Applications of Data-Driven Methods and Artificial Intelligence in Nuclear Reactor Engineering

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The Vietnam Conference on Nuclear Science and Technology – VINANST-14

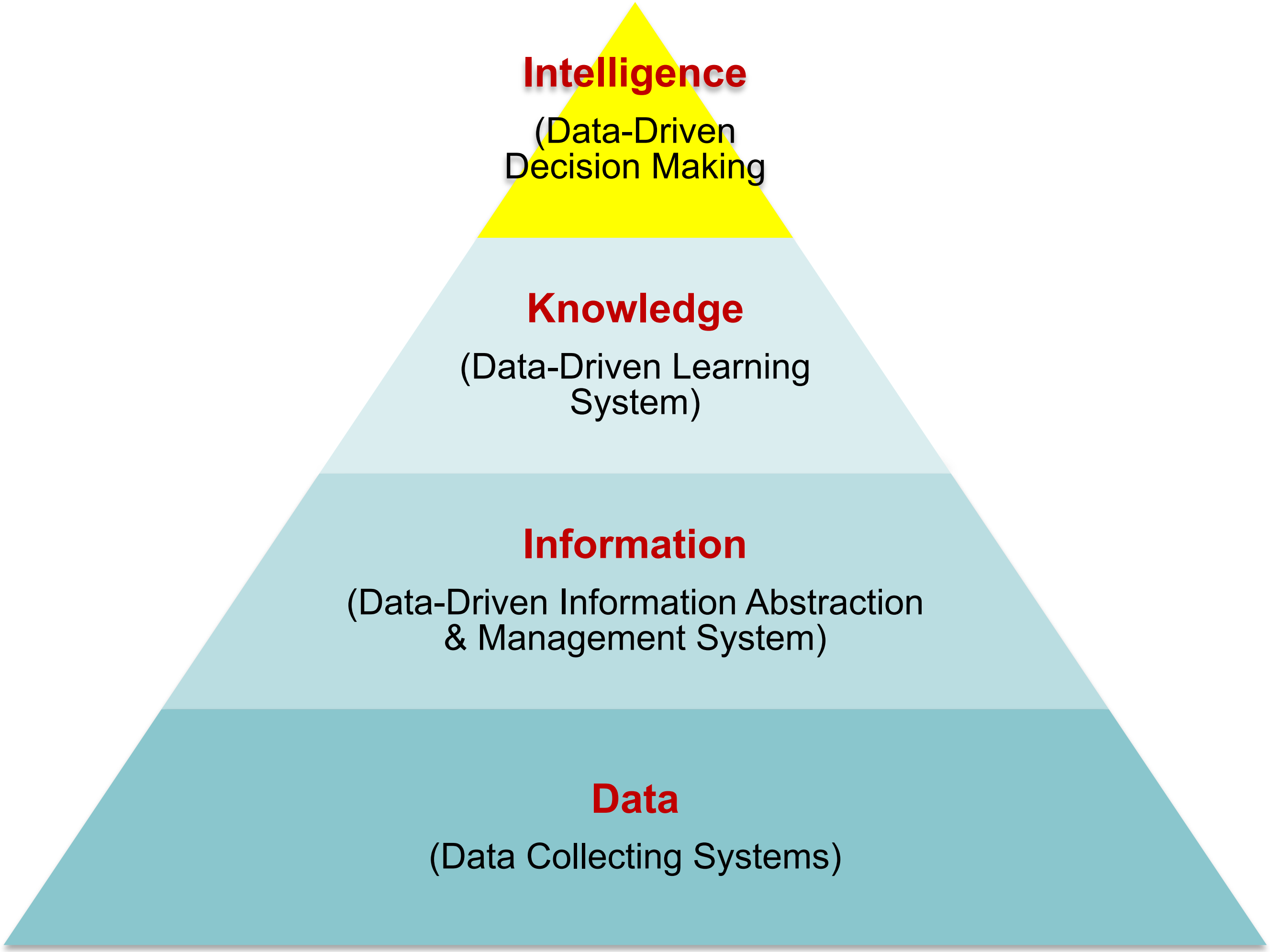
Da Lat, Lam Dong, December 9-10, 2021

Contents

Introduction

- Artificial Intelligence (AI)
  - Long history; broad range of methods and areas of application
  - Notable successes of machine learning (ML) (deep learning)
- AI in engineering research and technology applications
  - Fault detection, predictive maintenance, autonomous control
- Rapidly growing interest in applications of AI/ML/DA in diverse, complex tasks in nuclear reactor engineering
  - From LWRs to advanced reactors (SMR, microreactors) to NHES (Nuclear Hybrid Energy System)
  - Construction, O&M, fuel management
  - Research (e.g., multiscale bridging in T-H, multiphysics; core optimization)
  - …

