An Intelligent Fault Detection and Diagnosis Monitoring System for Reactor Operational Resilience

Mario Mendoza, BS'19, MS'21, PhD'23 | Dr. Pavel V. Tsvetkov

Introduction

- Challenges of new deployment scenarios for advanced reactors, SMRs, and microreactors

Dynamic operational regimes
- Expose reactor unit to different transients

Radically reduce operations and management costs
- Semi- or fully autonomous operations

Extended fuel cycles
- Limits inspection intervals

Integral designs
- Reduced access to critical components for inspection

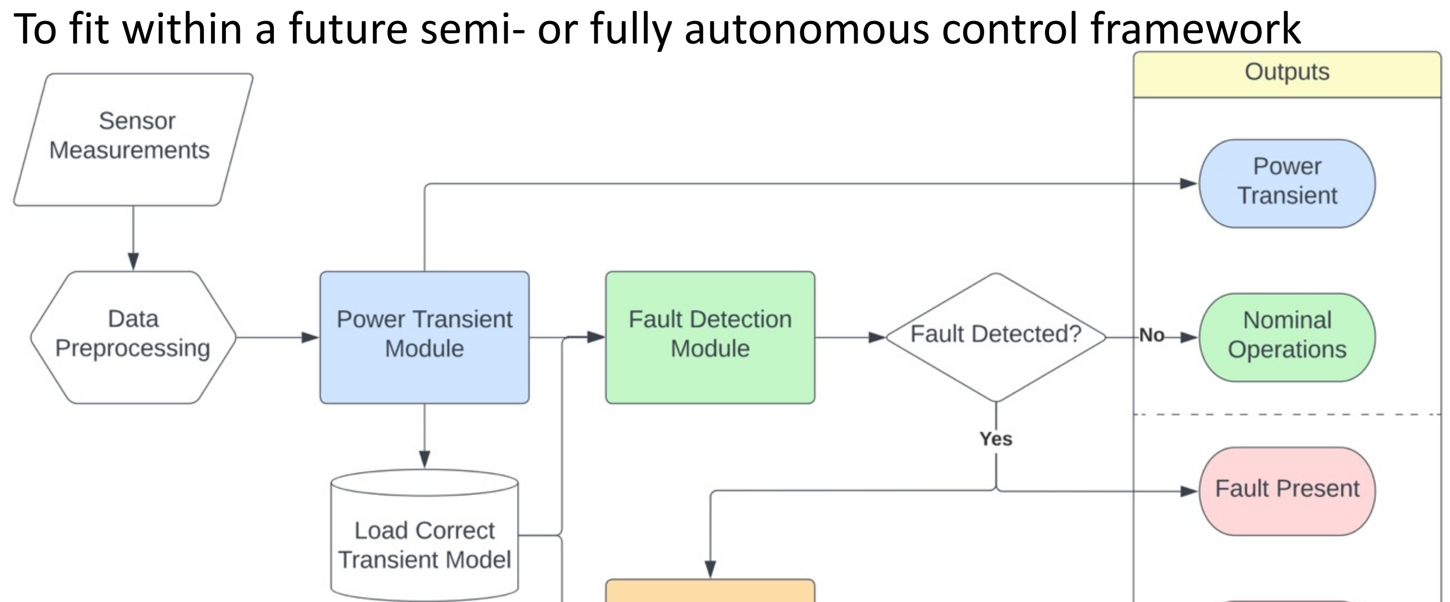
Challenge: Semi- or fully autonomous operations must be facilitated while guaranteeing safety and reliability in challenging and unique operational regimes

Solution: An on-line monitoring (OLM) system is needed to detect and diagnose malfunctions and faults in real-time for the various systems and components of the nuclear plant

Objective

Develop an intelligent Fault Detection and Diagnosis Monitoring System (FDDMS)

- To provide automatic and reliable power transient dependent detection and diagnosis of system and component malfunctions
- During reactor operations by observing arrays of sensor signatures in real-time
- To fit within a future semi- or fully autonomous control framework

