Development of A Nearly Autonomous Management and Control System for Advanced Reactors

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05/15/2022

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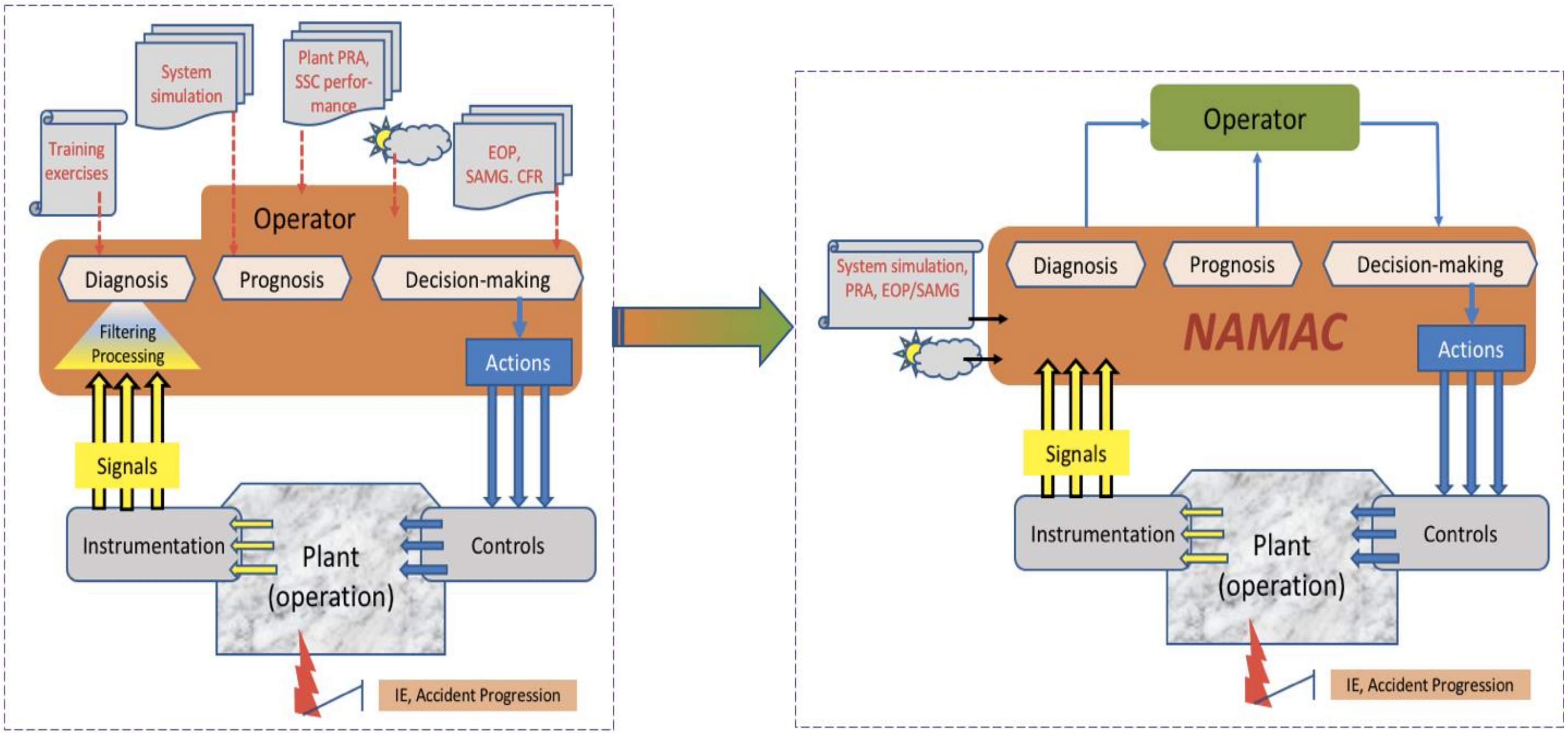
NAMAC as Nearly Autonomous Management and Control



Transition from Operator-Centric Plant Control Architecture to NAMAC-enabled Plant Control Architecture

Project Overview

- The project is fully supported by ARPA-E MEITNER program under the project entitled “Development of a Nearly Autonomous Management and Control System for Advanced Reactors”

- The project is conducted with collaborative efforts from several department, universities, companies, and national labs

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Issues of Operator-Centric Control Room

Analog main control room [1]

- Highly proceduralized (paper)
  - Normal operating procedures, emergency operating procedures, etc.
  - 1000s pages of symptom-oriented paper procedures
- Rely on operator's training and knowledge
- Distributed control across multi-person crew
- Analog I/C

- Frozen and static procedures for control actions
  - Sequential presentation of steps in procedures
  - No jump ahead, no pause, and no start from the middle
  - One procedure at a time

- Operator's perception during various situations
  - Multiple signals at the same time
  - Limited knowledge or insufficient training
  - Subjective judgement

- High operation and maintenance costs
- Pandemic

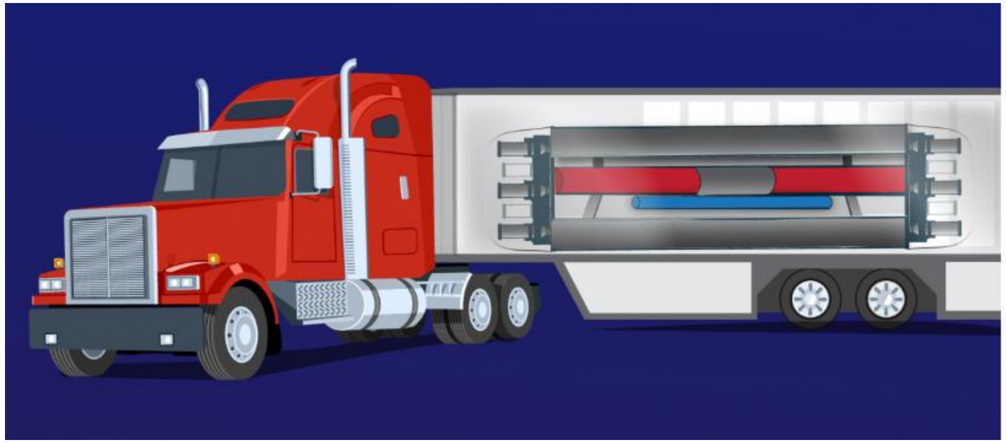
- Slow processing
- Hard to modify

- …

[1] R.L. Boring, "Human reliability considerations for the transition from analog to digital control technology in nuclear power plants", NUC Workshop, Raleigh, NC, 2019

New Challenges

- New designs of portable, operationally flexible, and economically viable microreactors
  - Small size and minimized structures, systems, and components (SSCs)
  - Simplified design, operation, and maintenance
  - Fast on-site installation
  - Decrease reliance on human actions

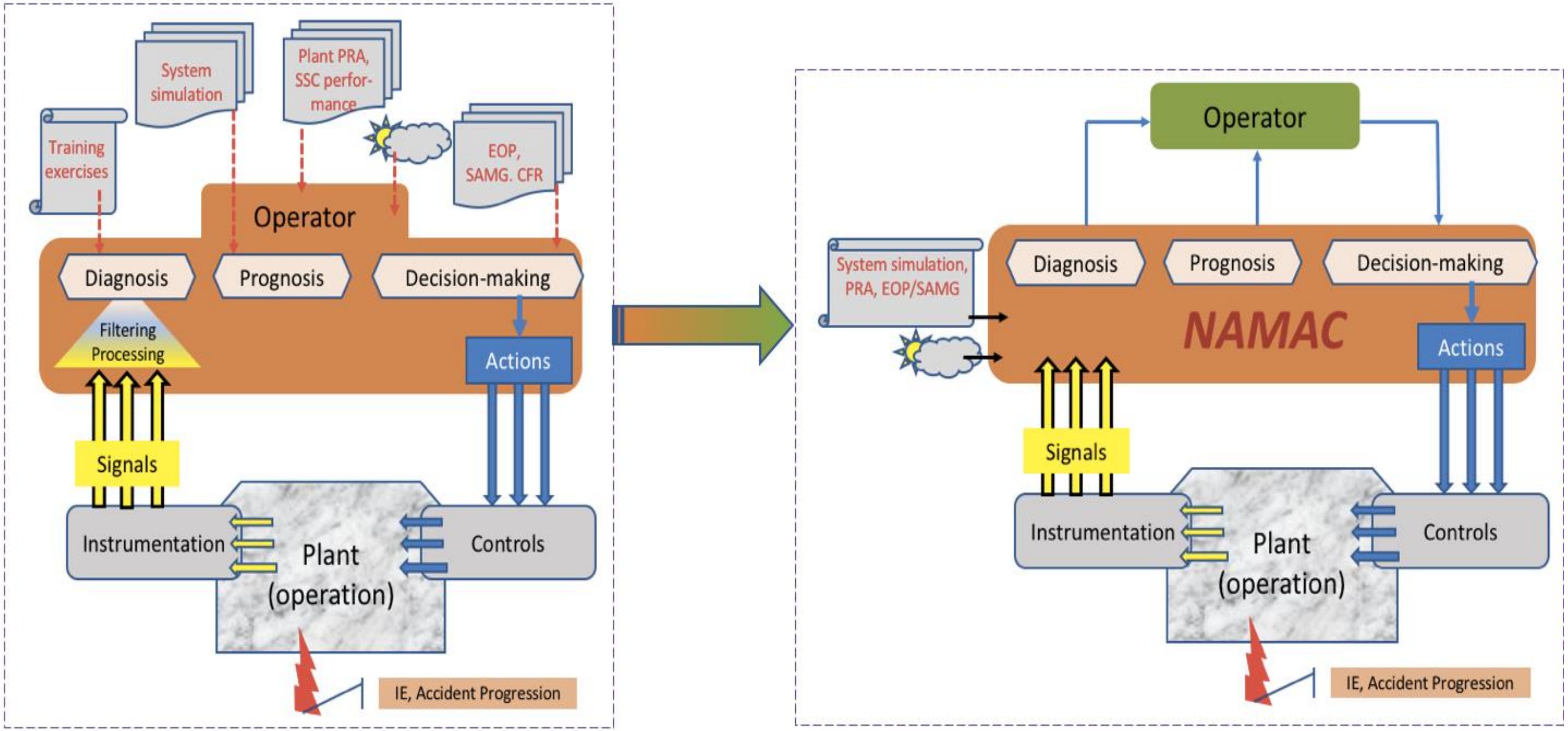


Need for autonomous control that could fulfill operator’s tasks in

- Diagnosis – Diagnosing faults and infer complete reactor states
- Prognosis – Forecasting short-term transients and consequence of control actions and procedures
- Decision-Making – Ranking and recommending the optimal control actions

[1] Office of Nuclear Energy, “What is a Nuclear Microreactor?”, Office of Nuclear Energy, “https://www.energy.gov/ne/articles/what-nuclear-microreactor”, 2018

NAMAC-Enabled Plant Control



Transition from Operator-Centric Plant Control Architecture to NAMAC-enabled Plant Control Architecture

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- An overview for the project
- Motivation and background
- Technical approach – How should we design and implement NAMAC?
- Case study
- Conclusion and Path Forward

Technical Approach

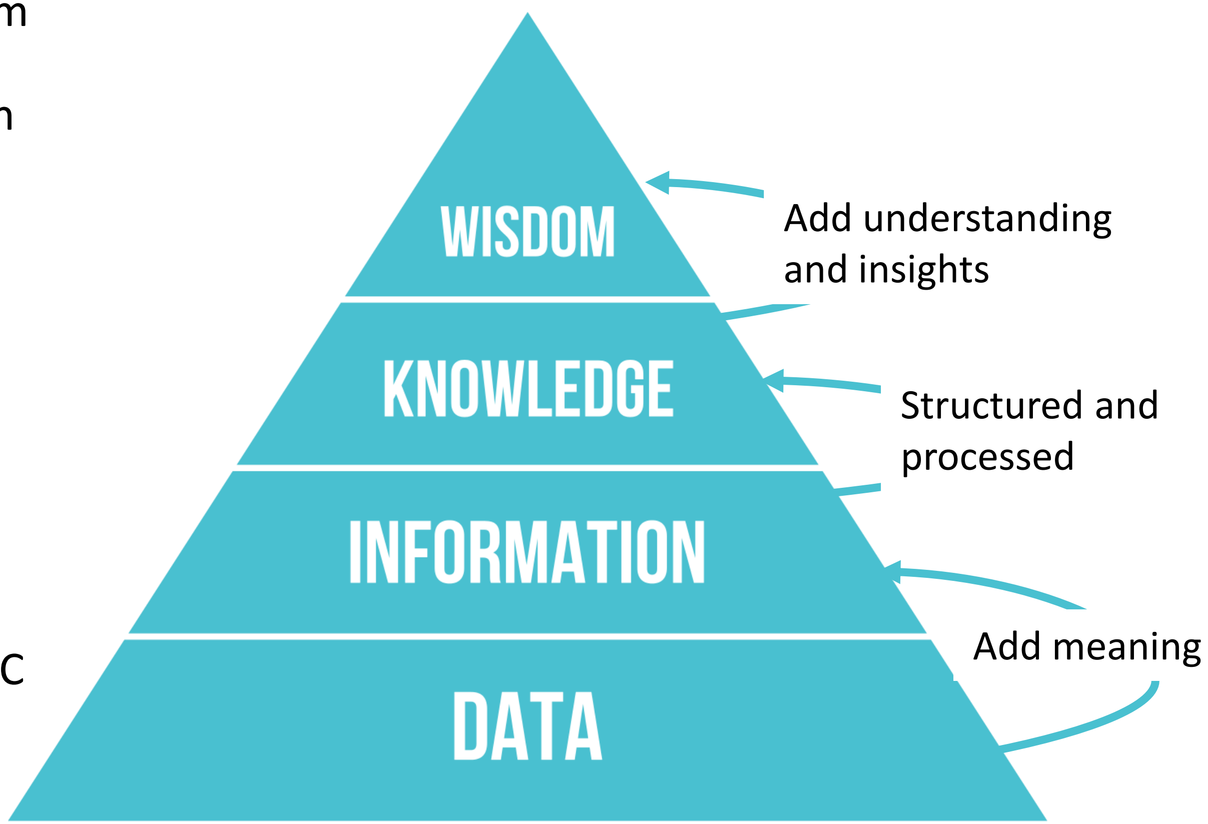
- Design principles for an intelligent autonomous control system
  - Three-Level Architecture
  - Development and Assessment Process

- Major technologies
  - Operational Workflow
  - Digital Twin Technology
  - Advanced Machine Learning Algorithms

DIKW Pyramid

DIKW Pyramid is proposed to pave the path from raw signals to insights and values [1]

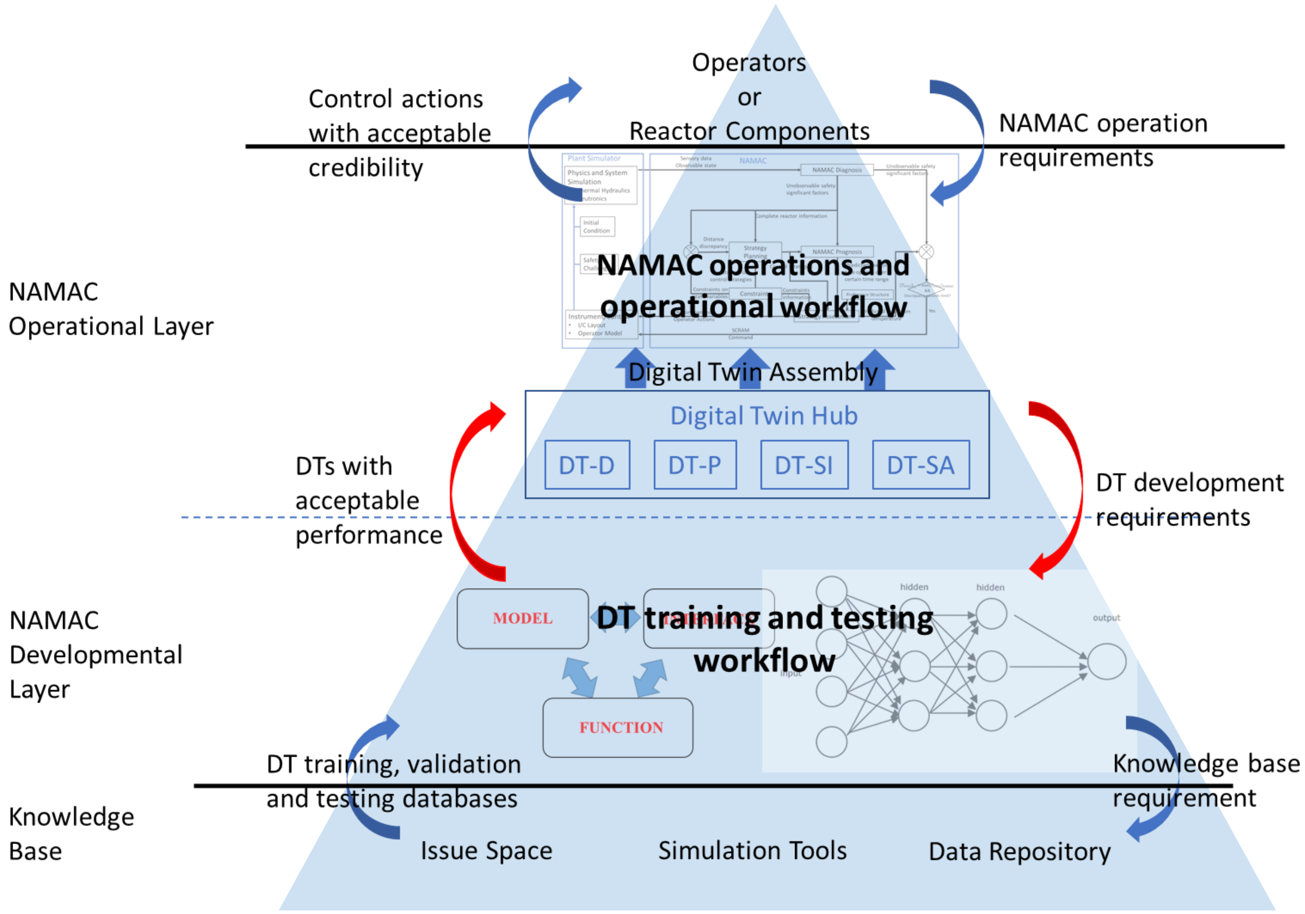
- DIKW Pyramid, also known as wisdom hierarchy, represents the structural and functional relationships between data, information, knowledge and wisdom.
- Computational representation for decision support system and intelligent system
- As an intelligent system, we adopted a similar structure to develop NAMAC



[1] J. Rowley, “The Wisdom Hierarchy: Representations of the DIKW hierarchy”, Journal of information Science, pp. 163-180, 2006

Three-Layer Architecture

- Acceptable DTs are assembled in an operational workflow to support decisions in operation, maintenance, safety management, etc.
- DT Developmental Layer is to extract useful information from the knowledge base and to implement DTs
- Digital Twin (DT) is a knowledge acquisition system from the knowledge base to support different functions
  - Digital Twin for Diagnosis (DT-D)
  - Digital Twin for Prognosis (DT-P)
- Knowledge base stores data from simulations, operations, documents, procedures, etc.



