cancellations, delays, or choice



# Previous work

- Gaming in airlines decisions
  - Tomlin, Waslander (CDC 2006)
  - Wojcik (ATIO 2004)
  - Greenbaum, Wojcik, Campbell, Cooper (ATM 2001)
  
- Evolving agent behaviors
  - De Jong (Evolutionary Computation. A Unified Approach, MIT Press, 2006)

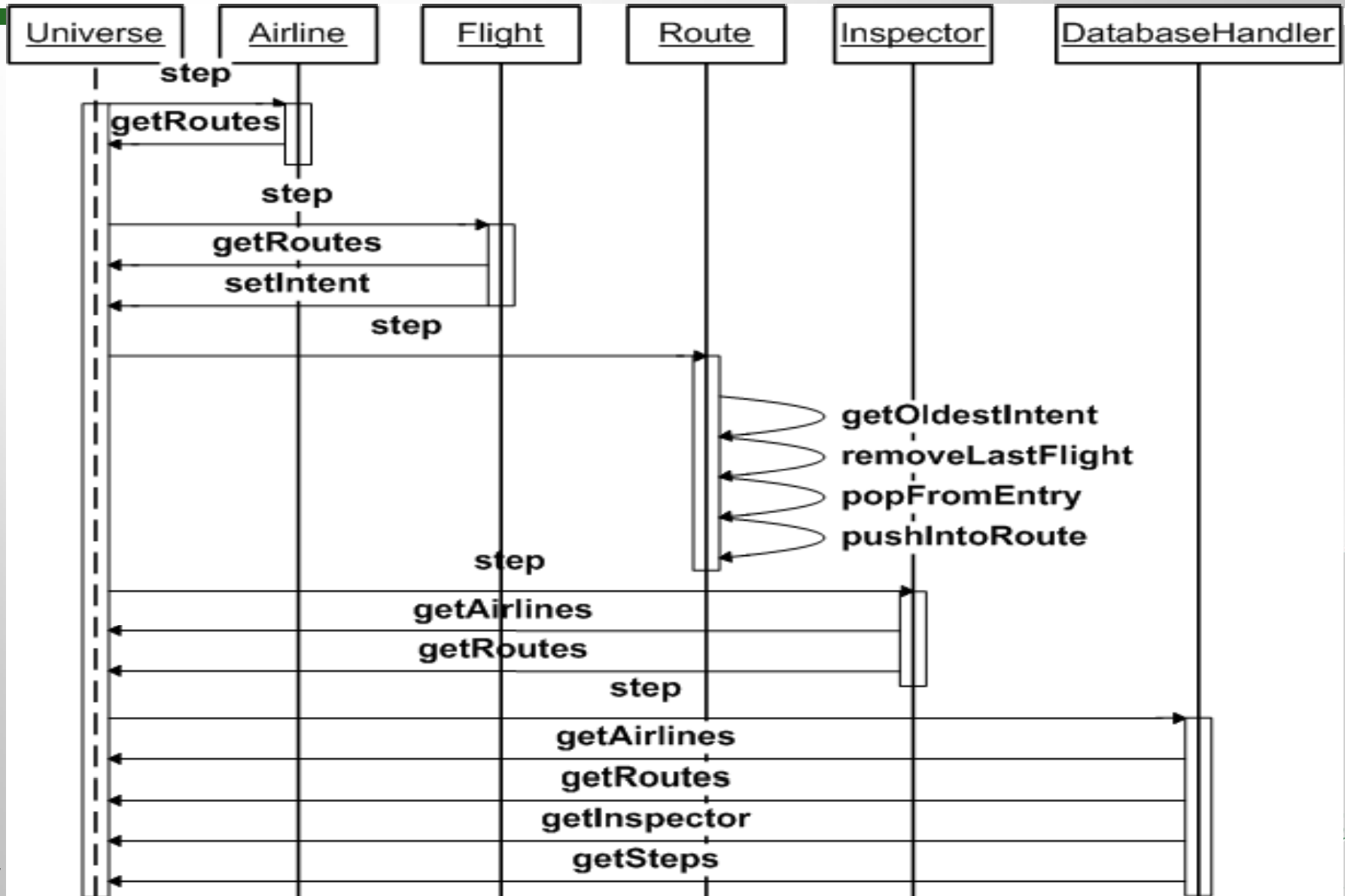