Data-Driven Hierarchy



Intelligence

(Data-Driven
Decision Making

Knowledge

(Data-Driven Learning
System)

Information

(Data-Driven Information Abstraction
& Management System)

Data

(Data Collecting Systems)

Adopted after Ackoff (1988) and Rowley (2006).

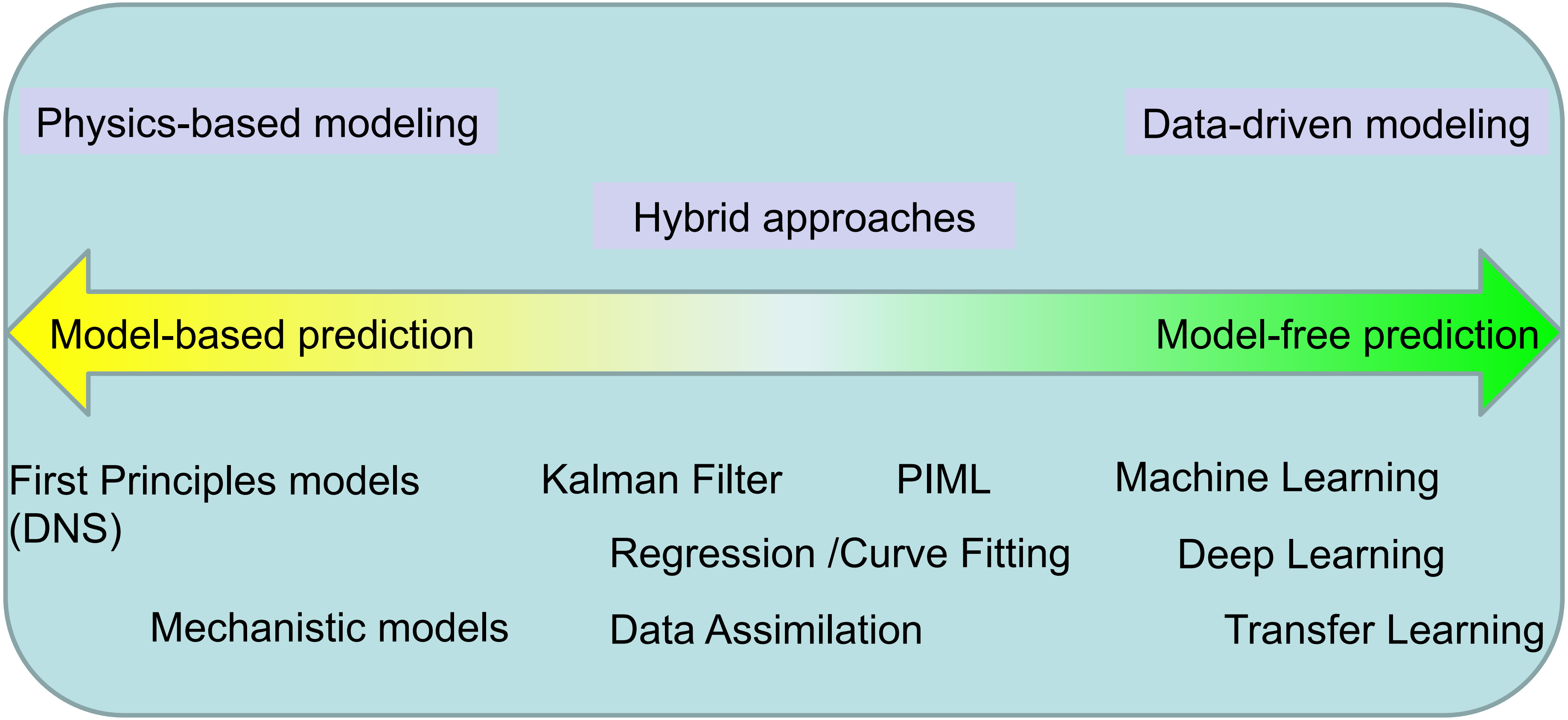
Data-Driven Techniques

- Data science (aka data analytics, predictive analytics, statistical learning, “big data” techniques, machine learning) are all built upon data mining algorithms that are recognized and executed by computer.

