Soft Computing (SC) in the Design of Anomaly Detection Models (AD)

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Outline

3 2 1

[Soft Computing in the Model Design of Anomaly Detectors]

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1 **Anomaly Detection**

Motivation: Prognostics and Helath Management (PHM)

2 **Model Generation**

Domain Knowledge and Field Data

3 **Soft Computing: Evolution of a Concept**

History (1991-2007)

Current Soft Computing View (2010)

4 **Applications of SC to Anomaly Detection**

Anomaly Detection for Aircraft Engine

Fusion of Models (Categorical & Time-series Data) to reduce false alarms

Use of EA +FS + AANN to improve model accuracy

5 **Conclusions & References**

Anomaly Detection

Motivation: Prognostics and Helath Management (PHM)

Why is Prognostics & Health Management Important

Without PHM

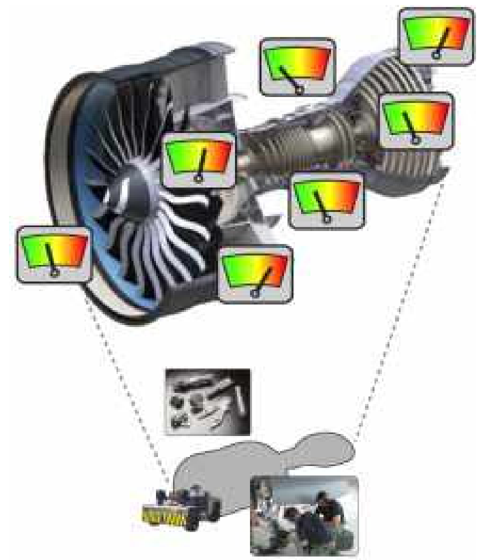
It's difficult to know useful life left in an engine

This leads to a large logistics footprint and higher operating costs

Conservative estimates are necessary to ensure reliability.
Parts replaced while they are still useful.
Even with large spares inventory unforeseen problems can cause major fleet disruptions.

With PHM

Specific engine part conditions are known.
Small problems can be addressed before they lead to larger more costly maintenance



Smaller logistics footprint - lower costs

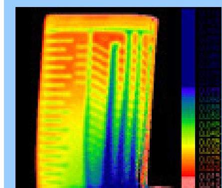
Reduced spares inventory.
Engine parts replaced only when necessary - reduced maintenance. Engines have longer life with better reliability.
Fleet maintenance is more manageable with fewer disruptions.

PHM is a major enabler for Condition Based Maintenance (CBM)

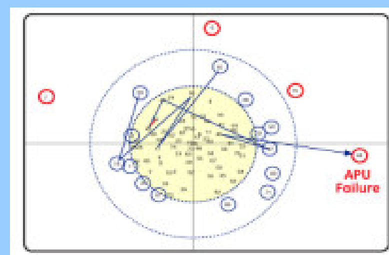
CBM Goals:	*Unplanned → Planned Maintenance Events*
PHM Evolution:	*Diagnostics → Prognostics → Optimization*

Technical Synergy in PHM

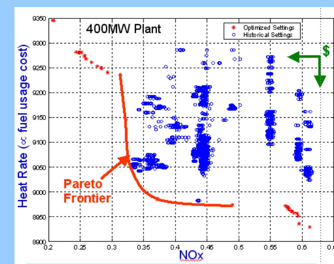
Prognostics and Health Management (PHM)



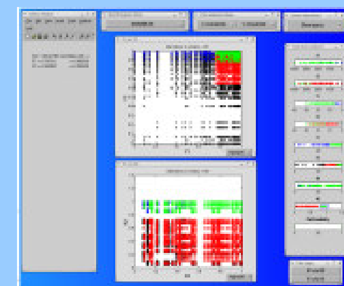

On-board Sensors & Off board Inspections



Anomaly Detection, Diagnostics & Prognostics Alg.



On-board / Off board Optimization Alg.

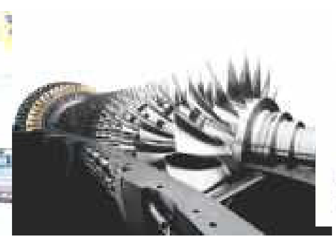


Visualization & Multi-Criteria Decision-Making Sys.

GE Installed Basis: 175K Assets (Planned Expansion: 175K→ 290K)

105K units	**33K units**	**22.7K units**	**1.1K units**	**12.4K units**
Imaging devices PACS servers/workstations	Engines / Aircrafts (fixed & rotary wings)	Turbines / Engines / Motors / Plants / towers	Turbines	Locomotives





GE Healthcare **GE Aviation** **GE Energy** **GE Oil & Gas** **GE Rail**

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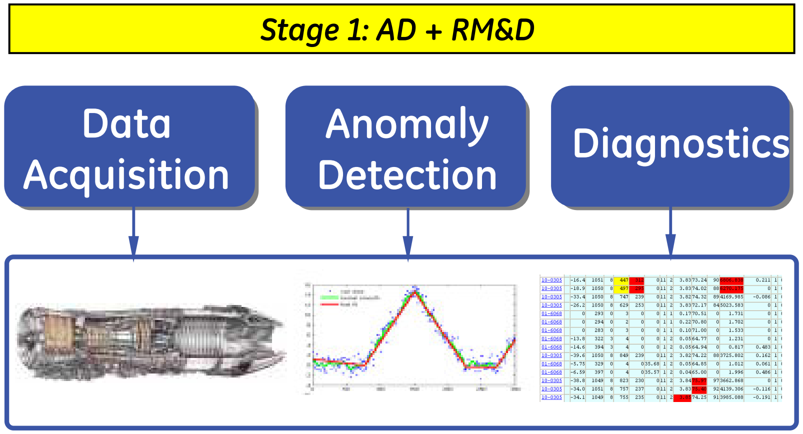
PHM Capabilities and Enabling Technologies



Data Acquisition: Remote Monitoring of a fleet of assets (legacy fleets use existing instrumentation)

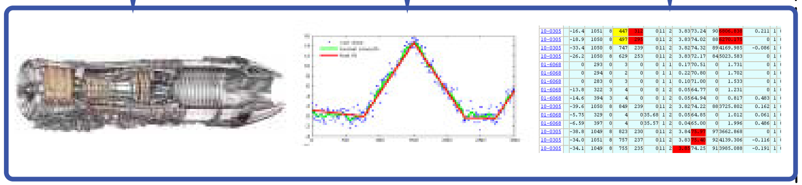
Anomaly Detection: Identification of assets deviating from the rest of the fleet (Anomaly detection)

Diagnostics: Root Cause Isolation for each asset exhibiting anomalous behavior

PHM Capabilities and Enabling Technologies

Stage 1: AD + RM&D

Data Acquisition | **Anomaly Detection** | **Diagnostics**



Data Acquisition: Remote Monitoring of a fleet of assets (legacy fleets use existing instrumentation)

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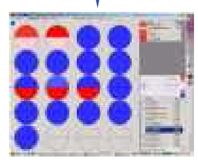
Stage 2: Prognostics

Prognostics



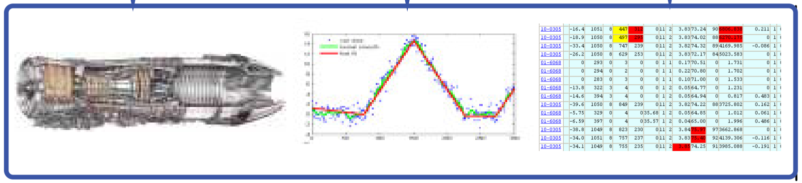
Prognostics: Prediction of each asset's remaining useful life (RUL) : the decision's time-horizon.

Unplanned → Planned Maintenance

PHM Capabilities and Enabling Technologies

Stage 1: AD + RM&D

Data Acquisition | Anomaly Detection | Diagnostics



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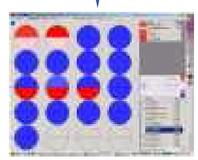

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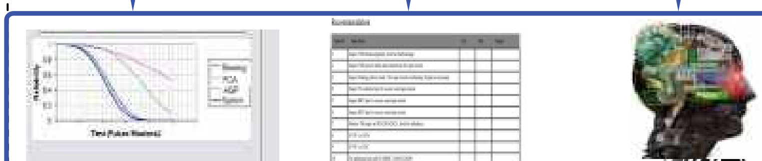
Unplanned → Planned Maintenance

Stage 3: Control & Optimization

Control / Advisory Generation | Optimization | Feedback & Learning



Control / Advisory Generation Real-time decisions: safety actions, fault accommodation & recovery

Optimization: Offline decisions: Optimize maintenance actions, supply chain mgmt., production

Feedback & Learning Validation of maintenance cases, automated learning of patterns

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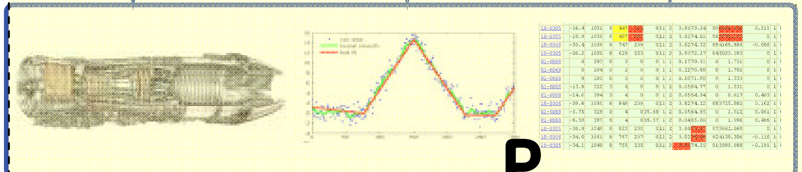
PHM Capabilities and Enabling Technologies

Stage 1: AD + RM&D

Data Acquisition | Anomaly Detection | Diagnostics



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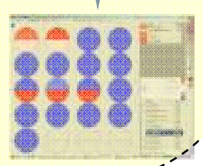
Stage 2: Prognostics

Prognostics



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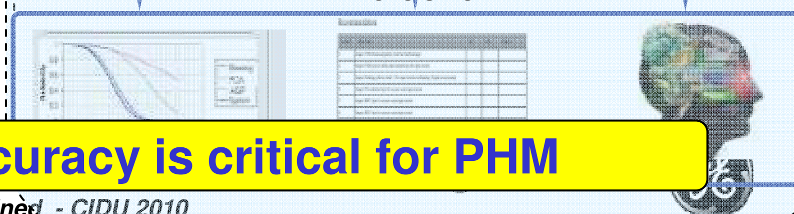


Control / Advisory Generation Real-time decisions: safety actions, fault accommodation & recovery

Optimization: Offline decisions: Optimize maintenance actions, supply chain mgmt., production

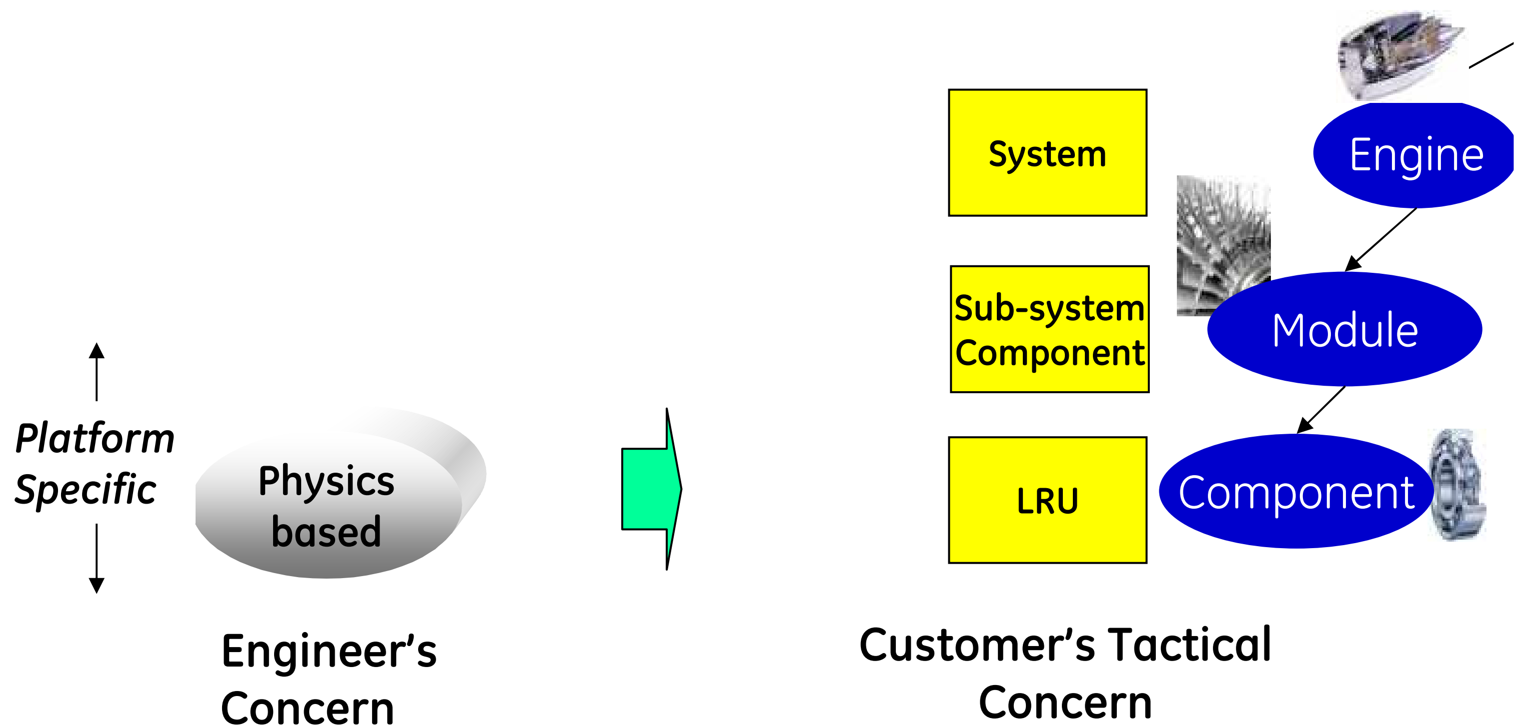
Feedback & Learning Validation of maintenance cases,

Increasing Anomaly Detection Accuracy is critical for PHM

Model Generation for Decision Making

Domain Knowledge and Field Data

Classical Engineering Approach



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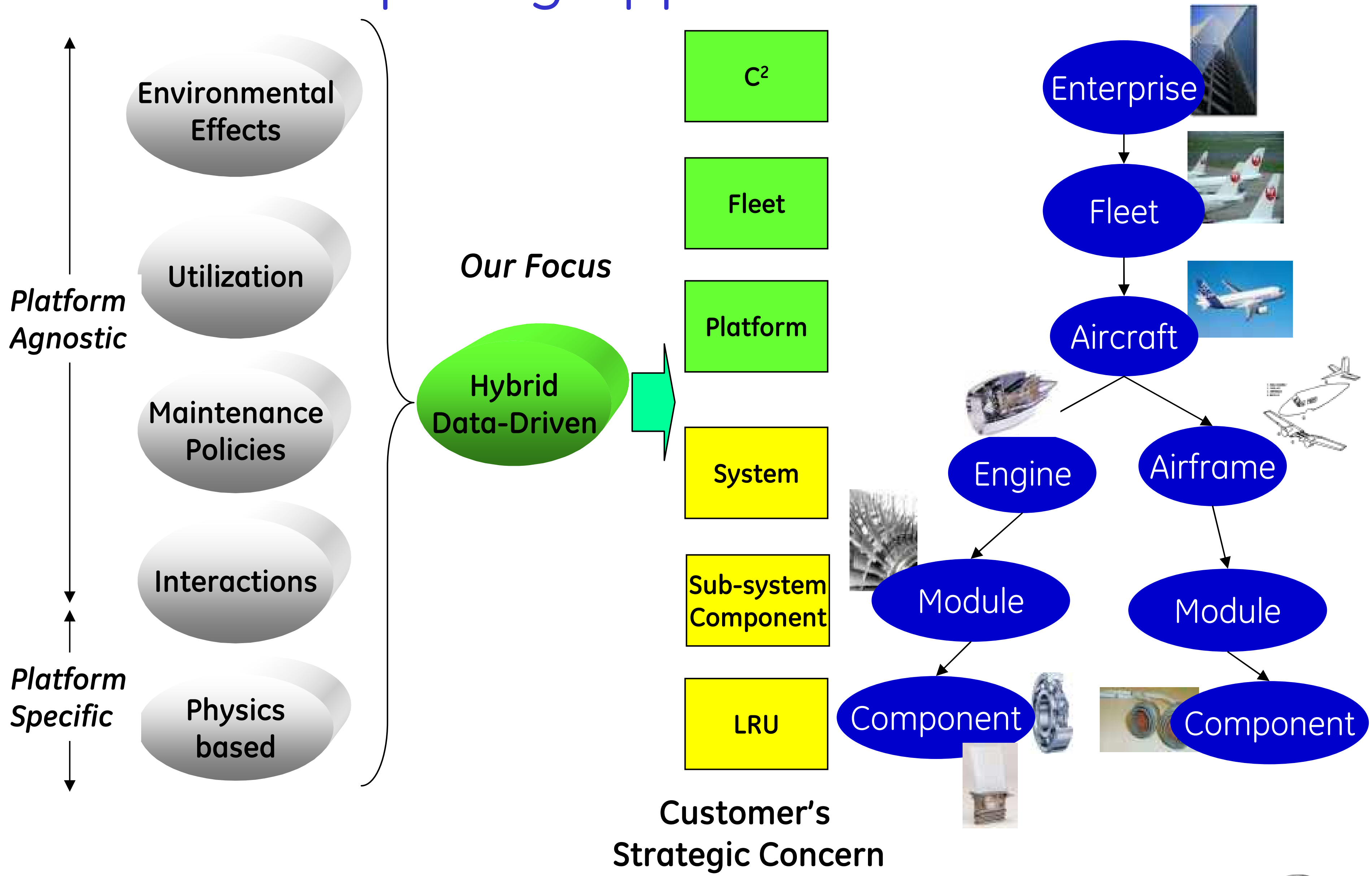
Soft Computing Approach



Integrating physics-based with data-driven approaches into hybrid systems

Model Generation

Model =

Representation (Structure + Parameters)

+ Reasoning Mechanism + Search Method

Examples of Modeling Methodologies:

- Differential Equations
- Bayesian Belief Networks
- Neural Networks
- Fuzzy Systems (Mamdani or TS type)
- Instance Based Systems

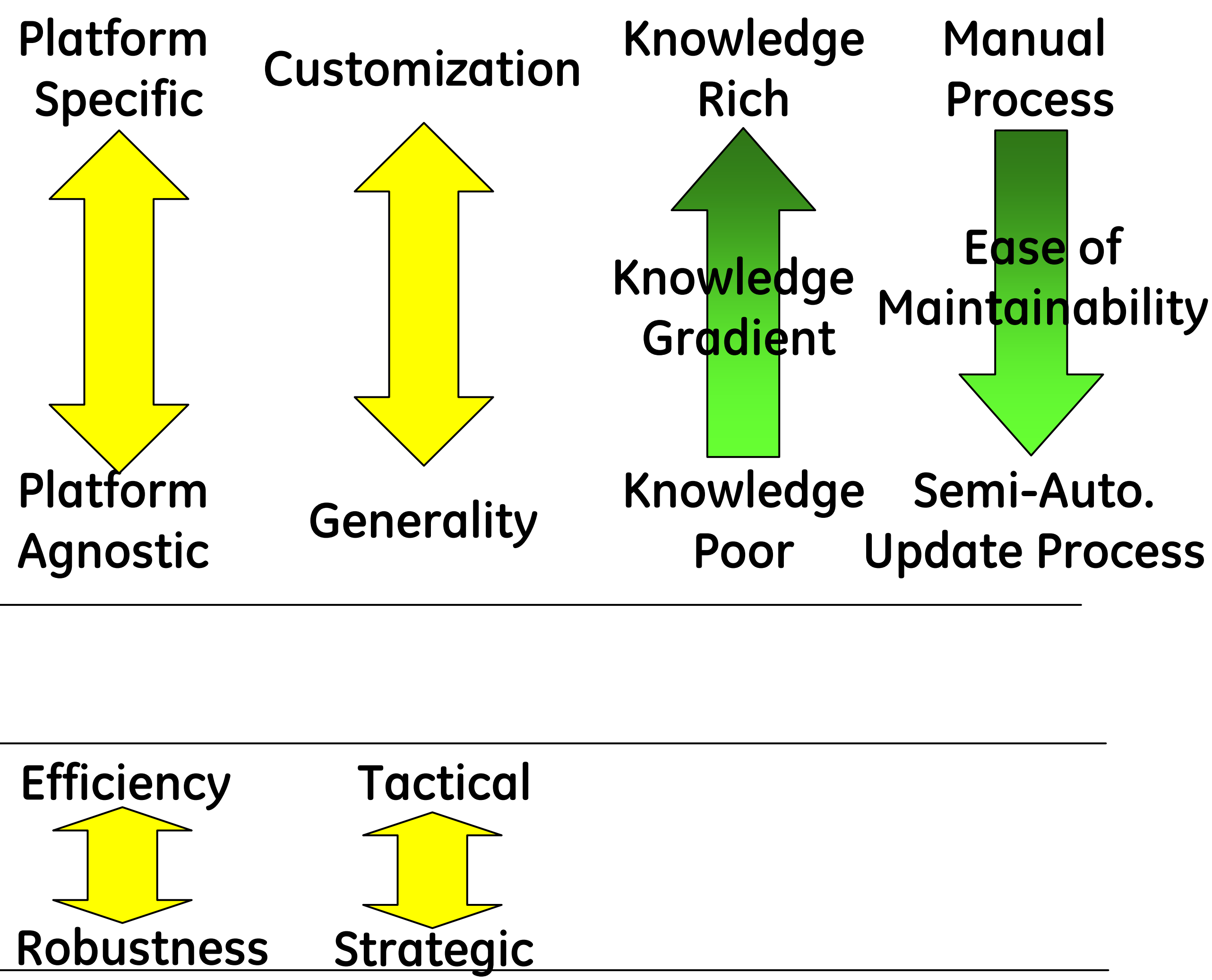
Representation, Reasoning & Design Search

REPRESENTATION

Modeling Techniques	*Linear Differential Equations*	*Bayesian Belief Networks*	*Neural Networks*	*Fuzzy Systems (TSK)/(ANFIS)*	*Instance Based Reasoning*
Model Structure	Order	Topology	Topology	Rule Set	Attribute Space
Model Parameters	Coefficients	Prior Prob. Conditional Prob.	Biases Weights	Term sets Scaling Factors Coefficients	Attribute weights Similarity parameters
Reasoning Mechanism	Solve equations - Closed form - Approximation	Propagation	Propagation	Node evaluation & Propagation	Local Model evaluation & Output combination
Design Search Method	First principle Energy balance methods (Bond Graphs)	Manual EM EA …	Manual EA Backpropagation Conjugate gradient,	Manual EA Backpropagation …	Manual EA …
			…		

PHM Modeling and Optimization: Dynamic Models

	Modeling
Control, Statistics Core Competence (leveraged as needed)	*Dynamic Models*
	Statistical Models
AI, SC, Statistics Core Competence	*KB Models Probabilistic &/or Deterministic Mappings*
	Implicit Models (Data-driven only)
	Optimization (Model Lifecycle) (Design, Tune, Update)
AI, SC, OR Core Competence	*Local Search*
	Global Search



PHM Modeling and Optimization: Dynamic Models

Modeling

Dynamic Models

Statistical Models

KB Models Probabilistic &/or Deterministic Mappings

Implicit Models (Data-driven only)

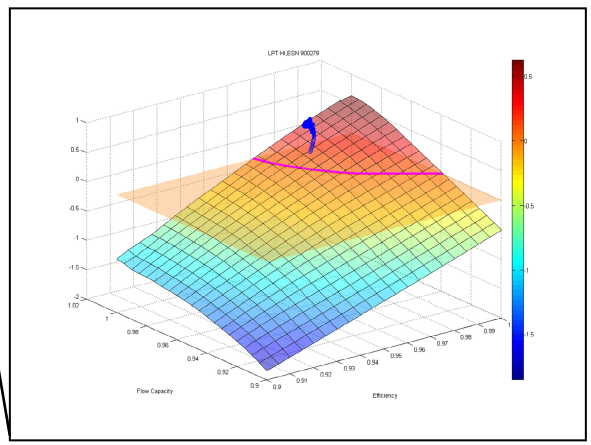
Optimization (Model Lifecycle) (Design, Tune, Update)

Local Search

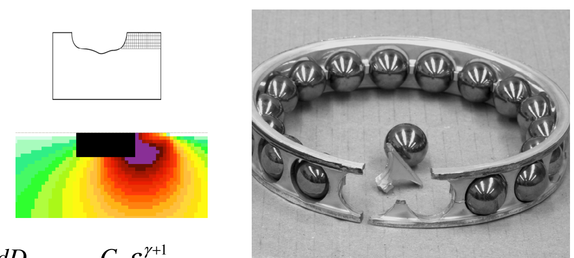
Global Search

Data Req.	Knowledge Req.	Underlying Science/Eng	PHM Functions	Examples
High sampling Frequency; Parametric data	Traditional Eng.: Analytical Models CFD Models	System Theory; Control Theory; Signal Processing; Mech. Eng. & Mat.'l Sciences	Anomaly ID, Diagnostics, Fault Accommodatio n	Tracking Filter CycleDeck Physics-based Fault Propagation

Calculating RUL in Flow-Efficiency Space using Cycledeck



Fault Propagation



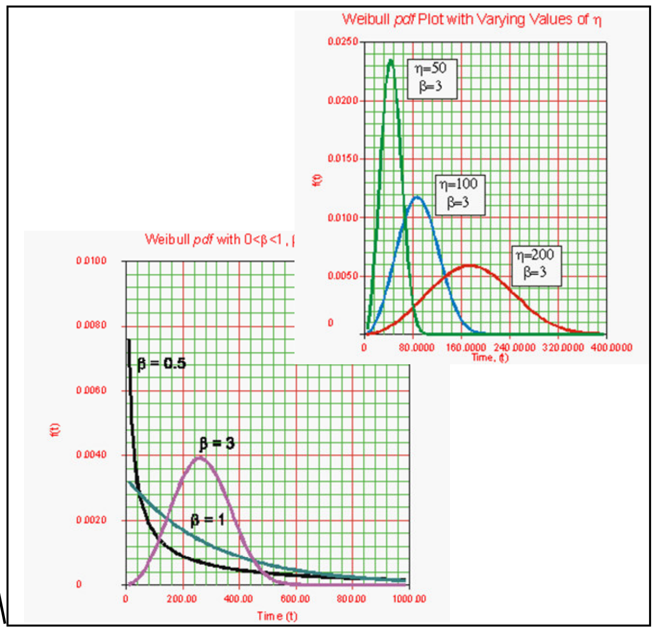
$$\frac{dD}{dN} = \frac{C_{tr}\varepsilon_P^{\gamma+1}}{\Gamma(\gamma+1)(1-D)^2}$$

PHM Modeling and Optimization: Statistical Models

Modeling
Dynamic Models
Statistical Models
KB Models Probabilistic &/or Deterministic Mappings
Implicit Models (Data-driven only)
Optimization (Model Lifecycle) (Design, Tune, Update)
Local Search
Global Search

Data Req.	Knowledge Req.	Underlying Science/Eng	PHM Functions	Examples
Large data sets to derive distributions; Parametric data	Main Variables; Distributions & Relationships;	Statistics Operational Research	Anomaly Det. Lifing (deterioration)	Weibull Mixture of Models

Weibull effects of changing shape and scale parameters



3 parameter Weibull

$$f(T) = \frac{\beta}{\eta}\left(\frac{T-\gamma}{\eta}\right)^{\beta-1} e^{-\left(\frac{T-\gamma}{\eta}\right)^{\beta}}$$

$$MTBF = \overline{T} = \gamma + \eta \times \Gamma\left(\frac{1}{\beta}+1\right)$$

η = scale parameter,
β = shape parameter (or slope),
γ = location parameter

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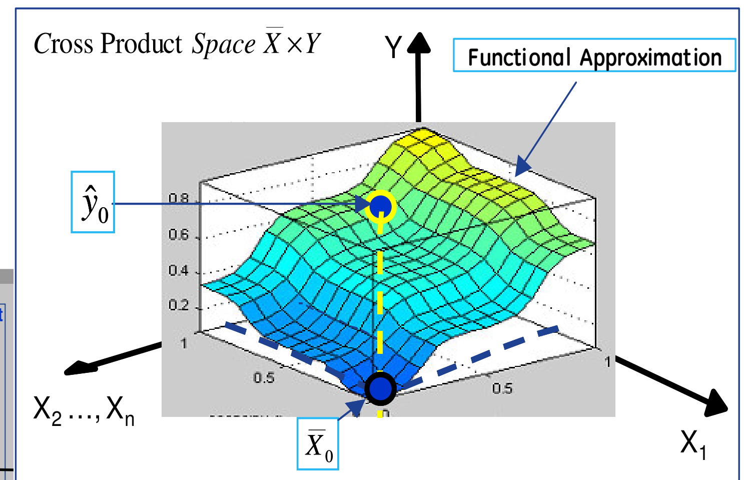
PHM Modeling and Optimization: KB Models

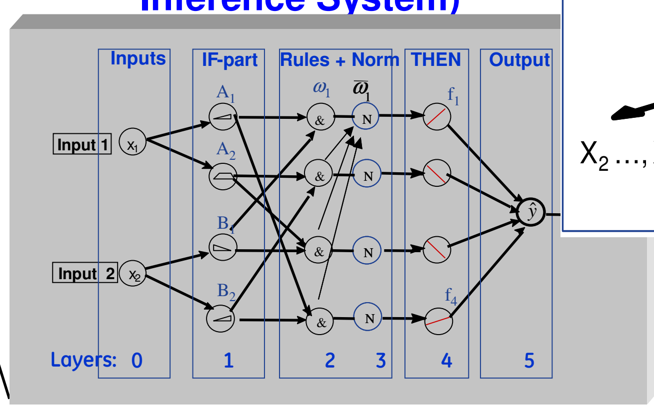
Modeling
Dynamic Models
Statistical Models
KB Models Probabilistic &/or Deterministic Mappings
Implicit Models (Data-driven only)
Optimization (Model Lifecycle) (Design, Tune, Update)
Local Search
Global Search

Data Req.	Knowledge Req.	Underlying Science/Eng	PHM Functions	Examples
Medium-size training set; Parametric &/Or Non-parametric data Labeled & Unlabeled	Relevant input variables Causal Relationships	Functional Approximation Theory Soft Computing (SC): Fuzzy-Neural Nets, Bayesian Models, Fuzzy Models	Anomaly ID, Diagnostics Fault Accommod. Prognostics	ANFIS BBN FS NN

Functional Approximation



Adaptive Neural Fuzzy Inference System)



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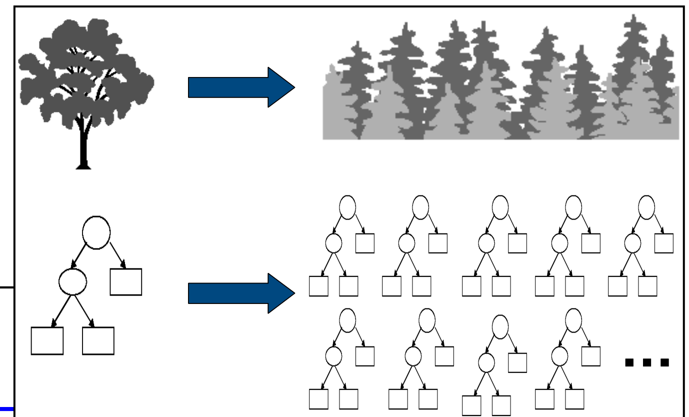
PHM Modeling and Optimization: Implicit Models

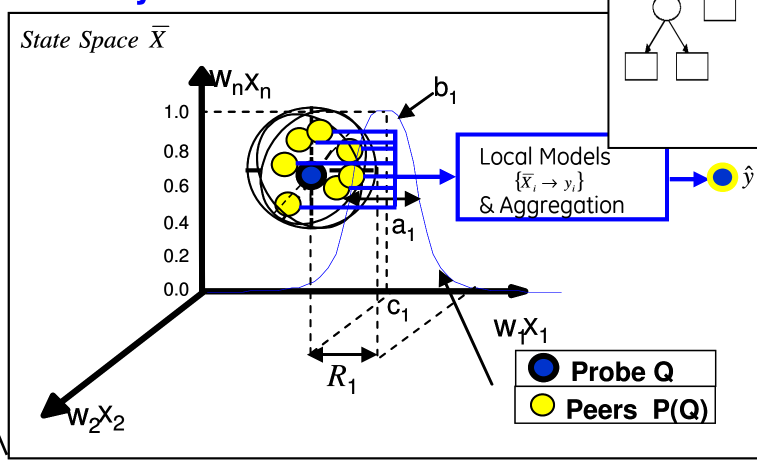
Modeling
Dynamic Models
Statistical Models
KB Models Probabilistic &/or Deterministic Mappings
Implicit Models (Data-driven only)
Optimization (Model Lifecycle) (Design, Tune, Update)
Local Search
Global Search

Data Req.	Knowledge Req.	Underlying Science/Eng	PHM Functions	Examples
Medium-size Data sets; Parametric &/Or Non-parametric data	Relevant input variables	AI (ML) & SC:, Instance-Case- Based Reasoning; Kernel Based models Instance Based models	Anomaly ID, Diagnostics Fault Accommod.	RF SVM RBF

Random Forest



Fuzzy Instance Based Model

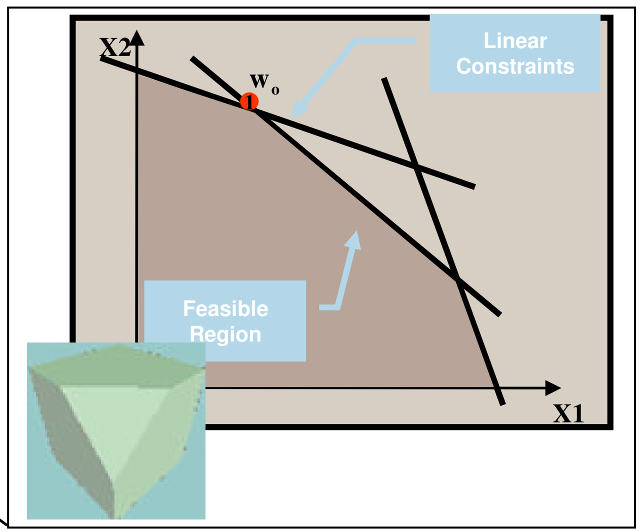


PHM Modeling and Optimization: Local Optimization

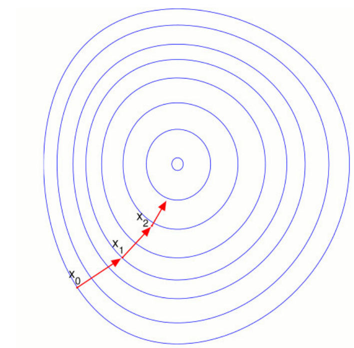
Modeling
Dynamic Models
Statistical Models
KB Models Probabilistic &/or Deterministic Mappings
Implicit Models (Data-driven only)
Optimization (Model Lifecycle) (Design, Tune, Update)
Local Search
Global Search

Data Req.	Knowledge Req.	Underlying Science/Eng	PHM Functions	Examples
Gradient Information Geometry, Topology	Problem Structure & Constraints	OR (Mathematic Programming)	Model Parametric Tuning	LP, Integer Programming, etc.

