



# **NAS Performance Models**

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FAA Strategy Simulator: analyze impact on NAS of

- major policy initiatives/changes
- significant infrastructure changes
- macro-economic shifts/demand shifts
- changes in industry structure

*Need to model airline and other user behavior as well as basic NAS behavior*

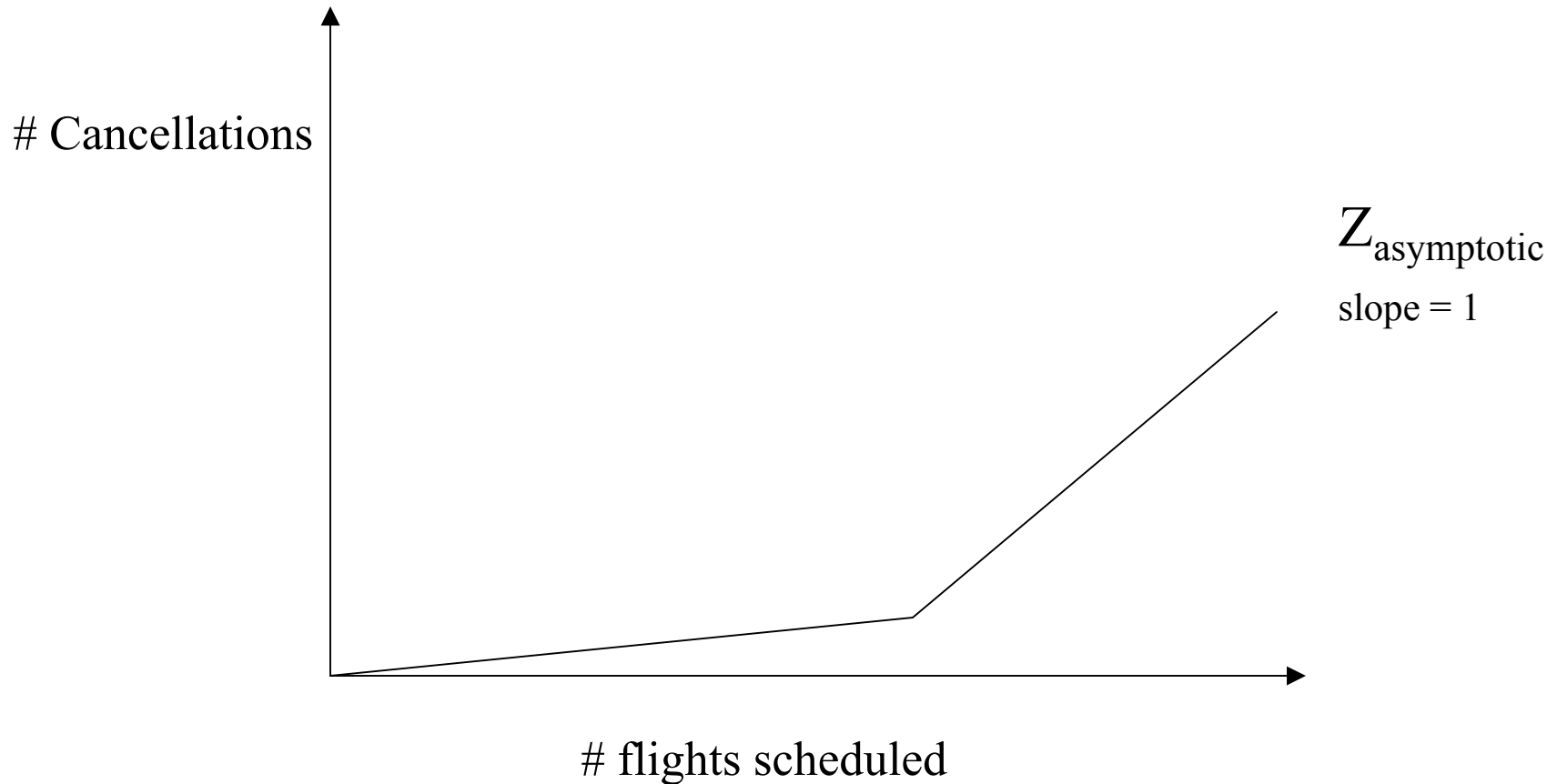
**Challenge of performance modeling: predict NAS performance based on small number of key parameters**



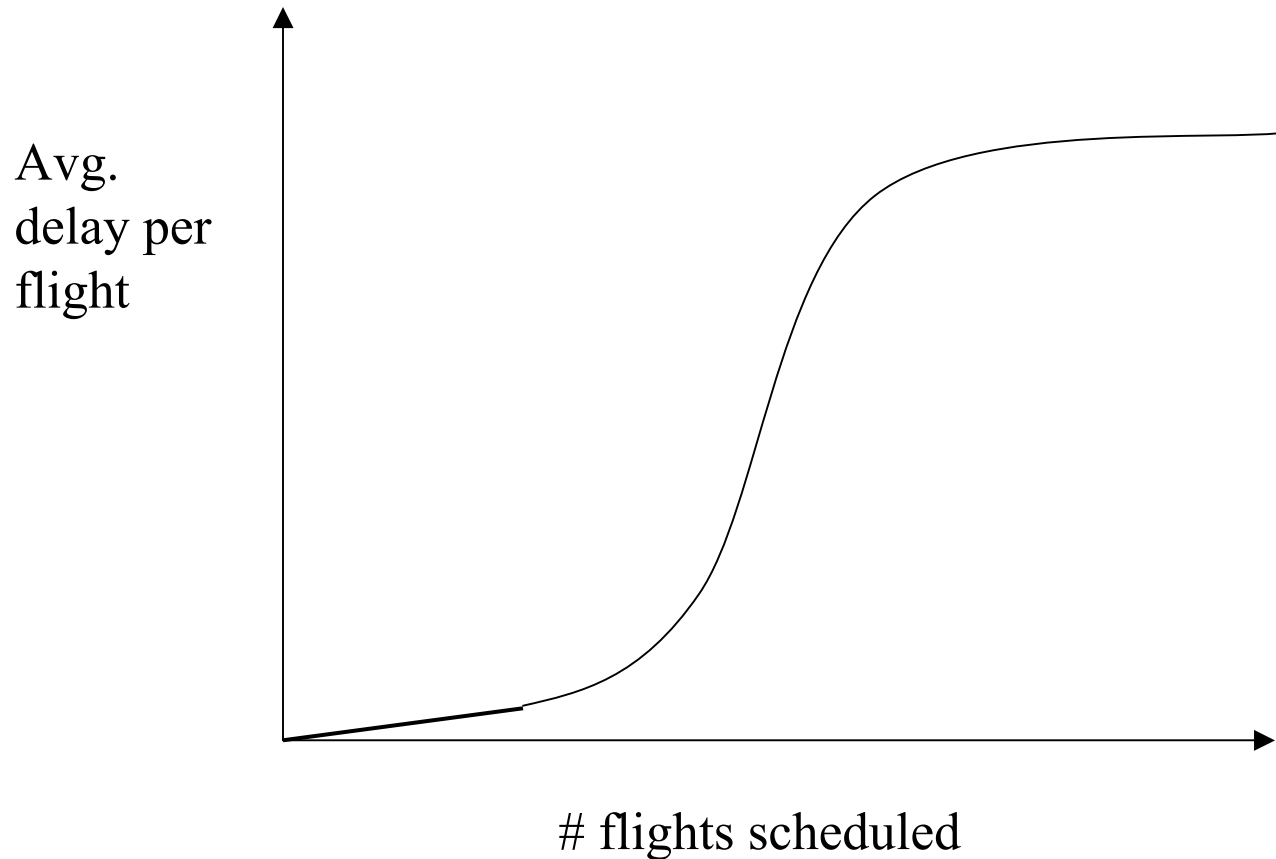
# Performance Metrics

- ⌘ Average Delay per Flight (more refined flight delay distribution info);  
% of flights on time.
- ⌘ % of Flights Cancelled
- ⌘ NAS-wide OAG Service level metric
- ⌘ NAS-wide Actual Service level metric

