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Data-driven Quasi-static Surrogate Models for Nuclear-powered Integrated Energy Systems

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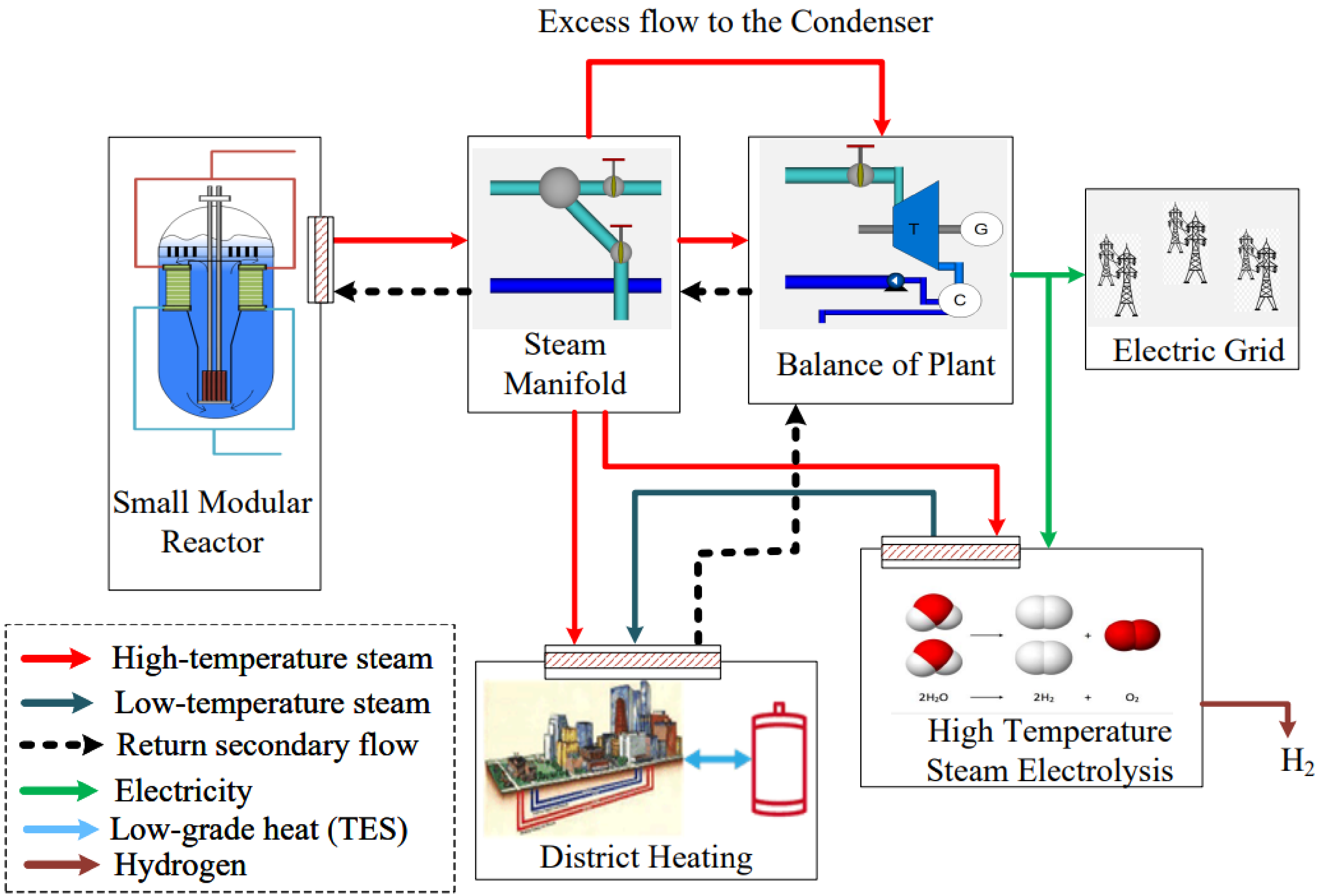
Outline

- Introduction
- Nuclear-powered Integrated Energy System (IES)
- Surrogate Model Development
- Results and Discussion (Training, Evaluation, and Validation)
- Conclusion and Future Work

Introduction

- The urgency to mitigate carbon emissions across the industrial and residential sectors has underscored the significance of nuclear-powered integrated energy systems (IES).
- High-fidelity physics-based models of nuclear-powered IES have been developed to understand and represent the dynamics and interactions among various components of the IES
- The physics-based model, however, while comprehensive, are burdened by their complexity and computational intensity.
- The development of a surrogate model for IES represents a pivotal step in bridging the gap between the intricacies of physics-based models and the necessity for quick and accurate predictions in real-world applications.