- The objective is to extract knowledge and insight from massive data and information automatically.

- Advanced data science techniques (e.g., signature identification, feature selection, clustering analysis, dimensionality reduction) have been found instrumental, capable, and effective in extracting patterns and knowledge from large amounts of data of complex systems

Complex Systems Modeling Approaches



Physics-based modeling

Data-driven modeling

Hybrid approaches

Model-based prediction

Model-free prediction

First Principles models (DNS)

Mechanistic models

Kalman Filter

PIML

Regression /Curve Fitting

Data Assimilation

Machine Learning

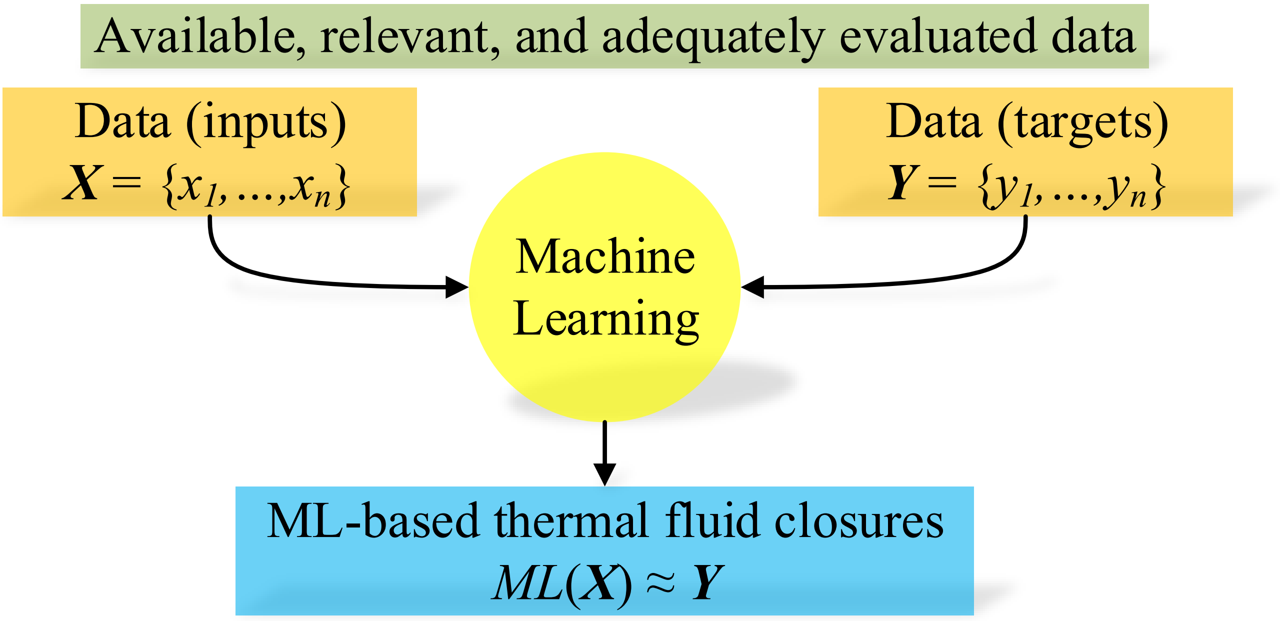
Deep Learning

Transfer Learning

DNS: Direct Numerical Simulation
PIML: Physics Informed (Constrained) Machine Learning

