Air Traffic Metrics to Quantify Disruption From Natural (Weather) and Man-made (Cyber) Causes

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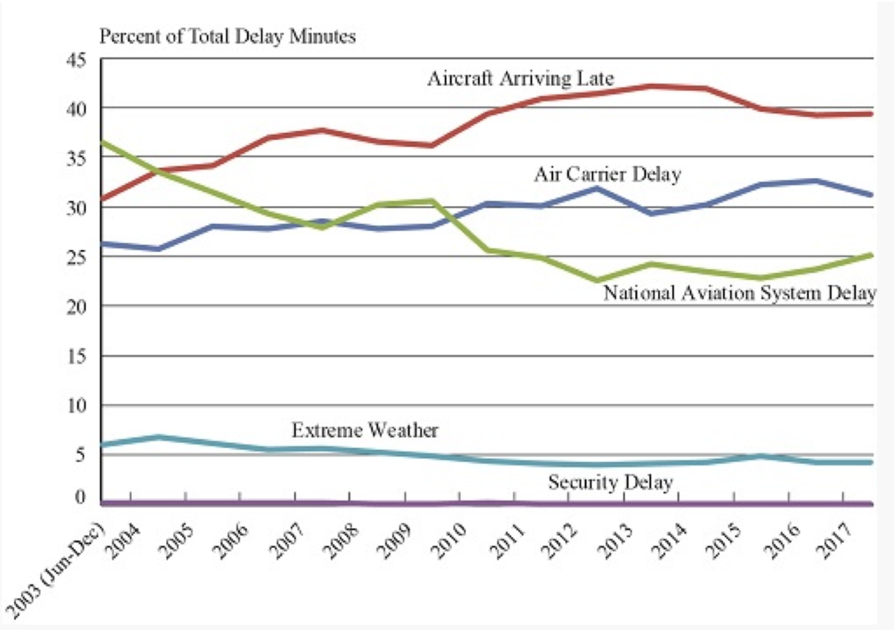
Airline On-Time Performance

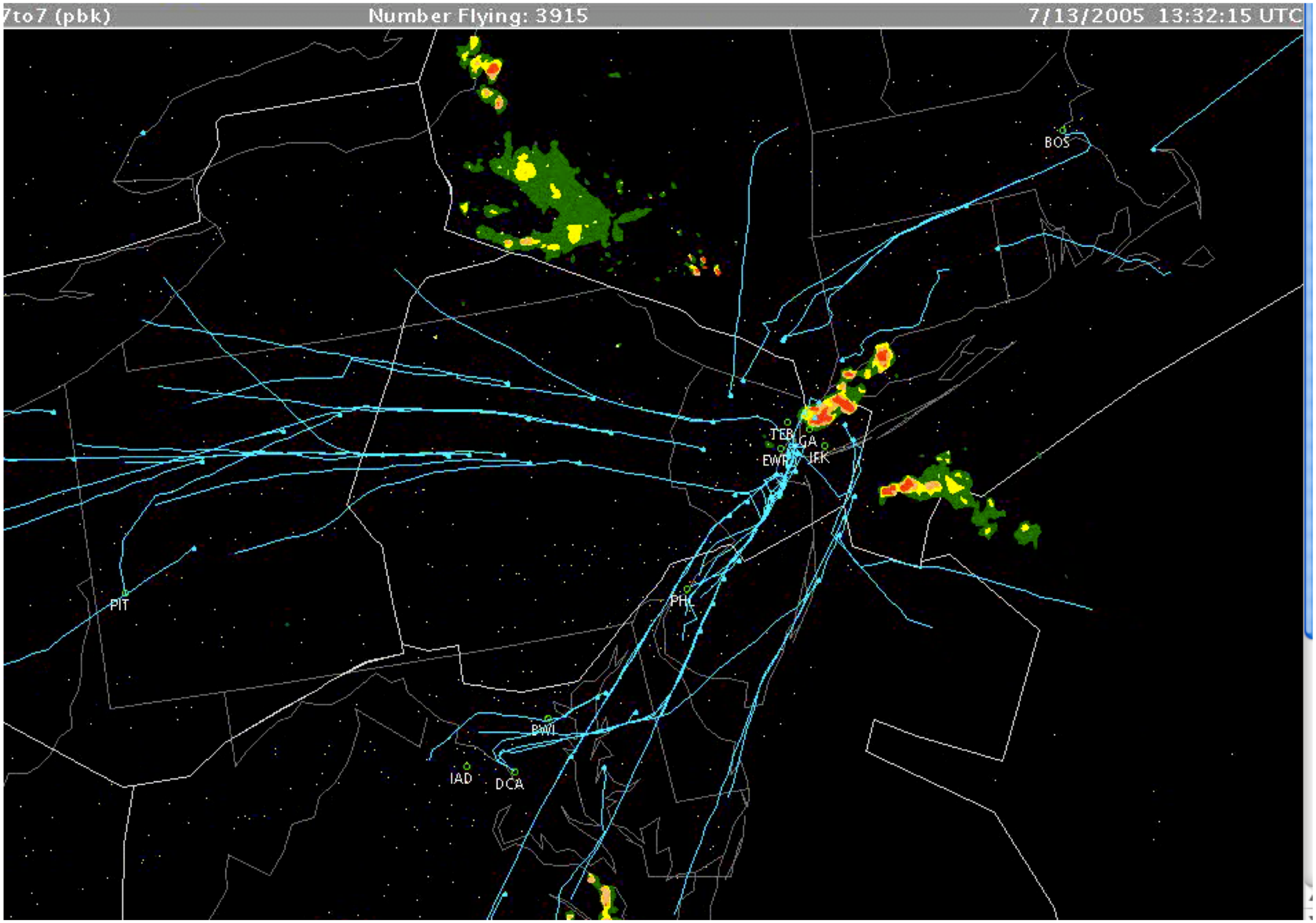
- Air Carrier delays cost $22.5 Billion in 2016

- Delay Causes
  - Air Carrier
    - Maintenance, Crew problems
  - Extreme Weather
    - Actual or predicted weather events (Hurricanes, Tornado, blizzards) that prevents flying
  - National Airspace System (NAS)
    - Weather slowing operations, Airport operations, Heavy traffic
  - Late Arriving Aircraft
  - Security
    - Varied between 0.1% to 0.3%

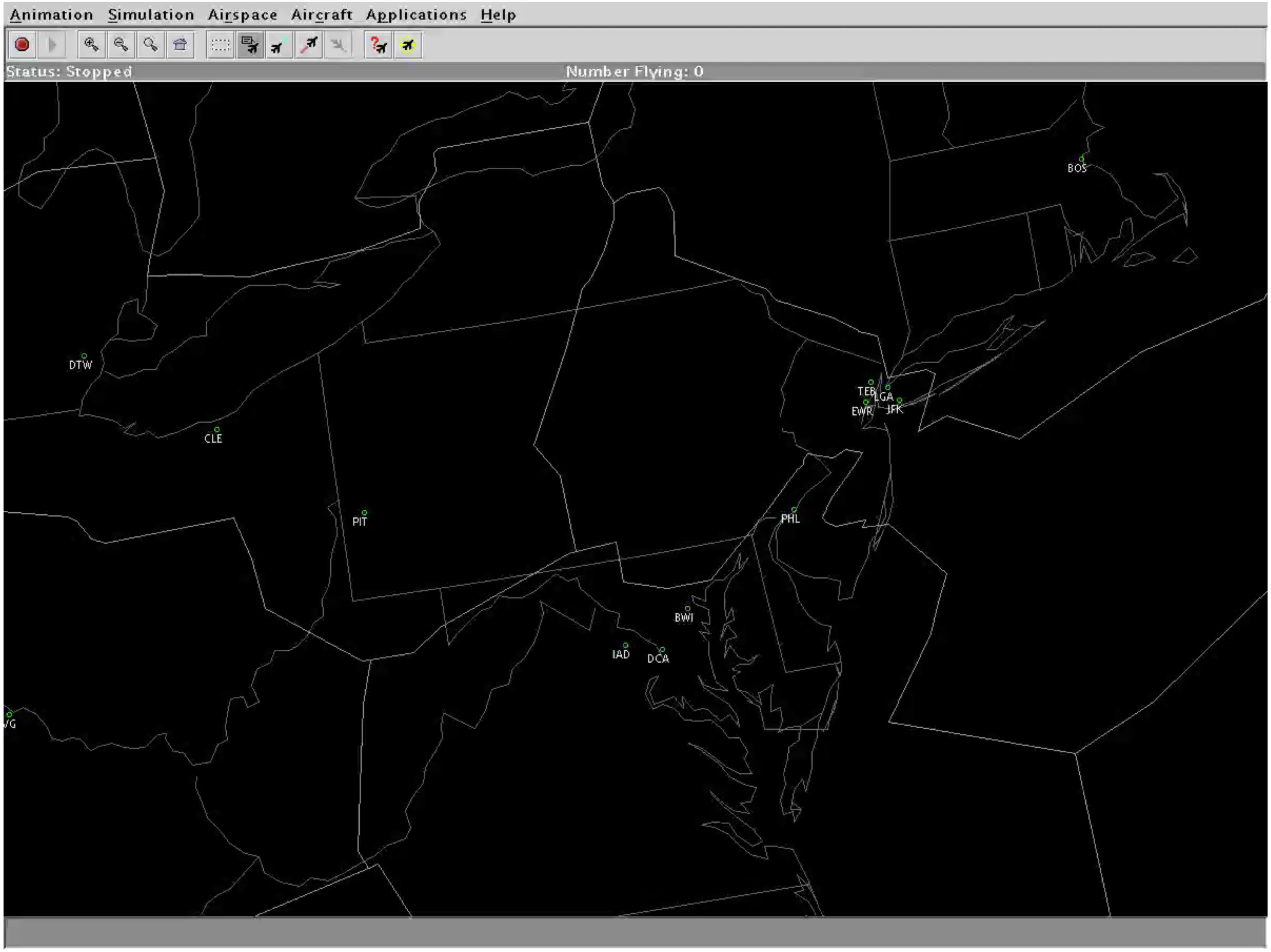


Source: Bureau of Transportation Statistics
FAA: Air_Traffic_by_the_Numbers_2017_Final.pdf/ 45