Linear Programming



Gradient Descent



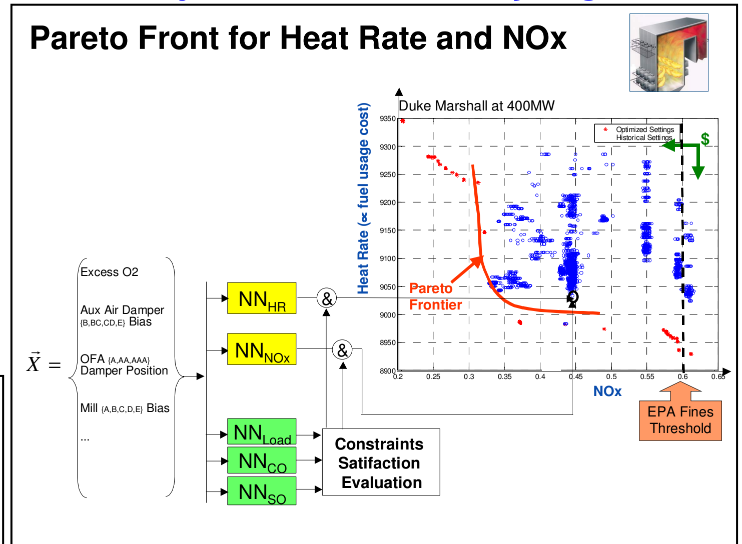
$$\Delta w = -\eta \nabla_w E + \alpha \Delta w_{prev}$$

PHM Modeling and Optimization: Global Optimization

Modeling
Dynamic Models
Statistical Models
KB Models Probabilistic &/or Deterministic Mappings
Implicit Models (Data-driven only)
Optimization (Model Lifecycle) (Design, Tune, Update)
Local Search
Global Search

Data Req.	Knowledge Req.	Underlying Science/Eng	PHM Functions	Examples
Solution Evaluation (Fitness Function)	Problem Structure Constraints, Encoding, …	Soft Computing (SC): Evolutionary Algorithm, Meta-heuristics Hybrid Optimization	Model Structural & Parametric Tuning	GA, GP, PSO, Ants Colonies, Tabu Search

Multi Objective Evolutionary Algorithm



Evolutionary Algorithms

$$\boxed{x[t+1] = s(v(x[t]))}$$

$x[t]$: population at time t under representation x

v : variation operator(s)

s : selection operator

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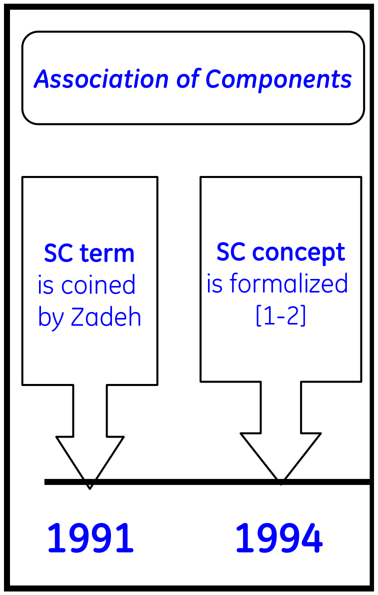
Soft Computing: Evolution of a Concept

History: 1991-2007

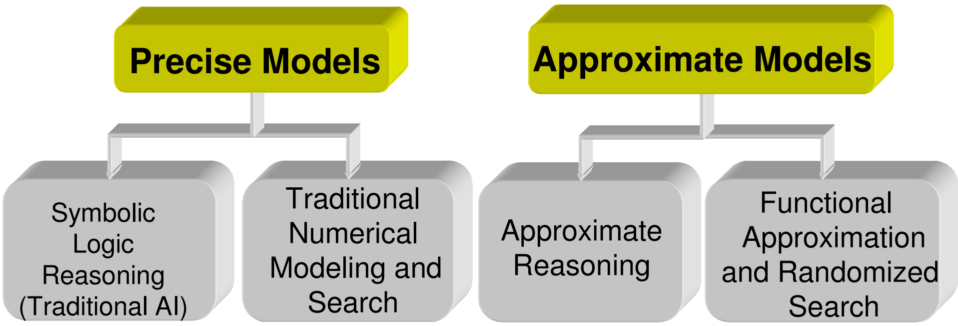
- Current Soft Computing View (2010)

    Offline Meta to design Online Meta and Object models

Soft Computing (SC): The Origins

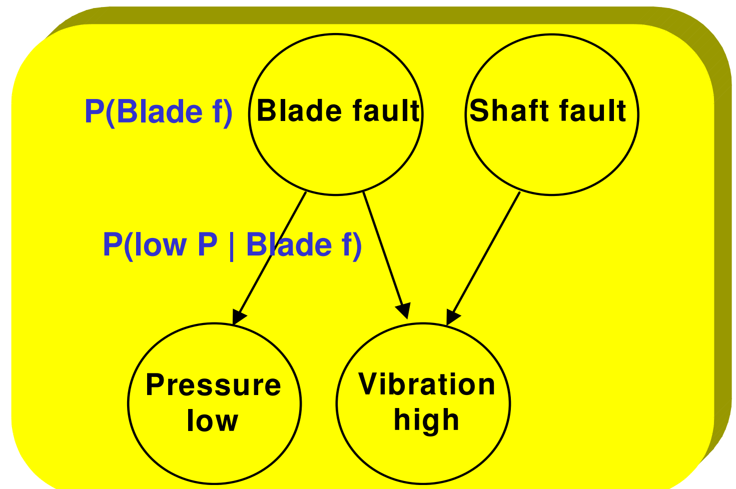


"In contrast to traditional hard computing, soft computing exploits the tolerance for imprecision, uncertainty, and partial truth to achieve tractability, robustness, low solution-cost, and better rapport with reality" (Zadeh 1991)



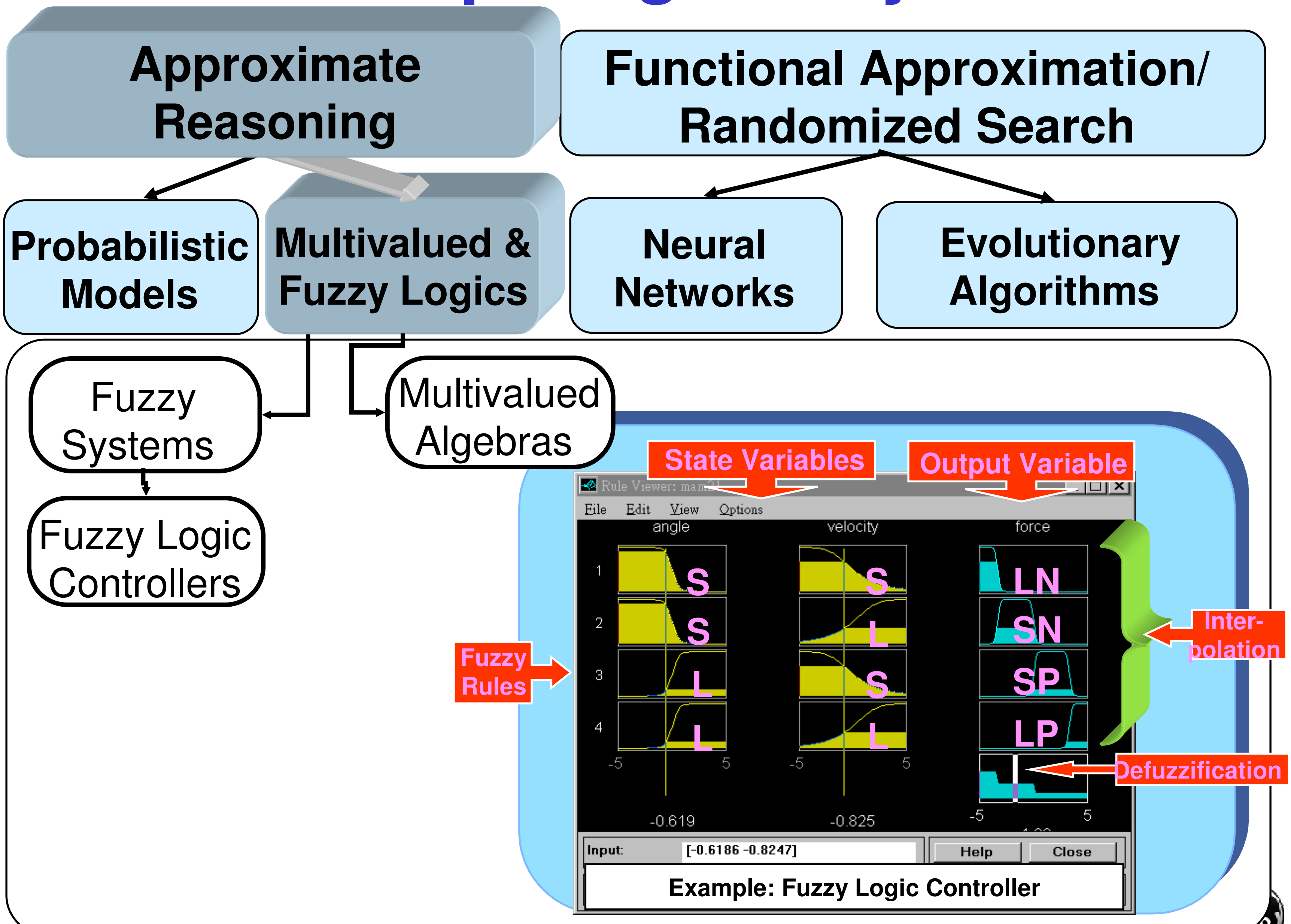
Soft Computing: Probabilistic Systems

- **Approximate Reasoning**
  - **Probabilistic Models**
    - Bayesian Belief Nets
    - Dempster-Shafer
    - CART Trees
    - Random Forest
  - **Multivalued & Fuzzy Logics**
- **Functional Approximation/ Randomized Search**
  - **Neural Networks**
  - **Evolutionary Algorithms**