# Intuition: # Cancellations vs. # Flights Scheduled (capacity held constant)



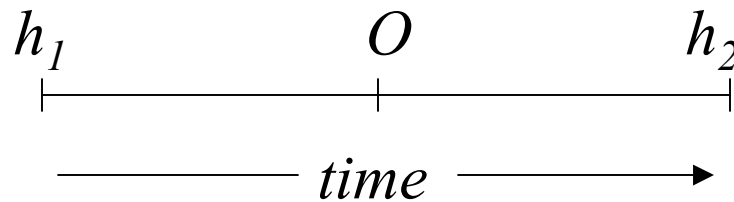
## Intuition: Delay vs. # of Flights Scheduled (capacity held constant)



## $\rho$ - Measure of congestion around a scheduled operation

Assume an airport operation is either a flight departure or a flight arrival. Then for each operation,  $O$ , we compute  $\rho_o$  as follows:

Consider the time interval,  $I$ , starting  $h_1$  hours before  $O$  is scheduled and  $h_2$  hours after  $O$  is scheduled

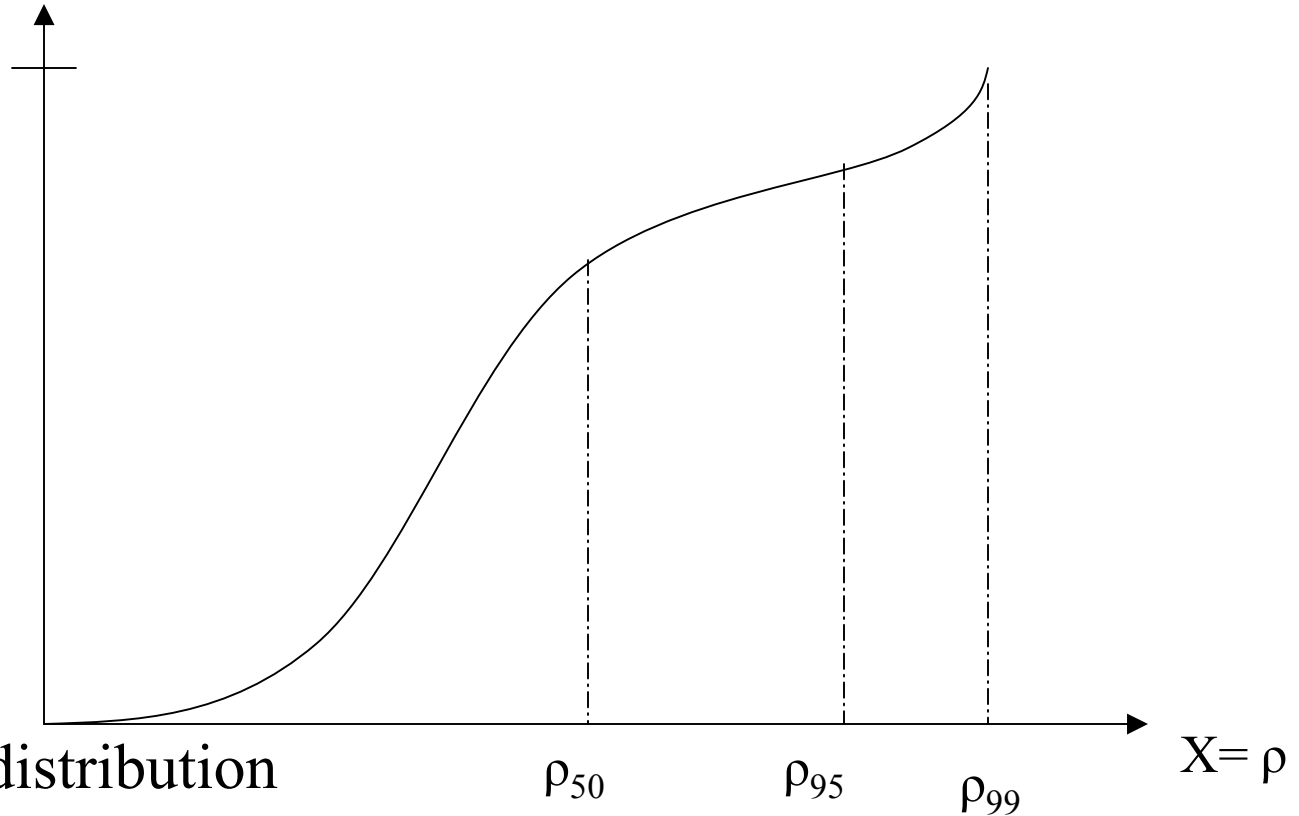


$$\rho_o = \left[ \frac{\text{\# Operations scheduled during } I \text{ at } O\text{'s airport}}{\text{Capacity( in \# operations) during } I \text{ at } O\text{'s airport}} \right]$$

$\rho_o$  is the queueing system utilization for an interval around  $O$  ; because of the way scheduling is done and also because of GDPs and other disruptions  $\rho_o$  could sometimes be  $> 1$

# Cumulative Distribution of $\rho$

$Y = \% \text{ of}$   
operations  
with  $\rho \leq X$



Characterize distribution  
by a few parameters

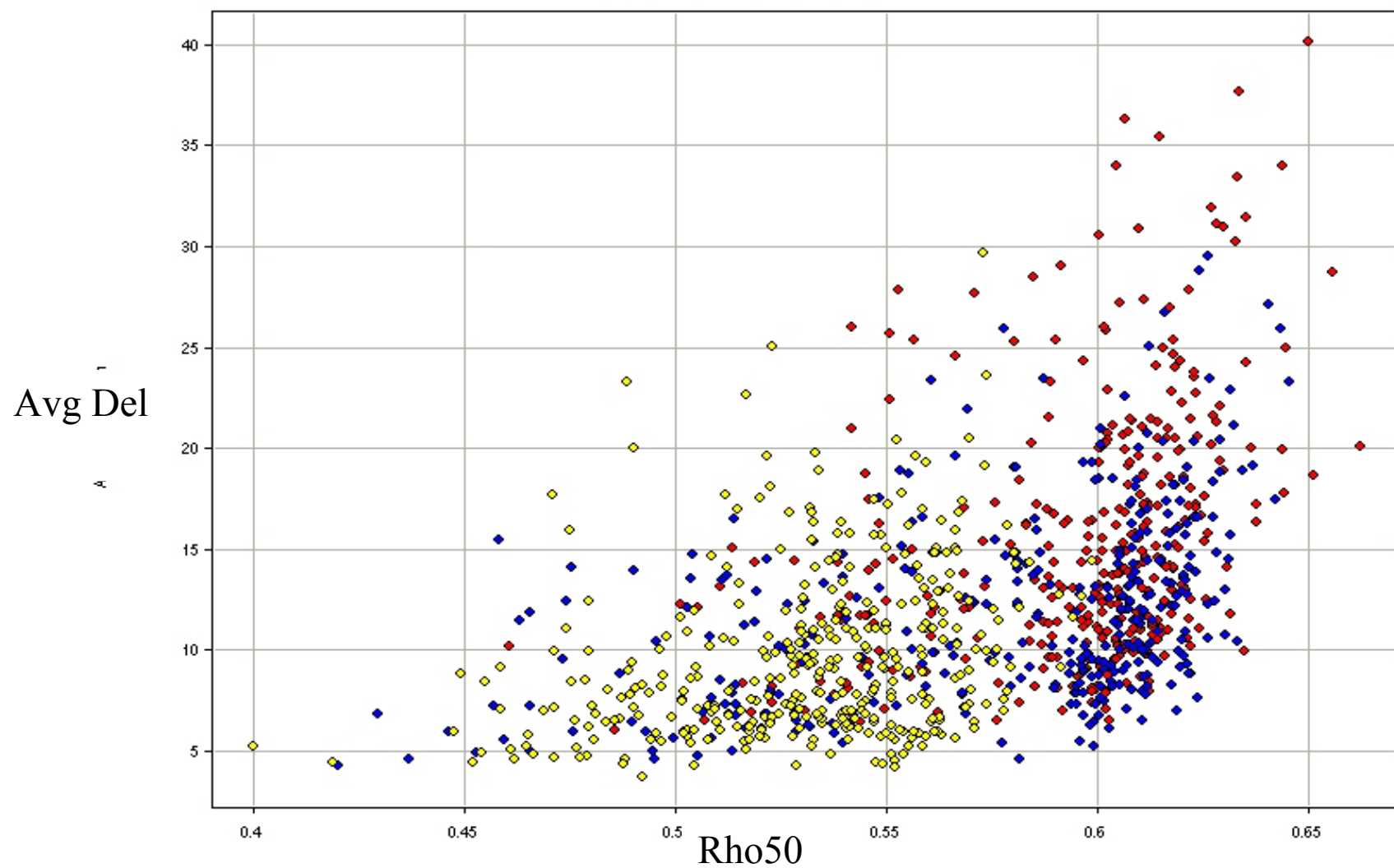
- Distribution of  $\rho$  (or any of  $\rho_{50}$ ,  $\rho_{50}$ ,  $\rho_{50}$ ) could be calculated for a single airport on a single day, the NAS on a single day, the NAS over a week, etc.
- For a given day,  $\rho$  is determined by the OAG schedule and the airport capacity profile *for that day*. Airport capacity on a given day depends on VMC/IMC status (VMC = visual meteorological conditions, IMC = instrument meteorological conditions), runway configuration, etc. →  *$\rho$  has potential to capture impact of weather and VMC/IMC capacity differences.*
- *Modeling challenge:*  
Capacity + demand →  $\rho$  → average flight delay, flight cancellation probability.