Technical background

- Machine learning
  - Regression



Available, relevant, and adequately evaluated data

Data (inputs)
$\boldsymbol{X} = \{x_1, \ldots, x_n\}$

Data (targets)
$\boldsymbol{Y} = \{y_1, \ldots, y_n\}$

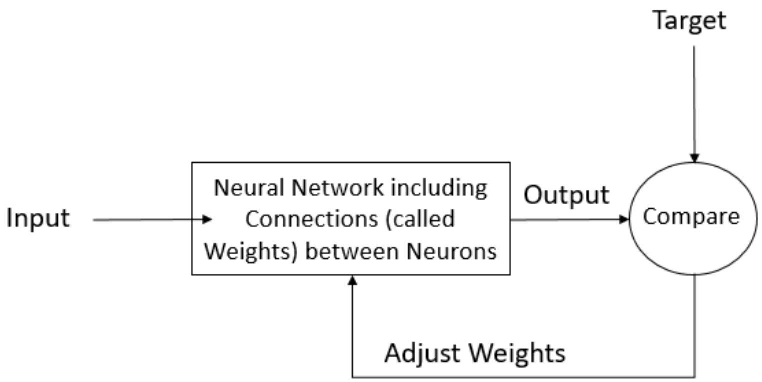
Machine Learning

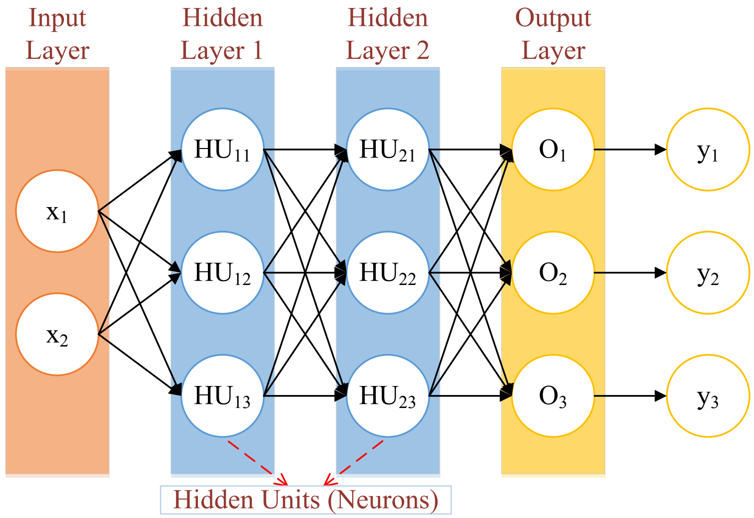
ML-based thermal fluid closures
$ML(\boldsymbol{X}) \approx \boldsymbol{Y}$

Deep Neural Networks (DNN)

Deep neural networks exhibit good properties

- Expressiveness
  - DNN with proper weights set up can approximate any continuous functions
- Optimization
  - DNN can be optimized and converges with stochastic gradient descent (SGD)
  - Hyperparameters has strong influence on DNN performance, requires trial-and-error along the training process
- Generalization
  - DNN usually has good performance in predicting the case it has not been trained on