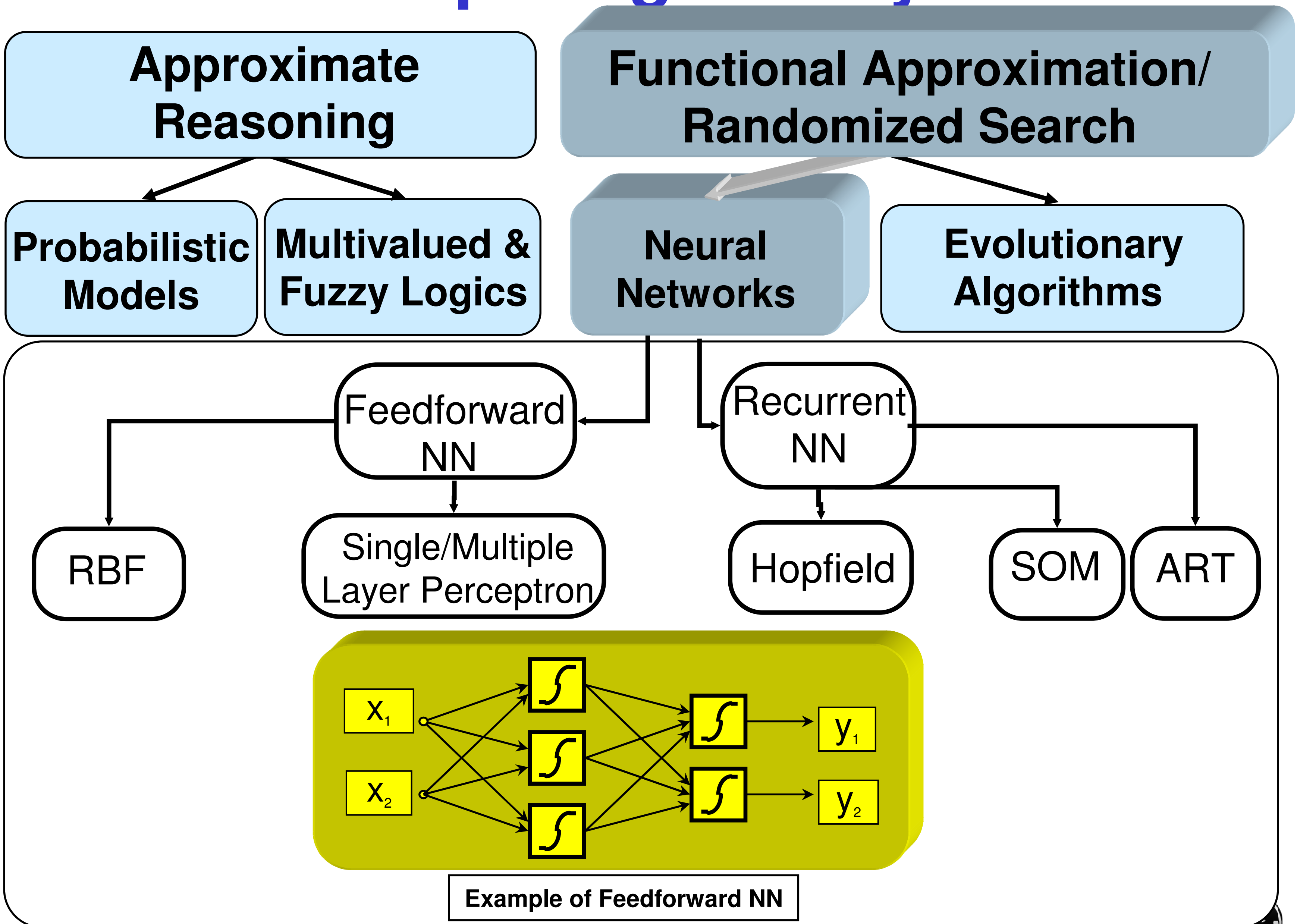


Example: BBN used for Generators Fault Diagnosis

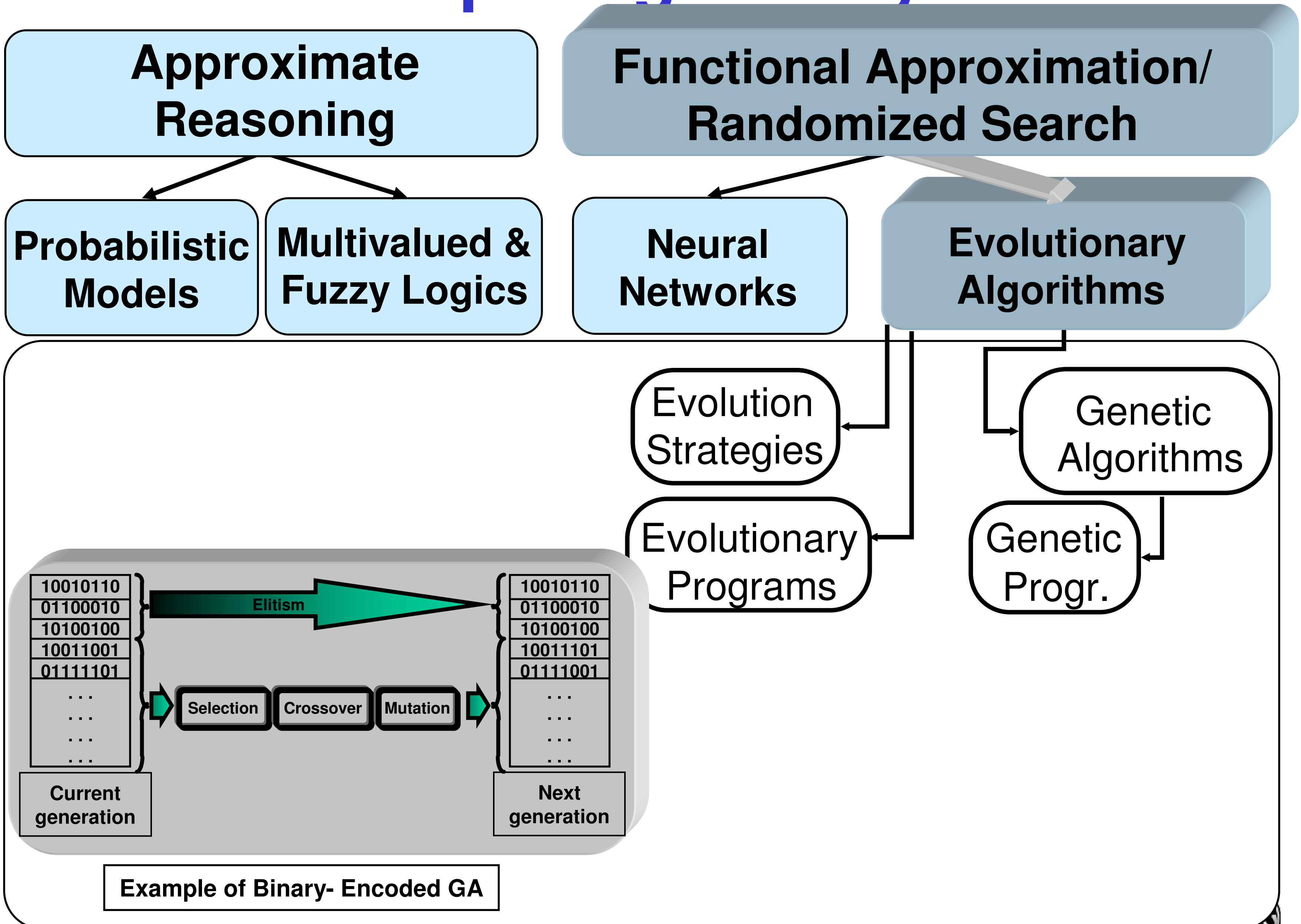
Soft Computing: FL Systems



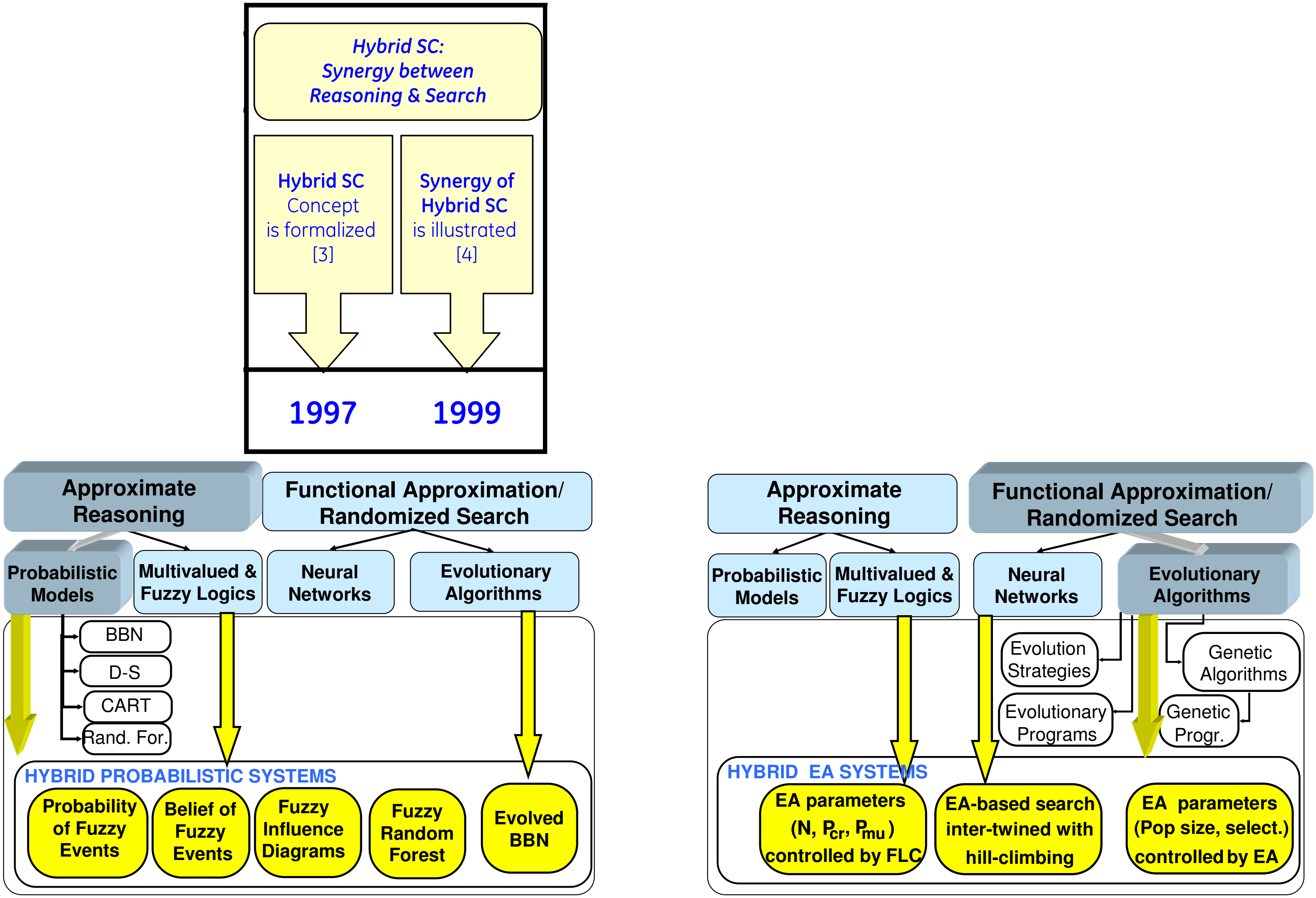
Soft Computing: NN Systems



Soft Computing: EA Systems



Hybrid Soft Computing (H-SC): A Personal Timetable



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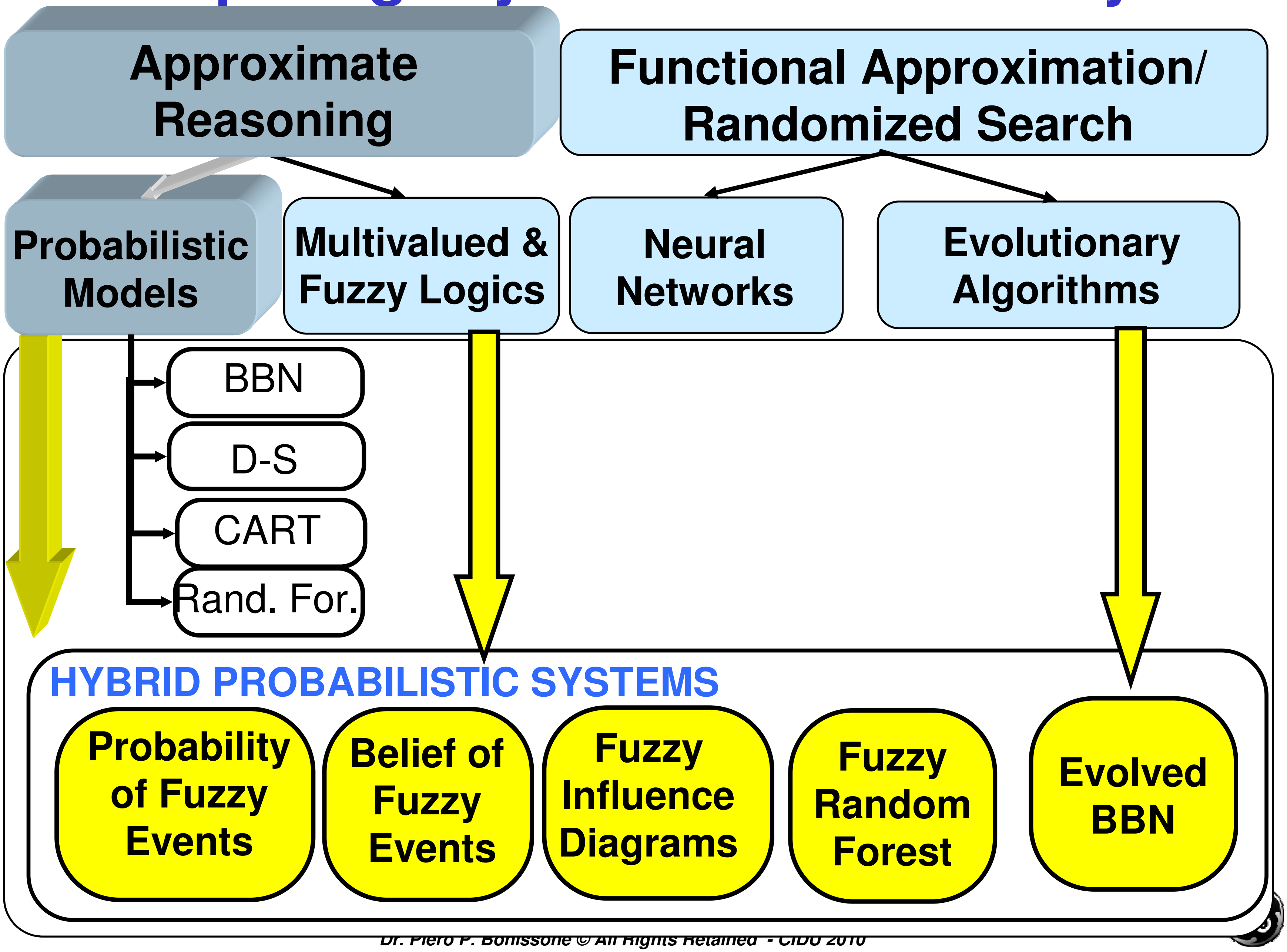
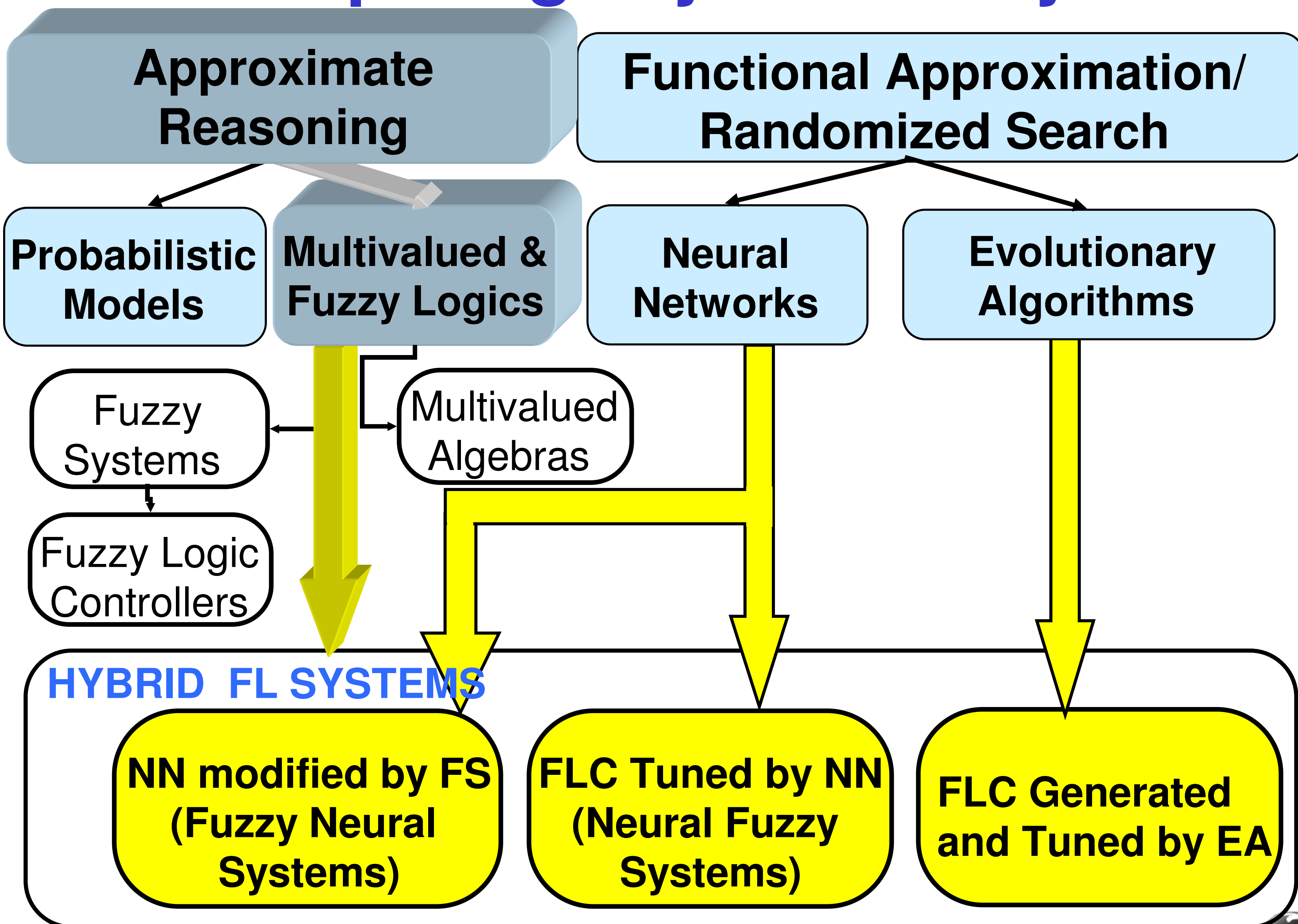
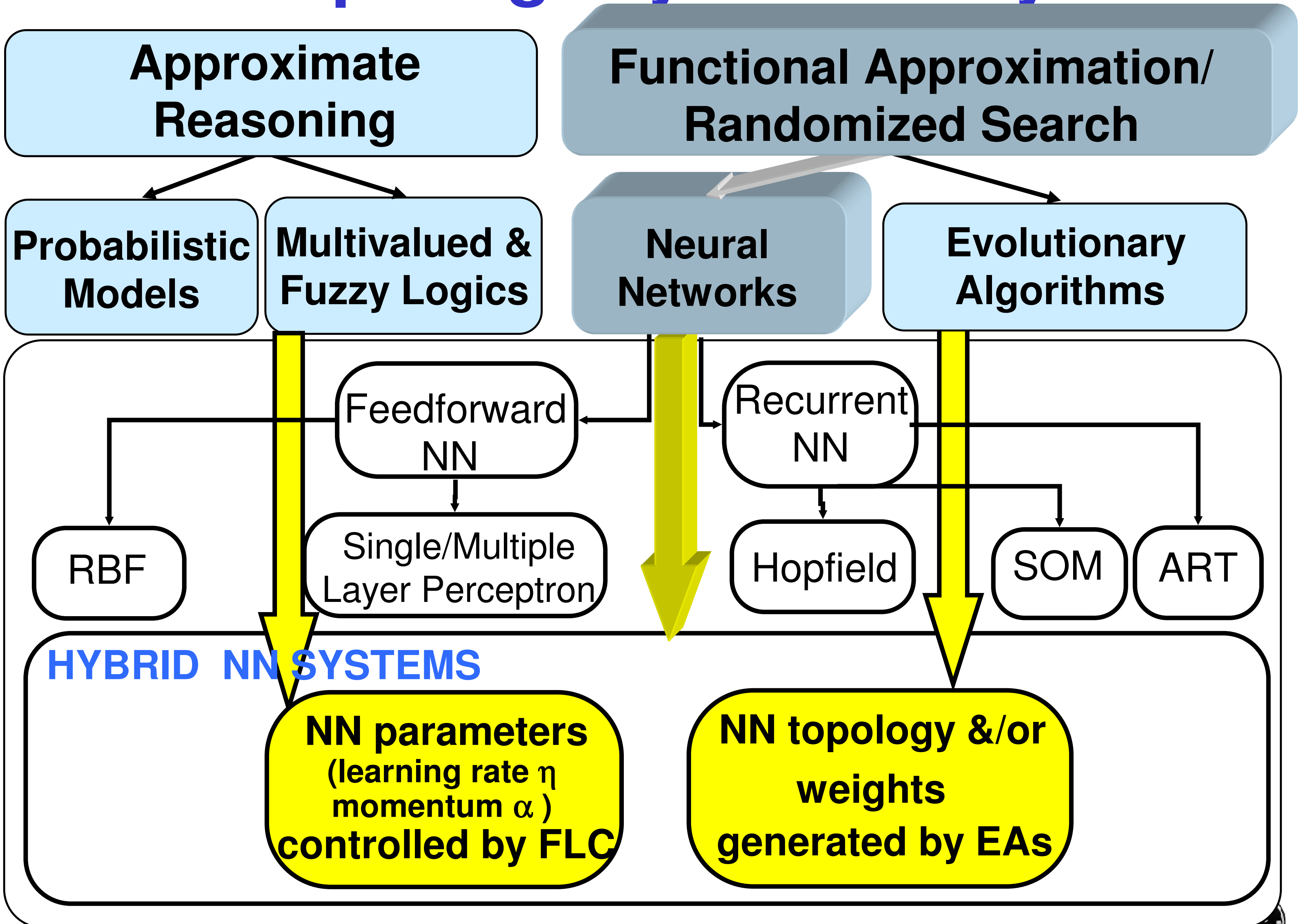
Soft Computing: Hybrid Probabilistic Systems



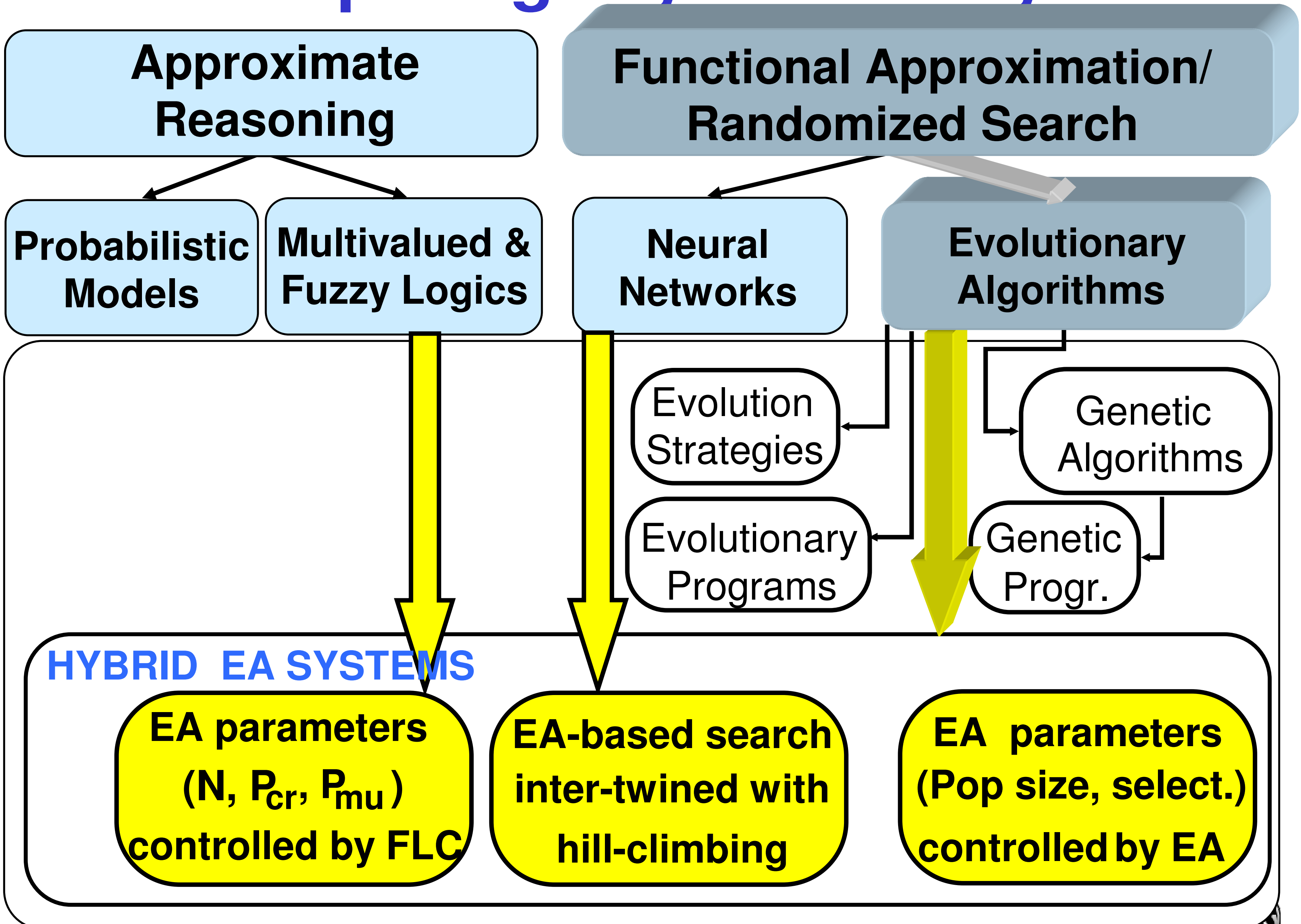
Soft Computing: Hybrid FL Systems



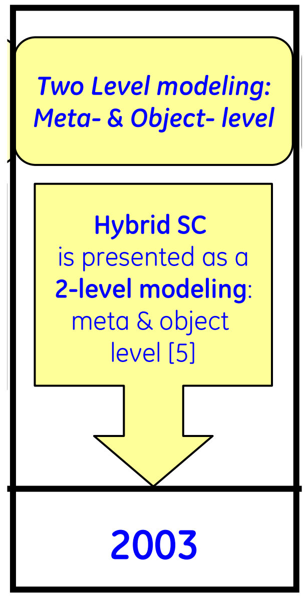
Soft Computing: Hybrid NN Systems

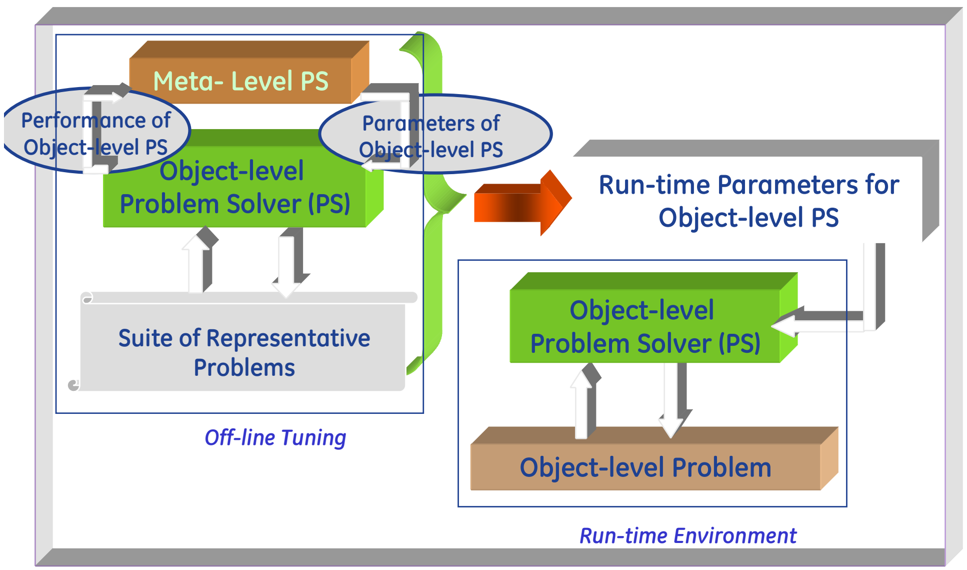


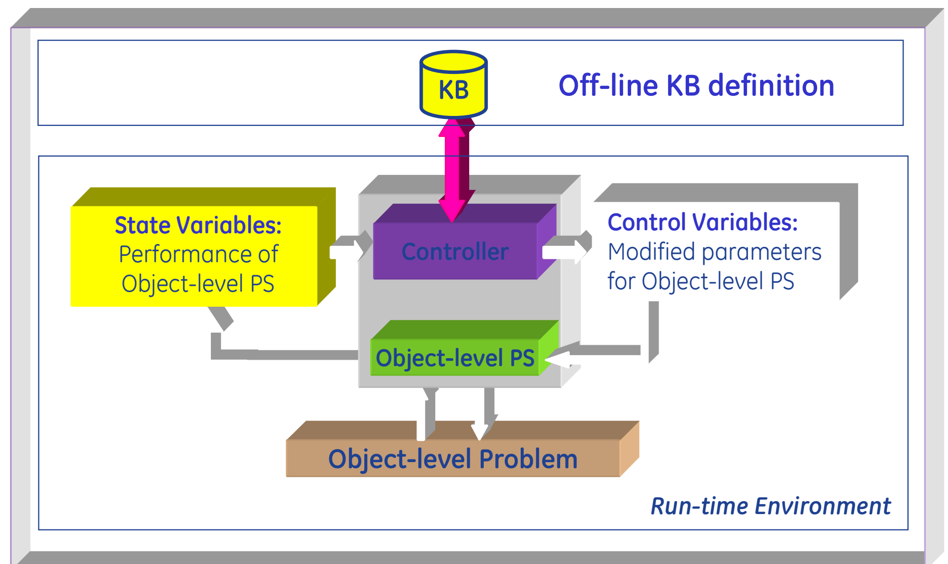
Soft Computing: Hybrid EA Systems



Hybrid Soft Computing (H-SC): Two Level Modeling







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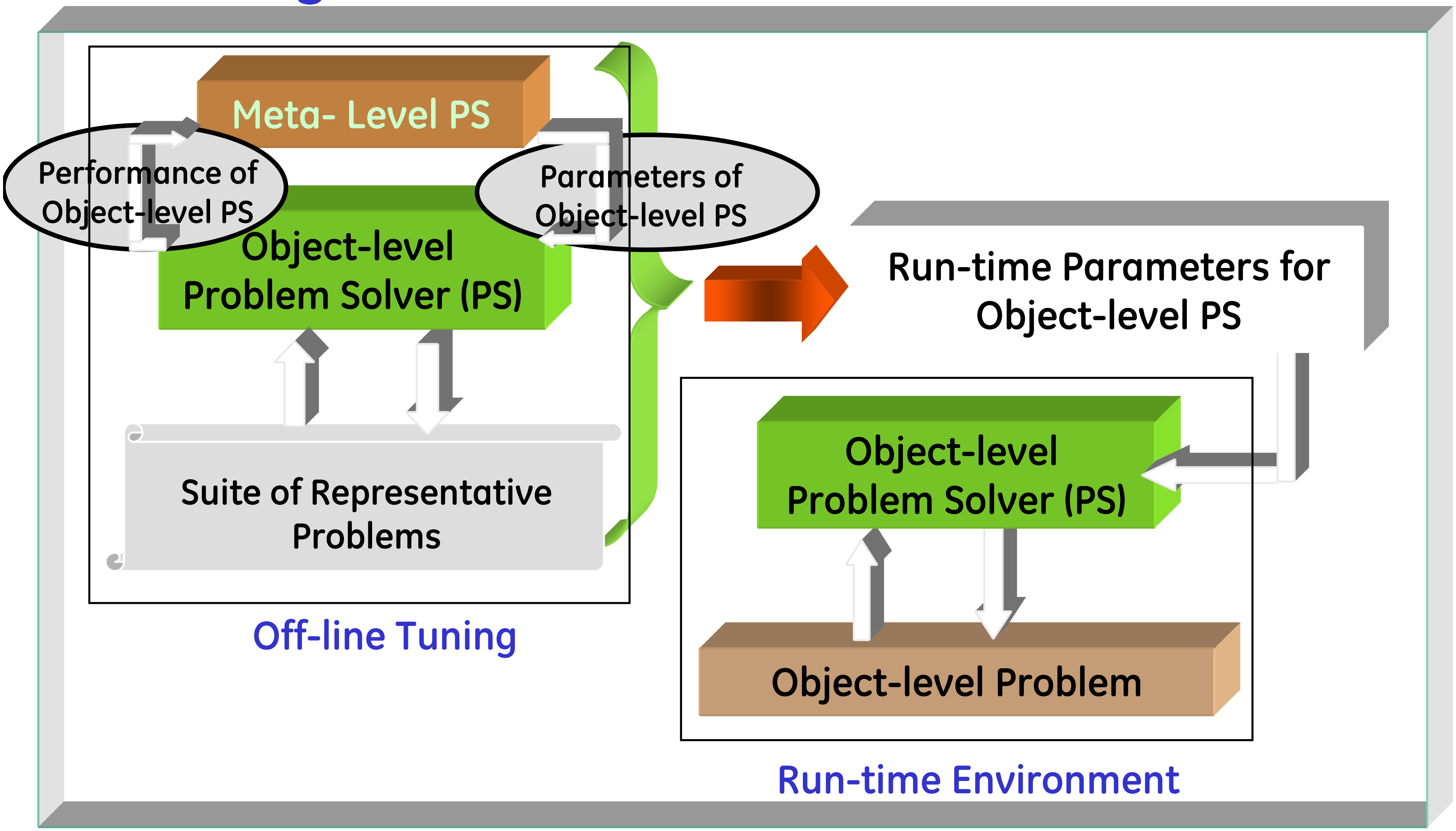
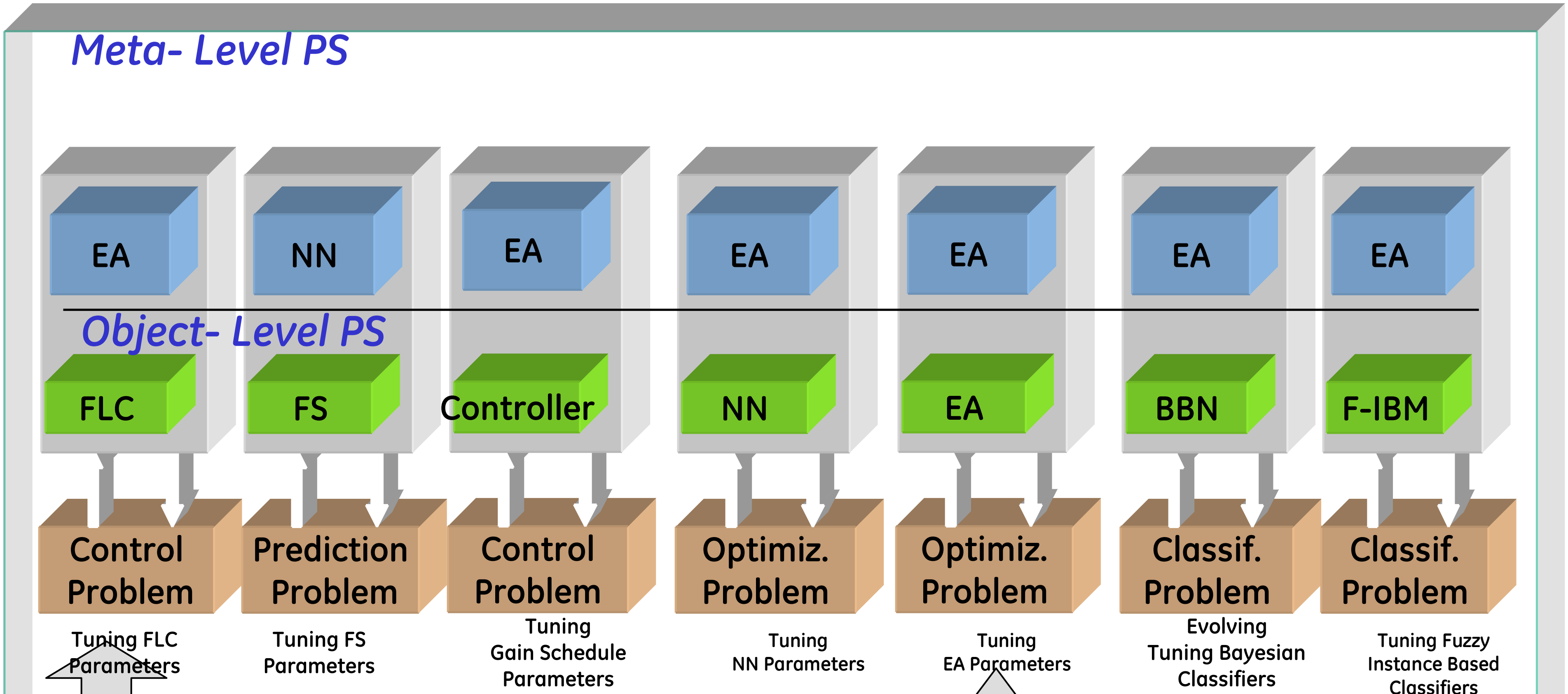
Offline Meta-Heuristics:
EA generates Structure & Parameters

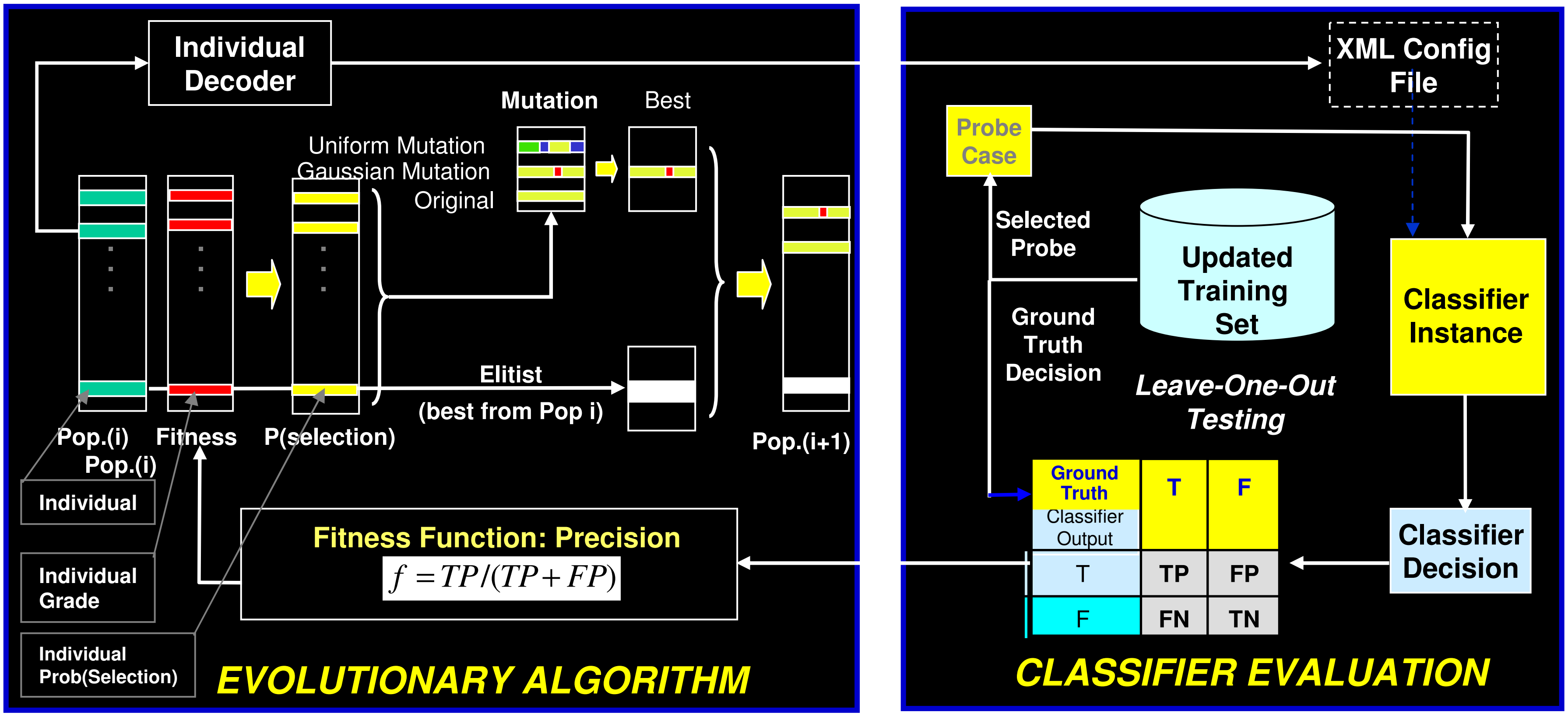


Examples of Offline Meta-Heuristics



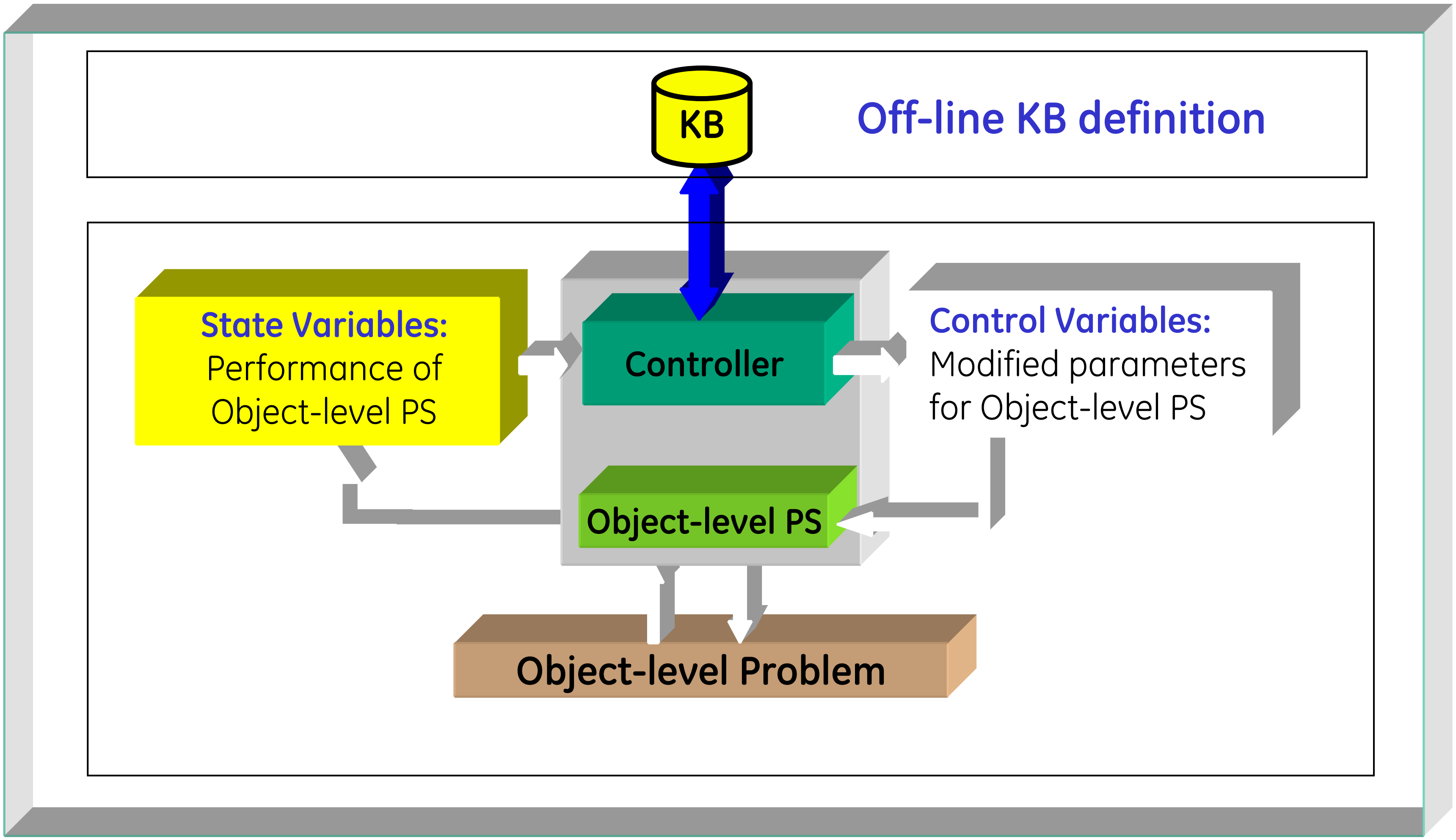
Generation and tuning of fuzzy *rule-based* systems for classification, control, fusion, etc.	EA: *Pragmatics* FS: *Semantics*
Tuning of Evolutionary Algorithm Parameters	EA: *Pragmatics* FS: *Semantics*
Generation and tuning of fuzzy *instance- or case-based* systems for classification, prediction, etc.	EA: *Pragmatics* FS: *Semantics*

Example: Use of EA to Design a Classifier [using a Wrapper Approach]

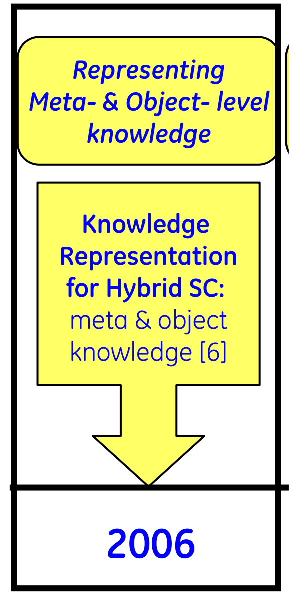


On-Line Meta-Heuristics:

KB Controller for Object-Level Problem Solver



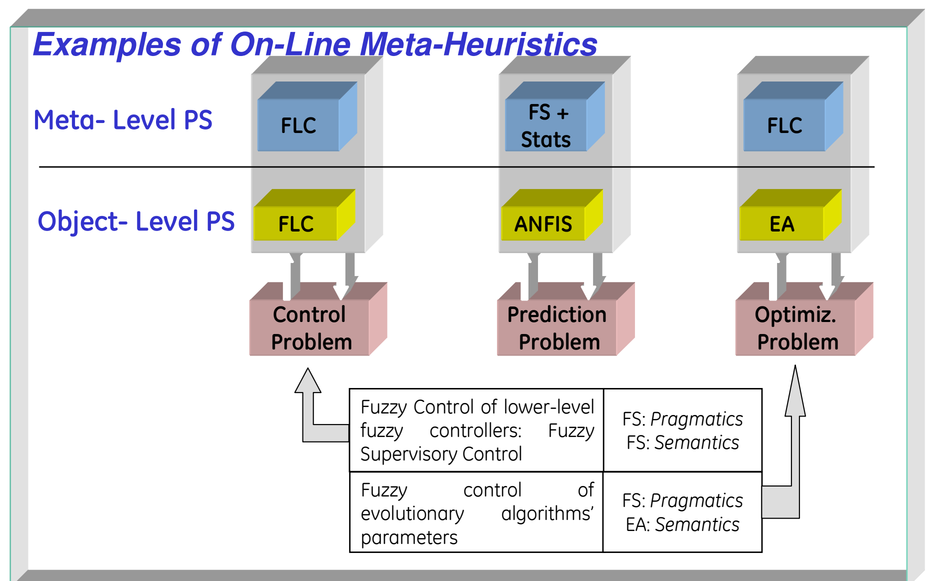
Hybrid Soft Computing (H-SC): Two Level Modeling