Nuclear-powered Integrated Energy System (IES)



- SMR rated capacity = 60 MWe (200 MWth)
- Rated steam production rate = 84 kg/s
- Rated steam temperature = 310°C
- HTSE rated capacity = 53.3 MWe
- Rated hydrogen production rate = 0.4 kg/s
- Rate capacity of steam turbine = 60 MWe
- District heating rated temperatures (supply= 90°C, return= 40°C)

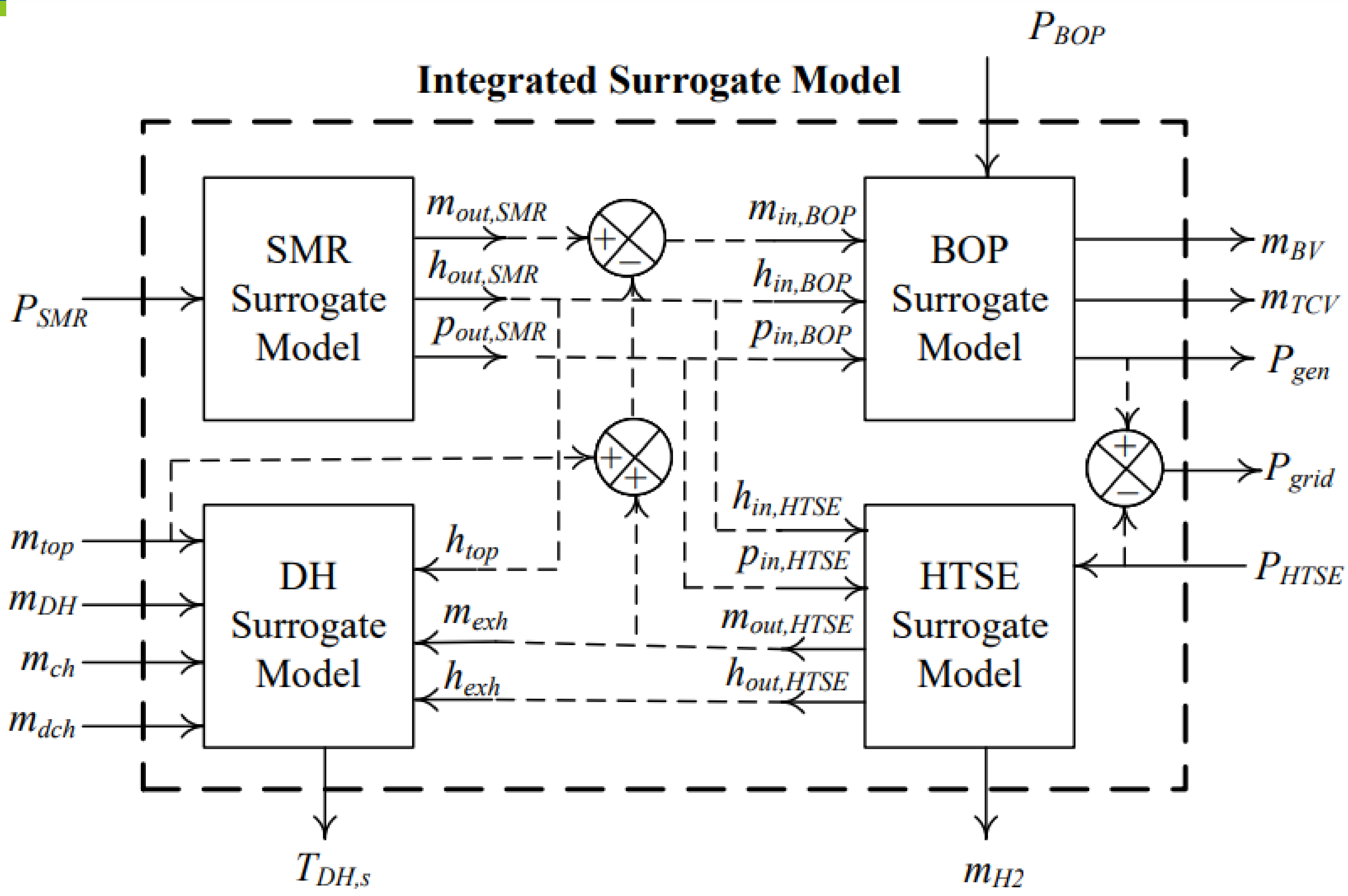
Surrogate (or Reduced Order) Model

- Surrogate models are simplified and approximate versions of more complex models.
- They are used when the original model is computationally expensive or time-consuming to evaluate.
- Types of surrogate (or reduced order) models:
  - **Parametric models**:
    - It is based on mathematical equations that describe the behavior of the system using reduced number of parameters.
  - **Data-driven models**:
    - These models are developed using data collected from the original system.
  - **Hybrid models:**
    - In some cases, both parametric and data-driven approaches can be combined to create hybrid models that take advantage of the strengths of each approach.

Data-driven Surrogate Model Development

1. Identifying input and output variables
2. Data Generation
3. Data Pre-processing
4. Selecting a modeling technique
5. Training and testing of the model

Data-driven IES Surrogate Model



- Training data are generated for individual components such as SMR, HTSE, DH, and BOP using Dymola-Python interface.
- The individual surrogate model and sub-models are trained using the generated data.
- The trained models are later combined to form a complete IES surrogate model.

Training of Multi-layer Perceptron (MLP)-based Surrogate Models

- Individual MLP-based surrogate model used for each IES component.
- After data normalization, the random partitioning of the original dataset is done by splitting training and test set at a ratio of 80:20.
- Optimal set of hyperparameters are obtained by searching from the hyperparameter distribution using Randomized Search Technique.