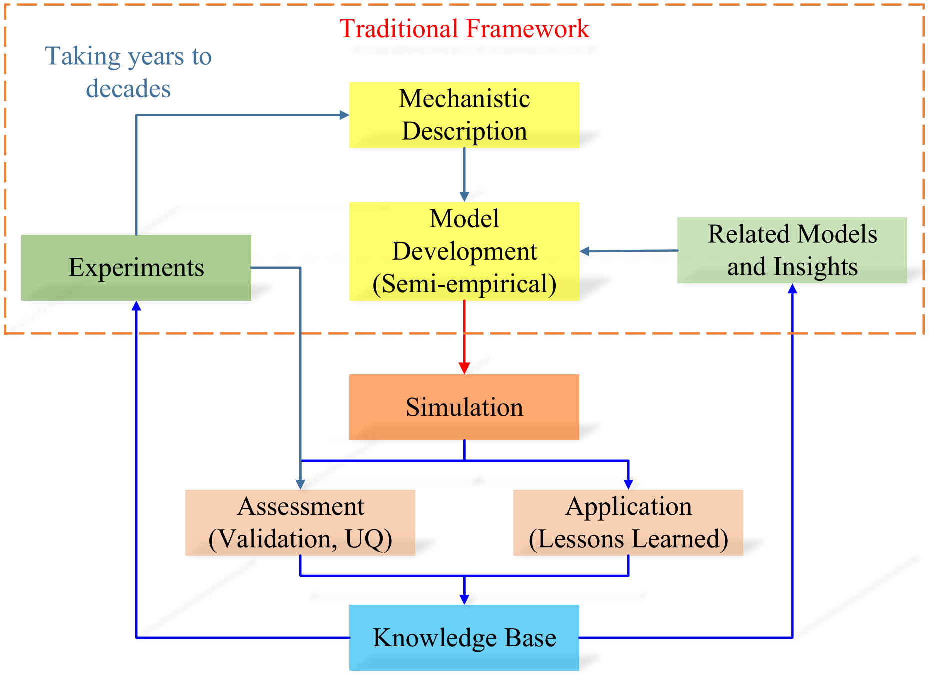
Needs and Opportunities

- Sub-grid-scale (SGS) physics models (or so-called closure relations) determine the accuracy of thermal-fluid modeling, and they are essential for simulation codes.

- "Big" data in thermal-hydraulics become available with advanced thermal and flow diagnostic methods such as infrared thermometry and PIV (Particle image velocimetry) techniques, and high-fidelity simulation (LES, DNS, ITM)

- Deep learning (DL) is a universal approximator [Hinton, 1989],
  - Capturing multi-scale, multi-physics processes
  - Discovering the underlying correlations behind the data to achieve the cost-effective closure development for
    - new geometries, new coolants or system conditions (new designs).

Mechanistic vs. Data-Driven Modeling Framework



Traditional Framework

Taking years to decades

Mechanistic Description

Model Development (Semi-empirical)

Related Models and Insights

Experiments

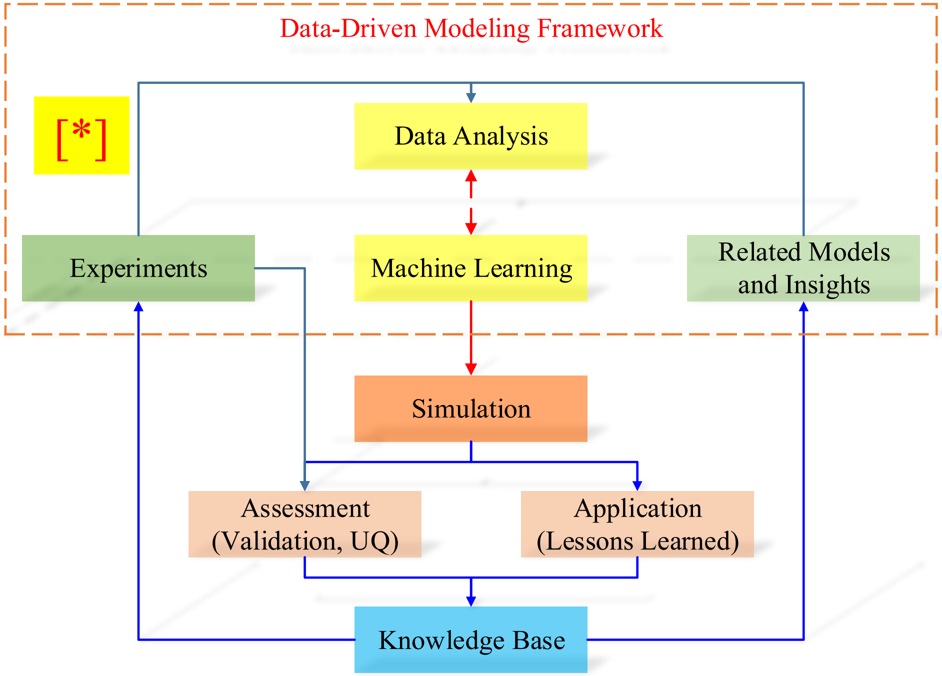
Simulation

Assessment (Validation, UQ)

Application (Lessons Learned)

Knowledge Base

Theory-based Modeling Framework



Data-Driven Modeling Framework

[*]

Data Analysis

Experiments

Machine Learning

Related Models and Insights

Simulation

Assessment (Validation, UQ)

Application (Lessons Learned)