Time Horizon

	One Shoot	Tactical	Operational	Strategic	Lifecycle
Lexicon		Anomaly Detection			
Morphology		Anomaly Detection Anomaly Identification			
Marked-up Lexicon					
Syntax		Anomaly Id. Diagnostics	Scheduling		
Semantics	Transactional Decision	Anomaly Id. Diagnostics Prognostics Control	Scheduling Planning Readiness Assessment Asset Allocation Optimization DM	Long-Term Planning Contingency Planning Asset Management MOO, Tradeoffs, MCMD	
Pragmatics					Model Update & Maintenance

Domain Knowledge



Representing Domain Knowledge for PHM Decisional Tasks

Time Horizon

<table>
<tr><th></th><th>One Shoot</th><th>Tactical</th><th>Operational</th><th>Strategic</th><th>Lifecycle</th></tr>
<tr><td>Lexicon</td><td></td><td>Anomaly Detection</td><td></td><td></td><td></td></tr>
<tr><td>Morphology</td><td></td><td rowspan="2">Anomaly Detection
Anomaly Identification</td><td></td><td></td><td></td></tr>
<tr><td>Marked-up Lexicon</td><td></td><td></td><td></td><td></td></tr>
<tr><td>Syntax</td><td></td><td>Anomaly Id.
Diagnostics</td><td>Scheduling</td><td></td><td></td></tr>
<tr><td>Semantics</td><td rowspan="2">Transactional Decision</td><td rowspan="2">Anomaly Id.
Diagnostics
Prognostics
Control</td><td rowspan="2">Scheduling
Planning
Readiness Assessment
Asset Allocation
Optimization
DM</td><td rowspan="2">Long-Term Planning
Contingency Planning
Asset Management
MOO, Tradeoffs,
MCMD</td><td></td></tr>
<tr><td>Pragmatics</td><td>Model Update & Maintenance</td></tr>
</table>

Domain Knowledge

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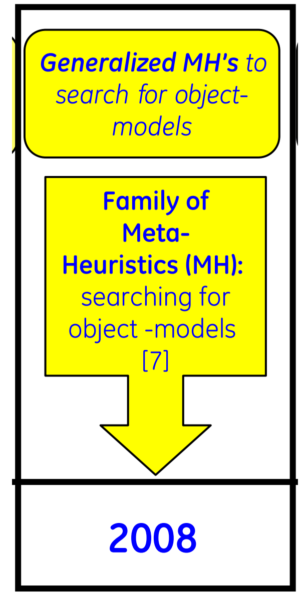
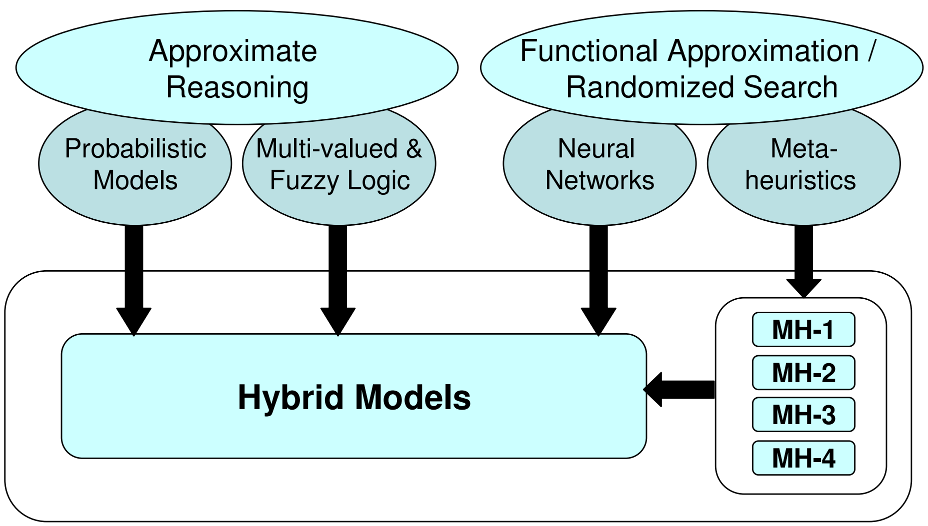
SC Techniques & Domain Knowledge

SC/Stat/AI Techniques	Domain Knowledge
Self-Organizing Maps (SOM) Kolmogorov Complexity, One-class Support Vector Machine, Neural Networks, Unsupervised Machine Learning techniques, fuzzy clustering, non-parametric statistics	Lexicon and Morphology
Supervised Machine Learning techniques, NN, Fuzzy Classifiers, CART, Random Forest, MARS	Marked-up Lexicon
Automated Kernel Splitting, Grammatical Inference, Evolutionary Algorithms (EA)	Syntax
Feature extraction/selection, fuzzy models, 1st Principle based simulations, temporal reasoners, Case-based Reasoners, planners, Evolutionary Algorithms	Semantics
Model Selection/Mixing, EA, MOEA, Fuzzy models for preference aggregation and tradeoffs	Pragmatics

Hybrid Soft Computing (H-SC): Family of MH’s





MH-1 = Evolutionary MH
MH-2 = Relaxation MH
MH-3 = Search MH (Individual Search, Cooperative Multiple Search, Non- Cooperative Multiple Search)

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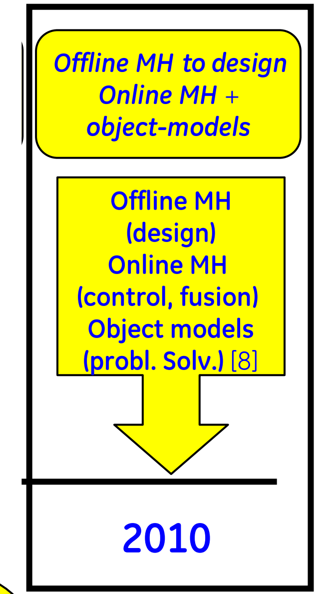
Soft Computing: Evolution of a Concept

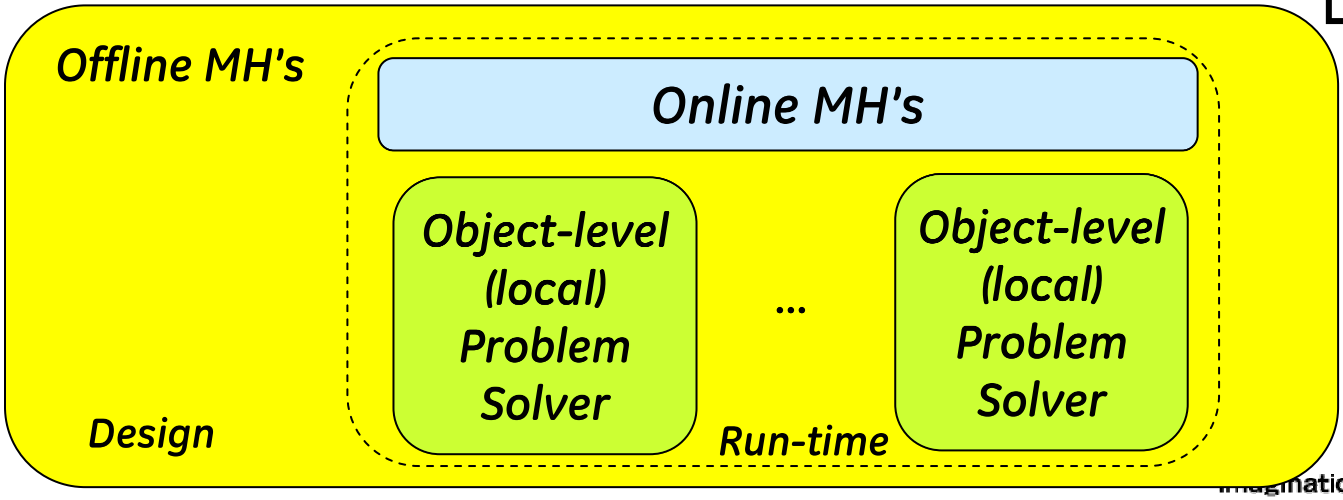
- History: 1991-2007

Current Soft Computing View (2010)

Offline Meta to design Online Meta and Object models

Hybrid Soft Computing (H-SC):
On- line MH for Model Design; Off-line MH for Model Control;Object Model for Problem Solving





SC Techniques for *Offline MH's*, *Online MH's*, and *Object-level Models*

Problem Instance	**Problem Type**	**Model Design (*Offline MH's*)**	**Model Controller (*Online MH's*)**	**Object-level models**	**References** *[As listed in Bonissone 2010]*
Anomaly Detection (System)	Classification	Model T-norm tuning	Fuzzy Aggregation	*Multiple Models:* SVM, NN, Case-Based, MARS	[24]
Anomaly Detection (System)	Classification	Manual design	Fusion	*Multiple Models:* Kolmogorov Complexity, SOM. Random Forest, Hotteling T2, AANN	[25, 26]
Anomaly Detection (Model)	Classification & Prediction	EA tuning of fuzzy supervisory termset	Fuzzy Supervisory	*Multiple Models:* Ensemble of AANN's	[27, 28]
Insurance Underwriting: Risk management	Classification	EA	Fusion	*Multiple Models:* NN, Fuzzy, MARS,	[29, 30]
Load, HR, NOx forecast	Prediction	Multiple CART trees	Fusion	*Multiple Models:* Ensemble of NN's	[31, 34]
Aircraft engine fault recovery	Control/Fault Accommodati on	EA tuning of linear control gains	Crisp supervisory	*Multiple Models (Loop):* SVM + linear control	[14]
Power plant optimization	Optimization	Manual design	Fusion	*Multiple Models (Loop):* MOEA + NN's	[32, 33, 34]
Flexible mfg. optimization	Optimization	Manual design	Fuzzy supervisory	EA	[10, 35]

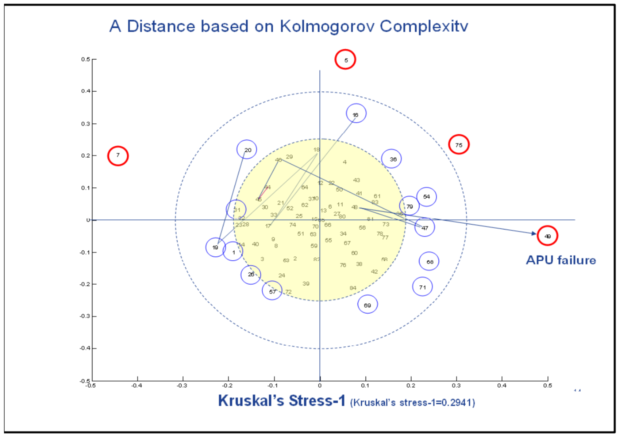
Applications of SC to Anomaly detection

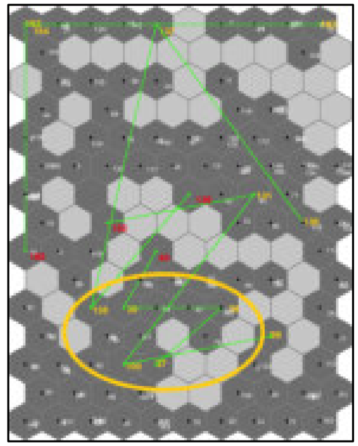
(for Aircraft Engine)

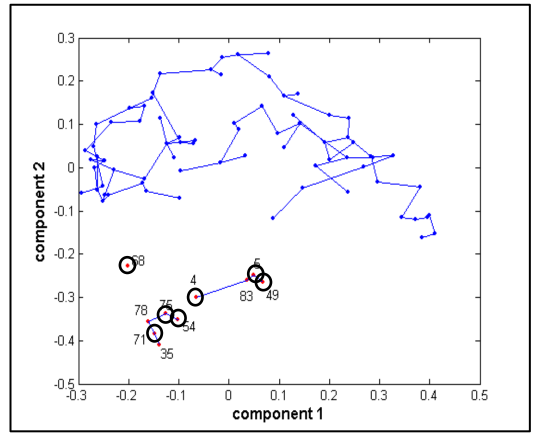
- Fusion of Models (Categorical & Time-series Data) to reduce false alarms

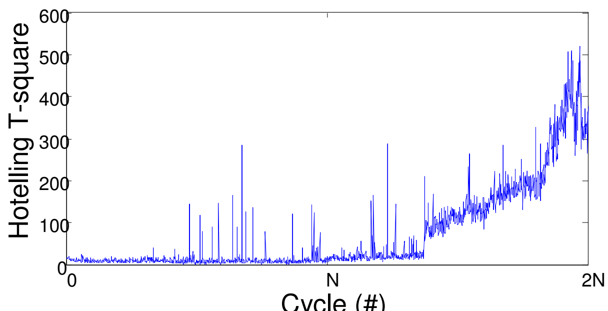
- Use of EA +FS + AANN to improve model accuracy

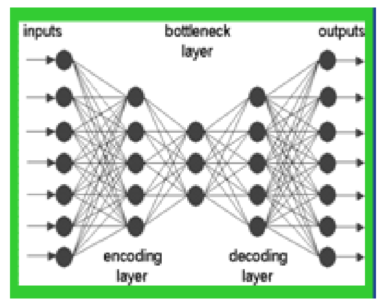
Anomaly Detection (Fusion)









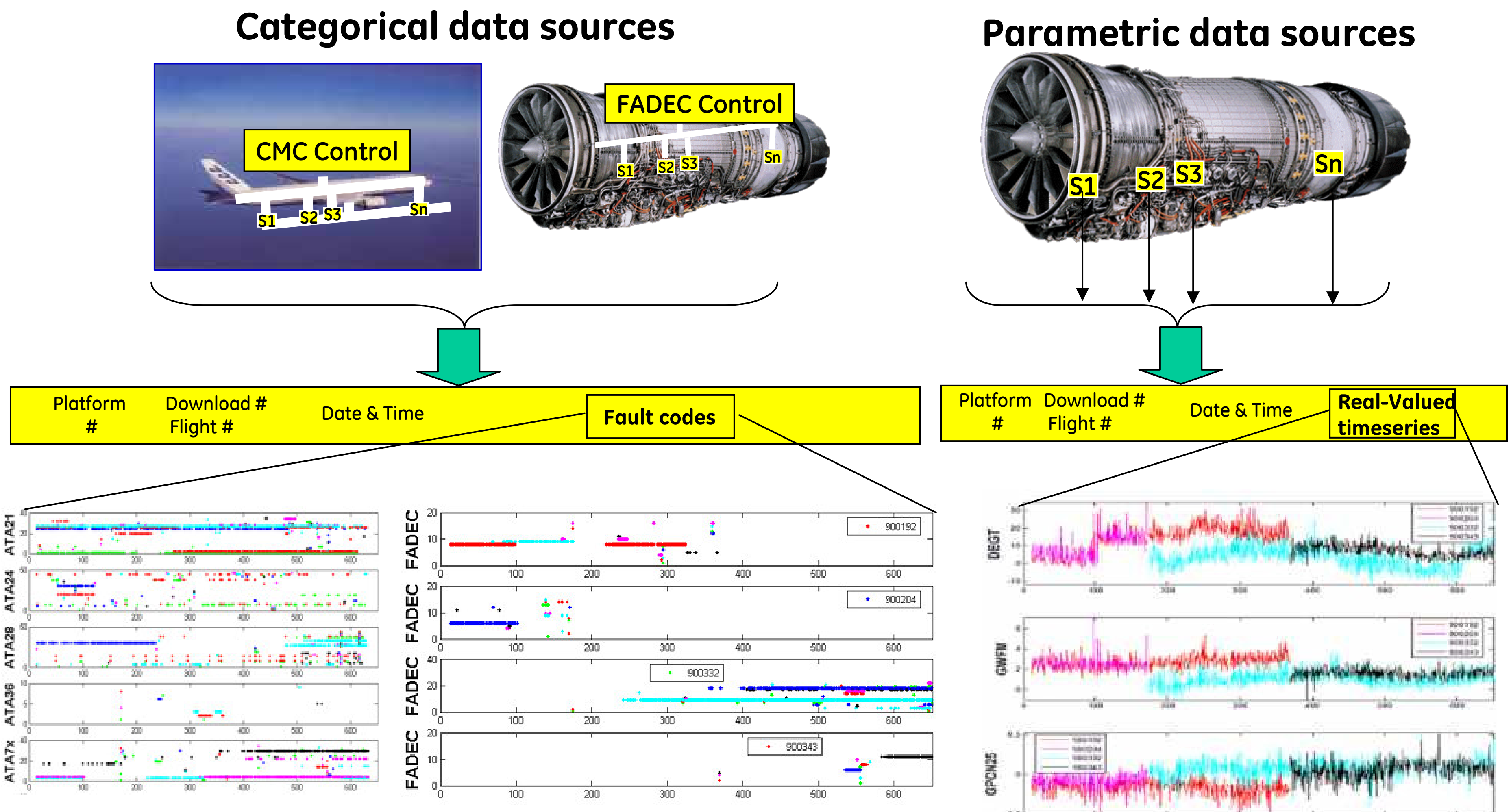


Problem Instance	Problem Type	Model Design (Offline MH's)	Model Controller (*Online MH's*)	Object-level models
Anomaly Detection	1-class Classification	Manual	Fusion	*Multiple Models:* Kolmogorov Complexity, SOM, Random Forest, Hotteling T2, AANN

Reference: Integrated System Health Management (ISHM) and Software Technologies Support, P. Bonissone, N. Eklund, N. Iyer, H. Qiu and A. Varma, 2007GRC928, November 2007, Public (Class 1)

Anomaly Detection (AD) using both Parametric and Categorical Data Sources

Anomaly Detection



Leverage ALL the information you have BEFORE the flight

Source: Integrated System Health Management (ISHM) and Software Technologies Support, P. Bonissone, N. Eklund, N. Iyer, H. Qiu and A. Varma, 2007GRC928, November 2007, Public (Class 1)

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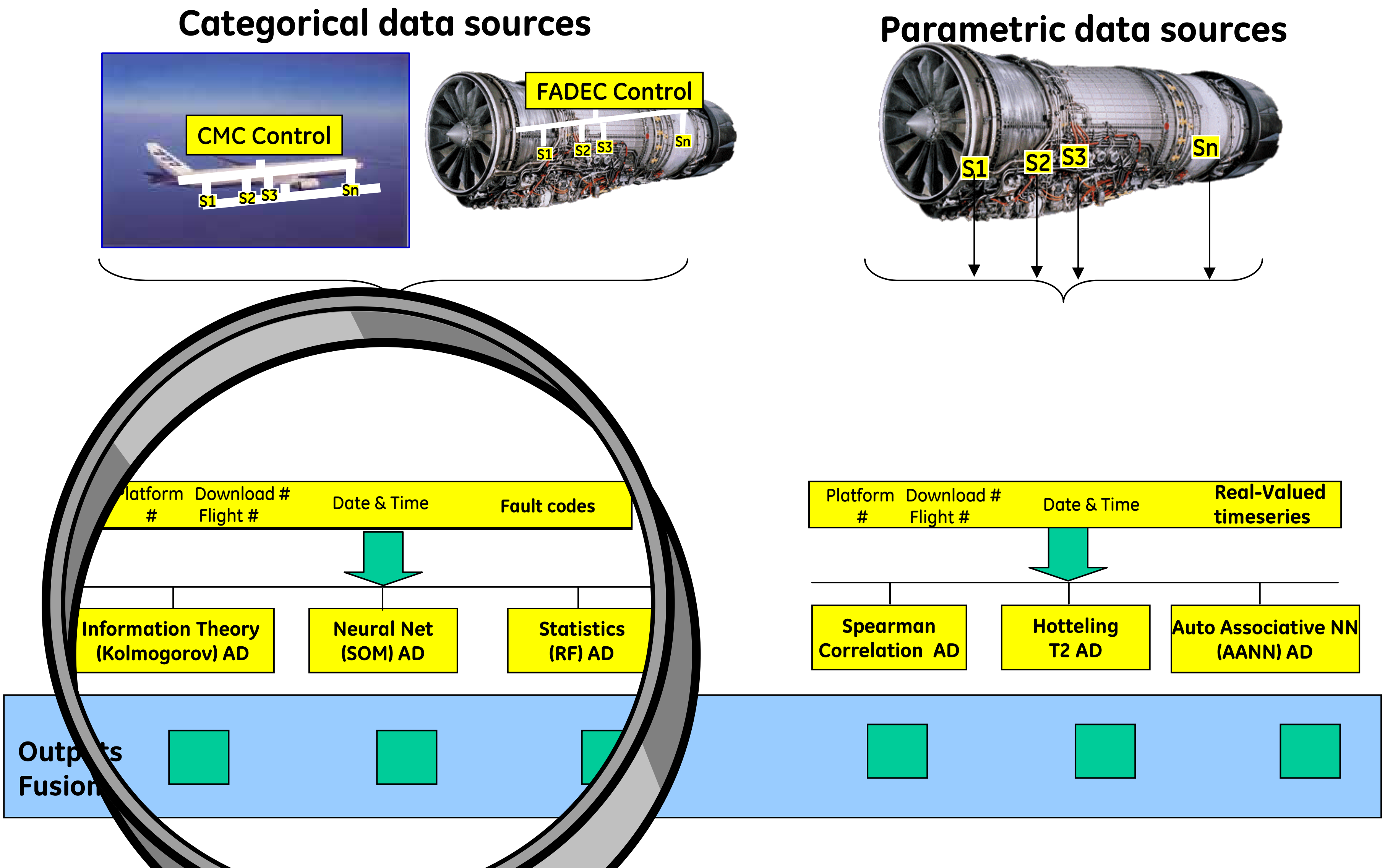
Fusion within Anomaly Detection Modules

Anomaly Detection



ted System Health Management (ISHM) and Software Technologies Support,
. Eklund, N. Iyer, H. Qiu and A. Varma, 2007GRC928, November 2007, Public (Class 1)

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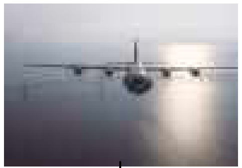
Anomaly Detection Using Information Theory



FADEC Messages

Frequency extraction

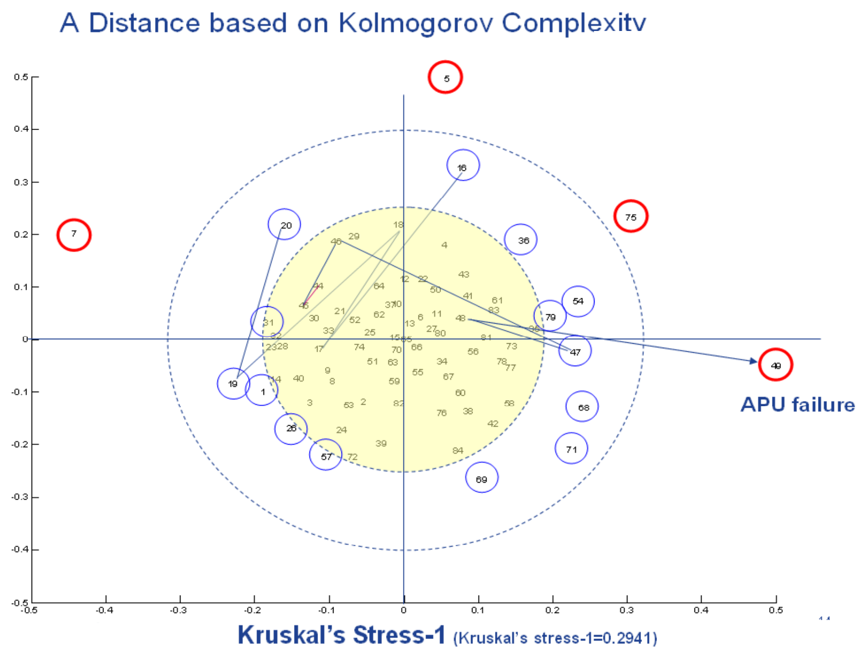
String Encoding

NCD Matrix Computation

Labeling Normal and Anomalous Regions

Visualization: 1D or 2D Anomaly Projection

Information Theory Detector



Units with Large Anomalies

Units with Medium Anomalies

Region of Normal Operations

Detector based on Kolmogorov Complexity

- 2D Display obtained by projecting 84-dimensional object while minimize distorsion

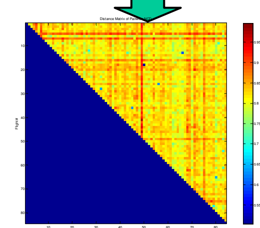
Flight x

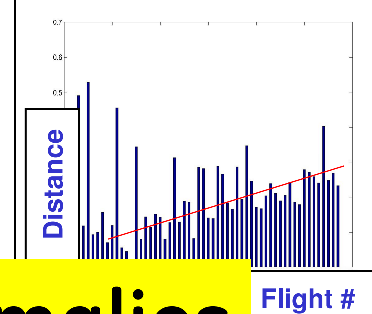
Flight y

f(1,1)	f(1,2)	f(1,3)	f(1,4)	f(1,5)	f(2,1)	f(2,2)	f(2,3)	f(2,4)	f(2,5)	...
f(1,1)	f(1,2)	f(1,3)	f(1,4)	f(1,5)	f(2,1)	f(2,2)	f(2,3)	f(2,4)	f(2,5)	...

$$NCD(x,y) = \frac{C(x,y) - \min\{C(x),C(y)\}}{\max\{C(x),C(y)\}}$$

NCD Matrix





Clear Identification of anomalies

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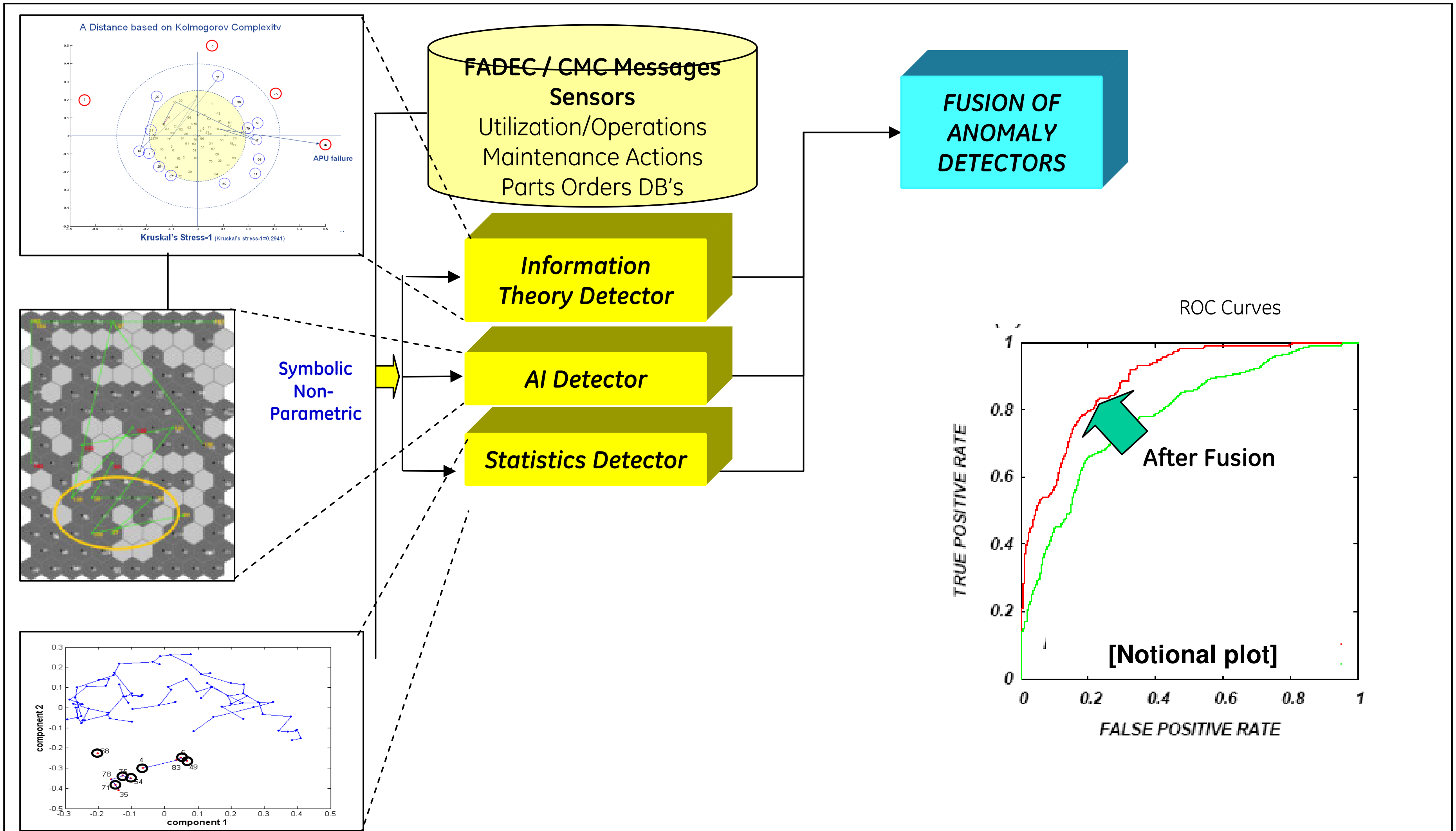
Fusion of Anomaly Detection Algorithms based on categorical data