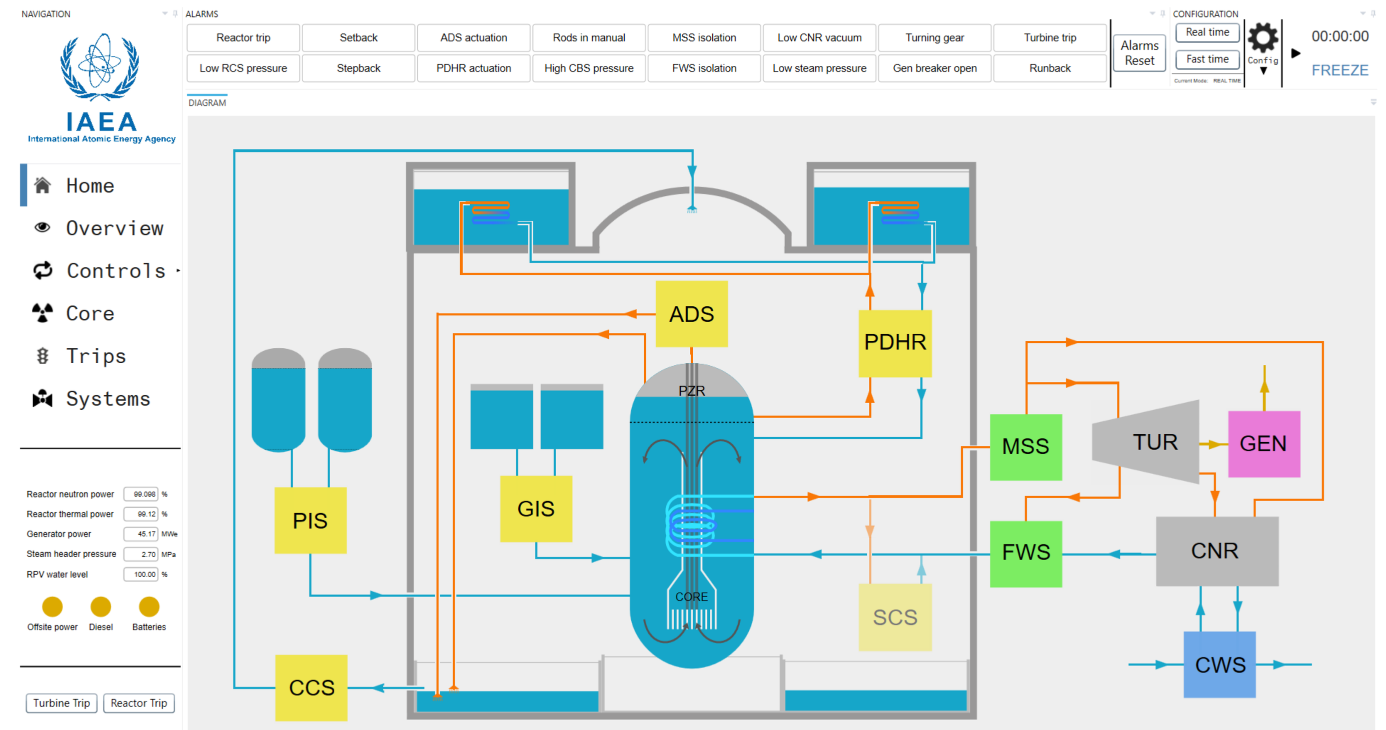


Data Acquisition

- Due to lack of operational data for advanced reactors/SMRs/microreactors, data-driven FDD methods must rely on simulator data for development
- iPWR broad-scope simulator used → Built by Tecnatom (Madrid-based Westinghouse subsidiary) and provided by IAEA
  - Proof of concept for the FDDMS methodology
  - Qualifies as an SMR (45 MW_e < 300 MW_e)
  - Shares common features and components with other designs
    - Integral design, natural circulation, passive safety systems, etc.
- **As the FDDMS relies on data-driven algorithms, the methodology can be extended to any reactor plant design when given adequate data**