Knowledge Base

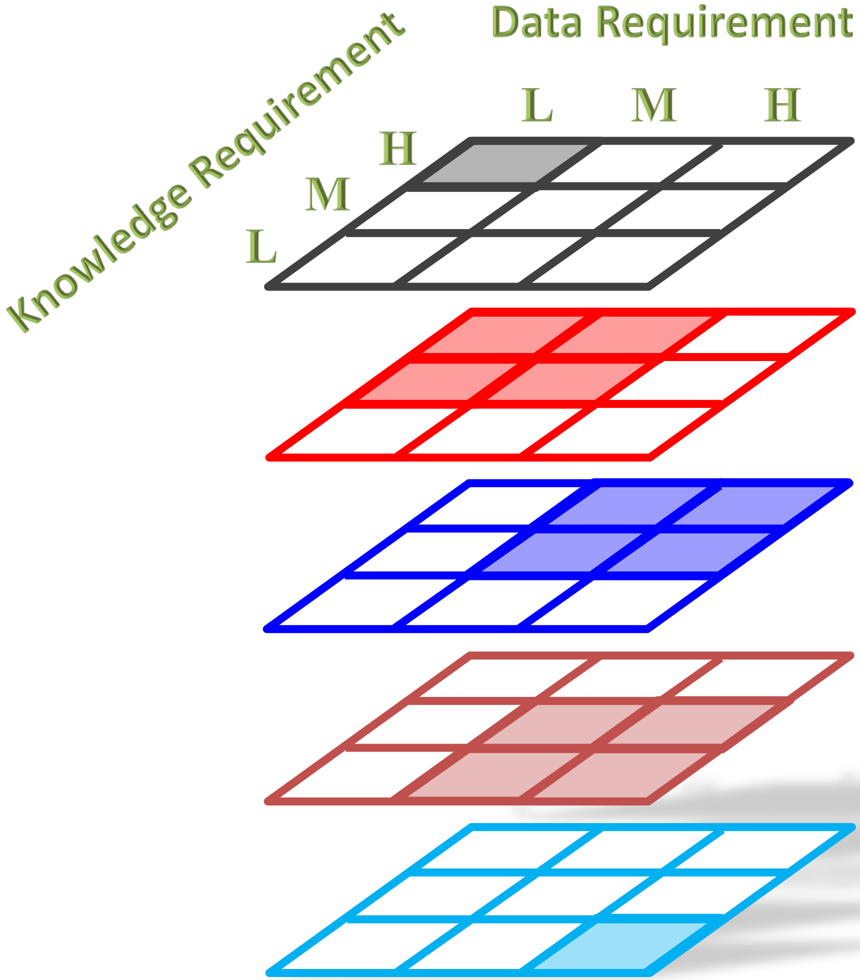
Data-Driven Modeling Framework

[*] -potential to shorten the time and efforts required for development and assessment of predictive capability

Lessons learned

- Deep learning can assist in development of data-driven nuclear thermal-hydraulics simulation.
  - Allowing cost-effective model developments.
  - Using non-parametric models to capture underlying correlations behind a substantial amount of data.
  - Making use of information content of large datasets generated in advanced experiments and numerical simulations.
- Collection, qualification, and management of data are instrumental for the “Big Data” to become useful in data-driven modeling (DDM)
- The growing interest and potential application of DDM creates a new domain in V&V of scientific and technical computing, namely of Verification and Validation of codes that involve machine-learning-based data-driven models.
- No “one shoe fits all”

Physics-informed data-driven frameworks for model development



Type-I (physics-separated) ML

Type-II (physics-evaluated) ML

Type-III (physics-integrated) ML

Type-IV (physics-recovered) ML

Type-V (physics-discovered) ML

Classification of machine learning frameworks for data-driven thermal fluid models

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International Journal of Thermal Sciences 135 (2019) 559–579