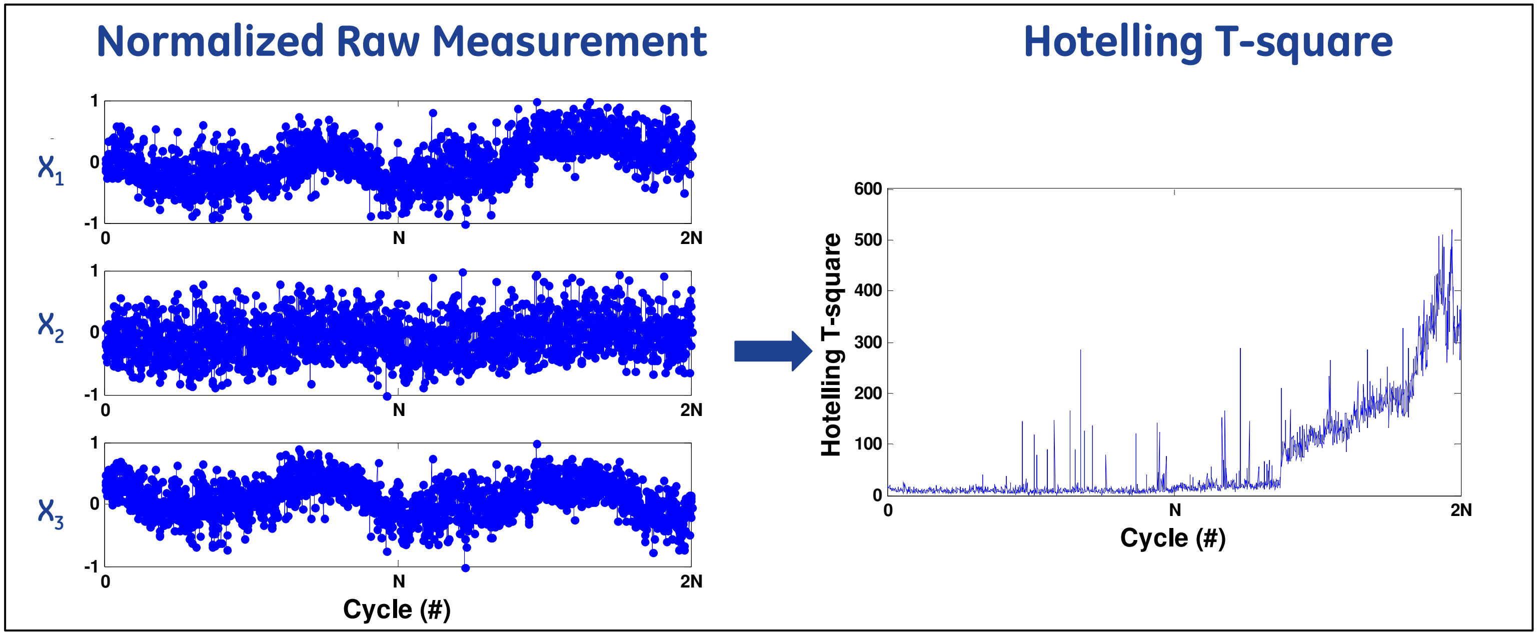
Anomaly Detection

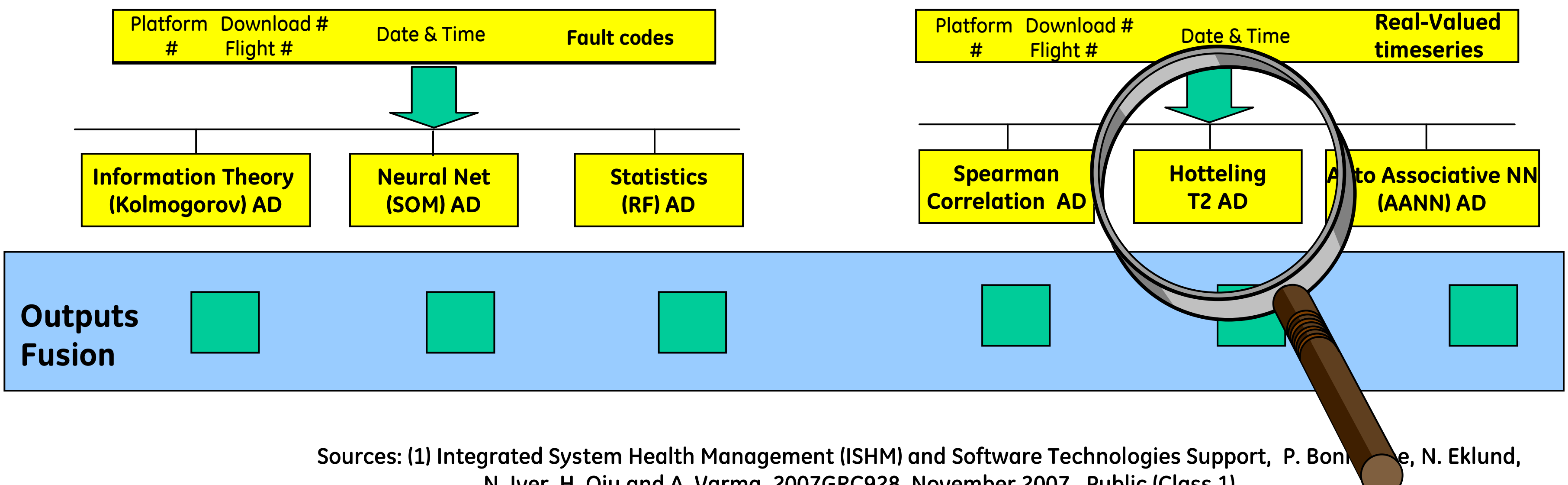


Fusion of error-uncorrelated detectors increases robustness & accuracy

Source: Integrated System Health Management (ISHM) and Software Technologies Support,
P. Bonissone, N. Eklund, N. Iyer, H. Qiu and A. Varma, 2007GRC928, November 2007. Public (Class 1)

AD Fusion: Output fusion for Categorical & Parametric Models





Sources: (1) Integrated System Health Management (ISHM) and Software Technologies Support, P. Boni e, N. Eklund, N. Iyer, H. Qiu and A. Varma, 2007GRC928, November 2007, Public (Class 1)
(2) X. Hu, R. Subbu, P. Bonissone, H. Qiu, N. Iyer, "Multivariate Anomaly Detection in Real-World Industrial Systems", IJCNN 2008, WCCI 2008 . Hong Kong, China, June 1-6, 2008

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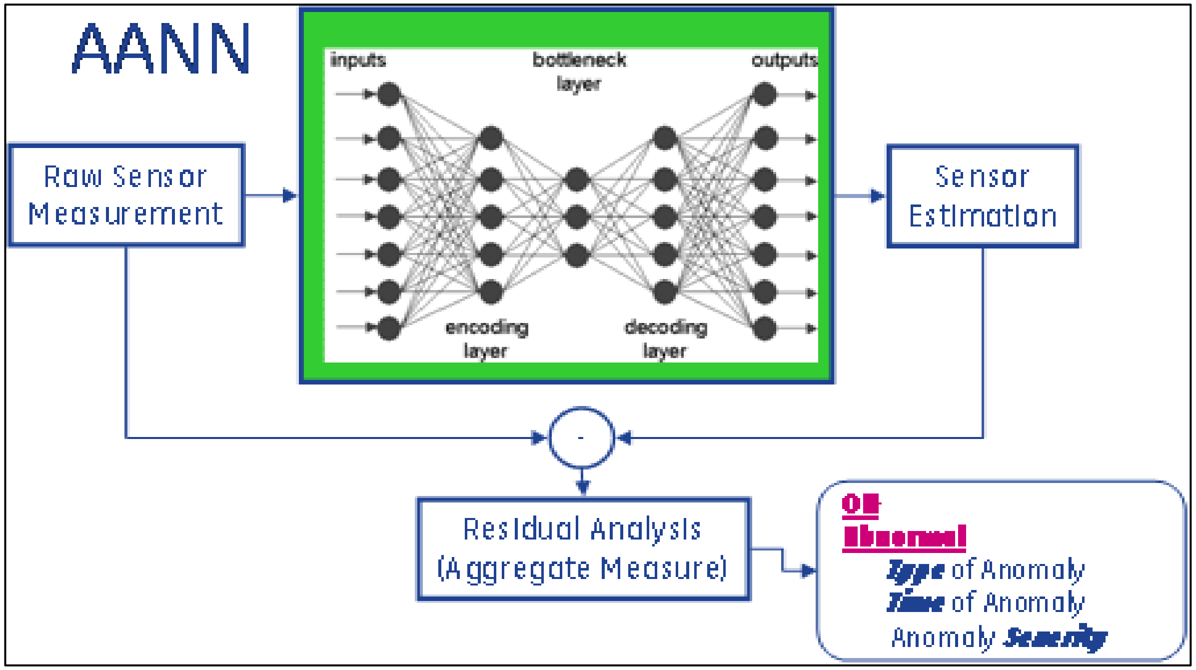

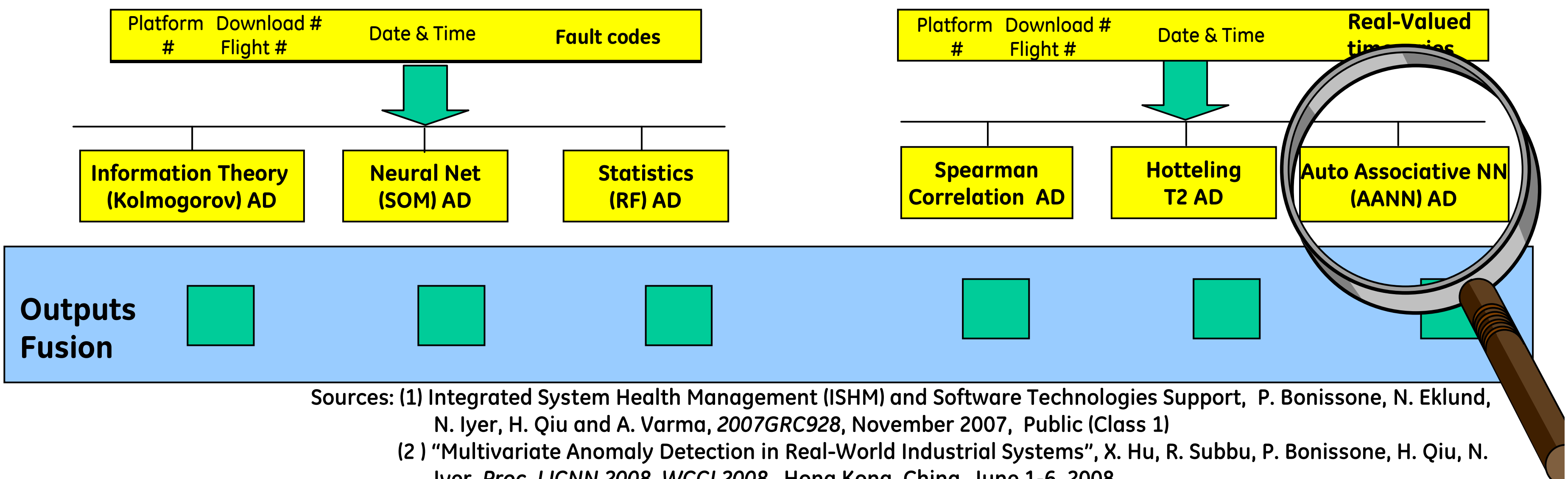

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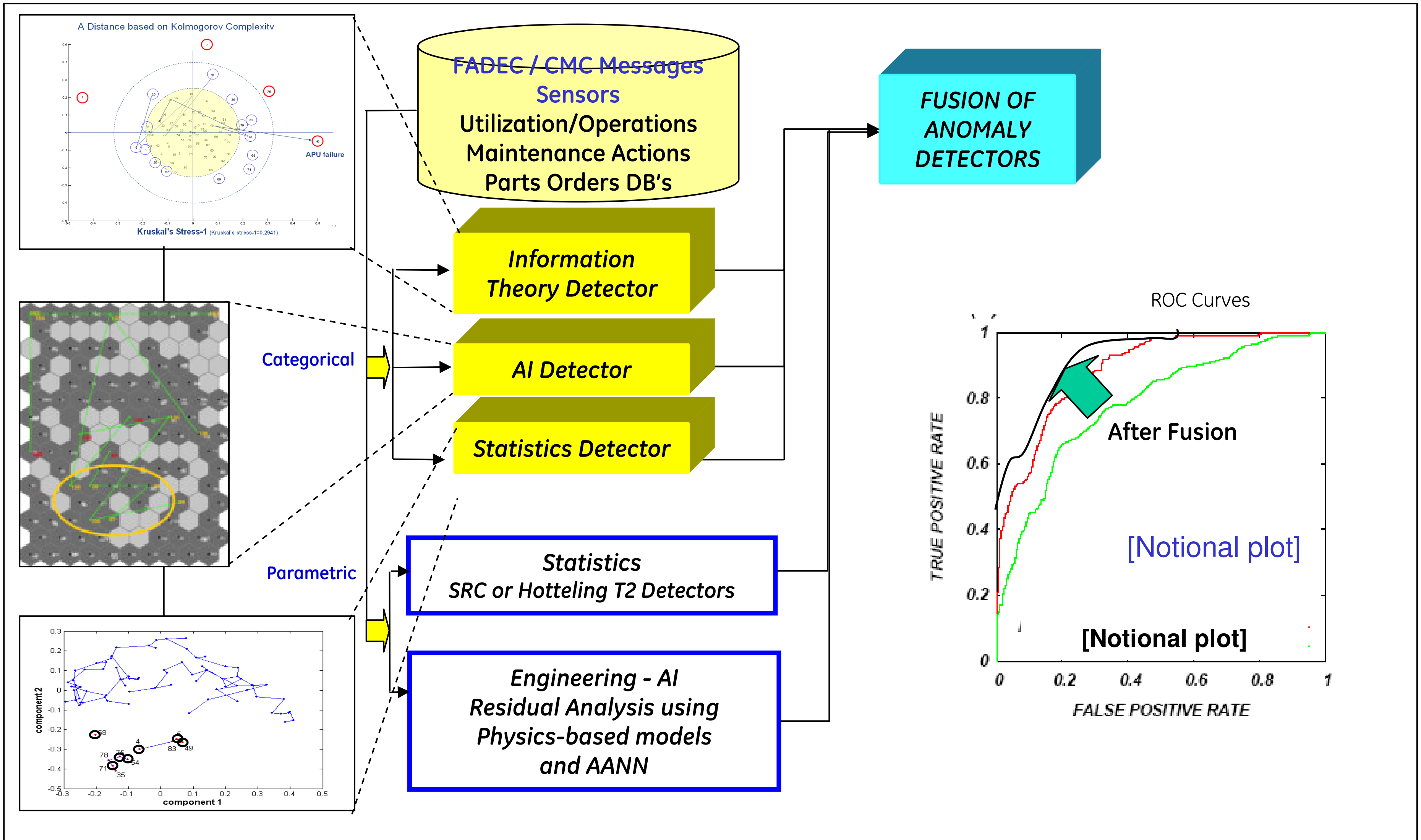
(3) A Systematic PHM Approach for Anomaly Resolution: A Hybrid Neural Fuzzy System for Model Construction", P. Bonissone, X Hu, R. Subbu, *Proc. PHM 2009*, San Diego, CA, Sept 27, 2009. – *2009GRC839 Public (Class 1)*

Fusion of all Anomaly Detection Algorithms

Anomaly Detection



Fusion of error-uncorrelated detectors increases robustness & accuracy

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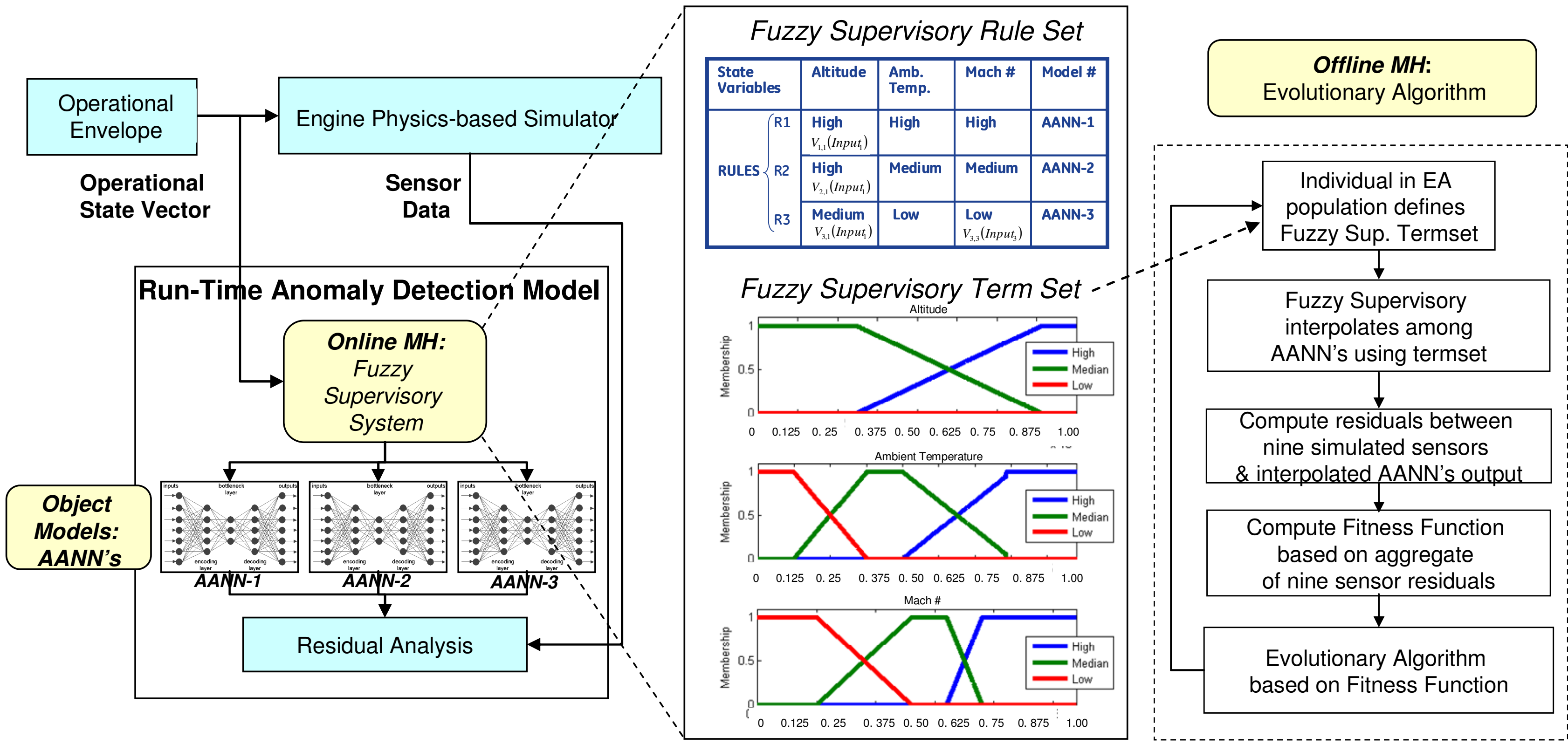
Applications of SC to Anomaly detection

(for Aircraft Engine)

- Fusion of Models (Categorical & Time-series Data) to reduce false alarms

- Use of EA +FS + AANN to improve model accuracy

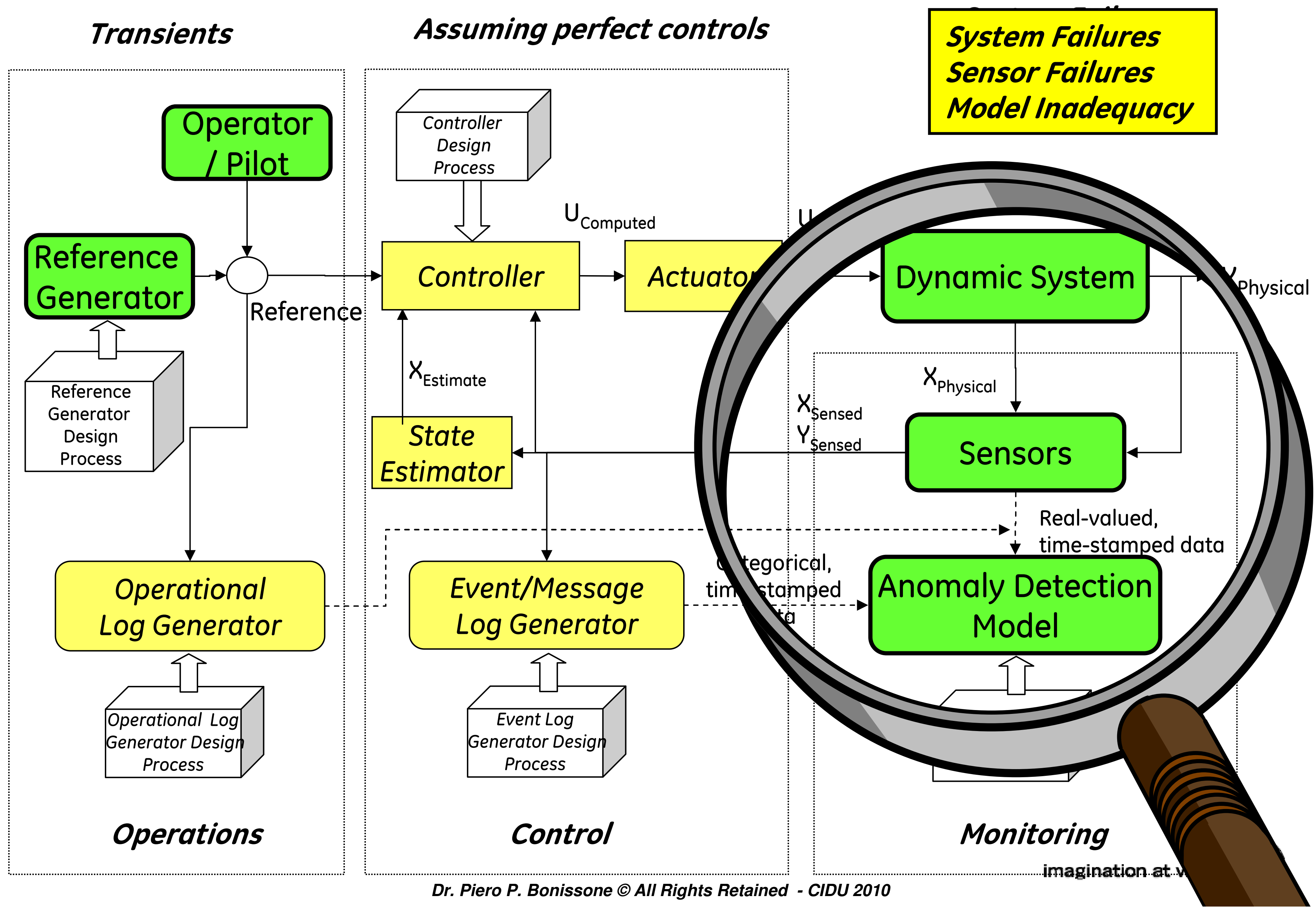
Anomaly Detection (Model Improvement)



Problem Instance	Problem Type	Model Design (Offline MH's)	Model Controller (*Online MH's*)	Object-level models
Anomaly Detection	1-class Classification	**EA tuning of fuzzy supervisory termset**	**Fuzzy Supervisory**	***Multiple Models:*** **Ensemble of AANN's**

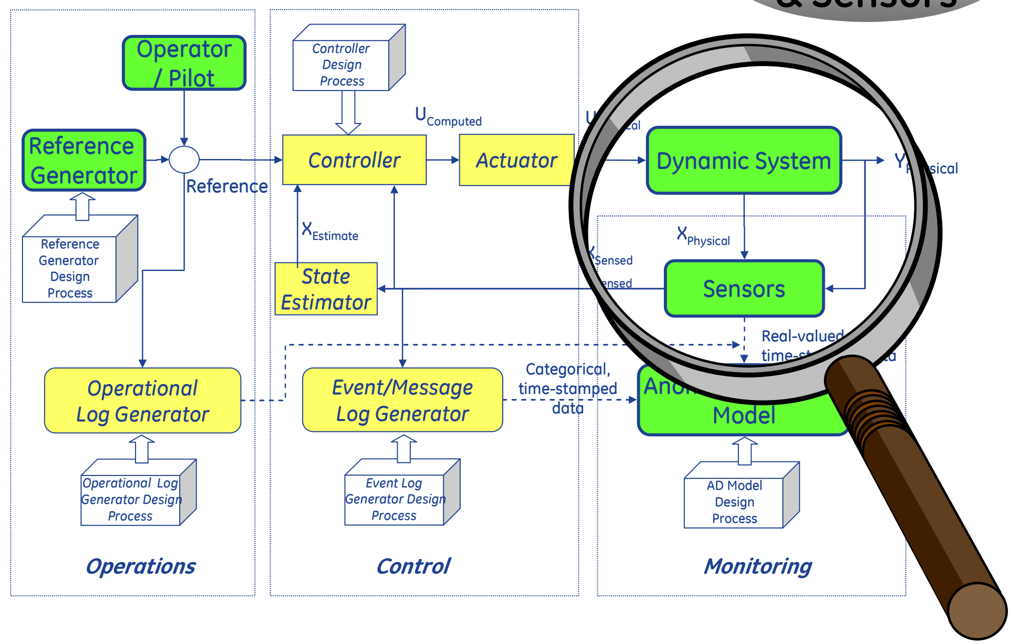
Reference: "A Systematic PHM Approach for Anomaly Resolution: A Hybrid Neural Fuzzy System for Model Construction", Proc. PHM 2009, San Diego, CA, Sept 27-Oct 1, 2009. - [GE GR Technical Report, 2000, GRC839, Sept. 2009]

Sources of Anomalies



Dynamic System: Simulated Aircraft Engine [GE 90]

Dynamic System & Sensors



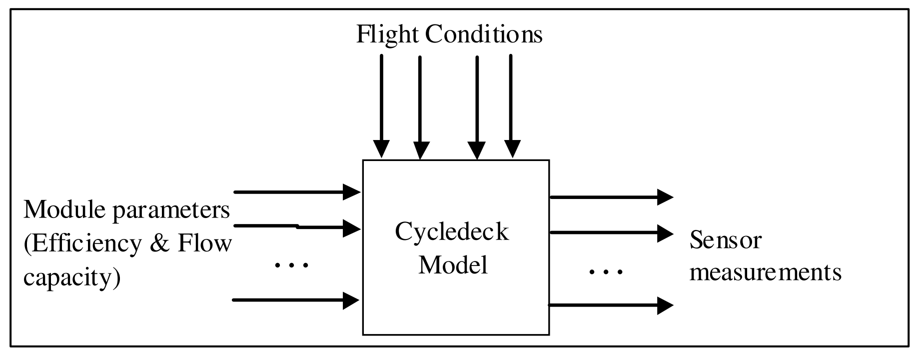
Physics-Based Simulation

–**CLM:** Component Level Model is a physics-based thermodynamic model widely used to simulate the performance of a commercial aircraft engines.

–**Flight Regime:** Flight conditions, such as altitude, Mach number, ambient temperature, and engine fan speed, and a large variety of model parameters, such as module efficiency and flow capacity are inputs to the CLM

–**Outputs:** CLM's outputs are the values for **pressures, core speed and temperatures** at various locations of engine, which simulate sensor measurements.

–**Noise**: Realistic values of sensor noise can be added after the CLM calculation.



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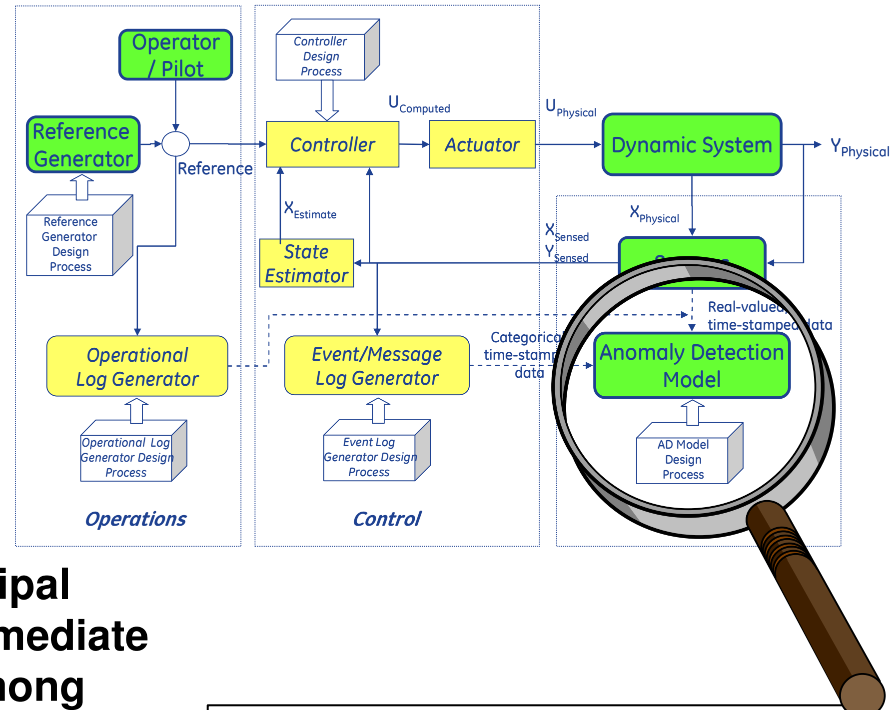
Basic AD Model: Auto-Associative Neural Network

AD Model

Rationale

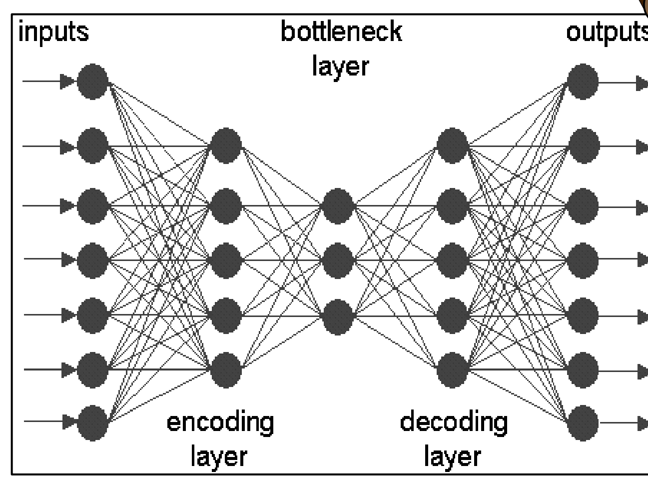
The Auto-Associative Neural Network (AANN) leverages covariance information like other approaches (SRC and T2). The AANN also produces sensor estimated values to replace the ones generated by faulty sensors. This approach provides a better discrimination between sensor faults and system component faults.



Definition/Properties

AANN computes the largest Non-Linear Principal components (NLPCA) - the nodes in the intermediate layer – to identify and remove correlations among variables.

NLPCA uncover both linear and nonlinear correlations, without restriction on the type of the nonlinearities present in the data.