Impact of Weather on Aviation

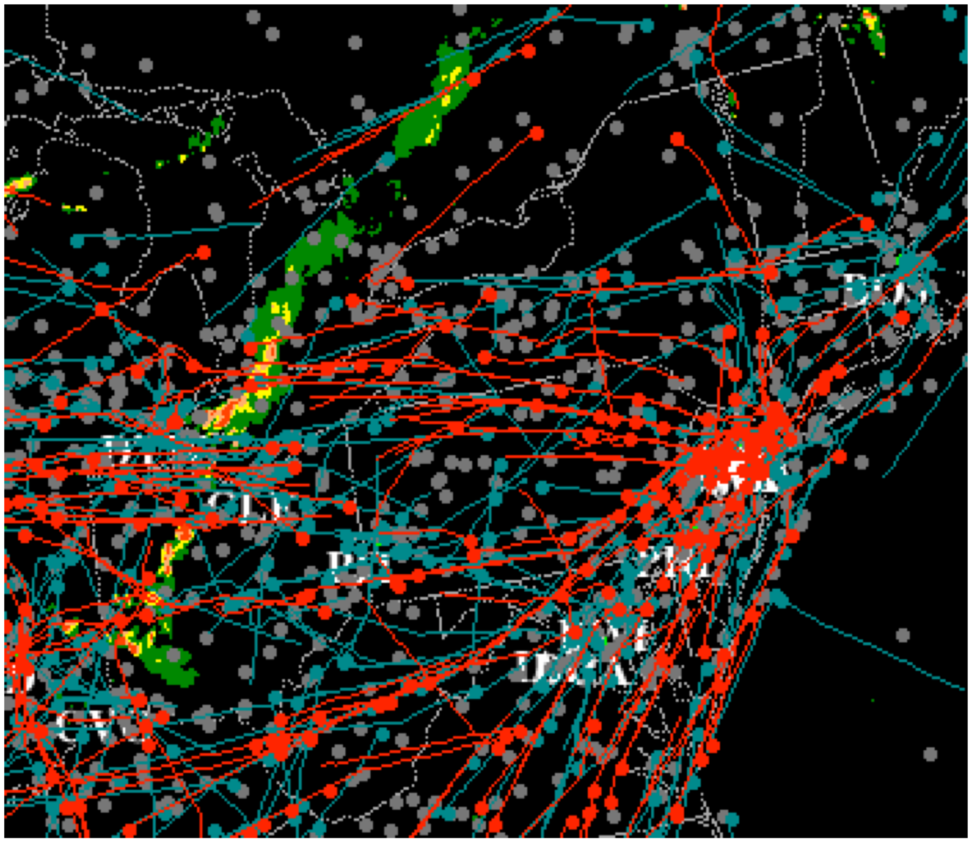


Impact of Weather on Aviation



Motivation: Disruptions to Aviation Services

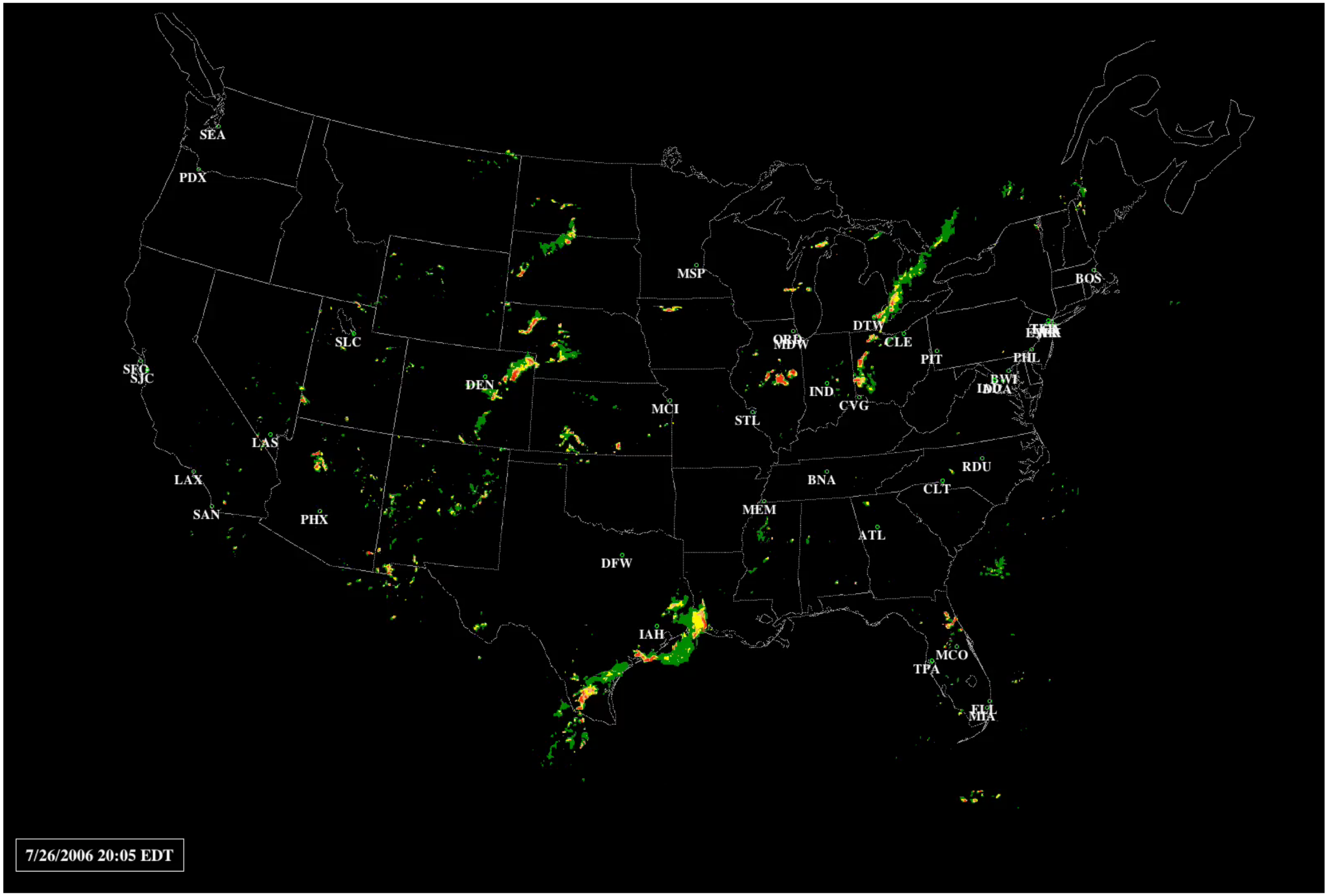
- Natural: Weather is the major cause of delay in the US National Airspace System (NAS)



Date	# of flights	Delayed flights	Total Delay (minutes)
07/05/07	23,051	6,094	341,431
07/12/07	24,557	7,129	382,876
07/19/07	24,576	12,114	939,956
07/26/07	24,573	9,606	595,779

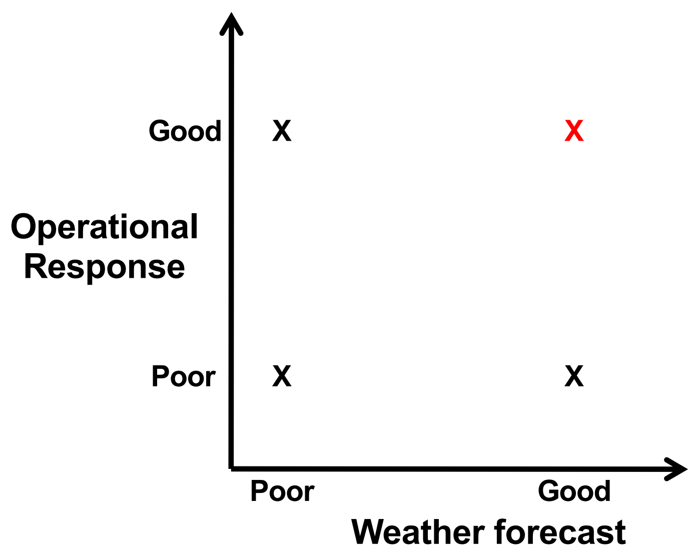
- During 2017, 331,179 flights delayed due to weather for a total of 21,864,200 minutes (66 minutes/flight)

Delays on a Bad Weather Day



Motivation: Disruptions to Aviation Services

- Man-made: Cyber attack caused service disruption for two hours and affected 530 flights disrupting passengers schedules.



How to measure, model and mitigate the impact of disruptions using decision support tools?

- Weather disruptions are frequent and degrade NAS performance
- Although catastrophic failures are extremely rare and unpredictable, recent cyber attacks have caused impacts at longer intervals
- Significant research to improve Traffic Flow Management by relating delay, cancellations and other NAS performance metrics to the weather conditions
  - Understand the change in operations from year to year nationally, in different regions and airports to make better strategic decisions
  - Measure forecast accuracy of convective weather products
  - Predict growth of delay in future traffic scenarios
- Research on modeling and reducing the impact of man-made disruptions is nascent

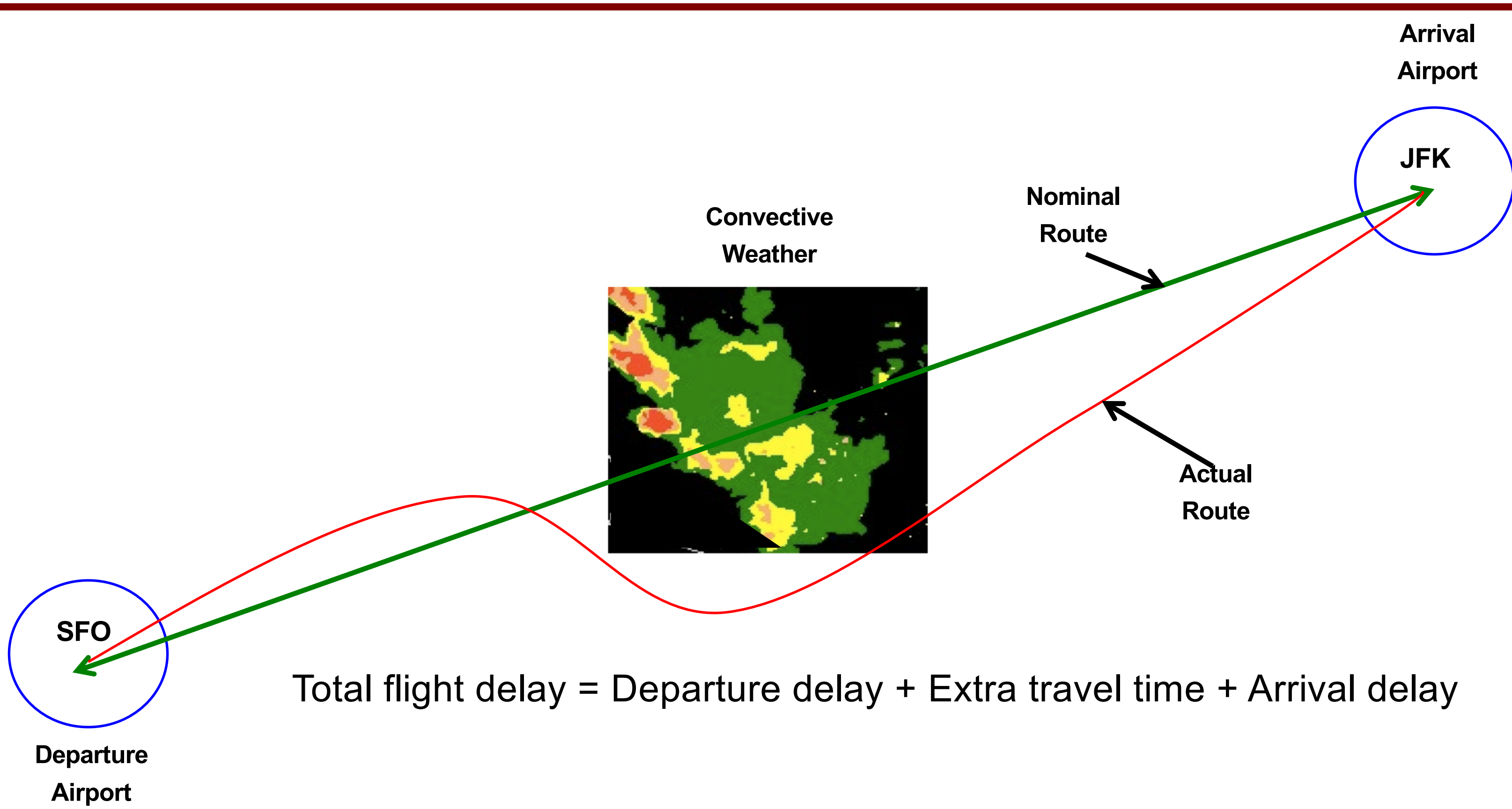
Outline

- Factors in Modeling/Estimation of Metrics
- Weather
- Cyber Disruption
  - Aggregate Models, Assumptions, Vulnerability Metrics
- Preliminary Results
- Concluding Remarks

Factors in Modeling Metrics

- Objectives
  - Tactical, Strategic, Improve operations,….
- Available observations/Databases
- Choice of nominal traffic (basis for improvement)
- Weather
  - Predicted Weather
  - Actual Weather
- Cyber disruptions

Flight delays due to Weather

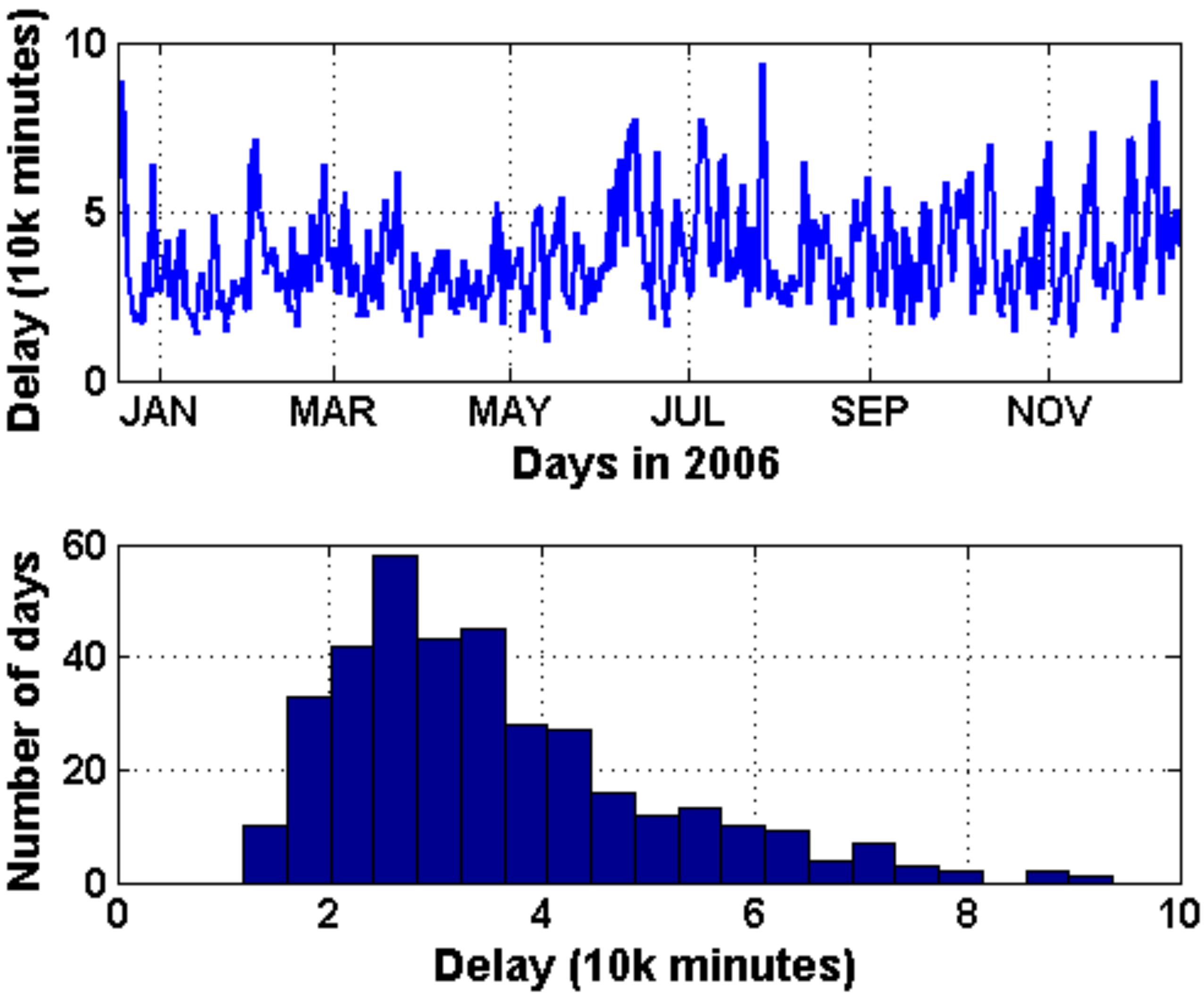


- Can we use past data and predicted weather to estimate delays to improve operations?

