EVALUATION OF AIRCRAFT ENGINE DIAGNOSTIC METHODS THROUGH PRODIMES

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Contents

Introduction

- A fair and common way of comparing the performance of gas path diagnostic methods had to be established
- A benchmark diagnostic problem named Propulsion Diagnostic Method Evaluation Strategy was created and made publicly available by NASA for this purpose
- In 2013, the performance results of 4 diagnostic methods were made publicly available

- This work presents
  - The performance results of 6 diagnostic methods that were developed at LTT/NTUA
  - A comparison of diagnostic method performance results through common *blind test cases*
  - Discussion about the evaluation results and the ProDiMES software

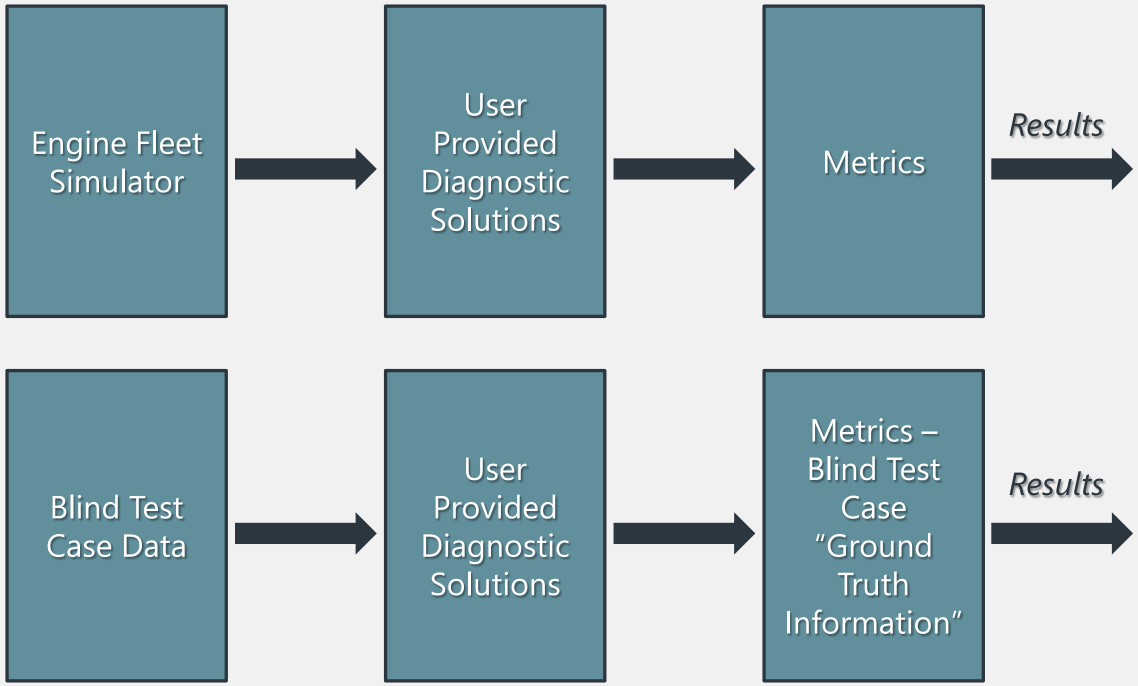
Contents

ProDiMES

- Offers a benchmark aircraft engine diagnostic problem
- Enables the side-by-side comparison of candidate diagnostic algorithms
- Two-fold functionality

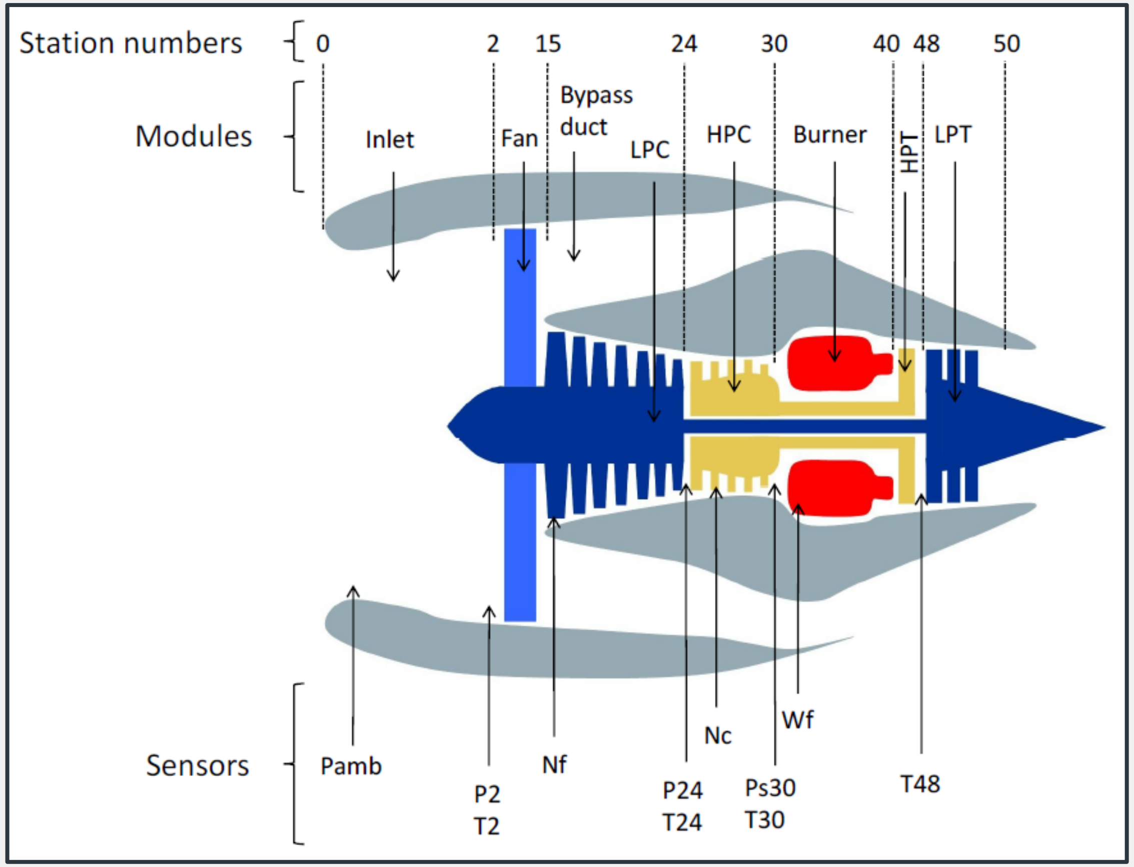
Independent development and evaluation of diagnostic methods

Comparison of diagnostic methods through a blind-test-case data set



ProDiMES

- **Generic turbofan engine**
  - High Bypass
  - Two Spools
- **19 fault scenarios (abrupt/rapid)**
  - No fault
  - 5 component faults
  - 2 actuator faults
  - 11 sensor faults
- **Snapshot Data**
  - Takeoff
  - Cruise

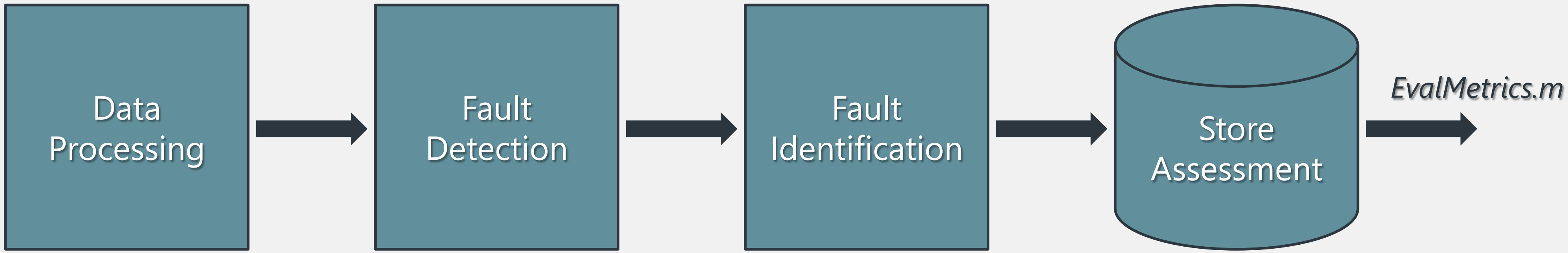


Diagnostic Framework

A diagnostic framework was developed in order to

1. evaluate all methods in an equal manner
2. to effectively control the false alarm rate