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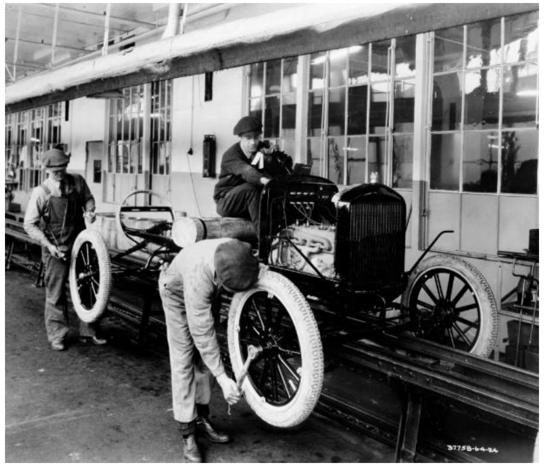
The Development and Assessment Process (DAP)

- Instead of claiming to have a perfect autonomous system for a specific reactor during a specific scenario, our objective is to have a formalized and optimized Development and Assessment Process (DAP) that produces NAMAC systems for various types of reactors based on requirements from all stakeholders.



1924 – Ford assembly line

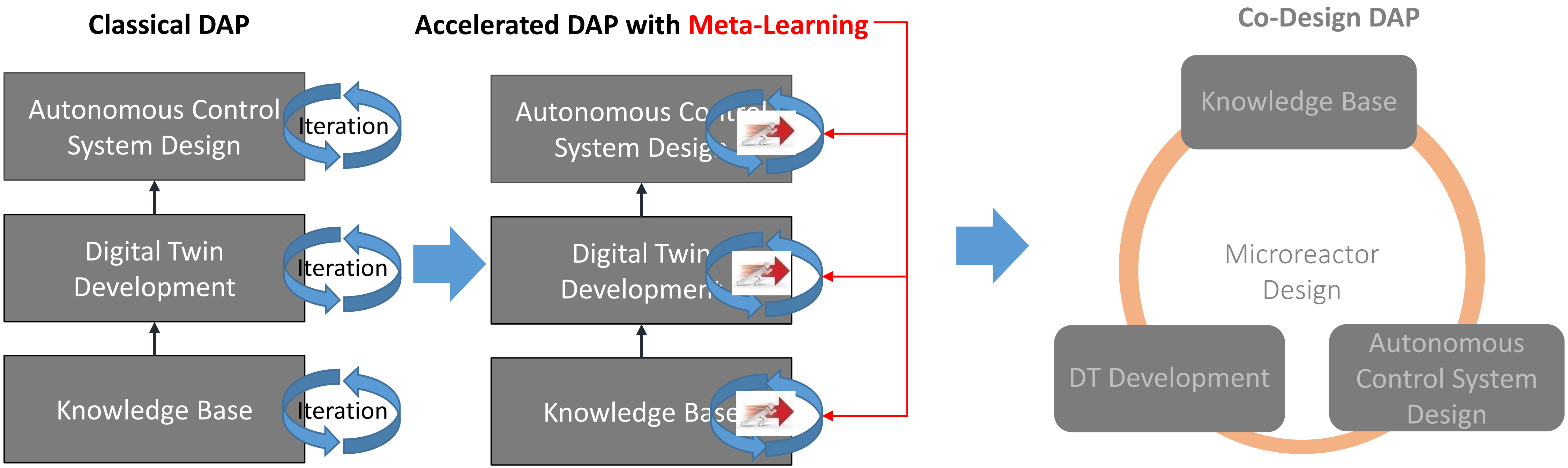
1965 – Ford assembly line

2019 – Tesla smart factory

Evolvement of "Development and Assessment Process (DAP)" for Automobile

[1] [2] Picture by Ford, "The evolution of assembly lines: A brief history", https://robohub.org/the-evolution-of-assembly-lines-a-brief-history/, 2014
[3] Picture from "Popular Mechanics", https://ottomotors.com/blog/what-is-the-smart-factory-manufacturing, 2019

Development and Assessment Process (DAP)



Formal Methods is proposed to improve the reliability and robustness of computer programing and software development with **frameworks, workflows, and process.**

e.g. U.S.NRC RG 1.203: Transient and Accident Analysis Methods

Meta-Learning refers to the "**learning to learn**" techniques that could accelerate and optimize the development of databases, machine learning algorithms, artificial intelligent system, etc.

e.g. Bayesian learning, physics-guided machine learning

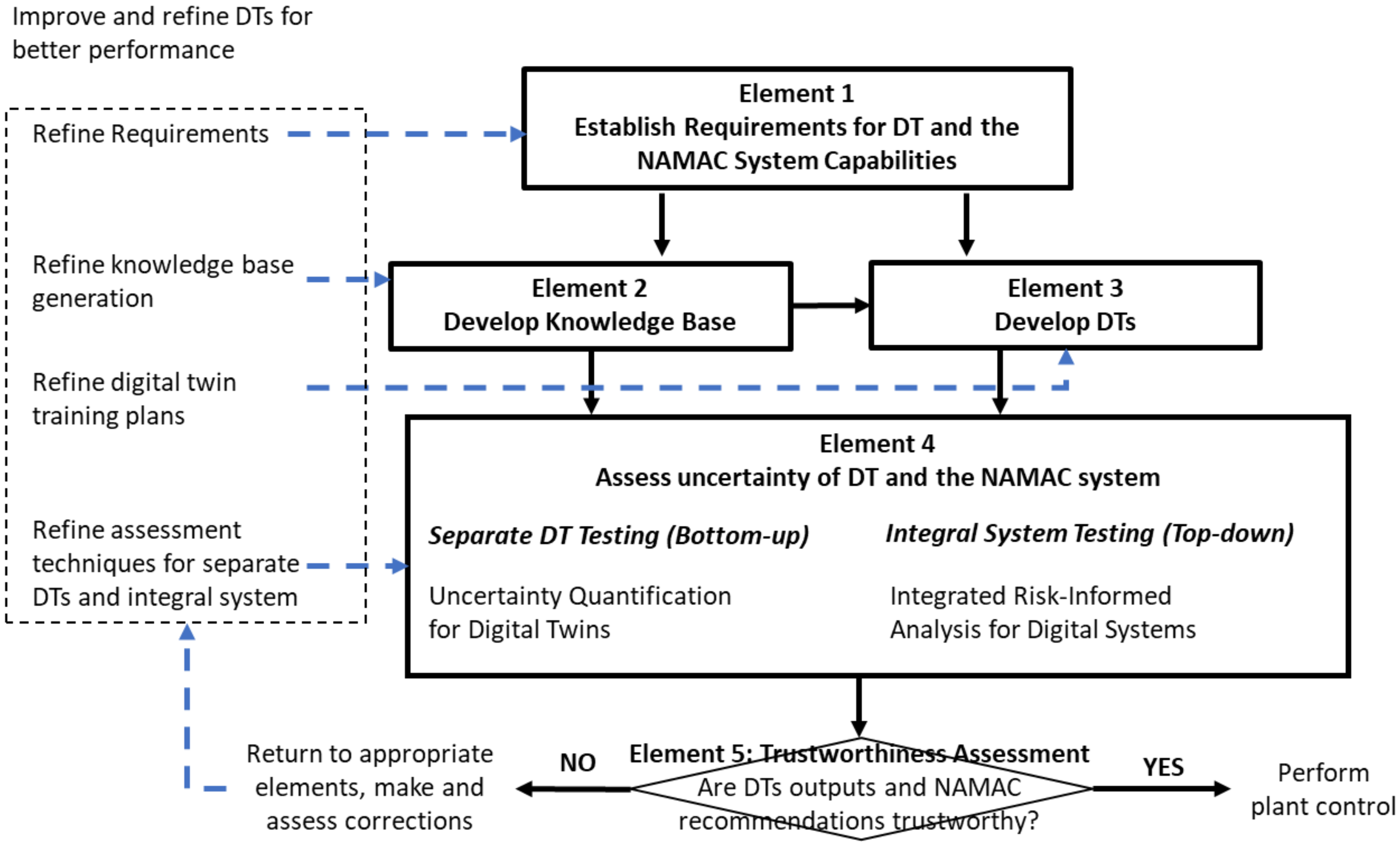
Co-design (participatory design) is an approach attempting to **involve** [illegible] **process** to help ensure the design solution meets all their need

Evolvement of NAMAC Development and Assessment Process

Digital Twin Development and Assessment Process

- A formalized DAP for identifying major sources of uncertainty and avoid biases due to implicitness.

- Driven by the trustworthiness assessment results, the DAP are conducted iteratively, and the corresponding elements are refined until an acceptable set of DTs are delivered:
    - *Element 1*: Refined requirements.
    - *Element 2*: More complex and more applicable knowledge base.
    - *Element 3*: Refined training plan with machine-learning approaches and optimized hypermeters.
    - *Element 4*: Uncertainty quantification, software reliability analysis.



Adopted from U.S. NRC RG 1.203 “Transient and Accident Analysis Methods”

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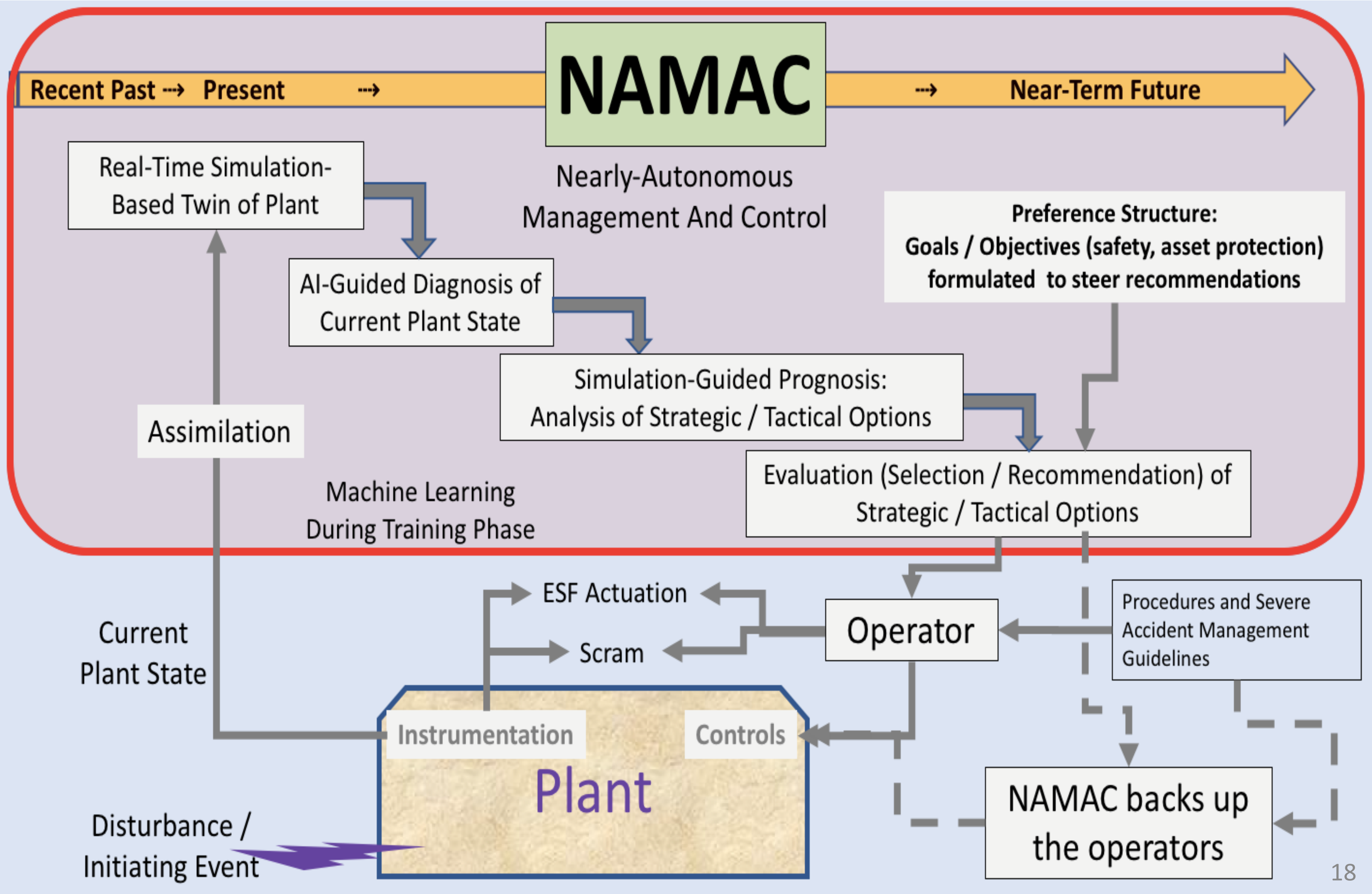
Operational Workflow

- A structured argument, supported by evidence from different components, intended to justify that a system is acceptably safe for a specific application in a specific operating environment

- Requirements
  - Accurate representation (twin) of the plant
  - Real-time: diagnosis, prognosis, and evaluation during operations
  - Credible: outputs can be justified



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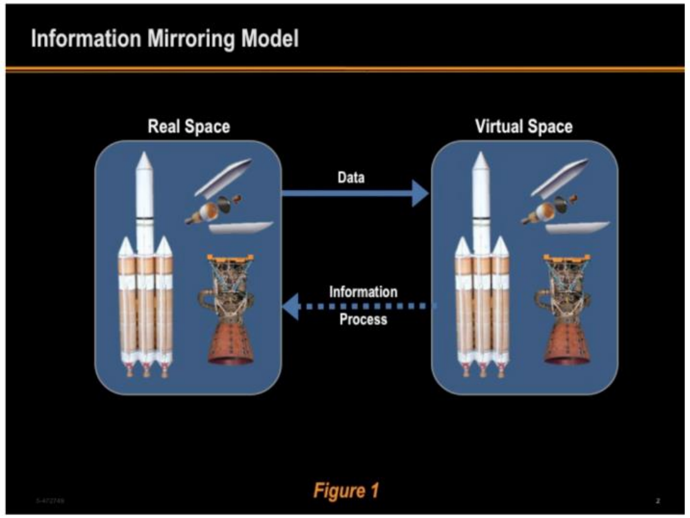
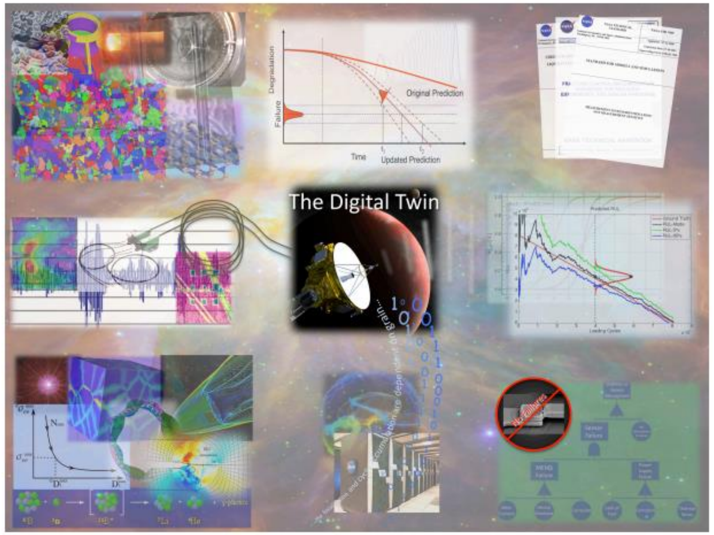
Digital Twin

"Information mirroring model for the lifecycle of physical systems"



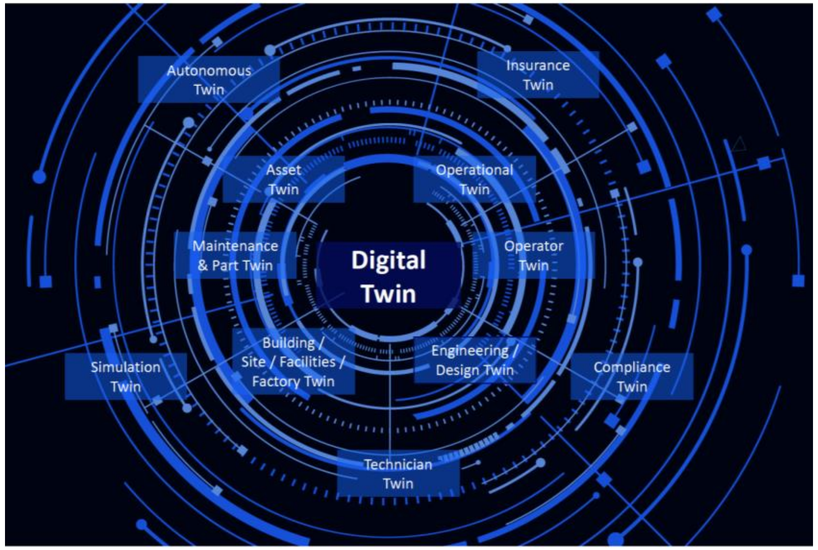
Shifts from paper-based and manual product data to a digital model for life-cycle management of the product, M. Grieves, 2003

"An integrated Multiphysics, multiscale, probabilistic simulation to mirror the life of its corresponding flying twin"



Real-time and high-fidelity management of complex materials, structures, and systems for a self-aware vehicle, NASA, 2010

"A virtual representation of a physical system and its associated environment and processes that is updated through the exchange of information between the physical and virtual systems"



The overall system that comprises at a minimum the physical system, the virtual system, and the relationships between physical and virtual systems, e.g., information and data flows, NRC, 2021

Elements of "Digital Twin" Technology

[1] M. Grieves, 2014, Digital twin: manufacturing excellence through virtual factory replication, White paper.
[2] M. Shafto, et al., 2010, Modeling, simulation, information technology & processing roadmap – technology area 11. NASA.
[3] V. Yadav, et al. 2021, The state of technology of application of digital twins, NRC.