Computation

Traditional NN training with back-propagation

Variable Contribution

Residuals magnitude/distribution

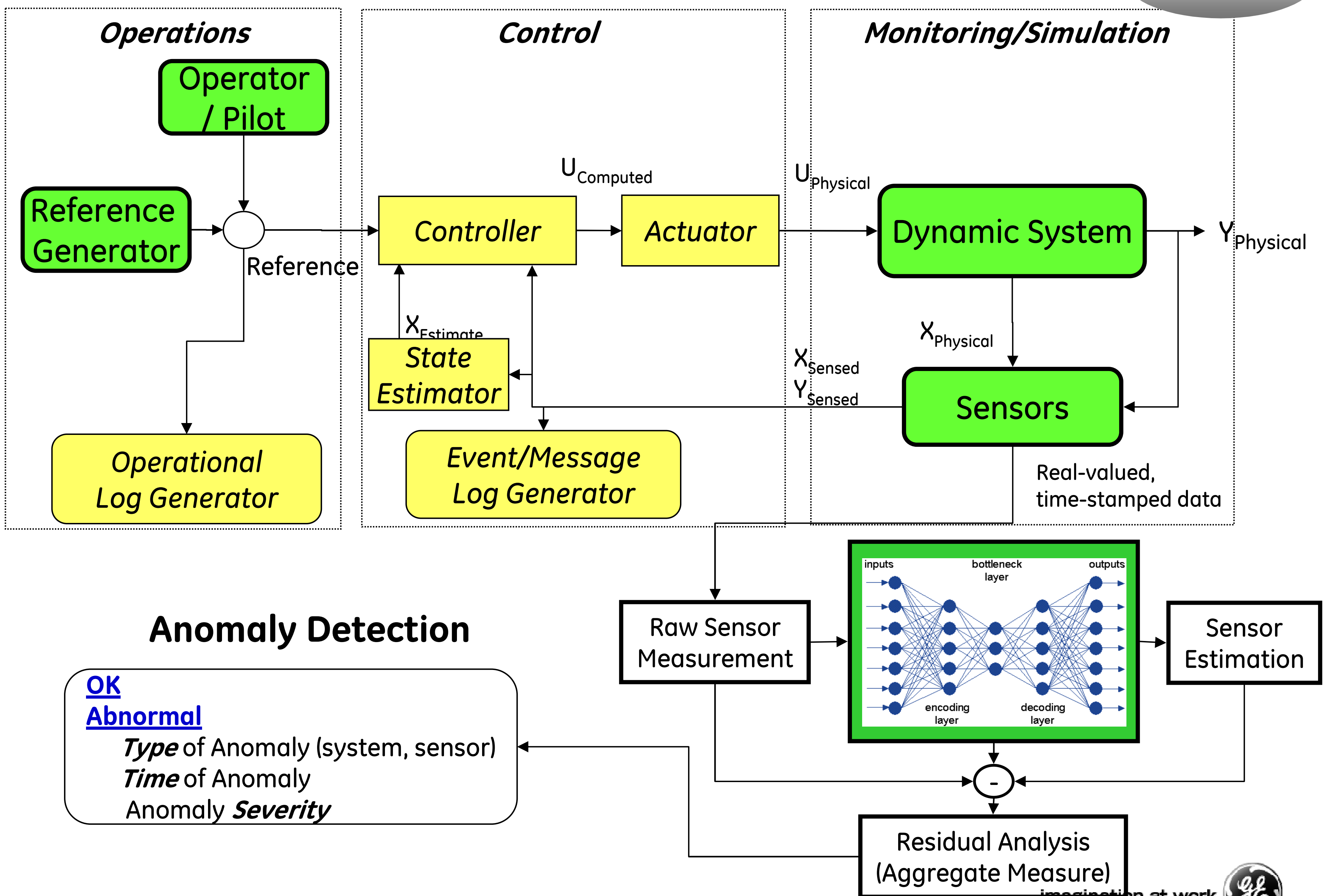
Experiments with Simulated GE90 Aircraft Engines

- Experiment Setup
- Segmentation of the Operating Space
- Experiments

1st	- 3 local models
2nd	- 1 Global Model
3rd	- 3 local Models + Supervisory Model

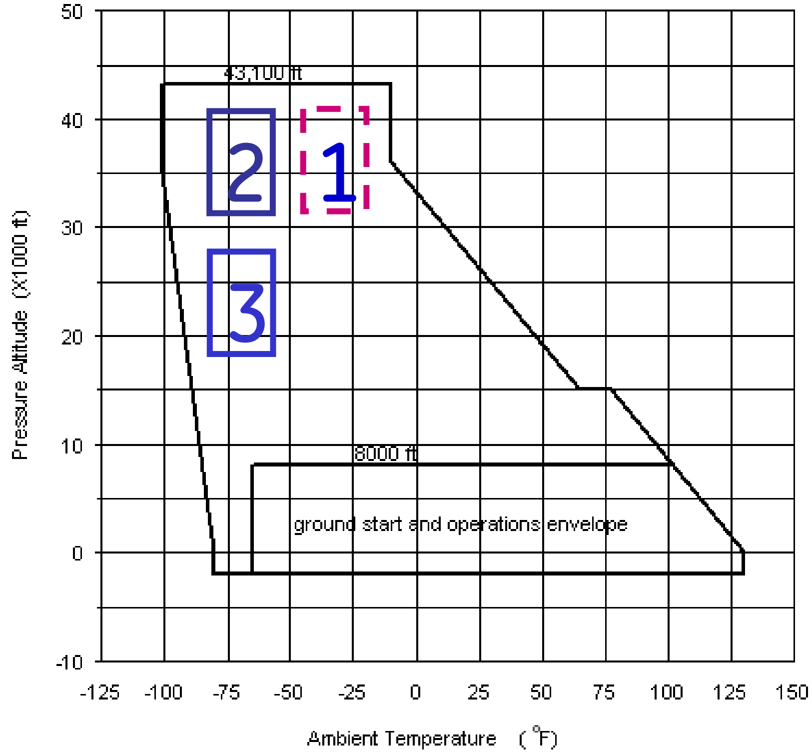
Experiment Setup

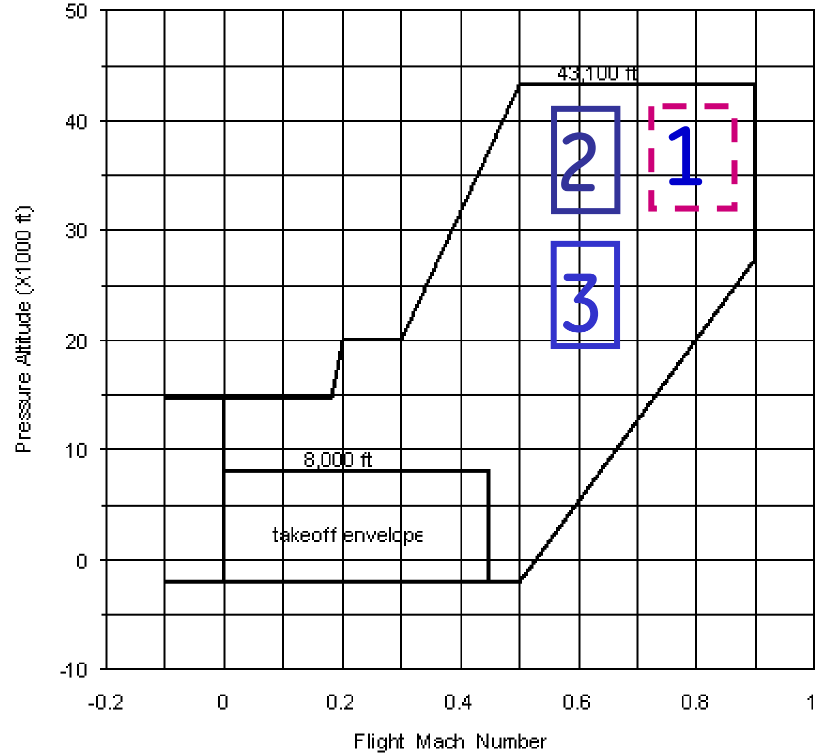
Experiements

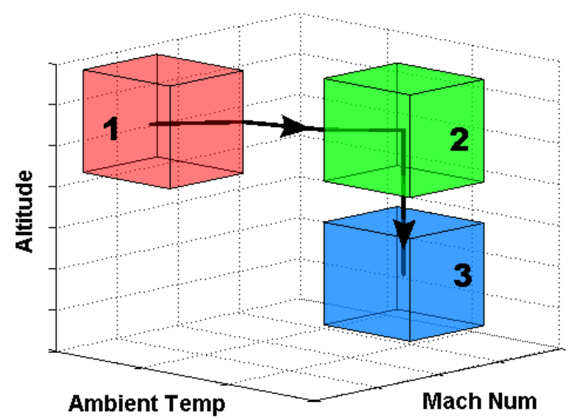


Segmentation of the Operating Space Three regions in the Flight Envelops

Operating Space







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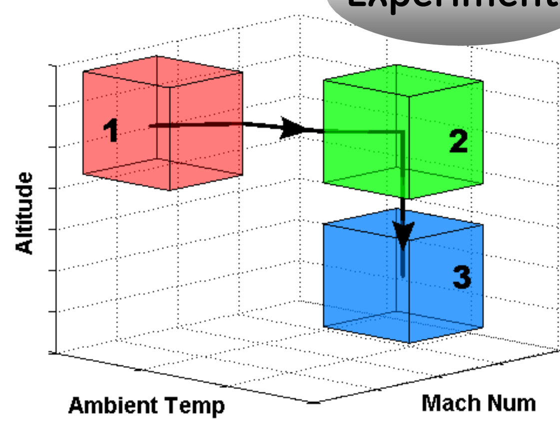
Experiments

Experiments

Experiments Settings

– We used a **steady state CLM** model for a commercial, **high-bypass, twin-spool turbofan engine**.

– We can manipulate flight conditions to simulate different operation regimes (i.e. flight envelops of aircraft) and generate data corresponding to them



1st Experiment

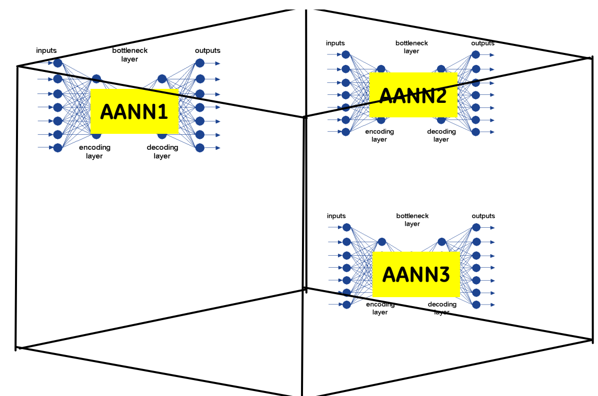
Three AANN's: **One for each region in the flight envelop (region)**

Vary ALT, Mach and Tamb ->1000 normal operating pts for each region

Run each operation point through CLM to generate a 9x1 sensor vector

900 points for training (200 for validation); 100 points reserved for test

Each local model performs very well (better than global model) in region of competence, and performs poorly outside its limited scope)



2nd Experiment

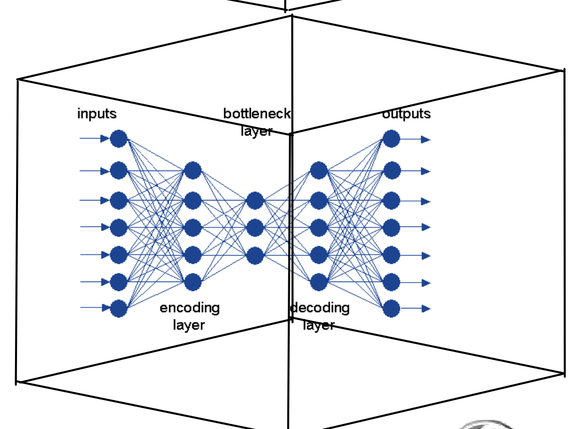
One Global AANN

Train on same 2700 training data points from experiment 1

Run each operation point through CLM to generate a 9x1 sensor vector

Test on the left 300 points

Global model performs fair across all three regions - shows higher variance than each local AANN operating within its scope



3rd Experiment

Three AANN's: One for each region in the flight envelop

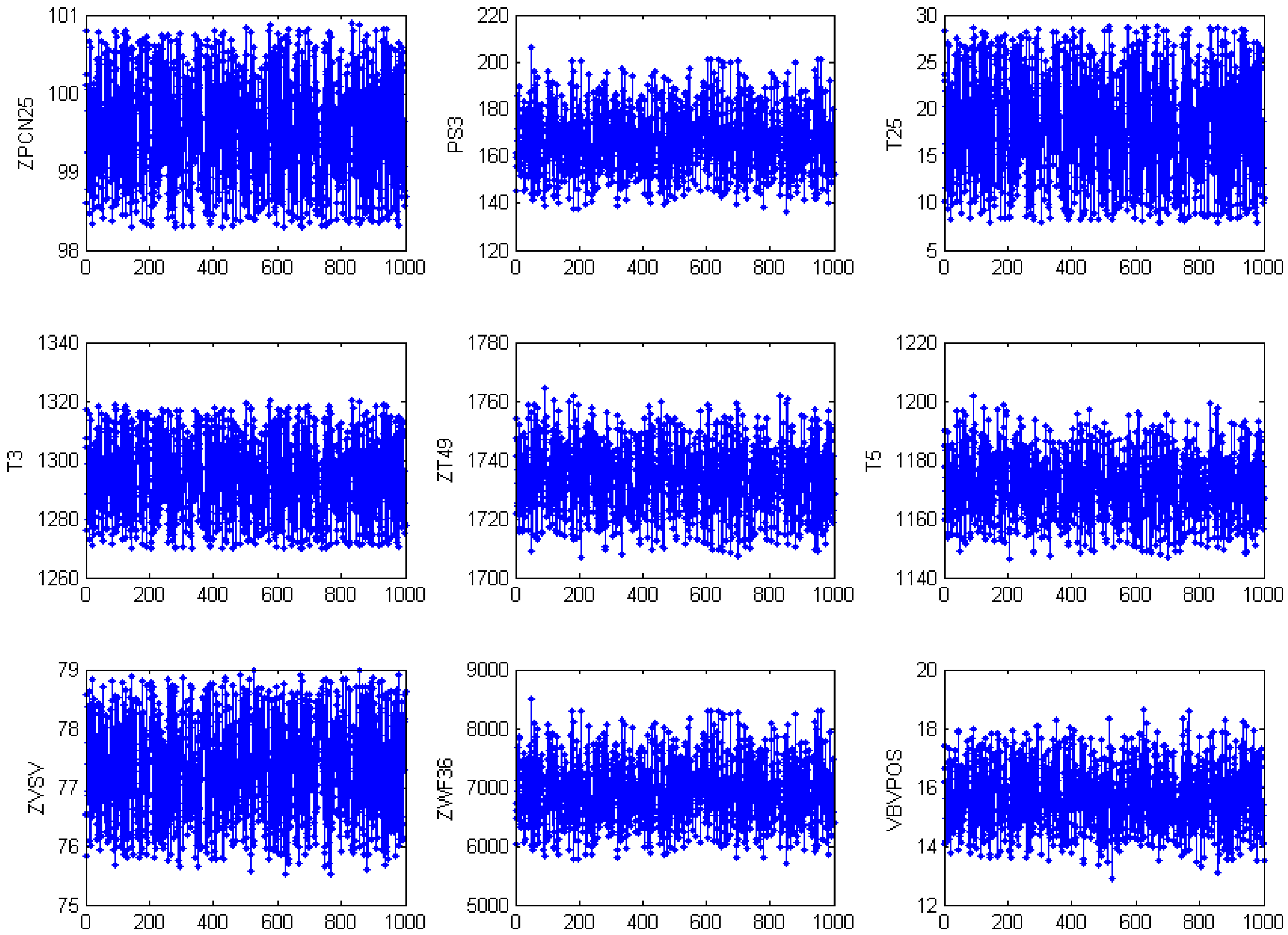
Fuzzy Supervisory Model (FSM) to interpolate among local AANN's

Experiment 1

- Vary ALT, Mach and Tamb ->1000 normal operating pts for each flight envelop
- Run each operation point thru CLM to generate a sensor vector (9x1)
- Three AANN's: One for **each region** in the flight envelop
- 900 points for training (200 for validation); 100 points reserved for test

Goal: Create **three local models**
Results: High performance when in scope
inadequate performance when out of scope

Raw Data from Flight Env 1



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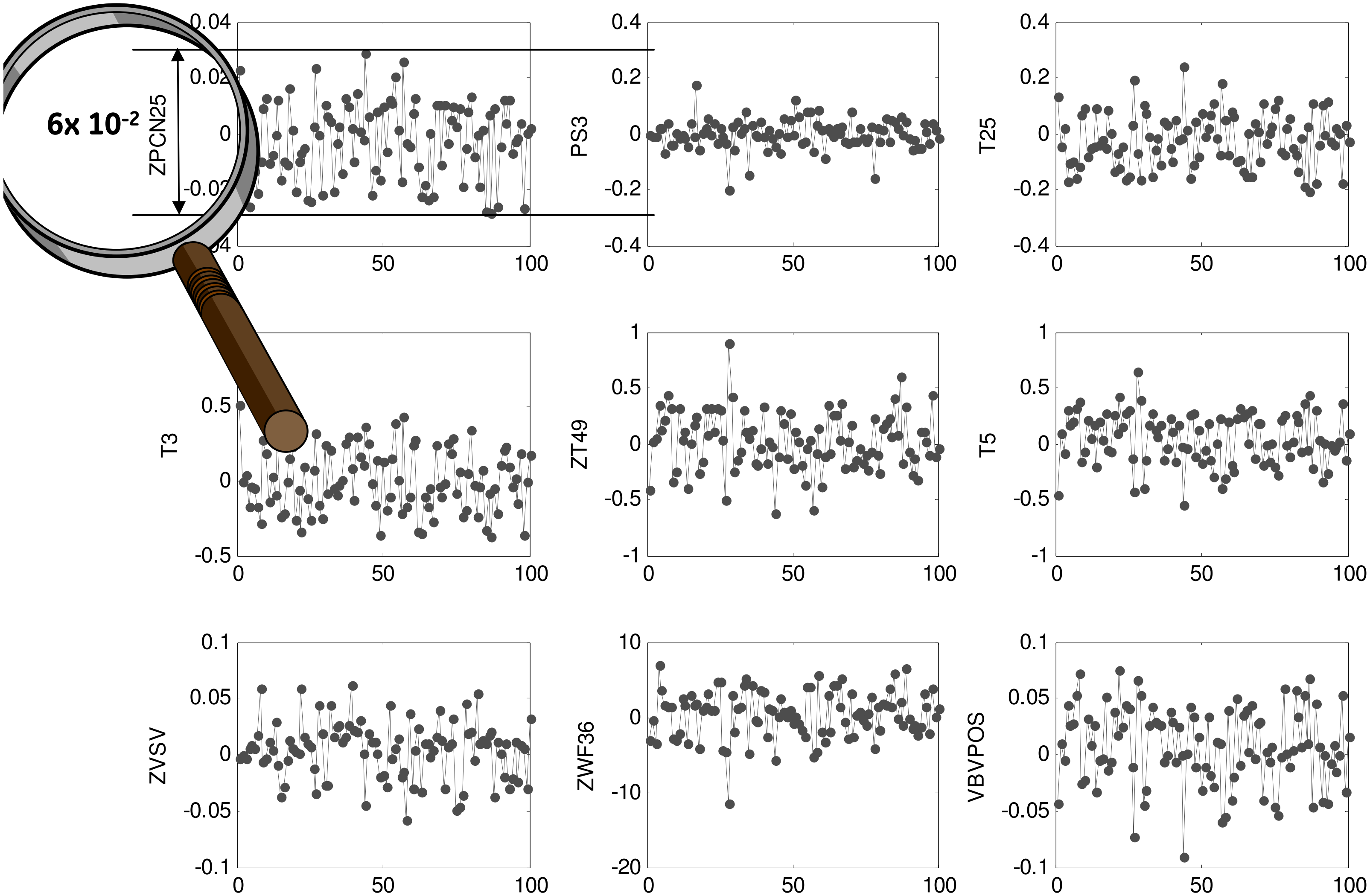
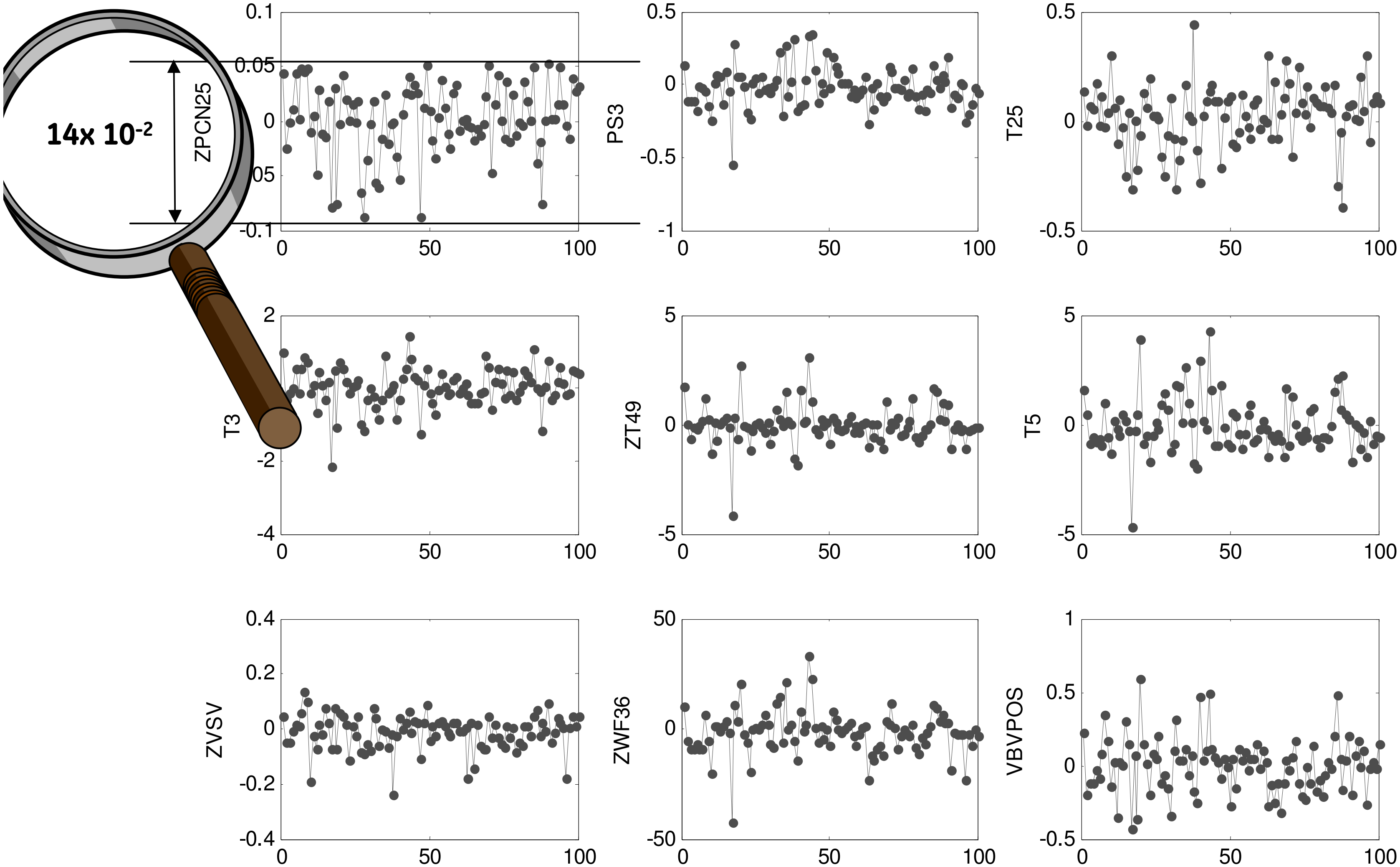
Residuals: test set from FE1 on AANN1



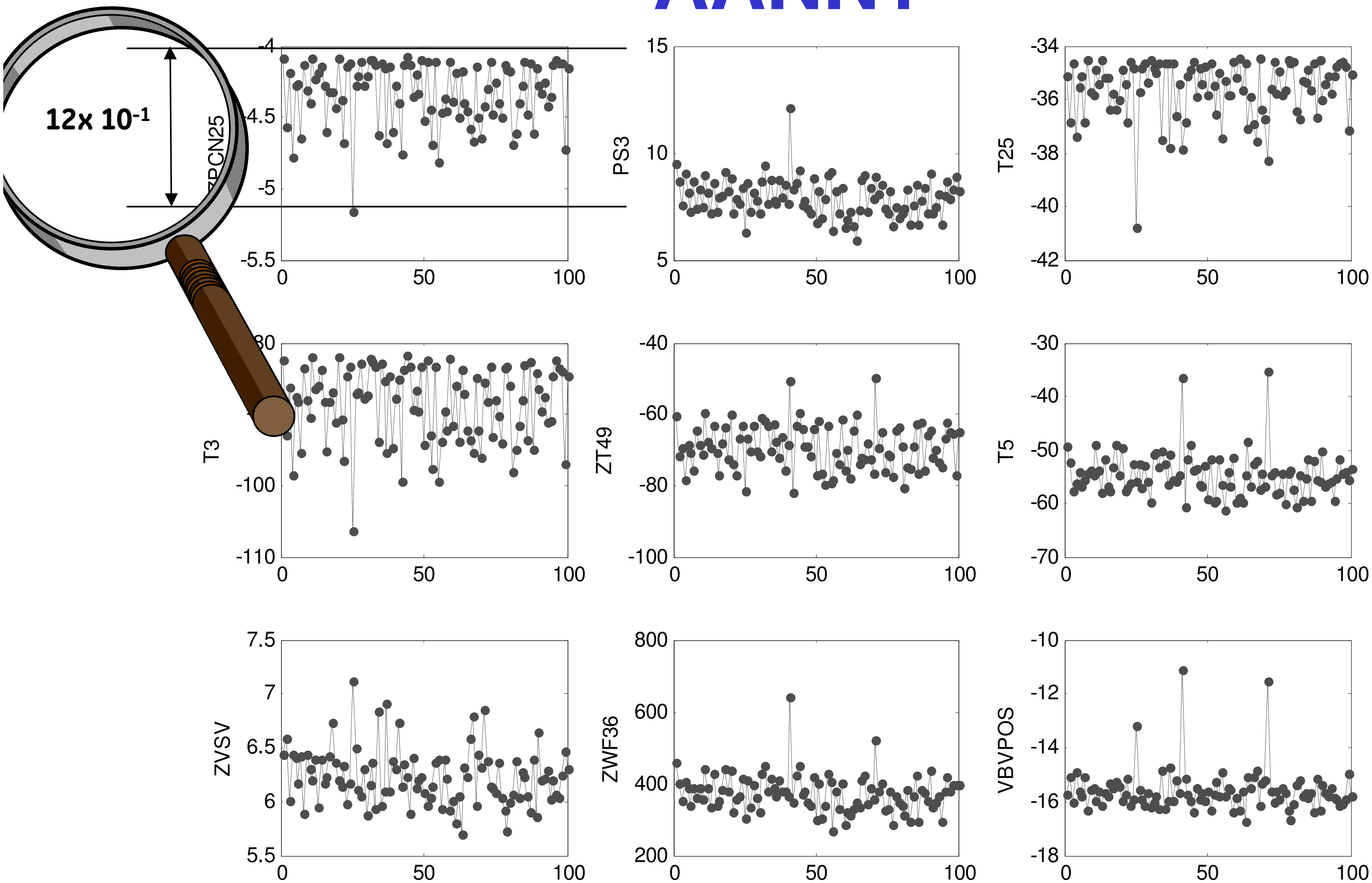
Correct Scope of local model: Small Residuals!

Residuals: test set from FE3 on AANN3



Correct Scope of local model: Small Residuals!