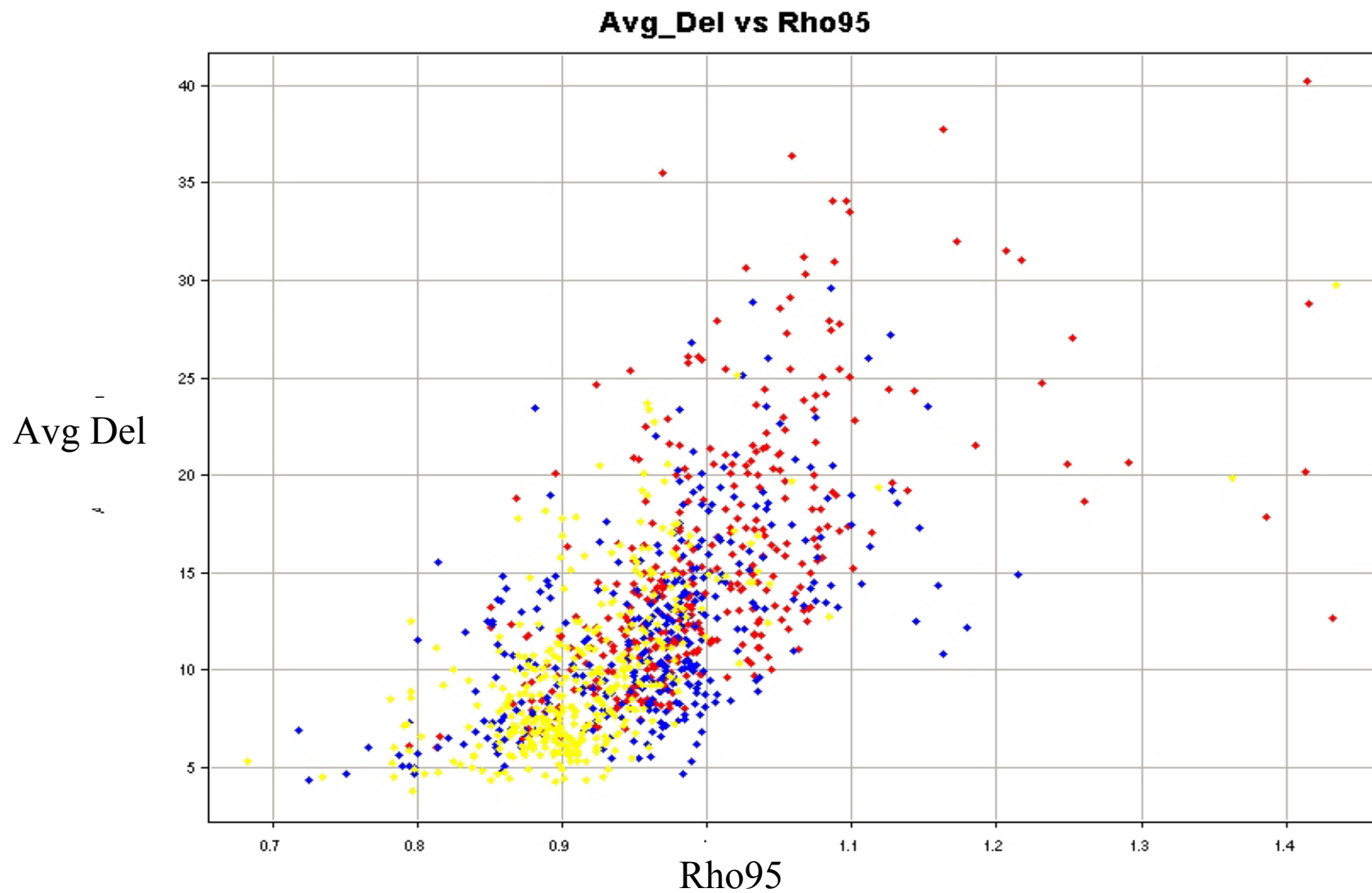


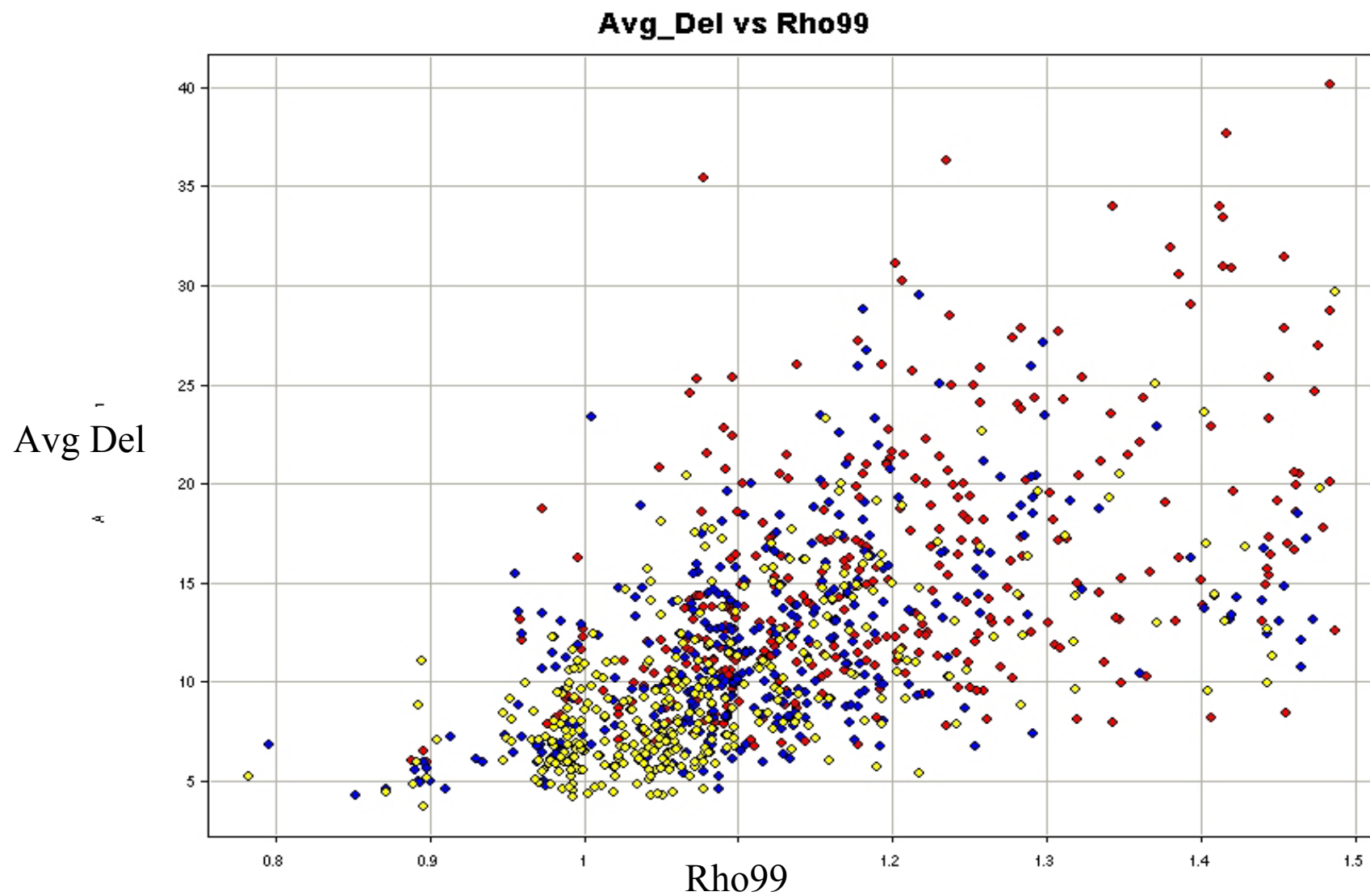
# Data Analysis

- For each day under consideration:
  - Set up 24 1-hour buckets at each airport
  - Determine number of scheduled operations (from OAG)
  - Determine capacity (max number of ops) – depends on IMC/VMC, runway config, etc
  - Calculate  $\rho$  for each bucket – assign this  $\rho$  value to each operation in bucket
- Create buckets based on  $\rho$ -values; create  $\rho$  distribution by combining data from all days and all airports under consideration.