Diagnostic Framework Steps

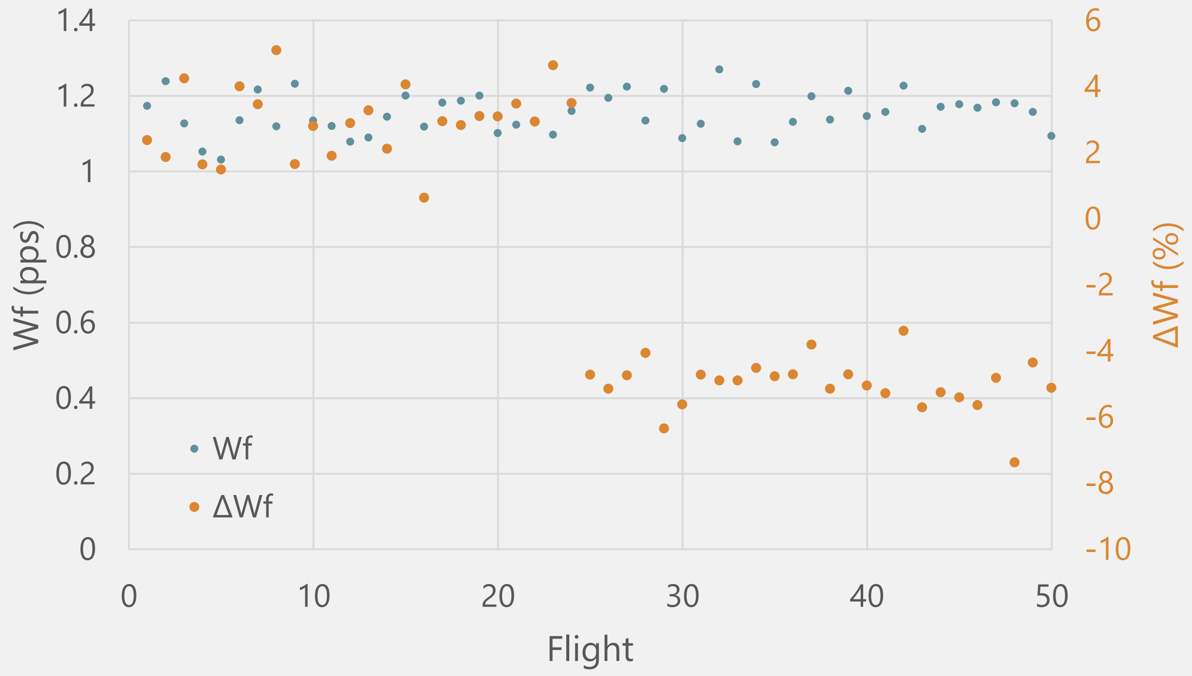


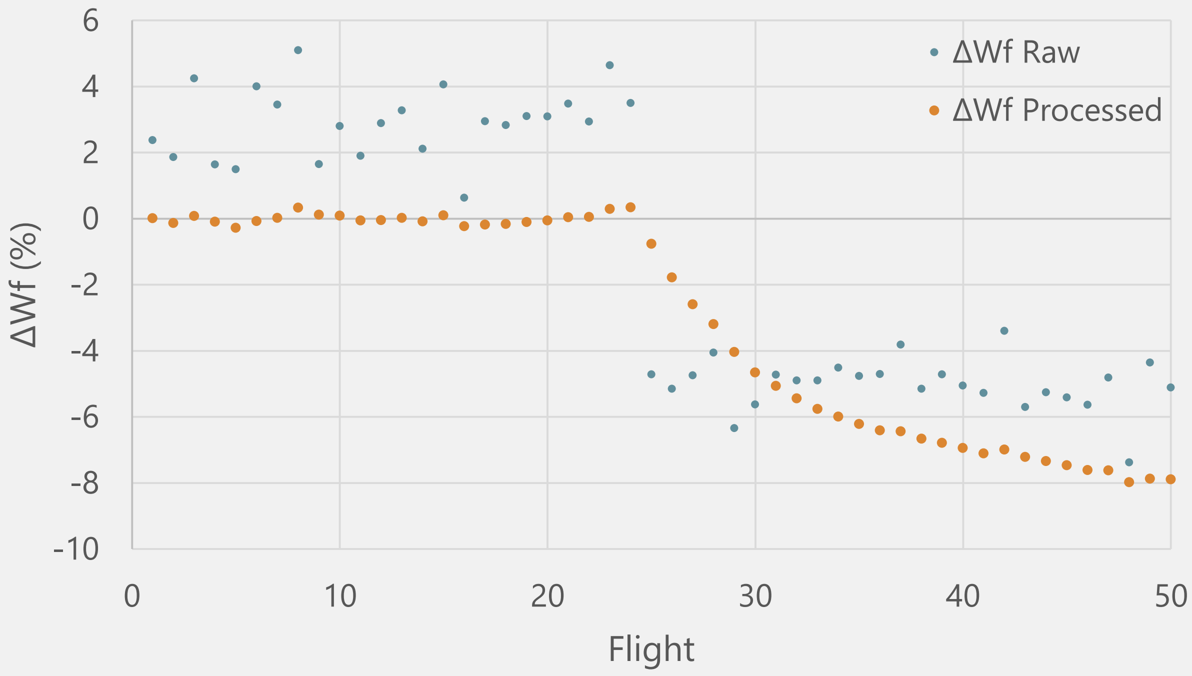
Diagnostic Framework Data Processing

1. Calculation of "Measurement Deltas"

$$\Delta Y = \frac{Y - Y^0}{Y^0} * 100$$

2. Deterioration Removal
3. Smoothing (EMA)
4. Reconstitution of measurements



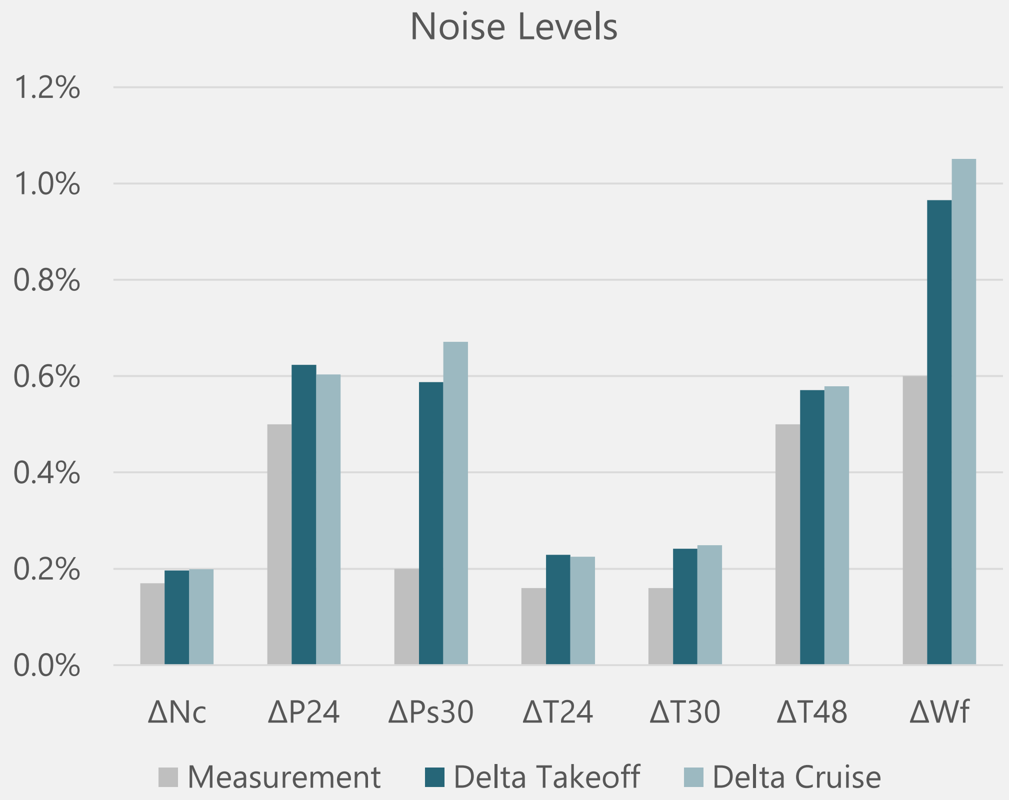


Diagnostic Framework Fault Detection

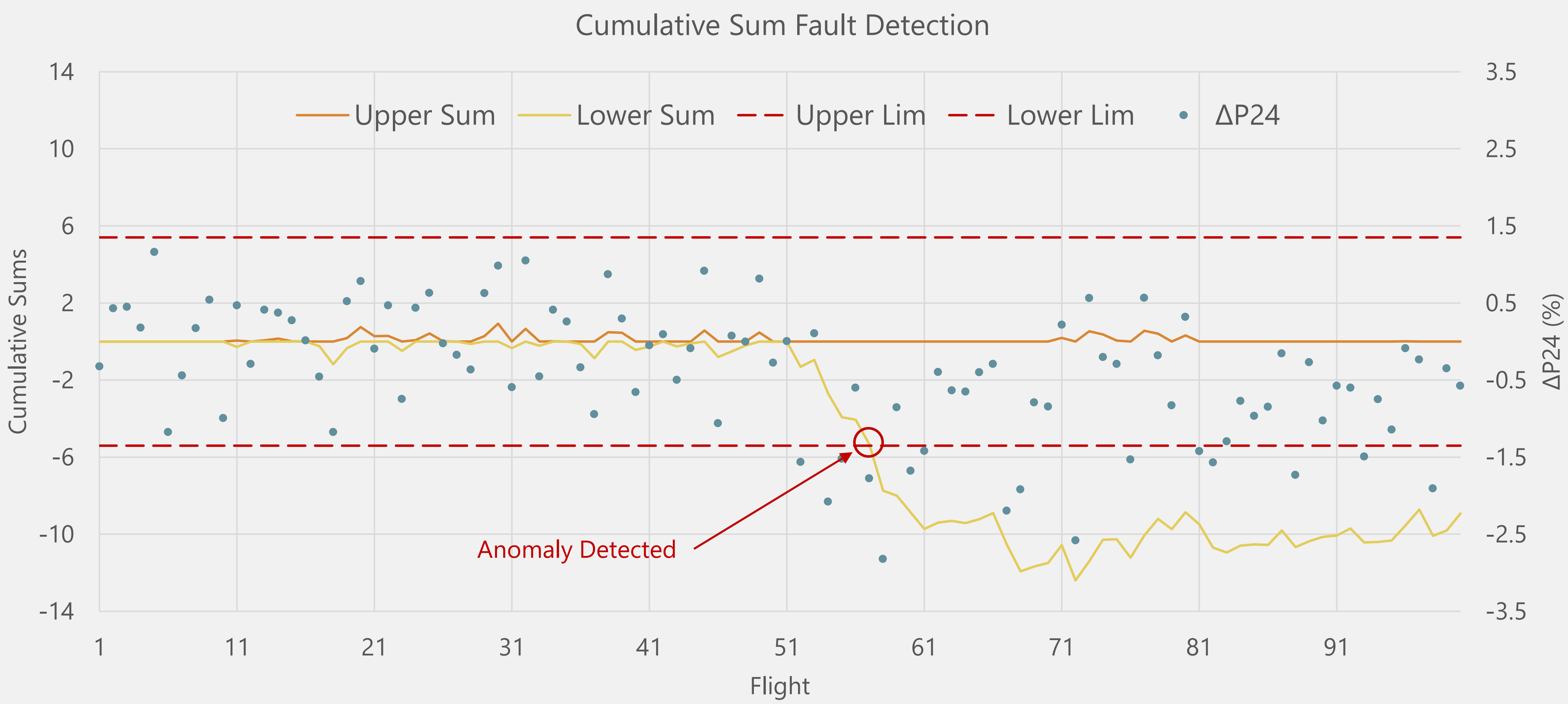
- Monitoring of "measurement deltas"
- Cumulative Sum (CUSUM)
- Derivation of the measurement deltas' variance