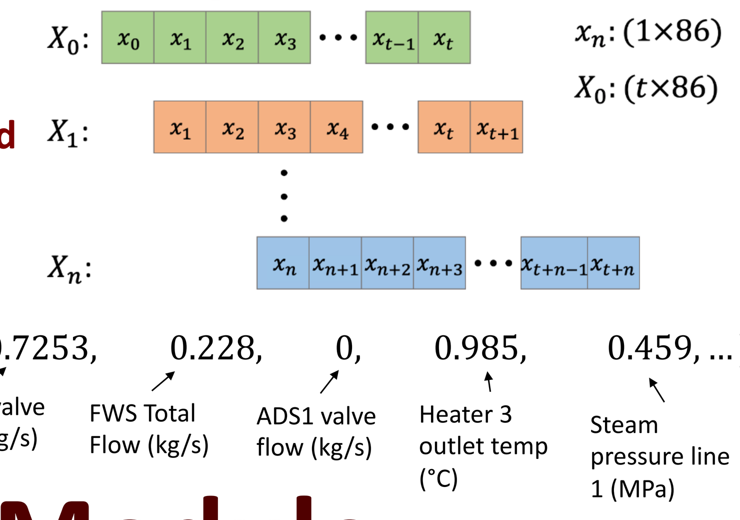
Plant Subsystem	Fault Label	Description	Activation Mechanism	Development Time
-	Nominal	Reactor plant operating as expected	-	-
FWS	FWS 01	Loss of feed water heating	On/Off	-
	FWS 02	Abnormal increase in feed water flow	On/Off	-
	FWS 03	Loss of normal feedwater flow (pump trip)	On/Off	-
	FWS 04	Feed water system pipe break	50% Severity	30 s
MSS	MSS 01	Steam header break	50% Severity	30 s
	MSS 02	Tube failure in integral steam generator	50% Severity	30 s
	MSS 04	Major steam supply system piping failure within containment	50% Severity	30 s
RCS	RCS 02	One bank of shutdown control rods drop into the core	On/Off	-
	RCS 03	Charging (feed) valve fails open	On/off	-
	RCS 04	Inadvertent operation of pressurizer heaters	On/off	-
	RCS 06	Pressure control system of the pressurizer fails	On/Off	-
TUR	TUR 01	Turbine spurious trip	On/Off	-
	TUR 02	Turbine spurious runback	On/Off	-
	TUR 03	Turbine trip with bypass valves failed closed	On/Off	-
CBS	CBS 01	Loss of containment vacuum	50% Severity	30 s
GEN	GEN 01	Station blackout, loss of AC power	On/Off	-

Training	Validation	Testing
Power Level	**Power Level**	**Power Level**
$20\%^{N,F}$	$30\%^{F}$	$50\%^{F}$
$40\%^{N,F}$	$90\%^{F}$	$70\%^{F}$
$60\%^{N,F}$	$50\%^{N}$	$30\%^{N}$
$80\%^{N,F}$	$70\%^{N}$	$90\%^{N}$
$100\%^{N,F}$		



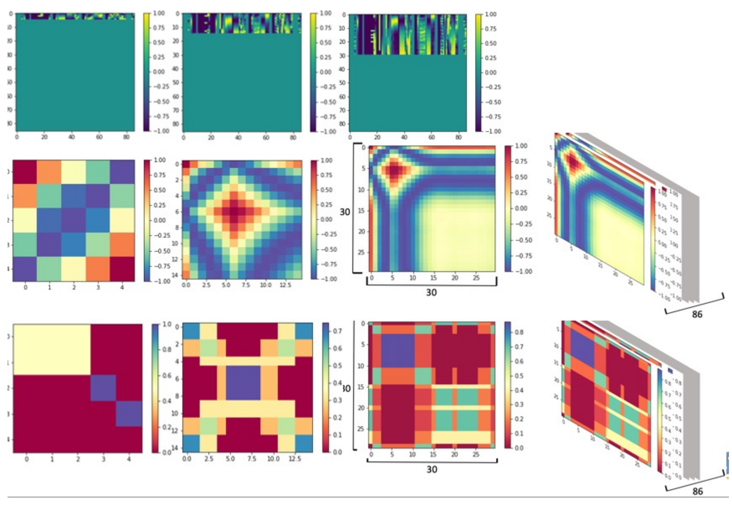
Data Preprocessing

- Analyze 86 plant parameters for each measurement
  - Temperatures, pressures, flow rates, positions, etc.
  - **The specific number of tracked sensors is expected to be derived from the details of the reactor plant configurations of interest.**
- Sliding time-window method for generating data samples
  - Allows for real-time (second by second) monitoring while still including temporal patterns in the data
  - Sensor values normalized to [0,1]