Digital Twin in NAMAC

- Digital Twin: a digital replica (twin) for the real reactors and transients for the intended use
  - NAMAC manifestation: digital twins is a knowledge acquisition system from the knowledge base to support the intended use

- NAMAC DTs provide insights equivalent to Modeling and Simulation (M&S) **BUT** DTs are tightly coupled with operation
  - Assimilating and adapting to past histories and real-time information from the operating environment
  - Providing insights and guide decision-making faster than the typical development and application of M&S
  - Interacting with other (physical and virtual) components and user

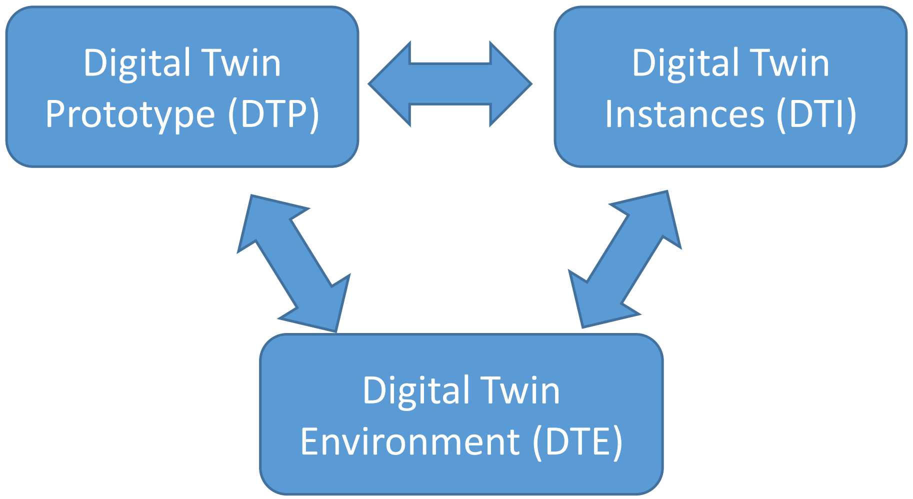
Definitions for DTs [1]

MODEL

- Data-driven model
- Mechanistic model
- Reasoning-based model

INTERFACE

- API
- I/O
- Interface Program



FUNCTION

- Diagnosis and Prognosis for control
- Maintenance

[1] F. Kahlen, et al., "Transdisciplinary perspectives on complex systems - new findings and approaches", Springer, 2017

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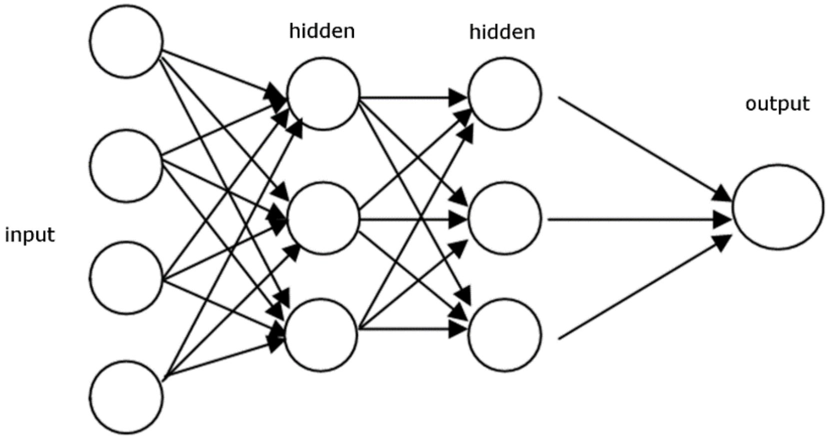
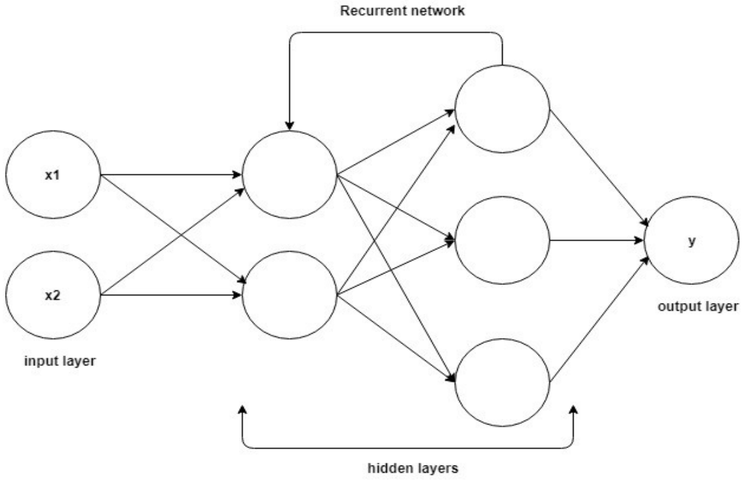
Artificial Neural Networks

- As one of the most popular Data-Driven Methods, Artificial Neural Network (ANNs) is used as a major technology in constructing Digital Twins and NAMAC system.
  - Neurons: basic elements that receive inputs, combine inputs with their internal state, and produce outputs
  - Connections and weights: ways to connect the output of one neuron as an input to another neuron, e.g. feedforward, recurrent, convolutional
  - Hyper-parameters: constant parameters that are set before the learning process, e.g. learning rate, number of layers, neurons, max. epoch



Feedforward Neural Network

- Information flows in one direction
- Very straightforward and easy to develop
- Memoryless: each input-output pair is independent.
- Able to capture complex and nonlinear correlations between variables

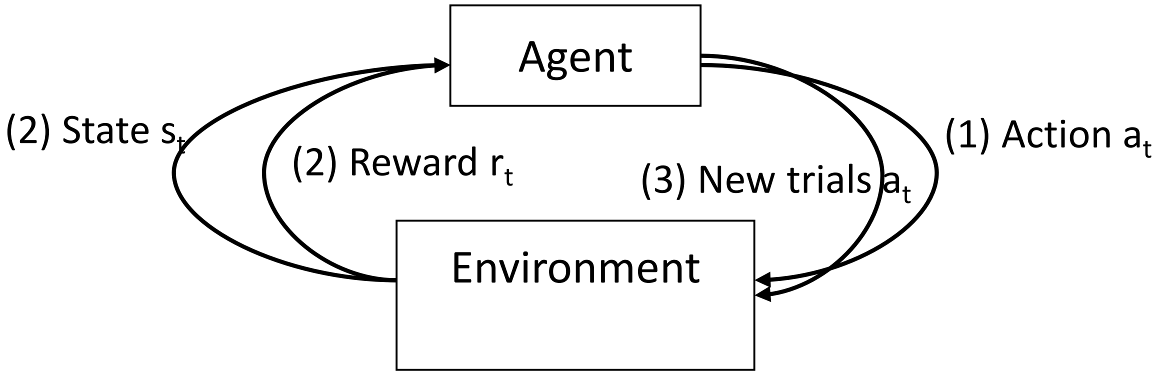


Recurrent Neural Network

- Information travels in both directions with a loops
- Designed to handle sequences, e.g. time sequence, image sequence, word sequence
- Suitable for forecast and prognosis functions

Reinforcement Learning

- In addition to making structured arguments with operational workflow, an optimal control action can also be found by having a machine-learning agent which
  - (1) Interacts with the environment
  - (2) Receive state and reward signals
  - (3) Induces an optimal policy with maximum rewards



- As a member of this project, a team in the computer science department at NC State University is leading the development and deployment of Reinforcement Learning into NAMAC [1]

An example of reward function

learning rate

discount factor ∈ [0, 1]

$$Q(s_i, a_i) \leftarrow (1-\alpha)\cdot Q(s_i, a_i) + \alpha \cdot (r_i + \gamma \cdot max_a Q(s_{i+1}, a)) \quad (1)$$

state-action value function

state

action

reward

Estimate of optimal future value

[1] Time-Aware Deep Reinforcement Learning for NAMAC, Kim & Chi, 2020

Answer Set Programming

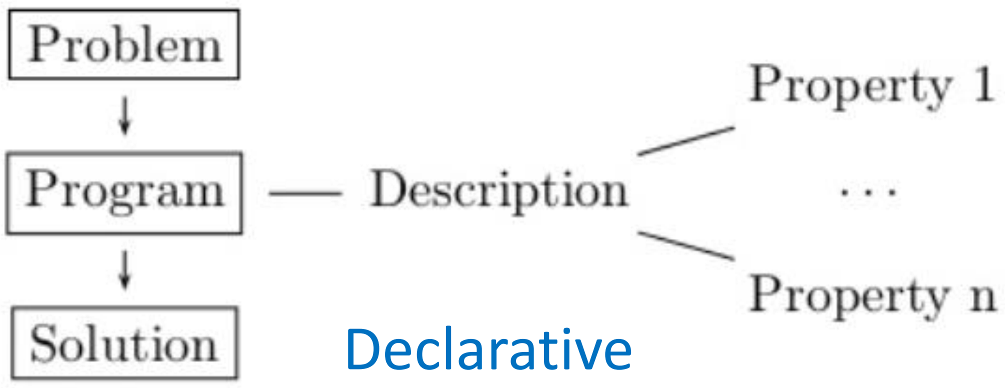
- However, the observed correlations do not necessarily imply causation, while causality tends to be more robust in prediction [1].
  - Adding more variables can be risky as they can pollute the model with noises and biases, e.g. X-> Y ->Z
  - Not adding variables can also be risky because of spurious correlation or confounding e.g. X <- Y -> Z

- Therefore, data-driven methods cannot be solely used without a method that performs **reasoning** and represents human **knowledge**

- Answer Set Programming is a form of declarative programming oriented towards difficult search problems

- As a member of this project, a team in the computer science department at the New Mexico State University is leading the development and deployment of ASP into NAMAC [2]

Given descriptions and problem, ASP can find a solution that is consistent with properties



Declarative programming

[1] J. Pearl, “The book of why: the new science of cause and effect”, 2018
[2] B. Hanna, et al., “An Artificial Intelligence-Guided Decision Support System for The Nuclear Power Plant Management”, NURETH-18, Portland, 2019

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Case Study

- Knowledge base construction
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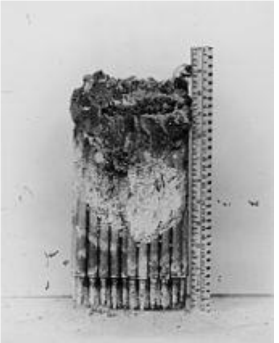
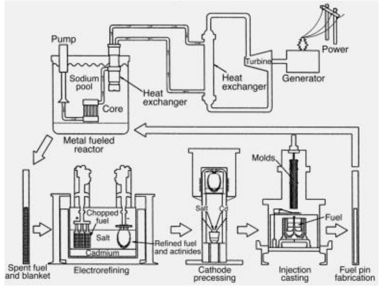
Experimental Breeder Reactor – II (EBR-II)

- As there is no operating advanced reactor, to make a proof-of-concept for NAMAC, EBR-II is selected as a prototype for small modular reactors with liquid-metal coolant and fast neutrons



First Metallic fuel:
- poor irradiation performance
- EBR-I, Fermi-1, SRE melted partially for coolant blockage
- EBR-II was constructed

International Nuclear Fuel Cycle Evaluation (non proliferation) → Metal fuel surprising advantages over oxide in low occurrence accidents → new alloy better performance → Clinch River Breeder Reactor Project shutdown



Integral → every element developed simultaneously
- The reactor system,
- treatment of the spent fuel
- fabrication of the new fuel
- treatment of the waste for final form suitable for disposal

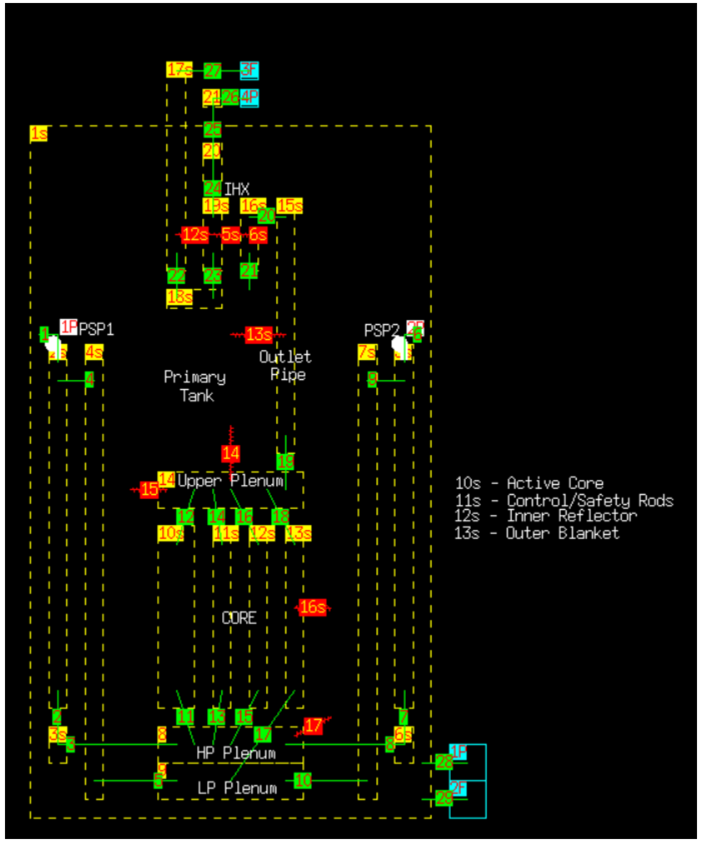
Achievements:
- very high burnups 20%
- fuel can be fabricated remotely
- passive safety