# Method



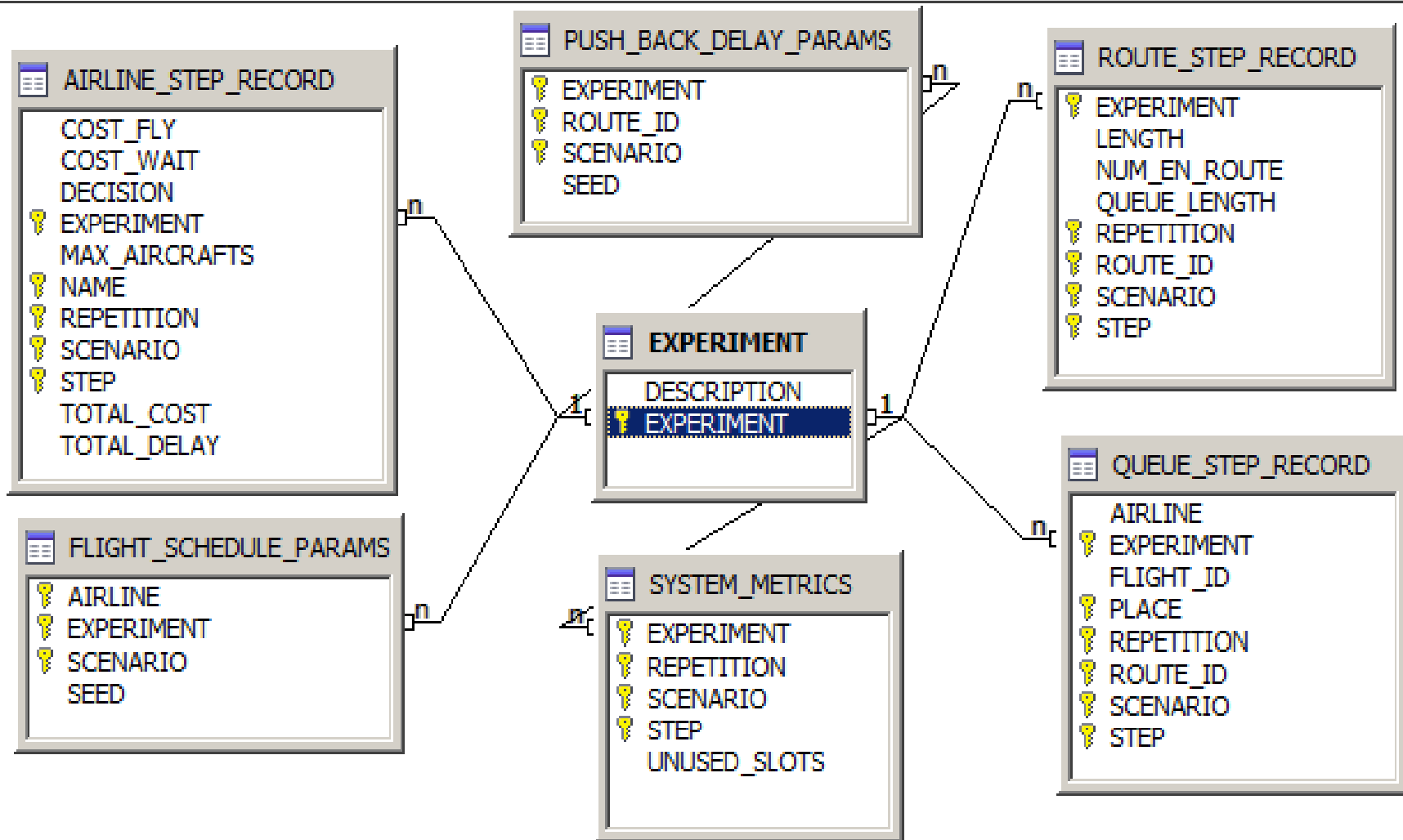
- Multi-agent simulation (*MAS*)
  - 95 agents: 3 airlines, 90 flights, 2 routes
- *Evolutionary computation (EC)* platform
- Stochastic behavior
  - *Ties resolution, push-back delays, and order of agent processing* are random
- *Monte Carlo* simulation
  - Scenarios repeated 30 times
  - Computing *averages & variances*