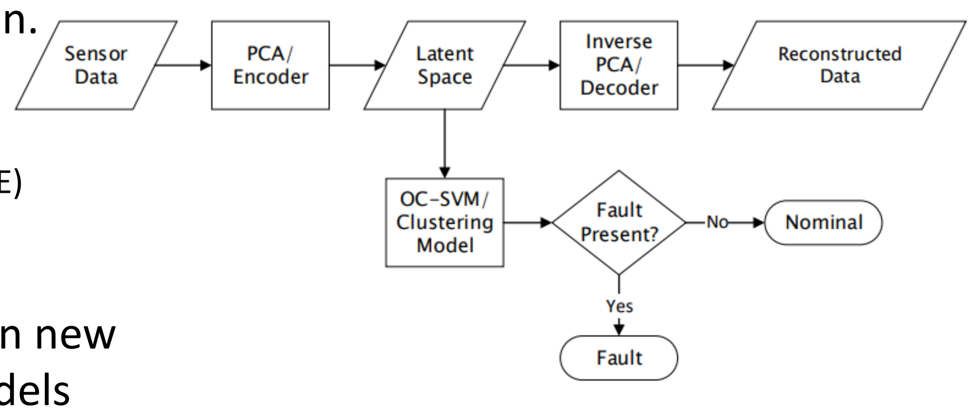
Power Transient Module

- Goal: Classifies the operational state of the reactor as:
  - Steady State, Ramping Up, or Ramping Down
- Output: Outputs transient state and notifies subsequent modules
  - **Nominal reactor conditions vary significantly between the 3 transients**
  - Different dataset loaded for each power transient in other modules
- Supervised learning classification problem
- Compared different time-window sizes
  - 5 s, 15 s, 30 s
- Compared different data transformation methods
  - Raw Data, Gramian Angular Fields, Markov Transition Fields
- Compared different data-driven methods
  - PCA+SVM, DNN, CNN



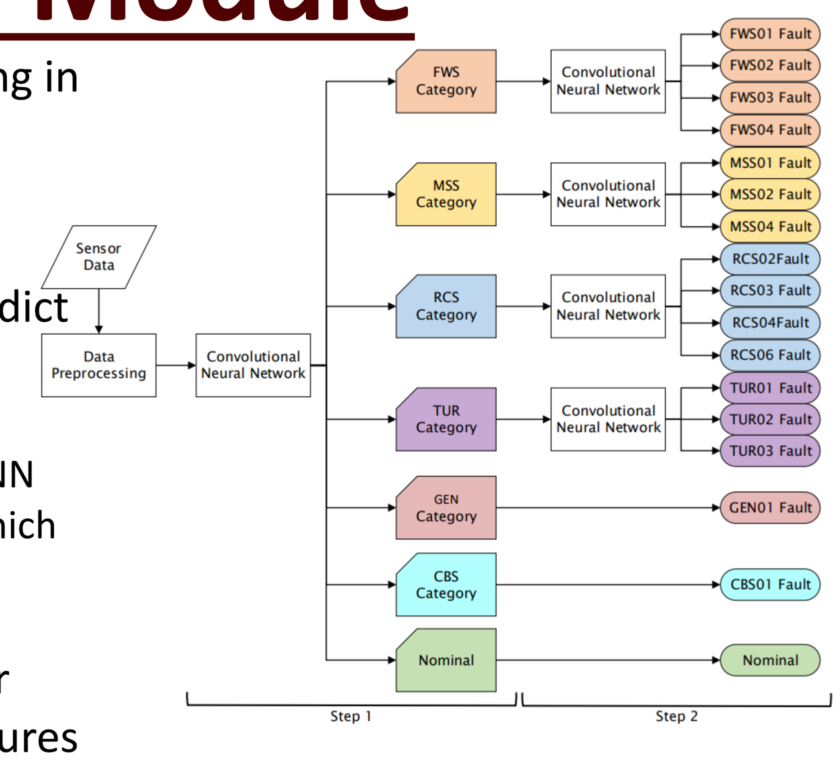
Fault Detection Module

- Goal: Identify each measurement as nominal or abnormal
  - Is a malfunction present in the system or not?
- Output: Binary nominal or abnormal. If nominal, outputs "Nominal". If abnormal, data passed to Diagnosis Module for classification.
- Compare unsupervised learning data-driven techniques
  - Dimensionality reduction
    - PCA, DNN-based autoencoder (DNN-AE), CNN-based autoencoder (CNN-AE)
  - Anomaly detection
    - One-class SVM (OC-SVM), Clustering, Reconstruction Error Thresholding
- Fit and train algorithms to only nominal data. When testing on new data, fault cases will create unexpected outputs from the models
  - Detect any unknown fault in the system