Error Propagation Law

$$C_Y = H_x * C_x * H_x'$$

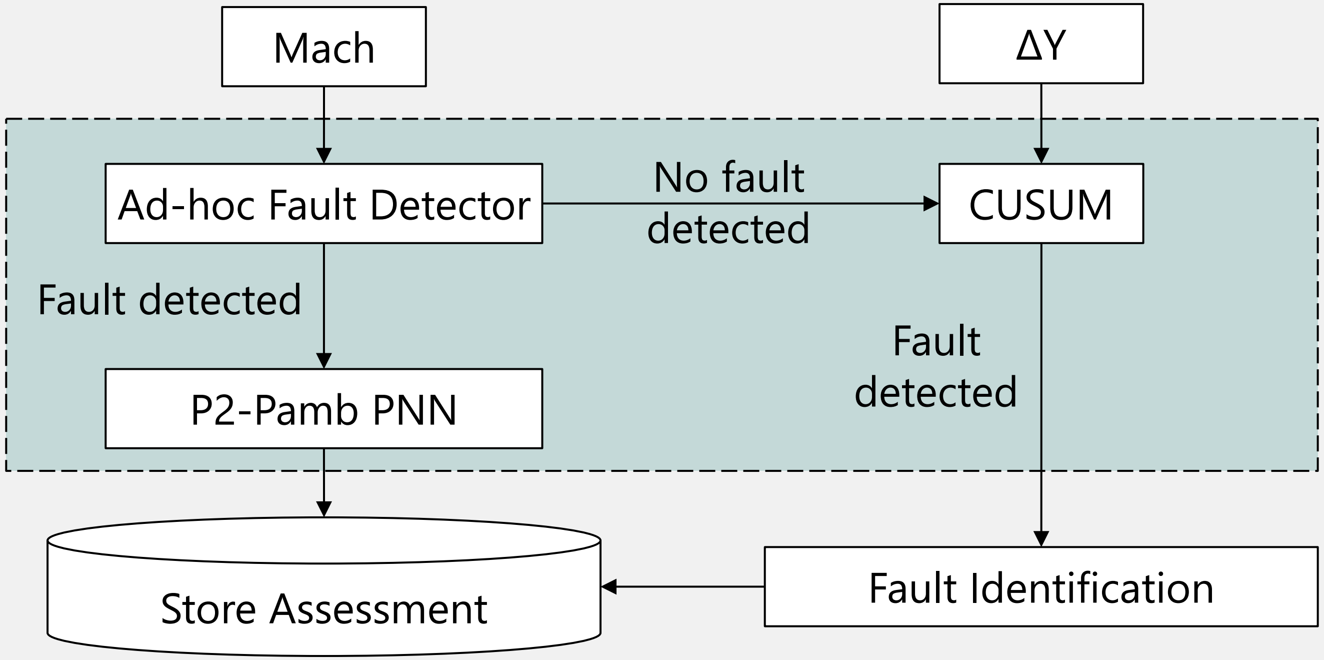


Diagnostic Framework Fault Detection



Diagnostic Framework P2 & Pamb Fault Detection

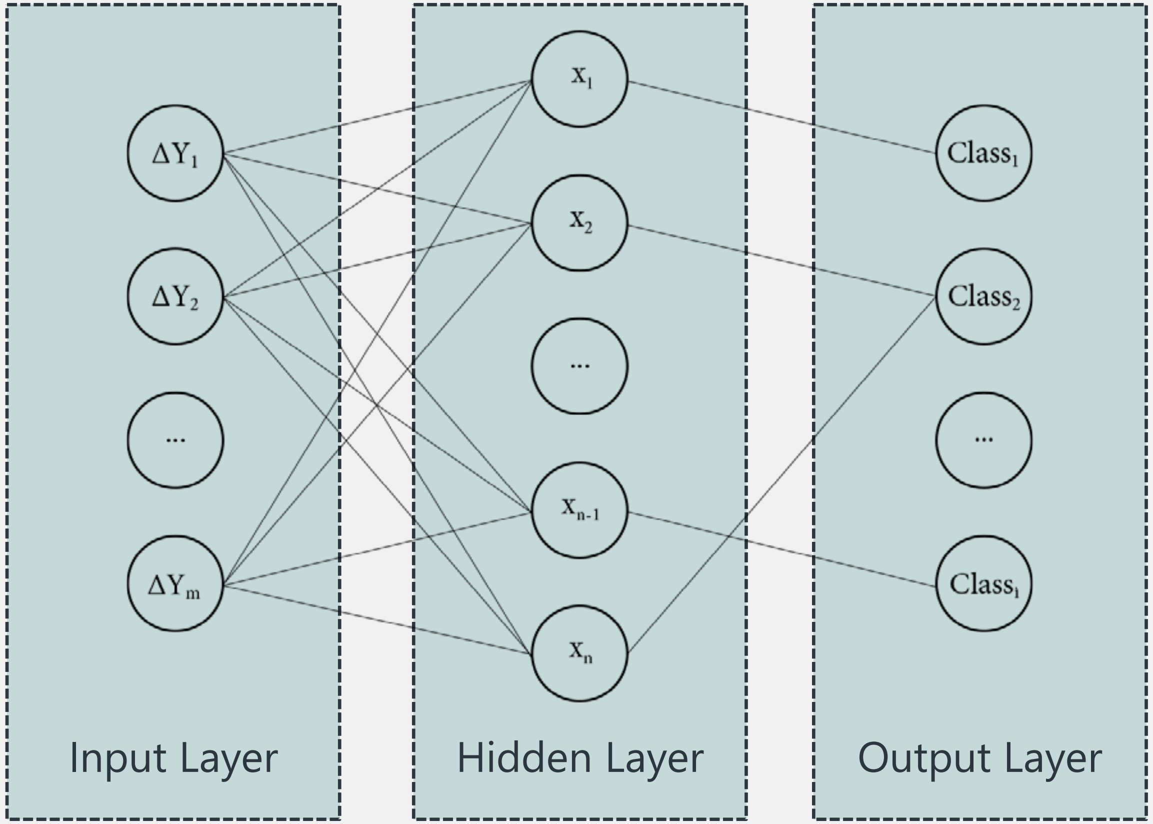
- Ad-hoc Detector
- Estimated Mach number
- Dedicated PNN



Contents

Probabilistic Neural Network (PNN)

- Multi-layer feed-forward network
- Estimates the probability of the input pattern to belong to each of the output classes



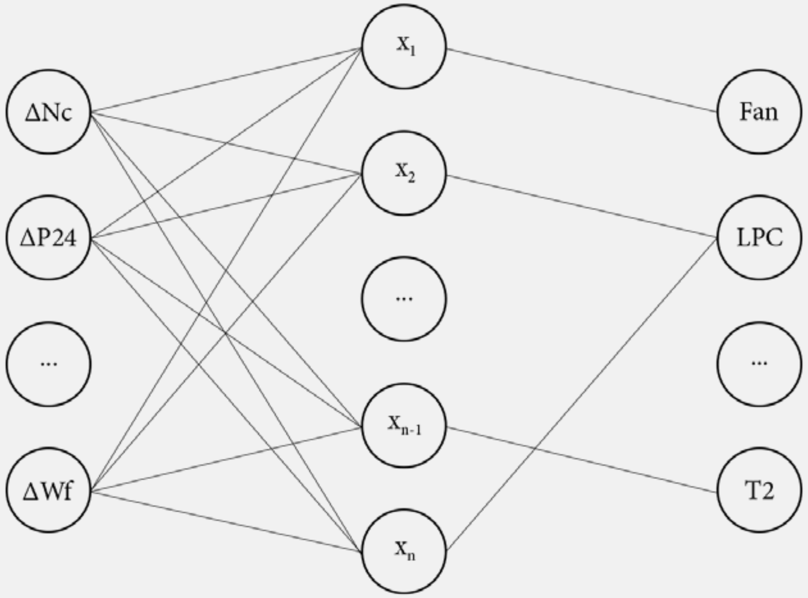
* Romesis, C. and Mathioudakis, K. "*Setting Up of a Probabilistic Neural Network for Sensor Fault Detection Including Operation with Component Faults.*" Journal of Engineering for Gas Turbines and Power Vol. 125, No. 5 (2002): pp.634-641. DOI 10.1115/1.1582493