Residuals: test set from FE2 on AANN1



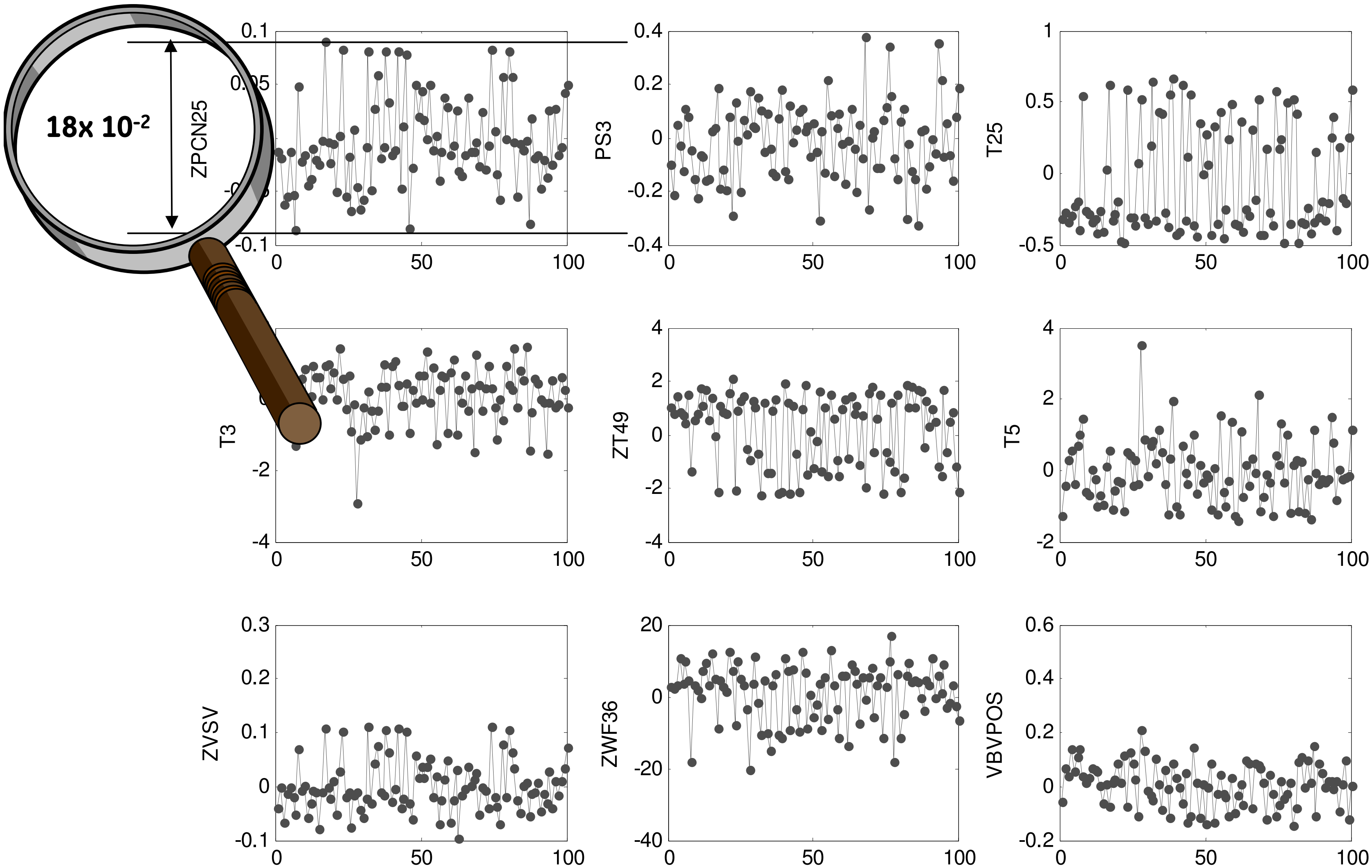
Incorrect Scope of local model: Larger Residuals (10x)

Experiment 2

- One global AANN
- Train on the 2700 training data points from experiment 1
- Test on the left 300 points

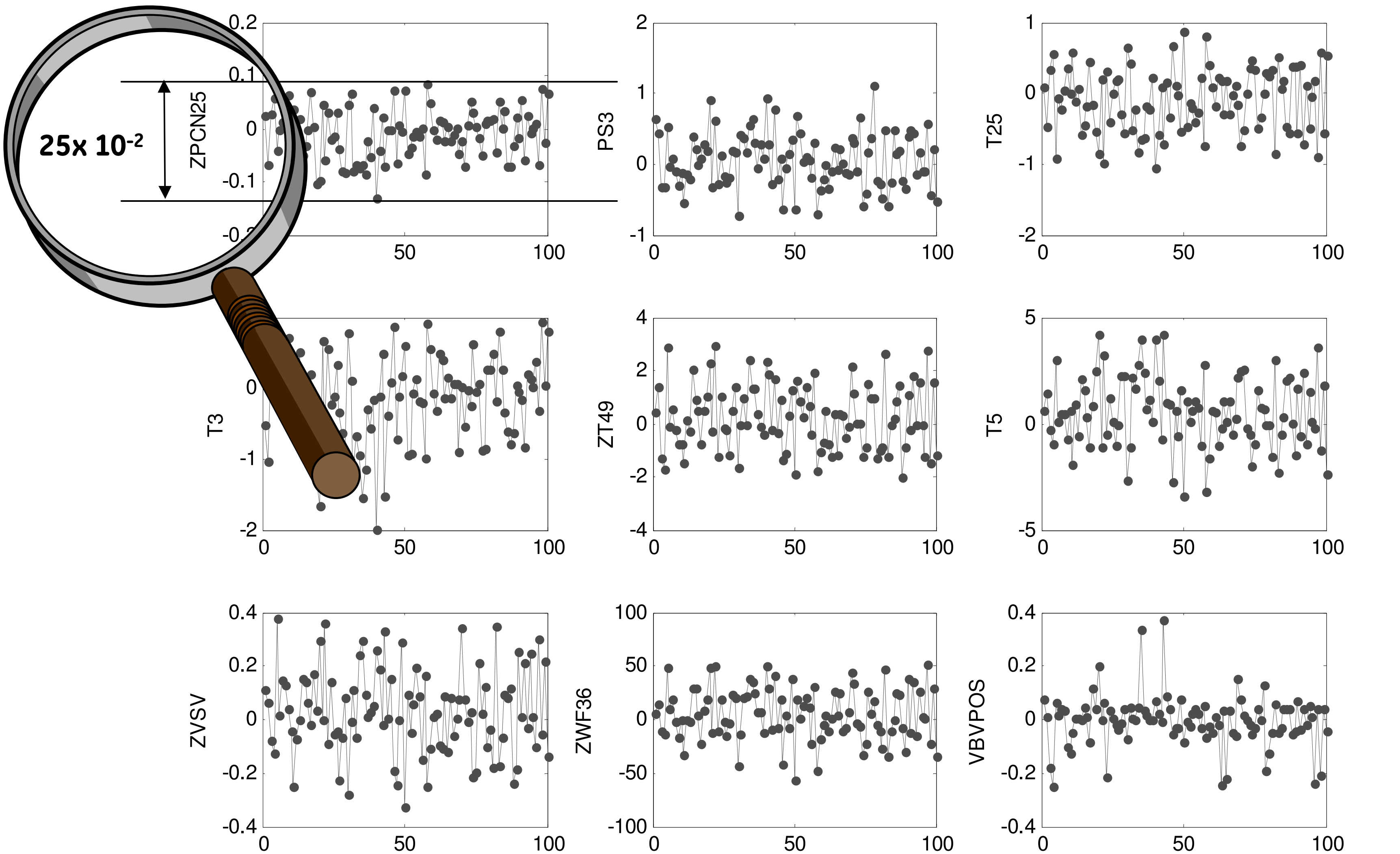
Goal: Create **one Global model**
Results: Mediocre performance across entire space
– better than worse performance of local models

Test data from FE1



Increased variance (3x) compared to experiment 1

Test data from FE3



Increased variance (2x) compared to experiment 1

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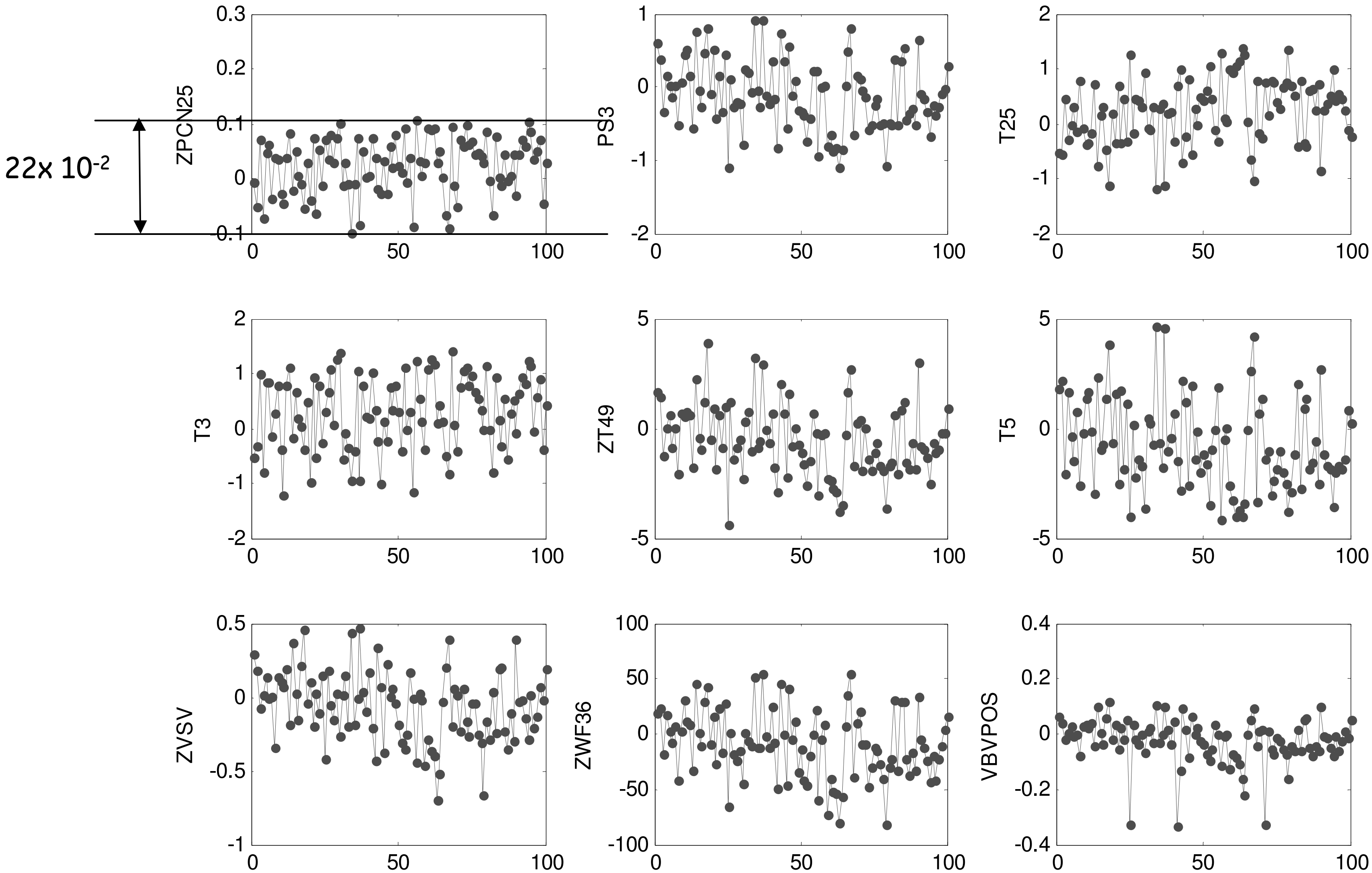
Test data from FE2



Smaller residuals (20%) compared to FE2 on NN1

Experiments (con't)

3rd Experiment

- **Three AANN's:** One for each region in the flight envelop

- Fuzzy Supervisory Model (FSM) to interpolate among local AANN's

Simulate the change of flight conditions

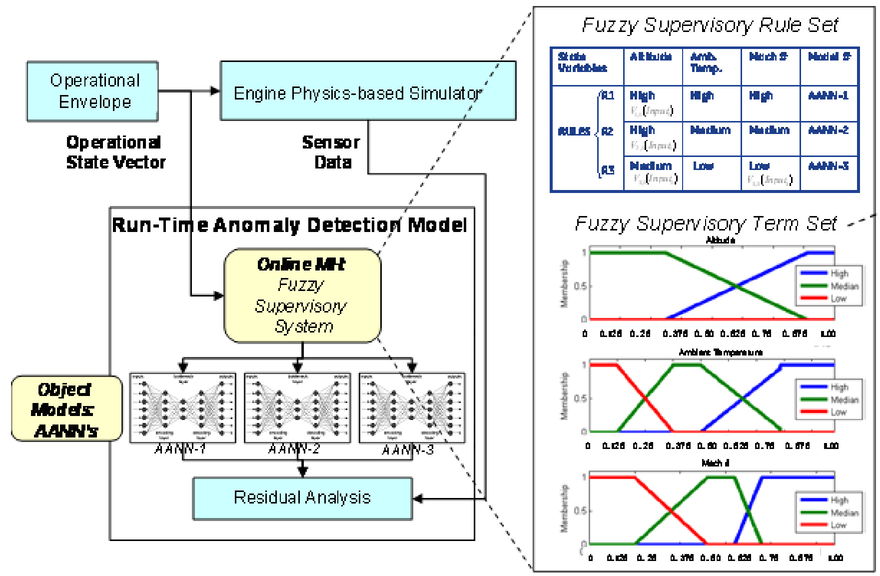
FE1: 200 pts

FE1 → FE2: 200 pts

FE2: 200 pts

FE2 → FE3: 200 pts

FE3: 200 pts



Test the simulated data on the Fuzzy Supervisory Model + AANN1, AANN2, AANN3

Intentionally making transitions in the space not covered by any pre-trained flight envelop

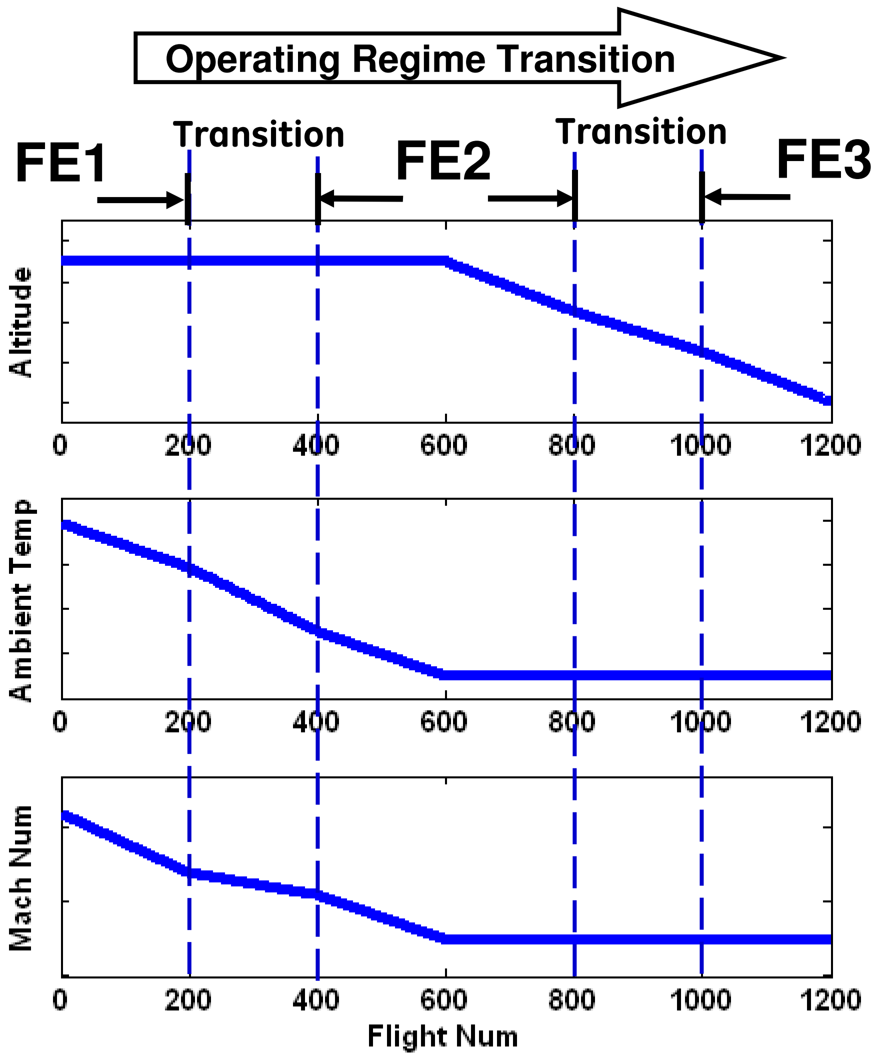
Hierarchical structure performs very well across all regions – including transitions

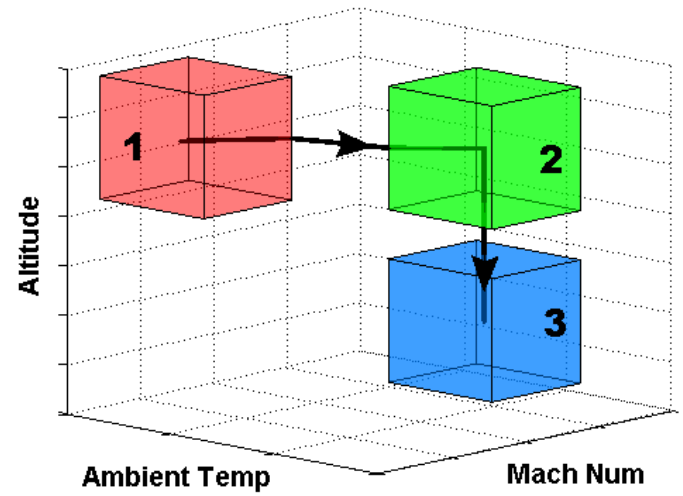
Goal: Create a **Fuzzy Supervisory for three local models**

Results: Higher performance across all regions

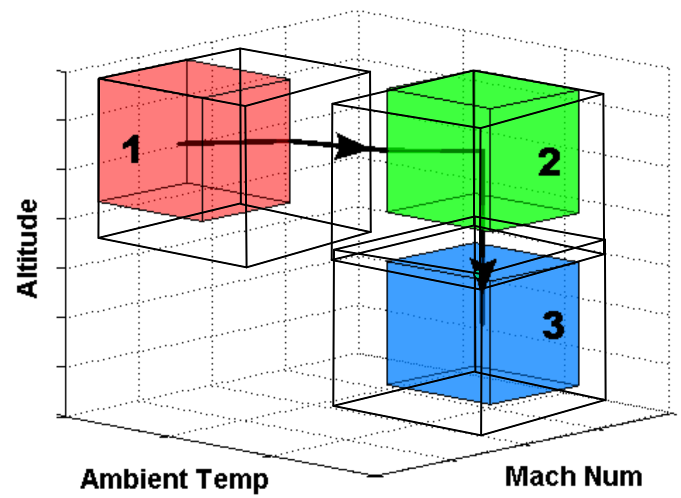
Flight Envelop Transitions

Operating Space





Crisp Model-Transition



Fuzzy Model-Transition

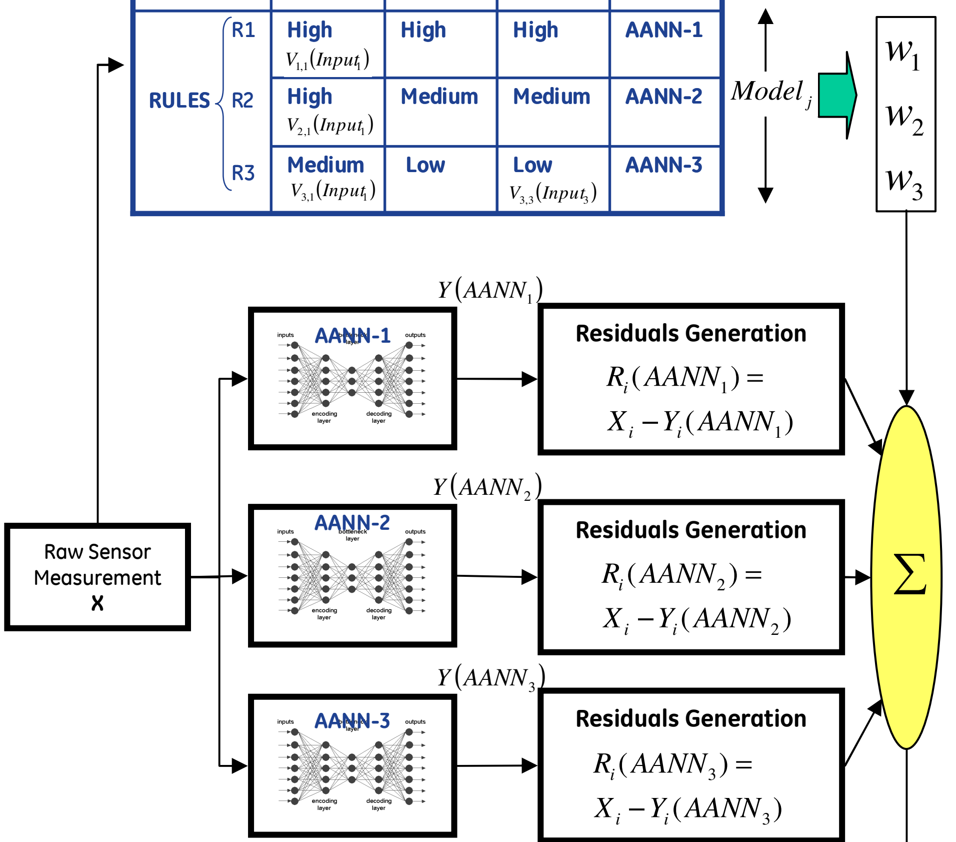
Transition Management Using Fuzzy Supervisory Model

AANN Interpolation by Fuzzy Supervisory

$\longleftarrow Input_k \longrightarrow$

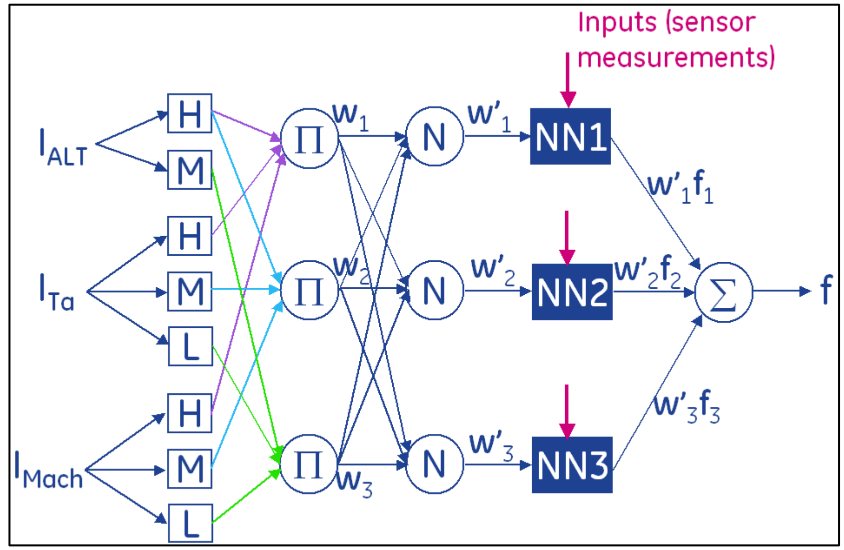
State Variables		Altitude	Amb. Temp.	Mach #	Model #
RULES	R1	High $V_{1,1}(Input_1)$	High	High	AANN-1
	R2	High $V_{2,1}(Input_1)$	Medium	Medium	AANN-2
	R3	Medium $V_{3,1}(Input_1)$	Low	Low $V_{3,3}(Input_3)$	AANN-3

$$w_j = \prod_{k=1}^{3} V_{j,k}(Input_k)$$



$$\widehat{R} = \frac{\sum_{j=1}^{3} w_j \times R_i(AANN_j)}{\sum_{j=1}^{3} w_j} = \sum_{j=1}^{3} w_j^{'} \times R_i(AANN_j)$$

Network Implementation



$w_i = \prod_{j=1..3} X_{ij}(I_i)$ $\quad w'_i = w_i/(w_1+w_2+w_3)$

Figure Of Merit (FOM)

$$FOM = \sqrt{\frac{1}{nm}\sum_{i=1}^{n}\sum_{j=1}^{m}\left(\frac{R_{ij}}{\overline{X}_i}\right)^2}$$

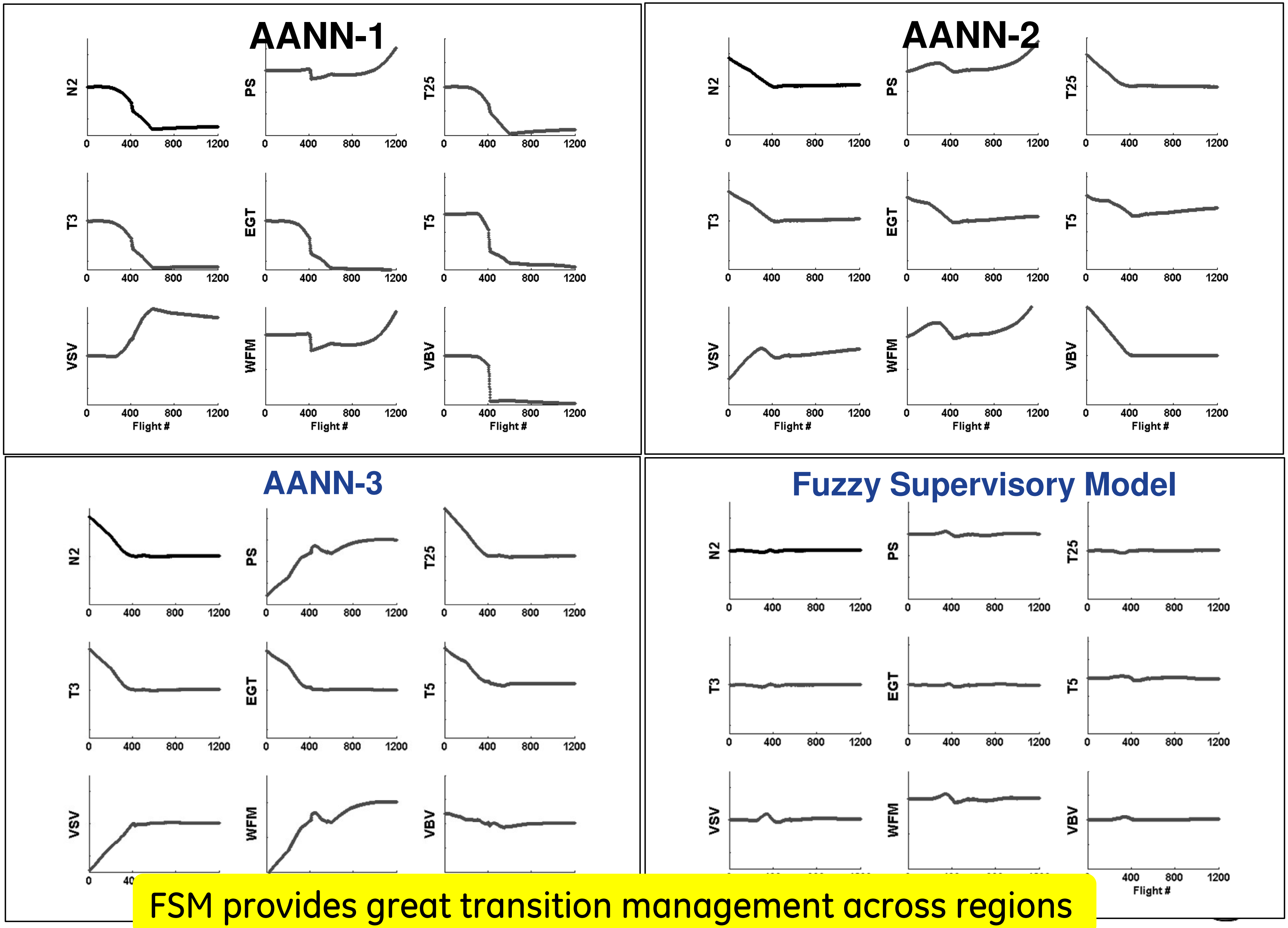
n is the number of the variables (sensors)

m is the number of data points (measurement)

R_{ij} is the residual between true measurement and AANN estimation,

$\overline{X}_i$ is the mean of the true measurement

Residuals for each AANN and for hierarchical system (with FSM)

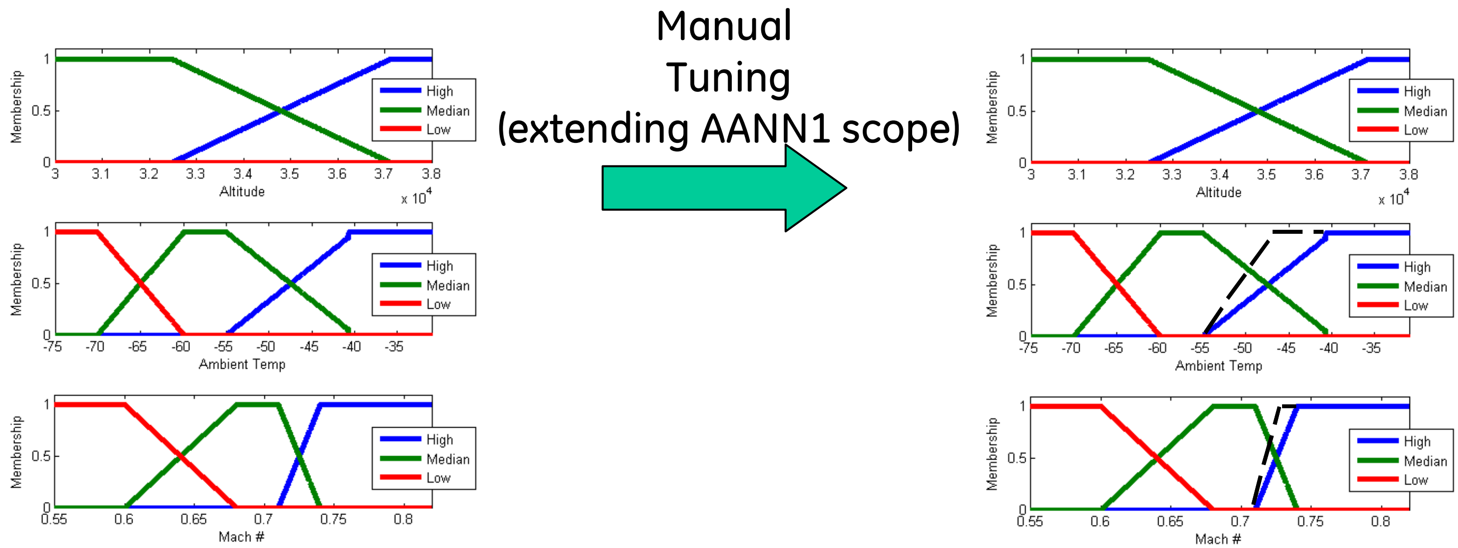


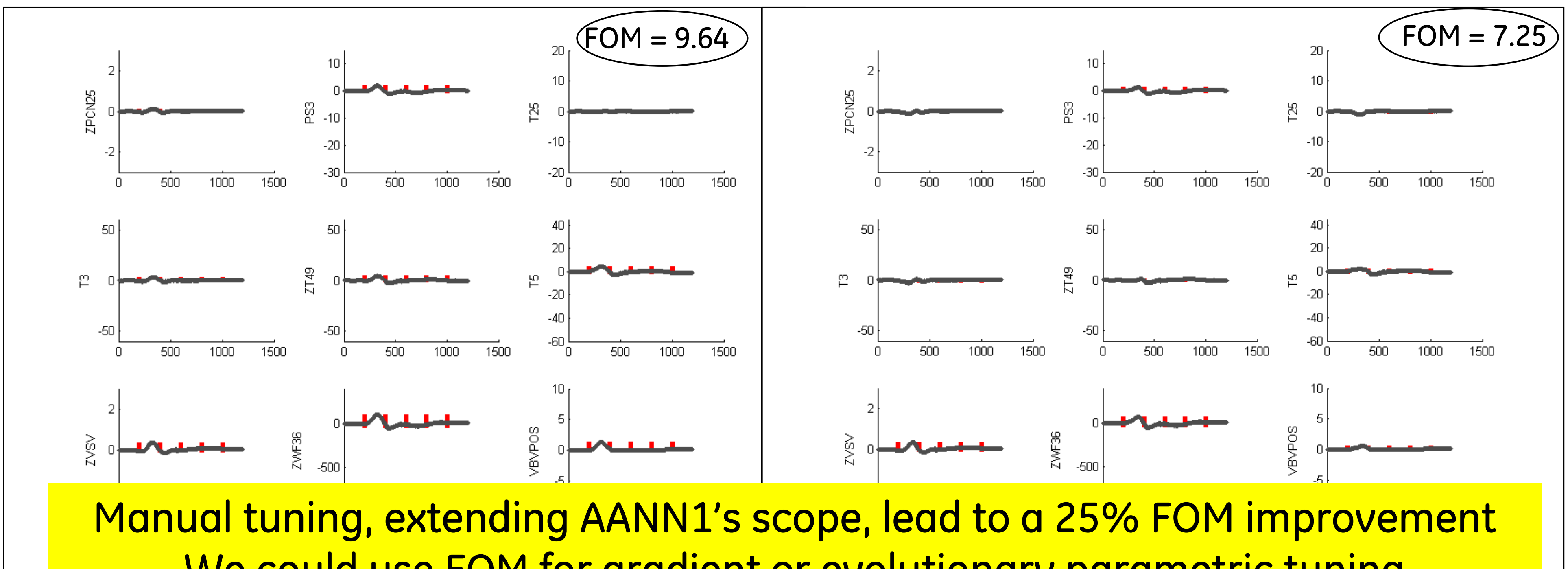
FSM provides great transition management across regions

Design Tuning

- Design Choices in the Fuzzy Supervisory Model (FSM)
- Tuning the Fuzzy Supervisory Model
    - Manual tuning of FSM State Partitions
    - Automated tuning of FSM State Partitions