Databases

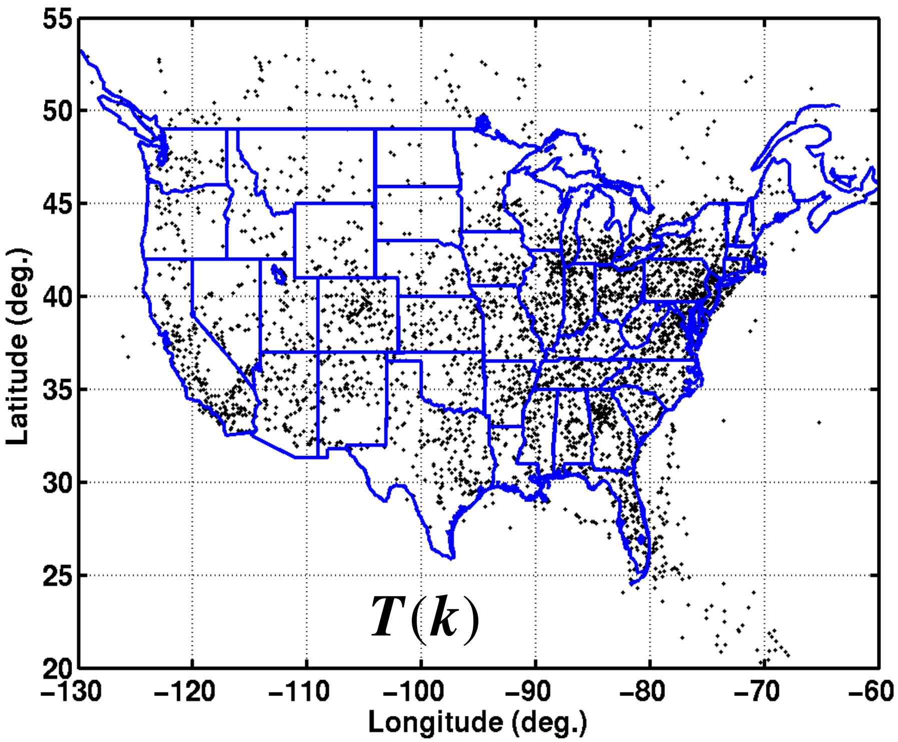
- FAA Operations Network (OPSNET)
  - Data available from 1990
  - Daily values
  - 45 airports
  - Total national delay
- Aviation System Performance Metrics (ASPM)
  - Data available from 2000
  - Every 15 minutes
  - 75 airports
  - Total OAG-based and flight-plan based arrival delays, EDCT hold minutes, airborne delay, flight cancellations
- Results uses data from 2004-2006

National Airspace System (NAS) Performance Metrics

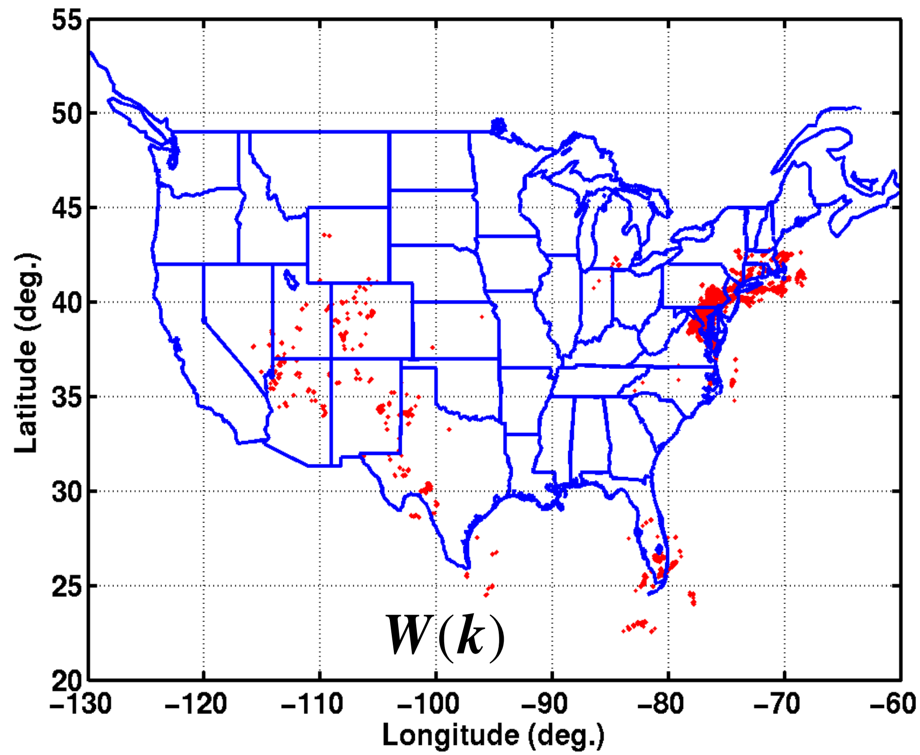


Weather Impacted Traffic Index (WITI)

Aircraft positions



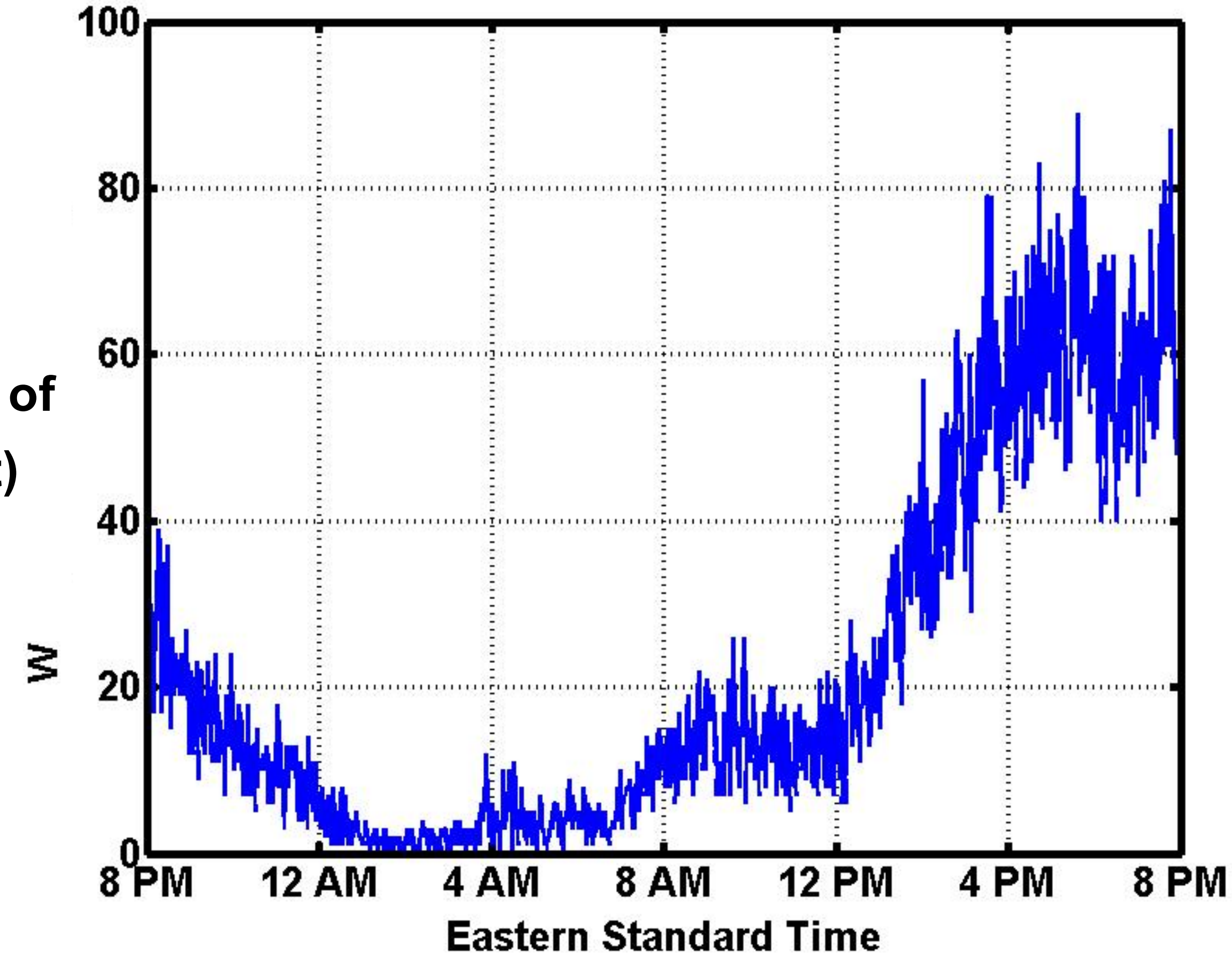
Severe weather



$$WITI(k) = \sum_{1 \le j \le m} \sum_{1 \le i \le n} T_{i,j}(k) W_{i,j}(k)$$

National WITI

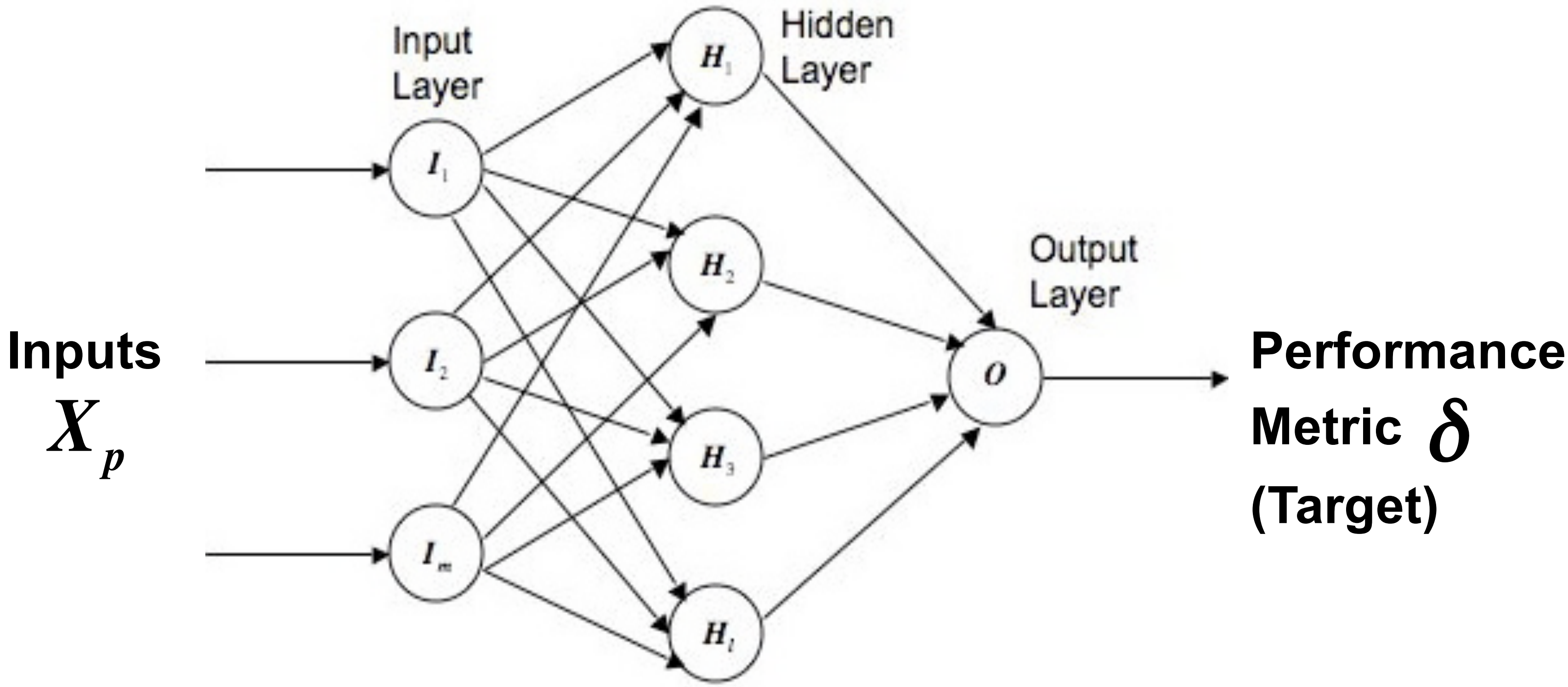
WITI
(Number of
Aircraft)