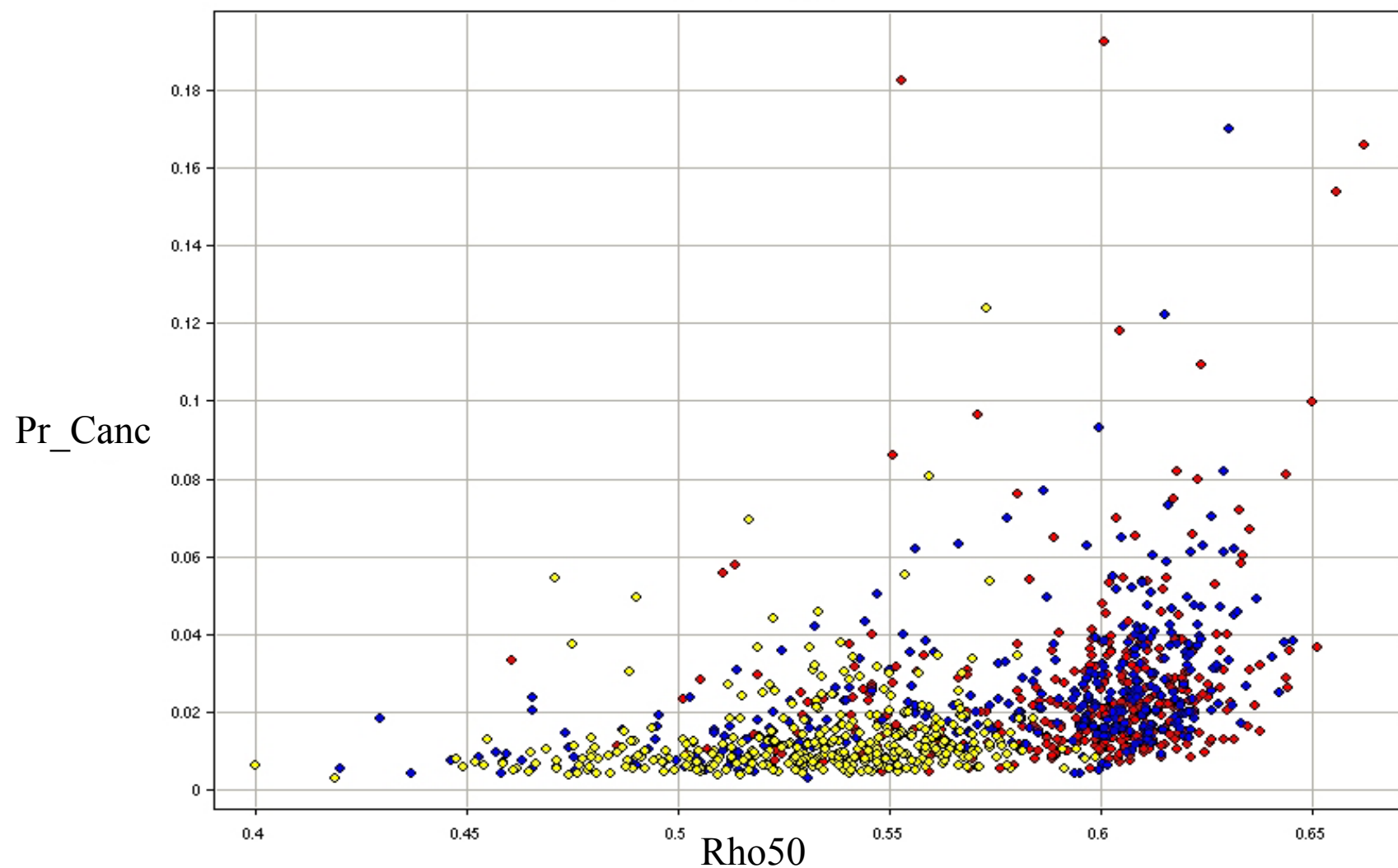
**Avg\_Del vs Rho50**

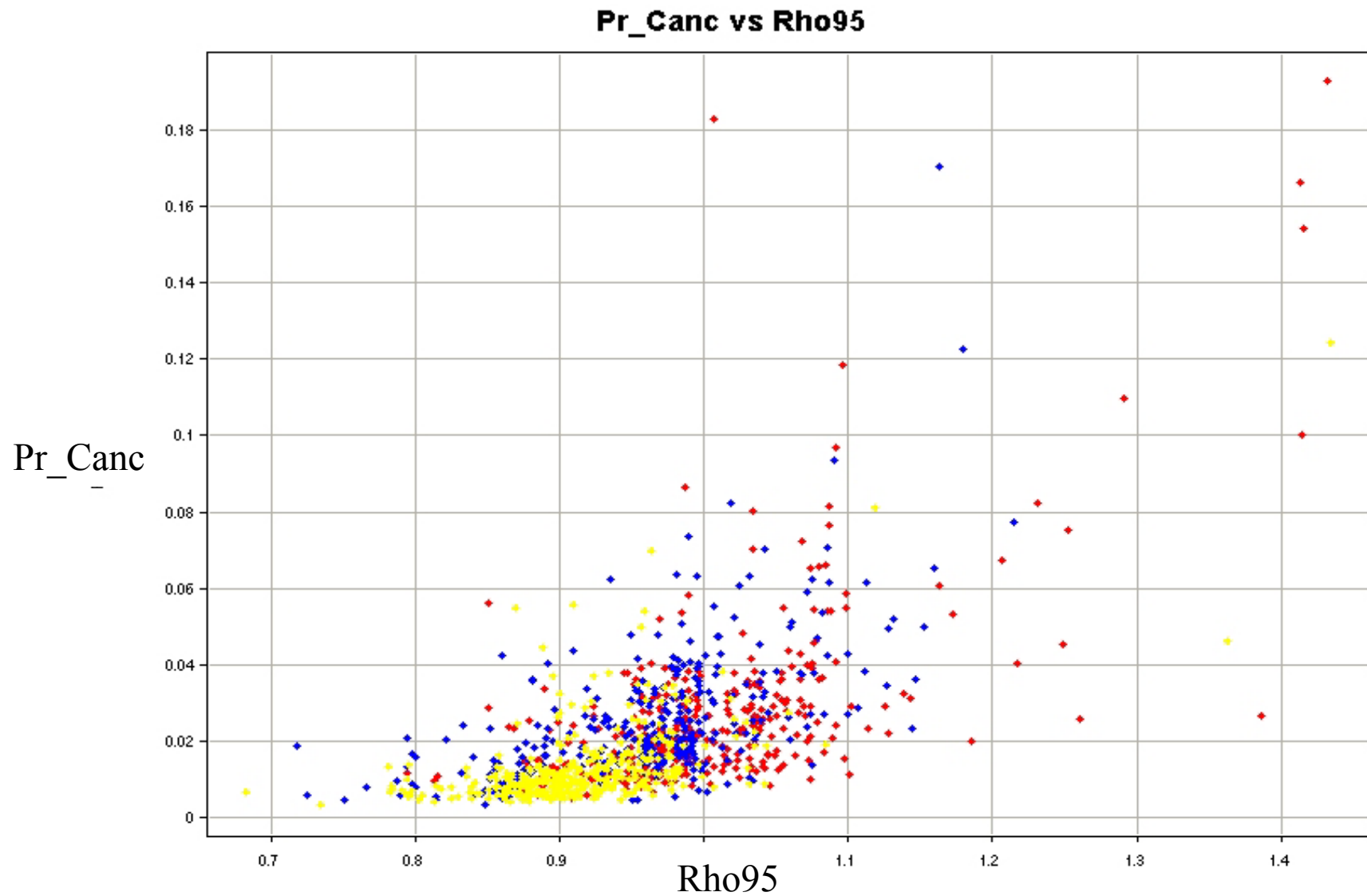




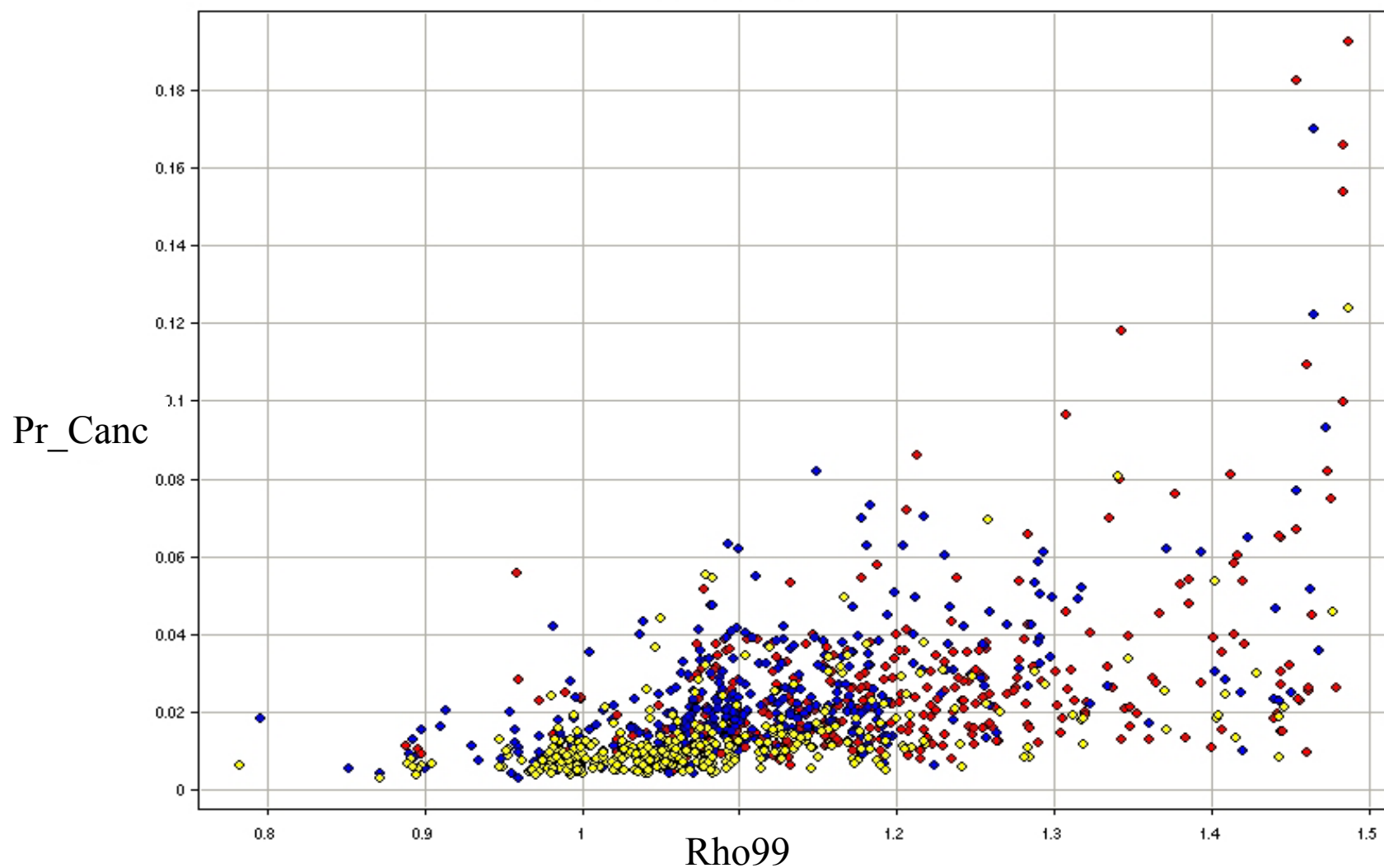


Pr\_Canc vs Rho50



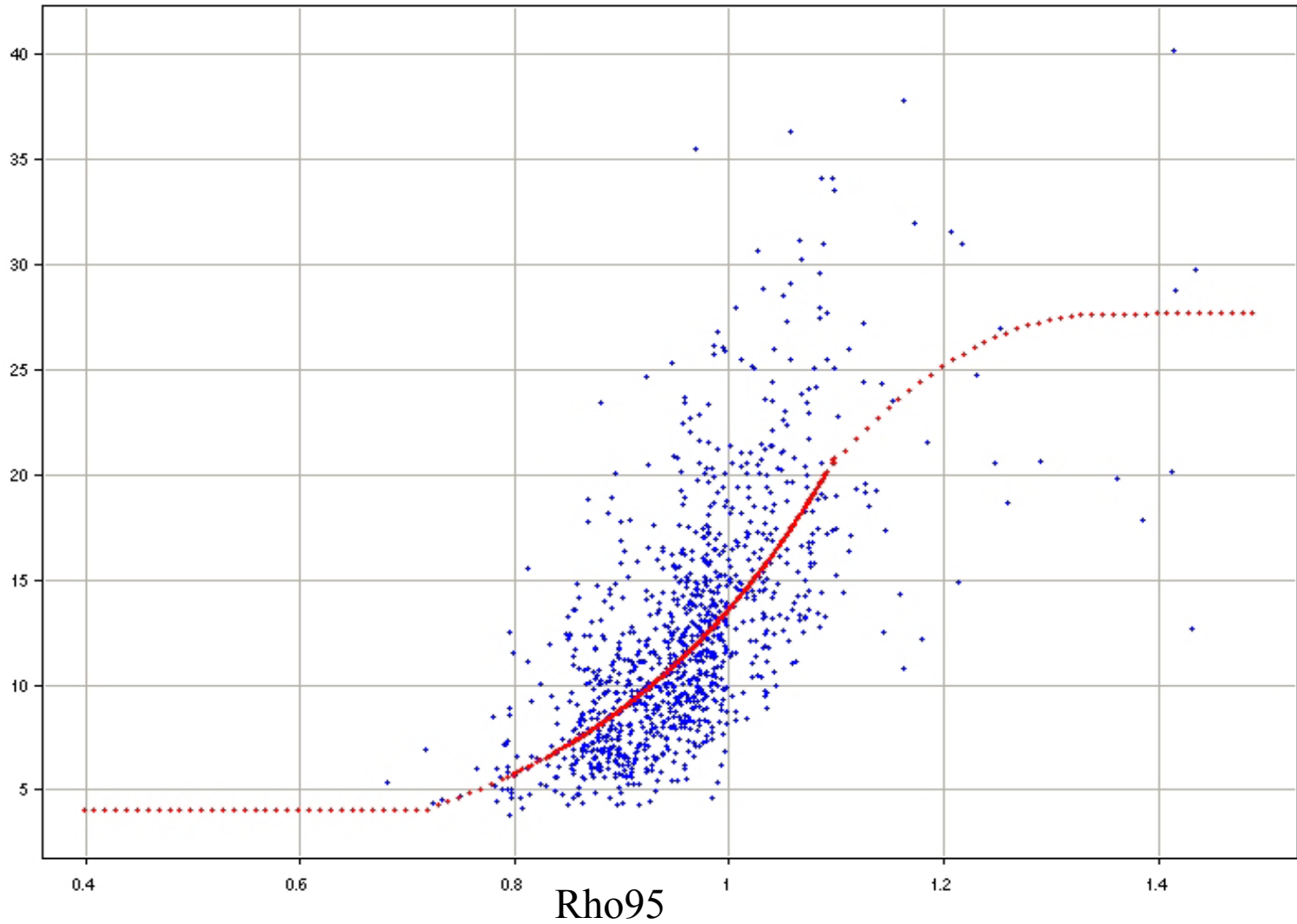


**Pr\_Canc vs Rho99**



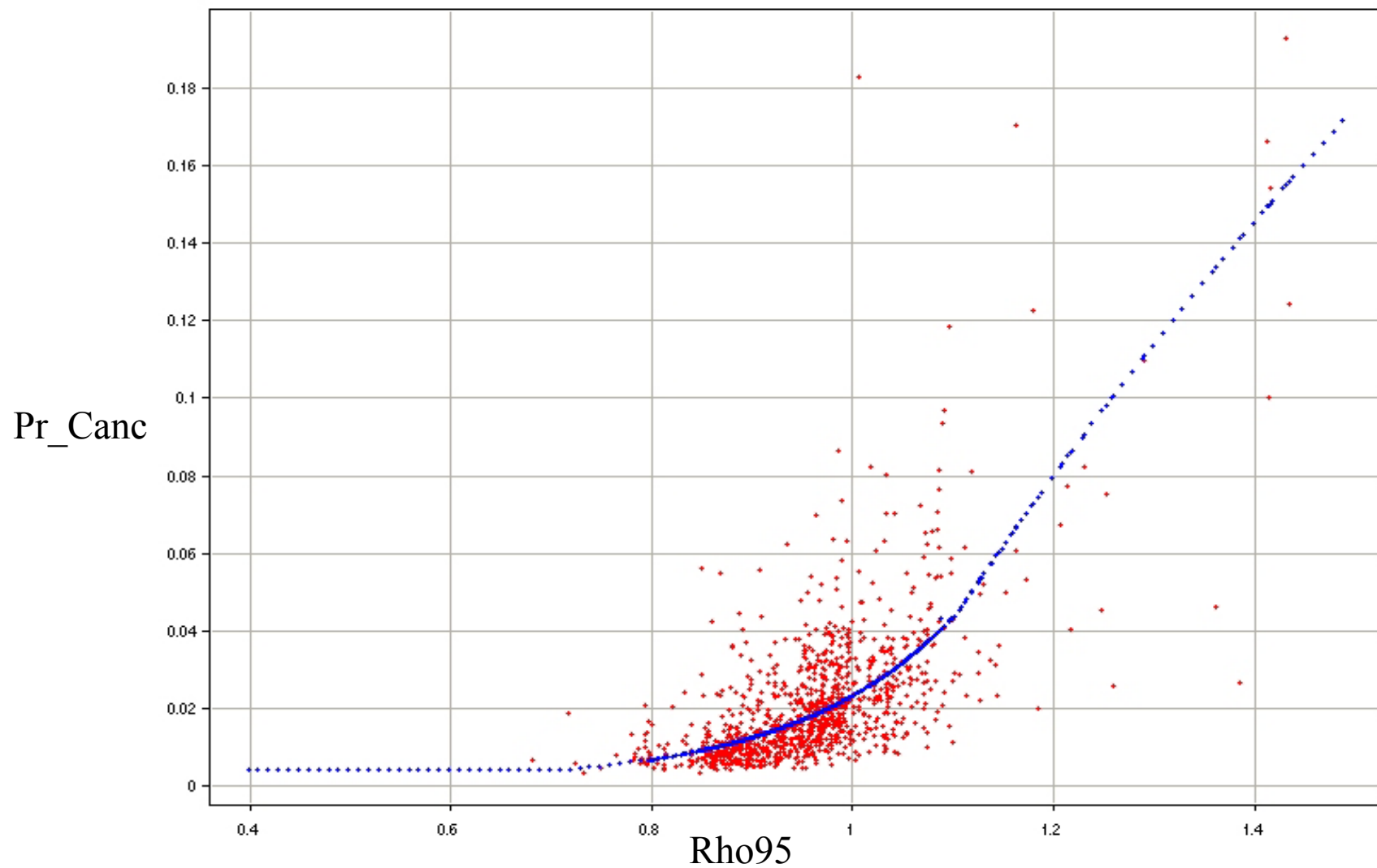
### Avg Delay Equation

Avg Del





## Probability Cancellation Equation



- *Average\_Delay*

- Avg\_Del = 4.0048       $0.4 \leq \text{Rho95} < 0.72$
- Avg\_Del =  $0.178 \cdot \text{EXP}(4.3247 \cdot \text{Rho95})$        $0.72 \leq \text{Rho95} < 1.09$
- Avg\_Del =  $-115.41 \cdot (\text{Rho95}^2) + 310.87 \cdot \text{Rho95} - 181.8$        $1.09 < \text{Rho95} \leq 1.35$
- Avg\_Del =  $27.25 + \text{LN}(\text{Rho95})$        $1.36 \leq \text{Rho95} < 1.49$