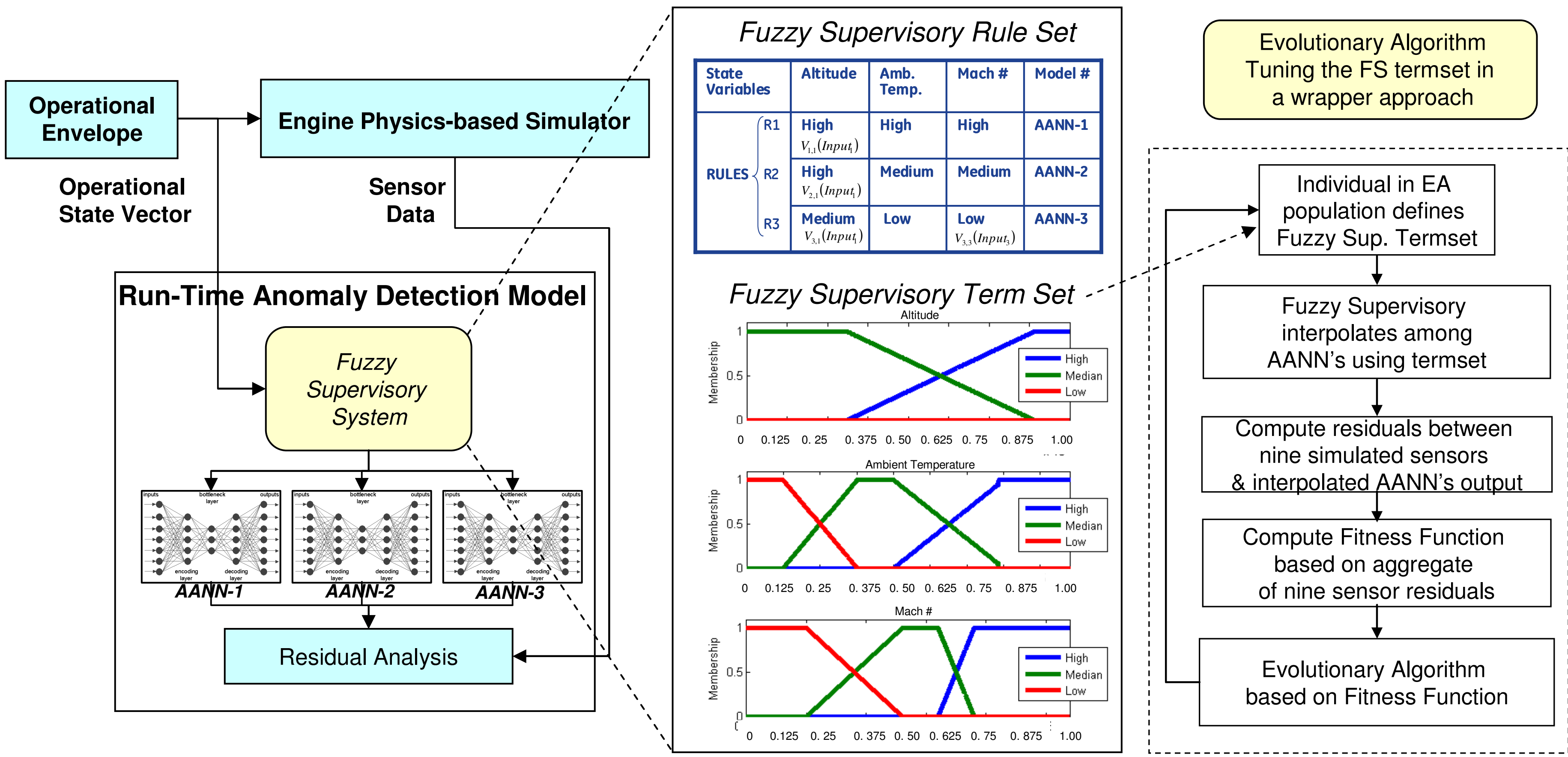
Manual FLS Tuning: Membership function parameters



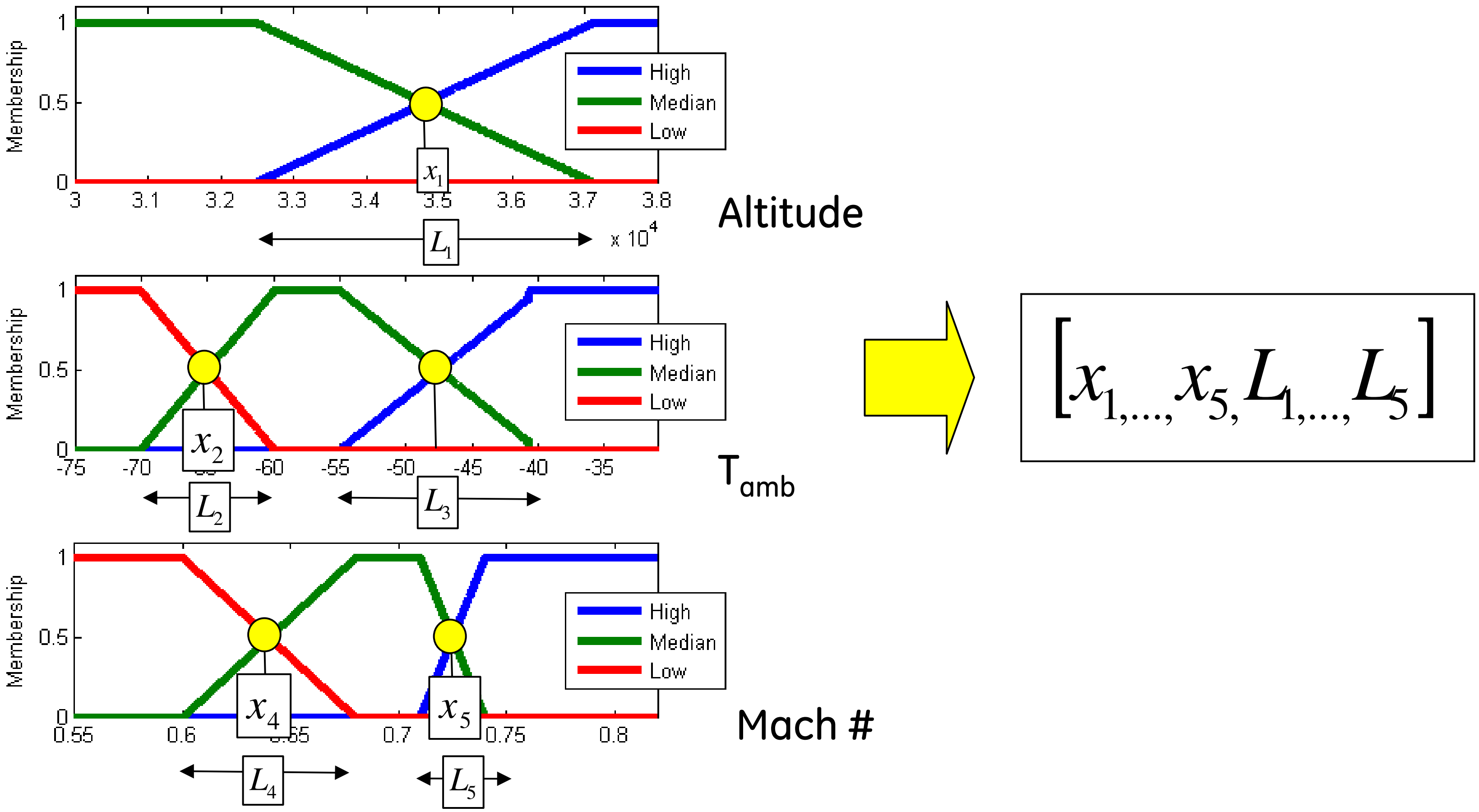


Manual tuning, extending AANN1's scope, lead to a 25% FOM improvement
We could use FOM for gradient or evolutionary parametric tuning

Automated FLS Tuning with an EA using a Wrapper Approach



Automated FLS Tuning: Encoding Trapezoidal Membership functions



Encoding the abscissa of the slope intersections (x_i) and the lengths of the bases of each triangle (L_i) as an individual in the Evolutionary Algorithm population

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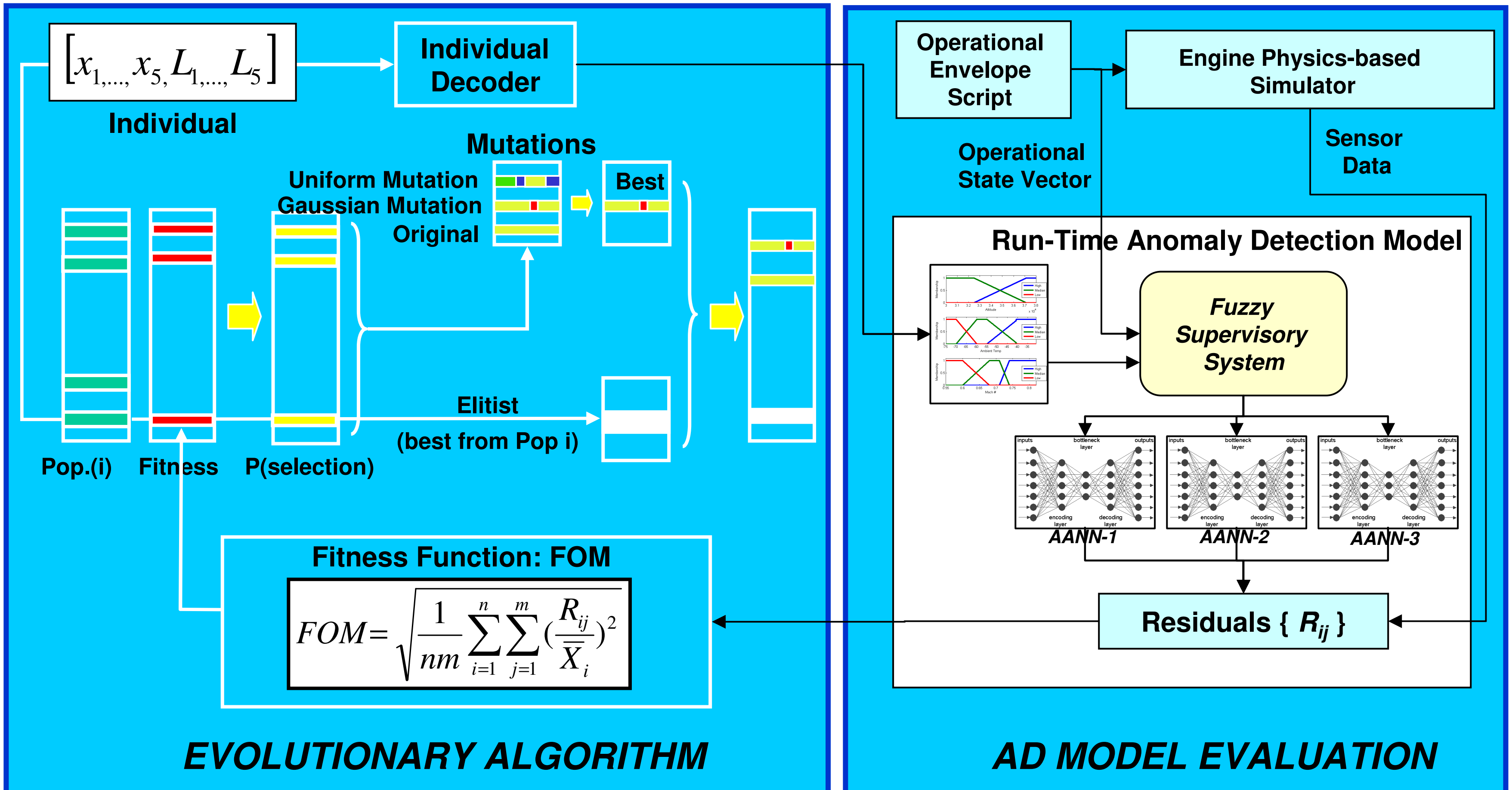
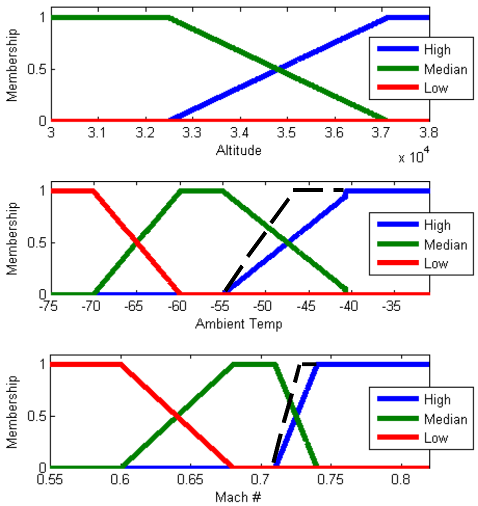
Evolutionary Search for Tuning a Fuzzy Supervisory System using a Wrapper Approach



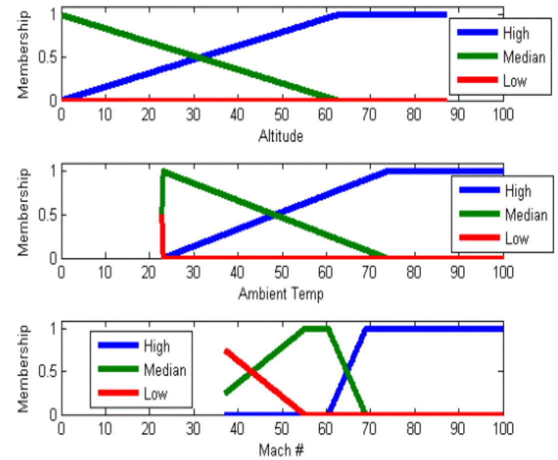
Pop Size = 500 individuals
GenMax = 1,000 generations

Anomaly Detection - Results
Automated FLS Tuning: Membership function parameters



Meta-Heuristic
Tuning

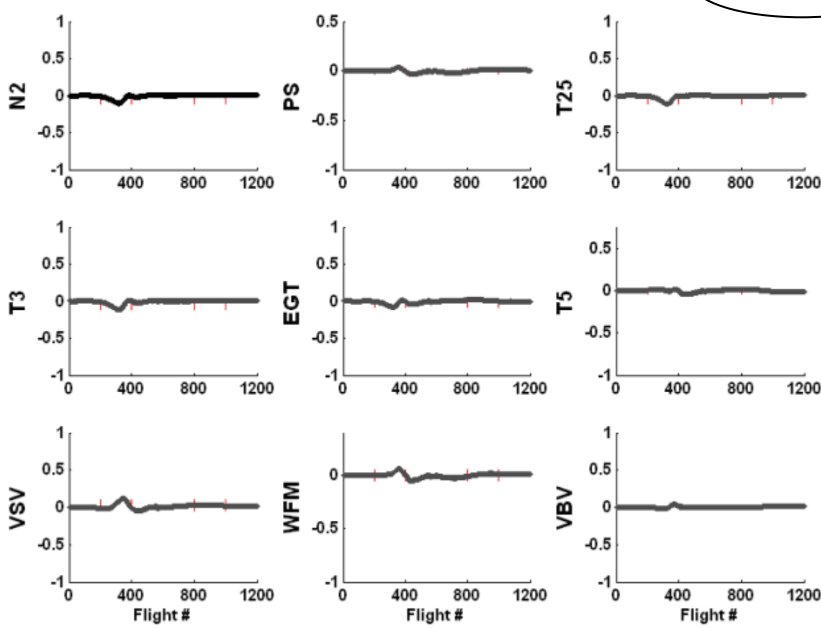
Use **Global Tuning**
(based on FOM fitness function
and Genetic Algorithm)
to further improve results



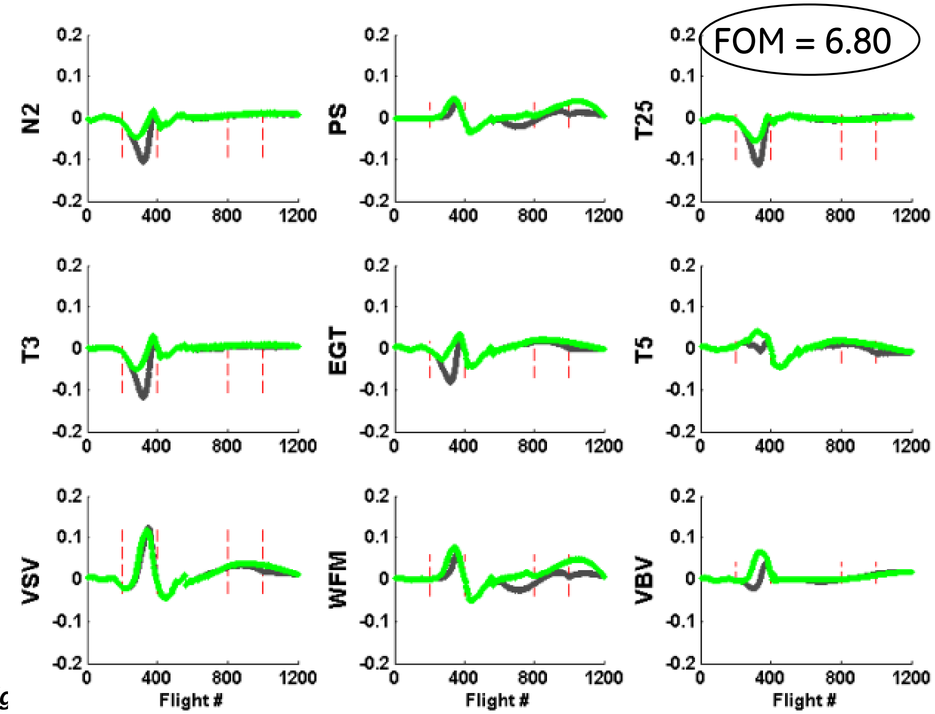
Note: Magnified scale to
enhance comparison

Before GA After GA

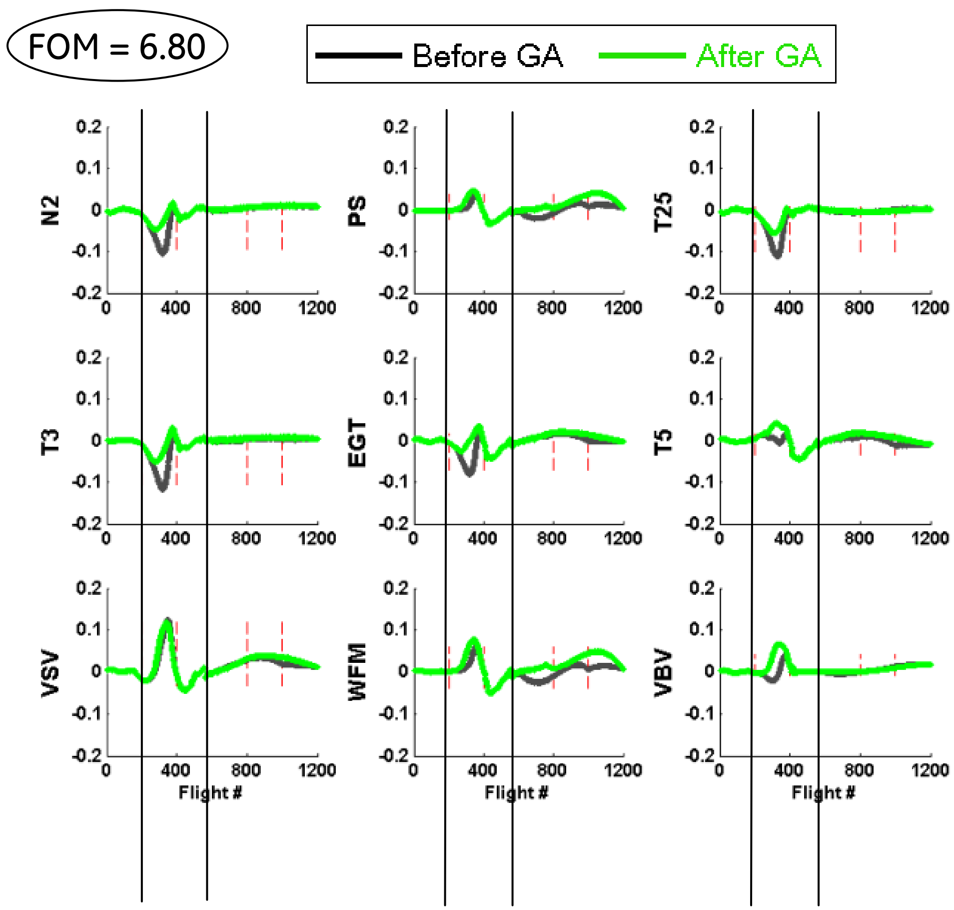
FOM = 7.25

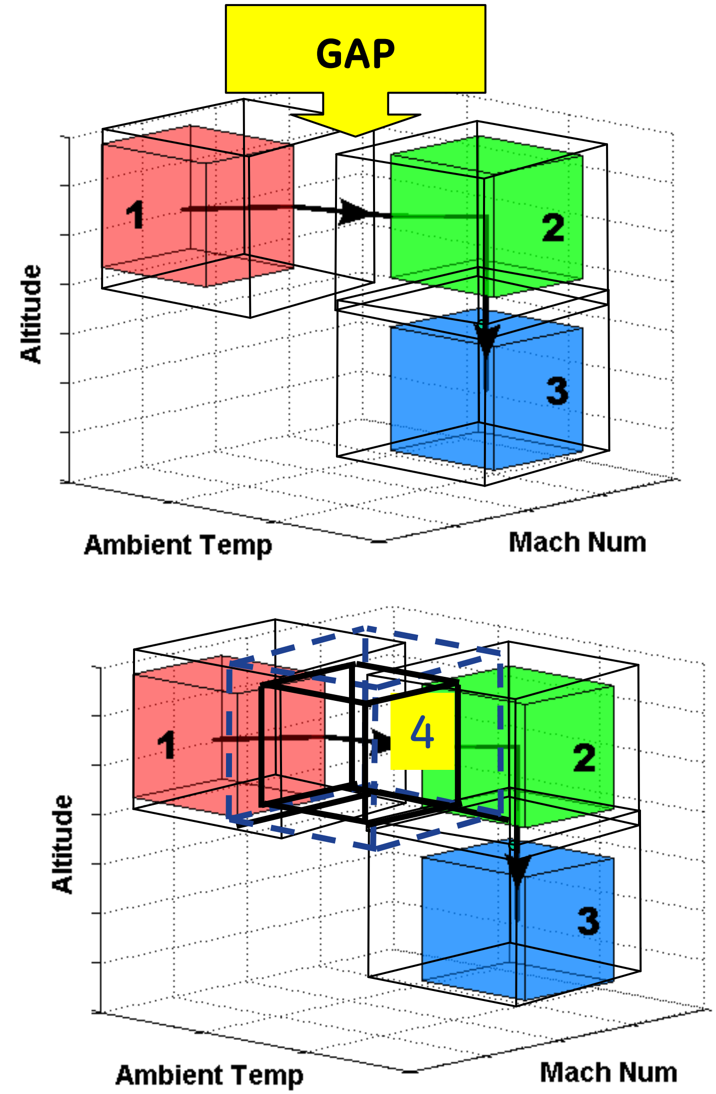


FOM = 6.80



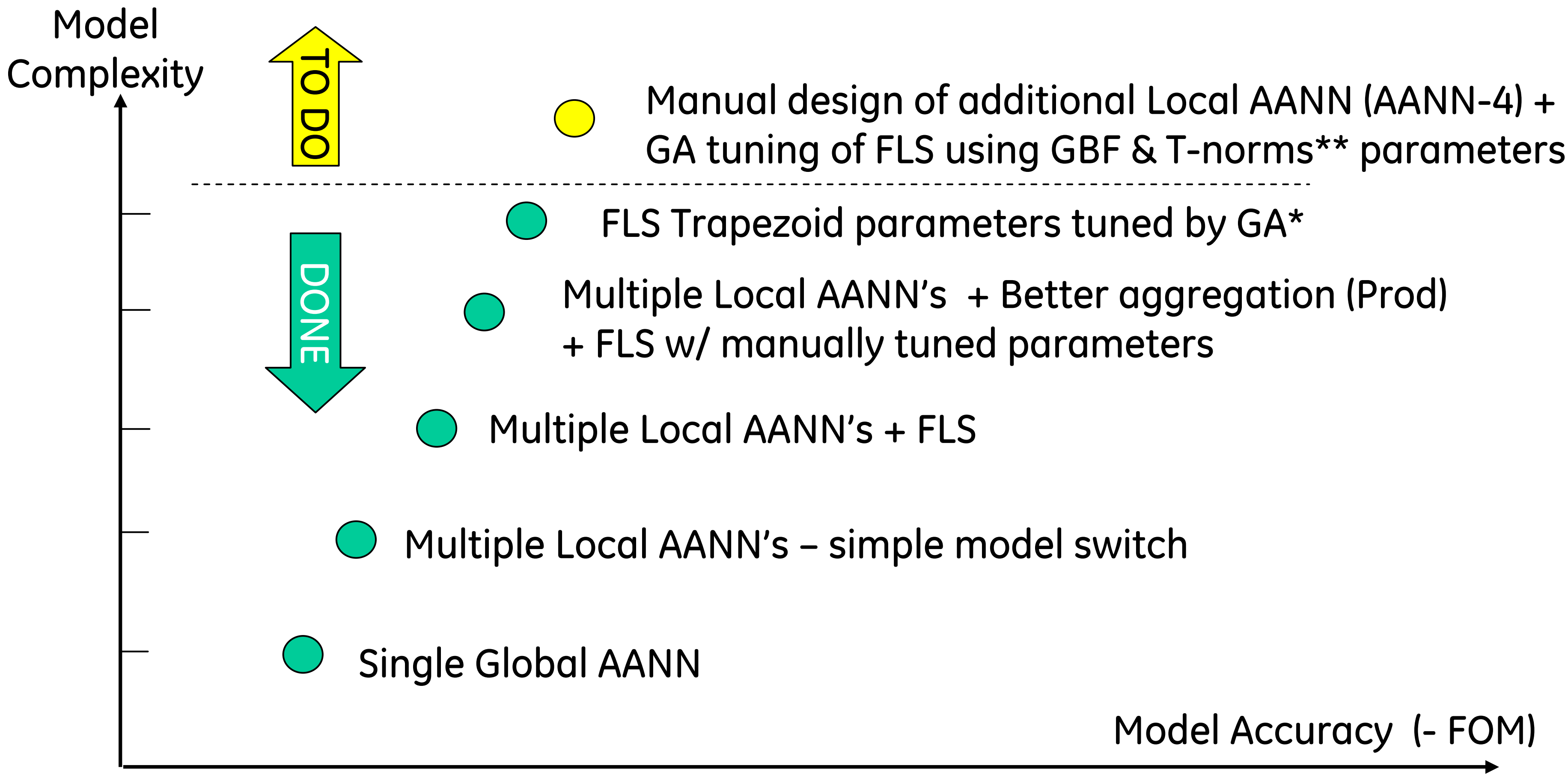
Improving AD Design : Add AANN-4 & retune FLS





Most residual errors occur in the [200, 600] interval, indicating a performance limit that cannot be addressed only by tuning the FLS. Rather it suggests the need for an additional AANN-4 to provide better coverage in that region

Design Tradeoffs



* Chromosome: $[x_1,\ldots,x_5,L_1,\ldots,L_5]$

** Chromosome: $[(a_{11},b_{11},c_{11}),\ldots,(a_{13},b_{13},c_{11}),\ldots,(a_{n3},b_{n3},c_{n3}),p]$

Future Work

- **Hierarchical Design (to Improve Accuracy and Extend Region of competence)**

  + Used Offline Metaheuristics (EA) and Online Metaheuristics (FLS) with AANN model

  - Use a more complex encoding for the EA individual to evolve BOTH structure and parameters:

  # AANN Models
  Scope of AANN Models
  Evolve membership Functions (GBF) in FLS
  Evolve Aggregation operators (parameterized T-norms)

- **Model Lifecycle (to maintain model Vitality)**

  - Use Offline Metaheuristics (EA) to create/retune hierarchical design with updated data sets (e.g. reflecting more recent engine degradation)

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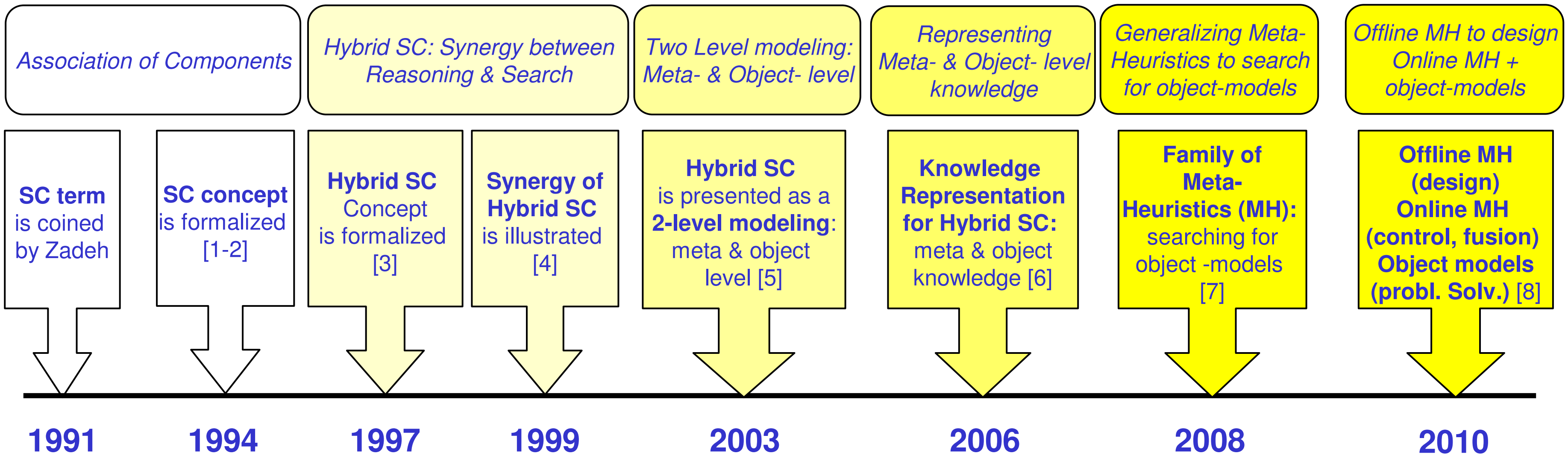
Conclusions & References

Summary

- **Role of Anomaly Detection in PHM**
- **Modeling with SC**: Combining Domain Knowledge with Field Data
- **SC Evolution** (1991-2010)
  - Association
  - Symmetric Hybrid Systems (Reasoning & Search)
  - Structured Hybrid Systems (Meta- & Object- Level Reasoning)
  - Offline MH and On-Line MH
  - Offline MH (model design); On-Line MH (models control or fusion); Object-models (problem solving)
- **Model Lifecycle Management**
  - Use Offline MH to **design and update** the On-line MH and Object-level models
- **Applications of SC to Anomaly Detection for AIrtcraft Engine**
  - Anomaly Detection (System): Kolmogorov, SOM, RF, Hotteling T2, AANN + Fusion
  - Anomaly Detection (Model): EA +FS + AANN
- **Other SC Applications to Classification and Prediction (not covered)**
  - Classification Digital Underwriting (EA +FS)
  - Prediction Power Plant Management (EA + CART + Fusion + NN)
- **Hybrid SC allows to easily integrate a broad set of techniques for leveraging knowledge and data**

Hybrid Soft Computing (H-SC): A Personal Timeline References



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Questions?

Comments?