Modeling/Estimation of Metrics

- Number of aircraft affected by weather (X)
- Number of aircraft affected by weather in each Center or Airport (X_p)
- Performance metric (δ)
- Models
  - Linear Regression (LR) $\boldsymbol{\delta = \alpha X + \beta}$
  - Multiple Linear Regression (MLR) $$\delta = \sum_{p=1}^{20} \alpha_p X_p + \beta_p$$
  - Neural Networks $\boldsymbol{\delta = f(X_p)}$
  - Dynamic Models $$\delta(t) = f(X_p(t-k), \ldots X_p(t-1), X_p(t), X_p(t+1) \ldots X_p(t+r))$$

Neural Network Models

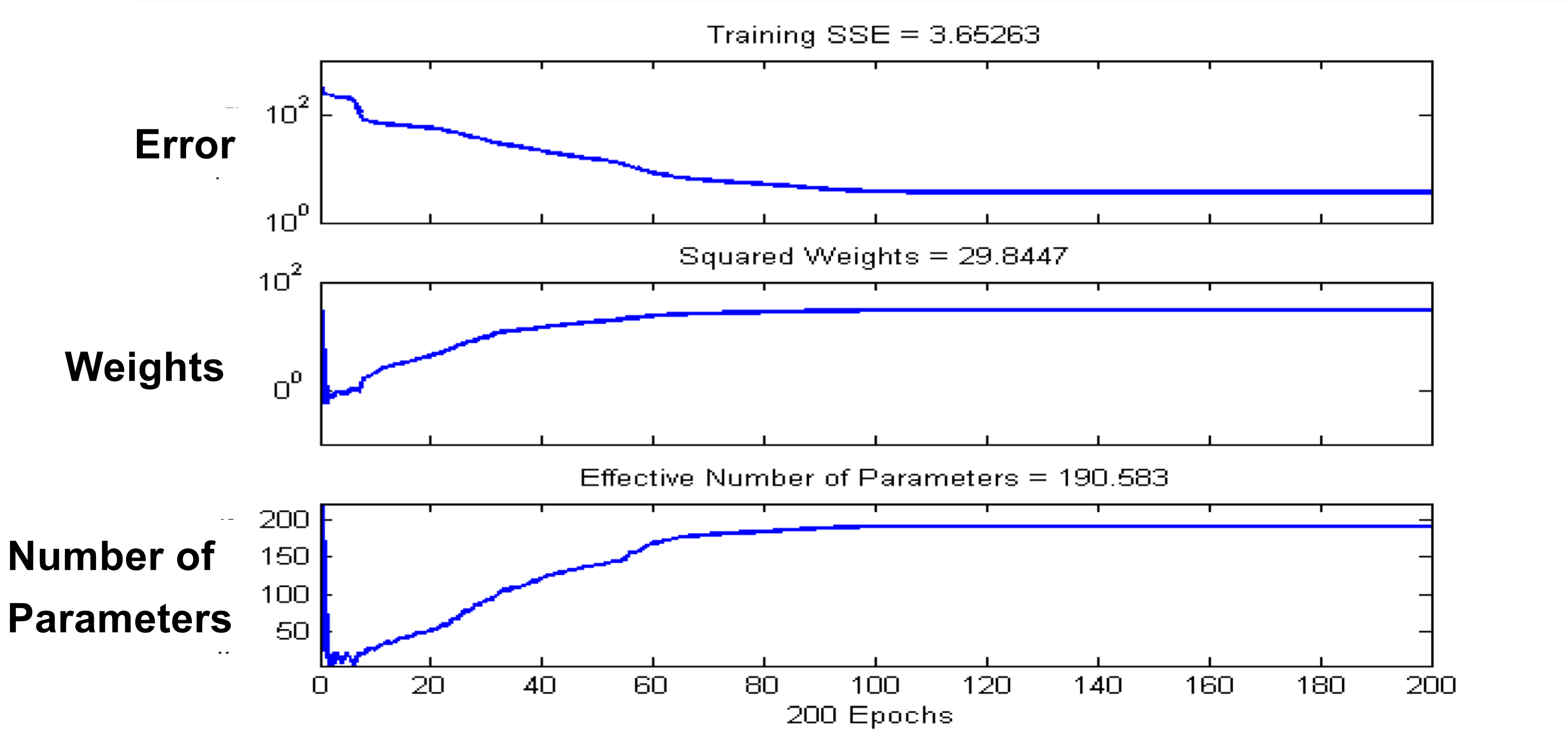


- Good general purpose modeling approach
  - Ability to model large class of input/output relations
  - Generalization capability
- Quality of the model depends on the design and data

Neural Network Training

- Data includes pairs of inputs and desired outputs
- m(l+1) weights
- Weights updated using a gradient procedure until the sum of squares error (SSE) between the neural network output and the desired output is minimized
- Balance between over fitting and under fitting

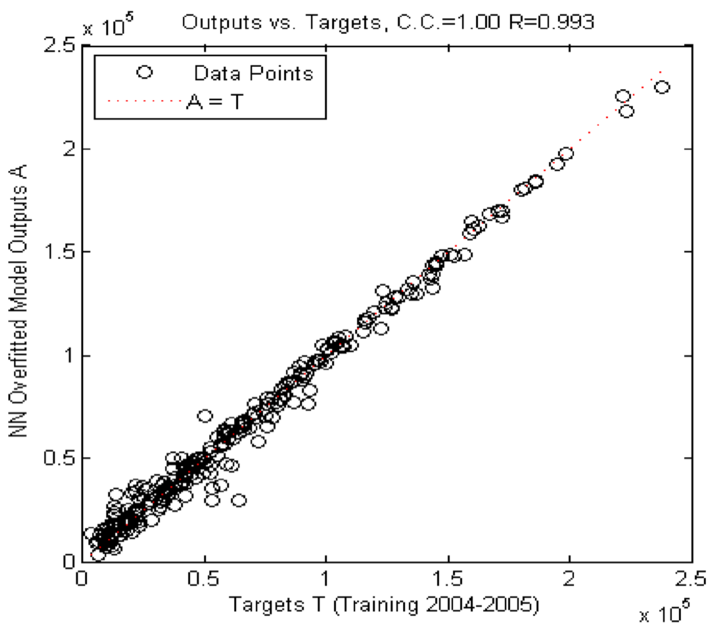
Variation of Training Error



- Result of training after 200 epochs
- Neural network represents total delay training data extremely well

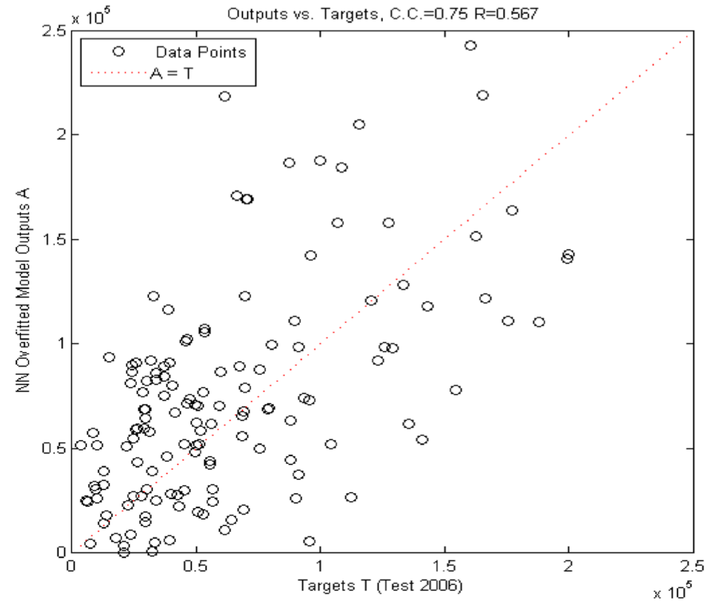
Over fitted Neural Network

Neural Network Output



Target (Training 2004-2005)

Neural Network Output



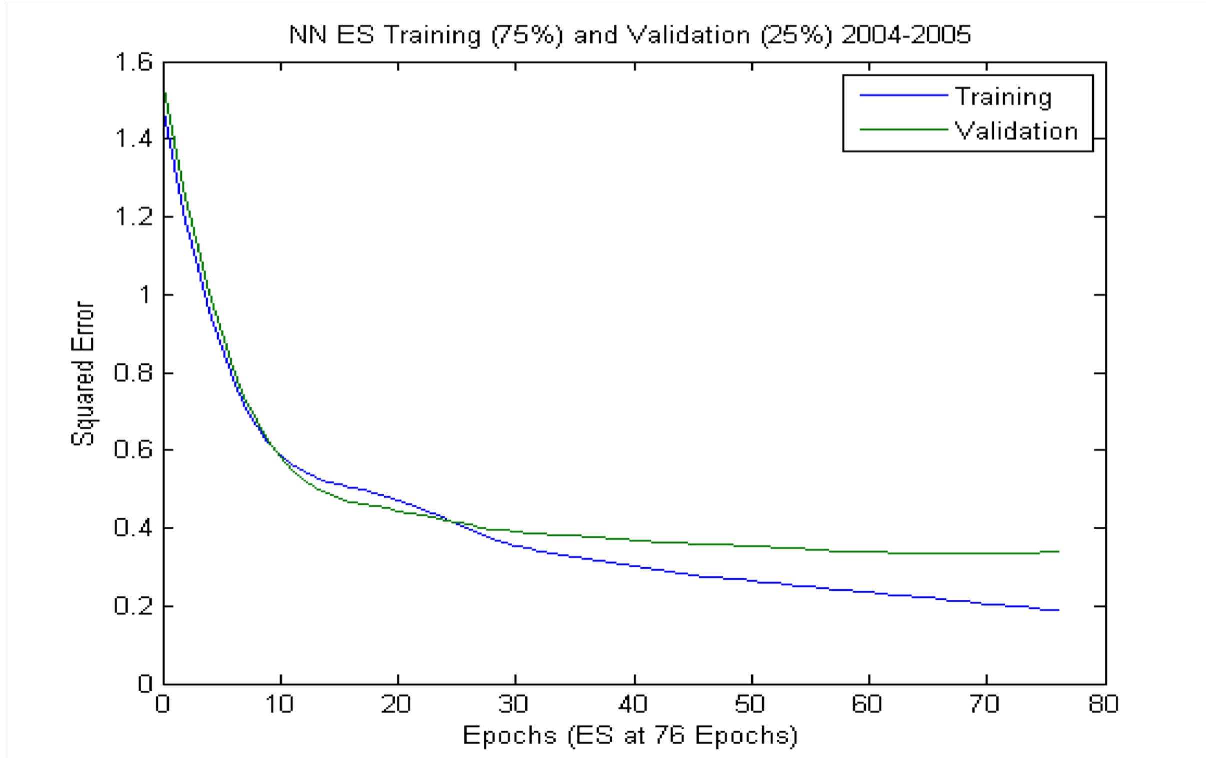
Target (Test 2006)

- Model fits the total delay training data (2004-2005) well, but does not generalize (correlation coefficient for test set is significantly less)

Methods for Good Neural Network Design

- Training data should be sufficiently large and statistically representative
- Overly complex models should be avoided
- Methods to reduce complexity
  - Early Stopping (ES)
  - Principal Component Analysis (PCA)
  - Stepwise Regression (SR)
  - Bayesian Regularization (BR)