# Collaboration diagram



# The database structure



# Flight agent behavior

- Parametric behavior decide on *cost*
  - Weight of *airborne cost*  $\rightarrow \varphi \in [0,1]$
- Aircraft chooses route according to:

$$r = \operatorname{argmin} [ (\varphi * f_f * d_r) + ((1-\varphi) * w_f * t_r) ]$$

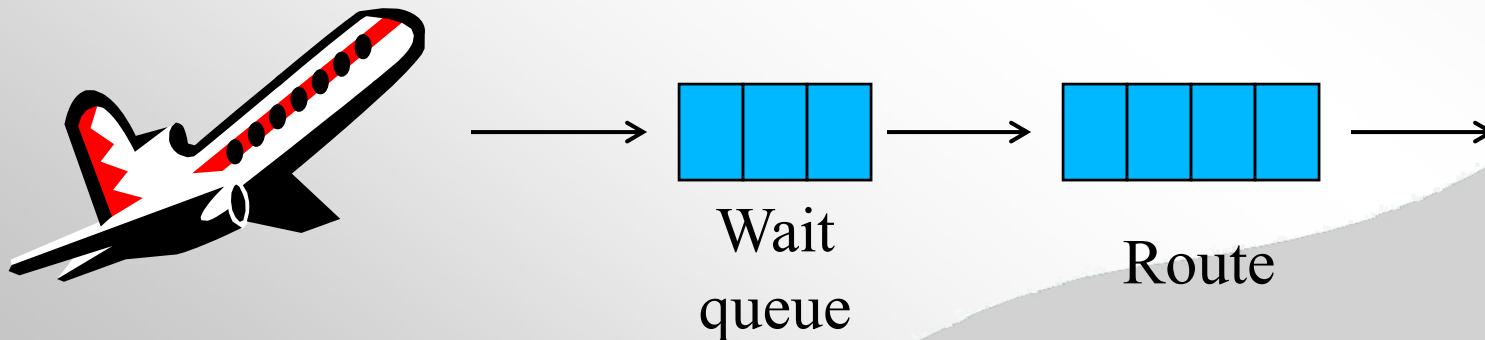
- Conversion factors  $f_f$  &  $w_f$  in \$/slot
  - “ $d$ ” in distance slots & “ $t$ ” in time slots
- In case of ties  $\rightarrow$  *choose route randomly.*

# Airline policy ( $\approx$ behavior)

- Determines *acceptable range* of  $\varphi$  for the flights
- Described by  $\langle \beta, \alpha \rangle$  pair
  - Condition:  $0 \leq \beta \leq \alpha \leq 1$
  - $\beta$  lowest acceptable value for  $\varphi$
  - $\alpha$  highest acceptable value for  $\varphi$
- Could change in time  $\rightarrow$  *adaptation*
- Flight's  $\varphi$  *randomly chosen* before push back occurs

# Route agent behavior

- Pushes airline route *selection* into entry queue
- Removes last flight from route (if it reached end of route)
- Takes oldest flight from entry queue and pushes it into route