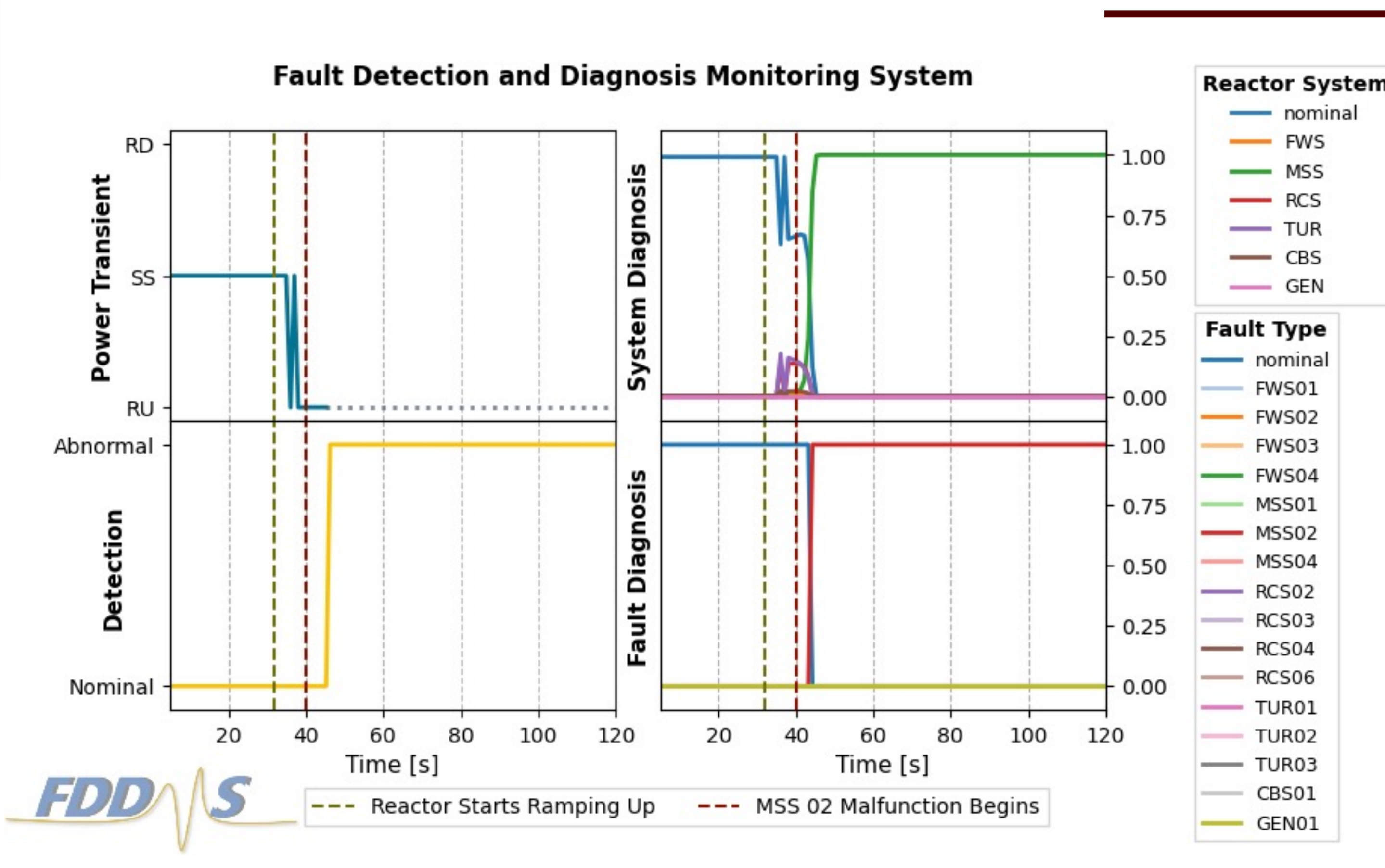


Fault Diagnosis Module

- Goal: Classify the specific malfunction type occurring in the system
- Output: The probability for a specific malfunction affecting the system
- Supervised classification problem with CNNs to predict all 17 faults
- Compare two diagnosis architectures
  - End-to-End: Directly classify all possible faults with 1 CNN
  - Hierarchical: Stage 1- Classify the plant subsystem in which fault occurs with 1 CNN; Stage 2- Use 1 CNN for **each** subsystem to classify final fault
- Leverage the hyperband intelligent hyperparameter optimization method to find optimal CNN architectures while efficiently utilizing computational resources



Conclusion



Data-driven techniques
- Health and status of reactor system is evaluated by simply interpreting numerous modalities of sensors collecting various process signatures.
- Can be quickly and reliably created, adapted, extended, and improved.

Power-transient Dependency
- First data-driven FDD methodology to accurately monitor the health of reactor system during various operational regimes.
- Especially applicable for load-following operations

Real-time Monitoring
- Provides evaluations on the health of the system in real-time with each measurement
- Shortest delays in detection or diagnosis compared to previous methods

NEUP Nuclear Energy University Program
U.S. Department of Energy
FDDMS
TEXAS A&M UNIVERSITY
Department of Nuclear Engineering