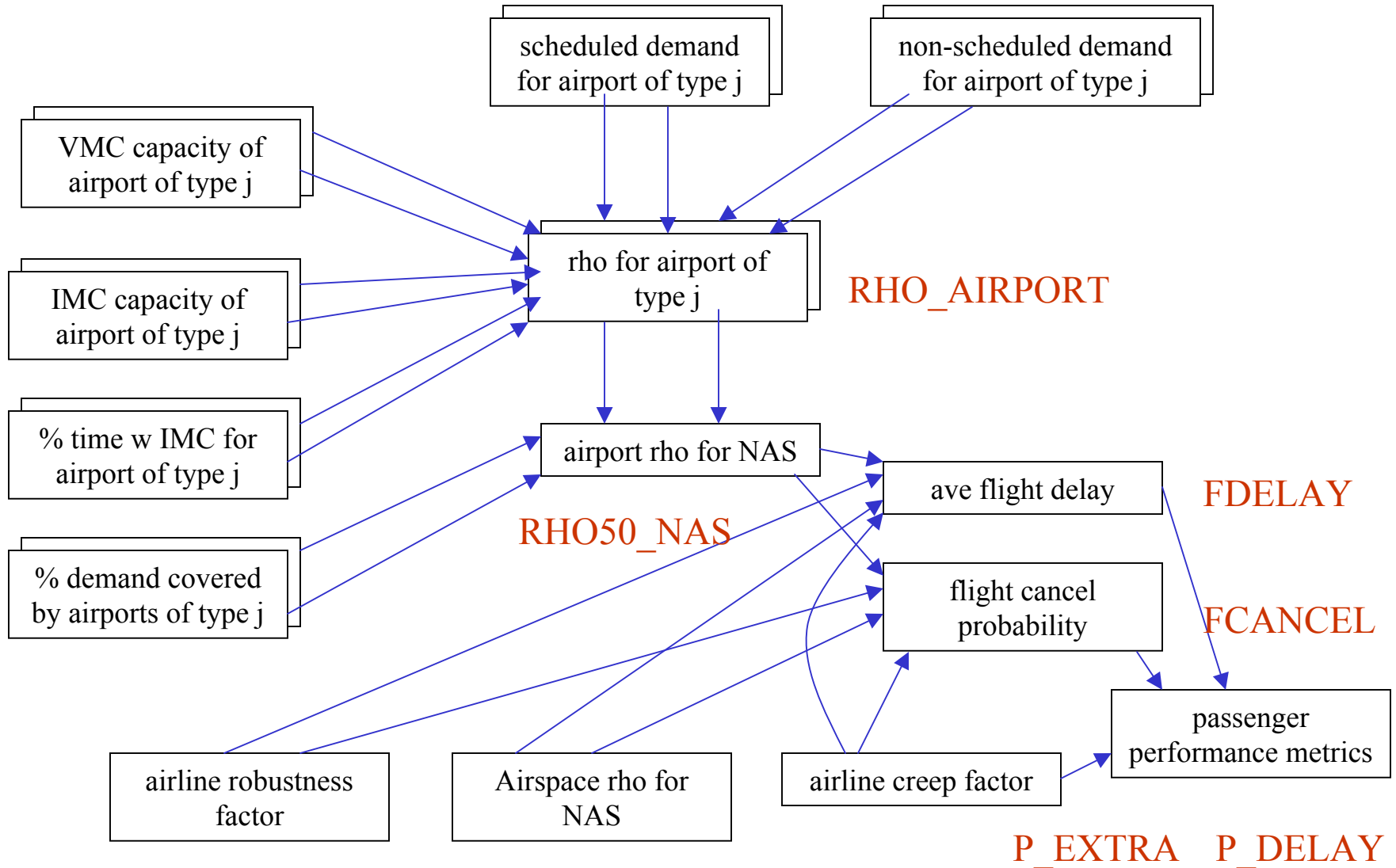
**R – Square = 63.2%**

- *Probability Cancellation*

- Pr\_Cancel = 0.0040       $0.4 \leq \text{Rho95} < 0.72$
- Pr\_Cancel =  $0.00004 \cdot \text{EXP}(6.3406 \cdot \text{Rho95})$        $0.72 \leq \text{Rho95} < 1.0$
- Pr\_Cancel =  $0.425 \cdot \text{LN}(\text{Rho95}) + 0.0015$        $1.0 \leq \text{Rho95} < 1.49$

**R – Square = 84.6%**

# NAS Performance





*Results of multiple regression for Ln(AvgDel\_Flight\_Min)*

Avg Delay (min)			Delay Cancellation (90)		Delay Cancellation (120)		Delay Cancellation (150)	
	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
Constant	-1.1018	0.0000	-1.1356	0.0000	-1.1772	0.0000	-1.2118	0.0000
Rho50	1.4293	0.0000	1.3588	0.0000	1.3569	0.0000	1.3615	0.0000
Rho95	1.7996	0.0000	1.9610	0.0000	2.0463	0.0000	2.1173	0.0000
Rho99	0.8615	0.0000	0.8823	0.0000	0.8857	0.0000	0.8900	0.0000
R-Square	46.29%		50.09%		51.38%		52.21%	

*Results of multiple regression for Ln(Pr\_Canc)*

	Coefficient	p-value
Constant	-9.6486	0.0000
Rho50	2.3942	0.0000
Rho95	3.0201	0.0000
Rho99	1.1391	0.0000
R-Square	45.38%	

### Ln(AvgDel\_Flight\_Min)

$$= -0.741 + 1.36 \text{ Rho50} + 1.68 \text{ Rho95} + 0.835 \text{ Rho99} \\ - 0.207 \text{ Month\_Fall} - 0.128 \text{ Month\_Spring} \\ - 0.0682 \text{ Pre 9/11\_N} - 0.127 \text{ Day\_Mon} \\ - 0.183 \text{ Day\_Tue} - 0.146 \text{ Day\_Wed}$$

Predictor	Coeff	P-value
Constant	-0.7409	0
Rho50	1.3622	0
Rho95	1.6774	0
Rho99	0.8346	0
Month_Fall	-0.2071	0
Month_Spring	-0.1283	0
Pre 9/11	-0.0682	0.012
Day_Mon	-0.1271	0
Day_Tue	-0.1827	0
Day_Wed	-0.1457	0

R-Sq = 54.3%

### Ln(Pr\_Canc)

$$= -6.95 - 1.98 \text{ Rho50} + 3.07 \text{ Rho95} + 1.13 \text{ Rho99} \\ - 0.163 \text{ Month\_Fall} - 0.229 \text{ Month\_Spring} \\ - 0.513 \text{ Pre 9/11\_N} + 0.118 \text{ Day\_Mon} \\ + 0.217 \text{ Day\_Tue} + 0.172 \text{ Day\_Wed}$$

Predictor	Coeff	p-value
Constant	-6.9512	0
Rho50	-1.981	0.001
Rho95	3.0686	0
Rho99	1.1257	0
Month_Fall	-0.1626	0
Month_Spring	-0.2291	0
Pre 9/11	-0.513	0
Day_Mon	0.1182	0.006
Day_Tue	0.2171	0
Day_Wed	0.1725	0

R-Sq = 54.9%



## Based on Fridays from 2000, 2001, 2002

*Results of multiple regression for  $\text{Ln}(\text{AvgDel\_Flight\_Min})$*

*Results of multiple regression for  $\text{Ln}(\text{Pr\_Canc})$*

Avg Delay (min)		
	Coeff	p-value
Constant	-1.3918	0.0000
Rho50	1.9297	0.0270
Rho95	1.9451	0.0045
Rho99	0.8749	0.0116
Month_Fall	-0.1893	0.0016
Month_Spring	-0.0920	0.1100