Probabilistic Neural Network (PNN)

1ST PNN

All fault scenarios (16 Output Classes)

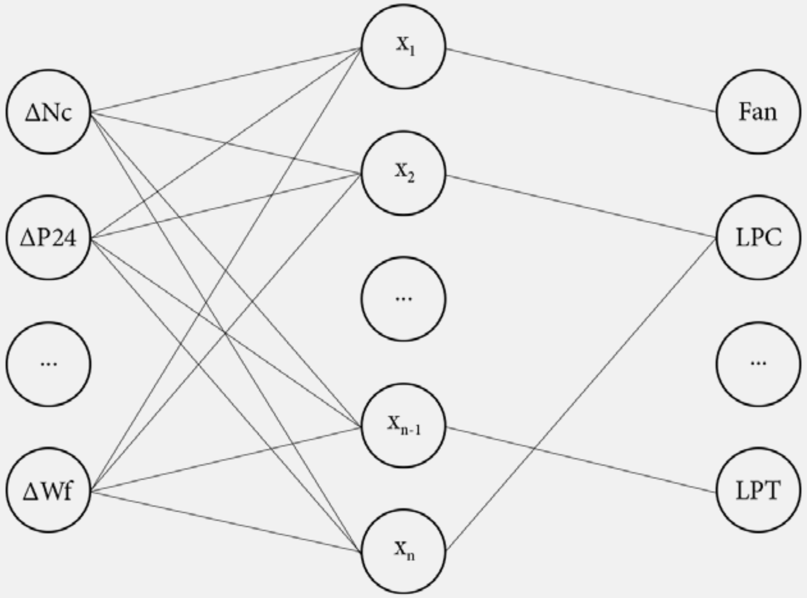
Except P2 and Pamb sensor faults



2ND PNN

Only component faults (5 Output Classes)

Enable the comparison with methods that do not have sensor or actuator fault identification capabilities



k-Nearest Neighbor (kNN)

- Non parametric classification technique
- Classifies the input pattern by assigning it the label most frequently represented among the *k* nearest training patterns
- 2 classifiers trained (same output classes as the PNNs)
- Same training patterns as the PNNs

Optimization

- Estimation of engine health parameters from a given set of measurements
- Optimization problem
  - 10 unknown health parameters
  - 7 equations
- Objective Function $OF_Y = \sum_1^7 \left(a_i * \frac{Y_i^{calc} - Y_i^{given}}{Y_i^{given}} \right)^2$
- Optimization Constraints

Turbomachinery	Bound	Linear
Compressor	$-0.1 \le SE \le 0$	$SW - SE \le 0$
	$-0.1 \le SW \le 0$	$2SE - SW \le 0$
Turbine	$-0.1 \le SE \le 0$	$SE + SW \le 0$
	$0 \le SW \le 0.1$	$-0.5SE - SW \le 0$

* Mathioudakis, K., Kamboukos, Ph., Stamatis, A. "*Turbofan Performance Deterioration Tracking Using Nonlinear Models and Optimization Techniques*." Journal of Power and Energy Vol. 218, No. 8 (2004): pp.609-618. DOI 10.1115/1.1512678

Combinatorial

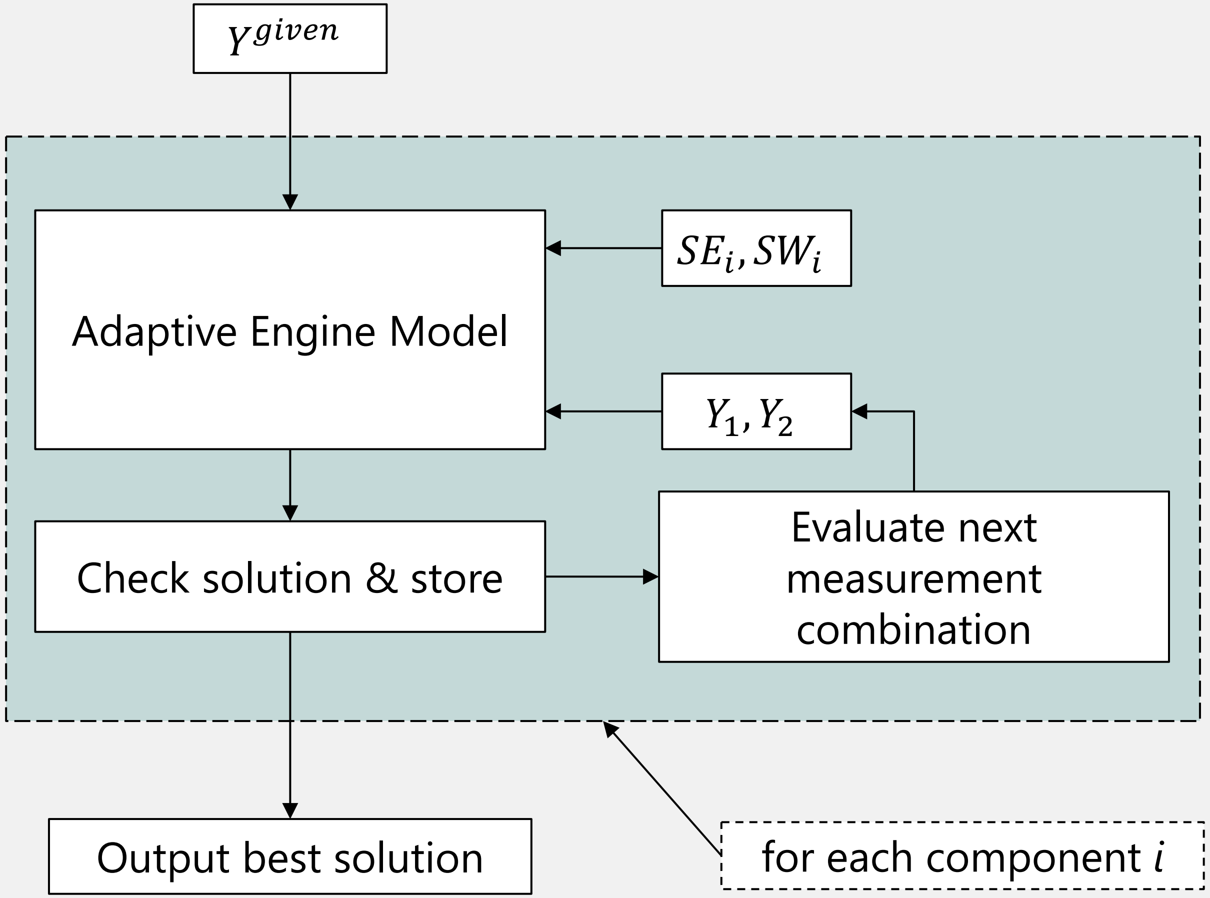
- Appropriate combinations of measurements and health parameters are fed in the adaptive engine model
- Statically processing of the health parameter results
- Calculation of Diagnostic Index $$DI = \sqrt{\left(\frac{|\overline{SE}_i|}{\left|\sigma_{|\overline{SE}_i|}\right|}\right)^2 + \left(\frac{|\overline{SW}_i|}{\left|\sigma_{|\overline{SW}_i|}\right|}\right)^2}$$
- Maximum DI points to the faulty component

* Stamatis, A., Mathioudakis, K., and Papailiou, K. "*Optimal Measurements and Health Indices Selection for Gas Turbine Performance Status and Fault Diagnosis*." Journal of Engineering for Gas Turbines and Power Vol. 114, No. 2 (1992): pp.209-216. DOI 10.1115/1.29065

* Aretakis, N., Mathioudakis, K., and Stamatis, A. "*Non-Linear Engine Component Fault Diagnosis From a Limited Number of Measurements Using a Combinatorial Approach*." Journal of Engineering for Gas Turbines and Power Vol. 125, No. 5 (2003): pp. 642-650. DOI 10.1115/1.1582494

Adaptive 2×2

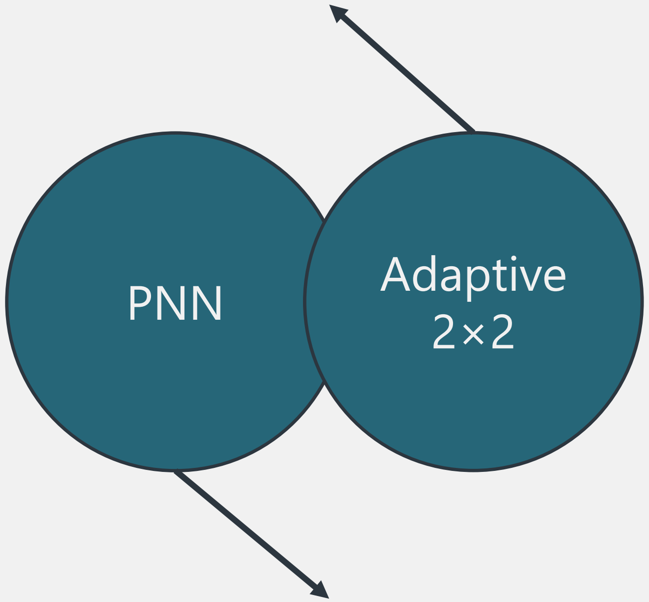
- ❑ Only one component is faulty
- ❑ Adaptive engine model
- ❑ A determined system (2×2) is solved
- ❑ Store best solution (RMSE)
- ❑ Provides an **estimation of the fault's magnitude**