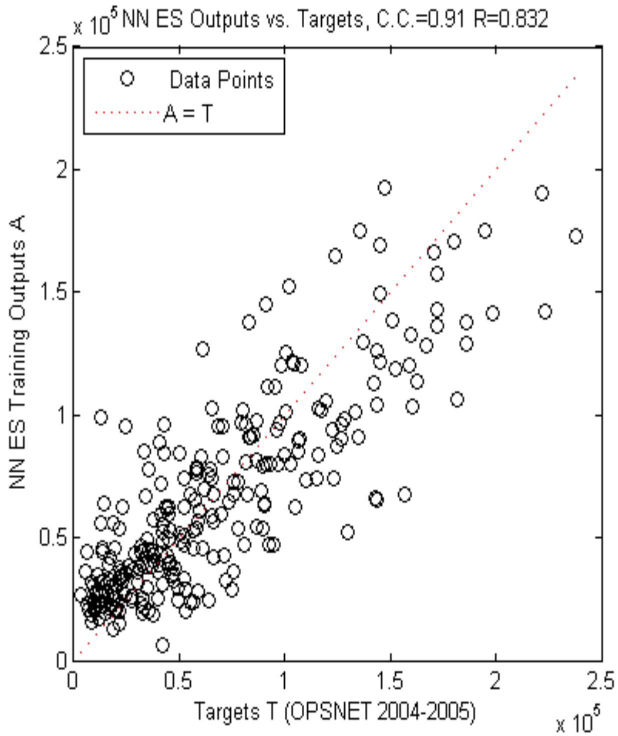
Early Stopping



- Training data (2004-2005) divided into two parts
  - Training set (80%) used to update weights
  - Validation set (20%) used for stopping criterion

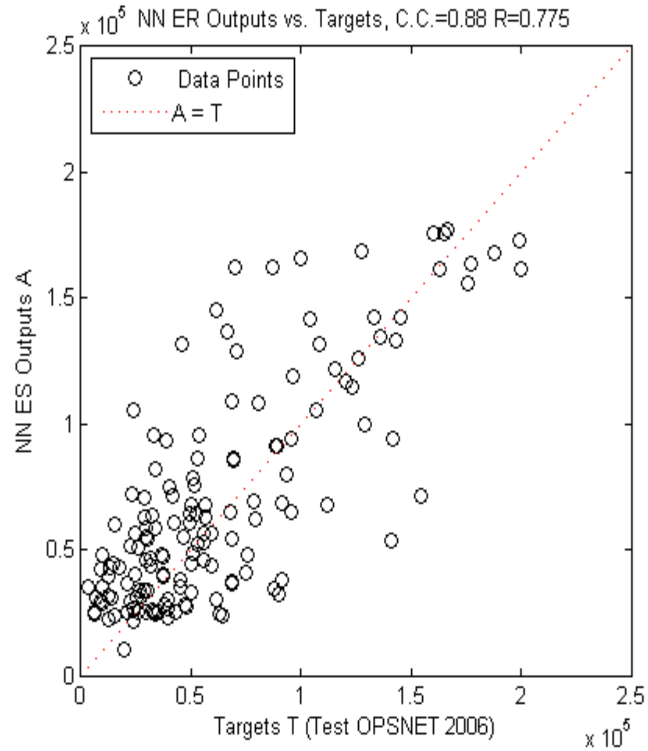
Performance with Early Stopping

Neural Network Output



Target (Training 2004-2005)

Neural Network Output



Target (Test 2006)

- 2004-2005 total delay training data with Early Stopping produces a more balanced model with better generalization capability

Validation of Neural Network Models

- Resist analytical error analysis
- Models constructed from an initial state to a trained state
- Model should be tested using a different dataset
- 2004-2005 data used for training and 2006 data used for validation
- N-fold cross-validation

Computational Results: Delays

OPSNET total delay

Method	CC	RMSE	MAE
LR	0.71	32700	26600
MLR	0.77	31200	24500
BR	0.88	30000	23300
ES	0.88	30900	23200
PCA	0.88	30100	23100
SR	0.88	29600	22300

ASPM Scheduled delay

Method	CC	RMSE	MAE
LR	0.75	99200	74300
MLR	0.76	97600	72900
BR	0.88	95800	74300
ES	0.88	94200	70800
PCA	0.88	91700	68600
SR	0.87	99100	73800

Five-fold cross-validation

Method	CC	RMSE	MAE
BR	0.88	29100	22000
ES	0.88	31500	23900
PCA	0.87	30500	23300
SR	0.89	29600	22500

Five-fold cross-validation

Method	CC	RMSE	MAE
BR	0.87	93700	70300
ES	0.87	95000	72000
PCA	0.87	94900	70800
SR	0.85	96100	73000

LR Linear Regression
MLR Multiple Linear Regression
Methods to reduce complexity of Neural Network
ES Early Stopping
PCA Principal Component Analysis
SR Stepwise Regression
BR Bayesian Regularization

Computational Results: Cancellations

- Similar results for estimating the number of cancellations

Flight Cancellations

Method	CC	RMSE	MAE
LR	0.73	146	106
MLR	0.77	131	94
BR	0.88	131	93
ES	0.88	135	98
PCA	0.87	134	98
SR	0.88	131	94

Five-fold Cross-validation

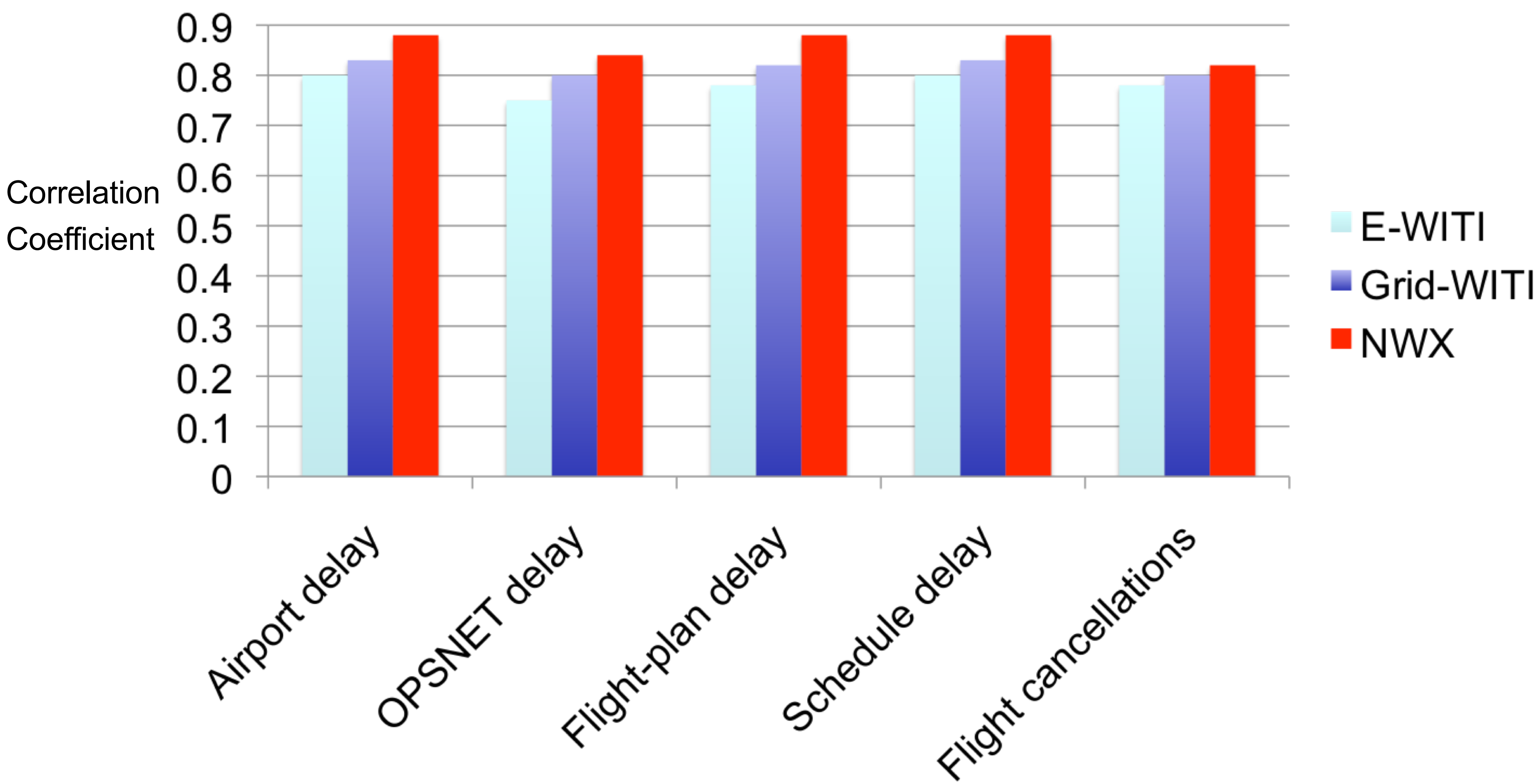
Method	CC	RMSE	MAE
BR	0.86	139	97
ES	0.84	144	102
PCA	0.85	142	100
SR	0.86	136	96

LR Linear Regression
MLR Multiple Linear Regression
Methods to reduce complexity of Neural Network
ES Early Stopping
PCA Principal Component Analysis
SR Stepwise Regression
BR Bayesian Regularization

National Weather Index (NWX)

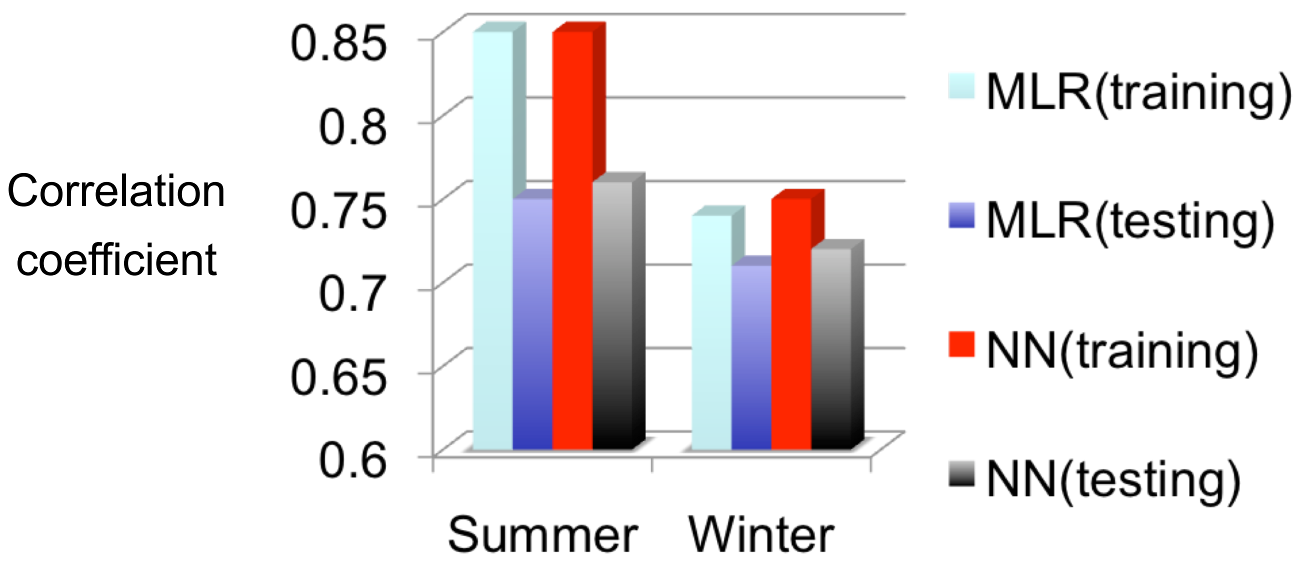
- Models weather and congestion at airports and terminal area
- Three components
  - En-route WITI (E-WITI), representing convective weather impact on major flows between city pairs
  - Terminal WITI (T-WITI), representing weather impact on major airports
  - Airport Queuing Delay (Q-Delay), representing surface and terminal-airspace weather impact on major airports in a non-linear fashion

Comparison of WITI Definitions (MLR)



- Models using NWX perform slightly better and the difference varies with the estimation method