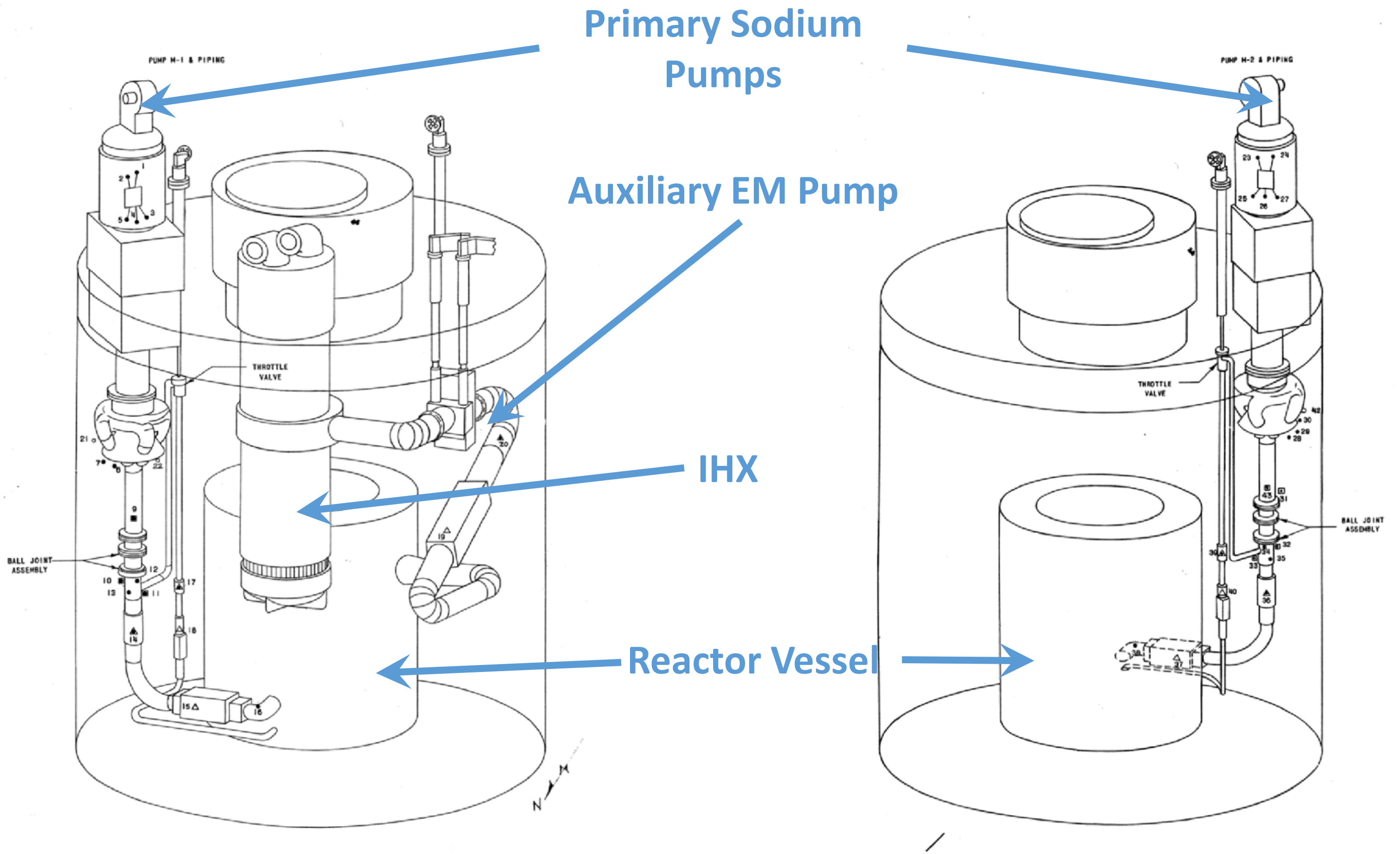
"We will terminate unnecessary programs in advanced reactor Development" → shutdown of the project

60's | 1977-84 | 1984-94 | 1994

Plant Simulator and Knowledge Generation Engine

Nodal representation [1] of the EBR-II primary system model in GOTHIC [2]



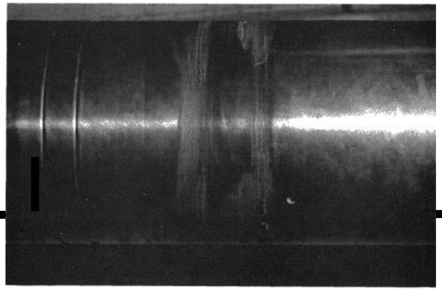


[1] R.C. Berkan, et al., “Low-order dynamic modeling of the experimental breeder reactor II”, Oak Ridge National Lab, 1990
[2] J.W. Lane, et al., “Benchmark of GOTHIC to EBR-II SHRT-17 and SHRT-45R Tests”, Nuclear Technology, 2020

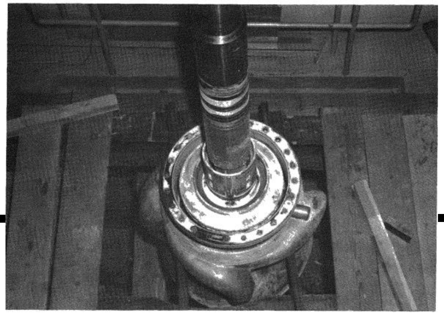
Loss of Flow Accident (LOFA) Scenario

- Since the operation of EBR-II from 1963, there were 1 major and 3 minor binding for the Primary Sodium Pump (PSP)
- There were two complete LOFA tests (SHRT-17 & SHRT-45)
- Partial LOFA due to single pump malfunctions as one of the dominant initiating events – Our Focus in NAMAC project

Apr 23 & Aug 18, 1963
PSP #1 & PSP #2: Severe galling of the labyrinth seal and pump shaft



Jul 12&17, 1965 & May 18, 1970
Minor bindings after long shutdown periods due to accumulation of sodium oxide in the clearance



Apr 16, 1963
Final phase of EBR-II construction and first operation

Jun 20, 1984
SHRT-17 tests with tripped primary pumps and a full control-rod insertion

Apr 3, 1986
SHRT-45R tests with tripped primary pumps and no scram

Sep 1994
Decommission

Issue-Space Characterization

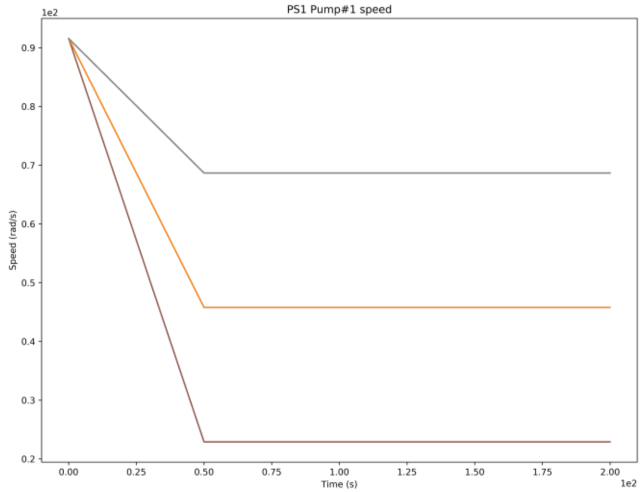
- Linear equation for PSP#1 malfunctions: starting from t_{acc}, PSP#1 rotational speed $w_1(t)$ ramps down to $\alpha_1 \cdot w_0$ after T_1 sec

$$w_1(t) = w_0 - \frac{w_0 - \alpha_1 \cdot w_0}{T_1}, \qquad t_{acc} + T_1 \geq t \geq t_{acc}$$

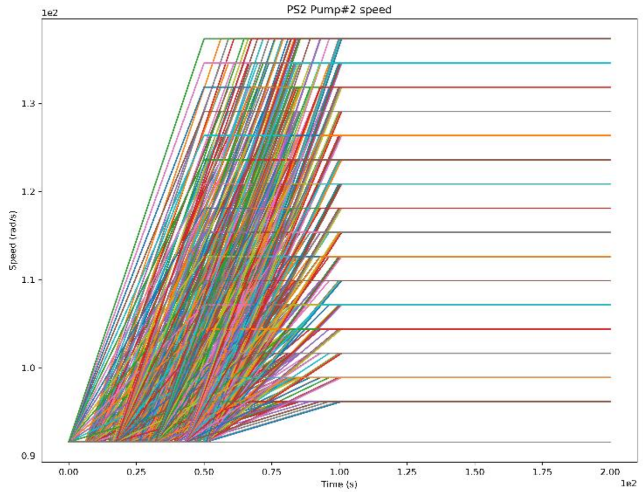
- Similar equation for recovering control actions: starting from t_{trip}, PSP#2 rotational speed $w_2(t)$ ramps up to $\alpha_2 \cdot w_0$ after T_2 sec

$$w_2(t) = w_0 + \frac{\alpha_2 \cdot w_0 - w_0}{T_2}, \qquad t_{trip} + T_2 \geq t \geq t_{trip}$$

PSP#1 malfunctions with three samples of end speed

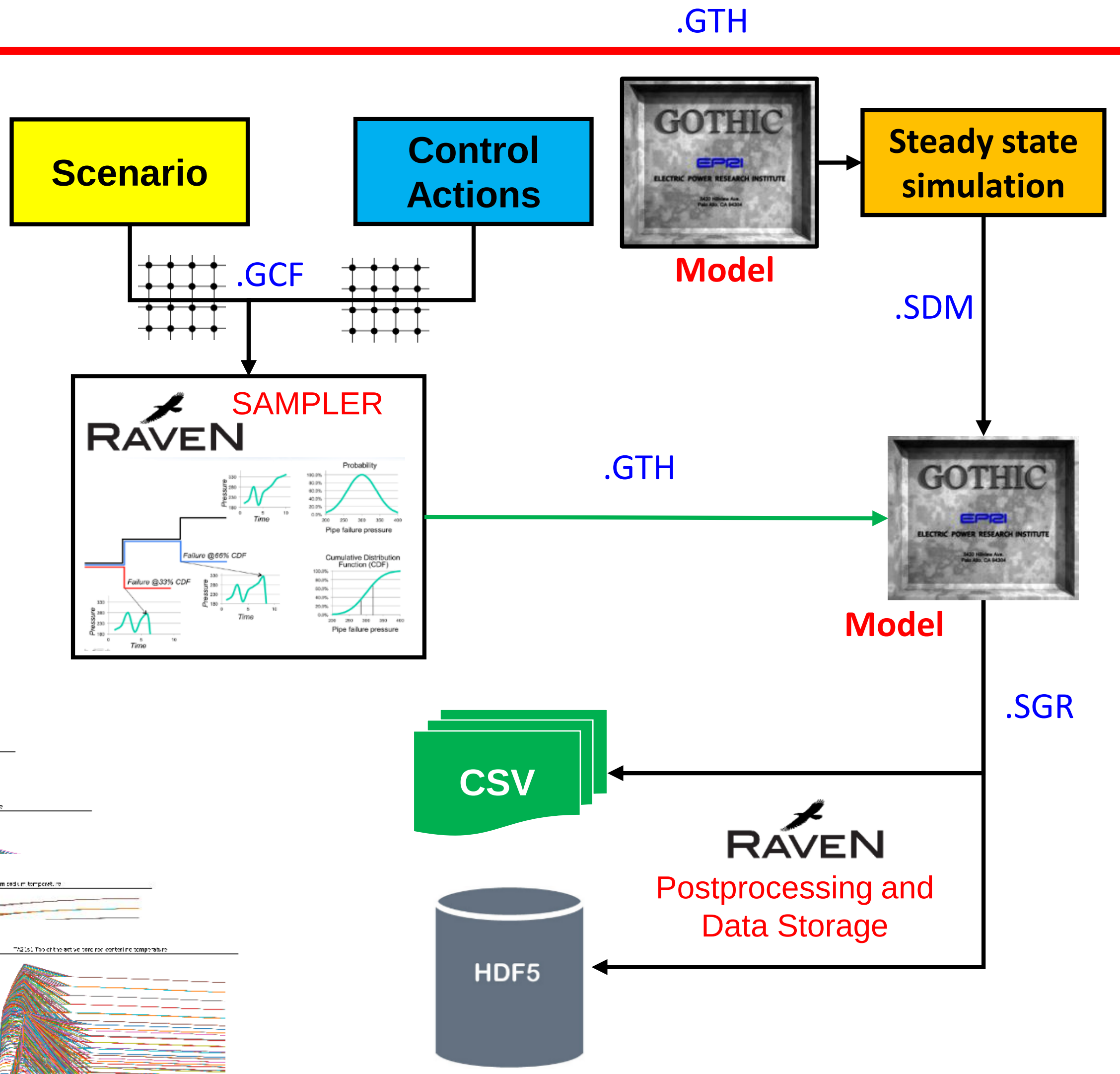


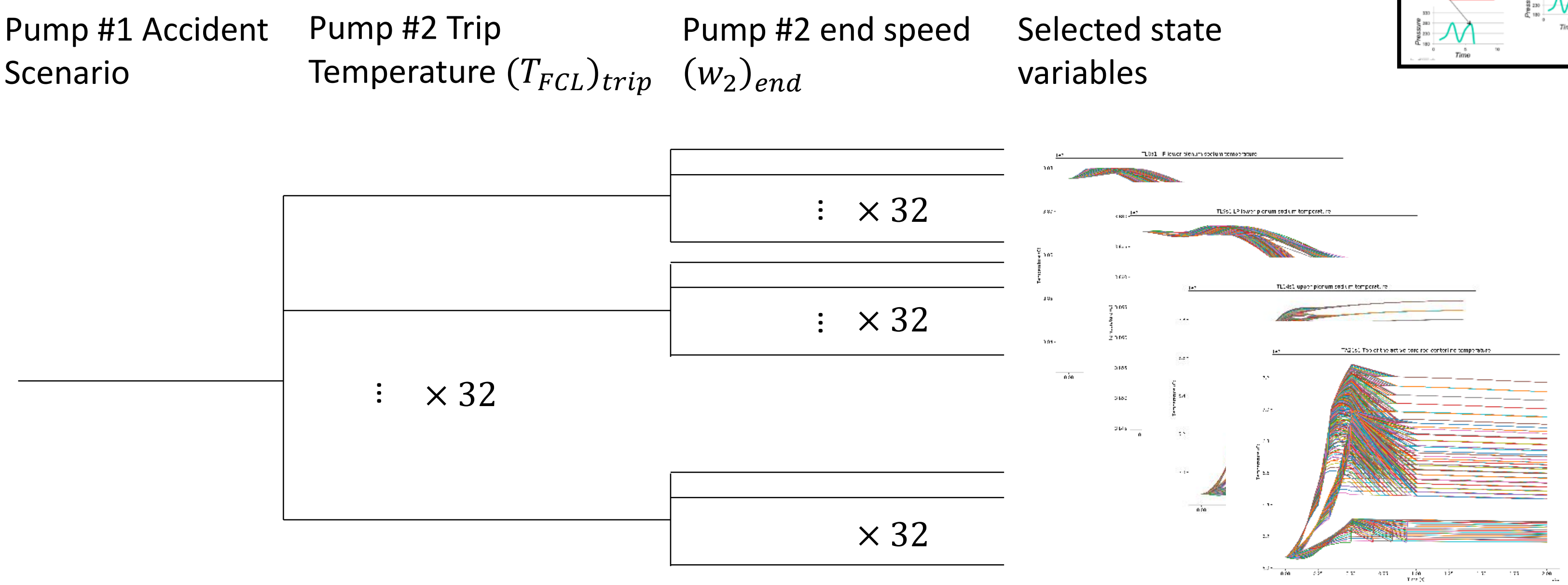
PSP#2 recovering control actions with 32 samples of α_1 and 32 samples of t_{trip}



Database Generation

- NAMAC Database generation:
  - GOTHIC is coupled with RAVEN for .GCF (GOTHIC Command File) preprocessing and .SGR (GOTHIC Graphical Data) postprocessing.
  - Training databases are generated by sampling the $(T_{FCL})_{trip}$ and $(w_2)_{end}$ by two uniform distributions.
  - The Digital Twin are constructed according to the databases for supporting diagnosis and prognosis.





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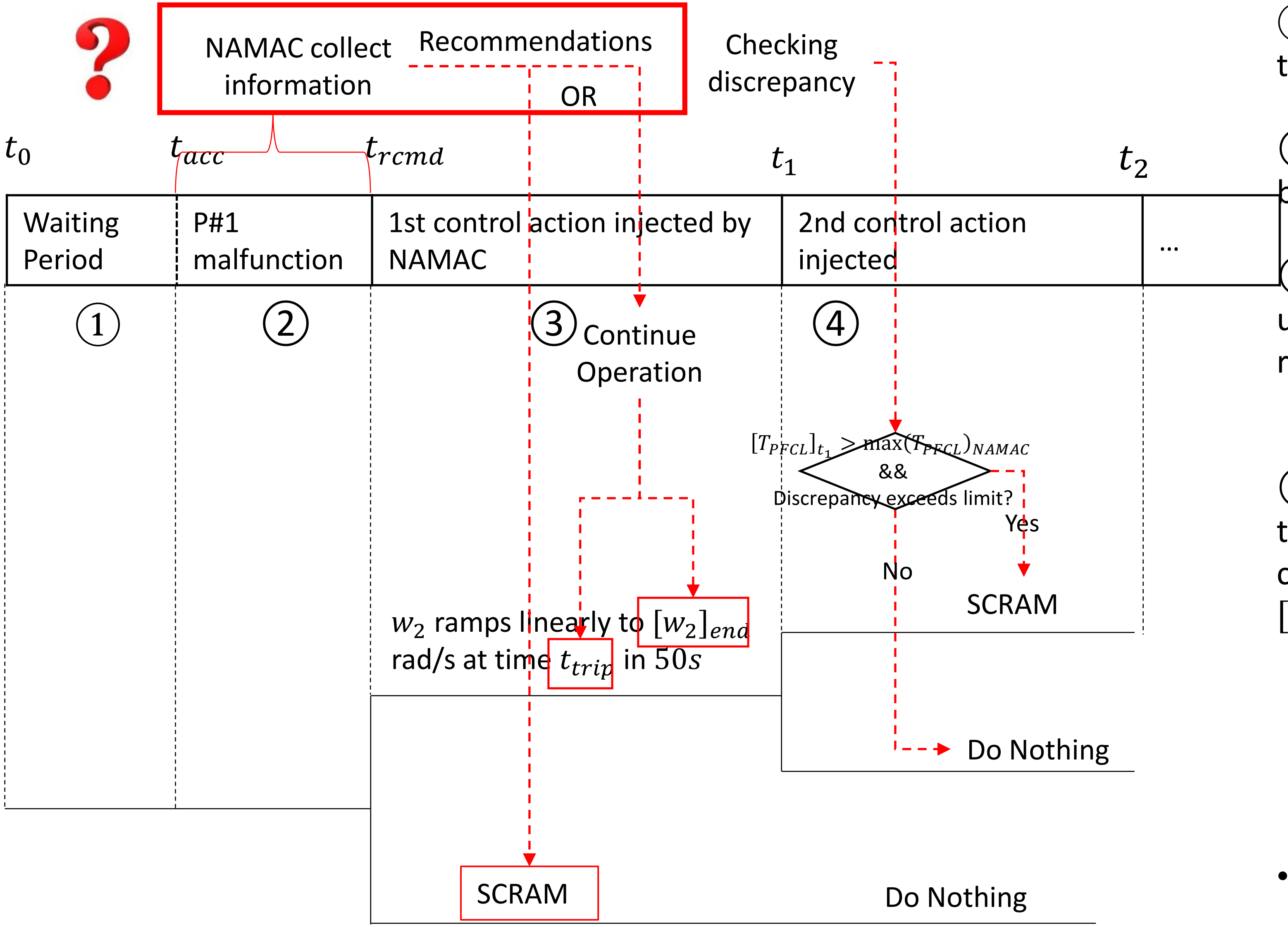
NAMAC Operation