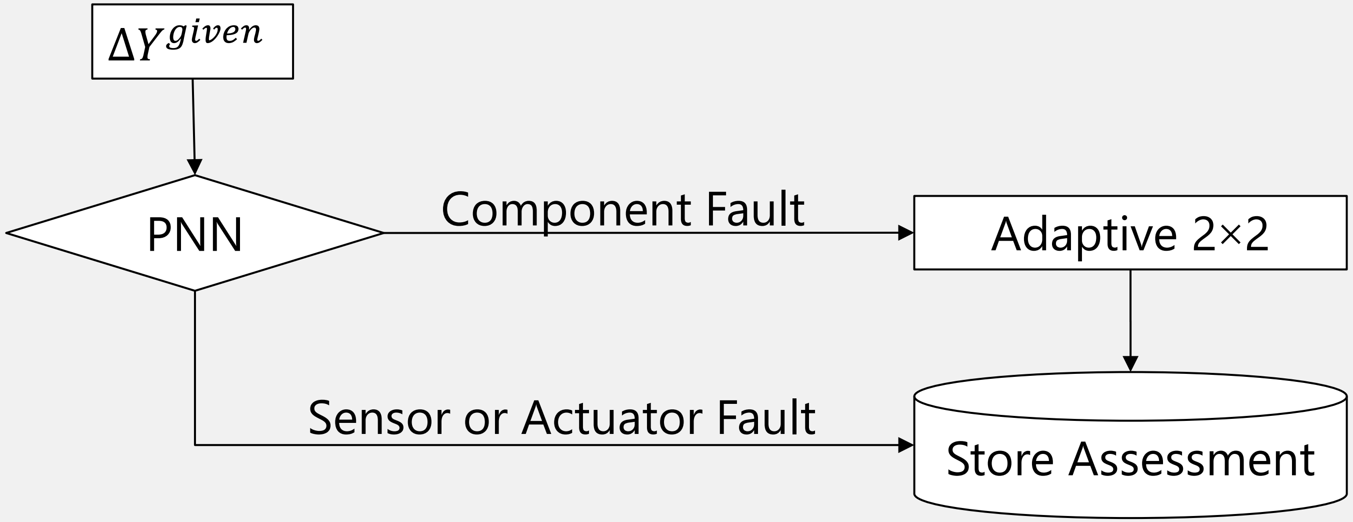
* Introduced for the first time by NTUA

PNN & Adaptive 2×2

Provide an **estimation of the** component fault **magnitude**



Ability to identify actuator/sensor faults



* Introduced for the first time by NTUA

Contents

Independent Test Cases

- Produced using ProDiMES
- 2 categories of test cases
- Fair comparison
- Evaluate performance in component faults only

Category	Faults	Engines	Flights	Total Test Cases	Diagnostic Methods
1	Component Only	600	50	30000	PNN, kNN, Optimization, Combinatorial, Adaptive2×2
2	All	9480	50	474000	PNN, kNN, PNN+Adaptive2×2

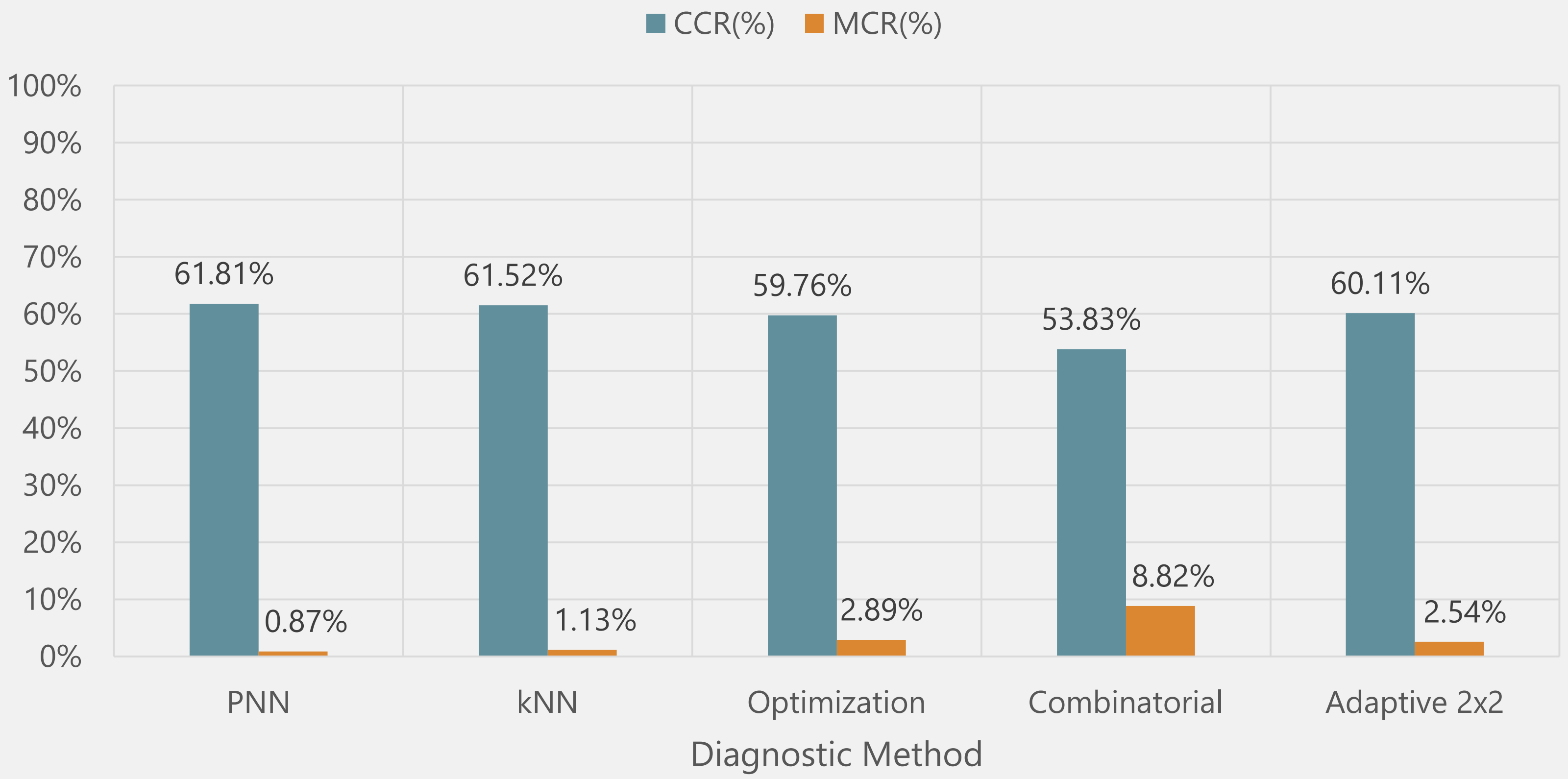
Independent Test Cases Component Faults

CCR

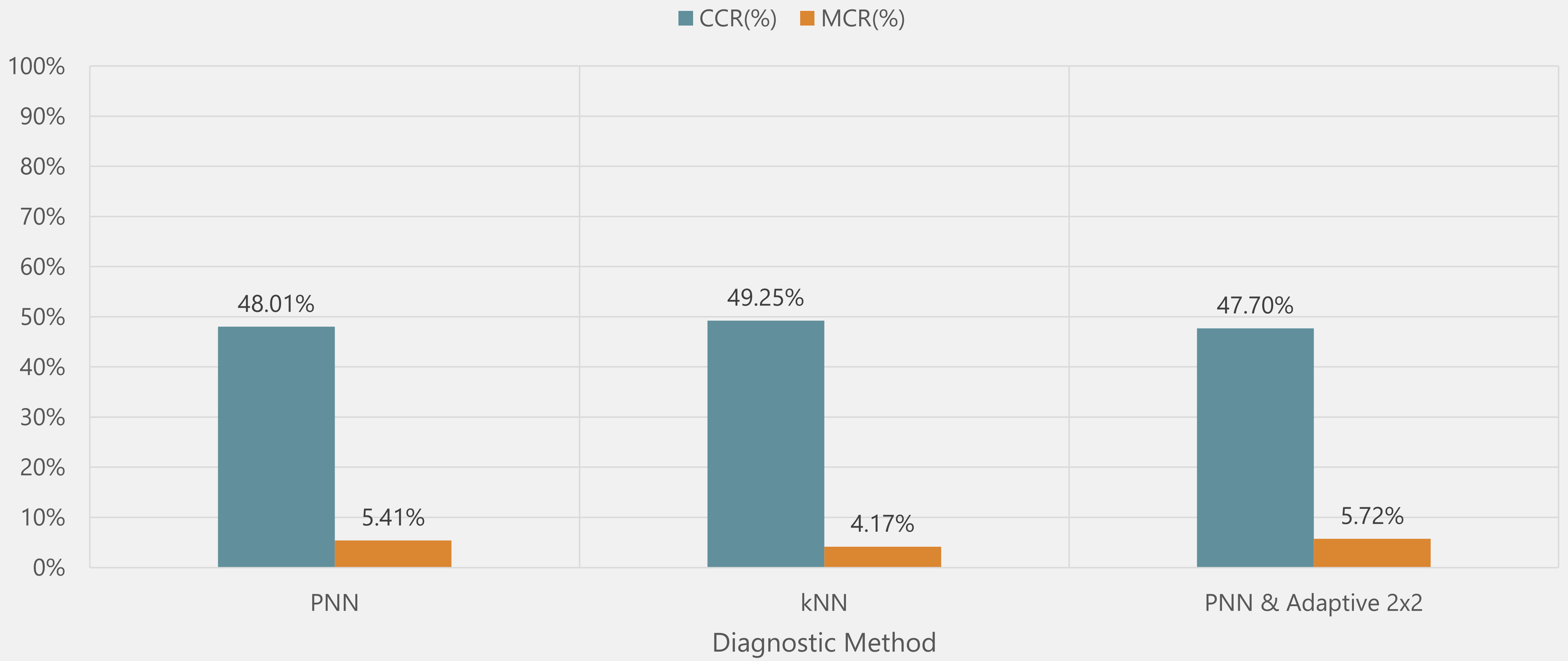
$$CCR = \frac{\text{Correct classifications of a fault}}{\text{Cases of that fault}}$$