Seasonal Performance of National Delay Models



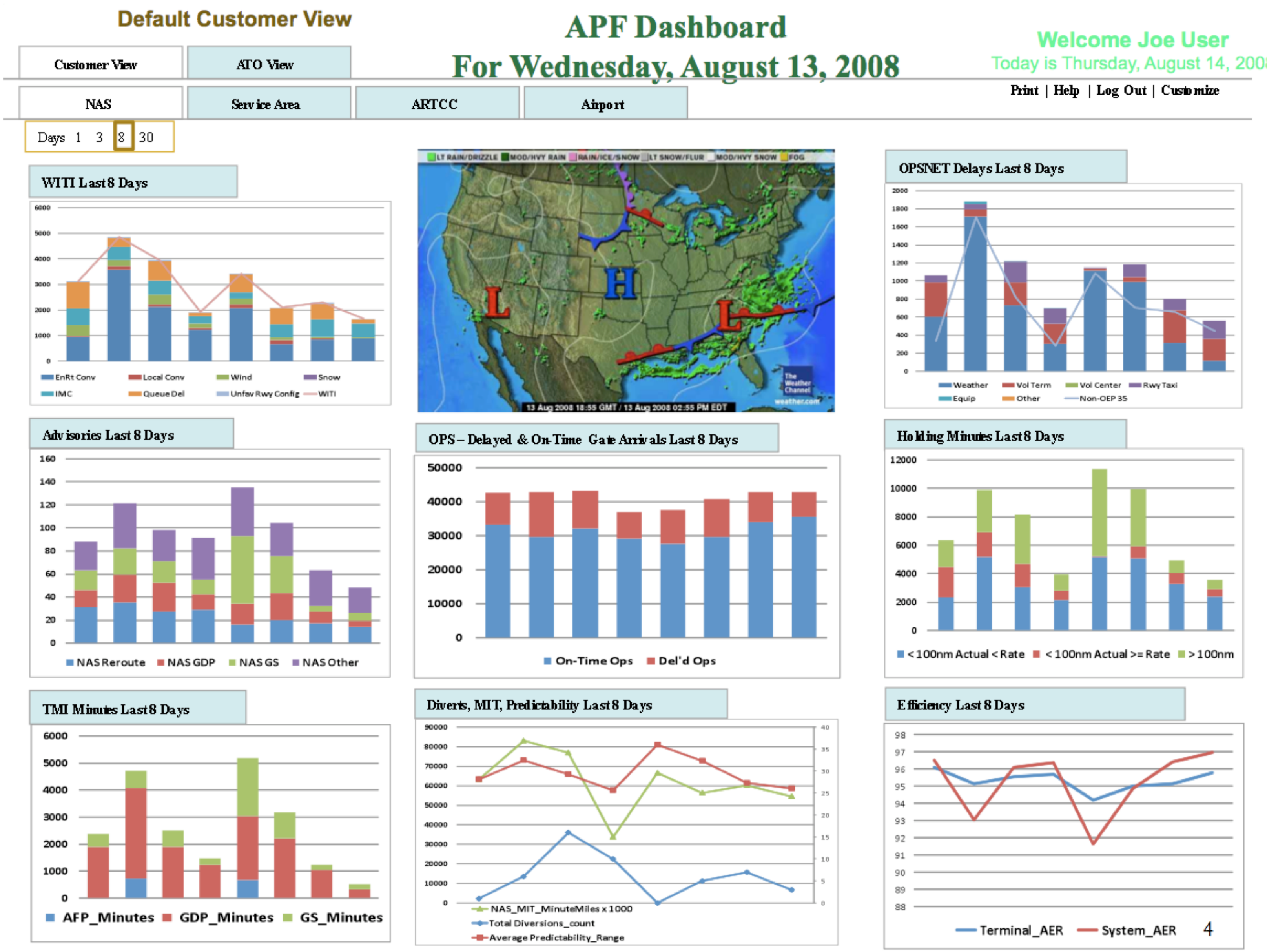
- Neural networks and MLR trained using 2005-2007 data and tested using 2008 data
- Higher correlation during summer
- Lower correlation in winter may be due to higher number of cancellations on days with heavy snow, very low ceilings/visibility

Airport Delay Models using Regression Analysis

Airport	γ_{LR}	γ_{MLR}	$\gamma_{MLR} / \gamma_{LR}$ - 1
ORD	0.743	0.803	0.08
ATL	0.752	0.777	0.03
EWR	0.640	0.725	0.13
PHL	0.764	0.805	0.06
DFW	0.577	0.646	0.12
JFK	0.618	0.670	0.08
LGA	0.685	0.723	0.06
LAX	0.195	0.496	1.54
IAH	0.684	0.725	0.06
DEN	0.550	0.664	0.21

- Modeled 34 major airports in the U.S.
- Good delay estimates for ORD, ATL,..
- Delay at major airports in Eastern U.S not influenced by NWX in the neighboring Centers

NAS Performance Metrics



NAS Performance Metrics

Default Customer View

APF Dashboard
For Wednesday, August 13, 2008

Welcome Joe User
Today is Thursday, August 14, 2008

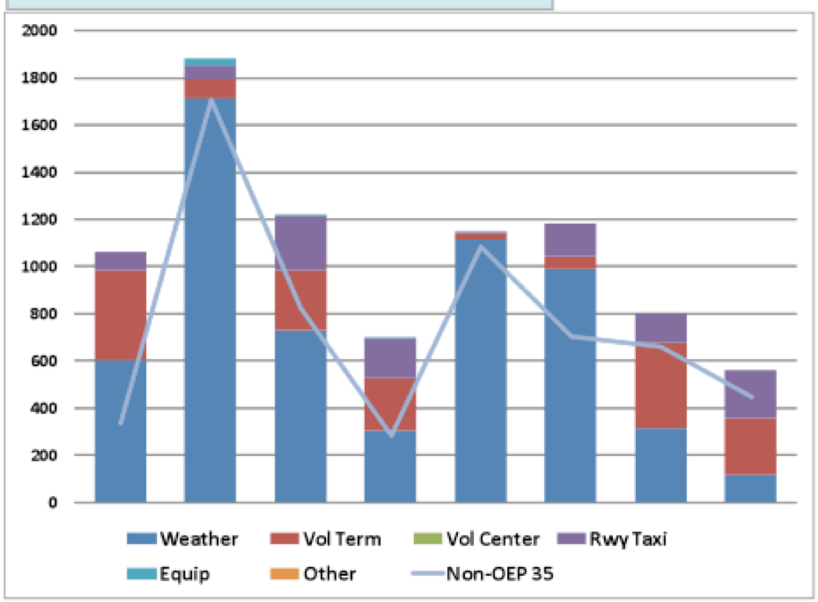
Customer View | ATO View

NAS | Service Area | ARTCC | Airport

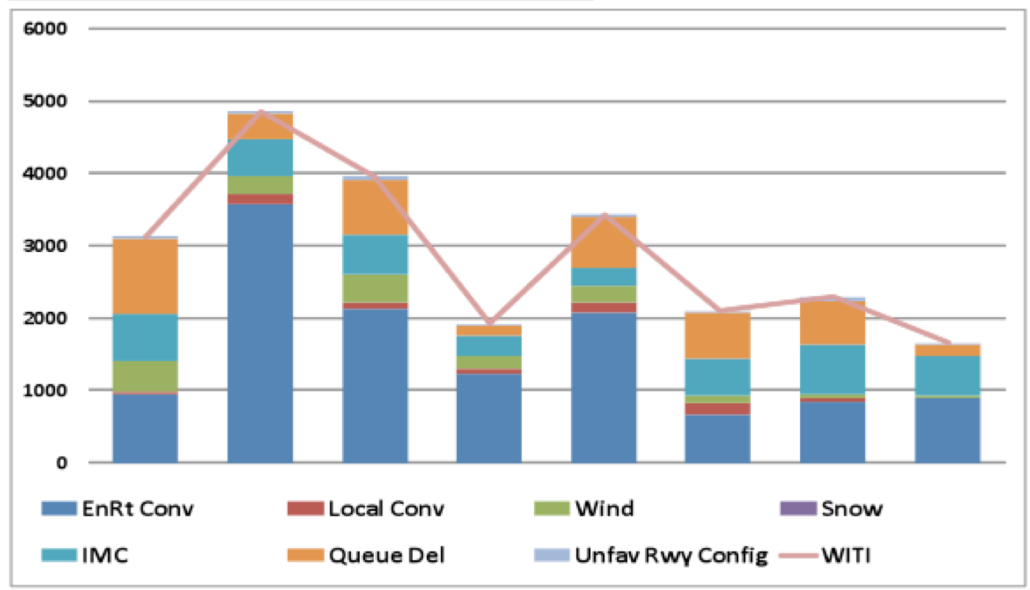
Print | Help | Log Out | Customize

Days 1 3 8 30

OPSNET Delays Last 8 Days



WITI Last 8 Days



Concluding Remarks: Weather Disruption

- WITI-based models provide a good basis for estimating delay due to convective weather
- Estimation/Modeling of performance metrics resulting from the use the two databases are complementary
- Models have higher correlation during summer than during winter
- For all metrics, neural networks produce higher correlation and reduced errors than regression methods
- Different models for summer and winter
- All metrics can be estimated to same level of accuracy

Non-Weather Events

- Non-Weather Events

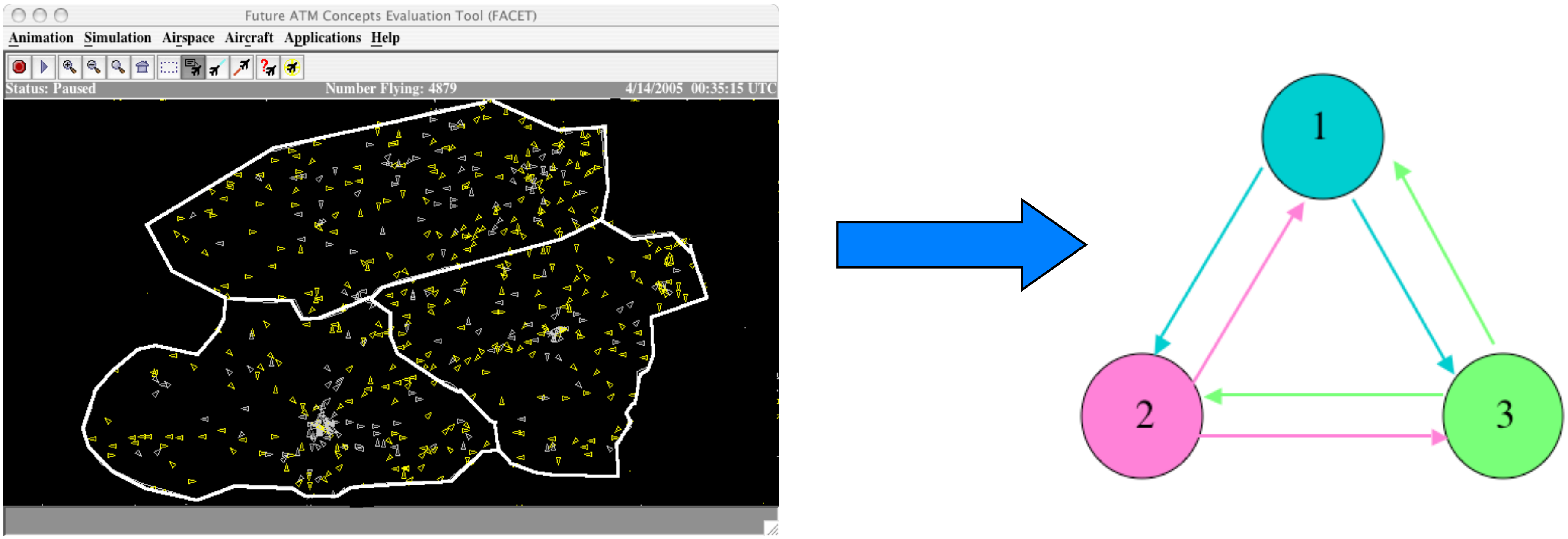
Modeling of Man-made Disruptions

- Need for alternate to simulation-based approaches
  - Lack of models for emerging disruptions like cyber attack
  - Computational difficulty of evaluating NAS behavior across possible scenarios and likely disruptions
  - Incomplete knowledge of traffic models
  - Difficulty in quantifying performance
- Approach: Design for building and evaluating robustness based on simple metrics
  - Robustness (Vulnerability Metrics) dependent on the structure of the NAS network and location of the disruption in the network
  - Computation of the vulnerability metrics based on limited knowledge of the network
- Objective: Establish easy-to-evaluate, topology-based VM for Air Traffic Management systems

Metrics Characteristics and Assumptions

- Characteristics/What to look for in a good metric?
  - Provide relative vulnerabilities to sets of traffic flows and sets of disruptions
  - Provide spatial and temporal impact of a disruption to a set of flows
  - Overall impact on the network to a unknown or stochastically described disruption
- Assumptions/Which disruptions have a major impact?
  - Large nominal flow
  - Flow path is subject to constraints
  - Lack of good alternative paths
- Examine Laplacian matrix representation of the network together with nominal flows as a candidate

Network Flow Models for Air Traffic Management



- 4D aircraft trajectories replaced with region counts, transition probabilities and departure rates