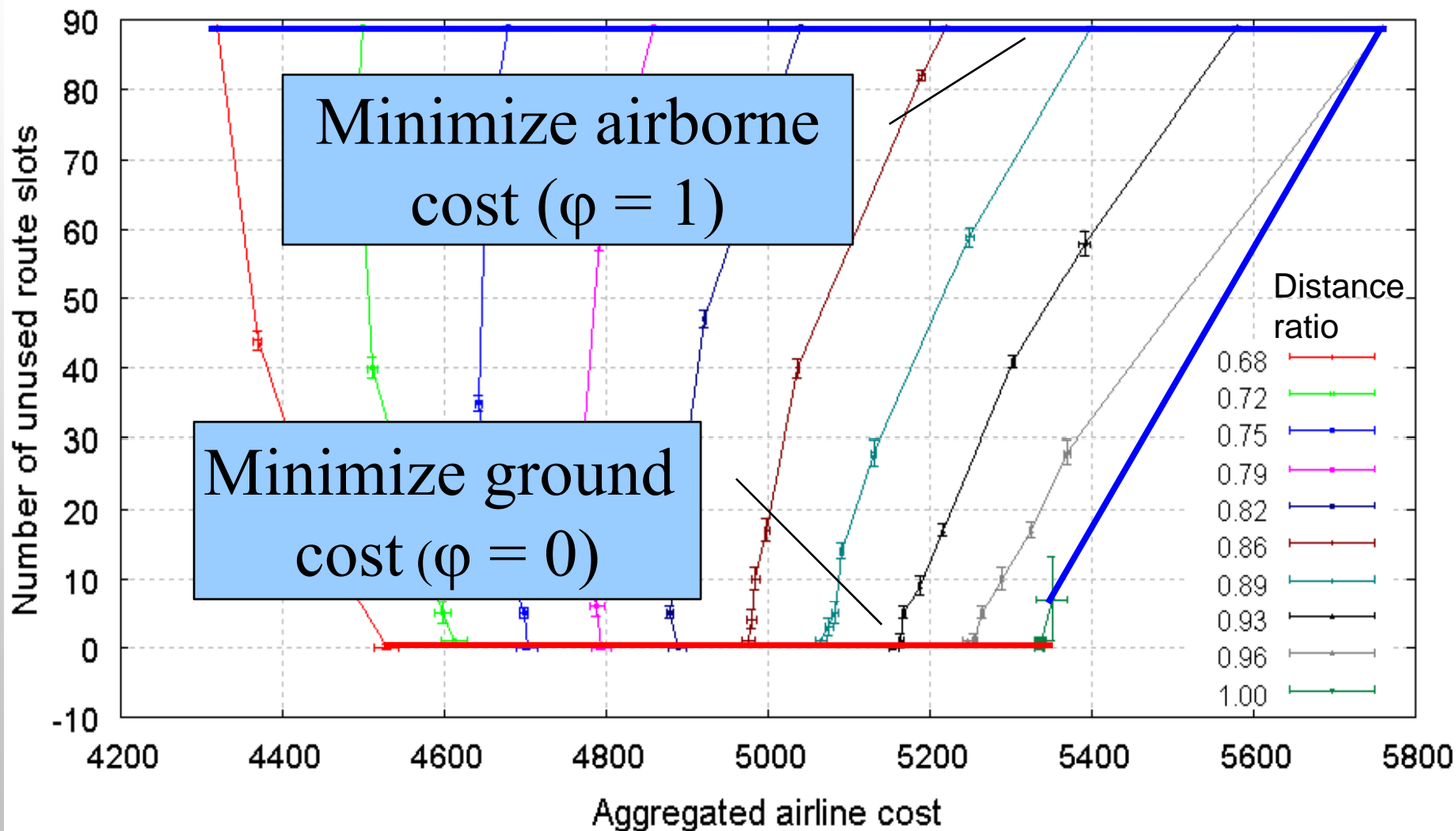


# Assumptions for simulation

- All flights with same (normalized)  $f_f = 1.0$
- All flights @ *constant speed*  $\rightarrow$  300 ks
- *Time slot* = 5 min, *distance slot* = 25 nm
- All airlines with 30 scheduled flights
  - 1 flight per time slot (before push back delay)
  - No gaps between flights
- Flights & airlines are *partially informed*
  - “d” and “t” are known to flights
  - Do not know other's decisions (until next tick)
  - No *learning* or *prediction*

# Detailed results (Experiment #0)

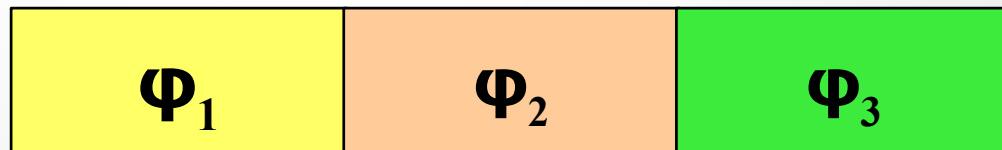
Aggregated cost vrs unused route slots with equal strategies