MCR

$$MCR = \frac{\text{Incorrect classifications of a fault}}{\text{Cases of that fault}}$$



Independent Test Cases All Faults



Contents

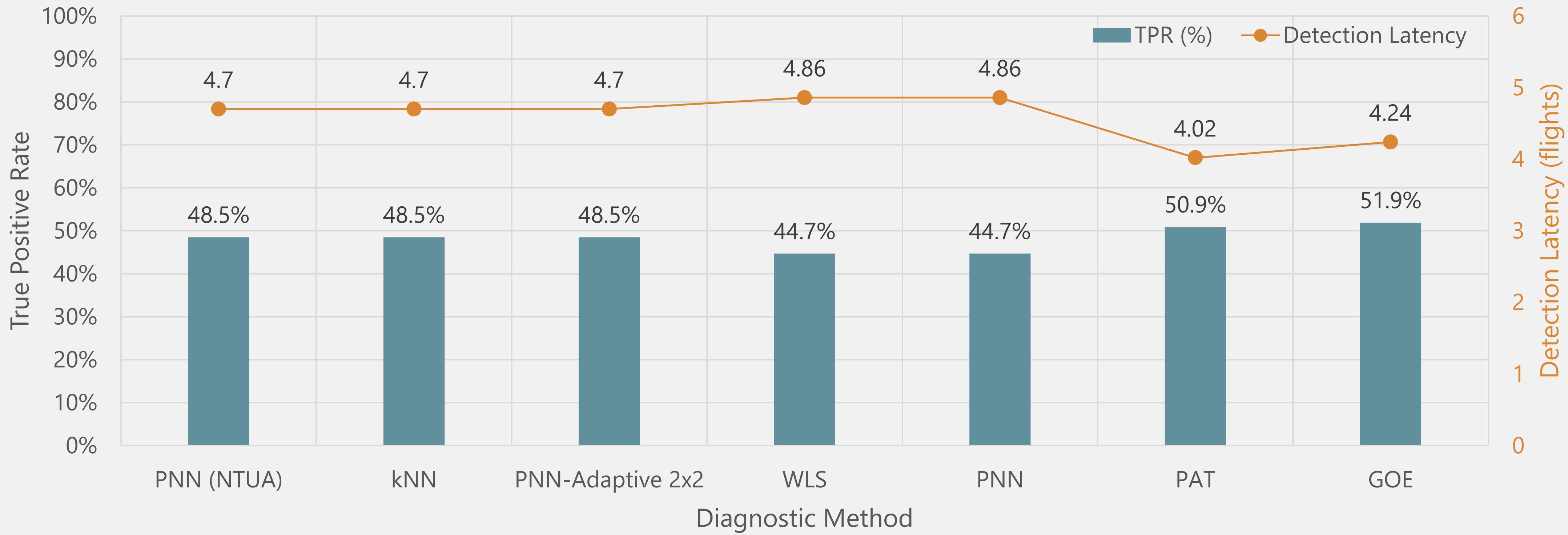
Blind Test Cases

LTT/NTUA	PUBLIC BENCHMARKING RESULTS
▪ Probabilistic Neural Network (PNN^{NTUA}) ▪ k-Nearest Neighbor (kNN) ▪ PNN & Adaptive 2×2	▪ Weighted Least Squares (WLS) ▪ Probabilistic Neural Network (PNN) ▪ Performance Analysis Tool (PAT) ▪ Generalized Observer/Estimator (GOE)

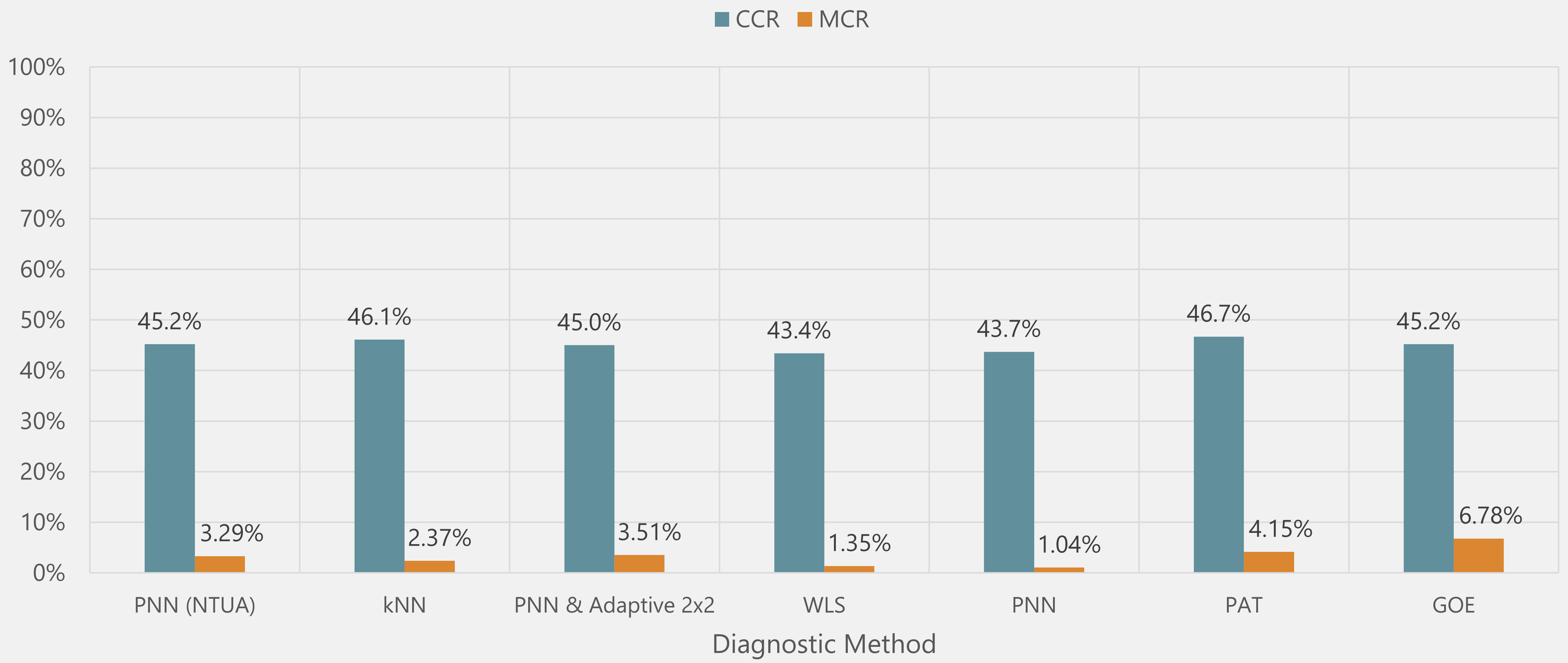
Blind Test Cases True Positive Rate – Detection Latency

TPR: Correct fault detections / Fault Cases

Detection Latency: Average number of flights before first true positive detection