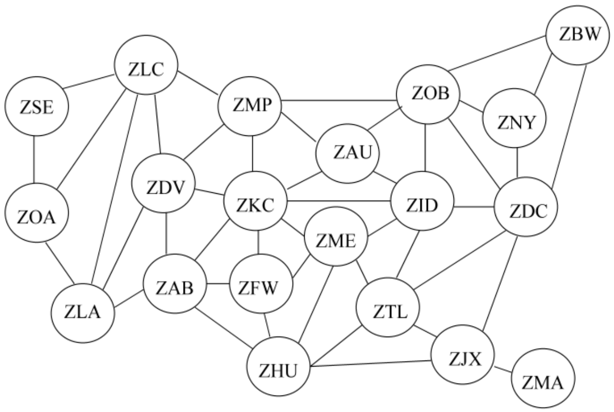
- Aggregate model reduces the number of states from hundreds to three

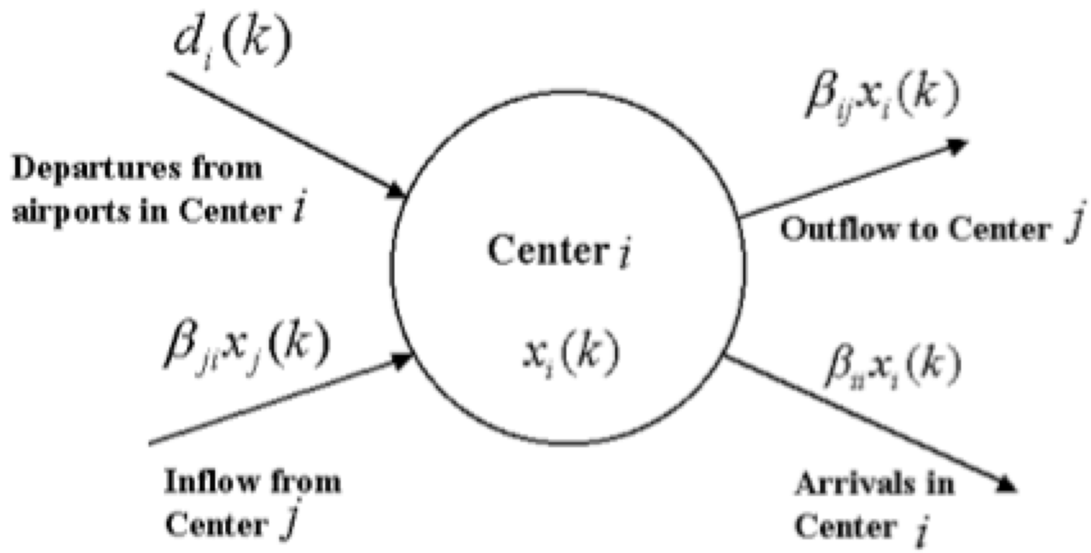
- Reduces dimensionality and complexity of the problem

- Previously shown to accurately reproduce traffic at the Center-level[1]

[1]Sridhar, B., Soni, T., Sheth, K., and Chatterji, G., “An Aggregate Flow Model for Air Traffic Management,” AIAA GN&C Conference, Providence, RI, Aug. 2004

Aggregate Flow Model





$$x_i(k+1) = x_i(k) - \sum_{j=1}^{N} \beta_{ij} x_i(k) + \sum_{\substack{j=1 \\ j \neq i}}^{N} \beta_{ji} x_j(k) + d_i(k)$$

$$d_i(k) = u_i(k) + w_i(k)$$

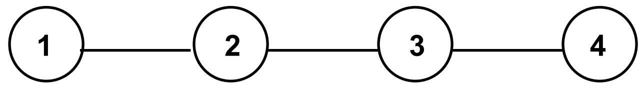
$$\mathbf{x}(k+1) = \mathbf{A}(k)\mathbf{x}(k) + \mathbf{B}(k)\mathbf{u}(k) + \mathbf{C}(k)\mathbf{w}(k)$$

Flow Matrix (May 6, 2003: 6 hour average, 5-11P.M, PST)

	zla	*zoa*	*zse*	*zlc*	*zdv*	*zab*	*zmp*	*zkc*	*zfw*	*zhu*	*zau*	*zme*	*ztl*	*zob*	*zid*	*zny*	*zbw*	*zdc*	*zjx*	*zma*
zla	.91	.05	0	.03	.02	.05	0	0	0	0	0	0	0	0	0	0	0	0	0	0
zoa	.04	.91	.03	.04	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
zse	0	.02	.93	.03	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
zlc	.01	.01	.02	.86	.06	0	.01	0	0	0	0	0	0	0	0	0	0	0	0	0
zdv	.01	0	0	.03	.86	.03	.05	.02	0	0	0	0	0	0	0	0	0	0	0	0
zab	.03	0	0	0	.02	.87	0	.01	.03	.01	0	0	0	0	0	0	0	0	0	0
zmp	0	0	0	0	.03	0	.85	.01	0	0	.05	0	0	0	0	0	0	0	0	0
zkc	0	0	0	0	.01	.02	.02	.84	.02	0	.02	.03	0	0	.02	0	0	0	0	0
zfw	0	0	0	0	0	.03	0	.01	.85	.06	0	.05	0	0	0	0	0	0	0	0
zhu	0	0	0	0	0	0	0	0	.05	.88	0	.01	0	0	0	0	0	0	.01	0
zau	0	0	0	0	0	0	.06	.03	0	0	.84	0	0	.03	.03	0	0	0	0	0
zme	0	0	0	0	0	0	0	.04	.06	.01	0	.84	.04	0	.03	0	0	0	0	0
ztl	0	0	0	0	0	0	0	0	0	.01	0	.04	.84	0	.05	0	0	.03	.06	0
zob	0	0	0	0	0	0	.01	0	0	0	.05	0	0	.75	.05	06	.01	.01	0	0
zid	0	0	0	0	0	0	0	.05	0	0	.04	.03	.04	.07	.81	0	0	.02	0	0
zny	0	0	0	0	0	0	0	0	0	0	0	0	0	.07	0	79	.05	.07	0	0
zbw	0	0	0	0	0	0	0	0	0	0	0	0	0	.02	0	08	.82	.01	0	0
zdc	0	0	0	0	0	0	0	0	0	0	0	0	.03	.03	.01	06	.01	.83	.03	0
zjx	0	0	0	0	0	0	0	0	0	.01	0	0	.05	0	0	0	0	.02	.86	.07
zma	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	.04	.88

Flow Matrix(A) - 23x23; Represented by 1 to 24 values for the entire day (144 time steps each 10 minutes)

Networks and Laplacian Matrix

- Network 

- Adjacency Matrix: *A*
  - $A(i,j)=1$ if nodes (i,j) are connected and 0 otherwise
- Diagonal Matrix of Degrees: D= Diag{1 2 2 1}
- Laplacian Matrix: L=D-A

$$A = \begin{matrix} 0100 \\ 1010 \\ 0101 \\ 0010 \end{matrix} \qquad L= \begin{matrix} 1 & -1 & 0 & 0 \\ 1 & 2 & -1 & 0 \\ 0 & -1 & 2 & -1 \\ 0 & 0 & -1 & 1 \end{matrix}$$

- Properties of the Laplacian Matrix
  - 0 is an eigenvalue; $0=\lambda_1 \le \lambda_2 \le \lambda_3 \le .....\lambda_n$
  - λ_2: Fiedler eigenvalue is a measure of algebraic connectivity of a graph; Graph is more connected as it moves away from zero

Vulnerability Metrics (VM)

- Normalized Right eigenvector, ϑ, associated with the smallest non-zero eigenvalue, λ_2, characterizes the connective properties of the graph
- $|\vartheta_i - \vartheta_j|$: Indicator of presence or absence of alternative short paths from node *i* to node j
  - Small, many short alternate paths between the nodes
  - Large, sparse long paths between nodes
- Vulnerability depends on nominal flow, f_{ij}
  - Larger the flow more alternate paths are needed
- Vulnerability Metric for traffic flow from node *i to j*

$$V_{ij} = f_{ij} \left| \vartheta_i - \vartheta_j \right|^2$$

- Event Vulnerability Metric to disruption S

$$V_E = \sum_{(i,j) \in S} p_{ij} V_{ij}$$

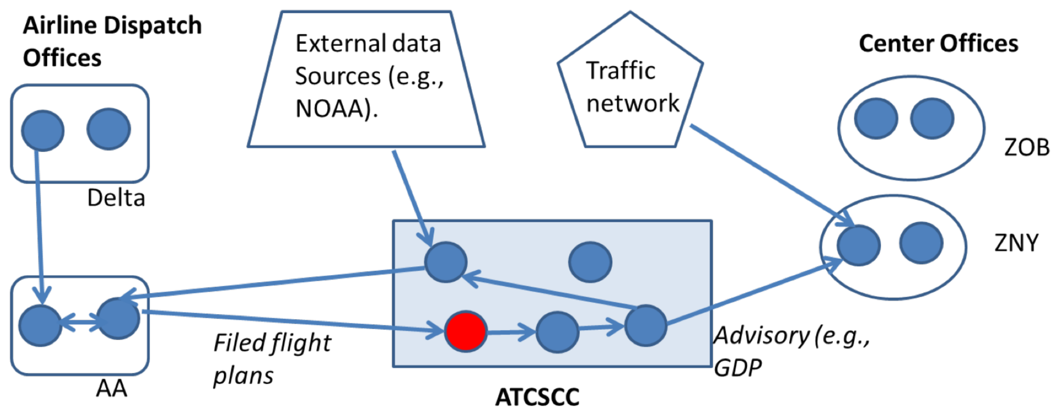
Vulnerability Metrics (Continued)

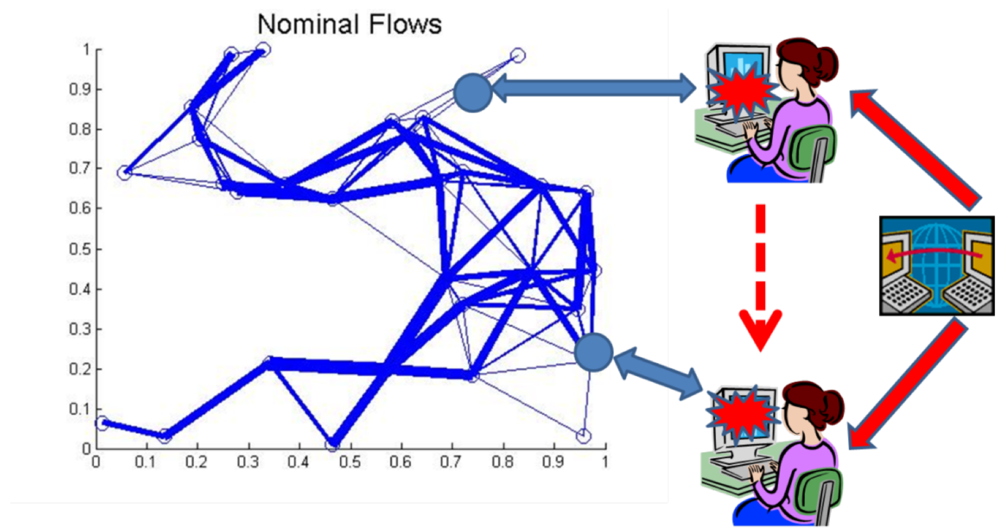
- Event Vulnerability Metric approximates impact of several flow disruptions as equivalent to the sum of disruptions to individual flows
- Total Vulnerability Metric: overall sensitivity of the network to disruption or the expected impact level of a completely unmodeled disruption

$$V_T = \sum_{(i,j)} V_{ij} / \lambda^2 = \sum_{(i,j)} f_{ij} \left| \vartheta_i - \vartheta_j \right|^2 / \lambda^2$$

Modeling Cyber Systems

- Cyber system provides information for the effective management and control of the Air Traffic System
  - Specialized data transfer for air traffic system
  - General information from the broader Internet
  - Use standard protection technologies (standard firewalls, virus checking software, limited amount of encryption)
  - Subject to failures and deliberate software and hardware attacks





Modeling Cyber Systems: Information network

- Information network with m nodes, i=1,2,..m and each node provides information needed to manage ATS
- Each node x(i) has two states: Normal (N) or Failure (F)
- Simple model
  - Node x(i) is in state F with probability p(i) independently of all other nodes
  - Suitable for component and localized failures; structured deterministic failures; phishing attacks
- More general model
  - Models information flow according to a specified network and thus correlation of disruptions of information
  - Used in the context of spread of computer-virus
  - Stochastic percolation model