① At $t_0 = 10000$s, steady-state calculations are loaded through .SDM files

② At $\boldsymbol{t_{acc}} = 10010$s, a pump malfunction is injected by ramping pump #1 to $\alpha_1 = 50\%$ in $50s$

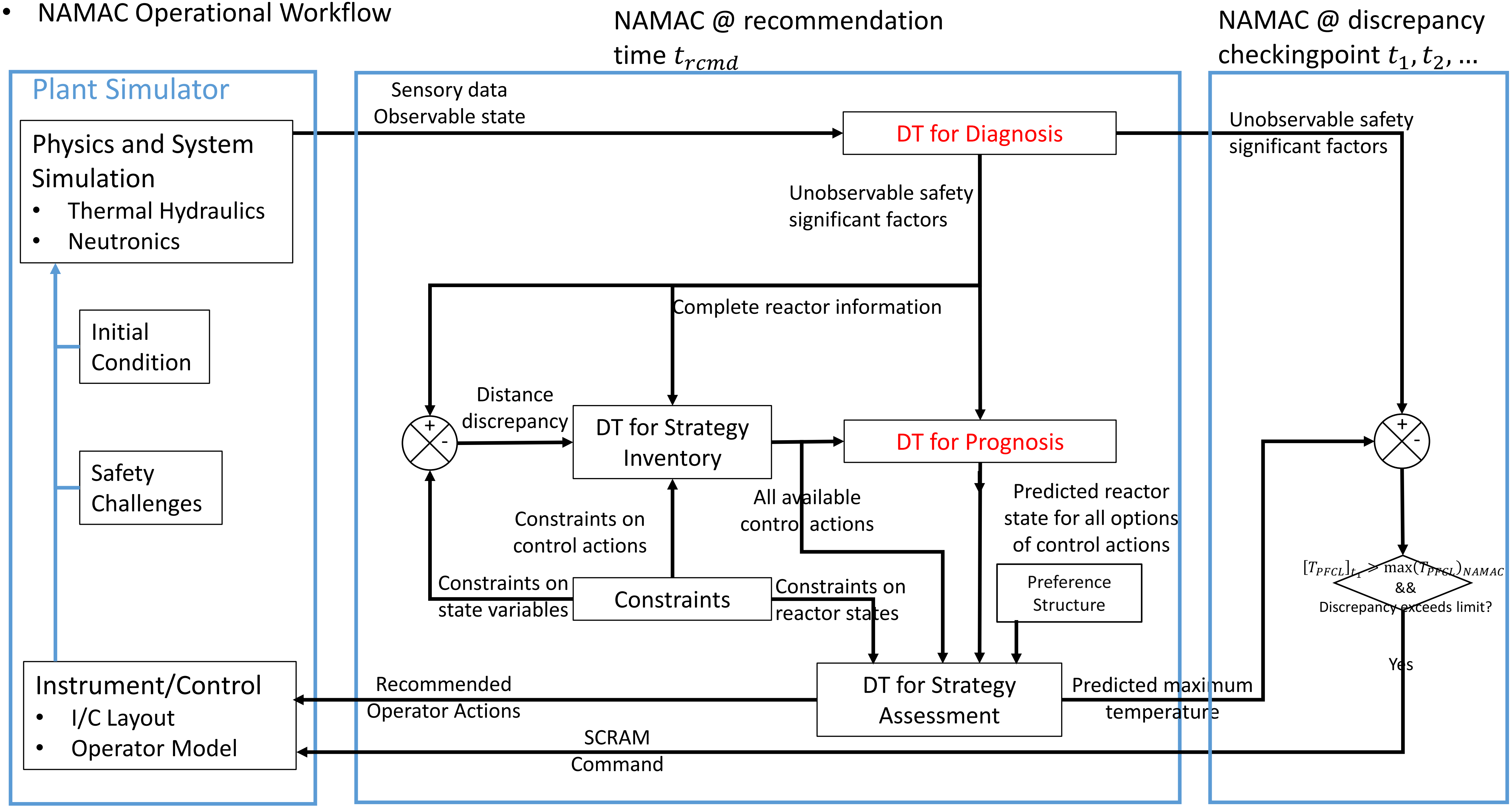
③ At $\boldsymbol{t_{rcmd}} = 10011$s, GOTHIC data files (.SGR) are updated and sent to NAMAC for making recommendations

④ At $\boldsymbol{t_1} = 10050$s, discrepancy checker will evaluate the discrepancy between $\max(T_{PFCL})_{NAMAC}$ and the current diagnosed Peak fuel centerline temperature $[T_{PFCL}]_{t_1}$

- If $[T_{PFCL}]_{t_1} > \max(T_{PFCL})_{NAMAC}$, and the discrepancy exceeds the limit, a scram command will be sent to GSIM
- Otherwise, previous actions will continue

- ④ At $\boldsymbol{t_2} = 10100$s, $\boldsymbol{t_3} = 10150$s..., continue checking discrepancy

- NAMAC Operational Workflow



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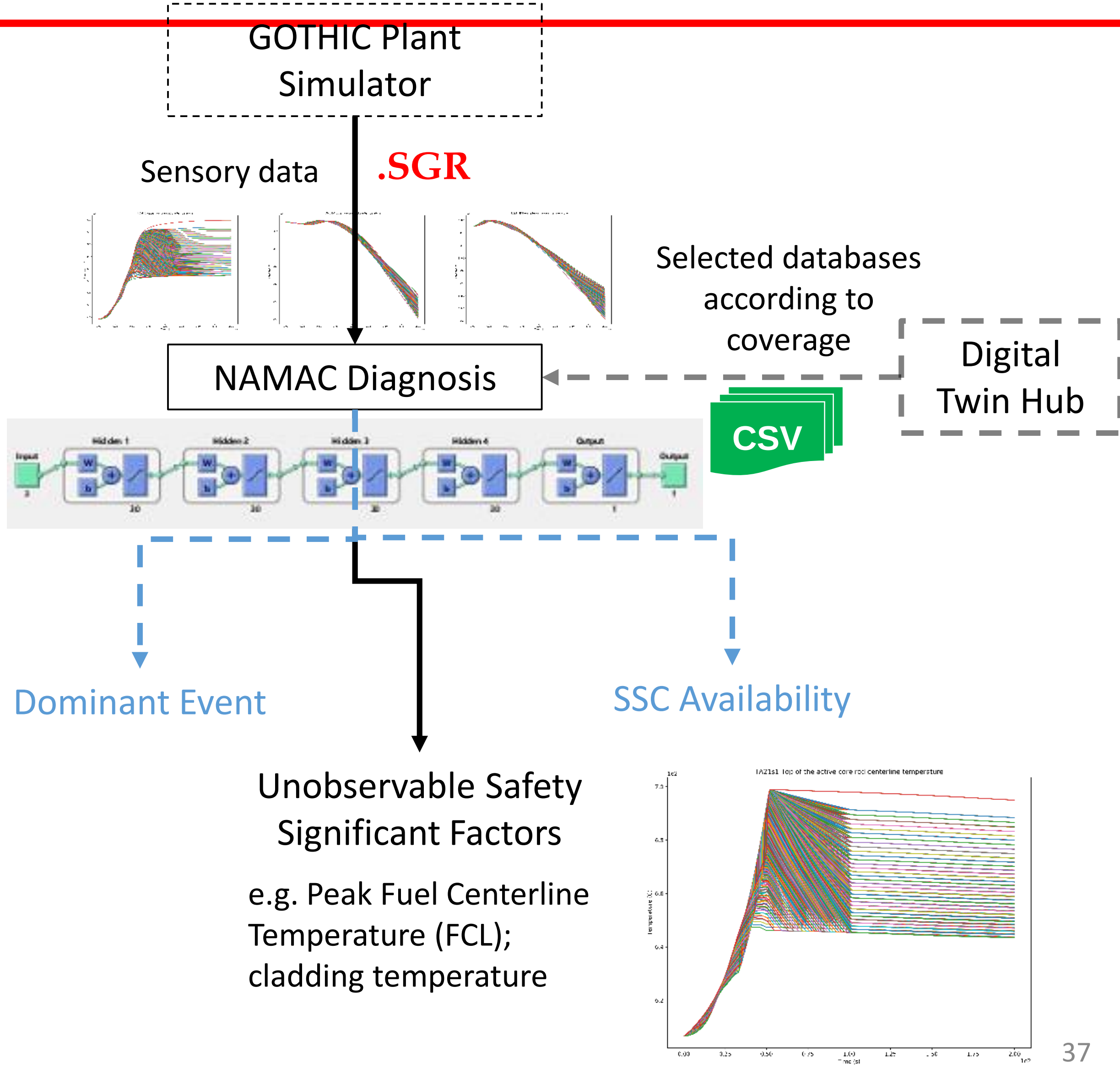
Digital Twin for Diagnosis (DT-D)

- DT-D aims to infer unobservable Safety Significant Factor (SSF) based on sensory data and digital twin.
    - SSFs include peak fuel temperature and/or peak cladding temperature

- A DT-D model (SSF Inference Model) can be:
    - Mechanistic model (e.g. Kalman filtering)
    - Data-driven surrogates (e.g. Artificial Neural Network)

- Current study explores the capability of data-driven surrogate by Feedforward and recurrent networks.
    - Data-driven model is friendly to big operation data and easy to implement.
    - Data-driven model has flexible forms and well-aware sources of uncertainty
    - Learning and training algorithms are transparent and mathematically defendable



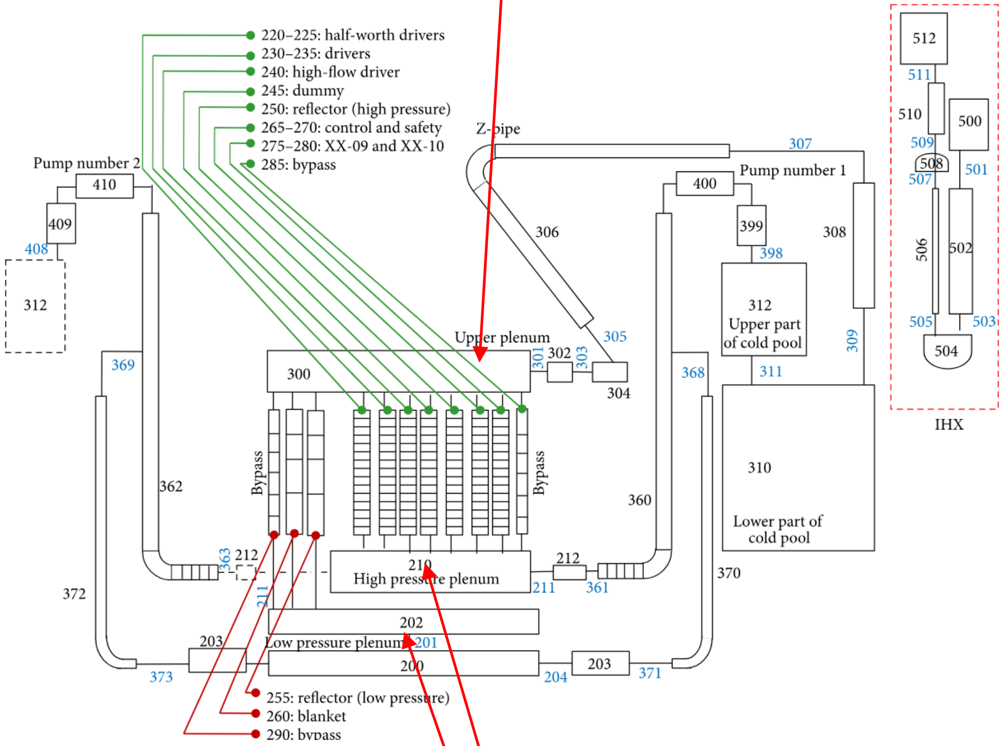
Digital Twin for Diagnosis (DT-D)

- The objective is to train a Neural Network by MATLAB that satisfies:

$$SSF(t) = f_{DT-D}(X_D, P_D, KB_D) + \varepsilon_D$$

  - X_D: A set of state variables, including Temperature at High-Pressure Lower Plenum T_{HPP}, Low-Pressure Lower Plenum T_{LPP}, and Upper Plenum T_{UP} are used as the input variables
  - P_D: The set of machine-learning hyper-parameters, including number of neurons per layer (20), number of layers (3), activation function (ReLU), etc.
  - KB_D: Knowledge base for training the Neural nets, which is NAMAC dabase from GOTHIC-RAVEN interface

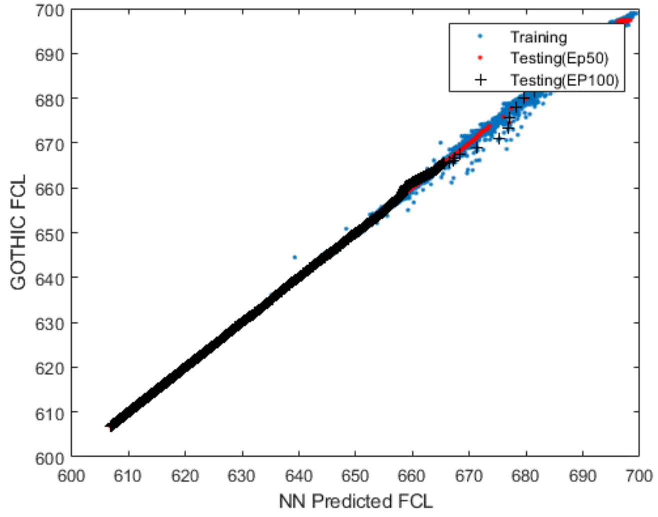
$T_{UP}(t)$: upper plenum temperature



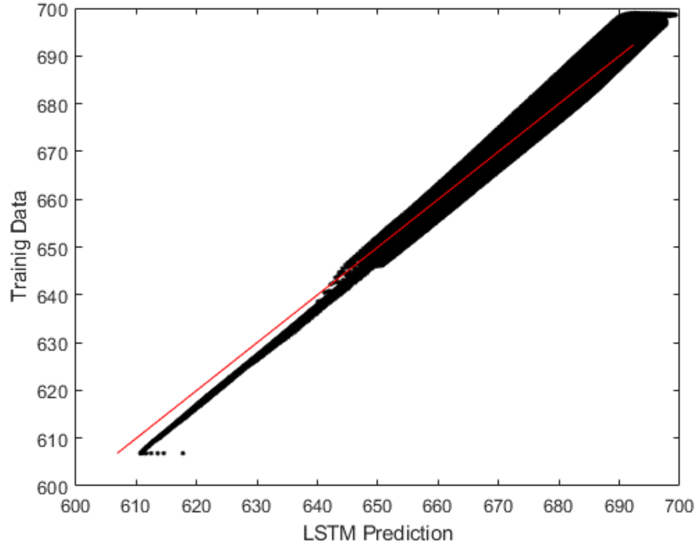
$T_{HPP}(t)$: high pressure plenum temperature