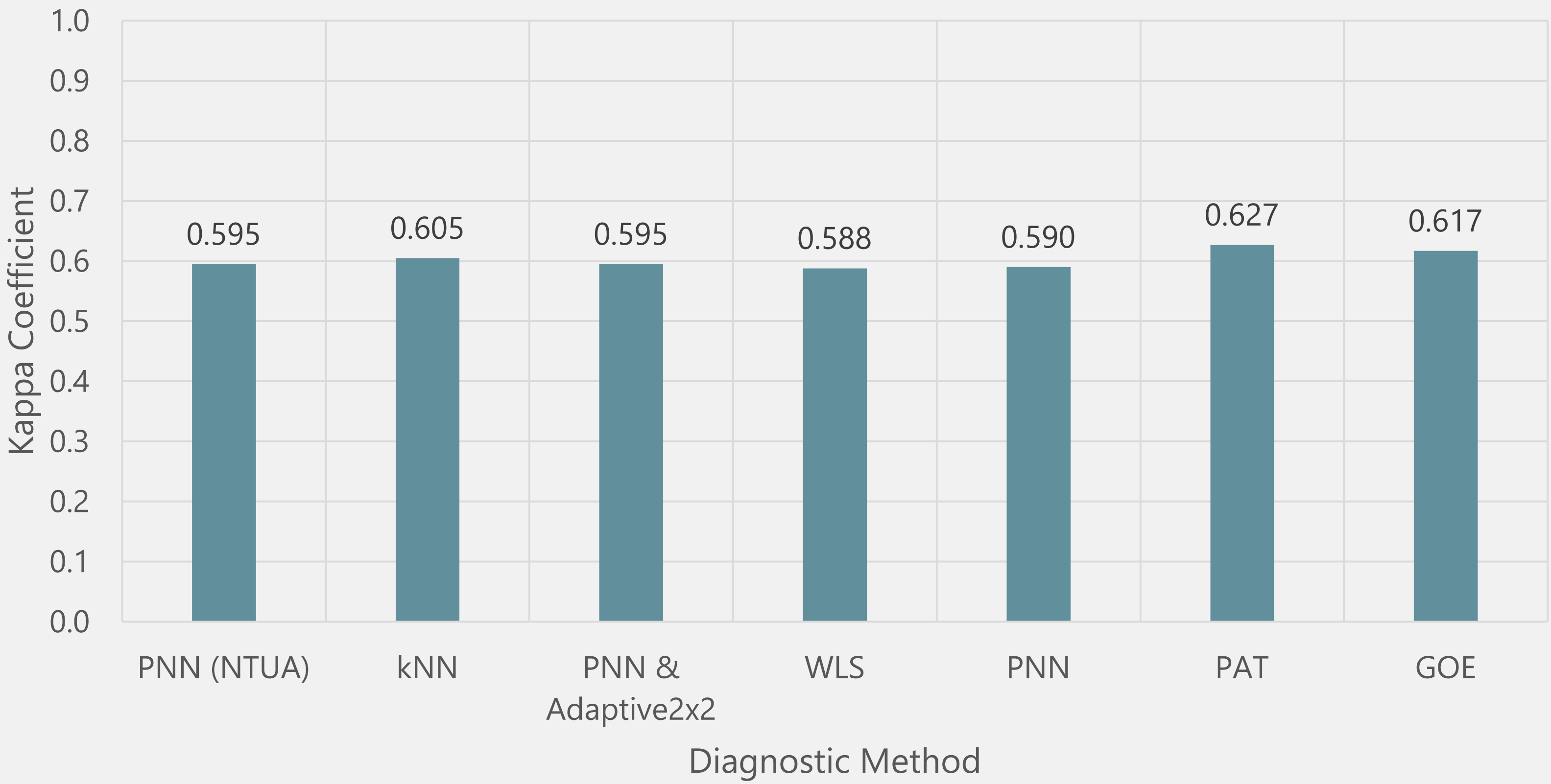
Blind Test Cases Correct Classification Rate – Mis Classification Rate



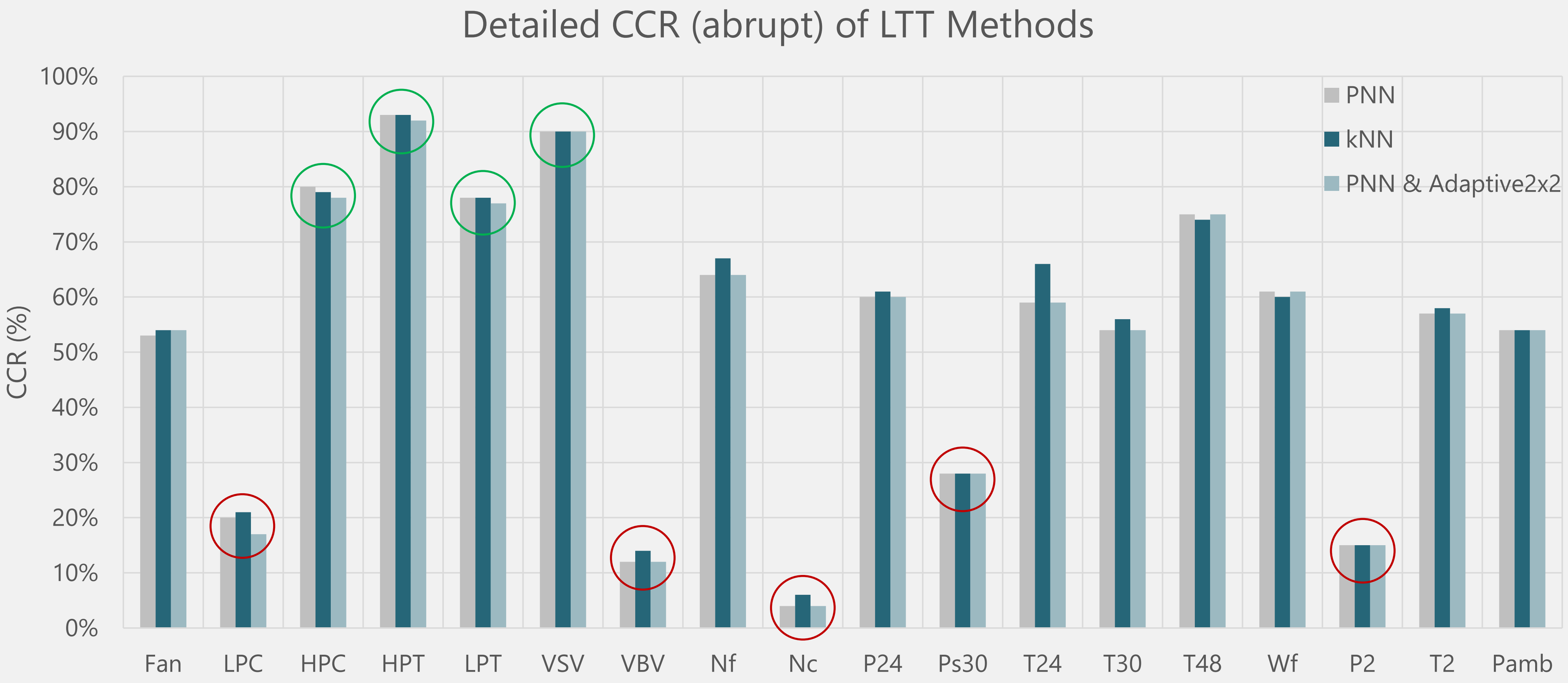
Blind Test Cases Kappa Coefficient

Kappa Coefficient

Measure of an algorithm's ability to consistently provide correct classifications

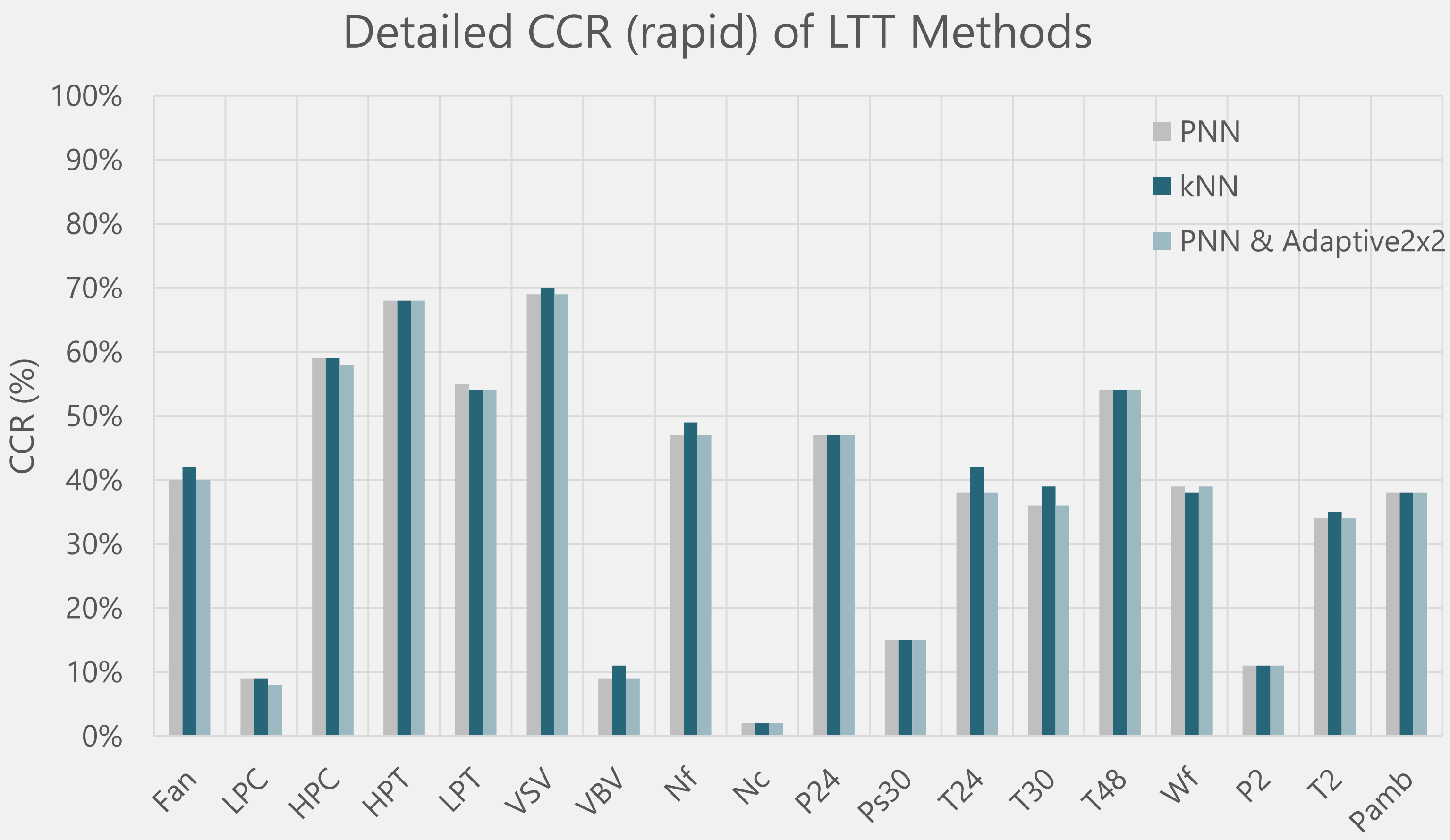


Blind Test Cases Detailed CCR (Abrupt Faults)