Stochastic Percolation Model

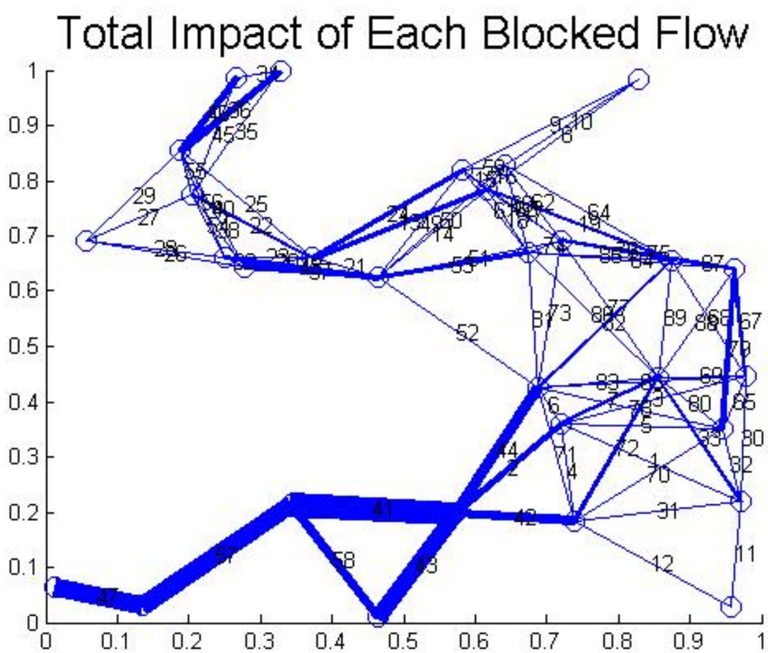
- Each node *i* has a probability, $p_0(i)$, of being infected at initial stage k=0
- At stage k, each node i that has just been infected at stage (k-1) may further infect neighboring node j with probability, $p_k(j,i)$,depending on the network.
- Generalizes the simple model
- Cyber model interacts with the traffic layer model as information necessary for a certain operation over a period of time (a major flow, jet route, a sector or a group of sectors, or airline traffic information) by affecting nominal parameters in the traffic system

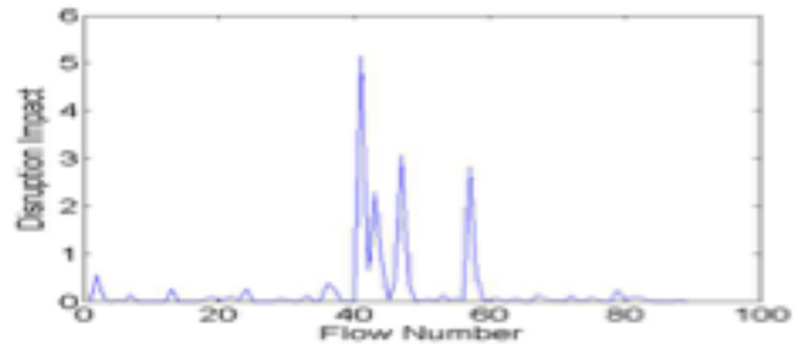
Evaluation of Link-Vulnerability Metric (VM)

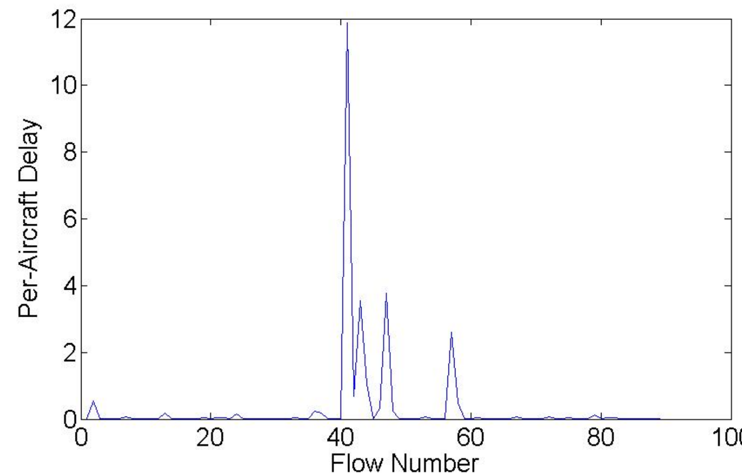
- Evaluate VM by comparing results by simulating traffic flow and disruptions using Aggregate (Eulerian) and queueing network models
- Aggregate Model: Traffic flow simulation involving 30 waypoints and 88 links representing traffic flow to 3 destinations (airports or regions) from 10 origin points (airports or regions)
- Queueing network: Traffic flow simulation representing 16 waypoints, 6 sectors, 4 O-D pairs, 24 links

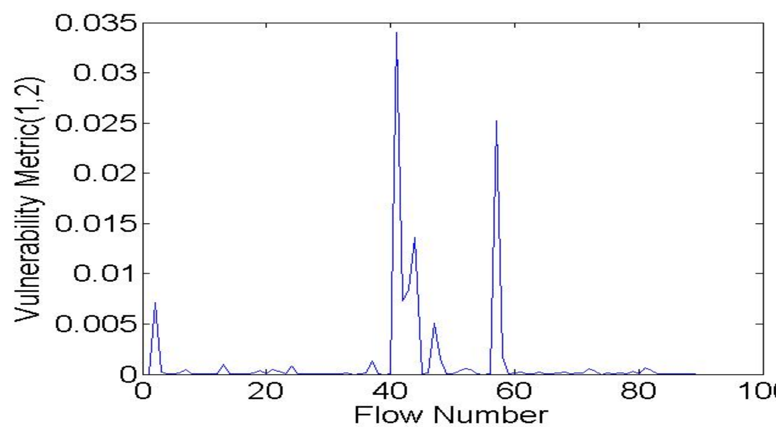
VM comparison using Linear Aggregate Models

- Disruption impact
  - Measured by creating flows with and without blockage
  - Sum of squared differences in flows
- VM high for links with strong impact



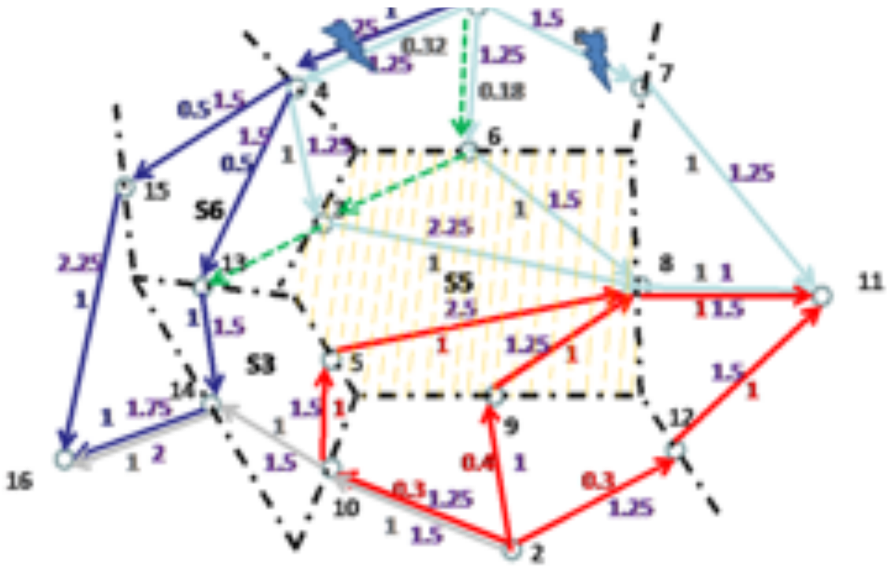






VM comparison using Queueing Network Model

- Extensively used as a tool for predicting delays, congestion and designing traffic management systems
- Simulated network used for comparison
  - 16 waypoints, 6 sectors, 4 O-D pairs, 24 links
- 3 Most vulnerable flows based on metrics:10-14,1-4, 2-10
- For each blockage provide realistic alternate routes and compare impact of (1-4) with (1-7)



	Delay	Deviation	Metric
Nominal	17.7	0.0	
Block (1-4)	67	7.6E3	0.144
Block (1-7)	19.2	3.2E3	0.028

Concluding remarks

- More details in the paper on evaluation of VM
- Presented results on the estimation of NAS performance metrics using past data and weather prediction to estimate delays in Air Traffic management
- Presented preliminary results on Vulnerability Metrics as a way to capture the impacts of cyber attacks on the system
- WITI and VM represent high level measures on the impact of natural and man-made disruptions on Air Traffic Systems

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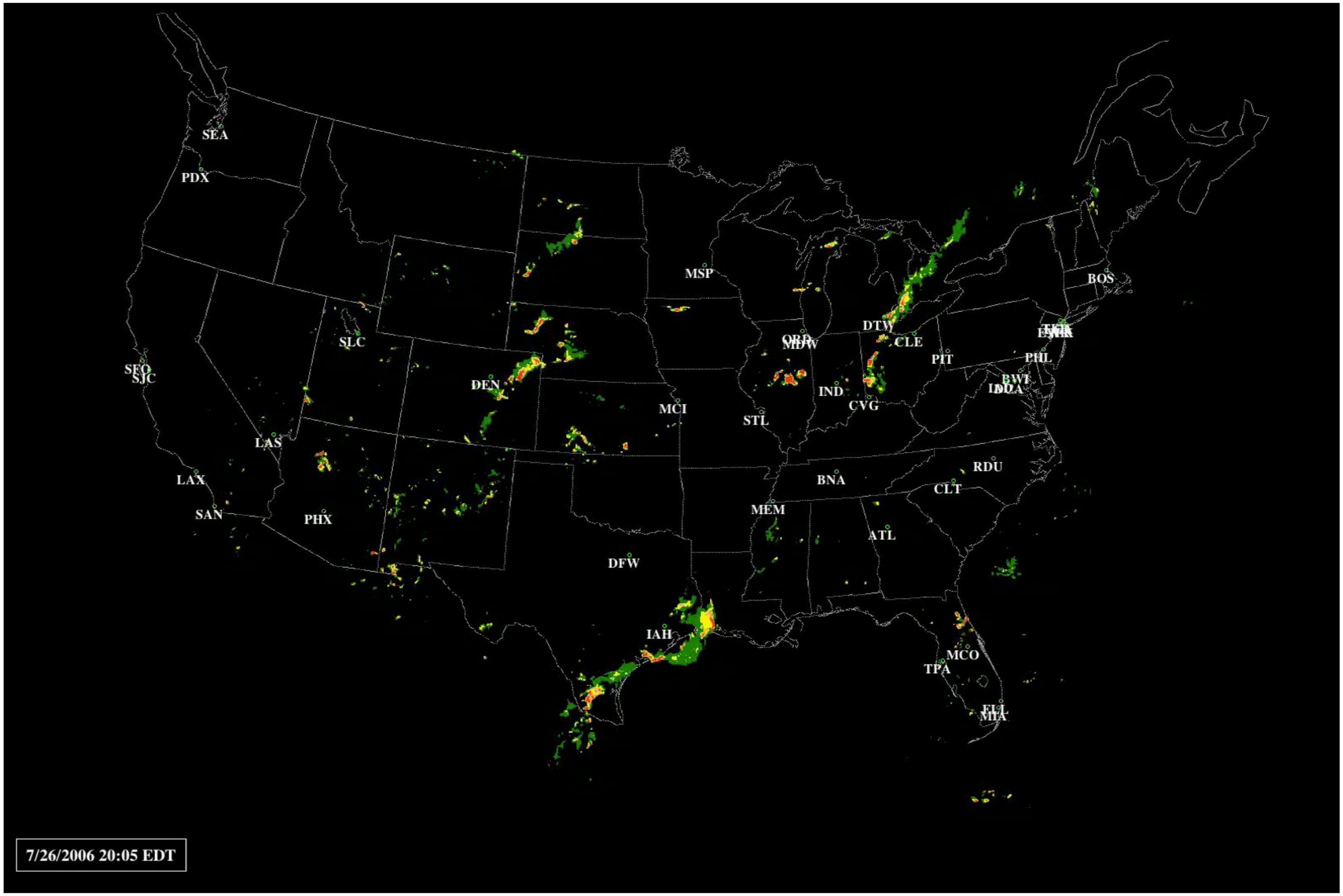
- …….

Additional Viewgraphs

Delayed Flights



Neural Network Models

- Number of hidden layer
  - One was found adequate
- Number of neurons
  - Different values were used and errors for each were estimated
  - Neurons in the range 2/3(sum of number of inputs and outputs) provided consistent results and error
- Activation function
  - Nonlinear sigmoid function

Concluding remarks

- Described linear time varying models to represent traffic flow for developing strategic TFM decisions.
- Linear dynamic system model with a few transition matrices and Gaussian departure distribution adequately represents traffic behavior at the Center-level.
- Advantages of linear model
  - The model order is reduced by several orders of magnitude from 5000 aircraft trajectories to 23 states at any given time.
  - Tools and techniques of modern system theory can be applied to this model due to its form.
- Capabilities of this class of models for strategic traffic flow management will be explored in the future.