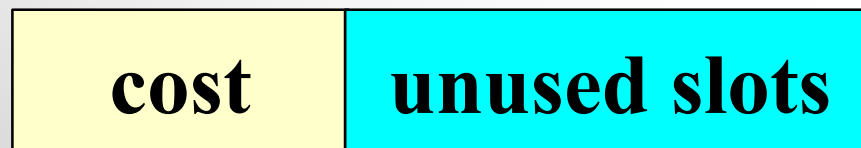
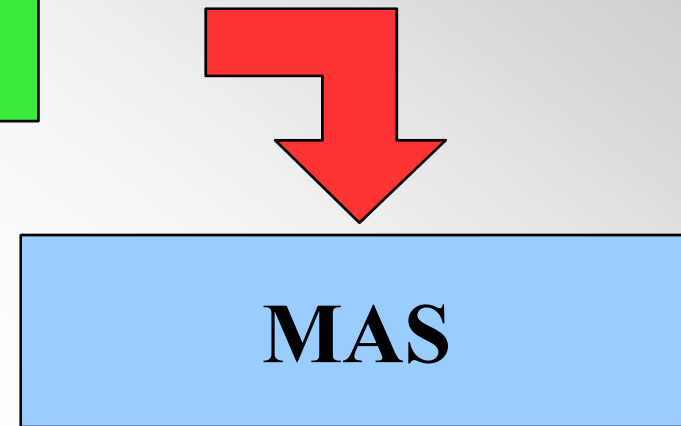
# What if policies are not equal?

- Use *evolutionary computation* to explore the space
- *Parameter* optimization (Experiment #1)
  - Requires new parameter
- *Multi-objective* optimization (Experiment #2)
  - Approximate Pareto surface

# Description (Experiment #1)



$$0 \leq \varphi \leq 1$$



$$0 \leq \omega \leq 1$$

$$f = -(\omega * \text{cost} + (1-\omega) * \text{unused\_slots})$$

$\omega$  is *social value*  $\rightarrow$  importance of cost

# Conditions (Experiment #1)



- Evolutionary Algorithm
  - *Evolutionary Strategy*
  - Population size: 15 (offspring 15)
  - Overlapping populations
  - Parent selection: fitness proportional
  - Survival selection: fitness proportional
  - Mutation & recombination
  - 300 iterations (birth counts)

# Conditions (Experiment #1)



- MASON simulation
  - 3 “*Policy Airline*” agents
  - 30 scheduled “*Flight Agents*” per airline
  - Push back delays random (exponential),  $\lambda = 5$
  - 2 “*Route*” agents. One 57 slots, another 39 slots
  - Each scenario repeated 30 times

# Detailed results (Experiment #1)

Importance of cost ( $\omega$ )	$\varphi_1$	$\varphi_2$	$\varphi_3$	Aggregated cost	Unused slots
0.0	0.756	0.009	0.025	4518.0	1
0.1	0.756	0.009	0.025	4518.0	1
0.2	0.888	0.010	0.027	4517.4	1
0.3	0.565	0.020	0.031	4516.0	1
0.4	0.565	0.020	0.031	4516.8	1
0.5	0.010	0.115	0.011	4516.3	1
0.6	0.002	0.016	0.436	4515.7	1
0.7	0.014	0.884	0.010	4516.8	1
0.8	0.508	0.028	0.031	4512.9	1
0.9	0.244	0.520	0.021	4383.1	19
1.0	0.716	0.651	0.034	4320.4	33

23 NOTE: distance ratio 0.68 and wait/fly cost 0.3

# Detailed results (Experiment #1)

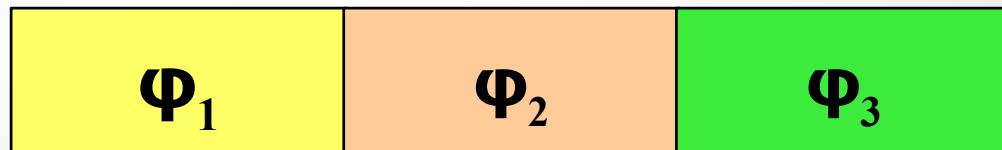
Importance of cost ( $\omega$ )	$\varphi_1$	$\varphi_2$	$\varphi_3$	Airline <sub>1</sub> cost	Airline <sub>2</sub> cost	Airline <sub>3</sub> cost
0.0	0.756	0.009	0.025	1248.6	1757.7	1511.7
0.1	0.756	0.009	0.025	1249.5	1757.7	1510.8
0.2	0.888	0.010	0.027	1248.9	1758.3	1510.8
0.3	0.565	0.020	0.031	1252.8	1632.3	1632.9
0.4	0.565	0.020	0.031	1254.0	1632.0	1632.0
0.5	0.010	0.115	0.011	1632.6	1249.2	1636.2
0.6	0.002	0.016	0.436	1634.1	1634.1	1249.8
0.7	0.014	0.884	0.010	1636.5	1248.0	1633.5
0.8	0.508	0.028	0.031	1252.2	1630.2	1635.6
0.9	0.244	0.520	0.021	1378.2	1303.5	1701.3
1.0	0.716	0.651	0.034	1322.7	1322.1	1675.2