Blind Test Cases Detailed CCR (Rapid Faults)

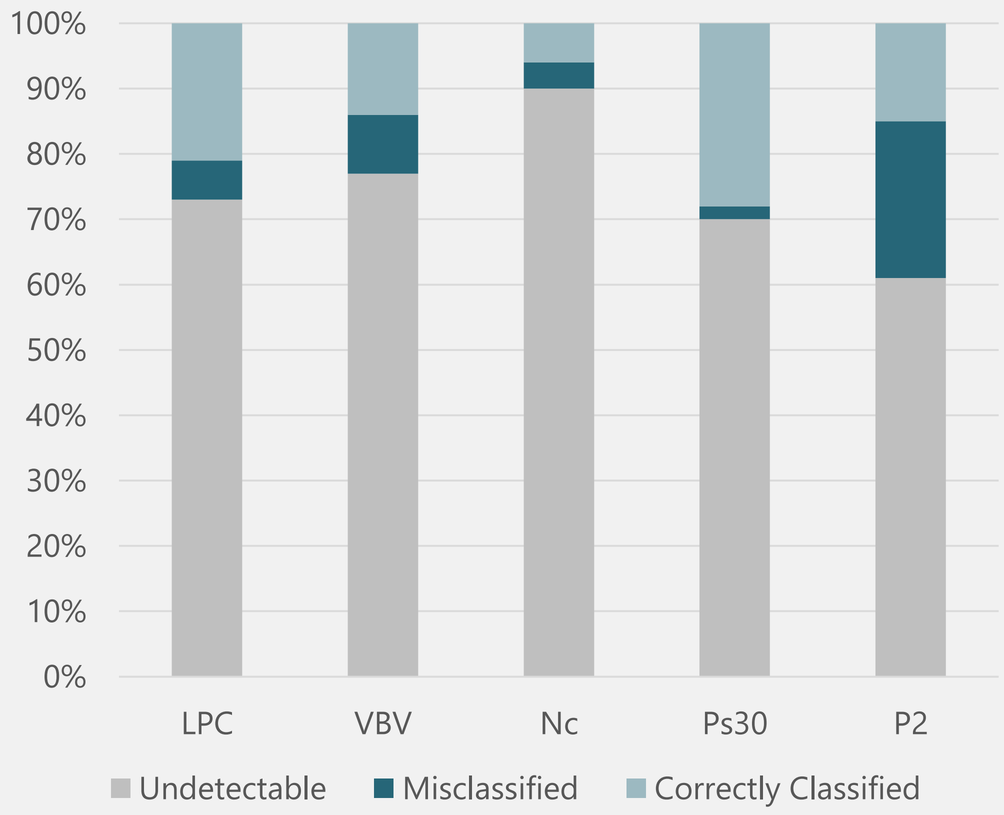
- Similar qualitative results to abrupt faults.
- Uniform decrease due to increased detection latency.



Contents

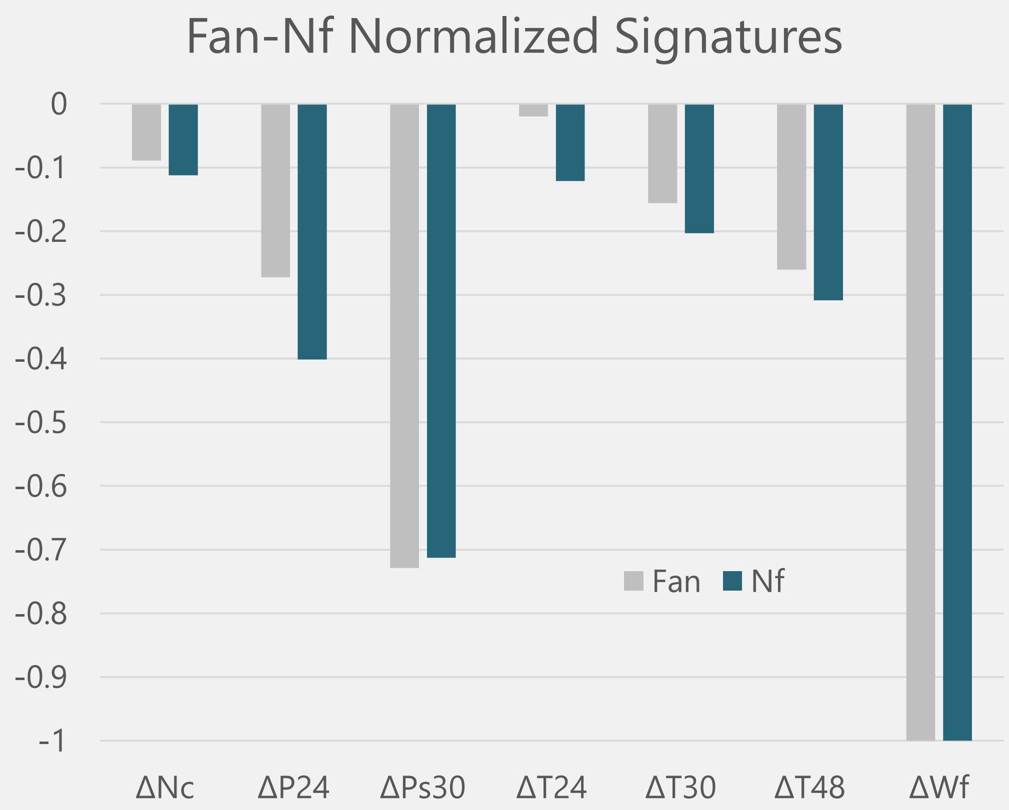
Discussion

- **Challenging Fault Scenarios**
  - LPC component fault
  - VBV actuator fault
  - Nc sensor fault
  - Ps30 sensor fault
  - P2 sensor fault



Discussion

- **Increased misclassifications**
  - Nf sensor faults (positive bias)
  - Fan component faults

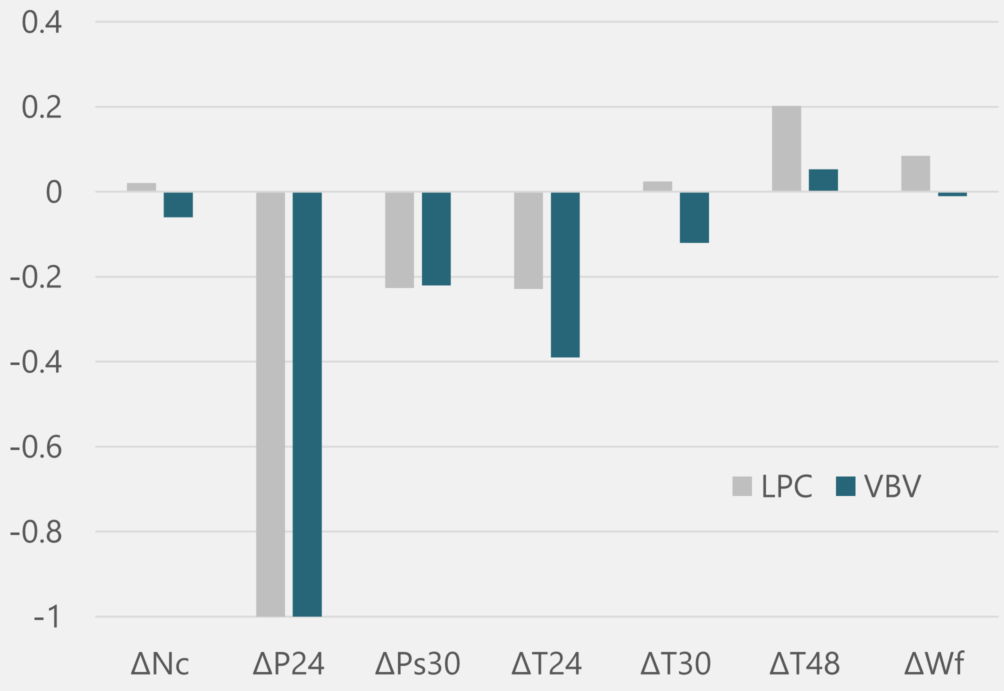


Discussion

- **Increased misclassifications**
  Nf sensor faults (positive bias)
  Fan component faults

- **Increased misclassifications**
  LPC component faults
  VBV actuator faults

LPC-VBV Normalized Signatures



Contents

Conclusions

- Challenging diagnostic problem
  - *18 fault cases – 7 measurements*
  - *High noise levels*
- Fault detection performance has to be increased to increase classification performance
- Ad-hoc detector significantly improved *P2* and *Pamb* fault classifications
- Most Challenging Faults
  - *LPC – VBV – Nc – Ps30 – P2*
- Most Detectable Faults
  - *HPC – HPT – LPT – VSV*
- Significant Signature Correlation
  - *Fan - Nf*
  - *LPC - VBV*

Conclusions

➢Independent Test Cases

- Equivalent performance – Except the Combinatorial
- Slight advantage of *kNN*
- *PNN & Adaptive2×2* performs nearly as good as the *PNN*
  BUT it *provides an estimation of the component's fault magnitude*

➢Blind Test Cases

- PAT and GOE methods have a slightly better performing detection algorithm
- All NTUA methods have *equivalent or higher CCR* to PAT and GOE and *half the misclassifications*

Thank you for your attention!