$T_{LPP}(t)$: low pressure plenum temperature

Comparison of DT-D predictions against real values in the knowledge base with Feedforward networks



with Long short-term memory Recurrent networks

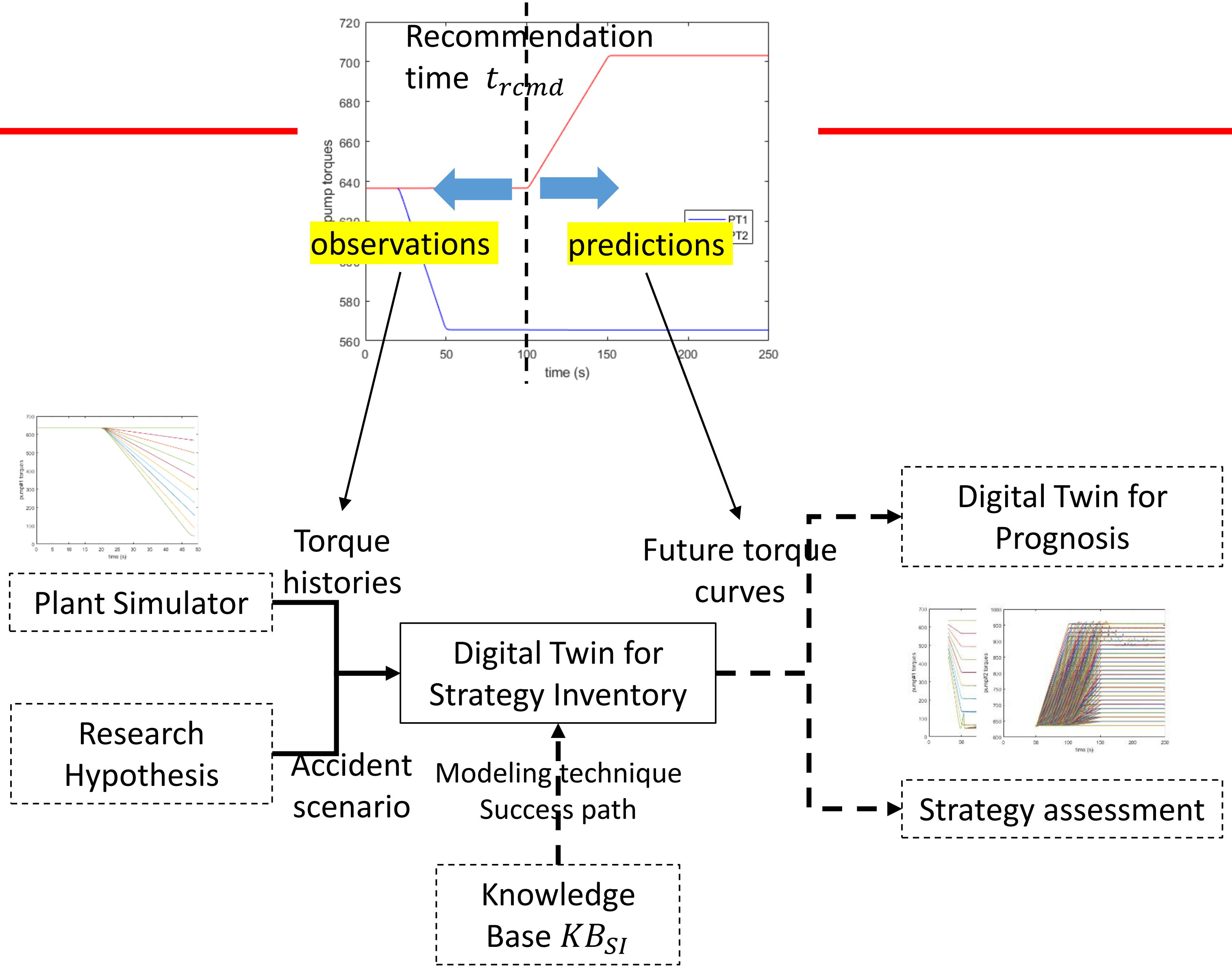


Strategy Inventory

- DT-SI aims to identify all available control actions based on the current reactor states (DT-D), safety and component limits

- Strategy inventory takes in
  - Research hypothesis: the accident time t_{acc} and magnitude $[\tau_1]_{end}$ are known
  - Knowledge base: A list of optional strategy injection time t_{trip} and magnitude $[\tau_2]_{end}$
  - Plant Simulator: History of pump torques from sensors before the recommendation time $\tau_s(t)$

- Strategy inventory produces torque curves of two primary pumps after the recommendation time
  - Future behaviors of malfunction pump
  - Optional strategies for available pump



Strategy Inventory

- Q4: Enforcing research hypothesis about pump malfunctions (discrete)

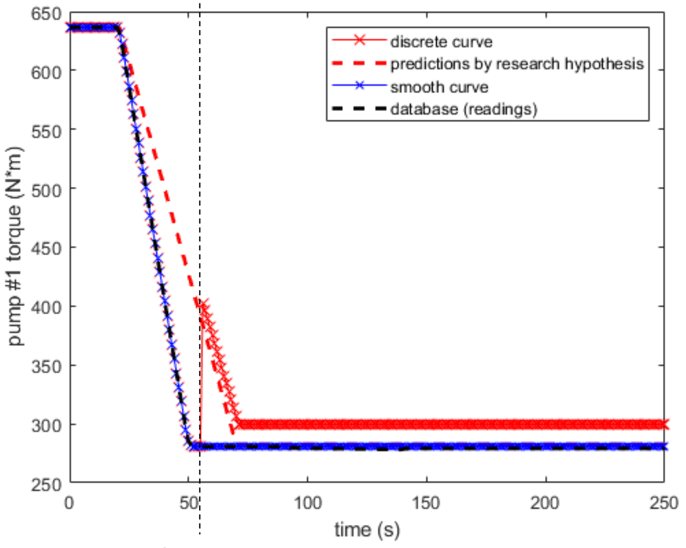
$$\tau_1(t) = \begin{cases} \tau_r(t), & t < t_{rcmd} \\ \tau_0 - \dfrac{\tau_0 - [\tau_1]_{end}}{50}(t - t_{acc}), & t_{rcmd} \le t < t_{end} \\ [\tau_1]_{end}, & t_{end} \le t < T \end{cases}$$

Updated to

- Q8: Enforcing curve smoothness between history and predictions (continuous)

$$\tau_1(t) = \begin{cases} \tau_r(t), & t < t_{rcmd} \\ \tau_r(t_{rcmd}) - \dfrac{\tau_r(t_{rcmd}) - [\tau_1]_{end}}{50 - (t_{rcmd} - t_{acc})}(t - t_{acc}), & t_{rcmd} \le t < t_{end} \\ [\tau_1]_{end}, & t_{end} \le t < T \end{cases}$$

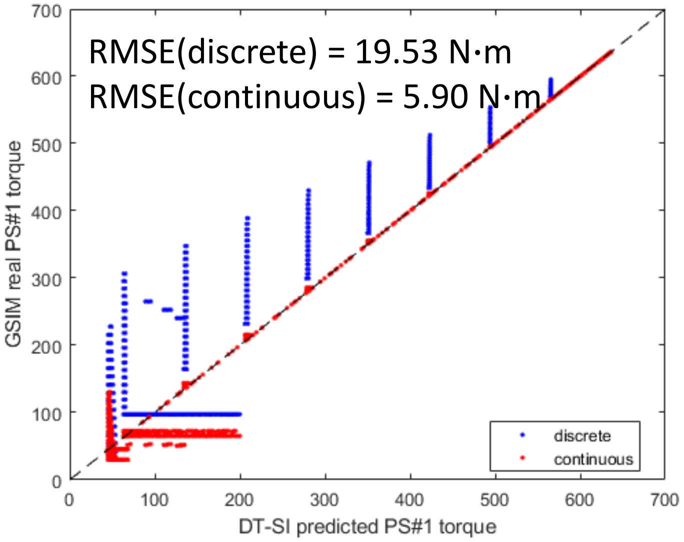
Histories SI predictions



t_{rcmd}

- Malfunction starting time: $t_{acc} = 20$ sec
- Malfunction ending time: $t_{end} = 70$ sec
- Malfunction magnitude: $[\tau_1]_{end} \in [0, 1]\tau_0$
- Recommendation time: $t_{rcmd} \in [50, 100]$ sec
- Transient ending time: $T = 250$ sec

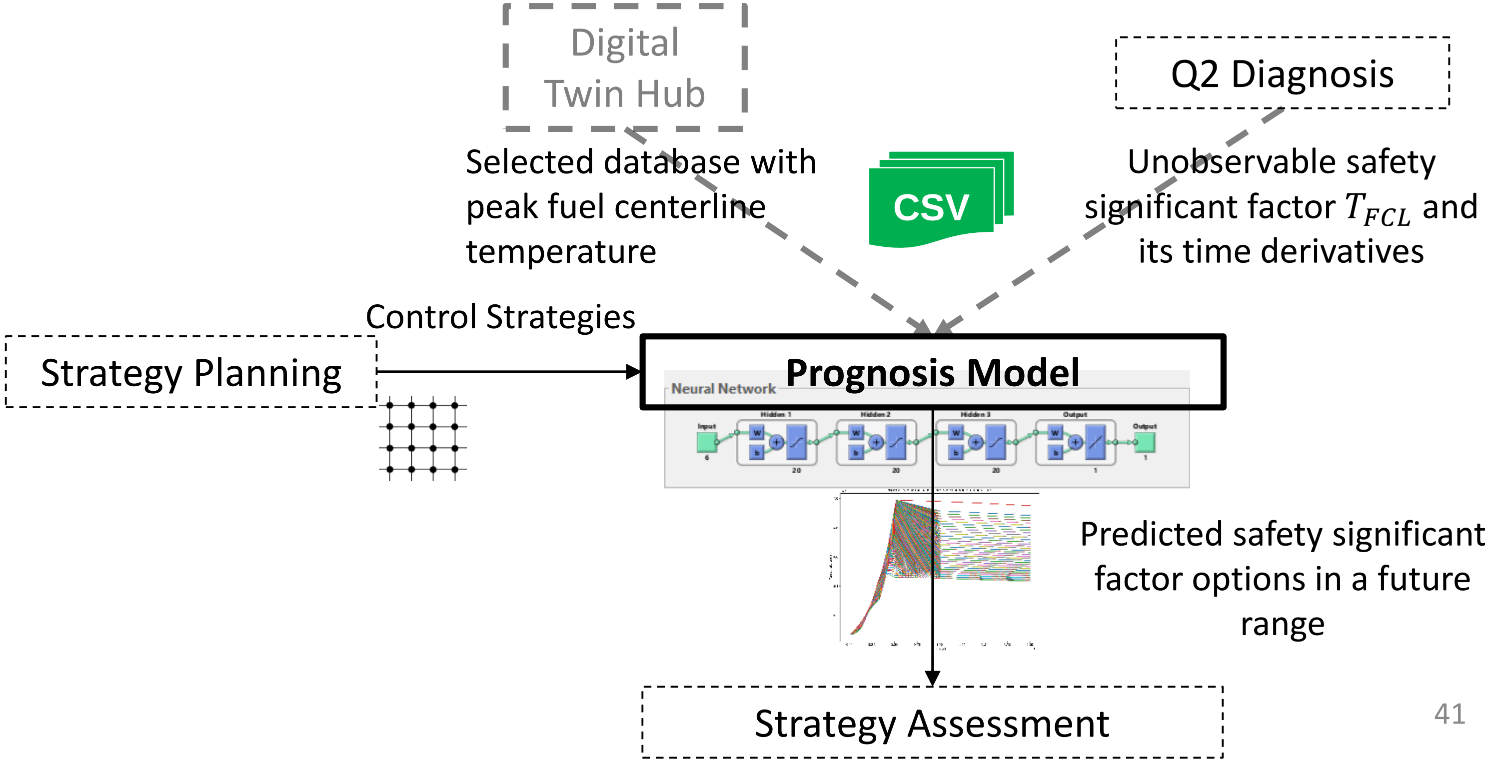
- DT-SI errors are reduced by enforcing smoothness in addition to the hypothesis
  - Improved modelling to bridge the gaps between assumption and reality



Digital Twin for Prognosis (DT-P)

- DT-P aims to predict the future transient of reactor states for all available control actions from DT-SI
- A DT-P model can be:
  - Numerical simulation tools (physical model and numerical solver)
  - Data-driven surrogate (Artificial Neural Network)

- Current study explores the capability of data-driven surrogate by Feedforward and recurrent networks
  - Predictive simulations can be started from any point in a transient with data-driven models
  - Acceptable accuracy and fast computational speed when data-driven models are applied within the training domains



Digital Twin for Prognosis (DT-P)

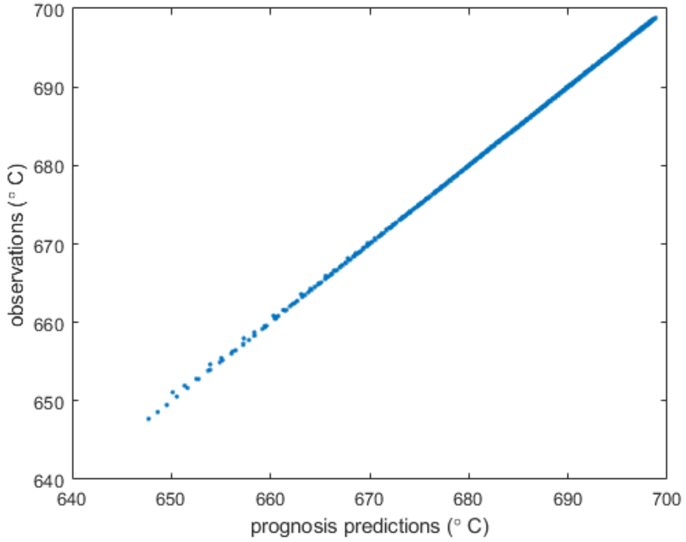
- The objective is to train a Neural Network that satisfies:

$$C_{A,X} = f_{DT-P}\left(A, X_{t_0}, P_P, KB_P\right) + \varepsilon_P$$

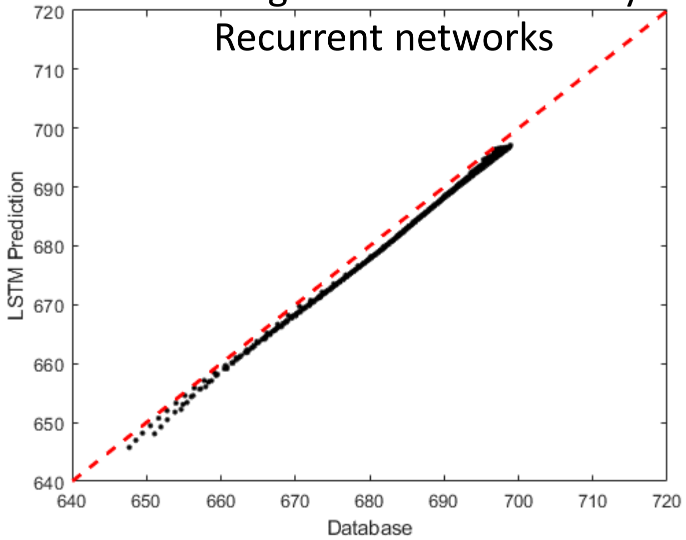
  - A: A set of control actions from the DT-SI, including trip temperature $[(T_{trip})_1, \dots, (T_{trip})_{32}]$ pump ramping-up fractions $[(\alpha_2)_1, \dots, (\alpha_2)_{32}]$
  - X_{t_0}: A set of state variables for current reactor conditions, including fuel centerline temperature T_{FCL}, core sodium temperature, flow rate, etc.
  - P_D: The set of machine-learning hyper-parameters, including number of neurons per layer (20), number of layers (3), activation function (ReLU), etc.
  - KB_D: Knowledge base for training the Neural nets, which is NAMAC dabase from GOTHIC-RAVEN interface

With similar training performances, RNN shows better predictive capability outside the training domain with stabler and smaller errors

Comparison of DT-P predictions against real values in the knowledge base with Feedforward networks



with long short-term memory Recurrent networks



Development and Assessment of Digital Twin for Prognosis

- Given the nonlinear relationship between LSTM training and DT-P outputs, we iteratively refine the training plan to reduce DT-P errors in performing multi-step predictions (*Element 3*)

- Hyperparameter optimization:

$$\lambda^* = \operatorname*{argmin}_{\lambda \in \Lambda} c(x \in G_x; A_\lambda(\mathrm{X}^{train}))$$

  - Manual Search
  - Bayesian learning (Sequential Model-based Optimization SMBO by Optuna)

- Physics-guided machine learning

$$\mathcal{L} = \mathcal{L}_{acc} + \lambda_{con}\mathcal{L}_{con}$$

$$\mathcal{L}_{con} = \frac{1}{T}\sum_{t \in T}\left(ReLU\left|\left(\hat{T}_{PFCL} - T'_{PFCL}\right) - \tau\right|\right)^2$$

$$T'_{PFCL} = T'_{co} + \sum_{r_c}\frac{q'}{2\pi k_c(r_c)} ln\left(\frac{r_c + \Delta r}{r_c}\right) + \sum_{r_f}\frac{q'}{4\pi k_f(r_f)} + \rho_f c_f \delta(T'_{PFCL})_t$$

- Hyperparameter optimization and physics guided machine learning can better reduce multi-step prediction errors than manual search
  - Fuel temperature°C : 1.70 > 1.18 (SMBO) / 1.07 (PGML)
  - Core power rate MW: 0.69 > 0.38 (SMBO) / 0.34 (PGML)