# Detailed results (Experiment #1)

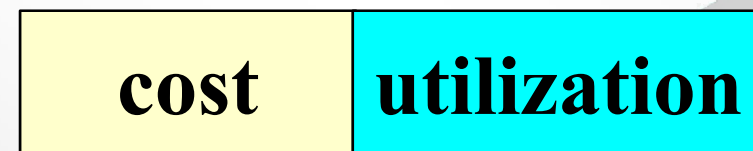
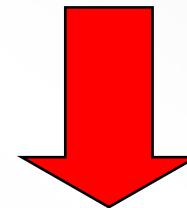
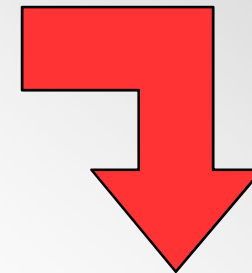


- Need to normalize values outputs
  - No upper limit for aggregated cost (using 5000)
  - Lower limit hard to compute (using 3510)
- If cost is less important → 1 greedy, 2 polite
- If cost is most important → 2 greedy, 1 polite
- *Several individuals* with same best fitness
- Highest  $\phi$  results in lowest airline cost
  - Differences are statistically significant

# Experimental design (Experiment #2)



$$0 \leq \phi \leq 1$$

# Experimental design (Experiment #2)



- Evolutionary Algorithm
  - Type: Pareto
  - Population size: 50+ (offspring 50+)
  - Birth count: 500+
  
- MAS remains the same

# Detailed results (Experiment #2)

<b>Fitness</b>	$\varphi_1$	$\varphi_2$	$\varphi_3$	<b>Aggregated cost</b>	<b>Unused slots</b>
39.0	0.031	0.943	0.403	4320.0	31
39.0	0.031	0.943	0.403	4320.0	31
39.0	0.031	0.446	0.878	4320.0	31
39.0	0.861	0.811	0.008	4320.0	31
40.0	0.031	0.943	0.403	4320.0	31

NOTE: distance ratio 0.68 and wait/fly cost 0.3

# Detailed results (Experiment #2)

<b>Fitness</b>	$\psi_1$	$\psi_2$	$\psi_3$	<b>Airline<sub>1</sub> cost</b>	<b>Airline<sub>2</sub> cost</b>	<b>Airline<sub>3</sub> cost</b>
39.0	0.031	0.943	0.403	1692.3	1314.9	1312.8
39.0	0.031	0.943	0.403	1692.0	1313.1	1314.9
39.0	0.031	0.446	0.878	1692.6	1313.1	1314.3
39.0	0.861	0.811	0.008	1315.5	1312.5	1692.0
40.0	0.031	0.943	0.403	1692.6	1313.1	1314.3

NOTE: distance ratio 0.68 and wait/fly cost 0.3

# Detailed results (Experiment #2)



- Fitness is relative to population
  - Need to implement *Hall of fame*
- Two minimize airborne cost & minimize ground cost
- Lowest policy value gets the highest costs
- Fitness has not reached the highest value

# Conclusions

- Experiment #0 (equal strategies)
  - Trade-off controlled by policy
- Experiment #1 (single objective)
  - Procedure favors utilization...
- Experiment #2 (multi objective)
  - Finds a balance between objectives...

# Future work

- *Evolve* behaviors
  - Different MAS implementation required
- Set airlines to *compete* or *cooperate*
  - Observe individual & global results
- *Learn* from past results
  - Can be combined with behavior evolution
- Effects of *imperfect information*
  - Delayed
  - Uncertain

# Future work

- Alternate airline / flight behaviors
  - *Minimize delay*
  - *React* to other agents actions
  - *Predict* and adjust accordingly
- Relax assumptions
  - Aircraft speed
  - Different costs
  - Different schedules

# Questions?



More info?

Visit the Center for Air Transportation Systems  
and Research (CATSR) website

<http://catsr.ite.gmu.edu/>