TABLE I
HYPERPARAMETER DISTRIBUTION FOR RANDOMIZED SEARCH.

Hyperparameter	**Values**
Hidden Layer Sizes	(20,), (50,), (100,), (50, 20), (100, 50, 20), (100, 50, 20, 20), (100, 50, 20, 10)
Activation Function	Identity, Sigmoid, Tanh, ReLU
Optimizer	SGD, Adam, L-BFGS

Evaluation Results of the Isolated Surrogate Models

TABLE II

ISOLATED SURROGATE MODELS EVALUATION RESULTS WITH BEST HYPERPARAMETERS.

Surrogate Model	Output Variable	Hidden Layer Size	Activation	Optimizer	RMSE	R-squared Score
SMR	$m_{out,SMR}$	(100, 50, 20, 10)	Identity	L-BFGS	0.00002	0.99999
	$h_{out,SMR}$	(100,)	Sigmoid	L-BFGS	0.06911	0.99999
	$p_{out,SMR}$	(100,)	Tanh	L-BFGS	0.00229	0.99999
HTSE	$m_{out,HTSE}$	(100, 50, 20, 20)	Tanh	L-BFGS	0.11324	0.99936
	$h_{out,HTSE}$	(100,)	Sigmoid	L-BFGS	9.48567	0.99898
	m_{H_2}	(50,)	Tanh	L-BFGS	0.00275	0.99829
BOP	P_{gen}	(100, 50, 20)	ReLU	L-BFGS	0.04105	0.99999
	m_{TCV}	(50,)	Sigmoid	L-BFGS	0.05367	0.99999
	m_{BV}	(50, 20)	ReLU	L-BFGS	0.03424	0.99999
DH	T_s^{DH}	(50, 20)	Sigmoid	Adam	0.09521	0.99949

Conclusion and Future Work

- In this paper, a simplified, data-driven surrogate models for a nuclear-power IES was developed by combining individual MLP-based surrogate models representing key components: SMR, HTSE, BOP, and DH.
- The models demonstrated the ability to capture the complexities of nuclear-powered IES components, offering insights into their behaviors without the computational overhead associated with traditional physics-based simulations.
- The alignment between predicted and actual values underscores the robustness and applicability of the approach, paving the way for its practical deployment in optimizing and managing energy systems.
- As the future work, the developed surrogate model will be integrated with the optimization tools to expand its capabilities. This future work aims to explore its potential in forecasting additional variables beyond its current scope.

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