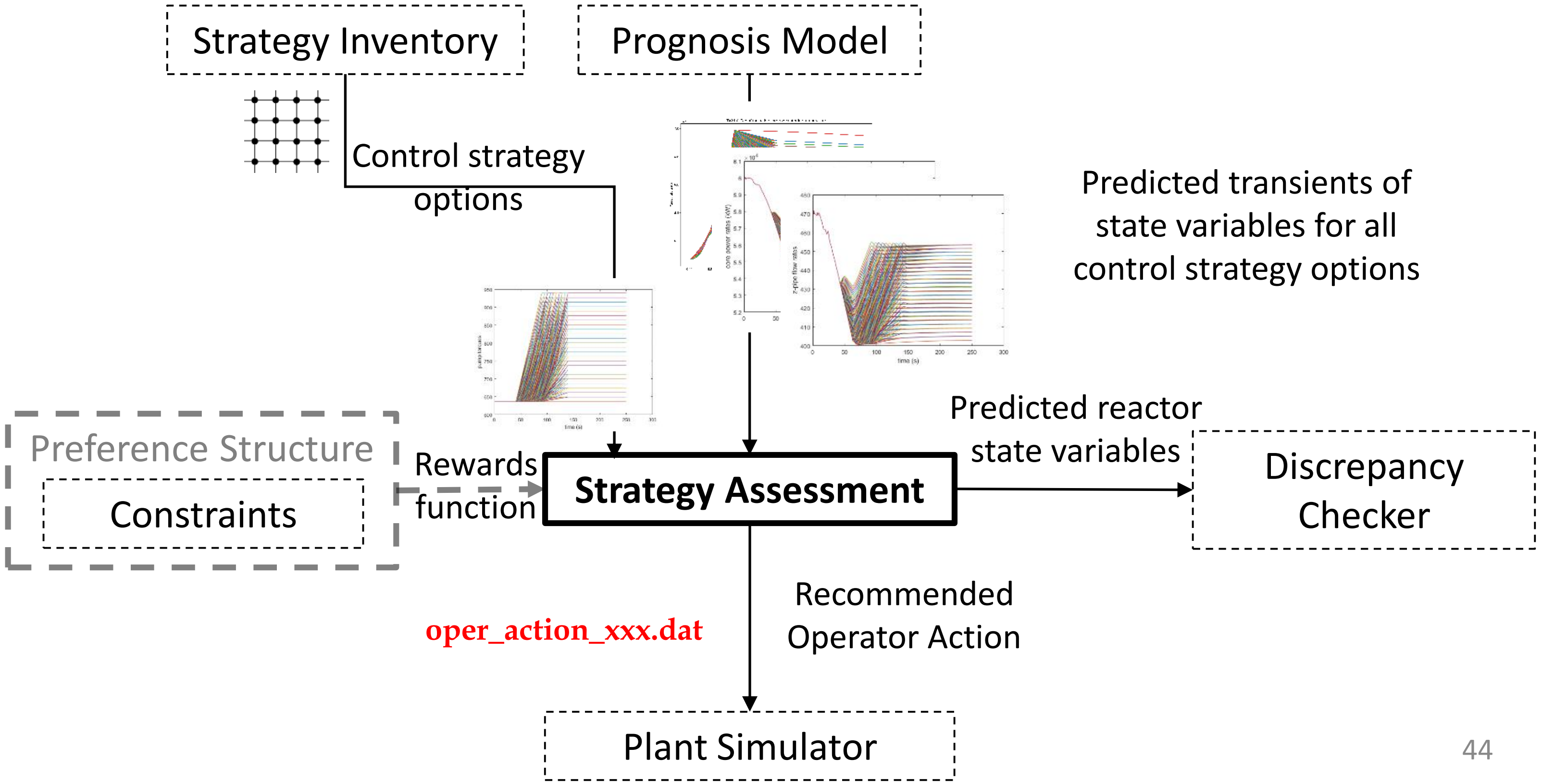
- Optimization or physics-guided ML cannot solve the generalization issue
  - Fuel temperature°C : 4.43 < 6.95 (SMBO) / 5.43 (PGML)
  - Core power rate MW 1.44 < 2.85 (SMBO) / 1.89 (PGML)

The applicability of knowledge base (*Element 2*) seems to have more dominant effects

Digital Twin for Strategy Assessment (DT-SA)

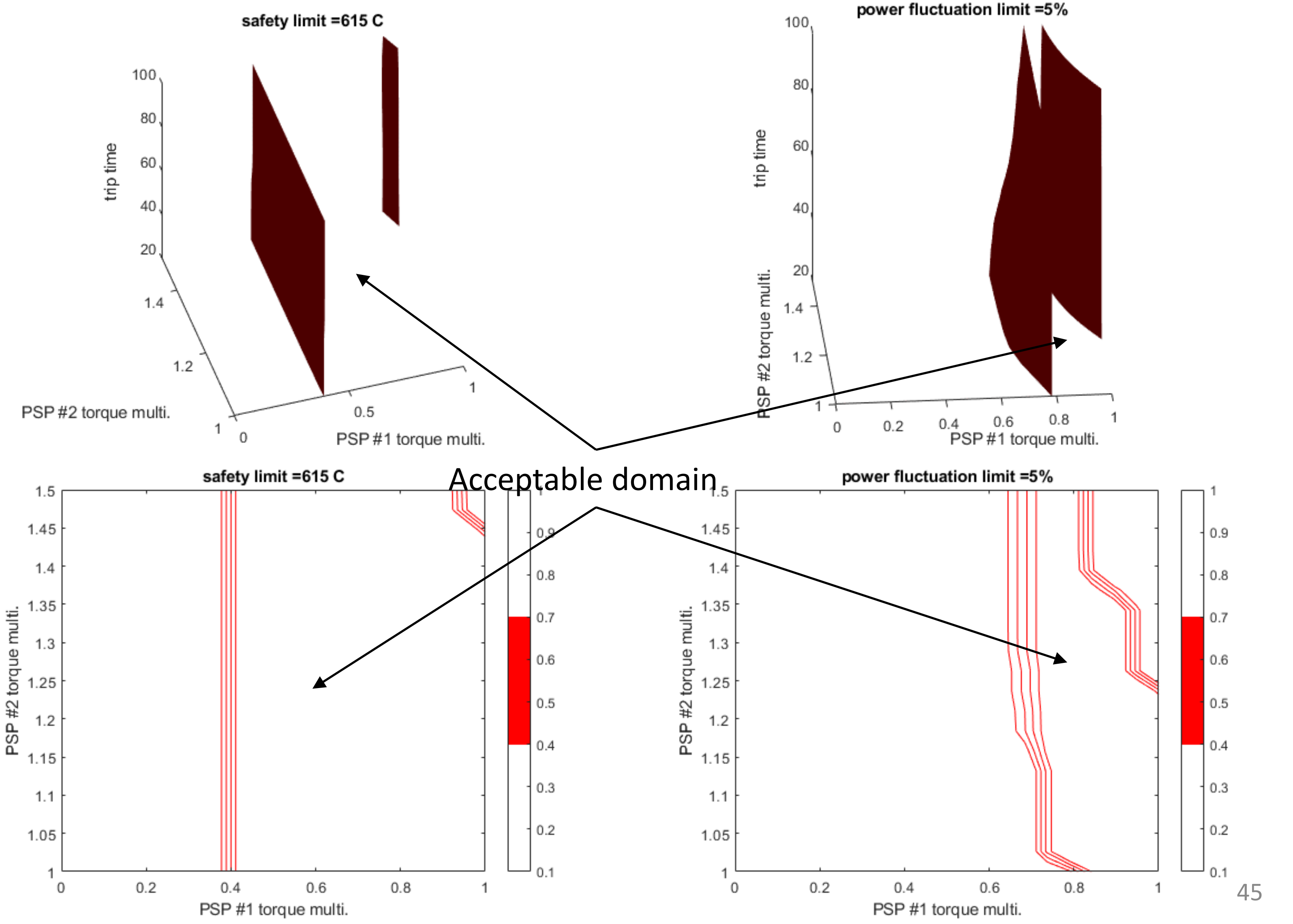
- Component requirements
  - Function: The objective is to rank strategies and to make recommendations on control actions according to preference structure and constraints.
  - Modelling:
    - Limit-surface approach
    - Utility/rewards function
  - Input Interface
    - Control strategy options by strategy inventory.
    - Predicted state variables for all control strategy options by prognosis.
    - Preference structure
  - Output Interface
    - Recommended operator actions
    - Predicted reactor states

Limit surface: the boundary in the input space between two simulated outcomes, e.g. failure or success, positive or negative



Strategy Assessment

- The limit surface can be constructed by
  - The maximum value of fuel centerline temperature
    - Prefer to stay close to the nominal temperature (nominal @ 605.83 ℃)
    - Prefer to stay away from the safety limit (685℃)
  - The power variation (sustain 100% availability)
    - Prefer to stay close to the nominal power rate (nominal @ 100% power rate)
  - The torque variation (component reliability)
    - Prefer to stay close to the nominal torque (assumed to be the best efficiency point)



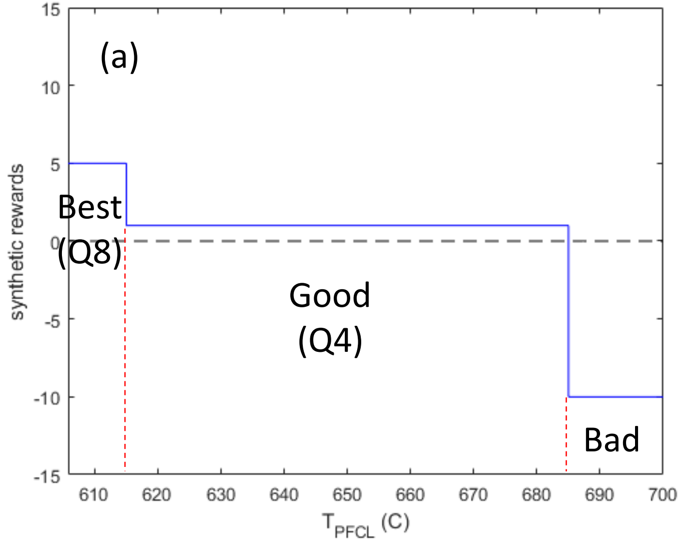
Preference Structure

- The preference structure is represented by rewards to the entire transients of:
  - Peak fuel centerline temperature
  - Fractional variations of core power rates
  - Fractional variations of pump torques

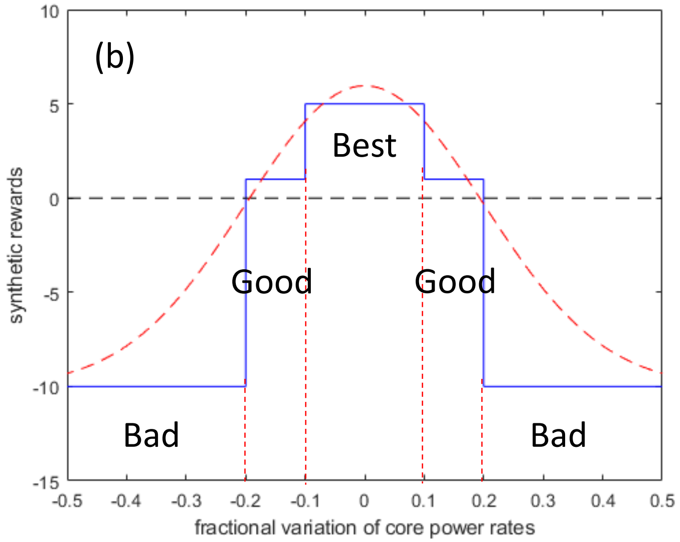
The goal is to synchronize all attributes of different time scales into the same time scale through preference structure

- Three levels of rewards are assigned based on the range of state variables
  - Best = 5; Good = 1; Bad = -10

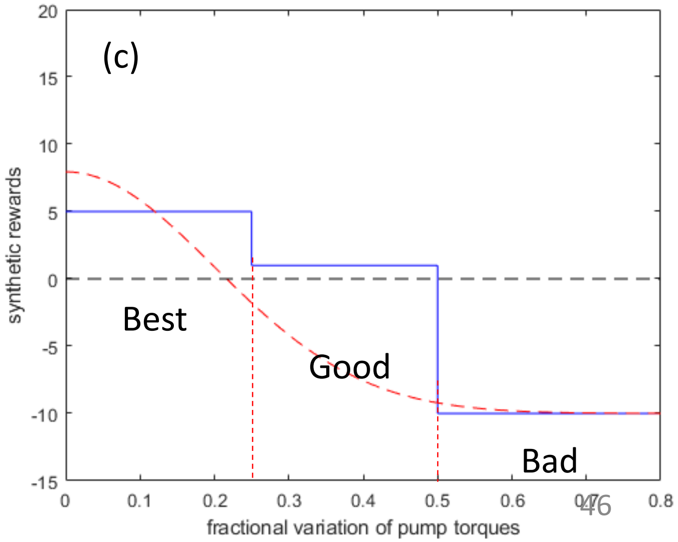
Rewards based on fuel centerline temperature



Rewards maximum core power rate variations (in %)



Rewards based on the torques variations of pump #2 (in %)



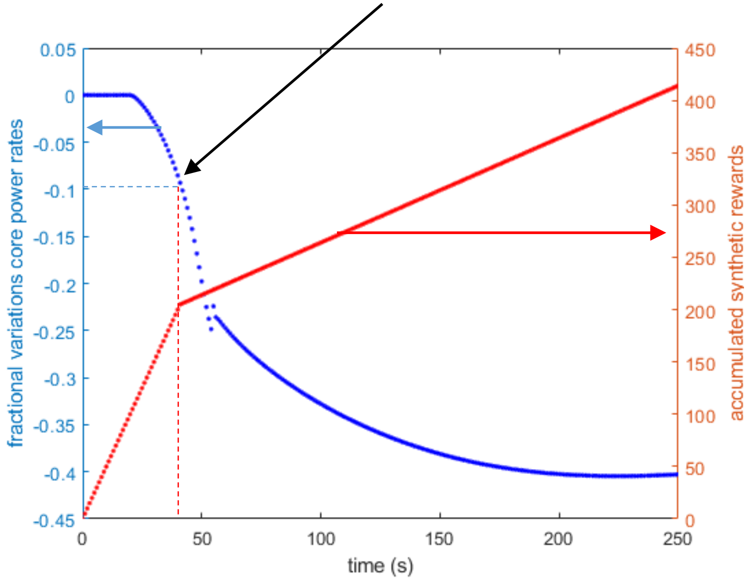
Strategy Assessment

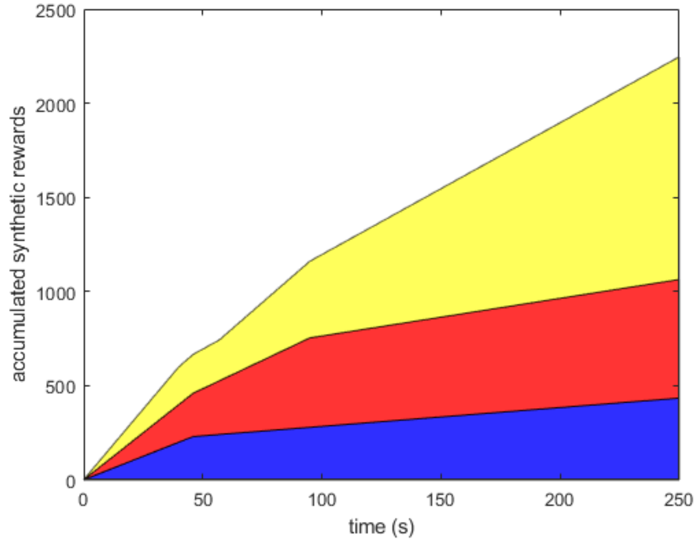
Transit from best-reward to good-reward region

- Rewards from fractional power variations
- Rewards from fractional torque variations
- Rewards from T_{PFCL}

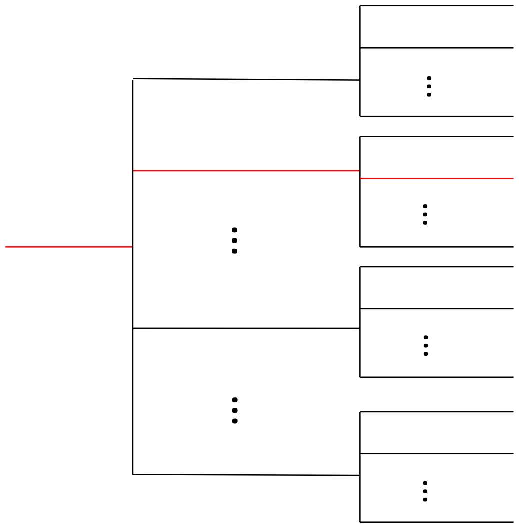
- The optimal actions should correspond to the highest rewards
  - Synthetic rewards
  - Rewards are additive
  - Uniform weights for each attribute

$$R = \int_0^{250} R_{T_{PFCL}} \cdot dt + \int_0^{250} R_{\dot{q}_{core}} \cdot dt + \int_0^{250} R_{\tau_2} \cdot dt$$





Action magnitude	Injection time	Total Rewards



2055
2060

2855 optimal

2020

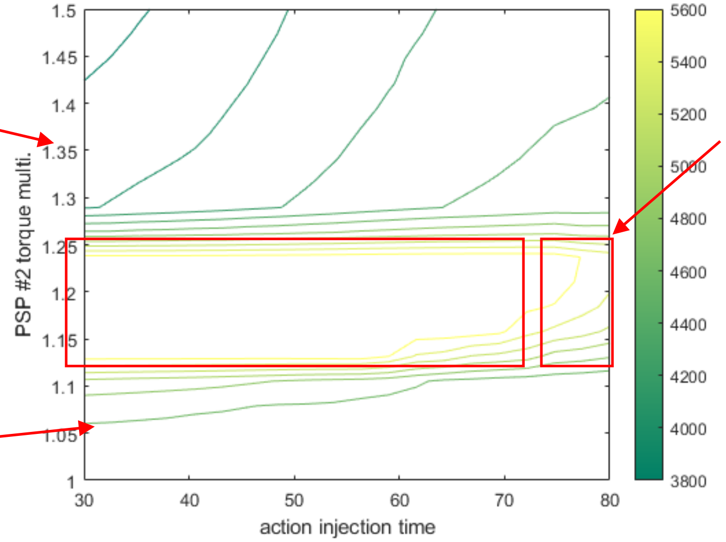
1845

2170

less preferred due to high torques

Most preferrable region

less preferred due to large power variations



less preferred due to high T_{PFCL}

Testing Summary #1

- Integral NAMAC system assessment with DT training databases
  - NAMAC performance is greatly improved
  - Errors may not be additive:

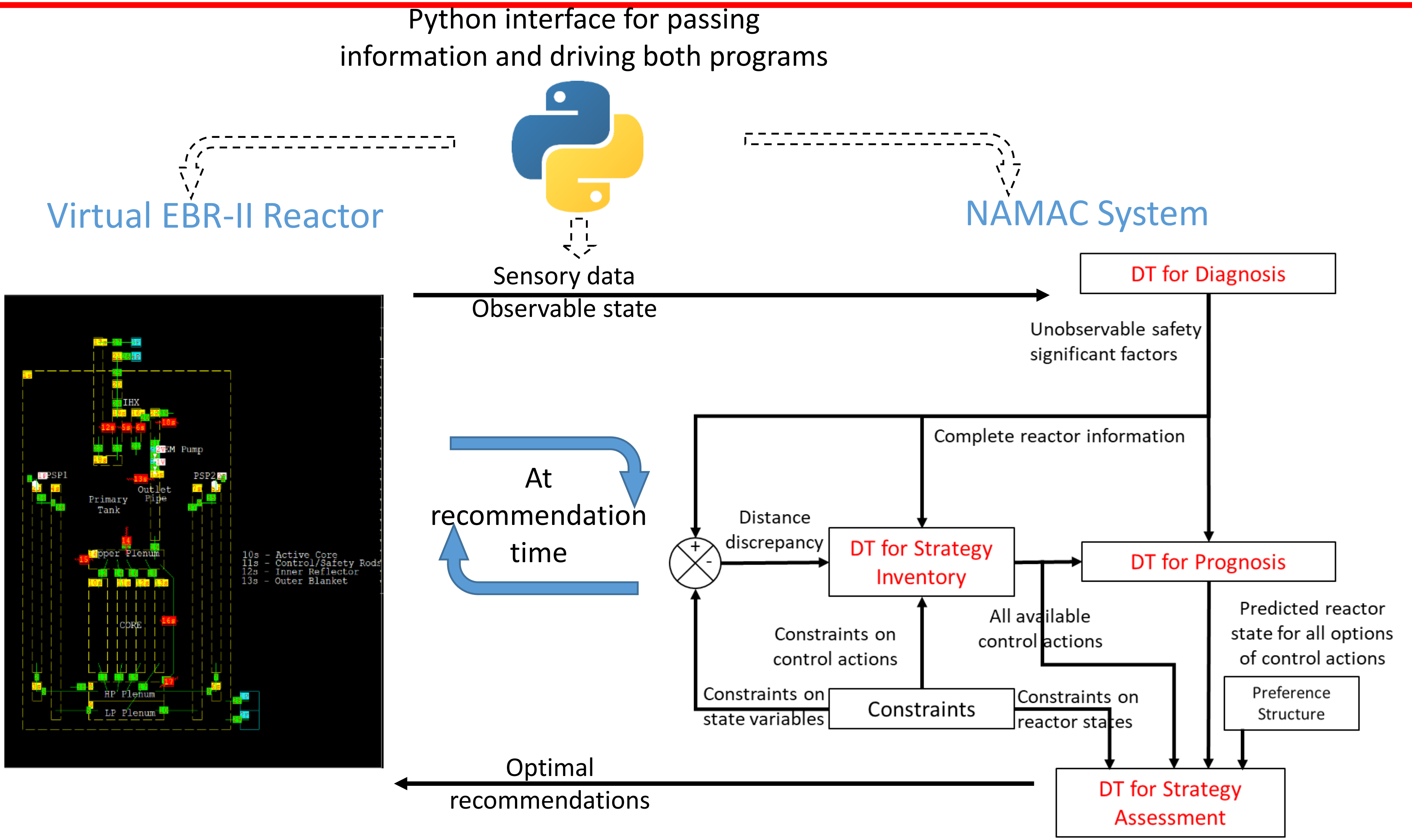
*False positive: predicted safe (1) when unsafe (0);
*False negative: predicted unsafe (0) when safe (1);

			Test Uncertainty (1-5000)						
			Diagnosis		**Strategy Planning**		**Prognosis**		**Strategy Assessment**
Diagnosis			RMSE(T_{PFCL}) 0.2(℃)	RMSE(T_{CL}) 0.3(℃)					
Strategy Inventory			PT1 curve 5.89 (N·m)	PT2 curve 6.53 (N·m)	PT1 curve 5.89 (N·m)	PT1 curve 6.53 (N·m)			
Prognosis			RMSE(T_{PFCL}) 2.41 (℃)	RMSE($\dot{q}_{core}$) 0.97 (MW)	RMSE(T_{PFCL}) 2.41 (℃)	RMSE($\dot{q}_{core}$) 0.97 (MW/s)	RMSE(T_{PFCL}) 1.74 (℃)	RMSE($\dot{q}_{core}$) 0.69 (MW/s)	
Strategy Assessment	**FP**	sep. crt.	0.1%	0.2%	0.1%	0.2%	0.9%	0.8%	0.0%
		cmb. crt.	0.2%		0.2%		0.8%		
	FN	sep. crt.	0.1%	1.7%	0.1%	1.7%	0.0%	0.2%	0.0%
		cmb. crt.	1.7%		1.7%		0.2%		

Case Study

- Knowledge base construction
- NAMAC operation
- Training and testing for DTs and NAMAC
- NAMAC assessment

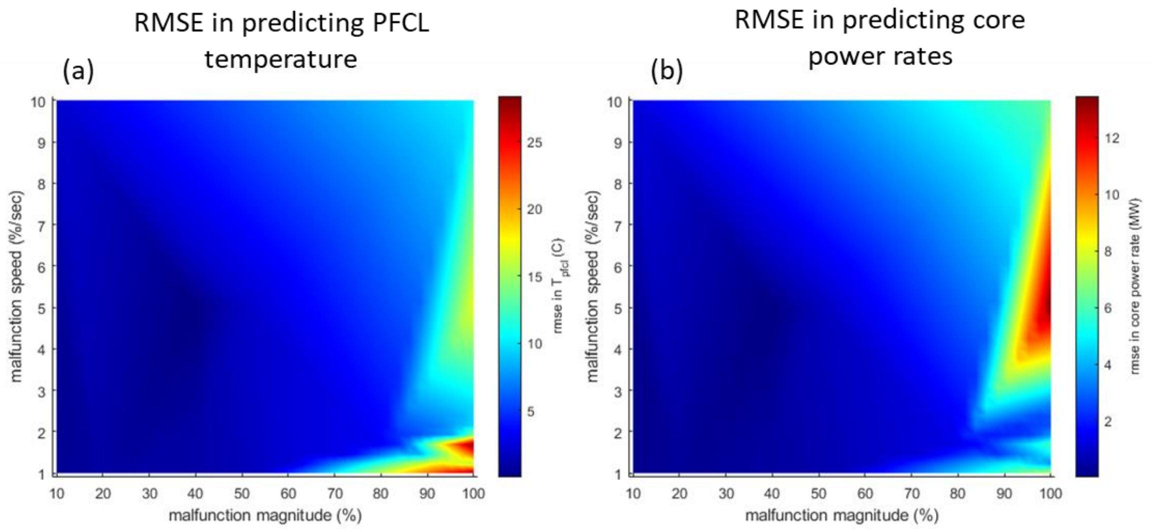
NAMAC Assessment

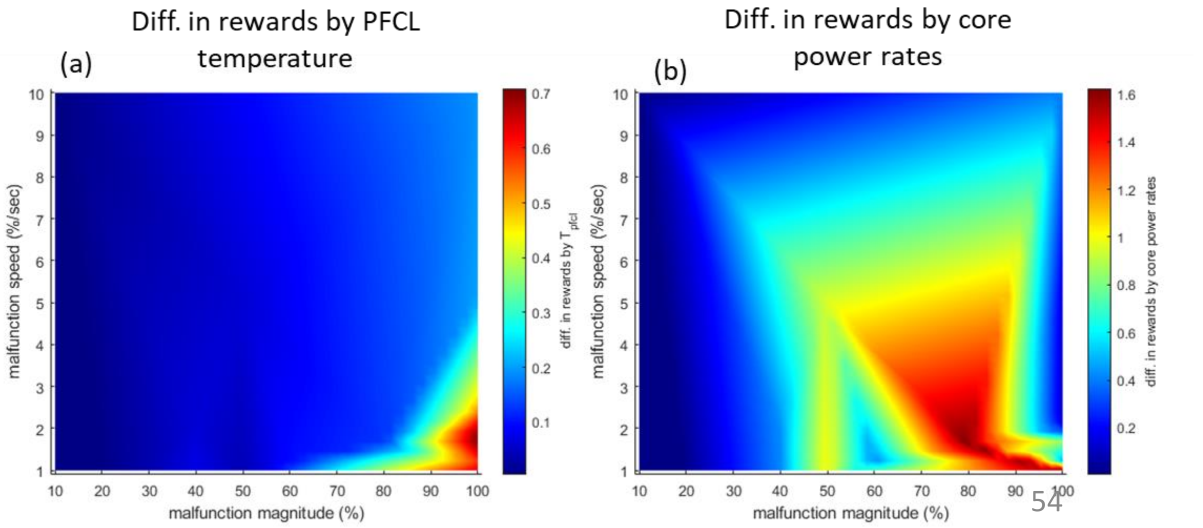


NAMAC Assessment

- NAMAC system is assessed with 46 instances of PSP#1 malfunctions
  - The speed of torque reductions in percentage/s as malfunction speed
  - The percentage of torque losses over the nominal torque in percentage as malfunction magnitude

- NAMAC error grows when the system is applied outside the training domains
  - NAMAC prediction errors in predicting the recommended transient of PFCL temperature and core power rates: 96% cases satisfy the requirements
  - NAMAC decision-making errors in determining rewards of recommended mitigation strategies: 67% cases satisfy the requirements (greatly reduced by relaxing the variation limits





Conclusion and Path Forward

- A NAMAC and corresponding DTs have been implemented for preventing fuel temperature from reaching safety limits during partial LOFA scenarios.
  - NAMAC is trained on an EBR-II plant simulator during the partial Loss of Flow Accident (LOFA) scenario
  - A reasonable plan of action is made with small confusion rates, which is consistent with historical norms for manual operations and control

- Assessments are performed for DTs and NAMAC system
  - A list of sources of uncertainty is suggested for NAMAC system, diagnosis and prognosis DTs.
  - Numerical results show both diagnosis and prognosis errors are acceptable with appropriate selections of hyper-parameters, issue space, input features, etc.
  - Numerical results show that DTs and NAMAC errors are growing when the testing scenarios are outside the training scenarios.

- Path Forward
  - Improved operational workflow with discrepancy checker for real-time fault detection and trustworthiness assessment
  - NAMAC demonstration in a more complex scenario (component aging, sequence actions, etc.)

Acknowledgment

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  - Jeff Lane, John Link (Zachry)
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- GOTHIC license is provided by Zachry Nuclear Engineering, Inc. GOTHIC incorporates technology developed for the electric power industry under the sponsorship of EPRI, the Electric Power Research Institute.

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Coverage Assessment

- "Coverage" between training and testing episodes is quantified according to mutual information of
  - The probability distribution function (PDF) of fuel centerline temperature from training episodes
  - … from testing episodes

- Fit the distribution of real fuel centerline temperature to Kernel Density Estimation (multi-variant distributions)

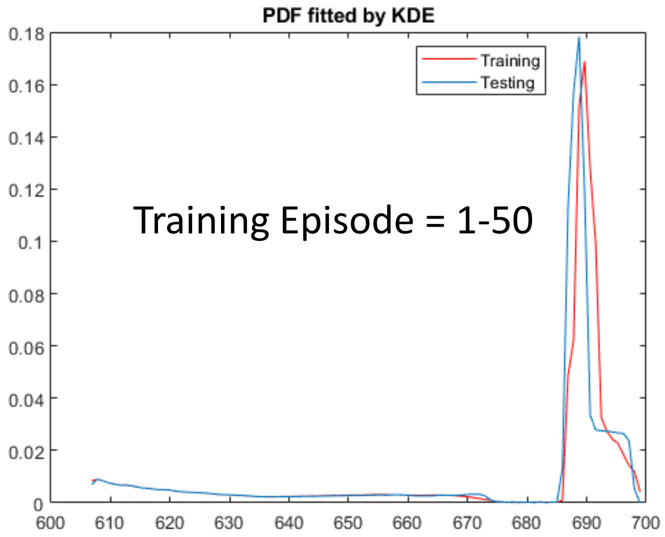
$$PDF(P_i) = \frac{1}{n}\sum_{i=1}^{n} K_H(x - y_i)$$

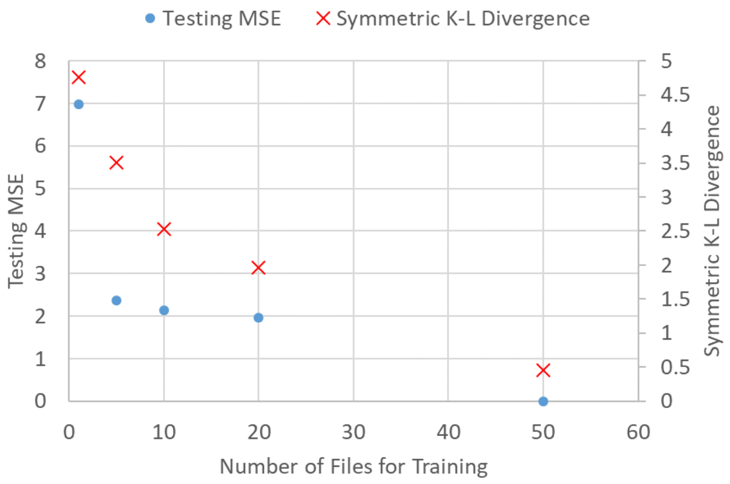
  - y_i are random samples drawn from P_i , x is the multi-dimensional random vectors with density function P_i

- K-L Divergence metrics for measuring the mutual information of two distributions

$$D_{KL}(P, D) = \sum_i P(i)\log\left(\frac{P(i)}{D(i)}\right) + D(i)\log\left(\frac{D(i)}{P(i)}\right)$$

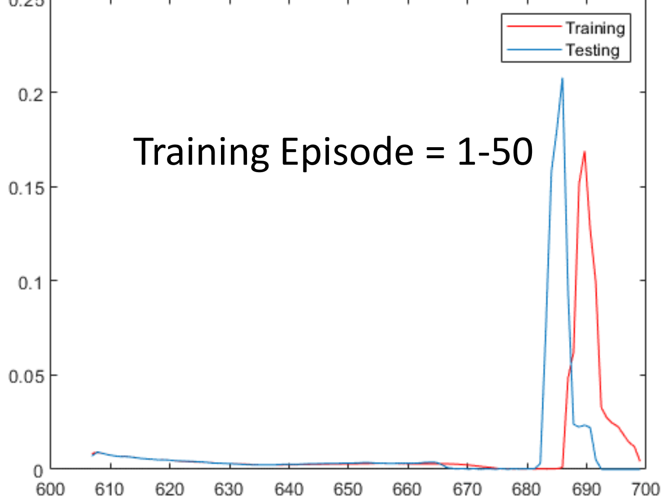
Testing Episode = 50

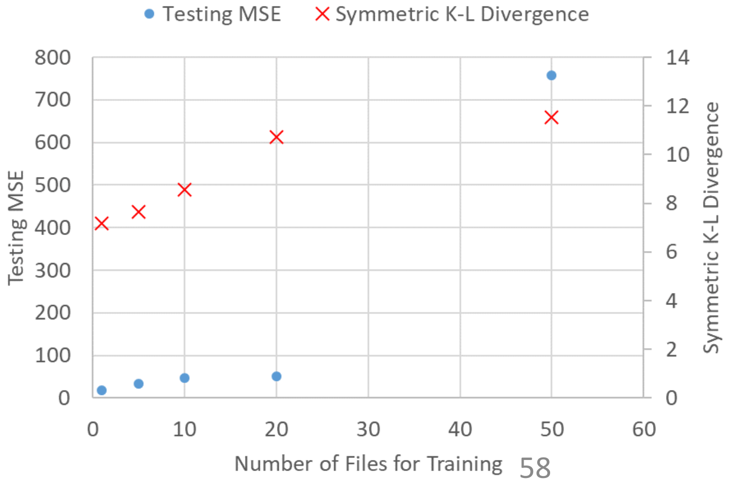




As training and testing data being more similar (episode 50 is more similar to episode 1 than episode 100), performance of data surrogate becomes better.

Testing Episode = 100





Coverage Assessment

- “Coverage” is defined qualitatively according to the interpolation and extrapolation conditions in global and local spaces
  - Global Extrapolation means the testing issue space is outside the training space
  - Local Extrapolation means the cluster of data points in testing databases falls outside the cluster of training databases – “visually not covered”
  - Preliminary results shows that machine learning trained by GELI and GILI conditions have better performance than GELE

Case	Coverage condition	Training error	Testing error
Case 1	GELE	0.01	43.03
Case 2	GELI	0.01	0.08
Case 3	GILI	0.10	0.08

Comparison of GELE, GELI, and GILI visualized by t-sne