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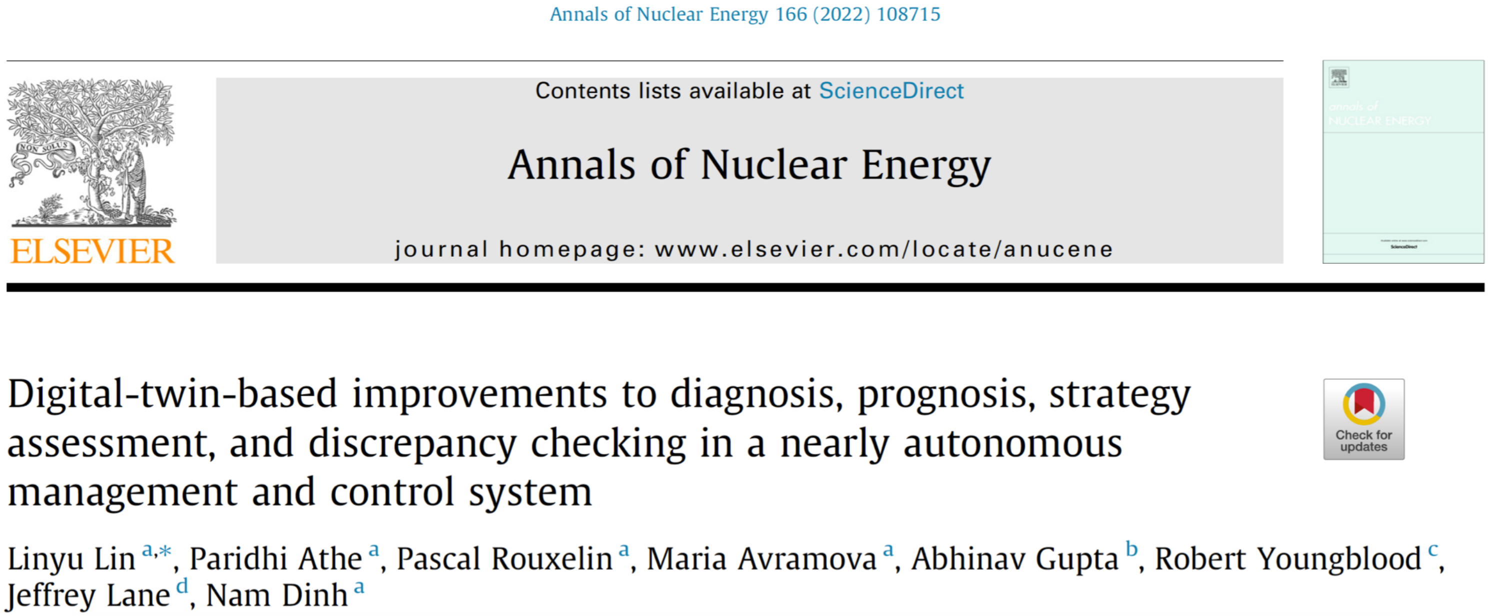
Development of a Nearly Autonomous Management and Control System (NAMAC) in Advanced Reactors

A comprehensive, data/knowledge-driven, AI-based control system for credible, consistent management of plant operations to improve safety and performance in advanced reactors