**R-Square**                      62.97%

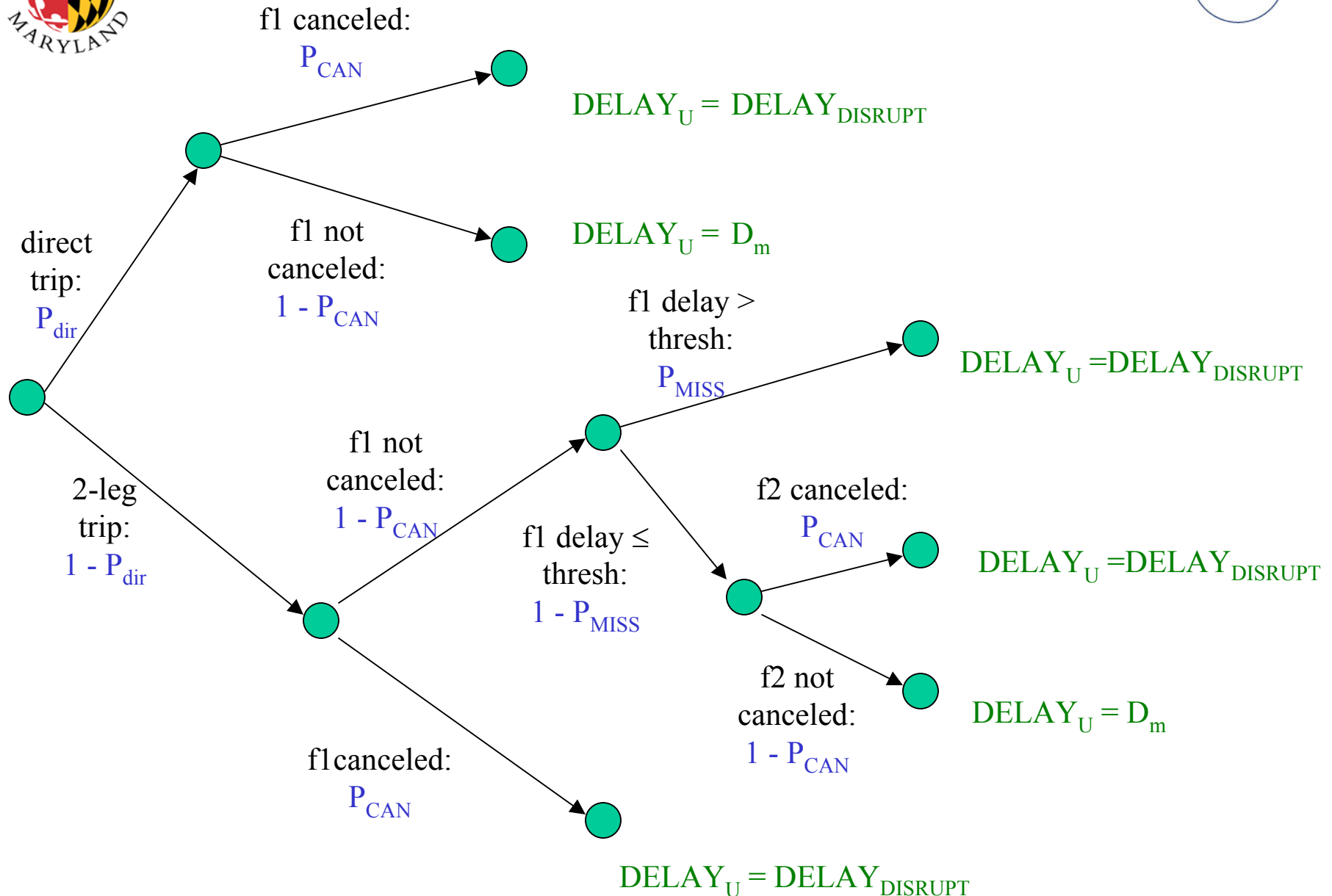
Pr_ Cancellation		
	Coeff	p-value
Constant	-8.0055	0.0000
Rho95	2.9864	0.0021
Rho99	1.0671	0.0610
Pre9/11_N	-0.3436	0.0005
Month_Fall	-0.2207	0.0284
Month_Spring	-0.2474	0.0104

56.25%

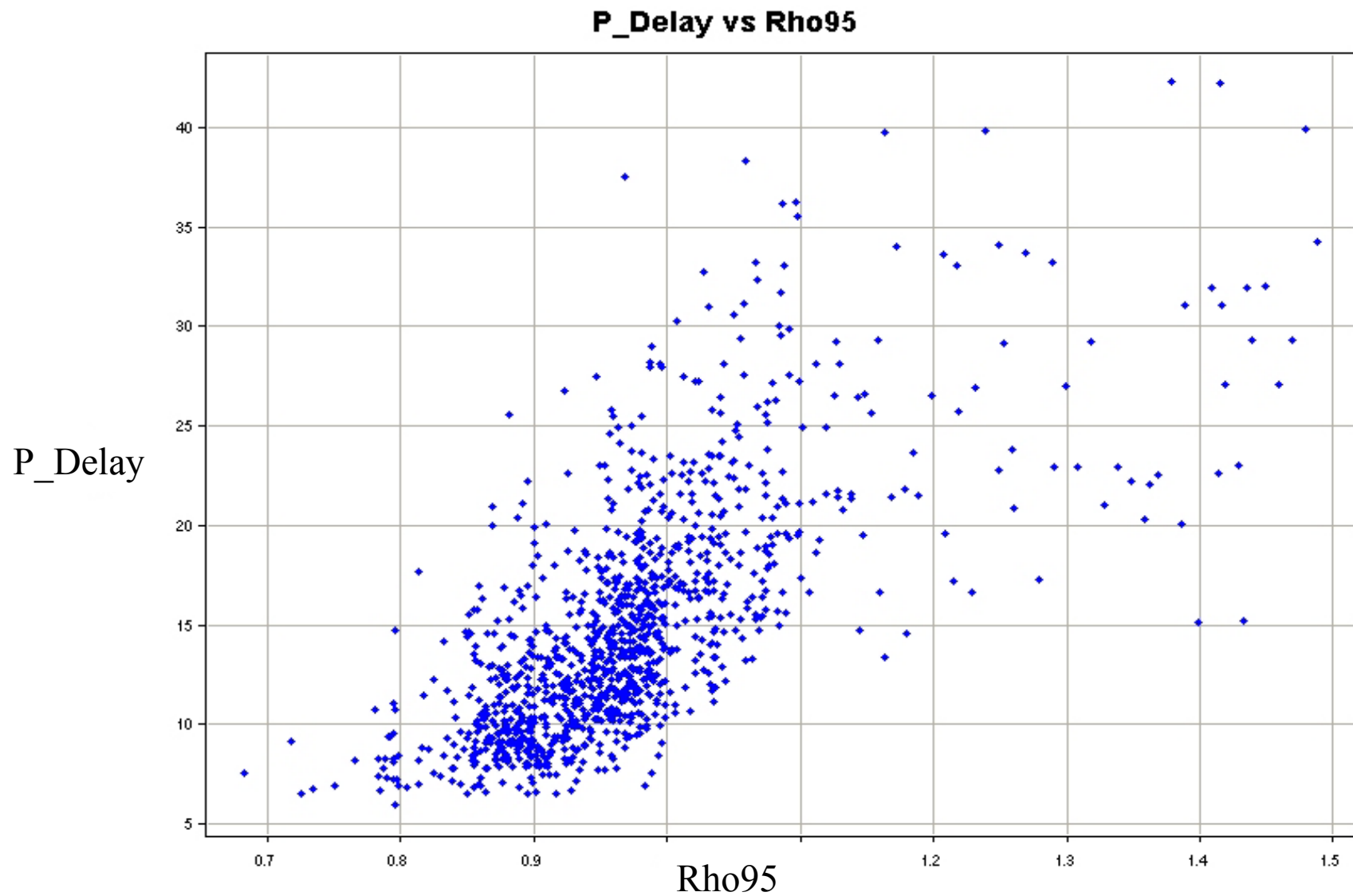
# Conclusions of Analysis

- Basic concepts are sound
- Rho95 is best single predictor
- Some variation remains to be characterized
- Airline behavior changes based on:
  - Load factor on that day, e.g. very high loads → fewer cancellations
  - Day-of-week

# Passenger Delay Metric







# Model Features

Track changes in NAS performance as a function of:

- Changes in airport infrastructure
- Changes in demand
- Changes in weather or ability of technology to adapt to weather, e.g. (VMC cap)/(IMC cap)
- Technology improvements that imply capacity enhancements



# On-Going Work

- Add independent variables, etc to achieve “best” model
- Create “best” model compatible with Vensim (focus this summer)
- Specific issues to address:
  - Control variable that drives cancellation and delay models
  - Daily → yearly model
  - Airspace effects
  - Refined passenger model
  - GA effect
  - Airport-specific effects (delay → airports; airports → delay)
  - Delay distribution information