Annals of Nuclear Energy 166 (2022) 108715

Contents lists available at ScienceDirect

Annals of Nuclear Energy

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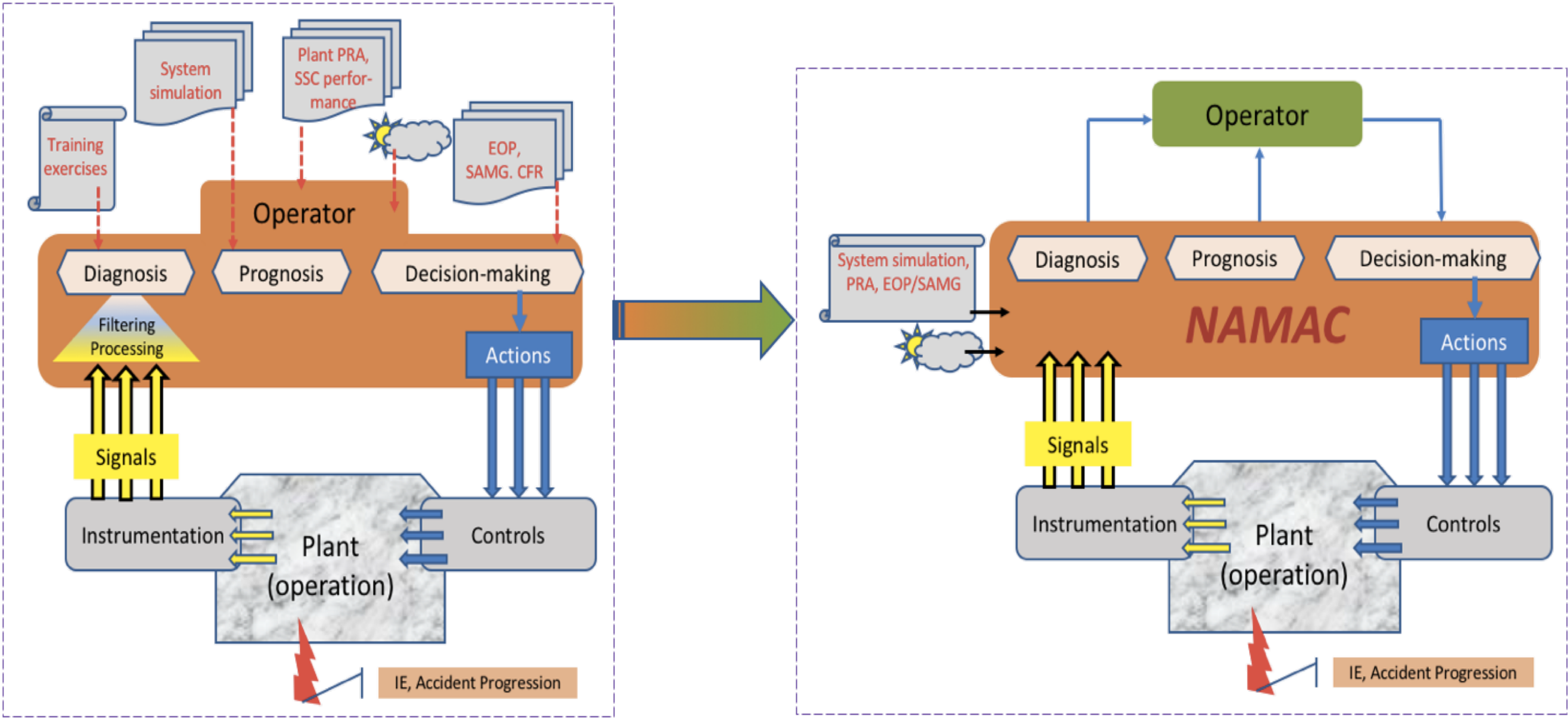
Digital-twin-based improvements to diagnosis, prognosis, strategy assessment, and discrepancy checking in a nearly autonomous management and control system

Linyu Lin [a,*], Paridhi Athe [a], Pascal Rouxelin [a], Maria Avramova [a], Abhinav Gupta [b], Robert Youngblood [c], Jeffrey Lane [d], Nam Dinh [a]

Operator-Centric to NAMAC-Enabled Control Architecture



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

NAMAC Technological Basis

- Comprehensive scenario-based model of plant.
- Digital-twin technology to effectively compute plant behaviors and keep track plant operational history while continuously assimilating current-plant-state data in ongoing simulation of plant behavior.
- Advanced algorithms in machine learning for effective search and optimization.

NAMAC Technology Impact

- NAMAC diagnoses the plant state, projects the effects of actions and uncertainties into the future behavior and determine the best strategy to cope any situation with respect to the plant safety, performance, and cost.

- NAMAC enables a smaller operational staff to manage the plant better than any human(s) currently can, assisted only by instrumentation, operator training, and procedures.

- NAMAC system implementation has potential to affect the plant risk profile (with implications for system design, SSC and EPZ) through reducing operator errors, and promoting dynamic and effective management of abnormal transient and accident scenarios.

Concluding Remarks

- AI and "Big Data" bring new challenges:
  - New risk profile, new threats and vulnerability
  - "AI Safety", reliability, human-AI-system interactions
  - Machine learning trustworthiness (V&V and UQ)
  - Data sharing, collaboration vs. competition
  - Regulation
- Education and Training:
  - Meeting industry projected needs and enabling trends
- R&D: demand on quality of data and data generation
  - "Data-friendly" nuclear engineering methods and tools
  - From getting on a ML/AI ride; to return to "driver's seat"

Thank you!

Wishing you a successful VINANST-14 Conference!